Real-time Event Detection Using Rank Signatures of Real-world PMU Data

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***Abstract*—Timely detection of power system events is a crucial task, which can facilitate the implementation of remedial actions to improve reliability, resiliency, and security of the system. Meanwhile, the widespread deployment of phasor measurement units (PMUs) makes it possible to develop data-driven event detection techniques. However, relying purely on data without incorporating domain knowledge for the event detection task in power systems poses substantial security and stability risks due to issues associated with data misinterpretation and model accuracy. In this regard, we propose a real-time event detection method using real-world PMU data by incorporating domain knowledge to adequately capture the event signatures. Specifically, we track the change in rank signatures of PMU data to accurately localize the events. To optimize the detection process, we incorporate an offline Bayesian optimization algorithm to tune the parameters by efficiently searching for the best values. The experiments using the real-world PMU dataset from a U.S. interconnection show that the proposed event detection approach can efficiently detect the events from PMU data streams with high accuracy.**

***Index Terms*—Phasor Measurement Units (PMUs), Event Detection, Low-rank Property, Bayesian Optimization.**

I. Introduction

With the ever-increasing deployment and installation of phasor measurement units (PMUs), more advanced data-driven monitoring and control techniques have become feasible, which in turn facilitates the efficient, secure and reliable operation of power system [1]. The benefits offered by PMUs include the development of faster grid analytics and modeling, better grid asset management, and sub-second automatic control actions, all of which can help system operators avoid grid outages, enhance operations, and reduce costs [2]. Moreover, the abundance of fine-grained PMU data has paved the way for the system post-event applications where advanced data-driven techniques are developed to identify event types [3–5]. Nevertheless, due to the massive scale of the streaming PMU data, it becomes difficult for the system applications to accurately detect the events in a timely manner. Thus, developing an efficient real-time event detection algorithm for the streaming PMU data is of paramount importance for harvesting the benefits offered by PMUs.

Reviewing the existing literature reveals three major challenges in designing event detection algorithms in power system applications. First is the lack of domain-dependent knowledge in designing the detection algorithms. This issue stems from the fact that most of the detection algorithms leverage model-free methods based on statistical and signal processing techniques [6–13]. However, issues related to data misinterpretation can significantly degrade the performance of the model-free methods due to their data-dependent nature [14–17]. Besides, most of these techniques fail to show the precise start-time of PMU-based events which is crucial for planing the remedial actions by the system operators [18]. The next challenge is to incorporate the spatio-temporal correlations of the PMU data into the event detection algorithms [19], [20]. Most of the existing literature fail to incorporate both of the features in the detection process simultaneously. For example, spatial correlations among different PMUs are ignored in the [10], [11], [21] while temporal dependencies of the streaming PMUs are not directly modeled in [7], [13]. Note that exploiting spatio-temporal characteristics of PMU data can significantly improve the detection accuracy. Finally, the third and most common challenge is the lack of systematic approach for optimally tuning of the parameters for the event detection algorithms. Previous studies in the literature mainly leverage sensitivity analysis to find the best set of parameters while there is no guarantee on the optimality of the obtained parameters [21]. Besides, the larger number of parameters makes it difficult to tune the parameters using sensitivity analysis.

As reported in the existing literature (e.g., [7], [14–16]), the PMU data shows a low-rank property in normal conditions. In other words, there is a strong inter-dependency among data from different PMUs, and if the data from different PMUs are constructed as a matrix, the data can be accurately reconstructed by using only a few principal components. However, the low-rank property does not hold when events occur. Using such features, a few studies (e.g., [14], [15]) have developed PMU data driven event detection methods with a few model parameters. However, these works leverage such features using only one measurement signal (e.g., voltage magnitude) and heuristically tune the model parameters. By analyzing real-world PMU data, we observe that the change of the rank property of PMU data

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can be observed from different measurement signals and such changes across different measurement signals are different (see Fig. 3 in the result section). Moreover, different event types show different features. For example, voltage magnitude can be used to detect line outage events, while frequency signal can be used to detect frequency events. Thus motivated, this paper aims to leverage the unique event features from multiple measurement signals to enhance real-time event detection, and tune the model parameters in an optimization framework.

