

# Enhancing Smart Grid Resilience through 5G Enabled Distributed State Estimation

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**Abstract**—With transition towards 5G, mobile cellular networks are evolving into a powerful platform for ubiquitous large-scale information acquisition, communication, storage and processing. 5G will provide suitable services for mission-critical and real-time applications such as the ones envisioned in future Smart Grids. In this work, we show how emerging 5G mobile cellular network, with its evolution of Machine-Type Communications and the concept of Mobile Edge Computing, provides an adequate environment for distributed monitoring and control tasks in Smart Grids. Furthermore, we present in detail how Smart Grids could benefit from advanced distributed State Estimation methods placed within 5G environment. We present an overview of emerging distributed State Estimation solutions, focusing on those based on distributed optimization and probabilistic graphical models, and investigate their integration as part of the future 5G Smart Grid services.

## I. INTRODUCTION

In recent years, two main trends can be observed in the evolution of power grids: i) the de-regulation of energy markets; and ii) the increasing penetration of renewable energy sources. The former results into an increased exchange of large amounts of power between adjacent areas, possibly under the control of different regional utilities. The latter leads to larger system dynamics, due to the intermittency of such renewable energy sources. To ensure power grid stability, such variations must be timely and accurately monitored.

State Estimation (SE) is a key functionality of electric power grid's Energy Management Systems (EMS) [1]. SE aims to provide an estimate of the system state variables (voltage magnitude and angles) at all the buses of the electrical network from a set of remotely acquired measurements in selected nodes. The aforementioned trends pose a number of challenges to such SE functionalities. First, a totally independent operation of

such areas is, clearly, no longer viable. However, centralized (classical) SE schemes are not directly applicable either. This is mainly due to data security and privacy concerns of regional utilities, or high computational complexity considerations. Hence, the interest of the community is gradually shifting from centralized to distributed SE algorithms and towards more sophisticated

optimization techniques beyond the classical iterative Gauss-Newton approaches [2]. Instrumental to this evolution is the deployment of synchronized phasor measurement units (PMUs). Due to cost considerations, only a limited number of PMUs can be deployed and, therefore, such (linear) measurements must be complemented by legacy (non-linear) ones. This advocates for the development of novel hybrid SE schemes leveraging on both types of measurements. Last, but not least, the development of a reliable communication infrastructure to collect the measurements of the aforementioned metering infrastructure and, by doing so, underpin such advanced SE schemes is also a challenge, as we discuss next.

5G mobile cellular system is evolving as an ideal platform to provide both distributed information processing and information acquisition services necessary to support distributed SE. In terms of the former, the concept of Mobile Edge Computing (MEC) represents an emerging architecture suitable for distributed information processing which is capable of accommodating distributed SE [3]. Furthermore, MEC provides SE with the additional benefits such as localized decision making, context-awareness, low latency, etc. In terms of the latter, 5G will continue the evolution of the cellular Internet of Things (IoT) standards initiated in 4G by introducing the two new services: massive Machine-Type Communications (mMTC) and Ultra-Reliable Low-Latency Communications (URLLC) [4]. They provide suitable options for information acquisition in Smart Grid, whether large-scale deployment of smart meters or ultra-reliable and low-latency service for PMUs, is required.

The purpose of this work is twofold: i) to discuss the suitability of 5G network architectures as an enabler of advanced distributed SE schemes; and ii) to set and investigate two promising distributed SE solutions (based on distributed optimization and probabilistic graphical models) in such a scenario. We first describe how



distributed SE can be integrated into the framework of MEC, while acquiring measurements via 5G Machine-Type Communications (MTC) services. Then, we focus on the two distributed SE approaches suitable for distributed deployment in 5G system: the first based on distributed optimization methods and in particular the Alternating Direction Method of Multipliers (ADMM), and the second based on probabilistic graphical models and Belief-Propagation (BP) algorithms. We provide their performance analysis compared to the centralized solution, and discuss their application for the distributed SE as part of the future 5G Smart Grid services.

