A Novel Approach for Anomaly Detection in Power Consumption Data

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Abstract: Anomalies are patterns in data that do not follow the expected behaviour and they are rarely encountered. Anomaly detection has been widely used within diverse research areas such as credit card fraud detection, image processing, and many other application domains. In this paper, we focus on detecting anomalies in power consumption data. The identification of unusual behaviours is important in order to foresee uncommon events and to improve energy efficiency. To this end, we propose a model to precisely identify anomalous days and another one to localize the detected anomalies. Normal days are identified using a simple Auto-Encoder reconstruction technique, whereas the localization of the anomaly throughout the day is performed using a combination of LSTM and K-means algorithms. This hybrid model that combines prediction and clustering techniques, permits to detect unusual behaviour based on the assumption that identical daily consumption can appear repeatedly due to users' living habits. The model is evaluated using real-world power consumption data collected from Pecanstreet in the United States.

1 INTRODUCTION

Global demand for energy is rising, and the lack of energy resources such as oil, has hindered the progress of global economies (F. Jovane et al.,2008). Improving the efficiency of power consumption is of great importance, since the increase of energy consumption may become environmentally hazardous enhancing global warming (S. Bilgen, 2014) (F. Jovane et al., 2008). One promising approach to improve energy efficiency is to identify anomalies in building energy consumption. This information can be useful to the building managers in order to reduce wasting energies by applying energy saving procedures.

The large amount of data generated makes the problem of detecting anomalies and localizing it very challenging. Although many studies have been conducted to propose low energy buildings, buildings often exceed the energy saving objectives indicated by the buildings' energy design. Thus, building administrators want to know how to minimize the failure rate and how to discover power consumption measurements highly differing from old observed data.

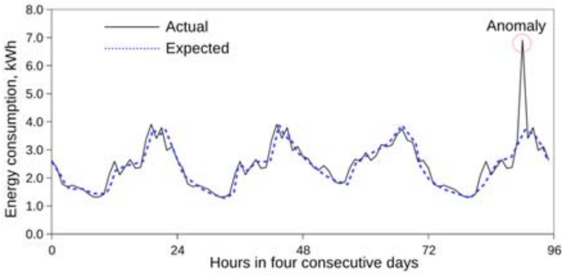


Figure 1: An example of an anomaly in a typical household energy consumption.

In recent years, the weather conditions affected the electric power demand, especially in heating and cooling systems. Nowadays, it is widely accepted that anomaly detection is of paramount importance to reduce energy waste. Anomaly detection can be used for example to determine if there is a faulty equipment consuming more power than required. Moreover, it can be used to detect power theft and intrusions. Fig. 1 shows an example of an anomaly in power consumption data, where a considerable difference between the actual consumption and the expected consumption can be detected (X. Liu et al., 2016).

In this paper, we build an anomaly detection mechanism to improve energy efficiency and to detect abnormal behaviours. In particular, we propose to use machine learning techniques to detect anomalous days in order to avoid taking them into account when building models representing the normal behaviour of the users. K-means algorithm are used to learn different scenarios representing the energy consumption behaviour of each user, and LSTM (Long Short Term Memory) is used to predict the power consumption of the next hour. Identifying outliers not only has the benefit to detect abnormal events like power theft or a faulty equipment, it can also be used as indicator for residents to help them to change their living habits and to warn them of device failures.

The rest of the paper is organized as follows: Section 2 introduces the related work. Our proposed framework as well as the experimental results are presented in section 3. Section 4 concludes the paper and provides the direction for the future works.

2 RELATED WORK

Anomaly detection also known as outlier detection is the process of discovering patterns in data that do not conform to expected behaviour (V. Chandola et al., 2007). There is a tremendous research being performed in anomaly detection in a wide variety of application domains. Table 1 gives a summary of anomaly detection categories (L. Li, 2013).

Table 1: Anomaly detection categories.

Problem	Categories
Input	Binary, Univariate, Multivariate, time series, continuous…
Supervision	Supervised, Unsupervised, semi-supervised
Anomalies	Pattern anomalies, context anomalies, point anomalies, correlation anomalies

In this paper, the data provided is not annotated and cannot be annotated manually. Therefore the approach we develop here is unsupervised. The input of the algorithm is univariate and time series and the outliers are context anomalies and point anomalies. Context anomalies are data that are considered abnormal in one context but normal in another. For example, a lighting source in a school might be anomalous on weekends but not on weekdays when there are classes. Point anomalies occur when an instance is considered abnormal compared to the rest of the data.

