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A Novel Multi-Area Distribution State Estimation Approach with Nodal Redundancy

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Abstract: State estimators based on load flows and applied in electrical power systems (EPS) are a basic and crucial function in energy management systems (EMS), since they must guarantee the quality of their results for decision-making. In this research, we propose a new method for partitioning an electrical system within distributed estimation processes. This method is developed under the concept of nodal redundancy and considers the number of measurements associated with each bus of the electrical system. By distributing the measurements in subsystems, such that each redundancy is evenly distributed, the proposed method aims to improve the performance of both centralized and distributed estimation techniques developed in the literature. We evaluate the proposed method by using the IEEE 14-bus and IEEE 118-bus systems, considering several operating cases and a wide array of measurements of the electrical power system. Results demonstrate the quality of the estimate and the processing time for both traditional and distributed estimates under the proposed methodology.

Keywords: partition; distributed state estimation; measurements; redundancy; nodal grouping

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1. Introduction

The continuous interconnection of electrical power systems, the new generation technologies, the new FACTS technologies, the new developments in measurement systems (PMU), and the need to satisfy a continuously growing demand has forced the evolution of energy management systems (EMS), which must comply with safety and reliability indices to guarantee the continuous operation of the system. The key role of energy management systems (EMS) lies in their ability to provide real-time knowledge of the electrical system's situation, which enables the system operator (SO) to make decisions to prevent disruptions in the operation and/or blackouts in the electrical network [1]. Based on the information provided by an EMS, the main function of the SO is to maintain the system's security, ensuring that all demands are supplied with energy according to a generating park without violating the operating limits such as the capacities of the transmission lines, voltage limits, and generation limits [2,3]. For the system monitoring process, a state estimator (SE) is one of the fundamental tools used to determine or approximate the optimal value of a deterministic or random variable that, due to its nature, often cannot be captured using a measurement system [4]. State estimators applied to electrical power systems play an essential function in the energy industry, as the estimation is relevant for understanding the state of the system [5]. The centralized approach called weighted least squares (WLS) has been the technique most widely used and is based on a non-linear measurement model. In recent years, phasor measurement units (PMU) have been introduced within the measurement process to provide voltage and current phasors, where the linearized measurement model reduces the complexity of the calculation [6,7].

In this context, a state estimation process is a tool that provides reliable information for the operation of an electric power system (EPS), calculating in real time the best estimate of the current situation of a system. To carry out this task, it is necessary to acquire and process large volumes of information in a control center, which increases the cost of the economic and computational resources available [8]. A good estimation of the state improves the supervision and control of an electrical power system, it being necessary to consider an estimation criterion, redundancy of the measurements, and the probability distribution of random errors. A state estimator is a basis within the operation and control of the electrical system; it allows for performing tasks such as economic dispatch (ED), automatic generation control (AGC), automatic voltage control (AVC), stability analysis of voltage, security analysis (SA), and power transactions between remote locations separated by one or more control areas [9–11].

The architecture of state estimators has evolved with the development of new algorithms, which may be classified into centralized, hierarchical, and distributed models. In the centralized estimation model, a single control center processes all the existing measurements in an EPS, providing the estimation of the state variables of the entire network. In the 1980s, the first hierarchical estimation techniques were formulated [12,13]. Cutsem and Ribbens proposed a hierarchical estimation method for a multitasking electrical system, which develops a local estimate (first level of hierarchy), and then coordinates at a higher level [14]. However, to obtain a global estimate, this technique requires a centralized coordinator [11].

Centralized and hierarchical approaches to condition estimation can suffer from bottlenecks and reliability issues because the measurements are traditionally captured by a supervisory and data acquisition (SCADA) system, presenting intrinsic limitations, that is, low sampling rate and precision of the measurements that reduce the reliability of the estimation process. In modern EPSs, the integration of fast processing devices is more frequent, such as phasor measurement units (PMU), which makes possible a linear state estimation [15–18]. However, high investment costs are a limitation of having a PMU in each local area. Second, the politics and market price competition in certain systems require utility companies to share more information and monitor the power grid in large-scale areas [19].

The distributed state estimation model considers a system partition, without losing the physical link through its transmission system and continuous information communication from neighboring measurements [4,10]. Under stationary operating conditions, the power system is treated as a quasi-static system whose operating condition is fully characterized by variables, such as bus loads, line fluxes, generation, and bus voltages at the same instant of time. Among these interdependent variables, the bus phasor voltages $[\boldsymbol{V},\boldsymbol{\theta_0}]$ can be chosen as the system's state vector [20]. Many studies have addressed distributed static estimation problems; in [21], a weighted least squares (WLS) estimation method is proposed for the estimation of the static state with the property that the local estimates converge to the same estimates obtained through a centralized estimator. In this scheme, each local estimator needs to know its local measurements and border information from neighboring nodes, which implies a higher communication load.

The partition of networks and data packets is not new in the scientific literature; Kron and Happ were pioneers in the study of diakoptica under the premise of resolving large systems into small systems, which emphasizes the importance of reducing the associated computational processes, with large-scale systems analysis [22].

There are several approaches to divide an electrical system into subsystems or areas of operation, allowing operator to determine control areas for reactive energy markets and areas or zones for evaluating voltage safety [5,12,17,23]. Within the partition of a large-scale electrical system, the location of the PMU determines the reference bars. This allows a parallel process of the areas; however, it is important to guarantee the precision of the results [9]. Li et al. [24] proposed a hierarchical clustering method that characterizes the active and reactive power mismatch between zones. Recent studies have shown that the partitioning of an EPS facilitates the integration of renewable sources [25].

In this article, a new partition scheme for the distributed state estimation process is proposed. The proposed partitioning method is based on the concept of nodal grouping, where the number of measurements associated with a node determines the areas or subsystems, regardless of the number of physical elements that constitute it, such as bus, lines, generators, and loads. As a metric, the redundancy of the area or subsystem is calculated in the partition process; the proposed approach guarantees that the systems comply with the principle of observability, a necessary condition in the estimation. From the results, it is expected to improve the processing time of a distributed state estimate as compared to a centralized estimate and to reduce the mean square error of the state variables.

In the MATLAB (Mathworks, Inc., Natick, MA, USA) environment, a code was developed for the process of partitioning an electrical power system, which allows determination of the number of state variables, measurements, and elements per subsystem, as well as the redundancy of each one of them.

The article is organized in the following fashion. Firstly, Section 2 describes the proposal for partitioning an electrical power system by means of nodal grouping. Secondly, Section 3 develops the model in the distributed state estimation process for a large-scale system. Then, the simulation results for different proposed scenarios are presented in Section 4, and the discussion and conclusions are summarized in Section 5.

2. Nodal Grouping

Clustering is a technique that associates items that generally have similar characteristics. Among the clustering techniques developed, we have the K-mean, electrical distance, spectral clustering, or hierarchical clustering algorithms [9,23,26–28]. The proposed nodal grouping method is based on the set of measurements associated with the bus of an electrical system. What is sought with this estimation model is to build areas or regions of the system where there is a distribution of the measurements so that the redundancy of its regions is as homogeneous as possible.

The principle of nodal grouping consists of determining the belonging of the measurements to a specific bus; under this consideration, we must establish two types of measurements, bus measurements ($\boldsymbol{M_B}$) and line measurements ($\boldsymbol{M_l}$). Figure 1 presents the physical arrangement of measurements in an electrical system.

