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ScienceDirect

Energy Procedia 62 (2014) 246 – 255

Energy Procedia

SEB6th International Conference on Sustainability in Energy and Buildings, SEB-14

# Malfunction and bad behavior diagnosis on domestic environment

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**Abstract**

Greenhouse gas emissions from homes arise primarily from fossil fuels burned for heat, the use of products that contain greenhouse gases, and the handling of waste. Human activities are responsible for almost all of the increase in greenhouse gases in the atmosphere over the last 150 years. The household sector is one of the biggest aggregate consumers and this is the reason why increasingly policies have been considering it. One of the key factors in curbing energy consumption in this sector is widely recognized to be due to erroneous behaviors and systems malfunctioning, mainly explained by the lack of awareness of the final user; so, training the final user to energy awareness can be more effective and cheaper than other policies. In this context, energy management in homes is playing, and will play even more in future, a key role in increasing the final consumer awareness towards its own energy consumption and consequently in bursting its active role in smart grids. The aim of this paper is to highlight the economic benefits of low cost intelligent control domestic devices, to identify energy behavior, system status and improve energy efficiency. The scope is to develop interaction between final users to create a network of energy consumption efficiency. The paper presents an application of Multi-scale Principal Component Analysis to diagnose inefficient occupant behavior and systems malfunctioning and suggest good practices of energy conservation.


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*Keywords:* Bad behavior, Fault diagnosis, Malfunction, Multi-Scale principal component analysis;

## 1. Introduction

The reduction of the greenhouse gasses is a worldwide growing challenge. Looking at how the different sectors contribute to the total anthropogenic greenhouse gas (GHG) emissions, the contribution from residential and commercial buildings is 7.9 % of the total emissions [1]. These data reflect the fact that this sector is, by no means,one of the major contributors. Nevertheless, the sector is considered one of the most interesting when it comes to the estimated economical mitigation potentials with respect to GHG reduction in the 2030 forecast done by IEA.
The challenge is to implement flexible, easy-to-install and easy-to-use solutions with built-in intelligence capable of i.e. timing the energy consumption with the availability of surplus energy from renewable energy sources. Development of smart sensors, advanced control systems and complex communications architectures for use in private households makes possible to have technology assistance to solve this challenge.
The household sector has a wide and undeveloped potential basically due to economical causes. Energy efficiency initiatives lead to remarkable reduction of the energy bills and consequently in a short payback period for large users of both the tertiary and the industrial sectors compared to household sector. On the other hand, investments in energy


Selection and peer-review under responsibility of KES International
doi:10.1016/j.egypro.2014.12.386

efficiency in the domestic sector are sometimes paid back in a period considered too long by the energy final users. The consequence is that, recently, energy efficient technologies have been penetrating tertiary and industrial sector, while the technology stock of the household sector is still backward compared to the available technologies in commerce. One of the aims of this paper is to highlight the economic benefits of low-cost intelligent control domestic devices to identify energy behavior, system status and improve energy efficiency. The further goal is to develop interactions between final users to create a network of energy consumption efficiency. Signal system technology could be a useful tool to expand this system on a large scale of interactive building networks.

It is worth noting that energy efficiency is one of the household consumption challenges; another relevant key factor is the "occupant behavior". In fact, the benefits achievable with energy efficiency could be either amplified or neutralized by, respectively good or bad practices carried out by the final users [2]. In particular, it is important to point out that often the final user bad practices are driven by lack of unawareness or ignorance rather than bad faith. Training the final user with respect to energy awareness can be more effective and the cheapest than other policies [3] and it can be achieved coordinating the activities of energy consumers and energy providers in order to best fit energy production capabilities with consumer needs and, in this way, avoiding energy demand peaks, which generally have adverse environmental impacts and increase energy production costs.