## II. 5G ARCHITECTURE FOR DISTRIBUTED INFORMATION ACQUISITION AND PROCESSING IN SMART GRIDS

With transition towards 5G, mobile cellular networks are evolving into a powerful platform for ubiquitous large-scale information acquisition, communication and processing. 5G IoT services and MEC concepts are the main enablers for future 5G services that target new and yet unaddressed mission-critical and real-time applications, such as connected vehicles, connected industry and the smart grid, as we briefly review next.

### A. Cellular IoT standards in 5G

Connecting IoT devices to mobile cellular systems as part of the MTC service is a topic of intensive research and development. Although MTC solutions exploiting GSM/GPRS/UMTS connectivity have been in use, the first 3GPP standards for cellular IoT came only recently within 3GPP LTE Release 13. Three solutions are introduced for mobile operators to enter the IoT market: enhanced Machine-Type Communications (eMTC), Narrow-Band Internet of Things (NB-IoT), and Extended Coverage GSM Internet of Things (EC-GSM-IoT) [5]. eMTC reuses most of the features of the LTE standard, while introducing low-cost user equipment operating in a 1.08 MHz band with physical layer (PHY) enhancements for extended coverage. NB-IoT makes a step further in reducing the end device costs by introducing a new LTE signal that fits into a 180 kHz band. NB-IoT targets up to 50K devices per macro-cell with extended coverage and is an ideal solution for static and low-rate devices such as smart meters. Similar features are available by replacing legacy 200 kHz GSM channels with EC-GSM-IoT. At the present state, cellular IoT is capable of providing massive access to low-rate low-priority devices such as smart meters (NB-IoT). For more demanding devices, such as remote measurement systems, the solution exists (eMTC) albeit with the same reliability and delay guarantees as provided by the standard LTE PHY.

3GPP 5G standardization of the New Radio (NR) interface is initiated in Release 13 with requirements and architecture study. Following ITU 5G requirements, NR will support two IoT services: massive Machine-Type Communications (mMTC) and Ultra-Reliable Low-Latency Communications (URLLC). The former is motivated by massive connectivity provision with extended range support for billions of low-rate low-cost devices, while the latter targets mission-critical services such as vehicular connectivity and industrial control. 3GPP formulated explicit requirements for mMTC connection density in urban dense scenario of 106 devices/km<sup>2</sup> satisfying packet drop rates less than 1%. For URLLC, the generic latency target is 0.5 ms, while reliability targets packet loss rate of 10<sup>-5</sup> for 32 byte packets and 1 ms latency. However, in order to meet the stringent URLLC requirements, not only radio interface, but mobile core network architecture will play a significant role, as we discuss in the next subsection.

### B. Mobile Edge Computing in 5G

5G evolution is not only about NR interface, it is very much the evolution of the packet core architecture that will enable new services. Borrowing ideas, solutions and rich experience from cloud and virtualization technologies, mobile core networks are currently undergoing transition towards flexible and reconfigurable architecture based on software defined networking (SDN) and network function virtualization (NFV) [6], [7]. Centralization and virtualization of cellular network functions reduces complexity of radio access network (RAN) densification and results in so called Cloud RAN (C-RAN) architecture. Extending C-RAN to accommodate user applications and services leads to emergence of MCC architecture, where user equipment uses MCC to offload computation and store data. However, the major drawback of MCC architecture is a large delay between the end user and a remote cloud center, limiting the applicability of MCC to URLLC services. This has led to a recent surge of interest for MEC architecture, where cloud computing and storage is distributed and pushed towards the mobile network edge [3]. With MEC, many applications and services will benefit from localized communication, storage, processing and management, thus reducing the load on the core infrastructure, increasing service responsiveness, and improving context-awareness [8]. The distributed MEC architecture is not in collision with the centralized MCC; they complement each other in building flexible and reconfigurable mobile core using "network slicing" approach, where different services may be easily instantiated using different virtualized architectures on top of the high-performance and general-purpose

network computing and storage MEC host nodes. Thus 5G mobile core network will provide a distributed information processing and storage architecture, comprising a number of MEC hosts capable of providing localized, low-latency and context-aware user data processing.

