

Building energy simulation coupled with real data for enhanced monitoring analysis

Patrick Béguery¹, Melec Petit-Pierre¹, Henri Obara¹,
Romain Brunet², Sophie Marat³, Max Boegli⁴

¹ Schneider Electric, Grenoble, France

² AMEG, Grenoble, France

³ ALTEN, Grenoble, France

⁴ CSEM, Neuchatel, Switzerland

Abstract

Building Energy Simulation (BES) is typically used in the design phase, but predicted performances are often quite different from the real building performances later measured. In recent years, a number of studies have focused on using BES in the construction and operation phases (Sterling, 2015). Use in these phases involves complex data management, advanced algorithms and targets for non-simulation experts. This paper addresses innovative calibration based on the identification of zone level Key Parameter Modifiers (Azar, 2015), fault detection methods using Kernel Principal Component Analysis, and the development required to make them usable by building energy managers.

Introduction

Buildings represent more than 40% of EU energy consumption and 36% of EU CO₂ emissions. To reach the 2020 20% energy efficiency target, the EU energy efficiency directive sets binding measures to be implemented by EU members by the end of 2016 (EU, 2012). A new package of measures has recently been proposed to extend the energy efficiency target to 40% for 2030, including proposed revision of European Building Performance Directive (EBPD, 2016). Building Energy Performance Simulation (BEPS) tools are widely used for modern mid-size to large buildings. When used across the building commissioning and operation phases, BEPS models can be powerful tools to assist building operators and facility managers in creating virtual sensors, performing sensitivity analyses, assessing building energy performance, detecting anomalies and identifying potential retrofit solutions. A review of these potential usages is proposed in (Sterling, 2015).

European Tribute project FP7 is exploring various BES applications to enable building energy managers to understand BES, and to reduce the gap between predicted and real performances. The pre-requisites for the deployment of analytics are a commissioned building and a calibrated model as proposed in (Sunnam, 2015). The analytics proposed entail a large number of real data and related simulations. To facilitate use by building facility managers, not only does all data management have to be automatic (real data collection and storage, simulation of settings, processing, and real versus simulated mapping); the execution of analytics and display of results must be automatic as well.

The first part of the paper gives a brief description of a pilot site and the model used. The second part discusses data collection and the framework for developing analytics and on-line operation. The third and fourth parts describe the work performed on two analytics: 1) the Support Vector Regression (SVR) auto-calibration model, and 2) fault detection based on Kernel Principal Component Analysis (KPCA).

Description of building and model

The City of Turin and the Urban Community of La Rochelle are Tribute project partners, and public building portfolio managers. They represent potential operation-phase analytics users, and provide the project with real pilot sites. The paper focuses on one of these sites, the 'Vaucanson' building in La Rochelle, France. It is a 3750 m² two-floor office building, erected in 1986 and retrofitted in 2012.

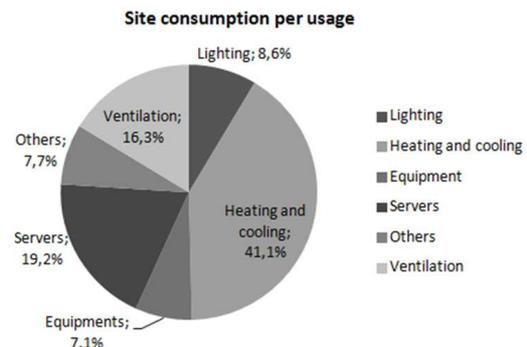


Figure 1: Yearly energy consumption

The building features a small data center that consumes about 25% of the total energy, and a complex heat production system including a heat pump mounted on ground river pipes and heat recovery from the data center. Building models were developed using the IDA Indoor Climate and Energy (IDA-ICE) tool developed by EQUA Simulation AB, a TRIBUTE partner. IDA-ICE is a whole-building simulation tool, based on dynamic multi-zone computations to provide results on thermal indoor climate and energy consumption.

The Vaucanson model has 23 thermal zones (for about 100 rooms). The simplified model takes less computation time and matches available zone ambient sensors. It can run a whole year in 1.5 hours, and log some 100 time-series for real data mapping.

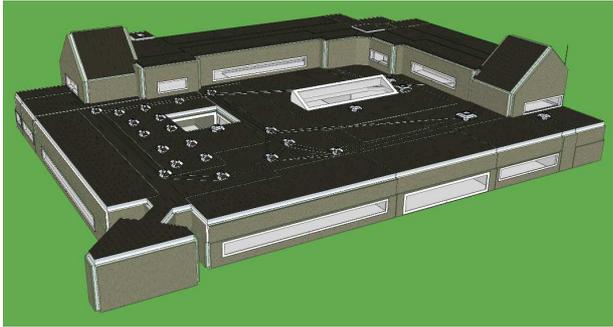


Figure 2: Vaucanson model in IDA-ICE 3D view.

Data collection

Massive data collection is implemented on all TRIBUTE pilot sites. The Vaucanson data includes:

- Electrical and thermal energy (40 sensors).
- BMS data (124 sensors).
- Ambient sensors for temperature (110 sensors), humidity (75 sensors) and CO₂ (21 sensors).
- Weather station (9 sensors).

