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Review

Fault Detection and Efficiency Assessment for HVAC Systems Using Non-Intrusive Load Monitoring: A Review

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Abstract: Heat, ventilation, and air conditioning (HVAC) systems are some of the most energy-intensive equipment in buildings and their faulty or inefficient operation can significantly increase energy waste. Non-Intrusive Load Monitoring (NILM), which is a software-based tool, has been a popular research area over the last few decades. NILM can play an important role in providing future energy efficiency feedback and developing fault detection and diagnosis (FDD) tools in smart buildings. Therefore, the review of NILM-based methods for FDD and the energy efficiency (EE) assessment of HVACs can be beneficial for users as well as buildings and facilities operators. To the best of the authors' knowledge, this paper is the first review paper on the application of NILM techniques in these areas and highlights their effectiveness and limitations. This review shows that even though NILM could be successfully implemented for FDD and the EE evaluation of HVACs, and enhance the performance of these techniques, there are many research opportunities to improve or develop NILM-based FDD methods to deal with real-world challenges. These challenges and future research works are also discussed in-depth.

Keywords: non-intrusive load monitoring; HVAC; fault detection and diagnosis; energy efficiency

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1. Introduction

Buildings are responsible for 40% of the total consumption of electrical energy and 20% of total CO_2 emissions [1,2]. The impact of occupants and their behavior on building energy consumption is considerable [3]. Studies have demonstrated that approximately 30% of this consumption is wasted due to sub-optimal operation or malfunctioning of building system equipment or the behavior of consumers [4,5]. For instance, over USD 7 billion are wasted in the U.S. due to faulty conditions in commercial buildings in 2017 [1]. The European Energy Council has suggested using various energy efficiency (EE) approaches in buildings, such as utilizing automatic fault detection and diagnostics (FDD), to achieve the goal of European Union policy in becoming an efficient and 100% renewable energy system by 2050 [5].

Since heat, ventilation and air conditioning (HVAC) systems are some of the most energy-intensive equipment in buildings, their faulty operation or inappropriate thermostat setpoint account for substantial unnecessary energy use. Therefore, the development of FDD methods and EE evaluation techniques are two key tools in the implementation of feedback tools and reducing power consumption in buildings. FDD strategies could prevent wasteful or excessive energy use by identifying faults in a timely and cost-efficient manner. Studies have shown that from 20–30% of building energy can be saved by utilizing FDD methods in HVAC systems [5,6]. Implementing the EE assessment approaches is another way to decrease the electrical power consumption by identifying sub-optimal operation or wrongly configured HVAC systems.

Various techniques have been developed for FDD in buildings. These methods are categorized into two groups according to [7]: data driven-based approaches [1,8,9] and knowledge-based strategies [5,10–12]. Knowledge-based approaches rely heavily on domain knowledge. In other words, prior knowledge is used to develop rules or models for fault detection. In most cases, these methods utilize physical variables or parameters [7].

Knowledge-based methods are relatively complex approaches and require extensive efforts from expert engineers. Moreover, knowledge-based models are constructed for specific systems and conditions and are hard to adapt to different ones [10].

Data-driven methods rely mainly on the similarity of patterns [7]. These methods can automatically extract the pattern for FDD based on data-driven approaches that generally do not use physical variables. The main limitation of these data-driven methods is the need for separate datasets of both faulty and fault-free operations. Training by unknown faulty data leads to wrong FDD results or the lack of faulty data could reduce the diagnosing capability of the FDD system. In most cases, and due to the lack of data, these FDD approaches cannot be utilized for newly installed systems or new operational conditions.

In recent decades, most research on FDD has focused on data-driven methods [7]. For instance, Namburu et al. [8] presented a data-driven method for modeling, FDD and optimal sensor selection for maximum diagnosability in HVAC chillers. To detect and classify the chiller's faults, three well-known pattern recognition techniques were utilized i.e., support vector machine (SVM), partial least squares, principal component analysis. A genetic algorithm was also used for optimal sensor selection and maximum diagnosability. They examined their approach using a dataset that contained 64 monitored variables for 27 different operation modes during normal and eight faulty conditions. The results showed that the classification precision was more than 95% in any operating condition. In recent decades, non-intrusive load monitoring (NILM) has been developed to identify the power consumption of home appliances and equipment using an aggregated power measurement at power entry. NILM is a data-driven approach that could help to assess the EE of HVACs and detect its faults or anomalous operation by identifying the ON/OFF events and the analysis of time and other characteristics of normal/faulty HVAC operation.

NILM can remarkably decrease the cost of monitoring and diagnostic systems for HVACs. For instance, the number of installed sensors on packaged air conditioners could be reduced, significantly decreasing the capital and installation costs of remote monitoring systems [9]. Moreover, by implementing the NILM for packaged air conditioners, which are usually inefficiently operated or poorly maintained, consumed energy for space conditioning could be reduced in 90% of commercial buildings and the 55% of commercial floor area that these units operate [9]. Furthermore, by decreasing the costs of remote monitoring for packaged HVACs, NILM could help in the implementation of conditioned-based maintenance instead of the schedule-based preventive and reactive maintenance strategies commonly used today. Figure 1 presents a general framework for EE assessment and FDD methods using NILM-based strategies.

With advancements in the performance of NILM methods in recent years [13,14], many startups and researchers have focused their efforts on utilizing NILM outputs for EE assessment and FDD in HVACs. Although many articles have proposed the FDD methods for HVACs [15,16], utilizing NILM methods in this area and their advantages and disadvantages have not been sufficiently covered. A review of this research topic could be helpful to provide a better understanding of NILM application in HVAC systems and provide an overview of the recent advancements, which is the prerequisite for the development of novel approaches in the studied area.

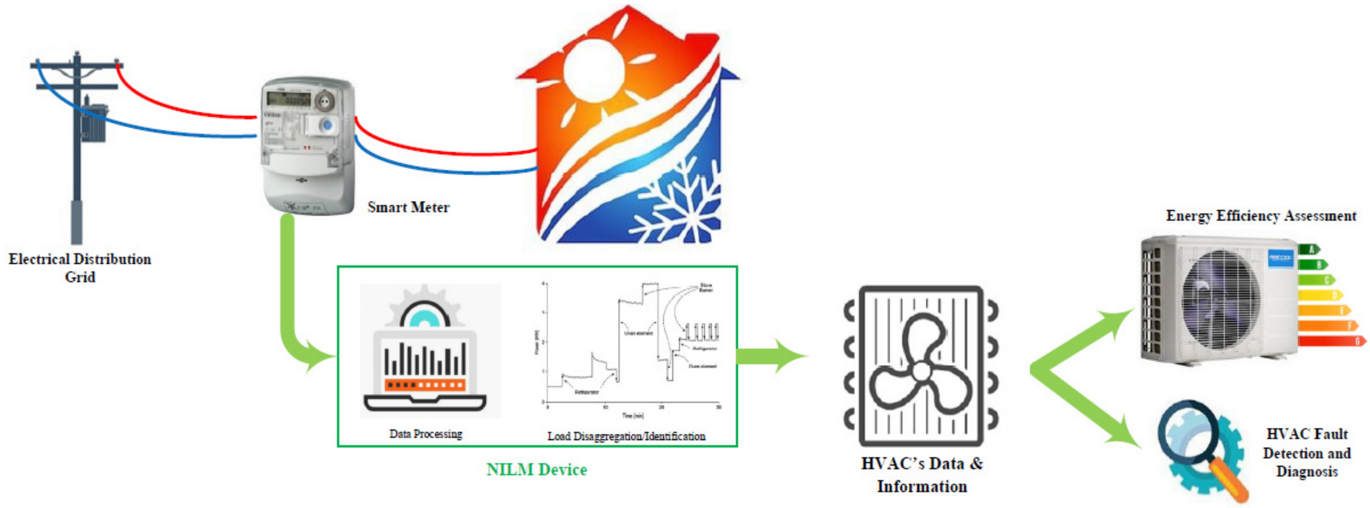

Figure 1. A general framework for energy efficiency assessment and FDD methods using NILM-based strategies.