### C. Smart Grid Services over 5G

With novel solutions for cellular IoT and evolution of MCC/MEC concepts in mobile core, 5G network will provide an ideal platform for large-scale distributed information acquisition and processing services. EMS contains modules that will require architectural change towards distributed and hierarchical organization and in this work, we focus on the distributed SE as one such example. To this end, in Figure 1, we present 5G architecture for smart grid services considered in this paper.

The lowermost layer represents the physical grid segmented into generation, transmission/distribution and consumption. The grid is equipped with a large number of measurement devices, ranging from legacy remote terminal units (RTUs), PMUs and massive-scale smart meter infrastructure. As detailed earlier, 5G will offer flexible wireless interfaces for different measurement devices: massive-scale smart meters will upload their data via mMTC service, while more stringent reliability and latency can be offered to RTUs and PMUs via URLLC service. We assume

Fig. 1. 5G network architecture for Smart Grid services.

that the smart metering data will be locally aggregated using data aggregation units (DAG) and delivered as local aggregated measurements.

Both grid topology and measurements are conveniently represented using bus/branch model (second layer, Figure 1). We assume the grid is logically segmented into areas and such a multi-area SE problem represents an input to the distributed SE algorithms discussed in Section 3.

The physical grid is covered by a network of base stations of evolved 4G/5G radio access network (E-UTRAN) (third layer, Figure 1). Base stations (eNBs) are connected to the packet core gateways (S-GW/P-GW) via S1 interfaces and mutually interconnected via X2 interfaces, both in the form of highspeed backhaul links.

The support for MCC/MEC is provided in the form of a central data center (MCC) within the evolved packet core (EPC), and a large-scale deployment of MEC nodes deep inside the mobile edge (E-UTRAN), in the proximity of (a subset of) base stations. MEC nodes will host the

distributed smart grid applications such as distributed SE that we illustrate as the MEC-SE module (fourth layer, Figure 1). Using NFV concepts, distributed MEC-SE modules may run within the virtualization environment of MEC nodes, remotely instantiated and orchestrated using the centralized NFV orchestrator. Data flows between MEC-SE modules can be flexibly established using SDN concepts, by employing the centralized SDN controller. Each MEC-SE module will run a distributed SE entity whose scope is the area geographically surrounding the MEC node location. Measurements collected in this area will be delivered to the area MEC-SE module via mMTC or URLLC services, thus providing minimum latency, while exploiting local context awareness. The collection of MEC-SE modules will jointly provide the global state estimate, as we describe in the next section. The central MCC-SE module may or may not participate in the distributed SE process, but may serve as a central repository interfacing other EMS functions. We note (Figure 1) that other elements of the state estimator, such as Observability Analysis (OA), Topology Processor (TP) and Bad Data Processing (BDP), may also be distributed in a similar way as the SE function. Furthermore, not only state estimator, but other smart grid services such as frequency regulation, demand side management, voltage and reactive power control, energy trading, etc., may run as distributed 5G smart grid services too.

### III. DISTRIBUTED STATE ESTIMATION METHODS FOR SMART GRID

As discussed earlier, the deregulation of energy markets along with utilities' data security and privacy concerns substantiate the need for developing hierarchical [2], [9], and distributed [10]–[12], SE methods for multi-area settings. In hierarchical SE scenarios, a central authority controls the local processor in each area or level. In distributed approaches, on the contrary, each local processor communicates only with its neighbors, since no central computer exists. Going one step beyond, other authors [13], [14], have considered fully distributed SE approaches where interaction takes place at the bus level rather than the area level. Next, we briefly review those approaches.

