Graph Signal Denoising in Power Systems and its Effects on GSP-based State Estimation

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***Abstract*—Noise in measurement data is not a new challenge, but the rise of graph-aware data processing tools, such as Graph Signal Processing (GSP), offers new opportunities to improve noise handling by capturing the relationships and interactions among data points. Due to the physical structure of the power systems, the measurements collected from these systems can be represented in the form of graph signals and various GSP-based techniques are emerging to process such data. This work first examines the sensitivity of a GSP-based state estimation technique to measurement noise. It then presents various denoising techniques, ranging from classical signal processing methods to novel GSP-based graph filters, and studies their impact on the quality of graph signals. Finally, the effects of these denoising filters on state estimation in power systems are evaluated. The results show that denoising processes that consider both the underlying graph of interactions and the temporal relationships in data outperform other denoising techniques. While the denoising techniques presented here are examined in the context of power systems, they are general enough to be applied to any graph signal.**

***Index Terms*—Graph Signal Processing, Noise, Denoising, Graph Filter, Power Systems**

I. Introduction

The integration of advanced data collection and analytics techniques has significantly improved power system monitoring and operation. However, like in any engineered system, the collected data and measurements are susceptible to noise. Noise in measurements can introduce uncertainty in the data processing and can reduce the performance and accuracy of system functions; for instance, state estimation.

Graph Signal Processing (GSP) has emerged as a promising approach in power system data analysis with exciting new developments. In GSP, a graph signal refers to measurements or data values that are associated with the nodes of a graph. A key strength of GSP-based approaches is their ability to capture the interactions among the data or system entities through the graph framework. Representing power system measurements as graph signals, enables applying powerful tools and techniques from GSP to power systems. Specifically, recent works have applied GSP-based methods to various power system functions, such as state estimation [1]–[3] and stress detection [4]–[6]. The application of GSP in power system data processing is fast growing; however, the impact of noise on these techniques has not been thoroughly examined.

In classical signal processing, measurement noise can degrade data processing performance, and denoising techniques are employed to mitigate this issue. While classical signal denoising techniques (e.g., low pass filtering) can be applied to individual temporal measurement signals collected at each each component in power systems, leveraging the additional information about interactions among components captured by graph signals can enhance the denoising process. In this paper, first, the effects of noise in the power systems' graph signals on a GSP-based state estimation, introduced in [7], are presented. Next, various denoising techniques including graph filter-based denoising and a novel technique based on modified heat kernel have been presented and their performance are compared with classical signal denoising methods. Finally, the impact of these denoising techniques on the performance of GSP-based state estimation are evaluated. The results confirm that capturing the interactions among data points using the underlying graph of graph signals in addition to the temporal relations captured in classical signals improves the denoising process. Although this study and the presented graph signal denoising techniques are discussed in the context of power system state estimation, they are general enough to be applied to graph signals in other application domains.

The rest of this paper is organized as following. Section II presents an overview of related work in the domain of GSP and denoising. Various noise models in graph signals and the GSP-based state estimation technique used in this study are reviewed in Section III and the effects of measurement noise on the performance of the GSP-based state estimation are presented. Denoising of graph signals and various techniques to perform denoising are discussed in Section IV. The results on the impact of different denoising techniques on the performance of the GSP-based technique are presented in Section V. Finally, conclusion and future research directions are discussed in Section VI.

II. Related Works

The literature relevant to this work is reviewed under two main categories. First, an overview of graph-aware data analytics techniques applied to power systems, including Graph Neural Networks (GNN) and GSP, is presented. Next, studies on modeling, assessing, and addressing noise in these techniques are reviewed.

Since power systems can be represented as graphs and their measurements processed as graph signals, various GSP-based approaches are emerging to tackle different problems in power systems. The applications of GSP ranges from modeling of power system measurements through graph filters [8]–[10], detecting and locating stresses in the system including physical and cyber stresses [11]–[13], state estimation [7], [14] and GSP-based analysis for the resilience of power systems [15]. In addition to GSP, GNN has gained lots of attention in addressing power system problems. Examples of GNN applications in power systems include state estimation [16] and stress detection [17].

