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Block-Wise Compressive Sensing Based Multiple Line Outage Detection for Smart Grid

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ABSTRACT Smart grids, which have the ability to detect and monitor necessary system parameters and user behaviors, have gradually become the development trend for future power networks. With increasing scale and access of new energy source, SGs become more unstable and vulnerable when changes of network topology occur abruptly. Among different kinds of abrupt changes, unexpected line outages may give rise to significant potential damages to SGs and lead to the very bad user experience. Thus, accurate and rapid detection of line outages turn into one of the important tasks and challenges in SGs. By utilizing the sparse property of line outages, compressive sensing (CS)-based line outage detection schemes have been proposed recently, in which the phase information collected from phasor measurement units is also fully utilized. In this paper, a novel block-wise CS (BW-CS)-based multiple line outage detection scheme is proposed for SGs. Firstly, by exploiting the sparsity of line outages and topology structure of the power grid, a novel reactance model is introduced, which makes the block-wise CS algorithm can be adopted. Then, by modifying one step of the conventional CS algorithm with the redefined element selection, criterion is modified to improve the recovery accuracy. Finally, the proposed scheme is extended into a three-phase power system. The simulation results show that our proposed BW-CS method can achieve superior precision with the similar complexity compared to the traditional methods.

INDEX TERMS Phasor measurement unit, smart grid, line outage detection, block-sparsity, compressive sensing.

I. INTRODUCTION

Smart grids (SGs), not similar to conventional power networks, are capable to monitor users behaviors and system parameters automatically through the application of different types of sensors, which is thought to be a promising approach of power networks in the future, and attract large number of research [1]–[3]. With the rapid development of SGs, various sorts of new energy is accessed into the network and the scale of SGs is much larger than before, which may reduce the ability of SGs to resist bursting breakdown [4]–[6]. The line outage, which is defined as unexpected breakdown happening on branches, has an immense influence on normal operation of SGs, such as resulting in cascading or catastrophic failures [7]. Hence, considering that SGs are time-varying and dynamic networks, the multiple line outages detection simultaneously with high accuracy and acceptable complexity becomes one of the most major challenges in future SG researches, and can be applied in the renewable energies as well.

Several previous articles which discussed line outage detection topic in power networks have proposed different types of detection schemes. The early schemes were put forward to solve the outage line detection problem with limited amount of line outage, which has only single or double line outage situation [4], [8]. Later, lots of researches attempt to work out the localization problem with multiple line outages. The Markov-dependency graph model [9], message passing method [10], ambiguity group scheme [11] as well as many other models [12], [13] are adjusted and adopted to realize the problem of multiple line outage detection. Besides these methods, the compressive sensing (CS) based method, which belongs to the sparse signal recovery algorithm, is proved feasible and considered to be an alterative solution with an acceptable accuracy and complexity [14], [15].

The basic idea of CS theory can be generalized that by the transformation of an observation matrix, a high dimensional but sparse vector can be recovered precisely from a lower dimensional measurement vector. CS theory has been widely investigated in recent years and obtain significant performance in many other fields, such as static channel estimation [16], [17], dynamic channel estimation [18], noise mitigation [19], training sequence design [20], graph detection [21], and clipping noise cancelation [22]. However, in the previous line outage detection method based on CS, the observation matrix was derived directly from the physical model, which may not be fulfilled with the restricted isometry property (RIP) due to the high coherence of the observation matrix and achieves unsatisfied recovery performance [23]. After unifying the branches connected to the same buses, an improved structure is investigated by exploring the QR decomposition on the observation matrix [23]. The QR decomposition is a kind of matrix factorization method, which transform a matrix into a product between an upper triangular matrix and an orthogonal matrix, and can solve the RIP problem with high coherence to a certain extent. However, the computational complexity of the QR decomposition grows rapidly with the increase of the size of SG because of the complicated matrix decomposition.

In this paper, a novel line outage detection method, called block-wise compressive sensing (BW-CS) method is proposed based on the block sparsity of occurring line outage and the block-wise modification on the conventional CS method. In our proposed method, the reactance formulation of SGs is reconstructed, which makes signals to be block-wise structure. Then, by utilizing the block sparse property, the selection criterion of elements is redefined to precisely select the location of sparse elements in the CS framework. The main contribution of the proposed method is that a new block-wise CS applicable equation and the novel selection criterion by taking advantage of the connection relationship are derived. This modification on the traditional CS framework can solve the problem of observation matrix with high coherence and avoid the matrix decomposition with high complex at the same time. Some computer simulations are evaluated to compare the proposed method with the QR decomposition-based method and the conventional CS-based method. The simulation results demonstrate the effectiveness of the proposed method with high robustness compared with the conventional counterparts under different line outage scenarios and various noise level environments.

The rest of this paper is organized as follows. In Section II, the direct-current (DC) power flow model is introduced. The variety of electrical parameters before and after occurring line outage and the novel block-wise structure are addressed. The QR decomposition based detection method is also discussed in this section. In Section III, the proposed BW-CS based detection scheme with complexity analysis are addressed. The application on the three-phase power network is provided together as well. The numerical simulation results and related analysis are shown in Section IV. Finally, conclusions are drawn in Section V.

Notation: Lowercase and uppercase boldface letters are used to denoted column vectors and matrices, respectively. $(\cdot)^{-1}$, $(\cdot)^H$, $(\cdot)^T$, diag$(\cdot)$, and $\|\cdot\|_p$ denote the matrix inversion, Hermitian transpose, transpose, diagonal matrix, and l_p norm operations, respectively. $\mathbf{\Phi}(\Pi)$ denotes the submatrix comprised of the Π columns of the matrix $\mathbf{\Phi}$, and $\boldsymbol{p}_i$ denotes the i-th entry of the vector $\boldsymbol{p}$.

