Near Real-Time Distributed State Estimation via AI/ML-Empowered 5G Networks

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Abstract—Fifth-Generation (5G) networks have a potential to accelerate power system transition to a flexible, softwarized, data-driven, and intelligent grid. With their evolving support for Machine Learning (ML)/Artificial Intelligence (AI) functions, 5G networks are expected to enable novel data-centric Smart Grid (SG) services. In this paper, we explore how data-driven SG services could be integrated with ML/AI-enabled 5G networks in a symbiotic relationship. We focus on the State Estimation (SE) function as a key element of the energy management system and focus on two main questions. Firstly, in a tutorial fashion, we present an overview on how distributed SE can be integrated with the elements of the 5G core network and radio access network architecture. Secondly, we present and compare two powerful distributed SE methods based on: i) graphical models and belief propagation, and ii) graph neural networks. We discuss their performance and capability to support a near real-time distributed SE via 5G network, taking into account communication delays.

Index Terms—Smart Grids, 5G, State Estimation, Wide-Area Monitoring Systems, Phasor Measurement Units

I. INTRODUCTION

Fifth-Generation (5G) mobile cellular networks are evolving towards a ubiquitous platform that offers large-scale and distributed communication and computation capacities to support future Machine Learning (ML) and Artificial Intelligence (AI)-based services [1]. Integration of Smart Grid (SG) with 5G network will foster accelerated transition to a flexible, softwarized, data-driven and intelligent grid, recognised by the Third Generation Partnership Project (3GPP) work plan for Release 18 of 5G standards [2]. 5G networks provide necessary bandwidth, connection density, low latency and ultra-reliability to support different SG services [3]. Additionally, 5G networks are continuously upgraded to offer an increasing in-network support for ML/AI-enabled services [4].

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This paper has received funding from the European Union’s Horizon 2020 research and innovation programme under Grant Agreement number 856967.
ized cloud-based 5G CN and distributed edge-based 5G RAN.

A. 5G Core Network Service-Based Architecture

Evolution and deployment of novel services with ever increasing requirements motivated 3GPP to adopt a new 5G CN system architecture called Service-based Architecture (SBA). Fast and flexible service deployment in 5G SBA is critical for commercial viability of 5G [14], [15]. 5G SBA is defined as a set of interconnected Network Functions (NFs) that have permission to access each other’s services [16]. Becoming cloud-native means that the 5G CN employs Network Functions Virtualization (NFV) and Software-Defined Networking (SDN) approaches, and service-based interactions between control-plane functions [17], [18].

The 5G CN architecture consists of a number of NFs responsible for network control and management, as shown in Fig. 1 [15], [16]. The CN design principles include: separation of the control and user planes, modularization of the functional and interface design, support for direct interaction of NFs, reduction of mutual reliance of the 5G RAN and CN, support for stateless NFs by separating computing and storage resources, exposure of capability, and allowance of concurrent access to both local and centralized services [16], [19], [20]. Besides standard NFs [19], novel data analytics functions: Management Data Analytics Function (MDAF) and Network Data Analytics Function (NWDAF), have been introduced. MDAF manages data analytics for one or more NFs while NWDAF collects and analyzes data for both centralized and edge computing resources. NWDAF simplifies the production and consumption of CN data, and provides insights and take actions to improve the end-user experience and network performance [15], [16].

Application Functions (AFs) communicate securely with other 5G NFs via the 5G SBA. AFs can be created for a variety of application services, e.g., Smart Grid AFs (SGAFs), and owned by the network operator or trusted third parties. For services considered trusted by the operator, the AFs can access NFs directly, while untrusted or third-party AFs access NFs through the Network Exposure Function (NEF). NEF acts as a communication mediator with the external systems and its role is to store and retrieve NFs exposed capabilities and events. In 5G CN, this data is exchanged among NFs via NEF, but it can be securely exposed to third-party and edge-computing entities outside of the 3GPP network, e.g., for the purpose of data analytics [15], [16].

