Optimal PMU Restoration for Power System Observability Recovery After Massive Attacks

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***Abstract*— Cyber-physically resilient power system operation requires rapid recovery of situational awareness after disastrous scenarios such as massive cyber attacks. In this paper, the concept of optimal sequential restoration of Phasor Measurement Units is introduced, aiming at rapid recovery of power system observability in post-attack scenarios. The observability recovery problem is formulated as a Mixed Integer Linear Programming problem to maximize the cumulative observability level gained over time during the restoration process. Three alternative objective functions—maximizing the number of observable buses, the number of observable branches, and the total amount of observable power flow—are considered. The effectiveness of the proposed optimal strategy is verified by comparing it with heuristic approaches on the IEEE 57-bus system.**

***Index Terms*—Cyber-physical system, observability, phasor measurement unit, power system restoration, resilience**

I. Introduction

The ability to restore power systems quickly after a partial or complete blackout is crucial for a resilient supply of electricity. Large-scale blackout events occurring around the world [1, 2] definitively show the need for a proper restoration plan to effectively mitigate the negative impact of a blackout [3]. The main objective of power system restoration is to bring the system back to normal operating conditions as quickly as possible so as to minimize the power supply losses and restoration time. The procedure of power system restoration includes determining the state of the system, preparing the equipment for restoration, reintegrating the system, and balancing generation and load in a controlled manner [4]. Over the years, researchers have attempted to solve power system restoration problems with the help of various algorithms such as case-based reasoning, genetic algorithms, artificial neural networks, fuzzy logic, Petri nets, and multi-agent technologies (see [3] for a detailed review).

With the rapid development and deployment of communication and information technologies, the concept of cyber-physical systems has been introduced into power system research [5]. A cyber-physical system can be defined as an integration of physical elements in the real world and the sensing, communication, and computing elements in the cyber space [6]. As cyber infrastructures are increasingly interacting with physical power systems, cyber security becomes a major factor to be considered in power system operations [7-9]. In order to fully address the operational challenges arising from the cyber domain, the cyber and physical components of power systems should be modeled and analyzed coordinately. Recently, an increasing amount of research has been dedicated to the cyber-physical resilience of power systems [10-13]. This research has explored enhancement of the ability to absorb disturbances, as well as to recover from the disturbances with full consideration of both the cyber and physical domains of a power system. Obviously, the concept of power system restoration should no longer be limited to the restoration of physical electricity delivery infrastructures, but should be extended to the restoration of cyber infrastructures on which system operation depends.

In power system operation, state estimation is the core function for developing situational awareness [14]. In order to effectively estimate system state variables, observability has to be secured by integrating a sufficient number of reliable measurements from various locations. In recent years, synchronized Phasor Measurement Units (PMUs) have emerged as highly accurate sensing devices for delivering system observability. For planning purposes, the problem of optimal PMU placement for ensuring system observability has been extensively studied (see [15] for a detailed review).

Although a large volume of research has been conducted on PMU placement, a vast majority of the proposed strategies only aim at maintaining full observability after the loss of a small number of PMUs (in most studies, only the loss of a single PMU is considered). Nevertheless, under disastrous scenarios such as a massive cyber attack, a large number of PMUs can be compromised simultaneously, and none of the existing PMU placement strategies may provide effective solutions in such circumstances. In fact, there is no way to ensure that full observability can be maintained under disastrous scenarios, even if resilient PMU configurations have been implemented ahead of time. Rather, optimal restoration strategies for the compromised PMUs should be considered in order to re-establish system observability as quickly as possible after the disasters. So far, no systematic solution has been provided to address this challenge.

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In parallel with the conventionally discussed optimal restoration of physical components of power systems for rapid recovery of electricity delivery, this paper conceptually proposes the optimal restoration of cyber components of power systems, especially PMUs, for rapid recovery of system observability after disastrous scenarios. We formulate the PMU restoration problem as a sequential decision-making problem, whose goal is to maximize cumulative observability levels over time with the optimal order of PMU restoration actions under limited-resource scenarios. Instances of both full blackout and partial blackout are taken into consideration for the observability recovery problem. The problem is formulated as a Mixed Integer Linear Programming (MILP) problem, which can be readily processed by well-developed MILP solvers. The contributions of this paper can be summarized as follows:

1) For the first time in the literature, we formally establish the concept of observability recovery of power systems by means of restoration of cyber components of the power systems, specifically PMUs.
2) We formulate the observability recovery (PMU restoration) problem as a MILP problem. The solution to the problem provides the optimal strategy for PMU restoration, which facilitates situational awareness for system operators after disastrous scenarios such as massive cyber attacks.
3) Through comparative simulation results, we demonstrate the need for systematic development of optimal PMU restoration strategies for rapid observability recovery of power systems, which cannot be achieved by naive heuristic methods such as the greedy strategy.

The rest of this paper is structured as follows. Section II reviews basic concepts of observability analysis for power systems measured by PMUs. Section III describes the mathematical formulations of optimal observability recovery (PMU restoration) problems with various objectives, and indicates the solution algorithms. In Section IV, detailed simulation results are presented to compare the optimal solution with heuristic solutions such as greedy and random assignments. Concluding remarks are given in Section V.

II. Observability of Power Systems Measured by PMUs

In order to operate power systems securely, constant monitoring of system operating conditions is necessary. It is essential to gain observability of the system, which means that bus voltage phasors can be uniquely estimated with the available measurements. Full observability implies that voltage phasors at all buses can be uniquely estimated, and partial observability implies that voltage phasors at certain subsets of buses can be uniquely estimated.

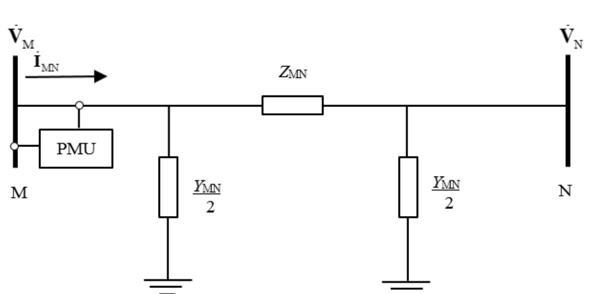

Fig. 1. Observability of systems measured by PMUs

Monitoring power systems with recently deployed PMUs has some advantages over traditional SCADA measurements: higher sampling rate, measurement synchronization, availability of phase angles, and linear state estimation formulations. As a PMU installed at a given bus can measure the voltage phasor at the bus as well as the current phasors along all the branches incident to that bus, there is no need to place PMUs on each bus to make the system fully observable [16]. Before discussing the observability recovery problem, the basic concepts of observability analysis in the presence of PMUs will be briefly reviewed in this section.

