CALIBRATION OF ENERGYPLUS HVAC MODELS USING OPTIMIZATION

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ABSTRACT

Calibration of building energy models is rarely performed in practice given the amount of time, information and expert knowledge required to perform this task. A calibrated simulation is a very useful tool to perform detailed energy analysis of buildings, evaluate different energy conservation measures, and to assess energy system performance. This paper proposes a methodology to modify a baseline energy model for calibration purposes. Using synthetic data and appropriate control volume, secondary level HVAC components model parameters are estimated using a constrained numerical optimization algorithm. Tests carried out in this paper indicated that certain parameters might not be of significant importance to be accounted for in the estimation process. The proposed methodology has the potential of supporting quick calibration of energy model sub-domains, which could lead to an improved global calibration and better prediction of the performance of HVAC systems.

INTRODUCTION

Building energy models (BEM) have reached an extremely high level of detail translating to thousands of inputs in simulation software. BEM are used mainly for code compliance in the design process to evaluate if the predicted building performance achieves a certain energy consumption requirement while maintaining indoor air quality and thermal comfort (ASHRAE 90.1, CNÉB 2011). The idea of using the same tools during the operation of the building is slowly gaining acceptance; BEM are useful tools to evaluate the performance of existing buildings as well. A calibrated BEM of an existing building can lead to more detailed and precise analysis of the thermal and electrical load profiles, end-uses repartitions, retrofits potential savings and return on investment. A calibrated BEM can also be used for continuous commissioning, fault detection, optimal control sequences, etc.

However, preparing a BEM for an existing building requires additional efforts and is quite challenging. The model development process is different since the information needed to specify the different model inputs is not easily accessible or non existent. The performance of the heating, ventilation and air conditioning (HVAC) equipment might vary considerably from the manufacturer's data, in response to the real zone loads and actual schedules. The challenge lies in ensuring that the BEM output matches the measured data and correctly represents the behaviour and performance of the building.

To assess the quality of the BEM of an existing building, different criteria are proposed by ASHRAE Guideline 14-2002 (ASHRAE 2002) in order to draw a line between an acceptable model and an unacceptable one. The first iteration of the BEM of an existing building has a good chance of falling short of the requirements outlined in the guideline. Model inputs then have to be adjusted to match the utility bills to reduce the discrepancies between simulated and measured data. This task is usually performed iteratively by an expert resulting in substantial engineering time investment that is rarely economically justifiable.

Direct digital control (DDC) of current HVAC systems provides an interesting source of information for many practical and research applications. It provides insights regarding the actual performance and operation of the building. However, there are still few applications where this source of data is used to assist the calibration problem.

In this paper a new calibration approach of building energy models that could further enhance the resolution of the calibration problem at the system level is proposed. This paper presents the proposed methodology, the EnergyPlus component models used, the input file modification strategy and a trial application with synthetic sensor data over selected component models and component models groups for a typical office building.