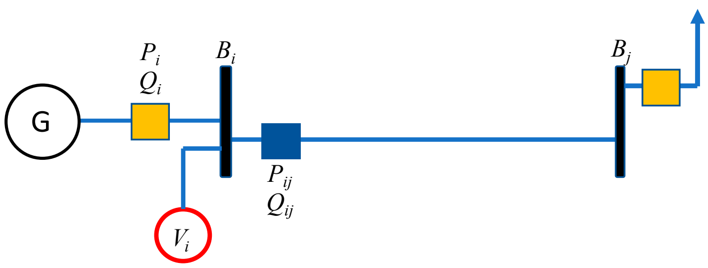

Figure 1. Electrical layout of the set of measurements associated with a bus.

In $\boldsymbol{M_B}$ measurements, those that are connected directly to the system bus are subdivided into two types, corresponding to voltage measurements ($\boldsymbol{M_V}$), and active power P ($\boldsymbol{M_P}$) and reactive power Q ($\boldsymbol{M_Q}$) injection measurements, which are connected between a generator and bus or a load and a bus. So, for the $\boldsymbol{i}$-th bus, we have:

$$\boldsymbol{M_{Bi}} = \begin{cases} \boldsymbol{M_{Vi}} \\ \boldsymbol{M_{Pi}} \\ \boldsymbol{M_{Qi}} \end{cases} \tag{1}$$

The measurement data defined as $\boldsymbol{M_l}$ are the active y reactive power flow measurements between node $\boldsymbol{i}$ and node $\boldsymbol{j}$, and the membership of the measurement will be established with the closest bus under the following consideration:

$$\boldsymbol{M_l} = \begin{cases} \boldsymbol{M_{Pij}} \in \boldsymbol{B_i} \\ \boldsymbol{M_{Qij}} \in \boldsymbol{B_i} \end{cases} \tag{2}$$

Therefore, the set of total measurements associated with bus $\boldsymbol{i}$ is as follows:

$$\boldsymbol{M_i} = \boldsymbol{M_{Bi}} + \boldsymbol{M_{Li}} \tag{3}$$

Based on the above categorization, the concept of nodal grouping determines redundancy ($\boldsymbol{R}$) as a control metric, which is calculated as the relationship between the measurements ($\boldsymbol{M_i}$) and the number of state variables of the electrical system ($\boldsymbol{N}$). In each iteration of the partitioning process, redundancy must be computed and compared between the subsystems by using the following formula.

$$\boldsymbol{R^K} = \frac{\boldsymbol{M}}{\boldsymbol{N} - 1} \tag{4}$$

3. Nodal Partition Method

In applying a distributed estimate DSE, the initial system is partitioned into several groups (subsystems); at this level, a local estimate is calculated by using measurements of each cluster. Then, the global estimate of the electrical system is evaluated by integrating the information of neighboring measurements between the subsystems.

3.1. Preliminary Concept

1. State estimation: The state estimation process for an AC system is based on a mathematical model composed of non-linear functions, which allow the set of measurements to be related to the state variables of the system:

$$\boldsymbol{z} = \boldsymbol{h}(\boldsymbol{x}) + \boldsymbol{e} \tag{5}$$

where:

$\boldsymbol{x}$ is the state vector to be estimated of size 2N;
$\boldsymbol{z}$ is the set of measurements of the system of size M (M > 2N concept of observability);
$\boldsymbol{h}$ is the set non-linear functions, relationship between measurements and state variables (power equations and power flows);
$\boldsymbol{e}$ is the error present in the measurements.

In conventional state estimation models, the state vector is defined by the voltage phasor $[\boldsymbol{V}, \boldsymbol{\theta}_0]$, and the set of measurements is determined by voltage levels $\boldsymbol{V_i}^{\boldsymbol{h}}$, active and reactive power injections, and active and reactive power flows [17]. The non-linear equations that relate the state variables in the model of an electric power system are:

$$\boldsymbol{P_i}^{\boldsymbol{m}} = \sum_{j=1}^{N} \boldsymbol{V_i V_j}\left(\boldsymbol{G_{ij}}\,\mathbf{cos}\boldsymbol{\theta_{ij}} + \boldsymbol{B_{ij}}\mathbf{sin}\,\boldsymbol{\theta_{ij}}\right) \tag{6}$$

$$\boldsymbol{Q_i}^{\boldsymbol{m}} = \sum_{j=1}^{N} \boldsymbol{V_i V_j}\left(\boldsymbol{G_{ij}}\,\mathbf{sin}\boldsymbol{\theta_{ij}} - \boldsymbol{B_{ij}}\mathbf{cos}\boldsymbol{\theta_{ij}}\right) \tag{7}$$

$$\boldsymbol{P_{ij}}^{\boldsymbol{n}} = \boldsymbol{V_i V_j}\Big(\boldsymbol{G_{ij}}\mathbf{cos}\boldsymbol{\theta_{ij}} + \boldsymbol{B_{ij}}\mathbf{sin}\,\boldsymbol{\theta_{ij}}\Big) - \boldsymbol{G_{ij}}\boldsymbol{V_i^2} \tag{8}$$

$$\boldsymbol{Q_{ij}}^{\boldsymbol{n}} = \boldsymbol{V_i V_j}\Big(\boldsymbol{G_{ij}}\mathbf{sin}\boldsymbol{\theta_{ij}} - \mathbf{cos}\,\boldsymbol{\theta_{ij}}\Big) - \boldsymbol{V_i^2}\left(\boldsymbol{B_{ij}} - \boldsymbol{b_{ij}}\right) \tag{9}$$

where $\boldsymbol{h}$, $\boldsymbol{m}$, and $\boldsymbol{n}$ are the number of measurements of voltage, power injection, and power flow, respectively.

The Jacobian matrix $[H]$ of the measures of the system will be the following:

$$\boldsymbol{H} = \begin{bmatrix} \frac{\partial V_i}{\partial V_i} & \frac{\partial V_i}{\partial \theta_i} \\ \frac{\partial P_i}{\partial V_i} & \frac{\partial P_i}{\partial \theta_i} \\ \frac{\partial P_{ij}}{\partial V_i} & \frac{\partial P_{ij}}{\partial \theta_i} \\ \frac{\partial Q_i}{\partial V_i} & \frac{\partial Q_i}{\partial \theta_i} \\ \frac{\partial Q_{ij}}{\partial V_i} & \frac{\partial Q_{ij}}{\partial \theta_i} \end{bmatrix} \quad (10)$$

In the estimator model, the weighted least squares (WLS) minimizes the objective function that evaluates the related error between the estimated values of the measurements and the actual measured values, [7].

$$\min \boldsymbol{J} = \sum_{1}^{M} \frac{(z_i - h_i(\hat{x}))^2}{\sigma_i^2} = [z - H_x]^T W [z - H_x] \quad (11)$$

Being:

$z_i - h_i(\hat{x})$ is residual of the measure;

$\hat{x}$ is estimated state vector;

σ_i^2 is variance of measurement $\boldsymbol{i}$.

Within the development of the model, an iterative process is established, which estimates the values of the state variables in the $\boldsymbol{k}$ iterations:

$$x_{k+1} = x_k + G_k^{-1} H_k^T W[z - h(x_k)] \quad k = 1, \ldots, m \quad (12)$$

where:

$\boldsymbol{H_k}$ is Jacobian matrix evaluated at x_k;

$\boldsymbol{G_k} = \left(\boldsymbol{H}^T\right)_k \boldsymbol{W} \boldsymbol{H_k}$ is gain matrix;

$\boldsymbol{W}$ is weight matrix measurement error;

x_{k+1} is estimated state vector at $k_t + 1$ iteration.

The algorithm's convergence is reached when the value of the residual error of the objective function is less than a tolerance threshold, which is a control metric that must be established.

2. Concept of grouping: In the process of partitioning the system, the interconnected areas can present different physical configurations:
    (a) Non-overlapping areas, those whose bus belong to one of the areas, the link of the areas is given through their transmission system (Figure 2).