Data from the different sources are collected via gateways and pushed to StruxureWare™ Energy Operation. This flexible software-as-a-service (SaaS) tool offers scalable functionality, from simple, out-of-the-box reporting to in-depth energy analytics.

Energy data

A Com'X 200 gateway stores and pushes ordered, pre-formatted energy data time-series by FTP in xml files. The gateway requests data from the sub-meters every 10 minutes using Modbus protocol:

- 2 COP monitor systems acquire specific heat pump data.
- Electrical sub-metering includes the main meter, 3 plug load meters, 3 lighting meters, and specific meters for AHU coil, server UPS and cooling system, external lighting and PV production.
- Thermal energy meters are installed on heat pumps, ground river pipes and the primary hot and cold water collectors.

BMS variables

A computer with Niagara AX software acquires the relevant BMS data from two Honeywell Controllers. Data are sampled every 10 minutes and emailed twice a day to the Energy Operation FTP relay server. The server converts the raw CSV files to Energy Operation-readable CSV format.

Zone comfort data

Five Raspberry Pi3 ZigBee Green Power to Ethernet network gateways collect data from Vaucanson's 87 zone comfort sensors. Time-stamped sample files are sent to the FTP relay server. The temperature, humidity and light sensor samples are sent at less than 2 min intervals. Above the 600+ ppm threshold, samples from the twenty-one CO₂ sensors are sent every 2.5 min, and at 20 min intervals when the CO₂ ppm is below 600. This feature, combined with the ultra-low power Zigbee Green Power protocol, gives the battery-powered sensor a service life of more than 10 years.

Figure 3 shows the process, from global data collection to Energy Operation archives, and typical use of the platform with alarms and dashboards. A hierarchical browser is used to access stored data (see Figure 4).

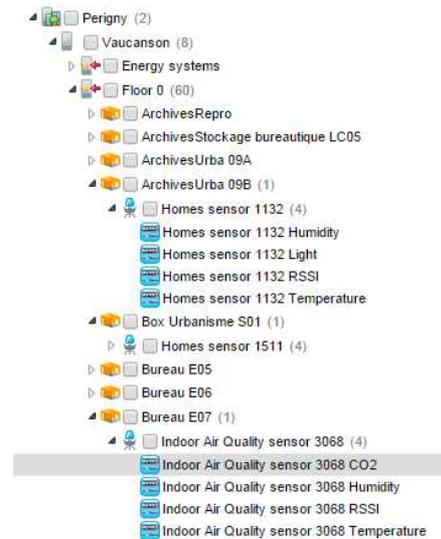


Figure 4: Hierarchical view of zone comfort sensors deployed in Energy Operation environment

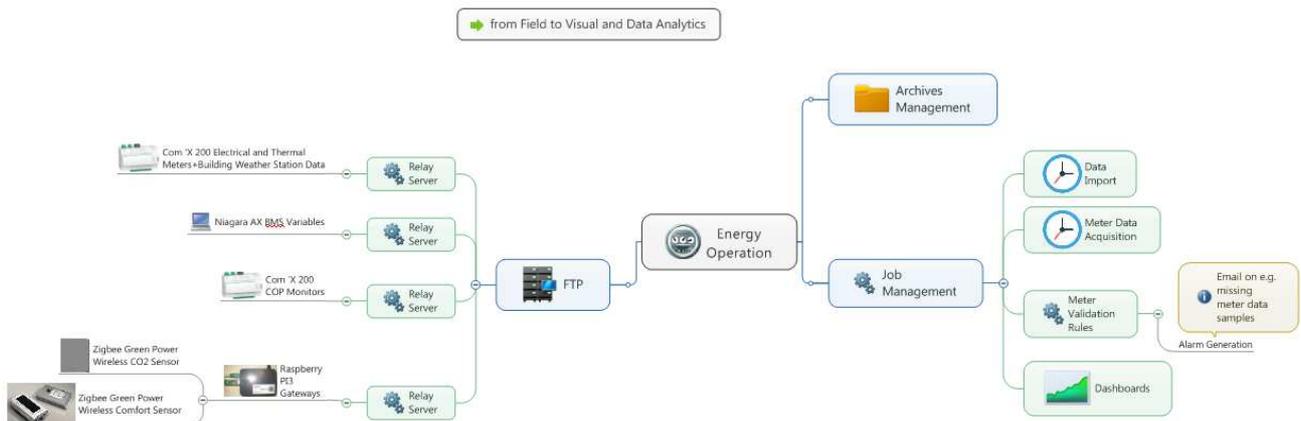


Figure 3: Complete data collection and standard monitoring by StruxureWare™ Energy Operation.

Analytics framework

The previous section described classical data collection and a monitoring platform based on simple data aggregation and visualization. For more advanced analytics based on complex algorithms, there is no easy way to use the products currently available. We therefore decided to develop a Matlab-based framework with the following features:

1. Access to raw data in Energy Operation archive, and classical data preprocessing.
2. Matlab toolbox to manage on-line simulation, including IDA-ICE model modification, pushing sensor data into the model, and running simulation.
3. Real and simulated data mapping.
4. Analytic development based on mapped data.
5. GUI to configure analytics and display results.