II. SYSTEM MODEL

A. POWER FLOW MODEL

In this subsection, the general DC power flow model will be introduced. In the theoretical analysis of SGs, the linear power flow model of DC system is broadly adopted as an applicable approximation of the nonlinear alternating-current (AC) model [24]. Constant voltage magnitude and negligible power loss are two vital assumptions to sufficiently simplify complex calculation in the DC power flow model. As a result of that, the DC power flow model can be easily applied to abstract the line outages into the mathematical formulations [25]. In the linear DC power flow model, the phase of each bus is an indispensable parameter which connects the transmission power to branch susceptance. To measure the realized phases of voltage simultaneously, phasor measurement units (PMUs) are adopted to solve line outage detection in many practical applications.

Without loss of generality, a power network with N buses and K branches is considered. Let B denote the susceptance matrix of the power network. The (i, j)-th element of B, $B_{i,j}$, is given by

$$B_{i,j} = \begin{cases} -\dfrac{1}{b_{i,j}} & i \neq j, \quad b_{i,j} \neq 0, \\ \sum_{j=1}^{N} \dfrac{1}{b_{i,j}} & i = j, \quad b_{i,j}, \neq 0, \\ 0 & b_{i,j} = 0, \end{cases} \tag{1}$$

where $b_{i,j}$ denotes the reactance value through the branch between the i-th and j-th buses. If the connection between the i-th and the j-th buses does not exist, $b_{i,j}$ should be set to 0. Let vector $\boldsymbol{\theta}$ with the size of $N \times 1$ denote the phases of voltage for the whole buses, the injected power on buses, which is represented by an $N \times 1$ vector $\boldsymbol{p}$ can be denoted as

$$\boldsymbol{p} = \mathbf{B}\boldsymbol{\theta}. \tag{2}$$

It should ne noted that, if the power line outage is short type, the element in B will be infinite, which may lead to unsolvable problem in CS. Therefore, only the open type of power line outage is discussed in this paper. Besides, like the injected power on buses, the transmission powers on each branch also have relationship with the phase and reactance. The matrix $\mathbf{D}$ with size of $K \times N$ is represented the relation of branches susceptance, and its (i, j)-th element is expressed as

$$D_{i,j} = \begin{cases} -\dfrac{1}{b_{i,j}} & j = \text{from-bus of the } i\text{-th branch}, \\ \dfrac{1}{b_{i,j}} & j = \text{to-bus of the } i\text{-th branch}. \end{cases} \quad (3)$$

Thus, the power transmitted on branches represented as the vector $\boldsymbol{p_f}$ with size of $K \times 1$, can be derived as

$$\boldsymbol{p_f} = \mathbf{D}\boldsymbol{\theta}. \quad (4)$$

Obviously, matrices $\mathbf{D}$ and $\mathbf{B}$ can be related by the connection relationship. Thus, we can approach an equation between $\mathbf{D}$ and $\mathbf{B}$ as

$$\mathbf{B} = \mathbf{C}^{\mathbf{T}}\mathbf{D}, \quad (5)$$

where the matrix $\mathbf{C}$ with size of $K \times N$ represents the topology of network. The (i, j)-th element of $\mathbf{C}$ is given by

$$C_{i,j} = \begin{cases} -1 & j = \text{from-bus of the } i\text{-th branch}, \\ 1 & j = \text{to-bus of the } i\text{-th branch}. \end{cases} \quad (6)$$

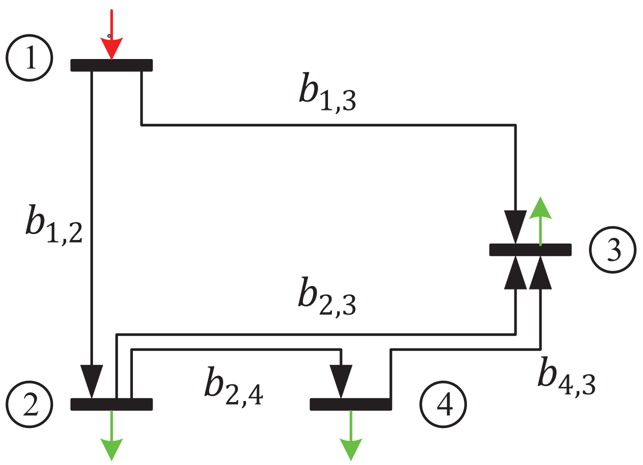

FIGURE 1. A sketch of the power network model.

A simple example of the system model is shown in Fig. 1 and Table 1, which describes a 4-bus power network model and its connection relationship as well. Based on (3) and (6), the matrix $\mathbf{C}$ in the power network can be illustrated as (7), where the matrix $\mathbf{D}$ has a similar structure of $\mathbf{C}$. The difference is $\mathbf{D}$ has reactance values on the corresponding positions, while there are nonzero values in matrix $\mathbf{C}$.

$$\mathbf{C} = \begin{pmatrix} -1 & 1 & 0 & 0 \\ -1 & 0 & 1 & 0 \\ 0 & -1 & 1 & 0 \\ 0 & -1 & 0 & 1 \\ 0 & 0 & 1 & -1 \end{pmatrix}. \quad (7)$$

TABLE 1. Connection relationship of the network.

Line	1	2	3	4	5
From-bus	1	1	2	2	4
To-bus	2	3	3	4	3

B. LINE OUTAGE DETECTION MODEL

When multiple line outages occur in some branches of the power network, the theoretical system model of SGs is briefly explained firstly. An important and concise assumption is that the amount of line outages happening at the same time is much smaller than that of the total lines, which means the distribution of line outages is sparse. Obviously, line outages will result in varieties on the electrical parameters and network topology. Let $\mathbf{B}^{'}$, $\boldsymbol{p}^{'}$, $\boldsymbol{\theta}^{'}$, $\mathbf{D}^{'}$, $\mathbf{C}^{'}$, $\boldsymbol{p}_{\mathbf{f}}^{'}$ denote the new corresponding parameters after line outages occur, and T represents the amount of line outages. Without loss of generality, we simply suppose that a line outage on the l-th branch refers to $b_l = 0$ [11]. Considering changes of the connection relationship of power network and zero admittance on broken lines, we can approach

$$\mathbf{C}^{'} = \mathbf{C} - \mathbf{X}\mathbf{C}, \quad (8)$$
$$\mathbf{D}^{'} = \mathbf{D} - \mathbf{X}\mathbf{D}, \quad (9)$$

in which the matrix $\mathbf{X} = \text{diag}(\mathbf{x})$ has a size of $K \times K$. The vector $\mathbf{x}$ with size of $K \times 1$ is a binary vector whose i-th entry is 1 if the i-th line is outage, and 0 otherwise. Therefore, vector $\mathbf{x}$ has a T-sparse property which can be accurately reconstructed based on CS, where T represents the amount of line outages.

