Quek YT, Woo WL, Logenthiran T. [Smart Sensing of Loads in an Extra Low Voltage DC Pico-grid using Machine Learning Techniques](#). *IEEE Sensors Journal* 2017, 17(23), 7775-7783.

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DOI link to article:

<https://doi.org/10.1109/JSEN.2017.2723925>

Date deposited:

20/01/2018

Smart Sensing of Loads in an Extra Low Voltage DC Pico-grid using Machine Learning Techniques

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Abstract — Aiming at the rising number of dc appliances and the growing interest in their monitoring systems, this paper describes the injection of intelligence into dc pico-grids that are made up of “dumb” appliances and loads. Due to reality of economic, dc appliances and loads are usually low in cost and lack intelligence and communication features for effective monitoring and management. This paper proposes a smart sensor design for dc pico-grid with the use of a single sensor multiple loads and states detection in monitoring the “dumb” appliances. This eliminates the need to have intelligence and communication features for every appliance. With the smart sensor, several such smart dc pico-grids can be bundled into bigger scale of smart nano-grid or micro-grid. In addition to knowing how much energy or power the pico-grid is using; the smart sensor also provides load disaggregation and state-change detection. The states of the loads can be learnt and detected via the signatures and features obtained from the transient state or the steady state of the entire grid’s current waveform. Computational intelligence techniques, *k*-Nearest Neighbours, K-Means clustering and other algorithms are used in the system for loads classification and state-change detection. Working together with the software in the smart sensor are hardware implementation of low cost operational amplifiers and logic gates; these hardware help to share the burden on the controller and release resources for the controller to perform more advanced processes. Experimental results are presented to demonstrate the operation of the smart sensor in dc pico-grid.

Keywords— dc power systems, pico-grid, load classification, state-change detection, load management

I. INTRODUCTION

As early as the 1990s, there were many methods proposed to identify electrical loads and monitor their energy consumption [1, 2]. The purpose of these methods was mainly for energy management in the alternating current (ac) grid [3, 4]. Conventionally, this energy management was primarily used for major loads, such as heating and ventilation, washers, and refrigerators [5]. However, in the recent years, there is a significant increase in the number of smaller appliances in households and offices. Thus there is growing interest in the monitoring of smaller appliances such as lights and fans [6]. These smaller appliances are usually low in cost and do not have the economic sense to include intelligence and communication features. These appliances will only have simple turning On and Off function or with a few simple stages such as Off, Low, Medium and High. They neither are able to monitor their own power consumption nor have the intelligence to manage their power patterns. They do not have the means to communicate

with higher management system. Thus, they are classified as “dumb” appliances.

These smaller appliances and loads, when put together, can form even smaller grids, pico-grids. These pico-grids can bundle together to form nano-grids and mini-grids. The management approach of the grid can be done from bottom up where the monitoring starts at the pico-grids and move up the level and scale. Fig.1 shows multiple pico-grids forming into a micro grid.

Lately, along with the increase interest in smaller appliances monitoring, there has also been more research on the direct current (dc) mini and nano-grid [7, 8]. The scaled down version of micro-grid, which focus on dc instead of ac, [9-11] can operate independently on renewable power sources such as photovoltaic (PV) system or from energy storage such as the lead-acid battery banks [12]. Both the PV panels and battery banks are dc power source. The concept of dc grids is also build upon the recent upsurge in the use of dc-powered appliances and gadgets. There are increasing calls for more use of dc distribution and grids in buildings [13, 14]. This requires load management for dc appliances instead of that for ac appliances. In addition, this load management will have to be applied on extra low voltage (ELV) dc grids as most dc-powered appliances and gadgets are powered at 24V or less. For example, laptops are powered at 19V, fans at 12V, and LED lights at 5V. The concept of ELV dc pico-grid will have certain advantages over a LV ac grid. The ELV dc grid allows the sources, energy storages and loads to be connected without complicated power electronic interfaces such as ac/dc rectifier or dc/ac/dc converters. This reduces the losses and complexity [15]. With this increasing trend of dc power supplies and dc loads and the rise in the development of dc grids without the conversion between dc and ac, energy management for ELV dc pico-grids needs to be developed and optimized. This ELV dc pico-grid energy management can be used for an office desk dc pico-grid made up of dc motor table top fan, LED desk light, laptop and mobile phone powered by dc supply line or a residential dc pico-grid consisted of dc powered vacuum cleaner, massager, DVD player and TV which are supplied by photovoltaic sources. Energy management has been popular in the AC grid but there is a lack of research in this area of smart ELV dc pico-grid. Thus spurred the needs for smart ELV sensing.