B. 5G Open Radio Access Network Architecture

The 5G RAN is undergoing the process of RAN disaggregation, i.e., a transition from inflexible, monolithic and hardware-based RAN to a flexible, elastic, software-based and disaggregated RAN. The goal is to optimize radio resource management and efficient use of spectrum. The placement of RAN functions across different locations started in Fourth-Generation (4G) in the context of Cloud-RAN (C-RAN). Base stations (also called eNBs) are separated into BaseBand Units (BBUs) located in central offices and separated from Remote Radio Units (RRUs) [21]. Further disaggregation divides the BBU and the RRU into the Centralised Unit (CU), the Distributed Unit (DU), and the Radio Unit (RU). Such a disaggregation, adopted by the Open Radio Access Network (O-RAN) alliance, is under investigation within 3GPP targeting the most efficient functional split, i.e., the optimal allocation of RAN functions to CU/DU/RU [22], see Fig. 1.

The introduction of ML/AI-based services is gradually expanding from 5G CN towards 5G RAN. 3GPP is investigating possible locations for data collection, training and deployment of inference models [23]. In O-RAN, novel hierarchical RAN Intelligent Controllers (RIC) are introduced: i) Near-Real-Time (Near-RT) RIC deployed at the edge, and ii) Non-Real-Time (Non-RT) RIC deployed at the central cloud, connected via a new set of open interfaces (E2/O1/A1). Near-RT RIC supports a number of xApps operating at 10 ms - 1 s time scales: microservices capable of performing various ML/AI-based resource management functions (e.g., network slicing, radio resource management). In contrast, rApps have more information about the network traffic (understand the context), thus they are mainly used for making predictions and submitting policies to different network nodes. They also share policies with the near-RT RIC. Then, those policies are being enforced by the near-RT control loop. The near-RT RIC can also collect data from multiple CUs and DUs and make coordinated control decisions for multiple nodes [24]. Although xApps/rApps address RAN management and control, third-party xApps/rApps will enable integration and control of specific network service requirements, e.g., SG applications.

5G URLLC services are suitable for PMU-based WAMS in SG that target near real-time system state awareness. A URLLC-based distributed SE for SG with latency and reliability considerations is proposed in [13]. Similarly, the implementation of SE functions in 5G using 5G was recently introduced by [25]. The challenges and promises of URLLC for SG teleprotection are elaborated in [26]. In [27], a wireless line differential protection scheme based on URLLC is proposed and tested using the real 5G test network. A testbed composed of a microgrid and 5G network is introduced in [28] and used to evaluate IEC-61850 [29] protocols in the case of TCP/UDP message transmission. 5G network slicing for SG is implemented and verified in [30]. Unlike the above papers, we focus on ML/AI-based distributed SE methods and their synergies with ML/AI-empowered 5G network.

III. DISTRIBUTED STATE ESTIMATION ARCHITECTURE IN ML/AI-EMPOWERED 5G NETWORKS

A. PMUs: Near Real-Time Data Sources for 5G Network

WAMS relies on PMUs that generate synchronized voltage and current phasor measurements [31]. PMUs can be viewed as sensors used to perform wide-area phasor measurements in power systems [32]. PMUs are designed to support multiple data reporting rates, usually up to 100 frames per second in the case of 50 Hz power systems. In addition to PMUs, Phasor Data Concentrators (PDC) are used in communication
systems in order to correlate synchrophasor data by time stamps creating a system wide measurement sets [33].

Depending on SG architecture, both PMUs and PDCs can access the network as a 5G New Radio (NR) User Equipment (UE). PMUs can be deployed in two scenarios: i) as standalone devices that send data as UEs to a remote PDC, or ii) as part of a local field network deployed by a power system operator that connects multiple PMUs in a given region to a PDC, which in turn connects to the 5G network as a UE (see SG Substation block in Fig. 2). Besides local PDCs, power system operator may deploy regional or corporate PDCs envisioned as edge-cloud or central-cloud applications (Fig. 2). Edge PDCs are usually deployed by a Distribution System Operator (DSO) as part of the distribution network SE.

Corporate PDCs usually provide data to a single utility (state-level transmission network), while regional PDCs provide data at interconnection level (multi state-level transmission network).