In a general power network, the load power on buses $\boldsymbol{p}$ can be treated as stable in a short interval without a very small perturbation. Hence, the injected power on buses before and after occurring line outages are approximately equal. Assuming $\Delta\boldsymbol{p}_{\mathbf{f}} = \mathbf{D}^{'}\boldsymbol{\theta}^{'} - \mathbf{D}\boldsymbol{\theta}$, if we sum $\Delta\boldsymbol{p}_{\mathbf{f}}$ based on the new topology structure $\mathbf{C}^{'}$, the transmission powers of each branch change on each bus before and after occurring line outages can be expressed by the original $\mathbf{D}$ and $\boldsymbol{\theta}$. The mathematical expression is

$$\mathbf{C}^{\mathbf{T}}\text{diag}(\mathbf{D}\boldsymbol{\theta})\mathbf{x} = \mathbf{C}^{'\mathbf{T}}(\mathbf{D}^{'}\boldsymbol{\theta}^{'} - \mathbf{D}\boldsymbol{\theta}). \quad (10)$$

After substituting (8) and (9) into (10), and performing some necessary mathematical derivations, equation (10) can be overwritten as

$$\mathbf{C}^{\mathbf{T}}\mathbf{D}\Delta\boldsymbol{\theta} = \mathbf{C}^{'\mathbf{T}}\text{diag}(\mathbf{D}\boldsymbol{\theta}^{'})\mathbf{x}, \quad (11)$$

where $\Delta\boldsymbol{\theta} = \boldsymbol{\theta}^{'} - \boldsymbol{\theta}$. Thus, due to the sparse property of line outages, the line outage detection problem can be modeled as a general CS based formulation, and is expressed as

$$\mathbf{y} = \mathbf{A}\mathbf{x} + \boldsymbol{\eta}, \quad (12)$$

in which the vector $\mathbf{y}$ with size of $N \times 1$ and the matrix $\mathbf{A}$ with size of $N \times K$ can be given by

$$\mathbf{y} = \mathbf{C}^{\mathbf{T}}\mathbf{D}\Delta\boldsymbol{\theta}, \quad (13)$$
$$\mathbf{A} = \mathbf{C}^{'\mathbf{T}}\text{diag}(\mathbf{D}\boldsymbol{\theta}^{'}), \quad (14)$$

where $\boldsymbol{\eta}$ denotes the small perturbation of power load on buses $\mathbf{p}$ in the grid, which can be represented as $\boldsymbol{\eta} = \mathbf{B}'\boldsymbol{\theta}' - \mathbf{B}\boldsymbol{\theta}$ [30].

Therefore, due to the measurement matrix is flat and the power line outage is sparse, the CS theory's advantage can be adopted. In the previous line outage detection method based on sparse signal recovery, the CS method is adopted to solve the problem in (12) directly. However, since some branches in SGs may densely distributed on several buses, the coherence or average coherence is very high in specific columns of the observation matrix $\mathbf{A}$, which means the necessary guarantee, e.g. the RIP condition, is not fully satisfied in observation matrix $\mathbf{A}$.

On the other hand, the QR decomposition based scheme is also adopted to solve the line outage detection problem and had been proved to be feasible [23]. In the QR decomposition based scheme, equation (11) is rewritten as

$$\Delta\theta = \mathbf{B}^{-1}\mathbf{C}'^{\mathbf{T}}\hat{\mathbf{x}} + \mathbf{B}^{-1}\boldsymbol{\eta}, \tag{15}$$

in which

$$\mathbf{B} = \mathbf{C}'^{\mathbf{T}}\mathbf{D}, \tag{16}$$

$$\hat{\mathbf{x}} = \mathrm{diag}(\mathbf{D}\boldsymbol{\theta}')\mathbf{x}. \tag{17}$$

Then, the QR decomposition is operated on matrix $\mathbf{B}^{-1}$. Thus, we have

$$\mathbf{B}^{-1} = \mathbf{R}^{-1}\mathbf{Q}^{-1}, \tag{18}$$

$$\hat{\mathbf{y}} = \mathbf{R}\Delta\boldsymbol{\theta} = \mathbf{Q}^{-1}\mathbf{C}'^{\mathbf{T}}\hat{\mathbf{x}} + \mathbf{Q}^{-1}\boldsymbol{\eta}. \tag{19}$$

The observation matrix in QR decomposition based scheme $\mathbf{A_q}$ can be written as

$$\mathbf{A_q} = \mathbf{Q}^{-1}\mathbf{C}'^{\mathbf{T}}. \tag{20}$$

In (19), vector $\hat{\mathbf{x}}$ is proved that can be recovered using (19) and several basic compressive sensing algorithms such as OMP or CoSaMP [23]. However, the QR decomposition based scheme cannot achieve a high precision. Thus, we propose another approach to analyze the line outage detection in the next section with higher accuracy and equivalent complexity.

III. BLOCK-WISE COMPRESSIVE SENSING BASED MULTIPLE LINE OUTAGE DETECTION

As mentioned in Section II, exploiting CS directly on (12) may not be a good approach since the coherence of the observation matrix $\mathbf{A}$ is potentially high. On the other hand, it should be noted that when the matrix $\mathbf{A}$ has two non-zero entices in the same row, the vector $\mathbf{y}$ also has non-zero entices on buses connected by broken branches if we ignore the effect of perturbation. Thus, this distribution of non-zero elements in $\mathbf{y}$ can be adopted to enhance the recovery performance. By exploiting the block sparse property of the outage location in power grid, a novel CS based line outage detection method is proposed. Therefore, the main contribution of the proposed method is to transform the previous vector $\mathbf{x}$ into a new block-wise vector $\mathbf{w}$. Then, the corresponding modification on line outage detection is derived. Finally, by combining this block sparse property, an improvement of the traditional CS based algorithm in investigated. In this section, the proposed BW-CS line outage detection scheme is firstly introduced into a single-phase power network. Then, some necessary adjustment on the three-phase power network will be discussed. Finally, the complexity analysis about different schemes is provided.