In the smart ELV dc pico-grids such as office or home [16], load disaggregation is a key area in the energy monitoring and management. Appliances and loads are controlled by the energy management system, depending on the intermittent energy harvested from the PV or the available energy storage [17]. Determining the operating state of the appliances in the dc pico-grid is essential to our understanding. This can be done by

providing all appliances in the grid with an identity or address. However, this method is not feasible to implement for individual low cost ELV dc loads in an ELV dc pico-grid as most of the appliances, due to cost, are usually “dumb” with no intelligence. The other method is to implement sensor for each and every appliance in the pico-grid, which is costly and resource-intensive. The method proposed in this paper allows the use of single smart sensor for multiple loads classification and their state detections in the smart ELV dc pico-grid.

One common state detection routine of appliance is to wait until the appliance goes into steady state [18, 19]. The shortfall of these steady state algorithms is they might take a long time to be activated so as to wait for the system to. In contrast, working on the transient state where the appliance changes from one state to the other allows faster detection of the appliance. This paper will discuss both methods.

Fig. 1. Example of multiple pico-grids forming a micro-grid

Several computational intelligence methods have been explored for load disaggregation and classification, such as artificial neural networks (ANN) [20] and the k -nearest neighbors (k NN) algorithm [21, 22]. These methods, which are executed using software in a computer or controller, provided good results. However, the computational techniques are resource intensive and slow; time and resources are usually the tradeoff for improved accuracy; hence the selection of the methods is crucial and has to be optimized. This paper proposes a fresh approach of utilizing both the transient and steady-state process of the acquired waveform signal from the ELV dc pico-grid. The smart sensor will keep the load classification process in standby mode while running a low resource-intensive state-change detection. Hardware integration using low cost electronic components as an alternative to detect the state-change process and preliminary load classification during the transient process of the pico-grid can help the computer in the classification process and release resources for the computer for much higher-level processes such as steady-state detection and load confirmation during steady-state process. See Fig.2.

A state-change process is defined as a change in the operation of the appliance from one steady state to the other, e.g. from an Off steady state to an On steady state. The system will be in steady state if there is no state-change process. The proposed state-change detection method will be used to monitor the dc line; it is able to assume the system to be in steady state if it keeps between certain threshold levels. It will also be able to detect state-change occurrences and perform initial load and appliance classification. It can also act as a trigger for the more resource-intensive load classification method to take effect and

activate when necessary. This method will reduce data storage requirement as data will only be stored when significant change has occurred and been identified by the method. This will facilitate greater efficiency in the use of resources.

Fig. 2. Smart LV dc pico-grid system flow

The methodology of the proposed smart sensing of an ELV dc pico-grid is evaluated over 200 times on 15 appliances. It is able to detect the state change process when the appliances are changing from one state to the other and follow through with a load classification and state detection. It uses the acquired signal of the ELV dc pico-grid’s current waveform. An ELV dc pico-grid setup will be given in Section II. The details of the methodology will be elaborated in Section III. The results of the state-change methodology with comparison with other detection algorithms will be presented in Section IV. Various commonly-used dc appliances and gadgets were used to evaluate the accuracy and feasibility of the methodology. Finally, Section V will summarize and conclude the paper.

II. EXTRA LOW VOLTAGE DC PICO-GRID SET UP

Although public datasets for energy disaggregation research are available, they are mostly for ac loads and supplies [23, 24]. In comparison to the ac setup, which has more electrical parameters, such as real power (W), reactive power (VAR) and harmonic content [25, 26]; dc setup is limited to just the voltage and current. Although it is possible to acquire dc load electrical parameters through ac acquisition method, the acquired signal will sometime be polluted by the ac-dc rectifier characteristic and might not reflect the actual waveform. This section describes the ELV dc pico-grid setup and acquisition method used. More detail on the working principle and algorithm of the methodology will be given in the next section.