If the voltage phasor at a bus can be estimated with the available measurements, then the bus is referred to as an observable bus. Similarly, if the current flowing through a branch can be estimated, then the branch is considered as an observable branch. This concept can be understood by considering a two-bus local area of a system, as shown in Fig. 1. If a PMU is installed at bus M, then the voltage phasor at bus M ($V_{\mathrm{M}}\angle\theta_{\mathrm{M}}$) can be measured directly by the PMU. Hence, bus M will become observable. The PMU at bus M can also measure the branch current incident to bus M ($I_{\mathrm{MN}}\angle\delta_{\mathrm{MN}}$). If we know the line impedance (Z_{MN}), using Kirchhoff's Voltage Law:

$$\dot{\mathbf{V}}_{\mathrm{M}} = (\dot{\mathbf{I}}_{\mathrm{MN}} - \frac{Y_{\mathrm{MN}}}{2}\dot{\mathbf{V}}_{\mathrm{M}})Z_{\mathrm{MN}} + \dot{\mathbf{V}}_{\mathrm{N}}, \tag{1}$$

from which the voltage phasor at bus N can be obtained:

$$\dot{\mathbf{V}}_{\mathrm{N}} = (1 + \frac{Y_{\mathrm{MN}}Z_{\mathrm{MN}}}{2})\dot{\mathbf{V}}_{\mathrm{M}} - Z_{\mathrm{MN}}\dot{\mathbf{I}}_{\mathrm{MN}} \tag{2}$$

In the same way, if the voltage phasors of two adjacent buses are known, then the branch current can be calculated, and thus the branch will become observable. For example, if the voltage phasors at buses M and N are both known, we can rearrange (1) to calculate the current phasor along the line between bus M and bus N as follows:

$$\dot{\mathbf{I}}_{\mathrm{MN}} = \frac{1}{Z_{\mathrm{MN}}}[(1 + \frac{Y_{\mathrm{MN}}Z_{\mathrm{MN}}}{2})\dot{\mathbf{V}}_{\mathrm{M}} - \dot{\mathbf{V}}_{\mathrm{N}}] \tag{3}$$

From the above example, it is shown that if a PMU is placed at a bus, then all the neighboring buses, as well as all the incident branches, will become observable. Hence, the condition for a bus being observable becomes that either the bus has a PMU, or it is connected to a bus that has a PMU. Similarly, the general condition for a branch being observable becomes that both terminal buses of the branch are observable.

On the basis of observability analysis, the optimal PMU placement problem has been formulated by many researchers in the past [16-20]. Suppose there are n buses in a power system: the optimization problem can then be formulated as follows:

$$\begin{aligned} &\text{minimize} \quad \mathbf{w}^T\mathbf{x} \\ &\text{subject to} \quad \mathbf{C}\mathbf{x} \geq \mathbf{1} \end{aligned} \tag{4}$$

where $\mathbf{x} = [x_1, x_2, \ldots\ldots, x_n]^T$ is a binary decision variable vector, whose entries can be defined as

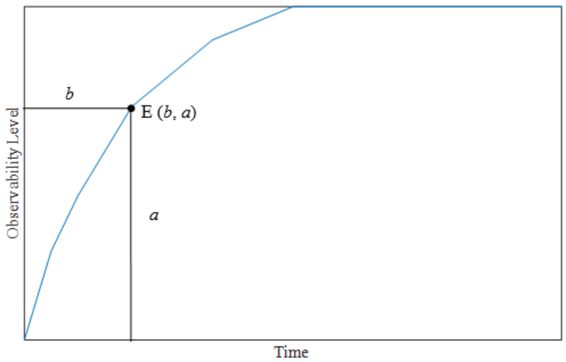

Fig. 2. Observability recovery process

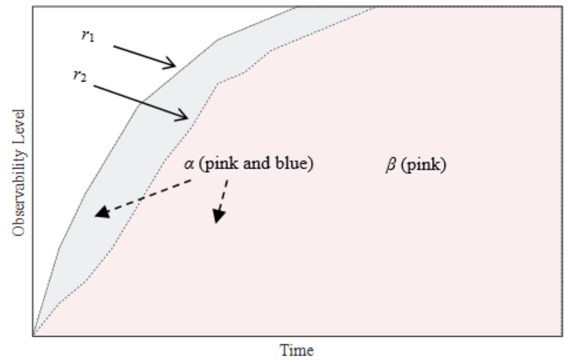

Fig. 3. Comparison between the performances of two restoration processes

$$x_i = \begin{cases} 1, & \text{if a PMU is installed at bus } i \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

$\mathbf{w}$ is the cost vector of PMU installation at different buses; $\mathbf{1}$ is a vector of ones; and the connectivity matrix $\mathbf{C}$ is defined as

$$C_{km} = \begin{cases} 1, & \text{if} \quad k = m \\ 1, & \text{if} \quad \text{bus } k \text{ and bus } m \text{ are connected} \\ 0, & \text{if} \quad \text{otherwise} \end{cases} \tag{6}$$

The constraint in (4) ensures that each entry of the vector $\mathbf{Cx}$ is equal to or greater than 1 to make sure that all the buses are observable with the resulting PMU configuration.

III. Optimal Observability Recovery Problem

A. Conceptualization

In contrast with the optimal PMU placement problem for planning purposes, in this paper, we will formulate the optimal PMU restoration (observability recovery) problem for operational purposes. It is assumed that the power system has already experienced a disastrous scenario such as a massive cyber attack, and most of the PMUs are not functioning properly. As we cannot obtain or trust measurements from the non-functioning or malfunctioning PMUs, the system inevitably loses its observability. At this point, observability can only be recovered by bringing the compromised PMUs back to the normal status. Since the operators have limited resources (for example, a limited number of cyber security rescue teams), the PMU restoration tasks have to be prioritized. In other words, we will need to develop an optimal sequence for restoring the compromised PMUs in order to expedite the recovery of system observability.

In order to formulate the optimal observability recovery (PMU restoration) problem, the following assumptions are made:

1) Cyber rescue teams have to be sent to the substations to repair the compromised PMUs, and each team can restore only one PMU at a time.
2) Restoration of each PMU takes the same amount of time.

Owing to limited resources, it is typically not possible to restore all PMUs at a single time step, and sequential decision-making needs to be performed.

In Fig. 2, we illustrate the objective of the observability recovery problem. The observability level of the system is plotted against the time of restoration for a specific restoration process. Our objective is to maximize the area under the curve. This can be interpreted as follows.

1) For a given time instant, we would like to maximize the level of observability.
2) For a given observability level, we would like to minimize the time taken to reach this level.

Consider point E in Fig. 2, for example. The consumed restoration time is b and the achieved observability level is a. If the restoration time b is given, then we would like to maximize the observability level a by pushing this point *upward*. On the other hand, if the observability level a is given, then we would like to minimize the restoration time b by pushing this point to the *left*. If we push every point on the curve upward and to the left, this is equivalent to *maximizing the area enclosed below the curve*.

We further illustrate the idea by considering two sequential PMU restoration processes r_1 and r_2, shown in Fig. 3. The area enclosed by restoration process r_1 is α, and the area enclosed by restoration process r_2 is β. Obviously, area α is larger than area β, and restoration strategy r_1 is more beneficial to system operators than restoration strategy r_2, since it reaches higher observability levels with shorter restoration times.

