

Article

Peer-to-Peer Distributed Algorithms for Wide-Area Monitoring and Control in Power Systems

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Abstract

This paper proposes peer-to-peer distributed algorithms for locally determining global power system quantities—specifically the total inertia and average frequency—which are critical for wide-area monitoring and control. These algorithms use a network of distributed measurement units that communicate locally, based on the push-sum protocol, to compute global information without centralized coordination. Applied to the large-scale European power system, these methods demonstrate an effective performance across varying time scales and system sizes, offering technical and economic advantages over centralized approaches.

Keywords: peer-to-peer; distributed; wide-area monitoring and control; WAMC; inertia estimation; frequency control; damping

1. Introduction

The electric power system is undergoing a profound transformation driven by the widespread deployment of distributed energy resources (DERs), such as photovoltaic panels, battery storage systems, electric vehicles (EVs), and flexible loads. These developments challenge traditional centralized control paradigms, which are often limited by scalability, communication bottlenecks, and vulnerability to a single point of failure. In response, peer-to-peer (P2P) distributed algorithms have emerged as a promising solution for achieving scalable, resilient, and decentralized coordination among networked agents in power systems. P2P distributed algorithms are designed to operate without a central coordinator, relying instead on local interactions among agents—such as prosumers, smart inverters, and microgrid controllers—organized into a communication network. These algorithms enable agents to collaboratively solve global optimization and control problems using only local information and message exchanges with their neighbors. The prominent algorithmic frameworks include consensus algorithms, gossip protocols, and distributed optimization techniques such as the alternate direction method of multipliers [1,2].

In the context of power systems, P2P approaches have been successfully applied in several domains. In the field of the Optimal Power Flow (OPF), distributed OPF algorithms have been proposed. Distributed OPF algorithms allow each agent (for example, a bus or microgrid) to optimize its local operation while coordinating with neighboring nodes to meet system-wide objectives such as cost minimization, voltage limits, and power balance [3]. P2P algorithms are also used in the field of demand response and energy trading. In transactive energy systems, P2P algorithms support decentralized energy trading among prosumers, enabling market-based coordination of flexible loads and DERs [4,5]. In this



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context, P2P algorithms can facilitate decentralized scheduling of EV charging, reducing the peak demand and grid congestion without centralized oversight [6]. Advanced voltage and frequency control can be achieved using distributed algorithms. Local control agents can regulate voltage and frequency using distributed feedback based on measurements from neighboring nodes, improving the stability and responsiveness in low-inertia systems [7]. Moreover, distributed algorithms can improve the resilience of the system and support the restoration process after blackouts. Following faults or cyberattacks, P2P coordination allows microgrids or DERs to reconfigure autonomously and maintain operational continuity, improving system resilience [8,9]. The main advantages of P2P methods include scalability, robustness, privacy preservation, and flexibility in integration. All of these aspects are particularly important for power system operation, especially within the perspective of the widespread deployment of distributed energy resources. However, challenges remain in ensuring convergence, dealing with asynchronous communications, preserving security and privacy, and integrating with legacy grid infrastructures. Recent research has begun to address these issues by incorporating event-triggered communication, machine-learning-enhanced P2P strategies, and secure communication protocols [10–12]. The problem of frequency regulation in power grids with distributed controllers is studied in [13], formulating the problem as an output agreement. The work in [14] examines distributed control protocols for first- and second-order networked dynamical systems, introducing a class of nonlinear consensus controllers where the each agent's input is the product of a nonlinear gain and a sum of nonlinear interaction functions. Distributed control represents an essential resource for addressing the challenges of modern electrical grids [15,16], for different scopes of applications and under different time scales [17–19]. In this sense, distributed and low-latency data processing is essential for wide-area monitoring and multi-frequency estimation [20], localized inertia identification [21], and an asynchronous consensus under network imperfections [22]. Other relevant works have addressed the application of distributed methods in resilience-oriented approaches to extreme event scenarios [23] and bio-inspired optimization algorithms [24].

Peer-to-peer distributed algorithms are therefore a promising solution providing a flexible and robust foundation for the next generation of decentralized power networks, and detailed research is needed to address open points and challenges related to the application of peer-to-peer algorithms to electric systems. The purpose of this paper is to contribute in this field, proposing a novel distributed algorithm for application to wide-area monitoring and wide-area control in power systems. Wide-area monitoring and control (WAMC) systems have become essential to enhancing the observability, stability, and resilience of large-scale power systems. Traditionally, WAMC architectures have typically relied on centralized control centers that aggregate data from Phasor Measurement Units (PMUs) and issued control commands based on system-wide assessments. However, this centralized approach is increasingly challenged by the growing scale of data, the complexity of grid dynamics, and the need for real-time responsiveness under uncertain and rapidly changing conditions. Peer-to-peer distributed algorithms represent a promising solution to these challenges by enabling decentralized processing and control across geographically dispersed agents—such as substations, regional controllers, and PMUs—without relying on a central coordinator. These algorithms leverage local computation and limited peer-to-peer communication to collaboratively perform global tasks such as state estimation, event detection, and emergency control, thus significantly reducing latency, the communication burden, and vulnerability to single-point failures.