Specifically, we leverage the unique rank features of PMU data to construct rank signatures for different measurement signals. For the rank signatures, we develop a threshold-based OR rule such that an event is detected if one of the rank signatures is greater than a threshold. Using the available event logs, we introduce a Bayesian optimization algorithm to tune the thresholds offline in order to optimize the event detection accuracy. Using a real-world PMU dataset provided by Department of Energy (DOE), experimental results show that the accuracy of the proposed detection algorithm can be greater than 99%. Moreover, the average running time of the proposed detection algorithm can be less than 0.08 ms using a regular computer, which is much faster than the PMU data generation speed (e.g., 17 ms for PMUs with 60 samples per second).

The rest of the paper is organized as follows. Section II presents the rank signatures based event detection method. Section III evaluates the proposed method using a real-world PMU dataset. The paper is concluded in Section IV.

II. Rank Signatures Based Real-time Event Detection

In this section, we first introduce the framework of the proposed rank signatures based event detection. Then, we present a three-step process for real-time event detection using the streaming PMU data. Finally, we develop an offline Bayesian optimization algorithm to optimize the detection algorithm's parameters.

A. Rank Signatures Based Real-time Event Detection

The framework of the proposed rank signatures based event detection is illustrated in Fig. 1, which includes two stages: event detection and parameter tuning. The event detection stage constructs rank signatures using the relative change in the ratio of the two largest singular values of the PMU measurement matrices. Using a threshold-based OR rule, an event is detected if one of the rank signatures is greater than a threshold.

The parameter tuning stage leverages Bayesian optimization to optimally tune the parameters in the event detection algorithm. The idea of Bayesian optimization is to model the unknown function between the parameters and the detection errors using a multivariate Gaussian distribution, and then use a computationally cheap acquisition function to guide the search. The main goal is to use all of the information available from previous evaluations to update the Gaussian model. This results in a procedure that can find the minimum of difficult non-convex functions with relatively few evaluations, at the cost of performing more computation [22]. The technical details of the event detection algorithm and the parameter tuning process are given in Section II.B and II.C, respectively.

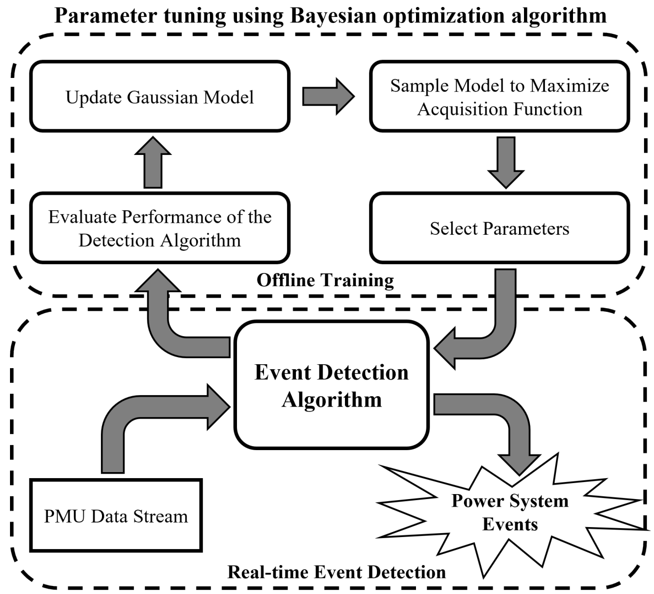

Fig. 1: The overall framework of the proposed event detection algorithm using Bayesian optimization for tuning parameters.

B. Event Detection Algorithm

By analyzing real-world PMU data, we observe that the low-rank property of PMU data does not hold when a disturbance occurs in the system (see Fig. 2), which can be quantified using the singular values of PMU measurement matrices. Therefore, we leverage this domain specific knowledge to develop a model-free event detection method to accurately detect the system events.

Let $M_s^w(t) \in \mathbb{C}^{w\times n}$ be a PMU measurement matrix for a measurement signal $s \in \mathcal{S}$, which embraces the past w measurements before the timestamp t from n PMUs. Here $\mathcal{S}$ denotes the set of measurement signals, e.g., the voltage magnitude (i.e., V_{pm}) and the current magnitude (i.e., I_{pm}) of positive sequence and frequency. We present a three-step process for detecting the abnormal events from PMU data streams.