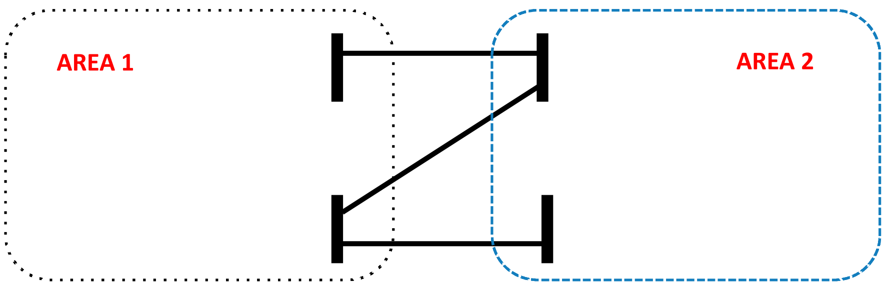

Figure 2. Physical layout of areas connected by their transmission system that do not overlap.

    (b) In overlapping buses, the bus are contained in various areas of the partition (Figure 3).

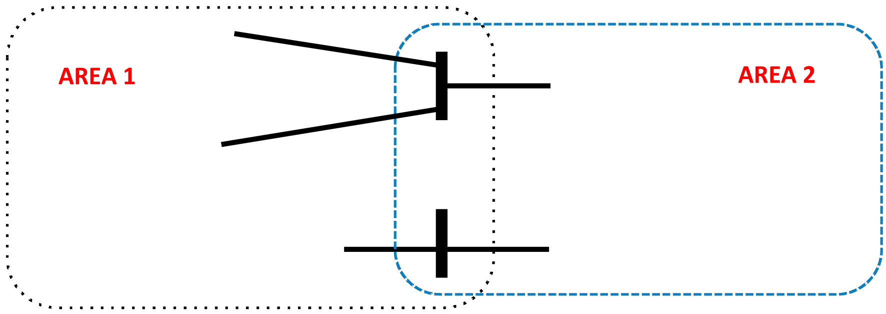

Figure 3. Physical arrangement of overlapping areas in a bus of the electrical power system.

(c) In overlapping links, the configuration considers that the link between two buses belongs to several overlapping areas (Figure 4).

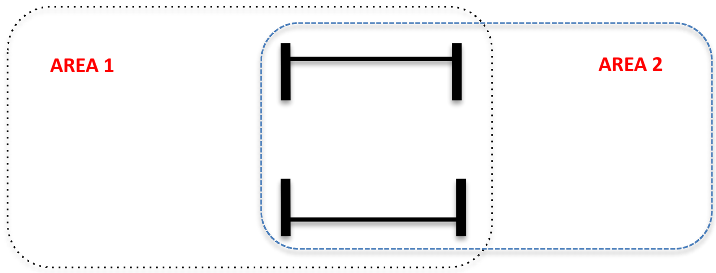

Figure 4. Physical arrangement of the overlapping transmission system.

3.2. Problem Formulation

The problem formulation considers an electrical power system that needs to be divided into non-overlapping areas while ensuring the physical connection of the subsystems through the transmission system. The proposal does not consider isolated systems. The observability criterion must be satisfied for the entire system and for each area into which it is divided. If an area is not observable, the proposal uses pseudo-measurements to restore observability.

$$(\mathbf{\Omega}_m \cap \ \mathbf{\Omega}_n) = \varnothing \tag{13}$$

Applying the concept of nodal grouping, the number of measurements associated with each bus is determined, which starts the system partition (Figure 5).

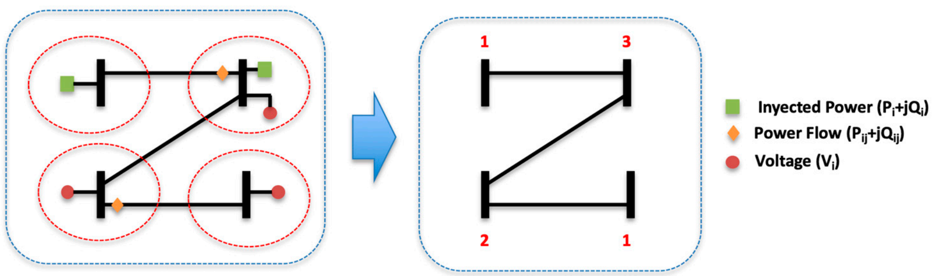

Figure 5. Determination of number of measurements per bus—bus nodal NB.

1. Nodal bus: those buses that concentrate the largest number of measurements; under this concept, the following scenarios are considered:
   (a) Having several BN nodal bus with the same number of measurements, in this scenario, the number of BN establishes the number of areas into which the system will be divided.

$$BN_k = max(\#M) \tag{14}$$

   (b) Having a single nodal bus implies that the estimation process corresponds to a centralized estimate; for this case, the following bus containing smaller measurements should be considered, and the same criteria of the previous literal are applied. This nesting identifies nodal buses with the same number of measurements; unique nodal buses are included in the partition by nodal redundancy (Figure 6).

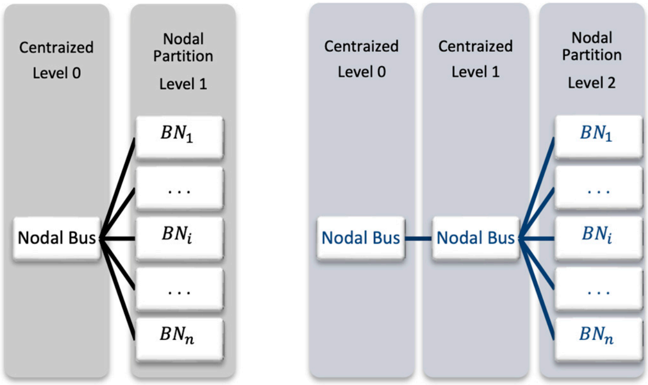

Figure 6. Determination of nodal bar hierarchy based on the number of measurements within the distributed state estimation process.

(c) Another criterion that can be applied as a strategy is to establish a minimum number of measurements per bus; the division of subsystems will depend on the number of buses that are within this threshold; in this case, measurements of the number for each nodal bus is not necessary: they are equal.

$$\boldsymbol{BN_k \geq \#M} \quad (15)$$

2. Link of nodes: Once the BNs are determined, the areas are built for which the adjacent bus connected through the transmission system must be linked, and the subsystems in each iteration grow radially (Figure 7). The system will extend through the lines between the nodes, and the number of buses is increased in each iteration.

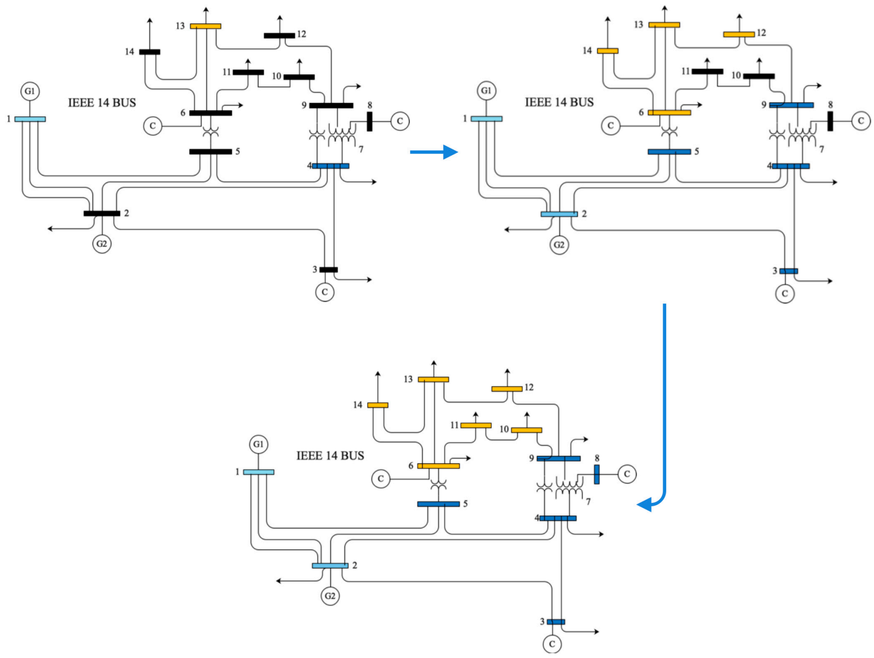

Figure 7. Construction process of the subsystems, determination of bus by area and physical links between areas.

