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Data Analytics Approaches in IoT based Smart Environments

Ph.D Thesis

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Análisis de datos en entornos inteligentes basados en el internet de las cosas

Tesis Doctoral

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Dedication and acknowledgements

Here goes the dedication.

Author's declaration

I declare that the work in this dissertation was carried out in accordance with the requirements of the University's Regulations and Code of Practice for Research Degree Programmes and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, the work is the candidate's own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the dissertation are those of the author.

SIGNED: .... DATE: ....

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2.1 Motivation and Goals

Smart environments

IoT

The massive collection of data via emerging technologies like the Internet of Things (IoT) requires finding optimal ways to reduce the observations in the time series analysis domain.

In short, the aim of this thesis is to study and improve every step in the data analytics process which leads to provide better services to the citizens in smart environments, that is, smart cities and smart buildings.

Below, we set out the objectives that must be attained for this aim to be fulfilled, which will serve as a guide to how the thesis is developed.

- O1. Identify and collect datasets relative to smart environments and determine the nature of the data under study
- 02. Find appropriate ways to reduce the volume of such data in order to follow the Big Data paradigm
- 03. Determine the models that better help predict and cluster information regarding energy efficiency
- 04. Develop an IoT platform oriented towards the proper processing, management and analysis of Big volumes of data

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BEATS: Blocks of Eigenvalues Algorithm for Time Series Segmentation

Aurora González-Vidal, Payam Barnaghi, *Senior Member, IEEE*, and Antonio F. Skarmeta, *Member, IEEE*

Abstract—The massive collection of data via emerging technologies like the Internet of Things (IoT) requires finding optimal ways to reduce the observations in the time series analysis domain. The IoT time series require aggregation methods that can preserve and represent the key characteristics of the data. In this paper, we propose a segmentation algorithm that adapts to unannounced mutations of the data (i.e., data drifts). The algorithm splits the data streams into blocks and groups them in square matrices, computes the Discrete Cosine Transform (DCT), and quantizes them. The key information is contained in the upper-left part of the resulting matrix. We extract this sub-matrix, compute the modulus of its eigenvalues, and remove duplicates. The algorithm, called BEATS, is designed to tackle dynamic IoT streams, whose distribution changes over time. We implement experiments with six datasets combining real, synthetic, real-world data, and data with drifts. Compared to other segmentation methods like Symbolic Aggregate approXimation (SAX), BEATS shows significant improvements. Trying it with classification and clustering algorithms it provides efficient results. BEATS is an effective mechanism to work with dynamic and multi-variate data, making it suitable for IoT data sources. The datasets, code of the algorithm and the analysis results can be accessed publicly at: https://github.com/auroragonzalez/BEATS.

Index Terms—BEATS, SAX, data analytics, data aggregation, segmentation, DCT, smart cities

1 Introduction

Less than 1 percent of the data that are nowadays captured, stored, and managed by means of the Internet of Things (IoT) and Big Data technologies is being analysed [1]. There exist several challenges in the analysis of data such as high dimensionality, high volume, noise, and data drifts. Data provided by IoT sources (sensory devices and sensing mechanisms) are multi-modal and heterogeneous. Since all of the above mentioned features hinder the execution and generalization of the algorithms, many higher-level representations or abstractions of the raw data have been proposed to address these challenges.

In this paper, we attempt to aggregate and represent large volumes of data in efficient and higher-granularity form. The latter is an attempt to create sequences of patterns and data segments that occur in large-scale IoT data streams. The contribution of our approach is to do such representation on-the-fly since usually data treatment has to be done very quickly, adapting to unpredictable changes in the data or even without prior knowledge.

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A use case where large and dynamic datasets are present is smart cities. Data aggregation and pattern representation enables us to find underlying patterns, providing further understanding of *the city data*. Big Data analytics, machine learning and statistical techniques are used to predict, classify and extract information that empowers machines with decision-making capabilities.

IoT data is usually related to physical objects and their surrounding environment. Normally, IoT data is collected together with a timestamp. The collection of several points spaced in time, having a temporal order is known as time series data. Time series can be analysed using various techniques such as clustering, classification and regression (as inputs of models) in the fields of data mining, machine learning, signal processing, communication engineering, and statistics.

Our proposed method is based on splitting time series data into blocks. These blocks can be either overlapping or non-overlapping and they represent subsets of the whole data structure. The method synthesizes independently the information that the blocks contain. It reduces the data points while still preserving their fundamental characteristics (loosing as little information as possible). We propose a novel technique using matrix-based data aggregation, Discrete Cosine Transform (DCT) and eigenvalues characterization of the time series data. The algorithm is called Blocks of Eigenvalues Algorithm for Time series Segmentation (BEATS). We compare BEATS with the state-of-the art segmentation and representation algorithms. We also compare and evaluate the approaches in two of the most common machine learning tasks, classification and clustering, by comparing metrics between each of the transformed datasets. We also present a use case that is related to smart cities showing the suitability of BEATS for real time data stream analysis. This is shown by explaining how to apply it within a Big Data framework.

The remainder of the paper is organized as follows: Section 2 describes the related work. Section 3 motivates the need of a new approach. Section 4 details the algorithm and briefly explains the mathematical background of the work. Section 5 includes the evaluations in several scenarios using different datasets and a use-case related to smart cities. Section 6 discusses the results of the experiments and Section 7 concludes the paper and describes the future work.

2 Related Work

There are several approaches to represent a numeric time-dependent variable (i.e., a time series). The most basic one is to compute the mean and standard deviation among other statistical measures (e.g., variance, mode). Using those statistics it is not possible to represent all the information that the time series contains. A classical example that supports this claim is the Anscombe's Quartet, [2] that shows how four very different datasets have identical simple statistical properties: mean, variance, correlation and regression coefficients.

In order to reduce the number of data points in a series and create a representation, segmentation methods can be used as a pre-processing step in data analytics.

Definition 1 (Segmentation). *Given a time series T containing n data points, segmentation is defined as the construction of a model $\bar{T}$, from l piecewise segments ($l < n$) such that $\bar{T}$ closely approximates T [3].*

The segmentation algorithms that aim to identify the observation where the probability distribution of a time series changes are called change-point detection algorithms. Sliding windows, bottom-up, and top-down methods are popular change-point detection based approaches. For sliding windows, each segment is grown until it exceeds an error threshold. The next block starts with the new data point not included in the newly approximated segment and so on. In the bottom-up methods, the segments of data are merged until some stopping criteria is met and top-down methods partition the time series recursively until a stopping criteria is met [4].

Another way of classifying the algorithmic methods for segmentation is considering them as online and offline solutions [5]. While offline segmentation is used when the entire time series is previously given, the online segmentation deals with points that arrive at each time interval. In offline mode, the algorithm first learns how to perform a particular task and then it is used to do it automatically. After the learning phase is completed, the system cannot improve or change (unless we consider incremental learning or retraining). On the other hand, online algorithms can adapt to possible changes in the environment. Those changes are known as "drifts". Whereas top-down and bottom-up methods can only be used offline, sliding windows are applicable to both circumstances.

After segmentation, the representation of the time series based on the reduction can be regarded as an initial step that reduces the load and improves the performance of tasks such as classification and clustering. The use of such algorithms can be generally regarded in two ways:

- Representation methods: Extracting features from the whole time series or its segments and applying machine learning algorithms (Support Vector Machines, Random Forest, etc) in order to classify them or compute the distance between the time series representation for clustering.
- Instanced based methods (similarities): Computing the distance matrix between the whole series and using it for clustering or classification applying a k-nearest neighbour approach [6] by finding the most similar (in distance) time series in the training set.

BEATS is based on the first perspective since as stated in *Bagnall et al The greatest improvement can be found through choice of data transformation, rather than classification algorithm* [7]. However, we review the work made using both approaches since the ultimate goal of our time series representation is to make the time series data more aggregated and better represented for further processing.

2.1 Whole Series Similarities

Similarity measures are used to quantify the distance between two raw time series. The list of approaches is vast and the comparison between well-known methods has lead to the conclusion that the benchmark for classification is dynamic time warping (DTW) since other techniques proposed before 2007 were found not significantly better [8].

Similar results have been stated in [9] when comparing DTW with more recent distance measures as: Weighted DTW [10], Time warp edit (TWE) [11] and Move-split-merge (MSM) [12] together with a slight accuracy improvement (1 percent) when using Complexity invariant distance (CID) [13] and Derivative transform distance (DTD_C) [14].

When computation time is not a problem, the best approach is to use a combination of nearest neighbour (NN) classifiers that use whole series elastic distance measures in the time domain and with first order derivatives: Elastic ensemble (EE) [15]. However, if a single measure is required a choice between DTW and MSM is recommended, with MSM preferred because of its overall performance.

In the clustering domain, the number of evaluated similarity distances is even higher, due to the nature of the problem. An extensive description of similarity measures can be found in [16]. DTW and CID are also used in clustering the raw time series [17], [18].

2.2 Intervals

Various algorithms focus on deriving features from intervals of each series. For a series of length m, there are $m(m-1)/2$ possible contiguous intervals.

Piecewise Linear Representation (PLR) [19] methods are based on the approximation of each segment in the form of straight lines and include the perceptually important points (PIP), Piecewise Aggregate Approximation (PAA) [20], and the turning point (TP) method [21].

The state-of-the-art models Time Series Forest (TSF) [22] and Learned pattern similarity (LPS) [23] generate many different random intervals and classifiers on each of them, ensembling the resulting predictions.

TSF trains several trees in a random forest fashion but each tree uses as data input the $3\sqrt{m}$ statistics features (mean, standard deviation and slope) of the $\sqrt{m}$ randomly selected intervals.

LPS can be regarded as an approximation of an autocorrelation function. For each series, they generate a random number l of series by randomly selecting a fixed number w of elements of the primitive one. A column of the generated $l * n \times w$ matrix is chosen as the class and a regression tree is built (autocorrelation part). After that, for every series the number of rows of the matrix (originated by the raw series) that reside in each leaf node is counted. Concatenating these counts the final representation of the series is formed. Then, a 1-NN classifier is applied to process the time series data.

2.3 Symbolic Aggregate Approximation (SAX)

Among all the techniques that have been used to reduce the number of points of a time series data, SAX has specially attracted the attention of the researchers in the field. SAX has been used to asses different problems such as finding time series discords [24], finding motifs in a database of shapes [25], and to compress data before finding abnormal deviations [26] and it has repeatedly been enhanced [27], [28], [29].

SAX allows a time series of length n to be reduced to a string of length l ($l < n$). The algorithm has two parameters: window length w and alphabet size α, and it involves three main steps [30]:

- Normalization: standardizes the data in order to have a zero mean and a standard deviation of one;
- Piecewise Aggregation Approximation (PAA): divides the original data into the desired number of windows and calculates the average of data falling into each window; and
- Symbolization: discretizes the aggregated data using an alphabet set with the size represented as an integer parameter α, where $\alpha > 2$.

  As normalized time series data assumes a Gaussian distribution for the data, the discretization phase allows to obtain a symbolic representation of the data by mapping the PAA coefficients to a set of equiprobable breakpoints that are produced according to the alphabet size α. The breakpoints determine equal-sized areas under the Gaussian curve [31] in which each area is assigned to an alphabet character.

Since SAX representation does not consider the segment trends, different segments with similar average values may be mapped to the same symbols. Among the multiple enhancements done to SAX (see related work section of [28] and [29]) we highlight the following works:

- Extended SAX (ESAX) [27]: adds maximum and minimum along with the original SAX representation.
- SAX Trend Distance ($SAX_T D$) [28]: defines the trend distance quantitatively by using the starting and ending point of the segment and improved the original SAX distance with the weighted trend distance.
- SAX with Standard Deviation (SAX_{SD}) [29]: adds the standard deviation of the segment to its SAX representation.

The Vector Space Model (VSM) is combined with SAX in [32] in order to discover and rank time series patterns by their importance to the class. Similarly to shapelets, SAX-VSM looks for time series subsequences which are characteristic representatives of a class. The algorithm converts all training time series into bags of SAX words and uses *tf-idf* weighting and cosine similarity in order to rank by importance the subsequences of SAX words according to the classes.

2.4 Shapelets

Shapelets are subsequences of time series that identify with the class that the time series belongs to.

The Fast shapelets (FS) [33] algorithm discretises and approximates shapelets using SAX. The dimensionality of the SAX dictionary is reduced through masking randomly selected letters (random projection).

Learned shapelets (LS) [34] optimizes a classification loss in order to learn shapelets whose minimal euclidean distances to the time series are used as features for a logistic regression model. An improvement of such model is the use of DTW instead of euclidean distance [35].

The Fused LAsso Generalized eigenvector method (FLAG) [36] is a combination of the state-of-the-art feature extraction technique of generalized eigenvector with the fused LASSO that reformulates the shapelet discovery task as a numerical optimization problem instead of a combinatorial search.

Finally, we take into consideration the clustering algorithm k-shape [37], a centroid-based clustering algorithm that can preserve the shapes of time-series sequences. They capture the shape-based similarity by using a normalized version of the cross-correlations measure and claims to be the only scalable method that significantly outperforms k-means.

2.5 Ensembles

So far we have reviewed how data transformation techniques are applied to different algorithms in order to improve their accuracy and to reduce the computation time. COTE algorithm [38] uses a collective of ensembles of classifiers on different data transformations.

The ensembling approach in COTE is unusual because it adopts a heterogeneous ensemble rather than resampling schemes with weak learners. COTE contains classifiers constructed in the time, frequency, change (autocorrelations), and shapelet transformation domains (35 in total) combined in alternative ensemble structures. Each classifier is assigned a weight based on the cross validation training accuracy, and new data are classified with a weighted vote.

The results of evaluations in COTE show that the simple collective formed by including all classifiers in one ensemble is significantly more accurate than any of its components.

3 Motivation and Contributions

As it can be seen among the segmentation techniques that we referenced in section 2, we have mentioned not only the representation techniques but also how the whole classification and clustering procedure is performed by combining representation with machine learning algorithms. We intended to show that our representation method is an efficient alternative segmentation method to be employed in time series data processing.

One commonality of the several studies that we have reviewed is that most of the existing algorithms use normalization that re-scales the data.

However, there are few studies that do not apply re-scaling and normalization. BEATS uses a non-normalized algorithm for constructing the segment representation.

The concept *drift* appears when a model built in the past is no longer fully applicable to the current data. Concept drift is due to a change in the data distribution according to a single feature, to a combination of features or in the class boundaries, since the underlying source generating the data is not stationary.

The potential changes in the data might happen in:

- The prior probability P(y_i);
- The conditional probability P($x|y_i$);
- The posterior probability P($y_i|x$); and
- A combination of the above.

  Where x is the predicted data and y_i is the observed data.

These changes can cause two kinds of concept drift: real and virtual [39].

If only the data distribution changes without any effect on the output, i.e., changes in P(y_i) and/or P($x|y_i$) that does not affect P($y_i|x$), it is called virtual drift.

When the output, i.e., P($y_i|x$), also changes it is called real concept drift.

In the IoT domain and especially in smart city data analysis, we are interested in the second type of drift which will be referred as *data drift* in this paper [40]. Some examples where a data drift may occur in smart cities are related to the replacement of sensors (different calibration), sensor wear and tear [41] or drastic changes to the topics of discussion in social media used for crowdsensing [42].

There are several existing methods and solution addressing the concept drift for supervised learning [41], and some recent ones also for unsupervised learning [40]. However, we focus on the initial step of the analysis (i.e., pre-processing). We claim that not only the model has to be adaptive but also the way that we segment the inputs has to take into account the dynamics of the data and be able to efficiently deal with the changes in the structure of the data.

A considerable challenge in segmentation is to find a common way to represent the data. This is due to the variety of ways to formulate the problem in terms of defining the key parameters (number of segments, segmentation starting point, length of segments, error function, user-specified threshold, etc.).

The first step in SAX algorithm is assuming that for a particular problem that we deal with, the data follows a normal distribution or at least we have a sufficiently large number of samples in order to say that the distribution of the data is approximately normal, appealing to the central limit theorem [43]. Nevertheless, this is a strong assumption because there are many scenarios in which this might not be the case; for example:

- Outliers and noise: data from physical devices usually contains noise and outliers that affect the identification of the correct parameters of the distribution.
- Data follows different distribution.
- Fast data: two of the V's from the 7V's Big Data challenges [44] are *velocity* and *variety*. Traditionally in data mining, batch data is processed in an offline manner using historical data. However, in IoT applications we need to consider short-term snapshots of the data which are collected very quickly. Thus, we need adaptive methods that catch up with the changes during their operation.

All mentioned algorithms lack of at least one of such 3 problems too. We have developed an algorithm that does not require normalization of the data. The latter will also help to preserve the value of the data points (i.e., magnitude of the data). The lack of sensitivity to magnitude in the algorithms that make assumptions about the normalized distribution and use Z-normalization makes them less efficient in analysing correlation and regression. Another requirement is the application of the algorithm in an online way and using sliding windows. Nonetheless, we have to be able to compute the distance between the aggregated time series. Considering these requirements we have designed the BEATS algorithm.

4 BEATS PRESENTATION

This section describes our proposed algorithm and discusses its mathematical and analytical background. We present BEATS and show the effect of each step of the algorithm in a block of data.

4.1 BEATS Construction

Transforms, in particular integral transforms, are used to reduce the complexity in mathematical problems. In order to decorrelate the time features and reveal the hidden structure of the time series, they are transformed from the time domain into other domains. Well-known transformations are the Fourier Transform, which decomposes a signal into its frequency components, and the Karhunen-Loeve Transform (KLT) which decorrelates a signal sequence.

Discrete Cosine Transform (DCT) is similar to Discrete Fourier Transform (DFT) but uses cosines obtained from the discretization of the kernel of the Fourier Transform. DCT transfers the series to the frequency domain. Among the four different cosine transformations classified by Wang [45], the second one (i.e., DCT-II) is regarded as one of the best tools in digital signal processing [46] (times series can be regarded as a particular case of signals). Due to its mathematical properties such as unitarity, scaling in time, shift in time, the difference property, and the convolution property, DCT-II is asymptotically equivalent to the KLT where under certain (and general) conditions KLT is an optimal but impractical tool to represent a given random function in the mean square error sense (MSE). KLT is said to be an optimal transform because:

- It completely decorrelates the signal in the transform domain;
- It minimizes the MSE in bandwidth reduction or data compression;
- It contains the most variance (energy) in the fewest number of transform coefficients; and
- It minimizes the total representation entropy of the sequence.

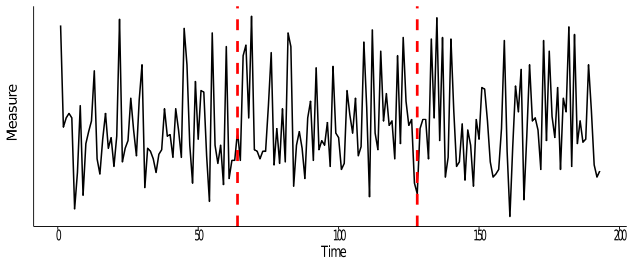

Fig. 1. An example of a time series divided into blocks of 64 observations.

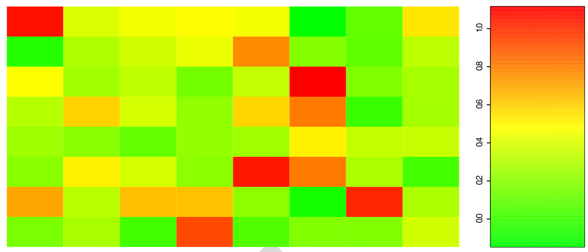

Fig. 2. The heatmap of the matrix obtained from the first block of time series data.

The details of the proof of the above statements can be found in [46]. Understanding the properties of the DCT, we use it to transform our time series data.

We apply the transformation essentially by using the compression of a stream of square 8x8 blocks, taking reference from the standards in image compression [47] where DCT is widely used (e.g., JPEG). Since 8 is a power of 2, it will ease the performance of the algorithm.

As an illustration, we provide an example. We have divided the time series shown in Fig. 1 as blocks of 64 observations that are shown using a dashed red line. If we arrange the first block row-wise into a squared matrix M, we can visualize that the information is spread through the matrix as the heatmap shown in Fig. 2.

It should be noted that while our raw time series data is represented in value/time, a 2D transformation is applied to the data. This is based on the assumption that in each block, the neighbour values of a selected observation m_{ij} (eg. $m_{i-1j}, m_{ij-1}, m_{i-1j-1}$ are correlated. In time series with very rapid changes in the data, small block sizes will be more suitable and if the changes are not very rapid size block can be larger. In this paper, we use a common 8×8 block size for our description.

Intuitively, each 8×8 block includes 64 observations of a discrete signal which is a function of a two-dimensional (2D) space. The DCT decomposes this signal into 64 orthogonal basis signals. Each DCT coefficient contains one of the 64 unique *spatial frequencies* which comprise the *spectrum* of the input series. The DCT coefficient values can be regarded as the relative amount of the spatial frequencies contained in the 64 observations [47].

Let M be the 8×8 input matrix. Then, the transformed matrix is computed as $D = UMU^{\mathsf{T}}$, where U is an 8×8 DCT matrix. U coefficients for the $n \times n$ case are computed as shown in Eq. 1:

$$U_{ij} = \begin{cases} \frac{\sqrt{2}}{2} & i, j = 1 \\ \cos\left(\frac{\pi}{n}(i-1)(j-\frac{1}{2})\right) & i, j > 1. \end{cases} \quad (1)$$

The formula of Eq. (1) is obtained using Eq. (5) (Appendix 8). Finally, we multiply the first term by $\frac{1}{\sqrt{2}}$ in order to make the DCT-II matrix orthogonal. After applying DCT, the information is accumulated in its upper-left part, as it is shown in the heatmap in Fig. 3.

Each of the 64 entries of the matrix D is quantized by pointwise division of the matrices D and Z, where the elements of the quantization matrix Z are integer values ranging from 1 to 255.

Quantization is the process of reducing the number of bits needed to store an integer value by reducing the precision of the integer. Given a matrix of DCT coefficients, we can divide them by their corresponding quantizer step size and round it up depending on its magnitude, normally 2 decimals. If the maximum of the DCT matrix is small, the number of decimals is selected by the operation $|\lfloor \log_{10} max \rfloor - 4|$, where $\lfloor \log_{10} max \rfloor$ returns the position of the first significant figure of the maximum number in the transformed matrix D. This step is used to remove the high frequencies or to discard information which is not very significant in large-scale observations.

The selected matrix Z is the standard quantization matrix for DCT [48].

After the quantization process, a large number of zeroes appears in the bottom-right position of the matrix $Q = \frac{D}{Z}$, i.e., it is a sparse matrix.

We extract the 4×4 upper-left matrix that contains the information of our 64 raw data and compute the eigenvalues, which in our case are: $0.18605, 0.02455, 0.00275+0.00843i, 0.00275 - 0.00843i$.

Using BEATS so far we have significantly reduced the number of points of our time series from 64 to 4 but we have also converted its components into complex numbers. These complex numbers (eigenvalues vector) represent the original block in a lower dimension. This eigenvalues vector is used in BEATS to represent the segments and hence, it is the potential input for the machine learning models. However, it is not always possible to feed machine learning algorithms with complex numbers and the eigenvalues could be complex numbers. To solve this problem, we compute the modulus of the eigenvalues and remove the repeated ones (they are presented in pairs so the information would be repeated).

In case that there are no complex numbers in the output of BEATS, we will conserve the first three values, since the latter values are sorted in a descending order. This means that we have represented the original 64 observations as

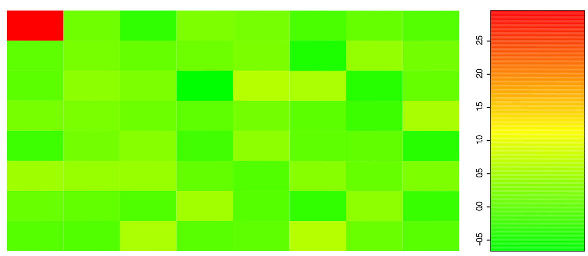

Fig. 3. The heatmap of the DCT matrix.

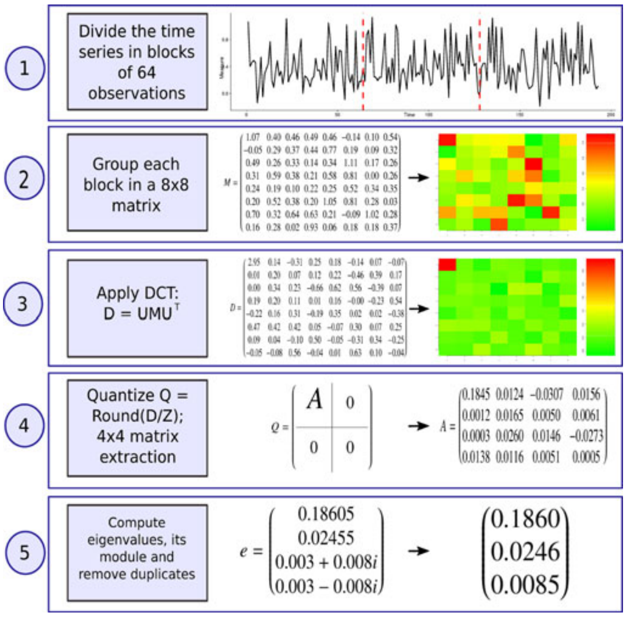

Fig. 4. BEATS is shown step by step with an example.

three values. In our example, the final representation (modulus of the eigenvalues) consists of $0.1860, 0.0246, 0.0085$.

The BEATS process is summarized in Fig. 4.

We also consider the relevance of the direct computation of the eigenvalues of the 8×8 matrix M in order to assure that the DCT and its quantization contribute to the aggregation of the information. We refer to this method throughout the paper as Eigen.

4.2 Complexity Analysis of BEATS

The time complexity is represented as a function of the input time series size (n). Regarding the different steps of BEATS, the processes that have a key impact on the run time are DCT, which is a double matrix multiplication, i.e., $O(n^3)$; pointwise matrix division for the quantization, i.e., $O(n^2)$ and eigenvalue computation, i.e., $O(\beta^3)$, where n is the size of the matrix block (square root of the amount of data that compounds each block), and β ($\leq n$) is the size of the extracted matrix from which we compute the eigenvalues. Although we have set the values to $n = 8$ and $\beta = 4$, we compute the complexity in general terms.

So far, the dominant task regarding the complexity is the DCT function. For about the past 40 years, many fast algorithms have been reported to enhance the computation of discrete cosine transforms [49]. In order to improve the efficiency of the algorithm, we have implemented a popular way of computing the DCT of our N-points time series. We use a 2N-points Fast Fourier Transform (FFT). This has reduced the complexity to $O(n^2 log(n))$ [50].

Hence, for each block we have a complexity of $O(n^2 log(n) + \beta^3)$. Let N be the size of our time series data; if we do not use sliding windows, we will apply the algorithm $\frac{N}{n \times n}$ times, so the complexity is $\frac{N}{n \times n} O(n^2 log(n) + \beta^3)$. As we can see, the complexity of the algorithm grows linearly depending on the number of blocks where we have to apply the computations.

By applying multiple processing architectures, the complexity problem nowadays can also depend on how efficiently we can parallelize the processing load. Parallelising the BEATS algorithm is very simple since the computations are *block dependent* and no information out of the block is required for each individual calculation. This makes the process ideal to be done using graphics processing units (GPUs), and thereby minimising the latency of the computation.

5 Experimental Evaluation

We perform two data mining processes: classification and clustering. Following our approach the data is going to be transformed by the two methods: BEATS and Eigen, summarized as follows:

- BEATS: 8×8 matrix blocks of the data, discrete cosine transformation, and quantization of each of the matrices, reduction to a 4×4 matrix, removal of the duplicated modulus of the complex eigenvalues and selection of the first three values.
- Eigen: 8×8 matrix blocks of the data, computation of the eigenvalues of the matrices, removal of the duplicated modulus of the complex eigenvalues, and selection of the first three values.

Having introduced several algorithms in Section 2, we compare BEATS and Eigen with common existing state-of-the-art methods that show an improvement in comparison with the primitive ones.

The algorithms' code has been accessed from the authors' public repositories when available. When not, R software and Python have been used in order to program them.

We perform each of the techniques using several datasets in order to analyse the type of problems that our algorithm performs better than other methods. It is possible to use sliding windows for our method. In the experiment, we consider a slide of 8 observations. The evaluations also include a cross validation step in order to find their parameters.

A smart cities use case where we cluster traffic data is also presented. The intention is to see how BEATS is suitable for different scenarios including online smart cities applications.

5.1 Datasets

We give a short explanation of the datasets that are used to evaluate the algorithm. Four of the datasets are obtained from the UCR Time Series Classification Archive [51]: ArrowHeads, Coffee, FordA, Lightning7 and ProximalPhalanxOutlineAgeGroup. For each dataset we use, when provided, the train sample in order to find the hyperparameters of the model and then, we test their classification performance with the test set. For clustering we use only the training set. When the split is not provided, which is the case in one of the datasets (the randomly generated by us), we use 75 percent of the samples for the training set and 25 percent of the samples for testing.

The datasets that are used in the experiments are briefly described below.

Arrow Heads (Real and Without Drifts). The Arrow Heads dataset[1] contains 211 series having 192 observations classified into three different classes. The arrowhead data consists

1. http://www.cs.ucr.edu/~eamonn/time_series_data/

of outlines of the images of arrowheads [52]. The shapes of the projectile points are converted into a time series using the angle-based method and they are classified based on shape distinctions such as the presence and location of a notch in the arrow. The classification of projectile points is an important topic in anthropology. According to our method, we reduced the dataset to 72 observations.

Lightning7 (Real and Long). We use the Lightning7 dataset that gathers data related to transient electromagnetic events associated with the lightning natural phenomenon. Data is gathered with a satellite with a sample rate of 800 microseconds and a transformation is applied in order to produce series of length 637.

The classes of interest are related to the way that the lightning is produced.[2]

Initially, each measurement (time series) carries 320 variables. Using our method, we have reduced the dataset to 96 variables.

Random LHS Generator Lift (Synthetic and with Drifts). A dataset with data drifts is also used in our experiments. In this case, we have evaluated the algorithms with the data generated by using the code from the Repository[3] described in [53], which was first used in [40]. The drift is introduced both by shifting the centroids in randomized intervals and by changing the data distribution function used to randomly draw the data from the centroids that are selected through Latin Hypercube Sampling (LHS). This dataset is created for smart cities data analysis and allows to create sample datasets that simulate dynamic and multi-variate data streams in a smart environment. The data generator is developed in the context of the CityPulse smart city project.[4]

The number of centroids is set to ten and we generated 300 series that follow three different distributions (triangular, Gaussian and exponential). Initially, each set (time series) carries 192 variables. Using our method, we reduced the dataset to 51 variables.

Coffee (Real-World Data). The Coffee dataset[1] contains 56 series having 286 observations classified into two different classes. The Coffee data consists of the series generated by the Fourier transform infrared spectroscopy of two species of coffee: Arabica and Robusta. Originally, such method intended to serve as an alternative to wet chemical methods for authentication and quantification of coffee products [54]. Using BEATS, we reduced the dataset to 57 observations which represent the patterns that occur in the dataset. This can be used for further analysis and classification of coffee types.

FordA (Real-World Data). The FordA dataset[1] contains 4921 series having 500 observations each classified into two different classes. The data was generated on the context of a classification competition. The problem is to diagnose whether a certain symptom exists in a automotive subsystem using the engine noise as a measurement. Both training and test data set were collected in typical operating conditions, with minimal noise contamination. Using BEATS, we reduced the dataset to 100 observations. The BEATS observations are more resilient to noise and provide an efficient way to discover and extract patterns from real-world raw data.

2. http://www.timeseriesclassification.com/description.php?Dataset=Lightning7
3. https://github.com/auroragonzalez/BEATS/tree/master/data/random_LHS_generator_drift
4. http://www.ict-citypulse.eu

ProximalPhalanxOutlineAgeGroup (Real-World Data from Images). The ProximalPhalanxOutlineAgeGroup dataset[1] contains 605 series having 80 observations each classified into three different classes. The dataset was created [55] for testing the efficacy of hand and bone outline detection and whether these outlines could be helpful in bone age prediction. The problem involves using the outline of one of the phalanges of the hand in order to predict whether the subject is one of three age groups . Using BEATS, we reduced the dataset to 9 observations per subject. This observations provide a reduced feature set that ease the analysis tasks.

5.2 Classification

Classification of time series analysis is a classic problem consisting of building a model based on labelled time series data and using the model to predict the label of unlabelled time series samples.

The applications of this technique are widely extended in many areas, ranging from epilepsy diagnosis based on time series recorded by electroencephalography devices (electrical activity generated by brain structures over the scalp) [56] to uncovering customers' behavior in the telecommunication industry [57], and predicting traffic patterns in a smart city environment.

After transforming our data using BEATS and Eigen, we followed the general data modelling process proposed in [58] to classify the series: standarization, splitting the dataset into training and test sets, choosing the model, selecting the best hyperparameters of each model using 10-fold cross validation on the training set and checking the accuracy of the model using the test set. With respect to the methodology followed in [58], we improve the way of looking for the hyperparemeters of the algorithms using the python package optunity since it contains various optimizers for hyperparameter tuning.

Among other options like grid search, random search and genetic algorithms, we have chosen particle swarm implementation since it is shown to surpass the performance of other solutions [59].

The models that we use to combine with BEATS and Eigen are the widely known Random Forest (RF) and Support Vector Machines (SVM) with Radial Basis Function Kernel.

Whereas Random Forest deals with *small n large p-problems*, high-order interactions and correlated predictor variables, SVMs are more effective for relatively small datasets with fewer outliers. Generally speaking, Random Forests may require more data. Both of the algorithm show better performance when combined with SVM.

The tuning of SVM has been done without deciding the kernel in advance. That means, the kernel (linear, polynomial or RBF) is considered as an hyperparameter.

According to the discussion in Section 2, we compare our method with:

- Original time series (i.e., raw data): DTW with 1-NN classification since, after many trials, it is still the benchmark of comparison for distance based classification. Having a complexity of $O(n^2)$ that under

TABLE 1
Accuracy of Each Method Using as Inputs Each of the Segmented Time Series

Model \ dataset	Arrow Heads	Lightning7	Random Generator	Coffee	Ford A	Proximal
BEATS-SVM	**0.81**	0.7	**0.75**	**1**	**0.75**	**0.85**
Eigen-SVM	0.79	0.72	0.73	**1**	0.74	0.8
DTW-1NN	0.67	0.75	0.71	0.87	0.66	0.81
SAX-VSM	0.68	0.59	0.52	0.96	0.09*	0.75
TSF	0.73	0.75	**0.75**	0.97	**0.75**	0.85
FLAG	0.57	0.76	0.67	**1**	0.73	0.64
COTE	0.78	**0.8**	0.7	**1**	**0.75**	0.83

**The bag of words generated by a wide majority of the test subjects is not related to the ones generated by the train step. This implies that their TF*IDF weights are not computed and it is not possible to compute the cosine similarity. In consequence, the method is not valid for many of the cases, producing the reported bad results.*

certain circumstances [60] could be reduced to $O(n)$ using lower bounds such as LB_{Keogh} or $LB_{Improved}$ [61].

- Intervals: We choose TSF in order to make the comparison since it is more modern and quicker than the rest.
  Its complexity is $O(t * m * n * logn)$, where t = number of trees and m = number of splits or segments.
- Symbolic approximations: In the classification task, we use SAX-VSM. The complexity is linear: $O(n)$.
- Shapelets: FLAG is the newest, the quickest and claims to be better than its predecessors.
  Its complexity is $O(n^3)$.
- Ensembles: COTE. It is an ensemble of dozens of core classifiers many of which having a quadratic, cubic or even bi-quadratic complexity. It is the most computationally expensive in this list.

The results are shown in Table 1. It is important to mention that not only accuracy results but also the time that it takes the algorithm to run both training and test phases including input transformation, has improved. This runtime is shown in Fig. 5, where a logarithmic transformation is applied to the data in order to improve visibility.

We have depicted both metrics: accuracy and running time in a plot that summarises the results over all the datasets. Both metrics have been scaled per dataset and we have computed the average performance per model that is represented by the bigger points in the plot.

In order to make a more consistent analysis of the results, we have generated 100 Random LHS Generator Lift datasets and the model accuracy of the models using violin plots (see Fig. 6), which together with the regular statistics that boxplot provide they show the probability density of the data at different values of accuracies. While the differences between BEATS-SVM, TSF and COTE are not statistically significant (p-value = 0.7 $>$ 0.05), BEATS-SVM is very quick in comparison to COTE and that BEATS is also more versatile than the rest since it can be combined with any classification algorithms.

5.3 Clustering

Clustering is used to identify the structure of an unlabeled dataset by organising the data into homogeneous groups where within-group-object similarity is minimized and between-group-object dissimilarity is maximized. The process is done without consulting known class labels. Clustering is an unsupervised machine learning method. In particular, time series clustering partitions time series data into groups based on similarity or distance; so that time series data in the same cluster are similar.

Clustering has tackled tasks such as the assignment of genes with similar expression trajectories to the same group [62]. The creation of profiles of the trips carried out by tram users [63] or the acquisition of energy consumption predictions by clustering houses [64] are among examples of using clustering methods.

After transforming our data using BEATS and Eigen, we applied the connectivity based algorithm *hierarchical agglomerative clustering* and the centroid based algorithm *k-means* to

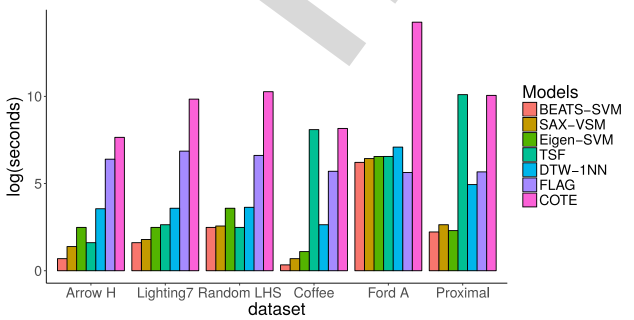

Fig. 5. Running time (log(sec)) and programming language of the algorithms.

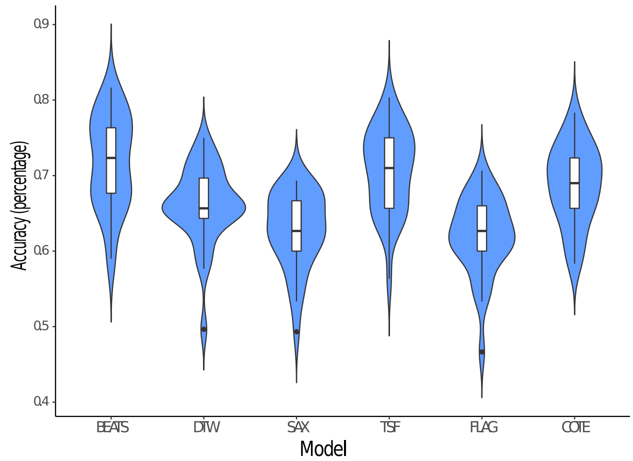

Fig. 6. Classification accuracy on the 100 randomly generated datasets.