1) *Step I*: For $M_s^w(t)$, we do the singular value decomposition (SVD) and compute the ratio of the largest σ_1 and the second largest singular σ_2 values, i.e., $\eta_t = \frac{\sigma_2}{\sigma_1}$.
2) *Step II*: The average relative change of this ratio in the time window w (i.e., rank signature) is calculated as
$$\xi_s^w(t) = \frac{\eta_t - \eta_{t-w}}{\eta_{t-w} \cdot w}. \tag{1}$$
3) *Step III*: Based on these $\xi_s^w(t)$ from different signals, we use a threshold-based OR rule to determine whether there is an event. In other words, an event is detected, if one of these $\xi_s^w(t)$ is greater than a pre-determined threshold θ_s.

Fig. 2 illustrates that a line outage event can be successfully detected by tracking the changes in rank signatures using the positive sequence voltage magnitude signal. The changes in the low rank property of the measurement matrix are captured by calculating the coefficient η and comparing with normal operating conditions. Any significant change indicates the occurrence of an event in the system. This simple approach can capture the exact start time of an event, which is crucial in planning

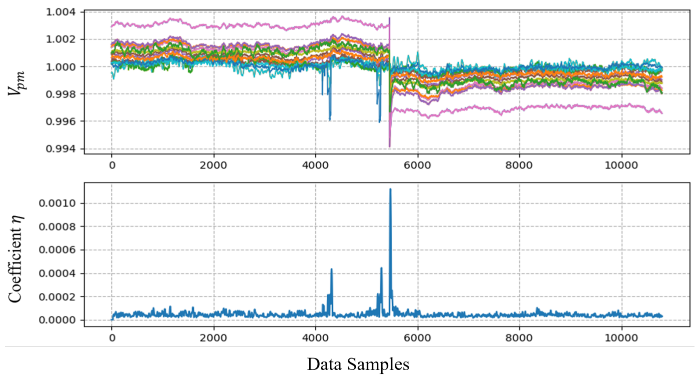

Fig. 2: Line outage detection using rank signatures, where coefficient η of the positive sequence voltage magnitude signal is shown.

remedial control actions.

C. Bayesian Optimization for Tuning Parameters

The proposed event detection approach is model-free with the parameters of the window size w and the detection thresholds $\boldsymbol{\theta} = \{\theta_s\}$ of the measurement signals $\mathcal{S}$. Using the available event logs, we tune the parameters by a Bayesian optimization algorithm, which can efficiently search for the best parameters. Bayesian optimization works offline by assuming an unknown function between the parameters and the detection errors. It models the unknown function by sampling the parameters based on a Gaussian process and running evaluations over the detection algorithm to obtain a posterior multivariate Gaussian distribution for this function. Finally, it leverages a computationally cheap acquisition function to guide the search towards the best set of parameters by minimizing the detection error. We introduce an acquisition function $\beta(\cdot)$ as the optimization objective, which characterizes the expected detection error improvement under $(\boldsymbol{\theta}, w)$:

$$\beta(\boldsymbol{\theta}, w) = \mathbb{E}[(e(\boldsymbol{\theta}^*, w^*) - e(\boldsymbol{\theta}, w))^+], \quad (2)$$

where $e(\boldsymbol{\theta}, w)$ denotes the detection error under $(\boldsymbol{\theta}, w)$, and $e(\boldsymbol{\theta}^*, w^*)$ denotes the lowest detection error that has been obtained so far. It is assumed that the detection errors are random variables following the multivariate Gaussian distribution: $\mathcal{G} \sim \mathcal{N}(m(\boldsymbol{\theta}, w), Cov(\boldsymbol{\theta}, w))$ with mean $m(\boldsymbol{\theta}, w)$ and covariance $Cov(\boldsymbol{\theta}, w)$. In each iteration, we find $(\boldsymbol{\theta}, w)$ that maximizes the acquisition function $\beta(\boldsymbol{\theta}, w)$. Then, $(\boldsymbol{\theta}, w)$ and the corresponding $e(\boldsymbol{\theta}, w)$ will be added into a sample set $\mathcal{B}$, and the mean $m(\boldsymbol{\theta}, w)$ and covariance $Cov(\boldsymbol{\theta}, w)$ of $\mathcal{G}$ will be updated accordingly [22]. The details of the Bayesian optimization based parameter search are given in Algorithm 1.