In [2], Gomez-Exposito et al. propose a *hierarchical* multi-level SE scheme. First, local estimates are computed at lower voltage levels. Subsequently, those estimates are transferred to higher voltage areas, up to the system operator level, in order to estimate the system-wide state. In each stage, the SE problem is solved via the classical Gauss-Newton algorithm. Still in a hierarchical context, Korres in [9] proposes to decompose, on a

geographical basis, the overall system into a number of subsystems in non-overlapping areas. Each area independently runs its own gradient-based SE scheme on the basis of local measurements. Such estimates are then communicated to the central coordinator which computes the system-wide solution.

The authors in [10], instead, propose a *decentralized* SE scheme based on primal-dual decomposition. Interestingly, this method merely requires the exchange of information between *neighboring* areas, namely, border state variables and the dual variables. The scheme is robust in that it incorporates a bad data detection based on the classical largest normalized residual test. For each area, the problem is solved through classical Gauss-Newton techniques. Differently, Kekatos and Giannakis [11] resort to the so-called Alternating Direction Method of Multipliers (ADMM) to solve the SE problem in a distributed fashion. In contrast to [10], the authors develop a robust version leveraging on the sparsity of bad data measurements. Going one step beyond, [15] proposes a hybrid scheme including *both* PMUs and legacy measurements. Here, the SE problem is casted into a Semidefinite Programming (SDP) framework and solved via convex semidefinite relaxation techniques (SDR-SE), both in centralized and decentralized settings. This approach may suffer from severe performance degradation in the absence of voltage magnitude measurements. In [12], the authors propose a hybrid multi-area state estimator based on Successive Convex Approximation (SCA) and ADMM as an optimization tool. The proposed distributed approach is equivalent to the centralized case in terms of estimation accuracy and is able to operate in broader scenarios where the SDR-SE fails.

As for *fully distributed* SE approaches, Hu et al [13] pioneered in the application of BP, a message-passing algorithm, to the SE problem in distribution networks. Unlike in the above mentioned works, here the system state is modeled as a set of stochastic variables. This provides a flexible solution for the inclusion of, e.g., distributed power sources, environmental correlation via historical data and time-varying loads, etc. in the model. In a recent work, a distributed Gauss-Newton algorithm based on factor graphs and BP algorithm is proposed and shown to provide the same accuracy as the centralized Gauss-Newton algorithm [14], while being flexible to accommodate both fully distributed and multi-area SE scenario.

The paragraphs above reveal that distributed SE can greatly benefit from advanced optimization techniques. Specifically, ADMM and BP seem to be particularly promising and, thus, they will be described with further

detail later in this section. Prior to that, we describe a system model suitable for both approaches.

### A. System Model

As discussed earlier, state estimation aims to determine the complex voltages at all the buses in a power grid from a number of system variables (active and reactive power flows or injections, voltage and current magnitudes and/or angles, etc.) measured in selected nodes. Thus, the SE problem reduces to solving the system of equations:  $\mathbf{z} = \mathbf{h}(\mathbf{x}) + \mathbf{u}$ , where  $\mathbf{h}(\mathbf{x}) = (h_1(\mathbf{x}), \dots, h_k(\mathbf{x}))$  may include both non-linear (from legacy metering devices) and linear measurement functions (from PMUs);  $\mathbf{x} = (x_1, \dots, x_n)$  is the vector of the state variables;  $\mathbf{z} = (z_1, \dots, z_k)$  is the vector of independent measurements (where  $n < k$ ), and  $\mathbf{u} = (u_1, \dots, u_k)$  is the vector of measurement errors. The state variables are bus voltage magnitudes and bus voltage angles, along with transformer magnitudes of turns ratio and transformer angles of turns ratio. Figure 2 below illustrates a possible scenario for the collection of measurements in a standard IEEE 30 bus test case.

