AI Driven Streamlining of Appliance Load Monitoring in Facilities Management

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***Abstract*—Facilities Management (FM) companies rely on effective and low cost data collection from Appliance Load Monitoring (ALM) devices to provide asset quality and energy monitoring services. The introduction of an automated appliance type classification pipeline during installation and inspection can offer huge improvements in reducing cost and installation errors. Most work focus on showcasing Voltage-Current (V-I) trajectory features based Machine Learning (ML) and Deep Learning (DL) algorithms on benchmarking datasets rather than providing mechanisms for deploying their model onto a production-ready system. This paper introduces a feature extraction preprocessing approach for ensuring the validity of detected steady-state events in VI trajectories that can be used with Machine Learning (ML) models to identify FM asset types during site installations of Appliance Load Monitoring (ALM) units. We introduce a framework in which the approach can be used as part of the training and deployment of ML models for verifying and monitoring assets in FM client environments.**

***Index Terms*—facilities management, appliance load monitoring, v-i trajectories, feature extraction, machine learning**

I. Introduction

In the Facilities Management (FM) industry, the ability to gather effective appliance (also termed asset) data at low cost is a key driver of the quality of service a FM company can provide. A major challenge faced by these companies is the current process of verifying appliances to be monitored during the on-site installation of Appliance Load Monitoring (ALM) units, more specifically the type of appliances that are connected to the ALM units for monitoring their operating behaviour and energy consumption.

The current ALM installation process involves three manual steps. First, a surveyor visits each sites to determine the number of Distribution Board (DB)s and appliances to be monitored. Then, engineers manually identify if a connected appliance matches an entry in a database of known appliance types. Finally, a secondary check is done to verify if the signal data received from each appliance matches their appliance type. This process is time consuming, resource intensive, and error prone since it can take several days and a lot of the engineers' time to complete.

One method to tackle this inefficiency is the introduction of an automatic appliance type identifications pipeline. Developments in this area centres around introducing Machine Learning (ML) and Deep Learning (DL) algorithms trained on limited benchmarking datasets [1]. However, these works are not production-ready as real-world data requires more rigorous preprocessing steps before it resembles the format expected by the algorithms in those works. In addition, to the best of our knowledge, there has been no work done to showcase a deployment mechanism for such a pipeline to be integrated into an existing production system. The contributions of this work are as follows: (1) We introduce a V-I Trajectory features extraction approach that uses the Approximate Entropy of steady-state current to ensure V-I Trajectories are extracted from the correct data points in non-uniformly sampled signals. (2) A deployment framework integrating the proposed approach within an FM production system to automate on-site asset verification during installation of ALM units.

This paper is structured as follows. Section II outlines related work. Section III details the proposed feature extraction approach. We then provide an analysis of the results in Section IV. The paper ends with conclusions and a discussion on future work in Section V.

II. Related Work

Approaches for Appliance classification rely on V-I Trajectories based features as input to ML and DL algorithms [2], [3], [4], [5], [6], [7], [5], [8], [9], [10], [11], [12]. The common theme among these works is that they focus on maximising the models' evaluation score on limited benchmarking datasets that are collected under controlled environments. Such focus leaves two gaps before these works can be deployed into a large scale production-ready system needed by companies in the FM sector. First, in a real-world environment, signal data received from appliances are not uniformly sampled. Prior to storing signals data received from each appliance, FM companies often fed the raw the signal data through a data reduction algorithms that remove unnecessary data points with the aim to reduce storage requirements. This causes steady-state detection algorithms relied upon by these works to incorrectly select a data point for V-I Trajectory feature extraction. Second, to the best of our knowledge, no work has been done on illustrating how such a model can be integrated into a production system. Some algorithms adopted by those

