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A Practical Approach to Residential Appliances On-Line Anomaly Detection: A Case Study of Standard and Smart Refrigerators

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ABSTRACT Anomaly detection is a significant application of residential appliances load monitoring systems. As an essential prerequisite of load diagnosis services, anomaly detection is critical to energy saving and occupant comfort actualization. Notwithstanding, the investigation into diagnosis of household anomalous appliances has not been decently taken into consideration. This paper presents an extensive study about operation-time anomaly detection of household devices particularly, refrigerators, in terms of appliances candidate, by utilizing their energy consumption data. Energy as a quantitative property of electrical loads, is a reliable information for a robust diagnosis. Additionally, it is very practical since it is low-priced to measure and definite to interpret. Subsequently, an on-line anomaly detection approach is proposed to effectively determine the anomalous operation of the household appliances candidate. The proposed approach is capable of continuously monitoring energy consumption and providing dynamic information for anomaly detection algorithms. A machine learning-based technique is employed to construct efficient models of appliances normal behavior with application to operation-time anomaly detection. The performance of the suggested approach is evaluated through a set of diagnostic tests, by utilizing normal and anomalous data of targeted devices, measured by an acquisition system. In addition, a comparison analysis is provided in order to further examine the effectiveness of the developed mechanism by exploiting a public database. Moreover, this study elaborates sensible remarks on an effective management of anomaly detection and diagnosis decision phases, pivotal to correctly recognition of a faulty/abnormal operation. Indeed, through experimental results of case studies, this work assists in the development of a load monitoring and anomaly detection system with practical implementation.

INDEX TERMS Appliance load monitoring, on-line anomaly detection, energy consumption, load modeling, load diagnosis.

I. INTRODUCTION

With a 66.5 TWh electricity saving potential, residential sector becomes the world primary energy saving target among end-use sectors. The residential energy saving is reinforced by an inevitable increase in electricity prices and thus, customers affordability of spending on electricity consumption [1], [2]. Residential sector accounts for nearly a portion of 60% over 2017-25 and 70% over 2025-40 of building electricity demand rise. A significant share of this demand is due to the huge growth in the quantity and size of in-operation appliances in the projection period to 2040. Therefore, efficient operation and appropriate usage of household appliances play an important role in the achievement of energy saving targets [3], [4].

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A. HOUSEHOLD ANOMALOUS APPLIANCES

Household electrical appliances can undergo operational conditions that violate their normal operation. These abnormal conditions can be attributed to different causes that identify an appliance as anomalous. The consumption pattern of an anomalous appliance deviates from its expected behavior that complies with normality [5], [6]. From the perspective of normal behavior, both faulty operation due to electrical defects and abnormal usage due to customers' neglect can be defined as anomaly. Anomalous appliances can impede energy saving, reduce operation performance, and jeopardize safe operation. Accordingly, household appliances anomaly detection tools are highly useful for both customers to reduce the energy costs and system operator to enable energy efficiency improvements [7], [8]. Indeed, a reliable and efficient operation of household appliances, preserved by anomaly detection systems can increase energy saving up to 12% [9].

B. MOTIVATION AND CONTRIBUTION

Careful anomaly detection requires a framework that is capable of continuously monitoring appliances loads and providing their in-operation information for estimation algorithms. Accordingly, durable household load monitoring systems are emphasized as key enabler to designate such a structure [10], [11]. Although, these systems have been thoroughly probed from both intrusive and non-intrusive aspects, their anomaly detection capability has not been fairly taken into consideration. In terms of Non-Intrusive Load Monitoring (NILM), few studies have only investigated the proficiency of load disaggregation methods for anomaly detection [12], [13]. Furthermore, in [11], we have aimed to design a NILM system for diagnosis purposes. Nevertheless, state-of-the-art NILM methods are not adequate to provide efficient anomaly detection and thus, diagnosis services [11], [12]. In fact, anomaly in electrical appliances has a dynamic stochastic nature, for which providing a training class is a tedious task. The complication increases since a house consists of a range of appliances with completely different operating features due to their various manufactures/models. Notwithstanding a wide range of loads, the anomalous data is very limited that worsens the above problems [5], [14]. Therefore, an appliance-level anomaly detection approach is suggested that investigates the sub-metered data of a targeted-appliance in-depth and subsequently develops its efficient anomaly detection method. This concept is augmented by the inadequacy of aggregate-level anomaly detection techniques and advancements in cost-efficient smart plugs technology [15]. However, it has been almost ignored due to the interesting topic of a NILM with diagnosis abilities.

This paper provides a comprehensive study on household appliance-level anomaly detection by using energy consumption information of a smart and a standard refrigerator as appliances candidate. Particularly, it thoroughly examines anomalous behavior of the targeting loads that is ascribed to irregularity in their time of operation. Accordingly, this study proposes: 1) an on-line operation-time anomaly detection system with generalization ability that is dynamic to capture any deviation from normality in terms of faulty and abnormal operations; 2) a robust structure that is performed by a set of straightforward algorithms and requires minimum intrusion, least amount of information, and low resolution data (highly compatible with current metering technologies); 3) an efficient model of appliances normal behavior that is developed with practical application to diagnosis of an operation-time anomaly; 4) a highly accurate anomaly detection of appliances candidate, specifically periodic loads that consume a notable energy and are important for household energy saving; 5) the idea of diagnosis decision (as distinct from anomaly detection) that is resulted from an in-depth examination of operational conditions of anomalous appliances in terms of faulty or abnormal.

The rest of the paper is organized as follows. Section II provides a review of anomaly detection concept and its applications. Section III presents a thorough investigation into anomalous behavior of household appliances. Section IV describes the proposed approach through an in-depth discussion. Section V represents the results of the case studies and evaluates the method performance. Section VI discusses important remarks about anomaly detection and load diagnosis concepts in accordance with the provided analyses. The concluding remarks are presented in Section VII.

II. BACKGROUND

Anomaly detection plays a key role in load monitoring and predictive maintenance [16]. In the following, this concept is outlined from different perspectives and consequently discussed with regard to power system sectors, especially residential zone. Generally, an anomaly detection method is determined based on the nature of anomaly, which is categorized in three different classes. The simplest type, known as 'point anomaly', is a single data instance that is anomalous considering the rest of the data. The second class, expressed as 'contextual anomaly', refers to a deviation in a particular context regarding the structure of the data. For example, a temperature record of −30°C during hot seasons can be anomalous however, in the context of cold seasons, this report can occur. The third category, defined as 'collective anomaly', implies a data portion that is collectively, not necessarily individually, anomalous [5]. For instance, a washing-machine program consists of individual events such as rinse, drain, and spin. Although these actions are individually normal, their occurrence in a wrong sequence can lead to a collective anomaly. From another viewpoint, anomaly detection methods are classified into 'data-driven' and 'model-based' practices, according to the way of acquiring a priori knowledge. In the former it is presumed that a notable amount of data is available, while in the latter some fundamental comprehension about the physics of the system is used to create a model [8]. From the standpoint of formulating an anomaly detection problem, machine-learning techniques have been widely utilized [17], [18]. In this regard, three different mechanisms can be defined, accounting for: 'Supervised', that is training a classifier by using labeled classes of both normal and anomalous data instances; 'Semi-supervised', that is training only by utilizing a labeled set of normal data; 'Unsupervised', that requires no training set since it groups the data under several clusters and defines dissimilar samples as anomaly. It should be noted that the supervised techniques simply consider an anomaly detection as a classification problem. On the other side, the semi-supervised methods are broadly exploited to separate outliers regarding normal samples (especially, when the classes are imbalance) [6]. The aforementioned perspectives can be further explored in the specified references.

The concept of anomaly detection has been broadly explored in different research domains such as computer network, image recognition, and machine operation [19]–[23]. In the context of power systems, this concept has been generally studied in the main grid sectors. Wang *et al*. have proposed a deep-learning based method for fault diagnosis in a power network by using the power flow information [24]. Hong *et al*. have analyzed an integrated anomaly detection system for network intrusion in the substations [25]. Shaw *et al* have focused on the anomaly detection of loads operation power in distribution systems [26]. They have employed a supervised method based on high sampling rate data of transient events to provide a classification between anomalous and normal instances. It should be noted that Shaw has considered a non-intrusive approach. In small-scale grids such as institutional sectors, Cui and Wang have explored the anomalous behavior of a school's electricity consumption by visualization of its related data [27]. They have utilized the half-hourly energy consumption data to assist with the challenging task of eyeballing of data for detecting anomalies.

At the household level, NILM ability to detect anomalies has recently drawn researchers' attention. The authors have previously investigated the NILM capability to provide diagnosis services [11]. Actually, in [11], we have aimed to enable NILM diagnosis capacity by designing a time-variant load modeling system. This framework exploits a recurrent pattern recognition and model construction mechanism to capture the dynamic of power consumption. Nevertheless, the essence of our analysis implies the difficulty of NILM methods to execute anomaly detection. Besides, other studies have mainly examined the proficiency of NILM methods for anomaly detection. Rashid *et al*. have evaluated the ability of household appliances load disaggregation techniques for anomaly detection [13]. Likewise, they have concluded that enhanced NILM algorithms are required to achieve such an ability. Furthermore, Rashid has made another similar study, where the inadequacy of NILM methods to provide anomaly detection has been inferred [12]. This inference has been made by manually inserting anomalies into limited number of appliances data from publicly available datasets. Therefore, their method of generating a synthetic anomalous data can point out further challenges of NILM in the presence of actual anomalies. Notwithstanding the above, in a prior study, Rashid *et al* have proposed a NILM system for anomaly detection [9]. Similarly, they have used publicly available databases such as ECO that can bring about further questions on their inference about anomalous appliances. For example, they have employed weather data to assist with their visualization of abnormal consumption. However, ECO dataset provides no information about the weather. Furthermore, their method, applied to power-level ratings of a set of known appliances, provides a low performance compared to the accuracy of current supervised NILM methods [11], [14]. This becomes more critical as they have not reported appliance-level anomaly detection results. Moreover, Jonetzko *et al* have suggested a non-intrusive load detection and diagnosis by exploiting high-frequency data with 4kHz sampling rate [28]. However, their study lacks to report any diagnosis results. Furthermore, due to utilizing a NILM method with a very low accuracy, they have reduced the dataset by removing the loads to increase the accuracy. Therefore, their method is not practical.

