Towards a Data Driven Platform for Energy Efficiency Monitoring: Two Use Cases

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Abstract. The paper describes an ongoing work to define a framework to support monitoring procedures for distribution systems in smart cities. Specific use cases, involving data driven methods for energy monitoring, benchmarking and forecasting in urban scenarios are analysed. The objective is to identify services required in such framework to define the requirements of a reference architecture to support data-driven methods for energy efficiency monitoring and assessment. Use cases focus on multi-entity buildings monitoring and consumption forecasting.

Keywords: Energy Monitoring, Short-term Forecasting, Data mining, Services

1 Introduction

Urban distribution systems (energy, water, mobility, etc.) are large CPS (Cyber Physical Systems) governed by social demand subject to environmental changes constrained to the infrastructure and control capabilities. Assessment and efficiency of such distribution systems require new monitoring solutions capable to infer system state from an ecosystem of heterogeneous data (Smart meters, weather stations, sensor networks, Intelligent Electronic Devices –IEDs-, social networks, etc.) flowing at different time rates that range from seconds (events, alarms, control, etc.) to minutes and hours (metering, weather, etc.). At different scale, neighbourhoods, communities or multi-entity buildings and malls can also be considered large CPS continuously operated accordingly to demand affected by user's activities. As important is to know physical system constraints as consumer's behaviour, and interactions between both.

Major ICT vendors have made efforts for developing smart city transversal platforms (PlanIT Operating System, the IBM® Intelligent Operations Center or Oracle's Smart City Platform Solution) oriented to integrate city information and making it available to end-users. On the other hand, the utilities (water, electricity, gas, etc.) have their proprietary solutions (SCADAs, AMIs, etc.) specifically designed to operate and supervise these infrastructures and providing managing and billing services. This work falls in between these two scopes and shares the IoT (internet of Things) vision, focusing not only in making data available but also providing the required services to facilitate advanced data analysis, monitoring and assessment procedures in the domains of urban energy and water distribution and consumption. The necessity of providing unified solutions for water and energy efficiency in municipalities is pointed in [15]. Positive effects of consumer awareness to increase savings is a key point of Directive 2012/27/EU on energy efficiency [1] at the same time that exist some contrasted experience in the power consumption domain. The work presented in this papers aims to analyse specific use cases in order to identify services that are required in a platform that supports the development of energy efficiency monitoring and assessment applications for urban infrastructures.

1.1 Context and related work

A wide vision of basic energy management services (monitoring, prediction, management, optimisation, billing and brokerage) at city level are identified in [13] providing an insight on their functionality, usage and development challenges. Relevance of energy signatures, for monitoring at district level, and efforts towards its better energy efficiency, are highlighted in [15] to increase energy savings. In the same direction, Measuring and Verification (M&V) guidelines used for the evaluation of energy efficiency, as those proposed by IPMVP (International Performance Measurement and Verification Protocol, http://www.evo-world.org), emphasises the necessity of simple models to be used with contractual purposes by ESCOs (Energy Service Companies) and customers. Particular examples at building level are proposed in SG-BEMS [12] focused on large public buildings. In case of buildings, methodologies to improve adjustment and calibration of tools to support the monitoring are studied in [5]. Energy efficiency models for urban environments and buildings usually are calibrated with hourly data and typologies of days and seasons are used to introduce corrections. Improvements supported by wireless sensors have been proposed in [6]. They served to propose recommendations when monitoring energy performance of buildings. Principal Component Analysis (PCA) has been used to analyse electricity consumption in residential dwellings [2] and in office buildings [3]. Multivariate analysis using Principal Component Regression and Partial Least Square Regression was proposed in [4] to find relationships between building information (occupancy level, control signals, water and air temperatures) and energy use (heating, electricity and fans). An example of improved energy supervisory system aligned with this work was recently proposed in [8]. On the water side, one of the biggest problems in the operation of water distribution networks (WDN) is to know beforehand the consumption demand due to the large delays in the process. This problem is analogue in the electricity domain but motivated for the necessity to adjust generation and demand accurately. Usually, water demand forecasting methods use statistical and contextual information providing models for different time scales [11]. Relevance of ICT solutions in the WDN are highlighted in [16] at the same time that points the importance of energy savings in water distribution. Important activity in the water distribution domain has been done in Spain including works of fault detection and sensor reconstruction [17] in the field, or abnormal water quality detection and isolation based on simulated models [18], and operation optimisation [19] for specific distribution networks. Several water management projects such as those undertaken in Quebec (Canada) [10], Emscher/Lippe (Germany)[11], or Barcelona [9], integrate fully automated systems with telemetry and telecontrol elements to provide real-time control over the network and optimization. These trends are aligned with the necessity of providing new software infrastructure to deal with new data being generated in these distributed infrastructures and linked with consumer profiles.