The paper presents a work based on the evaluation of the potential reduction of heating energy consumption achievable by means of a system able to diagnose inefficient occupant behavior and systems malfunctioning in the household sector and suggest good practices of energy conservation. Since the main challenge is the retrofit of existing buildings, the components of a system proposed are the least intrusive and cheapest available.
The procedure proposed to monitoring the system is based on Multi-Scale Principal Component Analysis (MSPCA).
MSPCA formulation extracts contributions from events occurring at different scales, that are captured by Principal Component Analysis (PCA) models at the corresponding scale. Moreover wavelets, with their time-frequency localization and multi-resolution property, can be used as a useful framework for multi-scale representation of data [4]. To isolate the defects a KDE algorithm is used on the PCA residuals, and thresholds are computed for each sensor signal to determine if, for each wavelet matrix, the signals are involved in the defect or not. KDE method is widely recognized as a robust methodology to determine numerically the probability density function (PDF) of data, in particular such estimation technique is introduced where Gaussian assumption is not recognized [5].

The evaluation of the energy consumption has been made by the use of HAMBASE Simulator [6]. HAMBASE, Heat Air Moisture Model for Building and Systems Evaluations, the evaluation of heating and steam flows within the buildings. For a specific building model, it is possible to calculate the internal temperature, internal humidity, and the energy need to heat and cool the dwelling.

## 2. Recalled Results

In [7] the Multi-Scale Principal Component Analysis (MSPCA) diagnosis technique has been tested using a set of ambient parameters generated from a building simulation code where a series of bad practices and malfunctioning events were embedded. The MSPCA proposed in [8] deals with processes that operate at different scales, and have contribution from: (i) events occurring at different localizations in time and frequency, (ii) stochastic processes whose energy or power spectrum changes with time and/or frequency, (iii) variables measured at different sampling rate or containing missing data. The MSPCA is a way to combine two techniques, Principal Component Analysis (PCA) and Wavelet Transform (WT), to extract maximum information from multivariate sensor data. The goal of [7] was evaluating the environmental and economic gain achievable by interactive building network (IBN). In the IBN sector MSPCA takes advantages from the fact that it does not need the building model since the diagnostic procedure is data driven and this is useful to adapt the algorithm to different buildings [7]. Furthermore, MSPCA gives a response to the fault with a delay that depends on the scale depth that is only of few samples [4], [9]. The proposed IBN architecture in [7] had the aim of increasing the energy awareness of household final users.
Preliminary results in [7] have shown the best practices of the users have a fundamental role in curbing energy consumptions for thermal heating. It has been also shown that the higher initial energy performance the lower marginal energy and economic benefits.

*2.1 Principal Component Analysis*

PCA is a dimensionality reduction technique able to simplify and improve process monitoring procedures. It creates a lower-dimensional representation in a way that preserves the correlation structures between the process variables. PCA rotates the original coordinate system along the direction of maximum variance.

Consider a data matrix $X \in \Re^{n\times m}$ with *n* sample rows and *m* variable columns that are normalized to zero mean and unit variance. The matrix $X$ can be decomposed into a score matrix $x = \hat{x} + \tilde{x}$ and a loading matrix $P$ whose columns are the right singular vectors of $X$ as follows:

$$X = TP^T + \tilde{X} = TP^T + \tilde{T}\tilde{P}^T, \tag{1}$$

where $\tilde{X} = \tilde{T}\tilde{P}^T$ is the residual matrix [10], it follows that:

$$\tilde{x} = (I - PP^T)x \in S_r, \tag{2}$$

where $S_r$ is the projection on the Residual Subspace (RS) [9]. For fault detection of new sample *x*, a deviation in *x* from the normal correlation could change the projections onto the subspaces, either $S_p$ or $S_r$. Consequently, the magnitude of either $\tilde{x}$ or $\hat{x}$ could increase over the values obtained with normal data. The Square Prediction Error (SPE), also known as *Q*, is a statistic that measures lack of fit of a model to data. The SPE statistic indicates the difference, or residual, between a sample and its projection into the *k* components retained in the model. The exact description of the distribution of SPE is given in [11]:

$$SPE = \|\tilde{x}\|^2 = \|(I - PP^T)x\|^2. \tag{3}$$

The process is considered normal if:

$$SPE \le \delta^2, \tag{4}$$

where $\delta^2$ is a confidence limit for SPE. A confidence limit expression for SPE, when *x* follows a normal distribution, is developed in [10, 12-14].The drawbacks of SPE index for fault detection are mainly two: the first is related to the assumption of normal distribution to estimate the threshold of this index, the second is that the SPE is a weighted sum, with unitary coefficients, of quadratic residues $\tilde{X}_i^2$. To improve the fault detection, these two drawbacks are faced assuming that the process is considered faultless if, for each *i*:

$$\tilde{X}_i^2 \le \delta_i \qquad i = 1, \dots, m, \tag{5}$$

where $\delta_i$ is a confidence limit for $\tilde{X}_i^2$. To estimate the confidence limit $\delta_i$, even when the normality assumption of $\tilde{X}_i^2$ is not valid, the solution is to estimate the PDF directly from $\tilde{X}_i^2$ through a non parametric approach. In [15-17], KDE is considered because it is a well established non parametric approach to estimate the PDF of statistical signals and evaluate the control limits. Assume *y* is a random variable with density function denoted by $p(y)$. This means that:

$$P(y < k) = \int_{-\infty}^{k} p(y)dy. \tag{6}$$

Hence, by knowing $p(y)$, an appropriate control limit can be determined for a specific confidence bound $\alpha$, using Eq. (8). Replacing $p(y)$, in Eq. (8), with the estimation of the probability density function of $\tilde{X}_i^2$, called $\hat{p}(\tilde{X}_i)^2$, the control limits will be estimated by:

$$\int_{-\infty}^{\delta_i} \hat{p}(\tilde{X}_i)^2 d\,\tilde{X}_i^2 = \alpha. \tag{7}$$

Fault isolation and diagnosis are performed by the PCA contributions: defining the new observation vector $x_j \in \Re^m$, the total contribution of the $i^{th}$ process variable $X_i$ is

$$CONT_i = \sum_{j=1}^{N} \tilde{x}_{ij}^2 \qquad j = 1, \dots, m. \tag{8}$$

*2.2 Wavelet transform*

The Wavelet Transform (WT) is defined as the integral of the signal $x(t)$ multiplied by scaled, shifted version of basic wavelet function $\psi(t)$, a real valued function who's Fourier transform satisfies the admissibility criteria [18]. Then the wavelet transformation $C(\cdot,\cdot)$ of a signal *s(t)* is defined as:

$$\begin{gathered} c(a,b) = \int_R s(t) \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right) dt, \\ a \in \Re^+ - \{0\}, \\ b \in \Re, \end{gathered} \tag{9}$$

Where *a* is the so-called scaling parameter, *b* is the time localization parameter. Both *a* and *b* can be continuous or discrete variables. Multiplying each coefficient by an appropriately scaled and shifted wavelet yields the constituent wavelets of the original signal. For signals of finite energy, continuous wavelets synthesis provides the reconstruction formula:

$$s(t) = \frac{1}{K_\psi} \int_{\Re} \int_{\Re^+} c(a,b) \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right) \frac{da}{a^2} db, \tag{10}$$

where:

$$K_\psi = \int_{-\infty}^{+\infty} \frac{|\hat{\psi}(\xi)|}{|\xi|} d\xi, \tag{11}$$

denotes a (Wavelet specific) normalization parameter in which $\hat{\psi}$ is the Fourier transform of $\psi$. Mother wavelets must satisfy the following properties:

$$\begin{gathered} \int_{-\infty}^{+\infty} |\psi(t)|\, dt < \infty, \quad \int_{-\infty}^{+\infty} |\psi(t)|^2\, dt = 1, \\ \int_{-\infty}^{+\infty} |\psi(t)|\, dt = 0. \end{gathered} \tag{12}$$

To avoid intractable computations when operating at every scale of the Continuous WT (CWT), scales and positions can be chosen on a power of two, i.e. dyadic scales and positions. The Discrete WT (DWT) analysis is more efficient and just as accurate. In this scheme *a* and *b* are given by:

$$(j,k) \in Z^2: \quad a = 2^j, \quad b = 2^j k, \quad Z \coloneqq \{0, \pm 1, \pm 2, \cdots\}. \tag{13}$$