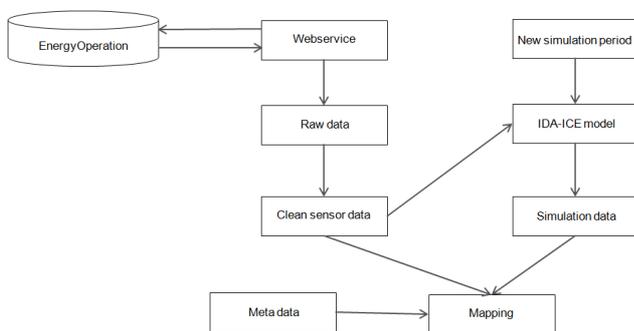


Figure 5: Automated sensor data and model update process.

An automatic process was developed to build the mapped data for analytics (see Figure 5). The process runs periodically (in our case, every week). Data are extracted from EnergyOperation via a Web service and formatted for easy use in Matlab. The data are also cleaned (resampling, unit correction, pulse meter management, interpolation, etc.).

Some of the data are formatted for input to IDA-ICE (weather data, process consumption, etc.). When the real data are integrated, a simulation is run in the data-record

time range. The simulation data are extracted and mapped with the real sensor data, and metadata are added for easier analytic and GUI development.

Note that some analytics had long run-times (especially those requiring simulations). Long run-time analytics can be included with the automated process to provide additional results at given intervals, ready for display in the different GUIs. Examples of these analytics include automatic calibration, described later in the paper, and the retrofit option analysis tool under development.

One of the first uses of the framework is commissioning of the building and model. A sensor quality visual analytic was developed for a quick analysis of sensor data availability (see Figure 6). This analytic shows the amount of available data in terms of the number of data points per day. There is a row for each sensor and a column for each day. The heat map colors display the percentage of available data (in our case, dark blue means all data are available, and yellow means less than 30% of data available for the day). The heat map enables quick assessment of data collection quality. Events such as gateway malfunctions, global site shutdowns and random behavior are easily identified. Stored data may be recovered manually according to gateway capacity. Similar heat maps were developed for specific analytics using only the data specifically required. Set of sensors required by specific analytics can also be displayed; in that case, the heat map rapidly displays the periods for which the analytics provide meaningful results.

Another commissioning tool is a browser that compares real and simulated data. Using the mapped data, real and simulated signals are displayed in the same graph, with the same time-steps and units. All real data can be browsed via the interface, enabling deep real-data analysis. The tool can also evaluate gaps between real and simulation data. Simulation model parameters are then adjusted by the simulation developer, in accordance with the data viewed and the gaps. This operation, referred to as ‘manual calibration’, results in the ‘as designed model’, which is then used for all other analytic developments.

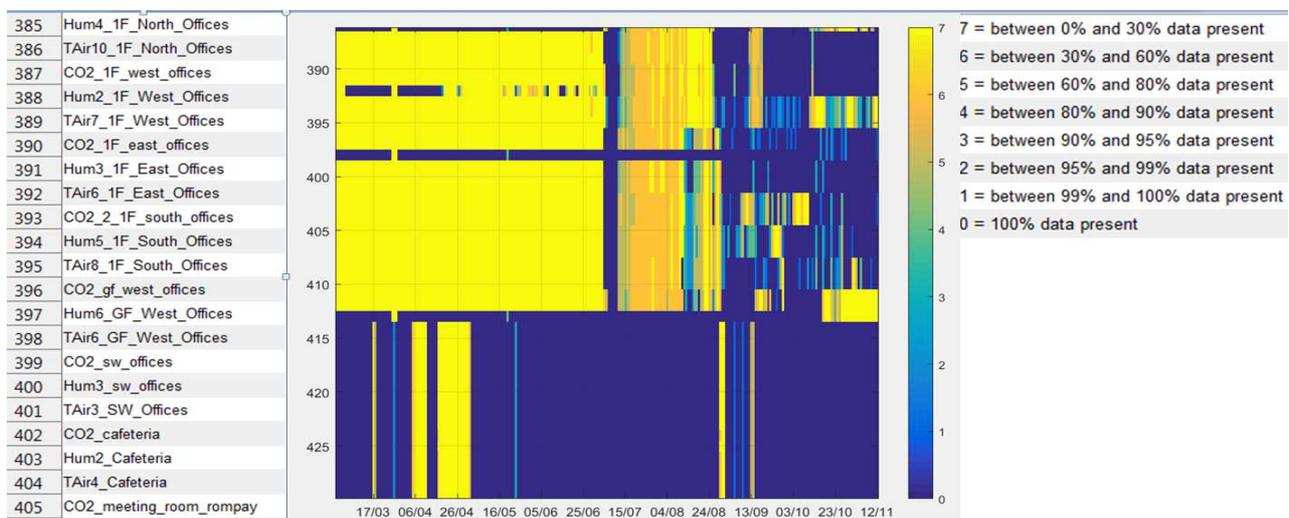


Figure 6: Sensor quality heat map for Vaucanson Building.