2 Vision

A generic platform to facilitate the development and deployment of solutions for monitoring and assessment of such urban systems and subsystems has to consider not only the infrastructure itself but also the interaction with consumers. It has to support advanced data analytics services for the deployment of energy management procedures as audits (EN16247-1, IS050002, measure and verification (IPMVP, ISO 50015:2014), or implantation of global energy management procedures as ISO50001 or ISO 50006:2014 (energy performance). In all of these procedures, the elaboration of performance indicators and baseline models require data collection, treatment, analysis and modelling. Complexity in data management resides, not only in the integration of existing heterogeneous data management infrastructures (Building Energy Monitoring systems, BEMs; Supervisory Control and Data Acquisition, SCADAs; Advanced Metering Infrastructures, AMIs; Wireless Sensor Networks, WSN; web sensors, etc.), but, also in the differences in data formats, transmission protocols, time references and so on.

After data integration, the next challenge is to analyse data flows conducting to advance monitoring services and adopting data mining/knowledge discovery methodology (DM/KDD) to deal with learning and modelling tasks and fault detection and diagnosis methodologies to implement advanced monitoring schemas. Thus, the aim is to guarantee the access and management of data and providing a set of goal oriented services to systematically exploit data for energy management purposes (Fig. 1). Two main elements can be distinguished, the data distribution and management platform and the energy monitoring and assessment services. Services have been grouped in four basic categories:

- **Data analysis and modelling:** Set of services in charge of pre-processing data (data cleansing, filtering), preparing (feature selection, aggregation, transformation, etc.) and modelling (including model validation) according to specific goals. A variety of models can be obtained depending on data nature, learning paradigm and goals (monitoring, forecasting, classification, process understanding, etc.).
- **Data driven monitoring:** Set of services oriented to evaluate the performance of the (sub)system with respect to a reference model. Thus, monitoring takes advantage of a model created by means of a selection of methods from the previous group with data during normal operating conditions. This model will serve as a reference model to detect deviations (residuals or discrepancies) that can be considered abnormal (faults, anomalous behaviour, disturbances, etc.). Typical tasks include alarm generation, fault detection, fault isolation and fault diagnosis and implementation will be according to modelling strategy.

- **Benchmarking:** that is, services oriented to asses individual and global performance. Typically includes definition of KPIs (individual and aggregated) at consumer level and metrics to evaluate and rank individual performance with respect to their peers or with respect to pre-defined absolute reference models.
- **Decision Support:** this category includes tools to assist decision making. Optimisation, forecasting, what-if analysis or reasoning methods useful to infer new information relevant for situation assessment based on available data and models fall in this group.

From a methodological point of view, services in the first and fourth group, follows a DM/KD (data mining and knowledge discovery) approach, whereas services in the second and third group consist in exploitation of modelling results of previous two according to FDI/DX (fault detection and isolation/Principles of Diagnosis) principles.

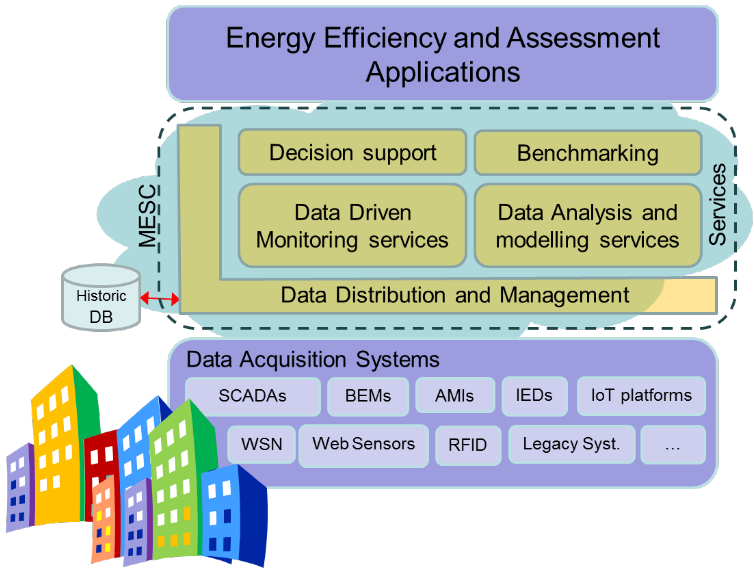

Fig. 1. Block diagram of the platform

Two use cases focusing on energy monitoring and forecasting are proposed in the next sections in order to identify services involved, required functionalities and possible interactions.

3 Energy Monitoring of neighbourhoods and multi-entity buildings

A major challenge on energy efficiency procedures is to monitor groups of entities in a defined boundary, affected by coupled behaviours, as a single unit allowing at the same time an overall monitoring of the infrastructure and an individualized monitoring of each sub-entity. Coupled behaviours usually exist because multiple reasons; among them, the physical contact among entities, mobility and habits of population within the boundaries or the existence of common resources and infrastructures (water/energy production or distribution). Examples include social buildings, hotels, malls, resorts, neighbourhoods, communities, etc. The analysis of these scenarios concluded with the definition of a generic data model capable to unify the development of monitoring solutions. A modelling strategy consisting on the Principal Component Analysis (PCA) based on previous work of the authors, validated in social buildings [21] and within a university campus [20], has been used to construct a reference model and exploit it for monitoring and assessment. The goal is to identify requirements, in terms of software services, to deal with the implementation of such solutions. Historic data has been used for modelling normal operating conditions based on the correlation among observed variables and at the same time separating noise and other uncorrelated information from the model. This model is used as reference for further monitoring tasks.