Then defining:

$$(j,k) \epsilon Z^2: \quad \psi_{j,k} = 2^{-j/2} \psi(2^{-j} t - k), \tag{14}$$

the discrete wavelet analysis can be described mathematically as:

$$c(a,b) = c(i,j) = \sum_{n \in Z} s(n)\psi_{j,k}(n),\quad a = 2^j, b = 2^j k,\quad j \in Z, k \in Z. \tag{15}$$

The inverse transform, also called discrete synthesis, is defined as:

$$s(n) = \sum_{j \in Z} \sum_{k \in Z} c(j,k)\psi_{j,k}(n). \tag{16}$$

The detail level $j$, and the approximation at level $j$ are defined as:

$$D_j(t) = \sum_{k \in Z} c(j,k)\psi_{j,k}(t),\quad A_{j-1} = \sum_{j>J} D_j, \tag{17}$$

and the following equations hold:

$$A_{j-1} = A_j + D_j,\quad s = A_j + \sum_{j \leq J} D_j. \tag{18}$$

## 3. Developed Algorithm

MSPCA can be used as a tool for fault detection and diagnosis by means of statistical indexes. In particular, faults are detected by use the SPE and the diagnosis is conducted by the SPE contribution method. The contribution is the technique of computing the SPE of the sensors separately. In this way it is possible to detect which sensor is most affected by fault [10], moreover contribution plots at each scale represent the fault signature. Process monitoring by MSPCA involves computing independent principal components loadings and detection limits for the scores and residuals at each scale from data representing normal operations. For new data, a statistically significant change is indicated if the residuals, based on wavelet coefficients computed from the most recent measurements, violate the detection limits at any scale. Since the wavelet coefficients are sensitive only to changes, if a variable goes outside the region of normal operation and stays there, the wavelet coefficients will be statistically significant only when the change first occur. The change is first detected at the finest scale that covers the frequencies present in the feature representing abnormal operation. If the change persists, it is detected by wavelet coefficients at coarser scales present in the abnormal feature. In this condition, the most recent scaling function coefficients are the last ones to violate the detection limit, and continue to do so for as long as the process remains in an abnormal state. Similarly, when a process returns from abnormal operation, the change will be detected by wavelet coefficients, but the scaling function coefficients will continue to indicate abnormal operation for several samples due to the coarser scale of representation. Thus, process monitoring based only on PCA of the wavelet and scaling function coefficients will not allow quick and continuous detection of faults, and may create false alarms. The last MSPCA step consists of reconstructing the signal to the time domain, and computing the scores and residuals for the reconstructed signal improves the speed of detection abnormal operation and eliminates false alarm [8]. The following algorithm is derived from [14] and [4], and it is improved to include the diagnosis by means of SPE contribution. The algorithm consists of two stages: first, the training step, the faultless data are processed and a model of this data is built. MSPCA training steps are summarized below:

T1. Data are preprocessed and outlier replacement algorithm is used [19] and [20];

T2. The Wavelet analysis is used, to refine the data, with a level of detail L;

T3. Normalize mean and standard deviation of detail and approximation matrices and apply PCA to the approximation matrix $A_L$, of order $L$, and to the L detail matrices $D_j$, where $j = 1, ...L$;

T4. The PCA transformation matrix $\boldsymbol{P}$ and the signal covariance matrix $\boldsymbol{S}$ are computed for each approximation and detail matrices;

T5. The $\tilde{X}_i$ signals are computed, for each wavelet matrix;

T6. The $\delta_i$ thresholds are computed, for each detail matrix and for the approximation matrix of order $\boldsymbol{L}$, using the KDE algorithm (Eq. 9) and a confidence bound $\alpha$;

In the second phase, the diagnosis step, the model previously obtained is online compared with the new data and a statistical index of failure is calculated. MSPCA diagnosis step are summarized below:

D1. The previous steps, except threshold computation, T1, T2, T3, T4, andT5 are repeated for each new dataset, the data are standardized as in the training step T3 and the PCA and $\tilde{X}_i$ signals are computed using the $\boldsymbol{P}$ and $\boldsymbol{S}$ matrices, obtained in the training step;

D2. **If** any of the $\tilde{X}_i$ signals is over the thresholds $\delta_i$, the fault is detected and the diagnosis is performed by the $\left\|\tilde{X}_i\right\|$contributions, **else** the next data set is analyzed (return to D1);

D3. Compute all the residual contributions $\left\|\tilde{X}_i\right\|$, for each sensor, for all details and approximation matrices and diagnose the fault type.