Table 1 shows the calibration metrics obtained in the various steps of the manual calibration process.

- ‘Before calibration’: the simulation model is based on the site audit and building construction and/or retrofit documents. It may still contain some simulation software default parameters. Global energy difference and CVRMSE (see equation (1) in next part) were considered too high to be acceptable, and model calibration was required.
- ‘Real signals pushed in BEM’: in this step, real signals were identified as being influential on building consumption but difficult to calibrate (hardly any available information or independent variables). These signals are used as inputs for the simulation model. Site outdoor temperature, for instance, is a signal used as a model input. For the Vaucanson building described above, server power is another input used. Global energy difference and CVRMSE were improved, but still considered unacceptable.
- ‘Parameter manual calibration’: the real and simulated data comparison interface was used in this step. This calibration includes among other HVAC control parameters set accordingly to BMS signal and system efficiency parameters tuned based on real measurements. Calibration resulted in a 1% difference in global yearly energy consumption and an hourly CVRMSE of 21.1%.

Table 1: Model performance according to project phases

Step	Global energy difference	CVRMSE Energy (%)	
		Monthly	Hourly
Before calibration	-38,4%	50,5	66,5
Real signal pushed in BEM	13,4%	22,6	40,8
Parameter manual calibration	-1,0%	14,1	21,1

With calibration criteria below the target values given in ASHRAE Guideline 14 (monthly CVRMSE<15% and hourly CVRMSE<30%), the manually calibrated model is already fit for energy performance follow-up, IPMVP option D or retrofit option analysis.

For other analytics, however, such as fault detection and energy flow optimization, calibration needs to be even more accurate. A number of different auto-calibration methods were investigated by the Tribute project, including simplex, gradient descent, the Levenberg-Marquardt method, genetic algorithm and the SVR approach, which is described in the section that follows.

Moving towards auto-calibration tools

A comprehensive review of auto-calibration methods is found in (Coakley, 2014). Model calibration for retrofit analysis is well presented in (Heo, 2012) and real-time implementation is tackled in (Azar, 2015). A review of optimization methods applied to building performance analysis is found in (Nguyen, 2014).

Multiple methods for model calibration have been considered by the Tribute project partners as described previously. In this part, we focus on what we considered as the most innovative calibration method, namely the

automatic tuning of zone level Key Parameter Modifiers (KPM). Based on the framework described in previous part, methods were developed for automatic calibration of the underlying simulation model. Continuous learning from operation resulted in a 15% reduction of the energy gap on test sites.

The following 3-step method is proposed:

- First, the simulation model is established and initial calibration is done.
- Second, a sensitivity study is run to determine the simulation model parameter with the greatest influence on building energy performance. Parameter selection is done using screening techniques (Olivero, 2014), (Heo, 2012) and expert knowledge (Azar, 2015).
- Third, the parameters are continuously learnt, with trends indicating building aging or faults, as presented below.

These developments are currently being validated on the Vaucanson building (see Figure 2).

Methodology

The gap between building simulation and measured data is aggregated in a cost function. Two metrics are commonly used in building energy calibration (Coakley, 2014): the coefficient of variation of the root mean square error (CVRMSE):

$$CVRMSE = \frac{n}{\sum y_i} \sqrt{\frac{\sum (y_i - \hat{y}_i)^2}{n}} \quad (1)$$

and the normalized mean bias error (NMBE):

$$NMBE = \frac{\sum (y_i - \hat{y}_i)}{\sum y_i} \quad (2)$$

where y_i and \hat{y}_i are respectively the measured and simulated data points for each time instant ‘i’, and n is the number of hourly data points in a specific timeframe of a few weeks or months.

Optimization using whole-building energy models is often challenging due to the computationally expensive nature of the simulation as well as discontinuities likely to be found in the full model representation. In order to circumvent these issues, a meta-model of the full energy model was created using a machine learning regression technique, i.e. support vector regression (SVR), as proposed in (Eisenhower, 2012) and (Manfren, 2013), among others, while using the SVR toolbox developed by (De Brabanter, 2013). To train the SVR model, a Latin Hypercube Sampling (LHS) design was used for more efficient spanning of the model parameter multi-dimensional input space.

Based on a meta-model, the calibration procedure then applies optimization, using techniques that are either gradient-based (Levenberg-Marquardt algorithm) or gradient-free (Nelder-Mead method).

Application

This example looks into the calibration of a temperature envelope with the technical system turned off (i.e. no heating or air conditioning) using four model parameters

selected by expert knowledge (Azar, 2015) and parameter screening (Olivero, 2015): envelope conduction, thermal mass, envelope leakage, and moisture storage. These parameters can easily be tuned, either at the building level or zone level using the Key Parameter Modifiers introduced in (Azar, 2015).