3.1 Data integration and data model

Data sources in neighbourhoods and any other multi-entity scenario are diverse (BEMs, AMIs, weather stations, WSN, etc.) and probably spread in wide areas. Therefore, the data distribution and management platform has to be capable to deal with this integration complexity. Nowadays, IoT like technology provided by many vendors allows data integration at physical and logical level. However, in order to develop data mining models data has to be cleaned and reorganized in suitable data models to make them treatable for the modelling/learning services. The data model proposed for a multi-entity building, a community or a neighbourhood consisting in multiple entities (L) will be represented by three matrices. A three dimensional matrix, (LxJxK), containing information from the J variables (temperatures, energy /water consumption, occupancy, etc.) of the L entities during K time instants, a second matrix (KxN) with information from the N global variables common to the whole building (weather, global consumption, etc.) and a third matrix containing M static attributes (surface, social parameters, etc.) to characterize each entity (LxM). This basic data structure is represented in Fig. 2. The matrix lengths L, M, N and J are invariant during the whole process, whereas the time dimension K is expected to vary, depending if we are in the modelling or monitoring step. During the modelling step, historical data is used, and consequently a large data set is expected, whereas during monitoring, usually a single observation (K = 1) will be evaluated at each time instant.

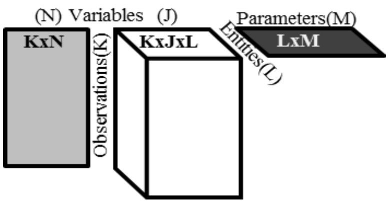

Fig. 2. Data Model for monitoring multi-entity buildings and neighbourhoods.

A social building composed by J=96 dwellings with a BEM reporting J=3 variables from each (water consumption –l-, heating energy -kWh- and water heating energy –kWh-) and a weather station with N=11 variables has been used to analyse capabilities and requirements in a real scenario and implement a monitoring strategy based on multivariate statistical method. Although particular attributes from each dwelling could be included in the LxM matrix, these have not been considered in this example for simplicity. Registers from K=636 days have been used to obtain the reference model.

3.2 Data analysis and modelling

Given a set of historic observations (K) represented in the previous data structure several learning methods could be applied to discover patterns or modelling behaviour contained in it. However, the majority of learning/modelling algorithms require as input a two dimensional matrix where columns represent variables and rows observations. This suggests that different analysis can be conducted with this data structure depending on how it is unfolded. From the different possible combinations only two of them have sense. We have called them the *time-wise* (Fig. 3) and *entity-based* (Fig. 4) unfolding views, respectively. Time-wise unfolding is appropriate to model the community as a whole, allowing modelling dependencies among variables within an entity and from different entities as well. Variables reporting general information (weather stations, general consumption, power generation, etc.) organised in a KxN matrix, this information can be also considered resulting in a Kx(LJ+N) 2D matrix as represented in **Fig. 3**.

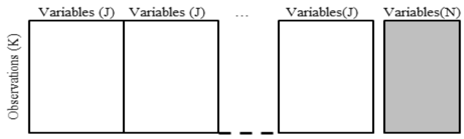

Fig. 3. Time-wise unfolding

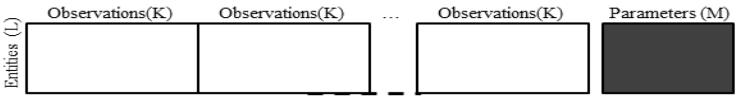

Fig. 4. Entity-wise unfolding.

On the other hand, entity-based unfolding will be useful when interest relies on capturing dependencies among variables over time that are common for all entities. Consequently, it is also appropriate to identify those entities that behave significantly differently from others during the observation period K (benchmarking). Characterisation of entities with M parameters (e.g. entity dimensions, socio-economic data of householders, etc.) can also be considered by appending it to the unfolded matrix resulting in a Lx(JK +M) matrix as depicted in Fig. 4. Therefore, with the same data structure we can perform different analysis of the neighbourhood, or multi-entity building. However, since the same 2D matrix structure is obtained, the same methodology can be applied to both, probably with different parametrisation.

As example, we propose performing a Principal Component Analysis (PCA) to gather interesting relationships among variables (Fig. 5). This method requires some data pre-processing known as auto-scaling (zero mean and unit standard deviation) to avoid dominance of variables with large magnitudes. After this pre-processing, the PCA method allows gathering linear relationships among variables, according to correlation criteria, in lower dimension subspace. The projection or loading matrix, P, is a unitary matrix that represents in certain manner the model of the data and gathers relationships among original variables. Transformed data in the lower dimensional space is represented by the score matrix, T. As a result original (auto-scaled) data, X, is projected into two orthogonal subspaces of lower dimension: the projection space, $\hat{X}$, capturing correlations among variables and the residual space, $\tilde{X}$, containing non correlated information (noise) according to relation (1).