## 4. Case study

In order to test the methodology used in [5], simulations have been done using HAMBASE to underline the applied methodology to diagnose inefficient occupant behavior and system malfunctioning in the household sector. In order to fulfill this goal, the present study is developed by simulating a building with a specific occupancy and thermal profile, a specific heating consumption level and a defined ambient temperature profile. Some “inefficient behaviors” and “systems malfunctioning” are simulated in order to test the diagnosis methodologies.
The analyzed building is a 80 $m^2$ apartment and it is composed of 4 spaces of different size, each one has a different usage: kitchen and living room, bathroom, and bedrooms (adults and kids); windows have a mean surface of 2.8 $m^2$. The flat is a single housing unit and it is located at the bottom floor of the building; its walls define the perimeter and walls and roof exchange heat directly with the external sides.
The following table presents the partition of the spaces in 4 sectors and their temperature set points.

Table 1.Table of flat dimensions, sectors partition, and temperature set point.

| | Type of sector: | Surface [$m^2$] | Volume [$m^3$] | Temperature Set Point [°C] |
|---|---|---|---|---|
| Sector 1 | Kitchen&Living room | 5x6=30 | 30x3= 90 | 20 |
| Sector 2 | Bedroom (adults) | 5x3=15 | 15x3=45 | 18 |
| Sector 3 | Bedroom (kids) | 2.5x4=10 | 10x3=30 | 20 |
| Sector 4 | Bathroom | (5x3)+(4x2.5)=25 | 25x3=75 | 18 |

The flat was simulated by means of HAMBASE. The heating consumption level of the building equals to 75kWh/$m^2$/y. The heating system consists of a boiler fed by natural gas whose efficiency has been assumed equal to 90%. The occupancy profile characterizes a dwelling occupied most of the day (by an old person or a housewife) and the heating system is considered to work continuously. The ambient temperature is controlled in each space by mean of radiator smart thermostats and valves. The radiator smart thermometers are located in each space in order to avoid that a single one affects the comfort of the others, and to have the possibility to choose different set point based on the usage of the specific space. The present study uses a solution where the temperature has a comfort set point equal to 20°C in the spaces mostly used during the day (kitchen, living room, and kids bedroom) and equal to 18°C in those which are less used during the heating system operating time (bathroom and adults bedroom).

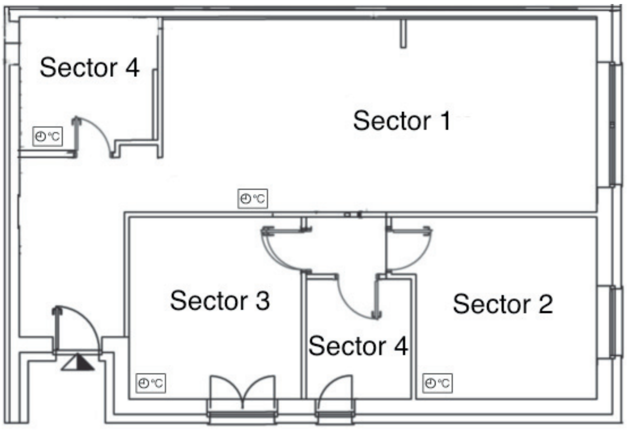


Figure1: Flat plan and sectors partition

The radiator smart thermometers are provided with a sensor that measures the following signals: valves, ambient temperature and relative humidity of each sector; external temperature and external relative humidity are also
In order to evaluate the diagnosis features of the presented model, some faults and bad behavior (open window) are simulated considering the following assumptions:

- Stuck Sensor: each room has a stuck sensor malfunction for 13 hours continuously, five times per year. Sixty-five hours during the all year for each room.
- Stuck Valve: each room has a stuck valve malfunction for 13 hours continuously, five times per year. Sixty-five hours during the all year for each room.
- Wear Sensor: each sensor follows a linear wearing process with variance equals to 0.5°C during the all year (February-December).
- Wear Valve: each valve has a hysteresis increase from 0.5 to 1°C. The wear starts in February and increases until December.
- Open window: each room has open window behavior of three hours for two days, six times per year. 36 hours during the all year for each room.

