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Mathematical and Statistical Model of Load Recognition in Microgrids

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ABSTRACT

The paper establishes a mathematical and statistical model of load recognition in microgrids to enhance automated demand response in energy-constrained systems. Efficient allocation of energy, load allocation, and stability of the system all require proper identification of electrical appliances. In contrast to other studies that are available, the current study concentrates on statistical validation, robustness, and reliability rather than accuracy. The energy usage of appliances is modelled as a stochastic process to represent the variability of the real-world usage. Deterministic and probabilistic models, as well as energy-based and event-based feature extraction methods, are compared. Both parametric and non-parametric tests are used to test performance in uncertain conditions. The findings indicate that there is no significant accuracy difference between deterministic and probabilistic models. However, energy-based features are significantly better than event-based features. The variability of appliance usage has statistical differences, but in terms of practical implications on performance in the models, it is not very significant, thus being stable. In general, the article offers a valid and evidence-based model that can help make effective and sustainable decisions regarding the management of microgrid energy.

INTRODUCTION

The learning of stochastic trends on microgrid loads can be useful in the study of human-system interaction and applied statistics in engineering fields. Stochastic trends represent the changes and patterns of data with time that tend to be rather random and unpredictable, although it is possible to comprehend them with the help of some statistical method (Fatichi et al., 2009). These trends assist us in energy systems to realize the sudden or unpredictable changes in electricity

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demand and production. Microgrid loads are the total electricity consumption in a localized small-scale power system (microgrid), such as that consumed by homes, businesses, and industries. Microgrids are becoming a well-known and stable service that can be used to provide power supply, particularly in remote, off-grid, and rural locations where there is a low centralized infrastructure (Ojo et al., 2025).

The growing global interest in dependable and sustainable energy systems has also increased the significance of microgrids, particularly in areas where there are shortage of energy and the reliability of grid connection. These systems are combined with distributed energy resources (DERs) like solar photovoltaic (PV) panels and wind turbines to conventional generators and energy storage systems (Krishan & Suhag, 2019). These benefits apart, microgrids have operational drawbacks because of the fluctuating nature of renewable energy production and the insufficient capacity of generation and storage in systems that are remote. It is thus important that the balance between supply and demand of electricity is done in real time, which has a direct impact on the stability of the system, its reliability, and its efficiency (Savulescu, 2009). Past literature has defined an inconsistency in renewable energy sources as a source of uncertainty in load management, and there is a need to have precise prediction and control mechanisms to allow effective microgrid operation.

Automated Demand Response (ADR) has been an efficient tool for dealing with these challenges. ADR is dynamically used to respond to the signal of supply or market demand to achieve stability in the system, avoid excessive loads, and use resources. ADR can be used in microgrids with small generation and where renewable intermittency is high so that operators can serve demand without using expensive and ineffective backup generation (Samad et al., 2016). Despite the developments, a very wide area of research is still missing in terms of integrating stochastic analysis of load behaviour and automated demand response strategies in microgrid settings. An effective ADR is founded on an appropriate load identification with the systems capable of identifying, classifying, and monitoring the behaviour of individual electrical equipment. The identification can be applied in assisting with load shedding according to the priority, effective energy allocation, and making operational decisions. Priorities can be applied when performing load curtailment in case of medical equipment or communication devices that are critical appliances, and the non-essential appliances may be switched off temporarily. This kind of selective control improves system stability and reduces service disruptions, thereby enhancing overall user experience (Chang et al., 2008).

Therefore, more analytical methods to include stochastic variations are needed to increase the precision of load identification and prioritization in dynamic energy systems. Several load recognition schemes have been proposed within the previous more than one decade that include the conventional pattern-matching, probabilistic models, machine learning and signal-processing schemes. Pattern-matching finds similar load signatures to the current profiles of a pre-trained database of appliances and probabilistic models, such as the Hidden Markov Models (HMMs). Machine learning technique, which consists of support machine learning and neural networks, and classifiers grouping, is more accurate and flexible (Zaidi et al., 2010). This study is new in that it integrates the stochastic trend analysis with the current load recognition and ADR models to enhance the systems sensitivity and accurate prediction of the microgrid under uncertainty.

