A Non-Intrusive Load Monitoring System Based on Blacklist Detection

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Abstract. — Electric utilisation safety is widely recognised as an important issue. Most electrical accidents can be concluded to the Unallowed access of certain kinds of electrical appliances, hence can be effectively prevented by a blacklist-based detection. However, this ability is lacked in many of the existing Non-Intrusive Load Monitoring (NILM) system. This paper proposes a novel blacklist-based NILM system capable of extracting valuable information from the main wire when unallowed risky appliances are switched on in a household. Comprehensive methods are proposed to optimise the accuracy of detection and the self-learning ability on blacklist extension. Experimental results show that the proposed methods yield outstanding performance. The proposed system is applicable for unallowed appliances management, from the inhabitants or from the grid operator’s point of view.

1. Introduction

Electrical accidents are the main cause of fire disasters, and has led to huge life and economy losses during the past decade [1]. Load monitoring systems detect the operation status of electric appliances, and thus play an important role in electrical accident prevention. Nevertheless, the existing intrusive load monitoring system are faced with challenges such as huge maintenance cost due to large number of distributed sensors and poor real-time response. To this regard, non-intrusive load monitoring (NILM) systems have been developed recently [2]. In some existing NILM systems, the appliances can be monitored through the active and reactive power collected on the main wires [3], and the power loads in each power unit can be disaggregated to single appliance level without installing sensors or meters to each user port.

Although NILM reduces the cost of maintenance and can achieve up-stream monitoring, they still face some challenges. First, the existing systems based on low sampling rate from 1 to 60 minutes may fail to respond quickly to the access of unallowed appliances and thus pose security risks [4]. Second, multi-state appliances with long operating cycles and complicated behaviors, such as washing...
machines and induction cookers, are hard to be detected [5]. Also, the existing signal process and black-or-white list assessment methods for NILM systems need to be optimized to enhance the system efficiency and accuracy [6].

In this paper, a novel NILM system is proposed to achieve real-time and blacklist-based load monitoring to the unallowed appliances access in a household. The system extracts the rising-edge of the electrical access signals from the main wires. Thus, in real-time monitoring and unallowed access prevention for multi-state appliances, the proposed system performs better than those based on daily power detection. In addition to that, the data at each single detection was simplified from time stamped power readings to a short list of current harmonic vector hence a highly integrated systems can be achieved by connecting one single processor to an array of sensors on the main wires in different households. Moreover, blacklist-based algorithms are developed and a systematic and feasible solution to the dilemma between misreporting and underreporting has been made through a matrix-based algorithm and large number of experimental data. The accuracy of data assessment can be automatically enhanced through the algorithm, and the blacklist possesses self-learning ability. From the smart grid point of view, the processors can achieve remote connection to cloud servers hence the system can be easily integrated to facilitate the up-stream monitoring system in the future.

2. **Blacklist-based assessment**

2.1. Preliminary signal process

To achieve real-time monitoring, the proposed system only detects the rising-edge of the current readings from the main wire at the appliance access in a household. The signal is sent into a bandpass Butterworth filter to enhance the anti-jamming ability. FFT is then performed and the harmonics vectors will be collected for the blacklist-based assessment.

2.2. Blacklist assessment

As is shown in Fig.1, when rising-edge is detected, the difference value of the two neighboring harmonic data is considered as from the accessed appliance. The harmonic data is first sent for a pre-classification after the preliminary process. The appliances below safe-power level are ignored whereas the others are sent into different sub-blacklists classified by the 1st harmonic. In each sub-assessment, harmonic vectors will be analyzed and compared with the database. The harmonics data processing is illustrated below.

![Figure 1. Blacklist-based assessment.](image-url)
2.2.1. Harmonic vector. The harmonic data lists obtained from pre-classification is turned into vectors. One defines the collected data as a harmonic vector:

\[ \theta = [y_1, y_2, \ldots, y_i, \ldots]^T \]  

where \( y_i \) is the amplitude of the \( i^{th} \) harmonic. The data in the database is defined as:

\[ \overline{\theta} = [\overline{y_1}, \overline{y_2}, \ldots, \overline{y_i}, \ldots]^T, \]  

where \( \overline{y_i} \) is the amplitude of the \( i^{th} \) harmonic in the database. \( \overline{\theta} \) is used as a reference vector, and the system makes assessment based on the difference between \( \theta \) and \( \overline{\theta} \). However, to directly evaluate the Euclidean distance as \( \|\theta - \overline{\theta}\| \) can cause problems, because some harmonics from different appliances show various randomness. Thus, based on the experimental data, each harmonic must be weighted differently in the assessment to reduce the influence of those harmonics with high randomness and increase the dependence on the stable ones. Moreover, harmonic vectors from different appliances need to be weighted differently.