Many studies have reviewed FDD methods in building applications [6,7,15,16]. Kim and Katipamula [6] have presented a general review of FDD methods for building systems while Li et al. [17] feature engineering methods for FDD in HVACs. To the best of the authors' knowledge, the present paper is the first paper that focuses on the review of NILM-based methods used for energy efficiency assessment and fault detection and diagnosis in HVAC systems. Table 1 presents a comparison between this study and other recent review papers within the context of FDD and EE assessment techniques in building applications. This paper also focuses on different aspects of these methods and highlights their benefits, limitations, and challenges.

Table 1. Comparison of this study with other recent review papers in the context of FDD and Energy Efficiency assessment techniques in building applications.

Reference	Year	Type of Application	NILM-Based Methods	Fault Detection and Diagnosis in HVACs	EE Assessment
[6]	2017	FDD methods for commercial buildings	-	√	-
[7]	2019	Building energy systems	-	√	-
[13]	2020	Home energy management	√	-	√
[15]	2019	Residential air conditioners	-	√	-
[16]	2020	large-scale HVAC	-	√	-
[18]	2019	Home energy management	√	-	-
[19]	2021	Abnormal energy usage in buildings	√	-	√
This paper		All types of HVACs	√	√	√

The paper is structured as follows; an overview of NILM has been presented in Section 2. NILM-based FDD methods for HVAC systems are reviewed in Section 3. Section 4 reviews the usage of NILM techniques in the energy efficiency assessment methods of

HVACs. Research challenges and future works are discussed in Section 5. Conclusions are presented in Section 6.

2. Overview of NILM

NILM is a software-based tool to identify power consumption and other characteristics of electrical home appliances from a single measurement point at power entry. In contrary to intrusive load monitoring, in which a separate measuring device is installed on each device, NILM does not require an individual measuring tool to be installed on each appliance. Therefore, NILM reduces the cost of sensing infrastructure, installations, and maintenance needs. Moreover, NILM approaches can be easily accepted by residents due to their convenience, maintaining residents' privacy, and economic efficiency [20].

Although NILM is an intensive computation process and requires complex software algorithms, recent developments in the availability and measuring technology of smart meters and continuous advancements in computational strategies have established NILM as a promising approach for the monitoring of electrical energy [21]. The NILM can not only provide useful information about residents, their habits, and daily activities but also takes into account other aspects such as consumers' privacy.

NILM is composed of two basic parts: smart metering and the load identification process [22]. NILM is a data-driven method and accurate measurements are crucial for the high performance of NILM systems. Moreover, the number and type of desired features that are used in load identification are highly relevant to specifications of metering hardware and measurement frequency [23]. For instance, to measure power characteristics that are required for extracting the frequency components or transient-based approaches, a high-frequency sampling rate sensor is required [13]. This high-cost hardware is not available in most commercial smart meters and leads to the restriction of the real-world, large-scale application of these approaches.

The main part of load identification is the load disaggregation that extracts the itemized information of household appliances using only the total measured power consumption data. The load disaggregation algorithms rely on two main strategies to identify appliances: event-based and non-event-based approaches. First, event-based strategies detect the switching ON/OFF events using identifying step changes by analyzing steady-state features or the transient analysis of patterns [24,25]. In comparison with using steady-state features, the transient analysis could provide better results, but it requires a high-frequency metering sensor that is not available in most commercial smart meters. This constraint restricts the real-world, large-scale application of transient approaches.

In contrast, the non-event-based strategies rely on the current and instantaneous values of voltage to identify the appliance status. These models are trained by existing classified data to itemize the electrical loads [26,27]. Recent non-event-based studies have focused on hidden Markov models (HMMs) and their variants [28] to identify the state of appliances. A detailed review of datasets, tools, algorithms, and future trends of NILM methods are presented in [13,18,29–31].

3. NILM-Based FDD for HVACs

Reducing the maintenance and electricity costs, decreasing carbon emissions, and lowering the peak demand are some of the benefits of using FDD methods in HVACs. Figure 2 illustrates the benefits of automated FDD methods in HVAC applications.

Faults change load signatures that could be analyzed for FDD. Various signatures can be captured by NILM methods for the identification of different faults [32–34]. Therefore, NILM can play a key role in the detection of electrical and non-electrical faults of HVACs. This approach can identify electro-mechanical and electrical faults that are difficult to detect by thermal measurements [33].