The possibility to combine renewable energy resources and the possibility to work without or in parallel with the main grid makes microgrids a critical part of the modern decentralized energy system. As the distributed energy resources (DERs) and smart appliances permeate, load behaviour has become very complex. This has resulted in the necessity of analytical frameworks that are highly analytical and capable of modelling, analysing, and predicting the patterns of load consumption under unpredictable and changing conditions. In this context the concept of load recognition is crucial in facilitating the achievement of smart energy control, automated demand response, and optimization of systems in micro grids (Wang et al., 2018).

Despite many load recognition methods based on deterministic, probabilistic, and machine learning methods are available, there is still no statistically proven framework that can be trusted to compare their performance under uncertainty. Most current research pays much more attention to the metrics of accuracy, without involving rigorous hypothesis testing or the discussion of stochastic variability in appliance usage. This introduces a knowledge gap of the effect of load recognition techniques in real-world microgrids regarding reliability, robustness and generalizability. Thus, the underlying research problem consists in creating a statistically based framework which combines stochastic modelling with hypothesis-based analysis to enhance the recognition of loads in microgrids.

Research Objectives

- To compare the performance of probabilistic and deterministic load recognition models with the statistical inference.
- To test the hypothesis of energy-based features being more accurate to recognize than event-based features.
- To examine how the variability in appliance use affects the output of load recognition models.

Research Contributions

This work contributes to the microgrid energy management and load recognition domain in several ways. It suggests a new integrated framework of stochastic modelling and statistical inference to load recognition. It offers a comparison of probabilistic and deterministic load recognition approaches through a hypothesis-based comparison. It uses severe statistical analysis to determine the efficacy of energy-based and event-based characteristics. It examines the difference in appliance use that affects model performance. It increases reliability, reproducibility, and interpretation of load recognition findings by means of formal statistical validation.

LITERATURE REVIEW

The theory behind the load recognition of microgrids is based on the principles of statistical signals processing and stochastic systems theory, as well as the energy management systems. The stochastic modelling theory is used to describe the random and time-dependent appliance behaviour in which the electrical loads are considered as probability processes that are affected by the interaction of the user and the environment. Moreover, the demand response theory gives the foundation of the way load flexibility can be employed to ensure system stability and efficiency. All these theoretical viewpoints would help in advancing data-driven and statistically proven load identification systems in contemporary microgrids. Load recognition and non-intrusive load monitoring (NILM) have been widely studied over the past two decades due to their importance in energy management, automated demand response, and microgrid optimization. The primary objective of load recognition is to identify and classify electrical appliances based on their power consumption patterns without requiring individual monitoring devices at each appliance. Accurate appliance identification enables efficient energy allocation, priority-based load shedding, and improved operational stability in both grid-connected and isolated microgrids (Hosseini et al., 2017).

Several empirical studies have investigated load recognition and energy management in microgrid environments. For instance, Hosseini et al. (2017) demonstrated the effectiveness of non-intrusive load monitoring (NILM) in improving energy efficiency through appliance-level identification. Similarly, Kalogridis et al. (2010) empirically evaluated privacy-preserving load recognition techniques using real smart meter data. More recent studies, such as Strielkowski et al. (2023) have applied machine learning models on large-scale datasets to enhance prediction accuracy. However, these studies primarily focus on performance metrics without incorporating rigorous statistical validation, highlighting a gap that this research aims to address.

Deterministic Approaches

Deterministic approaches, such as template matching, distance-based classification, rule-based systems, etc., are among some of the oldest strategies to use in load recognition. Template matching is a technique of comparing the appliance signatures as observed and a reference profile, typically a steady-state or transient feature profile. Distance-based classifiers like the Euclidean or Manhattan distance measures are similarity metrics that are used to measure the similarity between measured signals and reference templates (Prasath et al., 2017). Rule-based techniques use thresholds/heuristics depending on the attributes of the appliance, e.g. power factor, current or voltage. Deterministic techniques are relatively easy and computationally efficient; thus, they can be used in real time (Thane & Hansson, 2000).