Several previous studies utilized historical building power data to detect anomalies. Methods used for these unsupervised anomaly detection problems include: nearest neighbour, clustering and information theory. The nearest neighbour approaches try to analyse the neighbourhood of each sample to determine if it’s normal or not. The distance is calculated between samples, and anomalies are detected based on the assumption that samples with anomalies are distant form normal samples (V. Chandola et al., 2009). These approaches have the advantage of being applicable without making assumptions on the data distributions. The main disadvantage of these techniques remains in the fact that the assumption that samples with anomalies have no close neighbours is not always true.

Clustering approaches can also be applied for outlier detection. In (V. Chandola et al., 2009), a detailed review of these approaches has been presented. This approach is based on the idea that anomalies will not fit into any cluster or they will make sparse clusters. Moreover, even if they fit in a particular cluster, they will be distant from its centroid. The main disadvantage of these approaches is the computational complexity. Finally, the approaches based on information theory calculate entropy or Kolomogorov complexity. The performance of these approaches are determined by the choice of the theoretic measures.

2.1 Auto-Encoder

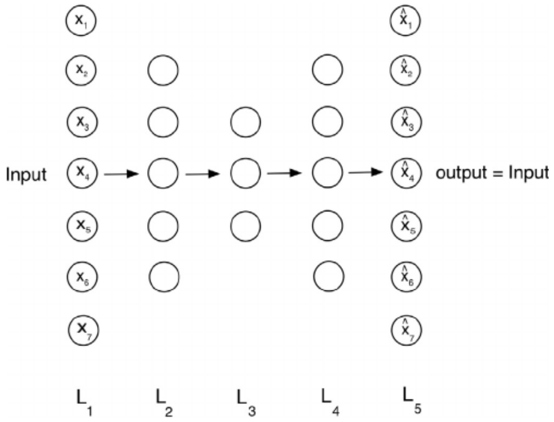


Figure 2: Auto-Encoder.

The Auto-Encoder is an artificial neural network that tries to reproduce input vectors {x1, x2,…, xm} as output vectors {x̂1, x̂2,…, x̂m} (Sakurada et al., 2014). An example of an Auto-Encoder is presented in Fig.2. L1 and L5 are the input and the output layers respectively whereas the others are hidden layers. Supposing the vectors representing each samples are made of D variables, the loss function used for reconstructions is presented Eq. (1):

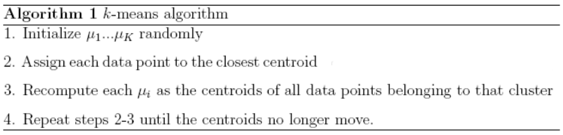
$$Err(i) = \sqrt{\sum_{d=1}^{D} \left(x_d(i) - \hat{x}_d(i)\right)^2} \tag{1}$$

Eq. (2) represents the activation of unit k in layer l, the sum is calculated in the (l-1) layer over all neurons j:

$$a_k^l = \mathrm{f}(\sum_j \left(W_{kj}^{l-1} a_j^{l-1}\right) + b_k^1) \tag{2}$$

Where **b** and **W** are the bias and weight parameters, respectively.

2.2 K-means Algorithm



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Algorithm 1 k-means algorithm
1. Initialize $\mu_1 ... \mu_K$ randomly
2. Assign each data point to the closest centroid
3. Recompute each $\mu_i$ as the centroids of all data points belonging to that cluster
4. Repeat steps 2-3 until the centroids no longer move.
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K-mean is another well-known unsupervised algorithm used for anomaly detection. Clustering vectors is grouping these vectors according to some characteristics. Given {x1, x2,…, xn}, this algorithm searches to attribute each sample to one of the k clusters that minimizes the distance between the data point and the cluster:

$$argmin \sum_{i=1}^{k} \sum_{x \in Ci} d(x, \mu_i) = argmin \sum_{i=1}^{k} \sum_{x \in Ci} ||x - \mu_i||_2^2 \tag{3}$$

The algorithm summarizing k-means is presented in Algorithm 1.