### B. Optimization-Based Methods for Distributed State Estimation

The ADMM is experiencing renewed popularity after its discovery in the mid-twentieth century. ADMM was conceived to overcome the weaknesses of its predecessors: the primal-dual decomposition method and the method of multipliers. The former is suitable for distributed optimization but presents convergence issues for non-differentiable objectives. Conversely, the method of

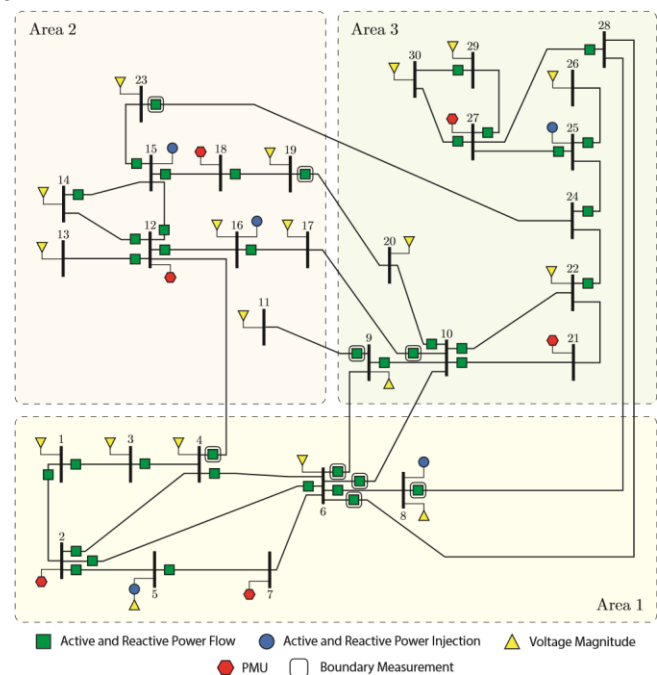


Fig. 2. The IEEE 30 bus test case segmented into three areas with a given collection of measurements.

multipliers can deal with non-smooth functions but couples the objective function which makes it barely suitable for distributed optimization. The ADMM brings the two features together: it is suitable for distributed implementation and can efficiently deal with non-differentiable objective functions.

The canonical optimization problem solved by ADMM is the minimization of a composite objective function, i.e.,  $f(\mathbf{x}) + g(\mathbf{z})$  (not necessarily differentiable), subject to a linear equality constraint of the form  $\mathbf{Ax} + \mathbf{Bz} = \mathbf{c}$ , with  $\mathbf{x}$  and  $\mathbf{z}$  being the optimization variables. To deal with non-differentiable functions, the ADMM augments the cost function by a quadratic penalty term that transforms the optimization problem into a strongly convex problem but with the same stationary solution. This transformation has major implications in the dual domain, as the dual function becomes differentiable. Then, the ADMM iterates sequentially on the primal optimization variables,  $\mathbf{x}$  and  $\mathbf{z}$ , and the dual variables, until convergence. The major difference with respect to the method of multipliers is the sequential optimization on the primal domain, which opens new ways to decentralize many optimization problems.

The classical procedure to decentralize an optimization problem via ADMM is to decouple the objective function with consensus variables. These consensus variables, which are accounted by equality constraints in the problem, separate the optimization problem into a number of subproblems [11], [12]. The resulting ADMM algorithm can be readily interpreted as an iterative message passing procedure, in which the agents solving the subproblems (e.g., utilities in the multi-area state estimation problem) exchange consensus and dual variables until convergence. Besides, ADMM can be used in conjunction with successive convex approximation approaches that efficiently deal with non-convex problems. By doing so, it becomes a versatile and powerful tool to solve many realistic engineering problems.

### C. Probabilistic Inference-Based Methods for Distributed State Estimation

The probabilistic graphical models provide a convenient methodology to represent mutual dependencies among the system of random variables, such as the state variables  $\mathbf{x}$  of the power system. The bus/branch model with a measurement configuration can be transformed into a corresponding probabilistic graphical model, such as the factor graph considered here.