The SVR method was applied to the Vaucanson building model simulation, paired with measurement in 16 zones, which amount to a total of $4 \times 16 = 64$ parameters to be calibrated. One can take advantage of optimizing all zones simultaneously without added time penalty, since each function evaluation call simulates the whole building (Azar, 2015).

Figure 7 shows a 3D view of SVR mapping of the CVRMSE cost function for two model parameters.

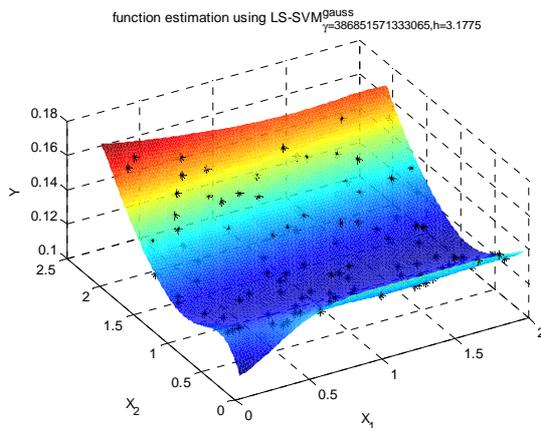


Figure 7: SVR cost-function model (CVRMSE) with 2 parameters (x_1 : thermal mass, x_2 : envelope conduction)

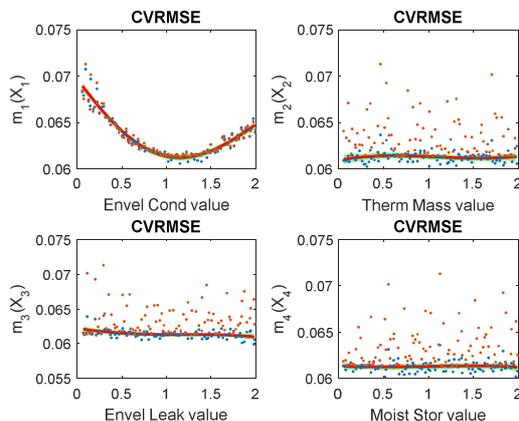


Figure 8: CVRMSE cost-function for four GF East Offices zone parameters, based on additive SVR model.

The additive kernel model option in the SVR (De Brabanter, 2013) provides a view of the influence of each parameter on the cost function. In Figure 8 for the CVRMSE and Figure 9 for the NMBE, the influence of four model parameters, i.e. envelope conduction, thermal mass, envelope leakage and moisture storage, is shown for the GF East Offices zone. The parameter value regression obtained by the additive SVR model offers a visual high-order sensitivity analysis in addition to

calibration. In this particular case, the major influence of envelope conduction is seen, whereas the other three parameters are relatively insensitive.

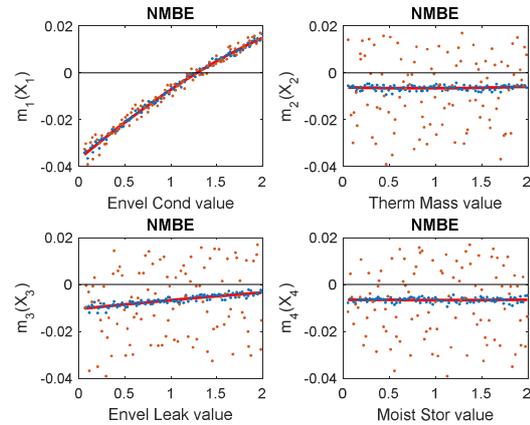


Figure 9: NMBE cost-function for four GF East Offices zone parameters, based on additive SVR model

In Figure 10, both metric errors are shown for each of the 16 zones, with uncalibrated parameters (in red) and calibrated parameters (in blue). The bars on the far right give a global indicator for all zones.

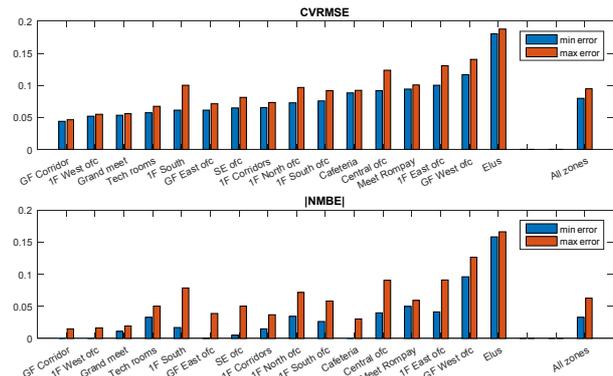


Figure 10: CVRMSE and $|NMBE|$ for all zones.

Estimating a regression function over a multi-dimensional input space becomes more and more difficult as with increasing dimensionality. The use of additive models in the SVR method combined with LHS design alleviates the curse of dimensionality while capturing the main error metric features.

The SVR method, and its extension using additive models, provides a visual high-order sensitivity analysis tool in addition to model parameters calibration.

Fault detection

Various methods exist for detecting building faults, including expert rules derived from experience, model-based approaches based on analytical models or physical equations, and data-driven approaches that rely on statistical analysis (Verron, 2010). The method we propose is a mixed model-based/data-driven solution in which errors between real and simulated data are compared to normal operating condition errors by statistical analysis.