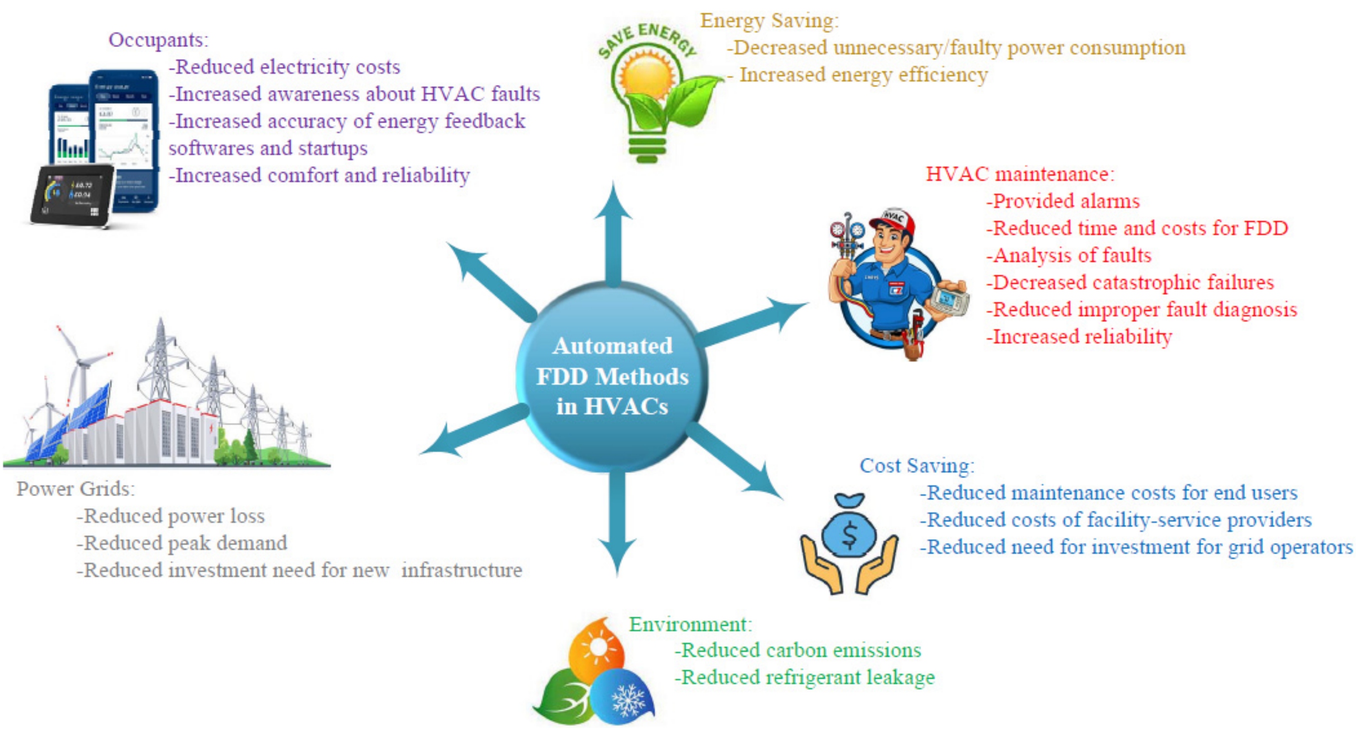

Figure 2. Benefits of automated FDD methods in HVAC applications.

In [34], NILM has been successfully used for FDD of various types of faults in a Rooftop Cooling Unit (RTU) such as flow blockage, fan imbalance, refrigerant undercharge and overcharge faults, short-cycling, bypass leakage, and liquid ingestion faults. The collected data in fault-free operation modes indicated that start transients were distinct and repeatable for fans and compressors. Therefore, the authors have suggested an analysis of both transient and steady-state electrical characteristics for the detection of various RTU faults. To collect the start transients, the measuring sampling rate was 120 Hz and each motor was started and run for five to ten seconds. This process was repeated five times and all measured values were recorded by NILM. For steady-state operation and using Fourier decomposition of the power signal, the active and reactive power were also collected for ten minutes.

Five generic methods have been implemented by NILM for fault detection in [34]: the change in the mean of steady-state power and reactive power, matching the patterns of start transients, the detection of anomalous transients, analyzing the real-power amplitude spectrum, the current (ratio) and voltage (threshold) monitoring for phase imbalance detection. For instance, a change in steady-state active and reactive power can be used for the detection of air-side blockage faults. However, identifying the change in directions and magnitudes related to blockage magnitudes requires investigating the interactions between different information such as fan curve, motor torque curve, air-side flow-pressure curve, and no-fault operating point. Therefore, the fault diagnosis needs more information in comparison with that required for fault detection e.g., using static pressure. Flow transitions could clearly affect the start transients of active and reactive power and also the pressure start transient. The short-cycling in RTUs could also be detected by NILM using two analyses of start transients; analyzing the change in individual start transients that is sensitive to the residual head, and the logging time between start transients. These two techniques are complementary and should be applied together. To diagnose a root cause, the thermal conditions and a time-stamp can be saved when a short-cycle occurs. The frequency analysis of shaft harmonics data is utilized to detect unbalanced impeller rotation of the condenser and supply fans. The results for both the condenser and the supply fans demonstrate that imbalance faults can be detected using features that are extracted by

NILM. This study has described ten different RTU faults in detail and introduced different NILM approaches to deal with these faults. The results show that 10 to 30% of total repair costs in RTUs are related to the faults that can be discerned by the standard NILM platform. Therefore, NILM-based fault detection can significantly reduce the total repair costs of RTUs.

In [35], Lai et al. proposed a method to warn the users about AC faults and help them to repair and replace the faulty device to save energy. They have focused on an NILM technique to detect the state of the AC. Two similar ACs were installed in similar closed environments and examined for different air conditioning volume modes, compressor ON/OFF state of operation, aging of the air conditioner, and abnormal operation. The normal and faulty AC operations were compared. It was concluded that machine faults and electronic faults, caused by accidental operation, are the most common faults of air conditioners, which are 32% and 29% of all faults, respectively. It is also noted that 44% of electronic part faults and 38% of machine faults lead to the complete failure of the air conditioning unit while most of the faults are associated with the refrigerant and compressor of the AC.

In the study, various air conditioning operation modes and status information of electrical equipment were predetermined for subtree classification and to create a state feature database of detected electrical devices and historical service conditions. These data were used to determine the switching time and operating state of electrical devices by searching and analyzing the characteristics of different electrical equipment. The state feature database was consistently updated by the continuous use of electrical devices and user feedback. The states and other parameters were modified to increase the detection accuracy of subsequent equipment and for searching the states of electrical devices. In the case of the AC, the power consumption samples were used to identify whether the AC was faulty or not. Two AC faults were investigated in this study: filter block and refrigerant leak or block. To artificially create a filter blockage case, 80% of the indoor unit air inlet was covered by A4 paper. The refrigerant leak case was identified by the retraction of refrigerant oil and increasing in the running time of compressor. The daily percentage of compressor operation in the "ON" state was easily calculated from the database information. However, the refrigerant block was detected by a low compressor usage rate. The electrical equipment information in the faulty condition was collected as another database for the detection of future faults.

Fault diagnosis was conducted in [35] using NILM and by processing the changes in current and voltage waveform, caused by ON/OFF events, using Fourier transform and spectral analysis. The results were used by a multi-dimensional k-nearest neighbor (KNN) technique to diagnose the faults and give automated feedback on the replacement, maintenance, and repair of electrical equipment to users. The energy data of a whole day was used as training and test data. A SVM was utilized for fault detection using a state feature database. The results show the proposed technique detects block and leak refrigerant faults with 94% accuracy.

Brambley [9] indicates that NILM could significantly reduce the number of sensors utilized in HVAC packages. These systems currently use between 10 and 20 sensors in diagnostic monitoring systems that can be reduced to 3 sensors if the NILM has been implemented. Hence, the capital cost of hardware of monitoring systems and the installation costs of packaged HVACs would be significantly decreased [9]. It demonstrates that the application of NILM in residential buildings for the detection of starting new individual devices using ON/OFF events and recognition of separate increase in consumption power, is troublesome due to the large number of devices in a home and because it requires a high sampling rate measuring tool. However, the number of components in a packaged HVAC unit that is of interest for event detection is much lower, such as the compressors, the condenser and supply fans, and the evaporator. Moreover, these devices could be distinguished by the changes in their power consumption magnitudes. Therefore, Brambley suggests using much smaller sampling periods of tens of seconds to a couple of minutes to quantify the electrical energy consumption of fans and compressors and to discern between the on and off events. He hypothesized that a combination of the power usages with one or two air temperature features (such as outdoor temperature and possibly return-air or supply-air temperature) could detect the changes in energy efficiency and major faults. This NILM approach utilizes a simple strategy and can only be used for packaged HVAC units whereas the variation in large consumed power can be easily detected by NILM.