The BP algorithm applied on factor graphs efficiently calculates marginal distributions of the system of random variables. BP has been applied to a variety of estimation problems where it was shown to provide ground-breaking performance, such as iterative decoding of sparse-graph codes, free energy approximations in statistical physics, object detection and segmentation in computer vision, etc.

In the initial step, a factor graph is formed that contains the set of factor nodes and variable nodes. The set of factor nodes is defined by the set of measurement devices, or more precisely, arbitrary factor node  $f$  is associated with measured value  $z$ , measurement error  $u$  and measurement function  $h(\mathbf{x})$ . The set of variable nodes is determined by the set of state variables  $\mathbf{x}$ . A factor node is connected by an edge to a variable node, if and only if the variable is an argument of the corresponding measurement function  $h(\mathbf{x})$ .

BP is a fully distributed algorithm that passes two types of messages along the edges of the factor graph: i) a variable node to a factor node, and ii) a factor node to a variable node messages. In general, the SE scenario is an instance of the loopy BP since the corresponding factor graph contains cycles. Loopy BP is an iterative algorithm and in standard scheduling, the messages are updated in parallel in respective half-iterations. Within half-iterations, factor nodes calculate and send messages to incident variable nodes, while subsequently, variable nodes calculate and send messages back towards factor nodes. As a general BP rule, an output message on any edge depends only on incoming messages from all other edges. BP messages represent beliefs about variable nodes, thus a message that arrives or departs from a certain variable node is a function (distribution) of the random variable corresponding to the variable node. Finally, the marginal inference will provide the estimated values of the state variables.

## IV. DISTRIBUTED STATE ESTIMATION IN 5G SMART GRID SERVICES

Both BP and ADMM-based distributed SE solutions may be integrated as part of the 5G Smart Grid services described in Section 2. For the case of BP, factor graphs of the power system can be flexibly segmented into areas and BP can easily accommodate both intra- and inter-area message exchange, not necessarily with the same periodicity, allowing for asynchronous message scheduling. Thus factor graphs corresponding to different areas in Figure 1 can be maintained as part of the distributed SE software modules within MEC nodes, with inputs from local topology processor and local measurements arriving from mMTC and URLLC services.

Inter-area BP messages may be exchanged using controlled periodicity over data paths established among MEC nodes via the central SDN controller. It is the exchange of these inter-area BP messages that establish a global factor graph and provide for the local SE modules ability to converge to the global solution. Similarly, for the case of ADMM, the local ADMM modules may reside in different MEC nodes and, based on local topology and measurements, may run local single-area optimization. By exchanging messages among neighboring areas, local ADMM modules iterate through the distributed optimization process converging towards the global solution.

#### A. Distributed SE Methods: Performance Results

In this section, we demonstrate that the state estimate of the distributed BP and ADMM based algorithms converge to the solution provided by the centralized Gauss-Newton method. The IEEE 30 bus test case with measurement configuration shown in Figure 2 contains 41 power flow, 5 power injection and 19 voltage magnitude measurement devices, and may include up to 6 additional PMUs. We tested algorithms using three scenarios: i) measurement configuration with no PMUs, ii) one PMU per area, and iii) two PMUs per area. For predefined value of noise variance, using Monte Carlo approach, we generate 500 random sets of measurement values and feed them to the BP, ADMM and centralized SE algorithms to obtain average performances. To evaluate both algorithms, we use the root mean square error (RMSE) after each iteration  $\rho$  ( $\text{RMSE}^\rho$ ), normalized by RMSE of the centralized SE algorithm using the Gauss-Newton method after 12 iterations ( $\text{RMSE}_{\text{wis}}$ ).

Next, we briefly describe how both BP and ADMM based algorithms proceed through the iterations of the distributed SE process. According to [14], we apply BP implemented as a nested-loop iterative algorithm, that interchangeably runs a number of inner BP iterations followed by a single outer iteration. After each outer iteration  $v$  that provides a new state estimate, a set of inner BP iterations is performed to estimate the increment vector of the state estimate. The following outer iteration  $v + 1$  then provides a new state estimate by adding the increment vector to the previous state estimate. For every outer iteration  $v$ , the number of inner iterations  $\rho$  increases as  $v^q$ , where we set to  $q = 3$ . The resulting algorithm represents the BP-based Gauss-Newton algorithm which can be interpreted as a fully distributed Gauss-Newton method.

