DC Signature Analysis Aided Power Source Identification

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Outline

Introduction

1. Most power plants generate AC power, while a few generate DC power, which is converted into AC and stepped-up for lossless transmission.
2. Unidirectional flow of DC provides more reliable alternative for powering electronics and storage[1].
3. Most electronic utilities use multi-input DC power to generate reliable DC power for the utility[2].
4. Power quality from various sources inject different harmonics in the output power, which degrade the performance and lifetime of the load[3].
5. These harmonics might propagate through various parts of the system, thereby causing damage[4].
6. Source identification at the DC distribution points is of great interest because of its generalized capability of dealing with any number of sources and the non-intrusive nature of the signal analysis module[5].
7. Such information could help utilities in understanding their billing.
8. DC output-based input source identification is a challenging problem due to 'source masking', where the intermediate rectifier makes it difficult to identify the input source[6].
9. As the source signatures are flattened and influenced by the rectifier-specific signature, the complexity of input source identification increases further.

[1] L. He *et al.*, "A flexible power control strategy for hybrid AC/DC zones of shipboard power system with distributed energy storages", *IEEE Trans Indus. Informat.*, vol. 14, no. 12, pp. 5496–5508, 2018.

[2] M. R. Khalid *et al.*, "A comprehensive review on structural topologies, power levels, energy storage systems, and standards for electric vehicle charging stations and their impacts on grid", *IEEE Access*, vol. 9, pp. 128 069–128 094, 2021.

[3] Y. He *et al.*, "Active cancelation of equivalent grid impedance for improving stability and injected power quality of grid-connected inverter under variable grid condition", *IEEE Trans. Power Electron.*, vol. 33, no. 11, pp. 9387–9398, 2018.

[4] A. K. Mandal *et al.*, "A multipath model for disturbance propagation in electrical power networks", *IEEE Trans. Circuits Syst. II: Express Briefs*, 2022.

[5] Y. Shan *et al.*, "Model predictive control of bidirectional DC–DC converters and AC/DC interlinking converters—A new control method for PV-wind-battery microgrids", *IEEE Trans. Sustain. Ener.*, vol. 10, no. 4, pp. 1823–1833, 2018.

[6] S. Beheshtaein *et al.*, "DC microgrid protection: A comprehensive review", *IEEE J. Emer. Select. Topics Power Elec.*, 2019.

Related Works

1. First set[7,8] undertook the identification of harmonic source distortion for AC devices using learning-based approaches.
2. None of these work with DC load signatures, which have become prevalent with rising electronic integration with electrical networks[9].
3. Furthermore, capturing extreme frequency components of the DC wave requires high sampling devices, which have not been reported with such classification capabilities in literature.
4. Second set[10,11] used signal processing and clustering approaches for identifying harmonic sources in DC pulsed load systems.
5. These methods show appreciable performance in harmonic recognition and fault identification in complete DC systems, they do not consider problem of input source identification from the DC bus.
6. To summarize, none of the approaches in the literature considered input source identification and the instants of switchover, from the load-end DC signature measurements.
7. To this end, this research proposes a filtered SVM (FSVM) approach for identifying the input power sources based on their remnant signatures after processing by the DC power module.
8. A high-sampling hardware module is designed that records timestamped voltage and current values, and employs an on-board FSVM processing to achieve source identification.

[7] D. Srinivasan *et al.*, "Neural-network-based signature recognition for harmonic source identification", *IEEE Trans. Power Deliv*, vol. 21, no. 1, pp. 398–405, 2006. DOI: 10.1109/TPWRD.2005.852370.

[8] H.-H. Chang *et al.*, "A new measurement method for power signatures of nonintrusive demand monitoring and load identification", *IEEE Trans. Indus. Appl.*, vol. 48, no. 2, pp. 764–771, 2012. DOI: 10.1109/TIA.2011.2180497.

[9] E. A. M. Ceseña and P. Mancarella, "Energy systems integration in smart districts: Robust optimisation of multi-energy flows in integrated electricity, heat and gas networks", *IEEE Trans. Smart Grid*, vol. 10, no. 1, pp. 1122–1131, 2018.