A. BW-CS SCHEME IN SINGLE-PHASE NETWORK

In this subsection, we will fully explain our proposed BW-CS line outage detection scheme. As shown in (6), it should be noted that there are two non-zero entries in each row of the matrix $\mathbf{C}$, which represents the from-bus and to-bus of each branch. Therefore, these two non-zero elements can be removed out of vector $\mathbf{w}$ and then construct a new block-wise vector. Let $\boldsymbol{\Omega}$ represents the label set of outage lines, $\boldsymbol{\Omega}_{from}$ and $\boldsymbol{\Omega}_{to}$ denote the labels of from-buses and to-buses for outage lines, respectively. The i-th entry of $\mathbf{w}$ is given by

$$w_i = \begin{cases} 1 & i = 2j, \quad i = 2j-1, \quad j \in \boldsymbol{\Omega}, \\ 0 & \text{otherwise}. \end{cases} \tag{21}$$

Thus, vector $\mathbf{w}$ with length of $2K$ has K blocks, where each block has a length of 2. Moreover, two succeeding elements in $\mathbf{w}$ denotes the same branch, which equal to 1 when their corresponding branch is broken and 0 otherwise. Similarly, to achieve an equivalent equation of (12), two matrices $\mathbf{M}$ and $\mathbf{L}$ are derived as

$$\mathbf{C^T D}\Delta\boldsymbol{\theta} = \mathbf{M}\mathrm{diag}(\mathbf{L}\mathbf{D}\boldsymbol{\theta}')\mathbf{w}. \tag{22}$$

The (i,k)-th element of the matrix $\mathbf{M}$ with size of $N \times 2K$ and the (k,i)-th element of the matrix $\mathbf{L}$ with size of $2K \times K$ can be described as

$$M_{i,k} = \begin{cases} 1 & i = \boldsymbol{\Omega}_{from,j}, \quad k = 2j-1, j \in [1,K], \\ -1 & i = \boldsymbol{\Omega}_{to,j}, \quad k = 2j, j \in [1,K], \\ 0 & \text{otherwise}. \end{cases} \tag{23}$$

$$L_{k,i} = \begin{cases} 1 & i = \boldsymbol{\Omega}_{from,j}, \quad k = 2j-1, j \in [1,K], \\ 1 & i = \boldsymbol{\Omega}_{to,j}, \quad k = 2j, j \in [1,K], \\ 0 & \text{otherwise}. \end{cases} \tag{24}$$

The matrices $\mathbf{L}$ and $\mathbf{M}$ reconstruct the sum order on the right side of (12) based on the block-wise property of vector $\mathbf{w}$, and they only related to the topology of a power network which can be constructed and restored beforehand. Meanwhile, the left side of (12) remains unchanged. Therefore, equation (12) with the perturbation can be simply rewritten as

$$\mathbf{y} = \mathbf{A_n}\mathbf{w} + \boldsymbol{\eta}, \tag{25}$$

where the matrix $\mathbf{A_n}$ represents

$$\mathbf{A_n} = \mathbf{M}\mathrm{diag}(\mathbf{L}\mathbf{D}\boldsymbol{\theta}'), \tag{26}$$

and $\boldsymbol{\eta}$ represents the weak perturbation in the grid.

To cope with (25), the Orthogonal Matching Pursuit (OMP) algorithm [26], which is one of the famous sparse signal recovery algorithms with the greedy policy and had been widely adopted in many aspects [27]–[30], is attempted to adopted. In the conventional OMP, after initialization, the location of sparse entries are selected greedily based on the maximum entry of vector $\boldsymbol{\beta}$, which is calculated as

$$\boldsymbol{\beta} = \mathbf{A}_{\mathbf{n}}^{\mathbf{T}}\mathbf{y}. \tag{27}$$

The OMP uses (27) to select the sparse elements in an iteration manner until all the sparse elements are found out or the residual is small enough.

Since the branch from or into the i-th bus has the largest transmitted power may not in outage condition, this selection criterion in (25) may result in error recovery. Specifically, the structure of $\mathbf{y}$ and $\mathbf{A}_{\mathbf{n}}^{\mathbf{T}}$ should be considered. When i belongs to $\boldsymbol{\Omega}_{from}$ or $\boldsymbol{\Omega}_{to}$, the i-th entry of vector $\mathbf{y}$ is non-zero element. If the $\lceil j/2 \rceil$-th branch connects the i-th bus, the non-zero element in matrix $\mathbf{A}_{\mathbf{n}}^{\mathbf{T}}$ denotes the transmitted power on the i-th column and j-th row. Moreover, two succeeding elements in vector $\mathbf{w}$ can be detected simultaneously to enhance the recovery performance by utilizing the block sparse property of vector $\mathbf{w}$. Thus, a new parameter to calculate $K \times 1$ vector $\boldsymbol{\beta}_{\mathbf{n}}$ is given by

$$\boldsymbol{\beta}_{\mathbf{n},i} = \frac{\|\boldsymbol{\beta}_{2i-1}\| \times \|\boldsymbol{\beta}_{2i}\|}{\big\| \|\boldsymbol{\beta}_{2i-1}\| - \|\boldsymbol{\beta}_{2i}\| \big\|}. \tag{28}$$