In the case of SCA-SE [12], the estimation algorithm comprises two nested loops. The outer loop is based on a

successive convex approximation scheme that replaces the non-convex objective function of the SE problem by a strongly-convex one. Specifically, the non-convex part is linearized in a feasible point of each outer iteration. Then, this sequence of strongly-convex functions is solved in a distributed fashion within the iterative framework of ADMM, that constitutes the inner loop.

Figure 3 shows that the BP algorithm converges to the solution of the centralized SE for each scenario. As expected, the BP algorithm converges faster for measurement configurations with PMUs. In general, configurations with PMUs can dramatically improve numerical stability of the BP algorithm and prevent oscillatory behavior of messages.

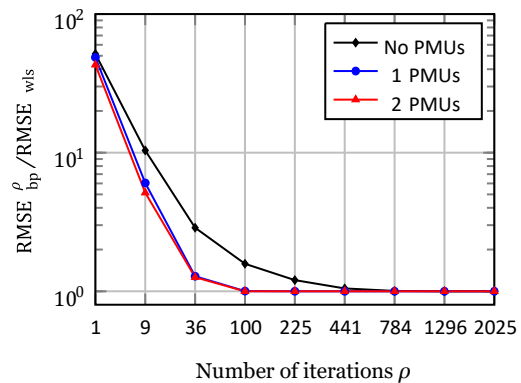
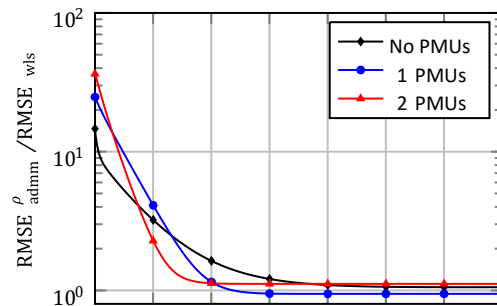


Fig. 3. The normalized RMSE for the BP algorithm (i.e.,  $\text{RMSE}_{\text{bp}}^\rho / \text{RMSE}_{\text{wis}}$ ) for three scenarios: without PMUs, one PMU and two PMUs per area.

Figure 4 illustrates the performance of the SCA-SE algorithm based on ADMM. Clearly, the scheme attains the same performance as the centralized solution based on the Gauss-Newton iterative method. In addition, as it was expected, we observe that the increased number of PMUs leads the algorithm to a significant improved convergence behavior.



#### B. Distributed SE Methods: Implementation Aspects

In this section, we briefly discuss benefits and drawbacks of BP and ADMM distributed SE for realistic implementation.

One of the main advantages of the probabilistic BP framework lies in its ability to flexibly integrate

distributed power sources and time-varying loads present in various emerging applications of upcoming smart grids. Moreover, placing the SE into the probabilistic graphical modeling framework opens for use a rich collection of useful tools, such as learning the parameters of graphical models. With respect to the computational and memory resources, the BP algorithm is flexible and easy to distribute and parallelize. In Figure 5, we demonstrate that the proposed BP-based algorithm can be designed to provide asynchronous operation and could be integrated as part of real-time systems. The algorithm processes the set of measurements without PMUs, and after iteration 8, the control center receives measurement values from PMUs at buses 2, 12 and 27. Using the new set of measurements, the BP algorithm in the continuous process provides a new state of the system.