A sample of the temperature dynamics in sector 1 and 2 and outside is illustrated in Fig.2 for the period from January to April 2007. Red and blue lines display the temperature trend of sector 1 and 2 respectively and the black line shows the outside temperature.

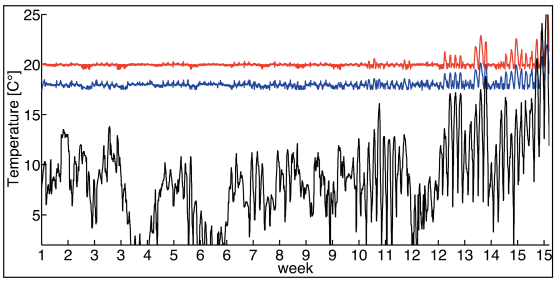


Figure 2: Temperature dynamics in Sector 1 (red line), Sector 2 (blue line) and outside temperature (black line).

## 5. Results

The present study has shown a reduction in costs and energy consumption when faults and bad behaviors are avoided. Table 2 presents the yearly consumption in kWh and euro evaluated in case of absence of malfunctions (faultless), for each single fault, and in case of bad behavior, considering the assumption given in Sec. 4.

Table 2: Energy Consumption (kWh) and costs (€) in case of faultless and malfunctions

| Malfunctions | Energy consumption *(kWh per year)* | Costs *(€ per year)* | Malfunction | Energy consumption *(kWh per year)* | Costs *(€ per year)* |
|---|---|---|---|---|---|
| Faultless | 4084 | 191 | Stuck Sensor | 4087 | 191 |
| Bad behavior (Window open 20%) | 4220 | 197 | Stuck Valve | 4087 | 191 |
| Wear Sensor (Sector 1) | 4095 | 191 | Wear valve (Sector 1) | 4196 | 196 |
| Wear Sensor (Sector 2) | 4105 | 192 | Wear valve (Sector 2) | 4327 | 202 |
| Wear Sensor (Sector 3) | 4092 | 191 | Wear valve (Sector 3) | 4334 | 203 |
| Wear Sensor (Sector 4) | 4111 | 192 | Wear valve (Sector 4) | 4336 | 203 |

### 5.1. *Faults: Stuck and Wear*

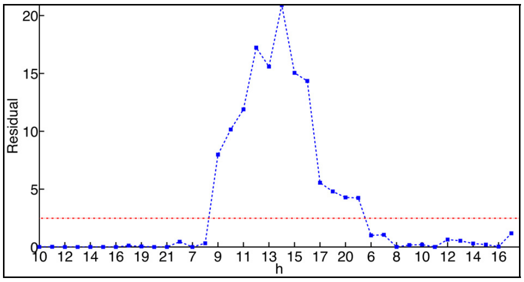


Figure3: Residuals of approximation A3, Fault sensor, Sector 4

The fault on a temperature sensor is here discussed, in detail the sector 4 sensor is considered. In Fig. 3 the residual computed on approximation matrix A3 of MSPCA is shown. The threshold, computed by KDE, is exceeded with a couple of minutes delay, due to the data window necessary for the computation (see Sec. 3). The fault is correctly detected and isolated by the temperature sensor in sector 4 residual and maintains for the fault duration. This early detection of the fault allows quick component remediation or replacement, avoiding discomfort and heating system management malfunction (as smart thermostat, valves and boiler).