Rashid and his colleagues proposed a rule-based anomaly detection algorithm called UNUM to identify anomalies using NILM. In [36], Rashid and Singh implemented a K-means clustering algorithm to identify ON and OFF states of the compressor of an appliance. They also proposed a rule-based anomaly detection algorithm called UNUM to identify anomalies that are artificially inserted on the disaggregated power consumption of both an air conditioner (AC) and refrigerator from the total power measurements of four homes of a public dataset (called Dataport). The accuracy of anomaly detection in UNUM is not an acceptable anomaly. In [37], Rashid et al. extended their previous work [36] using two well-known open-source NILM disaggregation techniques provided by NILMTK: Combinatorial Optimization (CO) [38] and the Factorial Hidden Markov Model (FHMM) [39]. They also applied some post-processing processes on NILM outputs to minimize the noise effects and then utilize UNUM to enhance the anomaly detection accuracy.

In another study, Rashid and his colleagues used the same approach with updated UNUM and evaluated two new disaggregation methods, Latent Bayesian Modeling (LBM) [40] and the Super-state Hidden Markov Model (SSHMM) [41]. The results show that NILM techniques could identify and track the power consumption changes in the AC when compared to the refrigerator. This is because the power changes in a refrigerator ($\pm$90–150 W approx.) are much smaller than AC power changes ($>\pm$1 kW). They illustrated that the NILM techniques could not be used for accurate anomaly detection in the AC or refrigerator if the disaggregation accuracy was not high. Thus, they have suggested some post-processing of NILM output signals to reduce the noise effects. Although they indicated that this approach could enhance the accuracy of anomaly detection, its anomaly detection performance and advantages and disadvantage of utilizing UNUM were not compared with other anomaly detection techniques.

In [42], the NILM methods have been applied to determine the power consumption and mechanical shaft speed of motors from an aggregate power measurement when other loads operate simultaneously. This paper demonstrates how the prior information about motor harmonics could be utilized for FDD in induction motors that are used in air conditioning and handling systems. They have also implemented an optimization technique to enhance the prediction accuracy while using a smaller data set.

Batra et al. [43] have developed new techniques that utilize the NILM outputs for providing actionable feedback to residential users. They have also focused on HVAC and refrigerator cases to evaluate the performance of this feedback on saving energy in homes. They have built a model to estimate HVAC setpoint temperature based on power consumption data and outdoor temperature patterns and classify homes with and without set-back schedules on the HVAC system. This approach has been evaluated using energy data of 240 homes and results show that it can recognize homes that need feedback with 84% accuracy. The results clearly demonstrate that NILM could be implemented for providing actionable and targeted feedback and have the potential to lead to sustainable energy savings. They have also re-evaluated the feedback methods using power data obtained by disaggregation techniques against those measured by direct sub-metering and reported very low accuracy of feedback despite the high accuracy of disaggregation. Thus, they suggested that evaluation metrics of disaggregation accuracy need to be revisited.

The Building Management System (BMS) system is extensively implemented in modern commercial and residential buildings. This system coordinates its control and sensing infrastructure, primarily used for the management of HVAC systems. Most commercial BMSs utilize simple FDD methods such as threshold monitoring in which an alarm is generated when a parameter is higher than a preset threshold. Narayanaswamy et al. have reported that more than 10,000 alarms per day have been generated by the BMSs at the campus of the University of California, San Diego [44]. This huge rate of alarms leads to the building managers ignoring the alarms and many faults remaining undetected for long periods, deterioration and failure of equipment, and also the increase in energy wastage. Therefore, a high false alarm rate decreases the reliability of FDD methods and can make these methods useless.

To reduce false alarms, Rashid et al. proposed a new technique called "Monitor" for abnormality detection in energy consumption using smart meter data only [4]. The main advantage of this technique is reducing false alarms and increasing the reliability of anomaly detection. In this approach, consumption patterns in past data are identified to detect abnormal energy usage. First, they clustered all past days in various categories having different energy consumption patterns. Finally, an instance is classified as faulty/abnormal if it is significantly different from the cluster's prominent pattern. They examined the Monitor for 16 weeks of data of real residential and commercial buildings, including HVAC Chiller, and demonstrated that it increases the accuracy up to 24% in the best scenario and on average by 14%. This accuracy enhancement significantly decreases the number of false-positive alarms and makes the method a more suitable choice for real-world applications.

Air leakage is another fault in HVAC systems that leads to excessive usage of HVACs and electrical energy consumption. Detection of air leakages is an expensive and time-consuming task. A NILM-based fault detection technique is employed in [45] to detect the potential homes with air leakages in the residential sector. The NILM is utilized to disaggregate the building's power consumption and obtain the HVAC data. Then, a convolutional Long Short-Term Memory (LSTM) and a de-noising autoencoder are implemented to recognize the 'ON' and 'OFF' state of the HVACs and calculate their operation periods. The analysis has been performed for 70 unique homes' data that is publicly available in a large-scale dataset called "Dataport". The performance of the NILM is also investigated using three data resolutions such as 1 min, 15 min, and 60 min to evaluate the impacts of data granularity on the classification accuracy of the leaky homes. Simulation results indicate that the disaggregation of 1 min of power consumption data can be utilized to identify and classify potential leaky homes with an accuracy of 86%. These results show the importance of NILM to identify the energy consumption of the AC for identifying leaky homes and preventing the waste of energy in large residential buildings. This approach has two major limitations: (1) the computational complexity of LSTM to perform larger-scale disaggregation and (2) the extreme dependency of the LSTM approach on a large and diverse dataset to improve disaggregation accuracy.

NILM-based FDD methods for HVAC systems are summarized in Table 2. This table presents a brief comparison of the measurement sampling frequency, input variables, detected faults, fault or anomaly detection, diagnosis techniques, and disaggregation algorithms used in these methods.

Table 2. Main characteristics of NILM-based FDD techniques for HVACs.