While some works in literature have addressed state estimation [25–27] and event detections [28–30], there are no works that have specifically addressed the distributed computation of global quantities in power systems such as the total inertia and average

frequency. This article proposes a peer-to-peer distributed approach to the determination of the total inertia and average frequency of the system, solely relying on peer-to-peer exchange between neighboring agents of local measurements and estimations. The proposed approach has been filed as a patent application [31]. It allows a central unit to be avoided, thus increasing the resilience, robustness, and security of the WAMC architecture. Our novel contributions are therefore summarized in terms of the following aspects:

- The definition of a peer-to-peer distributed algorithm for the determination of the total inertia for wide-area monitoring in power systems;
- The definition of a peer-to-peer distributed algorithm for the determination of the average frequency for wide-area control in power systems;
- Demonstration of the two proposed distributed algorithms in a real-world power system, referring to the case of the large-scale interconnected European system.

The remainder of this paper is structured as follows. The proposed P2P distributed algorithms are presented in Section 2, recalling the underlying concept and describing the main characteristics of the proposed algorithms for application to WAMC systems. The application of the distributed algorithms to a real-world power system is presented in Section 3, referring to a large-scale dynamic model of the European power system. Finally, Section 4 concludes this paper with a summary of the main findings and observations.

2. The Proposed Peer-to-Peer Algorithms

The underlying idea of the proposed peer-to-peer algorithms is to build upon the principles of the push-sum protocol. The push-sum protocol is a particular type of gossip algorithm, aiming to compute an aggregate function of the values held by the nodes of the network [32,33]. This type of algorithm falls within the category of node aggregation problems, where the aggregate functions can be the sum, average, count, and so on. The computation of these functions is performed in a decentralized and fault-tolerant manner, relying only on the exchange of small messages. In general, gossip algorithms are used in distributed systems to disseminate global information in the system through the periodical exchange of local information between selected neighbors (Figure 1). In a standard push-sum protocol, each node or agent stores two values: a sum and a weight. The sum is initially set to the own local value of the node. As the algorithm progresses, the sum of a given node accumulates portions of sums from other nodes. The weight instead is initially set to a value that depends on the aggregate function to be realized. The weight of a given node also accumulates portions of weights from other nodes. In each round of the algorithm, a given node i performs the following: it selects a neighbor node j to communicate with; divides its current sum and weight by two; and sends half of its sum and half of its weight to the neighbor j , retaining the other half of its sum and weight for itself. When a node j receives the pair of the sum and the weight from a neighbor i , it adds the received values to its own sum and weight. At any point in the process, each node or agent belonging to the network can estimate the global quantity by computing the ratio of its current sum to its current weight. A flowchart of the proposed method for a visual illustration of the information exchange and the update process used in the protocol is shown in Figure 2.

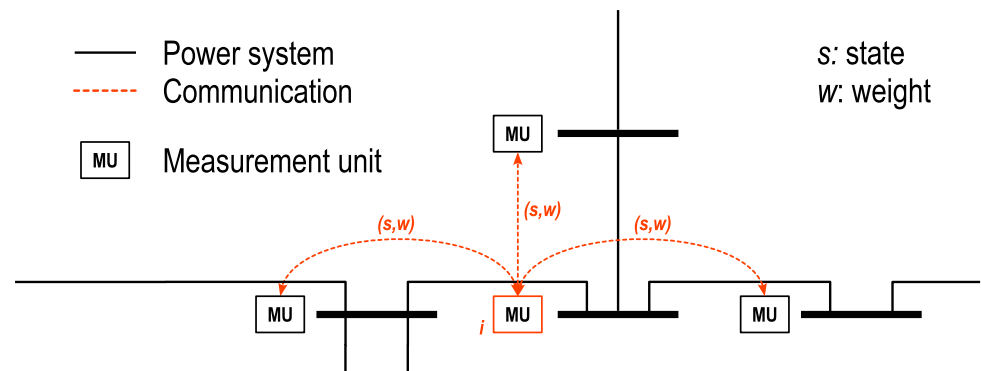


Figure 1. A conceptual representation of the proposed peer-to-peer distributed algorithms.