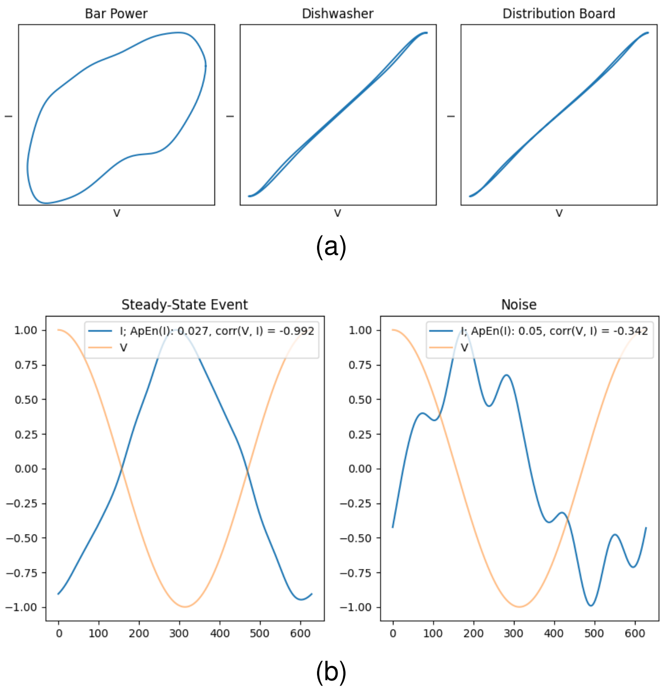

Fig. 1. (a) Samples V-I Trajectories of 3 Appliance Types. (b) Characteristics of Incorrectly Detect Events

work lack the implementation details needed for deployment. Furthermore, there are no explanation on how these models can be updated and retrained when new types of appliances are encountered.

Our work introduces a feature extraction approach to extract V-I Trajectories based on Approximate Entropy of the steady-state current and correlation between steady-state current and voltage to determine the validity of a detected steady-state events defining the Trajectory. With our proposed approach, we introduces a mechanism to deploy it to a production-ready system. The next sections discusses in details our proposed approach.

III. Proposed Feature Preprocessing Approach

The proposed feature extraction approach can be subdivided into two stages: (i) Extracting V-I Trajectories and (ii) Extracting shape features from V-I Trajectories.

In the first stage, moving median replacements were used to removed outliers from the per-appliance signal data files (Equation 2). Then, the resulting signal data is used to determine steady-state events in stage 2. For each of the first 10 events detected, the voltage and current at the start and end of the event were extracted and marked as V_a, V_b, I_a, and I_b. Equation 1 was used to calculate the steady-state voltage and current. Our observations show that events whose conditions matches Equation 3 can be discarded since it is a misclassified event. Figure 1b depicts the difference between a steady-state event and a noisy event.

Based on V-I Trajectories features identified in [13], 10 features were extracted comprising of: (i) Current Span (*itc*), (ii) Area (*ar*), (iii) Area with loop direction (*lpa*), (iv) Asymmetry (*asy*), (v) Curvature of mean line (*M*), (vi) Self-intersection (*sc*), (vii) Peak of middle segment (*mi*), (viii) Shape of middle segment (*sh*), (ix) Area of left and right segments (*alr*), and (x) Variation of instantaneous admittance (*D*). Apart from *itc*, the other features were calculated using normalised V-I Trajectories. For certain features the calculation method adopted by Wang et al. [13] were used that relies on the points in the trajectory to be sorted. Hence before the calculation of those features, the trajectory points were sorted based on their distance and direction from each other. Starting from the point with the maximum steady-state voltage (*vmax*), the next trajectory point to be selected would be the closest point in the same direction within a 40 degree angle.

TABLE I
Results on Test Set

	Acc	Precision	Recall	F1	mAP
Clean					
RF	0.903	0.890	0.841	0.863	0.863
DT	0.861	0.808	0.786	0.796	0.740
kNN	0.875	0.775	0.779	0.775	0.765
ML	0.748	0.700	0.636	0.641	0.705
With Noise					
RF	0.884	0.839	0.719	0.736	0.785
DT	0.840	0.695	0.667	0.665	0.631
kNN	0.866	0.690	0.708	0.697	0.686
ML	0.748	0.608	0.545	0.550	0.623

$$V = (V_a + V_b)/2;\; I = I_b - I_a \tag{1}$$

$$IQR = Q3 - Q1 \tag{2}$$

$$\text{ApEn}(m, r, N)(I) > 0.03 \vee |\text{corr}(V, I)| < 0.5 \tag{3}$$

where $Q1 =$ The first percentile of the signal.
$Q3 =$ The third percentile of the signal.

$$\text{corr}(V, I) = \frac{\sum_{i=1}^{N}(V_i - \bar{V})(I_i - \bar{I})}{\sqrt{\sum_{i=1}^{N}(V_i - \bar{V})^2}\sqrt{\sum_{i=1}^{N}(I_i - \bar{I})^2}}$$

$$m = 2;\; r = 0.2$$

IV. Results and Discussion

To evaluate our proposed feature extraction approach we used it to extract training/testing data from a real-world dataset provided by Cloudfm Group Ltd using their Mindsett PRISM ALM units.