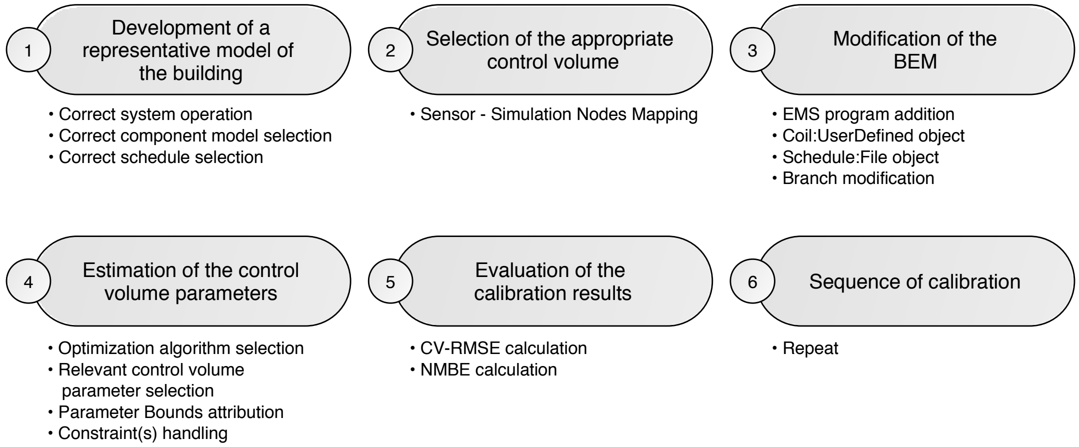

Figure 1
Different steps of the proposed calibration methodology

METHODOLOGY

The proposed methodology relies on using only part of the simulation model for calibration. The objective is to sub-divide the over parametrized global calibration problem into multiple, smaller, more manageable endeavours. The problem of identification consists of first choosing a model and then determining the coefficients of the models by fitting the data (Rabl 1988). In this paper, the models are taken as the EnergyPlus component models. Figure 1 illustrates the different steps proposed for the calibration process.

1 – Development of a representative model of the building

The first step is the development of a model that adequately represents the characteristics of the existing building. Building geometry, architectural elements, surfaces boundary conditions and type of constructions are defined accordingly. The type of HVAC systems and component models correctly representing the expected performance and operation of the installed HVAC systems is needed (e.g. correct coil model, economiser controls, etc.)

2 –Selection of the appropriate control volume

Using the available DDC sensors, a control volume over which the calibration will be performed must be selected. In this context, a control volume is defined as one or more equipement models. The inputs of the control volume are state variables and component models parameters. The output of the control volume are also state variables. Since controls and monitoring of HVAC systems is widely variable from one installation to the next, identification of the available measurement points and control volumes is made by the building energy modeler. Automatisation of the corresponding DDC sensors to the simulation nodes (i.e. so called "Mapping") is out of the scope of this article.

3 – Modification of the BEM

The developed model in step 1 is then modified to calibrate the control volume defined in step 2 using the measured DDC sensors trends directly into the simulation engine (i.e. EnergyPlus). The strategy used to perform this task is described in the section entitled EnergyPlus input data of this paper.

4 – Estimation of the control volume parameters

Using the previously defined control volume in step 2, parameters influencing the control volume output state variables are expertly selected. Associated parameter bounds are attributed to each selected control volume parameter to limit the parameter space of the optimization problem. As the output of building simulation software contains discontinuities (Wetter and Polak 2004), specific numerical optimization techniques are to be employed to avoid reaching local minima in the objective function minimization. The objective function used to estimate the control volume parameters is defined in Equation (1).

$$\tilde{f}\left(x,\mu\right) \triangleq f\left(x\right) + \mu \sum_{i=1}^{n} \max\left(0, g^{i}\left(x\right)\right)^{2} \qquad (1)$$

The objective function presents two terms. The first term is the least square estimator (LSE) defined in Equation (2) and is essentially a metric of distance between the observed (y_i, i.e. synthetic sensor data) and the iterated simulation generated data ($\hat{y}_i$), defined as a function of the component models parameters (x).

$$f(x) = LSE = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (2)$$

The use of this estimator assumes the following characteristics (Reddy 2011) :

- Errors should have zero mean;
- Errors should be normally distributed;
- Errors should have constant variance;
- Errors should not be serially correlated;
- Errors should be uncorrelated with the regressors;
- Regressors should not have any measurement error;
- Regressor variables should be independent of each other.

The second term is a regularization term used to help the optimization of the ill-posed problem (Larochelle Martin et al. 2015). The regularization coefficient (μ) is specific to each optimisation problem and was adjusted so that the first term (Equation (2)) equals to the second terms for the first objective function evaluation. The second element of the second term of Equation (1) is the constraint on the coefficients of the fan part load factor polynomial curve as defined in Equation (3).

$$c_1 + c_2 + c_3 + c_4 + c_5 = 1 \qquad (3)$$

This helps the estimation process by assuming a normalized fan part load factor curve (i.e. the curves passes through the nominal point of operation (maximum power and flow), which is not always the case when identifying the coefficients using tabulated manufacturers' data.