2.3 LSTM

Long Short Term Memory (LSTM) (Hochreiter et al., 1997) is one of the most popular Recurrent Neural Networks (RNN). It has presented an effective and scalable model for several learning problems related to sequential data by modelling long range dependencies. For the **t-th** element in a sequence, the LSTM takes as input the element $\mathbf{x}_t$, the previous output $\mathbf{h}_{t-1}$ and cell state $\mathbf{c}_{t-1}$ and computes the next output $\mathbf{h}_t$ and cell state $\mathbf{c}_t$. Both **h** and **c** are initialized with zeros.

3 PROPOSED METHOD AND EXPERIMENTAL RESULTS

This research proposes a combination of recurrent neural networks and clustering methods in order to detect and predict anomalies in power consumption data. We begin by building a LSTM with three hidden layers and we trained it to predict the power consumption of the next hour using the data of the last 24 hours using Adam optimizer. We trained it for up to 40 epochs with a batch size equal to 64. The learning rate was set to 0.0001 and a dropout of 0.2 was applied at the output of each of the three hidden layers.

The predicted value using LSTM is going to be used to form a vector representing the power consumption of the last 24 hours, then compared to all the possible scenarios defining the typical normal behaviour of this user at this specific hour. Thus, the second step of our work is to learn these typical behaviour scenarios using the k-means algorithm. We start by applying some data rearrangement in order to generate 24 groups representing the 24 hours of the day. Data rearrangement permits to represent each input instance using sliding window instead of single consumption value. To avoid unpleasant impact of missing real world data, some pre-processing techniques are used to adapt data to the algorithms used. All values less than zero are considered noisy as well as all the data points lying further than 3 box lengths in the boxplot representing the overall power consumption of the user.

Each hour is represented by a vector taking the last 24 hours of power consumption data. Then in each group, we apply the k-means algorithm in order to represent each hour by several possible behaviours. The value k for the clustering was set to 11. In other words, for each hour the user can have 11 different behaviours that can be considered normal. Using this technique, we can predict anomalies one hour before its occurrence. The predicted value generated by the LSTM take in consideration the changes in behaviours based on the assumption that recent data weights more than old data. And the k-mean algorithm searches for the closest centroids representing the power consumption at that time. When the predicted value is higher than the measured one by a threshold margin, an anomaly is detected. The threshold used for this user was set to 13.