The calibrated simulation model is fed with climate and occupation data collected on the site. The results are matched to the related measurements using the framework. The resulting differences are analyzed and compared to the difference database by fault detection (FD) analysis.

Kernel Principal Component Analysis (KPCA) is a variant of the widely used Principal Component Analysis (PCA), a multivariate data analysis which consists in transforming interrelated variables into new decorrelated variables named principal components (Garcia-Alvarez, D. 2009). Applied to a sample of data measured under normal operating conditions and coupled with distance metrics, the PCA method enables evaluation of the deviation of measures from the reference sample. The metric we chose is the Squared Prediction Error (SPE) which evaluates the difference in norm of the projection onto the principal components with the original point (see (3) and (4)). The reference data error density is then analyzed by a kernel density estimation to normalize to one the error with a certain significance (Botev, Z. I. 2007).

$$r = x(I_d - PP^T) \tag{3}$$

$$SPE = rr^T \tag{4}$$

with x the data to be analyzed, I_d the identity matrix and P the projection onto the principal components matrix.

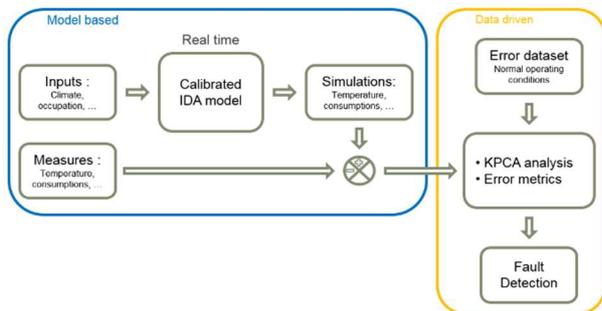


Figure 11: Proposed FD method.

Although the PCA analysis remains limited since it is not scalable to non-linear problems, the Kernel PCA solves this issue by transforming the data from the initial space into a feature space through a non-linear application Φ (Schölkopf B. 1998). The power of the KPCA method lies in the fact that the function Φ is never explicitly defined and appears only in the kernel definition. The kernel is a similarity measure that quantifies the similarity between two objects. For our study, we chose to use the Gaussian kernel (5).

$$k(x, y) = \langle \Phi(x), \Phi(y) \rangle = \exp\left(-\frac{\|x - y\|^2}{2\sigma^2}\right) \tag{5}$$

with σ the kernel parameter that defines distance sensitivity for the similarity measure.

The tuning of the kernel parameter is very important for adequate fault detection sensitivity, so we developed an automatic estimation method. The reference data are

mixed randomly and split into two groups. The first one is used to define the principal components and normalize errors, and the second one is used for cross validation to calculate the accuracy of the KPCA model. Since all the points are within the reference data, the accuracy should be good, but if the kernel parameter is too small, accuracy will drop. The accuracy is calculated several times for a certain range of σ , and then approximated with an inverted exponential. The optimal σ is evaluated when the accuracy model reaches a certain level of accuracy.

Depending on the number of points in the reference and testing data, computation time and memory requirements can be an issue. The reference data also needs to be coherent with the testing data, since the type of weather and the building setpoints may change from one period to another. It is important to maintain reasonable period lengths for reference data, e.g. one month for hourly measurements or one year for daily measurements. Since fault detection is run periodically, a sliding window is used, taking the previous data for the reference period as reference data, cleared of previous faults, and all data collected since the last analysis as testing data.

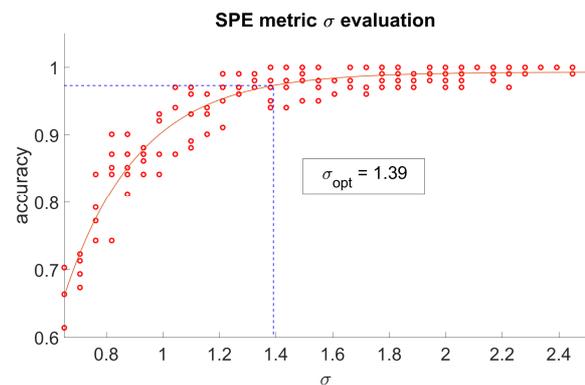


Figure 12: Optimal sigma estimation

It should be noted that testing period length has an effect on drifting fault detection capability. If the testing period is short, drifting behavior may not be detected. As it may also be normal behavior we do not want to consider as faulty, the parameters should be carefully selected.

