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Research Article

A Methodology for Unified Assessment of Physical and Geographical Dependencies of Wide Area Measurement Systems in Smart Grids

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Abstract
Wide Area Measurement Systems (WAMS) enable both real time monitoring and the control of smart grids by combining digital measurement devices, communication, and control systems. As WAMS consist of various infrastructures, they imply complex dependencies among their underlying systems and components of different types such as cyber, physical, and geographical dependencies. Although several works exist in the literature that studies cyber dependencies, other types of dependencies such as geographical dependencies have not yet been studied. In addition, there is a lack of dependency modeling methodologies that simultaneously capture different dependency types for WAMS. The main goal of this paper is a simultaneous modeling of the geographical and physical dependencies of WAMS infrastructures based on simple and well-defined rules. We define a probability density function to quantify these dependencies. Such a unified approach may support the design of WAMS infrastructures that are more resilient inherently to disruptions caused by different kinds of the unwanted events that may affect geographically dependent WAMS components. Through simulations, we demonstrate the applicability of the proposed methodology.

Keywords: Wide Area Monitoring Systems, Infrastructure dependency, Physical dependency, Geographical dependency, Graph centrality metrics.

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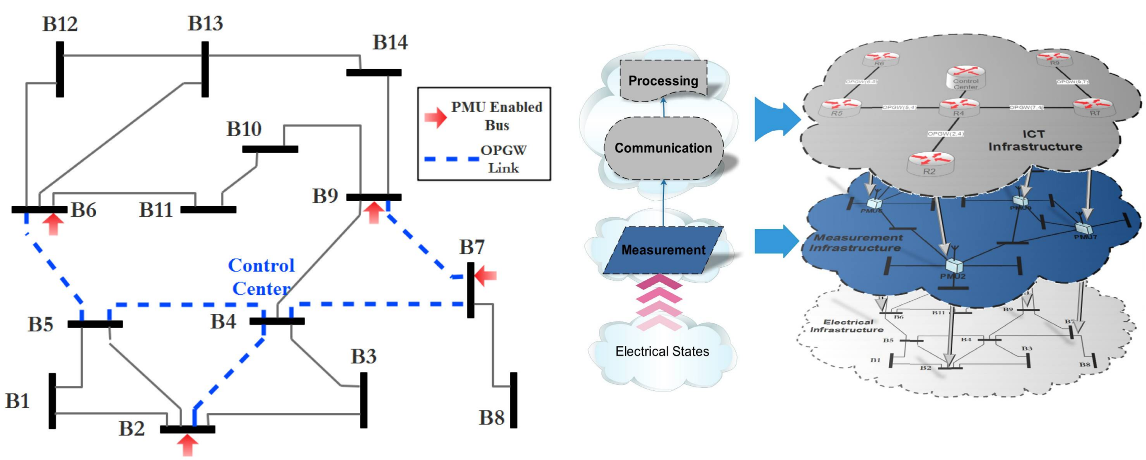
1. Introduction

A smart grid is a relatively new concept in the power system literature and refers to a modern electrical infrastructure which is equipped by digital measuring devices and high-speed/low-latency communication services for the purpose of the operation, monitoring, and control of such an infrastructure in awide geographical area [1-2]. "*Wide Area Monitoring Systems*" (WAMS) have been a new type of measurement system that is implemented in smart grids to achieve these goals [3-4].

In general, WAMS provides the ability to monitor, to protect, and to control a smart grid in a wide area by combining the capabilities of the new communication systems, digital measurement devices, and real-time actuators [3]. Normally, WAMS consist of three subsystems: measurement, communication, and processing sub-systems. The measurement subsystem is responsible for measuring system data at various and remote sites. In recent years, a new type of measurement system called "*Phasor Measurement Units*" (PMU here after) has been introduced which allows for the measurement of the system frequency and phasor synchronously in a wide geographic area. The communication sub-system conveys all measured data to a control center (or centers). Also, due to improved performance on this subsystem (speed increase and delay reduction), this subsystem has the ability to send control commands from the control centers to the actuators in real-time and near real-time fashion. The "*Optical Power Grand Wire*" (OPGW) is a particular optical fiber that is installed above the conductors of transmission lines and enables the simultaneous transmission of electrical energy and data on a single path [5]. Due to the high resolution of PMUs data, OPGW has been a preferable medium for PMU-based WAMS. The last one, the processing sub-system, has the task of receiving and processing data measured by the measurement subsystem using a software package tool called energy management system (EMS). The state estimation (SE) has been the main and the most important part of the EMS because this software package is receiving raw and noisy data of the measurement subsystem and provides a valid estimation of the system states (phasor and amplitude of buses' voltages). As a result, state estimation may be considered as the kernel functionality of EMS (also known as kernel of WAMS).

In the above-described sub-systems, the first two are geographically wide and distributed throughout the smart grid; the measurement sub-system has the task of data acquisition, while the communication sub-system is responsible for data transmission. Given this fact, it can be concluded that the implementation of smart grid in an electrical infrastructure indicates the implementation of two other infrastructures (i.e. measurement and communication) on this infrastructure. These three infrastructures of the smart grid (i.e. electrical, measurement and communication) are connected to each other in various points and receive service from each other. The infrastructure interconnection of WAMS is described in [1]. Fig. 1 depicts the cost-optimal WAMS for IEEE 14-Bus test system in Fig. 1(a) and its related infrastructures in Fig. 1(b).