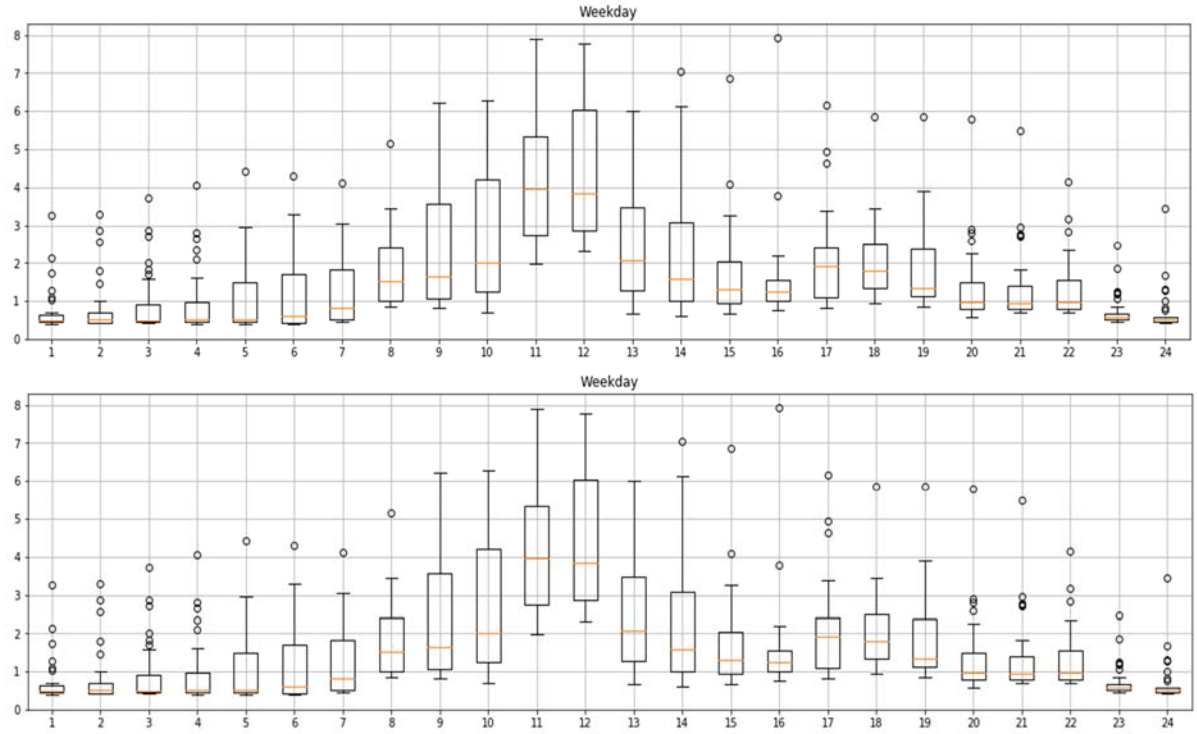

Figure 3: General characteristics of power consumption data (Weekdays and Weekends) using Boxplot.

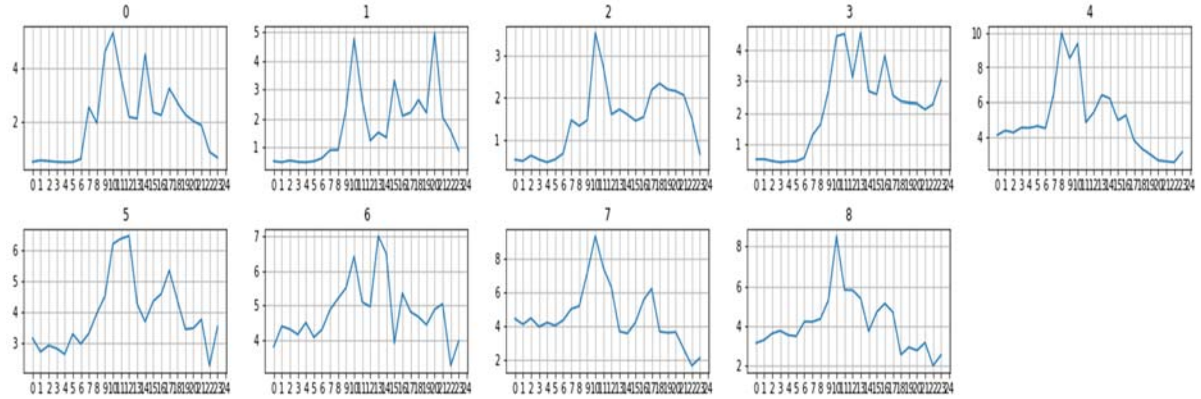

Figure 4: Power consumption data for Day0 to Day8.

3.1 Database

The real-world data used in this work are collected from Pecanstreet's dataport (https:// dataport.pecanstreet.org). This database works on smart meters owned by Pecan Street to provide real data for researchers around the world. The total database contains data from 67 devices in 820 households. The devices include lights plugs, refrigerators, microwaves, air conditioners, ovens heaters… A data sample is shown in Table 2 where the ID represents the ID of the user, hour represents the time of the reading, grid represents the energy used in the grid, bedroom represents the energy used by bedroom, and refrigerator represents the energy used by the refrigerator. In this paper we used the total usage of the user with 1 hour resolution. We randomly chose one user (ID 59) during the period January 2017 to December 2017. Fig. 3 presents an illustration of the power consumption of this user using Boxplots. The upper part represents Weekdays consumption and the lower part represents the Weekends. As can be seen, this user tends to use more energy in weekdays. The peak hours are mainly at 11 o'clock and 12 o'clock. In the following, we only use the data representing weekdays.

Table 2: Data sample.