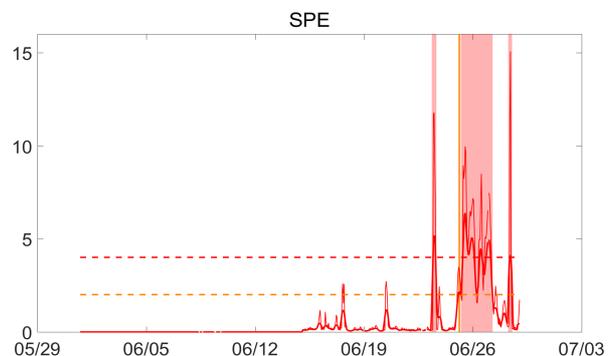


Figure 13: Error smoothing and fault thresholds

Due to outliers and data noise, the error signal can be very noisy. Since our intention is not to highlight every small novelty, the error signal is smoothed by a Gaussian filter,

and two different levels of alarms are implemented, enabling managers to quickly identify the significance of faults. To complete the limits, another threshold is applied to the raw error to detect simple outliers and remove them from the database. Figure 13 shows the raw error (thin red line) and the smoothed error (thick red line) with the two alarm level thresholds.

For building supervision, it was decided to split the variables into FD groups so that each group represents a system, such as a room or specific equipment unit. FD groups are composed of variables that drive the behavior of the system. In the following example, to supervise a specific room in our test building, we grouped the difference in room temperature between simulation and measures with a signal that represent the time of day.

Figure 14 shows the results of fault detection on the specified FD group. The solid line represents the measures and the dashed line represents the simulation results. The green lines are the reference data and the blue ones are the testing period. The red patches show the faults detected.

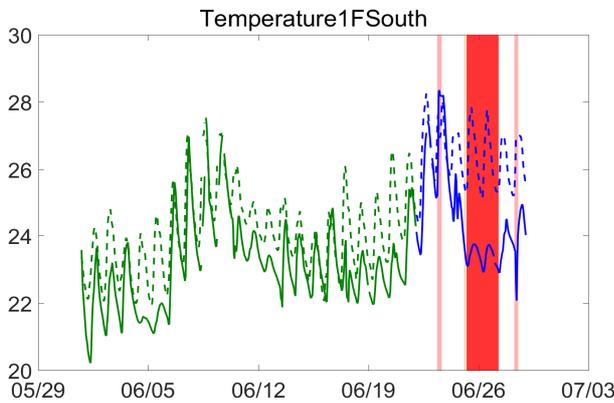


Figure 14: FD room temperature results

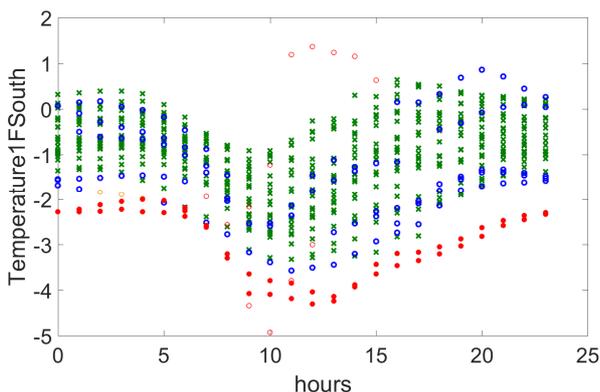


Figure 15: Scatter plot of FD results

Figure 15 shows the same results in a scatter plot, the x-axis representing the hour of the day and the y-axis the difference in temperature between measures and simulation with the same color code. It can be seen that the KPCA successfully detected the points distant from the reference points, even if the behavior of the system is quite complex.

A GUI (Figure 16) was developed to help energy managers to configure fault detection groups and analyze the results. They can define specific groups of variable and set the KPCA parameters, such as the learning and reference period, threshold levels, and smoothing parameters. The fault detection interface offers a quick overview of the faults in a colored calendar, indicating faulty days on the left. Building managers can display faults more specifically to understand what has happened. Faults can be displayed with time series or in scatter plots with information on error and time. If managers consider certain novelties as normal behavior, they can reset the specific period as normal and run fault detection again with this behavior considered normal in the following analysis.

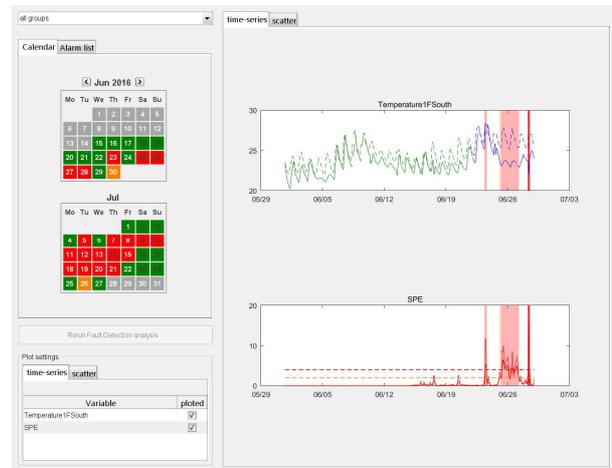


Figure 16: Fault Detection GUI for building managers

The KPCA analysis showed very promising results for fault detection, for both comparison between real measures and simulation results, and raw real measurement. However, the analysis is very sensitive to model calibration and the KPCA may face problems with seasonal transition. With the GUI linked to the framework, it is easy for building managers to create fault detection groups with the variables to be monitored and to tune the different parameters. The GUI also offers a clear and comprehensive way to analyze and manage novelties detected by the algorithm.