TABLE 2
Silhouette Coefficient of Each Method Using as Inputs Each of the Segmented Time Series

Model \ dataset	Arrow Heads	Lightning7	Random Generator	Coffee	Ford A	Proximal
BEATS-HC	**0.6**	0.25	**0.45**	0.25	**0.46**	0.4
Eigen-HC	0.58	**0.31**	0.25	0.26	0.36	0.38
DTW	0.33	0.21	0.44	0.21	0.12	0.31
SAX$_{SD}$- HC	0.53	0.06	0.19	0.13	0	0.33
k-shape	0.44	0.19	0.05	**0.43**	0.38	**0.5**

cluster the time series datasets. In the hierarchical clustering, the selected agglomerative method is *complete linkage*, meaning that the distance between two clusters is the maximum distance between their individual components (in each time series). Hierarchical clustering seems to be a better partner for both of them.

The dissimilarity matrix contains the distances between the pairs of time series. We use the cosine dissimilarity for the rest of the segmentations (BEATS and Eigen). The cosine dissimilarity is calculated as one minus the cosine of the included angle between elements of the time series (see Eq. (2))

$$\text{dissimilarity} = 1 - \frac{\mathbf{XY}}{\|\mathbf{X}\|\|\mathbf{Y}\|} = 1 - \frac{\sum_{i=1}^{n} X_i Y_i}{\sqrt{\sum_{i=1}^{n} X_i^2}\sqrt{\sum_{i=1}^{n} Y_i^2}}. \quad (2)$$

Finally, for both methods we have used a fixed number of clusters. As we were aware of the classification groups (our data is labeled), we applied the algorithms setting apriori the number of clusters k and used the silhouette coefficient as a metric for measuring the cluster quality.

The silhouette coefficient is an internal measure that combines the measurement of cohesion and separation. Cluster cohesion measures how closely related the objects in a cluster are. Cluster separation measures how well separated the clusters are from each other. The silhouette coefficient for a subject i is defined as

$$s(i) = \frac{b(i) - a(i)}{max\{a(i), b(i)\}}, \quad (3)$$

where $a(i)$ is the average distance between i and each of the points of the assigned cluster and $b(i)$ is the average distance between i and each of the points of the next best cluster. This value can be used to compare the quality of different cluster results.

From the definition it is clear that $s(i) \in [-1, 1]$. Meanwhile a silhouette coefficient value closer to 1 means that the clustering is good; a value close to -1 represents less efficiency in the categorization for the clusters. When it is close to 0, it means that the point is in the border between two clusters.

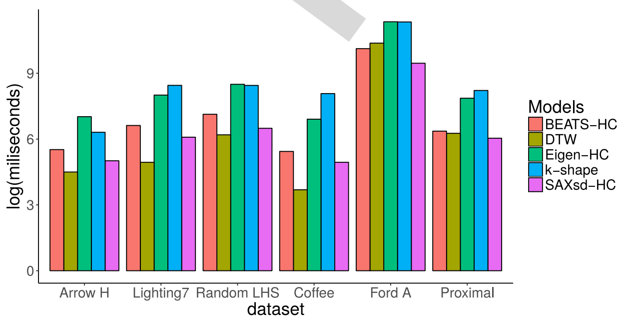

Fig. 7. Running time (log(milisec)) of the clustering algorithms.

According to the discussion in Section 2 we will analyse:

- Original time series: DTW distance using the tight lower bound of [61], that makes it faster.
- Symbolic approximations: We have taken the most modern improvement that SAX has experienced: SAX$_{SD}$. The MINDIST function that returns the minimum distance between the original time series of two words [65] is enhanced with the distance between the standard deviation of each segment.
- Shapelets: k-shape is the model chosen in this direction.

The results of the clustering experiments done in the training sets are shown in Table 2. The run time of the algorithms is shown in Fig. 7. In this case, all the algorithms have been coded using the same programming language so we consider that the graph is enough in order to estimate the different algorithms complexity regarding time.

5.4 Big Data Use Case: Traffic in Smart Cities

In this section we apply BEATS in a smart cities related use-case: traffic data clustering, done in an online and distributed way.

5.4.1 *BEATS Implementation for Big Data*

In contrast to the traditional analysis procedure where data is first stored and then processed in order to deploy models, the major potential of the data generated by IoT is accomplished by the realization of continuous analytics that allow to make decisions in real time.

There are three types of data processing: Batch Processing, Stream Processing and Hybrid Processing.

Batch processing operates over a group of transactions collected over a period of time and reports results only when all computations are done, whereas stream processing produces incremental results as soon as they are ready [66].

Regarding the available Big Data Tools, we have considered Hadoop[5] and Spark[6] Big Data frameworks. Hadoop was designed for batch processing. All data is loaded into HDFS and then MapReduce starts a batch job to process that data. If the data changes the job needs to be ran again. It is step by step processing that can be paused or interrupted, but not changed.

Apache Spark allows to perform analytical tasks on distributed computing clusters. Sparks real-time data

5. http://hadoop.apache.org/
6. https://spark.apache.org/

processing capability provides substantial lead over Hadoops MapReduce and it is essential for online time series segmentation and representation.

The Spark abstraction for a continuous stream of data is called a Discretized Stream or DStream . A DStream is a micro-batch of Resilient Distributed Datasets, RDDs. That means, a DStream is represented as a sequence of RDDs. RDDs are distributed collections that can be operated in parallel by arbitrary functions and by transformations over a sliding window of data (windowed computations).

5.4.2 BEATS Adapted to Spark Technology

For the online implementation of BEATS we have decided to use pyspark, the Spark Python API that exposes the Spark programming model to Python.

There are many works proposing online time series processing but few of them that have implemented it. In [67] is highlighted that MapReduce is not the appropiate techonology for rolling window time series prediction and proposes a index pool data structure.

Pyspark allows us to use the Spark Streaming functionalities that are needed in order to implement BEATS online. In Section 3 we have seen that BEATS algorithm can be separately applied to windows of the data. Therefore we associate the data received within one window to one RDD, that can be processed in a parallel way.

A suitable type of RDDs for our implementation is key/value pairs. In detail, the key is an identifier of the time series (e.g., sensor name) and the value is the sequence of values of our time series that fall in the window. That way the blocks are exposed to operations that give the possibility to act on each key in parallel or regroup data across the network.

The transformations that we use are:

- Window: use for creating sliding window of time over the incoming data.
- GroupByKey: grouping the incoming values of the sliding window by key (for example, same sensor data).
- Map: The Map function applied in parallel to every pair (key, value), where the key is the time series, values are a vector and the function depends on what has to be done.

5.4.3 The Applied Scenario

We use one of the real-world datasets obtained from the collection of datasets of vehicle traffic in the City of Aarhus in Denmark for a period of 6 months.[7] The dataset is provided in the context of the CityPulse smart city project.

The selected dataset gathers 16971 samples of data from sensors situated in lamp posts covering an area around 2345m.[8] The variables considered for the analysis are: flow (numbers of cars between two points) and average speed. Each variable is a time series.

In order to simulate an online application we consider that the BEATS segmentation is carried out on hourly based data.

7. http://iot.ee.surrey.ac.uk:8080/datasets.html#traffic
8. http://iot.ee.surrey.ac.uk:8080/datasets/traffic/traffic_june_sep/index.html

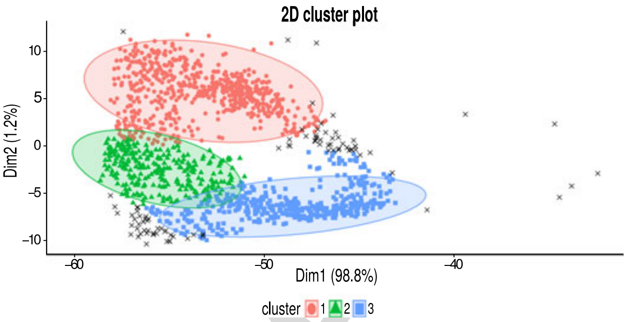

Fig. 8. Plot of the DBSCAN clusters using traffic data.

To achieve this, since the data is collected every 5 mins., a sliding window of size 12 is selected. The goal of the clustering is to determine the status of the road in terms of the traffic flow and occurrences. For every window of 128 observations (64 for each variable) BEATS obtains three flow related representatives and three speed related representatives.

Each observation of the final input dataset for the clustering model represents one window of the raw data. The final dataset has 6 variables and 1409 samples. This means a reduction of around 75 percent of data.

The data is gathered by anonymously collecting Wi-Fi and Bluetooth signals transmitted by travelers' smartphones or in-vehicle systems. This infrastructure provides noisy data in cases such as stopped vehicles in traffic jam, buses with a lot of passengers.

In order to tackle the presence of outliers and noise, the selected clustering technique is density-based spatial clustering (DBSCAN). DBSCAN groups points that are closely packed together. Points that do not fit into any of the main groups because they lie in low-density regions are marked as outliers. The hyper-parameters of DBSCAN are minimum number of points required to form a dense region (MinP) and ϵ in order to find the ϵ-neighborhood of each point. We set that clusters contain at least a 20 percent of the data and ϵ = 4.014. Using such configuration, we obtain 3 different clusters and a 8 percent of data that cannot be classified in any of the previous, i.e., outliers. The description of the clusters, including the number of points n that belong to each of the clusters and the mean μ and standard deviation sd for both flow and speed is:

- Cluster 1 (n = 618): High flow (μ = 30.97, sd= 12.66) and medium speed (μ = 102.5, sd= 10.2);
- Cluster 2 (n = 271): Medium flow (μ = 15.97, sd= 8.4) and high speed (μ = 110, sd= 9.21); and
- Cluster 3 (n = 432): Low flow (μ = 6.1, sd= 5.56) and low/medium speed (μ = 97.8, sd= 14.3).

In order to represent the data in lower dimension, we select the first two principal components of the data using Principal Components Analysis (PCA). The obtained clusters are shown in Fig. 8. Crosses in black colour represent the noise data. We have also projected the clusters in the three flow related components of BEATS, so that clusters can be visualized in a 3D form as presented in Fig. 9.

Regarding this application, we can conclude that clustering methods applied to the segments generated by BEATS are able to characterise the status of the roads by grouping the values in an effective form.

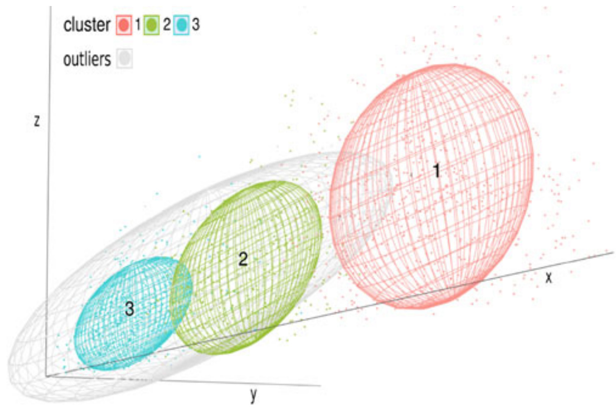

Fig. 9. 3D plot of the DBSCAN clusters using traffic data.

Using a computer with an Intel i5 Processor, 8GB RAM Memory, Ubuntu 16.04 operative system and the statistical software R 3.4.3 [68], the running time of DBSCAN using BEATS segmented data is 0.25 seconds. However, to run the DBSCAN with raw data it takes around 35 seconds. The later confirms again the suitability of BEATS in current IoT scenarios.

6 Discussion

As we have described in the paper, the randomness and predictability of a real-world time series changes over time due to several factors.

The existing solutions for pattern creation and abstraction in time-series data often work based on statistical measures (which have limited representation and granularity), symbolic methods such as SAX (which assumes that the data is normally distributed and requires normalization of the data), or signal processing and stream processing methods such as wavelet or Fourier transforms (which act as filters and can extract features from the data but do not provide a pattern representation/abstraction).

Our proposed model combines a series of methods to create a window based abstraction of time series data and uses a frequency domain function combined with characteristic value measures that represents the overall direction of the dataframe (i.e., an n-dimensional matrix constructed during our windowing/slicing process) as a vector.

BEATS is an algorithm that process data streams whose randomness and predictability varies depending on the segment of data. The proposed algorithm is useful specially in applications such as smart cities where results of the segmentation and processing algorithms are used in order to make fast decisions regarding traffic, energy, light regulation, etc. This can be made by combining various sensory data and other historical data. In general terms, the intention is to predict and manage what is occurring in order to provide informed or automated decisions for repetitive tasks that can be handled by machines. BEATS offers a powerful solution to aggregate and represent large-scale streaming data in a quick and adaptable way. It uses blocks of eigenvalues in a much lower-dimensionality (with a high aggregation rate) which preserves the main information and characteristics of the data. Since BEATS uses eigenvalues, it provides a homogeneous way to represent multi-modal and heterogeneous streaming data. In other words, all different types of numerical streaming data are transformed into vectors of eigenvalues that, in principal, preserve and represent the magnitude and overall direction of the data in a lower-dimensionality space. This not only allows to compare and combine different blocks of data from various data streams, but also provides a unified way to represent the blocks of data as patterns in the form of eigenvalues.

In this paper, we mainly target a key step after collection of the data: aggregation. Aggregation of data becomes a very significant task in order to extract the key characteristics of the data in lower-dimensionality. We segment the time series and make a reduction for each time series at a rate of 60 ~ 70 percent when using overlapping windows. The independence between blocks that our algorithm provides is one of its most important features. BEATS also presents other qualities such as adapting to drifts and low latency.

BEATS reduces the data by using the eigenvalues of a submatrix of the DCT transformation. These eigenvalues represent the key-characteristics of the data.

The evaluation is performed using classification and clustering, two of the classical machine learning tasks using several types of datasets. The inputs of the models are the different representations introduced in the paper: BEATS and Eigen together with raw data for the other models.

Classification is measured by accuracy. This allows us to perform a test for equality of proportions, that is a χ^2 test of independence in order to assure that the differences between accuracies are statistically significant.

For the Arrow Heads dataset we find that BEATS combined with SVM outperforms all the algorithms. However, the differences between COTE and BEATS are not statistically significant ($\chi^2(1) = 0.37$, p-value = $0.54 > 0.05$). On the other hand, the difference between TSF and BEATS are statistically significant ($\chi^2(1) = 4.8$, p-value = $0.04 < 0.05$).

In the case of Lightning7, there are several models that outperform BEATS. The winning one is COTE. Nonetheless, COTE is very complicated, time demanding and computationally expensive. The rest only overperforms BEATS by 6 percent at most.

In the case of Random LHS Generator Lift, TSF and BEATS perform similarly.

In the Coffee dataset, we observe that several approaches (including BEATS) achieve a 100 percent accuracy on classification.

In FordA, BEATS, TSF and COTE perform similarly. However, BEATS is the quickest amongst them.

Finally, in the Proximal dataset TSF and BEATS perform similarly in terms of accuracy. However, BEATS is again quicker.

Even though COTE and TSF are strong rivals to BEATS, it should be noted that the computation time and simplicity of BEATS makes it useful to use in rapid analysis having still good results. Also, due to its nature is very adaptable and easy to combine with any other classification algorithm different than SVM.

The clustering experiment is evaluated by comparing the hundredths of the silhouette coefficients, where each hundredth is going to be counted as *a point* in the below description.

BEATS is 7 points above SAX_{SD} for the Arrow Heads dataset, 1 point above DTW in the Random LHS Generator Lift set and 8 points above k-shape in Ford A. Being the most computationally expensive of all the clustering algorithms under study, as it can be seen in Fig. 7, k-shape outperforms BEATS in two datasets: Coffee and Proximal.

It can be said that in clustering, BEATS behaves better when we are using long datasets since it outperforms every algorithms in both metrics: silhouette coefficient and running time in the biggest dataset: *FordA*.

Finally, by applying DBSCAN to cluster traffic data, we noticed that BEATS performs efficiently since the clusters represent different situations of the use-case in terms of traffic flow and speed.

7 Conclusions and Future Work

In this paper, we introduce a novel algorithm called BEATS, which aggregates and represents time series data in blocks of lower-dimensional vectors of eigenvalues. BEATS is not sample dependent so it adapts to data drifts in the underlying data streams.

The BEATS abstractions can be combined with various machine learning models to discover patterns, identify correlations (within or between data streams), extract insights and identify activities from the data. In this paper, we have used several datasets and have shown several use cases that demonstrate how the BEATS abstractions can be used for clustering, analysis and grouping the activities and patterns in time-series data.

Compared to existing segmentation methods, BEATS shows significant improvements in representing datasets with drifts. When combined with classification and clustering methods, we have shown that it can obtain competitive results compared with other state-of-the-art but more complex and time consuming methods.

For the BEATS algorithm evaluation we have fixed the length of the segments at 64; so the only parameter to take into consideration was the slide of the window, that we have kept constantly equal to 8, so the blocks of transformed data intersect. Nevertheless, the optimization of the sliding window is an open issue to be addressed in future work.

For the clustering tasks, it is important to take into account that the definition of similarity is subjective. The similarity depends on the domain of application.

By using BEATS, we are able to restructure the streaming data in a 2D way and then transform it into the frequency domain using DCT. The algorithm finds a smaller sequence that contains the key information of the initial representative. This aggregation provides an opportunity to eliminate repetitive content and similarities that can be found in the sequence of data.

The eigenvalues vectors are a homogeneous representation of the data streams in BEATS that allow us to go one step further in understanding of the sequences and patterns that can be considered as the data structure of a data series in an application domain (e.g., smart cities).

Its applications can be extended to several other domains and various patterns/activity monitoring and detection methods. The future work will focus on applying 3D cosine transform and adaptive block size estimation.

Appendix A

Definition A.1 (Integral transform). *The integral transform of the funtion $f(t)$ with respect to the kernel $K(t,s)$ is*

$$F(t) = \int_{-\infty}^{\infty} K(t,s) f(t) dt, \tag{4}$$

if the integral exists.

The kernel of the Fourier Transformation is $K(t,s) = e^{-its}$, and, in particular for the cosine fourier transformation $K(t,\omega) = cos(t,\omega)$. If we discretize the kernel we can reach that $K_c(j,k) = cos(\frac{jk\pi}{N})$, where N is an integer.

Definition A.2. (Discrete Cosine Transformation (DCT) - II). *DCT is a linear and invertible function*

$$f : \mathbb{R}^n \longrightarrow \mathbb{R}^n$$

where $\mathbb{R}$ denotes the set of real numbers or, equivalently, on a $n \times n$ matrix, defined by:

$$f_j = \sum_{k=0}^{n-1} cos\left(\frac{\pi}{n} j \left(k + \frac{1}{2}\right)\right) \text{ where } j = 0, 1, \ldots, n-1 \tag{5}$$

Acknowledgments

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4.2 A methodology for Energy Multivariate Time Series Forecasting in Smart Buildings based on Feature Selection

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A methodology for Energy Multivariate Time Series Forecasting in Smart Buildings based on Feature Selection

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Abstract

The massive collection of data via emerging technologies like the Internet of Things (IoT) requires finding optimal ways to reduce the created features that have a potential impact on the information that can be extracted through the machine learning process. The mining of knowledge related to a concept is done on the basis of the features of data. The process of finding the best combination of features is called feature selection. In this paper we deal with multivariate time-dependent series of data points for energy forecasting in smart buildings. We propose a methodology to transform the time-dependent database into a form that standard machine learning algorithms can process, and then, apply different types of feature selection methods for regression tasks. We used *Weka* for the tasks of database transformation, feature selection, regression, statistical test and forecasting. The proposed methodology improves *MAE* by 59.97% and *RMSE* by 40.75%, evaluated on training data, and it improves *MAE* by 42.28% and *RMSE* by 36.62%, evaluated on test data, on average for 1-step-ahead, 2-step-ahead and 3-step-ahead when compared to not applying any feature selection methodology.

Keywords: Feature Selection, Energy Efficiency, Time Series, Smart Buildings, Smart Cities.

1. Introduction

Energy efficiency is the goal to optimise the amount of energy required to provide products and services. Energy consumption is increasing with the growing population and intensified in highly populated parts of cities [1]. Energy efficiency is in the interest of everyone, from individuals to governments, since it yields economical savings, reduces greenhouse gas emissions and alleviates energy poverty [2]. In order to achieve energy efficiency, smart grids, open data platforms and networked transport systems are proliferating for managing and monitoring resources automatically. This provides the emergence of smart cities, which thanks to the collection of data using sensors that are interconnected through the internet (*Internet of Things*) allow the extraction of insights that are necessary in order to provide better services to the citizens that also include energy efficiency.

The huge amounts of data that are collected via the IoT are consequently analysed in order to extract the knowledge necessary for achieving energy efficiency. However, in order to realise such analysis it is desirable to reduce the dimensionality of the data for easing the models performance. In order to do so there exist several approaches such as *segmentation* and *representation of attributes* [3] or *feature selection* [4]. We are going to focus on feature selection since it has shown its effectiveness in many applications by building simpler and more comprehensive models, improving learning performance, and preparing clean, understandable data.

In this work, we use *time series data* from the Chemistry Faculty of the University of Murcia to generate energy consumption *forecasts* [5, 6]. *Time series forecasting* is the process of using a model to generate forecasts for future events based on known past events. Time series data has a natural temporal ordering. This differs from typical machine learning applications where each data point is an independent example of the concept to be learned, and the ordering of data points within a data set does not matter. For this reason, standard machine learning methods should not be used directly to analyze time series data. In this paper, we propose a methodology to, firstly, transform the time series into a form that standard machine learning algorithms can process, and then, systematically apply a set of feature selection methods for regression that includes *univariate*, *multivariate*, *filter* and *wrapper* methods [7]. Time series data is transformed by removing the temporal ordering of individual input examples and adding a set of delays to the input which are called *lagged attributes* and provide the temporal information. The methodology also allows dealing with *intervention attributes*, which are to be considered external to the data transformation and closed-loop forecasting processes. This approach to time series forecasting is more powerful and more flexible than classical statistics techniques such as *ARMA* and *ARIMA* [8]. Feature selection methods are applied for the selection of both lagged and intervention attributes. *Random Forest*, *instance-based learning* and *linear regression* algorithms are used for regression with the different reduced databases. Finally, the best reduced database together with the best regression algorithm are used for the predictions *1-step-ahead*, *2-step-ahead* and *3-step-ahead* evaluated in training data and test data, and the results are compared with the predictions obtained with the original database. The experiments have been carried out using the *Waikato Environment for Knowledge Analysis* (*Weka*) [9].

With this background the paper has been organized as follows: section 2 defines the concept of feature selection and their categorization, shows the feature selection mechanisms in the *Weka* machine learning software and describes the data set used for experiments; section 3 proposes a methodology for the energy efficiency analysis in smart buildings based on feature selection; section 4 analyzes and discusses the results, and finally section 6 concludes the paper.

2. Background

2.1. Feature Selection

Feature Selection (FS) is defined in [4] as the process of eliminating features from the database that are irrelevant to the task to be performed. FS facilitates data understanding, reduces the measurement and storage requirements, the computational process time, and the size of a data set, so that model learning becomes an easier process. An FS method is basically a *search strategy* where the performance of candidate subsets is measured with a given *evaluator*. The search space for candidate subsets has cardinality $O(2^w)$, where w is the number of features. A *stopping criterion* establishes when the FS process must finish. It can be defined as a control procedure that ensures that no further addition or deletion of features produces a better subset, or it can be as simple as a counter of iterations. FS methods are typically categorized into *wrapper*, *filter* and *embedded*, *univariate* and *multivariate* methods. *Wrapper methods* [10] use a predetermined learning algorithm to determine the quality of selected features according to an evaluation metric [11]. *Filter methods* apply statistical measures to evaluate the set of attributes [12, 13, 14]. *Embedded methods* achieve model fitting and FS simultaneously [15]. *Multivariate methods* evaluate features in batches. *Univariate methods* evaluate each feature independently. Figure 1 illustrates graphically the FS flow. Figure 2 shows general schemes for multivariate and univariate FS.

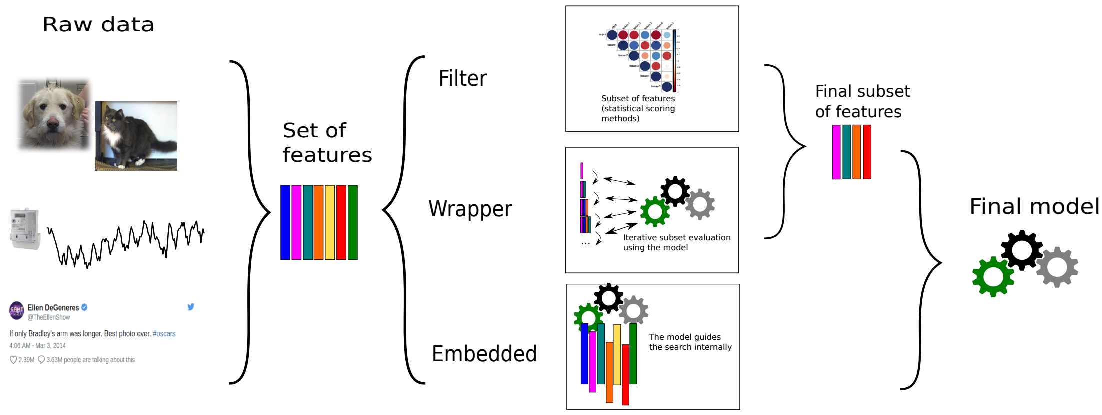

Figure 1: The feature selection flow.

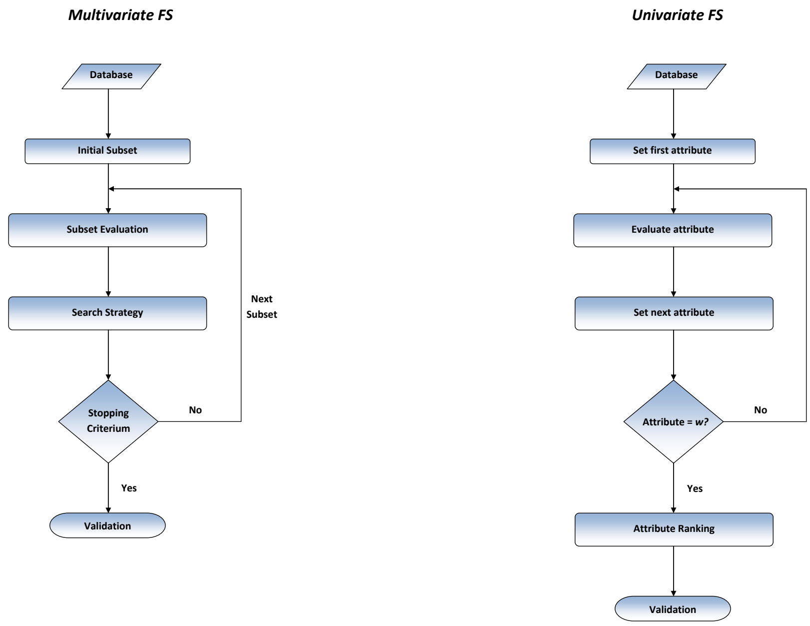

Figure 2: General schemes for multivariate and univariate feature selection.

2.2. Related Work

We have carried out an extensive search in order to find other academic works that have solved a similar problem than ours. Together with the works that address FS for energy consumption time series, we have also considered important to review FS for energy consumption when not treated as time series, and FS for time series problems in general, i.e. other approaches not specifically related to energy consumption.

The first paper that studied how the selection of subsets of features associated with building energy behaviours influences a machine learning model performance for energy consumption prediction used some filter methods for FS and support vector regression for forecasting [16]. A bit later, in the thesis [17], *Fast Correlation-Based Filter* (*FCBF*) is used for FS in load prediction error problems in four building areas. A meteorological dataset from several locations and also, the geographical factor are exploited by selecting variables from different locations. The baseline comparisons are done with *e-SVR*. According to this work, how the relationships between features change with distance motivates a greedy FS method for the electrical load forecasting. In the work [18], *correlation* and *principal components analysis* (*PCA*) are used for FS and transformation.

Feature selection for time series prediction has been carried out using neural networks[19]. By combining contemporaneous and lagged realisations of the independent variables and lagged dependent variables more general models of dynamic regression, autoregressive (*AR*) transfer functions and intervention models are constructed. Other studies have searched for the optimal time-windows and time lags for each variable based on feature pre-processing and sparse learning in order to configure the input dataset [20].

In other works, the forecasting of solar radiation time series in enhanced by using a train set of bootstrapped Support Vector Machines in order to perform FS [21]. They assure that this method is more robust than a regular FS approach because using the later, small changes on the train set may produce a huge difference on the selected attributes. Other studies related to solar radiation prediction mask the inputs as a FS step [22]. They create their own features by defining night, sunrise, day and sunset according to the moment that their instruments perceive those. This provides certain improvements on forecast accuracy. A data-driven multi-model wind prediction methodology using a two-layer ensemble machine learning technique is developed in [23]. A deep FS framework is employed where four different approaches are used in order to get the input vector: *PCA*, *Granger Causality Test*, *Autocorrelation and Partial Autocorrelation Analysis*, and *Recursive Feature Elimination*. Another ensembles way of selecting features in presented in [24] and it is used for predicting the amount of incoming calls for an emergency call center in a time series manner. They use five algorithms (*ReliefF*, *PCA*, *Freq. Discretization*, *Information Gain* and *K-means*) that are different in nature and combine the rankings computed grouping similar approaches and computing new weights as the mean of the individual weights. After that, all variables that are ranked among the top five positions in at least three of the groups compound the selected features. A possible way to perform FS for change detection in multivariate time series is the *Scenario-Based Random Forest* (*SBRF*) algorithm [25]. The aim of change detection is to figure out for a new scenario which label the current segment has at a give time-index by using only the information from the time series up to this point. The *SBRF* classifier is an extension of the Random Forest algorithm which estimates the generalization error on scenario level and not on time-stamp level. The methodology is used in a car crash detection application. Moreover, in the thesis work [26] they present three case studies in which FS is a step in the model creation. They used the following methods: *sequential forward/ backward selection* (*SFS*, *SBS*), *sequential forward/ backward floating selection* (*SFFS*, *SBFS*), the *n best features selection* (*nBest*) and the *best individual features*.

The main data characteristics of energy time series have been specifically analysed in [27]. To explore such data from different perspectives they consider two main categories: nature (nonstationarity, nonlinearity and complexity characteristics) and pattern (cyclicity, mutability or saltation, and randomicity or noise pattern). After that, FS for electricity load forecasting was done in a time series manner using correlation and instance based methods [28]. In [29] it is presented a survey on data mining techniques for time series forecasting of electricity. The survey focuses on the characteristics of the models and their configuration. *Wrapper* methods, *Artificial Neural Networks*, *mutual information*, *autocorrelation* and *ranking based methods* are mentioned as FS techniques used in the prediction of energy consumption. Finally, the work [2] uses temperature time series together with day of the week in order to estimate energy consumption.

2.3. Energy efficiency dataset

The reference building in which the energy consumption forecasting has been carried out is the Chemistry Faculty of the University of Murcia, which is a building used as a pilot for the H2020 ENTROPY project[1].

The dataset is composed of 5088 observations of 50 attributes that are measured hourly from 2016-02-02 00:00:00 until 2016-09-06 23:00:00, where time-stamps from 2016-02-05 00:00:00 until 2016-05-07 23:00:00 are missing data. Table 1 shows the number, name and sources of the dataset attributes. The output attribute is the *energy consumption* measured in KWh. Attributes *datetime* ("yyyy-MM-dd HH:mm:ss"), *season* (1–4), *day of the week* (1–7), and *holiday* (0,1) have been extracted from the date's observation. We have used meteorological data gathered from several sources and stations with the purpose to select the attributes from the most explanatory source according to our feature extraction analysis.

Weather Underground[2] is a web service that through its API provides the following real values: *temperature* (°C), *apparent temperature* (°C), *dew point* (°C), *humidity* (%), *wind speed* (m/s), *mean sea level pressure* (mbar), *visibility* (km) and *precipitations in last hour* (mm). We also use *one-hour predictions* for the first six previous attributes, together with *probability of precipitations* (%), *sky cover* (%) and *wind direction* (degrees) .

IMIDA[3] (The Research Institute of Agriculture and Food Development of Murcia) provides real time records of weather. We have selected two weather stations regarding proximity to the building: MO12 and MU62 and from each of them we have collected the following variables: *temperature* (mean, minimum and maximum) (°C), *humidity* (mean, minimum and maximum) (%), *radiation* (mean and maximum) (w/m^2), *wind speed* (mean and maximum) (m/s^2), *wind direction* (mean) (degrees), *precipitation* (mm), *dew point* (°C) and *vapour pressure deficit* (kPa).

3. A methodology for energy multivariate time series forecasting based on feature selection

We have followed the methodology shown in the Figure 3 to perform the energy time series forecasting. The following six steps have been systematically applied: database transformation, feature selection, regression, statistical

[1] http://entropy-project.eu
[2] https://www.wunderground.com/
[3] http://www.imida.es/

Number	*Name*	*Data source*
1–8	realWU_temp, realWU_feels, realWU_dewp, realWU_hum, realWU_wspd, realWU_visib_km, realWU_mslp, realWU_prep_1h	Weather Underground
9–17	pr_temp, pr_feels, pr_dewp, pr_hum, pr_pop, pr_wspd, pr_wdir_deg, pr_sky, pr_mslp	Weather Underground
18–33	stMO12_IMI_tmed, stMO12_IMI_tmax, stMO12_IMI_tmin, stMO12_IMI_hrmed, stMO12_IMI_hrmax, stMO12_IMI_hrmin, stMO12_IMI_radmed, stMO12_IMI_radmax, stMO12_IMI_vvmed, stMO12_IMI_vvmax, stMO12_IMI_dvmed, stMO12_IMI_prec, stMO12_IMI_dewpt, stMO12_IMI_dpv, stMU62_IMI_tmed, stMU62_IMI_tmax,	IMIDA MO12
34–45	stMU62_IMI_tmin, stMU62_IMI_hrmed, stMU62_IMI_hrmax, stMU62_IMI_hrmin, stMU62_IMI_radmed, stMU62_IMI_radmax, stMU62_IMI_vvmed, stMU62_IMI_vvmax, stMU62_IMI_dvmed, stMU62_IMI_prec, stMU62_IMI_dewpt, stMU62_IMI_dpv	IMIDA MU62
46	energy	Output attribute
47–50	season, day_of_the_week, holiday, datetime	Date's observations

Table 1: Attributes and data sources of the energy consumption dataset used in this paper.

tests, decision making and forecasting. Next, each step is described separately, and some of the names of the *Weka* classes and methods that are required throughout the process are indicated.

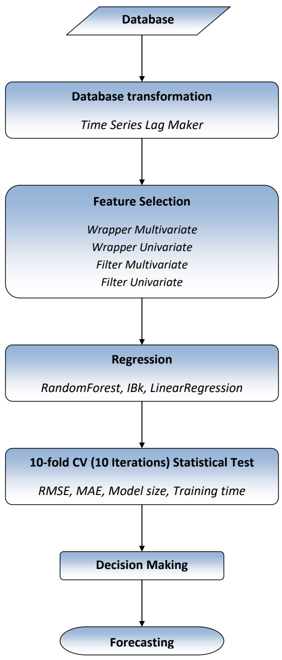

Figure 3: Methodology for feature selection for energy time series forecasting.

3.1. Database transformation

The first step of our methodology is to transform the database by creating lagged versions of variables for use in the time series problem. For this, the following steps are carried out:

1. Set an *artificial time-stamp* with start value 1. We use an artificial time index for convenience. In this way, no instances are inserted in the training data for the missing time-stamps.
2. Set the attributes to *lag*. The system can jointly model multiple attributes to lag simultaneously in order to capture dependencies between them. Because of this, modelling several series simultaneously can give different results for each series than modelling them individually. The rest of the attributes (*non lagged* attributes) are considered as *intervention* attributes (also called *overlay data*). We set attributes 1 to 46 as lagged attributes. Attributes 47, 48 and 49 are intervention attributes.
3. Set the minimum previous time step to create a lagged field. We set to 0 the *minimum lag length* to create. A value of 0 means that a lagged variable will be created that holds target values at time 0.
4. Set the maximum previous time step to create a lagged variable. We set to 3 the *maximum lag length* to create. A value of 3 means that a lagged variable will be created that holds target values at time −3. All time periods between the minimum and maximum lag will be turned into lagged variables. In this way, for example the variable *energy* will be transformed into 4 lagged variables *Lag_energy+0* (equivalent to the variable *energy*), *Lag_energy-1*, *Lag_energy-2* and *Lag_energy-3*.
5. Perform database transformation. A database of 189 attributes has been generated with the transformation.
6. Save transformed database with the name *TransformedDatabaseAux*. This auxiliary transformed database will be used later in the forecasting phase.
7. Remove *datetime* attribute. When using an artificial time index, the attribute *ArtificialTimeIndex* is added to the database, so the attribute *datetime* must be removed.
8. Save the final transformed database with the name *TransformedDatabase*. The final number of attributes of the transformed database is 188.

We use the class *weka.classifiers.timeseries.core.TSLagMaker* for this task. Data transformation can be done from the plugin tab in Weka's graphical "Explorer" user interface, or and using the *API* through a *Java* program.

3.2. Feature selection

Once the task of transforming the database is done, the next step is to apply FS on the *TransformedDatabase2* database. In *Weka*, FS is implemented with the class *weka.attributeSelection.AttributeSelection* through two components: the *search strategy* (*weka.attributeSelection.ASSearch* abstract class) and the *evaluator* (*weka.attributeSelection.ASEvaluation* abstract class). This allows users and programmers to configure a multitude of different methods for FS, both filter and wrapper, univariate and multivariate. Evaluators with names ending in *SubsetEval* configure multivariate methods, whereas those with names ending in *AttributeEval* configure univariate methods. For multivariate wrapper FS methods, the *weka.attributeSelection* package has the class *weka.attributeSelection.WrapperSubsetEval* which evaluates attribute sets by using a learning scheme with cross-validation and a performance measure. For univariate wrapper FS methods, the *weka.attributeSelection.ClassifierAttributeEval* class evaluates the worth of an attribute by using a user-specified classifier, cross-validation and a performance evaluation measure to use for selecting attributes. Since the FS and classification processes must be executed in batch mode, *Weka* offers the class *weka.classifiers.meta.AttributeSelectedClassifier* which is a meta-classifier where dimensionality of data is reduced by attribute selection before being passed on to a learning algorithm. Table 16 summarizes the packages and classes for FS in *Weka* used in this paper.

We applied eight different FS methods for regression shown in Table 2 and graphically in Figure 8. In Table 2, *Database #Id* denotes the identifier of the reduced database generated with each FS method. Each FS method is the result of a specific choice among the search strategy and the evaluator. We considered for this research five wrapper FS methods and three filter FS methods. Among them, five FS methods are multivariate and three FS methods are univariate. Table 14 shows the parameters used for each FS method. Next we show the search strategies and evaluators considered in this paper.

Database #Id.	*Type of FS method*	*Name*	*Search strategy*	*Evaluator*
#1	Wrapper Multivariate	*MOES-RF-MAE*	*MultiObjectiveEvolutionarySearch*	*RandonForest (MAE)*
#2	Wrapper Multivariate	*MOES-RF-RMSE*	*MultiObjectiveEvolutionarySearch*	*RandonForest (RMSE)*
#3	Wrapper Multivariate	*MOES-IBk-RMSE*	*MultiObjectiveEvolutionarySearch*	*IBk (RMSE)*
#4	Wrapper Multivariate	*MOES-LR-MAE*	*MultiObjectiveEvolutionarySearch*	*LinearRegression (MAE)*
#5	Wrapper Univariate	*RANKER-RF-RMSE*	*Ranker*	*RandonForest (RMSE)*
#6	Filter Multivariate	*GS-CFSSE*	*GreedyStepwise*	*CfsSubsetEval*
#7	Filter Univariate	*RANKER-RFAE*	*Ranker*	*ReliefFAttributeEval*
#8	Filter Univariate	*RANKER-PCA*	*Ranker*	*PrincipalComponents*

Table 2: Proposed feature selection methods for energy time series forecasting.