ID	hour	Bedroom	Grid	Refrigerator
499	2015-05-01 07:00	0	0.67	0.2
499	2015-05-01 08:00	0	0.39	0.12
499	2015-05-01 09:00	0	0.04	0.17

3.2 Results and Discussions

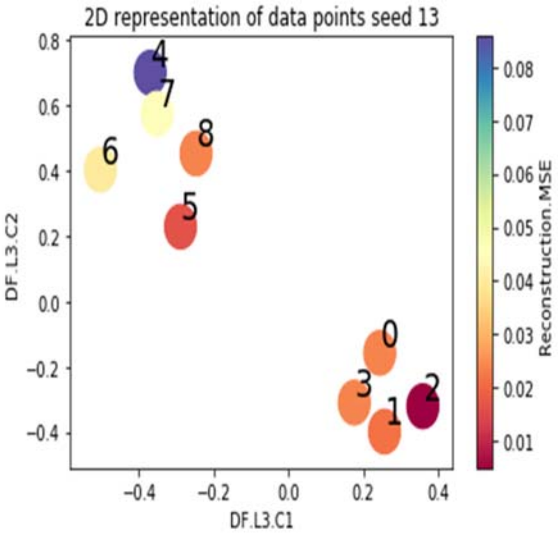

Figure 5: Visualization of different test days using Auto-encoders reconstruction. Different colors represent the reconstruction MSE.

We applied two different approach for two different scenarios. The first one is trying to detect anomalous days without localizing the anomaly. This can be useful to building managers to better understand consumers' behaviors and for making energy efficient home improvements. Fig. 4 represents the actual power consumption values of the test days. Fig. 5 shows a visualization of the Auto-Encoder reconstruction with 5 hidden layers as following [24, 50, 20, 2, 20, 50, 24]. Different colors represent the reconstruction MSE (Mean Square Error). The reconstruction error is then compared with a threshold in order to determine if the day in normal or not. For a threshold of 0.04, only days 4, 6 and 7 are considered as anomalous as can be seen in Fig. 5.

In the second scenario, we tried to localize the anomaly using the method we proposed in section 3. Fig. 6, Fig.7 and Fig. 8 illustrate the results of our proposed method on the same test days. As can be seen, our method localized two anomalies for day 4 (at 8 a.m. and 10 a.m.) and one anomaly for day 7 (at 10 a.m.). This can explain why days 4 and 7 have been considered anomalous by the auto encoders and can also explain day 4 has a higher reconstruction error than day 7 since day 4 has 2 anomalies whereas day 7 has only one anomaly. Contrary to the Auto-Encoder that considered the day number 6 as anomalous, our method conserves a consistent overall prediction as can be seen in Fig.7.

4 CONCLUSION

Finding anomalies in time series data is a very promising topic permitting to reduce the waste of energy and to better monitor building energy consumption. In this paper, we present a hybrid model combining LSTM and K-means algorithm in order to detect outliers in time series data. Auto-Encoders detects abnormal days, whereas the proposed algorithm identifies the typical scenario permitting to localize the detected anomalies. Despite of these encouraging results, this work needs the assistance of real expert users and analysts in order to better define the anomaly in this domain. Experts can also provide some annotations for the learning data in order to give us the possibility of applying semi-supervised approaches in this domain.