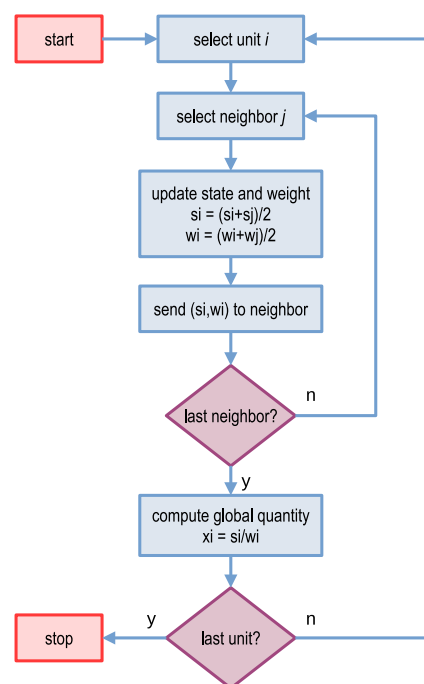


Figure 2. A flowchart of the proposed peer-to-peer distributed algorithms.

In the described algorithm, each node operates independently, without the need for centralized coordination. The nodes require information only from a few neighbors, even in cases of very large networks. The set of neighbors can be determined following two different approaches: the paired units can either be selected uniformly at random across the entire network or according to the geographical distances within a given radius. The first approach will guarantee high accuracy and performance since the random selection will increase the diversity of the averaging operation, pairing nodes which could hold very different values. The random selection of a neighbor ensures that the information spreads evenly throughout the network. This approach, however, would require an extensive communication network between nodes and a local cache of nodes identifiers, giving the implementation certain complexity. The second approach, instead, can be implemented more easily in practice since it necessitates communication interconnection only between pairs of nodes that are geographically close. This approach, however, might require a higher number of neighbors to achieve the proper accuracy and performance. Neighboring nodes can be identified according to geographic distance using specific greedy routing algorithms [34]. Gossip algorithms have been considered an efficient option for wide-area

sensor networks due to their advantages of decentralization and scalability, efficiency, flexibility, tolerance to failures, and resilience to topological changes. Additionally, gossip algorithms do not require nodes to share sensitive information with a central unit, so they can guarantee a certain level of privacy preservation and cybersecurity. All of these properties make gossip algorithms well suited to wide-area networks, where scalability, robustness, security, and efficiency are aspects of particular importance.

While push-sum protocols and gossip algorithms are generally considered for application to distributed sensor systems [35,36], the use of gossip algorithms for wide-area monitoring and control in power systems has not previously been addressed in the literature. The next sections address this research gap, with the presentation of specific distributed algorithms for the determination of global system quantities such as the total inertia and average frequency. Such global quantities can serve for different purposes and scopes of application, as summarized in Table 1.

Table 1. Scope of use and application for global quantities.

Global Quantity	Application
Total inertia	Online inertia level monitoring
	Security-constrained dispatch and reserve sizing
	Definition of advanced optimal inertia control
	Extended event classification
Average frequency	Enhanced situational awareness and grid stability monitoring
	Identification and damping of inter-area oscillations
	Enhanced detection of islanding and system separation
	Definition of advanced wide-area control schemes

The selection of the agents should be made according to a specific methodology, and it can be conveniently carried out according to the geographic distribution and connectivity requirement criteria. For this purpose, a given connectivity radius can be fixed in length, and centering the circle in a given measurement unit, all other units found within the radius will be flagged as neighbors. While there is a minimum number of units to select as agents according to the required performance (speed, accuracy), there is no practical limit in involving several units in the distributed algorithm. This guarantees the proper degree of scalability of the proposed approach, especially in cases of large and sparse power systems.

It is proven that the convergence of push-sum algorithms is guaranteed under the conditions of sufficient connectivity within the network and the inherent mass conservation property of the algorithm itself [32,37]. The convergence rate generally depends on the network topology, the number of units, and the communication strategy. In this sense, latencies and communication delays can affect the convergence speed and, in some nuanced cases, the accuracy of the final value reached with the consensus of all units. However, a remarkable advantage of the push-sum protocol is its robustness to delays. In fact, the mass conservation property of the algorithm—i.e., a global consensus (total sum/total weight) constant throughout the execution—helps in maintaining the correct final value, even in the presence of bounded, fixed, or time-varying random communication delays [38,39].

2.1. Algorithm #1: Total Inertia

Determination of the total inertia of the system according to the proposed peer-to-peer distributed algorithm can be illustrated as follows. Each measurement unit is installed in the electrical system, as in Figure 1, and knows the amount of local inertia at the point of installation. The local inertia can be estimated using the information obtained from the PMUs according to the most common measurement-based approach. Different techniques

can be applied for online inertia estimation in a fast and reliable manner [40–42]. Each unit initialises its state s_i and weight w_i in the following way: s_i assumes the value of the estimated local inertia at the point of installation; w_i assumes the value corresponding to the inverse of the total number of units in the system. Upon receiving data from a neighboring unit, each unit updates its state s_i and w_i by adding the received state and weight to its own pair and computing the half. Each unit then sends the updated state s_i and weight w_i to the neighboring units. This process is performed continuously and repeatedly until a consensus is reached on the total value of all local estimated inertia contributions after a sufficient number of iterations. For a given unit, it is assumed that data exchange can take place with a limited number of neighboring units within a given time interval, ranging from the order of minutes to the hour scale depending on the application purposes and requirements.