(a) Cost-optimal WAMS for IEEE 14-Bus test system.

(b) Three infrastructures corresponding to cost-optimal WAMS of IEEE 14-Bus system.

Fig. 1: Cost-optimal WAMS for IEEE 14-Bus system and its corresponding three different infrastructures [1]

The connection between different infrastructures can be interpreted as an "*Infrastructure Dependency*"- i.e. the unidirectional relationship between two infrastructures (or components of an infrastructure) - where the state of one system influences or correlates with the state of the other [1]. "*Infrastructure Interdependency*" is a similar but bidirectional relationship between two infrastructures [6].

In general, there are four different types of infrastructure dependency [1, 6]: physical, geographical, cyber, and logical. The "*Physical Dependency*" occurs when an infrastructure is dependent on the product or service of another infrastructure. For example, active components (e.g. switches and routers) in communication infrastructure are supplied by electrical energy, so they physically depend on electrical infrastructure. The "*Geographical Dependency*" stems from the close spatial proximity of infrastructure components and is exhibited in events and occurrences (such as natural disasters or military and terrorist attacks on a site). For instance, the transmission line that is equipped with OPGW fiber has a geographical dependency between electrical and communication infrastructures. The "*Cyber Dependency*" exists when an infrastructure needs information for its proper functioning. It is obvious that the electrical infrastructure has a cyber dependency because without the data and information, the operation of this infrastructure is not possible. It is also clear that the "smartization" of the electrical grids, along with the creation of the above capabilities, greatly increases their cyber dependencies. Finally, if the two infrastructures are dependent on each other in a way other than three ways described above, this dependency is known as a "*Logical Dependency*".

By reviewing the three sub-systems of WAMS and also considering different types of the above mentioned dependencies, it can be observed that different kinds of dependencies (i.e. physical, geographical, and cyber) exist in WAMS. And although some types of dependencies have extensively been studied in the literature such as the cyber dependencies of smart grids, other types such as geographical dependencies have not received the same level of attention. The main motivation of this research is to examine concurrently the informational and geographical dependencies of WAMS infrastructures. In our previous work [7], an initial approach was presented to concurrently model the information and the geographical dependencies of WAMS. As in [7], again we treat information exchange as a product exchange among WAMS elements, which is modeled through physical dependencies. Here we extend this model to quantify the physical dependencies and to properly identify the existing geographical dependencies.

The rest of this paper is organized as follows: Section 2 describes WAMS and its implementation. Also, the components of WAMS are introduced in detail. Regarding the obtained information about WAMS in Sections 3.1 and 3.2 respectively, we propose physical and geographical dependencies of WAMS by applying different *Rules*. The 4-Bus sample network and two related WAMS of it will be examined in Section 5. Some graph centrality measures are introduced for the purpose of dependency analysis. Also the IEEE 14-Bus test network and its cost-optimal WAMS will be examined in this section. This paper will end with concluding remarks in Section 6.

2. Wide Area Measurement System

As discussed before, SE has been considered as the kernel of WAMS. "*Observability Analysis*" has been an important procedure closely related to SE since sometimes estimation is not possible due to lack of enough and sufficient measurements. There are two kinds of observability analysis [8-9]: *algebraic* and *topological*. In modern SEs phasor measurement unit (PMU), regardless of its high prices, is a preferable data resource, since the SE equations become linear in such a case [8-10]. Also topological observability of such a linear case can be easily examined by power grid's "*Adjacency Matrix*" [8-9].

It is previously mentioned that due to high resolution of PMUs, high-speed and low-latency communication media are required, and OPGW is the most preferable one regardless of its high price.

High prices of PMUs and OPGWs as well as their high installation cost have led system operators to design cost-optimal WAMS by the simultaneous placement of PMUs and their related OPGWs [4, 22]. In such a plan, PMUs and their related OPGWs are placed at the same time in the way that the entire system will be observable, and all PMUs belong to "*OPGW Connected Grid*".

Let the power system represents by graph $G_E\,(V_E, E_E)$, while V_E and E_E are its buses and transmission lines respectively. Such a graph can be represented by an adjacency matrix A. By changing all elements of the main diagonal to 1, generalized adjacency matrix ($\overset{+}{A}$) will be created. Hence, the following optimization problem can obtain the cost-optimal WAMS [1, 4, 22]:

$$\begin{cases} Min\ (\mathrm{cost}_{PMU} + \mathrm{cost}_{OPGW}) \\ s.t.\ \begin{cases} \overset{+}{A}.\vec{PMU} \geq \hat{1} \\ G_{CO}(V_{CO}, E_{CO})\, is\, connected \end{cases} \end{cases} \tag{1}$$

where, cost_{PMU} stands for the normalized value of the total cost for all PMUs and their installation, and cost $_{OPGW}$ represents the normalized value of the total cost for all OPGW links and their installation cost. $\vec{PMU}$ is a vector that shows the location of the PMUs in the relative system buses, (i.e. the PMU placement). Finally $\hat{1}$ is the n-dimension vector, all arrays of which equal to 1.

Actually in the optimization problem represented by Eq. (1), the first constrain is for system observability, while the second one guarantees that all PMUs belong to OPGW connected grid.