2.2.2. Weighting matrix. Different appliances in the blacklist uses different sets of weighting coefficients. A set of weighting coefficients will be saved as a matrix, denoted as a diagonal matrix:

\[ W = \text{diag}(w_1, w_2, \ldots, w_i, \ldots) \]  

where \( w_i \) is the \( i^{th} \) weighting coefficient for the \( i^{th} \) harmonic. The weighting matrices are saved in the database to make a more reliable blacklist-based assessment.

2.2.3. Harmonic vector distance (HVD). The harmonic vector distance \( D \) is defined by harmonic vectors \( \theta \), \( \overline{\theta} \) and weighting matrix \( W \) as:

\[ D^2 = (\theta - \overline{\theta})^T \cdot W \cdot (\theta - \overline{\theta}) \]

\[ = w_1 (y_1 - \overline{y_1})^2 + w_2 (y_2 - \overline{y_2})^2 + \ldots + w_i (y_i - \overline{y_i})^2 + \ldots \]  

HVD obtained from (5) is used to assess the similarity between real-time signals and pre-saved data in the database. HVDs with respect to different standard vectors in the database correspond to different trigger values, which set the threshold for the assessment. The level of similarity between real-time signal and reference signal in the database is high if the HVD is below the trigger value, and the accessed appliance will be considered in the blacklist and illegal, and vice versa.

2.2.4. Weighting matrix adjustment. HVD also gives feedback to the weighting matrix \( W \). When the HVD is too close to the trigger level, denoted as \( T \), the program considers the assessment result as suspect. When a suspect assessment occurs, or when misreport feedbacks from the users are received,
the system provides a speculation and corresponding data of the appliance for manual analysis. The manual results are sent back and recorded in the database as a feedback to the system to do fine adjustment for $W$. A diagonal matrix $K$ is designed to adjust $W$, $K$ is denoted by:

$$K = diag\left(1,1,...,k_i,...,k_j,...\right)\left(i \neq j\right)$$ (6)

where $k_i$ and $k_j$ are the $i^{th}$ and $j^{th}$ elements in $K$. The updated weighting matrix is given by:

$$W^* = K \cdot W$$ (7)

To make the weighting operation valuable, there must be:

$$\sum w_{mi} = \sum k_{m} w_{m} = 1$$ (8)

$$w_i + w_j = k_i w_i + k_j w_j$$ (9)

where $k_m$ is the $m^{th}$ element in $K$.

If the suspect appliance is confirmed legal manually, then $W$ should be adjusted to make the new HVD $D^2$ away from trigger $T$. To ensure clearer future assessment, $D^2$ is set two times away from $T^2$:

$$D^2 + T^2 = 2D^2$$ (10)

Substituting (4) into (10), one has $T^2$ as:

$$T^2 = \left(\theta - \overline{\theta}\right)^T \left(2W - W^*\right)\left(\theta - \overline{\theta}\right)$$ (11)

$$= \left(\theta - \overline{\theta}\right)^T \left(2E - K\right)W \left(\theta - \overline{\theta}\right)$$ (12)

Thus, for each random pair of $i$ and $j$, $K$ can be solved from (9) and (12).

The influence of the adjustment operation should be minimized to avoid the divergence of $W$. Define an influence matrix as $\Delta$:

$$\Delta_{ij} = w_i \left(1 - k_i\right)^2 + w_j \left(1 - k_j\right)^2 \left(i \neq j\right)$$ (13)

$$\Delta_{ij} = 0\left(i = j\right)$$ (14)

where $\Delta_{ij}$ is the $i^{th}$ row, $j^{th}$ column element in $\Delta$. $i$ and $j$ are chosen as the cord of the minimum positive element in $\Delta$, denoted as $i_m$ and $j_m$. Thus, $K$ is given by:

$$K = diag\left( 1,1,...,k_{i_m},...,k_{j_m},... \right)$$ (15)

On the other hand, if the appliance is confirmed illegal, $D^2$ is given by:
\[ D^2 + D^2 = 2T^2 \] \hspace{1cm} (16)

\( K \) can be solved like (15).