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

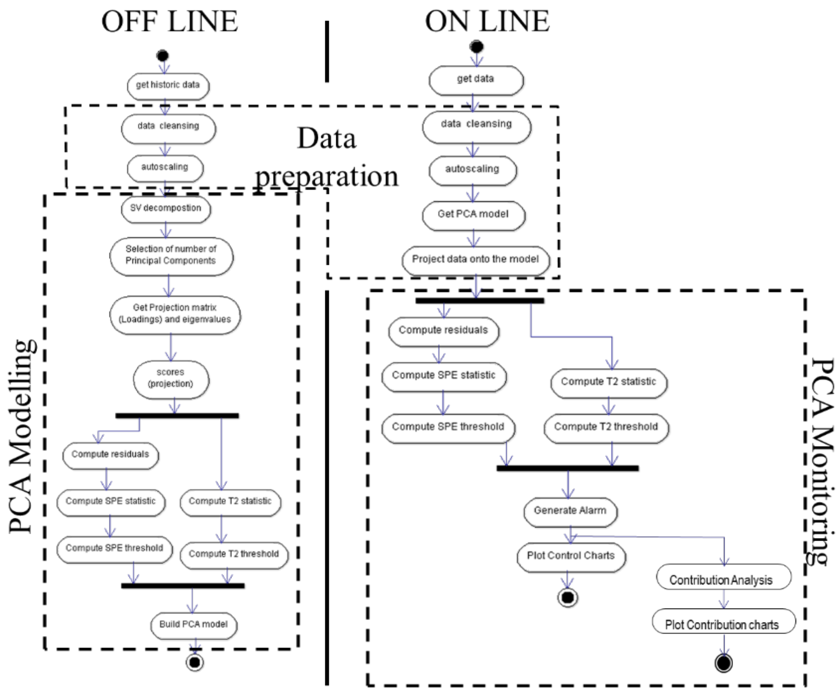

Fig. 5. Complete PCA strategy for modelling and monitoring

Statistics, T^2 and SPE, are used to evaluate the adequacy of an observation to this decomposition, T^2 evaluate distance to the centre of the model in the projection space, whereas SPE measures the distance of the observation to the projection space. These are known distributions that allow automatically compute statistic thresholds for a given sample (historic data used for modelling). Thus, the projection matrix, P, plus the T2 and SPE thresholds, defines the reference model. The flowchart used in this procedure is represented on the left of Fig. 5. Details of the method can be consulted in [21].

Table 1 PCA analysis and modelling services

	Computation	Output
Data analysis and modelling services		
Data preparation		
Unfolding	O	I
Data transformation	O	I
Autoscaling	C	I
PCA modelling		
Correlation matrix	C	I,O
Singular value decomposition	C	I
Selection of number of components	C	I
Projection	C	I
Residual computation	C	I
Computations of statistics (T^2, SPE)	C	I,O
Computation of contributions to T^2 SPE	C	I,O
Threshold computation	C	O

This general procedure allows creating a reference model in similar scenarios from historic data. Consequently, the method can be decomposed in services available through a common platform. Table 1 summarises the method as a library of services classified according to functionality. Columns on the right classifies the services in terms of two attributes: computational activity and output. Computation activity has been classified in four categories: O: data organisation and management, C: algorithm or service computational intensive, D: comparison, evaluation or decision service, V: visualisation service); and output differences between those that are addressed to users (O) or simply are intermediate results (I).

3.3 Data driven monitoring

Once a reference model has been created this can be exploited for monitoring. Following the previous example based on a PCA method, now the flowchart on the right in Fig. 5 represents the monitoring procedure that takes benefit of a model create previously with historic data. When monitoring, adequacy of new observation to the reference model is evaluated. The method requires applying the same pre-processing (data organisation and auto-scaling), projecting data using the loading matrix obtained in the model and computation of statistic T^2 and SPE associated to the new observation. Finally, the observation is considered consistent with the model if it falls below the statistic thresholds. Otherwise, a misbehaviour is detected and a decision has to be made about the possibility of generating alarms. In that case, the method also gives the possibility of projecting back the observation and analysing how original variables contribute to this out of control situation. Analysis of these contributions is used to isolate origin of the fault with respect to the variables used for monitoring. Usually the larger the contribution the major the probability that the corresponding variable was responsible for the misbehaviour.

The method follows the flowchart in Fig. 5 (right) and details are described in [21]. Associated services are listed in Table 2 including the same information as in the previous table. Columns on the right classifies the services in terms of computational activity (O: data organisation, C: computational intensive, D: decision, V: visualisation) and output (O: user oriented, I: Intermediate).