In (28), we product $\boldsymbol{\beta}_{2i-1}$ and $\boldsymbol{\beta}_{2i}$ as the numerator to show the combined effects of the two elements in one block, and adopt the difference of $\boldsymbol{\beta}_{2i-1}$ and $\boldsymbol{\beta}_{2i}$ as the denominator to reflect how close between these two elements. We observe that the matrix $\mathbf{A}_{\mathbf{n}}^{T}$ adds the power difference on buses into branches, vector $\mathbf{y}$ is sparse with entries on $\boldsymbol{\Omega}_{from}$ and $\boldsymbol{\Omega}_{to}$, and each two succeeding elements of vector $\mathbf{w}$ represent the same branch. Hence, the $\boldsymbol{\beta}_{2i-1}$ is very close to $\boldsymbol{\beta}_{2i}$ if the i-th branch is in outage. Consequently, the locations of sparse elements can be selected according to $\boldsymbol{\beta}_{\mathbf{n}}$ with a large probability as the correct detection. Besides, a simple equation is operated after vector $\boldsymbol{\beta}_{\mathbf{n}}$ has been calculated to eliminate the influence of properties near zero. The pseudo code of the improved BW-CS scheme is illustrated in Algorithm 1. Moreover, when the perturbation noise $\boldsymbol{\eta}$ is taken into consideration, the elements position selection noise $\boldsymbol{\lambda}$ is

$$\boldsymbol{\lambda} = \mathbf{A}_{\mathbf{n}}^{\mathbf{T}}\boldsymbol{\eta}. \tag{29}$$

Thus, the noise $\boldsymbol{\lambda}_{\mathbf{n}}$ added on $\boldsymbol{\beta}_{\mathbf{n}}$ can be denoted as

$$\boldsymbol{\lambda}_{\mathbf{n},i} = \frac{\|\boldsymbol{\lambda}_{2i-1}\| \times \|\boldsymbol{\lambda}_{2i}\|}{\big\| \|\boldsymbol{\lambda}_{2i-1}\| - \|\boldsymbol{\lambda}_{2i}\| \big\|}. \tag{30}$$

Because the random distribution of noise, the probability that $\boldsymbol{\lambda}_{\mathbf{n},i}$ and $\boldsymbol{\beta}_{\mathbf{n},i}$ is comparable is sufficiently low. Therefore, the selection criterion in (28) can decrease the influence of the perturbation noise.

As demonstration in **Algorithm 1**, the proposed BW-CS scheme generally comply with the basic structure of the classical sparsity adaptive matching pursuit (SAMP) dealing with sparse recovery with unknown sparsity levels and take $\boldsymbol{\beta} = \mathbf{A}_{\mathbf{n}}^{\mathbf{T}}\mathbf{y}$ into (28). Due to this improvement, the proposed BW-CS scheme can select the right location of line outages with high accuracy. Meanwhile, the proposed BW-CS scheme can simultaneously detect two succeeding elements in $\mathbf{w}$ during each iteration, which fully utilizes the block-sparsity of vector $\mathbf{w}$. The iteration stops when the residual error is smaller than the specific value or after T times iteration. Then, the output result, the recovered signal $\mathbf{h}$ with size of $2K \times 1$, is considered as the estimation of the signal $\mathbf{w}$. The four main points of the proposed BW-CS method is summarized as follow.

Algorithm 1 The Proposed BW-CS Method

Require:
1) Residual Error $\boldsymbol{\eta}$;
2) Noisy Measurement $\mathbf{m} \triangleq \mathbf{y}$;
3) Observation Matrix $\boldsymbol{\Phi} \triangleq \mathbf{A}_{\mathbf{n}}$.

Ensure: The sparse signal estimation $\bar{\mathbf{h}} \triangleq \bar{\mathbf{h}}_i$.

Initial Configuration:
1: $\bar{\mathbf{h}}^{(0)} \leftarrow \mathbf{0}$;
2: $\mathbf{R}^{(0)} \leftarrow \mathbf{m} - \boldsymbol{\Phi}\bar{\mathbf{h}}^{(0)}$;
Repeat:
3: $\boldsymbol{\beta} \leftarrow \boldsymbol{\Phi}^{H}\mathbf{R}$;
4: $\boldsymbol{\beta}_{\mathbf{n},i} \leftarrow \frac{\|\boldsymbol{\beta}_{2i-1}\| \times \|\boldsymbol{\beta}_{2i}\|}{\big\| \|\boldsymbol{\beta}_{2i-1}\| - \|\boldsymbol{\beta}_{2i}\| \big\|}$;
5: $\boldsymbol{\beta}_{\mathbf{n},i} \leftarrow 0, i \in \left\{ i | \boldsymbol{\beta}_{2i} < 0.1 \bigcap \boldsymbol{\beta}_{2i-1} < 0.1 \right\}$;
6: $\Pi \leftarrow \Pi \cup \{\arg \max_{2i-1,2i} \|\boldsymbol{\beta}_{\mathbf{n},i}\|_1\}$;
7: $\bar{\mathbf{h}}^{(t)} \leftarrow \mathbf{0}$; $\bar{\mathbf{h}}^{(t)}(\Pi) \leftarrow 1$;
8: $\mathbf{R} \leftarrow \mathbf{m} - \boldsymbol{\Phi}\bar{\mathbf{h}}^{(t)}$;
9: **if** $\mathbf{R} \geq \mathbf{R}^{(t-1)}$ **then**
10: break;
11: **else**
12: $\mathbf{R}^{(t)} \leftarrow \mathbf{R}$, $\Pi^{(t)} \leftarrow \Pi$, $t \leftarrow t+1$;
13: **end if**
Until: $||\mathbf{R}^{(t)}|| < \boldsymbol{\eta}$
14: $\bar{\mathbf{h}} \leftarrow \bar{\mathbf{h}}^{(t)}$.

1) By modifying the sum order of the reactance equation in (12), a novel one in (25) is reconstructed, in which the block-wise sparse vector $\mathbf{w}$ is adopted. This block sparse property can be utilized to further enhanced the recovery performance. Concretely, this modification separates the influence from different branches on one bus, which makes CS applicable.
2) To fully utilize the block sparse property, the selection criterion as (28) is redefined to choose the correct location of line outage elements. Two succeeding elements in one block are used to calculate a new element selection criterion. Taking the advantages of the connection relationship and physical restrictions, the adjusted criterion is more suitable to the line outage detection in SGs.