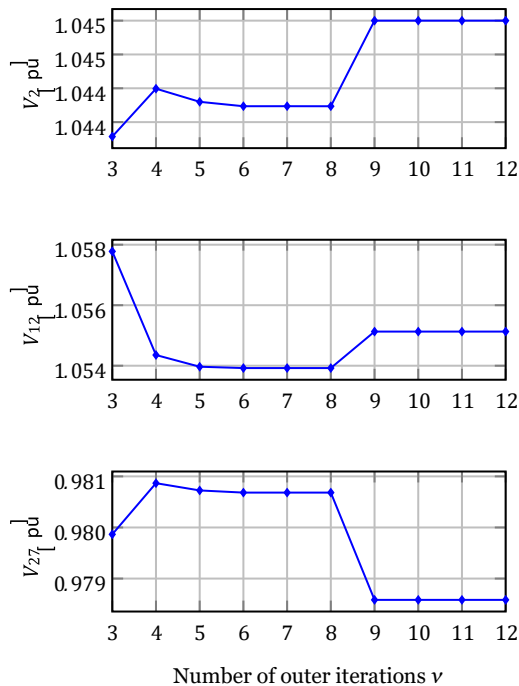


Fig. 5. Values of voltage magnitudes  $V_2$ ,  $V_{12}$  and  $V_{27}$  in asynchronous framework of the BP-based algorithm where after iteration 8, control center receives measurement values from PMUs at buses 2, 12 and 27.

In contrast to the above advantages, we note that the comprehensive theory about the convergence of the loopy BP algorithm is still missing, hence the convergence of loopy BP is not guaranteed. Furthermore, the proposed BP-based iterative algorithm assumes Gaussian distributions, and switching to another type of distributions is not a trivial task.

In many cases, part of the measurement set can be contaminated by outliers, e.g., due to malfunctioning of the meters and/or communication failures. These measurements, known as bad data, have to be detected and removed. Beyond classical methods for bad data

detection such as largest normalized residual test, the framework of ADMM is suitable for developing an algorithm that provides joint SE and bad data detection. This benefit arises from the fact that ADMM is able to deal with non-differentiable objective functions and hence, it can leverage on norm-1 in order to enhance performance to the estimator. However, this advantage comes at the price of an increased computational complexity.

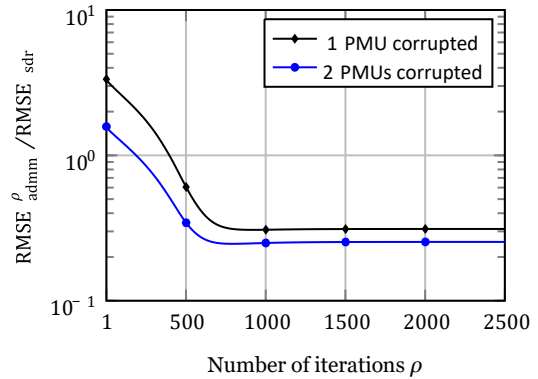


Fig. 6. The normalized RMSE for the ADMM algorithm (i.e.,  $\text{RMSE}_{\text{admm}}^{\rho} / \text{RMSE}_{\text{sdr}}$ ) for two scenarios: one corrupted PMU at bus 18 and two corrupted PMUs at buses 18 and 27.

In Figure 6 we present the performance of the robust SCA-SE in the IEEE 30 bus test case and the measurement configuration of Figure 2. We have investigated two scenarios: i) one PMU contaminated by outliers (at bus 18), ii) two PMUs contaminated by outliers (at buses 18 and 27). As in [11], when a PMU is placed at a given node, it provides the voltage phasor of this bus and all the complex current injections incident to it and for each corrupted measurement we have increased its magnitude by 20%. As an error metric, we normalize the RMSE over the iterations  $\rho$  by the RMSE of the centralized robust SDR-SE [15] algorithm ( $\text{RMSE}_{\text{sdr}}$ ). Figure 6 reveals that the robust SCA-SE can effectively deal with the presence of corrupted measurements and maintains high accuracy compared to the benchmark.

To summarize, both probabilistic graphical models and distributed optimization are very active and attractive research areas and we expect many new results will appear in the future that will further enhance the applicability of the above solutions in real-world systems.

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