III. Experimental Results

We present numerical experiments using the real-world PMU dataset from the DOE to evaluate the performance of the proposed event detection method. The detection results are evaluated using the available event logs. The computation platform has a CPU of Intel Xeon E5-2630 v4 @ 2.20GHz and 64 GB of memory.

A. Dataset and Event Description

This paper uses real-world PMU data from the Western Interconnection of continental U.S. transmission grid. The measurement data is collected from 23 PMU streams over a two-year period (2016–2017). The sampling rate of PMUs is 60 samples per second. The measurements used in the experiments are voltage magnitude of positive sequence (i.e., V_{pm}), voltage angle of positive sequence, current magnitude of positive sequence (i.e., I_{pm}), current angle of positive sequence, and frequency. We also calculate active power (i.e., P) and reactive power signals (i.e., Q) by leveraging the available signals. Besides, event logs are also provided for the period of two years which contains 3427 total events, including 2830 line outages, 136 transformer outages, and 368 frequency events. For each event, start timestamp, end timestamp, event type, event cause, and event description are provided.

Algorithm 1 Bayesian optimization based parameter search

Initialization: Initialize $\mathcal{B} = \{((\boldsymbol{\theta}, w), e(\boldsymbol{\theta}, w))\}$.
For each iteration:
1) Find the parameters $(\hat{\boldsymbol{\theta}}, \hat{w})$ that maximize β, i.e., $(\hat{\boldsymbol{\theta}}, \hat{w}) = \arg\max_{((\boldsymbol{\theta},w),e(\boldsymbol{\theta},w))\in\mathcal{B}} \beta(\boldsymbol{\theta}, w)$.
2) Use $(\hat{\boldsymbol{\theta}}, \hat{w})$ for event detection and compute the corresponding detection error $e(\hat{\boldsymbol{\theta}}, \hat{w})$.
3) Add $((\hat{\boldsymbol{\theta}}, \hat{w}), e(\hat{\boldsymbol{\theta}}, \hat{w}))$ into the sample set $\mathcal{B} = \mathcal{B} \cup ((\hat{\boldsymbol{\theta}}, \hat{w}), e(\hat{\boldsymbol{\theta}}, \hat{w}))$, and update the parameters of $m(\boldsymbol{\theta}, w)$ and $Cov(\boldsymbol{\theta}, w)$ using $\mathcal{B}$.

B. Event Detection Performance

In this section, we present the accuracy of the proposed detection algorithm for each event type. First, the Bayesian optimization algorithm is applied to tune the model parameters using the event and non-event data. In this sense, three minutes (i.e., 10800 samples) of data are extracted around the event time according to the event logs. We split the extracted events into 25% for training and 75% for testing. The training set contains 50% event data and 50% non-event data, which are used by the Bayesian optimization algorithm for tuning the parameters. Here the non-event data are not recorded in the event logs and are extracted from the PMU dataset with no event signatures. Moreover, the proposed detection algorithm requires one threshold value for each signal (i.e., θ_s) and a time window value (i.e., w) as parameters. The test set also contains 50% event data and 50% non-event data to evaluate the performance of the detection algorithm.

Table I shows the detection results for different types of events. The outputs from the event detection algorithm are classified into TP (i.e., True Positive), TN (i.e., True Negative), FP (i.e., False Positive), and FN (i.e., False Negative) instances. The following metrics are used to evaluate performance of the event detection algorithm, i.e., accuracy (ACC), precision (PRE), recall (REC), and F1 score, which are defined as follows:

$$\text{ACC} = (\text{TP+TN})/(\text{TP+TN+FP+FN}),$$
$$\text{PRE} = \text{TP}/(\text{TP + FP}),$$
$$\text{REC} = \text{TP}/(\text{TP + FN}),$$
$$\text{F1} = 2 \times (\text{PRE} \times \text{REC})/(\text{PRE + REC}),$$

where TP denotes number of events that are correctly classified and FP denotes number of events that are misclassified as non-events. The overall accuracy for all the event types is 99.79%

which is calculated based on the reported events from the event logs. Note that the results in Table I are based on the optimized parameters derived from the Bayesian optimization algorithm for the fixed window size of $w = 30$. The suggested window size value provides better accuracy results as well as lower computational complexity.