3.2.1. Search Strategies

As multivariate FS methods, we use a *probabilistic search strategy* and a *deterministic search strategy*. *MultiObjectiveEvolutionarySearch* [30] is the probabilistic strategy, and *GreedyStepwise* [31] is the deterministic strategy. *MultiObjectiveEvolutionarySearch* use multi-objective evolutionary computation where two objectives are optimized: the first one is a performance metric or statistical measure chosen by user with the evaluator, while the second one is the attribute subset cardinality, and it is to be minimized. The final output is given by the non-dominated solutions in the last population having the best fitness score for the first objective. *MultiObjectiveEvolutionarySearch* class has two multi-objective evolutionary algorithms implemented, *ENORA* and *NSGA-II*. *ENORA* is our *MOEA*, on which we are intensively working over the last decade. We have applied *ENORA* to constrained real-parameter optimization [32], fuzzy optimization [33], fuzzy classification [34], feature selection for classification [35] and feature selection for regression [36]. In this paper, we apply it to feature selection for regression in times series forecasting. *NSGA-II* algorithm has been designed by K. Deb et al. and has been proved to be a very powerful and fast algorithm in multi-objective optimization contexts of all kinds. In [36] is statistically tested that *ENORA* performs better than *NSGA-II* in terms of *hypervolume* [37, 38] for regression tasks, for which we have decided to use *ENORA* in this work. *GreedyStepwise* performs a greedy forward or backward search through the space of attribute subsets, stopping when the addition (forward direction) or deletion (backward direction) of any of the remaining attributes results in a decrease in evaluation, thus, it has no backtracking capability.

For univariate FS methods, *Ranker* method [39] is required. *Ranker* method ranks attributes by their individual evaluations. A threshold, or the number of attributes to retain, allows reducing the attribute set.

3.2.2. Evaluators

We considered the multivariate filter evaluator *ConsistencySubsetEval* [40]. *ConsistencySubsetEval* scores a subset of features as a whole, by projecting the training instances according to the attribute subset, and considering the consistency of class values in the obtained instance sets. As far as univariate filter evaluators are concerned, *ReliefFAttributeEval* [41] and *PrincipalComponents* [42] were considered. *RelieffAttributeEval* evaluates the worth of an attribute by repeatedly sampling an instance and considering the value of the given attribute for the nearest instance of the same and different class. Can operate on both discrete and continuous class data. *PrincipalComponents* performs a principal components analysis and transformation of the data. Dimensionality reduction is accomplished by choosing enough eigenvectors to account for some percentage of the variance in the original data (default 95%). Attribute noise can be filtered by transforming to the principal components space, eliminating some of the worst eigenvectors, and then transforming back to the original space.

We use the wrapper *WrapperSubsetEval* [10] for multivariate FS methods and *ClassifierAttributeEval* [43] for univariate FS methods in conjunction with the predictors *RandomForest* [44], *IBk* [45] and *LinearRegression* [46], and with the metrics *root mean squared error* (*RMSE*) and *mean absolute error* (*MAE*) [47]. *RandomForest* is an *ensemble learning* method which constructs a forest of random trees with controlled variance, for classification or regression purposes. *IBk* is a simple instance-based learner that uses the class of the nearest k training instances for the class of the test instances and it is also valid for regression. *LinearRegression* uses the *Akaike* criterion for model selection, and is able to deal with weighted instances. Note that not all regression algorithms can be used as evaluators in wrapper FS methods due to their high computational time. *RandomForest*, *IBk* and *LinearRegression* are learning algorithms that offer a good compromise between performance and computational time so they are suitable as evaluators in wrapper FS methods.

3.3. Regression

Once FS was made, the next step was to perform regression with the reduced and *TransformedDatabase2* databases using different regression algorithms. We considered *RandomForest*, *IBk* and *LinearRegression* since these algorithms were used as evaluators in the wrapper FS methods. Additionally we used *Support Vector Machines* [48] and *Gaussian Processes* [49], which are widely used for time series forecasting [50], concretely the *Weka* implementations *SMOreg* and *GaussianProcesses*. *SMOreg* [51] implements the support vector machine for regression. The parameters can be learned using various algorithms, being *RegSMOImproved* the most popular algorithm. *GaussianProcesses* implements Gaussian processes for regression without hyperparameter-tuning. To make choosing an appropriate noise level easier, this implementation applies normalization/standardization to the target attribute as well as the other attributes. Both *SMOreg* and *GaussianProcesses* can use *Polykernel*, *PrecomputedKernelMatrixKernel*, *Puk*, *RBFKernel* or *StringKernel*. Table 15 shows the parameters used for the regression methods. Tables 3 and 4 show the evaluation in full training set for the *RMSE* and *MAE* metrics respectively.

	#1	***#2***	***#3***	***#4***	***#5***	***#6***	***#7***	***#8***	***TransformedDatbase***
RandomForest	5.0930	5.0286	5.2923	5.5701	5.9543	7.2083	5.3704	13.5680	7.8809
IBk	3.0201	3.5134	2.4937	1.3826	2.7927	1.5093	1.4044	0.0000	2.1045
LinearRegression	19.5455	18.4759	18.7110	18.3092	18.7878	22.1723	18.2264	53.5429	17.2416
SMOref	20.2988	19.1824	19.2648	19.0136	19.3193	23.1186	19.1566	55.5580	18.4857
GaussianProcesses	21.9302	21.7321	24.7275	19.4525	18.9750	22.1774	18.4000	54.5592	17.4686

Table 3: *RMSE* with full training set.

	#1	***#2***	***#3***	***#4***	***#5***	***#6***	***#7***	***#8***	***TransformedDatbase***
RandomForest	2.5667	2.6015	2.7341	2.8990	3.1639	3.7101	2.7528	8.5778	4.7050
IBk	0.0730	0.0824	0.0465	0.0271	0.0559	0.0231	0.0284	0.0000	0.0419
LinearRegression	11.2387	10.0955	10.2126	9.6797	10.1295	13.2144	10.4735	38.2477	10.1297
SMOref	10.0226	8.9893	9.0665	8.9401	9.0363	11.5677	8.9673	36.6050	8.7132
GaussianProcesses	15.2061	15.0741	17.8833	11.9989	10.5405	13.3437	10.9358	38.7237	10.5050

Table 4: *MAE* with full training set.

3.4. Statistical test

In order to detect over-fitting and prediction ability, the regression models have also been evaluated with cross-validation. Tables 5, 6, 7 and 8 show the evaluation in 10-fold cross-validation, 3 repetitions (a total of 30 models with each regression algorithm in each database), for the metrics *RMSE*, *MAE*, *Serialized_Model_Size* and *User_Time_training*[4] respectively. The result of the experiment has been analysed through a *paired t-test (corrected)*, with 0.05 significance, being *#1* the test base. For each result, a mark $*$ denotes that the result is statistically worse than the test base; similarly, a mark *v* denotes a statistically better result, and no mark denotes no statistically meaningful difference.

	#1	***#2***	***#3***	***#4***	***#5***	***#6***	***#7***	***#8***	***TransformedDatbase***
RandomForest	12.6685	12.9133	13.3814 $*$	14.4111 $*$	15.4203 $*$	18.7996 $*$	13.9174 $*$	36.7834 $*$	21.3455 *v*
IBk	17.7612	20.8112 $*$	17.2423	25.0447 $*$	25.8680 $*$	25.7792 $*$	22.7562 $*$	37.8315 $*$	29.5936 $*$
LinearRegression	19.3960	18.3234 *v*	18.5017 *v*	18.1808 *v*	18.6416	22.0898 $*$	18.1092 *v*	53.6083 $*$	17.7597 *v*
SMOref	20.0636	18.8337 *v*	18.9237 *v*	18.6714 *v*	18.9697 *v*	23.0016 $*$	18.8051 *v*	55.5770 $*$	18.2458 *v*
GaussianProcesses	21.9231	21.7133	24.7083 $*$	19.4114 *v*	18.8832 *v*	22.1160	18.3440 *v*	54.6361 $*$	17.8482 *v*

Table 5: *RMSE* with 10-fold cross-validation (3 repetitions).

[4] Intel (R) Core (TM) i5-4460 @ 3.20 GHz 3.20 GHz RAM 8.00 GB Operating Systems 64 bits, processor x64.

	#1	*#2*	*#3*	*#4*	*#5*	*#6*	*#7*	*#8*	*TransformedDatbase*
RandomForest	5.8264	6.0012 ∗	6.2785 ∗	6.8621 ∗	7.5242 ∗	9.0191 ∗	6.4675 ∗	23.3071 ∗	12.6164 ∗
IBk	8.8796	10.0150 ∗	8.6797	13.1307 ∗	13.3098 ∗	12.7038 ∗	11.0927 ∗	17.4372 ∗	14.3159 ∗
LinearRegression	11.2708	10.1276 *v*	10.2363 *v*	9.7287 *v*	10.1738 *v*	13.2454 ∗	10.5091 *v*	38.3269 ∗	10.6126 *v*
SMOref	10.0410	9.0122 *v*	9.0806 *v*	8.9702 *v*	9.0669 *v*	11.5835 ∗	8.9962 *v*	36.7292 ∗	8.9314 *v*
GaussianProcesses	15.3332	15.1402 *v*	17.9369 ∗	12.0857 *v*	10.6294 *v*	13.3943 *v*	11.0307 *v*	38.8031 ∗	10.9028 *v*

Table 6: *MAE* with 10-fold cross-validation (3 repetitions).

	#1	*#2*	*#3*	*#4*	*#5*	*#6*	*#7*	*#8*	*TransformedDatbase*
RandomForest	11.9955	11.9149 *v*	13.4332 ∗	12.6169 ∗	14.7657 ∗	16.3795 ∗	14.9757 ∗	20.3033 ∗	16.7962 ∗
IBk	0.5064	0.5796 ∗	0.4330 *v*	0.8735 ∗	0.5798 ∗	0.4329 *v*	0.5799 ∗	0.5804 ∗	0.7081 ∗
LinearRegression	0.1278	0.1274 *v*	0.1275 *v*	0.1285 ∗	0.1285 ∗	0.1275 *v*	0.1285 ∗	0.1278 ∗	0.1604 ∗
SMOref	0.1734	0.7654 ∗	0.6609 *v*	0.1060 ∗	0.1028 ∗	0.8805 ∗	1.1013 ∗	0.7658 ∗	7.6196 ∗
GaussianProcesses	168.4590	168.4900 ∗	168.3855 *v*	168.7841 ∗	168.7528 ∗	168.6051 ∗	168.8259 ∗	168.4904 ∗	175.3427 ∗

Table 7: *Serialized_Model_Size* ($\times 10^6$ bytes) with 10-fold cross-validation (3 repetitions).

	#1	*#2*	*#3*	*#4*	*#5*	*#6*	*#7*	*#8*	*TransformedDatbase*
RandomForest	0.9474	1.0349 ∗	0.7792 *v*	1.3432 ∗	0.9714	0.5708 *v*	0.7802 *v*	1.6078 ∗	3.0609 ∗
IBk	0.0005	0.0005	0.0000	0.0000	0.0005	0.0000	0.0016	0.0000	0.0005
LinearRegression	0.0042	0.0109	0.0026	0.0125 ∗	0.0089	0.0063	0.0115	0.0057	4.2172 ∗
SMOref	31.9255	29.0380 *v*	26.4307 *v*	62.5958 ∗	87.1901 ∗	75.5521 ∗	141.1615 ∗	9.0995 *v*	1626.4151 ∗
GaussianProcesses	115.4714	115.3620	115.4219	115.5542	110.7714 *v*	110.4302 *v*	110.5990 *v*	110.6505 *v*	114.0536

Table 8: *UserCPU_Time_training* (seconds) with 10-fold cross-validation (3 repetitions).

3.5. Decision making

Looking at tables 5 to 8 we can make a decision for choosing the best reduced database and, therefore, the best FS method. The best results have been obtained with the FS method *MOES-RF-MAE* (database *#1*) when *RandomForest* is used as regression algorithm, which show statistically significant differences with respect to the rest of the analysed FS methods for the *MAE* performance metric. For *RMSE* performance metric, FS method *MOES-RF-MAE* is also superior to the rest of FS methods, with statistically significant differences except for the FS method *MOES-RF-RMSE*. With respect to the *Serialized_Model_Size* and *UserCPU_Time_training* performance metrics, the results of the FS method *MOES-RF-MAE* by using *RandomForest* are acceptable in comparison to the rest of the methods. We can then choose the FS method *MOES-RF-MAE* and the database *#1* for the final forecasting process.

Table 9 shows the selected attributes with *MOES-RF-MAE*. Tab. 9 shows the selected attributes and their ranks and importances for each of the datasets. The rank and importance of the attributes has been obtained through a univariate wrapper feature selection method, where the search strategy is the *ranker* method, and the *evaluator* is *ClassifierAttributeEval* with *classifier* = *RandomForest* (with default parameters), *evaluationMeasure* = *MAE*, and *leaveOneAttributeOut* = *true*. An attribute is evaluated by measuring the impact of leaving it out from the full set.

Input attribute	*Rank*	*Importance*
Lag_energy-1	1	7.398
Lag_stMO12_IMI_radmax+0	2	1.337
holiday	3	0.367
Lag_energy-3	4	0.357
ArtificialTimeIndex	5	0.302
Lag_stMO12_IMI_radmed-3	6	0.273
Lag_pr_feels-2	7	0.248
Lag_pr_temp-2	8	0.172

Table 9: Selected attributes with *MOES-RF-MAE* (database *#1*) and their ranks.

3.6. Forecasting

Finally, in this section we analyse the prediction ability of the forecaster obtained with the selected attributes. We use the class *weka.classifiers.timeseries.WekaForecaster* for this task. Forecasting can be done from the plugin tab in Weka's graphical "Explorer" user interface, or using the *API* through a *Java* program. When an evaluation is performed, firstly the forecaster is trained on the data, and then it is applied to make a forecast at each time point (in order) by stepping through the data. These predictions are collected and summarized, using *MAE* and *RMSE* metrics, for each future time step predicted. We use in this paper three time units to forecasts, i.e. all the 1-step-ahead, 2-steps-ahead and 3-steps-ahead predictions are collected and summarized. This allows us to see, to a certain degree, how forecasts further out in time compare to those closer in time.

Tables 10 and 12 show the evaluation of the forecaster, with the database *#1*, on training data (70%) and test data (30%) respectively. The last 500 training data and the first 500 test data of these evaluations are also shown graphically in figures 4 and 6 respectively. To verify if the FS process has been effective both for the reduction of the complexity of the model and for the increase of its predictive capacity, the forecasting process has also been carried out on the database *TransformedDatase* (with all lagged variables and all overlay variables). Tables 11 and 13 show the evaluation of the forecaster with the database *TransformedDatase*, and figures 5 and 7 show graphically the evaluation of the last 500 training data and the first 500 test data respectively.

	1-step-ahead	*2-steps-ahead*	*3-steps-ahead*	*Average*
Number of instances	3559	3558	3557	-
MAE	2.6684	4.3897	5.8962	4.3181
RMSE	5.3008	9.4352	13.0256	9.2539

Table 10: Evaluation on training data (3562 instances) with *RandomForest* - database *#1*.

	1-step-ahead	*2-steps-ahead*	*3-steps-ahead*	*Average*
Number of instances	3559	3558	3557	-
MAE	4.4041	9.6858	18.2695	10.7865
RMSE	7.5987	14.0861	25.1676	15.6175

Table 11: Evaluation on training data (3562 instances) with *RandomForest* - *TransformedDatabase*.

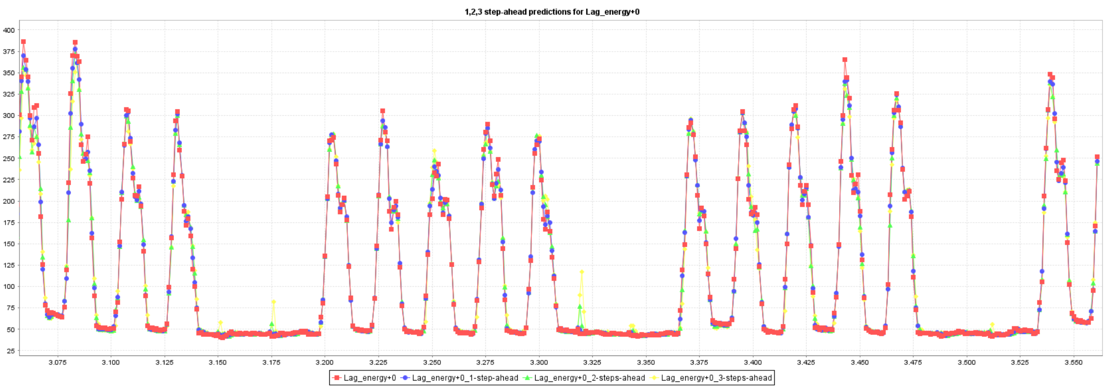

Figure 4: 1,2,3-step-ahead predictions for Lag-energy+0 evaluated on the last 500 training data with *RandomForest* - database *#1*.

4. Analysis of results and discussion

When observing the results of the experiments carried out using the proposed methodology, the following statements can be derived:

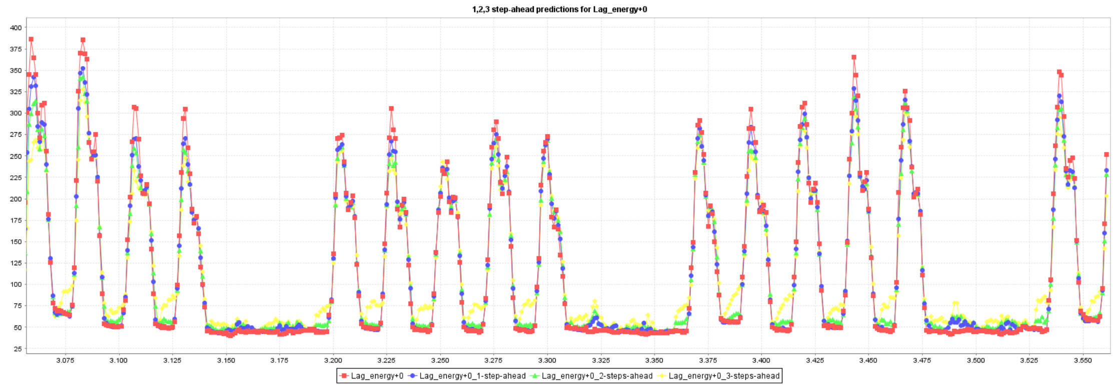

Figure 5: 1,2,3-step-ahead predictions for Lag-energy+0 evaluated on the last 500 training data with *RandomForest - TransformedDatabase*.

	1-step-ahead	*2-steps-ahead*	*3-steps-ahead*	*Average*
Number of instances	1526	1525	1524	-
MAE	10.9941	20.4655	32.7499	21.4032
RMSE	16.0509	28.7680	44.8343	29.8844

Table 12: Evaluation on test data (1526 instances) with *RandomForest* - database *#1*.

	1-step-ahead	*2-steps-ahead*	*3-steps-ahead*	*Average*
Number of instances	1526	1525	1524	-
MAE	26.7583	34.7768	49.7004	37.0785
RMSE	36.5563	45.0787	59.8209	47.1520

Table 13: Evaluation on test data (1526 instances) with *RandomForest - TransformedDatabase*.

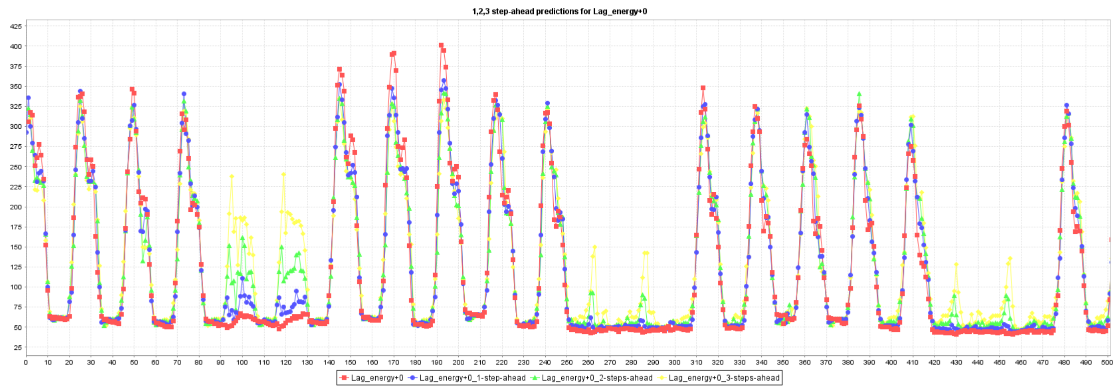

Figure 6: 1,2,3-step-ahead predictions for Lag-energy+0 evaluated on first 500 test data with *RandomForest* - database *#1*.

A. Regarding the FS process:

- As expected, wrapper FS methods show better performance than filter FS methods, and multivariate FS methods show better performance than univariate FS methods. Multivariate methods can identify interaction amongst features simultaneously, specially wrapper-based FS methods [52]. To make it possible, multivariate methods

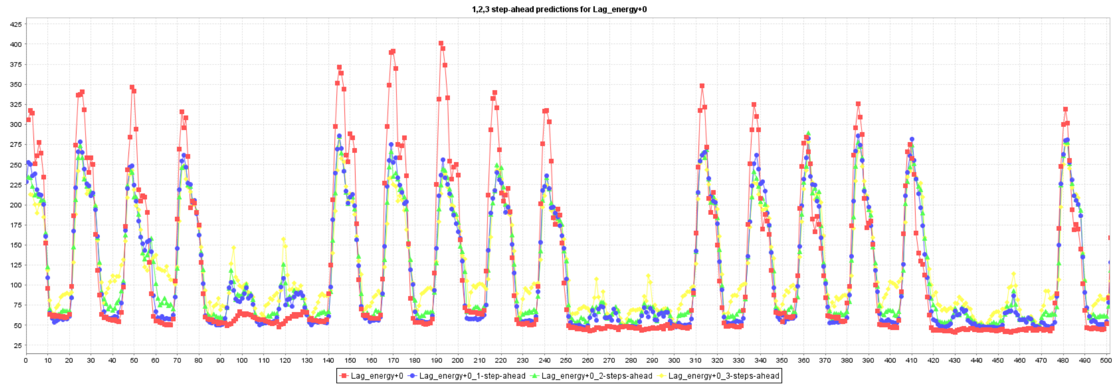

Figure 7: 1,2,3-step-ahead predictions for Lag-energy+0 evaluated on first 500 test data with *RandomForest* - *TransformedDatabase*.

evaluate the relevance of sets of features to determine which are the bests according to certain performance measure for a given task. However, multivariate wrapper feature selection methods present a high computation costs, since the number of possible subsets of feature is very high (2^w, being w the number of features) making the problem of finding the best subsets to be NP-Hard. To reduce the computational time, some deterministic search strategies, such as *GreedyStepwise*, can be used. The main disadvantage of these deterministic search techniques is that hidden and basic interactions could be missed due to the way the search space is traversed [53]. Probabilistic search techniques, such as *MultiObjectiveEvolutionarySearch*, can overcome this difficulties by allowing to generate new subsets in different locations of the search space guided by a metaheuristic. In this paper, we propose to use a multivariate wrapper feature selection method where the search strategy is based on multi-objective evolutionary computation, thus intrinsically overcoming the problem of interactions between features.

- For wrapper FS methods, the *RandomForest* evaluator has proven more effective than *IBk* and *LinearRegression* based evaluators. *SMOreg* and *GaussianProcesses* are discarded as evaluators for wrapper methods because of their excessive computational time. Run time of *RandomForest* is acceptable for wrapper FS methods setting the number of iterations to 10 (-I 10), and this method is not very sensitive to the variation of its parameters. However, *RandomForest* generates regression models larger than *IBk*, *LinearRegression* and *SMOreg*.
- *IBk* is very prone to over-fitting. Although in the evaluation on full training data the best results have been obtained with *IBk*, these results become poor when the evaluation is done on cross-validation, which indicates that *IBk* over-fits the regression models.
- *LinearRegression*, *SMOreg* and *GaussianProcesses* are not prone to over-fitting, but it has not been efficient for this problem.
- *MAE* has shown better behaviour than *RMSE* as metric performance in evaluators for wrapper FS methods. This can be seen in Table 5: the FS method *MOES-RF-MAE* (database *#1*) produces better results than the method *MOES-RF-RMSE* (database *#2*) when evaluated on cross-validation with *RandomForest* using the *RMSE* metric.

B. Regarding the forecasting process:

Tables 10 to 13 show how 1,2,3-steps-ahead predictions using the reduced database *#1* improve the 1,2,3-steps-ahead predictions using the database without performing feature selection. Using the averages of the 1,2,3-steps-ahead predictions (shown also in tables 10 to 13) we can calculate the percentage differences between the average predictions by doing feature selection and without doing so. With our methodology, *MAE* is improved by 59.97% and *RMSE* by 40.75%, evaluated on training data, and *MAE* is improved by 42.28% and *RMSE* by 36.62%, evaluated on test data.

5. Comparison with other methods proposed in literature

The metrics RMSE and MAE are two of the most common metrics used to measure accuracy for continuous variables and they are appropriate for model comparisons because they express average model prediction error in units of the variable of interest. However, in order to compare energy consumption prediction within several papers that do not use the same dataset or the same values of energy to be predicted it is not useful to compare such metrics whose magnitude depend on the range of the output data.

For that reason, we choose the coefficient of variance of the RMSE. CVRMSE is a non-dimensional measure calculated by dividing the RMSE of the predicted energy consumption by the mean value of the actual energy consumption. For example, a CVRMSE value of 5% would indicate that the mean variation in actual energy consumption not explained by the prediction model is 5% of the mean value of the actual energy consumption [**?**].

In the work with similar objectives [18], the preprocessing is carried out through correlation and *Principal Components Analysis* [42] and each day is divided in three moments alluding to occupation: morning, afternoon and night. That way, 3 different models are trained and the results are the following: *Random Forest* is selected at night and in the afternoon providing a *RMSE* of 1 and 3.87 *KWh* and *Bayesian Regularized Neural Networks* [54] is selected for the morning with *RMSE* = 7.08 *KWh*. In that sense, we could say that our FS approach overcomes this method in general. In the work [2], the temperature time series together with day of the week are used in order to estimate energy consumption. Results show again Random Forest as the outstanding model and the daily *CVRMSE* = 9%.

For current and future comparisons with further research, we obtained an hourly CVRMSE = 20 % and we have also averaged it per day obtaining a daily CVRMSE = 11 % for the 1-step case.

Multivariate ARIMA: we have also carried on the energy consumption forecasting using the traditional time series method ARIMA with exogenous regressors [55]. Results are much worst than using out machine learning oriented approach. Using our selected features, mean MAE is 119 and mean RMSE is 126. This results are way worst than ours but still better than using all variables with ARIMA: MAE increases between 35 and 55 KWh and RMSE incresaes between 37 and 58 Kwh.

6. Conclusions

In this work we have proposed a methodology for energy multivariate time series forecasting. The methodology is based on, firstly, database transformation into a form that standard machine learning algorithms can process, and then, systematically apply a set of feature selection methods for regression. The methodology deals with both lagged and intervention variables, unlike other works in the literature where only lagged variables are treated or the time series problem is univariate. The results of the experiments carried out show that the proposed methodology effectively reduces both the complexity of the forecast model and their *RMSE* and *MAE* in 1,2,3-steps-ahead predictions. The results of our methodology improve those obtained with other works reported in the literature, as well as those obtained with the *marima* package for multivariate time series forecasting.

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Appendix

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[4] H. Liu, H. Motoda, Feature Selection for Knowledge Discovery and Data Mining, Kluwer Academic Publishers, Norwell, MA, USA, 1998.

Database #Id.	***Parameters***
#1	-E "weka.attributeSelection.WrapperSubsetEval -B weka.classifiers.trees.RandomForest -F 5 -T 0.01 -R 1 -E DEFAULT – -P 100 -I 10 -num-slots 1 -K 0 -M 1.0 -V 0.001 -S 1" -S "weka.attributeSelection.MultiObjectiveEvolutionarySearch -generations 500 -population-size 100 -seed 1 -a 0 "
#2	-E "weka.attributeSelection.WrapperSubsetEval -B weka.classifiers.trees.RandomForest -F 5 -T 0.01 -R 1 -E MAE – -P 100 -I 10 -num-slots 1 -K 0 -M 1.0 -V 0.001 -S 1" -S "weka.attributeSelection.MultiObjectiveEvolutionarySearch -generations 500 -population-size 100 -seed 1 -a 0 "
#3	-E "weka.attributeSelection.WrapperSubsetEval -B weka.classifiers.lazy.IBk -F 5 -T 0.01 -R 1 -E DEFAULT – -K 1 -W 0 -A "weka.core.neighboursearch.LinearNNSearch -A "weka.core.EuclideanDistance -R first-last"" -S "weka.attributeSelection.MultiObjectiveEvolutionarySearch -generations 500 -population-size 100 -seed 1 -a 0"
#4	-E "weka.attributeSelection.WrapperSubsetEval -B weka.classifiers.functions.LinearRegression -F 5 -T 0.01 -R 1 -E MAE – -S 0 -R 1.0E-8 -num-decimal-places 4" -S "weka.attributeSelection.MultiObjectiveEvolutionarySearch -generations 500 -population-size 100 -seed 1 -a 0"
#5	-E "weka.attributeSelection.ClassifierAttributeEval -execution-slots 1 -B weka.classifiers.trees.RandomForest -F 5 -T 0.01 -R 1 -E DEFAULT – -P 100 -I 10 -num-slots 1 -K 0 -M 1.0 -V 0.001 -S 1" -S "weka.attributeSelection.Ranker -T -1.8E308 -N 10"
#6	-E "weka.attributeSelection.CfsSubsetEval -P 1 -E 1" -S "weka.attributeSelection.GreedyStepwise -T -1.8E308 -N -1 -num-slots 1"
#7	-E "weka.attributeSelection.ReliefFAttributeEval -M -1 -D 1 -K 10" -S "weka.attributeSelection.Ranker -T -1.8E308 -N 10"
#8	-E "weka.attributeSelection.PrincipalComponents -R 0.95 -A 5" -S "weka.attributeSelection.Ranker -T -1.8E308 -N 10"

Table 14: Parameters of the proposed feature selection methods for energy time series forecasting.

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Name	*Parameters*
RandomForest	-P 100 -I 100 -num-slots 1 -K 0 -M 1.0
	-V 0.001 -S 1
IBk	-K 1 -W 0
	-A “weka.core.neighboursearch.LinearNNSearch
	-A “weka.core.EuclideanDistance -R first-last””
LinearRegression	-S 0 -R 1.0E-8 -num-decimal-places 4
SMOreg	-C 1.0 -N 0
	-I “weka.classifiers.functions.supportVector.RegSMOImproved
	-T 0.001 -V -P 1.0E-12 -L 0.001 -W 1”
	-K “weka.classifiers.functions.supportVector.PolyKernel -E 1.0 -C 250007”
GaussianProcesses	-L 1.0 -N 0
	-K “weka.classifiers.functions.supportVector.PolyKernel
	-E 1.0 -C 250007” -S 1

Table 15: Parameters of the regression methods.

Name	**Description**
weka.classifiers.timeseries.core.TSLagMaker	Class for creating lagged versions of target variable(s) for use in time series forecasting
weka.attributeSelection	Package for feature selection
weka.attributeSelection.AttributeSelection	Class for feature selection
weka.attributeSelection.ASSearch	Abstract class for search strategy
weka.attributeSelection.ASEvaluation	Abstract class for evaluation
weka.classifiers.AbstractClassifier	Abstract classifier
weka.classifiers.SingleClassifierEnhancer	Abstract utility class, extends *AbstractClassifier*
weka.classifiers.meta.AttributeSelectedClassifier	Meta-classifier for feature selection + classification/regression, extends *SingleClassifierEnhancer*
weka.attributeSelection.GreedyStepwise	Class for greedy stepwise search strategy, extends *ASSearch*
weka.attributeSelection.MultiObjectiveEvolutionarySearch	Class for multi-objective evolutionary search strategy, extends *ASSearch*
weka.attributeSelection.PSOSearch	Class for particle swarm optimization search strategy, extends *ASSearch*
weka.attributeSelection.Ranker	Class to rank attributes in univariate feature selection methods, extends *ASSearch*
weka.attributeSelection.WrapperSubsetEval	Class for multivariate wrapper feature selection methods, extends *ASEvaluation*
weka.attributeSelection.ConsistencySubsetEval	Class for multivariate filter feature selection methods, extends *ASEvaluation*
weka.attributeSelection.ClassifierAttributeEval	Class for univariate wrapper feature selection methods, extends *ASEvaluation*
weka.attributeSelection.ReliefFAttributeEval	Class for univariate filter feature selection methods, extends *ASEvaluation*
weka.attributeSelection.PrincipalComponents	Class for univariate filter feature selection methods, extends *ASEvaluation*
weka.classifiers.trees.RandomForest	Class for constructing a forest of random trees, extends *weka.classifiers.meta.Bagging*
weka.classifiers.lazy.IBk	Class that implements an instance-based learning algorithm, extends *weka.classifiers.Classifier*
weka.classifiers.functions.LinearRegression	Class for using linear regression for prediction, extends *weka.classifiers.AbstractClassifier*
weka.classifiers.timeseries.WekaForecaster	Class that implements time series forecasting using a *Weka* regression scheme

Table 16: Packages and classes for feature selection in Weka used in this paper.

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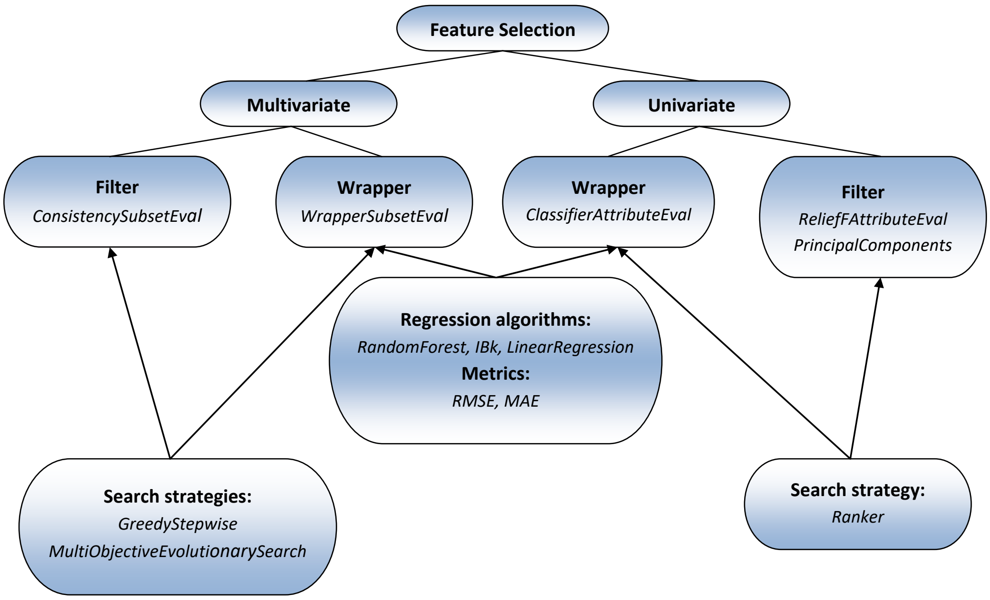

Figure 8: Organization chart of the proposed feature selection methods for energy time series forecasting.

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4.3 Commissioning of the Controlled and Automatized Testing Facility for Human Behavior and Control (CASITA)

Title	Commissioning of the Controlled and Automatized Testing Facility for Human Behavior and Control (CASITA)
Authors	Ignacio Rodríguez-Rodríguez, Aurora González-Vidal, Alfonso P. Ramallo-González and Miguel Ángel Zamora
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Commissioning of the Controlled and Automatized Testing Facility for Human Behavior and Control (CASITA)

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Abstract: Human behavior is one of the most challenging aspects in the understanding of building physics. The need to evaluate it requires controlled environments and facilities in which researchers can test their methods. In this paper, we present the commissioning of the Controlled and Automatized Testing Facility for Human Behavior (CASITA). This is a controlled space emulation of an office or flat, with more than 20 environmental sensors, 5 electrical meters, and 10 actuators. Our contribution shown in this paper is the development of an infrastructure-Artificial Intelligence (AI) model pair that is perfectly integrated for the study of a variety of human energy use aspects. This facility will help to perform studies about human behavior in a controlled space. To verify this, we have tested this emulation for 60 days, in which equipment was turned on and off, the settings of the conditioning system were modified remotely, and lighting operation was similar to that in real behaviors. This period of commissioning generated 74.4 GB of raw data including high-frequency measurements. This work has shown that CASITA performs beyond expectations and that sensors and actuators could enable research on a variety of disciplines related to building physics and human behavior. Also, we have tested the PROPHET software, which was previously used in other disciplines and found that it could be an excellent complement to CASITA for experiments that require the prediction of several pertinent variables in a given study. Our contribution has also been to proof that this package is an ideal "soft" addition to the infrastructure. A case study forecasting energy consumption has been performed, concluding that the facility and the software PROPHET have a great potential for research and an outstanding accuracy.

Keywords: modelling; energy; buildings

1. Introduction

Energy is one of the most important topics of study worldwide. Most governments have implemented initiatives that aim at more energy-efficient societies because of an urgent need to decelerate (1) energy resources exhaustion and (2) greenhouse gas emissions. Buildings are responsible for up to 40% of the carbon emissions in developed countries [1]; it has been seen that their energy use can be reduced substantially not only via renovation of their thermal envelope [2,3] but also via the modification of users' behavior [4].

This opportunity to reduce energy use via changes in behavior has come at the same time as a technological revolution. There now exist sophisticated information management systems to control the different working points of building infrastructures. These systems have already been proved to be effective solutions to the problem of high energy consumption associated with comfort spaces in buildings, see for example [4–6].

Energy consumption is a complex phenomenon in which many aspects play a role; only a comprehensive way of studying it can fully cover its social, economic, and behavioral aspects. The effectiveness of technological solutions for modifying human behavior seems to vary depending on the study [7,8]. It is for this reason that more experimental research on human behavior is needed. This is a topic that was being studied as early as 1960 when Newton et al. [9] outlined the difficulties of understanding human behavior in buildings. Today, there have been advances in the understanding of human behavior, such as the work of [10,11]. However, more testing is needed to continue improving this field of research. A research facility that can serve as a testing arena for this kind of experimentation with the control of all aspects of functioning systems in a building is highly valuable in this field.

The analysis of energy efficiency in built environments has received growing attention in the last decade [12–14]. One possible method to lower energy use could be to generate a management system to tackle this challenge. A home automation system based on the internet of things (IoT) can monitor and control intelligently the different infrastructures involved in a building's energy consumption, while being able to provide comfort, security and communication, energy efficiency, and promote water, electricity, and fuel conservation. Hence, the research community is not only interested in the understanding and modeling of human behavior, but also on the developing and testing of control strategies for building automation based on IoT.

With respect to the advances in sensing and control infrastructure, the growth on information and communication technologies (ICT) offer an even greater potential in the near future [15], and has opened a door for considering homes as environments with many more devices (such as sensors controllers or actuators). A facility that serves to understand the interactions between humans and buildings will need to have all those components to perform valid research.