Table 2 PCA monitoring services

	Computation	Output
Monitoring:		
Data preparation		
Unfolding	O	I
Autoscaling	C	I
Projection	C	I
Residual computation	C	I
Computation of statistics (T^2, SPE)	C	I
Fault detection and alarm generation		
Evaluation of statistics w.r.t threshold	D	I
Alarm generation	O	O
Control charts	V	O
Fault Isolation:		
Computation of contribution (for both statistics, T^2 and SPE)	C	I,O
Contribution Charts	C	O

Following the same example of multi-entity social building, Fig. 6 and Fig. 8 show the T^2 and SPE charts respectively where circles on the left represent projection of days used for modelling under the time-wise unfolding. Crosses on the right correspond to new days being monitored. Distance to the horizontal axis represent how data fits the model.

Those that fall outside the thresholds are suspicious to behave different from normal. Then, contribution analysis (Fig. 7 for T^2 and Fig. 9 for SPE) allows analysing which variables (now represented in the horizontal axis) are responsible for such situation.

Solid line in these figures represent the statistical threshold for contribution of each variable and bars the magnitude of the contribution for the date under study. Variables, in the horizontal axis, are the three measured in each one of the 96 dwellings (separated by grey vertical lines) and weather station has been situated on the right. A rapid view reveals that dwelling number 45 performed significantly different in hot water consumption (volume and energy) the date 11/03/13.

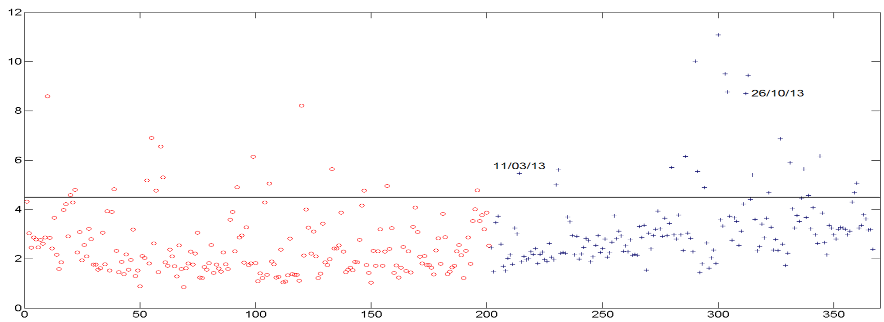

Fig. 6. T2 control Chart for time-wise monitoring

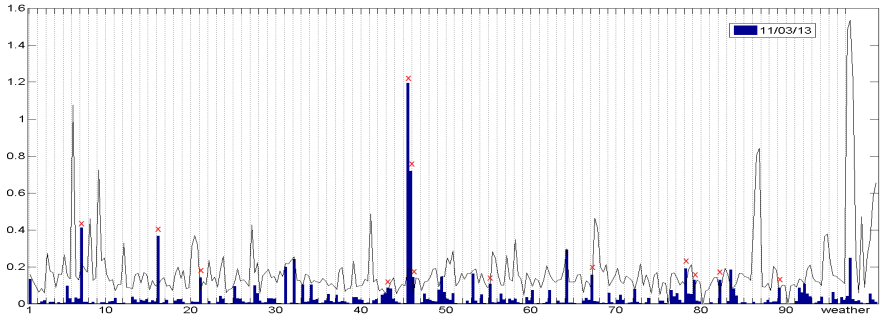

Fig. 7. Contribution chart for the day 11/03/13.

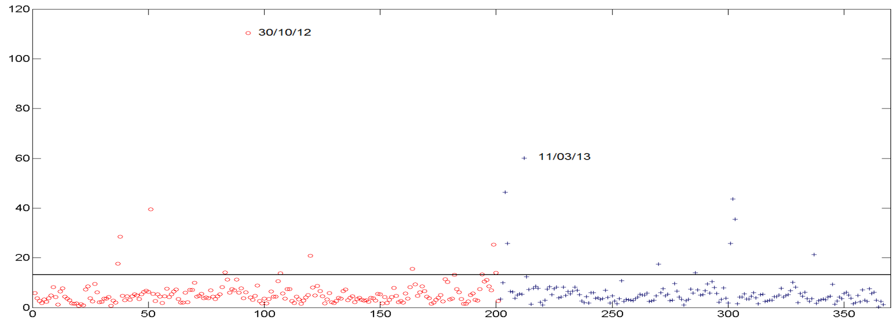

Fig. 8. SPE chart for time-wise monitoring

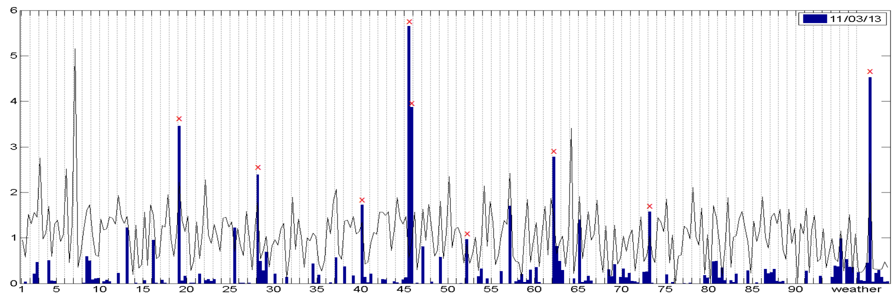

Fig. 9. Contribution chart for the day 11/03/13.