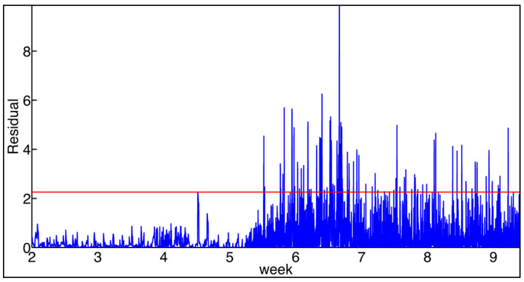


Figure 4: Residual approximation A3, Wear sensor, Sector 4

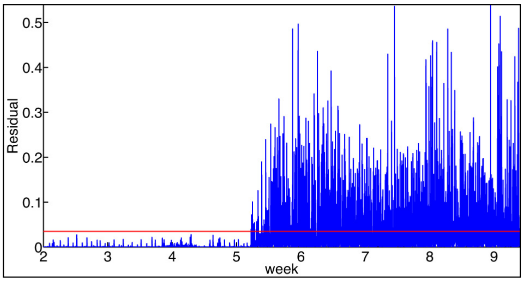

Figure 5: Residual detail D3, Wear sensor, Sector 4

The issue of prevent wear in the domestic heating system is of great concern for authors, because the total amount of energy waste is great, considering that typically these malfunctions are not recognized for years and the number of heating system subject to wear. Moreover wear often arise as a slow drift in one or more system parameters and users comfort are not immediately affected by this class of faults.

Using the proposed data-driven procedure, both sensor and thermostat wear are recognized.

Figs. 4 and 5 show the residuals on the temperature sensor in room 4, for approximation matrix A3 and detail matrix D3 respectively. Residual depicted in Fig. 4 shows that after few days from the wear beginning, it exceeds the threshold but does not maintain over, unlike Fig. 5, where the wear condition is correctly identified along the remaining simulation time.

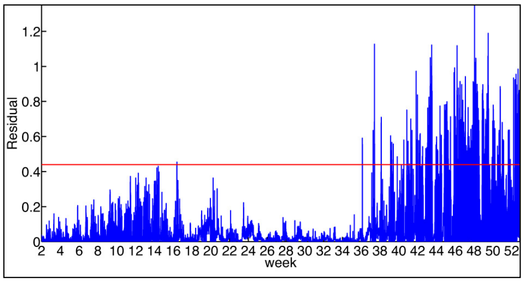

Figure 6: Residuals of approximation A3, Wear valve, Sector 4

Another wear condition involve the thermostat hysteresis, that could increases over the time due to the wear effect.

In Fig. 6, the residual on the valve position signal is shown, in this case the identification of the wear condition is more difficult, but after two months it is detected by the MSPCA.

### *5.2. Bad behavior: Opened windows*

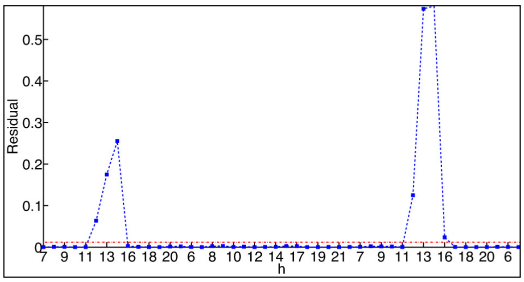

Figure 7: Residuals of approximation A3, bad behaviour: open window (20%)

The first out of tolerance samples refer to a window opened at about 20% of its nominal surface, while the second set of samples indicate the window is opened at 100%. So, the Fig. 7 shows the residual of the approximation matrix A3, that is the more sensitive for this behavior.

The issue of detect an opening window with a reduced set of sensor, and specifically, without contact sensor (on the windows) is an interesting challenge in developing low cost systems for monitoring and diagnosis. In Fig. 7 two bad behavior are detected and diagnosed. The detection delay is about 20-30 minutes, but the aim consists of detect an open window, inform the user and assess the situation.

## 6. Conclusion

The methodology has proved to be very powerful since it allowed to diagnose several "faults" simply monitoring the trend of ambient temperature, the of each room of the apartment. One of the main advantages of detecting more "faults" by monitoring just one parameter is the low price of the BEMS (Building Energy Management System) due to the reduced the number of sensors. As an example, the methodology proposed allowed to detect an open window by real-time, monitoring the room ambient temperature without installing a contact sensor in each window.