Evaluating and addressing noise is not a new challenge; however, addressing it for graph-aware data analytics is a new research direction. The noise in this domain is addressed mainly in two categories of topology noise and measurement noise. For instance, the works presented in [18], [19] evaluate and address the effects of topology noise on GNN models for state estimation, while the work in [20] evaluates the robustness of a Graph Convolutional Neural network to measurement noise and errors.

The literature on the denoising process of a noisy graph signal in power systems is limited. For instance, the effects of topology noise in GSP techniques is studied in [21]. In another example, Kroizer et al. in [8] present a two-stage framework for recovering non-linear graph signals under noise through finding the graph filter that best approximates the measurements. Examples of studies on noise in graph signals in other fields include denoising of 2D sensor array [22], transportation systems [23], biomedical signals [24] and image processing [25]–[27].

This work investigates the impact of noise in measurement graph signals on the performance of a GSP-based state estimation. It then presents various denoising processes, ranging from classical signal processing filters to graph filters and their combinations, to evaluate their effects on signal quality. Finally, through numerical evaluation, it demonstrates how denoising graph signals in power systems can enhance the performance of GSP-based state estimation.

III. Modeling Noise in Graph Signals

A. Graph Signals Review

In GSP, unlike conventional signal processing, which utilizes Euclidean space for signal representation, signals are defined based on values assigned to the vertices/nodes $V = \{v_1, v_2, \ldots, v_N\}$, within a graph $G = (V, E)$, where E represents the connection between nodes, expressed as $E = \{e_{ij} : (i,j) \in V \times V\}$. In power systems, the nodes can represent the buses and the connections can represent the power lines connecting the buses in the system. Therefore, a time-varying graph signal is described by a vector $\mathbf{x}(t)$ with dimension N, where the elements are the mapping of each node to a real number $x : V \to \mathbb{R}$. For an easier mode of notation, the graph signal at a specific vertex n and time instance t can be represented by $x(n,t)$ rather than $x(v_n, t)$. The $x(n,t)$ values associated with the nodes of the graph in the power system at time instance t can represent various power attributes including voltage angle, voltage magnitude and phase angle. When the discussion is about a fixed time instance, i.e., a snapshot of the time varying graph signal at a specific time, we use the simplified notation of $x(n)$ for the value of the node n and $\mathbf{x}$ for the vector of values at vertices. In this work, the graph signals are defined based on the voltage angles of the buses.

The Laplacian matrix of the graph, denoted as $\mathbf{L}$, and its elements l_{ij} are defined according as $\sum_{n=1}^{N} w_{ij}$ if $i = j$ and $-w_{ij}$, otherwise. Here, w_{ij} denotes the weight associated with each line. The weight, w_{ij} can be defined to capture some physical concept about the system. One common way of defining weights in GSP-based analysis in power systems is defining the edge weight as the reciprocal of the geographical distance, d_{ij}, between the nodes as $w_{ij} = \frac{1}{d_{ij}}$, if $e_{ij} \in E$ and w_{ij}, otherwise. The second approach in defining the weights is to utilize the admittance of the branch between nodes i and j as the weight for the link between nodes i and j. In the analyses presented in this paper, the first type of weights is utilized unless otherwise stated (the second type of weights is used in one of the proposed denoising filters as discussed in Section IV). Graph Laplacian matrix acts as the Shift Operator for GSP functions and enables defining the spectral domain for the graph signal analysis. The eigen-decomposition of the Laplacian matrix, i.e., $L = V\Lambda V^\top$, enables defining the basis of the graph frequency domain. Here, $\Lambda = \mathrm{Diag}(\lambda_1, \ldots, \lambda_n)$ is the diagonal matrix of eigenvalues, and $V = (v_1, \ldots, v_n)$ is the matrix of eigenvectors. Eigenvalues are the diagonal elements in Λ, ordered from smallest to largest. Eigenvectors are the columns of V, each corresponding to an eigenvalue. The eigenvectors form the basis of the graph frequency domain. The graph Fourier transform can be defined as $X(\lambda_f) = v_f.\mathbf{x}$.