Indeed, for a power system presented by graph G_E (V_E, E_E), the above optimization problem forms a tree subgraph as the OPGW connected graph. In this study, such a subgraph is called as the "*Cost Optimal Subgraph*", denoted as G_{CO} (V_{CO}, E_{CO}). Therefore, in the case of using OPGW communication for PMU-based SEs, such a WAMS can be presented by three different items as follows:

$$\begin{cases} G_{CO}(V_{CO}, E_{CO}) \\ \vec{PMU} \\ \vec{PDC} \end{cases} \quad s.t. \begin{cases} V_{CO} \subset V, E_{CO} \subset E \\ G_{CO}(V_{CO}, E_{CO})\, is\ connected \\ \vec{PMU} \cup \vec{PDC} \subset E_{CO} \end{cases} \quad (2)$$

where in OPGW subgraph the V_{CO} is the set of system buses that should be equipped by routers, and E_{CO} is the set of transmission lines that OPGWs attach on them. $\vec{PMU}$ and $\vec{PDC}$ are vectors that show the locations of the PMUs and PDCs in the relative system buses-- i.e. the PMU and PDC placements in the $G_E(V_E,E_E)$.

2.1. WAMS Components and Abbreviation

As discussed before, WAMS consists of three different infrastructures (i.e. electrical, measurement, and communication) which are dependent and interdependent in different fashions. To simplify, we have used the following abbreviations for components of each infrastructure:

1) Electrical Infrastructure:
- $\mathcal{S}_i$: The state of the i^{th} bus.
- $i\mathcal{L}j$: The transmission line between i^{th} and j^{th} buses.

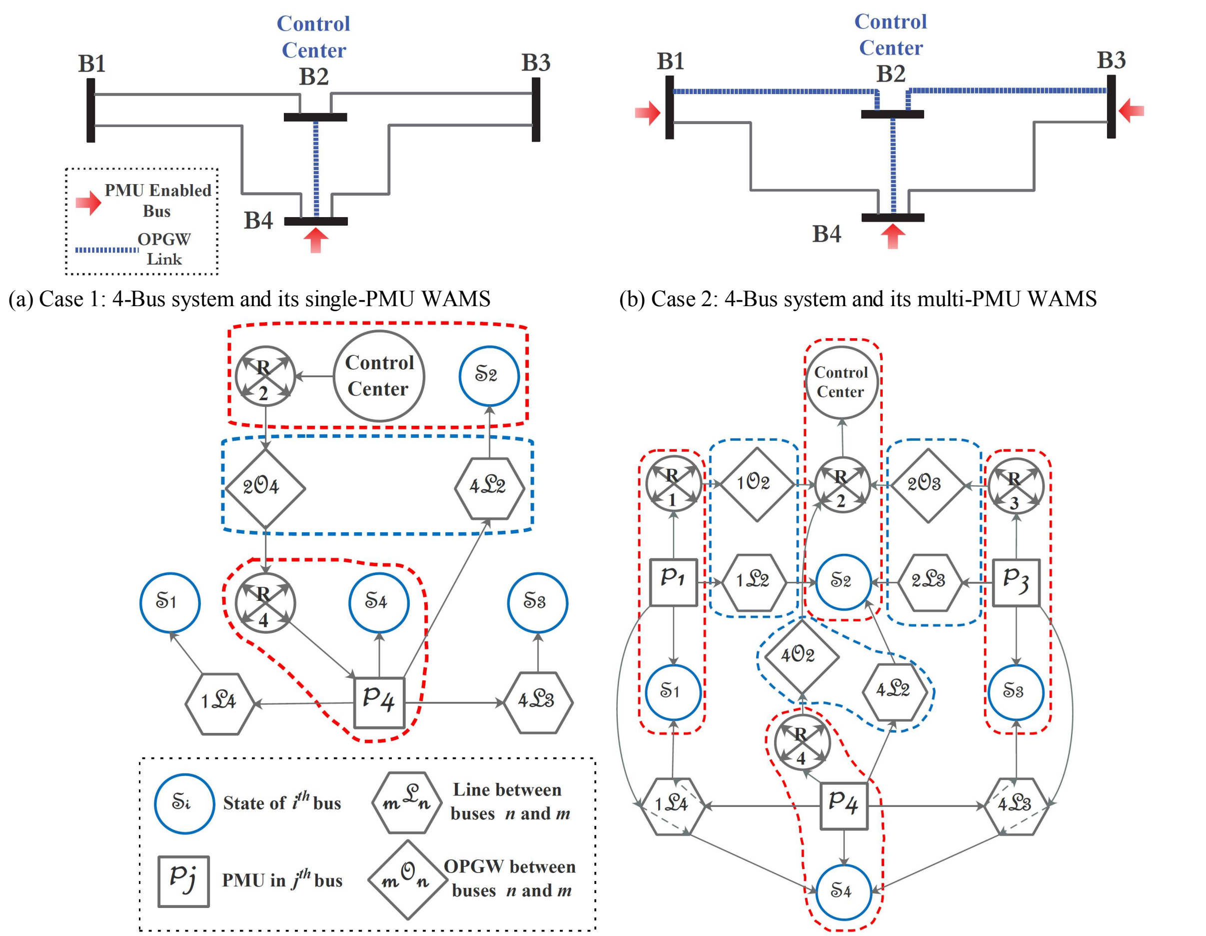
2) Measurement Infrastructure:
- $\mathcal{P}_j$: The PMU located at the j^{th} bus.
- PDC_k: The PDC located at the k^{th} bus.