From the above observations, it can be concluded that the performance of the restoration process can be evaluated by the area enclosed below the curve.

Assume that a power system has n buses and m branches, and we need k steps to restore the compromised PMUs. Define a set of binary vectors $\mathbf{x}^{(1)}, \mathbf{x}^{(2)}, \ldots\ldots, \mathbf{x}^{(k)}$ to record the locations of PMUs that have been restored up to each step. For example, $\mathbf{x}^{(j)} = [x_1^{(j)}, x_2^{(j)}, \ldots\ldots, x_i^{(j)}, \ldots\ldots, x_n^{(j)}]^T$ is a binary decision vector for the j^{th} step, which is defined as follows:

$$x_i^{(j)} = \begin{cases} 1, & \begin{array}{l} \text{if the PMU at bus } i \text{ is restored} \\ \quad \text{at step } j \text{ or prior to step } j \end{array} \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

Next, we will develop all the constraints that will be used by various formulations of observability recovery problems.

B. Formulating Constraints

1) Constraints on observable buses. For a given step j, the constraint for determining observable buses can be formulated as

$$\mathbf{Cx}^{(j)} \geq \mathbf{y}^{(j)} \tag{8}$$

where $\mathbf{C}$ is the connectivity matrix, whose entry satisfies the following:

$$C_{i_1 i_2} = \begin{cases} 1, & i_1 = i_2 \\ 1, & \text{bus } i_1 \text{ and bus } i_2 \text{ are connected} \\ 0, & \text{otherwise} \end{cases} \quad (9)$$

and $\mathbf{y}^{(j)} = [y_1^{(j)}, y_2^{(j)}, \ldots\ldots, y_i^{(j)}, \ldots\ldots, y_n^{(j)}]^T$ is a binary vector for the j^{th} step. Its i^{th} entry, $y_i^{(j)}$, can take the value of 1 only if there is at least one PMU at bus *i* or its neighboring buses, i.e., only if bus *i* has become observable at step *j*.

2) Constraints on observable branches. In order for a branch to be observable, both terminal buses of the branch have to be observable. The constraint can be formulated as

$$\frac{1}{2}\mathbf{A}\mathbf{y}^{(j)} \geq \mathbf{z}^{(j)}, \quad (10)$$

where **A** is a branch-bus incidence matrix that relates branches with their terminal buses. For this matrix, each row represents one bus, and each column represents one branch. The entries of this matrix satisfy the following:

$$A_{li} = \begin{cases} 1, & \text{if branch } l \text{ is connected with bus } i \\ 0, & \text{otherwise} \end{cases} \quad (11)$$

where $\mathbf{z}^{(j)} = [z_1^{(j)}, z_2^{(j)}, \ldots\ldots, z_l^{(j)}, \ldots\ldots, z_m^{(j)}]^T$ is a binary vector for the j^{th} step. Its l^{th} entry, $z_l^{(j)}$, can take the value of 1 only if both of its terminal buses are observable.

3) Constraints on the amount of observable power injections. Observable power injections can be defined as the power injections at a bus that can be effectively estimated. It should be noted that when a bus becomes observable (voltage phasor being known), it does not automatically follow that the net injection at this bus will become observable. Instead, the constraint on observable power injections can be formulated as

$$\mathbf{D}\mathbf{z}^{(j)} \geq \mathbf{u}^{(j)}, \quad (12)$$

where **D** shows how each bus is related to all of its incident branches, and can be formulated as follows:

$$\mathbf{D} = \mathbf{N}\mathbf{A}^T \quad (13)$$

Here, **N** is a diagonal matrix, whose diagonal entries consist of the reciprocal of the number of incident branches at a particular bus, satisfying the following condition:

$$N_{ij} = \begin{cases} \dfrac{1}{\sum \text{branch incident at bus } i} & \text{if } i = j \\ 0 & \text{if } i \neq j \end{cases} \quad (14)$$

$\mathbf{u}^{(j)} = [u_1^{(j)}, u_2^{(j)}, \ldots\ldots, u_i^{(j)}, \ldots\ldots u_n^{(j)}]^T$ is a binary vector for the j^{th} step, which represents the buses where the net injections are observable. Its i^{th} entry, $u_i^{(j)}$, can take the value of 1 only if the power along all the incident branches is observable.

4) Constraints on the number of PMUs that can be restored at each step (i.e., number of cyber rescue teams). The number of PMUs that can be restored at each step is constrained by the number of rescue teams, which can be formulated as follows:

$$\mathbf{1}^T(\mathbf{x}^{(j)} - \mathbf{x}^{(j-1)}) \leq d^{(j)}, \quad (15)$$

where $d^{(j)}$ is a scalar representing the number of PMUs that can be restored at step *j*.

5) Constraints on maintaining the normal status of already-restored PMUs. It is assumed that the PMUs which are not affected by the disaster or have been restored via the previous steps will remain in the normal status during the following steps, i.e., the restoration process does not reverse:

$$\mathbf{x}^{(j)} - \mathbf{x}^{(j-1)} \geq \mathbf{0}, \quad (16)$$

where $\mathbf{0}$ is a null vector.

With all the constraints available, we will now formulate the observability recovery (PMU restoration) problems with various objectives in Section III.C through Section III.E. Three possible objectives are considered: (1) maximizing the number of observable buses; (2) maximizing the number of observable branches; and (3) maximizing the total amount of observable power. As the restoration process is carried out in steps, the area enclosed below the restoration curve (as discussed in Section III.A) is evaluated as a summation of discrete functions, instead of using an integration of continuous functions.

C. Formulating Optimization Problem for Maximizing the Number of Observable Buses

In this subsection, we will formulate the PMU restoration problem for maximizing the number of observable buses. The number of observable buses is used as the metric for the "observability level" shown as the vertical axis of Fig. 2. For maximizing the area enclosed below the curve, the optimization problem can be formulated as follows:

$$\begin{aligned} \text{maximize} \quad & \sum_{j=1}^{k} \mathbf{p}^T \mathbf{y}^{(j)} \\ \text{subject to} \quad & \mathbf{C}\mathbf{x}^{(j)} \geq \mathbf{y}^{(j)} \\ & \mathbf{1}^T(\mathbf{x}^{(j)} - \mathbf{x}^{(j-1)}) \leq d^{(j)} \\ & \mathbf{x}^{(j)} - \mathbf{x}^{(j-1)} \geq \mathbf{0} \end{aligned} \quad (17)$$

In (17), $\mathbf{p} = [p_1, p_2, \ldots\ldots, p_i, \ldots\ldots, p_n]^T$ is a weight vector. In order to maximizing the area enclosed below the observability recovery curve in Fig. 2, this vector should be assigned as a vector full of 1s. However, system operators can readily assign its values as per the importance of each bus empirically, such that the observability for more important buses can be prioritized. In (17), the value of *k* can be determined using the number of steps required by a heuristic method, as the number of steps needed by a heuristic method is typically greater than or equal to the number of steps needed by the optimization method. More details on examples of heuristic methods can be found later in Section IV. The solution vectors $\mathbf{x}^{(j)}$ (j = 1, 2, …, k) of optimization problem (17) will provide the optimized sequential PMU restoration strategy for improving observability of the system as quickly as possible, and vectors $\mathbf{y}^{(j)}$ (j = 1, 2, …, k) will indicate the specific buses that become observable after each step of restoration.

