Detection of Anomalies in Household Appliances from Disaggregated Load Consumption

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Detection of Anomalies in Household Appliances from Disaggregated Load Consumption

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***Abstract*—The detection of anomalous power consumption in household appliances plays a key role for the optimization of grid operations and for reducing unwanted electrical absorptions in residential buildings. Smart Plugs, Smart Appliances and other appliance-level monitoring devices allow to continuously monitor the power consumption of individual appliances present in the house. This work is aimed at detecting electrical anomalies in household appliances by analyzing the disaggregated load consumption derived from appliance-level monitoring devices. For this purpose, we implemented an anomaly detection framework which monitors the hourly energy consumption of three common sources of power absorption: the baseline, the fridge and the electrical devices. Here, we focused our analysis on two kinds of anomalies: single-point deviations and anomalous trends. The analysis of single-point deviations allowed us to identify short-term power peaks due either to unexpected electrical faults or sudden variations in end-users routines. The analysis of anomalous trends revealed several cases in which the end-users gradually increased their ordinary power consumption profile towards more energy-intensive practices. In summary, the results of our work showed that the power consumption derived from appliance-level load monitoring can be used to detect several anomalous power consumption in household appliances.**

***Index Terms*—Smart Grids, Anomaly Detection, Appliance Load Monitoring, Anomalous Appliance, Machine Learning**

I. INTRODUCTION

Smart Grids completely revolutionized the sector of energy distribution by integrating the traditional grid infrastructure with the capabilities offered by Information and Communication Technologies (ICT) [1]. Smart Grids introduced a novel paradigm where end-users play an active role in the distribution process by constantly providing information about their energy consumption, possibly changing their power demand according to network requirements [2].

In this scenario, it is crucial to collect useful information about the end-users power consumption. On the one hand, grid operators can benefit from detailed power consumption information to perform a better scheduling of their resources, which can be better allocated depending on the specific end-user needs [3]. On the other hand, the end-users can cooperate with grid operators by changing their power consumption habits with the aim of reducing their overall energy consumption [4]. It has been demonstrated that user engagement can introduce an important reduction in the overall energy consumption of the household [5].

In Smart Grids, energy anomalies can represent a serious problem that can hinder the optimal scheduling of energy distribution. Indeed, the presence of outliers in the energy consumption of end-users makes difficult to estimate their future power consumption, thus preventing grid operators from performing an optimal energy distribution [6]. Therefore, it is important to identify those outliers as soon as possible in order to preventively take them into account and adjust the power consumption estimates of end-users accordingly. Energy anomalies can represent a serious problem also on the consumer side, in which electrical anomalies in the household appliances can remain unnoticed for a long period of time, resulting in higher power consumption or severe damages in the most critical cases.

In order to extract valuable information, we need to analyze the power consumption of individual appliances present in the house. Monitoring devices such as Smart Plugs allow to extract the power consumption of several appliances by inserting an intermediate socket between the appliance plug and the wall socket [7]. The costs for deploying these kinds of metering devices are becoming more accessible thanks to the economy of scale, and allow to monitor an ever increasing number of devices throughout the house. Furthermore, manufacturers started to harness the appliances with smart functionalities for monitoring their power consumption, that can also be transmitted to other devices thanks to the concept of Internet of Things (IoT) [8]. Given the spread of appliance-level monitoring devices, it is crucial to study how we can leverage this kind of information in order to improve the overall energy efficiency of residential buildings.

The remaining sections are organised as follows: in Section II, we give a brief overview of the related works on anomalous appliance detection; in Section III, we introduce the methodology with an exhaustive description of the anomaly detection algorithms implemented in this study; in Section IV, we discuss the results by reporting the main achievements for the different use cases analyzed; finally in Section V, we conclude with the most relevant findings of this work.