An important process on graph signals is the graph filtering operation. Similarly to the classical signal filtering, graph filtering has applications in graph signal sampling, reconstruction and denoising. A linear graph filter is described as the linear operator [28]:

$$\mathbf{H} = \sum_{p=0}^{P} h_p L^p = V \left(\sum_{p=0}^{P} h_p \Lambda^p \right) V^T \tag{1}$$

where P is the filter order and $\{h_p\}_{p=0}^{P}$ are the filter coefficients. This expression shows that the graph filter is analogous to a linear time-invariant (LTI) filter in discrete-time signal processing, with graph shifts in alternative to time shifts. In the work on denoising filters presented in Section IV, the order, P of the graph signal is set to be 1.

B. Noise in Graph Signals

Noise in the graph signal can perturb different aspects of the signal from the graph data (i.e., V and E, and the weights of the lines) to the measurement data associated with the nodes of the graph. Here, a review of various forms of noise in graph signals is presented. In this work, the focus is on the noise that is corrupting the measurement values at nodes. Note that these noises can originate from different sources, including physical processes, measurement devices, communication channels, and data processing techniques.

*1) **Measurement Noise**:* This type of noise corrupts the measurement values at nodes. Such corruption can be modeled simply by $y(n) = x(n) + r(n)$ at node n. For the additive white Gaussian noise (AWGN) case, $r(n)$ is modeled as a Gaussian distribution with zero mean and a constant standard deviation. The AWGN can mask low-amplitude signals and can make it difficult to detect subtle changes and variations in the power system signals. It is assumed that this noise affects all the nodes in the system with the same distribution. This is the noise model considered in this work.

Another variation of the measurement noise could be named, *nodal noise*, in which the additive noise is only present at certain nodes in the system (i.e., heterogeneous noise distribution over the nodes). This could occur in power systems due to uncertainties in current injection or voltage variations at specific buses. This type of noise is more straightforward to address for the individual signals at the nodes, while the general AWGN for the graph signal is more relevant in the graph signal analysis. To address nodal noise and the extension of the techniques presented in this paper can be a future research direction.

2) ***Topology Noise****:* This type of noise affects the graph data (i.e., V and E) and will cause uncertainty in the underlying graph used in graph-aware data analytics techniques including GSP. In power systems, this kind of noise could be mistaken for the components' state of operation (e.g., bus or link failure or shut-down due to maintenance and switching operations or their re-connection). As such, topology noise can be modeled by node/edge removal, addition or a combination of both in the topology. This type of noise could be modeled using a Bernoulli random variable affecting the status of the components. Similar to measurement noise, it could be modeled based on a homogeneous or heterogeneous distribution across the nodes/links.

Note that noise in the weight of the lines could be modeled either as measurement noise when the weights are attributes of edges varying in time or it can be modeled as topology noise, when the weights are static and fixed based on the properties of the system.

C. GSP-based State Estimation

State estimation is a crucial function in power systems for monitoring and planning the operation of the system. Specifically, state estimation is either used for predicting the next-step ahead of the states of the components or for recovering the unobservable and missing state information. In this work, a GSP-based technique for recovering the state of unobservable nodes in the system (e.g., due to PMU failures or disconnection or cyber-attacks) presented in [7] is used as an example to show how the noise in the measurements and denoising can affect the performance of key functions in power systems.

Next, this GSP-based state estimation is briefly reviewed. The idea behind this GSP-based state estimation is to use GSP-based features of the graph signals and to estimate the missing information using the information in the rest of the nodes. Specifically, it assumes that the power system graph signals are smooth under normal conditions. Two GSP features, global and local smoothness are used in the estimation process.

Local smoothness measures the degree of change from one vertex to its corresponding neighboring vertices, and hence contains the local information in the grid. The local smoothness of a graph signal for each vertex is given by $s(n) = \frac{l_x(n)}{x(n)}$, $x(n) \neq 0$, where $l_x(n)$ is the n-th element of the vector l_x in the Laplacian matrix, L. The global smoothness of the graph signal $x(n)$, denoted as $s_{\text{global}} = \frac{x^T L x}{x^T x}$, measures the overall fluctuations between vertices. The state estimation is then formulated as an optimization problem with the goal of maximizing the likelihood of local smoothness across all the buses while minimizing the global smoothness of the graph signal (which means assuming a smooth signal). Considering the non-linearity of this optimization, surrogate optimizer is utilised to find the solution. The details of the optimization formulation and the process to solve it can be found in [7]. In this work, this approach is used to simply show the sensitivity of functions in power systems to measurement noise.