D. Formulating Optimization Problem for Maximizing the Number of Observable Branches

Using the number of observable branches as the observability metric, the optimization problem can be formulated as follows:

$$\begin{aligned} \text{maximize} \quad & \sum_{j=1}^{k} \mathbf{q}^T \mathbf{z}^{(j)} \\ \text{subject to} \quad & \mathbf{C}\mathbf{x}^{(j)} \geq \mathbf{y}^{(j)} \\ & \frac{1}{2}\mathbf{A}\mathbf{y}^{(j)} \geq \mathbf{z}^{(j)} \\ & \mathbf{1}^T(\mathbf{x}^{(j)} - \mathbf{x}^{(j-1)}) \leq d^{(j)} \\ & \mathbf{x}^{(j)} - \mathbf{x}^{(j-1)} \geq \mathbf{0} \end{aligned} \tag{18}$$

In (18), $\mathbf{q} = [q_1, q_2, \ldots\ldots, q_l, \ldots\ldots, q_m]^T$ is a weight vector, which represents the importance of each branch, which can be set similarly as in (17). Solutions to vectors $\mathbf{x}^{(j)}$ (j = 1, 2, …, k) here will provide the optimized sequential PMU restoration strategy, and vectors $\mathbf{z}^{(j)}$ (j = 1, 2, …, k) will indicate the specific branches that become observable after each step of restoration.

E. Maximizing the Amount of Observable Power

In this subsection, we consider the total amount of observable power as the observability metric. It is the summation of all the net power injections and branch power flows that can be estimated:

$$\begin{aligned} \text{maximize} \quad & \sum_{j=1}^{k} (\mathbf{f}^T \mathbf{z}^{(j)} + \mathbf{g}^T \mathbf{u}^{(j)}) \\ \text{subject to} \quad & \mathbf{C}\mathbf{x}^{(j)} \geq \mathbf{y}^{(j)} \\ & \frac{1}{2}\mathbf{A}\mathbf{y}^{(j)} \geq \mathbf{z}^{(j)} \\ & \mathbf{D}\mathbf{z}^{(j)} \geq \mathbf{u}^{(j)} \\ & \mathbf{1}^T(\mathbf{x}^{(j)} - \mathbf{x}^{(j-1)}) \leq d^{(j)} \\ & \mathbf{x}^{(j)} - \mathbf{x}^{(j-1)} \geq \mathbf{0} \end{aligned} \tag{19}$$

In (19), $\mathbf{f} = [f_1, f_2, \ldots\ldots, f_l, \ldots\ldots, f_m]^T$ is a weight vector, which represents the branch power flow associated with each branch. For example, for branch l, which connects bus i_1 to bus i_2, the corresponding entry can be evaluated as follows:

$$f_l = \sqrt{\frac{1}{2}(\mathrm{P}_{l_1}^{\;2} + \mathrm{Q}_{l_1}^{\;2} + \mathrm{P}_{l_2}^{\;2} + \mathrm{Q}_{l_2}^{\;2})}\ , \tag{20}$$

where P and Q denote real and reactive power, respectively, and subscripts l_1 and l_2 denote the flows measured at bus i_1 and bus i_2, respectively; f_l represents the root mean square of the apparent powers at the two terminals of the branch.

Similarly, $\mathbf{g} = [g_1, g_2, \ldots\ldots, g_i, \ldots\ldots, g_n]^T$ is a weight vector, which represents the net power injections associated with each bus. For example, for bus i, the corresponding entry can be evaluated as follows:

$$g_i = \sqrt{\left(\mathrm{P}_{\mathrm{G}i} - \mathrm{P}_{\mathrm{D}i}\right)^2 + (\mathrm{Q}_{\mathrm{G}i} - \mathrm{Q}_{\mathrm{D}i})^2}\ , \tag{21}$$

where subscripts G and D denote generation and load, respectively.

By solving the optimization problem (19), the optimal sequence of PMU restoration, which makes the largest amount of power observable as quickly as possible, can be obtained.

It should be noted that after the system loses observability, it becomes impossible to accurately estimate the net injections and branch power flows so as to set the weight vectors exactly. However, the power flow data from before the disaster takes place or from historically similar days can be used for approximating these values.

F. Maximizing the Amount of Observable Power for Multi-area Power Systems

Finally, we consider the situation where a large-scale power system needs to be partitioned into smaller areas, and each individual area has a specific amount of resources to be allocated within itself. This problem formulation becomes practical when the traveling distances of rescue teams becomes a concern, or when the power system is owned by multiple entities and the restoration resources cannot be allocated across different entities. Assuming that the power system is divided into t areas, the binary decision vector $\mathbf{x}^{(j)}$ for the j^{th} step can be divided into subvectors as: $\mathbf{x}^{(j)} = [\mathbf{x}_1^{(j)}, \mathbf{x}_2^{(j)}, \ldots\ldots, \mathbf{x}_v^{(j)}, \ldots\ldots, \mathbf{x}_t^{(j)}]^T$, where each subvector corresponds to an area. For an area v, the constraints on the number of cyber rescue teams can be reformulated as follows:

$$\mathbf{1}^T(\mathbf{x}_v^{(j)} - \mathbf{x}_v^{(j-1)}) \leq d_v^{(j)} \tag{22}$$

where $d_v^{(j)}$ is a scaler representing the number of cyber rescue teams available in area v at step j.

Using total amount of power as observability metric, the optimization problem can be formulated as follows:

$$\begin{aligned} \text{maximize} \quad & \sum_{j=1}^{k} (\mathbf{f}^T \mathbf{z}^{(j)} + \mathbf{g}^T \mathbf{u}^{(j)}) \\ \text{subject to} \quad & \mathbf{C}\mathbf{x}^{(j)} \geq \mathbf{y}^{(j)} \\ & \frac{1}{2}\mathbf{A}\mathbf{y}^{(j)} \geq \mathbf{z}^{(j)} \\ & \mathbf{D}\mathbf{z}^{(j)} \geq \mathbf{u}^{(j)} \\ & \mathbf{1}^T(\mathbf{x}_1^{(j)} - \mathbf{x}_1^{(j-1)}) \leq d_1^{(j)} \\ & \quad \vdots \\ & \mathbf{1}^T(\mathbf{x}_v^{(j)} - \mathbf{x}_v^{(j-1)}) \leq d_v^{(j)} \\ & \quad \vdots \\ & \mathbf{1}^T(\mathbf{x}_t^{(j)} - \mathbf{x}_t^{(j-1)}) \leq d_t^{(j)} \\ & \mathbf{x}^{(j)} - \mathbf{x}^{(j-1)} \geq \mathbf{0} \end{aligned} \tag{23}$$

By solving optimization problem (23), the solution vectors $\mathbf{x}^{(j)}$ (j = 1, 2, …, k), which provides the optimized sequential PMU restoration strategy, can be obtained.