TABLE I
PERFORMANCE OF THE PROPOSED DETECTION ALGORITHM FOR DIFFERENT EVENT TYPES

Event type	TP	FP	FN	TN	ACC (%)	PRE (%)	REC (%)	F1(%)
Line Event	2818	12	0	3427	99.8	99.57	100	99.78
Frequency Event	366	2	0	3427	99.94	99.45	100	99.72
Transformer Event	136	0	0	3427	100	100	100	100
All Events	3413	14	0	3427	99.79	99.6	100	99.79

C. Parameter Tuning

Fig. 3 illustrates the value of $\xi_s^w(t)$ based on positive sequence voltage magnitude and frequency signals for frequency, line, and transformer events. The change in the value of $\xi_s^w(t)$ is significant around the event time, which indicates a disturbance in the low-rank property of the measurement matrix. We leverage this rank signature to detect the events in the streaming PMU data. It should be noted that the value of $\xi_s^w(t)$ around the event time varies for different event types, which makes it challenging to derive consistent thresholds for all the events. In this regard, we leverage the Bayesian optimization algorithm to obtain the best thresholds.

Table II shows the detection results for different sets of parameters. The results indicate that the sub-optimal parameter values can significantly degrade the performance of the detection algorithm. Hence, it is of paramount importance to leverage a systematic approach (e.g., Bayesian optimization) instead of using sensitivity analysis to derive the optimal parameter values for the proposed event detection algorithm.

TABLE II
PERFORMANCE OF THE PROPOSED DETECTION ALGORITHM FOR DIFFERENT SET OF PARAMETERS

Parameters set $\{\theta_{V_{pm}}, \theta_{I_{pm}}, \theta_f, \theta_P, \theta_Q, w\}$	TP	FP	FN	TN	ACC (%)	PRE (%)	REC (%)	F1(%)
{0.2, 0.5, 0.5, 0.4, 0.3 , 30}	3413	14	0	3427	**99.79**	**99.6**	**100**	**99.79**
{0.2, 2.2, 0.5, 0.2, 0.3, 30}	3352	75	0	3427	98.9	97.8	100	98.88
{1, 1.8, 0.1, 0.1, 0.1, 30}	3156	271	1	3426	96.03	92.1	99.96	95.86
{0.7, 0.8, 1, 0.1, 0.1, 30}	2694	733	1	3426	89.29	78.6	99.96	88.00
{1.2, 0.3, 1.2, 0.3, 0.3, 30}	2689	738	0	3427	89.23	78.4	100	87.89
{1.5, 0.5, 1, 0.4, 0.4, 30}	2095	1332	0	3427	80.56	61.1	100	75.85

D. Computational Complexity

In this section, we evaluate the computational complexity of the proposed event detection algorithm. The time complexity of performing SVD operation on $M_s^w(t) \in \mathbb{C}^{w \times n}$ is $O(w \times n \times \min(w, n))$. This means that adding more PMUs to the measurement matrix linearly increases the running time of the detection algorithm (assuming $n >> w$).

Fig. 4 shows the average running time of the detection algorithm using different numbers of PMUs. In this experiment, the detection algorithm scans through multiple event data (i.e., extracted three minutes data). The results indicate that the average running time is fixed for different numbers of events. However, increasing the number of PMUs in the measurement matrix would increase the average running time for each sample. Note that the average running time for each sample at $w = 30$ is less than 0.08 ms which is much faster than the PMU data generation speed (i.e., 17 ms for PMUs with 60 samples per second). If the number of PMUs is excessively high, the measurement matrix can be partitioned into smaller matrices in order to satisfy the real-time requirements. Since PMU data are low-rank, combination of matrix decomposition methods (e.g., QR decomposition) and SVD of smaller partitioned PMU matrices can be leveraged to reduce the computational complexity of the SVD process [23].

Table III shows the total running time for different values of w. The results support our time complexity analysis where the increase of the window size would significantly increase the running time of the detection algorithm. Hence, it is important to strike a balance between detection accuracy and computational complexity by choosing a proper value for window size w. Note that each event contains three minutes data and the detection algorithm scans through the data for one event in 1.8, 2.4, 3.9 and 21.9 seconds for window size values of $w = 30$, $w = 60$, $w = 120$, and $w = 240$, respectively. When a proper window size is chosen (e.g., $w = 30$), the proposed event detection algorithm can also be used for offline analysis on a large PMU dataset to efficiently detect events. For example, it would take only 15 minutes to scan one day PMU data of almost 5.2 million samples.