Information stored in PMU/PDC should be formatted as defined in IEEE C37.118.2 [33]. The most widely used protocols for the transfer of synchrophasor data are IEEE C37.118.2 [33] and IEC TR 61850-90-5 [34]. IEC TR 61850-90-5 protocol bridges the gap between IEC 61850, recommended for Intelligent Electronic Devices (IEDs) at electrical substations [29], and IEEE C37.118.2 designed specifically for PMUs. It enables wide-area synchrophasor data transfer using Routed Sampled Value (R-SV) and Routed Generic Object-Oriented Substation Event (R-GOOSE) protocols. Application, transport, and network layer encapsulation related to PMU communications compliant with IEEE C37.118.2 and IEC TR 61850-90-5 protocols, are shown in Fig. 3. Upon UDP/IP encapsulation of PMU/PDC data frames, they are transmitted by 5G UE using URLLC service [28].

B. Distributed SE in ML/AI-Empowered 5G Networks

The SE is a key functionality of the EMS whose aim is to provide a timely estimate of the system state variables (magnitude and angle of the voltage) at all the buses of the

Fig. 1. 5G network architecture support for SG services.

Fig. 2. Example of SG service deployment over 5G network architectures.

Fig. 3. OSI layers related to PMU wide-area communications, and compliant with IEEE C37.118.2 and IEC TR 61850-90-5 protocols.
power system [13]. Traditional EMS is centralised, where data collection and its processing is concentrated at a single node. 5G supports centralised EMS by deploying its functions as cloud-native applications within the 5G central cloud (see Centralized EMS module in Fig. 2). Centralized EMS runs the centralised SE algorithm based on the set of PMU measurements collected at the 5G central cloud either from local or regional (edge) PDCs. Centralized EMS may interact with the 5G CN through SGAF deployed in the 5G central cloud. SGAF may expose its own data and access relevant network statistics exposed by other 5G CN data analytics functions such as MDAF or NWDAF in order to improve EMS services.

Recent trends see shifting the SE functionality from centralised to distributed system architecture. Distributed SE implies the absence of the central coordinator, where each local area communicates only with its neighbors [35]–[38]. In terms of estimation accuracy, the distributed approach is equivalent to the hierarchical and centralised. For latency-critical scenarios, distributed SE over 5G networks with distributed information acquisition and processing represents the most promising approach. In the envisioned architecture, the distributed SE could be virtualized and deployed in numerous 5G edge cloud servers across the network (see Distributed EMS module in Fig. 2). Distributed SE modules receive local PMU measurements via 5G RAN either directly from 5G-connected PMUs, from 5G-connected local PDCs, or from edge PDCs. Based on the received measurements, distributed SE performs message-passing among neighboring SE modules, by exchanging UDP/IP packets through 5G CN. The following subsection provides more details on emerging distributed SE algorithms based on message-passing, while their performance is numerically evaluated in Section IV.

C. Model-Based versus Data-Based Distributed SE

1) Model-Based Distributed SE: The state-of-the-art model-based distributed SE algorithms exploit the matrix decomposition techniques applied over the Weighted Least Squares (WLS) method. In particular, the SE algorithms based on distributed optimization combined with the alternating direction method of multipliers (ADMM) have become popular in the literature. To decentralize an optimization problem, ADMM decouples the objective function with consensus variables. The resulting algorithm can be interpreted as an iterative message-passing procedure, in which agents solve subproblems independently [13].

Another efficient iterative message-passing algorithm for distributed inference is GBP. therein, the power system network with a given measurement configuration is mapped onto an equivalent factor graph containing the set of factor and variable nodes. Factor nodes are defined by the set of measurements, measurement error and measurement function. The variable nodes are determined by the set of state variables. When applied on factor graphs, the GBP algorithm calculates the marginal distributions of the system of random variables [13], [36].

2) Data-Based Distributed SE: The growing collection of historical measurement data in juxtaposition with complex, often untractable problems has increased interest in developing data-driven SE methods. Data-driven SE, unlike model-based methods, can be designed to avoid using power system's parameters if they are highly uncertain [39]. Deep learning-based approaches that are completely data-driven or hybrid, are typically designed using feed-forward or recurrent neural networks [40] [41] which must be trained on sets of samples with a fixed power system topology, and do not offer a possibility of distributed implementation.