3) Communication Infrastructure:
- $\mathcal{R}_i$: The router of i^{th} bus.
- $i\mathcal{O}j$: The OPGW fiber link installed between i^{th} and j^{th} buses.

Note that in the case of using single PDC in the WAMS, it is possible to consider such a component as the part of communication infrastructure.

3. Constructing WAMS Dependency Graph

After defining all WAMS components in different infrastructures (Section 2.1), *WAMS dependency graph* $\mathcal{G}$ ($\mathcal{V}$, $\mathcal{E}$) can be constructed, where $\mathcal{V}$ is set of its nodes and $\mathcal{E}$ represents its edges. We have specified all WAMS components in Section 2.1, and they are considered as $\mathcal{V}$-- i.e. nodes of dependency graph.



(a) Case 1: 4-Bus system and its single-PMU WAMS

(b) Case 2: 4-Bus system and its multi-PMU WAMS

(c) Graph 1: All dependencies of single-PMU WAMS

(d) Graph 2: All dependencies of multi-PMU WAMS

Fig. 2: 4-Bus sample system and its two different WAMSs and their overall dependencies

The next step is to specify the edges of dependency graph denoted by $\mathcal{E}$. In this work we are concerned with the correlation between geographical and physical dependencies. Hence $\mathcal{G}$ will capture these types of dependencies. In the dependency graph, the physical dependencies between will be defined as the edges of $\mathcal{G}$. As physical dependency is a directional relation between two elements, the members of $\mathcal{E}$ are directional and, thus, $\mathcal{G}$ ($\mathcal{V}$, $\mathcal{E}$) is a directional graph. In Sections 3.1, we will define all physical dependencies of WAMS by simple rules and, thus, $\mathcal{E}$ will be obtained. Finally, the co-location of elements of $\mathcal{G}$-- i.e. the members of $\mathcal{V}$ and $\mathcal{E}$-- can define geographical dependencies of WAMS as it will be described in Section 3.2.

3.1. Physical Dependencies of WAMS

In power system graphs represented by G_E (V_E, E_E), let PMU_i to be installed in i^{th} bus (i.e. $\mathcal{P}_i$) with m_i=*degree* (v_i) adjacent links. The installed PMU has one voltage channel and m_i current channels. Let V_i represents phasor voltage of i^{th} bus (i.e. S_i), and V_j ; j=1,...,m_i stand for the phasor voltage of all adjacent links (i.e. S_j ; j=1,...,m_i).

The PMU_i directly measures the state of i^{th} bus (i.e. V_i) via voltage channel. The states of m_i adjacent links can be calculated as follows:

$$V_j = V_i - X_{ij} . I_{ij} , \qquad j = 1, \cdots, m_i \tag{3}$$

where I_{ij} stands for the current phasor of j^{th} adjoint link measured by j^{th} PMU voltage channel, and X_{ij} is the admittance value of this link.

Actually, in Eq. (3), V_i (i.e. S_i) is measured by installed PT on i^{th} bus, and for each j= {1,..., m_i} the measured value I_{ij} (i.e. S_j) comes from CT which is installed on ($i\mathcal{L}j$).

3.1.1. Physical Dependency in WAMS Measuring

In this sub-section, we aim to capture all physical dependencies between system states and PMUs. With regard to Eq. (3) and based on the definition of physical dependency, for a PMU-enabled bus (PMU_i) the following physical dependencies can be extracted as follows:

- ***Rule I***: State of i^{th} bus depends on $\mathcal{P}_i$.
- ***Rule II***: State of each adjoin bus, j connected to i, firstly depends on the transmission line between i and j ($i\mathcal{L}j$) and secondly depends on $\mathcal{P}_i$.

For clarification, see 4-Bus sample case shown in Fig. 2(a). There is only one PMU in the system which is installed in bus 4. Based on the aforementioned rules defined for physical dependency of WAMS measuring, the state of bus 4 directly depends on $\mathcal{P}_4$, while the states of other buses firstly depend on the links that are installed between these buses and $\mathcal{P}_4$, and finally all remaining states depend on $\mathcal{P}_4$. Described dependencies are depicted in Fig. 2(c).

3.1.2. Physical Dependency in WAMS Communication

After acquiring the required data for system states by PMUs, such data should be transmitted to the PDC(s) located in the control center(s). The OPGW connected grid (referred to G_{OPG} (V_{OPG}, E_{OPG}) hereafter), which consists of OPGW fiber links E_{OPG} and routers $V_{OPG,}$ is responsible for data delivery from PMUs to PDC(s). We define "*Forward Path*" for the modeling of dependency in WAMS communication. The forward path (fp_{ik}) is a path between state of i^{th} bus and k^{th} PDC.

Based on above-mentioned description, the following dependencies can be defined:

- ***Rule I***: The $\mathcal{P}_i$ depends on the router $\mathcal{R}_i$.
- ***Rule II***: The router $\mathcal{R}_i$ depends on its next-hop router.
- ***Rule III***: In a forward path for $\mathcal{P}_i$, each router depends on its next-hop router.
- ***Rule IV***: Finally, PDC_k depends on the router $\mathcal{R}_i$.