[10] Y. Ma *et al.*, "Wavelet transform data-driven machine learning-based real-time fault detection for naval DC pulsating loads", *IEEE Trans. Transport. Electrific.*, vol. 8, no. 2, pp. 1956–1965, 2022. DOI: 10.1109/TTE.2021.3130044.

[11] P. Pietrzak and M. Wolkiewicz, "On-line detection and classification of PMSM stator winding faults based on stator current symmetrical components analysis and the KNN algorithm", *Electronics*, vol. 10, no. 15, p. 1786, 2021.

System Model

1. Power-up infrastructure for a high-value utility, such as a cellular base station, is described in Fig. 1.
2. Multiple input sources represented as 'Source i', $i = 1, 2, 3$ (Fig. 1, red box) are fed to the DC power management module, which manages the source switchover and conversion to DC power.
3. The output of the DC power management block is fed to the high value utility through the DC load bus.
4. The DC power management block is tasked with uninterruptible supply to the base station[12].
5. The default supply to the DC load bus is maintained through 'Source 1', which in-turn also charges an energy storage module (Source 2) to a pre-defined voltage V_0.
6. In the event of failure, the input is immediately switched to the battery source through the power management block maintaining an uninterrupted power supply.
7. The battery source remains functional until an η fraction depth of discharge is attained leading to a cutoff voltage $V_c = \eta V_0$.
8. Once this condition is met, the source is switched to 'Source 3', which powers the base station and the battery, through the DC power management block.

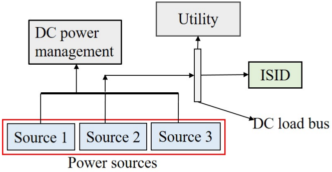


Figure 1: Powering and monitoring of high-value DC utility.

[12] *Management discussion and analysis-integrated report and annual financial statements*, Bharti Airtel Limited, 2018-19. [Online]. Available: https://www.airtel.in/airtel-annual-report-2018-19/pdf/MDA.pdf.

Contributions and Significance

Contributions:

1. A non-invasive high-sampling input source identification device (ISID) is designed.
2. An optimum moving average (MA) filter is employed to filter out high frequency outliers.
3. FSVM classifier using MA-based LDA-aided SVM is utilized to identify source signatures.
4. Optimum hyper-parameter-fed FSVM classifier is used for real-time detection of source switchovers.

Significance:

1. Preliminary lab tests demonstrate a sufficiently accurate signature recording and switchover identification using the proposed ISID.
2. The data recording module provides an adaptable sampling rate of up to 1000 samples per second (sps).
3. The processing module operates with an adaptable training length and filter-lag.
4. In our implementation, 2 lag samples, an optimum training length of 500 samples, and a training time of 0.5 seconds resulted in 76.47% enhanced accuracy of classification and 66.67% gain in sensitivity.

Extendability:

The proposed technology can additionally be used to identify load switchover in AC and DC grids, fault and islanding detection, harmonic identification in pulsed load systems, and classification of disturbance source in smart grid networks.

ISID Design

The design of the ISID consists of following basic modules:

Design of sensing module

The sensing module shown in Fig. 1 consists of a voltage and current sensing module, threaded parallely to a ADC. The voltage values are stepped down using a power metal resistive potential divider, and the current is captured using a high-accuracy programmable current sensor. These readings are quantized by the ADC, which provisions programming at a variable sampling rate, based on the source characteristics under observation. These timestamped values are passed to the filtering module.

Design of filter module

The filter operates by averaging the values of the signal over a sliding window of a fixed length, which moves over the data stream in a time division multiplexed manner. The moving average filter works by taking the weighted average of the current and previous $N-1$ input values at each time step.

Design of data analysis module

A linear discriminant analysis (LDA) aided SVM is used in real-time processing of this data. This method involves using LDA to transform the original feature space into a lower-dimensional space, followed by SVM to classify the transformed data. The goal is to learn a function that maps the feature space to the class labels.