2.2.5. Trigger value. When the system is operating, it automatically collects and analyses the distribution probability of the access HVDs of appliances to set a proper trigger value \( T \). Results in Section 4 show that the HVD of an appliance follows Gaussian distribution, and \( T \) is then given by:

\[ T = \mu + k\sigma \] \hspace{1cm} (17)

where \( \mu \) and \( \sigma^2 \) are the population mean and the population variance of the Gaussian distribution. \( k \) reflects the strictness of the assessment. The misreport rate can be reduced by small \( k \), but the underreport rate is increased. On contrary, a high \( k \) value reduces underreport rate, but may increase the misreport, so \( k \) should be chosen carefully. The system automatically updates \( \mu \) and \( \sigma \) of different blacklisted appliances based on the collected HVDs to calibrate the trigger level, hence the accuracy of the assessment can be maintained.

2.2.6. Automatic Extension on the Blacklist. Different types of appliances functioning similarly may have similar harmonic forms, and their harmonic vectors are nearly parallel. An algorithm was proposed to reduce underreporting of suspect appliances functioning similarly to unallowed ones but not on the blacklist. The harmonic vector of the suspect appliance is defined as \( X = (x_1, x_2, ..., x_i, ...) \).

The standard vector of the appliance recorded in the database is defined as \( Y = (y_1, y_2, ..., y_i, ...) \). \( w_i \) is the element in weighting matrix \( W \). \( c \) is defined as a parameter to reduce the difference of vectors in different lengths but similar directions and the new vector after the process will be \( \frac{1}{c}X \).

To make the HVD of \( \frac{1}{c}X \) and \( Y \) minimum, (5) is used as (18):

\[ \frac{\partial}{\partial c} \sum w_i \left( \frac{x_i}{c} - y_i \right)^2 = 0 \] \hspace{1cm} (18)

\[ c = \frac{\sum w_i x_i^2}{\sum w_i x_i y_i} \] \hspace{1cm} (19)

2.2.7. Integration to the future smart grid. A preliminary idea of the NILM system in the future smart grid is shown in Fig 2. The local stations collect and process current signals from main wires in different households. Then it uploads data to the main station nearby, where real-time data assessment is performed. From the smart grid point of view, data from the main stations all over the grid is sent to
a cloud server for remote monitoring and control. This update is based on remote communication protocols like 4G or NB-IoT, which support long standby time and high connection stability.

![Diagram of NILM system in future grid.](image1)

**Figure 2.** NILM system in future grid.

### 3. System design

#### 3.1. Design of the prototype

The prototype consists of two parts: a current clamp (FLUKE i200) and a processor centered on the Raspberry Pi 4. The processor consists of a DAQ expansion board model MCC-118, and a Raspberry Pi 4. As an ADC center, MCC-118 receives the signal that the FLUKE i200 collects from the main wires. After the preliminary progress, Raspberry runs the algorithm written in Python to compare the harmonic vector of the signal with the pre-measured data. The whole device is powered by 5V/2A DC Battery through a USB-C cable, which makes the device portable. In future study, more accessories can be installed easily using the 40-pin port to the Raspberry. The prototype is shown in Fig.3.

![Prototype](image2)

**Figure 3.** Prototype.
3.2. Process Optimisation

Several methods are used to enhance the performance of data collection.

3.2.1. Butterworth filter. After ADC, a bandpass Butterworth filter was attached to reduce the signal at 50Hz and above Nyquist frequency. The reduction of the signal at 50Hz strengthens the anti-jamming capability of running on a main wire full of huge current noise at power frequency, thus, the rising-edge is more readable. 8 order Butterworth filter with Low cut-off at 80Hz guarantees a significant reduction in the first harmonic without apparent loss in the 2nd harmonic.

3.2.2. Harmonic vector collection. Because a very short sampling time is chosen to enhance the real-time performance, the collection must be done in low frequency resolution. An algorithm is designed to collect harmonic vectors effectively in low frequency resolution.

In FFT, a small neighbourhood of each harmonic will be captured as a short list. To obtain accurate harmonic data, a Lagrange Polynomial of each temporary list will be calculated.