There are two criteria that can guide system partitioning in practice:

(1) Ownership and maintenance responsibility of PMU assets: Typically, a large-scale power grid can be divided into multiple areas, each of which is owned by a utility company or managed by an area control room. It is reasonable for each utility company or control room personnel to have its own cyber crews, and in case of a cyber attack, these crews will be responsible for restoring the PMUs in their respective service areas.

(2) Geographical feasibility for PMU restoration activities: The area should be divided reasonably for cyber crews to travel. To this end, the choice should be left to the users of the proposed algorithm (e.g., grid operators), who can divide the areas based on their specific transportation conditions and

available resources. The choice of system partitioning by the users does not affect the general effectiveness and applicability of the proposed approach.

It is noteworthy that the system is partitioned only to limit the use of restoration resources within each area, and not to split the power system into smaller subsystems for observability analysis. As a result, the produced strategy still ensures that the entire system will become observable. In this case, it is possible to run multi-area state estimation for each partitioned area [21, 22], but it is not required.

Problems (17) – (19) and (23) formulated above can be readily solved by well-developed MILP algorithms [23-26], which will not be elaborated here.

Finally, before moving forward to the simulation section, it should made clear that this paper only addresses scenarios where PMUs are compromised, and does not address scenarios where there is a physical system blackout induced by compromised PMUs. It should be noted that cyber attacks on PMUs do not necessarily or inevitably lead to physical system blackouts, for two obvious reasons. (1) Many types of PMU attacks do not aim to inflict massive physical system blackout. Denial of service attacks and false data injection attacks may aim to interrupt system monitoring or create inefficient system dispatch [27-31]. (2) PMU signals are not directly fed to relay protection systems. Relay protections have separate sensing and communication infrastructures which are not likely to be impacted by PMU data problems. It is certainly possible that cyber attacks on PMUs may lead to physical system blackouts, but such scenarios are not covered by this single paper.

IV. Simulation Results

In this section, we will illustrate the proposed observability recovery problems and solution strategies on the IEEE 57-bus system, and compare the performance of the proposed optimization approach with two heuristic approaches: random assignment and the greedy algorithm. These two heuristic approaches are developed to mimic the possible behaviors of system operators after cyber attacks on PMUs, as there is no existing optimization tool for the restoration of the PMUs to recover the system observability. For random assignment, random PMUs are selected to be restored at each step. For the greedy algorithm, the PMUs which provide the greatest immediate boosts of system observability are selected to be restored at each step.

A one-line diagram of the IEEE 57-bus system is shown in Fig. 4; it has 57 buses, 80 branches, 7 generators, and 42 loads. 37 PMUs are installed to make the whole system observable, with some redundancy. The locations of the installed PMUs are marked by red circles in Fig. 4.

In order to evaluate the performances of different approaches, we introduce the concept of *observability loss*, which can be defined as the cumulative difference between the observability levels and the full observability condition over all time steps before the restoration process is completed. It is calculated from the area enclosed between the observability curve and the full-observability line for a specific restoration process. Specifically, we define three indices, R, S, and T, to represent observability losses.

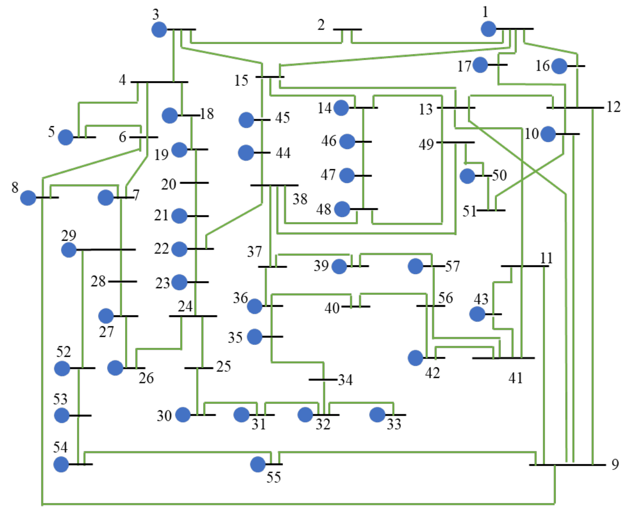

Fig. 4. IEEE 57-bus test system

For the restoration strategy that maximizes the number of observable buses, i.e., the solution to problem (17), the observability loss can be calculated by subtracting the number of observable buses at each step from the total number of buses n and then taking the summation:

$$R = \sum_{j=1}^{k} (n - \mathbf{p}^T \mathbf{y}^{(j)}) . \tag{24}$$

In the same way, for the restoration strategy that maximizes the number of observable branches, i.e., the solution to problem (18), and the restoration strategy that maximizes the amount of observable power, i.e., the solution to problem (19), the observability loss indices can be calculated as

$$S = \sum_{j=1}^{k} (m - \mathbf{q}^T \mathbf{z}^{(j)}) \tag{25}$$

and

$$T = \sum_{j=1}^{k} (s - \mathbf{f}^T \mathbf{z}^{(j)} - \mathbf{g}^T \mathbf{u}^{(j)}) , \tag{26}$$

respectively, where m is the number of branches and s is the total amount of apparent power.

In addition, we define two more indices, F, and H, to evaluate the performance of different restoration strategies, which represent the number of steps required to reach half observability level and the number of steps required to reach full observability level, respectively.

In order to solve the MILP problems (17) - (19) and (23), MATLAB 2019b is used to conduct the following simulation cases. Besides MATLAB, any other commercial software with an MILP solver can be used to solve the problems.