II. RELATED WORK

Himeur et al. in [9] introduce one of the most comprehensive surveys on anomaly detection in building energy consumption. Among other observations, the authors point out that anomaly detection algorithms performed at the aggregate-level can not provide enough details about the specific appliance causing the anomaly. As a matter of fact, anomaly detection algorithms performed at the appliance-level can precisely identify the faulty appliance, thus providing more informed recommendations to stop electrical anomalies.

Mao et al. in [10] present an anomaly detection approach based on frequent pattern mining aimed at identifying anomalous power-usages caused by the intrusion of attackers or failures in household appliances. In detail, the authors describe the behaviour of multiple appliances in terms of their number of daily usages, considering anomalous all days that significantly deviate from the expected number of occurrences. To validate their approach, the authors randomly inserted or deleted some usages to create synthetic anomalies and trained a set of classifiers to recognize the injected anomalies.

Patricio et al. in [11] investigate the application of anomaly detection algorithms to detect anomalies in the behaviours of elderly people. To this aim, the authors analyze the hourly power consumption of multiple household appliances. Firstly, the daily patterns are fed into an autoencoder neural network to extract a better data representation of the inputs, then a random forest classifier is trained on the extracted representations to detect days with anomalous activities. The authors validated their methodology by artificially injecting anomalous activities in the dataset, such as unexpected appliance's usages during the nights.

Himeur et al. in [12] propose two new approaches for abnormality detection in energy consumption: i) an unsupervised method based on one-class support vector machines, and ii) a supervised method based on the classification of micro-moment classes. The different micro-moments are extracted by means of a rule-based algorithm which analyzes the device's behaviours in terms of consumption range, operation time and standby consumption. According to the authors, the supervised approach based on a K-nearest neighbours (KNN) classifier is more appropriate to identify anomalous power consumption.

Hosseini at al. in [13] propose a semi-supervised anomaly detection framework for detecting faulty behaviours in the refrigerators. Their algorithm characterises the fridge by means of its daily energy consumption and average power consumption. The two factors are modelled by assuming a Gaussian distribution and by computing their mean and variance. During the monitoring phase the framework detects anomalies whenever the estimated parameters deviate from their mean values by more than three standard deviations.

Rashid et al. in [14] investigate the performance of anomaly detection algorithms when applied directly to the appliance signature extracted by Non-Intrusive Load Monitoring (NILM) techniques, which are able to estimate the power consumption of different appliances through the analysis of the house's aggregate signal. The authors focused their study on the fridge and air conditioner, describing their normal behaviours in terms of duration and energy consumption of ON and OFF states. The authors concluded that the current state-of-the-art on NILM accuracy does not suffice to support anomaly detection algorithms, encouraging the development of novel NILM techniques suitable for anomaly detection.

The literature on anomalous appliance detection is still very limited and surely needs further investigations in order to sustain the increasing amount of information provided by smart plugs, smart appliances and NILM algorithms. In particular, we believe that supervised learning solutions as those proposed in [10] [11] [12] are not practical in a real-world scenario, in which the ground truth annotations are rarely available. Furthermore, the supervised approaches have been always evaluated by using artificially injected anomalies, which can hardly depict an authentic anomalous behaviour. On the other hand, the unsupervised solution presented in [13] is quite promising from a feasibility point of view and it was tested on real fridges with true anomalies. However, it would be interesting to test the unsupervised approach on additional appliances. In [14] the authors expanded previous experiments by including also the air conditioners, showing very good results when using sub-metered input data.

A. Contribution

In this work, we propose a framework for detecting anomalous power consumption in household appliances by leveraging the disaggregated loads extracted by appliance-level monitoring devices. The framework targets two kinds of anomalies: single-point deviations and anomalous trends. To this aim, we monitored the hourly energy consumption of three common sources of power absorption: baseline, fridge and electrical devices. Among them, the fridge is certainly the most relevant for reducing the overall household's power consumption, since it is present in almost every house and constitutes a significant percentage of the total consumption. Notice that the proposed framework can be easily extended to other energy-intensive appliances given that the disaggregated loads are available.