3) Since the realistic line outage number is variable and unknown, we adopt SAMP which does not require the sparsity level to be known. Moreover, the classical algorithm of SAMP is improved with the aid of the block-wise property in this paper, which will enhance the accuracy and robustness of the recovery performance for power line outage detection.
4) Compared to the QR-decomposition based method that utilizes the QR decomposition to reduce the coherence of the observation matrix, our proposed method exploit the physical connection and block-wise sparsity to increase the possibility of choosing right position.
5) The proposed BW-CS method avoid the QR decomposition based calculation and increase the matrices size on the contrary. Compared to the QR-decomposition method with the complexity of $\boldsymbol{O}(KN^2)$, the proposed BW-CS method has similar complexity of $\boldsymbol{O}(KN)$, where the detailed complexity analysis is drawn in the following section. Moreover, due to the lower computational complexity of the proposed method, the detection time is shorter compared to the conventional methods with higher accuracy and larger applicability.

B. EXTENDED TO THREE-PHASE POWER NETWORK

Three-phase electric power is a common polyphase system which is widely used by electric networks to transfer power [31], [32]. In a three-phase power system, three equal voltages on three lines with a phase separation of one-third cycle are generated synchronously, which uses less conductor material than an equivalent single-phase system. In this subsection, the proposed BW-CS scheme is extended to three-phase power network with the application of structured compressive sensing.

In a balanced three-phase system, three equal-magnitude voltages can be represented as

$$\mathbf{V}_1 = \mathbf{V}\angle\phi, \tag{31}$$
$$\mathbf{V}_2 = \mathbf{V}\angle(\phi + 120^\circ), \tag{32}$$
$$\mathbf{V}_3 = \mathbf{V}\angle(\phi - 120^\circ), \tag{33}$$

where $\mathbf{V}_1$,$\mathbf{V}_2$, and $\mathbf{V}_3$ denote three voltages, $\mathbf{V}$ and ϕ denote the magnitude and the reference phase, respectively. Considering the perturbation in a three-phase network, two of these three voltages are independent with the relationship that the vector sum of $\mathbf{V}_1$,$\mathbf{V}_2$, and $\mathbf{V}_3$ is zero. Considering the same topology for two independent voltages, we can achieve two similar equations by following the same derivation procedure in (25) as

$$\mathbf{y}_1 = \mathbf{A_{n1}}\mathbf{w}_1 + \boldsymbol{\eta}_1, \tag{34}$$
$$\mathbf{y}_1 = \mathbf{A_{n2}}\mathbf{w}_2 + \boldsymbol{\eta}_2. \tag{35}$$

The difference between $\mathbf{y}_1$ and $\mathbf{y}_2$ or $\mathbf{A_{n1}}$ and $\mathbf{A_{n2}}$ comes from the imbalance of the three-phase system. Due to the physical similarity between $\mathbf{y}_1$ and $\mathbf{y}_1$, $\mathbf{w}_1$ and $\mathbf{w}_2$ can share the common sparse support. Therefore, we can incorporate the noisy parts and integrate (34) and (35) as

$$\begin{bmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \end{bmatrix} = \begin{bmatrix} \mathbf{A_{n1}} & \mathbf{0} \\ \mathbf{0} & \mathbf{A_{n1}} \end{bmatrix} \begin{bmatrix} \mathbf{w}_1 \\ \mathbf{w}_2 \end{bmatrix} + \begin{bmatrix} \boldsymbol{\eta}_1 \\ \boldsymbol{\eta}_2 \end{bmatrix}. \tag{36}$$

The matrix formulation can be rewritten as

$$\dot{\mathbf{y}} = \boldsymbol{\Phi}\dot{\mathbf{w}} + \dot{\boldsymbol{\eta}}, \tag{37}$$

where $\dot{\mathbf{y}} = [\mathbf{y}_1^{\mathbf{T}}, \mathbf{y}_2^{\mathbf{T}}]^{\mathbf{T}}$, $\dot{\mathbf{w}} = [\mathbf{w}_1^{\mathbf{T}}, \mathbf{w}_2^{\mathbf{T}}]^{\mathbf{T}}$, and $\dot{\boldsymbol{\eta}} = [\boldsymbol{\eta}_1^{\mathbf{T}}, \boldsymbol{\eta}_2^{\mathbf{T}}]^{\mathbf{T}}$. Under the assumption that the line outages have a large probability to emerge at the same branch, we can exploit our BW-CS method on (25) to realize the multiple line outages detection in the three-phase power system because of the relation between $\boldsymbol{\Phi}$, $\mathbf{A_{n1}}$ and $\mathbf{A_{n2}}$ as

$$\boldsymbol{\Phi} = \begin{bmatrix} \mathbf{A_{n1}} & 0 \\ 0 & \mathbf{A_{n2}} \end{bmatrix}. \tag{38}$$

By integrating two equations into one, the line outages in the three-phase system can be detected simultaneously with an acceptable accuracy.

C. COMPLEXITY ANALYSIS

In this subsection, to analyze the computational complexity of the proposed BW-CS method, let K denote the branches number, N denote the buses number of a power network, and T denote the number of line outages. The computational complexity of the proposed BW-CS line outages detection method and QR decomposition method include the following three parts:

1) In the first step, two schemes need to preprocess the data obtained from PMUs and compute vector $\mathbf{y}$ and observation matrix $\mathbf{A_n}$. The difference is the QR decomposition based scheme acquire an additional QR decomposition which has a complexity of $\boldsymbol{O}(2KN^2)$ [33]. However, because the QR decomposition can be computed in advance using the parameter under a steady state, this may not be taken into consideration of complexity analysis. Hence, the calculation of $\mathbf{y}$ and $\mathbf{A_n}$ require $\boldsymbol{O}(8KN)$ and $\boldsymbol{O}(2KN^2)$ in our proposed BW-CS scheme and QR decomposition scheme, respectively.
2) Then, two schemes utilize different criterions to select the position of sparse elements. The calculation of vector $\boldsymbol{\beta}$ costs $\boldsymbol{O}(KN)$ and $\boldsymbol{O}(2KN)$ in the QR decomposition scheme and our proposed BW-CS scheme, respectively. After that, our proposed BW-CS scheme requires $\boldsymbol{O}(3K)$ to select the accurate position of sparse elements and QR decomposition scheme needs $\boldsymbol{O}(K)$ to accomplish the same thing.
3) In the step of residual computation, the complexities are $\boldsymbol{O}(2KN)$ and $\boldsymbol{O}(KN)$ in our proposed BW-CS scheme and QR decomposition scheme, repsectively.