A. Single sensor multiple load pico-grid

Voltage and current are the two most commonly acquired pieces of information and analyzed parameters in load identification. The voltage waveform can be acquired by tapping the pair of measurement probes across the appliance. The acquisition of the current waveform will require an intrusive current transducer along the live line. Using the principle of Hall’s effect, the current transducer produces a difference in voltage across a conductor in response to the magnetic field caused by the electric current. This voltage can be easily acquired by another pair of measurement probes.

Fig. 3 shows an image of the lab experiment setup. This lab setup provides lots of flexibility so as to cater to different settings of the dc pico-grid. Power supplies are available in both ac-dc rectifiers (orange dashed box) and dc-dc converters (orange box). Power inputs (yellow box) are also made available for 5V USB, 12V cigarette lighter plugs (size B) and screw terminals for other voltages. The power outputs to loads

(yellow dashed box) provides similar connections. The current sensors are shown in the red dashed box.

Two equipment are used in this experiment setup for data acquisition. The Hioki LR8431 Memory HiLogger is a compact and lightweight data logger that allows up to 10 ports of data acquisition at up to 100Hz frequency. The National Instrument CompactDAQ NI cDAQ-9188 is a customizable platform which allows plug and play of modules to suit the experiment.

Fig. 3. Lab experiment setup

In data collection of loads' waveforms, the usual practice is to install a sensor for each load in the ELV dc pico-grid to acquire individual load's data. This method is costly and resource-intensive. The proposed smart sensor in this paper uses single sensor for multiple load classification in the ELV dc pico-grid. The lab setup was configured to as illustrated in Fig. 4.

Fig. 4. Data acquisition setup

B. Appliances and their states in the ELV dc pico-grid

The voltage and current waveforms of 15 dc appliances that are commonly found in an ELV dc pico-grids were experimented on using the above-mentioned setup (see Table I). In general, two state-change processes were considered in the experiment, namely starting up (switch on) and shutting down (switch off). However, some appliances have more state-change processes. For example, if a tabletop fan has 2 different speeds then it has four state-change processes: starting up to low speed, starting up to high speed, switching off from low and high speed.

The current of the grid is the summation of the current draw from all the loads. Thus it will change according to the required power of the load. The relationship between power consumed by the load, P_l , load voltage, V_l , and load current I_l , is as below.

$$P_l = V_l I_l \quad (1)$$

C. Steady state, transient state and state change process

The ELV dc loads exhibited features and characteristic that can be used in load disaggregation during their transient and steady states. This allows load disaggregation and state-change detection of the multiple loads in the ELV dc pico-grid. The state-change process of an appliance is defined as the appliance shifting from a steady state to another steady state. In most cases, it is seen as the transient state but it is not true if the load is to undergo a few transient states before it settles down.

The appliances exhibited rather unique waveforms during state-change process, for example, the LED desk light shown in Fig.5 had a clean and steady change in states. In contrast, the tabletop fan shown in Fig.6, similar to all motors, experienced an initial surge in the current waveform that allowed it to overcome the inertia before settling down after approximately three seconds. The fan's operating waveform was also noisy and irregular. The signal waveform has different characteristics and therefore various features can be extracted from the waveform to form signatures that can be used to identify the loads.

Fig. 5. Signal waveform from a LED light

Fig. 6. Signal waveform from a fan

III. STATE-CHANGE DETECTION AND LOAD CLASSIFICATION

The state-change detection methodology and load classification in this paper minimizes resources and time by only processing the acquired signal of current waveform in the dc pico-grid. Both the transient and steady state will be used in the proposed technique. This chapter will elaborate on the processes in the smart sensor for the ELV dc pico-grid.

A. Using the transient state

State-change detection and load classification can capitalize on the changes in the current's magnitude during the transient state of an appliance when it shifts from one state to another. This short transient period provides several features that can be extracted for load classification.