The internet of things represents a radical evolution of the current internet to a network of interconnected devices that not only harvest information from the environment (sensing), but also allow interacting, managing, and storing easily any kind of data [16–18]. Following an IoT approach, new home automation systems could allow fulfilling the requirements posed by the social changes and new trends in our way of life, facilitating the design of more human, personal, multifunctional, and flexible homes. This change seems to be coming soon as the European Commission has established that 16 of the European Union (EU) member states will implement a large-scale smart-meter rollout by 2020 [19].

The efficiency and accuracy of any home automation system is possible as far as good predictions can be achieved by developing models about the building status. Ergo, different variables have to be taken into account regarding their impact on the energy consumption of buildings, while attempting to consider them in an integral vision [20]. Making a suitable selection and analysis of them is not obvious. Not only do environmental parameters such as humidity and temperature have to be studied, others like human behavior, weather forecast, insulating materials, or thermal inertia should be also considered in order to obtain patterns that will make it possible to anticipate changes in order to avoid declines in comfortable conditions and rises in energy consumption.

With this purpose, the available data about a building and its context have to be interpreted to obtain valuable knowledge. Statistical and novel methods of data analysis allow researchers to establish correlations between variables and to generate performance models of a building, which can be used to ensure efficient responses by the automation system. Thus, in the context of data science, many new and more powerful technologies are bringing alternatives, or even breakthroughs, in the prediction of building energy consumption associated with thermal comfort [21].

The facilities we present for the Controlled and Automatized Testing Facility for Human Behavior (CASITA) have an IoT-based home automation system installed and operational, where experiments can be done in order to test human behavior and IoT solutions. It is located at the Technology Transfer Center of the University of Murcia, Murcia, Spain. This test lab has numerous sensors, actuators, and controllers providing data, which are able to be used to generate accurate models in order to predict energy consumption and many other variables related to building physics. In addition to this, we have coupled the software PROPHET as the soft component of the functioning of the infrastructure for variable forecasting and completion. In this work, two models of energy consumption forecasting will be presented and discussed.

For the commissioning of this infrastructure, a model of the energy consumption based on the novel PROPHET package has been developed within mathematical software R. It measures several variables and evaluates variables that are beneficial for weather forecasting, thereby filling the future time series of outdoor conditions to validate the infrastructure.

All the steps proposed in this paper describe how preliminary testing on the research facility was performed, which can be used to design efficient management systems for saving energy that are fully scalable and that can be applied with the same goal in other buildings with similar sensing and actuation levels. With this paper we contribute to the development of a facility that is pioneer according to the knowledge of the authors, as it sums up the IoT and hardware infrastructure to a soft facet consistent on algorithms of prediction included on the PROPHET library.

This paper is structured as follows: Section 2 describes the infrastructure. Section 3 describes the commissioning and a pilot study to verify the validity of the data and the analysis methods available in CASITA. Section 4 shows conclusions and further work, followed by the references.

2. The Controlled and Automatized Testing Facility for Human Behaviour (CASITA)

Currently, a smart building can be equipped with information and communication technology (ICT) systems, as can be seen in [22], where a sensor network is deployed in a house. Another example is shown in [23].

Although CASITA has been used before in other studies [6,24–29], the commissioning and description of the research facility had not been published yet. This paper aims to provide the necessary documentation to close this gap. CASITA (see Figure 1) is a case of a smart space with a wide deployment of sensors and devices integrated as if it was a home/office automation system.

In this highly sensed habitat, data referring to human behavior and to outdoor and indoor environmental parameters are collected.

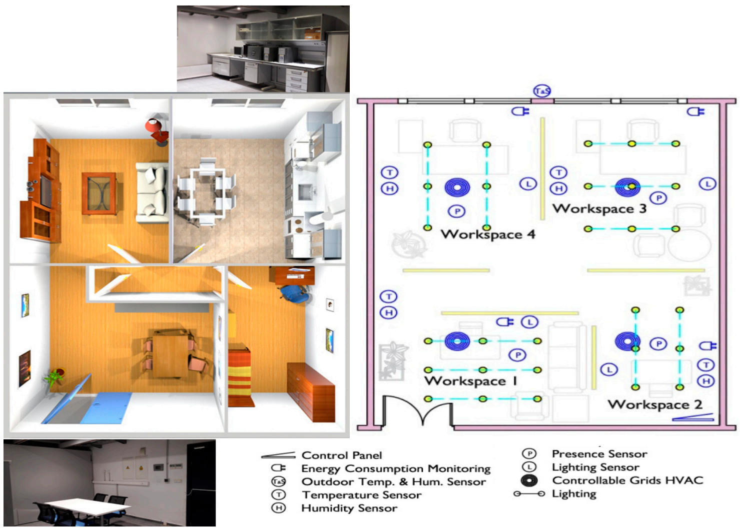

Figure 1. Infographic of a possible setup of the Controlled and Automatized Testing Facility for Human Behavior (CASITA) and distribution of all devices (sensors, actuators and controllers).

2.1. Hardware

The home automation system installed in this reference scenario is composed by Programmable Logic Controllers (PLC), and a Supervisory Control and Data Acquisition (SCADA) system. This system has been given the name Domosec Platform [30]. All the sensors and actuators have been selected in accordance with the principles suggested on [31].

The PLC is able to monitor the sensor status and regulate the infrastructures connected to a platform, while the SCADA system collects data and intercommunicates with the PLC using the actuators. This platform has been designed and developed in-house and more information can be provided on request as it is open-source.

The indoor temperature, humidity, and luminosity are measured in several points of the space. This makes possible to have an idea of how homogeneous the conditions are across the monitored areas. Outdoor conditions are also registered by a weather station located on the top of the building.

Human behavior and presence sensors using passive infrared technology are present. The control access system is based on Radio Frequency Identification (RFID) technology (more details about the device deployment can be found in [6]. Systems and location are exposed in Figure 1.

Due to the importance of outside weather in the studies that are being carried out in CASITA (for example, to measure adaptive thermal comfort), its framework also counts on an ad hoc weather forecast algorithm based on Agencia Estatal de Meteorología (AEMET), the Spanish Meteorology Agency [32], but post-processed further to improve accuracy. This will be explained further in the following sections.

Regarding the actuators deployed in CASITA, there are two Heating, Ventilating and Air Conditioning (HVAC) systems installed in the ceiling that consist on an electric air-to-air heat pump (TOSHIBA RAV-SM803AT-E and 2xTOSHIBA SM806BT-E, Toshiba Carrier Corporation, Tokyo, Japan). Therefore, the indoor temperature and humidity can be modified in CASITA at the user's will. The system has two levels of air velocity (fan power) and a thermostatic proportional control. The primary energy of the system is electricity.

Lighting is provided via light-emitting diodes (LED) placed in the ceiling in accordance with current Spanish regulations. However, they are easy to move as the ceiling space is formed by removable panels. All lighting can also be controlled via the SCADA using the internet. A schema of the hardware and communication architecture in CASITA is shown in Figure 2, and the connection of all this equipment can be seen in Figure 3.

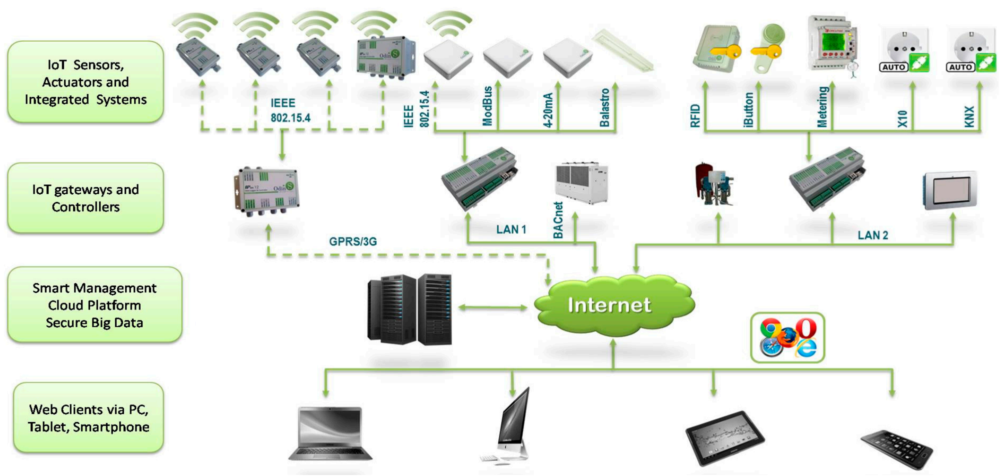

Figure 2. Hardware and communication architecture in CASITA.

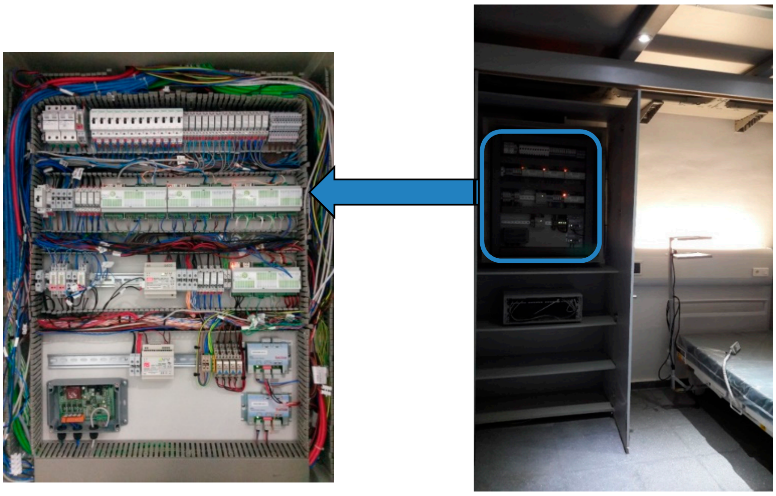

Figure 3. Wiring of data loggers, Supervisory Control and Data Acquisition (SCADA), and other devices in the main wiring cabinet of CASITA.

The electrical consumption of lights, HVAC units, and other electrical appliances are continuously being monitored and collected in the SCADA of the platform. Sensors can report at any given sampling period, which is at least 1 min long, but some of them are able to report at higher frequencies, e.g., high-frequency reporting of electrical grid to verify harmonics. Next table (Table 1) summarizes measured features and actuators that can be found in CASITA.

Table 1. Description of the sensors and actuators available in CASITA.

Features	Sensor Deployments Allow Measurement of a Wide Set of Data
Weather data	Temperature and humidity.
Weather forecast	Up to 4 days.
Indoor conditions	In four different locations, temperature and humidity.
Occupancy and activity	A control access system in the test lab entrance and volumetric detectors in each room let predict in an accurate way the tracking of human presence.
Energy consumption:	For this purpose, and to monitor each component separately, non-intrusive load monitoring techniques have been considered [33]. We distinguish:
Electrical devices	Computers and other appliance are monitored.
Lighting	Differentiating each room.
Heating, Ventilation, and Air Conditioning (HVAC)	Each air-conditioned machine is quantified but is much bigger than the previous consumptions, which makes it energetically undesirable.
Actuators	**It is Possible to Modify the Test Lab Features, Comfort and Energy Consumption, Adapting the Next Actuators**
Access	Test lab can be completely locked, rendering it impossible to enter.
Control of the energy supplies	The plugs can be disabled completely.
Control of the HVAC machines	It is possible to force a shutdown or a start. The temperature set point and fan velocity mode can be chosen.
Ventilation grilles	Each air supply duct ends in a motorized ventilation grille (one per room), which can be opened or closed depending on the nature of its use in the area.

With this infrastructure, different choices can be combined in order to reach a goal of sufficient comfort, reduced energy consumption, combination thereof, or other objectives.

2.2. Software: The PROPHET Package

The PROPHET package is an utility to model time series and that serves as the perfect soft counterpart of the infrastructure shown in this paper. PROPHET is an R library that has been recently developed and seems to give promising results in other disciplines [34–39]. It is a modular regression model with interpretable parameters that can be intuitively adjusted with domain knowledge about the time series [40].

PROPHET conducts an automatic procedure for forecasting time-series data. The implemented algorithm uses Stan modelling language (allows to share the same core procedure between Python and R implementations) for optimization in order to fit a non-linear additive model and generate uncertainty intervals.

The additive regression model has four main components: a piecewise linear or logistic growth curve trend. Prophet detects changes in trends by selecting changepoints from the data, a yearly seasonal component modeled using Fourier series, a weekly seasonal component using dummy variables, and a user-provided list of important holidays. PROPHET is robust enough to address missing data, shifts in the trend, and typically handles outliers well.

It allows the prediction of a horizon of observations for a given time series that fulfills some characteristics that are common to the time series generated by human actions, where factors such as holidays could be known in advance.

In order to create the model, a decomposable time series model with three main model components will be used: trend, seasonality, and holidays. This is shown in Equation (1),

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t, \tag{1}$$

where:

- $y(t)$: time series of interest.
- $g(t)$: represents non-periodic components (using piecewise linear or logistic growth curve trend). PROPHET implements two trend models that cover many applications: a saturating growth model and a piecewise linear model with automatic change point selection.
- $s(t)$: trend factor that represents periodic changes. Time series often have multi-period seasonality as a result of the human behaviors they represent. To fit and forecast these effects, we must specify seasonality models that are periodic functions of t. This part relies on Fourier series to provide a flexible model of periodic effects.
- $h(t)$: effects of holidays (a list provided by the user). Holidays and events provide large, somewhat predictable shocks to many time series and often do not follow a periodic pattern, so their effects are not well modeled by a smooth cycle.
- ε_t: error which will be assumed to follow a normal distribution.

This formulation is similar to a generalized additive model (GAM), a class of regression models with non-linear smoothers applied to the regressors. This approach has the advantage in that it decomposes easily and accommodates new components as necessary; for instance, when a new source of seasonality is identified. Thus, PROPHET frames the forecasting problem as a curve-fitting exercise which differs from the traditional models used for time series that account for the temporal dependence structure in the data: ARIMA This formulation provides several functional advantages with respect to ARIMA formulations: flexibility regarding seasonality with multiple periods, measurements do not need to be regularly spaced and missing values are handled, fitting is very fast, and the parameters of the forecasting model are easily interpretable [41].

3. Commissioning and Example of Data Analysis

For the commissioning of CASITA, we developed a test that involves the use of all of the main systems (sensors, meters, and actuators) that are found in CASITA. With this test, we verified the validity of the installations. We also made a valid test of a software package that has not been previously used for this purpose to forecast energy consumption. To do this, two models were built with the collected data. Their subsequent improvement became a topic of discussion as the inclusion of the weather forecast as a variable or not had to be determined.

The weather forecast was obtained from an official source (AEMET). The experiment consisted of generating simulated data of office use during 60 days from using the actuators, turning on and off equipment, and interfering with the conditioning system. This was done in an emulated manner to test the actuators and remote controllers of CASITA (all this was designed, run, and measured from an office 40 km away) and because it allowed us to access the ground truth. To ensure that other researchers interested in using CASITA would know appropriately what this facility has to offer, all of the data for this commissioning is available upon request.

The experiment was conducted from 10 June to 14 August 2017. In this period, up to 4 workers were working in a normal schedule from 9:00 to 17:00. It is presumed that they developed their usual functions in an office environment, working at their desks, but also sometimes working in pairs or holding meetings all together. We do not consider metabolic activity of the workers or their humidity emission. Some workers had the possibility to work from home, so the number of people at the office fluctuated between 1 and 4 people; at other times, the place was empty (without air conditioning). The occupancy was registered from presence detectors and door-opening sensors, as well as energy consumption and distribution of the operating grilles and HVAC machines that were activated by employees on-demand. All data were collected hourly, even outside of the working schedule (24 h). The operating temperature of the HVAC machines was fixed to 20 °C. Representative variables of this experiment can be seen in Figure 4.

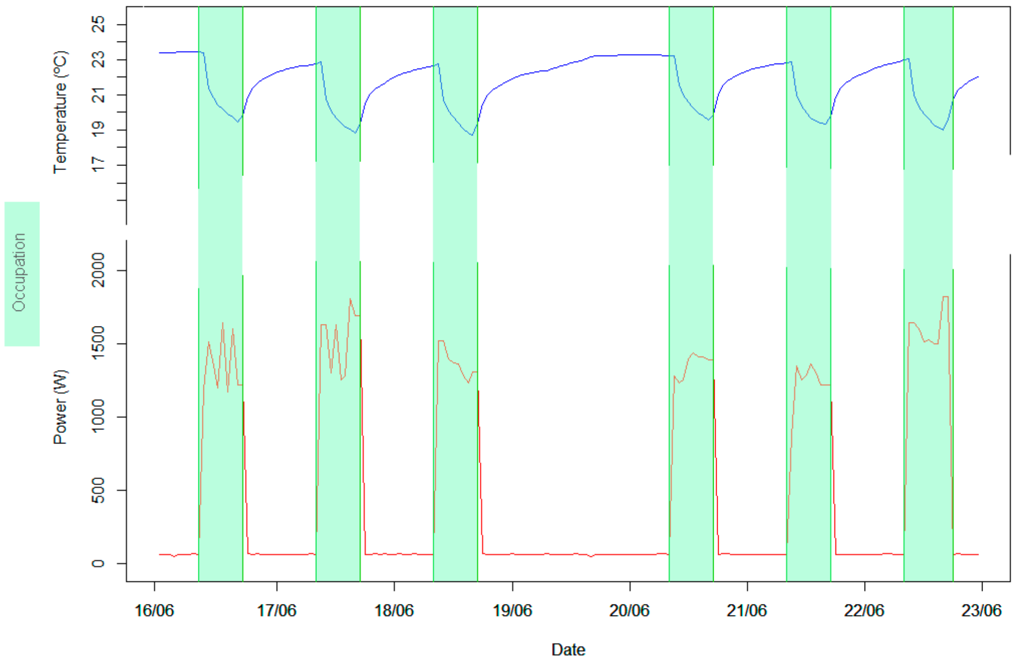

Figure 4. Representation of temperature and power for seven days of data in CASITA.

It is possible to appreciate that during the working time, energy consumption is triggered by the operation of office equipment air conditioning, which lowers the environmental temperature. In the graph, days are differentiated by higher or smaller occupancy and a local bank holiday, where no one was working at CASITA. Once the occupation is zero (in a working day at 17:00), it is easy to identify the fast rise of the indoor temperature due to the high temperatures outside. When night falls, the indoor temperature changes more slowly due to the lowering of the external temperature.

The aim of this verification is two-fold. First, we will evaluate the commissioning of CASITA, and second, as we have access to the ground truth of the test, we will verify the performance of PROPHET in the field of energy use prediction. We believe that if the results were positive, PROPHET could be used synergistically with CASITA for further research. We have aimed for a data-driven approach that does not take into account the physical properties of the building itself since it has been shown to be appropriate in similar scenarios [42]. Our models are used for predicting a horizon of energy consumption. This makes it different from other approaches [43], whose goal is the punctual prediction of a particular moment.

3.1. Verification of Accessible National Weather Forecasting in CASITA Using PROPHET

To make sure that CASITA offers well-tested weather data and weather forecasts, a stand-alone parallel study was performed.

For the start, it was necessary to study the relationship between the weather forecast obtained from the AEMET web page and the real outdoor conditions of our test lab. If the correlation between them was strong, it would be feasible to anticipate and predict the real outdoor conditions.

In the case of an observed discrepancy between prediction and real data, steps were taken that allowed us to understand that error and to create a correction algorithm that reduces it substantially, adding value to the CASITA research facility. This is seen in Figure 5.

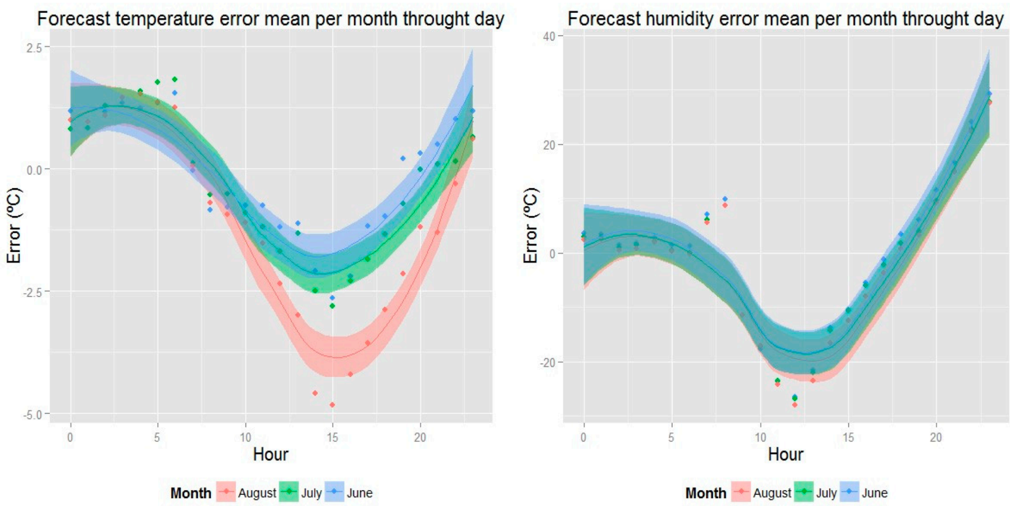

Figure 5. (**a**) Error mean between weather forecast (temperature) and outdoor temperature. (**b**) Error mean between weather forecast (humidity) and outdoor humidity.

When one signal was subtracted from another, an error signal was obtained (see Figure 5), in which the mean square error per hour of this signal, organized by month, shows that the value of the discrepancy is predictable; this makes it possible to conclude that the weather forecast always has a similar lack of precision per hour, which can be modeled. We considered this an effect of the geographical surroundings of CASITA that are different to those of the location of the closest weather station of AEMET (Fuente Álamo).

With this implemented, it is easy to introduce this correction into the weather forecast, and assess the achieved improvement that is related to the real outdoor conditions measured. As can be seen in Figure 6, the root-mean-square error (RMSE) has decreased substantially, (especially in August).

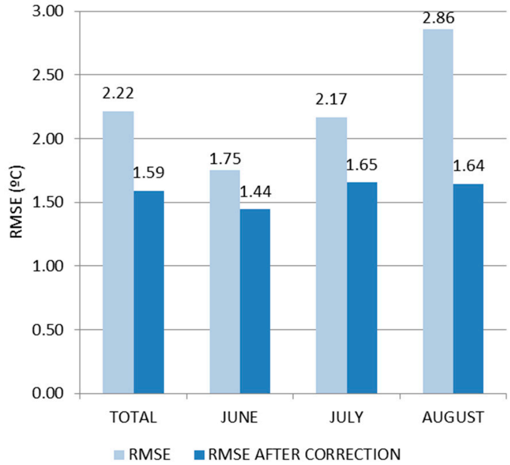

Figure 6. Root-mean-square error (RMSE) achieved after having into account the error mean evolution.

3.2. Validating Influence of the Variables Using PROPHET

A preliminary study of the data was done to ensure that there were no missing values or misleading results that could crash a computer code for data analysis and to perform preliminary sanity checks. The corrplot routine was applied to relevant variables of energy use. And the results can be seen in the following (see Figure 7).

Figure 7. Cross correlation between influential variables in energy consumption. Done with a native routine in R: corrplot.

Once the calculation was done, it was learned that the correlation between conditions out of the building and inside are not very strong, which demonstrates that the conditioning systems work well, and the space is not sensitive to fluctuations on the weather outside. Indoor conditions are clearly affected by the HVAC operation, which is directly in relation to occupancy. In other words, the more people are working, the harder the air-conditioning devices are working; this is an expected result that demonstrates the validity of the data.

In one part of this preliminary study, we performed a validation exercise that uses the software package PROPHET. It is an open source code that runs in R and performs predictions of time series for many kinds of variables due to its large popularity in other disciplines; we thought it was interesting to test its performance in building physics.

Focusing on the variable that aimed to be forecasted, after studying the results it is possible to conclude that there is a correlation between energy consumption and indoor temperature and humidity. If one sees the results, outdoor temperature is an important variable, instead outdoor humidity is not that significant as one could expect. The same interpretation could be made regarding the weather forecast; temperature is relevant, and humidity is not. Occupation is revealed to be the more influential variable, as the presence of people is an essential requirement to have energy consumption.

In order to make a model of the energy consumption, there are some variables which show this to be influential:

- Occupation;
- Indoor conditions: temperature and humidity;
- Outdoor temperature;
- Forecasted temperature.

The energy consumption in buildings has several characteristics appropriate for the PROPHET algorithm and thus should perform well for energy prediction. These are:

- Strong multiple human-scale seasonality (such as day of the week and the time of year);
- Important holidays that occur at irregular intervals that are known in advance; and
- A certain random component.

Together with previous observations about energy consumption, in our problem the domain knowledge was defined by the inclusion of external regressors that were selected after observing the results:

Model 1: Forecasting energy consumption in a 24-h predictive horizon.

- Previous energy consumption.
- Previous occupation and future values of this variable with a known pattern and schedule.

Model 2: Forecasting energy consumption in a 24-h predictive horizon.

- Previous energy consumption.
- Previous occupation and future values of this variable with a known a pattern and schedule.
- Outdoor temperature values with temperature predictions filling the time series to be predicted.

These models and their differences are explained in Figure 8. In Model 1 we forecast energy consumption only with previous values of this variable and previous occupation, completed with future occupation. Model 2 introduces, in addition, previous outdoor temperature measurements and the forecast are helped with future temperature values obtained from the national meteorological agency.

It was decided to perform the energy prediction using a sampling period of one hour, this was because that granularity captures most of the dynamics of the building without compromising the volume of data. An extra seasonality component was added that relates to the daily periodic of any energy-related variable linked to human behavior. The implementation was run on the R environment [41].

In order to make a first approximation, a prediction was performed for 12 August at 9:00, (start of working hours) with a predictive horizon of 24 h. In the following paragraphs, we studied two predictive models. These models are compared with the real measured energy consumption.

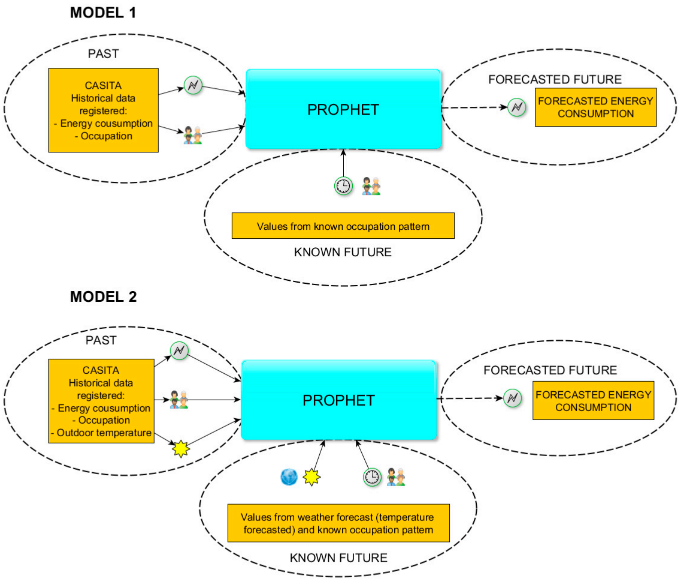

Figure 8. Schema of Model 1 and Model 2.

In the following points, two scenarios were tested, which contrasted with two different situations that provide the two different regressors previously mentioned.

After running the models, it was possible to ask for the next 24-h prediction. Figures 9 and 10 show the 24-h predictions performed with the fitter model (blue line) and the true values (black dots), while the last peak represents the forecasted energy consumption on 12 August, with a previously given occupation schedule.

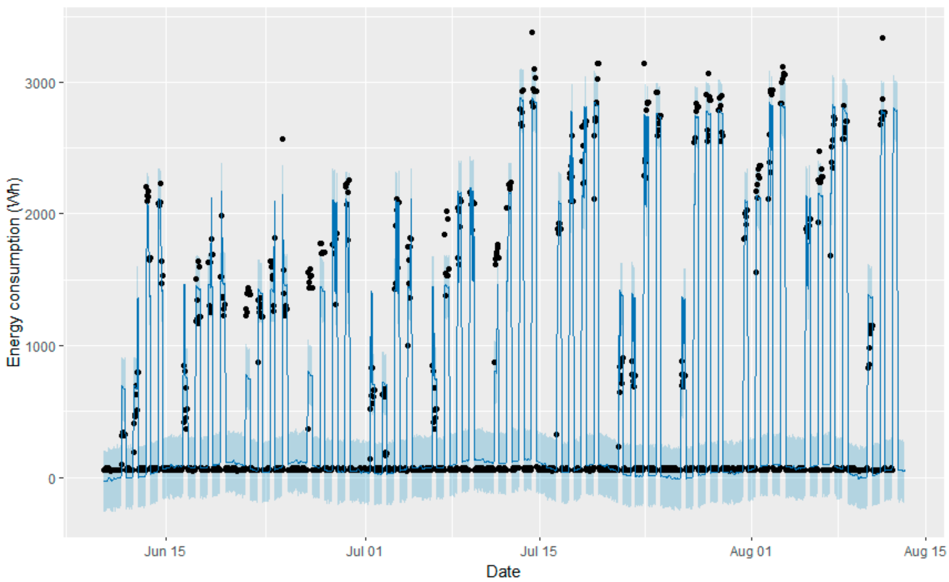

Figure 9. Twenty-four hour predictions performed with the fitter model (blue line) and the true values (black dots) with Model 1.

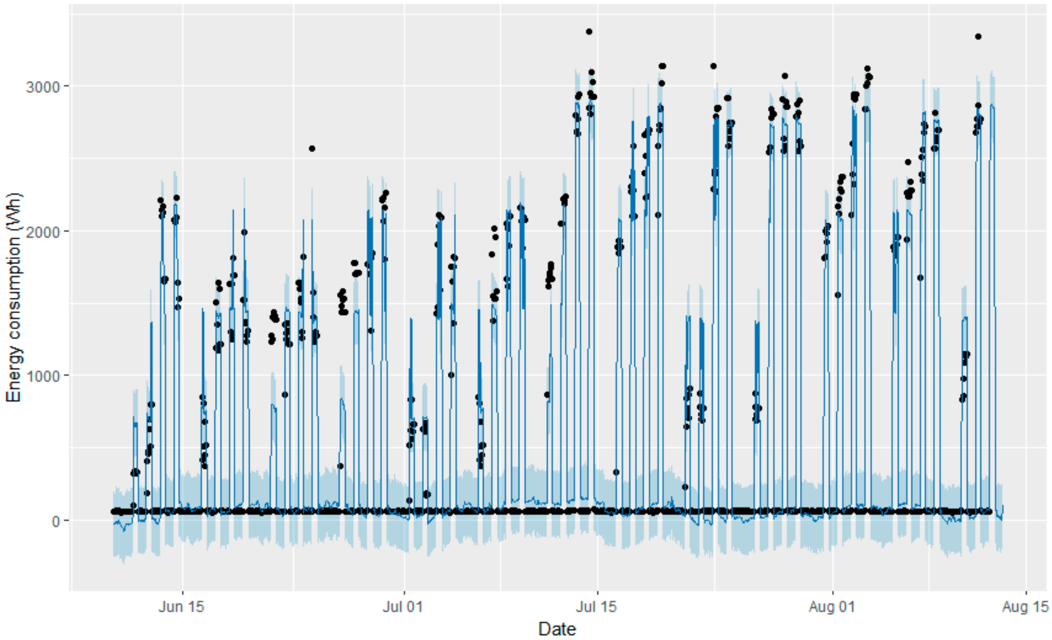

Figure 10. Twenty-four hour predictions performed with the fitter model (blue line) and the true values (black dots) with Model 2.

Although both graphs seem to be very similar, the forecasted hours of the predictions slightly differ for the two models. These results serve as proof that both models have a good approximation to real measurements, but that there are some slight differences. It seems that Model 2 is closer to reality. A comparison between the real measures, and the forecasts with Model 1 and Model 2, is shown in Figure 11.

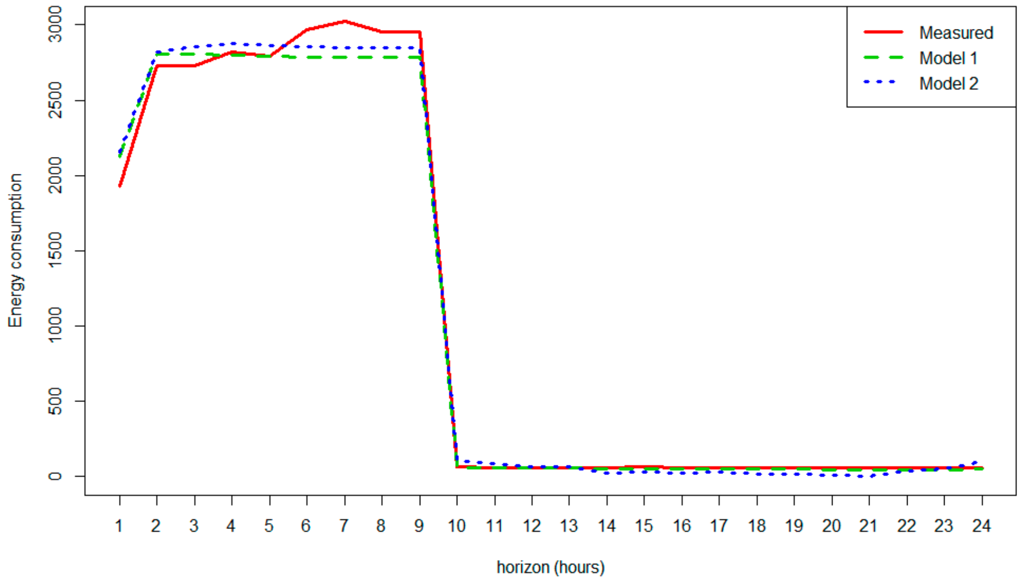

Figure 11. Energy consumption-real measures vs prediction (Model 1/Model 2).

After this example, and in order to evaluate this in a more comprehensive and general way, a cross validation was made to extract some conclusions of the different approaches. The cross validation assumes that these models could be generalized and that their accuracy of predictions estimated. In this iterative process, each hour is predicted using the rest of the available data, obtaining a measure of the error. This is done in Model 1 and Model 2 per hour several times. In addition, a visualisation of a given prediction is shown in Figure 12. It is then possible to estimate the mean absolute error (MAE) for each case under study by measuring the difference between the subsequent real measures and the predicted values. As we can see in Figure 12, combining the MAE per hour makes it possible to see that both have similar behavior. The MAE results in being higher in the working hours and are maximal at 9:00 when the HVAC starts; this is when the variability of the energy consumption is high and rapid. As is easily seen in Figure 12, Model 2 presents a better performance for nearly the entire day. Hence, the MAE is smaller and the accuracy of the model has been improved by adding outdoor temperature and temperature forecast in the prediction phase.

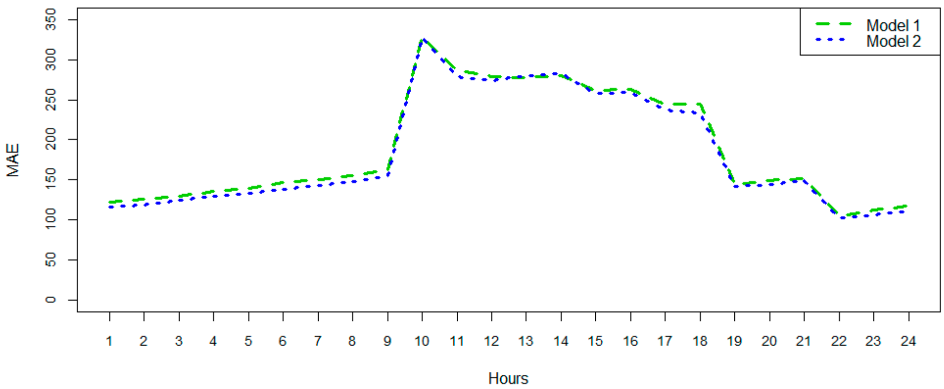

Figure 12. Mean absolute error (Model 1/Model 2).

The improvement achieved can also be shown in terms of RMSE, offering an increase of accuracy. Global reduction of RMSE has been quantified in 4.54%, from the data exposed in Table 2.

Table 2. Evolution of RMSE values over 24 h.

Hour	RMSE Model 1	RMSE Model 2	Improvement	Hour	RMSE Model 1	RMSE Model 2	Improvement
01	192.93	176.80	8.36%	13	378.35	384.33	−1.58%
02	200.24	182.96	8.63%	14	381.95	381.93	0.00%
03	210.39	191.86	8.81%	15	358.22	358.05	0.05%
04	222.05	202.28	8.90%	16	358.66	352.96	1.59%
05	231.73	212.67	8.23%	17	349.19	342.75	1.84%
06	243.96	222.99	8.59%	18	356.19	344.36	3.32%
07	251.60	230.77	8.28%	19	249.11	247.70	0.57%
08	262.76	239.10	9.00%	20	258.60	255.62	1.15%
09	275.33	250.72	8.94%	21	269.52	265.63	1.44%
10	427.56	432.00	−1.04%	22	160.57	149.72	6.75%
11	381.20	377.35	1.01%	23	172.48	159.43	7.57%
12	376.05	374.41	0.43%	24	181.99	167.22	8.12%

4. Conclusions and Future Work

This work describes the commissioning of a new testing facility that has been given the name of Controlled and Automatized Testing Facility for Human Behavior (CASITA). The facility includes a large variety of sensors, meters, and actuators that allow the research to focus on fundamental aspects of the interactions of humans with built environments. The new contribution is that we have conceived this facility as a pair between the hardware and the software package PROPHET that provides the soft components (algorithms and analysis tools) to make the facility complete.

The first testing of this facility consisted of an occupation experiment that was performed to facilitate the posterior analysis of the software package PROPHET. The results of this software used in publications in other fields convinced us that it could be an excellent addition to CASITA for experiments that involved prediction (as there are many).

Building energy consumption models with new techniques are a of considerable interest to the scientific community. Our test experiment was to evaluate the functionalities of CASITA, and to ascertain the improvement of the PROPHET algorithms. Once the correlations were studied, two models were presented. After a brief explanation about a new tool for modeling and forecasting, the PROPHET package of the R software, some parameter settings and a comparison between the models became topics of discussion. The results indicate that introducing outdoor temperature into the model that uses the forecasted temperature provided by AEMET (an official source of weather forecast) improves the accuracy of its predictions.

The variables chosen in this work can be found in any residential or commercial building. As far as a sensor network that would be deployed, the same data can be collected and the models replicated. Therefore, the approach in this paper proposes an improved general model for forecasting energy consumption in buildings. A good approximation to this problem could enable one to plan for energy requirements, achieve energy and economic savings, and contribute to a more effective energy consumption policy.

In essence, the results show that CASITA is an excellent research facility that can be used for the testing of human modeling algorithms, IoT platforms, control strategies, and many more applications. With respect to the prediction algorithms tested here, both models are acceptable and achieve a good level of representativeness.

In addition, it is necessary to note that the algorithms tested have good accuracy but that they have not been compared with other methods, as the main aim of this work was commissioning CASITA and evaluating PROPHET as a side tool for it. We believe that the testing of its suitability was sufficient.

In future works, other scenarios will be tested. Weather forecasting will be added again along with other possible forecasted variables. We also plan to introduce human components into the equation, which would be interesting and will exploit the capabilities of CASITA well. In another vein, the PROPHET package became a tool whose benefits need to be studied further in this and other fields.

Author Contributions: Conceptualization, I.R.-R. and M.Á.Z.; Methodology, I.R.-R. and A.G.V.; Software, A.G.V.; Validation, I.R.-R., A.G.V. and A.P.R.G.; Investigation, I.R.-R., A.G.V., A.P.R.G. and M.Á.Z.; Resources, M.Á.Z.; Writing-Original Draft Preparation, I.R.-R. and M.Á.Z.; Writing-Review and Editing, A.P.R.G.; Supervision, I.R.-R. and A.P.R.G.; Funding Acquisition, M.Á.Z.