The development and validation of a signal-based diagnostic system based on MSPCA method is augmented with a probability density function estimator to better compute the fault thresholds. The Kernel Density Estimation allows to deal with processes where signals do not match the Gaussian distribution hypothesis. The monitoring system by the proposed MSPCA algorithm promotes the detection of faults and human behaviors.

Future works involve the employment of an Interactive Interface with users to give them feedbacks about bad behaviors and tips to overcome energy wasting.

## 7. References

[1] Pachauri RK, Reisinger A. Climate change 2007: Synthesis Report. Geneva: IPCC; 2007.

[2] Faiers A, Cook M, Neame C. Towards a contemporary approach for understanding consumer behavior in the context of domestic energy use. Energy Policy 2007; 35:4381-4390.

[3] Lindén AL, Carlsson-Kanyama A, Eriksson B. Efficient and inefficient aspects of residential energy behavior: What are the policy instruments for change?. Energy Policy 2006; 34:1918-1927.

[4] Ferracuti F, Giantomassi A, Ippoliti G, Longhi S. Multi-Scale PCA based fault diagnosis for rotating electrical machines. 8$^{th}$ European Workshop on Advanced Control and Diagnosis ACD 2010; 296.

[5] Ferracuti F, Giantomassi A, Longhi S. MSPCA with KDE Thresholding to Support QC in Electrical Motors Production Line. Manufacturing Modelling, Management, and Control (MIM) 2013; 7:1542-1547.

[6] De Wit M. HAMBASE Heat air and moisture model for building and system evolution. Bouwstenen series of the department of Architecture, Building and Planning of the Eindhoven University of Technology, Eindhoven University Press, 2006.

[7] Comodi G, Giantomassi A, Arteconi A, Meloni C, Pizzuti S. Proposal of a system for diagnosing with inefficient occupant behavior and systems malfunctioning in the household sector. Transactions of the Wessex Institute 2012.

[8] Bakshi BR. Multiscale PCA with application to multivariate statistical process monitoring. AIChE Journal 1998; 44:1596-1610.

[9] Ferracuti F, Giantomassi A, Longhi S, Bergantino N. Multi-scale PCA based fault diagnosis on a paper mill plant. Emerging Technologies & Factory Automation (ETFA) 2011; p. 1-8.

[10] Misra M, Yue HH, Qin SJ, Ling C. Multivariate process monitoring and fault diagnosis by multi-scale PCA. Computers & Chemical Engineering 2002; 26:1281-1293.

[11] Jackson JE. A User's Guide to Principal Component. New York: John Wiley & Sons; 2003.

[12] Jackson JE, Mudholkar GS. Control Procedures for Residuals Associated with Principal Component Analysis. Technometrics 1979; 21:341-349.

[13] Lachouri A, Baiche K, Djeghader R, Doghmane N, Ouhtati S. Analyze and Fault Diagnosis by Multi-scale PCA. Information and Communication Technologies: From Theory to Applications (ICTTA) 2008; p.1-6.

[14] Ciandrini C, Gallieri M, Giantomassi A, Ippoliti G, Longhi S. Fault detection and prognosis methods for a monitoring system of rotating electrical machines. Industrial Electronics (ISIE) 2010; p. 2085-2090.

[15] Odiowei P-EP, Cao Y. Nonlinear Dynamic Process Monitoring Using Canonical Variate Analysis and Kernel Density Estimations. IEEE Transactions on Industrial Informatics 2010; 6:36-45.

[16] Yu J. Bearing performance degradation assessment using locality preserving projections. Expert Systems with Applications 2011; 25:7440-7450.

[17] Yu J. Bearing performance degradation assessment using locality preserving projections and Gaussian mixture models. Mechanical Systems and Signal Processing 2011; 25:2573-2588.

[18] Li X, Dong S, Yuan Z. Discrete wavelet transform for tool breakage monitoring. International Journal of Machine Tools and Manufacture 1999; 39:1935-1944.

[19] Jolliffe IT. Principal Component Analysis. Springer; 2002.

[20] Hoo KA, Tvarlapati KJ, Piovoso MJ, Hajare R. A method of robust multivariate outlier replacement. Computers and Chemical Engineering 2002; 26:17-39.