The gradient is the derivative of a function. It can also be defined as the rate of change of a system. In transient state, the gradient waveforms are very useful in simple-step detection algorithms by searching for spikes that indicate an increase of magnitude over a period of time. A positive spike would indicate an increase in the current, which can be inferred as a switch-on state-change process. On the other hand, a negative spike would

indicate a decrease in the current, which might mean a switch-off state-change process. The data samples of the raw current waveform are placed in a 1D matrix $\mathbf{I}$ as seen below, where m is the total number of samples logged.

$$\mathbf{I} = [i_1, i_2, i_3, \dots, i_m] \quad (2)$$

Given i_n is the element in the input signal $\mathbf{I}$ and M is the number of points in the window subset. $\bar{\mathbf{I}}$ in (3) is the computed output signal after the mean window filter.

$$\bar{\mathbf{I}} = [\bar{i}_{M+1}, \bar{i}_{M+2}, \bar{i}_{M+3}, \dots, \bar{i}_m] \quad (3)$$

$$\text{where } \bar{i}_n = \frac{1}{M} \sum_{j=n-M+1}^n i_j \quad (4)$$

The process to compute the gradient of the waveform at an individual data point. $\bar{\mathbf{I}}$ as seen in (5) is the gradient matrix of the processed waveform and T being the time interval between the two samples.

$$\bar{\mathbf{I}} = [\bar{i}_{M+1}, \bar{i}_{M+2}, \bar{i}_{M+3}, \dots, \bar{i}_{m-1}] \quad (5)$$

$$\text{where } \bar{i}_n = \frac{\Delta \bar{I}}{\Delta t} = \frac{\bar{i}_n - \bar{i}_{n-1}}{T} \quad (6)$$

One of the advantages of computing the gradient waveform is that the state-change and steady-state can be easily observed in the gradient waveform. The spikes in the gradient waveform indicate that the occurrence of the state-change process while the steady-state, which has a zero mean gradient value, will be shown with a small fluctuation along the x-axis, regardless of the number of loads that are operating in the grid.

The appliances in the ELV dc pico-grid will have different rates of change during the transient period, this characteristic can be used to detect the state change process as well as the preliminary classification of loads. This can be done by setting different threshold levels to detect the state change of different appliances in the ELV dc pico-grid.

Thresholding is an important segmentation operation used in image processing [27]. It has the advantage of removing noises and is mainly used to identify and extract a target from its background on the basis of the gray level distribution in image objects. It can also be applied in 1D waveform to identify the location of the abnormal large value. Traditional threshold operation will only provide binary output but it can be modified to 3 or more outputs to identify the occurrence of stage-change process in the current waveform, as in (7).

$$S_n = \begin{cases} 1 & \text{if } \bar{i} > +T\text{value} \\ -1 & \text{else if } \bar{i} < -T\text{value} \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

A positive threshold value can be set for identifying the change of state from off to on or from low to high and a negative value can be set for identifying when the appliance is switching off or in the reduction of current. The threshold value can be determined via observation. Multiple levels of threshold values can be set for different states of appliances. The method can be expanded to include abnormalities and faults.

Another state change detection method that can be used in the transient period is the second derivative zero crossing detection algorithms. [28] They work on the principle that the derivative of the derivative, $\ddot{i}$ (8), indicates the local minimums and maximums when its value crosses the zero. The zero crossing value can be obtained by interpolation from the

maximum and minimum values or by doing a search algorithm. As differentiation is very vulnerable to noisy signal, therefore to apply the second derivative zero crossing detection algorithm effectively, the raw waveform will have to be very clean or require extensive processing such as filtering.

$$\ddot{i} = \frac{\Delta^2 \bar{i}}{\Delta t^2} \quad (8)$$

In comparison to thresholding method, the second order zero crossing detection algorithms are more resource-intensive.

Another alternative is to engage the use of low cost operation amplifier (op amp) and logic gates for state-change detection and preliminary load classification. The more resource-intensive computational intelligence processes can be performed in the steady state for more accurate classification. This low-cost hardware can be applied for single sensor multiple load classification in ELV dc pico-grid, example is shown in Fig.7.