3. Overlapping criteria: In the proposed methodology, the expansion of the areas can produce overlapping, which means that a bus can be in more than two areas due to the physical connection between the elements through the system. To determine which area an overlapping bus corresponds to, the redundancy error minimization criterion is applied, which positions the overlapping bus in one of the areas (Figure 8). It is necessary to calculate the redundancies of the overlapping areas and verify which case minimizes the redundancy error. This process allows the overlapping bus to be placed in one of the areas and determines that the redundancy values between areas are as homogeneous as possible.

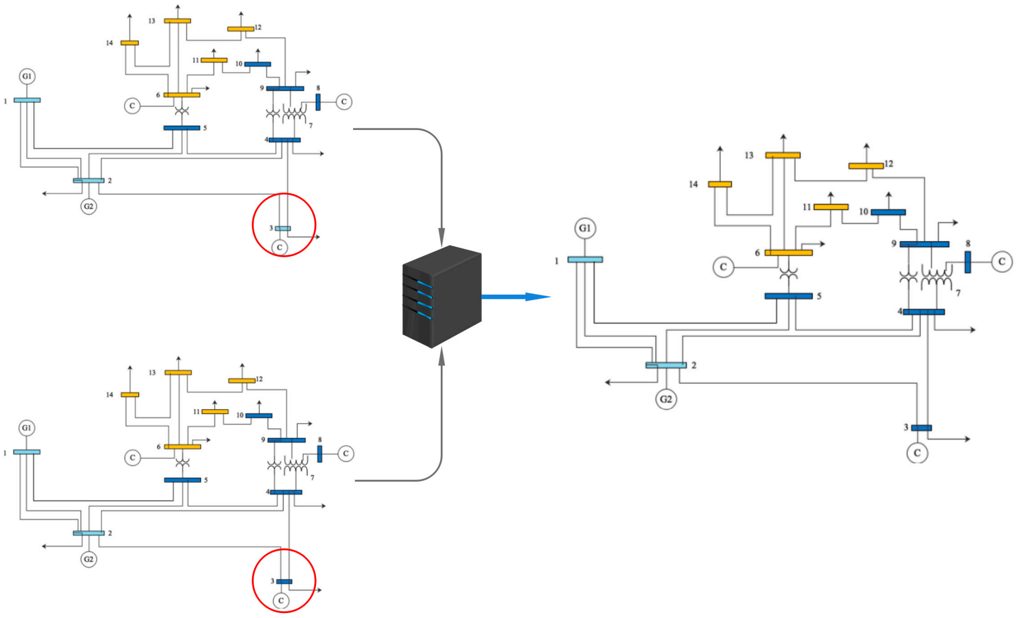

Figure 8. Selection of bars in the overlapping process between subsystems.

$$\begin{aligned} min e_R &= R_{Ai} - R_{Aj} \\ s.t.\ \ e_R^k &\leq e_R^{K*1} \end{aligned} \tag{16}$$

The electrical system partitioning algorithm ends when no more buses are found to assign to the areas into which the system was divided (Figure 9).

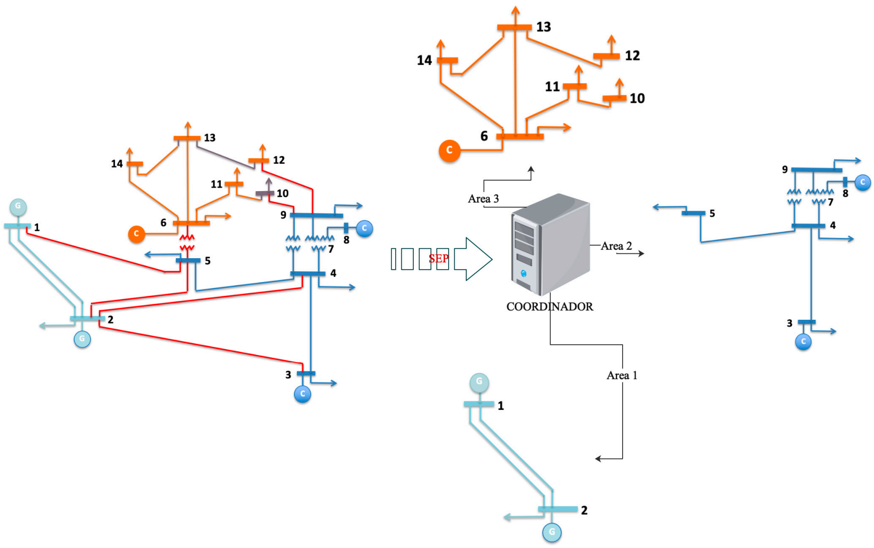

Figure 9. Determination of the subsystems in the distributed estimation process.

After the partitioning stage, the conditions that must be satisfied for the distributed estimation process are:

$$BN_i \in A_i \tag{17}$$

$$B_i \in A_i \tag{18}$$

$$n_i = \sum_{A_i} n_k \tag{19}$$

Figure 10 depicts the distributed estimation process in which each subsystem applies a local estimate. The construction of the global estimate involves a correction based on the information of its borders, which allows for the estimation of the state variables $[V, \theta_0]$ for the entire system.

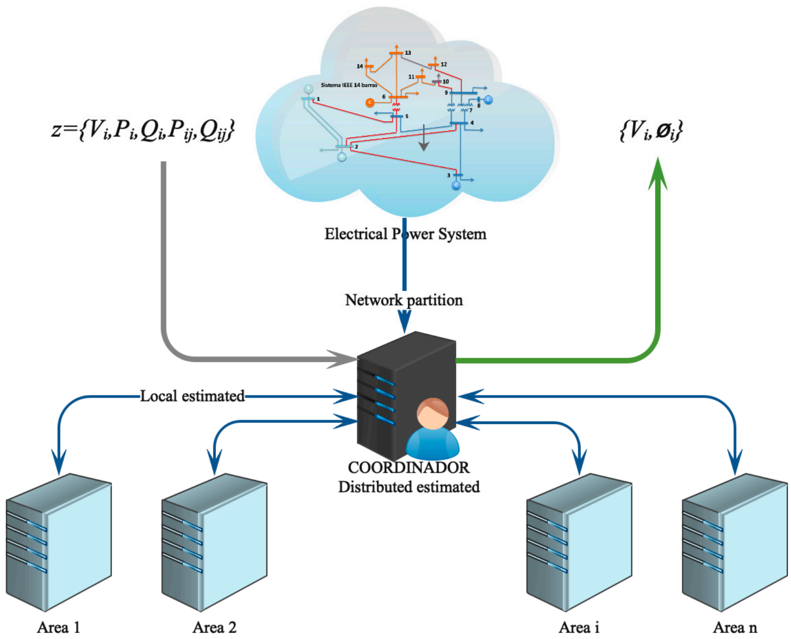

Figure 10. Link between the coordinator and the subsystems within the estimation process of the electric power system.

In the reconstruction of the system, a global estimate is calculated and the MSE is evaluated, which is compared with a control tolerance. If the error is within this threshold, the process is truncated and terminated.