With the development of modern appliances, however, especially the types of appliances that are based on inverter-based AC loads, DC appliances, and power-electronic controlled devices, however, their operational properties have become more dynamic and non-linear. Uncertainties in appliances behaviour can be caused by user interaction, environmental conditions, load modulation mechanisms and old age of devices. Modern appliances tend to have changed rather than fixed power consumption patterns. As deterministic models use previously-defined reference load profiles, they might have a hard time in accurately categorizing the appliances under different operating conditions or when noise is present in the measurements. As a result, it can be mentioned that, despite the efficiency of deterministic methods in controlled or stable conditions, their effectiveness in contemporary microgrids characterized by diversity in AC/DC and smart appliances can be questioned (Mehta & Basak, 2021).

Probabilistic and Stochastic Approaches

To deal with variability and uncertainty, probabilistic techniques assume the modelling of appliances as stochastic process. These techniques take into consideration random behaviour in the operation of appliances, user behaviour, and noise in the measurements. The most popular ones are Hidden Markov Models (HMMs), factorial HMMs, Bayesian networks, and other probabilistic graphical models. HMMs are an appliance state (e.g. ON and OFF, or multi-state) of the appliance (the hidden state) and the power consumption is the emitted signal. These models have probabilistic transitions between the states to reflect the stochastic nature of the operation of the appliances (Misra et al., 2023). Factorial HMMs are an extension of the model, which allows multiple appliances to be modelled and the aggregate load profiles can be disaggregated to determine contributions per appliance. The Bayesian networks and analogues use previous knowledge, dependencies of appliances and external variables, like time-of-day usage (Hawarah et al., 2010). The probability models are stronger against variability and noise than the deterministic models. They can deal with the overlapping appliance signatures and incomplete or flawed measurement data. Nevertheless, they need large amounts of training data, close probability distribution modelling, and more computational resources (Kalogridis et al., 2010).

The correlation of important variables in the load recognition is the key to the system performance. Whatever the type of model (probabilistic or deterministic), the type of features (energy-based or event-based) and the variability in appliance usage are vital elements to consider when determining the recognition accuracy. The probabilistic models are typically more flexible to variability and noise whereas deterministic models are effective in stable conditions. On the same note, because constant consumption patterns are reflected in energy-based features and discrete changes in event-based features, predictive performance also varies. These relationships are further moderated by variability in the use of appliances that bring in uncertainty in the load patterns.

Machine Learning and Data-Driven Methods

Over the last few years, machine learning (ML) and deep learning methods have gained popularity in load recognition. Applied ML models, such as support vector machines (SVMs), decision trees, random forests, and k-nearest neighbours (k-NN) are used to classify the appliance states based on features derived by electricity voltage and current signals. The features may be those of time (e.g., mean, variance, peak power) or frequency (e.g., harmonics, wavelet coefficients). Deep learning, e.g. convolutional neural network (CNN), recurrent neural network (RNN), and long short-term memory (LSTM) networks, can discover more sophisticated patterns in unprocessed data automatically. CNNs can be used to detect spatial or waveform patterns, whereas RNNs and LSTMs can capture temporal dependencies of sequential consumption information. Balanced methods between accuracy and running efficiency have also been sought by using hybrid methods that employ traditional feature extraction alongside deep models of learning (Strielkowski et al., 2023).

Even though machine learning approaches are highly accurate at classifying, their practical reliability may be restricted to overfitting, lack of interpretability, and sensitivity to appliance behaviour or microgrid structures. Moreover, the accuracy or error measures are described in many studies, but with no formal statistical confirmation; hence, it is hard to evaluate the uncertainty, robustness, or generalization (Linardatos et al., 2020).

Hypotheses

H_1: The performance of probabilistic models and deterministic pattern-matching methods in load recognition does not significantly differ.

H_2: The accuracy of load recognition of energy-based features and event-based features is not statistically different.

H_3: There is no statistically significant impact on the performance of probabilistic load recognition models by appliance usage variability.

Research Gaps and Limitations

According to the literature review, the formulation of hypotheses in this study is informed by the inconsistencies and gaps in the literature. Some of the studies indicate that probabilistic models are better, but some of them indicate the same performance with the deterministic models in the controlled conditions. On the same note, the performance of the feature types is also situational and the influence of the variability of appliances is not always explored. Such discrepancies qualify the development of hypothesis-based research to statistically test the differences and relationship between these variables. Although massive improvements have been made, the literature still has several limitations.