3.4 Benchmarking

The same procedure described before can be applied using the entity-based unfolding providing a different vision of the same building. In this case, only historic data is ben used, since no new dwellings can be projected. Thus, the analysis allows benchmarking the dwellings with respect to a reference model given by the average of all of them. Fig. 10 depicts the SPE control chart, where horizontal axis represents dwelling. Thus, a large variation over the threshold allows identifying those apartments that perform significantly different from others during the period of time used for building the model. Again, the contribution analysis, Fig. 11, is very useful to identify which variables, and dates, explain this behaviour. In the example dwelling M025 (circle, in Fig. 10) has been analysed and hot water and hot water energy at the first half of the observation time are the variables that explain the misbehaviour.

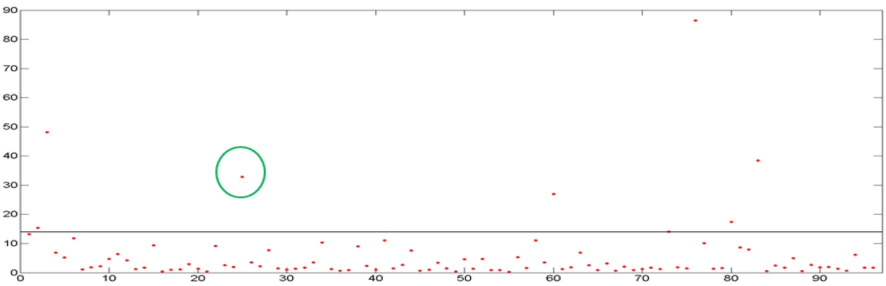

Fig. 10. SPE chart for entity-wise monitoring

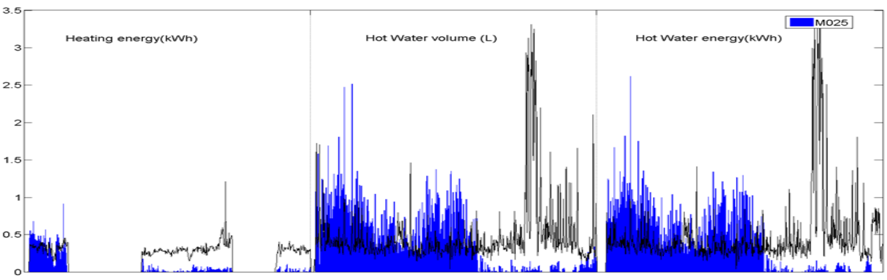

Fig. 11. SPE contribution chart of entity M025

4 Sort-term energy consumption forecasting

The purpose of this use case is to analyse the implementation of a decision support system that consists in forecasting energy consumption. In case of buildings for example, consumption is usually influenced by occupancy and temperature (external and internal set points) but other factors can also influence it (e.g. presence of renewable sources in the installation). Influence of variables and relationship among them variates depending on boundaries and many other contextual factors. Thus, a generic procedure for forecasting has to take maximum advantage of existing measures and create the best possible model. This implies selection of variables, pre-processing data, selectin appropriate algorithms, train them and evaluate performance of the model. Once a model with enough performance is obtained, it can be used for decision support. Thus, the platform has to support all the services required to create and exploit the model. Fig. 12 represents the complete flowchart required to create a model (on the left) and to reuse it for forecasting (on the right). The authors have validated this procedure with real data to forecasting consumption in academic buildings as it is described in [22]. The same example is used in this section for illustrative purposes.