In fact, NILM barriers to a useful anomaly detection stimulates taking advantage of sub-metered measurements with regard to low-priced smart plugs technology. Accordingly, Ganu *et al* have provided a limited study about an appliance-level monitoring system [29]. They have utilized several electrical features to explain appliances behavior. However, their method can be simply described by a Hidden Markov Model (HMM) [30]–[33]. Although they have stated their method is unsupervised, it is likely to be semi-supervised due to a training phase with predefined parameters. Additionally, they have neither proposed an anomaly detection method nor presented numerical results. In [13], Rashid has also reported the anomaly detection based on sub-metered data. However, by utilizing a window length of one day, his analysis is more suitable for an off-line run. In addition, as demonstrated in this study (Section IV), a daily analysis is not efficient for appliances anomaly detection especially, periodic loads. It can notably restrict normal model construction, threshold definition, and on-line applications. Furthermore, such a window size necessitates a longer training phase. On the other side, Rashid's proposed technique has not been fairly examined since it has been mainly tested on one type of appliance anomaly (a refrigerator with continuously ON state). Considering the anomaly detection rules, it can be concluded that his method is only suited for significant anomalous events. This can be related to the choice of the window range that has limited a more precise anomaly detection. Moreover, the results have not been adequately evaluated due to a limited diagnostic test that can be also sensitive to imbalance classes. On the other hand, this comprehensive study contributes to appliance-level anomaly detection through actual experimentation with the aim of sensible applications. To the best of our knowledge, household appliance-level anomaly detection and diagnosis decision by exploiting sub-metered data has not been properly investigated. Such a concept allows an effective analysis of occupants usage and appliances operation behavior towards a careful anomaly detection. This is pivotal since the fidelity of customers and system operator to diagnosis feedback is highly influenced by its accuracy. It should be mentioned that available products, for which there is no valuable scientific report, does not normally aim

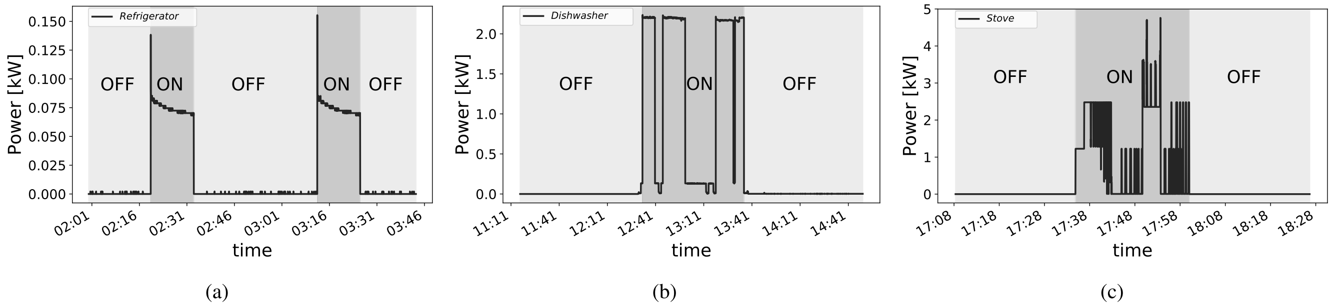


FIGURE 1. Two-state, (a) and multi-state, (b) and (c) household appliances can be expressed as two-state operation-time loads.

residential applications. Indeed, an extensive appliance-level study can aid in designing efficient aggregate-level methods.

III. PROBLEM DEFINITION OF APPLIANCE ANOMALY DETECTION

In fact, an effective strategy to approach an anomaly detection problem is to define its general features. Afterwards, the problem can be further elucidated with regard to case study and type of input information. In the context of a household, an anomaly detection problem can be characterized based on the following overviews.

A. OVERVIEW OF ANOMALY TYPE

Generally, household appliances demonstrate anomalous behaviors that can be attributed to either their operation-power or operation-time deviations. For two important reasons, the focal point of this analysis is the operation-time anomaly detection. First, irregular behavior of household appliances, especially with major power consumption (such as refrigerators, stoves, washing machines, and electric water heaters) is commonly implied by a faulty operation-time duration. Second, households electrical network has not been designed to capture this type of anomaly. Indeed, residential electric circuit is technically equipped to detect an operation-power anomaly within a normal consumption time rather than an operation-time anomaly with a normal power demand. According to the nature of anomaly, an operation-time anomaly can be expressed as a collective anomaly that occurs in the context of time [5]. For instance, a freezer with normal power demand that its ON state lasts for an unusually long time.

Moreover, the anomaly of household appliances is stochastic with a dynamic nature. Therefore, it is difficult to define an anomalous region that can be utilized to build a model. This issue deteriorates by knowing the fact that anomalous data instances are very limited and difficult to collect. Indeed, the number of abnormal occurrences are much less compared to normal ones, which causes highly imbalance classes [34]. Accordingly, semi-supervised machine learning methods are stimulated to deal with appliances anomaly detection due to the serious challenge of providing labeled class of anomalous data.

B. OVERVIEW OF APPLIANCE CANDIDATE

Household energy-intensive appliances are commonly finite-state loads that can be subject to malfunction at any operation state [35]. Nevertheless, from the perspective of operation-time anomaly detection, these appliances can be classified as two-state operation-time (ON/OFF) loads. This has been demonstrated for common household devices in Fig. 1. Such classification, as the essence of this study, facilitates providing a general anomaly detection method for finite-state loads.

In the context of a household, refrigerator is defined as a global energy-demanding appliance type. In both developing and advanced economies, refrigerators are among key factors for residential electricity consumption growth. They are the main purchased appliance with the increase of middle-income households in the world [3]. In fact, with more than two billion in-use numbers worldwide, refrigerators have a high penetration rate among main domestic equipment [36], [37]. On the other side, a refrigerator can undergo anomalous behaviors that can be attributed to different causes related to either a faulty operation or an abnormal usage. Despite other major domestic appliances, an anomalous refrigerator can bring about important energy saving issues since it is a permanently operating load with considerable energy consumption [38]. Although with most malfunctioning household devices, no (less) usage can avoid (reduce) anomaly impacts, this is not the case for refrigerators as permanent loads. Furthermore, an accurate anomaly detection of a refrigerator is complex since the causes of deviations from expected behavior are not always related to a failure. For example, the power profiles of an open-door refrigerator and a loaded one are very similar since both result in a lengthy operation time (discussed in Section IV). Indeed, the above remarks make refrigerators an appropriate candidate for an in-depth anomaly detection investigation with regard to two-sate operation-time appliances. It should be noted that this appliance has been also an interesting candidate for anomaly detection analysis in other researches [13], [29].

C. OVERVIEW OF SELECTED FEATURE

Our proposed appliance-level load monitoring and anomaly detection system utilizes the data of active power consumption with a one-minute sampling frequency, gathered by a sub-metered measurement system [39]. Therefore, it presents a data-driven approach for which, energy consumption is employed as the extracting feature to explore the anomaly in the targeted loads [8]. As a quantitative property of an electrical appliance, energy is a very practical feature for appliance-level anomaly detection systems. It is a reliable information for a robust diagnosis as a critical element of such systems. Energy is low-priced to measure and compatible with smart plug/meter structures. In fact, an energy-based anomaly detection method is easy to integrate with these structures since they both record energy consumption. Particularly, from the perspective of both customers and system operator, energy-based information is straightforward to comprehend since the electricity is delivered to customers in form of energy consumption [40].

According to the above analyses, an anomaly detection method is suggested for household two-state operation-time appliances that is semi-supervised, data-driven, and collective in the context of time. This work promotes an appliance-level anomaly detection problem in general rather than an appliance-specific one by using appropriate case studies. Even from the viewpoint of the latter, this study can be still general due to utilizing a basic method, a common electrical feature, and a low sampling rate (regarding energy-intensive loads) [41], [42]. Besides, the exploitation of sub-metered data is motivated by rapid influence of smart plug technologies. With the increasing significance of Internet of Things (IoT), smart plugs become beneficial for enabling smart appliances data connection [15], [43]. These appliances are not only equipped by an electricity connector but also a data connector according to digitalization aspect [3]. Smart plugs can provide a key opportunity for an extensive analysis of anomalous behaviors of major loads (specifically, refrigerators, washing machines, and air conditioners). Such an examination is essential to design efficient anomaly detection and diagnosis decision systems. It should be noted that current smart plugs are mostly normal operating systems and are not targeted to provide services for any specific type of appliances. Actually, future smart appliances can be themselves equipped with load monitoring and diagnosis services. As mentioned, this implies the practicality of the proposed approach since it can be integrated into different systems.