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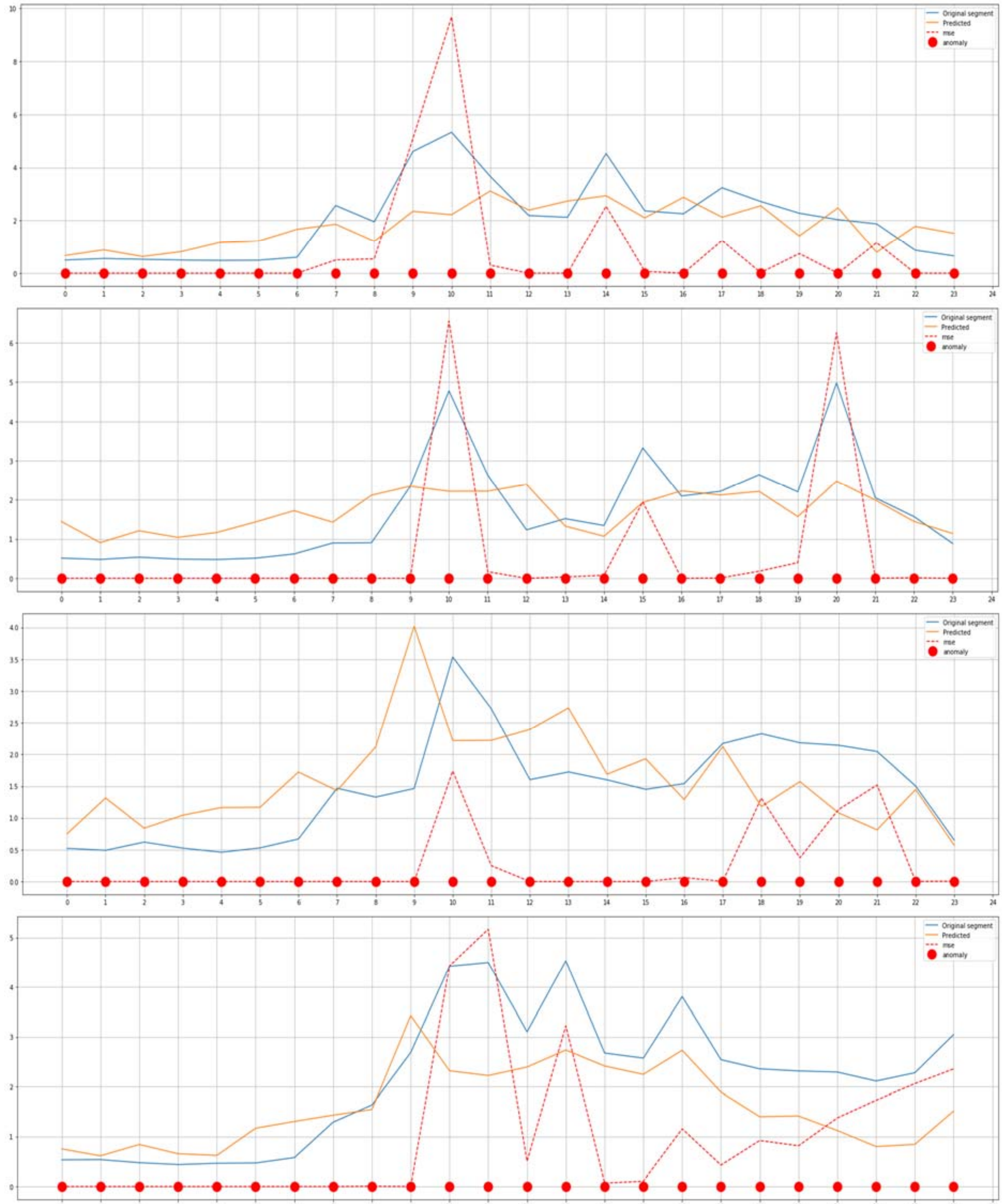

Figure 6: Power Consumption values for five test days (Day0 to Day3). The actual power consumption, the predicted one and the anomalies are presented.