5 – Evaluation of the calibration results

The resulting simulated control volume outputs are then compared with the original synthetic sensor data using the Guideline 14-2002 criteria as defined by Equations (4) and (5). It is recommended that the coefficient of variation of the root mean square error (CV-RMSE) be less than 10 % for monthly data or less than 30 % for hourly data. The net mean bias error (NMBE) should be less than 5% for monthly data or less than 10 % for hourly data .

$$\text{CV-RMSE} = [\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{(n-p)}]^{1/2}/\bar{y} \times 100 \qquad (4)$$

$$\text{NMBE} = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{(n-p) \times \bar{y}} \times 100 \qquad (5)$$

Where (n) represents the number of data points, (p) the number of parameters included in the control volume and ($\bar{y}$) the arithmetic mean of the synthetic sensor data. The use of those two equations to judge the validity of the calibration is arbitrary. Other criterions could be used but these are by far the two most commonly used by the scientific community for building model calibration.

6 – Sequence of calibration

This methodology creates multiples control volumes in the building model for which the parameters can be independently estimated. Hence, the HVAC component models are optimized sequentially using synthetic sensor data.

ENERGYPLUS COMPONENT MODELS

In this paper, only a few component models are used to test the proposed methodology over a typical part of an air-heating system. To adequately understand the proposed methodology, a brief review of the EnergyPlus component models used is essential. The analysis is presented only for specific fan and heating coil models and the only considered state variables are the air stream mass flow rate ($\dot{m}$) and temperature (T) since the models outlined in this paper do not influence the absolute humidity. The models and their parameters are presented in this section.

Fan models

Two EnergyPlus fan models have been used to evaluate the methodology: the *Fan:ConstantVolume* and *Fan:VariableVolume*. The *Fan:ConstantVolume* model is a constant volume fan that is in operation over the entire simulation time step as shown in Equations (6) and (7).

$$\dot{Q}_{tot} = \left(\frac{\dot{m} \cdot \Delta P}{\eta_{tot} \cdot \rho_{air}}\right) \qquad (6)$$

$$\dot{Q}_{toair} = \eta_{motor} \cdot \dot{Q}_{tot} + \dot{Q}_{tot}\,(1 - \eta_{motor})\, f_{motortoair} \qquad (7)$$

The mass flow rate ($\dot{m}$), pressure differential (ΔP), the total fan efficiency (η_{tot}) and standard air density (ρ_{air}) are used to calculate the fan power ($\dot{Q}_{tot}$). The motor efficiency (η_{motor}) and motor in-stream boolean ($f_{motortoair}$) are then used to compute the energy transfer to the air stream. The *Fan:VariableVolume* component model varies the fan power using the polynomial expressed in Equation (8).

$$f_{pl} = c_1 + c_2 \left(\frac{\dot{m}}{\dot{m}_{design}}\right) + c_3 \left(\frac{\dot{m}}{\dot{m}_{design}}\right)^2 + c_4 \left(\frac{\dot{m}}{\dot{m}_{design}}\right)^3 + c_5 \left(\frac{\dot{m}}{\dot{m}_{design}}\right)^4 \quad (8)$$

The total fan power is then modified using this fraction as described in Equation (9).

$$\dot{Q}_{tot} = f_{pl} \left(\frac{\dot{m} \cdot \Delta P}{\eta_{tot} \cdot \rho_{air}}\right) \quad (9)$$

Heating coil models

Two EnergyPlus heating coil models have been used to evaluate the methodology: the *Electric Air Heating Coil* and the *Hot-Water-Based Air Heating Coil*. A short description of the models is presented. The *Electric Air Heating Coil* component model simply adds the energy in the air stream using user input efficiency (i.e. 100 %). The capacity of the coil (Equation (10)) at a given time step is controlled by a *SetpointManager* object.

$$\dot{Q}_{coil} = \dot{m} c_p \left(T_{Setpoint} - T_{Coil_{inlet}}\right) \quad (10)$$