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4.4 Applicability of Big Data Techniques to Smart Cities Deployments

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Applicability of Big Data Techniques to Smart Cities Deployments

M. Victoria Moreno, Fernando Terroso-Sáenz, Aurora González-Vidal, Mercedes Valdés-Vela
Antonio F. Skarmeta, Miguel A. Zamora and Victor Chang

***Abstract*—This paper presents the main foundations of Big Data applied to Smart Cities. A general Internet of Things based architecture is proposed to be applied to different smart cities applications. We describe two scenarios of big data analysis. One of them illustrates some services implemented in the smart campus of the University of Murcia. The second one is focused on a tram service scenario where thousands of transit-card transactions should be processed. Results obtained from both scenarios show the potential of the applicability of this kind of techniques to provide profitable services of smart cities, such as the management of the energy consumption and comfort in smart buildings, and the detection of travel profiles in smart transport.**

***Index Terms*—Internet of Things; Smart City; Big Data; Predictive Models; Transit-card Mining**

I. Introduction

A Smart City emerges when the urban infrastructure is evolved through the Information and Communication Technologies (ICT) [1]. The paradigm of Internet of Things (IoT) [2] has enabled the emergence of a high number of different communication protocols, which can be used to communicate with commercial devices using different data representations. In this context, it is necessary an IoT-based platform to manage all interoperability aspects and enable the integration of optimal Artificial Intelligence (AI) techniques in order to model contextual relationships.

In urban environments there is a huge amount of different data sources. Plenty of sensors are distributed around cities, most of them installed in indoor spaces. This situation has brought new analytics mechanisms and tools that provide insight allowing us to have an effective and collaborative way to operate the machines [3]. Furthermore, there are numerous mobile data sources like smart phones, smart-cards, wearable sensors and, in the case of vehicles, on-board sensors. All these sensors provide information that makes possible to detect urban dynamic patterns. Nonetheless, most existing management systems of cities are not able to utilize fully and effectively this vast amount of data and, as a result, there is large volumes of data which is not exploited. In this direction, many AI techniques in Computer Science have been introduced to deal with the processing of huge amount of data to extract useful information (or termed by knowledge) from data [4], this trend is known as Big Data.

This paper is intended to analyze the interest of big data for smart cities. In order to face the above-mentioned aspects we propose a general architecture for smart city applications, which is modelled in four layers with different functionalities. Then, we show some applications of big data analysis in two scenarios, both dealing with sensed data coming from both static and dynamic sources. Among other objectives, the first scenario intends to create a distributed framework to share large volumes of heterogeneous information for their use in smart building applications. In this work we focus on presenting the deployments and implementations carried out in smart buildings to achieve energy efficiency. For this, different problems like indoor localization, thermal comfort characterization and energy consumption modelling have been solved through the application of big data techniques. The second example is centered on the public tram service in the City of Murcia (Spain), looking for giving insight into the great amount of data generated by the service's transit cards. In this scenario, big data techniques are applied to extract mobility patterns in public transport.

Hence, this paper faces up three aspects of nowadays smart cities which need to be solved, and for each one of them we provide some research contributions through the application of convenient big data techniques. These contributions are:

- The design and instantiation of an IoT-based architecture for applications of smart cities.
- The approach of an efficient management of energy in smart buildings.
- The extension of the data analysis for detection of urban patterns which can be used to improve public transport applied to the public tram service.

The structure of this paper is as follows: Section II enumerates the challenges that current smart cities still have to face, and proposes a general IoT-based architecture for smart-city services which is modeled in layers. Section III describes a first application of smart city where big data techniques have been applied to get energy efficiency in the buildings of a Smart Campus. Section IV presents a second smart city application that addresses the urban pattern recognitions in public transport. Section V summarizes the main benefits of applying big data techniques to the two scenarios of smart cities addressed in this paper. Finally, Section VI gives some conclusions and an outlook of future work.

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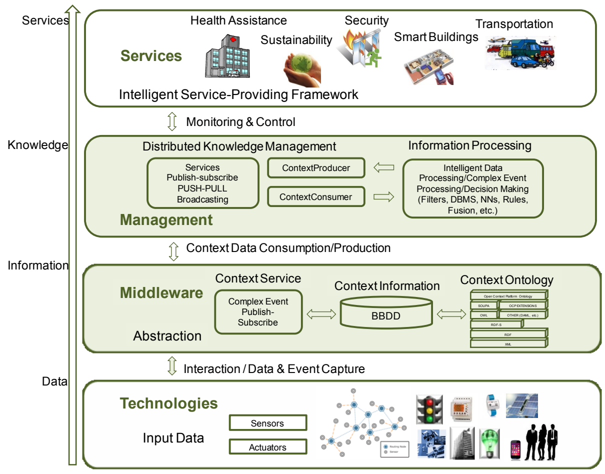

Figure 1: Layers of the base architecture for smart city services

II. IoT-based Architecture for Smart Cities

In this section we enumerate the main challenges that most current smart cities still have to face. Then, motivated by these challenges, we make a proposal of a general IoT-based architecture for smart city applications.

A. Challenges of Smart Cities

The global challenges that smart cities still have to face can be summarized in the following way:

- Sensors integration and abstraction capability. Provide means to integrate different sensor types in a common platform taking into account the different technologies, legacy systems and communication protocols with focus on IPv6 solutions.
- Individual intelligence and local reasoning. Apart from data fusion, more complex data processing can be implemented by smart objects.
- Learning and adaptation. Most of the patterns generated in smart cities are sensitive to contextual changes and are able to learn and adapt themselves to such changes as well as to human dynamicity.
- Dynamic human centric services. This work designs and implements smart mobility and smart building services that use the patterns generated to provide customized and efficient services taking into account the dynamicity of the citizens' behavior.
- User privacy and security control mechanisms. In the context of smart cities it is important to manage the way the user is able to control its data and how they are exposed to third parties and applications.

B. IoT-based Architecture

Several layers compound the proposed platform that was created with the goal of serving to many applications of smart cities. In Figure 1 is depicted this layered IoT-based architecture, which are detailed below.

1) Technologies Layer: In the basis part of Figure 1 it is observed that a plethora of sensors and network technologies provide the input attributes using wireless sensor networks, wired sensors, gateways, etc. which can be self-configured and remotely controlled through the Internet. Dealing with our first application that consists on the instantiation of the architecture for building management systems (BMS), in this layer it is gathered information from sensors and actuators deployed in strategic points of the building. But the aforementioned data sources in smart cities are not limited to static devices reporting measurements associated to a particular location, there are also moving ones capable to deliver measurements at different points within a geographical area. This is mainly due to the rapid development of wireless technology, mobile sensor networks and, above all, the advent of smartphones [5]. Although approaches based on mobile-phone sensing require a demanding usage of the communication, location and other attributes of the smartphone, which can bother some people due to battery draining [6], data captured by static, mobile and smart-phone sensors can be extended or enriched with the data generated by several social-media channels - like Twitter or Facebook - giving rise to a new generation of *soft sensors* from which extract relevant knowledge [7]. As a result, an alternative course of action aims at mining relevant knowledge from users on the basis of non-intrusive ways to obtain data, for example, transit cards in public transport scope.

2) Middleware Layer: The first layer provides us with a wide variety of data, so it is needed a second layer where all collected data from seamless sources are expressed in the same way, this is done in the middleware layer. The context information can be collected in an ontology defined according to the model that represents the knowledge of the specific application domain. Thus, for our energy efficiency semantic model, the devices and building concepts are borrowed by the SAREF ontology [8]. The agents representation is made using the DUL ontology [9], while the observation values of the monitored sensors are represented based on the SSN ontology [10]. However, when it comes to process the incoming data

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in a real-time manner, it is necessary to use a lightweight representation. As a matter of fact, [11] describes sensor-data representation using a simple attribute-value schema for event-based systems.

3) Management Layer: After having extracted information from the previous layers, the management layer is in charge of determining decisions bearing in mind the target services provided in smart cities. Different big data analytic techniques can be used for the intelligent decision making processes. Algorithms like Artificial Neural Networks (ANNs) using backpropagation methods [12] and Support Vector Machines (SVMs) [13] are good to solve non-linear problems, making them very applicable to build energy prediction issues, ranging from those associated to lighting and heating, ventilation and air condition (HVAC) [14] to the prediction of the heating energy requirements [15]. For optimization problems in Building Management System (BMS) addressing energy efficiency, Genetic Algorithms (GAs) constitute a commonly applied heuristic that can be used in several optimization scenarios such as scheduling cooling operation decisions [16]. Regarding to the smart public transport application, the extraction of users behaviors from transition records have been studied by using different algorithms and techniques like maximum likelihood estimation [17], probabilistic models [18], conditional random fields [19], graphical information system (GIS)-based processing [20] or Database Management System (DBMS)-based processing [21].

4) Services Layer: Finally, the upper layer (Figure 1) shows some examples of smart city services that can be provided following the proposed architecture. Thus, this architecture can be applied to provide applications of smart cities like environmental monitoring, energy efficiency in buildings and public infrastructures [22], environmental monitoring [23], traffic information and public transport, locating citizens, manage emergencies, saving energy and other services. These actions can either involve citizens or be automatically set.

III. Smart Campus of the University of Murcia

The University of Murcia (UMU) has three main campus and several facilities deployed throughout different cities in the Region of Murcia. One of these campus is currently serving as pilot of two European Projects, the SMARTIE [24] and the ENTROPY [25] project. The goal of this use case of smart city is to provide a reference system able to manage intelligently the energy use of the most relevant contributor to the energy use at city level, i.e. buildings. The BMS implemented as part of this smart campus adapts the performance of automated devices through decisions made by the system and the interaction with occupants in order to keep comfort conditions while saving energy. We start by the most representative source of energy consumption at building level: HVAC systems.

A. System Overview

Using a BMS system, it is possible to predict users future behaviour from their recorded activities that are measured with sensors. This information allows us to provide convenient environments looking for keeping their comfort while saving energy. The first need for a building to become smart is to know location of occupants. Once solved the indoor localization problem, it is time to propose a solution to the energy efficiency of buildings associated to the thermal comfort provisioning service related to the HVAC management. For this, energy consumption models of the building need to be generated and used to implement the optimization mechanism able to maximize comfort at the same time that energy consumption is minimized. Therefore, the different problems addressed in this scenario of smart city through the application of big data techniques are:

1) Indoor localization estimation.
2) Building energy consumption prediction.
3) Comfort provisioning and energy saving through an optimization problem.

In the following subsections these problems are described with more details, as well as the techniques implemented and the results obtained.

B. Indoor Localization Estimation

As well as considering the information concerning to the identification and location of the building's occupants, it is necessary to reach the required accuracy in the location in order to provide the indoor services in a comfortable and energy efficient way. Our technological solution to cover the localization needs (i.e. those required by smart buildings to provide occupants with customized comfort services) is based on a single active RFID system and several Infra-Red (IR) transmitters. In Figure 2 we can observe the data exchange carried out among the different technological devices that compose our localization system.

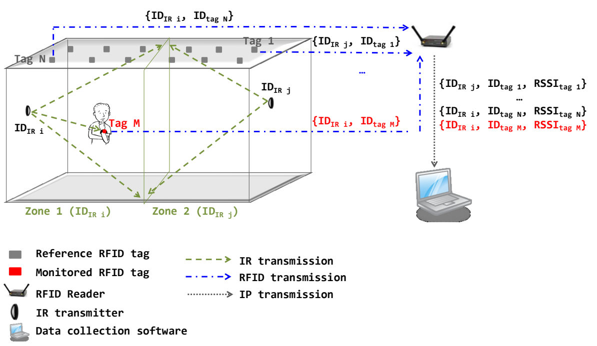

Figure 2: Localization scenario

The final mechanism implemented to solve the indoor localization problem is shown in Figure 3. In this figure, we can see that the first phase of the mechanism is the space division through the installation of IR devices in the walls of the building area where localization wants to be solved. Therefore, for each space division, there is an IR identifier value (ID_{ir}) associated to this region. For each one of these regions, we implement a regression method based on Radial Basis Functions (RBF) networks. The RBF estimates user positions given different RFID tags situated in the roof. Then,

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after the position estimation using the RBF network, a Particle Filter (PF) is applied as a monitoring technique, which takes into account previous user position data for estimating future states according to the current system model.

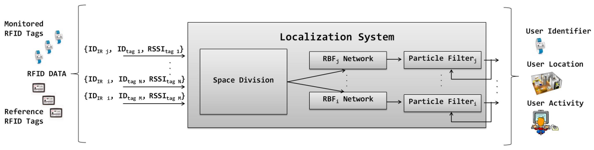

Figure 3: Data processing for location estimation

The PF used in this work is slightly different from its generic definition (which can be found in [26]). The main difference of our filter is in the correction stage. In this stage, the generic definition of the PF applies the resampling using the Sequential Importance Sampling (SIS) algorithm [26] to carry out the filtering of such particles which minimize the deviation of their predicted trajectory. In our implementation, in addition to apply the SIS algorithm to correct the particles positions, we also use in this step the information about the specific IR region at a given instant of time to benefit those particles which fall inside this area. Therefore, before applying the SSI algorithm, we filter according to the coverage area of the IR transmitter identified by the monitoring RFID tag. The main advantage of this constraint is the faster convergence of the filter, because extra information is available to carry out the correction stage of the filter.

C. Building Energy Consumption Prediction

The energy performance model of our BMS is based on the *CEN Standard EN 15251* [27]. This standard proposes the criteria of design for any BMS. It establishes and defines the main input parameters for estimating building energy requirements and evaluating the indoor environment conditions. The inputs considered to solve our problem are the data coming from the RFID cards of users, the user interaction with the building automation system through the control panels or the web access, environmental parameters coming from temperature, humidity and lighting sensors installed in outdoor and indoor spaces, the consumption energy sensed by the energy meters installed in the building, and the generated energy sensed by the energy meters installed in the solar panels deployed in our testbed. After collecting the data it is mandatory to continue with their cleaning, preprocessing, visualization and correlation calculation in order to find determining features, which can be used to generate optimal energy consumption models of buildings (management layer of the architecture presented in Section II). Over the input set, we perform the standardization and reduction of data dimensionality using Principal Components Analysis (PCA) [28], identifying the directions in which the observations of each parameter mostly vary.

Regarding the big data techniques that have been already applied successfully to generate energy consumption models of buildings in different scenarios (as such we mentioned in the management layer of the architecture presented in Section II-B3), we propose to evaluate the performance of Multilayer Perceptron (MLP), Bayesian Regularized Neural Network (BRNN) [29], SVM [30] and Gaussian Processes with RBF Kernel [31]. They were selected because of the good performance that all of them have already provided when they are applied to building modelling. All these regression techniques are implemented following a model-free approach, which is based on selecting - for a specific building - the optimal input set and technique, i.e. such input set and technique that provides the most accurate predictive results in a test dataset. In order to implement this free-model approach, we use the R [32] package named CARET [33] to train the energy consumption predictive algorithms, looking for the optimal configuration of their hyper-parameters (more information can be found in [34]). The selected metric to evaluate the models generated for each technique using test sets is the well-known RMSE (Root-Mean-Square Error), whose formulation appears in Eq. (1). This metric shows the error by means of the quantity of KWh that we deviate when predicting.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{1}$$

But in order to get a better understanding of the uncertainty of the model, we also show its coefficient of variation (CVRMSE). This coefficient is the RMSE divided by the mean of the output variable (energy consumption) for the test set (see Eq. (2)), giving us a percentage of error adjusted to the data, not just a number in general terms.

$$CVRMSE = \frac{RMSE}{\bar{y}} \tag{2}$$

D. Optimization Problem

Once the building energy consumption is modelled, we focus on the optimization of the HVAC operation trying to keep comfort conditions at the same time that energy consumption restrictions are considered. As starting point, we establish the comfort extremes considering location type, user activity and date [35]. Understanding the building thermal and energetic profiles allows us to quantify the effects of particular heating/cooling set point decisions. To derive a heating or cooling schedule, it is necessary to formulate the target outcome. In our buildings, it is possible to:

1) optimize the indoor temperature during occupation, i.e. minimize the building temperature deviations from a target temperature,
2) minimize daily energy consumption, or
3) optimize a weighted mixture of the criteria, a so-called multi-objective optimization problem.

The definition of building temperature deviation influences the results strongly: taking the minimum building temperature will result in higher set point choices and higher energy use than using, for instance, the average of indoor temperatures. Constraints on maximum acceptable deviation from target comfort levels or an energy budget can be taken into account to ensure required performance. In our optimization problem,

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we apply GA using the implementation provided by R (the "genalg" package [36]), to provide schedules for heating/cooling setpoints using the predictive building models (comfort and energy consumption models).

E. Evaluation and Results

1) Scenario of Experimentation: The reference building where our BMS for energy efficiency is deployed is the Technology Transfer Centre (TTC) of the UMU[1]. Every room of this building is automated through a Home Automation Module (HAM) unit. It permits us to consider a granularity at room level to carry out the experiments.

2) Evaluation. Indoor localization mechanism: Different tracking processes are carried out in the environments considered in our tests (the TTC building), applying for this the implementation of our PF. In Figure 4 an example of some tracking processes are carried out considering transition between different spaces of the TTC. For these paths, our system was configured to acquire data every $T = 10$ s. Taking into account the target location areas involved in comfort provisioning (lighting and thermal comfort, represented in different colors), and the real and estimated location data provided by our mechanism.

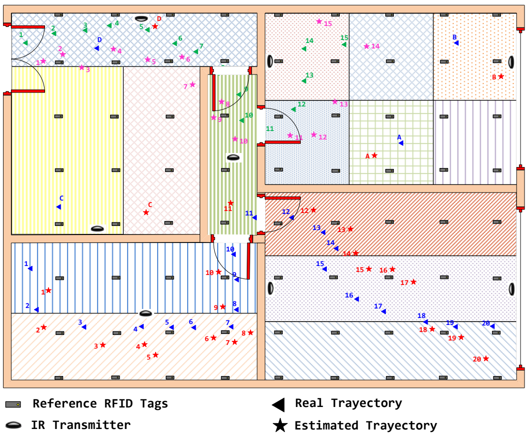
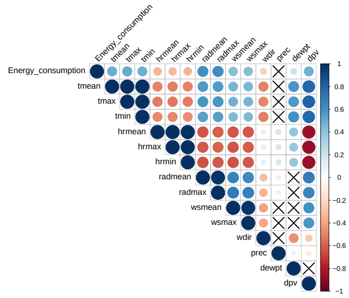


Figure 4: Tracking processes with a reference tag distribution of 1m x 1m

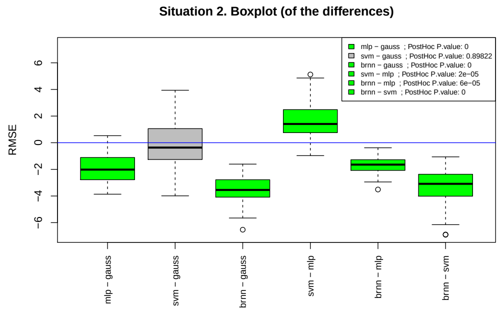
Thus, with a $1m$ x $1m$ distribution of reference RFID tags placed on the roof of the test room, a 65% success percentage in localization is obtained having an error lower than 1m. 98% of cases have as much 2.5m. of error. Therefore, it can be safely said that our localization system is able to track users with a sufficient level of accuracy and precision for the location requirements associated with the comfort and energy management in buildings. More details about this indoor localization system can be found in [37].

3) Evaluation. Energy consumption prediction: In Figure 5(a) it is shown the correlation heatmap between the electrical consumption of the TTC building and the outdoor environmental conditions. It is observed that energy consumption

[1]www.um.es/otri/?opc=cttfuentealamo



(a) Correlation heatmap between consumption and outdoor environmental conditions



(b) Boxplots comparing models pairwise (situation 2)

Figure 5: Modeling results

correlates significantly ($\alpha = 0.95$) and positively with temperature, radiation, wind speed variables, vapour pressure deficit and dew point; and negatively with wind direction and humidity variables. This means that we can use safely these variables as inputs of the energy consumption model of our reference building, because they have clear impact in the energy consumption. Otherwise, precipitation is so unusual that they don't have an association with the output.

Also, a logic differentiation between temporal situations has been considered in order to label behaviour. Situation 1: holidays and weekends; situation 2: regular mornings; and, situation 3: regular afternoons. The non-parametric Kruskall Wallis test shows that energy consumption differs significantly between situations (H(2) = 547.7, p < 0.01). Also, the post hoc pairwise comparisons corrected with Holm's method retrieve a p-value smaller than 0.01, supporting the decision of creating 3 different models [38]. Thus, for each of the three situations identified for the TTC building, we have evaluated not only the punctual value of RMSE, but also we have validated whether one learning algorithm out-performs statistically significantly the others using the non parametric Friedman test [39] with the corresponding post-hoc tests for comparison.

Let x_i^j be the i-th performance RMSE of the j-th algorithm, for this building, we have used 5-times 10-fold cross validation, so $i \in \{1, 2, ..., 50\}$ and four techniques, so $j \in \{1, 2, 3, 4\}$. For every situation, we find significant differences ($\alpha = 0.99$) between every pair of algorithms,

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except for SVM and Gauss RBF ($p > 0.01$), as it is shown in Figure 5(b) for the particular case of situation 2.

The three models have in common that BRNN yields a better result than the other tested techniques, based on the RMSE metric. Thus, BRNN is able to generate a model with a very low mean error of 25.17 KWh - which only represents the 7.55% of the sample (this is the most accurate result) in terms of the CVRMSE. And for the worst case, BRNN provides a mean error of 43.76 KWh - which represents the 10.29% of the sample in the reference TTC building - that is acceptable enough considering that our final aim is to save energy.

4) Evaluation. Optimization mechanism: To evaluate our GA-based optimization strategy, controlled experiments were carried out in the TTC building with different occupant's behaviours. The results show that we can accomplish energy savings between the 15% and 31%. Trying to validate the applicability of our proposal, we have also made experiments in a different scenario with limited monitoring and automation technologies, achieving energy saving of about the 23%.

IV. Public Tram Service of Murcia City

The second scenario is focused on the information analysis related to use of the tram service of the Region of Murcia [40]. In this case, the main goal was to perform a profiling process of the trips carried out by the users of such public service. For that aim, a fuzzy clustering algorithm is used to automatically extract tram user's profiles. Bearing in mind the architecture introduced in Section II, this system is enclosed in the management layer. The main tasks needed to reach the goal are explained in the following subsections.

A. Generation of the trip data set

According to the tram experts, information relevant to trip profiling must include data about: time (in terms of day of the week and time of the day), origin and destination stations and approximate age of the traveller. This information is being continuously recorded in different databases of the tram service. Nevertheless, certain operations of joining, transformation and preprocessing (discretization and numerization) have been performed in order to compile all this information into a set of tuples susceptible of feeding the subsequent fuzzy clustering algorithm. The two most remarkable operations are the following:

On the one hand, according to the infrastructure of the tram service, users only need to swipe the smart card when they get into the tram. Hence, the recorded data only comprises transactions at the origin of each user's trip so it can be regarded as incomplete. In order to deal with this incompleteness, a well known solution is the **trip-chaining method** which focus on recovering the origin and destination of the trips. In this case, such a method is based on the assumption that a traveller who takes the tram at an origin station, OS, ended their previous trip on that station OS. Due to the event-based nature of the card records, the Complex Event Processing (CEP) paradigm [11] was adopted to come up with a palette of event-condition-action rules to uncover the trips. While the condition part of the rules performs a match between consecutive records of the same traveller following the aforementioned trip-chaining method, the action part generates a new trip tuple (comprising the origin and destination stations) in case the condition is fulfilled.

On the other hand, as clustering techniques are based on distance calculations among data, a set of numbered (and ordered) geographical areas, each one covering some close stations are identified by the tram experts. Then, instead of having nominal values for origin and destination features these numbered areas make it easier to calculate the distance about tuples in the clustering process.

In summary, the tuples composing the data set for the subsequent clustering task are composed by the following attributes: tt_e*:{travellerAge, dayOfTheWeek, hourOfTheDay, originArea, destArea}*

B. Trip profiling

Clustering mechanisms are suitable when it comes to find out the most representative trips profiles. For that aim, the Gustafson-Kessel Clustering Method (GKCM) has been chosen since it is able to identify arbitrarily oriented ellipsoidal fuzzy clusters unlike, for instance, the Fuzzy C Means clustering Method, which impose spherical shapes to the data clusters. After the clustering task the identified prototypes (centroids) will summarize the whole data set of trips. GKCM requires to be supplied with the quantity of potential clusters (c). This is an important parameter since it determines the ability of the potential centroids to represent the real underlying structure of the data.

Therefore, several GKCM executions were performed with different values of *c* and the *goodness* of the different identified set of clusters was measured. One of the most used measurement is the one proposed in [41] and denoted here as r_{cs}. This magnitude quantifying both the total compactness within clusters and the total separation among them being the greater the better.

Once the number of clusters c has been decided on the basis of r_{cs}, GKCM is executed in order to find the c profiles that best represent the trip data set. Nevertheless, when exceed a time tp_{max} or a number of trips nt_{max} the algorithm is re-computed in order to detect new profiles which could rise up.

C. Evaluation and Results

The subject of evaluation is the tram service of the region of Murcia (Spain), which includes 18-km railway and 28 stations (see Figure 6). Figure 7 depicts the set of predefined geographical areas used in the experiment.

The evaluated dataset contained 378719 trips from 23400 users in November, 2013. For our experiment, the system was able to uncover 110697 trips. Expert knowledge was used to define the types of days and times of the day used in the aforementioned data pre-processing step as [*Monday-Thursday, Friday, Saturday, Sunday*] and [*0-6, 6-10, 10-12, 12-16, 16-20, 20-00*]. As a result, a generated TT_e dataset was split up into 4 different subsets based on the fact that traveller profiles depend on the day of the week (regarding, for example, differences of traffic flow between regular workdays

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Algorithm 1: Cluster-based Trip profiling process.

Input: TT: dataset of raw trip tuples.
Output: P_{TT}: Traveller profiles extracted from TT.

```
if t_now − t_prev > tp_max ∨ | TT | − | TT_prev | > nt_max then
    TT_e ← preProcessing(TT)
    foreach c ∈ {2, .., c_max} do
        clust_c = GKCM(TT_e, c)
        if clust_c.r_cs < r_cs^min then
            r_cs^min ← clust_c.r_cs
            P_TT ← clust_c.centroids
    t_prev ← t_now
    TT_prev ← TT
    return P_TT
```

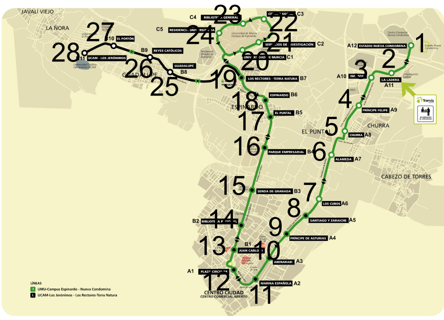

Figure 6: Line map of the tram service in Murcia.

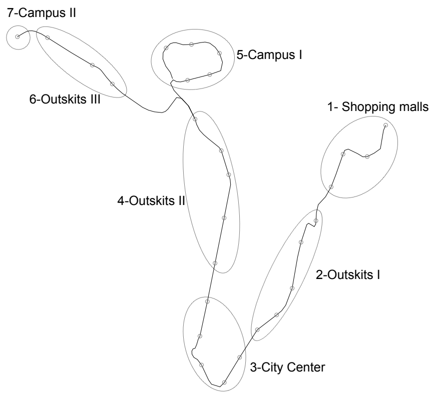

Figure 7: Geographical regions for the numerization of tuples' station fields.

and weekends). Next, the GKCM was launched with each of these subsets with different number of clusters.

In Figure 8, the cluster validation ratio r_{cs} is shown for every TT_e subset, being the lower value the better. As it can be observed, while the optimal cluster partition is reached at $c = 5$ for the Monday-Thursday subset, for the remaining subsets minima r_{cs} values are reached at higher number of clusters c. In other words, a higher number of profiles is needed to represent the weekend trips. This is reasonable given that most

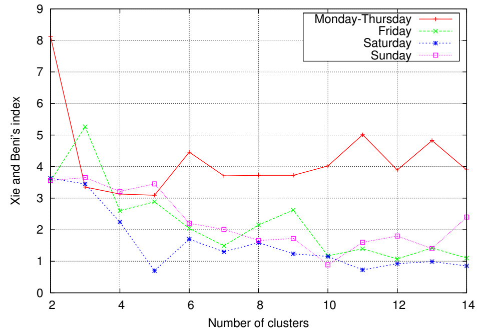

Figure 8: Cluster-validation rate for different cluster partitions.

people postpone leisure activities to the weekend and given that there exist a quite variety of leisure activities that can be done at different hours of the day.

As Table 1 shows, GKCM extracts five profiles for Monday-Thursday trips. Profiles 1 and 2 correspond to young people travelling in the morning to go towards one of the university zones from the station close the inner city. Besides, profile 5 represents a kind on traveller going back home from the university from 4 to 8 PM. Finally, profiles 3 and 4 correspond to middle-young age people (28-33 years) that take the tram around the outskirts and city center environments. These could reflect people going from residential areas.

Lastly, the heatmap shown in Figure 9 represents the membership of the Monday-Thursday trips to the defined profiles. If we interpret this plot as a time-framed sequence, a great amount of the traffic focuses on the right side of the line, which connects the city center and the university areas. Nevertheless, such load is more spread along the whole line during the evening.

V. Discussion

In this paper we propose a general IoT-based architecture which can be implemented for different applications of smart cities. This architecture is modeled in four layers, being the third one - the management layer - the layer where big data techniques are implemented to provide the different services offered then in the corresponding service layer (last layer).

The big data paradigm can be understood through the lens of 7 V's [42] (challenges). Regarding the application of different big data techniques to the specific scenarios of smart cities presented in this paper, we have overcame the challenge of *velocity* by collecting data hourly in the smart building application (consumption of energy, outdoor environmental conditions) and even in sorter intervals of time for the public transport application (many people validates their transit cards within seconds). Although we haven't tackled *volatility*, it is clearly a goal when looking for the real-time smart city because behavioural scenarios like ours change depending on many social aspects. The *veracity* of the data is guaranteed by the exhaustive pre-processing steps included in the modeling process. We have extracted *value*, making sense of the wide mentioned *variety* of data, and with the described analysis

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Profile	Age	Origin Area	Dest. Area	Time of the day
P1	23.37	*City Center*	*Campus I*	0-6
P2	25.74	*City Center*	*Campus I*	6-10
P3	28.22	*Outskits II*	*City Center*	12-16
P4	32.77	*Outskits I*	*Outskits II*	6-10
P5	22.20	*Campus I*	*City Center*	16-20

Table 1: Monday-Thursday trips' profiles.

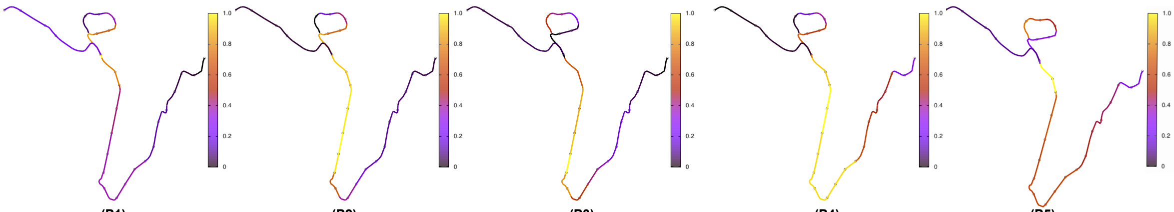

Figure 9: Tram-line heat-map of the five profiles for Monday-Thursday trips.

Smart City Application	Data	Information	Knowledge	Services
Smart Campus	IR Sensors. RFID tags. Environmental Sensors. Weather Station. Presence Sensors. Energy Consumption Meters. Weather Forecast	Data Transformation through SAREF ontology [8], DUL ontology [9] and SSN ontology [10]	Data Modelling. Predictive Regression (RBFs, SVM, ANN, RF, ARIMA). Tracking algorithm (PFs). Optimization Mechanism (GA)	Indoor localization. Building energy consumption prediction. Energy saving through the HVAC operation optimization
Public Tram Service	Mobile Sensors. Smart Cards	CEP-based filtering. Event Processing in Action [11]	Fuzzy Clustering	Infrastructure monitoring. Mobility patterns.

Table 2: Main features of the two architecture instantiations

and techniques, we have *validated* their usability for solving different problems of smart cities with high accuracy.

In both applications tackled in this paper, the huge *volume* of historical data is being stored using a NoSQL data base. At the moment, the storage system is been adapted so as to be compliant with the FI-WARE architecture[2], that intends to ease the development of novel applications based on the Future Internet. In particular, the Orion Context Broker (OCB)[3] and the COMET[4] modules are used in order to store in a NoSQL repository the historical data comprising the measurements from the different data sources.

On the whole, both instantiations of the architecture described above are summarized in Table 2. In the next subsections we summarize the main benefits obtained after applying the most suitable big data techniques to the two scenarios of smart cities addressed in this work.

A. Benefits of Big Data Applications in Smart Buildings for Energy Efficiency

Here we summarize the main findings extracted from all the experiments and analysis carried out during the application of big data techniques to the smart campus of the UMU.

[2]https://www.fiware.org [Available Feb. 2016]
[3]http://catalogue.fiware.org/enablers/publishsubscribe-context-broker-orion-context-broker [Available Feb. 2016]
[4]https://github.com/telefonicaid/fiware-sth-comet. [Available Feb. 2016]

1) **The resolution of the indoor localization problem.** Applying regression techniques based on RBFs and a tracking algorithm applying PFs to data coming from RFID and IR sensors installed in buildings, it was possible to solve the indoor localization problem with a mean accuracy of 1.5 m. Then, indoor localization data can be used to provide customized services in buildings.
2) **The resolution of the building energy consumption estimation.** Applying PCA and BRNN techniques to data related to outdoor environmental conditions and energy consumption of buildings, it was possible to generate energy consumption predictive models of buildings with a very low mean error of 43.76 KWh - which only represents the 10.29 % of the sample - in the worst case. Then, energy consumption predictions can be used to design the optimal strategies to save energy in buildings.
3) **The resolution of the optimization problem related to the maximization of thermal comfort and minimization of energy consumption in buildings.** Applying optimization methods based on GAs to optimize the energy consumption of buildings meanwhile comfort conditions are satisfied, and after including user localization data and user comfort preference prediction, it was possible to get energy savings in heating of about 23% compared with the energy consumption in a previous month without any energy BMS.

B. Benefits of Big Data Applications in Urban Pattern Recognition to Improve Public Tram Service

After applying Big Data techniques to the urban pattern extraction in the public tram service, all the results from the experiments allowed the service staff to draw up quite interesting conclusions. These are summarized below:

1) **Regarding the resolution of the trip extraction**. The formal discovery of the stations' load in terms of trips' origin and destination would allow the service provider and the city council to better plan the whole public transport service of the city. This way, the more important stations might be considered as "hub" points where commuters can easily transfer from tram to another kinds of transport. Moreover, such an information could be also useful so as to forecast future infrastructure needs in each part of the tram line (e.g. location and number of places of new parking lots for bicycles close to tram stations).
2) **Concerning the resolution of the urban profiles generation**. Experiments pointed out the importance of undergraduates as tram users. Hence, most of the traffic load concentrated in the line between the city center and the campuses. This was really helpful in order to design promotional campaigns for these type of travellers. Moreover, results also confirmed that the line segment towards the shopping-mall areas was underused. Thus, campaigns to promote the use of the tram to go shopping was also considered.

VI. Conclusions and Future Work

This paper displays the benefits of applying big data techniques over data originated by IoT-based devices deployed in smart cities. A general architecture modelled in four layers is proposed to be applied in smart city applications considering big data issues. As part of this overview, a differentiation between static and mobile data sources is made, proposing for each one of them suitable techniques to extract relevant knowledge from their data. Then, we describe two big data applications for smart city services. Specifically, the services of energy efficiency and comfort management in the buildings of a smart campus, and the public transport service of a city. In the first scenario of smart city we have demonstrated that, after applying appropriate big data techniques to problems like indoor localization, energy consumption modeling and optimization, we are able to provide mean energy savings of 23% per month, while indoor comfort is ensured. Regarding to the urban pattern recognition carried out using data related to the public tram service of the city of Murcia, experiments were performed to confirm that the proposed patterns ended up being of great interest for the service provider in order to better understand how travellers make use of the transportation system. This was fairly useful in order to come up with better planning protocols and more tempting promotional campaigns.

The ongoing work is focused on the inclusion of people behaviour during the operational loop of this kind of systems for smart cities. Thus, for the case of smart building applications, users will be encouraged to participate in an active way through their engagement to save energy. On the other hand, in the case of the public tram service, data coming from crowdsensing initiatives will be integrated to improve the estimation of the urban mobility patterns.

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4.5 An open IoT platform for the management and analysis of energy data

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An open IoT platform for the management and analysis of energy data

Fernando Terroso-Saenz *, Aurora González-Vidal, Alfonso P. Ramallo-González, Antonio F. Skarmeta

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HIGHLIGHTS

- IoT platform for the management of energy data in buildings.
- Includes several inner features to support data analytics in the energy domain.
- Based on the open IoT initiative FIWARE.
- Evaluated in a real pilot with comprising several buildings.

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ABSTRACT

Buildings are key players when looking at end-use energy demand. It is for this reason that during the last few years, the Internet of Things (IoT) has been considered as a tool that could bring great opportunities for energy reduction via the accurate monitoring and control of a large variety of energy-related agents in buildings. However, there is a lack of IoT platforms specifically oriented towards the proper processing, management and analysis of such large and diverse data. In this context, we put forward in this paper the IoT Energy Platform (IoTEP) which attempts to provide the first holistic solution for the management of IoT energy data. The platform we show here (that has been based on FIWARE) is suitable to include several functionalities and features that are key when dealing with energy quality insurance and support for data analytics. As part of this work, we have tested the platform IoTEP with a real use case that includes data and information from three buildings totalizing hundreds of sensors. The platform has exceed expectations proving robust, plastic and versatile for the application at hand.

1. Introduction

Several reports claim that residential and commercial buildings represent around 30%–40% of the overall energy consumption in Europe and in the United States [1,2]. Because of this, buildings are known to be the largest end-use energy contributor followed by transport and industry, and therefore they are a clear target for potentially reducing global energy consumption substantially.

Despite being great consumers, there is some evidence that shows that public and private buildings have not fully exploited all opportunities available to increase their energy efficiency. On the contrary, they suffer from a rather substantial energy waste that is partly due to inefficient heating, cooling, lighting and other power system (equipment) [3], due to bad use of the systems (behavior) [4] and due to poor fabric efficiency [5]. Although the implementations of measurements to improve the first or the third category can be rather expensive, it has been seen that soft measurements that focus on the change of behavior of buildings' users are cheap, but yet, can contribute greatly to the reduction of energy use [6].

In order to address the aforementioned inefficiencies due to lack of understanding on how the systems should be operated and other behavioral related aspects in the building sector, one could consider the use of Information and Communication Technologies (ICT) and, more specifically, of the Internet of Things (IoT). This new paradigm that also exists at the domestic level could be used as an instrument to make a realization of the so called *Smart Building*. In fact, it is foreseen that from 2 to 3 houses out of 10 will be equipped with up to 500 smart devices in the near future [7].