4. Simulation and Results of Application of Power System State Estimation Method

The centralized and distributed state estimation algorithm was implemented on a conventional uniprocessor computer (intel i7 PC clock at 3.40 GHz, with 4 GB of RAM). The proposed partition method by nodal grouping was tested by using the IEEE 14 system and the IEEE 118 bus system. In the simulations, the DSE algorithm used was the one proposed in [29]. The test cases were prepared with an observable heuristic approach. The MATPOWER package was implemented to perform state estimation using the MATLAB platform. The processing time and the mean square error of the estimated MSE states were used to evaluate the efficiency of the partition method applied to a distributed estimation.

$$MSE = \sum_{1}^{n} \frac{(x_i - \hat{x}_i)^2}{n} \tag{20}$$

Measurement errors are generated by adding a random component to the load flow. In all simulations, the assumed error is independent and identically distributed (iid) Gaussian. Table 1 shows the variance values of the simulations.

Table 1. Variance of the measurement systems.

Type of Measure	Variable	Values
Voltage	σ_V^2	0.01
Power Injection $\boldsymbol{P_i} + \boldsymbol{jQ_i}$	σ_I^2	0.15
Power Injection $\boldsymbol{P_{ij}} + \boldsymbol{jQ_{ij}}$	σ_F^2	0.2

4.1. Tests in the IEEE 14 Bus System

In the IEEE 14-bus system four scenarios were evaluated, which were selected according to the number of available measurements. For the distribution of measurements in each case, a random process was considered, guaranteeing the system's observability. Figure 11 shows the system IEEE14 bus.

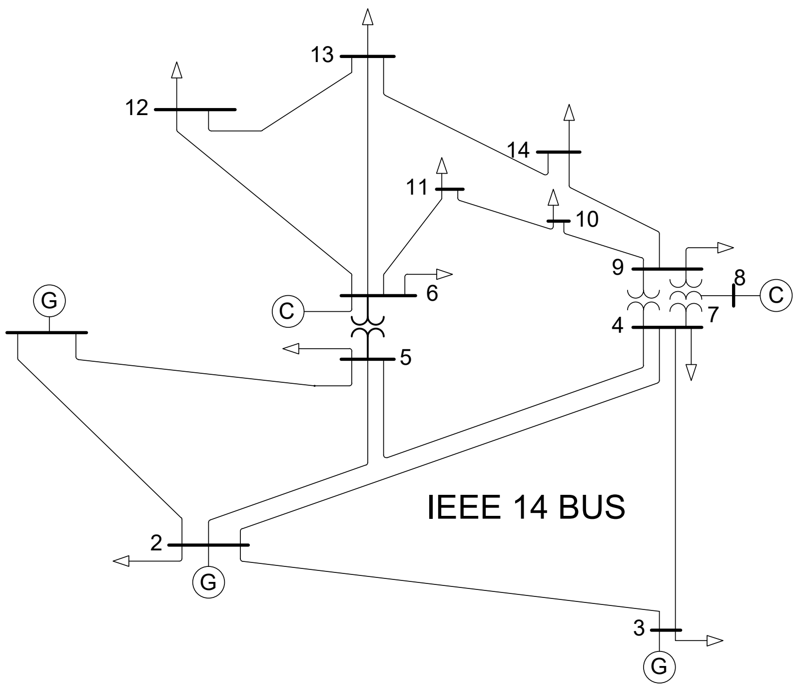

Figure 11. Case study electrical power system IEEE 14 bus.

Tables 2–5 present the results of the system partition process for each case. The physical configuration was not the same as the BNs do not turn out to be the same, even though the number of subsystems into which a system is divided is the same. As in the case of the 82 and 60 measurements system, the number of areas is the same, but there is a variation in the BN.

Table 2. Results of the IEEE 14 bus electrical system partition process with 82 measurements.

Area	Bn	Bus	Redundacy	Measure/Area
1	2	1–2–3	4.2	21
2	4	4–5–7–8–9–10–14	3	39
3	6	6–11–12–13	3.14	22

Table 3. Results of the IEEE 14 bus electrical system partition process with 60 measurements.

Area	Bn	Bus	Redundacy	Measure/Area
1	2	1–2–3	2.6	13
2	4	4–5–7–8–9–10	2.36	26
3	6	6–11–12–13–14	2.33	21

Table 4. Results of the IEEE 14 bus electrical system partition process with 55 measurements.

Area	Bn	Bus	Redundacy	Measure/Area
1	1	1–2–3–4–5–7–8–9	2.13	32
2	6	6–10–11–12–13–14	2.09	23

Table 5. Results of the IEEE 14 bus electrical system partition process with 49 measurements.

Area	Bn	Bus	Redundacy	Measure/Area
1	1	1–2–3–4–5–7–8–9–10	1.8824	32
2	6	6–11–12–13–14	1.8889	17

Figure 12 show the partition of the IEEE14 bus system for the cases developed applying the nodal method.

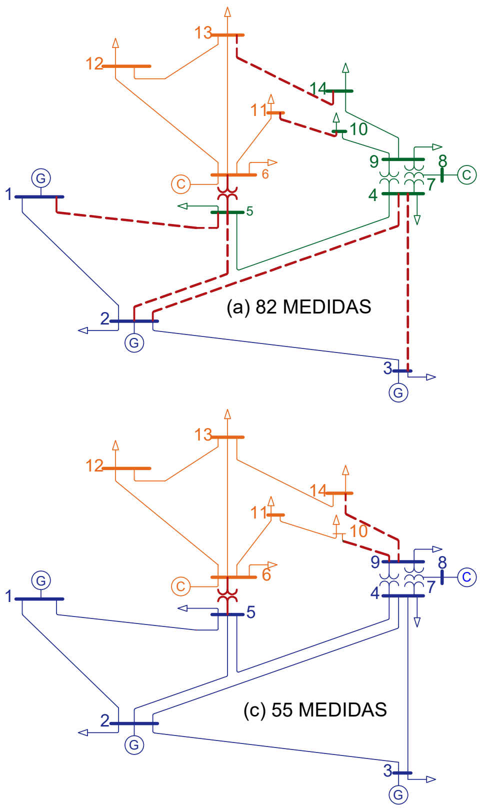

Figure 12. IEEE 14 bus partition: (**a**) 82 measurements, (**b**) 60 measurements, (**c**) 55 measurements, and (**d**) 49 measurements.

Table 6 presents the mean squared error (MSE) and processing time results for the simulations. The results demonstrate that increasing the number of measurements improves the MSE of the estimated values in the distributed estimation process.

Table 6. Comparison of the processing time between the case studies of a distributed estimation and centralized estimation.

Measure	Area	MSE	Time [s]	
			Distributed	Centralized
82	3	0.0087%	1.16	5.54
60	3	0.0367%	0.78	3.44
55	2	0.0734%	1.03	3.17
49	2	0.0923%	0.77	2.78

However, the processing time for each case analyzed is not significantly different compared to that obtained in the centralized estimate. Figure 13 shows the partition graph of the IEEE 14 bus system for a system of 82 measurements, distributed in 14 voltage measurements, 14 injection measurements $P_i + jQ_i$, and 20 power flow measurements $P_{ij} + jQ_{ij}$; the BN is located in bus 2, 4, and 6.