Author	Year	Data	Data Period	Sampling Frequency	Input Variables	Detected Fault/ Anomaly	Fault/Anomaly Detection Technique
Rashid et al. [4]	2018	Experimental data	1 August to 29 November 2015	30 sec	Power	Abnormal energy usage	-Detecting abnormalities using the previous patterns in past consumption data
Brambley [9]	2009	N/M	N/M [1]	0.125 sec 10 sec 60 sec	Power Temperature	Abnormal energy usage	-Electric power change, -Duty cycle -Degree of cycling under similar outdoor weather conditions
Armstrong et al. [34]	2006	Measured Data	N/M [1]	120 Hz	-Voltage -Current -Active Power -Reactive Power	-Flow blockage, -Fan imbalance, -Refrigerant undercharge and overcharge faults, -Short cycling, -Bypass leakage, and -Liquid ingestion faults	-Analysis of input variables -Frequency analysis of the amplitude spectrum of active power -Analysis of start transient patterns - Identifying anomalous transients
Lai et al. [35]	2014	Measured Data	1-day	1-sec	-Voltage -Current -Power -Reactive power	-Filter block -Refrigerant leak or block	-SVM -KNN
Rashid and Singh [36]	2017	-Dataport	3 months (June–August 2014)	1-min	Power	Anomaly in energy consumption of air conditioner and fridge	-A rule-based algorithm, called UNUM
Rashid et al. [37]	2019	-Dataport, -REDD -iAWE	Less than three months	1-min 1-sec	Power	Anomaly in energy consumption of air conditioner and fridge	-A rule-based algorithm, called UNUM
Orji et al. [42]	2010	Measured Data	N/M [1]	7800 Hz	-Current -Harmonics	Electro-mechanical faults including damaged bearings and rotor eccentricity	Harmonic analysis of motor current
Batra et al. [43]	2015	Dataport	7 months	1-min	Power	Abnormal energy usage	Evaluation of usage cycles
Pathak et al. [45]	2018	Dataport	1 year	1-min	Power	Air leakage	Air leakage classification using the disaggregated data

[1] N/M: Not mentioned.

4. Energy Efficiency Assessment of HVACs Using NILM

HVAC systems are responsible for up to 50% of a building's energy consumption. [46]. Consequently, air conditioners are considered as the main target of all EE assessment strategies in buildings. The increase in electrical energy efficiency of buildings is beneficial for both residential and commercial buildings. It helps to reduce the consumption of energy and could also decrease the cost of electrical energy. From the policy maker's perspective, the development of energy efficiency solutions has been considered as a crucial tool for reducing energy demands, lowering the need for new investments in electrical power generation, and decreasing greenhouse gas emissions and environmental deterioration.

The energy efficiency of a building is dependent on many factors including the type of appliances, weather parameters, and users' behavior and habits. Due to the variety of features and insufficient information, the assessment of EE in buildings is a challenging task. The disaggregated information of home appliances obtained by NILM is a great tool to help in the evaluation of the EE in buildings. In [47], a NILM-based assessment method is proposed to evaluate the EE of households. To enhance the accuracy, this study introduced an EE assessment index of residents using the analysis of both electrical and non-electrical factors that could affect energy efficiency. Resident's energy efficiency was analyzed and tested by a combination of the clustering of NILM data, an entropy weight method, and the "Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS)". Furthermore, 15-min energy consumption data of 20 residential users within 30 days were used by NILM to obtain the energy usage information of 51 different electrical home appliances including refrigerators, air conditioners, and washing machines. This information was analyzed for identifying the energy consumption patterns of users and detecting energy inefficiencies to give recommendations and feedback for energy saving. These suggestions could help the users to recognize their non-efficient behaviors and give them the opportunity to improve EE by changing the energy-use mode of appliances. The authors demonstrate that utilizing NILM data enhances the accuracy for delineating the manner of consumers' energy consumption. These accurate analyses could help power companies in conducting efficient and targeted marketing for various consumers, and also improve the level of service for electrical power utilities.

A new method for the evaluation of energy performance for buildings with a space cooling system is proposed in [48]. It has utilized actual measured data (i.e., the bills of energy) to develop energy models to disaggregate the building's electricity bill. The energy performance has been evaluated in both building and system levels using the disaggregation of the consumption of the whole-building into three groups of end-users consumptions: the HVAC users, internal-consumers, and other users. Two basic energy balance principles for the whole building and HVAC systems are used to model energy consumption. An optimization technique is also presented to minimize the balance residuals, i.e., the difference between the demand side and supply side of HVAC systems, and to obtain the best possible balance of energy. The outputs contain the disaggregated energy consumptions and the energy performance indicators of HVAC systems, e.g., the building cooling load and whole system efficiencies that could be used for performance assessment of the supply and demand side, respectively. Although the technique has provided an effective and simple tool for the evaluation of energy performance, its main limitation is that it can only be used in buildings in which electricity is the only energy source. Therefore, this method is not the right choice for buildings that use multiple sources of energy, such as hot water heating in winter, particularly in cold climates.

Energy use intensity (EUI) has been used as a popular indicator for energy performance evaluation in public buildings. It has been calculated by dividing the total annual energy consumption of a building by its total gross floor area. This indicator combines the energy consumption of all end-users and is not sufficiently indicative and may fail to properly evaluate energy performance, especially in large baseloads such as banks, hospitals, and data centers. To deal with this problem, Kim et al. [49] have introduced three new performance evaluation measures: heating, cooling, and baseload EUIs. These indicators can be calculated using monthly energy consumption data obtained by a disaggregation method. This approach disaggregated energy used for cooling/heating by subtracting the minimum required energy value (baseload energy) that is calculated based on the weather characteristics during the seasonal changes in South Korea. This approach is a non-parametric or model-free strategy because there is no linearity assumption between outdoor temperature and the energy use. However, the method has two constraints: (1) the building has to operate regularly throughout the year, (2) both heating and cooling loads must exist in summer and winter. The disaggregation accuracy is decreased if neither of them is satisfactory. Hence, the method cannot be implemented for buildings that have irregular heating and cooling loads or are vacant for some time.

Hopf et al. have identified new relevant energy efficiency household characteristics using machine learning [50]. This study utilized smart electricity meter data, weather information, and a Random Forests classifier to identify 19 household classes using 11 relevant EE household characteristics with an average accuracy of 69%. However, eight of these characteristics were revealed using 15-min data measured by smart meters (e.g., type and age of space heating, age of home appliances, type of water heating, using a heat pump in a home, presence of solar heating systems or photovoltaics, and a number of EE measures that were lately performed), the other three household properties were predicted (age of residents, number of home appliances, and cooking facility type). The results demonstrate that this method could have decent accuracy even with an hourly or daily data granularity, and the classification performance was not considerably affected by data from different seasons. The method could be used as a foundation for services with additional value that is beneficial for consumers, but it may be utilized to extract some characteristics that are considered to be private for users. Therefore, this approach has to be utilized with clear privacy guidelines and must be implemented only with the consent of data subjects. The results indicate that hourly or even daily values of electricity consumption data are sufficient for the detection of four properties with acceptable accuracy: a number of appliances, heat pump, water heating type, and space heating type. The main limitation was caused by using data of one Swiss city and its immediate vicinity which may bias the study.

In [51], an EE assessment method has been proposed for home appliances based on NILM. This method uses the disaggregated appliance data to classify electrical home appliances into predefined groups based on the working mechanism and the application of these devices. For instance, air conditioners are used to keep the indoor temperature in the desired range and are classified as an interruptible load in which the operation status of loads are substantially affected by environmental features. Then, specific EE functions are set up for appliance energy assessment, i.e., time EE function, EE function of illumination, and temperature EE function. For example, when the indoor temperature is in the desired range, the compressor of the air conditioner must work in OFF mode and if it operates in ON mode, the temperature EE function detects that the air conditioner operates inefficiently. Finally, the inefficient running time of each appliance is determined, and the wasted electrical energy of each appliance is calculated to inform the user by the feedback and energy-related behavior of residents.