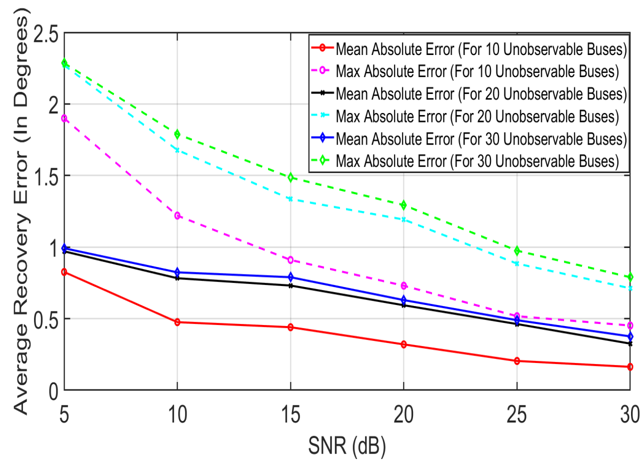

Fig. 1: Performance sensitivity of the GSP-based state estimation under different SNR levels for 10, 20 and 30 unobservable buses for the IEEE 118 bus system.

D. Experimental Setup and Evaluation

To assess the performance of state estimation under various measurement noise, particularly, the ones with low Signal to Noise Ratio (SNR), three scenarios with different unobservable buses (i.e., 10, 20, and 30) are considered over the IEEE 118 bus system. For each scenario, fifty different random sets of unobservable buses are selected.

For each of these scenarios, various levels of SNR (i.e., 5 to 30 dB) are simulated through AWGN added on the time series of bus voltage angles generated for the buses of the system using MATPOWER [29]. A load pattern from the NYISO [30] is added to the default MATPOWER loads to simulate the temporal variations and dynamics of the system.

The performance of state estimation for the unobservable buses are presented using mean absolute error (MAE) and maximum absolute error (MaxAE). As demonstrated in Fig. 1, this GSP-based state estimation shows higher recovery error in lower SNRs. The result confirms that for different numbers of unobservable buses, the accuracy of the state estimation method is sensitive to measurement noise.

IV. Denoising of Graph Signals

Denoising is the first common approach to alleviate the effects of noise in data processing. Denoising in classical signal processing has been long in use through designing low pass filters. However, graph signals have the extra dimension of the vertex domain in addition to the temporal domain of classical signals. As such, while in classical signal processing, denoising can be applied at individual time series associated

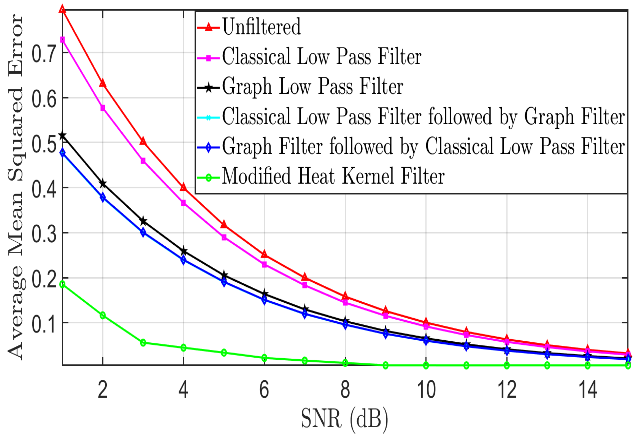

Fig. 2: Average mean square error (MSE) relative to the original signal when different denoising techniques are applied to the time-varying graph signals for the IEEE 118 bus system. The unfiltered case represents the noisy signal.

with the nodes, the interactions among the nodes through the graph are not considered in those denoising processes. In this section, four distinctive denoising processes to be applied to the time varying graph signals are presented. These include: A) Denoising each time-series signal using a classical sharp edge low pass filter (the classical signal processing approach); B) Denoising the graph signal using low pass graph filters; C) Denoising the graph signal by applying the classical low pass filter and the graph filter one after another (combination of approaches 1 and 2); and D) Denoising the graph signal by introducing a modified Heat Kernel Method. These approaches are discussed next.