From theory to real life

The Tribute data management and associated analytics such as automatic calibration and fault detection were developed and tested in an R&D project. For this kind of approach to be used in a real building environment, a number of major challenges need to be addressed:

1. Existing buildings should not be considered, except after a major retrofit. Otherwise, the cost to overcome the lack of design data, install meters, access control data and calibrate model are too high.
2. Having too many people involved in the design, installation, commissioning and monitoring of sensors and meters can result in delays, errors, tasks performed multiple times, etc. A single actor for the whole process would certainly be more efficient.

3. Moreover, this central actor should be also in charge of simulation model updating. An actor (or team) with the required expertise managing all of these roles is not typical in the building market.
4. Whatever the quality of data collection, there will always be missing data, that will have to be carefully managed for the advanced analytics to produce meaningful results.
5. Analytic and graphical display method need to be adapted for end-users. The analytic framework can run automatically and produce a large amount of interesting results. A critical role will be played by synthesis display to highlight the most critical issues and navigation tools to facilitate understanding.
6. On the other hand, there is no interest in deploying a complex energy follow-up approach if end-users are not prepared to spend a minimum amount of time analyzing the results and determining required corrective measures as soon as possible.

Conclusion

The Tribute project had to address a number of challenges in order to provide useful tools for energy managers to follow their building performance and understand the potential gap with simulated performance. The challenges included: clean real-data collection, simulation integrated as an application building block, real and simulation data mapping, and the development of advanced algorithms and GUIs for clear reporting and easy analysis.

The whole framework is now running on one pilot site, integrating the two analytics presented here as well as others such as comfort management, energy performance follow-up, energy flow optimization, and retrofit option analysis. Some GUIs are already available and the site team will begin using them.

The next steps will be to complete GUI development, extend the analytic framework to the second test site, and work with the site team to analyze feedback.

Acknowledgements

This work was developed under the auspices of the Tribute project, which receives funding from the European Union 7th Framework Programme under Grant Agreement No. 608790. It began in October 2013 and is due to end by October 2017. The project aims to reduce the gap between simulated and real performances.

References

Azar, M. and Sahlin, P. (2015). Narrowing the Gap – A Framework for Connecting and Auto-Tuning a Design BPS Model to a Physical Building. *Proceedings of Building Simulation 2015*.

Bonvini, M. et al. (2014). Bridging the Gap Between Simulation and the Real World An Application to FDD. *Proceedings of 2014 ACEE Summer Study*.

Botev, Z. I. et al. (2010). Nonparametric Density Estimation via Diffusion Mixing. *Annals of Statistics* 38(5), 2916-2957.

EPBD (2016), Proposal for amending Directive 2010/31/EU on the energy performance of buildings, <https://ec.europa.eu>.

EU (2012). Directive 2012/27/UE of 25 October 2012 on energy efficiency, <http://eur-lex.europa.eu>.

Coakley, D. et al. (2014). A review of methods to match building energy simulation models to measured data. *Renewable and Sustainable Energy Reviews* 37, 123–141.

De Brabanter, K. (2013). Nonparametric Regression via StatLSSVM. *Journal of Statistical Software* 55(2).

Eisenhower, B. et al. (2012). A methodology for meta-model based optimization in building energy models. *Energy and Buildings* 47, 292-301.

Garcia-Alvarez, D. (2009). Fault detection using Principal Component Analysis (PCA) in a Wastewater Treatment Plant (WWTP). *Saint-Petersburg, 2009. 62th Int. Student's Scientific Conf.*

Heo, Y. et al. (2012). Calibration of building energy models for retrofit analysis under uncertainty. *Energy and Buildings* 47, 550-560.

Ionesi, A. et al. (2015). Towards Seamless Integration of Model-Based Energy Performance Simulation and Multi-Objective Optimization Tools. *Proceedings of Building Simulation 2015*.

Manfren, M. et al. (2013). Calibration and uncertainty analysis for computer models – A meta-model based approach for integrated building energy simulation. *Applied Energy* 103, 627-641.

Nguyen, A. et al. (2014). A review on simulation-based optimization methods applied to building performance analysis. *Applied Energy* 113, 1043-1058.

Olivero, E. et al. (2015). On key parameters influencing building energy performance. *Proceedings of Building Simulation 2015*.

Schölkopf B., Smola A. and Müller K. (1998). Nonlinear component analysis as a kernel eigenvalue problem. *Neural computation* 10(5), 1299-1319.

Sterling, R. et al. (2015). IEA Annex 60 activity 2.3: model use during operation, approach and case studies. *Proceedings of Building Simulation 2015*.

Sunnam, R. et al. (2015). Utilizing Sensor Trend Data to Overcome the Challenges in Calibrating a Simulation Model for Measurement and Verification in a New Construction Project. *Proceedings of Building Simulation 2015*.

Taheri, M. et al. (2014). Optimization-based monitoring-supported calibration of a thermal performance simulation model. *Int. Journal of Optimization in Civil Eng.* 4(2), 261-271.

Verron, S. (2010). Fault detection and isolation of faults in a multivariate process with Bayesian network. *Journal of Process Control* 20(8), 902-911.