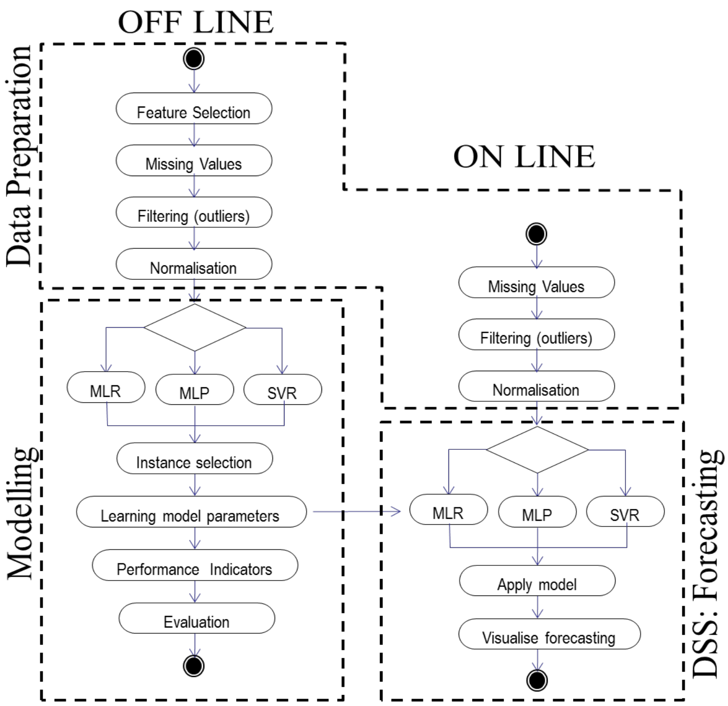

Fig. 12. Energy forecasting flowchart

4.1 Data analysis and modelling

Short term energy consumption forecasting consists on building a model where influence of other variables allows estimating consumption. Although, usually occupancy and temperature are the variables that better explain consumption in buildings, relation among them in not always direct or other variables can contribute to refine such models. Selection of variables and a model structure are crucial tasks and have implications on the performance of the forecasting model. Additionally, the existence of blank, corrupted or wrong data and outliers, has a great influence on results and has to be filtered. Finally, it is also common to normalize data in order to avoiding dominance effect due to large magnitudes of some variables. After this pre-processing available data is organized in matrices where columns correspond to variables and rows to observations at the same timestamp. It can require resampling data in some cases. It is also necessary to include some service in charge of subsampling data from the data base with two purposes, validation and model refinement. The services identified for data preparation can be consulted in upper part of Table 3.

Table 3 Analysis and modelling services for forecasting

	Computation	Output
Data analysis and modelling services		
Data preparation		
Attribute/Feature selection	C	I

Missing values	C	I
Outliers filtering	C	I
Normalisation	C	I
Forecasting Model		
Model selection	D	I
Multiple Linear Regression	C	
Multilayer Perceptron	C	
Support Vector Regression	C	
Training		
Sub_sampling / Instance selection	O	I
Learning algorithm	C	I,O
Compute performance indicators	C	I,O
Model evaluation	C,D	I,O

Forecasting models are usually parametric models that require adjusting some parameters by applying a supervised learning algorithm. According to literature, the three methods that better perform are multiple linear regression (MLR), multilayer perceptron (MLP) and support vector regression (SVR). Since decision is not clear, offering alternative methods is must, and at the same time it is necessary to provide performance indicators (e.g, correlation coefficient –CC- or the mean absolute percentage error –MAPE-) in order to facilitate the election of the best one. Lower part of Table 3 summarises these services.

Table 4 Performance of forecasting algorithms according to the example in [22]

All attributes and all instances.

Model	CC	MAPE	Computation time
MLR	0.1755	24.3%	3 s
MLP	0.2463	23.72%	1843 s
SVR	0.964	14.32%	7546 s

Outdoor temperature and calendar attributes with filtered instances.

Model	CC	MAPE	Computation time
MLR	0.7335	6.26%	2 s
MLP	0.8009	8.24%	744 s
SVR	0.8716	3.43%	4628 s

Outdoor temperature and occupancy attributes with filtered instances.

Model	CC	MAPE	Computation time
MLR	0.913	5.21%	1 s
MLP	0.9866	1%	41 s
SVR	1	0.06%	250 s

Considering the example of load forecasting in academic building analysed in [22] four data sources where available: electric consumption (from BEM), weather station (proprietary solution), indoor data gathered by a wireless sensor network and academic calendar (working/holiday dates).

Data integration before applying the method, again, is a major challenge to be accomplished by the data management platform. After applying the method Table 4 reports performance of electric forecasting of academic building described in [22] (being used here as a real scenario for illustrative purposes). Despite of considering a huge number of variables best results are obtained with external temperature and occupancy.

4.2 Decision support

After validating the model, exploitation requires executing the model every time that new data is available. Usually model exploitation is less exigent in terms of computation.Table 5 summarise the required services required in the platform according to workflow defined in Fig. 12.

Table 5 Forecasting: a decision support tool

	Computation	Output
Decision Support		
Forecasting		
Get input data	O	I
Prepare data		
Missing values	C	I
Outliers filtering	C	I
Normalisation	C	I
Apply model	C	O
Plot forecasting	V	O

5 Conclusions

This work presents a couple of use cases analysed in the MESC project to design a data driven platform for energy monitoring and assessment in urban environments. Emphasis has put on identifying required services when implementing those solutions. From these use cases it is clear the necessity of a layered architecture to provide separation of application and services from algorithms (statistical models, pattern discovering, etc.) and accessing data. This approach will keep the system scalable and allows to plug-in new services, algorithms, and data after an initial deployment. Variability is a common characteristic to be fulfilled at data, algorithms and service level in order to guarantee interoperability. On the other hand, lot of data will inexorably feed the distribution systems considering the large number of heterogeneous data sources such as city sensor data, city mobility data, energy efficiency data, water sustainability services, or city services and utility metering infrastructures. Big Data technology is able to leverage this data handling.