IV. METHODOLOGY

Our proposed mechanism for anomaly detection is the consequence of an exhaustive investigation into the behavior of the case studies based on their energy consumption. Accordingly, the following steps are executed to provide a thorough examination.

1- First, normal and anomalous behaviors of the appliances candidate (the standard and smart refrigerators) are explored through analyzing their specified electrical features, explained below.

2- Second, an on-line technique is proposed to efficiently monitor these electrical factors and provide dynamic information of targeted loads for consecutive anomaly detection algorithms.

3- Third, a semi-supervised anomaly detection method with low-complexity is developed that is capable of modeling the normal behavior of case studies and subsequently distinguishing their anomalous operation.

Moreover, useful remarks are elaborated as an explanation to the issues, discovered within our comprehensive analysis. As mentioned, in order to permit an actual implementation, the entire study is done by using the real data of our acquisition system.

A. COMPUTATION OF THE ANALYTICAL FEATURES

The behavior of the appliances candidate under different operation conditions is explored by the calculation of their energy consumption. These appliances consist of a standard single-door and a smart french-door refrigerator with completely different technical specifications. The energy consumption as the main analytical factor is computed through (1) [9],

$$u_w = \sum_{i=1}^{N_w} y_{k-i} \tag{1}$$

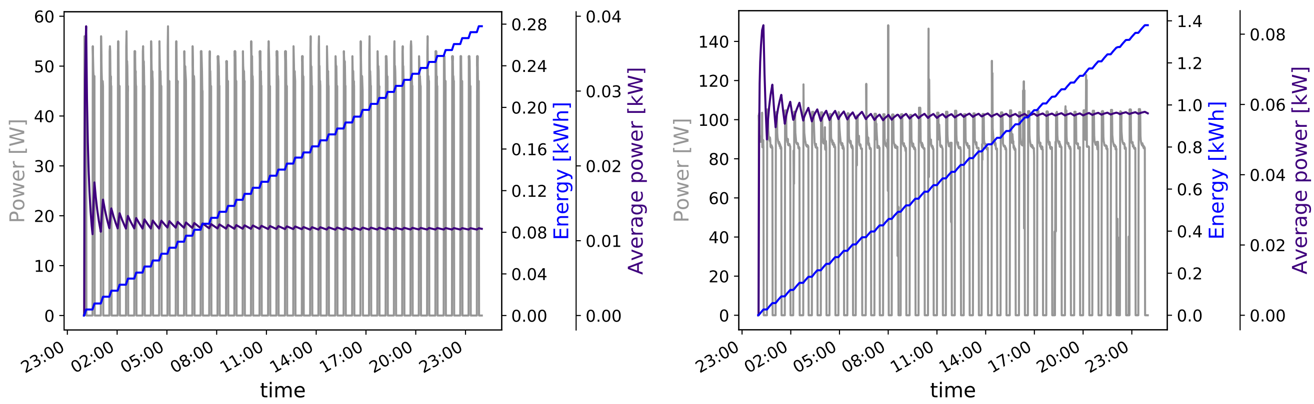
where k is the discrete time, during which a window size of w with N_w number of samples is captured for the energy analysis. y_k presents the active power demand at k, and u_w describes the energy consumption within w. Since energy, by definition, explains a constant power during a specific period of time, it is a convenient element to determine average power consumption within a targeted time duration. Therefore, average power usage, derived from energy based on (2), is another analytical factor that is employed,

$$\overline{u}_w = \frac{u_w}{N_w} \tag{2}$$

where $\overline{u}_w$ presents the average power use during time window w. Due to the accumulating nature of energy consumption, the average power quantity with no time dependency allows to recognize a stationary behavior and define the boundaries of variations over the time window of analysis. Furthermore, it eases the comparison between appliances different models of energy consumption behavior. As discussed in the following, this factor is critical for an accurate estimation of anomalous behavior of periodic loads such as refrigerators, freezers, and electric water heaters. This quantity can be easily converted to energy for a standard comprehension of electricity consumption in terms of kWh.

B. ANOMALY SCENARIOS

In fact, different conditions can cause the operation of a household refrigerator to deviate from normality. Therefore, four scenarios are considered to represent the common conditions that result in an anomalous behavior of a refrigerator. These scenarios are grouped into faulty and abnormal classes. Failure is attributed to a condition that cold air is constantly lost while abnormality is referred to as a situation that cold



(a) (b)

FIGURE 2. Daily energy and average power consumption of (a) standard and (b) smart refrigerators under normal operation.

air is finally kept inside by closing the door. The classes are numbered in an ascending order and explained as follow. The faulty class consists of cases 1: door not closed well; and 2: door with defective gasket. For the scenario 1, the door was left open at various angles for different time duration. For the scenario 2, the door gasket was deformed in different sides of the door for a long time to emulate a damaged one. The abnormal class comprises cases 3: door open/close overly; and 4: loaded refrigerator. For the scenarios 3, the door was overly open/close within several hours at different time of the day. For the scenario 4, the refrigerator was loaded with various amount of water at different temperature. Indeed, the variety of anomaly sources, which cause either a failure or an abnormality makes refrigerators a challenging load for a precise anomaly detection. This is not the case of other household energy demanding devices.

All aforementioned scenarios can lead to a notable waste of energy. Moreover, operating with dirty coils is another common condition that brings about an anomalous behavior. However, cleaning the coils, which requires customers' attention cannot make a considerable difference regrading the amount of energy usage of new refrigerators. Likewise, a freezer can be subject to the same scenarios and thus, the following examination can also provide valuable insights into the anomalous behavior of a freezer. It should be noted that refrigerators and freezers, recently along with air conditioners are the fundamental members of every single house [3], [44].

C. INVESTIGATION INTO NORMAL AND ANOMALOUS BEHAVIORS

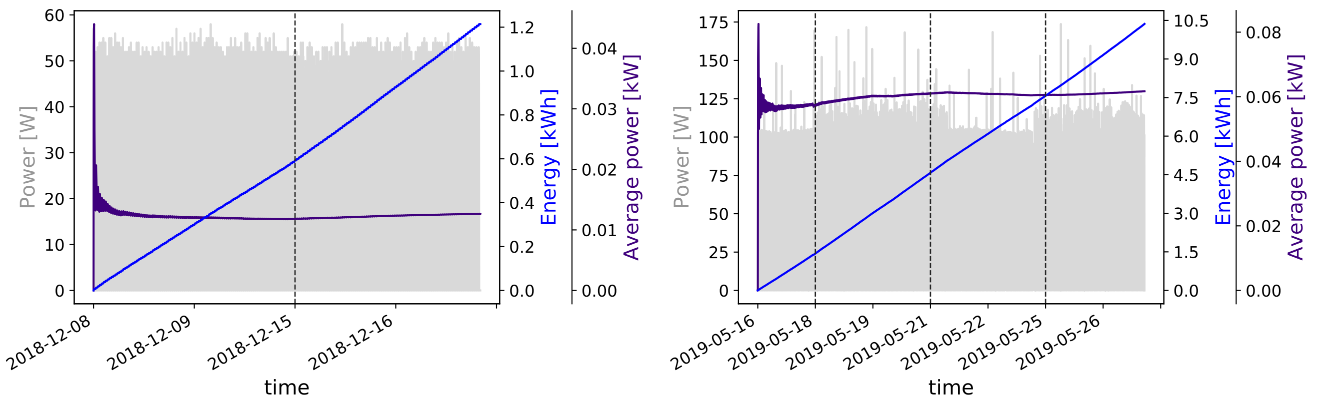
In our study, the anomalous behavior is deliberately induced by jeopardizing the normal operation based on the anomaly scenarios. Accordingly, an in-depth examination is provided in the following that outlines the key features of the proposed load monitoring and anomaly detection system. Furthermore, a detailed visualization is presented to assist with a clear comprehension. It should be mentioned that the following discussion is based on the exploration of the analytical factors, determined in Section IV.A.

1) NORMAL OPERATION OF APPLIANCES CANDIDATE

In order to capture the difference between normality and anomaly, the normal behavior is considered beforehand. Fig. 2 shows the daily energy and average power consumption for the normal operation of standard and smart refrigerators, respectively. It can be observed that the increase in energy consumption is consistently uniform. Furthermore, the average power usage demonstrates a stationary behavior within the time. More importantly, the consistency of energy growth and the stability of average power value is preserved over time. This has been demonstrated in Fig. 3, where the power profiles of non-consecutive days are coupled. It can be recognized that in concatenated days (black dashed lines), which are not successive, there is no inconsistency in the values of both examining factors. Consequently, the energy can be determined as a reliable criterion for normal behavior description due to the fact that the amount of energy use within normal operation cycles is almost identical. It is noted that the second factor is also stable since it has been computed by using the energy consumption. In addition, the modeling of energy and average power use of refrigerators and freezers is more efficient since their actual power consumption with notable transient is challenging to model (see Figs. 2 and 3).