Recent advancements in GNNs [42] solve the problems specific to applying deep learning in power systems. GNNs learn from the graph-structured data by recursively aggregating the neighboring node vector embeddings, and transforming them non-linearly into the new embedding space. The node embeddings are initialised by dataset inputs, followed by a predefined number of neighborhood aggregations k, the GNN outputs the final node embeddings that can be used for classification or regression problems. Apart from not being restricted to training and test examples with fixed topologies, GNNs have fewer trainable parameters, lower memory requirements, and can easily incorporate connectivity information into the learning process.

In recent proposals for GNN-based SE [43] [44], the GNN models are trained to predict state variables based on the dataset of power system's measurements annotated with the node voltage values. The centralised implementation of the trained GNN model's inference results in linear computational complexity with the number of nodes in the power system (assuming the constant node degree). Additionally, GNN-based SE can be computationally and geographically distributed across multiple processing units, with the requirement that all of the measurements in the k-hop neighbourhood are gathered and sent into the unit that predicts the state variables for each node. Furthermore, the study [44] examines the robustness of the GNN-based SE to communication failures or PMU malfunctions that make the SE problem unobservable, demonstrating that result deterioration occurs only in the neighbourhood of the lost measurements.

IV. Numerical Results and Discussion

In this section, we explore the SE supported by WAMS using the IEEE 30-bus and IEEE 118-bus test case. PMUs can accurately measure voltage and current phasors and send data at high reporting rates, requiring efficient algorithms with minimal computational latency to process their measurements. We select two linear computational complexity methods for comparison: the model-based GBP method and the data-based GNN method.

A. Accuracy of GBP and GNN-based SE

In all simulation models, we start with a given IEEE test case and apply power flow analysis to generate exact solutions. Furthermore, we induce errors in exact solutions of the magnitudes and angles of the branch currents and bus voltages by applying the additive white Gaussian noise of variance $\sigma^2 = 10^{-5}$ to exact values. The resulting set
of measurements represents the PMU data source for the SE model. In particular, each PMU placed at a given bus corresponds to the bus voltage phasor and current phasor measurements along branches incident to the bus. Using the optimal placement algorithm given in [45], we observe IEEE 30-bus and 118-bus power systems with 10 and 32 PMUs, respectively.

We compare the behaviour of the GBP and GNN algorithms in the dynamic scenario, where power systems change load values in discrete time instances \( \tau = \{1, 2, \ldots, 100\} \), described with 100 different measurement sets. To evaluate SE algorithms, we select the Weighted Residual Sum of Squares (WRSS) as an evaluation metric:

\[
WRSS(\tau) = \sum_{i=1}^{m} \frac{(z_i(\tau) - h_i(\hat{x}(\tau)))^2}{v_i(\tau)},
\]

where \( m \) is the number of measurements, \( z_i(\tau) \) and \( v_i(\tau) \) are the measurement value and variance in the corresponding time instance \( \tau \), and \( h_i(\hat{x}(\tau)) \) represents the measurement function evaluated at the point defined by the estimate vector \( \hat{x}(\tau) \).

Next, we normalize the metrics \( WRSS_{\text{GNN}}(\tau) \) and \( WRSS_{\text{GBP}}(\tau) \) obtained using GNN and GBP algorithm, respectively, by \( WRSS_{\text{WLS}}(\tau) \) produced by the WLS method. For the case when GBP or GNN algorithms output the same solution as the WLS method, defined ratio is equal to one, i.e., \( (WRSS_{\text{GNN}}(\tau)/WRSS_{\text{WLS}}(\tau)) = 1 \), \( (WRSS_{\text{GBP}}(\tau)/WRSS_{\text{WLS}}(\tau)) = 1 \).