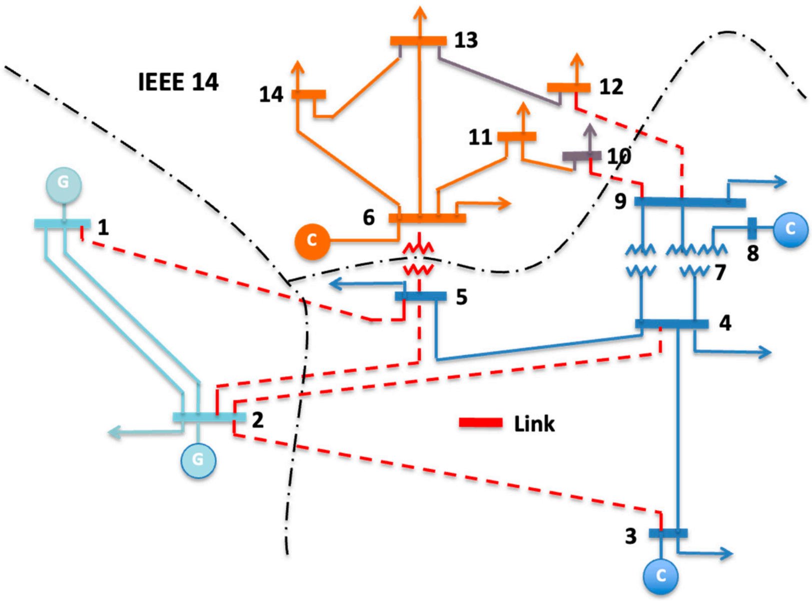

Figure 13. Case study electrical system 14 bus-82 measurements, divided into 3 subsystems.

4.2. Tests in the IEEE 118 System

For the analysis of the method in large electrical systems, the electrical network of the IEEE 118 bus was taken as a model. To have a frame of reference as the base case, the method applied in [29–32] was considered, in which a partition of three areas is developed, with bus 25, 66, and 69 being reference buses for local estimates. For the distribution of measurements, the data of the case developed in [16] was taken as a reference, where a measurement system of 441 measurements is applied, which are broken down into 134 measurements of flows $P_{ij} + jQ_{ij}$, 56 measurements of injections $P_i + jQ_i$, and 61 voltage measurements. Figure 14 shows the diagram of the electrical power system of the IEEE 118 bus used for the simulations.

Figure 15 shows the distribution of the measurements in each bar of the system and that will be used both in the base case and in the proposed scenarios according to the nodal bar hierarchy.

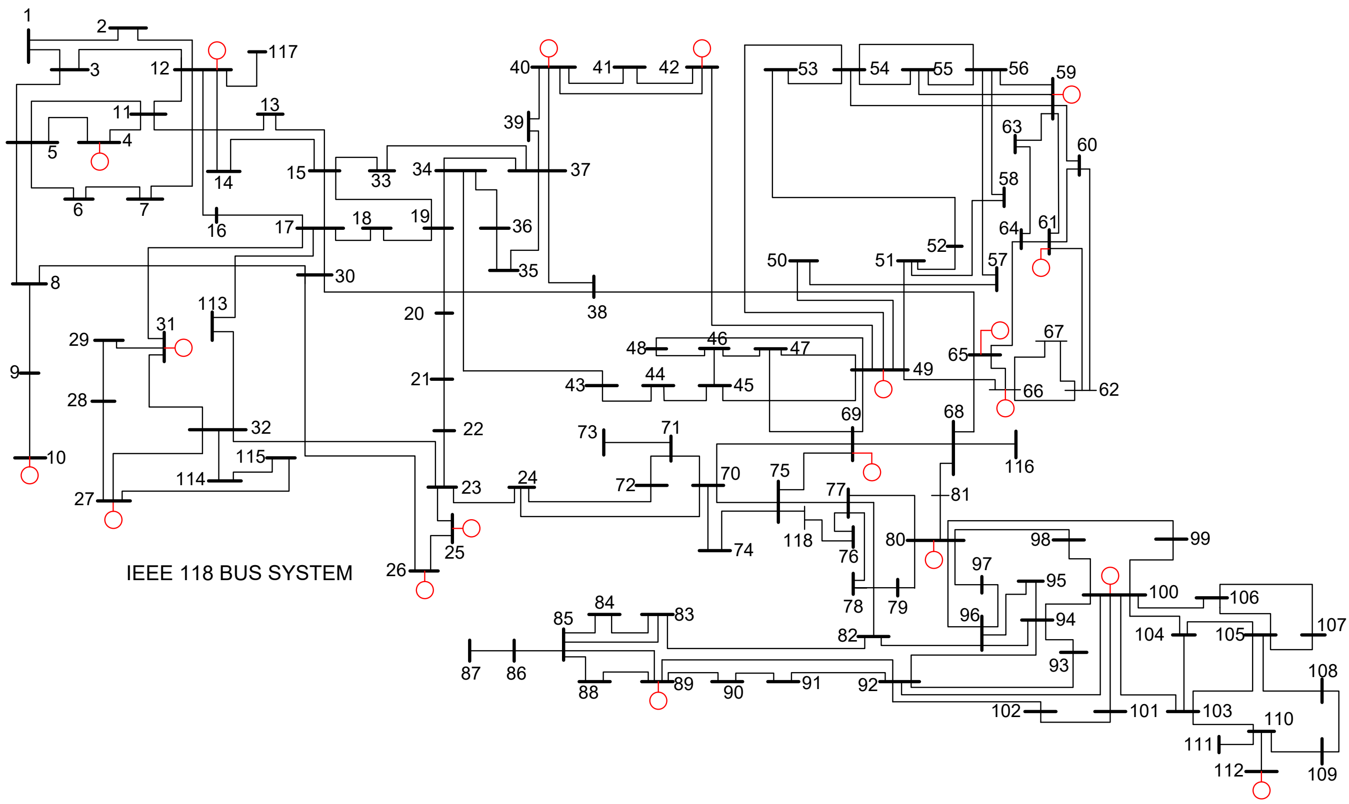

Figure 14. Case studies in IEEE 118 bus system.

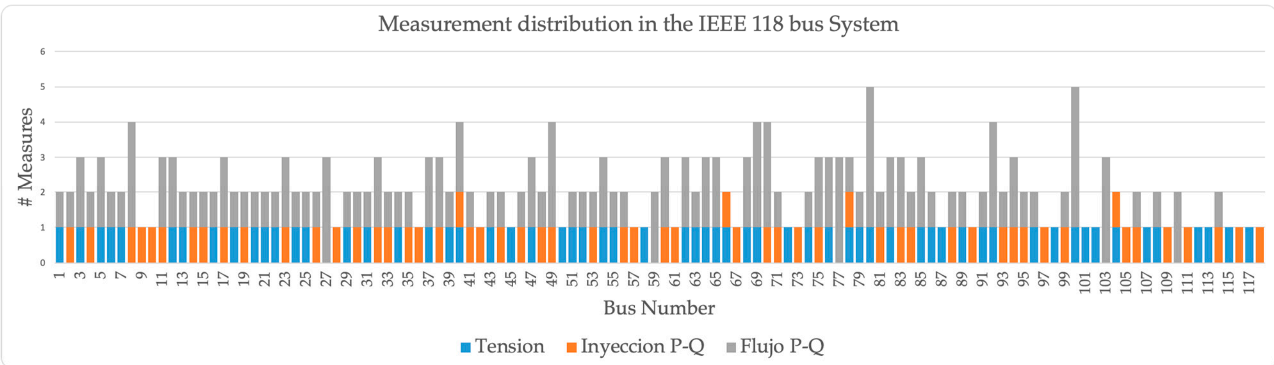

Figure 15. Distribution of number of measurements per bar in IEEE 118 bus.

The first hierarchy is given for the nodal bar made up of a total of nine measurements, which in the simulations correspond to bars 80 and 100. As the ranking process begins with the bus with the largest number of measurements, in our analysis case, a second ranking was considered with nodal buses of up to eight measurements per bus, which are located in bus 8, 49, and 70. A third hierarchy is given for nodal buses of seven measurements per bus, located in bus 40, 69, and 92. Minor hierarchies are not considered in our simulations, since the distribution of measurements means that there are more than two continuous BN, which does not allow the system to be partitioned.