Using the op amp integrated circuit (IC) such as 741, 358, 339 and 311 with logics gates IC such as 7404 NOT gate and 7408 AND gate, the circuit can perform low pass filtering, differentiation, inverting and non-inverting amplification and thresholding by comparison. See Fig.8.

Fig. 7. State-change detection and preliminary load classification design

The acquired signal will undergo a low pass filter to clean out the unwanted high frequency noise. As mean window filter is difficult to implement using hardware, another low pass filter which is the 1st order Butterworth low pass active filter is to remove unwanted noise with frequency above the cut-off frequency f_c . It can be constructed with resistor and capacitor (R_{lpf1}, C_{lpf1}) combination on the positive input of the op-amp.

$$f_c = \frac{1}{2\pi R_{lpf1} C_{lpf1}} \quad (9)$$

A differentiator is used after the filtered signal to obtain the rate of change value of the signal, . The differentiator is constructed using R_{df} and C_{d1} with the op amp, (10).

$$V_{out} = -\Delta v_{in} R_{df} C_{d1} \quad (10)$$

The differentiated signal needs to be amplified to a desired range for effective analysis in the later stage. There are 2 common amplification circuits that can be constructed with op amp, namely the inverting and non-inverting amplifier. The output of the inverting amplifier, V_{oi} , will reverse the polarity of the input during amplification for negative input, (11).

$$V_{oi} = -\frac{R_{if}}{R_{i1}} V_{ii} \quad (11)$$

The non-inverting amplifier maintains the polarity and amplifies the differential signal, giving V_{on} , (12).

$$V_{on} = (1 + \frac{R_{nf}}{R_{n1}}) V_{in} \quad (12)$$

These amplified signals will undergo thresholding process with the comparator circuits constructed from op amp. These comparators are used to indicate the change of state of the LV dc pico-grid by comparing the magnitude of the amplified differentiated filtered signals with pre-set reference voltages.

B. Using the steady state

The steady state occurs when the grid has pass the state change process and the current waveform's value does not fluctuate over a range of value. In general, a system during its steady state does not fluctuate beyond three multiples of standard deviation, σ , from its mean, μ , over a period of time.

$$\sigma = \sqrt{\frac{\sum_{n=1}^m (i_n - \mu)^2}{m-1}} \quad (13)$$

$$S'_n = \begin{cases} 1, & \text{steady state if } \mu - 3\sigma < i < \mu + 3\sigma \\ 0, & \text{non-steady state otherwise} \end{cases} \quad (14)$$

This steady state detection algorithm can also be used for load classification. The mean and standard derivation values of the various steady states are to be acquired before the start of the detection as prior knowledge. The load can be identified when the value of the current waveform falls between the $\mu \pm 3\sigma$ of that particular load. This is applicable for multiple load detection as under the assumption of uncorrelated and independent variables, the mean and variance are additive. The mean of summation of all the operating loads values is the summation of operating loads' mean value. Similarly, the variance of summation of all the operating loads is the summation of all operating loads' variance.

$$\text{var}(\sum X_i) = \sum \text{var}(X_i) \quad (15)$$

This steady state detection algorithm does not work well with noisy waveform as the fluctuation of signal frequently exceed the $\mu \pm 3\sigma$ condition of a steady state. Thus, an enhancement to this method is to include a comparison of two variances. The first variance, var , which is commonly used is the mean-square-standard deviation from average can be obtained from the above standard deviation as described in (13).

The second variance, $\widehat{\text{var}}$ is defined as the mean of squared difference of successive data, see (16). Ideally, steady state is defined when the ratio of the two variances is near to unity, however, this is a very stringent condition, thus a threshold value, $T\text{value}$, of near 1 such as 2 or 3 can be set as the boundary for occurrence of steady state. This algorithm is resource-intensive as it involved continuous calculation.

$$\widehat{\text{var}} = \frac{\sum_{n=1}^m (i_{n+1} - i_n)^2}{m-1} \quad (16)$$

$$R = \frac{\text{var}}{\widehat{\text{var}}}; S_n = \begin{cases} 3 & \text{if } R < T\text{value} \\ 0 & \text{otherwise} \end{cases} \quad (17)$$

Load aggregation is essentially a classification problem, thus computational intelligence technique such as K-Means and kNN can be used to solve the problem.