ISID Data Processing Procedure

Steps of idea execution:

Step 1: Voltage recorded using potential division, current recorded using hall-effect sensing
Step 2: Soft filtering using moving average filter
Step 3: Multiple filtered time samples are stacked and dimensionality is reduced using LDA
Step 4: Classification of the active source is achieved using standard SVM technique

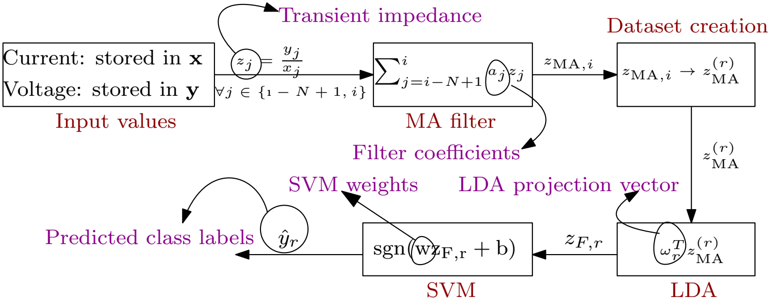


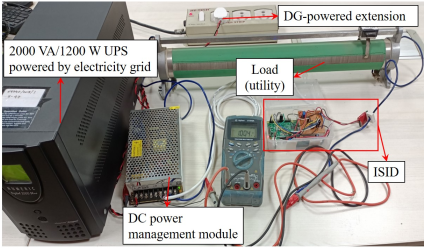
Figure 2: Source classification strategy for ISID.

How to determine these parameters?

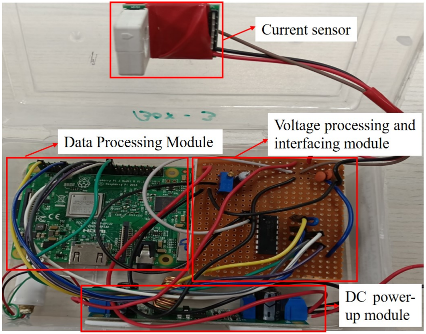
Derivation of Optimum Parameters

Determination of filter length and coefficient	Determination of SVM weight and bias
$(\mathbf{P}_1) : \min \sum_{j=1}^{D} \lvert z_{MA,i+j-1} - z_{i+j-1} \rvert^2$ $\mathbf{C}_1 : N \in \mathbb{N}, N \geq 1,$ $\mathbf{C}_2 : a_1, a_2, \ldots, a_N \in \mathbb{R},$ $\mathbf{C}_3 : \sum_{k=1}^{N} a_k = 1.$	$(\mathbf{P}_2) : \min_{w,b} \frac{1}{2} \lvert w \rvert^2 + \gamma \sum_{r=1}^{M} \xi_r$ $\mathbf{C}_4 : L_r(wz_{F,r} + b) \geq 1 - \xi_r$ $\mathbf{C}_5 : \xi_r \geq 0,\ r = 1, 2, \cdots, M.$
D: time-length for optimization; N: filter order; a_k: kth filter coefficient; $\mathbb{R}$: set of real numbers	w: SVM weight; γ: regularization parameter; ξ_r: slack variables accounting for mis-classification; L_r: class label; b: bias term; M: total classes
$N = \left\lceil \frac{2D}{\sum_{i=1}^{D} (\kappa_i)^2} \right\rceil$ $a_k = \frac{\sum_{i=1}^{k} (z_i - z_{MA,i-1}) \kappa_{i-k+1}}{\sum_{i=1}^{D} (\kappa_i)^2}$	$w = \sum_{r=1}^{M} \alpha_r L_r z_{F,r}$ $b = \frac{\sum_{r_1=1}^{M} \left(L_{r_1} - \sum_{r_2=1}^{M} \alpha_{r_2} L_{r_2} z_{F,r_2} z_{F,r_1} \right)}{N_s}$
$\kappa_i = \lim_{\delta \to \epsilon} \frac{z_i - z_{i-\delta}}{\delta}$: spike impedance, δ: sampling length, and ϵ: small number	α_r: mis-classification penalty; N_s: number of support vectors

ISID Hardware Design and Laboratory Test Setup



(a) Laboratory test setup



(b) Design of ISID

Figure 3

Construction of dataset: The data is captured using the ISID hardware on a 54 V, 1 A DC load fed by an electric grid, a 2000 VA/1200 W battery, and a diesel generator. The proposed module is operated for 30 minutes, during which natural switchovers are recorded and identified in real-time. Performance comparison and preliminary lab test results on the setup in Fig. 3(a) are presented in subsequent subsections.