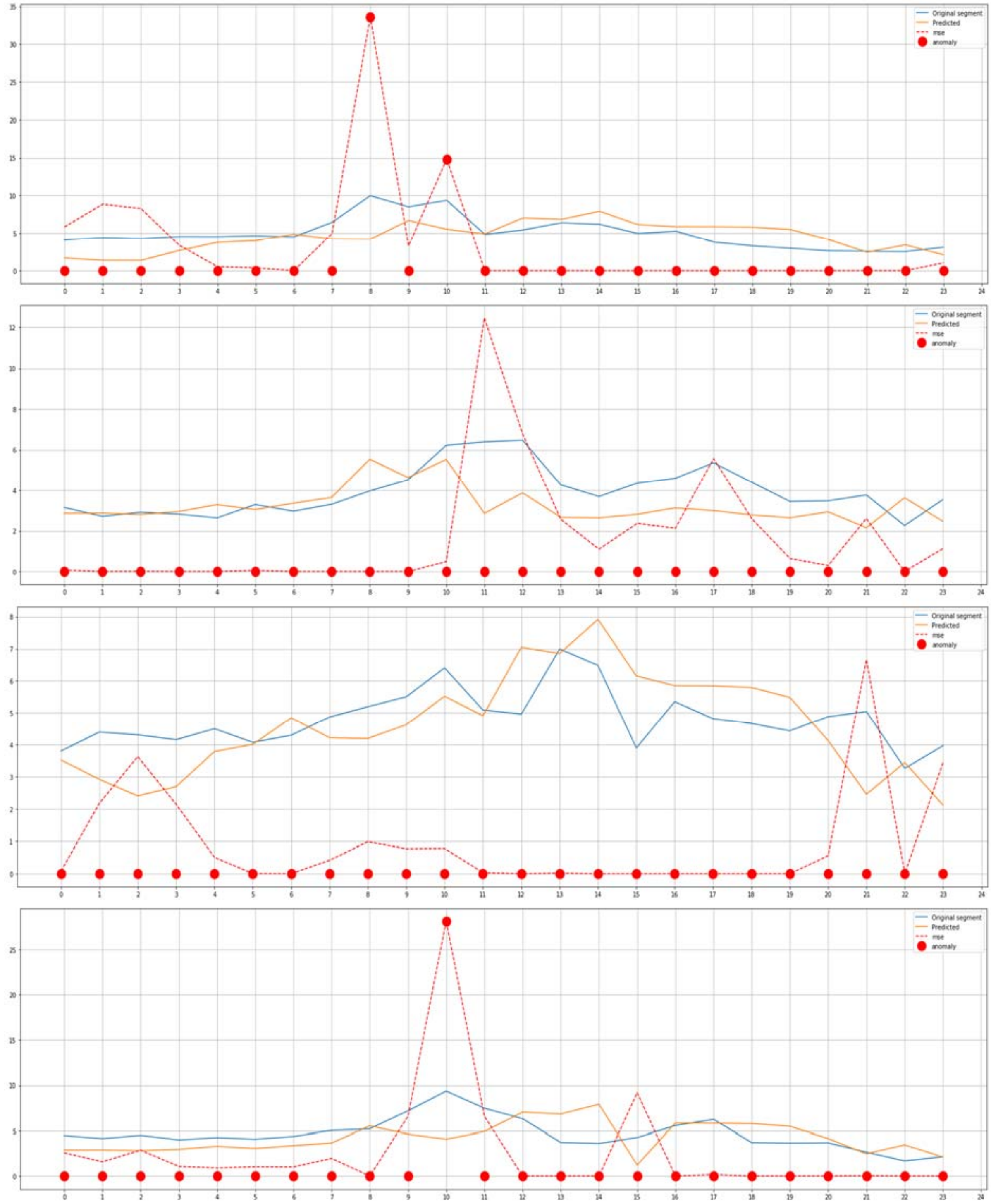

Figure 7: Power Consumption values for four test days (Day4 to Day7). The actual power consumption, the predicted one and the anomalies are presented.

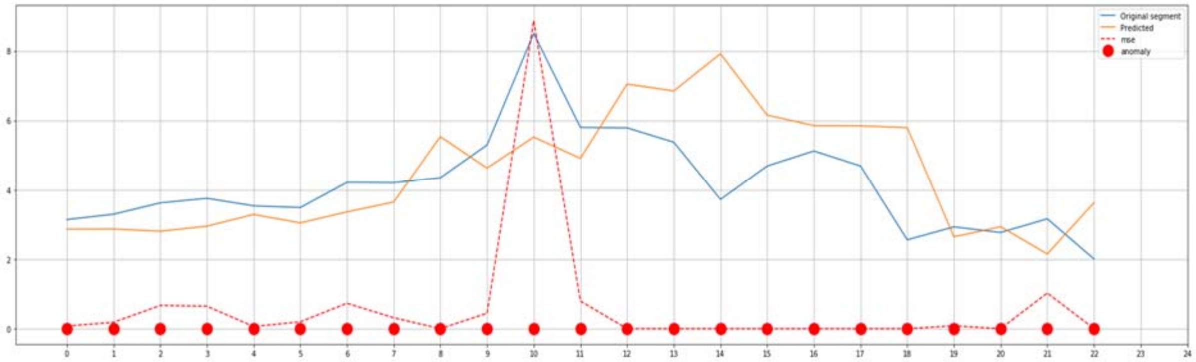

Figure 8: Power Consumption values for four test days (Day8). The actual power consumption, the predicted one and the anomalies are presented.

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