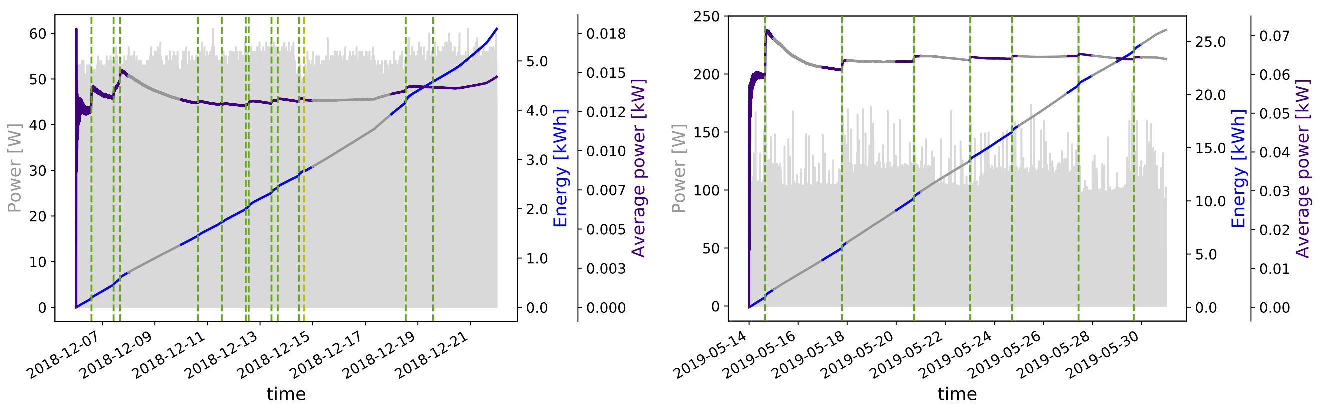
2) ANOMALOUS OPERATION OF APPLIANCES CANDIDATE

The anomaly scenarios have been executed during several days in order to provide sufficient evidences for the examination of their resultant irregular behavior. Accordingly, Fig. 4 illustrates the effect of anomaly scenarios on the energy and average power usage within a period of the experimentation. In this Figure, the green dashed lines illustrate the time in which an anomaly scenario has been experimented. Grey colors in-between energy and average power curves



(a) (b)

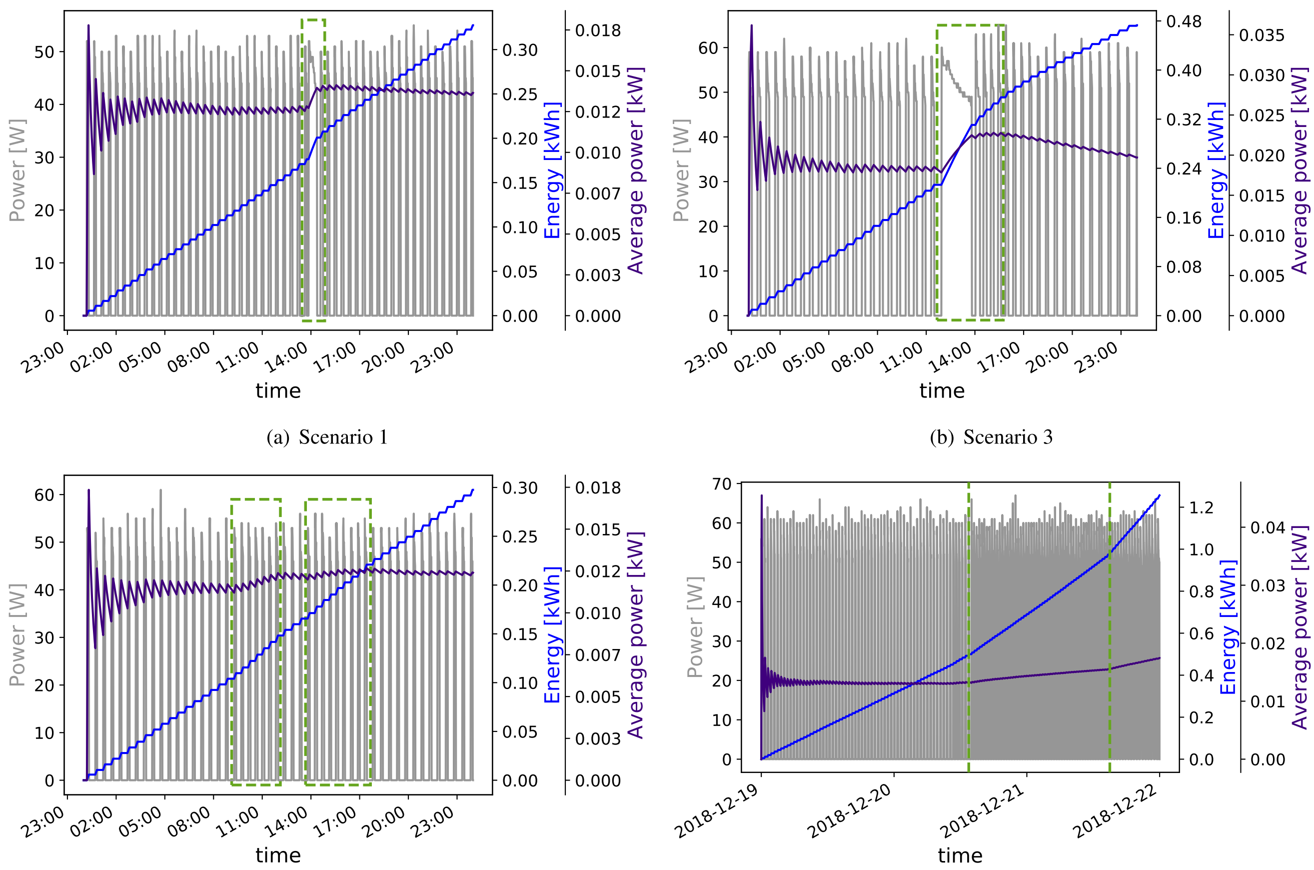
FIGURE 3. Consistent normality of energy and average power consumption of (a) standard and (b) smart refrigerators within non-sequential days under normal operation.



(a) (b)

FIGURE 4. Energy and average power consumption variations due to anomaly scenarios applied to (a) standard and (b) smart refrigerators. Each dashed line corresponds to the time of a specific anomaly test. Yellow dashed line presents an important case, explained in the text.

depict the days of normal operation with no anomaly test. It can be observed that all cases cause fluctuations in both the regular increase of energy demand and the regularity of average power use. These fluctuations occur exactly at the same time of the anomaly test that demonstrate the capability of the analytical factors for on-line applications. The variations can be acknowledged as a general alarm for an on-going anomaly when compared to the uniformity during normal operation. Generally, an anomalous behavior can be recognized by a sudden increase in both energy and average power consumption. Due to the normal behavior recovery, this increase is followed by a regular growth in the first factor and diminished steadily in the second one. The intensity of an anomaly depends on the extent of the induced scenario, for example the duration time of an open door. Nevertheless, no anomaly scenario has been exaggerated throughout the experiments. Even at the cost of a low accuracy, this study has avoided evident anomalies that can be easily captured. According to the operation condition that each scenario can cause, the following has been noticed. The scenarios 1 and 3 are more distinguishable. Scenario 2 is challenging to be differentiated from a normal condition, especially in a long term. These scenarios have been tested multiple times during every day of their experiment. Scenario 4 needs a longer period of time for the examination in comparison with other scenarios. Therefore, it has been executed within several days. With regard to the examined scenarios, there are relevant remarks that are discussed in details below through Fig. 5. In accordance with Fig. 4(a), there are other events that should be mentioned. The yellow dashed line with no scenario type is a noteworthy case that has been faced during the experiment. In fact, during the test days, a notable decrease in both factors has been experienced due to the loss of data in the acquisition system (zero consumption has been recorded in the database). However, in the lack of any clue about the source of such a behavior, it is yet difficult to attribute that to an anomalous refrigerator. The reason is that this event has caused a rapid reduction in the examining features (and not



(a) Scenario 1

(b) Scenario 3

(c) Scenario 2

(d) Scenario 4

FIGURE 5. A detailed demonstration of the energy and average power consumption fluctuations of the standard refrigerator due to the anomaly scenarios.

an increase based on the above explanation). Additionally, the unwanted growth during the normal days (after 2018-12-17) is due to deliberately decreasing the temperature set-point. Although this situation can be similar to an anomaly, the degree of a refrigerator is normally fixed by customers and its manipulation is not a common action.

Fig. 5 exemplifies the energy and average power demands behavior under each anomaly scenario. Although this is not the focus of this study, it can be observed that in a detailed view, the type of anomaly can be explored. Normally, the anomaly scenarios 1 and 3 lengthen the time duration of the refrigerator's ON operation within one to several cycles. Therefore, they provoke an immediate growth in both factors, as shown in Fig. 5(a) and 5(b). Actually, leaving the door open even slightly leads to a non-stoppable running that usually creates a cycle with long ON operation. Besides, the anomaly scenarios 2 and 4 boost the number of operation cycles. Consequently, they raise the slope of energy and level of average power consumption, as illustrated in Fig. 5(c) and 5(d). The scenario 4 should be studied in a longer period according to experimental observations that demonstrate gradual changes in the analytical factors under this case. During this scenario (Fig. 5(d)), it has been observed that the refrigerator operates with faster operation cycles (first slope change) and subsequently proceeds with longer ON operations (second slope change). In fact, door with defective gasket (scenario 4) is the only case that causes a permanent anomaly. These conditions can be generally encountered by other periodic-load appliances such as freezers.

According to the above analysis, it is deduced that the refrigerators are subject to an unexpected operation time growth in the presence of an anomaly. Likewise, this can be the situation for other energy-intensive appliances such as stove and electric water heaters that signifies our proposed approach to an operation-time anomaly detection system.