It is worth noting that in the case of designing a tree as OPGW grid (e.g. cost optimal OPGW grid), there is only one forward path for each PMU to PDC. Also, it is possible that a WAMS has more than one PDC (aka control center). In such cases, based on the number of bidirectional OPGW link, more than forward path may exist for some PMUs.

3.2. Geographical Dependencies of WAMS

In general, geographical dependencies of WAMS can be classified as: "*Site Dependency*" and "*Path Dependency*". The site dependency occurs when two or more components of WAMS are located at the same site. The path dependency, as its name implies, happens when two or more WAMS links are installed at the same path. Regarding the aforementioned definitions, one can obtain the following geographical dependencies:

- ***Rule I***: For i^{th} bus as a PMU-enabled bus, the state S_i, $\mathcal{P}_i$ and the router $\mathcal{R}_i$ have site dependency.
- ***Rule II***: For j^{th} bus as a communication-enabled bus, the state S_j and the router $\mathcal{R}_j$ have site dependency.
- ***Rule III***: For the control center which is located in k^{th} bus, the state S_k, the router $\mathcal{R}_k$, and PDC_k have site dependency.
- ***Rule IV***: The transmission line between i^{th} and j^{th} buses ($i\mathcal{L}j$) and the installed OPGW fiber link between those ($i\mathcal{O}j$) have path dependency.

Actually, both of the above geographical dependencies (i.e. site and path) are caused by intersection among the electrical graph represented by G_E (V_E, E_E), the OPGW subgraph represented by G_{OPG} (V_{OPG}, E_{OPG}), and the location of PMUs and PDCs which are respectively represented by $\vec{PMU}$ and $\vec{PDC}$. For instances, ***Rule I*** is obtain from $V_E \cup V_{OPG} \cup \vec{PMU}$, while ***Rule IV*** is obtained from $E_E \cup E_{OPG}$.

4. Quantifying Dependency Level

After constructing WAMS dependency graph, we graph centrality metrics which will be defined in order to measure the dependencies. Various types of centrality metrics exist [11]. "*Degree*" centrality is the simplest centrality metric, and it represents the connectivity of a node to the rest of the network. "*Betweenness*" centrality indicates whether a node is between many pairs; "*Closeness*" indicates whether a node tends to be close with many others, and "*Eigenvector*" shows the importance of neighboring nodes.