First, it is characterized by a weak application of rigorous statistical validation, with many studies being interested in classification accuracy, precision, or recall (but not hypothesis testing, confidence intervals, and robustness analysis), thus, weakening the reliability and reproducibility of reported results (Foody, 2023). Second, uncertainty is not always discussed, as appliance use is inherently unpredictable, and several studies do not even measure prediction accuracy or determine how their approach to the problem copes with noise and real-world dynamics (Touhs et al., 2023).

Third, feature-level analysis is not adequately done since most methods derive power consumption features but only a small number of methods determine the statistical significance or predictive value, which is necessary to optimize the model and make interpretations (Fan et al., 2019). Also, the question of scalability and flexibility is still present, as most of the methods are benchmark using limited datasets or on microgrids with setups, which is a questionable indicator of their ability to work with systems of varying sizes, user patterns, and appliances (Rahman Fahim et al., 2020). Lastly, the level of integration with microgrid control app is low, as load recognition performance is rarely associated with demand response, energy optimization, or operational stability, and there is the lack of a connection between recognition algorithms and feasible energy management results (Wang et al., 2015).

METHODOLOGY

In this study, the quantitative research design was adopted, where experimental comparative research methodology was applied to assess the performance of various load recognition schemes in microgrid settings. The design was based on the study of the key impacts of the model type (probabilistic vs. deterministic), feature type (energy-based vs. event-based), and variability in the appliance usage on the load recognition performance. The approach can be used to compare several variables at the same time in a systematic way and offer a logical framework to determine the impact of variation in the data representation and the appliance behaviour on the model accuracy, robustness, and reliability when used in real-world situations.

Data Source and Sample Selection

The data employed in this research were acquired via Kaggle which is a well-known open-source data collection frequently utilized in energy and machine learning research. The data set was composed of electrical consumption patterns of typical home devices which comprised of refrigerators, washing machines, air conditioners, televisions, kettles, ovens, microwaves, bulbs, fans, and computers. The data were screened to make it homogenous and suitable towards the research aims. Appliance records that had complete and reliable load profiles only were held to be analysed. As well, the various usage scenarios were taken into consideration to introduce variation in appliance behaviour to make sure that the dataset is representative of the real-world consumption behaviour in microgrids.

Variables

Dependent Variable: Load recognition performance, as a measure of classification accuracy and performance measures.

Independent Variables: Model type (probabilistic models e.g. Hidden Markov Models (Eddy, 1996) and Bayesian classifiers (Kim & Ghahramani, 2012), deterministic models e.g. threshold based and template matching models)

- Type of feature (energy-based features and event-based features)
- Variability in the use of the appliances (different operation patterns of the appliances)

Control Variables: Preorders Standardized preprocessing tools, the same choice of datasets, and the same measure used to evaluate all models so that they should be fairly compared.

Procedure

The experiment assumed the extraction of two kinds of features of appliance data to capture both steady-state and dynamic energy consumption patterns. These energy-based features represented the overall usage patterns and statistical properties of the usage patterns with time, whereas event-based features expressed dynamic behavioural aspects like on/off switching and abrupt changes in loads. The comparative experimental design was employed in the evaluation of probabilistic and deterministic models along the lines of the various types of features and the different patterns of appliance usage. It involved data prepossessing to eliminate noise and missing data, feature extraction and cross-validation-based training of the model to guarantee generalization. Variability analysis was also done to determine the model performance in various load conditions. To determine the differences between the models, feature type, and usage situations, statistical analysis was carried out with the help of the Mann-Whitney U test, the paired-samples t-test or Wilcoxon signed-rank test, and ANOVA or Kruskal-Wallis test. The data analysis and processing were done through SPSS where a level of significance was set at 0.05 to guarantee reliability and validity of the analysis.