A. Denoising temporal signals using classical Low-Pass Filter

This approach is the classical denoising process in signal processing. This includes applying a low pass filter to each of the time series associated with the nodes of the system to eliminate the high-frequency random noise. Generally, a cut-off frequency, λ_{cutoff}, is considered in defining the filter in the frequency domain. The filter can be applied to the spectral content of the temporal signal to denoise the noisy signal.

B. Denoising graph signals using a Graph Low Pass Filter

The denoising process using graph filters does not consider the temporal features of the graph signals. Instead it considers graph signals at specific time instances (snapshots in time) and considers the relations among the data points over vertices for denoising. The low-pass graph filter to eliminate the high-frequency noise generally aims to make the graph signal smooth over the vertices. An example of such graph filters used in this study is

$$\mathbf{H} = V \cdot \text{diag}\left(\frac{1}{1+\alpha\lambda_1}, \frac{1}{1+\alpha\lambda_2}, \ldots, \frac{1}{1+\alpha\lambda_n}\right) \cdot V^T \quad (2)$$

where λ_is are the eigenvalues of the graph Laplacian, and α is a parameter controlling the low-pass filter. In this paper, $\alpha = 0.1$ is considered. Note that as the eigenvalues increase, the filter will more significantly attenuate that frequency.

C. Denoising The Graph Signal Using Both Classical Low-pass and Graph low-pass filter

In this approach, in order to use both temporal and graph information for denoising, both of the previous approaches will be applied to the time-varying graph signal. Specifically, there are two orders in which these approaches can be combined. One could be the application of classical low-pass filter followed by the graph low-pass filter and vice versa. In the evaluation of these techniques both of these combinations are considered and they show the same performance.

D. Denoising using a Modified Heat Kernel Graph Filter

In this approach, we proposed a heat kernel graph filter combined with a moving average technique to denoise the graph signals. Though heat kernels are particularly suitable for diffusion models [31], the controlling parameter of the heat kernel modified for the power system can be effective in denoising graph signals. The process involves several key steps, which are detailed below.

Note that the Laplacian matrix L is constructed as discussed in Section III. The adjacency matrix A is constructed from the admittance matrix Y by defining the $w_{ij} = y(i,j)$, where $y(i,j)$ are the elements of the admittance matrix.

As the first step, a temporal moving average (MA) filter [32] is applied to the time-varying graph signal. To smoothen the noisy signal, moving average can be applied using the following expression $\mathbf{x}_{\text{mov}}(t_i) = \frac{1}{T}\sum_{k=t_i-T+1}^{t_i} \mathbf{x}(k)$, where $\mathbf{x}_{\text{mov}}(t_i)$ is the vector of moving average values at time instance t_i over the graph signal $\mathbf{x}(t)$ for a window of size T.

In the next step, GFT of the $\mathbf{x}_{\text{mov}}(t)$, denoted by $\mathbf{X}_{\text{mov}}(f)$ will be calculated for each instance in time. In the final step, a heat kernel graph filter will be applied to the GFT of the resulted moving average signal. The heat kernel graph filter is defined as $\mathbf{H} = V \cdot \left(e^{-\tau\Lambda}\right) \cdot V^T$. Here, $\tau = z_{\text{avg}}$ is defined to be the average impedance of the lines in the system. It represents the exponent scaling factor, which specifies the rate of filter magnitude decrease over frequencies. The filter is applied in the spectral domain of the signal as $\mathbf{X}_{\text{filtered}}(f) = \mathbf{H}\mathbf{X}_{\text{mov}}(f)$, where $\mathbf{X}_{\text{filtered}}(f)$ is the spectral domain representation of the signal after the filter is applied.

V. Performance Evaluation

In this section, the performance of the discussed filters in Section IV as well as the effects of various denoising techniques on the performance of the state estimation are presented. For the evaluation in this section, the experimental setup presented in Section III. D has been used.