The main contributions of our work consist of the study of some rarely investigated sources of power absorption such as the baseline and the electrical devices. The analysis of the fridge is interesting as well, because it covers a quite long monitoring period (3 years) characterized by the presence of several trends and deviations. Most importantly, we used a real-world dataset, which guarantees the authenticity of the anomalies found. Finally, the restrictions imposed by the Covid-19 pandemic represent a unique chance for the study of behavioural anomalies without precedents in the literature.

III. Methodology

Figure 1 depicts the data pipeline of the anomaly detection framework presented in this work. On the left side, we reported the *Dataset* of disaggregated power consumption extracted by means of appliance-level monitoring devices, which includes the power consumption of the baseline, fridge and electronic devices. The central *Preprocessing* block extracts the actual features from the disaggregated loads that are used by the following anomaly detection algorithms. The pipeline terminates with the application of *Anomaly Detection* algorithms aimed at detecting single-point deviations and anomalous trends in the power consumption of the disaggregated appliances. In this section, we provide a description of the dataset, followed by the preprocessing steps for generating the input features. Then,

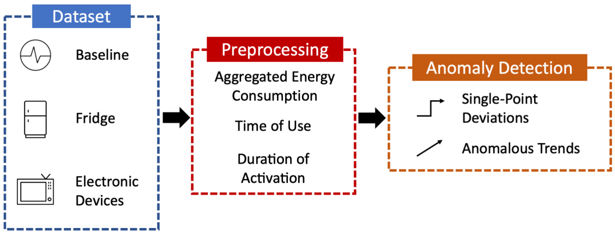


Fig. 1: Pipeline of the framework.

we give a description of the anomaly detection algorithms used to identify single-point deviations and anomalous trends.

A. Dataset

The dataset used in this work is obtained from the power consumption of 20 houses located in the northern region of Italy, collected during a period of more than three years from January 2018 to February 2021 with a sampling frequency of 1Hz. The dataset contains the disaggregated power consumption of three types of sources: baseline, fridge and electronic devices. The baseline represents appliances and equipment in off or "standby" mode which continuously draw power. The baseline includes two features: i) the power in Watts, and ii) the duration in minutes of the extracted instances. The fridge consists of two consecutive ON/OFF states which periodically alternate between an idle state and a cooling state. The set of electronic devices mainly includes the power consumption of TVs and PC monitors, occasionally accompanied by other entertainment devices such as radios and stereos. The raw power consumption data are reported in terms of instantaneous power values measured in Watt.

B. Preprocessing

A set of preprocessing steps are performed in order to extract meaningful features for the anomaly detection algorithms. As reported in the preprocessing block of Figure 1, we firstly aggregated the input loads into *Hourly and Daily Energy Consumption* expressed in kWh. Then, we derived two additional features characterizing the single activation of the appliances, which are the *Time of Use* and the *Duration of the Activation*. In this way, we can account for both power consumption information and house-specific usage habits, that combined together allow to get a reliable model of the normal behaviour of the household under study. At the end of the *Preprocessing* steps, we have three input features: the hourly/daily energy consumption, the appliance's time of use and the duration of activation.

C. Anomaly detection

The anomaly detection framework proposed in this work is aimed at detecting two common kinds of anomalies, which are *1) single-point deviations* and *2) anomalous trends*. The former represents anomalies affecting a single instance in the dataset, which typically presents characteristics statistically different from the majority of other instances. The latter concerns anomalous trends involving multiple instances in the dataset which manifest an anomalous behaviour for a prolonged period of time. In the literature, there are many valid candidates for detecting single-point deviations and anomalous trends. For our purposes, we exploited the Isolation Forest [15] algorithm for detecting single-point deviations and Change Point Detection [16] methods for recognising anomalous trends.