Therefore, due to the average iteration times T, the total computational complexity of our proposed BW-CS scheme is $\boldsymbol{O}(T(4KN + 3K) + 8KN)$. As a comparison, the QR decomposition based scheme requires a complexity of $\boldsymbol{O}(T(2KN + K) + 2KN^2)$. In practical power networks, K is much larger than N. Therefore, the complexity analysis reveals the complexity of these two schemes are $\boldsymbol{O}(KN)$ and $\boldsymbol{O}(KN^2)$ in short, respectively. Moreover, our proposed BW-CS scheme requires more on elements selection and matrix calculation which leads higher accuracy.

For 3-phase scenario, due to the integration of two equations into one, the sizes of the matrix and vector have been extended to two times of that in conventional algorithm. Moreover, the upper bound of the total number of iterations is also T in the structured BW-CS algorithm. Hence, the total complexity of 3-phase is on the order of $\boldsymbol{O}(T(8KN + 6K) + 16KN)$.

IV. SIMULATION RESULTS

In this section, the performances of the proposed BW-CS method is evaluated. To completely illustrate the performance of our proposed BW-CS scheme, we carry out simulation of our proposed BW-CS method, while the QR decomposition based method and the conventional OMP based method are also performed for comparison under different conditions. Equation (12), (19), and (25) are solved by the conventional OMP based method, the QR decomposition based method, and the proposed novel BW-CS method, respectively. The MATPOWER, which is an open-source Matlab-based software toolbox for power system simulation package, is adopted to simulate IEEE 300-bus, IEEE 118-bus power network, and IEEE 30-bus network under the common DC mode with different levels of noise. MATPOWER has strong ability to solve DC and AC optimal power flow problems even with large scale network and can provide a high-level calculation on power flow with high accuracy [34], [35]. The topology of IEEE 30-bus network is illustrated in Fig. 2 in which arrows pointing inward the nodes denote generators and arrows pointing outward the nodes denote power loads at different buses.

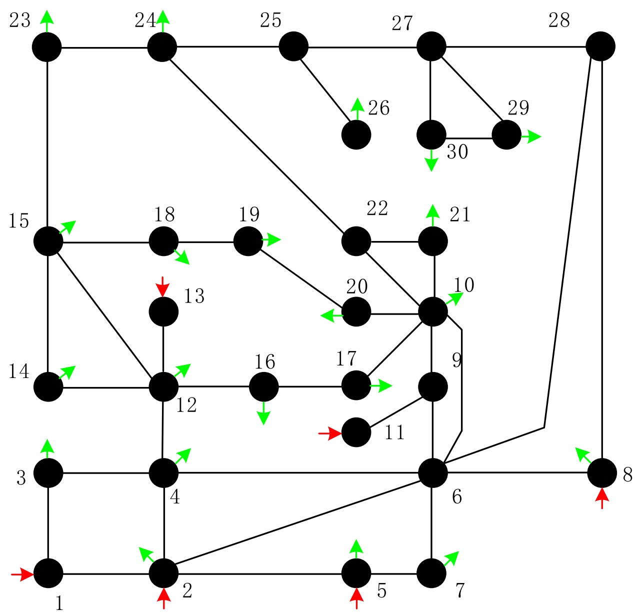

FIGURE 2. IEEE 30-bus system. The red arrows denote generator and the green arrows denote power load. The dotted lines denote line outages.

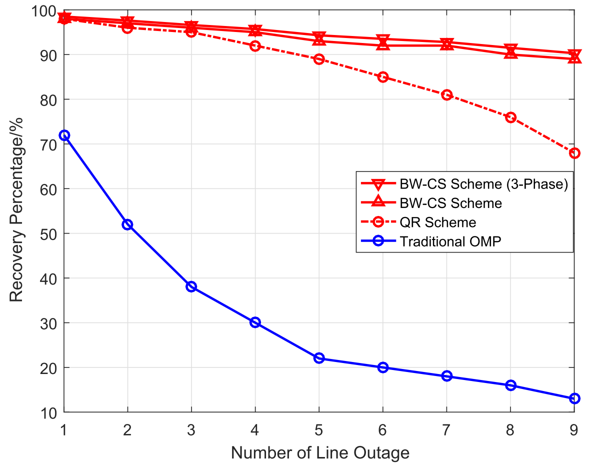

FIGURE 3. Performance of different numbers of line outages in IEEE 118-bus.

TABLE 2. Recovery performance with different numbers of line outages for IEEE 30-bus.

No. of line outages	Scheme	Recovery performance
1	BW-CS scheme	100%
1	QR scheme	100%
1	OMP scheme	83.4%
2	BW-CS	98.9%
2	QR scheme	97.4%
2	OMP scheme	63.2%

For the simulation process, the branches which have the same from-bus and to-bus are firstly merged for the original network of the adopted IEEE buses. This operation has little impact on the line outages location accuracy. In order to evaluate the performance of the proposed BW-CS method, 1000 groups with different numbers of line outages from 1 to $0.05K$ and different noise levels are randomly chosen. The line outage detection is considered to be correct only when all of the positions of the line outages are detected precisely. It should be noted that the line outages cannot result in an island condition for any group of buses as the vital assumption in our simulation, especially when multiple line outages is considered. When an island situation happens, the power load in correlated region of the power network will become zero, which means our model is not suitable. The example of line outage situation is shown in Fig. 2 with dotted lines. Also, our proposed BW-CS scheme assumes to utilize the phase information of the whole buses, which is same as the QR decomposition based Scheme.