Table 3 summarizes the NILM-based methods for the energy efficiency assessment of HVACs. The data source, metering frequency, input variables, load disaggregation technique, energy efficiency assessment approaches, as well as the evaluation metrics of these methods, have also been compared.

Table 3. NILM-based methods for energy efficiency assessment of HVACs.

Author	Year	Data Period	Sampling Frequency	Input Variables	Disaggregation Method	EE Assessment Approach	Location	Evaluation Metrics
Kong et al. [47]	2020	30 days	15-min	Power	Hidden Markov Model (HMM)	Entropy weight method and TOPSIS	Tianjin, China	TOPSIS evaluation method
Yan et al. [48]	2012	1 year	Monthly	-Electricity bills -Building design data -Weather conditions -Data of HVAC system	Electricity consumption balances and the cooling energy balances	Predefined metrics	Hong Kong and Beijing	-System coefficient of performance -Energy ratio
Kim et al. [49]	2019	4 years (2012–2015)	Monthly	-Monthly electricity bills -Weather conditions	Subtracting of the base-load energy from the monthly total EUI	Defining new metrics	South Korea	-Yearly total base-load energy -Yearly heating energy -Yearly cooling energy
Hopf et al. [50]	2020	1 June 2014 to 31 May 2015.	15-min	-Power -Weather conditions	Automatically identify specific "characteristics" of a household from its power consumption	Using Random Forest to predict energy efficiency	Switzerland	-Accuracy of Matthew's Correlation Coefficient -Area under the curve
Jiang et al. [51]	2021	Not mentioned	1-min	-Power -Weather conditions	Not mentioned	Three EE function	China	Time, light, and temperature EE function

5. Research Challenges and Future Direction

Using NILM techniques for EE assessment and FDD of HVAC systems is a relatively new research area and needs more attention. In this section, the main research challenges and future works are demonstrated and discussed in detail.

5.1. Availability of Public Datasets

The lack of public datasets impedes the development of NILM-based methods for FDD and EE assessment of HVACs. The shortage of real-world data is more drastic for FDD due to the low-occurrence rate of faults. Although some researchers have introduced artificial approaches to simulate or identify the real faults [34,35], greater efforts must be made to collect and publicly provide the real-world HVAC datasets for various types of buildings such as residential, industrial, commercial, and public buildings. Due to the different climates worldwide, the usage rates of heating and cooling equipment are surprisingly different. Therefore, providing reliable high-resolution labeled HVAC datasets is a critical solution for dealing with the challenges of the development and implementation of FDD methods in real-world HVAC systems.

5.2. Development of NILM Techniques for FDD or Energy Assessment of HVAC Systems

HVACs are the most intensive power consumers in buildings and their ON/OFF states of operation can be easily recognized by NILM techniques. In recent years, various NILM techniques have been developed to enhance the disaggregation accuracy. These state-of-the-art NILM methods can be implemented for the assessment of HVAC efficiency or detecting various types of HVAC faults. Emerging temperature-based FDD methods or utilizing high-performance fault clustering techniques with NILM-based FDD methods are other areas for future research. These methods can be implemented in a complementary manner to enhance the performance of FDD. Another avenue of research is the implementation of NILM-based methods for FDD in various types of HVAC systems (split type, packages, and others) for residential or commercial buildings.

5.3. Development of NILM and FDD Techniques Compatible with Low-Resolution Data

In general, most NILM techniques require the installation of high-resolution smart meter or power quality meters (sampling rate in kHz) to monitor the events and other characteristics of electrical devices at the appliance level accurately. While this requirement is satisfied by recently installed smart meters, many utilities only collect and process data from smart meters at 15-, 30-, or 60-min resolutions because of the costs for data storage and communication. Therefore, the development of NILM methods and FDD techniques that could accurately work with low-resolution data is most suitable for wide adoption [52].

5.4. NILM Accuracy

Generally, for a good user experience, NILM must have a minimum accuracy in the range from 80–90% [53]. The accuracy of load disaggregation has a great impact on the performance of NILM-based FDD and EE assessment methods. However, the performance of load disaggregation approaches for FDD and the evaluation of EE has not been sufficiently investigated. An evaluation in [37] shows that NILM disaggregated outputs are often inaccurate enough to be used in anomaly identification. Although the availability of smart meters and the development of high-performance artificial intelligence algorithms could improve the accuracy of disaggregation, proposing FDD-aware NILM methods are of interest.

6. Conclusions

The NILM, which monitors the power consumption of home appliances by a single measurement in power entry, has been considered a popular research topic for the last three decades. With the recent development in the performance of load disaggregation techniques and also the availability of smart meters, the NILM-based FDD and energy efficiency assessment are considered as promising solutions for reducing building energy demands, decreasing the related greenhouse gas emissions. Studies have shown that utilizing FDD methods in HVAC systems could reduce building energy consumption by 20–30%.

This study has reviewed NILM-based approaches that are utilized for FDD and the energy efficiency assessment of HVACs and presented an overview of the recent progress in this area. To the best of the authors' knowledge, this paper is the first study on reviewing the NILM-based FDD methods in HVAC applications. Our investigation shows that NILM techniques can successfully identify electro-mechanical and electrical faults in HVACs that are difficult to detect by thermal measurements. For instance, the NILM approaches can successfully detect ten different RTU faults that are responsible for 10 to 30% of total repair costs in RTUs. Therefore, NILM-based fault detection can significantly reduce the total repair costs of RTUs. Another study demonstrated that the proposed NILM technique detects block and leak refrigerant faults in HVACs with 94% accuracy. NILM reduces the power consumption and the remote monitoring costs of packaged HVACs, especially in commercial buildings.

We have also investigated the capabilities of NILM approaches in the assessment of energy efficiency in HVAC systems. The investigation shows that the NILM has been successfully implemented for the energy efficiency assessment of HVAC's. The benefits, effectiveness, and limitations and drawbacks of NILM-based FDD and EE assessment techniques in HVAC systems are highlighted, and the main research challenges and future research opportunities are also discussed. Our review shows that NILM-based FDD and EE evaluation techniques must be developed and modified to be able to deal with the continuously increasing challenges of real-world applications.