K-Means clustering technique is an unsupervised machine learning algorithm that searches through the features of the elements in the training set and attempts to group elements with features together. It requires a pre-specified number of clusters, K , which is the number of loads in the ELV dc pico-grid. In the

training phase, the features are extracted from the elements of the training set. The elements of the training set are the data acquired for the current waveform of the ELV dc pico-grid. The number of features will determine the number of dimension of the space. The K-Means method goes through an iterative refinement process that seeks to minimize the distance between members of each cluster ($\xi_1, \xi_2, \xi_3, \dots$) and its centroid C . C is the mean of the cluster. One of the commonly used distance in K-Means clustering is the Euclidean distance d .

$$d(x, y, z) = \sqrt{(x_\xi - x_c)^2 + (y_\xi - y_c)^2 + (z_\xi - z_c)^2} \quad (18)$$

Scaling of attributes is required if the range of the attributes differ by a lot. Weights can be added in (19) to prevent distance measures from being dominated by the larger value attributes.

$$\text{dist}_w(x, y, z) = \sqrt{w_1(x_\xi - x_c)^2 + w_2(y_\xi - y_c)^2 + w_3(z_\xi - z_c)^2} \quad (19)$$

After the elements have been clustered and labelled, kNN can be applied in the real-time operation to classify the input of signal from the ELV dc pico-grid. Using the same features as those in the k-Means clustering, the kNN classification method will extract the features from the current waveform signal and classify it to a cluster. The election of class is decided through the majority voting on the labels of the k nearest elements. Similar to K-Means, this is a distance-based algorithm, thus the same Euclidean distance is used here. The extracted features from the steady state current waveform are the mean, μ , variance, var , and alternative variance, $\widehat{\text{var}}$. They contribute to the attribute values of the elements. Steady state can also be defined when several succession occurrences of the test elements within a boundary from the cluster centroid or it has been classified to the same class over a number of times.

C. Ignore Window process

Some of the loads will go through a series of activities after a state-change process and before it stabilize into steady state. This will result in erroneous detection and resource wastage. Hence an ignore window process is recommended if a load has unwanted after-effects or repercussions after a state-change process. The ignore window will also help to speed up the process by ignoring that period of data. Pseudo code as below.

```

Sub ignorewindow(start_point, no_of_samples)
  For tempCounter is 0 to no_of_samples
    Indicators[start_point+tempCounter] = 0
  End For loop
End Sub

```

D. Back tracking process

In the event where the accuracy of starting point of state-change detection is important, a backtracking algorithm can be implemented to enhance the method. An algorithm will be implemented on the mean filtered gradient waveform where state-change is as indicated by the thresholding process. In detecting the starting up of the appliance, the value of the spike is positive thus the algorithm will check whether the previous value is less than or equal to zero. If it is not, it will keep back tracking until it finds a previous value that is less than or equal to zero. That data point will be the start of state change process of the appliance. In detecting the shutting down of appliance, if the previous value is larger or equal to zero, it means that the

appliance has just started the shutting down process and thus that data point is the start of the state change process. The state-change indicated by the backtracking process is much closer to the actual starting point as compared to just the thresholding process. The pseudo code is as follows.

```

Sub findstarttime(Time, Gradient)
  While gradient is more than 0
    Get time at previous sample
    Find gradient at time
  End While
  Print time, gradient
End Sub