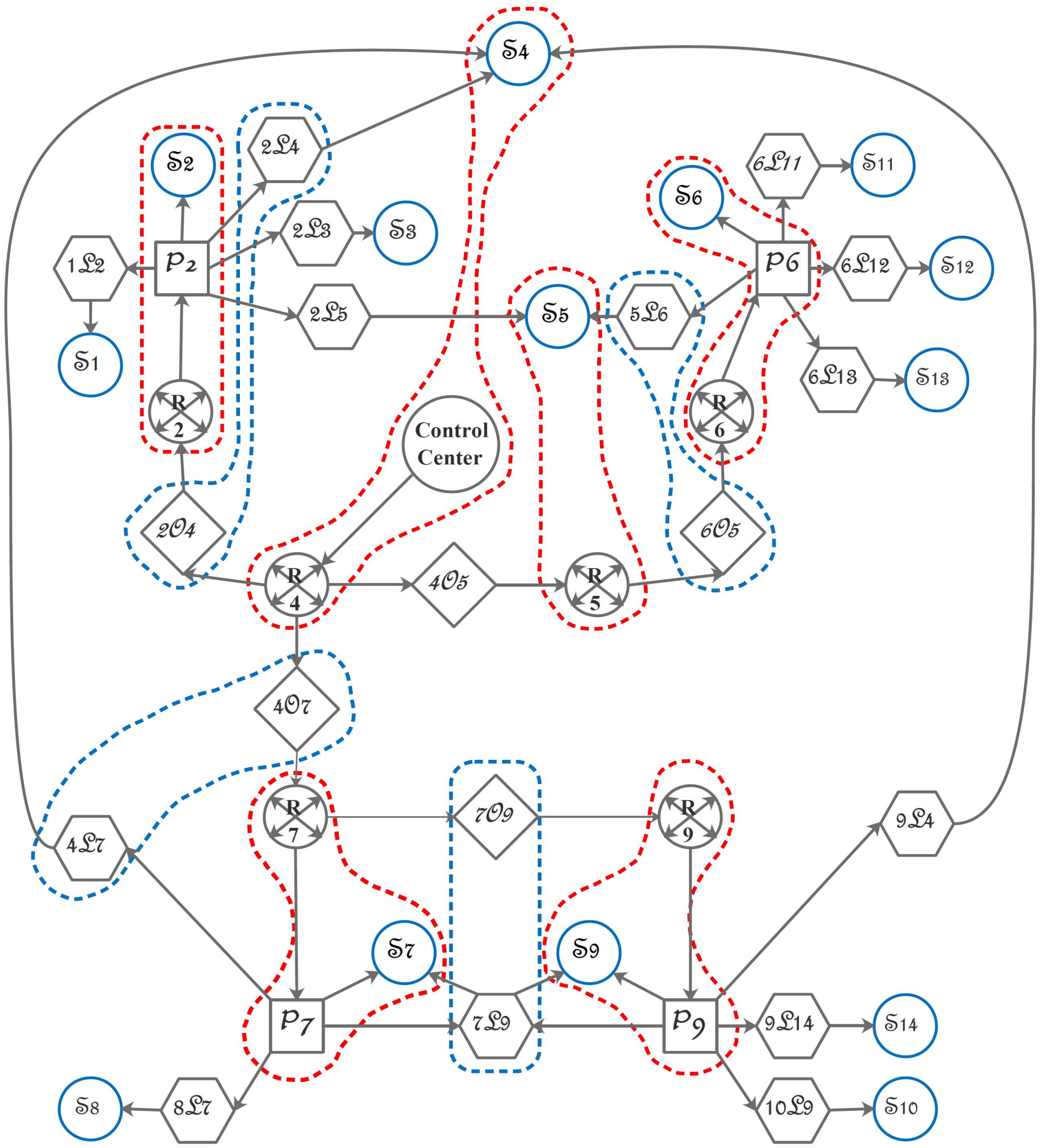


Fig. 3: Overall dependencies of cost-optimal WAMS for IEEE 14-Bus system

Using centrality measures for dependency analysis is not a new idea [1], [12-17]. In [14], in order to specify nodes that significantly impact the overall dependency risk, the relationship between dependency risk paths and graph centrality measures has been explored. There, the ability of centrality measures has been shown. In [1], we have examined all the centrality measures for dependency graph of WAMS, and the result has been revealed that degree is the most appropriate from the centrality metrics, to capture the importance of WAMS elements in dependency chains.

According to [14], degree centrality measures the number of edges attached to each node. For a unidirectional graph G (V, E) with N vertices, degree centrality is defined as:

$$deg(v) = N(v) \quad (4)$$

where, $N(v)$ is the set of direct neighbors of vertex v.

For directed graphs, two variants of the degree centrality are defined: "*indegree*" $deg^-(v)$ is the number of incoming edges at vertex v, while "*outdegree*" $deg^+(v)$ is the number of outgoing edges that originate from vertex v.

As mentioned before in the dependency graph, the components are expressed by the nodes, while dependencies are represented by directional edges. It has already been mentioned that different types of degree measure are able to count different types of edges for a node. Therefore, degree centralities have been frequently utilized as dependency measures in researches [1], [13-14].

In the dependency graph, there are some definitions based on degree centralities [18]: Nodes with high indegree centrality are known as "*Cascade Resulting*" nodes (also referred to as "*sinkholes*" according to [14]), while nodes with high out degree centrality are known as "*Cascade Initiating*" nodes.

Degree centrality can also be extended to power networks as follows [19]:

$$C_{d_Y}(v) = \frac{\|Y(v,v)\|}{n-1} \quad (5)$$

where $C_{dY}(v)$ in electrical degree centrality of v^{th} bus, $Y(v,v)$ is the diagonal elements of the v^{th} entry in the network admittance matrix, and n is the size of power network.

Having different types of degree centralities, now we are able to define a measure to capture the dependency of a sinkhole node in a dependency graph.

Based on the rules for physical dependency of WAMS measuring described in Section 3.1.1, the state nodes ($\boldsymbol{S}_i$) are sinkholes since they depend on their related measuring units (i.e. $\mathscr{P}_i$). For v^{th} bus, the number of observations of $\boldsymbol{S}_v$ is specified by its indegree centrality-- i.e. $deg^-(v)$. Therefore, higher $deg^-(v)$ measure for a node implies lower dependency due to having more redundant measuring units for this node. Based on topological observability definition, indegree centralities of all system states can be obtained as follows:

$$\overrightarrow{deg^-} = \overset{+}{A}.\overrightarrow{PMU} \quad (6)$$

where $\overrightarrow{deg^-}$ is n-dimensional vector that represents indegree of all states in the dependency graph. Based on the above description, a system is fully observable if and only if there is no any zero element in $\overrightarrow{deg^-}$.

On the other hand, buses in a power grid and accordingly their states have different levels of importance due to the structure of such a grid. We previously examined different approach to define the importance metric for system buses in [1], and structural importance is chosen. *Structural importance*, as its name implies, only considers the structure of the power grid as a complex network. As electrical degree centrality $C_{dY}(v)$ represents the electrical connectivity of a node to the rest of the power grid; it is considered as structural importance of a node in the power grid [1].

Considering all above facts, for the state of v^{th} bus represented by $\boldsymbol{S}_v$, the dependency measure is defined as follows:

$$C_{DEP}(v) = \frac{C_{d_Y}(v)}{deg^-(v)} \quad (7)$$

where $C_{DEP}(v)$ is dependency measure, $C_{dY}(v)$ and $deg^-(v)$ are electrical degree and indegree centralities for $\mathscr{B}_v$ and $\boldsymbol{S}_v$ respectively.

Using Eq. (6), n different dependency measures ($C_{DEP}(v)$ v=1, 2,..., n) will be obtained for n-bus power grid. For a dependency graph $\mathcal{G}$ ($\mathcal{V}$, $\mathcal{E}$), a quantified level of dependency can be obtained by histogram of dependency measures and the fitted *Beta distribution*. The Probability Density Function (PDF) for a Beta X~Beta(a,b) is [20]:

$$f_X(x) = \begin{cases} \frac{1}{\mathrm{B}(a,b)} x^{(a-1)}(1-x)^{(b-1)} & 0 < x < 1 \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

where, $\mathrm{B}(a,b) = \int_0^1 x^{(a-1)}(1-x)^{(b-1)}dx$

Actually, Beta distribution is expressed by two different values (i.e a and b), and, consequently, it has more flexibility in distribution fitting. This approach will fully be discussed in the next Section.