1) Single-Point Deviations: Single-point deviations concern anomalies that occur for very short periods of time and that can be summarized by unusual peaks or minima in one of the different dimensions of the dataset. The framework exploits the Isolation Forest algorithm [15] to detect single-point deviations. The Isolation Forest is an unsupervised learning algorithm for anomaly detection that works by isolating the anomalous points of the dataset through the examination of their features. The working principle of the Isolation Forests states that if a point is *easier* to isolate, then it is very likely to be an anomaly. The Isolation Forest assigns to each instance x an *Anomaly Score* defined by the following equation:

$$s(x, n) = 2^{-\frac{E(h(x))}{c(n)}} \quad (1)$$

where n is the number of instances, $h(x)$ is the path length of the instance in a tree structure, $E(h(x))$ is the average of $h(x)$ in the set of isolation trees and $c(n) = 2H(n-1) - (2(n-1)/n)$ is the average path length of unsuccessful search, where H is the harmonic number. The anomaly score s assumes values between 0 and 1, where 1 indicates an anomalous instance and 0 indicates a normal instance. In general, anomalous instances receive anomaly scores very close to 1. The threshold must be explicitly specified in the algorithm in order to modify the ratio between true positives and false negatives: if the value is lower, the algorithm will capture more actual anomalies, but it will also probably detect some false positives.

The inputs of the Isolation Forest algorithm for detecting single-point deviations depend on the specific source of power absorption analyzed: in the case of the baseline analysis, the inputs are represented by the mean power and the duration of the baseline instance; in the case of the fridge, the inputs consist of the daily energy consumption of the fridge; in the case of the electronic devices, the inputs are the hourly energy consumption of the electrical devices together with their time of use (hour of the day).

2) Anomalous Trends Detection: The Change Point Detection (CPD) [16] is a statistical tool which tries to identify when the probability distribution of a stochastic process changes. In particular, among the many different implementations of CPD, we utilised the Pruned Exact Linear Time (PELT) [17], an *exact* algorithm aimed at solving the following optimization problem:

$$\text{minimize} \quad \sum_{i=1}^{m+1} L(\mathbf{y}_{(\tau_{i-1}+1):\tau_i}) + \beta P(m) \qquad (2)$$

where L is a cost function for a single segment of the time series (e.g., the negative maximum log-likelihood), m is the number of change points, $\beta \geq 0$ is a constant, and $P(m)$ is a penalty term to prevent overfitting. The algorithm has three main input parameters: i) the *penalty* constant which is used to reduce the problem of overfitting and limit the number of change points detected in the time series; ii) the *jump* that is used to improve the execution time; iii) the *cost* which is the most important parameter and needs to be explicitly expressed, since its choice encodes the type of changes that can be detected in the signal. Our implementation was developed in *Python* with a jump set to 1 (since our time series were not extremely large), a *Radial Basis Function* (RBF) as cost and a penalty value changing depending on the use case, generally set to an integer smaller than 10 (this value was found after some tests on the accuracy of the algorithm).

The PELT algorithm applied to the different time series outputs the start time and the end time of all the detected trends. These trends are then studied in a following process, in which the statistics of the current trend are compared with the statistics of the preceding trend: an anomalous trend is detected whenever the mean value of the current trend exceeds the previous range of normal values (defined by the mean and standard deviation of the previous trend).

IV. Experimental Results

In this section, we present the anomalies found in the disaggregated power consumption of the baseline, fridge and electronic devices. It is worth noticing that some of them present very interesting interpretations that highlight a clear change in the consumption habits of the end-user. This information can be crucial to preventively identify unhealthy habits in the user and suggest potential corrections to reestablish a normal power consumption regime.