D. ANOMALY DETECTION TIME-WINDOW

An extensive examination of normal and anomalous behaviors of appliances candidate has been provided in the previous subsection. The main objective of such an analysis is to elaborates important remarks that can assist with the development of an efficient anomaly detection framework. In accordance with this investigation, it can be acknowledged that the time is a critical element in an energy-based anomaly detection. In fact, the time to capture an anomaly becomes crucial for two main reasons. First, the rapid response of energy-based

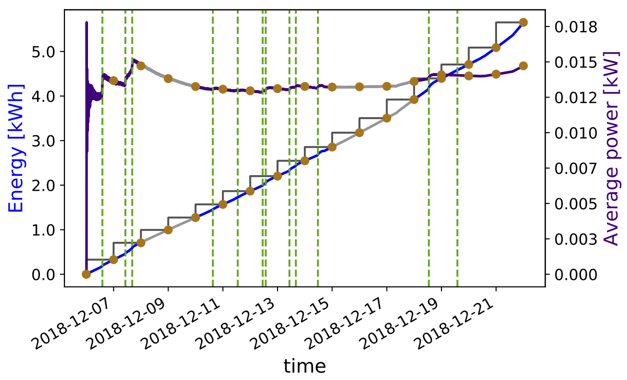


FIGURE 6. **Daily energy and average power consumption of the standard refrigerator.**

factors to an anomaly that promotes an actual on-line application. Second, the accumulative manner of energy usage and stationary behavior of average power use that necessitates a quick action. Actually, amassing the energy quantity over a notable time makes it difficult to distinguish a deviation in the consumption value. Likewise, the tendency to steady-state amount of average power demand causes a fluctuation to fade over a short time.

The time restriction to detect an abnormality can be explored by the analysis of both factors based on a daily time-window. Fig. 6 depicts the daily energy and average power demands during the same period as Fig. 4(a) for the standard refrigerator. For most of the scenarios, it can be observed that the amount of average power use at the end of a day (brown dots within the anomalous days) is lower than its value at the time that the anomaly has occurred. In fact, by the end of the day, this amount can be attributed to a normal condition instead of an anomalous event. On the other side, daily energy usage can be more useful because of its accumulating quality. Notwithstanding, it can be noted that anomalous and normal days produce similar step changes (brown dots within all the days) in their daily energy consumption. This situation becomes more challenging when the duration time (intensity) of an anomaly is not significant.

To more clarify, a Gaussian-based Kernel Density Estimation (KDE) based on (3) has been applied to daily energy and average power consumption data for the same duration as Fig. 6,

$$\hat{f}(x) = \frac{1}{N}\sum_{i=1}^{N} \mathcal{K}_h\left(x - x_i\right) \tag{3}$$

that for N number of data instances, x defines the discrete support, $\hat{f}(.)$ is the KDE function, $\mathcal{K}(.)$ presents a Gaussian Kernel, which is centered at each data sample x_i, and h specifies the bandwidth parameter. As a non-parametric method, KDE is a suitable choice for this analysis since the data stream includes the samples of anomalous days with completely random behavior. KDE is able to create an empirical probability density function (pdf) of every data point in order to estimate an unknown underlying distribution [11]. In order to reduce the complexity, a constant bandwidth with an empirical value has been chosen that has resulted in a better estimation through the experiments. Furthermore, the ability to offer an adequate description of normal behavior of energy-intensive appliances is the logic behind choosing a Gaussian Kernel [45].

Accordingly, Fig. 7 illustrates the results of KDE, applied to energy and average power consumption within a daily time-window. It can be seen that for the analytical factors of both case studies, a distinguishable region can be defined. For the standard refrigerator (Fig. 7(a) and 7(b)), this region deviates from the general region and can be highly related to anomalous events. Nevertheless, it contains very few data samples. For the smart refrigerator (Fig. 7(c) and 7(d)), the situation is the same however, the few instances in this region can be hardly associated to an anomalous operation due to their lower values (as discussed above). Therefore, for this case, the general region encompasses all anomalous samples. In fact, for the two refrigerators, the general region accounts for both normal and anomalous instances. It can be deduced that a daily analysis is inefficient to capture deviations from the common behavior that can be related to anomalous operation. Indeed, such an analysis is useful when a deviation is highly significant. Additionally, a daily examination can reduce the usability of the examining factors, considering the similarity between both distributions (locations of the samples). Consequently, the following remarks can be realized from the underlying distributions of data samples, captured through a daily time-window investigation.

1- Accumulating and stationary behaviors of energy and average power consumption over a day reduce the influence of a deviation (anomaly) over the normality.

2- Considering a specific amount of data, a daily time-window supplies the analysis with less number of samples and requires a lengthy duration of data acquisition [46]. Additionally, daily data can suppress detailed information that are valuable.

3- On a daily basis, defining a threshold to increase the number of correctly detected anomalies is challenging since in the general region, differentiating between normal and anomalous instances is more uncertain.

Regarding the KDE analysis, presented in Fig. 7, it should be mentioned that higher/lower values for bandwidth parameter do not improve the results. The former forms one region that means all data samples present the same behavior while the latter shapes several regions that means data instances offer different classes standing for multiple behaviors.

Generally, the time-window of the anomaly analysis can affect the influence degree of the analytical factors, the number of correctly detected deviations, and on-line implementations. Since an anomalous refrigerator demonstrates an unexpected periodic behavior, a cyclic time-window examination of energy and average power consumption is suggested. Fig. 8 demonstrates the KDE results of the cyclic investigation during the same period as daily analysis.

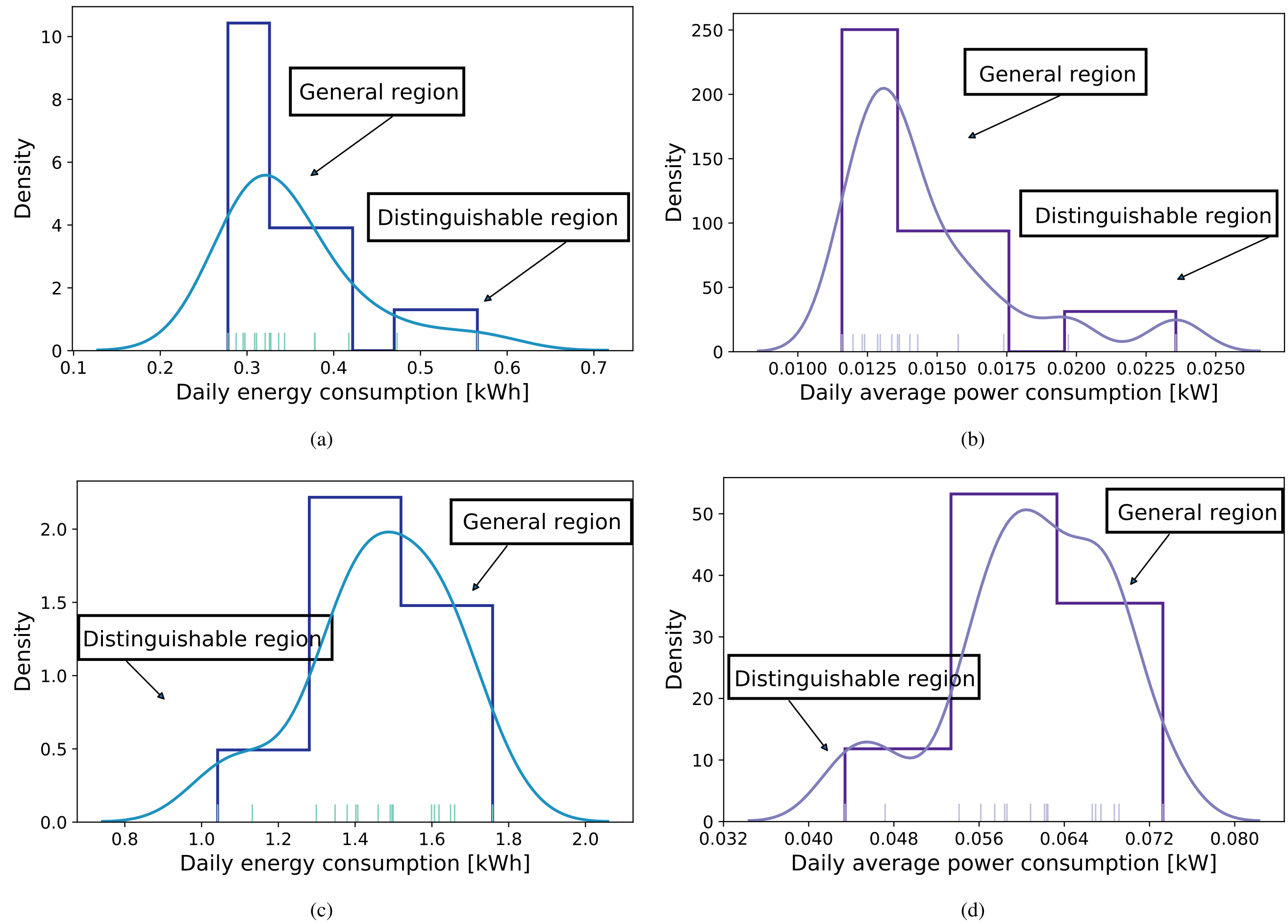


FIGURE 7. **KDE of daily energy and average power consumption of standard (up) and smart (down) refrigerators.**

The detection of operation cycle has been realized by constructing the operation-state (ON/OFF) sequence of the refrigerators based on a threshold. Consequently, a cycle is determined as an event that falls between two ON (or OFF) state transitions. As it can be observed in Fig. 8, a cyclic estimation results in distinguishable regions that can be distinctly segregated from general regions. Particularly, for the smart refrigerator, a distinguishable region has been created that in spite of its daily analysis, can be related to anomalous operations. Moreover, the cyclic analysis demonstrates that the analytical factors have different sensitivity with regard to resultant distributions (samples location) and the number of instances in the distinguishable regions. The samples of this region can be highly presented as anomaly since it is almost impossible to present them in a single category due to their random behavior. Subsequently, the general region as the only dominant class can be significantly associated with normality and in turn, assist with capturing an exact model of normal behavior. Therefore, it can be concluded that the capability of energy and average power consumption for anomaly detection remarkably improves by exploring the cyclic operation of the refrigerators (in comparison with the daily operation). Considering the remarks about the daily analysis, the following notes are emphasized for the cyclic one:

1- Analyzing the energy and average power consumption during an operation cycle can dramatically increase the impact of an anomaly on the normality. Therefore, this technique realizes a definite distinguishable region with larger instances of probable anomalies.