To make a fair comparison, we observe the normalized WRSS metric obtained after the first iteration of the GBP algorithm to that of the GNN algorithm, when both algorithms provide a solution for the same time complexity. Fig. 4 compares the normalized WRSS metric, \( WRSS_{\text{GBP}}(\tau)/WRSS_{\text{WLS}}(\tau) \), obtained using the GBP, and \( WRSS_{\text{GNN}}(\tau)/WRSS_{\text{WLS}}(\tau) \) calculated according to the GNN algorithm, for each time instance \( \tau \) for the power systems with 30 and 118 buses. As shown in Fig. 4, GNN gives better and more consistent results compared to GBP in terms of SE accuracy. This result is intuitive as GNN has ability to extract more complex non-linear patterns from data compared to the pure linear GBP approach.

![Fig. 4. The normalized WRSS metrics of the GNN and GBP algorithms (we observe WRSS of the GBP algorithm obtained after the first iteration), for power systems with 30 buses (subfigure a) and 118 buses (subfigure b).](image)

Fig. 5 shows the normalised WRSS metric of the GBP algorithm after the first iteration. The GBP in a few iterations outperforms the prediction of the GNN. Therefore, it can be concluded that the combination of these two algorithms can be a promising solution for fast inference (e.g., GNN can provide a more accurate starting point for GBP, significantly reducing the total number of iterations), especially since both algorithms are distributed and operate on the same graphical model.

![Fig. 5. The normalized WRSS metrics of the GBP algorithm during iterations, for power systems with 30 buses (subfigure a) and 118 buses (subfigure b).](image)

### B. Computation and Communication Delays in SE using 5G

Critical to establishing a near-real time SE is the delay introduced by 5G communication network. Given the PMU reporting periods of 10 – 20 ms, the SE process needs to produce outputs within the time frame of consecutive reports. At the bottom of Fig. 1, we identify the key delay components for end-to-end PMU-to-edge or PMU-to-Cloud connectivity. Initial delay is embedded in the PMU reporting process and data concentration at PDCs [31]. Once the data frame is encapsulated as UDP/IP packet, it is transmitted via 5G NR interface. 5G URLLC service is designed to support sub-1 ms latency, however, the exact latency the data will experience in disaggregated O-RAN system should be carefully examined. In [46], [47], delay components across CU/DU/RU split are investigated, including the delays on fronthaul and midhaul networks. After the UDP/IP packet is received at a nearby 5G CN User Plane Function (UPF), it is routed to a local SG edge cloud to distributed EMS module for processing at the local distributed SE agent. Communication between neighbouring distributed SE agents (that run GBP or GNN-based SE) proceeds via 5G CN packet delivery between edge cloud servers via one or more UPFs. Providing precise estimate of delays for GBP and GNN-based SE is out of the scope of this paper, but we note that it strongly depends on the mapping of power system factor graph to different edge cloud computation nodes. We note that GNN approach may be extremely fast, especially if the \( k \)-hop neighbourhood nodes are all mapped to the same edge cloud node. In contrast, GBP always requires several iterations of message exchanges between neighbouring edge cloud nodes.
V. CONCLUSION

In this paper, we presented our initial insights on matching recently proposed ML/AI-based distributed SE algorithms to the evolving ML/AI-empowered 5G network services. Our preliminary investigation indicates the potential of data-based SE methods to provide near real-time state estimates consistent with PMU reporting rates. However, more work is needed, in particular, in the domain of characterization of complex end-to-end delay statistics, age of information analysis, and overall performance versus delay optimization of distributed SE functions over 5G networks.