A. Baseline analysis

In order to detect electrical anomalies in the baseline consumption, we firstly managed to split the power consumption of the baseline in two sets corresponding to active and inactive periods. The active periods include hours of the day in which we expect the presence of human activities, while inactive periods include hours of the day in which we expect very low human activities. To this aim, we computed the average energy consumption in each hour of the day and we marked as inactive periods those hours that account for less than 2% of the average daily energy consumption for that house. Then, we decided to apply the Isolation Forest algorithm solely to the power consumption of the inactive periods, in order to identify unexpected peak in the mean power of the baseline or in its duration. Figure 2 shows the results of the Isolation Forest algorithm applied to a single household, in which the baseline instances have been divided into normal and anomalous clusters (blue and red dots in Figure 2, respectively). The results

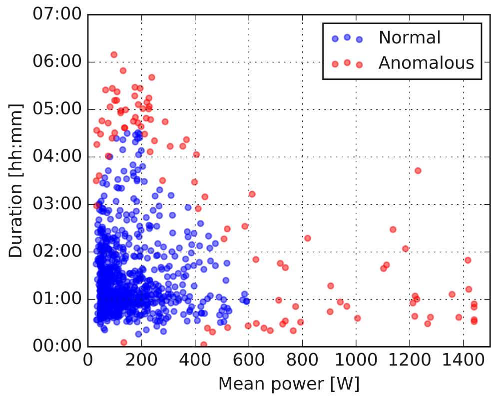


Fig. 2: Single-point deviations identified in the baseline of a single house.

reveal that the anomalous instances in the baseline correspond either to inactive periods with an unexpectedly high power consumption, or to very prolonged periods of inactivity in the house.

B. Fridge analysis

The daily energy consumption of the fridge have been analysed by applying both the Isolation Forest algorithm and the Change Point Detection algorithm. The Isolation Forest algorithm is in charge of recognizing abrupt changes between consecutive days, thus identifying short-term deviations in the power consumption of the fridge. The Change Point Detection algorithm instead is aimed at detecting long-term variations in the daily energy consumption of the fridge. Figure 3 shows both the single-point deviations and the anomalous trends identified in a sample house of our dataset. The single-point deviations are denoted by the red dots in Figure 3, while the anomalous trends are highlighted by the continuous red areas. The two algorithms target different kinds of anomalies: in fact, the CPD algorithm tries to find all the significant trend variations involving long periods of time, whereas the Isolation Forest tries to identify abrupt changes affecting the energy consumption of single days. We suppose that short-term deviations may correspond to a misuse by the user (e.g. door left open). However, they are useful to produce appropriate alerts aimed at timely solve them. On the other hand, the increasing trends during the summer season are due to higher temperatures that inevitably cause a more intensive activity in refrigerators. The seasonal trends in the power consumption of the fridge do not represent a concern for the end-user, since they are expected. However, a persistent or unexpected trend in the power consumption of the fridge may indicate a fault in one of its components, and should be clearly notified to the user in order to repair or substitute the refrigerator.

C. Electronic devices analysis

Anomalous events in the daily usage of electronic devices are often caused by a change in the habits of the end-user, that

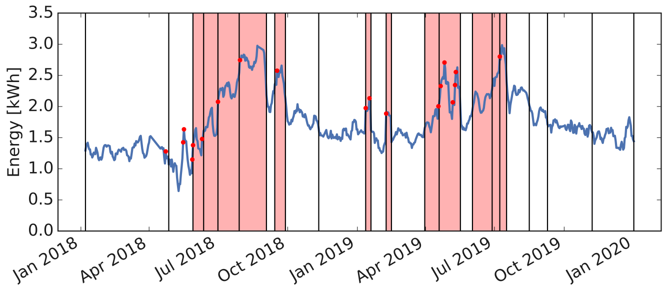


Fig. 3: Single-point deviations and anomalous trends identified in the fridge of a single house.