2- Knowing the fact that both examinations have been applied to the same amount of data, a time window with the length of a cycle provides the analysis with a substantial number of samples. Furthermore, it uncovers the detailed information to enable an explicit anomaly detection.

3- A cyclic investigation not only facilitates the choice of a threshold but also increases its flexibility due to the wide distribution of anomalous samples. The latter is significantly important since not all the anomalies require an (quick) action.

Moreover, a cycle-based mechanism can offer an on-line anomaly detection framework by enabling a faster estimation of analytical factors. It should be emphasized that in the cyclic analysis, the same bandwidth has been chosen to

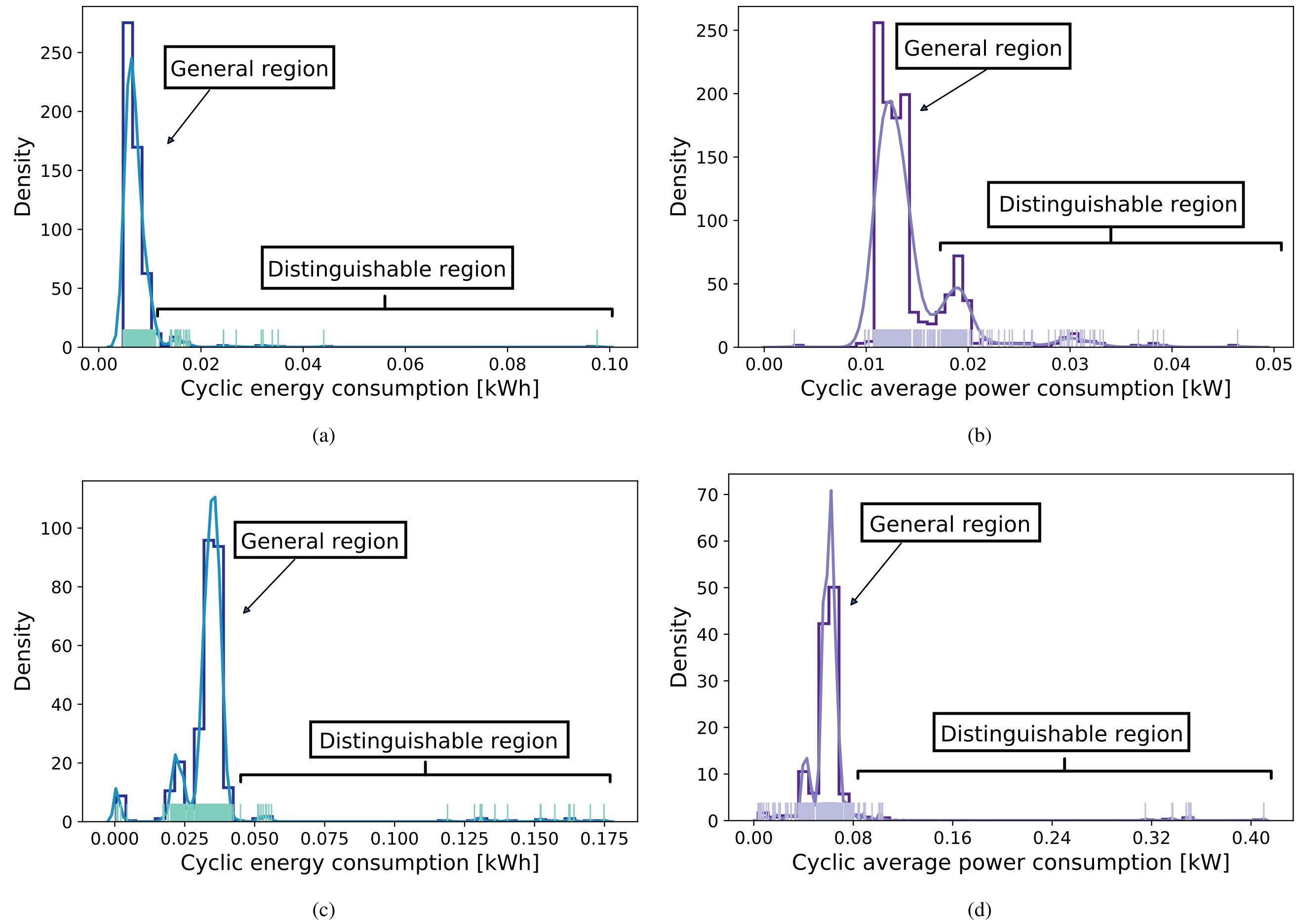


FIGURE 8. KDE of cyclic energy and average power consumption of standard (up) and smart (down) refrigerators.

provide acceptable results for KDE through all the cases. Regarding the completely different electrical features of the refrigerators, this can evidence the ability of such a mechanism to assist with the construction of general models of normal behavior. Therefore, a cyclic time-window is employed for the development of the proposed load monitoring and anomaly detection structure.

E. ANOMALY DETECTION FRAMEWORK

The comprehensive study, given above has provided a clear understanding about the refrigerators behavior from different viewpoints that can make an anomaly detection system feasible. Therefore, it is used to design both load monitoring and anomaly detection systems. In fact, the designated structure that is based on the operation cycles, consists of three procedures of normal behavior modeling, anomaly inference, and load monitoring.

As mentioned, the modeling process utilizes a semi-supervised machine learning method since it only constructs the model of the normal behavior. The cyclic energy and average power consumption are modeled in terms of Gaussian distributions $\mathcal{N}(.)$, due to the fact that a Gaussian Kernel has been able to provide a plausible explanation about these factors. Accordingly, the Gaussian parameters of each analytical factor are defined based on (4) and (5),

$$\mu = \frac{1}{C}\sum_{w=1}^{C} v_w \tag{4}$$

$$\sigma^2 = \frac{1}{C}\sum_{w=1}^{C} (v_w - \mu)^2 \tag{5}$$

that within C number of training cycles, μ and σ^2 presents the mean and variance of the modeling factor $v \in \{u, \overline{u}\}$. According to the related models, the anomaly is inferred through two steps. First, the probability density, $f(.)$ of energy and average power usage of a captured cycle is estimated by means of (6),

$$f\,(v \mid \mu,\ \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(v-\mu)^2}{2\sigma^2}\right) \tag{6}$$

Afterwards, the estimated densities are compared with their relevant thresholds to be identified as either normal or anomalous. These thresholds are computed by using the Inverse

Normal Distribution function of every Gaussian model. Accordingly, $\mu - \delta\sigma \leq T_v \leq \mu + \delta\sigma$ presents the lower and upper bounds of each threshold, T_v, respectively, where δ is defined based on three-sigma rule of thumb. As an essential prerequisite for the proposed anomaly detection structure, an on-line load monitoring framework is developed. This framework provides in-operation information of appliances candidate power consumption. It creates a data-frame according to the sampling time of data arrival. This data-frame, D is continuously expanded by storing the power consumption and the relevant state, z_k of every appliances candidate in order to capture its operation cycle. Consequently, the energy and average power consumption of the detected cycle is computed for model construction and anomaly inference phases. It is noted that the same state detection method, explained in the previous subsection is used for the on-line process. The above procedures result in an on-line load monitoring and anomaly detection system. In this system, an anomaly is detected by applying the diagnosis algorithm to the calculated analytical factors within a detected cycle, expressed by Algorithm 1.

Algorithm 1 On-Line Load Monitoring and Anomaly Detection

procedure $\mathcal{N}_v$ & T_v
  $D = \{\}$
  for (y_k, k) **do**
    # Step 1:
    define z_k
    $D = \{d_k \mid d_k = (y, z)_k\}$
    if $\Delta z_{k,k-1} = 1$ & $\Delta z_{k-N_w,k-N_w-1} = 1$ **then**
      # Step 2:
      calculate v_w ▷ According to (1) & (2)
      calculate f_{v_w} ▷ According to (6)
      # Step 3:
      if f_{v_w} *outof* T_v **then**
        $label_{v_w} \leftarrow Anomaly$
        $alarm_{v_w} \leftarrow ON$
      end if
    end if
    return *ON* alarms
  end for
end procedure

V. RESULT AND EVALUATION

The power consumption data of appliances candidate, measured by our acquisition system has been utilized to examine the proposed on-line anomaly detection approach. The developed structure is able to concurrently construct the model and estimate the anomaly. However, due to the importance of a robust detection, a practical model of normal behavior has to be ensured first. Accordingly, the normal behavior models of the refrigerators have been constructed within a time period of normal operation, in which no anomaly test has been executed. Nevertheless, the least amount of data has been exploited to build a feasible model and examine its performance with regard to a real-time implementation. It should be noted that normal condition presents a normal usage and does not mean a constantly close-door refrigerator. Subsequently, the most efficient model of each case study, captured by minimum amount of data has been employed to detect anomalous events, caused by different anomaly scenarios. Given the above, it can be comprehended that the algorithm is semi-supervised from the perspective of anomaly detection (due to the lack of an anomaly class) and supervised from the standpoint of model construction (due to utilizing a training phase). In fact, based on actual events that have been faced during the tests, a continuously unsupervised update of the normal model can be unreliable.