The installation of smart meters and In Home Energy Displays to make households aware of their energy consumption is not new [8,9]. The adoption of these devices seems to be an opportunity to exploit them for the reduction of energy use when looking at the available scientific literature (will be detailed later). However, one may also think that the technological effort to deploy such systems may be substantial and become a barrier to achieve this level of technification of the buildings. Nevertheless this technification seems to be happening naturally.

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0167-739X/

The large amounts of IoT data that will be coming from buildings in the near expected future will have to be analyzed to reveal insights that could help to obtain, expose and understand knowledge from buildings. In turn, this derived knowledge should be able to help to achieve meaningful energy saving strategies and interventions in the targeted buildings [10].

These wealth of information about energy use, offers a great opportunity according to some literature on energy feedback that suggests that intelligent feedback, (that with an extra larger of computation over simple observation) is an effective technique for the reduction of energy demands via behavioral change [11]. Only with a platform capable of making this possible, the implementation of this new paradigm will be successful.

In the IoT ecosystem, several platforms have emerged providing support from the sensorization stage to the stage of management and storage of the data in different forms [12]. In that sense, one of the most large-scale affords is the FIWARE platform, a key initiative of the Future Internet Public–Private Partnership (PPP) to create a well-aligned set of open enablers to receive, process, contextualize and publish IoT data from and for smart cities including from city-wide information to dwelling specific data.[1]

Despite all the reasons exposed before, little efforts have been made so far in order to adapt such platforms to building energy management. This energy ecosystem comprises a set of particularities that should be targeted in a specific manner. After analyzing the few examples of studies that have tried to tackle this problem, one can see that it exists a pressing need to apply different data mining techniques in the building energy domain mainly focusing on consumption prediction and pattern discovery or failure tolerance [13]. Thus, IoT energy platforms should include functions for data analysis among their features.

Although giving insighting knowledge behind data is an instrumental aspect of the wealth produced by the IoT, existing platforms are still limited when it comes to integrate data processing and analytic techniques suitable for IoT ecosystems [14]. This is a fundamental limitation of the state of the art as it is key to ensure that the platform will work on the new paradigm of providing tailored, real-time energy feedback to people. This also includes features to support the easy extension of platforms to allocate new data mining techniques comprising common steps in the data mining process. Examples of such features are built-in data-cleaning mechanisms for data pre-processing and storage solutions that would facilitate the execution of online and offline data mining algorithms.

All the aforementioned limitations have motivated us to envision, design, develop and validate what we called the IoT Energy Platform (IoTEP). The key strength of IoTEP is that it is, to our knowledge, the first holistic solution to large scale building energy data management from IoT.

Unlike existing IoT platforms, IoTEP is mainly oriented to support and ease the analysis of large amounts of heterogeneous energy data. A simplified overview of the platform IoTEP is shown in Fig. 1 representing its key features.

To begin with, IoTEP has been designed to easily retrieve either the most up-to-date readings of each sensor within a building, or to retrieve the historic data from such sensors. By means of these two types of access, the platform facilitates the application of both online and offline data analyses over the collected data. As we will see on further sections, this functionality is implemented with two FIWARE storage components, the ORION context broker and COMET. For both enablers, a NGSI-based information model has been defined in order to homogenize all the measured energy-related data.

1 https://catalogue.fiware.org/.

Secondly, a real-time data cleaning module has been designed as a built-in component of IoTEP. With this, sensor readings are filtered by discarding potential outliers before injecting them in the storage components. This ensures a more efficient use of the resources. For this feature, we have followed a Complex Event Processing (CEP) approach that allows the real-time processing of event streams.

In addition to the above mentioned features, the platform includes also a mechanism to detect volatility changes in the incoming energy data. This mechanism intends to perceive meaningful shifts in such data that might need to re-launch the data-mining services that run within the platform.

Finally, IoTEP features a novel mechanism to automatically identify high-level areas in a building with certain energy-related similarities by means of clustering techniques. The benefit of these virtual areas is twofold. Firstly, they provide alternative representations of the energy status of a building beyond its physical structure; and secondly, they can help in the performance of other data mining analyses by reducing redundancies and defining different granularity levels in the captured sensor data.

Summarizing, the platform presented in this paper intends to be the first stage towards the full adaptation of the IoT paradigm in the retrieval, management and, above all, analysis of energy data in buildings. Considering the need of developing tools that are able to provide personalized real time feedback to change behaviors, and with them, have the potential to reduce energy use, IoTEP is intended to become the stepping stone for the development of such tools.

The paper is structured as it follows: Section 2 provides an overview of the state of the art in this research area. Section 3 looks into the IoT energy platform, including its architecture and its functional modules. Section 4 provides an evaluation of some of the features of the platform; and Section 5 concludes the paper with some final remarks and conclusions.

2. Related work

The present work is based upon two different lines of research, the management of energy data and the implementation of IoT platforms. Consequently, an overview of both lines is put forward in this section.

2.1. Energy data management systems

During the last years, some initiatives within the cloud computing domain have been made to intelligently manage energy data of buildings. In that sense, Zhou et al. [15] described a model for big-data energy management ranging from the collection and preprocessing of data to its further analysis and the final exposition to services. However, it only provides a theoretical approach.

From a practical perspective, the Dynamic Demand Response (D^2R) platform [16] makes use of public and private clouds combined with infrastructure and platform as a service for data storage. This platform was extended with *Cryptonite*, a repository to store sensitive *Smart Grid* data [17]. Then, different classes of data-driven forecasting models were generated on top of the whole platform with the purpose of carrying out energy prediction among others.

ElasticStream also provides a prototype solution for energy data management and analysis. In this case, the proposed mechanism transfers energy data to a cloud platform for further analysis on the basis of rate changes in the input data streams [18]. Moreover, Vastardis et al. [19] described a centralized architecture to monitor energy consumption in houses including features of pattern-matching related to the behavioral habits of the target users.

In the work of Ozadowicz [20], the authors propose different approaches to calculate the power demand related to energy

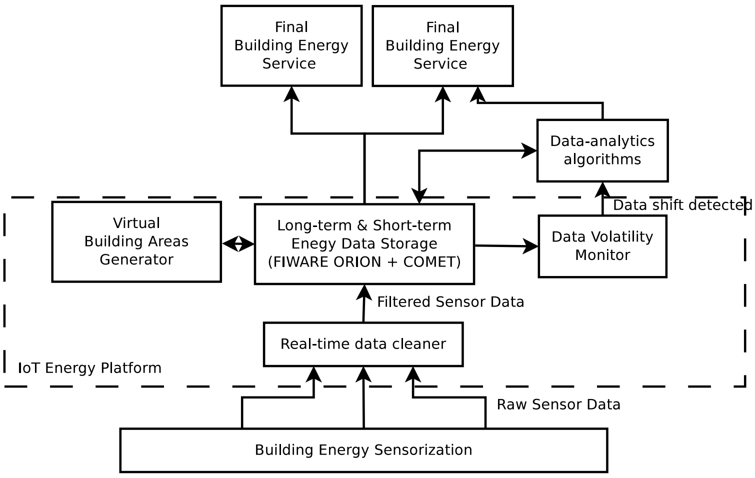

Fig. 1. Conceptual view of the IoT Energy Platform (IoTEP).

consumption using time-driven and event-driven mechanisms for Building Automation and Control Systems. Their Building Energy Management Systems (BEMS) implementation is realized with an IoT platform, introduced by Echelon Corp that includes chips, stacks, communication, application interfaces (API) and management software. Their approaches to calculate the energy demand are based in time (fixed or sliding length of the time windows with the possibility of overlapping) and in events (occupancy).

The MultiAgent System (MAS) named SAVES (Sustainable multiAgent systems for optimizing Variable objectives including Energy and Satisfaction) defined in [21] is used in [22] regarding actual occupant preferences and schedules, actual energy consumption and loss data measured from a real test bed building at the University of Southern California in order to predict energy consumption at different levels (frequency of prediction and device aggregation).

Other works provide energy data management solutions without focusing on analytic aspects. This is the case of the Virtual SCADA architecture for cloud computing (VS-Cloud) that encompasses Cloud Computing for energy data storage [23]. VS-Cloud mainly focuses on the orchestration of components in Smart Grids and the safety storage of sensitive data executed actions, incidents or alarms. Therefore, its domain of application is more related to risk management.

Similarly, the work in [24] proposes an automation platform for energy monitoring. However, such platform does not provide any particular feature to support energy data analytics as it focuses more on the definition of control strategies for energy saving.

Unlike the aforementioned initiatives, our work provides a holistic energy data management and analysis solution. Our platform also follows an open approach by relying on the well-established FIWARE initiative. In that sense, the present work includes explicit features like data volatility monitoring and outliers detection to ease the deployment of data mining algorithms and other services over of the stored data.

FIWARE brings other advantages with respect to previous solutions: firstly, the whole platform orchestration is done by means of lightweight RESTful APIs, that facilitate its further extension; and secondly, the definition of an information model compliant with NGSI standard allows to come up with a homogeneous view of the energy-related data within a building. This feature is key to exploit the potential of gathering energy data. What we propose here is not only an archive of data, but a comprehensive flexible and powerful tool that will serve as the breeding ground for the creation of context-aware tailored energy feedback platforms that could be realized at a scale never considered before, even reaching national levels.

2.2. IoT platforms

The Internet of Things paradigm is the second pillar of this initiative. All the literature indicates that small devices connected to the internet in buildings will be the norm in the near future. With the right algorithms and communication mechanisms, this situation will enable the monitoring and characterization of energy behaviors and energy consumption in buildings.

The need of effective instantiation of IoT under realistic conditions has generated a varied ecosystem of methodologies and tools taking the form of integrated IoT platforms. In that sense, it is possible to find several surveys in the literature that review existing proprietary and open-source platforms in the IoT ecosystem [12,14,25]. Other important aspects like data ownership, security and privacy [26] or data storage [25] have been also deeply studied in the IoT domain. The reader is referred to this sources to expand on the state of the art.

According to such reviews, some relevant IoT platforms follow a similar open-source and centralized approach along with heterogeneous sensor support like IoTEP. This is the case of Nimbits[2] that provides an open source Java library for developing Java, Web and Android solutions to connect to a Nimbits Server. This back-end part enables simple processing of the collected data based on rules. However, it does not comprise any advanced data-analytics support. ThingSpeak[3] features the acquisition, visualization and analysis of data but this is done by means of the proprietary Matlab tool, what may make more difficult the popularization of the platform.

One feature frequently neglected by existing IoT platforms is the support of built-in data mining features able to generate new useful knowledge from the collected and stored data [14]. In real IoT deployments, this processing and analysis task has been frequently done by third-party services. However, integrating certain data mining functionalities as built-in features of platforms would provide a great benefit in a wide range of domains, for example: quick statistics, easy to generate digests or sanity checks. In

2 https://www.nimbits.com/.
3 https://thingspeak.com/.

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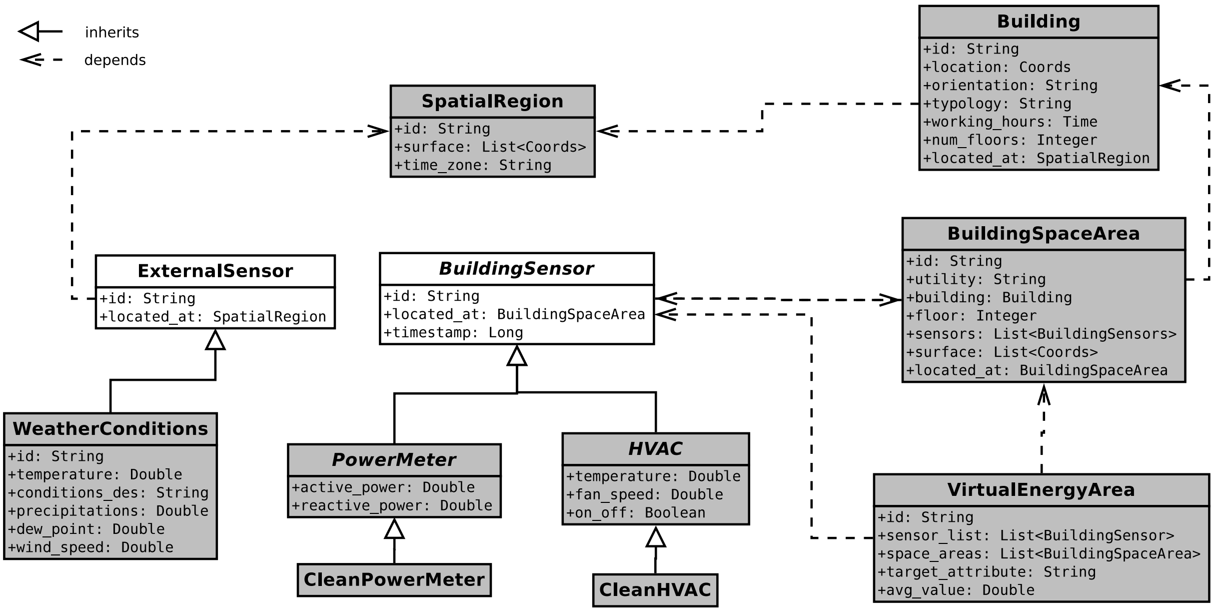


Fig. 2. IoTEP information model.

that sense, only a few IoT platforms actually include native data-analytics features. As a matter of fact, SensorCloud[4] enables a simple interface for common operations like smoothing, filtering and interpolation whereas GroveStreams[5] provides some real-time data analytics mechanisms. However, none of them support sensor heterogeneity nor follow an open source approach like IoTEP does.

As for the energy ecosystem, several research lines have already stated the feasibility and suitability of data analysis in order to increase energy awareness within a building [13]. In that sense, IoTEP provides one of the first steps towards such a data-mining enrichment by providing several features fully focused on easing the analysis of IoT energy data namely, real-time data cleaning, data volatility detection and data reduction procedures.

Finally, our work is enclosed within the FIWARE architecture. The high-level goal of this architecture is to build the Core Platform of the Future Internet, introducing an innovative infrastructure for cost-effective creation and delivery of versatile digital services, providing high QoS and security guarantees. In that sense, FI-LAB [27] conforms live instances of generic enablers, available to developers for free experimentation within this technology.

Some initiatives have started to profit from FIWARE in several domains. One of the most ambitious works is the application on [28] which established a world-wide semantic interoperability solution combining the NGSI, which is part of the core of the FIWARE initiative, and oneM2M context interfaces. Apart from that, [29] demonstrated the suitability of the FIWARE paradigm to compose Future-Internet applications by means of the integration of generic enablers. In a similar manner, [30] put forward a semantic mechanism to integrate data from different types of devices by also using FIWARE components. Finally, in a more functional domain, [31] made use of certain enablers, like ORION context broker, to create a cloud-based gesture recognition application. Also, [32] describes a sensor management for seaports based on the FIWARE platform. It is therefore possible to say that our work seems to be one of the first efforts to make use of FIWARE enablers in the building energy domain, and furthermore in the energy domain in general.

3. IoT Energy Platform (IoTEP)

This section explains in detail the proposed IoTEP solution. Since the management of the energy data is its key feature, we firstly describe the information model used to define all the data within the IoTEP ecosystem; next, we put forward the specific architecture of the platform that deals with the energy data according to the model.

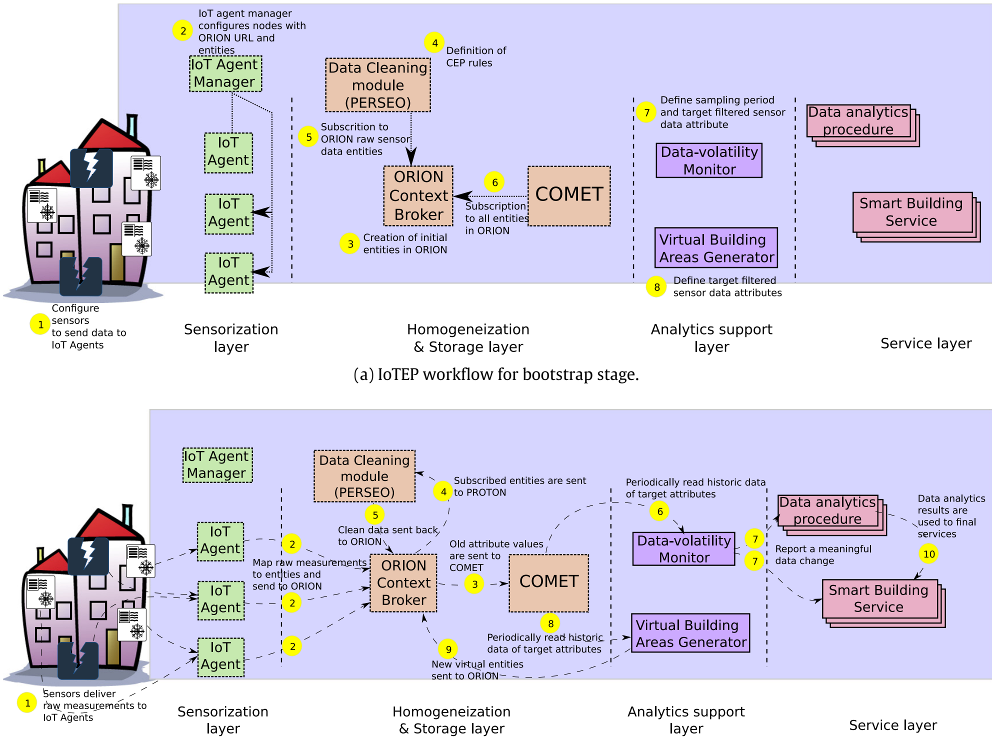
3.1. Information model

One of the first steps towards the realization of IoTEP was to define a common information model for the whole platform. Such a model must be compliant with the NGSI information model commonly accepted in the FIWARE ecosystem, what facilitates interconnection with other models and other users. This information model follows an entity–attribute approach where entities represent real or virtual elements of interest. Each entity has a type what allows to define type-based hierarchies. In this way, an entity has its own defined attributes and the inherited ones from its ancestors. The IoTEP information model is depicted in Fig. 2. The model design follows the UML class notation with two types of relationships, inheritance and dependence. Each of them is represented by a different arrow in the figure. Whilst inheritance indicates that the child element comprises all the attributes of its parent element, the dependence relationship indicates that an instance of the element at the arrow's origin contains an attribute referencing at one or more instances of the element at the arrow's destination.

Focusing on the content of the model, one can find among its components three key elements related to the energy ecosystem of a building by means of NGSI entities.

To begin with, the entity *building* models the target building. Several operational and architectonic details of the building are included as attributes on this entity. Examples of information in

4 http://www.sensorcloud.com/.
5 https://grovestreams.com/.



(a) IoTEP workflow for bootstrap stage.

(b) IoTEP workflow for operational stage.

Fig. 3. Platform general workflow.

this section are: opening hours or building use (e.g., company headquarters, university faculty, etc.) but also physical relevant attributes such as fabrics, windows, orientation, and so forth. Moreover, the *spatial region* entity defines the geographic region containing the building. This entity would help to link together buildings located in similar geographic regions that, as a consequence, might share certain energy-related characteristics. The inner structure of a building is represented with the *building space area* entity. This entity gathers the different spatial areas within a building (e.g., classrooms, corridors, halls, landings, etc.). Furthermore, a recursive structure of these areas can be made with their *located at* attribute to represent, for example, that a classroom is inside a *teaching zone*.

This way of introducing data about the buildings and the spaces will made the communication between a Building Information Modeling (BIM) platforms and the IoTEP platform straight forward, what would facilitate the transfer of information among members of a given team.

The second group of entities refers to the energy sensors deployed in the building and the data they collect. This is modeled by means of the *building sensor*, *power meter* and *hvac* entities. Each entity includes the set of attributes monitored by the corresponding energy sensor along with other metadata (e.g., location of the sensor or timestamp of each observation). The *clean* version of these entities refer to the sensor data generated after the data filtering process as described in Section 3.2.2.

The third group of entities focus on representing sensors that are not necessarily within the infrastructure of the building but that may provide useful when collecting energy data. This is the case, for example, of weather stations reporting conditions of the building site. As Fig. 2 shows, this is defined by means of the *external sensor* and *weather conditions* entities.

Finally, only the entities in gray in Fig. 2 have instances stored in ORION and COMET as we will see later.

3.2. Platform architecture

The proposed IoTEP has been structured in four different layers in an incremental approach (this is shown in Fig. 3). In the upcoming sections, a detailed description of each layer is given.

3.2.1. Sensorization layer

This layer is in charge of connecting physical devices or actuators that are going to provide energy data to the platform. Once this is done, it maps the collected data to the NGSI entities of the information model (described in the previous section) and sends the mapped information to the upper homogenization and storage layer.

For the realization of this layer, we have made use of the FIWARE IoT Agent enabler [33]. In a nutshell, this enabler allows to automatically perform the aforementioned data mapping. Different types of this enabler support transport protocols to connect to the physical devices like MQTT.[6] or Lightweight M2M (LwM2M)[7].

Consequently, during the bootstrapping phase of the platform, a set of IoT Agents are configured with the NGSI entity type associated to each of its associated sensor by means of the IoT Agent Manager (see Fig. 3(a)). In particular, power meters deployed in the target building are mapped to the *power meter* entity type whereas HVAC devices are mapped to the *hvac* one. Furthermore, we developed an ad-hoc agent to parse the weather conditions coming

6 http://mqtt.org.
7 http://openmobilealliance.org/iot/lightweight-m2m-lwm2m/.

from an external third-party weather service to the *weather conditions* entity on a regular basis. During the operational phase (see Fig. 3(b)) each time an IoT Agent receives the raw measurements from a physical device, it *inflates* the entity instance associated to the device in upper layer by means of a RESTfull API, in the homogenization and storage layer (will be described in the next section).

3.2.2. Homogenization and storage layer

In this layer, all the collected energy data from the previous layer is conveniently stored in a uniform solution. This way, this layer addresses the heterogeneity of the incoming energy-related data. Moreover, it contains real time data cleaning stage what ensures the quality of the data collected.

Sensor data repository. Regarding the energy-related data storage, this has been achieved by integrating two FIWARE components.

Firstly, ORION context broker [34] implements a publish–subscribe store providing data access by means of the NGSI-10 API [35]. In IoTEP, this enabler stores the entity instances of the information model. By means of the NGSI update operation, IoT Agents in the sensorization layer update the sensor entities' attributes in real time with the new readings from the devices.

Secondly, the COMET enabler [36] is used for supporting access to historic time series data extending the ORION functionality. In that sense, COMET adheres to the same information model, thus, it does not require any further data harmonization process. It incorporates an ad-hoc API to retrieve raw historical sensor data along with several built-in simple aggregation functions over such data (e.g., provide the sum, min or max of the collected observations for a specific time period).

During the bootstrapping phase of the platform, ORION is initiated with the *static* attributes of the entities in the information model (e.g., 'identifier', 'located at' or 'orientation' attributes) and COMET subscribes in ORION to the *dynamic* attributes of the entities to receive each new value (see Fig. 3(a)).

Sensor data cleaning. Concerning the data quality assurance, we developed a data cleaning module to remove the outliers that might be contained in the raw measurements from the sensors. In that sense, outliers have been reported to be the most prominent quality issue of energy data [37,38].

This module had two key requirements. To begin with, the data cleaning process must be done in a timely manner in order to avoid potential bottlenecks. Furthermore, in an IoT ecosystem we should expect a great variety of data formats and structure. Thus, such data cleaning should be done after data homogenization in order to simplify the overall computational cost of the cleaning stage.

In order to cope with the time-processing constraints, we opted for following the Complex Event Processing (CEP) paradigm to develop a real-time data cleaning module. CEP focuses on timely processing streams of information items, so-called events, by filtering, aggregation or pattern discovery using predefined rules following the event–condition–action paradigm [39]. In the present setting, the incoming events are the readings from the energy sensors, the conditions to be detected are whether a reading should be considered or not an outlier and the action of the final insertion of the cleaned data in the storage structure of the platform.

For the outlier definition, we followed a strategy based on quartiles with fences [40]. In brief, such a strategy extracts the median, the lower $\mathcal{Q}_1$ and upper quartiles $\mathcal{Q}_3$ (aka 25th and 75th percentiles) along with the interquartile range $\mathcal{IQ}(= \mathcal{Q}_3 - \mathcal{Q}_1)$ of the data set under study. On the basis of such statistics, two fences are defined,

- Lower outer fence: $\mathcal{Q}_1 - 3 \times \mathcal{IQ}$
- Upper outer fence: $\mathcal{Q}_3 + 3 \times \mathcal{IQ}$

This way, a measurement beyond such fences is considered an *extreme outlier*.

The translation of this strategy to CEP allows to calculate such fences incrementally and update their boundaries each time that a sensor pushes in new data. In particular, two types of CEP rules were defined. The first one comprises the rules in charge of computing for each sensor the aforementioned statistics with respect to each of its parameters. For the sake of clarity, the pseudocode of the CEP rule in charge of calculating the fences for power meter sensors is shown here and it looks as it follows:

```
CONDITION PowerMeter.groupBy(id).within(t_int^clean) as A
ACTION    new PowerMeterStats(A.id,
          calculateLowerOuterFence(A.active_energy))
          calculateLowerOuterFance(A.reactive_energy),
          calculateUpperOuterFence(A.active_energy)
          calculateUpperOuterFence(A.reactive_energy))
```

where `groupBy` and `within` are two sliding windows. While `groupBy` splits the stream of power-meter data with respect each particular device, `within` defines a time window to retain the last power-meter data generated during the last t_{int}^{clean} time units. After this, the action part of the rule, generates a new `power meter stats` event comprising the percentiles for each sensor's attribute considering the data included in the time window. It is important to note that this rule would fire each time that new power meter data is injected into the CEP system.

The second set of rules performs the actual extreme outliers detection. Again, there is one rule per sensor type in charge of this task. The pseudocode of the CEP rule to detect the outliers in the power meter data is shown next,

```
CONDITION PowerMeter as A
          AND PowerMeterStats as B
          AND A.id = B.id
          AND A.active_energy ∈ [B.active_energy_lowerFence,
          B.active_energy_upperFence]
          AND A.reactive_energy ∈ [B.reactive_energy_lowerFence,
          B.reactive_energy_upperFence]
ACTION    new CleanPowerMeter(A.id, A.timestamp, A.located_at,
          A.active_energy, A.reactive_energy)
```

Describing it briefly, this rule fires each time that a new power-meter reading is received. The condition part of the rule matches such reading with its associated statistics and checks whether each parameter is contained in its own fences. If that is the case, the reading is considered that has been cleaned. As a result, the action part creates a new `clean power meter` event with the pre-processed data.

A very similar approach is followed for the HVAC data but, this time, using the thermostat temperature attribute of this type of sensor in order to give rise to `clean hvac` events.

The implementation of this CEP mechanism has been made with the Perseo FIWARE enabler [41]. This component incorporates a CEP engine and an SQL-based event processing language to define and execute the CEP rules. Furthermore, it leverages the publish-subscription capabilities of ORION. This way, the engine receives each entity instance, which data has been just updated in ORION, as incoming events; and the cleaned events generated by the rules, automatically update their associated entities in ORION (Fig. 3(b)). Hence, during the bootstrapping phase (see Fig. 3(a)) this component is configured with the rules to be executed and the list of entities in ORION to subscribe (in this case, *power meter* and *hvac* entities).

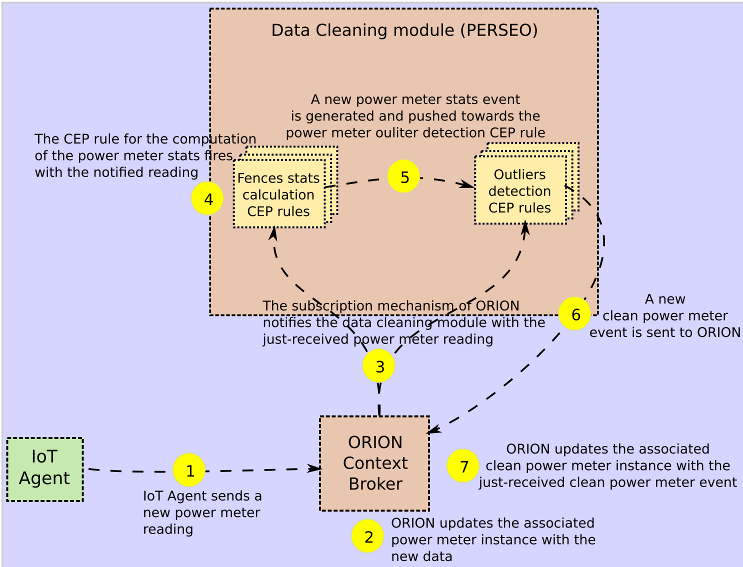


Fig. 4. Workflow of the cleaning of power meter readings.

Finally, Fig. 4 shows an illustrative example of the workflow of the CEP cleaning mechanism and its connection with the sensor data repository. As this figure depicts, each raw sensor reading coming from the IoT Agents is initially stored in ORION by updating its associated *building sensor* instance. In the figure's scenario, a new power-meter reading will update the *power meter* instance representing the sender's sensor (steps 1 and 2 in the figure).

Next, ORION automatically notifies to the data cleaning module the new reading (step 3). This notification fires the two types of CEP rules described before (steps 4 and 5). At the end, the module outcome takes the form of a `clean power meter` event that updates the associated *clean power meter* instance in ORION. This *clean power meter* instance represents the cleaned version of the power meter sensor updated in step 2. Moreover, we should note that all the aforementioned interactions occur following a push-style communication enabling the real-time processing.

3.2.3. Analytics support layer

The third layer of the platform embraces all the functionalities of the platform to provide support for data mining services that can run on top of the platform. In particular, two features have been included in this layer, an energy data volatility detector and a virtual entities generator.

Virtual energy building areas generator (VEBAG). The amount of data that we are able to collect in smart buildings by means of large sensor networks sometimes does not increase the *information volume* because of redundancy. Depending on its nature, this redundancy is treated using different approaches: redundancy detection, data compression, feature extraction, and some others [42].

IoTEP works under the hypothesis that a clever way to reduce the number of variables taking part in the models can not only decrease the computation costs but also increase the accuracy on predictions and classification. In this way, the creation of abstract entities will be justified from the data analytics side, based on the assumption of the existence of this redundancy.

Therefore, the goal of the VEBAG module is the creation of high level entities that preserve as much information as possible in the data set but yet, reducing the volume of it. In this case, we want to create virtual areas comprising several *building space areas*, finding patterns in the energy-related use and defining these virtual areas according to such information to optimize the content of information.

To do so, we aggregate each attribute per energy device daily. This aggregation can be easily done with the built-in RESTful aggregation functions provided by COMET within the homogenization and storage layer. That way, we can represent each device as a time series having one attribute measurement per day and with this, it is possible to find a clustering algorithm that groups every attribute of the time series finding some distinctions between them, like DBSCAN or longitudinal k-means.

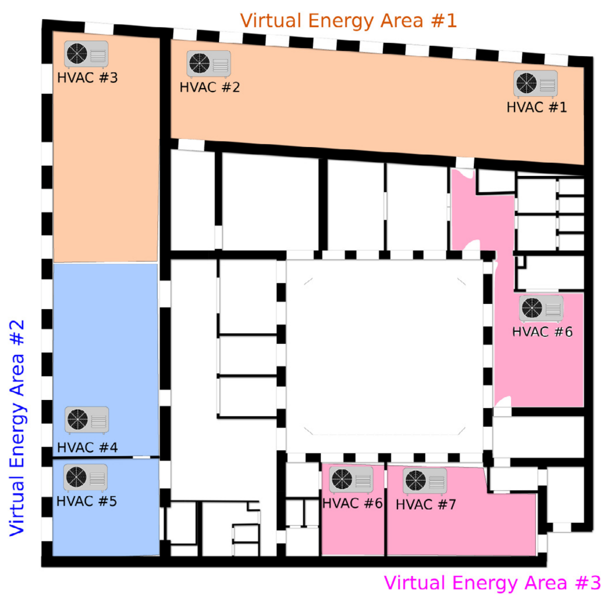
Once every device is assigned to a cluster or virtual area, the generator computes the mean of the elements of each cluster to get an average measurement. Finally, each generated cluster is stored in the storage layer as an instance of the *virtual energy area* entity (see Fig. 3(b)). In that sense, this generator is launched on a regular basis or when certain data shifts are detected in the data by the data volatility monitor (described in the next section). Fig. 5 depicts an illustrative example of this process given the building's floor.

Firstly, Fig. 5(a) shows the distribution of room-based building space areas along with their HVACs. It should be recalled that each of these areas and sensors will be stored as different instances in IoTEP. Furthermore, the figure also shows an example of a possible time-series plot of the regulated temperature for each HVAC for illustration purposes.

Next, Fig. 5(b) shows the *virtual energy areas* generated on the basis of the aforementioned temperature time series. As we can see, the six initial room-based building space areas have been merged into three instances of *virtual energy areas* by grouping together the HVACs with similar time series. This way, rooms 4, 5 and 6 and their associated HVACs have been merged into a single area (*virtual energy area 3* in the figure).

All in all, the generation of these virtual energy areas enables the platform to provide multiple views of the energy status of a building. In a low-level setting, we can monitor energy parameters from a single-sensor point of view. Over such simple view, we can also extract energy parameters related to a particular building spatial area (e.g., room, corridor and the like) by simple aggregation

(a) HVACs and room-based building space areas.



(b) Virtual Energy Areas generated based on the HVACs' temperature time-series.

Fig. 5. Example of generation of *virtual energy areas* considering the HVAC temperature in a building floor.

using the *building spatial area* instances. Finally, *virtual energy area* instances enrich the energy awareness by providing an extra layer of perception that is not constrained by the building architectural structure. This way, it is possible to monitor building areas with similar energy behaviors simultaneously.

Data volatility monitor. In order to come up with real energy-aware services, the monitoring of certain energy parameters of a building becomes paramount. This includes detecting either abnormal energy consumption related to building spaces or an abnormal temperature setting related to HVACs.

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For that goal, the data volatility monitor focuses on computing the current rate of change of each energy sensor parameter included in the storage layer. This is done in three steps.

Firstly, we extract the historic data set of the target energy parameter for a particular sensor with respect to a pre-defined time period t_{int}^{vol} from COMET. Then, the average rate of change among pairs of consecutive observations of the attribute is computed. Finally, if such averaged value is substantially different that the historic rate of change of that attribute then an alarm is triggered. For the sake of clarity, the pseudo-code of this process is shown in Algorithm 1.

Algorithm 1: Data volatility calculation.

Input: Type, identifier and energy parameter of the monitored sensor ($sensor_{type}$, $sensor_{id}$, $sensor_{attr}$), time interval under study (t_{int}^{vol}) and historic rate of change of the considered parameter for the target sensor (rh_{attr}^{sensor}).
Output: Data volatility alarm, if any.

`/* Historic data extraction */`
$\mathcal{D} \leftarrow$ get_COMET_raw_historic_data($sensor_{type}$, $sensor_{id}$, $sensor_{attr}$, t_{int}^{vol})
`/* Average data-rate change calculation */`
$d_{prev} \leftarrow 0$ $r_{avg} \leftarrow 0$ $n \leftarrow 0$
for each $d \in \mathcal{D}$ **do**
  $r \leftarrow |d - d_{prev}|$
  $r_{avg} \leftarrow r_{avg} + \frac{d - r_{avg}}{n}$
  $d_{prev} \leftarrow d$ $n \leftarrow n + 1$
`/* Meaningful data-rate change detection */`
if $r_{avg} >> rh_{attr}^{sensor}$ **then**
  return data_volatility_alarm($sensor_{type}$, $sensor_{id}$, $sensor_{attr}$, r_{avg})

This alarm is received by the final energy services on top of the platform and the VEBAG module. If this module receives a set of consecutive alarms related to the same energy parameter in a short period of time then it might indicate that the energy similarities in between building areas have changed. In order to capture such shift, VEBAG re-launches the clustering process to reconfigure the virtual areas related to such energy factor. In that sense, this monitor is endlessly executed every t_{int}^{vol} time units in order to keep a continuous control over the sensor data streams.

Finally, we would like to notice that this last mechanism along with the CEP data cleaning described in Section 3.2.2 might provide some clues to building operators about data inconsistencies due to sensor interferences. In particular, the data cleaning module can remove readings that are not consistent with the normal operation of a sensor whereas the data volatility mechanism can also detect abnormal disturbances in the data rate change of a sensor reporting that something unusual is happening.

3.2.4. Service layer

Although not that central when considering the architecture of the platform here developed, the Service Layer is the last level of the IoTEP. This layer serves as interface between the IoTEP and the user, that could be anything from a building services manager to the back end of a smartphone application.

At this level, the data analytics procedures can be invoked and their results visualized. Also, smart-building services that may be the norm when the smart-building paradigm is fully established will be nested at this level of the IoTEP platform, and will allow features such as advanced HVAC predictive control, home automation, fuel poverty evaluation, sick building syndrome diagnostics, risk situations for vulnerable people (as in heat waves), smart tariff strategies, and many others.

4. Validation of the platform

In order to test the feasibility of the proposed platform, IoTEP has been instantiated in a real pilot that allowed us to evaluate functionalities of the new platform. Here we provide some details of the evaluation scenario.

4.1. Pilot description

IoTEP was instantiated at the University of Murcia, Spain. During the last three years, this university has carried out an ambitious plan to monitor and control its buildings' infrastructures distributed across the university premisses. The number of buildings monitored and the automated services have increased quickly in the last years, what serves well the purpose of testing the plasticity of the platform presented in this paper. It should be noted that the sensorization of the buildings at the University of Murcia was done independently of this project, so the fact that the platform was able to allocate the data coming from all the sensors was already a proof of its validity.

In this context, IoTEP was used as the main enabler of an energy efficiency campaign at three cases, namely the Faculty of Chemistry and two multi-disciplinary research and technological transfer centers within the university. Details of the three buildings are provided in Table 1.

Lastly, the evaluation of IoTEP covered a three-month winter campaign from 01/10/2016 to 28/02/2017.

Platform configuration. IoTEP was installed in a centralized server with CentOS 6.7 as operating system, 8 GB RAM and 250 GB hard disk. Besides, Table 2 sums up the configuration of the inner parameters of the platform. It should be reminded that t_{int}^{clean} defines the time interval used by the CEP cleaning mechanism to compose the quartile fences (Section 3.2.2) whereas t_{int}^{vol} indicates the length of the time series considered by the data volatility mechanism to infer meaningful data shifts (see Algorithm 1).

Before the deployment of IoTEP in the pilot, a full covering of energy related variables was done in the buildings under study. After preliminary evaluations, it was discovered that there are three families of data that are fundamental to understand the energy behavior of the building users and heat losses of the envelopes. The three families are: building characteristics, energy streams and building state.

The building characteristics are the physical description of the building. Detailed blueprints of the building were obtained from the department of estates of the university together with detailed plans of constructions. This information together with visual inspections carried out by the members of our team have allowed as to have a rather full description of the condition of the building thermal envelope. With this, it was possible to use building physical models to analyze and predict the heat flows of the building and therefore the energy performance of the fabrics.

About the second family, we were able to monitor in real time with a sampling period of 10 min the operation of more than 200 conditioning units in real time. This included the status of the machines (on/off) and the set point temperatures. It was also possible to obtain the technical characteristics of the machines, what together with the rest of the data allowed us to have a rather accurate proxy of specific power consumption in real time. To contextualize this individual power consumption, the total power consumption of the building was also measured.