for some reason may increase the utilization of digital devices during certain periods of the year or hours of the day. Therefore, for detecting long-term changes in the habits of the user, we employed the Change Point Detection algorithm, while for detecting short-term variations involving specific hours of the day we used the Isolation Forest algorithm. We remind that the set of monitored electronic devices mainly include entertainment devices such as TV, computer monitors, radios and stereos. Figure 4 reports the results of the Change Point Detection algorithm applied to the daily usage of electronic devices in a single house of our dataset. It is evident that the algorithm successfully recognizes the presence of prolonged variations statistically different from the overall trend of usage. In particular, in the detected anomalous trends in Figure 4, we also displayed the expected daily usage (in green) of the current trend, which is estimated by taking into consideration the range of normal values from the previous trend. In this way, the normal range is automatically adapted to the new habits of the end-user. As shown in Figure 4, there are periods of time with a lower usage than the expected one, whereas there are several anomalous periods with increasing trends that could be caused by unhealthy or unexpected situations.

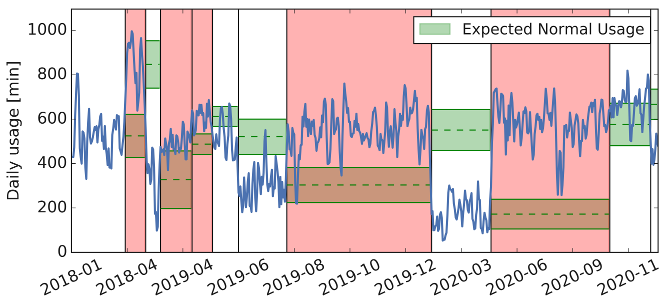


Fig. 4: Anomalous trends identified in the usage of electronic devices of a single house.

Figure 5 shows the average deviation from the normal usage of electronic devices computed across all the 20 houses composing our dataset for the entire monitoring period. Interestingly, we can notice a very large deviation from the normal use at the beginning of the Covid-19 pandemic in March 2020, in which a severe lockdown was imposed in Italy from March 2020 to June 2020. As a result of the restrictions, people incremented the use of their electronic devices, which explains the large amount of upward trends detected by our algorithm during this period.

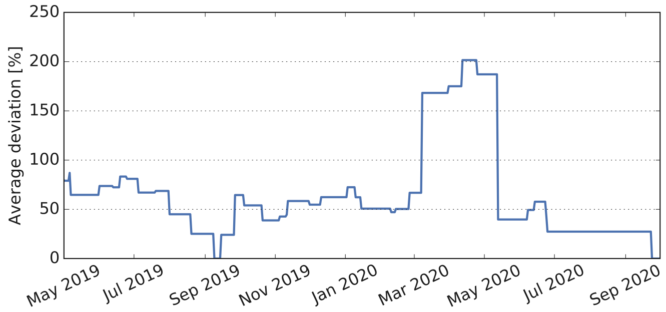
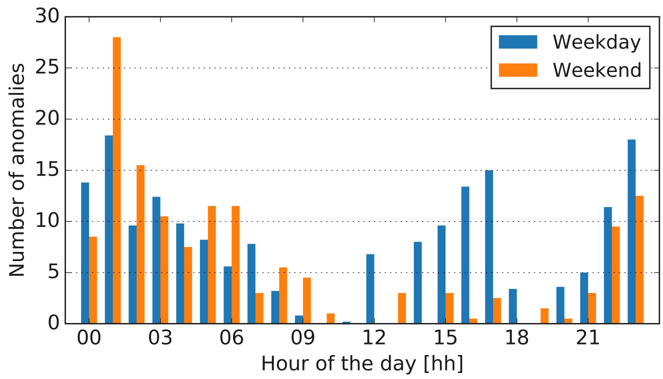


Fig. 5: Anomalous trends identified in the usage of electronic devices across all 20 houses.