Besides, an appropriate diagnostic test is required to demonstrate the performance of the method. In fact, the accuracy metrics, reported in literature have been utilized to estimate either operation states or load profiles of a set of targeted appliances in the context of a load monitoring problem. However, in an anomaly detection system, the first target should be a correct diagnosis of the anomalous event. In such a system, the estimation of energy waste is also crucial, but this is not always the case. For example, informing the customers about an open-door refrigerator or left-on stove is sufficient since these incidents are not among poor behavioral consumption to be avoided by energy saving awareness. In this study, a set of diagnostic tests are employed that not only evaluate the general ability to detect an anomaly but also estimate the specific operation cycles that are affected by it. From the view point of the latter, the metrics are similar to those utilized in load monitoring studies for load profiling. Therefore, the accuracy metrics that are exploited to describe the results of anomaly detection are formulated as below,

$$Spe = \frac{tn}{tn + fp} \tag{7}$$

$$Acc = \frac{tp + tn}{tp + fp + tn + fn} \tag{8}$$

$$F1 = \frac{2 \times precision \times recall}{precision + recall} \tag{9}$$

that Spe, Acc, and $F1$ stands for specificity, accuracy, and F_1-score, respectively. t_p describes true positives (number of correct detection of anomalous cycles), f_p explains false positives (number of false detection of a normal cycle as anomalous), t_n defines true negatives (number of true detection of normal cycles), and f_n expresses false negatives (number of false detection of an anomalous cycle as normal). Consequently, $precision = \frac{t_p}{t_p+f_P}$ and $recall = \frac{t_p}{t_p+f_n}$. The specificity metric determines the robustness of the model through its capability in correctly capturing the true normal events. This diagnostic test is essential for the performance evaluation of a household anomaly detection system due to the infrequent occurrence of anomalies in electrical appliances operation. It should be noted that specificity has not been necessitated for the evaluation of load monitoring processes. F_1-score is the harmonic mean of precision and recall that presents the

TABLE 1. Standard refrigerator modeling within normal operation cycles.

NoC		$\mathcal{N}(\mu, \sigma)$	Specificity(%)	F_1-score(%)	Accuracy(%)	E_A(%)
49	u	$(0.59,0.034)10^{-2}$	72	57	77	150.34
	$\overline{u}$	$(11.97,0.69)10^{-3}$	85	76	86	95.97
97	u	$(0.58,0.029)10^{-2}$	69	54	74	155.24
	$\overline{u}$	$(11.74,0.61)10^{-3}$	79	71	82	95.14
142	u	$(0.63,0.072)10^{-2}$	98	92	98	103.70
	$\overline{u}$	$(12.24,0.99)10^{-3}$	93	84	92	99.51
186	u	$(0.65,0.081)10^{-2}$	97	84	95	106.9
	$\overline{u}$	$(12.59,1.10)10^{-3}$	94	81	91	102.84

TABLE 2. Smart refrigerator modeling within normal operation cycles.

NoC		$\mathcal{N}(\mu, \sigma)$	Specificity(%)	F_1-score(%)	Accuracy(%)	E_A(%)
46	u	$(3.4,0.8)10^{-2}$	90	83	92	107.64
	$\overline{u}$	$(6.4,1.0)10^{-3}$	76	76	82	90.46
87	u	$(3.3,0.07)10^{-2}$	98	98	99	101.32
	$\overline{u}$	$(5.9,1.0)10^{-3}$	98	93	96	101.34

accuracy of the model to identify the anomalous events. Due to the sensitivity of F_1-score to imbalance classes, the accuracy score is also utilized to define the general correctness of the results. In addition, the ability to correctly estimate the amount of energy usage and average power consumption of anomalous cycles has been examined through (10),

$$E_A = 1 - \frac{\sum_{w=1}^{C} \left(\hat{x}_w - x_w\right)}{2\sum_{w=1}^{C} x_w} \tag{10}$$

where E_A is utilized for both the energy and average power estimations. $\hat{x}_w$ and x_w are estimated and actual quantities of analytical factors within C cycles, respectively. In fact, E_A is applied to the estimated energy and average power of detected anomalous cycles during testing phase of each scenario. In order to report the overestimation, this metric has been revised to consider the real value of the nominator since the absolute value can only interpret the underestimation. Actually, the performance evaluation of an anomaly detection procedure is not simple. It should be noticed that the load monitoring process has been mainly reported in literature by using F_1-score and energy estimation (based on the absolute value). Although our ambition is to uncover an anomaly, a severe evaluation process has been used that examines both state detection and load profiling abilities.

Accordingly, Table 1 presents the results of normal behavior modeling of standard refrigerator. The model has been examined over an overall set of anomalous events based on the four predefined scenarios. In such manner, the model is not tuned to a specific scenario since anomaly is a general description, given to any kind of deviation from normality. In addition, Table 2 describes the modeling procedure of the smart refrigerator. The term 'NoC' explains the Number of Cycles with normal behavior that have been utilized to construct the model. The resultant Gaussian models of both analytical factors have been also presented. It can be noticed that their parameters vary through normal operation cycles. Although low variations demonstrate the stability of normality to rapidly extract an efficient model, it is observed that they can notably influence a precise anomaly detection. It should be mentioned that the energy has been presented based on kWh and averaged over the number of samples of the detected cycle to compute the average power (kW).

The minimum number of the cycles to capture an efficient model of the standard refrigerator is 142 that accounts for around three days of normal operation. The tests have shown that enlarging the modeling period cannot yield a notable improvement. Besides, as it can be noticed, this number of cycles has provided highly accurate results. On the other side, 87 number of normal operation cycles, associated with around two days, is the least number to extract an effective normal model of smart refrigerator. The corresponding model has provided a remarkable anomaly detection performance as well. It should be highlighted that the less modeling period of the smart refrigerator is due to a more sensitive response to any deviation, and not because of a more stabilized normal behavior. Nevertheless, the minimum time to ensure a standard model is completely depend on the user behavior. For example, a refrigerator with less utilization requires more time to offer an acceptable model since the boundaries of normality have to be defined with respect to customers' usage behavior.

Accordingly, the performance of the on-line load monitoring and anomaly detection method to capture a specific anomaly scenario is estimated based on the efficient models. In fact, the feasible model of normal behavior can provide a valid estimation of the anomaly scenarios. Accordingly, Table 3 expresses the on-line anomaly detection results of the four scenarios for the standard refrigerator. It can be observed

TABLE 3. On-line load monitoring and anomaly detection of test scenarios applied to standard refrigerator.

Scenario		Specificity(%)	F_1-score(%)	Accuracy(%)	E_A(%)
1	u	99	86	99	106.57
	$\overline{u}$	97	80	97	93.01
2	u	-	-	-	-
	$\overline{u}$	100	63	87	103.33
3	u	98	75	98	110.28
	$\overline{u}$	89	50	89	92.59
4	u	100	96	96	96.65
	$\overline{u}$	97	99	99	98.83

TABLE 4. On-line load monitoring and anomaly detection of test scenarios applied to smart refrigerator.

Scenario		Specificity(%)	F_1-score(%)	Accuracy(%)	E_A(%)
1	u	99	91	99	99.35
	$\overline{u}$	100	80	98	91.93
Blackout	u	96	98	98	100.79
	$\overline{u}$	100	87	89	105.43

that the efficient model is highly accurate to distinguish anomaly from normality for any type of deviation (caused by different scenarios). Furthermore, it is able to estimate the deviating consumption in the analytical factors with high performance. Although the energy consumption factor has not been able to recognize the scenario 2, this has not been interpreted as a failure. This scenario mainly influences the duration time of OFF state rather than ON. Actually, overly opening/closing of the door has caused the standard refrigerator to operate with less OFF periods. However, the energy consumption (as it can be noticed) computes the amount of energy demand due to an ON operation condition. Therefore, the average power consumption has been also considered as a complementary factor to uncover the OFF-state deviation and its impact on the whole cycle due to an abnormal operation. In addition, this factor is useful in explaining the anomalous behavior corresponding to scenario 4 since this scenario influences both operation states. Furthermore, the average power consumption can reflect the abnormality due to the loss of data as it interprets that as OFF period. Such a situation has been encountered during our tests (yellow dashed line in Fig. 4(a)).

Besides, Table 4 reports the on-line anomaly detection results of the efficient model of the smart refrigerator. The anomaly detection algorithm has been tested for the smart refrigerator after several months of its effective model construction. It can be observed that the model is notably correct in detecting the anomalous behavior related to the scenario 1. The high accuracy of diagnostic tests particularly, specificity score after a long time demonstrates the stability of the normal operation and in turn the robustness of the model. During the anomaly tests of smart refrigerator, we have suddenly experienced a rapid blackout. Afterwards, a permanent anomalous behavior has been warned by our on-line anomaly detection algorithm, while no anomaly test has been proceeded. Therefore, the power consumption behavior of the refrigerator has been observed. As illustrated in Fig. 9, the blackout event (grey dashed line) has totally disrupted the normal behavior of the refrigerator. Nevertheless, this unexpected event has not been considered as a disturbance. On the contrary, this advantageous incident has enabled a critical evaluation of the on-line anomaly detection system within an actual failure. Therefore, the blackout has been examined in terms of a scenario. The results indicate that the method has a high accuracy to detect this event especially, regarding the energy consumption factor. Furthermore, both factors are very efficient to estimate the deviations due to the blackout experience. The continuation of this incident is comparable with the behavior of the scenario 4. The blackout examination has been done during several days before stopping the system for required inspections. However, this has not brought a major concern with the tests of scenarios 2 and 3 (considering the benefits of such a realistic incident) since these scenarios are very similar in behavior to scenarios 4 and 1, respectively. In addition, they are not classified as an actual failure, as mentioned in Section IV.