5. Simulation Results

In this section, we will show the ability of the proposed method to construct the overall dependencies of WAMS. To do this, we first examine a simple 4-Bus network with two different WAMS in Section 5.1. We also fully describe the steps to obtain physical and geographical dependencies in this sample case. Finally, in order to show the ability of the proposed method for real cases, the IEEE 14-Bus test case will be examined in Section 5.2.

5.1. Small sample Case

To clarify WAMS, we consider a small 4-Bus sample test system, and two different WAMS cases are designed for this case. The central control center (i.e PDC) location is *a priori* defined and considered to be in the bus 2. **Case 1** is a single-PMU WAMS which is consist of only one OPGW link, while **Case 2** is a multiple-PMU WAMS with many measurement redundancies and their required OPGW links. In order to construct the WAMS dependency graph, the following steps have sequentially been undertaken:

5.1.1. Constructing Physical Dependencies

Based on the method proposed in Sections 3.1, the dependency chains start from the system buses. Therefore, in the first step of dependency modeling for *n*-bus power grid, *n* states should be considered as the end points of dependency chains. Then, using the rules introduced in Section 3.1.1 and based on the PMU vector (i.e. $\vec{PMU}$), all physical dependencies among system states and PMUs can be constructed. In the next step, based on the rules introduced in Section 3.1.2 and based on G_{OPG} (V_{OPG}, E_{OPG}) subgraph and $\vec{PDC}$, the dependencies of the communication infrastructure of WAMS can be obtained. Finally, based on $\vec{PDC}$, the start points of physical dependency chains-- i.e. PDCs-- can be specified.

Note that in the case of using multiple PDC in the WAMS, the information flow among PMUs and PDCs should be defined in the direction of G_{OPG} (V_{OPG}, E_{OPG}) subgraph. The simplest case is a single-PDC WAMS, which has atree structure for G_{OPG}. The communication loop (i.e. non-tree structure of G_{OPG}) can also be captured by the method proposed in Section 3.1, but if the power network size increases, such a modeling will be very complicated and difficult.

5.1.2. Constructing Geographical Dependencies

After constructing physical dependencies, the overall structure of the dependency graph will be determined. Now, it is possible to determine the geographical dependencies of the WAMS by using rules described in Section 3.2.

Three kinds of site dependency may exist in the WAMS which are defined by ***Rule I*** to ***Rule III***. Intersections of $V_E \cap V_{OPG} \cap \vec{PMU}$, $V_E \cap$ (V_{OPG}- $\vec{PMU}$), and $V_E \cap V_{OPG} \cap \vec{PDC}$ specify such dependencies. Finally, intersection of $E_E \cap E_{OPG}$ obtains the path dependencies, which is previously described in ***Rule IV*** in Section 3.2.

Using the above mentioned steps, the overall physical and geographical dependencies of both WAMSs are obtained and depicted in figures 2(c) and 2(d). The site dependencies are specified by red-dash lines, while path dependencies are specified by blue-dash lines.

As it can be observed in both dependency graphs, in general, an increase in the size of $\vec{PMU}$ (i.e. number of installed PMUs) causes an increase in the number of site dependency. Also, it can be seen that an increase in size of G_{OPG} (V_{OPG}, E_{OPG}) causes an increase in the number of path dependency.

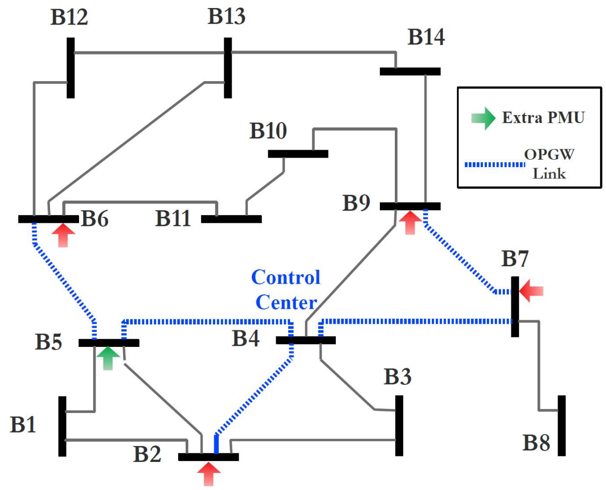


Fig. 4: Modified WAMS for IEEE 14 bus test system with one extra PMU

5.2. IEEE 14-Bus Test System

In order to show the ability of proposed method, the overall dependencies of cost-optimal WAMS for IEEE 14-Bus system (depicted in Fig. 1(a)) will be obtained in this section. The obtained overall dependencies are depicted in Fig. 3.

As it can be seen in the Fig. 3, the state of bus 4 is the sinkhole with a maximum number of indegree, and, thus, it can be considered as a state with the lowest physical dependency. This fact is clear since bus 4 is observed by three PMUs. Also, PMU 2 and 6 are considered the PMUs with highest physical dependency since their outbound degree value is equal to 5. This is also clear as such since a PMU with more measurement channels has more important role in the WAMS, which means such a PMU has more physical dependency.