A. Maximization of the Number of Observable Buses

Using the system topology and PMU configuration shown in Fig. 4, we simulate the restoration process after all the available PMUs are compromised. Fig. 5 shows the comparison between the observability restoration curves of the optimized strategy, the greedy strategy, and the random strategy when the resources are limited to restoring 1 PMU per step. For the simulation cases, the weight vectors are considered as vectors with all 1s, which yields the factor that all the PMUs are of equal importance. As the random

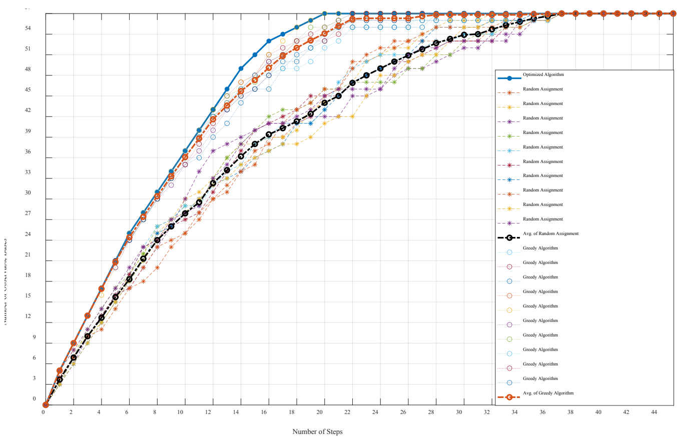

Fig. 5. Observability recovery processes (maximizing number of observable buses, 1 PMU/step)

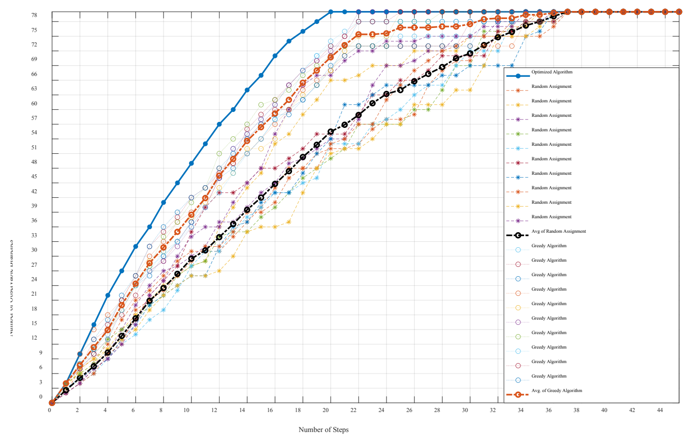

Fig. 7. Observability recovery processes (maximizing number of observable branches, 1 PMU/step)

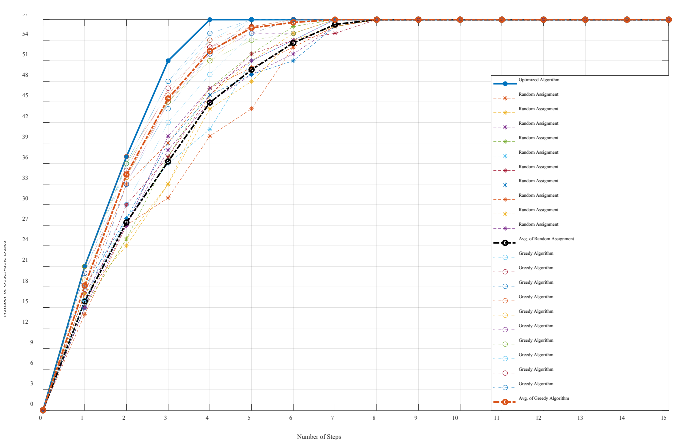

Fig. 6. Observability recovery processes (maximizing number of observable buses, 5 PMUs/step)

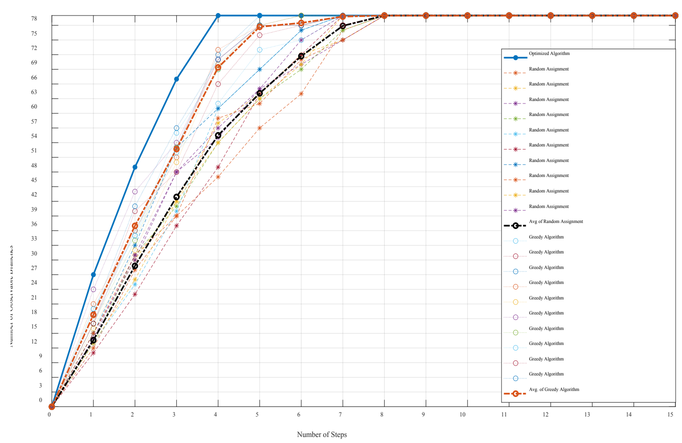

Fig. 8. Observability recovery processes (maximizing number of observable branches, 5 PMUs/step)

assignment and the greedy algorithm both involve random procedures (for the greedy algorithm, when there are multiple PMUs that provide the same immediate boost of observability, they will be selected randomly), more than one possible PMU restoration sequence can be obtained. For that reason, the results for random assignment and greedy algorithm are generated 10 times, and averages of the results are taken to compare with the proposed optimized strategy. From Fig. 5, it can be seen that both the random strategy and the greedy strategy take 37 steps to make all the buses observable, whereas the optimized strategy takes only 20 steps to make all the buses observable. Although the random strategy takes the same number of steps as the greedy algorithm to complete the restoration, during the restoration process, the random strategy makes fewer buses observable than the greedy strategy in each step; this can be seen from the fact that the random-strategy curve is lower than the greedy- strategy curve throughout the entire restoration process. The optimized strategy outperforms all samples of the heuristic strategies. In particular, the curves of the optimized strategy and greedy strategy remain close at the beginning, but they gradually deviate from each other, with the curve of the optimized strategy being higher. This owes to the fact that the optimized strategy is obtained by treating the multi-step process as a global problem, whereas the greedy algorithm seeks a local optimum step by step, yielding an overall suboptimal solution for the entire restoration process.

We also examine the case where there are sufficient resources to restore 5 PMUs per step, and compare the results of the three algorithms, as shown in Fig. 6. In this case, we can see that both the random assignment and the greedy algorithm take more steps than the optimization algorithm to make all the buses observable. If we compare the curves of the greedy strategy for this case and for the previous case, it can be found that the greedy strategy falls behind the optimized strategy even from the first step. The reason is that as the number of PMUs to be restored at each step increases, the number of combinations of candidate PMUs increases drastically. As a result, it is not feasible to check the exact observability boosts for all the combinations, but instead, it is only practical to evaluate the summation of observability boosts brought about by each member of a combination. Since there might be overlapping buses that multiple candidate PMUs make observable simultaneously, this selection algorithm cannot exactly find the candidate combination that gives the greatest boost of observability as a whole for the given step. The optimized strategy, on the other hand, is always able to select the combination that is most beneficial for improving system observability.

For a quantitative comparison between different strategies, the observability loss indexes, R, for the cases of 1 PMU per

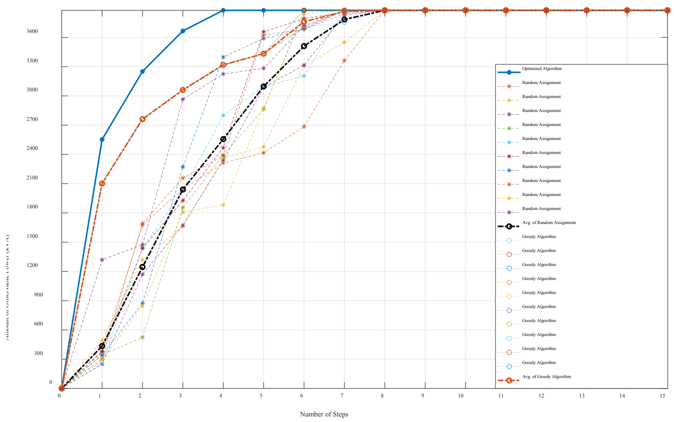

Fig. 11. Observability recovery processes (maximizing amount of observable power, 5 PMUs/step)