We carry out simulation of our proposed BW-CS scheme for the traditional power flow scenario and the 3-phase case on IEEE 118-bus, IEEE 300-bus, and IEEE 30-bus network respectively for different numbers of line outages without considering noise level. The simulation results can be shown in Fig. 3, Fig. 4, and Table 2. The QR decomposition based

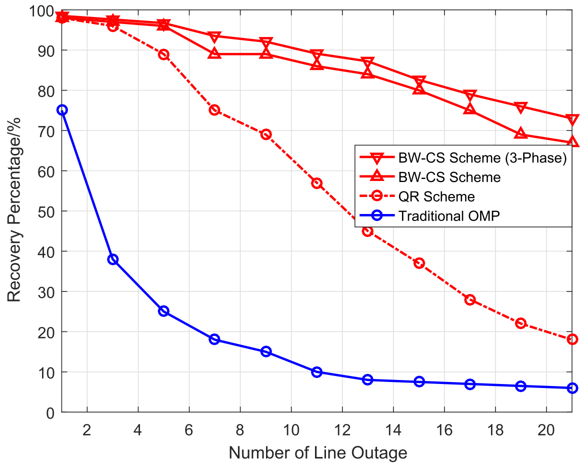

FIGURE 4. Performance of different numbers of line outages in IEEE 300-bus.

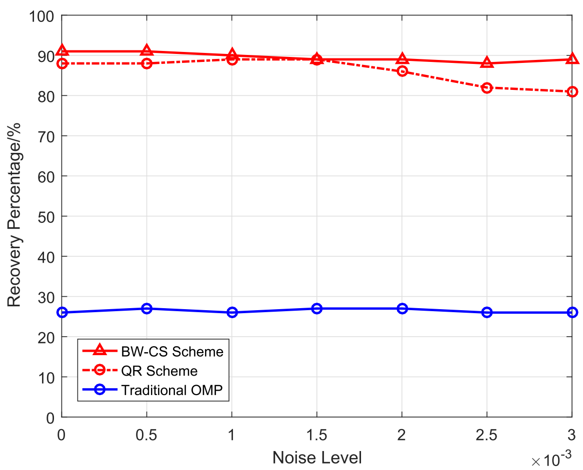

FIGURE 5. Performance of different levels of noise in IEEE 118-bus.

and conventional OMP based methods are also illustrated for comparison. As shown in the figures, the proposed novel BW-CS method can effectively detect the positions of the line outages with more than 90 percentage accuracy even in nearly 7 outage situations, which shown its advantage compared to the conventional OMP based method. Moreover, the proposed BW-CS scheme also has superior performance compared to the traditional QR decomposition method in multiple line outage situation. Moreover, the 3-phase case can achieve even superior performance, which indicates that the structure BW-CS algorithm exploiting the spatial correlation can recover the power line outage at larger sparsity level and higher recovery accuracy. These results reveal that our proposed BW-CS scheme can be adapted to conditions with a larger number of line outages.

Since the perturbation noise η cannot be neglected in practical scenario for SGs, the performance of the proposed BW-CS algorithm is also verified in different levels of noise under 5 line outage condition for IEEE 300-bus and IEEE 118-bus environments. Due to the small number of branches, the permutation noise $\boldsymbol{\eta}$ is added according to the power load on buses as

$$\eta = CN(0, \gamma \|\mathbf{p}\|), \tag{39}$$

in which γ denotes the noise level.

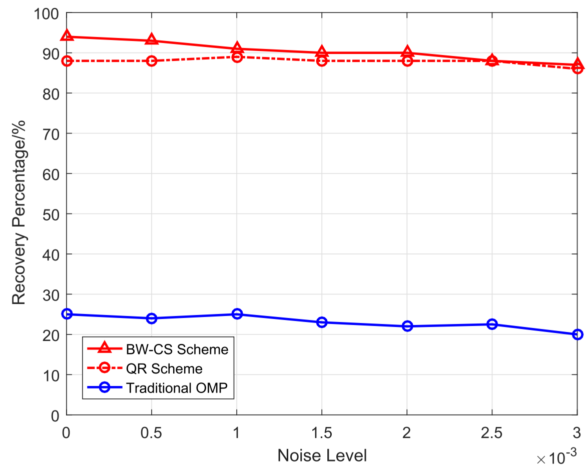

FIGURE 6. Performance of different levels of noise in IEEE 300-bus.

In Fig. 5 and Fig. 6, noise η is served as x-axis instead of number of line outage. According to simulation results in Fig. 5 and Fig. 6, our proposed BW-CS scheme is not sensitive to noise as well as the QR decomposition based scheme in the DC model. Concretely, our proposed BW-CS method has superior performance than the QR-decomposition method under the low level of noise scenario. Also, both the BW-CS method and the QR-decomposition method have higher recovery percentage than the traditional OMP scheme.

V. CONCLUSION

In this paper, a line outage detection scheme with the advantages of the block-sparsity of line outages is proposed and the improvement on conventional OMP method is achieved. In the proposed novel BW-CS method, the reactance equations were reconstructed and the signal to be recovered was transformed into a block-wise formulation. Then, a novel CS based algorithm, called BW-CS scheme, is investigated, in which the process of the conventional OMP is modified due to the block-sparse property in order to improve the recovery accuracy. Meanwhile, the phase measurements from real-time synchronized PMUs are exploited in the proposed scheme. The proposed scheme fully considers the connection relationship of SGs and utilizes the information of block-wise signal structure, which may become a novel and new direction to handel the line outage detection problem in SGs. Moreover, some simulation results were carried out to compare with the conventional OMP based method and the QR decomposition based method. The results show that the proposed method has superior performance with higher accuracy under severe multiple line outage conditions with various levels of noise.

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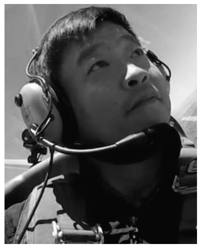

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