RESULTS & FINDINGS

The Shapiro Wilk test was used, as displayed in Table 1, to determine the normality of the data and it showed that the distribution of the accuracy values of both deterministic and probabilistic models was not normal ($p < 0.05$). Thus, a non-parametric test of Mann-Whitney U was utilized to test the difference in the performance of the two models. The descriptive statistics revealed that the probabilistic model ($M = 0.750$, $SD = 0.144$) had a marginally higher mean accuracy as compared to that of the deterministic model ($M = 0.745$, $SD = 0.144$). This was however a small difference. The two groups were also very similar in terms of the median values, meaning that the patterns of their distribution were similar. The outcome of the Mann Whitney U test (4596385385 = 0.151) demonstrated that there was no significant difference between accuracy of the two models. Since the p-value was greater than the significance level of 0.05, the null hypothesis was retained. The study failed to reject H_{01}, indicating no statistically significant difference in accuracy between the deterministic and probabilistic models.

Table 1

Normality, Descriptive Statistics, and Mann–Whitney U Test

Model Type	N	Mean	SD	Median	Min	Max	SWS	p-values
Deterministic	3000	0.745	0.144	0.740	0.50	1.00	0.955	0.001
Probabilistic	3000	0.750	0.144	0.750	0.50	1.00	0.954	0.001

Mann–Whitney U = 4,596,385, Z-value = 1.437, p-value = 0.151,
SD = Std. Deviation, SWS = Shapiro–Wilk Statistic

The descriptive statistics shows that the Energy-Based approach ($M = 0.899$, $SD = 0.028$) is more accurate in mean than the Event-Based approach ($M = 0.874$, $SD = 0.029$). A Wilcoxon Signed Ranks Test revealed that Energy-Based features yielded significantly higher values than Event-Based features, as all cases showed negative ranks ($N = 3000$), indicating a consistent directional difference between the two feature sets. The results of the Wilcoxon Signed-Rank test showed the Z value of -47.445 and p-value of.000 (2-tailed), which illustrate that the difference between the two methods is statistically significant at the .05 level. The Wilcoxon Signed-Rank test results showed that there was significant difference between the Energy-Based and Event-Based approaches (Z = -47.445, p <.001). The Energy-Based method was far much more accurate (M = 0.899) as opposed to the Event-Based method (M = 0.874). This means that the Energy-Based method is more accurate compared to the Event-Based method hence null hypothesis is rejected.

Table 2

Descriptive Statistics and Wilcoxon Signed Ranks Test for Load Recognition Accuracy

	N	Mean	SD	Min	Max	N	MR	SoR
Energy Based	3000	.899	.028	.850	.950	3000[a,b]	1500.50	4501500.00
Event Based	3000	.874	.029	.812	.937	0	.00	.00

Ties = 0, Total = 3000, Z test = -47.445, Sig. (2-tailed) = .000,
SD = Std. Deviation, MR = Mean Rank, SoR = Sum of Ranks

The Kruskal-Wallis was performed to test the hypothesis of the varying accuracy of probabilistic load recognition models, when the variability categories of appliance use are low, medium, or high. The test presented a statistically significant finding (2 = 37.509, p =.001) meaning that, statistically speaking, at least one of the groups is not the same as the rest of them (Table 3).

Table 3

Kruskal–Wallis Test and Pairwise Comparisons for Probabilistic Accuracy across Usage Variability

	Null Hypothesis	Test	Sig.[a]	Decision
1	The distribution of Probabilistic Accuracy is the same across categories of Usage Variability	Independent-Samples Kruskal-Wallis Test[b]	.000	Reject the null hypothesis.

The significance level is .050, Asymptotic significance is displayed
N = 2400, Test Statistic = 37.509, Degree of Freedom = 2, Sig.(2-sided test) = .001

The pairwise comparisons with Bonferonni adjustments showed that the distributions of the Low-High (p <.000) and Medium-High (p =.009) groups were significantly different, whereas the difference between the distributions of the Low-Medium (p =.145 after adjustment) was not significant. The real means are quite similar (e.g., Low 1 = 0.91, Medium = 0.915, High = 0.92), although these are statistically different, indicating that the real effect of the usage variability on the performance of probabilistic models is insignificant, and the models are robust. The Kruskal-Wallis test yielded a statistically significant result ($\chi^2(2) = 37.509$, $p < .001$), so the null hypothesis was rejected. The statement was found to be false in practical terms; appliance usage variability did not meaningfully affect probabilistic model performance (Table 4).