The *Hot-Water-Based Air Heating Coil* component model is modeled as an ε-NTU heat exchanger. The heat transfer rate is calculated at each timestep from the specified UA value at design temperatures and flowrates and maximum capacity using Equation (11).

$$\varepsilon = 1 - \exp\left(\frac{e^{-NTU \cdot Z \cdot \varphi} - 1}{Z \cdot \varphi}\right)$$
$$\varphi = NTU^{-0.22}, Z = \frac{\dot{C}_{min}}{\dot{C}_{max}} \quad (11)$$

ENERGYPLUS INPUT DATA

The methodology described above contains the hypothesis that sensor data can be used directly into the simulation engine at a specific point in the HVAC systems. However, no specific input object is available in EnergyPlus to perform this task. Therefore, to pass down the sensor data into the simulation software, an additional component must be added. This is not new to building performance simulation as workarounds have been used for years in DOE2.2 models (Zweifel and Achermann 2003).

In the proposed methodology, a virtual heat exchanger is inserted before the desired input point to pass down the synthetic sensor data to each simulation used in the optimization process. More specifically, the *Coil:UserDefined* object and an *Energy Management System* (EMS) program are used to transfer the data from text files to the required node of the simulation software. Since the EnergyPlus software uses a predictor-corrector scheme based on zone loads to model the HVAC systems, the calling point of the EMS program was expected to be of importance. All the calling points explicitly available to the user were tested with no difference to the output of the control volumes described in this paper. The effect of these modifications to the input file on the simulation results were investigated to validate the proposed methodology.

A small difference between the simulated temperature profiles with the proposed input file modification and the original simulation was noticed on the output temperature of the control volume (i.e. min ± 0.0001ºC, max ± 0.06ºC). The value of the imposed flow rate is exactly the same. Since real sensor data will undoubtedly contain a level of uncertainty greater than the induced error from the input file modification, this method was considered acceptable to be used as part of the proposed methodology.

SYNTHETHIC SENSOR DATA

To test the proposed steps of the methodology, different BEMs were developed to assess different aspects of the estimation process. Figure 2 illustrates the typical shoebox building geometry used for the different building models.

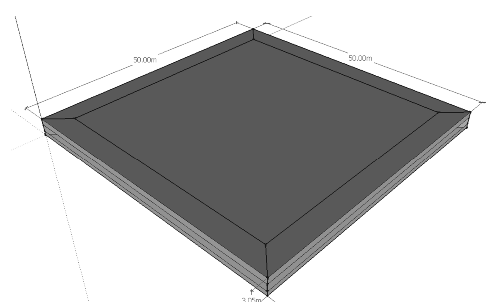

Figure 2
Geometry of the BEM used for the cases

The building is a single story, 2500 m² (26 909 ft²) office with a 40 % window to wall ratio. The different building characteristics were derived from ASHRAE 189.1-2009 (ASHRAE 2009) resulting in an exterior walls insulation value of 2.07 RSI (R-11.75), a roof insulation value of 4.35 RSI (R-24.7) and a window U-value of 2.56 W/m²·°K (U-0.451 BTU/(h·ft²·°F)). The different HVAC systems are available from 6:00 to 21:00 and electric baseboards are used to provide heating whenever required during the unoccupied period. The simulation is performed at a 15 minutes timestep over a period of one week to generate the system level state-variables that are used as synthetic sensor data. At this stage, the methodology is focusing on heating systems; therefore, the first week of January was used to complete the calibration. The underlying assumption is that a week of error-free simulated data is enough to estimate the given model parameters to obtain a data fit that respects the Guideline 14-2002 criteria (ASHRAE 2002). As previously specified, the proposed models do not modify the moisture content of the air. The only state variables used are the mass flow rate and temperature of the air stream. Figure 3 illustrates the interaction between the different files and tools used to generate the synthetic sensor data and estimate the control volume selected parameters.