A. Performance Evaluation of Denoising Techniques

There are in total five denoising techniques that have been applied to the time-varying voltage angle graph signals simulated for the IEEE 118 test case. The performance of these techniques in terms of mean-square error (MSE) relative to the actual value of the signal is shown in Fig. 2. The MSE for

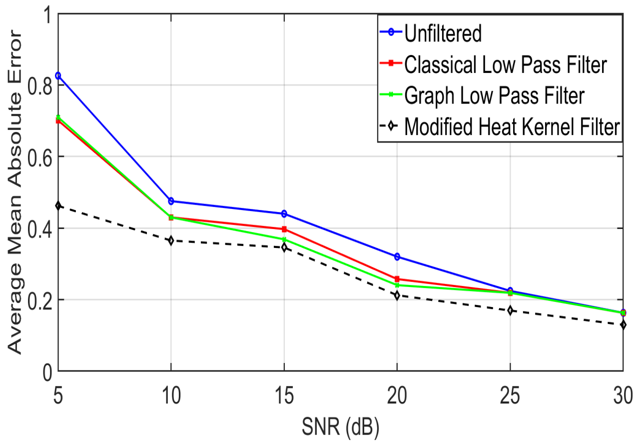

Fig. 3: Performance of the GSP-based state estimation for different SNR levels and 10 unobservable buses in the IEEE 118 bus system when different denoising techniques are applied to the noisy time-varying graph signal. Unfiltered case shows the performance for GSP-based state estimation directly applied to noisy signal.

the denoising techniques is compared to the unfiltered case and each other at different SNR levels. It can be observed that the classical low-pass filter denoising, which only considers the temporal features of the signal, can improve the quality of the signal. However, graph filters, which consider the vertex-domain interactions among values, can improve the quality of the signal further. Moreover, techniques that use both the temporal and spatial (vertex domain) interactions (i.e., combined classical low-pass and graph filter and Modified Heat Kernel filter) improve the quality of the signal and reduce MSE more relative to the previous two techniques. Finally, our proposed technique based on modified heat kernel filter demonstrates significant improvement in terms of performance, especially for the challenging cases of lower SNRs.

The parameters of the filters for different denoising techniques are listed below for reference. The cut-off frequency for the classical filter is assumed to be $\lambda_{\text{cutoff}} = 0.7$. As discussed earlier, the parameter α for the graph low-pass filter is set to $\alpha = 0.1$. For the combined classical and graph filters, both orders with the same aforementioned parameters are used. Note that as the results suggest the order of the application of these two filters does not change the quality of the signal notably. Finally, in the modified kernel method, the average line impedance z_{avg} of the IEEE 118 bus system is calculated as 0.1105 ohms and the window size of MA block is set to $T = 20$.

B. Performance Evaluation of State Estimation using the Denoising Filters

When the quality of the signal improves through the denoising process, the performance of the functions using such data is expected to improve. In this section, the performance of the GSP-based state estimation is evaluated for the case of 10 random unobservable cases when different denoising techniques are applied. Due to the unavailability of data in certain nodes in the system, prior to channeling the signal through the filters for denoising (specially for the ones that are graph-based filters), the past time instance estimation of the values of the unobservable nodes has been used to fill the value gaps over the graph. While other techniques can also be used in filling the unobservable data for applying the graph filters, this technique enables the focus of performance evaluation to remain on the denoising process. Specifically, for any node that is unobservable at time instance t_n, the value will be estimated by taking the mean of all the past estimated state values for that node. As can be observed from Fig. 3, applying the classical graph filter and the graph low pass filter leads to improved performance for state estimation in comparison to the case of using noisy and unfiltered time-varying graph signals. Moreover, it can be observed that the novel modified heat kernel filter results in the best performance by effectively capturing both temporal and spatial information in the signal for the denoising process.

VI. Conclusion

This work explores the effects of noise in graph signals within power systems on a GSP-based state estimation technique and methods to mitigate these effects. It demonstrates that noise in graph signals can significantly impact the accuracy of GSP-based state estimation. By analyzing the performance of state estimation under varying signal-to-noise ratios (SNRs) and different numbers of unobservable buses, the sensitivity of the state estimation process to noise is highlighted. Various denoising techniques, ranging from classical signal processing low-pass filters to graph filters, are presented and their effects on signal quality are assessed. Finally, the impact of these denoising filters on state estimation in power systems is evaluated. The results indicate that denoising processes that account for both the underlying graph of interactions and the temporal relationships in data outperform other techniques. While these denoising methods are examined in the context of power systems, they are general enough to be applied to any graph signal.

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