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Abbreviations

The abbreviations in this manuscript are as follows:

AC	Air Conditioner
BMS	Building Management System
CO	Combinatorial Optimization
EE	Energy Efficiency
EUI	Energy Use Intensity
FDD	Fault Detection and Diagnostics
FHMM	Factorial Hidden Markov Model
HMM	Hidden Markov Model
HVAC	Heating, Ventilation, and Air-Conditioning
KNN	K-Nearest Neighbor
LBM	Latent Bayesian Melding
LSTM	Long Short-Term Memory
NILM	Non-Intrusive Load Monitoring

NILMTK	NILM Toolkit
NN	Neural Network
RTU	Rooftop Cooling Unit
SEPAD	Sample Efficient Home Power Anomaly Detection
SSHMM	Super-state Hidden Markov Model
SVM	Support Vector Machine
TOPSIS	Technique for Order Preference by Similarity to an Ideal Solution
UNUM	A method presented in [36]

References

1. Mattera, C.G.; Shaker, H.R.; Jradi, M. Consensus-based method for anomaly detection in VAV units. *Energies* **2019**, *12*, 468. [CrossRef]
2. Shaker, H.R.; Lazarova-Molnar, S. A new data-driven controllability measure with application in intelligent buildings. *Energy Build.* **2017**, *138*, 526–529. [CrossRef]
3. IEA EBC-Annex 79. Available online: https://annex79.iea-ebc.org/n.d. (accessed on 17 December 2021).
4. Rashid, H.; Singh, P. Monitor: An Abnormality Detection Approach in Buildings Energy Consumption. In Proceedings of the 2018 IEEE 4th International Conference on Collaboration and Internet Computing (CIC), Philadelphia, PA, USA, 18–20 October 2018; pp. 16–25.
5. Bang, M.; Engelsgaard, S.S.; Alexandersen, E.K.; Riber Skydt, M.; Shaker, H.R.; Jradi, M. Novel real-time model-based fault detection method for automatic identification of abnormal energy performance in building ventilation units. *Energy Build.* **2019**, *183*, 238–251. [CrossRef]
6. Kim, W.; Katipamula, S. A review of fault detection and diagnostics methods for building systems. *Sci. Technol. Built Environ.* **2017**, *24*, 3–21. [CrossRef]
7. Zhao, Y.; Li, T.; Zhang, X.; Zhang, C. Artificial intelligence-based fault detection and diagnosis methods for building energy systems: Advantages, challenges and the future. *Renew. Sustain. Energy Rev.* **2019**, *109*, 85–101. [CrossRef]
8. Namburu, S.M.; Azam, M.S.; Luo, J.; Choi, K.; Pattipati, K.R. Data-driven modeling, fault diagnosis and optimal sensor selection for HVAC chillers. *IEEE Trans. Autom. Sci. Eng.* **2007**, *4*, 469–473. [CrossRef]
9. Brambley, M.R. *A Novel, Low-Cost, Reduced-Sensor Approach for Providing Smart Remote Monitoring and Diagnostics for Packaged Air Conditioners and Heat Pumps*; Technical Report; Pacific Northwest National Laboratory: Richland, WA, USA, 2009.
10. Mattera, C.G.; Jradi, M.; Skydt, M.R.; Engelsgaard, S.S.; Shaker, H.R. Fault detection in ventilation units using dynamic energy performance models. *J. Build. Eng.* **2020**, *32*, 101635. [CrossRef]
11. Xue, P.N.; Zhou, Z.G.; Fang, X.M.; Chen, X.; Liu, L.; Liu, Y.W.; Liu, J. Fault detection and operation optimization in district heating substations based on data mining techniques. *Appl. Energy.* **2017**, *205*, 926–940. [CrossRef]
12. Du, Z.; Fan, B.; Jin, X.; Chi, J. Fault detection and diagnosis for buildings and HVAC systems using combined neural networks and subtractive clustering analysis. *Build. Environ.* **2014**, *73*, 1–11. [CrossRef]
13. Ruano, A.; Hernandez, A.; Ureña, J.; Ruano, M.; Garcia, J. NILM techniques for intelligent home energy management and ambient assisted living: A review. *Energies* **2019**, *12*, 2203. [CrossRef]
14. Gopinath, R.; Kumar, M.; Chandra, C.P.; Srinivas, K. Energy management using non-intrusive load monitoring techniques-State-of-the-art and future research directions. *Sustain. Cities Soc.* **2020**, *62*, 102411. [CrossRef]
15. Rashid, H.; Stankovic, V.; Stankovic, L.; Singh, P. Evaluation of Non-Intrusive Load Monitoring Algorithms for Appliance-Level Anomaly Detection. In Proceedings of the CASSP 2019–2019 IEEE International Conference on Acoustics, Speech and Signal Processing, Brighton, UK, 12–17 May 2019; pp. 8325–8329.
16. Rogers, A.P.; Guo, F.; Rasmussen, B.P. A review of fault detection and diagnosis methods for residential air conditioning systems. *Build. Environ.* **2019**, *161*, 106236. [CrossRef]
17. Mirnaghi, M.S.; Haghighat, F. Fault detection and diagnosis of large-scale HVAC systems in buildings using data-driven methods: A comprehensive review. *Energy Build.* **2020**, *229*, 110492. [CrossRef]
18. Li, G.; Hu, Y.; Liu, J.; Fang, X.; Kang, J. Review on fault detection and diagnosis feature engineering in building heating, ventilation, air conditioning and refrigeration systems. *IEEE Access* **2021**, *9*, 2153–2187. [CrossRef]
19. Himeur, Y.; Ghanem, K.; Alsalemi, A.; Bensaali, F.; Amira, A. Artificial intelligence based anomaly detection of energy consumption in buildings: A review, current trends and new perspectives. *Appl. Energy* **2021**, *287*, 116601. [CrossRef]
20. Linge, N.; Liu, X.; Liu, Q.; Lu, M. Non-intrusive load monitoring and its challenges in a NILM system framework. *Int. J. High. Perform. Comput. Netw.* **2019**, *14*, 102. [CrossRef]
21. Rehman, A.U.; Lie, T.T.; Vallès, B.; Tito, S.R. Non-intrusive load monitoring of residential water-heating circuit using ensemble machine learning techniques. *Inventions* **2020**, *5*, 57. [CrossRef]
22. Bacurau, R.M.; Duarte, L.F.C.; Ferreira, E.C. Focus on energy efficiency through power consumption disaggregation. In *Energy Efficiency Improvements in Smart Grid Components*; Eissa, M.M., Ed.; IntechOpen: London, UK, 2015; pp. 21–40.
23. Klemenjak, C.; Goldsborough, P. Non-intrusive load monitoring: A review and outlook. *arXiv* **2016**, arXiv:1610.01191.
24. Buddhahai, B.; Wongseree, W.; Rakkwamsuk, P. An energy prediction approach for a non-intrusive load monitoring in home appliances. *IEEE Trans. Consum. Electron.* **2019**, *66*, 96–105. [CrossRef]