```

IV. RESULTS, COMPARISONS AND DISCUSSIONS

A. State-change detection and preliminary load classification

The state-change detection process that uses the transient state's data of the ELV dc pico-grid current waveform undergoes several stages as seen in Fig.9. Stages (a) to (d) can be achieved using low-cost hardware of Op Amp and logic gates. As dc is assumed to be 0Hz, a very low cut-off frequency, $f_c \sim 2\text{Hz}$ is set in Fig.9b by setting $R_{lplf}=22\text{k}\Omega$ and $C_{lplf}=3.3\mu\text{F}$ of (9) to remove any higher frequency noise. The amplification factor in the differentiator will help to amplify the change occurs during the transient state but it cannot be too large as it will exceed the voltage range of the op-amp. It is selected to be 4.7 times by setting $R_{df}=100\text{k}\Omega$ and $C_{df}=47\mu\text{F}$ in (10). The inverting amplifier is needed to invert the negative gradient caused by appliances shutting down. It is set at 2 times with $R_{if}=2\text{k}\Omega$ and $R_{il}=1\text{k}\Omega$ in (11). The non-inverting amplifier is necessary if the amplification at the differentiator is not enough, in this experiment, it is also set at 2 times, where $R_{nf}=R_{nl}=1\text{k}\Omega$ in (12). By setting the threshold values, the system separates the loads that are causing the change of state in the ELV dc pico-grid. On the hardware, this can be done using the trimmers ($5\text{k}\Omega$) or potentiometers to adjust the comparator's value through observations. These values for resistors and capacitors are adjustable based on user's requirements.

The additional stages of backtracking and ignore window will have to be done in software hosted by controller or computer. These are the resources and time trade-off for the improvement in accuracy. Fig.9e shows that the backtracking algorithm returns more accurate result. Fig.10 and Table I compares the result of state-change detection with classification with different methods.

B. Steady state detection and Load confirmation

Upon the detection of steady state, the computational intelligence techniques of K-Means and $k\text{NN}$ is combined for load confirmation. The variables used are mean (μ), variance (var) and alternative variance ($\widehat{var}$). These are features extracted from the elements to form the 3-dimensional space. Fig.10 shows the clusters and centroids after K-Means clustering. The clusters are labelled according to the loads. During operation mode in steady state, $k\text{NN}$ technique is triggered by the state-change detection, which occurs in transient state, to classify the test data by majority voting. It shows an example of the test element of a TV data classified by $k\text{NN}$ technique.

Fig. 8. Stage-change detection process

Fig. 9. Comparison between the algorithms

TABLE I. COMPARISON OF RESULTS

Legend	Algorithm	T (s)	ΔT (s)
←	Actual state change	0.196	-
	State-change detection with enhancement	0.200	0.004
	State-change detection without enhancement	0.218	0.022
	2 nd Derivative zero crossing algorithm with interpolation	0.272	0.076
	2 nd Derivative zero crossing algorithm using search	0.276	0.08
	Steady state algorithm using variance ratio	0.150	-0.046

Fig. 10. Example of K-Means clustering with $k\text{NN}$ technique

C. Validation and accuracy

The proposed technique is put to test in the 5-fold cross-validation. Its performance is evaluated by the cross-validation error E_{cv} as seen in (20). K is the number of fold and E_K is the error of individual fold. SD_E in (21) is the estimated standard deviation of the error in the validation. N is the sample size.

$$E_{cv} = \frac{1}{K} \sum_{K=1}^K E_K \quad (20)$$

$$SD_E = \sqrt{\sum_{N=1}^N \frac{(E_N - \bar{E}_N)^2}{K-1}} \quad (21)$$

For the testing of every class in the ELV dc pico-grid, a base load or no load was set and the additional appliance was switched on and off over a period to shift between the classes. The cross validation error of the proposed method is dependent on the ELV dc pico-grid setup and it is not possible to present all variation of ELV dc pico-grid. Thus only two examples of ELV dc pico-grid are shown and discussed. Grid A hosted 3 “dumb” appliances, namely 12V Table top fan, 5V Desk light and 12V mini-fridge. Grid B hosted another 3 intelligent appliances, namely 19V laptop, 5V mobile phone and 12V LED TV. During On state, the laptop was used to do simple word processing task and the LED TV was showing a movie. A variety of voltages were used to test the robustness of the technique. The experiments were done over a few hours with the appliances turning on and off with sampling rate of 100Hz. Table II shows cross-validation errors.