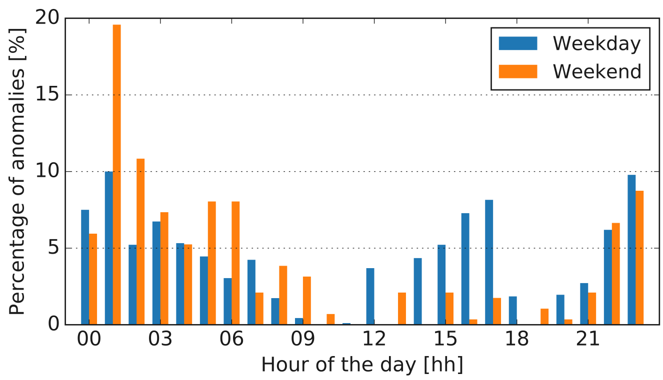
The detection of single-point deviation revealed also very interesting insights about the habits of end-users. We decided to distinguish anomalies occurring during the days of the week from the anomalies occurring during the weekends, since the users usually present very different habits during the end of the week. Therefore, we applied the Isolation Forest algorithm to the hourly energy consumption of weekdays and weekends, separately. Figure 6, shows the anomalies found in the usage of electronic devices for each hour of the day across the entire dataset. In detail, Figure 6a reports the absolute number of anomalies weighted by the number of weekday days and weekend days, while Figure 6b shows the distribution of anomalous instances among the different hours of the day. In the weekdays (blue bars) we can notice that the majority of anomalous instances are detected during the night from 22:00 to 4:00. Furthermore, some anomalous power consumption are also present in the afternoon from 16:00 to 18:00. The weekends (orange bars) present a small amount of anomalies during the daylight, while most of the anomalies are detected during the nights, with a significant peak at 1:00. The greater number of anomalies registered during the weekend nights are probably due to the fact that the users naturally change their sleeping habits as a consequence of greater free time. A potential application of this case study can be in the assistance of at-home elderly people, which are more likely to incur in these kinds of bad behaviours.

V. Conclusion

In this work, we introduced a framework for detecting anomalous power consumption in household appliances by exploiting the disaggregated loads extracted by appliance-level monitoring devices. To this aim, we monitored three sources of power absorption: the baseline, the fridge and the electrical devices. In particular, we focused on identifying two kinds of anomalies: single-point deviations and anomalous trends. The analysis of the baseline found several anomalies presenting higher power consumption during the inactive periods of the



(a) Absolute number of anomalies.



(b) Distribution of anomalies.

Fig. 6: Single-point deviations identified in the usage of electronic devices across all 20 houses.

day. Since baseline anomalies mainly occurred during hours of the day with lower human activities, noticing them can be beneficial to reduce the overall power demand without excessively affecting the routines of the users.

The analysis of the fridge's power consumption revealed the presence of some sporadic single-point deviations, which may indicate an occasional misusage from the end-user. On the other hand, the analysis of anomalous trends for the fridge identified some upward trends during summer seasons, that can be easily explainable with the higher temperatures that usually induce a more intensive activity in refrigerators. However, if an upward trend persists also in other seasons, it is a clear sign that the fridge is operating in faulty conditions and must be repaired or substituted.

Finally, we analyzed the power consumption of some electrical devices dedicated to the user's entertainment, such as TV, computer monitors, radios and stereos. The analysis of single-point deviations revealed the presence of several anomalies during the nights, demonstrating the effectiveness of the algorithm which adapts to the normal behaviours of the different users. A persistent rise in the night activities may denote a potential change in the sleeping habits of the end-user, which can progressively develop unhealthy lifestyle behaviours. Furthermore, we recognized a large amount of anomalous upward trends in the use of electrical devices in almost every monitored household between March 2020 and June 2020, as a consequence of the severe restrictions imposed by the spread of Covid-19 pandemic.

Overall, the results presented in this work demonstrated that disaggregated loads extracted by appliance-level load monitoring can be used to detect several kinds of anomalies concerning both electrical faults and bad consumption behaviours. As a future work, we want to extend our methodology to other energy-intensive appliances commonly present in residential houses, such as washing machine and dishwasher. We also want to adopt a non-intrusive approach to collect the power consumption of individual appliances.

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