Table 7 presents the results of the partitioning process of the IEEE 118 bus system applying the proposed methodology, in which the number of areas, number of buses, and measurements in each system are detailed. Figure 16 shows the partitions that are considered in the IEEE118 base case system and that have been developed in the literature.

Table 7. Nodal partitioning method applied to large electrical power systems IEEE 118-bus, case study.

Simulated Cases	Area	BN	# Bus	Measurement	
				for Bn	for Area
CB-3_AREAS	1	25	36	3	134
	2	66	34	3	126
	3	69	48	7	181
BN9-2_AREAS	1	80	92	9	355
	2	100	26	9	86
BN8-3_AREAS	1	8	30	8	114
	2	49	71	8	263
	3	70	17	8	64
BN7-3_AREAS	1	40	38	7	142
	2	69	51	7	200
	3	92	29	7	89
CENTRA	1	69	118	7	441

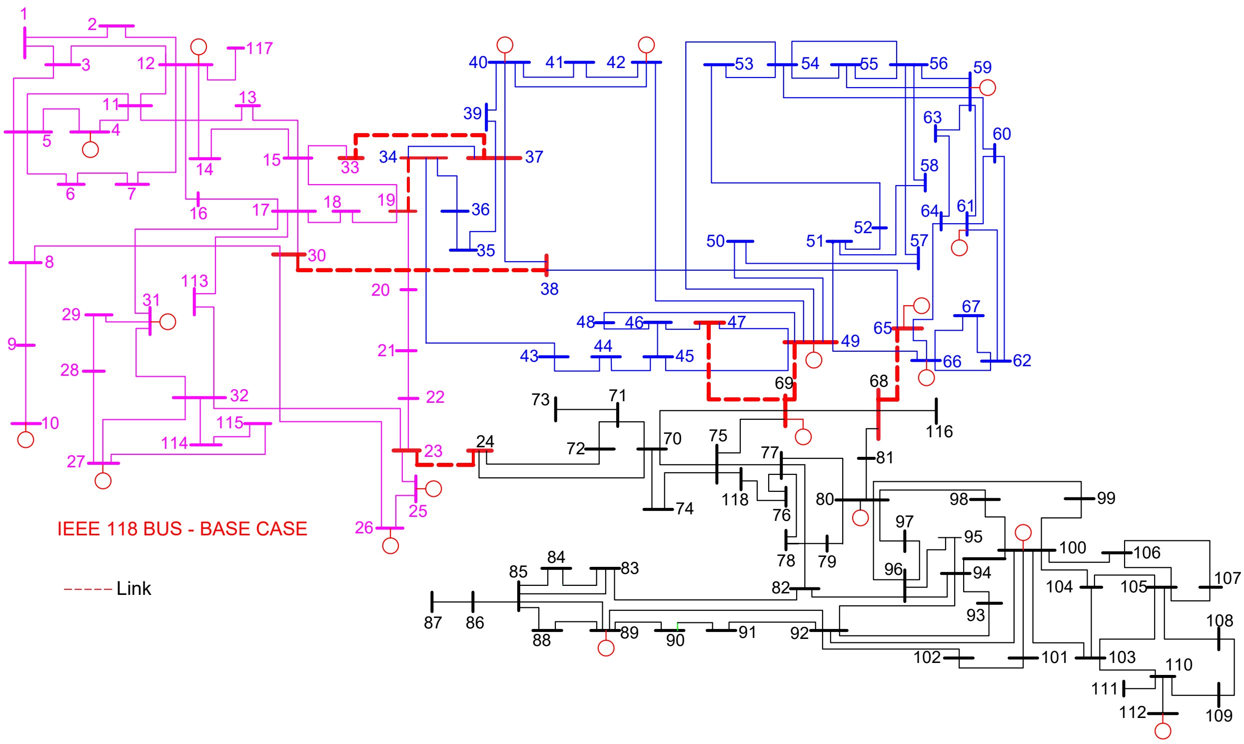

Figure 16. IEEE118 power system partition: base case developed in [30–32].

Meanwhile, Figure 17 shows the configuration resulting from the simulations based on the proposal presented in this investigation.

Table 8 shows the values of the mean square error (MSE) in the simulated cases, BN9, BN8, BN7, and the base case; a reduction in the MSE value is observed. However, the processing times in the BN9 and BN8 scenarios are longer than in the base case. This is because the proposed partition process considers a homogeneous redundancy between areas, while the distribution of the measurements in the subsystems does not necessarily turn out to be homogeneous (Table 5). Therefore, the numerical process requires more convergence time in the estimation for larger subsystems.

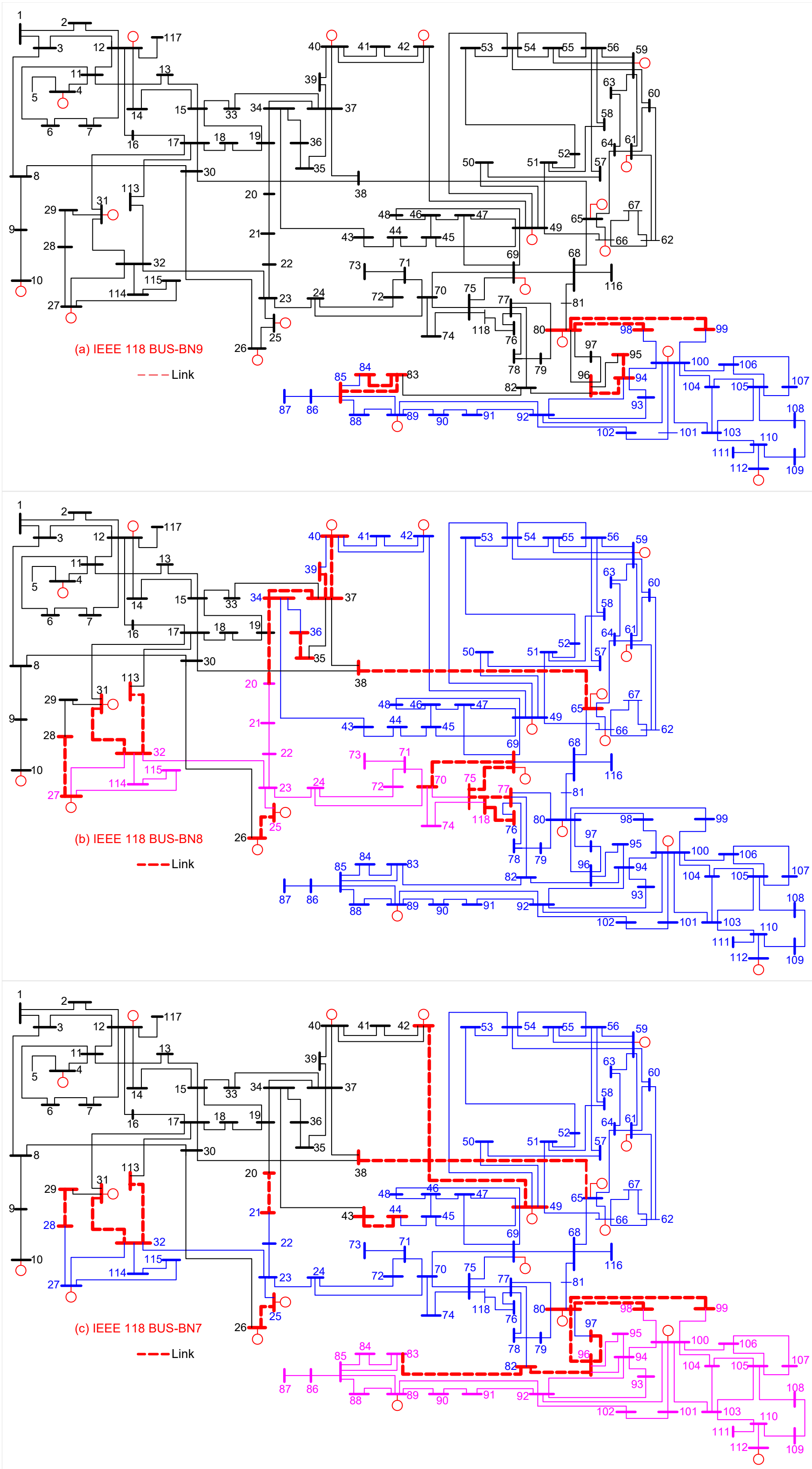

Figure 17. IEEE118 electrical system partition: (**a**) BN9 nodal bar case, (**b**) BN8 nodal bar case, and (**c**) BN7 nodal bar case.