ELV Grid A managed to have a very good average error of 2.65%, with the classification error being largest for refrigerator. This is due to the transient state of the refrigeration taking a longer time as compared to the rest. This can be avoided by setting a very long ignore period which could result in slow detection. A compromise was done and the error percentage is at 8.0%. Some of the classes were quite distinct from each other therefore managed to have 0% error. An example of the implementation of the technique is as shown in Fig.11.

ELV Grid B, which consisted of intelligent loads, proved to be more challenging. It averaged a 6.6% error. In order to achieve low error percentage, there were tradeoff in delay in detection. Most of the error occurred during the transient states as these appliances possessed complicated waveforms. Thus high ignore windows were required. As the waveforms were more complicated, large kNN window period was set. The detection in Grid A was also much cleaner. The kNN classification in Grid B was called into action every time there was a spike which might not be due to the state-change.

Another experiment that used conventional kNN classification during steady state without information from transient state was done for comparison. As shown in Table III, in Grid A, the paper’s proposed technique and the conventional kNN classification had about the same error percentage but the paper’s proposed technique excel in resource utilization, the number of detection done using the proposed technique was only 0.1% as compared to continuous classification of every data points in conventional kNN classification. In Grid B, the paper’s proposed technique ignored the transient periods and therefore had less error and it used only 2.8% of resources as compared to conventional kNN classification. Intelligent loads such as laptop will go through several transient states when they are performing different tasks, but will eventually return to their steady states.

However, if they were to perform at different level such as power setting of “Power saving” and “High performance”, then this situation will be similar to a fan with 2 speeds and will need to be trained as 2 different classes.

TABLE II. RESULTS OF 5-FOLD CROSS VALIDATION

ELV Grid A: Mini-fridge, Fan and Light (kNN window = 2s)				
Class	Base load	Switching load	ignore window (s)	E_{cv} %
1	No Load	Mini-fridge	20	8.0
2	No Load	Lights	1	0
3	No Load	Fan	5	4.62
4	Mini-fridge	Lights	1	0
5	Mini-fridge	Fan	5	5.95
6	Light	Fan	5	0
7	Mini-fridge + Light	Fan	5	0
Overall average error				2.65
ELV Grid B: Mobile phone, LED TV and Laptop (kNN window = 10s)				
Class	Base Load	Switching Load	Ignore window(s)	E_{cv} %
1	Standby	Phone	1	0
2	Standby	Laptop	30	7.69
3	Standby	LED TV	10	2.53
4	Phone	Laptop	30	5.7
5	Phone	LED TV	10	7.67
6	LED TV	Laptop	10	6.0
7	Laptop+Phone	LED TV	30	16.5
Overall average error %				6.6

Fig. 11. Example of multiple load detection

TABLE III. RESULTS OF 5-FOLD CROSS VALIDATION

Grid	E_{cv} %	SD_E %	ξ %	E_{ss} %
A	2.65	3.77	0.1	2.88
B	6.6	5.21	2.8	14.7
E_{cv} is the cross-validation error, SD_E is standard deviation of the error, E_{ss} is the error of kNN classification using steady state only and ξ is the percentage of resource used in proposed technique as compared to conventional kNN classification using steady state only				

V. CONCLUSION

The paper showed that it is possible to inject intelligence into an ELV dc pico-grid of “dumb” appliance by implementing a smart sensor that perform multiple load classification. This method is more cost-effective as compared to adding a sensor and intelligence in every single appliance. It is proposed to have several ELV dc pico-grids congregated to form nano-grids and expandable to micro-grid. The proposed technique makes use of both features in the transient and steady-state of the current waveform. State-change detection and preliminary load classification are performed during the transient state and upon

detection of steady state, k NN classification is triggered to perform the load classification. Prior to the k NN classification process, unsupervised K-Means can be performed to obtain clusters of elements that represent the various loads in the ELV dc pico-grid. Experiments show that the proposed technique worked very well with “dumb” appliances with very low error percentage. It is able to perform acceptable well with intelligent loads, but with trade off in applying bigger ignore and k NN window. The presented method edged out conventional steady state k NN load classification by using significantly less resources. This method can be designed and integrated in smart sensors for load monitoring and management system of dc home or office pico-grid.

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