25. Wójcik, A.; Łukaszewski, R.; Kowalik, R.; Winiecki, W. Nonintrusive appliance load monitoring: An overview, laboratory test results and research directions. *Sensors* **2019**, *19*, 3621. [CrossRef]
26. Haq, A.U. Appliance Event Detection for Non-Intrusive Load Monitoring in Complex Environments. Ph.D. Thesis, Technical University Munich, Munich, Germany, 2018.
27. Dan, W.; Xiao, H.; Ye, L.; Ce, S. Review of Non-Intrusive Load Appliance Monitoring. In Proceedings of the 2018 IEEE 3rd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), Chongqing, China, 12–14 October 2018; pp. 18–23.
28. Yuan, X.; Han, P.; Duan, Y.; Alden, R.E.; Rallabandi, V.; Ionel, D.M. Residential electrical Load monitoring and modeling- state of the art and future trends for smart homes and grids. *Electr. Power Components Syst.* **2020**, *48*, 1–19. [CrossRef]
29. Nalmpantis, C.; Vrakas, D. Machine learning approaches for non-intrusive load monitoring: From qualitative to quantitative comparation. *Artif. Intell. Rev.* **2018**, *52*, 217–243. [CrossRef]
30. Iqbal, H.K.; Malik, F.H.; Muhammad, A.; Qureshi, M.A.; Abbasi, M.N.; Chishti, A.R. A critical review of state-of-the-art non-intrusive load monitoring datasets. *Electr. Power Syst. Res.* **2020**, *192*, 106921. [CrossRef]
31. Pereira, L.; Nunes, N. Performance evaluation in non-intrusive load monitoring: Datasets, metrics, and tools—A review. *WIREs Data Min. Knowl. Discov.* **2018**, *8*, e1265. [CrossRef]
32. Norford, L.K.; Wright, J.A.; Buswell, R.A.; Luo, D.; Klaassen, C.J.; Suby, A. Demonstration of fault detection and diagnosis methods for air-handling units (ASHRAE 1020-RP). *HVAC&R Res.* **2002**, *8*, 41–71.
33. Armstrong, P.R.; Laughman, C.R.; Leeb, S.B.; Norford, L.K.; Ave, M. Fault Detection Based on Motor Start Transients and Shaft Harmonics Measured at the RTU Electrical Service. In Proceedings of the International Refrigeration and Air Conditioning Conference at Purdue, West Lafayette, IN, USA, 12–15 July 2004; pp. 1–10.
34. Armstrong, P.R.; Laughman, C.R.; Leeb, S.B.; Norford, L.K. Detection of rooftop cooling unit faults based on electrical measurements. *HVAC&R Res.* **2006**, *12*, 151–175.
35. Lai, Y.H.; Tsai, I.J.; Chiu, C.Y.; Lai, C.F. Non-intrusive Load Monitoring Applied in Energy Efficiency of the Smart Manufacturing Industry: A case of air-conditioner. In Proceedings of the 2014 IEEE International Conference on Automation Science and Engineering (CASE), Taipei, Taiwan, 18–22 August 2014; pp. 1127–1132.
36. Rashid, H.; Singh, P. Poster: Energy disaggregation for identifying anomalous appliance. In Proceedings of the 4th ACM International Conference on Systems for Energy-Efficient Built Environments, Delft, The Netherlands, 8–9 November 2017; pp. 1–2.
37. Rashid, H.; Singh, P.; Stankovic, V.; Stankovic, L. Can non-intrusive load monitoring be used for identifying an appliance's anomalous behaviour? *Appl. Energy.* **2019**, *238*, 796–805. [CrossRef]
38. Hart, G.W.; Member, S. Nonintrusive appliance load monitoring. *Proc. IEEE* **1992**, *80*, 1870–1891. [CrossRef]
39. Kolter, J.Z.; Jaakkola, T. Approximate Inference in Additive Factorial HMMs with Application to Energy Disaggregation. In Proceedings of the Fifteenth International Conference on Artificial Intelligence and Statistics (AISTATS), La Palma, Spain, 21–23 April 2012; pp. 1472–1482.
40. Zhong, M.; Goddard, N.; Sutton, C. Latent Bayesian melding for integrating individual and population models. *arXiv* **2015**, arXiv:1510.09130.
41. Makonin, S.; Popowich, F.; Baji, I.V.; Gill, B.; Bartram, L. Exploiting HMM sparsity to perform online real-time nonintrusive load monitoring. *IEEE Trans. Smart Grid.* **2016**, *7*, 2575–2585. [CrossRef]
42. Orji, U.A.; Remscrim, Z.; Laughman, C.; Leeb, S.B.; Wichakool, W.; Schantz, C.; Cox, R.; Paris, J.; Kirtley, J.L.; Norford, L.K. Fault Detection and Diagnostics for Non-Intrusive Monitoring Using Motor Harmonics. In Proceedings of the 2010 Twenty-Fifth Annual IEEE Applied Power Electronics Conference and Exposition (APEC), Palm Springs, CA, USA, 21–25 February 2010; pp. 1547–1554.
43. Batra, N.; Singh, A.; Whitehouse, K. If You Measure It, Can You Improve It? Exploring the Value of Energy Disaggregation. In Proceedings of the 2nd ACM International Conference on Embedded Systems for Energy-Efficient Built Environments, BuildSys '15, Seoul, Korea, 4–5 November 2015; pp. 191–200.
44. Narayanaswamy, B.; Balaji, B.; Gupta, R.; Agarwal, Y. Data Driven Investigation of Faults in HVAC Systems with Model, Cluster and Compare (MCC). In Proceedings of the 1st ACM Conference on Embedded Systems for Energy-Efficient Buildings, BuildSys 2014, Memphis, TN, USA, 3–6 November 2014; pp. 50–59.
45. Pathak, N.; Lachut, D.; Roy, N.; Banerjee, N.; Robucci, R. Non-intrusive Air Leakage Detection in Residential Homes. In Proceedings of the 19th International Conference on Distributed Computing and Networking, ICDCN'18, Varanasi, India, 4–8 January 2018; pp. 1–10.
46. Trothe, M.E.S.; Shaker, H.R.; Jradi, M.; Arendt, K. Fault isolability analysis and optimal sensor placement for fault diagnosis in smart buildings. *Energies* **2019**, *12*, 1601. [CrossRef]
47. Kong, X.; Zhu, S.; Huo, X.; Li, S.; Li, Y.; Zhang, S. A household energy efficiency index assessment method based on non-intrusive load monitoring data. *Appl. Sci.* **2020**, *10*, 3820. [CrossRef]
48. Yan, C.; Wang, S.; Xiao, F. A simplified energy performance assessment method for existing buildings based on energy bill disaggregation. *Energy Build.* **2012**, *55*, 563–574. [CrossRef]
49. Kim, D.W.; Kim, Y.M.; Lee, S.E. Development of an energy benchmarking database based on cost-effective energy performance indicators: Case study on public buildings in South Korea. *Energy Build.* **2019**, *191*, 104–116. [CrossRef]

50. Hopf, K.; Sodenkamp, M.; Staake, T. Enhancing energy efficiency in the residential sector with smart meter data analytics. *Electron. Mark.* **2020**, *28*, 453–473. [CrossRef]
51. Jiang, W.; Tang, L.; Wei, X. Home Energy Efficiency Evaluation Based on NILM. In Procedia Computer Science. *Procedia Comput. Sci.* **2021**, *183*, 53–60.
52. Liang, M.; Meng, Y.; Lu, N.; Lubkeman, D.; Kling, A. HVAC load Disaggregation using Low-resolution Smart Meter Data. In Proceedings of the 2019 IEEE Power Energy Society Innovation Smart Grid Technology Conference, (ISGT 2019), Washington, DC, USA, 18–21 February 2019; pp. 1–5.
53. Zhuang, M.; Shahidehpour, M.; Li, Z. An Overview of Non-Intrusive Load Monitoring: Approaches, Business Applications, and Challenges. In 2018 International Conference on Power System Technology (POWERCON2018), Guangzhou, China, 6–8 November 2018; pp. 4291–4299.