Moreover, the proposed approach is compared with the method that has been studied by Rashid in [13] using REFIT database [47]. In this study, discussed in Section II, a similar analysis is provided that has been applied to freezer as another household periodic appliance. Rashid has tested his technique within a period of three months. However, our suggested method is implemented for almost all the data (one year) of the freezers in the same homes of REFIT database to present an extensive examination. Accordingly, Table 5 presents the comparison results. Likewise, 'NoC' presents the number of cycles that have been used to construct an efficient model. In [13], the training duration is one month however, in our

TABLE 5. Accuracy results of the proposed approach in comparison with the method in [13], tested on REFIT database.

REFIT	NoC	Accuracy (%)	On-line anomaly detection system				Rashid [13]
			3 months	6 months	9 months	12 months	3 months
Home 10	76	Precision	100	83	95	95	100
		Recall	100	100	100	99	100
		F_1-score	100	91	97	97	100
Home 16	96	Precision	92	81	78	80	90
		Recall	92	91	91	90	90
		F_1-score	92	86	84	85	90
Home 18	156	Precision	100	92	92	88	100
		Recall	100	100	100	93	70
		F_1-score	100	96	96	90	80
Home 20	99	Precision	71	77	76	78	100
		Recall	100	100	100	100	60
		F_1-score	83	87	87	88	70

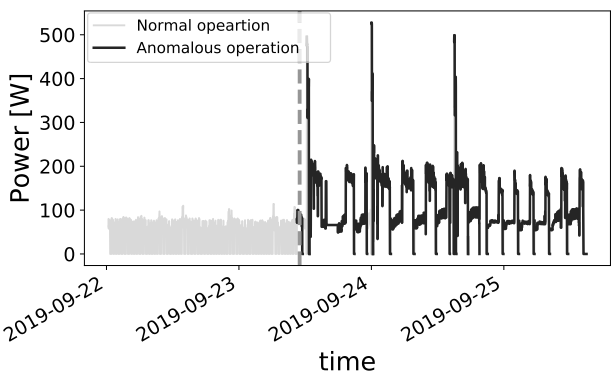


FIGURE 9. The blackout event during the anomaly experiment on the smart refrigerator; the gray dashed line indicates the approximate time of the event occurrence.

case, this period is maximum 156 cycles (House 18) that accounts for around 7 days. Besides, Rashid has used two factors to decide an anomaly. Therefore, in order to provide an equal analysis, a deviation has been identified as anomaly that has been detected by both analytical features (energy and average power usage). It should be detailed that one of the analytical factors, used in [13] is the daily number of operation cycles. Nevertheless, our actual experiments demonstrate that this factor varies in a sensible way (useful for anomaly detection), mostly when an intense anomaly occurs. The reason is that a noticeable anomaly can generally result in a lengthy operation time and thus, decrease the daily amount of cycles. The comparison has been made based on the same accuracy metrics. The results of the proposed approach have been reported every three months. It can be seen that the suggested method is notably accurate within the entire test period. This high performance that has been maintained over a long time validates the robustness of the designed framework. Particularly, the outcomes are very competitive regarding a three-month comparison (the test duration in [13]). In fact, except for precision score in House 20, the on-line anomaly detection system is more accurate in all the cases. It can be realized that the developed structure is also effective for other periodic appliances. Indeed, the correct results that have been obtained from other case studies (homes in REFIT dataset) demonstrate the generalization capability of the proposed mechanism.

It is worth to point out that author of REFIT database has declared the information of anomalous events [47]. However, by a complete examination of this dataset, it has been realized that there are other operation deviations and loss of data (similar to reported ones) that have not been mentioned. It should be noted that the comparison analysis has been concluded by considering these additional instances. Nevertheless, this has not notably influenced the results, compared to an assessment without such samples due to their few numbers. Actually, the evaluation of both conditions has resulted in the same accuracy during three months and an insignificant difference only after a long period (9 months and more).

VI. DISCUSSION

In accordance with the above results and analyses of the proposed on-line appliance-level load monitoring and anomaly detection system, the following remarks should be discussed.

1- Although this work has focused on household periodic energy-intensive appliances as the case studies, its approach to anomaly detection is general. It has explored the operation-time anomaly concept that can be applied to other types of appliances. Furthermore, the method has utilized a common electrical feature in a low-sampling frequency that is compatible with current metering technologies and household energy-demanding devices. Employing normal electrical properties is critical to develop a general method, however appliances, particularly refrigerators can still have basic signatures that are notably different.

2- Since the study has been done in the appliance-level with sub-metered information, a highly accurate anomaly detection process has been intended. Therefore, a careful set of diagnostic scores has been utilized to examine the results. These accuracy rules are very precise such a way that their estimation of the outcomes can be attributed to load profiling rather than load diagnosis. From the standpoint of anomaly detection, the proposed method is totally capable of recognizing any anomalous behavior particularly, the ones that are considered as failure.

3- A supervised machine learning algorithm that signifies an off-line process has been employed to create the normal behavior models of the appliances candidate. A supervised method can facilitate capturing an efficient model that can handle both the stochastic nature of anomalous behavior of an appliance and the variation of its normal electrical characteristics (due to different reasons, e.g. aging). In fact, ensuring effective models of loads regular patterns, which guarantees customers' fidelity to warning alarms, is pivotal for a usable anomaly detection system. Although an on-line model construction, mainly aimed by unsupervised methods, is interesting, the stationary behavior of household energy-intensive appliances reduce its necessity. The concern with an unsupervised modeling of normal behavior increases considering an anomaly detection system with poor performance. For example, it is possible that such a system considers the abnormal behavior of a refrigerator with defective gasket as normal (due to the continuation of this kind of anomaly).

4- It is advised that a load monitoring and diagnosis system should be capable of early diagnosis. Nevertheless, our thorough study has demonstrated that the term 'early' (one can read real-time) depends on different matters, characterized as below:

- The application: Among the chosen scenarios, two of them are actually a failure. However, all scenarios have been detected as anomaly since they cause similar variations on normal energy consumption. This is due to the operation-time anomaly nature rather than the model inadequacy. Therefore, an early detection should be defined based on the applications that generally account for fault (scenarios 1 and 4) and over-usage (scenarios 2 and 3) diagnosis.
- The time: Scenarios 1 and 4 express a failure. Although the energy consumption is rapidly influenced by an anomaly, these cases require different time period to ensure an abnormality. The anomaly detection system is quick to capture scenario 1 however, it needs more time to recognize scenario 4 (in our case more than one day). Furthermore, the time can affect the recognition of an irregular behavior due to aging problems. Subsequently, a load diagnosis system is real-time with respect to the type of anomaly that it seeks to detect.
- The urgency: Generally, an operation-time anomaly of a refrigerator can be dealt with as an energy saving issue. However, this is not the case for a stove that has been left ON. In fact, an anomalous stove can cause a dangerous situation instead of energy waste. Consequently, the early diagnosis should favor the type of a targeting appliance.

Accordingly, a load monitoring and diagnosis system is suggested that its diagnosis phase accounts for two separated steps of anomaly detection and diagnosis decision. As a result, the term 'early' can be an appropriate fit for the former. The anomaly detection should capture a deviation when it occurs (on-line distinguishability) and the diagnosis decision should confirm a malfunction when there is adequate evidences (e.g. continuation of a deviation).

VII. CONCLUSION

Anomaly detection is a significant application of load monitoring systems. In the residential sector, this application can assist with different kind of energy saving awareness. Due to the inadequacies related to an aggregate-level implementation from one side and future low-priced smart plugs from the other side, an appliance-level anomaly detection aspect is reinforced. Accordingly, this paper has provided an exhaustive investigation into different aspects of an appliance-level anomaly detection with regard to household energy-intensive appliances. As a result, an on-line load monitoring and anomaly detection approach has been proposed that is capable of expeditiously capturing any operation-time abnormality. The proposed approach has been examined by implementing an actual framework. This framework applies the suggested design to the measured data of a set of appliances candidate. These appliances account for a standard and a smart refrigerator with different electrical characteristics. Refrigerators are important household finite-state loads that can bring about challenging anomalous behaviors. Therefore, they are a suitable case study for anomaly detection of household energy-expensive loads. The results based on careful diagnostic tests have demonstrated the high performance of the proposed method. Furthermore, the efficiency of the suggested technique has been demonstrated through an extensive comparison analysis. Moreover, the utilization of a group of straightforward algorithms, examined on a physical operating system, has validated the pertinence of the developed structure to smart meters/plugs systems. With regard to the case studies, this analysis has elaborated important remarks on a full appliance-level load monitoring in terms of a system capable of continuous load observation, anomaly detection, and diagnosis decision.

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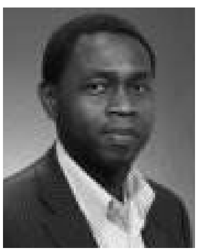

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