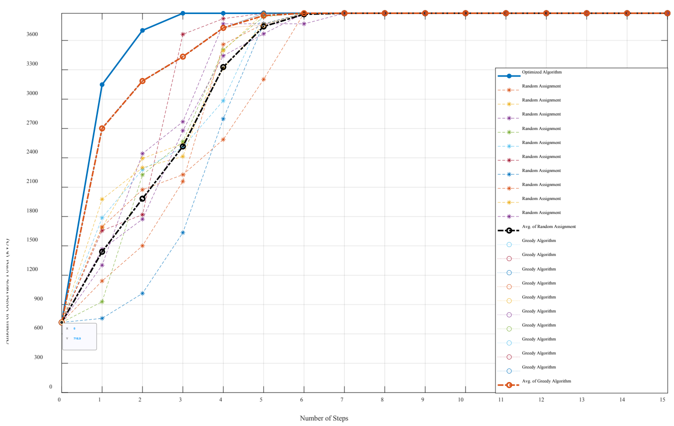

Fig. 12. Observability recovery processes (maximizing amount of observable power, 5 PMUs/step, 25% PMUs initially intact)

step and 5 PMUs per step are shown in Table I. The “random,” “greedy,” and “optimized” columns present the values of the observability loss index for those respective strategies. We also evaluate the percent reduction of observability loss index R brought about by the optimized strategy with respect to the random strategy (the “random vs. optimized” column), and with respect to the greedy strategy (the “greedy vs. optimized” column). For example, for the case of 5 PMUs per step, the optimization algorithm reduces observability losses by 36.89% and 15.89% relative to the random and greedy strategies, respectively.

TABLE I
OBSERVABILITY LOSS COMPARISON FOR BUS AND BRANCH INDICES

	Rand.	Greedy	Optimized	Optimized vs. Rand.	Optimized vs. Greedy
Observable Loss Index R					
1 PMU/ Step	702.2	483.5	444.5	-36.70%	-8.01%
5 PMUs/ Step	143.4	107.6	90.5	-36.89%	-15.89%
Observable Loss Index S					
1 PMU/ Step	1222.9	894	678	-44.56%	-24.16%
5 PMUs/ Step	245.5	186.1	137	-44.2%	-26.38%

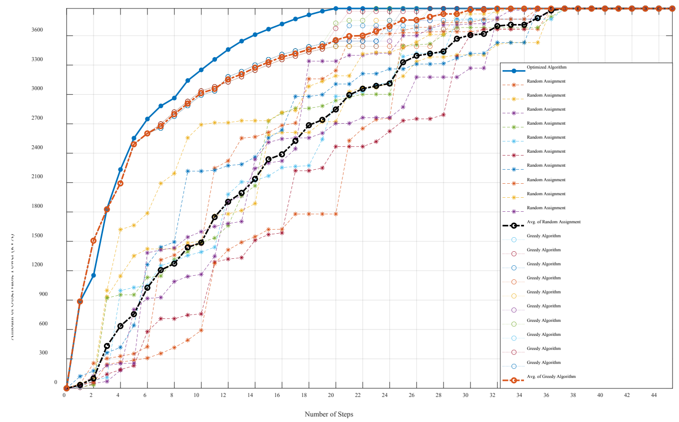

Fig. 9. Observability recovery processes (maximizing amount of observable power, 1 PMU/step)

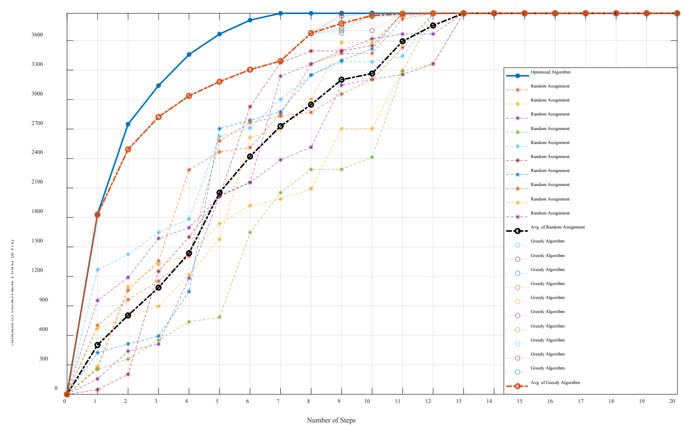

Fig. 10. Observability recovery processes (maximizing amount of observable power, 3 PMUs/step)

B. Maximization of the Number of Observable Branches

We also consider the case where the number of observable branches is taken as the metric for observability. Fig. 7 and Fig. 8 illustrate the simulation results for the three different algorithms, considering 1 PMU and 5 PMUs to be restored per step, respectively. All the curves of the random and greedy strategies are below the curves of the optimized strategy. For a better comparison, observability loss indexes, *S,* for the three algorithms are listed in Table I. It can be seen that the optimized strategy performs far better than the heuristics.

C. Maximization of the Observable Amount of Power

For the case of maximizing the amount of observable power, we simulated 4 cases: restoring 1 PMU, 3 PMUs and 5 PMUs per step after a full observability blackout, and restoring 5 PMUs per step after a partial (75%) observability blackout.

Figs. 9, 10, and 11 illustrate the cases of restoring 1 PMU, 3 PMUs and 5 PMUs per step, respectively, after a full observability blackout. The results for the case of 1 PMU per step are particularly interesting: compared with the optimized strategy, the greedy strategy brings slightly higher observability to the system during the first 3 steps, but starts to fall behind after the 4th step. Finally, the optimized algorithm achieves a much better performance over the entire restoration process compared to the greedy algorithm. Again, this owes to the fact that the greedy algorithm is only able to plan one step ahead instead of handling the problem in a global fashion. For the cases of 3 and 5 PMUs per step, the advantage of the proposed optimized strategy is even greater.

D. Maximization of the Amount of Observable Power

Comparing the results of maximizing observable power with the results of maximizing observable buses or branches, it can be found that curves for power are initially steeper; then, after several steps, they become "saturated." In contrast, the curves for the observable bus and the observable branch cases have relatively more stable slopes throughout the restoration processes. The reason is that each bus is typically connected to a limited number of buses and branches, and restoring one PMU cannot make a very large number of buses or branches observable. On the other hand, certain buses may have a very large amount of power flowing through them. As a result, with recovery of the observability of a bus handling a large amount of power, the curve will rise very quickly. After buses of this type are exhausted, the rate of recovery in terms of observable power will become slower.

We consider a case of partial blackout where 25% of the PMUs remain intact after the disaster, and 5 PMUs can be restored per step. As a result, 716.9 kVA of power is initially observable, and the observability of the remaining 3161.1 kVA of power needs to be recovered. As is apparent in Fig. 12, the optimized strategy completes observability recovery after 3 restoration steps, whereas the greedy and random strategies take 6 and 7 steps, respectively.