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in the context of Highly Innovative Building Control Tools Tackling the Energy Performance GAP (HIT2GAP)

References

1. Directive 2012/27/EU of the European Parliament and of the Council of 25 October 2012 on energy efficiency (http://www.boe.es/doue/2012/315/L00001-00056.pdf)
2. D. Ndiaye, K.Gabriel, "PCA of the electricity consumption in residential dwellings", In: Energy and Buildings, 43, pp. 446 - 453, Elsevier, (2011)
3. J. Lam, et al., "PCA of electricity use in office buildings", In: Energy and Buildings, 40, pp. 828-836, Elsevier, 2007
4. N. Djuric, V. Novakovic, "Identifying important variables of energy use in low energy office buildings by using multivariate analysis", In: Energy and Buildings, 45, pp. 91 – 98, Elsevier, (2012).
5. M. Hajdukiewicz, et al., "Formal calibration methodology for CFD model development to support the operation of energy efficient buildings", In: International Conference for Enhanced Building Operations (ICEBO), Kuwait, (2010).
6. B. O'Flynn, et al., "Development of miniaturized Wireless Sensor Nodes suitable for building energy management and modelling", In: eWork and eBusiness in architecture, engineering and Construction, Mnzel & Sherer (eds), pp: 253-258, Taylor and Francis, (2010)
7. J. Forsström, et al. "Measuring energy efficiency: Indicators and potentials in buildings, communities and energy systems", VTT Research Notes 2581, (2011).
8. X.Ma; R. Cui; Y. Sun, C. Peng, Z. Wu , "Supervisory and Energy Management System of large public buildings", in: International Conference on Mechatronics and Automation (ICMA), pp.928 – 933, (2010).
9. C. Ocampo-Martinez, et al., "Improving water management efficiency by using optimization-based control strategies: The Barcelona case study", In: Water Science and Technology: Water Supply, 9(5), pp: 565–575, IWA publishing, (2009)
10. Adamowski, J., Chan, H.F., Prasher, S.O., et al., "Comparison of multiple linear and nonlinear regression, autoregressive integrated moving average, artificial neural network methods for urban water demand forecasting in Montreal, Canada", in: Water Resources Research, 48, AGU Publications, (2012)
11. Barry, J.A., "Watergy: Energy and Water Efficiency in Municipal Water Supply and Wastewater Treatment, Alliance to Save Energy, (2007)
12. KyungGyu Park et al, "Building Energy Management System based on Smart Grid", In: 33rd IEEE Int. Telecommunications Energy Conf. (INTELEC), pp:1-4, (2011)
13. S. Karnouskos, and P.G. Da Silva, "Energy services for the smart grid city", in: 6th IEEE Int. Conf. on Digital Ecosystems Tech. (DEST), (2012)
14. Jian Yin ; P. Sharma; I. Gorton; B. Akyoli. "Large-Scale Data Challenges in Future Power Grids", In: IEEE 7th Int. Symposium on SOSE, pp: 324-328, (2013)
15. Charbel Aoun, "The Smart City Cornerstone: Urban Efficiency", Schneider Electric white paper
16. G.A. Pagani and M. Aiello, "An ICT overview of water management", (2012)

17. F. Nejjari, R. Pérez, V. Puig, J. Quevedo, R. Sarrate, M. A. Cugueró, G. Sanz, and J. M. Mirats, "Abnormal quality detection and isolation in water distribution networks using simulation models", In: Drinking Water Engineering and Science, 5, pp: 67-72, (2012)
18. J. Quevedo, V. Puig, G. Cembrano, J. Blanch, J. Aguilar, D. Saporta, G. Benito, M. Hedo, A. Molina, "Validation and reconstruction of flow meter data in the Barcelona water distribution network", In: Control Engineering Practice, 18(6), pp: 640–651, Elsevier, (2010)
19. J. Pascual, J. Romera, V. Puig, G. Cembrano, R. Creus, M. Minoves, "Operational predictive optimal control of Barcelona water transport network", In: Control Engineering Practice, 21(8), pp: 1020–1034, Elsevier, (2013)
20. L. Burgas, J. Melendez, J. Colomer, "Principal Component Analysis for Monitoring Electrical Consumption of Academic Buildings", In: 6th International Conference on Sustainability in Energy and Buildings, SEB-14, Energy Procedia, Vol. 62, pp: 555–564, (2014)
21. L. Burgas, J. Melendez, J. Colomer, J. Massana, C. Pous, "Multivariate statistical monitoring of buildings. Case study: Energy monitoring of a social housing building", IN. energy and Buildings, 103, pp: 338–351, Elsevier, (2015)
22. J. Massana, C. Pous, L. Burgas, J. Melendez, J. Colomer, "Short-term load forecasting in a non-residential building contrasting models and attributes", E&B, 92 , pp: 322–330, (2015)