Finally, it was needed to know what the conditions on the interior of the spaces of the building were. For this, we monitored in real time the temperature of more than 200 spaces. This temperatures are in accordance with the data taken from the conditioning systems what allowed us to create virtual control volumes/zones in which to evaluate energy flows.

Table 1
Use case building characterization.

	Faculty of chemistry (FC)	Technological transfer center (TTC)	Research center (RC)
Location (coords)	38.02, −1.16	37.72, −1.09	38.02, −1.17
Orientation	south-west	south-west	south-west
Surface area	1500 m^2	3323 m^2	1000 m^2
Floors	6	4	2

Table 2
IoTEP parameters setting.

Parameter	Description	Value
t_{int}^{clean}	Time window length for sensor stream fence calculation	30 days
t_{int}^{vol}	Time period for data volatility calculation	2 hours

Table 3
Information model entities distribution per building.

Entity	Number of instances		
	FC	TTC	RC
Spatial region	1	1	1
Building	1	1	1
Building space area	344	16	10
HVAC	239	0	4
Clean HVAC	239	0	4
Power meter	1	13	4
Clean power meter	1	13	4
Weather conditions	1	1	1

The IoTEP was created in such manner that it allows to allocate all this information in two ways: in the form of data stream, and in the form of "static" information. In this way, the description of the building is allocated on the *building* entity previously described. The characteristics of the conditioning system and the data stream can be placed on the *HVAC* and *power meter* entities created for this purpose.

This comprehensive set-up fully monitors the most important energy related aspects of the building, what could be a two-bladed sword. In principle, this allows to do high level reasoning on the data with the high added value that this represents; however, such a large flow of data may render the infrastructure slow and inefficient with such a heterogeneous data. With the solution proposed in this paper we overcome the problems, leading to a platform that, because of the efficient handling of data inherited from FIWARE, allows for the true real time comprehensive data analysis of buildings. With the advantages that this represents.

As a result of this study, Table 3 shows the distribution of instances of the entities of the IoTEP information model stored in ORION per building.

4.2. Pilot objectives

The goal for this testing campaign was to develop a new service able to predict the next-day energy consumption of each of the three buildings, and with this to evaluate the framework we present at all the different levels. However, it should be reminded that this is only an example of the variety of features that could be implemented on IoTEP. The service tested would be instrumental for the department of estates of the university in order to plan energy-saving actions and advanced versions of model predictive control.

As Fig. 6 shows, this service was developed on top of IoTEP i.e. on the service layer shown in Section 3.2.4, by using its functionalities. It was implemented as a web application allowing the control of some of the IoTEP features by the buildings manager to carry on decisions according to data analysis results. Consequently, this application acts as a dashboard that allows users to control the platform and access the aforementioned energy consumption service (see Fig. 7).

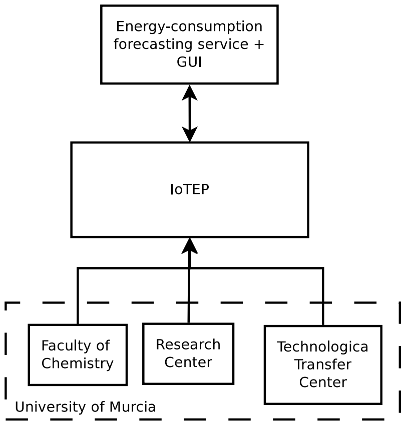

Fig. 6. Representation of the IoTEP pilot evaluation.

In terms of access of the inner features of IoTEP the application includes the following actions,

- Firstly, it is possible to visualize the most recent readings of the HVAC devices per each room of the building. For this feature, the application makes use of the ORION component of the platform.
- Secondly, it is also possible to visualize the HVAC data given a time range defined by the user. For this purpose, the application leverages the raw historic data extraction method of COMET.
- Moreover, this dashboard also allows to control and visualize the results of the *virtual energy areas* generation of the platform (VEBAG module). In that sense, the user can also select the clustering method, and the number of clusters will be selected automatically by the Calinski–Harabasz index.

Finally, the energy consumption prediction service was also integrated in this application. On this way, building managers have full control over all the data analytic process starting from data visualization, aggregation and clustering to the final energy prediction procedure. This integration allows to perform such prediction for several granularity levels targeting from single devices, space areas or *virtual energy areas*. This multi-faced prediction is a key innovation aspect of the application.

For the evaluation of the platform, we studied the suitability and feasibility of the multi-layered view of the energy-related information proposed by IoTEP by means of the *virtual energy areas* generation. Additionally, we also studied the accuracy of the

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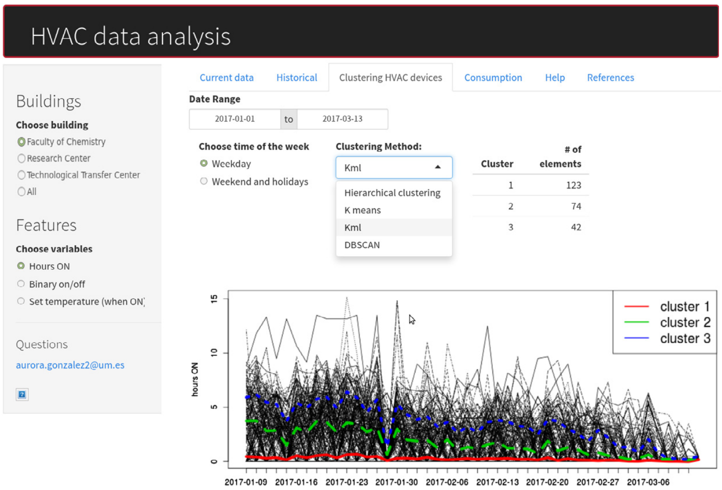

Fig. 7. IoTEP dashboard and energy consumption prediction service.

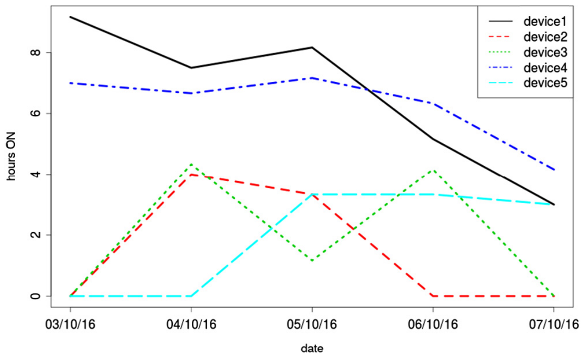

Fig. 8. Time series of 5 HVAC devices.

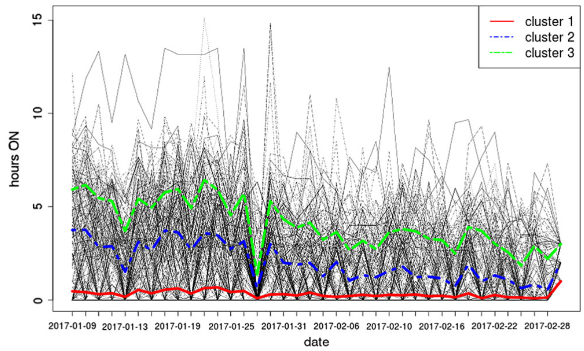

Fig. 9. Cluster evolutions.

energy prediction service when such areas are included as the target entities.

For the generation of these areas, the daily aggregation of data made by the VABAG module was based on counting the hours that each device is tuned on during the day (24 h). As an example, the number of hours that five devices were on during five days is shown in Fig. 8

For the clustering of such aggregated data, we relied on the k-means algorithm [43], but as mentioned before, more algorithms can be used for this purpose. We arbitrarily selected 3 clusters, but a different number can be selected if needed. In Fig. 9 we show the three evolutions of the groups of HVAC within FC that this algorithm identified for working days during the period of study. That way, we found rooms in this building with high use pattern (cluster 3, comprising 47 devices), rooms with little use (cluster 1 with 118 HVACs) and rooms presenting an intermediate frequency of use of the HVAC system (cluster 2 with 74 HVACs). The separation of these clusters could be the first step to an intervention strategy to modify the behavior of big consumers.

In the same way, and looking at the infrastructure level, we represent 239 values taken from the HVAC devices into 3 variables providing a 98.7% reduction of data.

Regarding the energy-prediction service, it makes its prediction according to the previous HVAC grouping within FC. Hence, we compare its performance with the use of the raw data set and in combination with environmental variables. Being the inputs and outputs of the model identified, we followed the next steps [44]: Being the inputs and outputs of the model identified, we followed the next steps [44]:

1. Standardization of inputs
2. Splitting the data into training (75%) and test set (25%)
3. Validation: 10-fold cross validation and 5 repetitions over the training data set using several models: random forest, artificial neural networks and support vector regression.
4. Evaluation: Using the RMSE metric to evaluate the models and its coefficient of variation for comparison.

The scenarios to compare are based on the different inputs to consider:

- "Hours on" average per cluster of the previous day
- Weather predictions from Weather Underground API.[8]
- Raw HVAC data (every HVAC device daily usage)
- Both average per cluster and weather predictions

As we can see in Table 4, with a really reduced number of inputs (only 3 variables), for every model we obtain very good results compared to the others. That way, the use of clusters for creating

8 https://www.wunderground.com/.

Table 4
RMSE (and CV-RMSE) of the different models and inputs.

Model	HVAC clusters	Weather	Raw HVAC	Clust + Weath
RF	0.32 (10.53)	0.513 (17.74)	0.358 (11.83)	0.356 (11.76)
SVM	0.316 (11.03)	0.635 (22)	0.446 (14.76)	0.461 (15.23)
BRNN	0.281 (9.48)	0.423 (14.63)	0.347 (11.47)	0.398 (13.15)
# Inputs	**3**	23	239	26

higher level entities is proved to be useful. Although this is a rather arbitrary method, we prove with this that the platform serves to host algorithms for data analysis and prediction on a very versatile way

Comparative results. In the work [22], CV-RMSE is used in order to validate their results. They are evaluating both aggregated (total) and disaggregated (cooling and ventilating) energy consumption in a daily, weekly and monthly basis. When we compare our results with theirs, we are obtaining 6% less of variance for the RMSE, which is very satisfactory.

In addition, the Recommended Values for Baseline Model from ASHRAE Guideline 14 [45] account for the CV-RMSE smaller than 30% for daily predictions which we reach with ease (our best performance returns a 9.48 %, see Table 4).

To sum up, with this small example we show what can be implemented on the service layer of the IoTEP. With this, we intend to prove how rather complex methods can be implemented on a simple way in our platform. Also, we have shown an example of reducing data volume taking advantage of data redundancy reduction doing clustering. For this specific example we have taken three clusters as an arbitrary number and we have shown that total energy can be predicted with them. This was done as it evaluates all the features of the platform that we show in this paper, but many other applications and examples can be developed following the principles shown in Section 2.

4.3. Lessons learnt

From this first deployment of IoTEP, we can draw up some remarks.

Firstly, the results of the preliminary sensorization study of pilot were easily integrated in the IoTEP information model. This allowed to homogenized all such results in a common format and showed the versatility of the model.

Secondly, the integration of data mining support procedures as part of the platform made possible the easy development of a final service for energy data mining. In that sense, developers only needed to focus on the actual functionality of the service related to the prediction algorithms since other important tasks of the data analysis like data pre-processing or clustering were already provided by the platform.

Finally, the idea of providing a multi-layered view of the energy status of a building by means of clustering techniques has proved its suitability in the energy prediction service in two aspects. From a data-mining point of view, it reduces the redundancy of data and, thus, making up lightweight models. From a more functional point of view, the level of abstraction that the virtual energy areas provide might help building managers to better understand certain energy behaviors within the building.

All in all, this pilot has helped us to confirm that the integration of data analytics support features as part of the IoT platform is currently a key requirement in the energy domain. This enables the development of more sophisticated energy-aware services in a fast-pace process what seem to be the next natural step towards a more efficient energy-literate society.

5. Conclusions

Due to the importance of the building sector in the end-use energy consumption, it becomes a foremost task to achieve meaningful energy savings that will reduce this energy use in reality.

Despite the fact that IoT technologies have been widely used for the realization of the smart building concept, the simple sensorization of buildings is not enough to make a housing stock that consumes fewer energy resources a reality. IoT is also required to properly process, manage and, above all, analyze the energy-related data that would help to develop final energy-aware services targeting the energy efficiency goal.

In this context, several multi-purpose IoT platforms already provide generic solutions to manage IoT data. However, there is a lack of platforms in this field focusing on (1) the household energy domain and (2) providing support for data analytics. As a result, the present work shows an IoT Energy Platform (IoTEP) that covers the two aforementioned needs by following an open approach based on FIWARE enablers. IoTEP provides several functionalities oriented to the data analytics domain like the CEP data cleaning module or the times series storage along with functionalities for the correct energy management like the data volatility monitoring or the virtual energy areas detector that will allow with personalized energy feedback for the improvement of energy behavior.

Lastly, the platform has been instantiated in a real use case having a large energy sensor network. In that sense, one of the key novelties of IoTEP is that the virtual areas detection has proved to be of great help when it comes to develop an end-use energy prediction service over the platform, but many other services could be implemented with trivial computational effort under this paradigm.

Regarding further work, IoTEP has been developed re-using several open source components that are orchestrated following lightweight RESTfull calls what allows other scientists and engineers to contribute to this platform, opening the door to crowd sourced development. Consequently, new modules and enablers can be smoothly integrated in the existing architecture. In that sense, the integration of other types of sensing approaches beyond mote-class sensors, like crowdsensing, it foreseen as future actions in the platform. This would allow to capture and analyze other forms of human behavior also relevant for the building energy domain.

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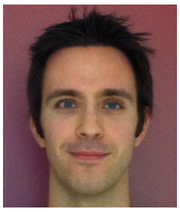

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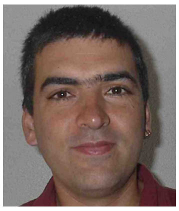

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4.6 Providing Personalized Energy Management and Awareness Services for Energy Efficiency in Smart Buildings

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Providing Personalized Energy Management and Awareness Services for Energy Efficiency in Smart Buildings

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Abstract: Considering that the largest part of end-use energy consumption worldwide is associated with the buildings sector, there is an inherent need for the conceptualization, specification, implementation, and instantiation of novel solutions in smart buildings, able to achieve significant reductions in energy consumption through the adoption of energy efficient techniques and the active engagement of the occupants. Towards the design of such solutions, the identification of the main energy consuming factors, trends, and patterns, along with the appropriate modeling and understanding of the occupants' behavior and the potential for the adoption of environmentally-friendly lifestyle changes have to be realized. In the current article, an innovative energy-aware information technology (IT) ecosystem is presented, aiming to support the design and development of novel personalized energy management and awareness services that can lead to occupants' behavioral change towards actions that can have a positive impact on energy efficiency. Novel information and communication technologies (ICT) are exploited towards this direction, related mainly to the evolution of the Internet of Things (IoT), data modeling, management and fusion, big data analytics, and personalized recommendation mechanisms. The combination of such technologies has resulted in an open and extensible architectural approach able to exploit in a homogeneous, efficient and scalable way the vast amount of energy, environmental, and behavioral data collected in energy efficiency campaigns and lead to the design of energy management and awareness services targeted to the occupants' lifestyles. The overall layered architectural approach is detailed, including design and instantiation aspects based on the selection of set of available technologies and tools. Initial results from the usage of the proposed energy aware IT ecosystem in a pilot site at the University of Murcia are presented along with a set of identified open issues for future research.

Keywords: energy efficiency; behavioral change; personalized recommendations; energy analytics; behavioral analytics; big data analytics; Internet of Things (IoT); Drools; rules management system; semantic reasoning

1. Introduction

Energy consumption in residential and commercial buildings is estimated to account for around 40% of total energy consumption, making the need for promoting solutions that can potentially lead to significant reductions compelling. As stated by the U.S. Energy Information Administration, in 2015, about 40% of total U.S. energy consumption was consumed in residential and commercial buildings [1], while a similar percentage is reported by the European Commission for the overall consumption of the buildings sector in the EU [2].

The design and adoption of novel information and communication technologies (ICT) towards achieving higher levels of energy efficiency in the buildings sector is considered promising, as stated in the Global e-Sustainability Initiative SMARTer2030 report [3]. ICT has the potential to enable a 20% reduction of global CO_2 equivalent emissions by 2030, holding emissions at 2015 levels [3]. The application of ICT-enabled solutions is going to provide residents with greater insight and control, and an enhanced living experience whilst saving energy and resources. However, the application of novel ICT technologies for energy efficiency has also to rely on people adjusting their energy consumption behavior. As stated in the report of European Environment Agency [4], up to 20% of energy savings can be achieved through different measures targeting consumer behavior.

In this article, ENTROPY, an energy-aware IT ecosystem is detailed. ENTROPY aims to support energy efficiency in the buildings sector through behavioral change of the occupants with regards to their daily energy consumption patterns [5]. The main distinguishing characteristic of ENTROPY is that it exploits the advantages provided by a set of novel ICT technologies for enabling the design, development and provision of personalized energy management and awareness services in smart buildings. The philosophy of the proposed approach is based on the provision of personalized services that can lead to behavioral change through energy consumption awareness and motives provided to occupants based on their behavioral profile.

The main adopted ICT technologies include Internet of Things (IoT), information fusion, semantic web, rule-based recommendations, big data mining, and analysis mechanisms. Novel IoT node configuration, networking, and efficient data aggregation mechanisms, including mobile crowd-sensing mechanisms, are applied for the interconnection of any type of sensor (e.g., low-cost sensors such as Arduino and Raspberry Pi), a collection of data, and the application of data quality enhancement mechanisms (e.g., removal of outliers, fix missing values in time-series data). Information processing, semantic mapping, and fusion mechanisms are applied for representing the collected data in a unified way, boosting in this way their exploitability and interoperability with existing services, as well as their interlinking with available data. Recommendation mechanisms are applied for real-time reasoning over the available data and provision of suggestions for personalized actions that can lead to improving energy efficiency through behavioral change. Big data mining and analysis mechanisms are also supported for producing behavioral and energy consumption analytics, targeting at providing advanced insights and increasing the energy-awareness level of end users.

All the aforementioned technologies are supported through an integrated IT ecosystem that comprises the basis for the consumption of existing services, as well as the design and development of further energy management and awareness services, personalized mobile applications, and serious games.

The structure of the paper is as follows: In Section 2, the overall architectural approach for the design of the energy-aware IT ecosystem is provided, including subsections for the description of the IoT nodes management and aggregation mechanisms, the description of the two designed semantic models for representing energy management and occupants' behavioral concepts, and the description of the set of services provided to end users, namely, the personalized recommendations services, the data mining and analysis services, and the set of APIs for the development of personalized mobile applications and serious games. Following this, in Section 3, initial results based on the deployment of the proposed IT ecosystem at the University of Murcia in Spain and the realization of an energy efficiency campaign are presented, while Section 4 provides a set of conclusions and identifies open issues for future research.

2. Energy-Aware IT Ecosystem Architectural Approach

Prior to delving into the description of the ENTROPY energy-aware IT ecosystem architectural approach, the type of users that interact with the ecosystem along with a concise overview of an indicative workflow for realizing an energy efficiency campaign is provided. Two types of users are considered in ENTROPY, namely, campaign managers and end users. Campaign managers are responsible for setting up an energy efficiency campaign and may consist of smart buildings administrators, energy efficiency experts, data scientists and behavioral scientists. The combination of knowledge, with regard to energy efficiency, data science, and behavioral aspects, is considered necessary towards the setup of sensor data monitoring, data analysis, and personalized recommendation delivery processes considering the infrastructure in the smart buildings and the type of users engaged in the campaign. End users regard the set of users participating in the campaign and they may consist of citizens, students, academic personnel, employees in enterprises, etc.

The basic steps followed by campaign managers for initiating and running an energy efficiency campaign are depicted in Figure 1. Upon registration to the ENTROPY ecosystem, a campaign manager obtains access to the ENTROPY services and is able to define the set of buildings taking place in the campaign, along with their division in subareas. For each area or subarea, a set of characteristics related to the surface, the working hours, the capacity in number of people, the location, the energy class of the building, etc., are provided. The next steps regarding the assignment of sensors per area or subarea and the configuration of the set of sensor data monitoring streams that have to be activated. Based on these, a set of data queries can be designed through a query design editor, the results of which are being used as input for data mining and analysis processes. The latter also have to be specified including information regarding the algorithm to be executed and the type of input and output data. Following this, the campaign can be initiated through the activation of the sensor data monitoring streams and the initiation of interaction with the end users. Continuous monitoring, evaluation and undertaking of corrective actions can be realized by the campaign administrator. It should be noted that the aforementioned steps do not need to be followed in a strict sequential way, depending on the specificities of each campaign.

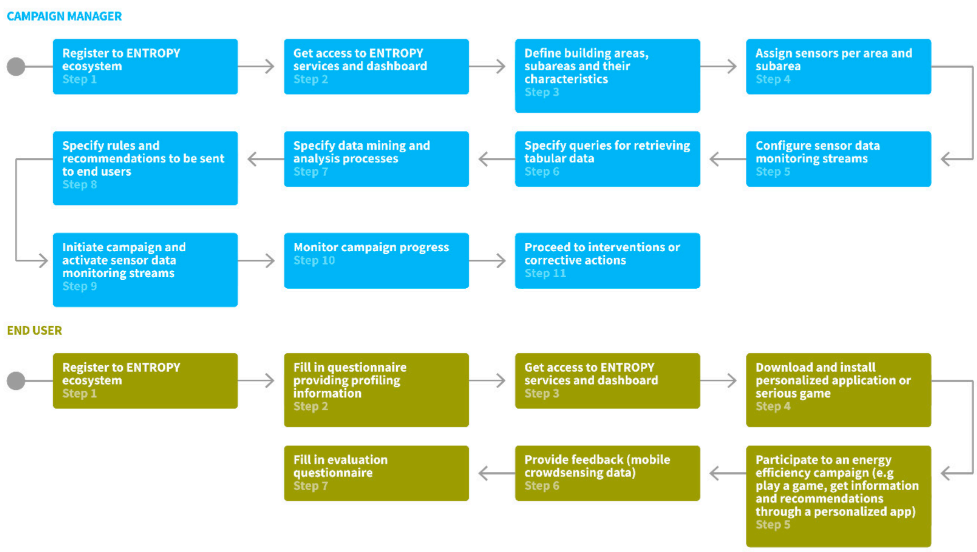


Figure 1. ENTROPY users and basic platform usage workflow.

The basic steps followed by end users for participating at an energy efficiency campaign are also depicted in Figure 1. Upon registration to the ENTROPY ecosystem, the end user has to fill in a questionnaire targeted at providing a user profile with regards to the type of employee personality, work engagement, energy conservation habits, and game interaction preferences. Following, the end user gets access to the ENTROPY services and is able to install and run ENTROPY mobile applications and serious games and, thus, participate to an energy efficiency campaign. Through the ENTROPY applications, the end user gets information regarding energy consumption, as well as environmental parameters in the areas that he has activities, receives personalized recommendations and requests for action while he is also able to provide feedback to the ENTROPY platform (e.g., information regarding malfunctioning of equipment). At the end of an energy efficiency campaign, the end user is requested to fill in an evaluation questionnaire, targeting at measuring perception of behavioral change, as well as any changes with regards to their gaming profile.

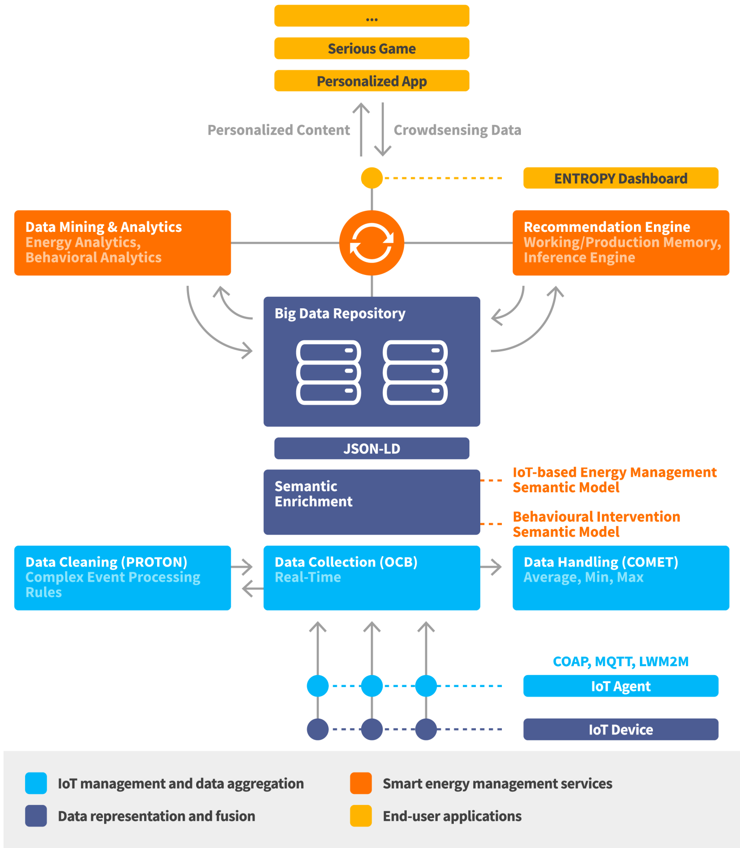


Figure 2. Energy-aware IT ecosystem architectural approach.

A high-level view of the ENTROPY energy-aware IT ecosystem architectural approach is provided at Figure 2. As depicted, a layered architecture is followed with discrete layers for IoT management and data aggregation, data representation and fusion, smart energy management services and end user applications. The IoT management and data aggregation layer is responsible for IoT nodes registration, management and data aggregation and cleaning functionalities at the edge part of the infrastructure. The data representation and fusion layer is responsible for representing the collected data based on a set of defined semantic models as well as supporting a set of data fusion mechanisms over active data streams. The smart energy management services layer is responsible for providing advanced analytics and recommendations to end users, as well as incorporating learning techniques for continuously exploiting the produced output by each service. The end user applications layer is responsible for the design of personalized mobile applications and web-based serious games able to take advantage of the set of services provided by the lower layers. Following this, detailed information is provided for the designed and implemented mechanisms per layer.

2.1. Internet of Things Node Management and Data Aggregation

The mechanisms designed for the IoT management and data aggregation layer follow an edge computing approach. Edge computing facilitates the processing of information, where required, in the logical extremes of a network, improving in this way the performance and efficiency of applications in terms of usage of resources. It should be noted that the design of energy and information management systems is considered one of the main application areas that combine IoT and edge computing technologies [6,7]. The set of mechanisms support the easy registration, configuration and lightweight management of the infrastructure sensors deployed in the target buildings and a set of data aggregation, pre-processing and cleaning functionalities. The design and development of such mechanisms is based on the adoption and extension of a set of cloud-based open enablers, provided by the European platform for Future Internet FIWARE [8]. These enablers are orchestrated together by means of lightweight RESTful Application Programming Interfaces (APIs) according to the Open Mobile Alliance Next Generation Service Interface (NGSI) 9–10 standard [9].

In the provided approach, a set of different enablers provided by the FIWARE platform may be used, given that we are based on decoupled and self-contained modules. Data access and processing mechanisms can be designed in a future-proof way, given that the NGSI standard intends to provide a uniform cross-domain interface for advanced data access and processing. Since FIWARE enablers are compliant with such an interface, this facilitates the interoperability of FIWARE solutions with other architectures avoiding a silo-effect and making FIWARE an open solution that can be easily adopted by private and public stakeholders.

It should be noted that a set of initiatives and approaches are using FIWARE enablers in various domains. Indicatively, the Global Services Mobile Alliance (GSMA) has defined a generalized architecture for the delivery of "Internet of Things" "Big Data" services to support an ecosystem of third-party application developers [10]. Within this architectural approach, the FIWARE NGSIv2 interface has been specified as the recommended standard for certain interfaces, while a set of FIWARE enablers are used for supporting specific functionalities, including the data and control broker. In [11], a system architecture for achieving world-wide semantic interoperability solution is presented, combining the NGSI, which is part of the core of the FIWARE initiative, and oneM2M context interfaces. In [12], a semantic mechanism to integrate data from different types of devices by using FIWARE components is presented, while, in a more functional domain, and [13] made use of certain enablers, like the ORION context broker, to create a cloud-based gesture recognition application. Furthermore, in [14] it is described a sensor management system for seaports based on the FIWARE platform, while in [15] a novel patient monitoring system based on FIWARE enablers is proposed. Following the existing works on a set of diverse domains, the proposed work in this manuscript in one of the first efforts to make use of FIWARE enablers in the energy management in smart buildings domain and, thus, in the energy domain in general.

Regarding the usage of the FIWARE enablers in the ENTROPY ecosystem, the first step regards the registration of the sensor nodes and the collection of sensor data in real-time. The FIWARE enabler called IoT Agent is used for this purpose [16]. The IoT Agent acts as a gateway for hardware devices. It supports a set of communication protocols (e.g., Constrained Application Protocol (COAP), MQ Telemetry Transport (MQTT), Lightweight Machine-to-Machine (LWM2M)) for establishing connectivity with the sensor nodes and retrieving data in real-time.

The way that this data is stored and managed is tackled by another FIWARE enabler called Orion Context Broker (OCB) [17]. OCB supports the creation of real or virtual elements of interest by using the term "entities". Each entity is considered as a virtual sensor node that can obtain data from infrastructure sensor nodes. In the ENTROPY ecosystem, an information model comprising one entity per type of infrastructure sensor has been defined, facilitating the collection of data for all the registered sensor nodes in a homogeneous way. For instance, for collecting energy consumption data, an entity type named "energy_sensor" representing an energy meter installed in the considered building is created. Each entity includes the set of attributes monitored by the infrastructure sensor nodes along with metadata regarding the location of the sensor and the timestamp of each observation.

Following, a sensor data cleaning process takes place for improving the overall data quality through the usage of the FIWARE Complex Event Processing (CEP) enabler called PROTON [18]. CEP focuses on timely processing streams of information items, so-called events, like filtering or aggregation by means of predefined rules following the event-condition-action paradigm [19]. A filtering mechanism is implemented that discards extreme outliers of the different attributes that a sensor measurement contains, avoiding the further transmission of erroneous data. Specifically, a first set of CEP rules focus on calculating certain statistical features of each sensor's attribute stream (e.g., first, third, and inter-quartile values) over a particular time window. Next, a second set of CEP rules is applied for each new sensor observation, discarding it in case it is considered as an outlier based on the previously defined statistical features.

Given the existence of high quality data, the COMET FIWARE enabler is used for supporting access to historic time series data [20]. COMET adheres to the same information models as the OCB enabler that gets the real-time data, thus, it does not require any further data harmonization process. It incorporates several built-in simple aggregation functions over the historic sensor data (e.g., provide sum, minimum, or maximum values). Access to such data is considered very helpful for realizing comparisons, providing input to data mining and analysis processes as well as describing rules that can lead to personalized recommendations.

2.2. Semantic Representation Models and Data Fusion

Upon making the collected data available through the IoT management and aggregation layer, sensor data streams towards the ENTROPY platform can be activated. Sensor data streams may regard real-time data or aggregated data. For each of the activated data streams, the collected data is mapped to the ENTROPY semantic models [21,22], as detailed in the following subsections, and then stored in the big data repository that is based on MongoDB. The semantic enrichment module is integrated with the ENTROPY platform and operates as an intermediate layer between data coming from FIWARE and the ENTROPY platform (user interface and REST-API) and the MongoDB. Upon the activation of a new sensor data stream, the end user is responsible to denote the mapping between the monitored sensor metric with the relevant parameter in the semantic model, as depicted in Figure 3. Following this, the collected data is stored based on the semantic model denoted parameter, supporting the unified access to the collected data.

The semantic models provide a set of advantages in terms of management and exploitation of the collected data. Through the representation of the main concepts and their relations and the mapping of the data into these concepts, unified data representation and data access mechanisms are designed and implemented. Exchange and reuse of data are also facilitated, especially following the evolving open and linked data principles. By exploiting the plethora of existing linked data tools, interlinking of data collected via the sensor data streams with available open or privately-owned data can be realized. Within ENTROPY, interconnection with the LinDA workbench [23] is realized, that is a complete open-source package of enterprise linked data tools to quickly map and publish your data in the linked data format, interlink them with other public or private data, analyze them, and create visualizations. Such functionalities for data interconnection, exchange and reuse are considered crucial for energy data in the buildings sector for realizing comparisons among data collected via similar campaigns in different regions, as well as setting up target values for energy efficiency. Interconnection of energy data with other environmental monitoring parameters provided as open data by meteorological authorities or socioeconomic data made available by national or international statistics authorities can be also achieved (e.g., similar to the study realized in [24]), leading to advanced analysis and insights without requiring too much data management effort on behalf of the data scientists. Furthermore, through the semantically-represented data, reasoning mechanisms may be applied by taking advantage of the denoted semantics and leading to advanced insights or recommendations, as they are detailed in Section 2.3.1. Finally, linked data analytics can be produced considering the representation of a data mining and analysis process in the semantic models and the interlinking of the input and output datasets of an analysis. The enriched datasets can be exploited in a twofold way. On one hand, they can be used by data scientists for analysis results comparison purposes, while on the other hand, they can be used for defining set of rules for producing recommendations considering the analysis results.

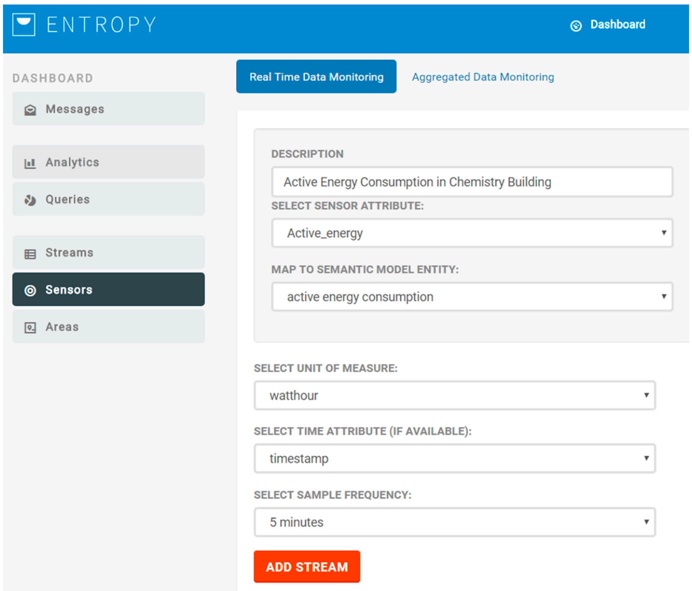


Figure 3. Sensor data stream configuration.

As already mentioned, data is stored in a MongoDB database that is a NoSQL database. Such a choice is made mainly by taking into account the supported load balancing and sharding characteristics. In order to support the storage of data without losing their expressivity in terms of their mapping to the semantic models and in parallel ensure high-performance characteristics during data management and reasoning processes, data is stored in JSON-LD format that stands for JavaScript Object Notation for Linked Data. JSON-LD is a method of encoding linked data using JSON. It is considered as an ideal data format for programming environments, REST web services, and unstructured databases, such as MongoDB. Using MongoDB and JSON-LD together is considered optimal in cases that combination of efficient representation schemes along with efficient data retrieval mechanisms has to be realized. Actually, JSON-LD was created for developers who are working with data and it showcases the power of linked data without having to go through the somewhat steep learning curve that the semantic web usually has. JSON-LD facilitates publishing data through APIs while it splits the representation layer (HTML) from the semantic layer (JSON-LD), characteristics that are not supported through other formats (e.g., Resource Description Framework—RDF). Finally, the representation of the data in JSON-LD format enables the design and implementation of reasoning mechanisms that overcome the performance limitations of ontology-based reasoning through the processing of SPARQL rules. Such an approach has been adopted in the presented IT ecosystem, through the adoption of Drools for semantic reasoning purposes over JSON-LD-represented data.

2.2.1. IoT-Based Energy Management Semantic Model

The IoT-based Energy Management semantic model (IoT-Energy) [21,22] aims to represent the set of concepts related to the support of energy efficiency in smart buildings (Figure 4). It includes conceptualization of the buildings, their structure, the deployed sensor networking infrastructure, the activation of sets of sensor data streams, as well as the realization of analysis over the collected sensor data. IoT-Energy inherits and builds upon well-known ontologies, such as the Friends of a Friend (FoaF), the Smart Appliances REFerence (SAREF), the Semantic Sensor Network (SSN), and the Linked Data Analytics Ontology (LDAO) [22,23].

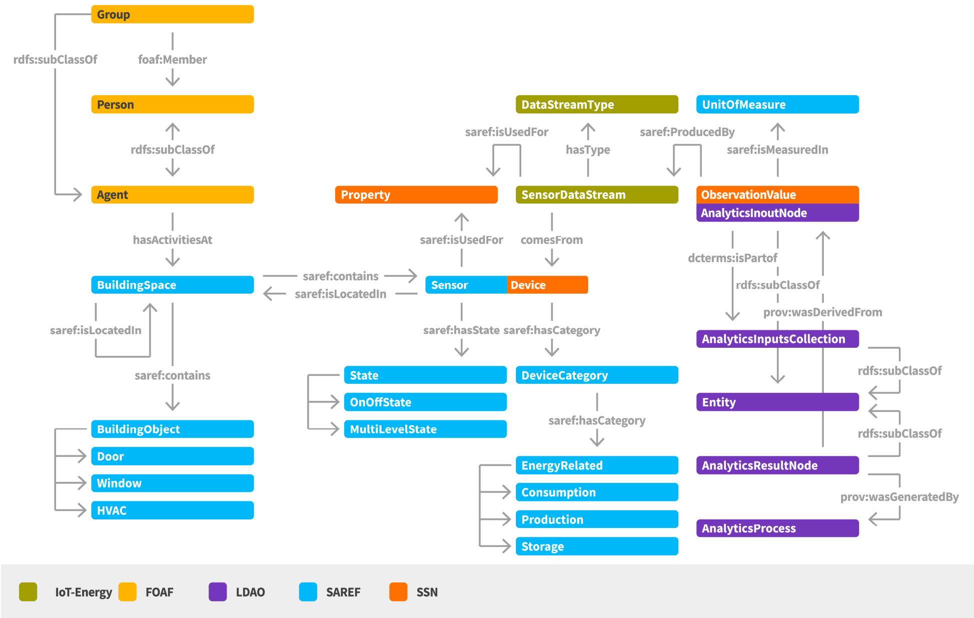


Figure 4. IoT-based energy management semantic model.

A main entity regards the *BuildingSpace* that represents any space in the building. A *BuildingSpace* may be located in another *BuildingSpace*, supporting in this way a hierarchy of building spaces. A set of *Persons* or *Groups* may have activities at a *BuildingSpace*, information that is highly helpful for providing personalized content and recommendations to the associated persons per location.

A *BuildingSpace* contains *BuildingObjects* and *Sensors/Devices*. By *BuildingObjects* we refer to objects that exist within the building space (e.g., door, window, projector, heating, ventilation and air conditioning (HVAC) device) and may be used for realizing an action (e.g., in case of an object of type "window", send a recommendation for closing the window). By *Sensor/Device* we refer to any sensor node able to provide data upon getting measurements for a specific parameter, denoted as *ObservedProperty* in the semantic model. Each *Sensor/Device* has a category type that in case of energy related sensors can be related with the monitoring of consumption, production or storage of energy.

Another basic concept that is introduced by IoT-Energy is the sensor data stream, denoted as *DataStream*. A *DataStream* generates *ObservationValues* for a specific *ObservedProperty* of a *Device/Sensor*. Different types of *DataStreams* may be activated for providing real-time or aggregated data.