Three different tests are performed for each of the cases described in Table 1 for the building presented in figure 2. These tests use synthetic sensor data generated with the different BEMs prior to the estimation with real measured data to test the methodology and tools used (Bos 2007). First, the model is run with the component model parameters used to generate the synthetic sensor data (Test A). This test provides the expected minimum of the objective function using the proposed data input method as described in this paper. Secondly, the estimation of the control volume parameters is attempted using the same component models parameters as the algorithm initial point (Test B). This test provides the expected minimum objective function using the chosen optimization algorithm coupled to the data input strategy. Lastly, slightly varied values (i.e. ± 5 %) of the component parameters used in the previous two tests are used as initial point (Test C) to evaluate convergence near the expected global minima.

Table 1
Description of the cases used to evaluate the proposed methodology.

Case	***Case description***
1	*Fan:ConstantVolume*
2	*Fan:VariableVolume*
3	*Hot-Water-Based Air Heating Coil*
4	*Electric Air Heating Coil*
5	*Fan:ConstantVolume* *+ Hot-Water-Based Air Heating Coil*
6	*Fan:ConstantVolume* *+ Electric Air Heating Coil*
7	*Fan:VariableVolume* *+ Hot-Water-Based Air Heating Coil*
8	*Fan:VariableVolume* *+ Electric Air Heating Coil*
9	*Hot-Water-Based Air Heating Coil* *+ Fan:ConstantVolume*
10	*Hot-Water-Based Air Heating Coil* *+ Fan:VariableVolume*
11	*Electric Air Heating Coil* *+ Fan:ConstantVolume*
12	*Electric Air Heating Coil* *+ Fan:VariableVolume*

Each of the cases includes a control volume of one or more EnergyPlus component models located on a single air stream. Since the models used in the cases do not influence the vapor content of the air and the mass of air, the control volume temperature output is used to

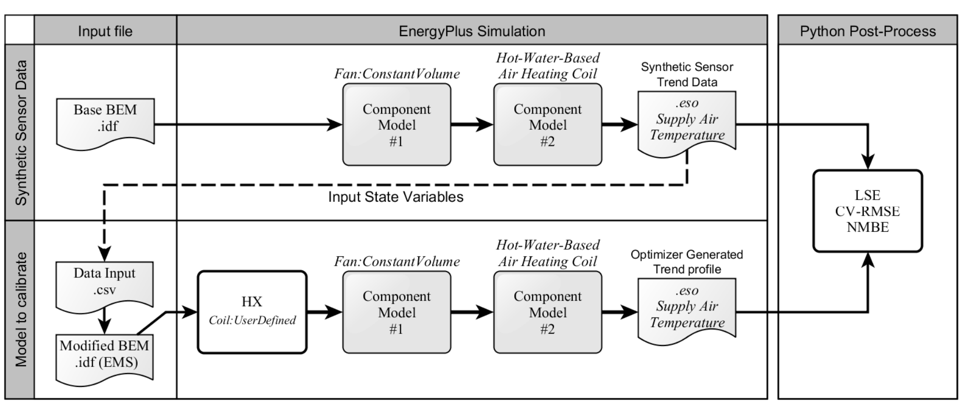

Figure 3
Diagram of the methodology used to calibrate the components models of the case #5 (Table 1)

estimate the associated parameters. Table 2 presents the list of selected control volume parameters expected to influence the control volume output temperature. For the *Fan:VariableVolume* component model, the fifth polynomial coefficient of Equation (8) is taken as void and was not included in the control volume parameters.

Table 2
Description of the cases control volume parameters.

Component Model	***parameter description***
Fan:Constant Volume	P1: Fan Total Efficiency P2: Motor Efficiency P3: Motor In Airstream Boolean P4: Pressure Rise (Pa)
Fan:Variable Volume	*Fan:Constant Volume +* P5 to P8 : Fan Part load power polynomial c_1 to c_4
Hot-Water-Based Air Heating Coil	P9: Rated Capacity P10: UA Value P11: Maximum Water Flow Rate
Electric Air Heating Coil	P9: Rated Capacity

Parameter bounds are then used to limit the parameter space of the optimization problem. The upper and lower bounds were taken as ± 20 % of the values used to generate the synthetic sensor data. Depending on the selected control volume, specific algorithms might be better suited depending on the nature of the selected parameters (i.e continuous vs discrete). For the scope of this article, the optimization algorithm used to minimize the objective function is an hybrid generalized pattern search algorithm with particle swarm optimization algorithm (Wetter 2008) with the parameters described in Table 3.