The maximum of the polynomial for each harmonic will be added to the harmonic data list. Then the data list containing far less useless noises than the original FFT will be sent for blacklist-based assessment.

4. Case study

4.1. Data collection

Examples of risky appliances used in student dormitories are listed in Table 1.

| Appliances     | Hairdryer | Kettle | Microwave Oven |
|----------------|-----------|--------|----------------|
| 1st            | 0.18      | 0.25   | 0.66           |
| 2nd            | 0.49      | 0.17   | 2.41           |
| 3rd            | 0.05      | 0.11   | 4.35           |
| 4th            | 0.32      | 0.06   | 0.101          |
| 5th            | 0.08      | 0.05   | 0.53           |

The bandpass filter reduces the first harmonic so the harmonics of an appliance can be compared and the directions of the exampled harmonic vectors are shown to be very different from each other.

4.2. Blacklist assessment.

To give a reasonable reference for trigger level \( T \), the research has been made to analyze the distribution probability of the appliance access. The program was run for 2000 times to detect the rising-edge of the exampled appliances (Data of the appliances is in Table 1). The HVDs of the assessment have been collected and are shown in Fig. 4.
The HVDs have converged to form a Gaussian distribution. Based on the law of Gaussian distribution, the system can adjust the trigger level automatically. For example, the parameter $\sigma$ of kettle is low, which means the distribution of assessment on kettle will be quite concentrated, hence a low trigger value can be working fine on kettle. As for appliances like Hairdryer, the $\sigma$ value is much higher, which means trigger level should be set high enough to reduce the under-reporting.

4.3. Result

Blacklist assessment and the automatic adjustment function are tested individually. The prototype has run with the adjustment function closed to detect the appliances access for 50 times. Then the system was rebooted with the adjustment function on and ran the test again.

As is shown in (a), Fig. 5, when wrong assessment occurred, the $W$ was adjusted, and in the next assessment, the HDV was shown to have converged to the other side of $T$. The convergence stopped after the difference value of HVD and $T$ was higher than the set value (which is 0.015 in this case).

To compare the success rate before and after the adjustment, the prototype was run for another 50 time. The result in (b), Fig. 5 shows that the adjustment can increase the accuracy of assessment up to 23 percent (In Hairdryer) in 50 detections. In long time operation, the success rate will eventually maintain stable, but the update of $\sigma$ and $\mu$ will continue and the threshold of the assessment will be more accurate. The result in Microwave oven shows that the system behaves extra well in appliances with complex harmonics. In this case, the assessments were all correct even before the adjustment, so the system did not change the $W$ for Microwave.
5. Conclusions

In this paper, a blacklist-based NILM system is proposed to detect unallowed appliances access. Algorithms based on HVD and K are utilised to achieve blacklist-based assessment with high accuracy and automatic adjustment. The case study shows that the presented system has practical value. From the inhabitants or from the grid operator’s point of view, the system is applicable for electrical safety management in households or in factories.

References

[1] National Fire Data Center, U.S. Fire Administration – Fire Estimate Summary, May 2017.
[2] G. W. Hart, “Nonintrusive appliance load monitoring,” Proceedings of the IEEE, vol. 80, no. 12, pp. 1870–1891, 1992.
[3] M. Valenti, et al., "Exploiting the Reactive Power in Deep Neural Models for Non-Intrusive Load Monitoring," 2018 International Joint Conference on Neural Networks (IJCNN), 2018, pp. 1-8.
[4] K. Basu, V. Debusschere and S. Bacha, "Appliance usage prediction using a time series-based classification approach," IEEE 2012 - 38th Annual Conference on IEEE Industrial Electronics Society, Montreal, QC, 2012, pp. 1217-1222.
[5] Y. Lin and M. Tsai, "An Advanced Home Energy Management System Facilitated by Nonintrusive Load Monitoring with Automated Multiobjective Power Scheduling," in IEEE Transactions on Smart Grid, vol. 6, no. 4, pp. 1839-1851, July 2015.
[6] A. U. Rehman, T. T. Lie, B. Valles and S. R. Tito, "Low Complexity Event Detection Algorithm for Non- Intrusive Load Monitoring Systems," 2018 IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia), Singapore, 2018, pp. 746-751.