Table 4

Pairwise Comparisons of Usage Variability

Sample 1 & 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.[a]
Low-Medium	-101.411	51.392	-1.973	.048	.145
Low-High	305.947	51.392	5.953	.000	.000
Medium-High	204.535	69.296	2.952	.003	.009

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.
Asymptotic significances (2-sided tests) are displayed. The significance level is .050.
a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

Discussion

The results of this study highlight that there is no statistically significant difference between probabilistic and deterministic models in terms of load recognition accuracy, indicating that both approaches perform similarly under the given conditions. This suggests that model selection alone is not the primary factor influencing performance (Prasath et al., 2017; Fan et al., 2019). In contrast, feature type was found to be a critical determinant, as energy-based features significantly outperformed event-based features, demonstrating their effectiveness in capturing stable appliance behaviour.

Additionally, although appliance usage variability showed statistical differences, its practical impact on probabilistic model performance was minimal, indicating robustness under varying conditions. Overall, the findings emphasize the importance of feature selection and statistical validation in load recognition studies, providing more reliable and interpretable results for practical applications in microgrid energy management systems.

CONCLUSION

The research paper has proposed an extensive mathematical and statistical model of load recognition in microgrid, combining stochastic appliance modelling and significant hypothesis-driven statistical validation. The study fills important gaps in the literature of load recognition by treating appliance behaviour as stochastic processes and systematically assessing recognition performance in terms of model types, feature extraction and variation of usage. The statistical analyses proved that the probabilistic model and the deterministic model had similar recognition accuracy, which proved that the model selection itself does not ensure high performance. Conversely, feature type was statistically significantly influential, and energy-based features were always more effective than event-based features in predicting the accuracy of load recognition. Also, the findings affirmed the variability in the use of appliances did not significantly impact the performance of probabilistic models, and therefore, they are robust under different conditions of operation. Generally, the presented framework increases the credibility, reproducibility, and reliability of load recognition investigations and gives statistically sound evidence to justify automated demand response, energy allocation optimization, and stable work of current microgrid systems.

Limitations

Although there are tremendous improvements, a few constraints exist in the literature. First, rigorous statistical validation is used less often, with most studies mostly depending on classification accuracy, precision, or recall and not on hypothesis testing, confidence intervals, and robustness analysis, which makes reported results less reliable and reproducible. Second, uncertainty is not commonly taken care of; due to the inherent unpredictability of appliance usage, several studies do not quantify prediction confidence or examine the way their approaches treat noise and real-life dynamism. Third, the feature-level analysis is also lacking as although different methods extract features of power consumption, not many of them assess their statistical significance or predictive value, which is crucial to optimize the model and interpret results. Furthermore, scalability and adjustability problems still exist, as currently most approaches are evaluated on small datasets or on microgrids of design, so their functionality on a variety of systems, user behaviour, and appliances remains unknown. Lastly, it has little interconnection with microgrid control applications since the performance of load recognition is rarely associated with demand response, energy optimization, and operational stability, which disconnects recognition algorithms with actual energy management performance.

Recommendations

According to the results of the present research, it is advisable that the microgrid operators and system designers should emphasize statistically proven load recognition strategies instead of the reported measures of accuracy. Practical implementation should use features that are energy based because they exhibit high recognition performance. The probabilistic models are well-suited in areas that have different usage patterns of appliances as they are known to be consistent even when there is a change in conditions. Lastly, the automated demand response frameworks should be implemented in the future with statistically robust load recognition frameworks, which would provide reliable evidence-based energy management and stability in operations of microgrids.

Future Work

Future studies can further expand upon this framework by using larger and more varied dataset related to the various types of microgrids, weather conditions and user behavioural patterns to further test whether the system is scalable and generalizable. The fusion of high-level machine learning models and deep learning models into the same statistically-validated system could offer more information on the performance-complexity trade-offs. Moreover, as a continuation of the current research, the statistical significance of features at the level of features could be studied, as well as to quantify the uncertainty with a confidence interval or quantify the posterior distribution to enhance the reliability of decision-making in real-time microgrids control systems.

Competing Interests

The authors declared no competing interests.

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