For supporting the representation of data mining and analysis processes and the relations among the provided input and output data, concepts from the Linked Data Analytics Ontology (LDAO) are inherited [23]. Each *ObservationValue* is considered as an *AnalyticInputNode*. A set of *AnalyticInputNodes* are used as an *AnalyticInputCollection* for the realization of an *AnalyticProcess* and the production of *AnalyticResultNodes*.

2.2.2. Behavioral Intervention Semantic Model

The Behavioral Intervention Semantic Model (EBIO) [21,22] aims to represent a set of concepts related to the behavioral profile of occupants in smart buildings and, thus, to facilitate the categorization of users in specific profiles and the provision of personalized content and recommendations for achieving behavioral change (Figure 5). The main concepts represented in EBIO regard the *Agent* and the *Recommendation*.

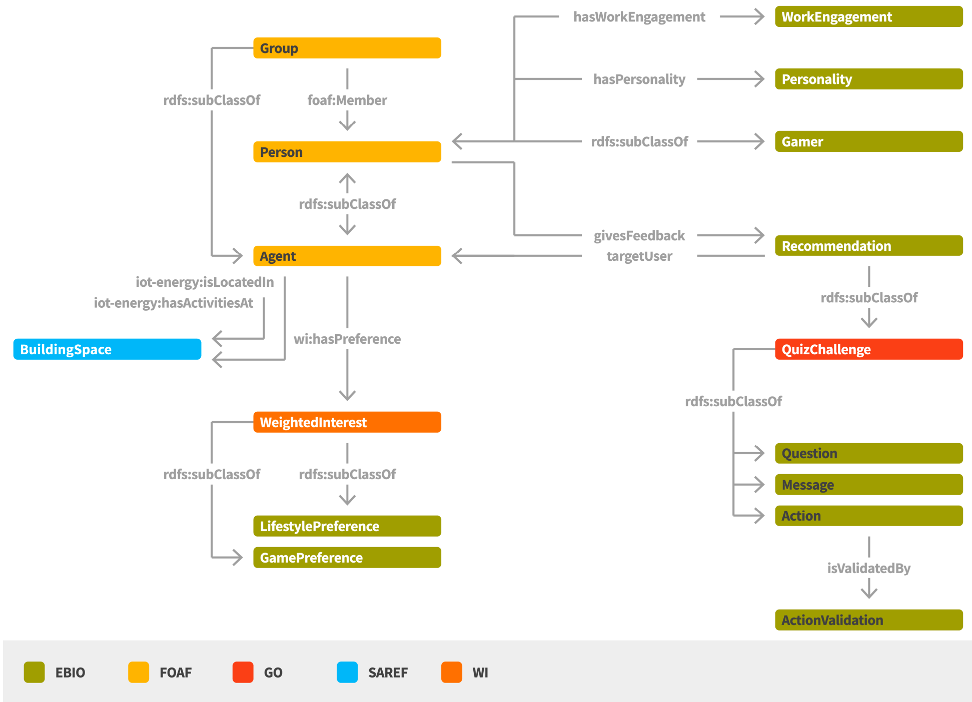


Figure 5. Behavioral intervention semantic model.

An *Agent* can be a *Person* or a *Group* where personalized recommendations can be sent. A *Person* has a "Personality" profile for denoting personality traits (e.g., extraversion, agreeableness, conscientiousness, emotional stability, openness to experiences). *WorkEngagement* characteristics can be also associated with a *Person*, mainly by providing indications with regards to the positive work-related state of fulfilment that is characterized by vigor, dedication, and absorption. A *Person* can be also be classified with regards to its gaming preferences, classification that can be proven very useful for providing the suitable content and application interaction mode (e.g., socializer, free spirit, achiever, disruptor). A *Person* may also have a set of interests denoted as *WeightedInterests* that may regard, among others, its game preferences (e.g., rewards, badges, points, levels) or lifestyle preferences.

Different types of *Recommendations* can be provided to *Persons* targeting at their behavioral change. Such *Recommendations* can have the form of a *Message*, a *QuizChallenge*, an *Action* or a *Question*. An *Action* is associated with an activity or a series of activities whose result contributes to elimination of a certain energy waste cause. A *Question* can be posed to a group of people, leading to the collection of crowd-sensing feedback (e.g., information regarding their comfort level). It should be noted that in the context of ENTROPY, the *Group* concept represents a group of users that share a common characteristic (e.g., tendency to sacrifice comfort for energy efficiency). A user can give a positive or negative *Feedback* to a *Recommendation* that is later utilized for the generation of new personalized recommendations.

2.3. Intelligent Energy Management and Awareness Services

Based on the semantically-mapped storage of the collected data in the ENTROPY big data repository, and through the definition of a set of REST APIs, various services can be designed and provided through the ENTROPY platform. Such services include the recommendation engine for providing personalized recommendations to end users, as well as the data mining and analysis mechanisms for providing behavioral and energy analytics. It should be noted that these mechanisms work in a complementary fashion, since produced output from an analysis process can trigger the provision of a new recommendation. Similarly, the feedback provided by end users based on the consumption of recommendations can lead to analysis and classification of end users in specific personality or gamer types.

2.3.1. Recommendation Engine

The recommendation engine is responsible for providing context-aware and personalized recommendations taking into account the occupants' behavioral profiles. It is implemented based on Drools, a rules-based management system [25]. It consists of the working memory, where facts are introduced based on the provided data, the production memory, where the set of defined rules are available, and an inference engine that supports reasoning and conflict resolution, as well as triggering of the appropriate recommendations (see Figure 6).

Triggering of recommendations follows a continuous match-resolve-act approach. Specifically, the match phase regards the mapping of the set of applied rules which are satisfied based on the available data, the resolve phase regards the process of conflict resolution, if any, among the satisfied rules, while the act phase regards the triggering of the recommendations towards the group of the target users. Rules are mostly related with the identification of context change, especially with regards to the location of the end users or changes in the observed values in the activated data streams.

A rule consists of a condition element and a recommendation template in the action part, which connects a context change with specific target user group criteria. When a rule is fired due to a context change (e.g., when average CO_2 measurement within an hour exceeds the defined threshold), the recommendation engine selects the set of target users based on the defined user attribute filters (e.g., players who have activities at a certain location, users that are classified as highly responsive at the proposed actions through the personalized recommendations, users that satisfy specific behavioral criteria) and creates a personalized recommendation for each of them by using the defined recommendation template. Following this, the set of recommendations are published in a publish/subscribe framework and made available for consumption by the set of personalized applications and serious games.

A produced recommendation contains the target user, the related content, the measurement attributes that are involved in the creation of the recommendation, the possible reward for the completion of the recommendation, as well as the validation method for it. The attributes involved in the creation of the recommendation is provided for gamification purposes, since different measurements may work towards earning different rewards (e.g., the points earned from completing a task regarding CO_2 may have an impact on earning a so called "Refresher Badge"). The rewards are registered to a user upon the completion and validation of a recommendation, which differs per type of recommendation. For instance, an action may be validated by checking the status of the sensors on the involved building objects (e.g., a window), while the validation of a quiz is done inherently by answering all the questions. A set of indicative recommendations are provided in Figure 7.

It should be noted that reasoning mechanisms are applied based on the designed ENTROPY semantic models. An implementation of a reasoning business logic is realized based on Drools, mainly for exploiting the high performance and scalability characteristics of Drools-based systems, compared to ontology-based reasoning [26], as well as the separation of the rules-definition business logic from the core ENTROPY functionalities. Campaign managers are able to define and update or extend the set of rules applied for inference purposes in a dynamic way, compared to static approaches realized in ontology-based reasoning, while rules declaration can be realized in a non-technical way in order to be understandable to people that are not domain experts [27]. In this way, both performance and rules definition complexity aspects are tackled.

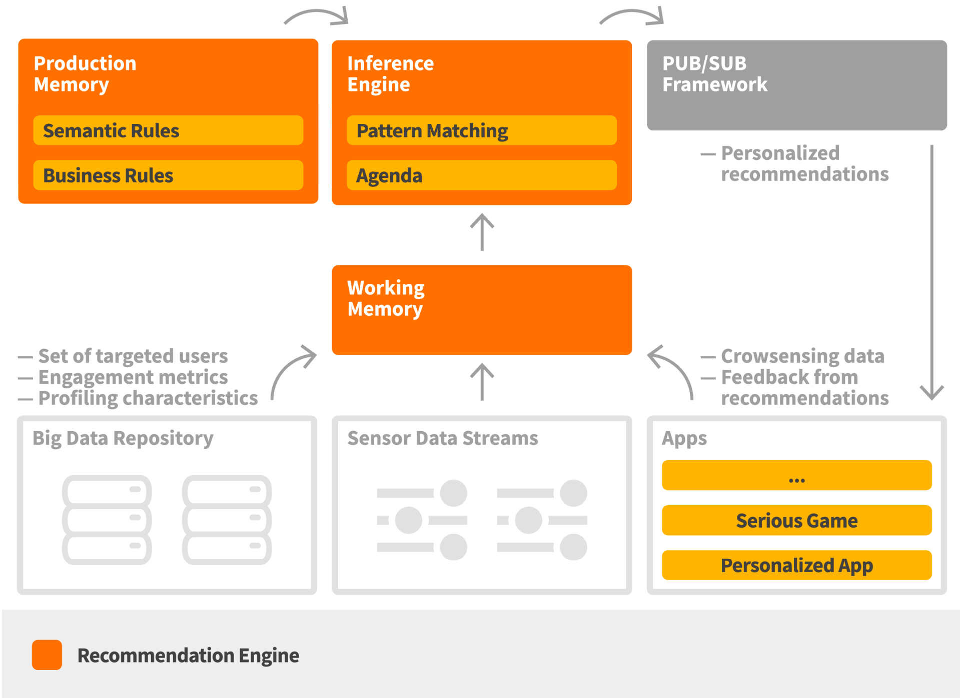


Figure 6. Recommendation engine workflow.

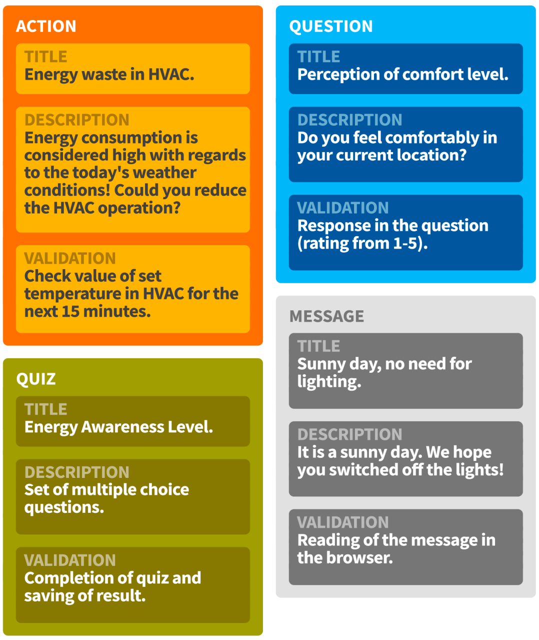


Figure 7. Indicative recommendations.

However, given that an OWL implementation offers advantages in terms of rules expressiveness as well as exploitation of the semantic properties of a semantic model, the development of a module is realized, denoting set of rules in Drools native rule language (DRL) able to support the set of semantic properties. It should be noted that the examination of such a solution was also suggested by existing performance evaluation studies comparing Drools and ontology-based reasoning [28]. In more detail, dynamic production of new knowledge is supported through the execution of specific rules that are responsible to produce reasoning on the fly. These rules are able to perform class transitiveness (i.e., if a base-class belongs to a class that has also a parental class, then the new knowledge is the fact that the base-class belongs also to the parental class), supertype inheritance (i.e., if there is an instance of class that has a parental class then the new knowledge is the fact that a replica of the same instance instantiates the parental class), property transitiveness and sub-property transitiveness. The inference business logic is implemented using the first-order logic capabilities of the Drools engine instead of relying on third-party reasoners, enhancing a significant amount of the overall system efficiency.

Drools-based reasoning mechanisms are also considering a set of axioms that are denoted throughout the usage of the platform for declaring advanced relationships that are observed. For instance, given that by the interpretation of a first set of questionnaires results, it is denoted that humanitarian-oriented persons show a preference for badges and roles in the used mobile applications, we can define a class axiom in OWL Manchester syntax such as "(hasPreference value Badge and hasPreference value Role) subClassOf Humanitarian". Such an axiom is included in the real-time reasoning process, leading to production of the relevant knowledge each time the axiom description is validated.

2.3.2. Data Mining and Analysis Services

Another service that is implemented and provided within the ENTROPY platform regards the support of a set of big data mining and analysis techniques towards the extraction of energy and behavioral analytics. Insights provided with regards to the energy usage in smart buildings, as well as the behavioral characteristics of the occupants, may lead on one hand on increase of their energy awareness and on the other hand on targeted recommendations for reducing energy consumption.

The supported set of analytics processes concerns descriptive, predictive, classification, clustering, and prescriptive analytics [5,29]. Descriptive analytics are providing summary information regarding the energy usage, as well as other environmental or behavioral attributes. Predictive analytics are providing estimates for usage of energy the upcoming period, as well as examining the relationship among energy consumption and set of parameters, such as average temperature, heating or cooling degree days, day of the week, etc. The considered algorithms include linear regression, multiple linear regression, support vector regression, and principal component analysis. Classification and clustering analytics are applied for identifying or classifying collective behaviors among the involved users. Based on the identification of groups, targeted interventions may be planned, while the produced groups may be also considered as input towards a group-aware forecasting analysis. The considered algorithms include artificial neural networks, Bayesian regularized neural networks, random forest, k-means, density-based spatial clustering, and hierarchical clustering. Prescriptive analytics are applied for combining analytics results with automation solutions considering the interplay among energy efficiency and comfort level of occupants.

The workflow followed for the support of data mining and analysis techniques is depicted in Figure 8. An analysis process is based on the selection of an analysis template and the selection of the queries to be executed for providing the input datasets (training and/or evaluation datasets). Each analysis template represents a specific algorithm and provides to the user the flexibility to adjust the relevant configuration parameters. Such parameters include input parameters for the algorithm along with their description and their default value, as well as output parameters along with their type (text, image, data, html). An indicative analysis template for the calculation of heating or cooling degree days per day [30] for a monthly period is depicted in Figure 9. A set of analysis templates can be made available and be used for initiating an analysis. It should be noted that an analysis process is also associated with a set of execution parameters that denote whether an analysis should be realized in a manual or automated way, as well as the periodicity factor for the latter case.

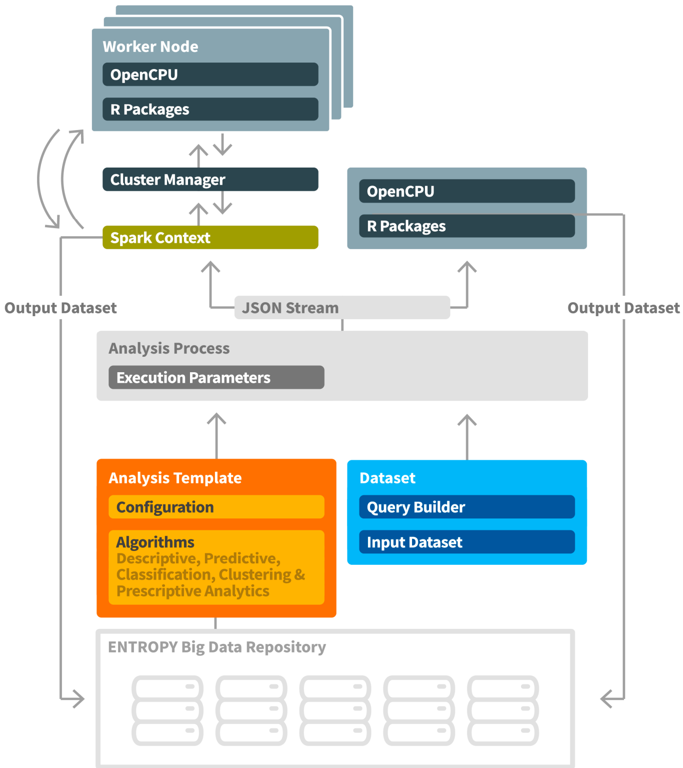


Figure 8. Data mining and analysis workflow.

The design of queries for obtaining the input datasets for the analysis is based on the development of a query builder over MongoDB, facilitating end users to easily prepare their input datasets. Two categories of queries are supported, namely queries for fetching data collected by sensor data streams (e.g., energy consumption, humidity, and indoor temperature data per hour for a specific room) and queries for fetching data related to the set of users participating at the energy efficiency campaign (e.g., a set of users with an educational level relevant to a Master's degree). An indicative query for getting the average power consumption and the external temperature per hour is depicted in Figure 10. Upon the execution of the queries, streams of the input training or evaluation datasets are provided to the analysis toolkits.

In ENTROPY, the R Project for Statistical Computing [31], and the Apache Spark fast and general engine for large-scale data processing [32] are used for this purpose. Depending on the analysis needs in terms of big data management and performance aspects, the optimal tool per case may be selected. Interconnection of the ENTROPY components with the analysis toolkits is based on the OpenCPU system for embedded scientific computing that provides a reliable and interoperable HTTP API for data analysis based on R. In the case of large-scale data processing and the need for a big data analysis framework, the Apache Spark engine is used, where the analysis process is realized in a set of worker nodes, each one of which is hosting an Apache Spark OpenCPU Executor [33]. The set of worker nodes are formulating a cluster orchestrated by a cluster manager.

Upon the realization of an analysis, the produced results (output dataset) are also made available through a set of URLs providing access to the set of results, as defined in the output parameters of the analysis template. It should be noted that analysis results are also semantically mapped to the ENTROPY semantic models, based on the adoption of the LDAO ontology, as mentioned in the previous section.

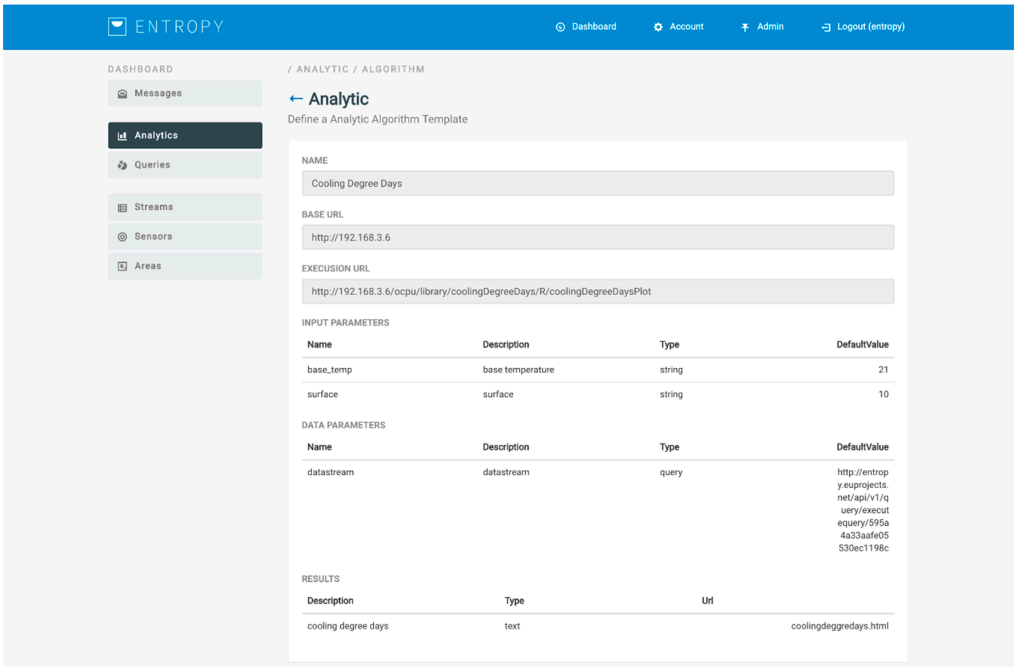


Figure 9. Indicative algorithm analysis template.

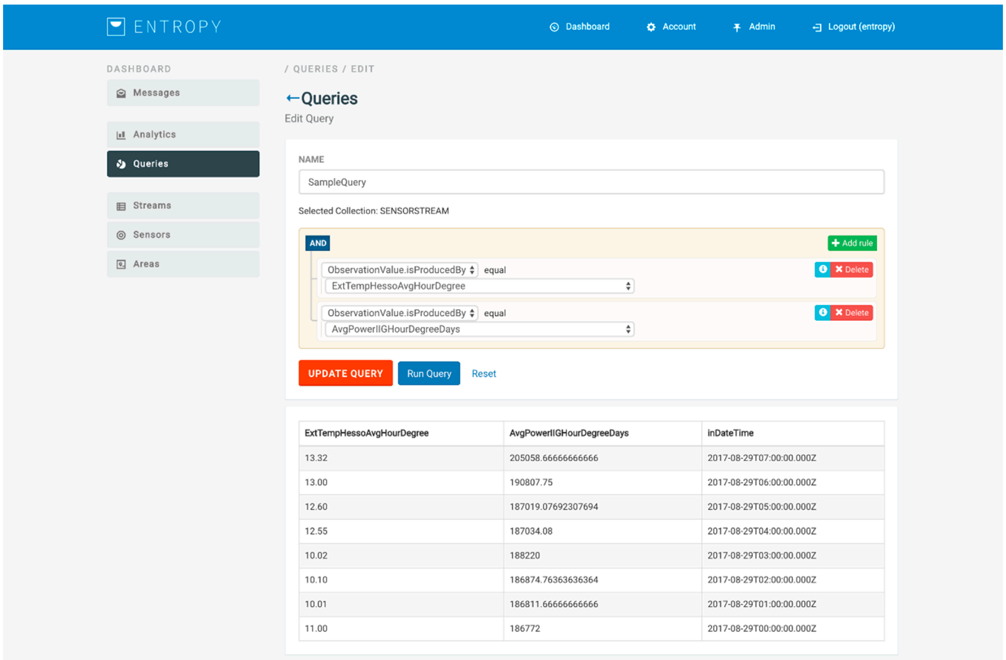


Figure 10. Indicative query design through the query builder.

At the current phase, a set of initial algorithms are considered, however, the overall implementation facilitates the incremental addition of further analysis mechanisms.

2.3.3. Personalized Applications and Serious Games Development

In addition to the set of intelligent energy management and awareness services supported by the ENTROPY IT ecosystem, the development of mobile applications is facilitated. Given the unified representation of data through the semantic models independently of the underlying sensor infrastructure, as well as the design and implementation of set of REST APIs for accessing and storing data to the big data repository, personalized applications and serious games development is enabled, while their applicability may regard various smart building cases. Such APIs include, among others, the provision of information for the available building spaces and their energy consumption profiles, the activated sensor data streams, latest data per sensor data stream, the recommendations provided per user along with the collected feedback, the set of actions that may be requested to be realized by an end user, the execution of queries, user demographic data, functionalities for user registration, authentication and login in the IT ecosystem, initialization and update of the user profile per application, as well as the retrieval of the top users per application. An overview of the developed APIs along with the associated input and output parameters is provided at Figure 11. In each case, the set of GET or POST body parameters, the headers and the type of the response are specified, as detailed in [34]. The aforementioned functionalities can be proven beneficial towards the development of smart applications that can combine energy and behavioral data, along with the services provided by the ENTROPY IT ecosystem, and lead to the improvement of energy efficiency in smart buildings.

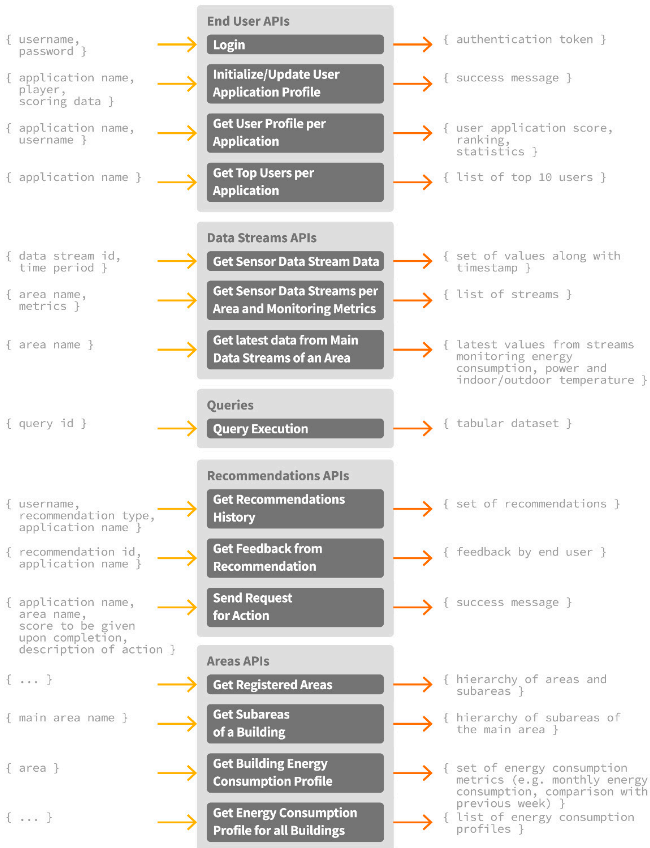


Figure 11. ENTROPY API overview.

3. Improving Energy Efficiency at the University of Murcia

One of the pilot cases where the ENTROPY IT ecosystem is instantiated is at the University of Murcia in Spain. The pilot regards an energy efficiency campaign at three cases, namely the Faculty of Chemistry and two multi-disciplinary research centers. In each of these cases, a set of infrastructure sensors and actuators have been installed to capture energy-related, as well as environmental data. The three cases comprise of 25 energy smart meters and 190 HVACs monitoring energy consumption and temperature in various building spaces, ranging from a room or corridor level to the overall building.

The targeted users regard students, professors and the administrative staff. While students' behavioral changes are tackled on the shared labs as a group, every professor has their own office, and so personal actions might be carried out. Contrary to the other two groups, the administrative staff is required to register when they enter or leave their offices by means of personal smart cards providing in this manner data regarding their presence.

Following some preliminary results of the aforementioned campaign for the building of the Faculty of Chemistry are detailed. These results regard the realization of a set of data mining and analysis processes with a twofold objective. On one hand, targeting at the prediction of the energy consumption for the following day and on the other hand targeting at the grouping of the set of considered building spaces based on the usage of the HVAC equipment during the day.

The first part of the analysis is realized per day at evening time and is based on weather forecasting data provided by the Weather Underground API service [35] and energy consumption data of the overall building. The output data regards energy consumption for the following day. The applied algorithms are random forest (RF), support vector regression (SVR), and Bayesian regularized neural network (BRNN), providing the root-mean-square error (RMSE) of the prediction, which varies between 0.4 and 0.6 for the tested algorithms, where $RMSE = \sqrt{\left(\frac{\sum(y_i - \overline{y_i})^2}{n}\right)}$. In Figure 12, the application of the built models to the test dataset is shown for a set of dates, where random forest provides the best results. When normalizing the RMSE by the mean of the real tested values, we obtain the coefficient of variation (CVRMSE). CVRMSE is used to avoid ambiguity when comparing models. In this case it varies between 9.5% (RF) and 12.7% (BRNN), meaning good predictive results. By having accurate predictions regarding the energy consumption, optimal planning of usage of energy can be achieved.

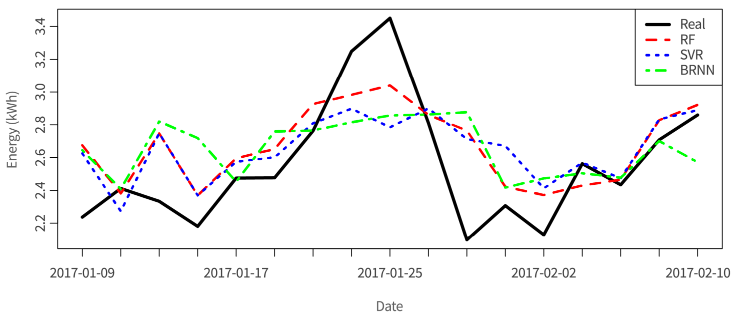


Figure 12. Analysis results: energy consumption prediction based on environmental variables.

In the second part of the analysis, information regarding the usage of the HVACs in a set of building spaces is collected and used for clustering purposes. Based on the cluster where a building space is assigned, targeted recommendations to the users that have activities in this building space may be provided. The information used for clustering purposes regards the state of the HVAC devices (on/off), the indoor and outdoor temperature, as well as the target temperature set. An indicative graph of the outdoor temperature for a weekly period is depicted in Figure 13, as it is produced by the ENTROPY platform, while an indicative figure of the configuration provided for a registration of building spaces and subspaces is also depicted in Figure 14.

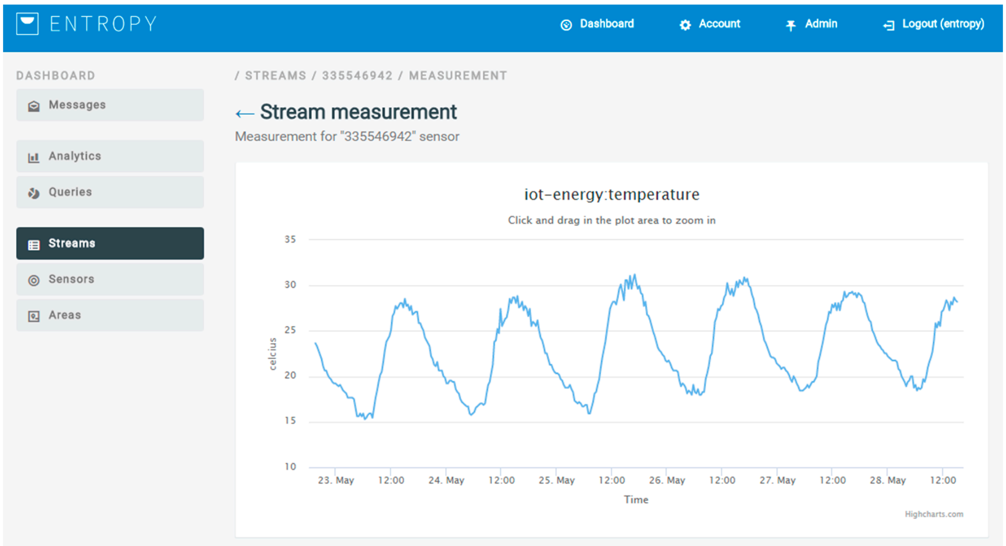


Figure 13. Outdoor temperature at the University of Murcia Campus.

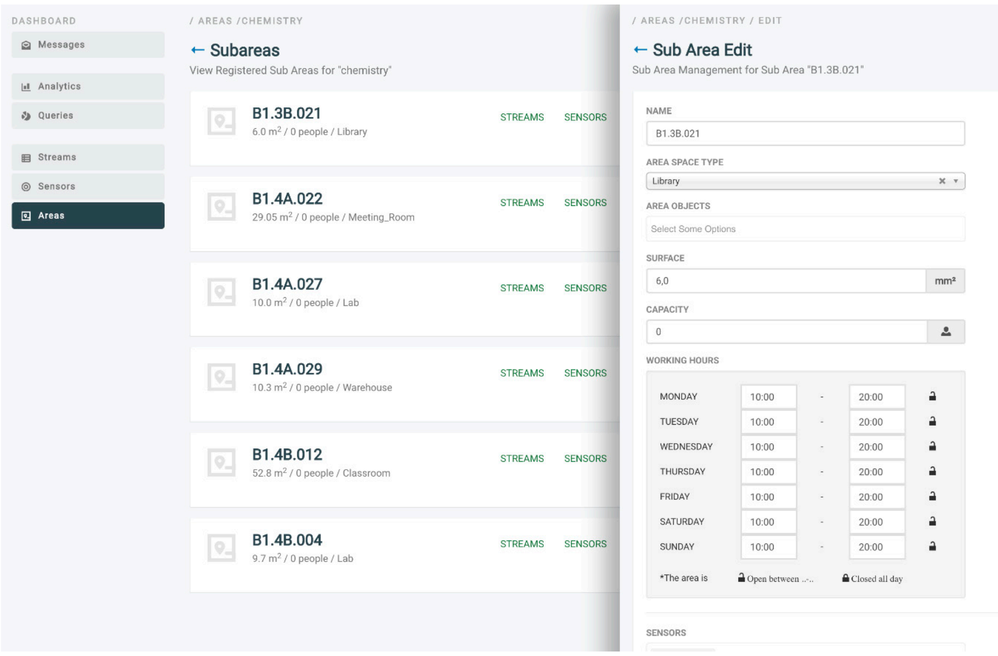


Figure 14. Building space and subspaces registration at the University of Murcia Campus.

The set of algorithms applied for clustering purposes are hierarchical clustering, longitudinal k-means and density-based spatial clustering of applications with noise. In Figure 15, the three trajectories of the HVAC groups that hierarchical clustering identifies for working days of January and February 2017 are colored. Each black line corresponds to the usage graph (percentage of daily active time period) of a single HVAC device through both months. Clusters 1, 2, and 3 regard building spaces with low, intermediate, and high usage patterns, accordingly. Each cluster trajectory line corresponds to the mean daily value of the set of building spaces that belong to the cluster. These clusters can be introduced in the energy consumption model as input variables, since the energy consumption is linearly dependent to the HVAC usage.

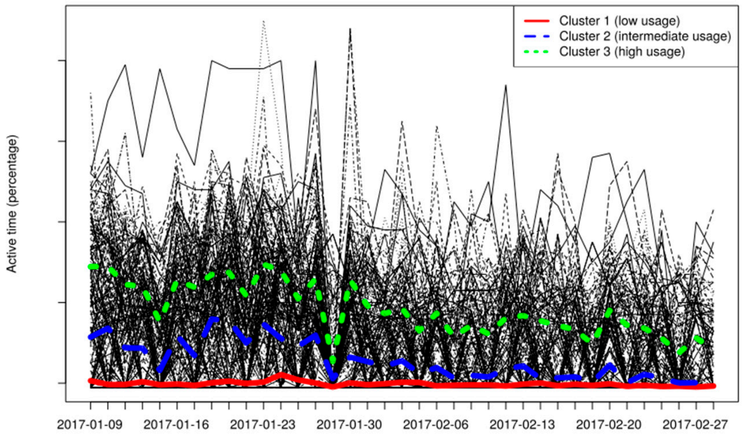
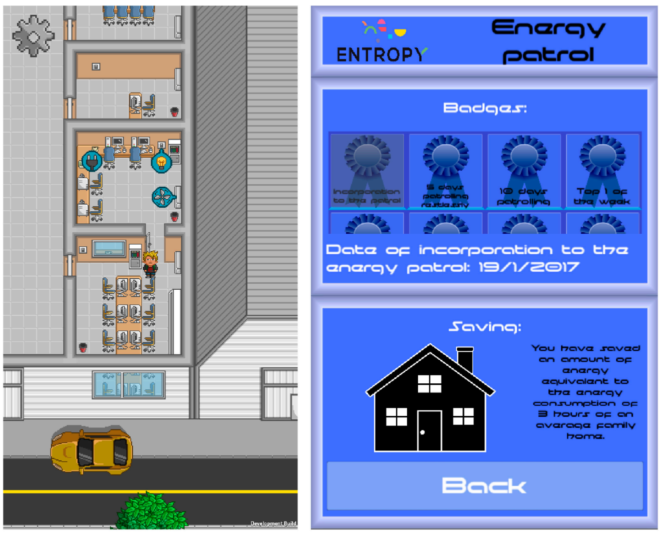


Figure 15. Analysis results: Clustering of building spaces according to their HVAC usage through time (Cluster 1/2/3: red/blue/green line denoting trajectory of set of building spaces with low/intermediate/high usage patterns, accordingly).



(**a**) (**b**)

Figure 16. Screenshots from interactive games: (**a**) My Green Avatar; and (**b**) The Energy Patrol.

For interacting with end users participating in the energy efficiency campaign and providing personalized recommendations, two games have been developed by exploiting the ENTROPY IT ecosystem. Indicative screenshots from these games are depicted in Figure 16. The first game (Figure 16a)—called "My Green Avatar"—allows users within the same building to report their actions to achieve energy savings (e.g., switch-off HVACs, turn off appliances or lights, and the like) by means of their own virtual avatar. Then, such actions are confirmed by analyzing the data streams of the related actuators. The second game (Figure 16b)—called "The Energy Patrol"—provides recommendations to users to undertake specific actions to improve the energy savings of their building like turning off the lights in potentially empty rooms or adjust the temperature of the HVACs to an efficient setting. Such recommendations are provided to end users based on a set of rules defined in the ENTROPY recommendation engine and are consumed in real-time through the deployed publish/subscribe framework. Validation of the successful realization of the proposed actions is also supported, exploiting the mechanisms provided by the recommendation engine.

4. Conclusions

In the current article, a novel IT ecosystem is presented that aims to improve energy efficiency in smart buildings through behavioral change of the occupants, based on the exploitation of emerging ICT technologies.

A set of innovative characteristics of the ENTROPY IT ecosystem are detailed. The set of open and extensible mechanisms for sensors registration, configuration, and sensor data management at the edge or the core part of the infrastructure facilitates the easy adoption of the overall solution and its instantiation in diverse and heterogeneous infrastructure cases. The representation of data based on the specification of energy and behavioral semantic models facilitate the unified access to them by numerous applications and services as well as their interconnection with available open and linked data for further processing. The set of data analysis and recommendation services, designed in a way that they collaborate among each other can lead to targeted recommendations, energy and behavioral analytics, actions and decisions with direct impact on behavioral change of occupants and, thus, energy efficiency increase. Finally, the set of REST APIs provided for consuming the set of available services can boost the design and development of personalized applications and serious games targeted to specific type of buildings with minimal effort.

The detailed IT ecosystem can be applied in diverse cases with minimal configuration effort, the supported energy management and awareness services can be easily consumed while the design and development of further services and mobile applications is highly facilitated through the exploitation of the unified way of representation of the collected data.

Building upon the presented energy-aware IT ecosystem and taking into account the set of initial results produced, several open issues and ideas for extensions are identified. Based on the existing implementation of data mining and analysis services, the design and implementation of a set of data mining and analysis processes stemming from various tools can be realized, leading to advance insights through the processing of energy data. Such tools include the R statistics project, SparkR as a light-weight frontend to use Apache Spark from R, as well as analysis software implemented via other tools (e.g., Python scripts), exploiting the interfaces provided through OpenCPU. With regards to the recommendation engine, extensive performance evaluation results for the usage of Drools for semantic reasoning purposes taking into account the number of introduced rules and the volume of the processed data can be realized, leading to meaningful and exploitable insights for adopting such a solution in energy management solutions as well as other domains. In parallel, collection of feedback for the provided semantic models can lead to extensions or minor modifications of them aiming to serve a wider community and improve data interoperability aspects. Further extensions in the FIWARE enablers can be also implemented and proven beneficial in order to introduce advanced complex event processing rules for improving data quality prior to transmitting and processing them at the centralized infrastructure. Finally, realization of a set of energy efficiency campaigns, part of which are already planned to be realized within the ENTROPY H2020 project, and evaluation of the potential for reducing energy consumption through the usage of the ENTROPY IT ecosystem services has to be achieved combined with a set of dissemination activities for adoption of the ecosystem by a wider community.

Supplementary Materials: The following are available online at http://www.mdpi.com/1424-8220/17/9/2054/s1; Video S1. Introduction to ENTROPY; Video S2. Walkthrough in the ENTROPY platform.

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Conflicts of Interest: The authors declare no conflict of interest.

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APPENDIX

A

APPENDIX A

Begins an appendix