Table 8. MSE value and processing time in the evaluated case studies.

CASE	CB-3	BN9-2	BN8-3	BN7-3
MSE	0.6149×10^{-4}	0.28×10^{-5}	0.3603×10^{-4}	0.3447×10^{-4}
TIME (min)	3.667	18.937	10.674	4.645

Figure 18 shows a comparative graph of the results, where it is evident that the numerical process of the algorithm requires more time for the convergence in the local estimation of the largest subsystems; however, the resulting MSE values are lower than those obtained in the base case due to the distribution of the measurements. In CB and BN7, the system is divided into three areas and the distribution of measurements turns out to be more homogeneous, while in BN8 and BN9, the partition is three and two areas, respectively. However, the results show that the distribution is not so homogeneous.

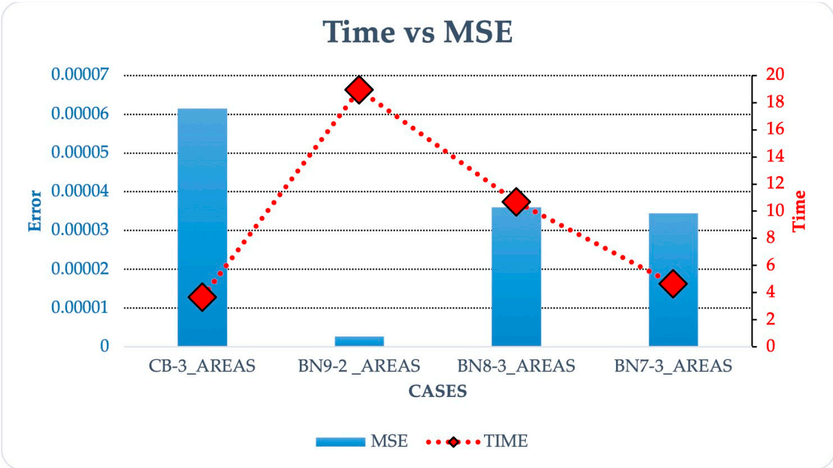

Figure 18. Relationship processing time and MSE.

Comparing the processing times, in the CB, the processing time is much lower than that used for BN8 and BN9; however, if we compare with BN7, the times are considerably reduced; this is due to the distribution of the measurements in the subsystems. Complementing the analysis of the results in Figure 18, the distribution of measurements is presented for different simulated cases according to the partition of the system under the hierarchy criterion. In CB and BN7, the partition is three clusters, resulting in a more homogeneous distribution of the measurements, while in BN8 and BN9 the partition is three and two clusters, respectively, and the distribution is less homogeneous. It is important to consider that, within the estimation process, the numerical calculations solve matrix operations. Thus, by increasing the size of the system, there will be an increase in the processing time.

In the simulation processes considering the centralized model, the base case considered for a distributed estimator, and the proposal under the concept of nodal redundancy in Figure 19, the voltage profile can be observed in each bar of the system once the estimation process is finished.

It can be considered that, in a DSE, the numerical processes are reduced due to the data set (cluster); in a centralized process, information management is for the entire system, which is evidenced in an effort of resources in numerical calculation. In the simulation processes considering the centralized model, the base case considered for a distributed estimator, Figure 20 shows the physical distribution of the system and the number of partitions in each case.

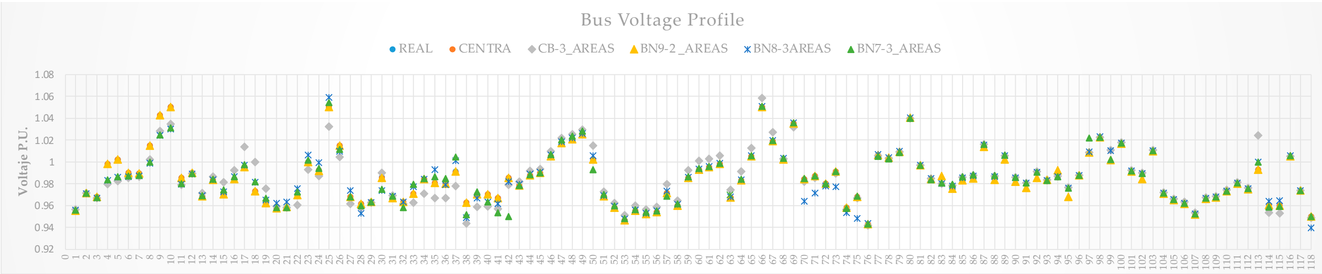

Figure 19. IEEE 118 bus system voltage profile.

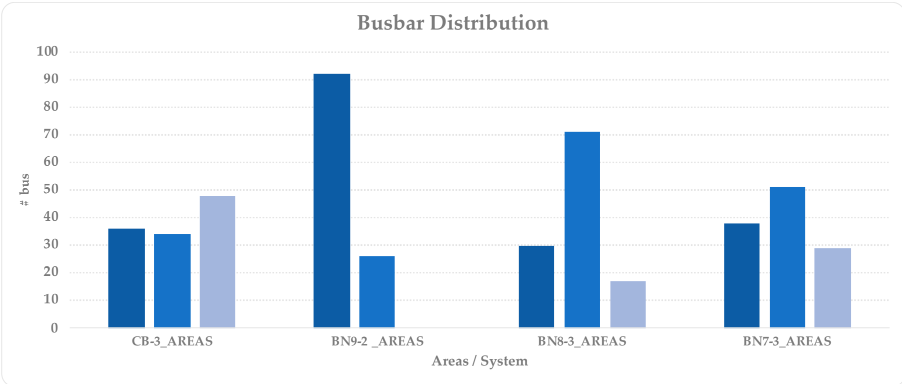

Figure 20. Physical distribution of the electrical system bus in the partitioning process for the case studies.

5. Conclusions

In this paper a method of partitioning an electrical system based on the concept of nodal grouping is proposed. The method, in its construction, considers redundancy as a control metric for the expansion process of the subsystems, which are then applied in the estimation process.

From the results, it can be concluded that the proposed methodology of partitioning in a DSE allows for the improvement of the results of the mean square error MSE of the state variables of the system. However, it is necessary to keep in mind the processing time of the local estimate due to the partitioning of the system; although there is an improvement in the MSE, the time can be very long for decision-making in the operation of the system.

A hierarchy of the nodal bus in the system partition process based on the MSE and processing time allows a SEP to be divided into a greater number of areas, which implies a reduction in processing time because there is a better distribution of the measures of the system between the areas of the partition, without producing an increase of the MSE.

From the simulations, it can be additionally concluded that the type of measurement selected in the method turns out to be relevant in the estimation process; the consideration of measurements between nodes (power flows) is more relevant in the results than the measurements at the node (power injection, voltage). The proposed partition and hierarchy method can be applied as a strategy within the estimation process, since the quality of the results must be guaranteed, by minimizing the processing time. This, in turn, will account for a reading of the electrical system within a window of time, thus allowing the OS to make timely decisions in the operation of the electrical system.

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