The dataset contained high frequency signals collected over the span of six months from 391 appliances spanning 60 types and seven locations. Applying our approach on to the raw dataset resulted in a dataset of 103,120 samples with 43 appliance types. We further removed samples that accounted for less than 0.1% of the total samples and samples labelled as *Mains* and *Sockets* since they did not reflect the underlying appliance type. These extra cleaning procedures produced a final dataset of 86,268 samples with 29 appliance types. We used stratified sampling to produce a training split (70%) and testing split (30%) from the 86,268 samples. Furthermore, to

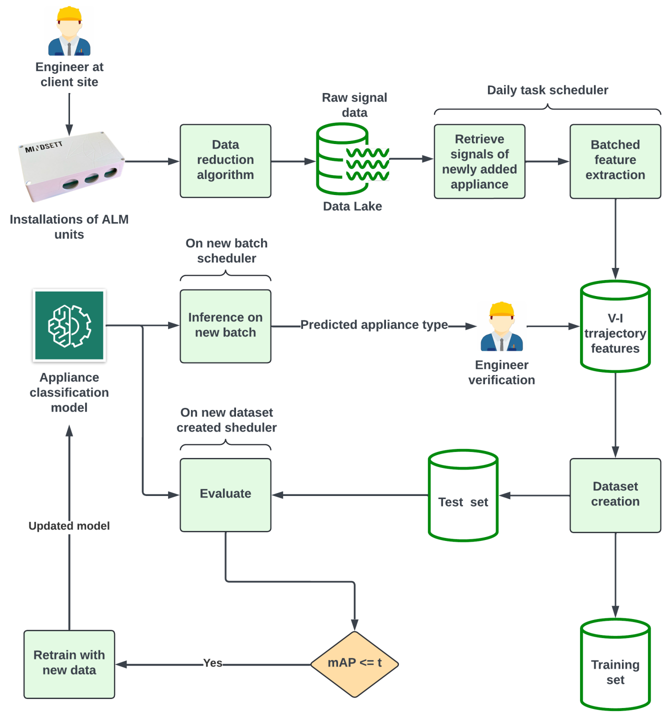

Fig. 2. AI driven framework for ALM installation and FM asset verification

demonstrate the effectiveness of our approach, we also created another training split of the same size and distribution without our appraoch applied to remove the noise.

We then trained and tested the data with four ML classifiers: (i) Decision Tree (DT), (ii) Random Forests (RF), (iii) k-Nearest Neighbours (kNN), and (iv) Multi-Layer Perceptron (MLP) using Accuracy, Precision, Recall, F1 Score, and Mean Average Precision (mAP) as evaluation metrics. The best configuration of each model were chosen based on the average mAP of a five fold cross-validation results where 20 parameters sets were produced for each models through Bayesian Optimisation [14].

A. Extracted Dataset Validity

The results show clear performance drops by the different algorithms trained with and without our feature extraction approach added to remove the noise (Table I). This indicates that our approach is effective when used to removed noise presented in real-world environment. Second, the performances of models trained on data with noise removed exceed 60% (highest being 86% by *RF*). This shows that the extracted dataset consists of useful patterns for appliance type classification.

B. Deployment Mechanism

A possible mechanism for deploying our feature extraction approach as part of a production-ready FM system for supporting ALM site installations is shown in Figure 2. Here parallel processing over batches of data collected through installed ALM units over a single day would be performed. More specifically, batches of signals from newly added or reconfigured appliances would be processed to extract the V-I trajectory features and inferences for appliance classification on the batched features. The predicted labels would then be sent for verification by human engineers and stored with their extracted features. A monitoring mechanism can be introduced by leveraging the V-I trajectory feature database to automatically create new training and testing splits. The current model can be evaluated on the newly created test set. If its *mAP* drops below a certain threshold *t*, then a retraining job can be triggered with the newly created training set. This mechanism reduces the cost of model retraining if the asset classification is operating under acceptable performance levels.

V. Conclusion

Our work describes an approach for correctly extracting V-I Trajectories from non-uniformly sampled high volume consumer electronics operational data. We demonstrate that Approximate Entropy of the steady-state current along with its correlation with steady-state voltage can provide an indicator for determining the validity of detected steady-state event for accurate V-I Trajectory extraction. This approach can be integrated and deployed as part of a production ready system for more scalable and cost effective monitoring of FM assets.

Future research will explore how the current feature extraction approach can be expanded to include more shape features as well as combine other recorded signal parameters. We will also explored the use of other ML approaches such as DL paradigms for modelling Appliance Type classification.

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