TABLE III
TOTAL RUNNING TIME FOR DIFFERENT NUMBER OF EVENTS

# of events	Total running time (s)			
	$w = 30$	$w = 60$	$w = 120$	$w = 240$
1	1.8	2.4	3.9	21.9
10	18.3	24.6	39.3	207.1
20	36.1	49.8	78.7	424.3
50	89.1	120.7	197.8	1300.7

IV. CONCLUSIONS

In this paper, a real-time event detection framework is developed by using the rank signatures of the real-world PMU data. Specifically, we construct measurement matrices based on PMU measurement signals and track their rank signatures over time. A threshold-based OR rule is developed such that an event is detected if one of the rank signatures is greater than threshold. To optimize the event detection accuracy, we introduce a Bayesian optimization algorithm to systematically tune the detection algorithm's parameters. Numerical experiments using the real-world dataset from the Western Interconnection of the U.S power transmission grid show that the proposed event detection algorithm achieves a detection accuracy over 99% while the running average time is well below PMU data generation speed. Besides, a Bayesian optimization algorithm is developed to tune the parameters, which significantly improves the detection accuracy.

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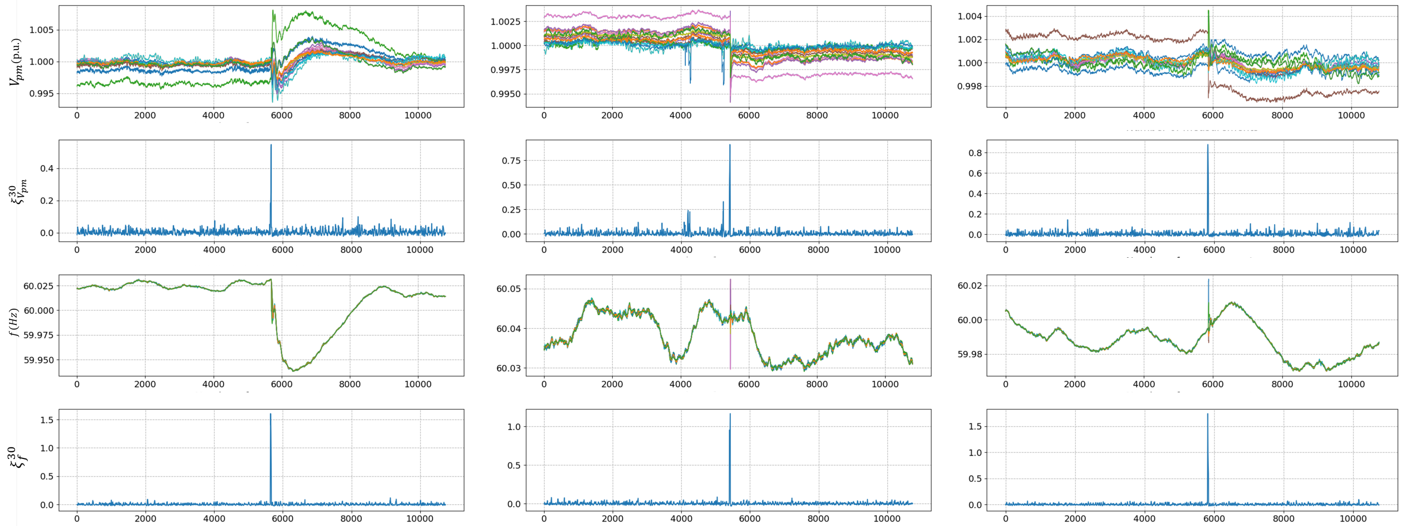

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Fig. 3: Frequency, line, and transformer event detection based on positive sequence voltage magnitude and frequency signals.

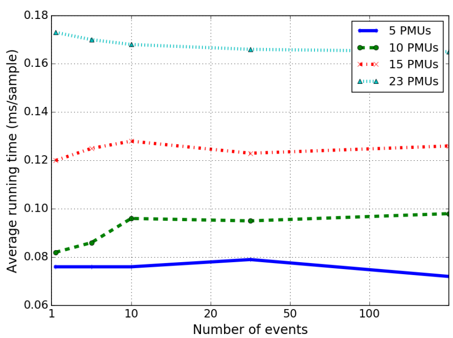

Fig. 4: Average running time for different number of PMUs.

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