Table 3
Hybrid optimization algorithm parameters

PARAMETER	***VALUE***
MaxIte	2000
MaxEqualResults	5
NeighborhoodTopology	vonNeumann
NeighborhoodSize	5
NumberOfParticle	20
Seed	1
CognitiveAcceleration	2.8
SocialAcceleration	1.3
MaxVelocityGainContinuous	0.5
MaxVelocityDiscrete	4
ConstrictionGain	0.5
MeshSizeDivider	2
InitialMeshSizeExponent	0
MeshSizeExponentIncrement	1
NumberOfStepReduction	4

RESULTS

Table 4 presents the objective function (Equation (1)) values obtained for each of the previously described tests for each of the cases. The objective function value obtained in test A are expected to be the absolute minimum of the objective function as it represents the comparison of the generated synthetic sensor data with the data generated with the modified input file using the same control volume parameters. The magnitude of the resulting objective function value varies considerably from one case to another. This might indicate that certain component models are more or less sensitive to the data input strategy used in this paper.

Lower values in test B or test C than test A indicates that a different combination of the case control volume parameters coupled with the input file modification proposed earlier produces a lower objective function value than with the parameters used to generate the synthetic sensor data. If small variations of the objective function value produces a large difference in the parameters estimates, this could indicate that not all the selected parameters of the control volume have an important effect on the temperature output. The small differences produced by the model modification (i.e. min ± 0.0001ºC, max ± 0.06ºC) are expected to be less than the actual accuracy of the installed sensor. If a parameter varies considerably from the known exact value with such small differences, its estimation using real measurements might prove difficult.

Table 4
Objective function values obtained for the different cases for each synthetic data validation tests.

Case *(Table 1)*	***Test A***	***Test B***	***Test C***
1	3.18e-03	8.71e-04	8.71e-04
2	3.62e-02	8.13e-07	1.77e-07
3	8.68	9.34	9.34
4	3.18e-03	0.25	0.25
5	1.28	9.51e-02	9.49e-02
6	1.22	2.54e-01	2.54e-01
7	12.98	9.92	9.92
8	45.78	43.43	43.63
9	1.25	7.64e-02	8.24e-02
10	10.98	10.54	10.54
11	1.22	2.54e-01	2.54e-01
12	153.38	149.31	149.32

The cases that included a heating coil (i.e. Case 3 and up) gave erratic parameter estimates values if the deck temperature setpoint was always reached during the selected run period. Different values of the coil heating coil model parameters will give a very low objective function value if the coil capacity is not exceeded. This might be a sign that not all the data points are relevant to the estimation process outlined in this paper and that a pre-selection of useful data points could benefit the proposed methodology.

Table 5 presents the obtained CV-RMSE and NMBE for the given cases of Table 1. The values presented in Table 5 all greatly exceed the requirements of ASHRAE Guideline 14-2002 (ASHRAE 2002). Those two criteria have been arbitrary applied to building simulation calibration and they might not be relevant for equipment level performance evaluation. The use of other criteria to compare temperature profiles in the context described in this paper could be investigated. Table 5 presents the relative difference between the original control volume parameters used to generate the synthetic sensor data and the parameter estimates values obtained in test C of the proposed methodology. By inspecting Table 5, one remarks that even if the objective function values of table 4 are very small, there is still a large gap for some parameters estimates of test C and the parameters used to generate the synthetic sensor data and the parameter estimates values obtained in test C (i.e. values approaching the ± 20% used as parameter bounds).

An additional test could take the form of a random number generator providing the initial starting point of the optimisation algorithm. This would provide (1) a test that the algorithm converges over the entire parameter space and (2) a distribution of the different parameters estimates. This would give a better overview than the values presented in Table 5.