REFERENCES

[1] R. Li, Z. Zhao, X. Zhou, G. Ding, Y. Chen, Z. Wang, and H. Zhang, “Intelligent 5G: When cellular networks meet artificial intelligence,” IEEE Trans. Wireless Commun., vol. 24, no. 5, pp. 175–183, 2017.
[2] X. Xia, C. Mei, X. Zhou, S. Wang, H. Wang, and Y. Xing, “A review of 3gpp release 18 on smart energy and infrastructure,” in Proc. ICC. IEEE, 2021, pp. 384–388.
[3] T. Dragičević, P. Siano, and S. S. Prabaharan, “Future generation 5G wireless networks for smart grid: A comprehensive review,” Energies, vol. 12, no. 11, p. 2140, 2019.
[4] A. Chatoum, D. M. Manias, and A. Shami, “Towards supporting intelligence in 5G/6G core networks: NWDAF implementation and initial analysis,” arXiv preprint arXiv:2205.15121, 2022.
[5] R. R. Mohassel, A. Fung, F. Mohammadi, and K. Raahemifar, “A survey on advanced metering infrastructure,” International Journal of Electrical Power & Energy Systems, vol. 63, pp. 473–484, 2014.
[6] Y. Song, P.-Y. Kong, Y. Kim, S. Baek, and Y. Choi, “Cellular-assisted d2d communications for advanced metering infrastructure in smart grid,” IEEE Syst. J., vol. 13, no. 2, pp. 1347–1358, 2019.
[7] J. B. Ekanayake, N. Jenkins, K. Liyanage, J. Wu, and A. Yokoyama, Smart grid: technology and applications. John Wiley & Sons, 2012.
[8] B. K. Bose, “Artificial intelligence techniques in smart grid and renewable energy systems—some example applications,” Proc. of the IEEE, vol. 105, no. 11, pp. 2262–2273, 2017.
[9] A. G. Phadke, P. Wall, L. Ding, and V. Terzija, “Improving the performance of power system protection using wide area monitoring systems,” Journal of Modern Power Systems and Clean Energy, vol. 4, no. 3, pp. 319–331, 2016.
[10] A. Monticelli, “Electric power system state estimation,” Proc. of the IEEE, vol. 88, no. 2, pp. 262–282, 2000.
[11] G. N. Corrêas, “A distributed multiarea state estimation,” IEEE Trans. Power Syst., vol. 26, no. 1, pp. 73–84, 2010.
[12] L. Xie, D.-H. Choi, S. Kar, and H. V. Poor, “Fully distributed state estimation for wide-area monitoring systems,” IEEE Trans. Smart Grid, vol. 3, no. 3, pp. 1154–1169, 2012.
[13] M. Cosovic, A. Tsitsimelis, D. Vukobratovic, J. Matamoros, and C. Anton-Haro, “5G mobile cellular networks: Enabling distributed state estimation for smart grids,” IEEE Commun. Mag., vol. 55, no. 10, pp. 62–69, 2017.
[14] J. Lu, L. Xiao, Z. Tian, M. Zhao, and W. Wang, “5G enhanced service-based core design,” Proc. WOCN, pp. 1–5, 2019.
[15] J. T. Penttinen, 5G explained: security and deployment of advanced mobile communications. John Wiley & Sons, 2019.
[16] 3GPP, “5G: System architecture for the 5G System (5GS),” ETSI TS 123 501 V16.6.0 (2020-10), 2020.
[17] R. Borgaonkar and M. G. Jaatun, “5G as an enabler for secure IoT in the smart grid,” in Proc. SA. IEEE, 2019, pp. 1–7.
[18] L. Xia, M. Zhao, and Z. Tian, “5G service based core network design,” in Proc. WCNCW, 2019, pp. 1–6.
[19] V.-G. Nguyen, A. Brunstrom, K.-J. Grinemo, and J. Taheri, “SDN/NFV-based mobile packet core network architectures: A survey,” IEEE Communications Surveys & Tutorials, vol. 19, no. 3, pp. 1567–1602, 2017.
[20] Y.-J. Choi and N. Park, “Slice architecture for 5G core network,” in Proc. ICUFN, 2017, pp. 571–575.
[21] A. Checko, H. L. Christiansen, Y. Yan, L. Scolari, G. Kardaras, M. S. Berger, and L. Dittmann, “Cloud ran for mobile networks—a technology overview,” IEEE Communications surveys & tutorials, vol. 17, no. 1, pp. 405–426, 2014.
[22] 3GPP, “Study on new radio access technology: Radio access architecture and interfaces,” 3GPP TR38.801, V14.0.0 (2017-03), 2017.
[23] 3GPP, “Study on enhancement for data collection for nr and en-dc,” 3GPP TR37.817, V1.4.0 (2022-03), 2022.
[24] M. Polese, L. Bonati, S. D’Oro, S. Basagni, and T. Melodia, “Understanding o-ran: Architecture, interfaces, algorithms, security, and research challenges,” arXiv preprint arXiv:2202.01032, 2022.