Device Details and Utilization

Table 1: ISID details.

DC power-up module	Current sensor module	ADC	Voltage processing and interfacing module	Filter module
EC-6635	WCS6800	MCP3208	PIM-01	FM-01 [0.7, 0.3]

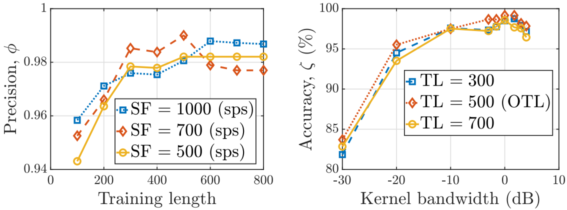
Table 2: ISID performance details.

Lag samples (samples)	Training length (samples)	Training time (s)	Classification accuracy gain (%) (over state-of-the-art)	Sensitivity gain (%) (over state-of-the-art)
2	500	0.5	76.47	66.67

The contributions of this research from industrial perspective are as follows:

1. Accurate utility billing for transparent economic flow and ensuring anti-theft measures
2. Power system harmonic source identification for enhanced power quality, reduced load cost, and lesser resource losses
3. Power system disturbance identification for stable system operation, leading to reduced resource wastage and economy

Determination of Optimal Hyper-parameters



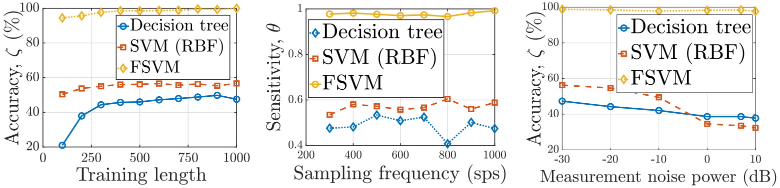
(a) (b)

Figure 4: (a) Precision versus training length at $\gamma = 1.5$ and (b) accuracy versus bandwidth of kernel function.

Table 3: Optimal hyper-parameter setting for ISID

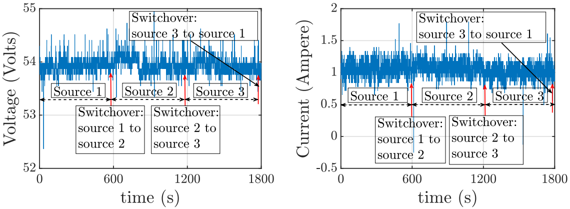
Parameters	**Values**
Sampling rate	700 sps
Optimum training length	500 samples
Kernel bandwidth	$\gamma = 1.5$
Filter order and coefficients	$N = 2$, $a = [0.7, 0.3]$
Maximum classification accuracy attained	100%
Maximum precision attained	99%

Performance of ISID



(a) (b) (c)

Figure 5: (a) Accuracy versus training length at sampling frequency of 1000 sps; (b) sensitivity versus sampling frequency at training length of 500 samples; (c) accuracy versus measurement noise at training length of 500 samples, and $\gamma = 1.5$.



(a) (b)

Figure 6: Source classification and switchover identification in (a) voltage and (b) current measurements; Source 1: electric grid; Source 2: battery; Source 3: diesel generator.

Conclusions

1. A novel input source identification device (ISID) for high accuracy detection of input power sources based on the load-end DC signature is designed.
2. An FSVM classification methodology was proposed for highly precise identification of source switchovers.
3. Optimal hyper-parameters were chosen based on the signature profile of the DC load voltage and current measurements.
4. The proposed ISID design was noted to achieve a significantly improved accuracy, sensitivity, and precision in input power source classification over the state-of-the art harmonic source identifiers.
5. The classification was achieved in fairly less time compared to the existing state-of-the-art classification approaches.
6. It was noted that the proposed module renders robust performance under varying order of measurement noise power, which is especially relevant considering the noisy industrial data measurement environment.
7. Preliminary lab tests corroborated the accuracy and robustness of the proposed ISID.

Thank You!

Any Questions?