CONCLUSION

In this paper a methodology to estimate secondary level HVAC component parameters and a method to input data into an EnergyPlus model were proposed. The different tests of the proposed methodology using synthetic sensor data are performed to evaluate the expected behaviour of the estimation process with almost error free measurements prior to the application using real building measured. The results showed that certain expertly selected control volume parameters might not affect sufficiently the output to be estimated by the proposed process. The identification of the control volume most influent parameters over the output used in the estimation process might help achieve better parameter estimates. The estimation of component model parameters is not only a function of the number of data points, but the operation of the system during the acquisition of those data points. The development of control volume specific rules for selecting the appropriate data from larger datasets could benefit the proposed methodology.

The use of statistical synthetic sensor data (i.e. white noise) and random starting point in additional tests could further evaluate the methodology before applying it to real sensor measurements given the expected non-negligible sensor drift and uncertainty.

Table 5

Relative difference between the original and estimated parameter values for test C applied to the cases of Table 1.

Case (estimate	***P1,%***	***P2,%***	***P3,%***	***P4,%***	***P5,%***	***P6,%***	***P7,%***	***P8,%***	***P9,%***	***P10,%***	***P11,%***	***CV-RMSE,%***	***NMBE,%***
1	2.9	-15.6	C	4.0	-	-	-	-	-	-	-	3.3e-03	3.7e-06
2	-1.3	-11.1	C	-2.6	7.4	-7.9	13.7	4.4	-	-	-	6.6e-05	1.1e-09
3	-	-	-	-	-	-	-	-	-12.0	0.0	-20.0	5.8e-01	6.9e-02
4	-	-	-	-	-	-	-	-	-0.3	-	-	6.3e-02	1.2e-03
5	12.9	-5.6	C	-17.0	-	-	-	-	-14.8	5.0	16.0	3.8e-02	4.6e-04
6	-12.1	-2.8	I	-7.0	-	-	-	-	0.0	-	-	6.3e-02	1.2e-03
7	9.0	-14.8	I	-19.0	-17.8	19.9	19.9	-1.6	-3.7	0.0	-3.2	6.0e-01	7.3e-02
8	7.3	-12.2	I	9.0	-10.1	16.4	-4.7	-10.8	0.0	-	-	1.2	3.0e-01
9	6.7	-12.2	I	-5.0	-	-	-	-	-6.8	5.0	-19.0	3.5e-02	3.9e-04
10	3.0	-7.9	C	9.0	-5.2	14.1	-3.3	-8.8	-0.2	-	-	1.1654	3.0e-01
11	1.4	-17.8	C	-6.0	-	-	-	-	0.0	-	-	6.3e-02	1.2e-03
12	-19.9	-8.6	C	20.0	0.0	-4.6	3.7	-5.8	0.0	-	-	2.0	0.9

* C : Correct, I : Incorrect for Boolean parameter

Finally, the trial application of the proposed methodology case studies on well-maintained secondary level HVAC equipment used in a real building with well-defined operation using sensor data acquired by a building control system is the defining test to verify the applicability of the proposed methodology to real world problems.

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NOMENCLATURE

ε = Efficiency
μ = regularization coefficient
η = efficiency
ρ = density (kg/m³)
c_n = polynomial coefficient
c_p = heat capacity (J/kg°K)
$\dot{C}$ = heat capacity rate (J/s°K)
CV-RMSE = coefficient of variation of the root mean square error
EMS = Energy Management System
f_{pl} = power fraction
$f_{motortoair}$ = motor in-stream boolean
$\tilde{f}$ = approximate objective function
LSE = least square estimator
$\dot{m}$ = mass flow rate (kg/s)
n = number of data points
NMBE = Net mean bias error
p = number of model parameters
ΔP = pressure differential (Pa)
$\dot{Q}$ = Power
NTU = Number of transfer units
T = Temperature
y = iterated simulation data
$\tilde{y}$ = synthetic sensor data

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