In order to show the ability of proposed method for quantifying dependency level of the WAMS in Section 4, we examine two different WAMS. One (case 1) is the cost optimal WAMS depicted in Figure 1(a). Another is the modified version, which is equipped by one extra PMU in bus 5. Indeed, we add measuring redundancy in second case (case 2), and we aim to show the improvement of dependency measures in the case of having measurement redundancy. Figure 4 shows the modified WAMS.

The electrical degrees of IEEE 14-Bus test system are previously presented in [1]. Note that we normalize electrical degrees by dividing all values by the largest electrical degree and, thus, all electrical degrees have a value between 0 and 1 (see the left column of Table 1). Also indegree centralities of all sinkholes in both cases can be obtained by Eq. (6). Having indegree and electrical centralities for all buses, one can obtain dependency measures of all system states for two cases by using Eq. (7). The results are shown in Table 1. As it can be seen in the results, adding an extra PMU reduces the dependency measures of the WAMS.

For the comparing of case 1 and case 2, the histograms and fitted Beta distributions are respectively depicted in Fig. 5(a) and Fig. 5(b). As it can be seen, by adding an extra PMU the density of dependency measures becomes higher in low values since the mean value of fitted beta distributions changes from μ_1=0.340469 in case 1 to μ_2=0.255628. Also, the "*log likelihood*" of fitting is better in case 2, and this shows the improvement of overall dependency.

Table 1: Dependency measures and their fitted beta distribution for two variations of WAMS

Bus No.	$C_{dY}(v)$	Case 1		Case 2	
		$d^-(v)$	$C_{DEP}(v)$	$d^-(v)$	$C_{DEP}(v)$
1	0.5579	1	0.5579	2	0.2789
2	0.7503	1	0.7503	2	0.3751
3	0.3688	1	0.3688	1	0.3688
4	1.0000	3	0.3333	4	0.2500
5	0.9739	2	0.4869	3	0.3246
6	0.3947	1	0.3947	2	0.1974
7	0.4361	2	0.2181	2	0.2180
8	0.1867	1	0.1867	1	0.1867
9	0.4385	2	0.2193	2	0.2193
10	0.3135	1	0.3135	1	0.3135
11	0.2352	1	0.2352	1	0.2352
12	0.1742	1	0.1742	1	0.1742
13	0.2583	1	0.2583	1	0.2583
14	0.1764	1	0.1764	1	0.1764
Beta Distribution Parameters		a=2.9303 b=5.6763		a=11.6662 b=33.9712	
		μ=0.340469 σ^2=0.0233747		μ=0.255628 σ^2=0.00408004	
		Log likelihood: 6.86278		Log likelihood: 18.785	

6. Conclusion

Modern WAMS infrastructures inherently create complex interdependencies between electrical, measurement, and communication components, effected by the informational flows and physical (electrical) flows among those systems as well as their geographical co-location. The cyber (inter)dependencies among WAMS components have received more attention than other types of dependencies since the cyber connectivity and control enables various cyber attacks against the smart grid (e.g. [21]). However, in order to increase the resilience of WAMS against all types of unwanted events, there is a need to model all types of dependencies in a unified way.

By "relaxing" the geographical dependencies of WAMS components, the system can be inherently designed to be more resilient to natural disasters. This can be implemented for example by removing or reducing the dependencies of WAMS components in an area that is more prone to physical disasters such as earthquakes or fires. In the same way, by relaxing or distributing the physical dependencies among the sub-systems, the WAMS infrastructure may be inherently more resilient to system faults, e.g. by applying controlled redundancy in measuring and/or communication devices.

By defining a set of simple sequential rules for physical and geographical dependencies and by applying those rules in a simple test scenario, we have demonstrated that a unified modeling of all types of WAMS dependencies is possible. Those rules try to capture and model the geographical and physical dependencies among the electrical, measurement, and communication components of WAMS.

In the future, our goal is to define ways to quantify those relations and utilize them in designing resilient WAMS infrastructures by extending our previous approach [1] that currently considers cyber dependencies only.

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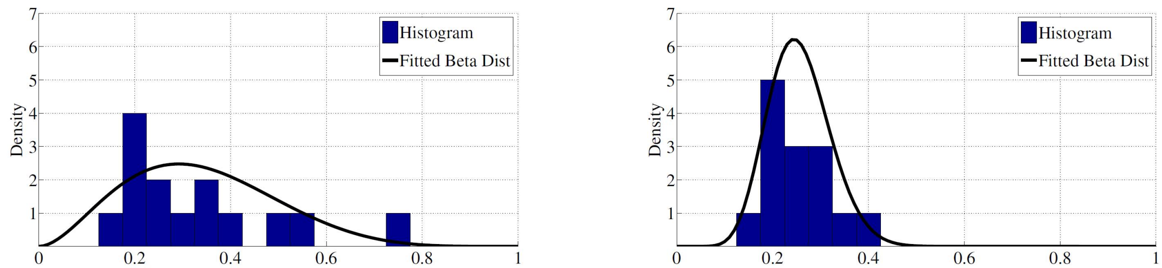

(a) Histogram of C_{DEP} and fitted Beta distribution for cost-optimal WAMS of IEEE 14 bus shown in Fig 1(a).

(b) Histogram of C_{DEP} and fitted Beta distribution for cost-optimal WAMS of IEEE 14 bus modified with an extra PMU in Fig 4.

Fig. 5: Histograms and fitted PDFs of C_{DEP} for two variations of WAMS of IEEE 14 bus test case depicted in Figures 1(a) and 4

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