TABLE II
OBSERVABILITY LOSS COMPARISON FOR POWER INDEX

	Rand.	Greedy	Optimized	Optimized vs. Rand.	Optimized vs. Greedy
Full Blackout					
1 PMU/ Step	54437	24757	19177	-64.77%	-22.54%
3 PMUs /Step	20682	9359.6	6546.9	-68.35%	-30.05%
5 PMUs/ Step	12415	6781.1	4101.9	-66.96%	-39.51%
Partial Blackout (75%)					
5 PMUs/ Step	6848.4	2944.5	1360.5	-80.13%	-53.80%

TABLE III
TIME TO REACH HALF OBSERVABILITY AND FULL OBSERVABILITY

	Rand.	Greedy	Optimized	Optimized vs. Rand.	Optimized vs. Greedy
Half Observability Index *F* for 1 PMU/Step					
Bus	10	7.2	7	-30%	-2.78%
Branch	14	10.5	7.8	-44.29%	-25.71%
Power	12	3.3	3.2	-73.33%	-3.03%
Full Observability Index *H* for 1 PMU/Step					
Bus	37	37	20	-45.95%	-45.95%
Branch	37	37	20	-45.95%	-45.95%
Power	37	32	20	-45.95%	-37.5%
Half Observability Index *F* for 5 PMUs/Step					
Bus	2.2	1.65	1.5	-31.82%	-9.09%
Branch	2.8	2.2	1.6	-42.86%	-27.27%
Power	2.8	0.9	0.7	-75%	-22.22%
Full Observability Index *H* for 5 PMUs/Step					
Bus	8	7	4	-50%	-42.86%
Branch	8	8	4	-50%	-50%
Power	8	8	4	-50%	-50%

The observability loss indices T for the random, greedy, and optimized strategies are listed in Table II. Again, remarkable reductions of observability losses can be achieved by using the optimized strategy.

The half observability level indices F and the full observability level indices H for the random, greedy, and optimized methods are shown in Table III for comparing the different methods quantitively. It can be concluded from the comparisons that the proposed optimized algorithm recovers the full observability of the power system more rapidly than the heuristic methods.

E. Maximization of the Amount of Observable Power in Multiple-area Power Systems

We consider a case where the power system is partitioned into four areas, and the observability metric is the amount of observable power. For each area, the number of resources that can be used per restoration step are limited such that three areas can restore 1 PMU per restoration step, and the remaining one can restore 2 PMUs per restoration step. The simulation results of the the three strategies without partitioning and with partitioning are shown in Fig. 13. As can be seen from the figure, all strategies perform better without

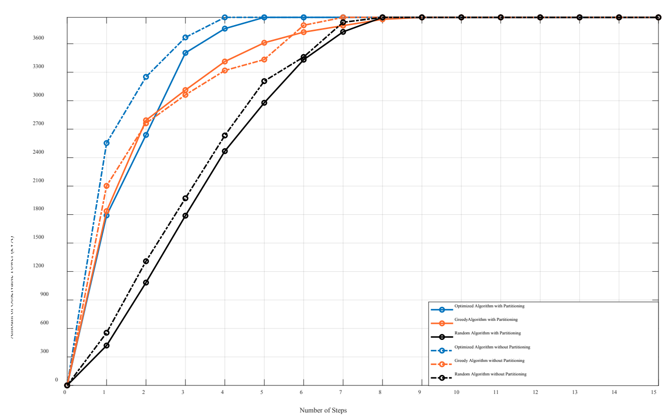

Fig. 13. Observability recovery processes (maximizing amount of observable power, 5 PMUs/Step, system partitioned into 4 areas)

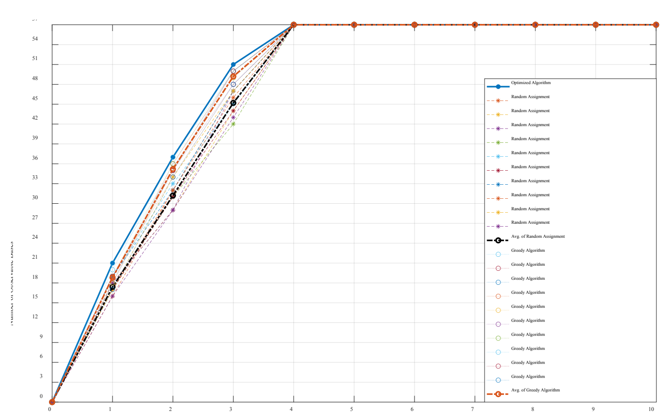

Fig. 14. Observability recovery processes (maximizing number of observable buses, 5 PMUs/step, 20 essential PMUs for heuristic methods)

partitioning compared to the respective curves with partitioning, which indicates that a slower restoration process will result after partitioning the system. This is because the algorithms are now forbidden to move restoration resources between different areas, which results in a local optimum within each area instead of a global optimum for the entire power systems. Under such condition, the optimized strategy is still able to improve the system observability upon the random and the greedy strategies.

F. Maximization of the Number of Observable Buses with Minimal Number of Candidate PMUs

The previous cases show the situation where the heuristic approaches do not have a priori knowledge about global system observability. Finally, we will examine the case where the greedy and random strategies have the a priori information of a minimum set of PMUs which can maintain system observability. With such knowledge in advance, the restoration process would be faster, in that all resources will be allocated to restore the PMUs belonging to this minimum set. The simulation results of this situation are shown in Fig. 14. In this case, it is assumed that 5 restoration resources can be used in each step, and a minimum set of PMUs which can recover full system observability, which obtains 20 PMUs, is found prior to the performing the greedy and random algorithms. From the observability curves shown in the figure, it is evident that although the number of steps required for all three strategies are the same (4 steps), the optimized strategy is still performing better than the heuristics strategies by optimal decision on the sequence of PMU restoration activities, which gains the highest level of observability during the restoration process.

V. Conclusion

In this paper, we develop the concept of observability recovery for power systems measured by PMUs after disastrous scenarios such as massive cyber attacks. We formally formulate the observability recovery (PMU restoration) problem as a MILP problem, and consider different objective functions for quantifying system observability level. The solution to the optimization problems will provide the locations of PMUs to be restored in a sequential manner, which will make the system reach a high observability level within a short period of time.

Through simulation results on the IEEE 57-bus system, we demonstrate that solving the formulated MILP problem provides the optimal strategy for the restoration process, which outperforms two heuristic methods, i.e., the greedy algorithm and random assignment methods.

The proposed algorithm can help recover the observability of the power system after cyber infrastructures of power systems are severely compromised, eventually helping to improve grid-wide situational awareness and the cyber-physical resilience of power systems.

Based on this work, one of the future research directions is the coordinated modeling of power networks and transportation networks, such that detailed models for the traveling of rescue teams between PMU locations can be accurately developed. Other important research topics for the future are to address both the cyber and physical power system restorations coordinately and to consider the detailed cost of PMU restoration.

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