The proposed procedure for the determination of the total inertia using a peer-to-peer distributed approach is summarized in Algorithm 1.

Algorithm 1 Algorithm #1 for determination of the total inertia

Require: $\mathcal{A}$, set of nodes or agents
Require: $\mathcal{N}_i$, set of neighbors of node i
Ensure: N_A , number of elements in $\mathcal{A}$
Ensure: r_{max} , maximum number of rounds
Ensure: x_i , estimation of the total inertia at node i

- 1: $r \leftarrow 0$
- 2: **for each** node i in $\mathcal{A}$ **do**
- 3: $s_i \leftarrow$ estimated local inertia H_i
- 4: $w_i \leftarrow 1/N_A$
- 5: Send (s_i, w_i) to i
- 6: $r \leftarrow r + 1$
- 7: **while** $r < r_{max}$ **do**
- 8: **for each** node i in $\mathcal{A}$ **do**
- 9: **for each** node j in $\mathcal{N}_i$ **do**
- 10: Let (s_j, w_j) be the pair received from j at $r - 1$
- 11: $s_i \leftarrow (s_i + s_j)/2$
- 12: $w_i \leftarrow (w_i + w_j)/2$
- 13: Send (s_i, w_i) to j
- 14: $x_i \leftarrow s_i/w_i$
- 15: $r \leftarrow r + 1$

From the point of view of a practical implementation, the algorithm requires the initialization of the state and weight for all units. In particular, the weights w are all initialized to the inverse of the total number of units that belong to the sensor network and participate in the algorithm. This requires knowledge of the total number of units in the system N_A , which is not a flexible approach and might not be feasible for large interconnected systems. A more practical approach is therefore to choose a limited number $N_R \subset N_A$ of reference units for initialization. The weights of these N_R units are then initialized to $1/N_R$, while the weights of all other remaining units will be instead initialized to 0. This non-uniform initialization of the weights might affect the convergence of the algorithm only if the network is not strongly connected. Network connectivity, however, is fundamental to the algorithm in all cases. Regardless of initialization, the underlying communication network must be strongly connected, for all units to eventually reach a consensus value [32]. If the network is disconnected, a consensus will only be formed within each connected group of units. Under the required conditions of network connectivity, an algorithm with non-uniform weight initialization based on the reference units converges

to the same result in the ideal case as uniform weight initialization for all units. With this modification, it is thus possible to implement a more flexible and resilient algorithm to determine the total inertia of the system.

Real-time knowledge of the system's overall inertia is of paramount importance to system operators, as it provides the system with the ability to instantaneously cope with any power imbalances. Knowledge of the total inertia is surely fundamental for monitoring and preventive action purposes. Additionally, this information might also be advantageously used for the development of advanced wide-area control schemes and architectures for the optimal inertia provision and distribution in the system, leading to technical benefits for the electric power system and economical benefits for the owners of the plants which provide this remunerated service. Finally, with proper adjustments to and extensions of the proposed peer-to-peer distributed method, it is also possible to determine the total inertia for a given area or part of the system, possibly based on the competence of a single system operator, thus leading to an enhanced and more precise situational awareness of the entire system.

2.2. Algorithm #2: Average Frequency

Determination of the average frequency of the system according to the proposed peer-to-peer distributed algorithm can be illustrated as follows. Each measurement unit is installed in the electrical system, as in Figure 1, and knows the measurement of the local frequency at the point of installation. The local frequency can be obtained using the information provided by the PMUs in terms of high-resolution and time-synchronized measurements. Each unit initializes its state s_i and weight w_i in the following way: s_i assumes the value of the measured local frequency at the point of installation; w_i assumes the value 1. Upon receiving data from a neighboring unit, each unit updates its state s_i and w_i by adding the received state and weight to its own pair and computing the half. Each unit then sends the updated state s_i and weight w_i to the neighboring units. This process is performed continuously and repeatedly until a consensus is reached on the average value of all local measured frequencies after a sufficient number of iterations. For a given unit, it is assumed that data exchange can take place with a limited number of neighboring units within a given time interval, which should ideally be equal to 2–3 cycles of the fundamental frequency to guarantee adequate performance requirements.

The proposed procedure for the determination of the average frequency with a peer-to-peer distributed approach is summarized in Algorithm 2.

From the point of view of a practical implementation, the initialization of the internal state of the units can be conveniently improved, taking advantage of the knowledge of the previous estimation of the global average frequency. Instead of assuming that the initial state is equal to the local frequency measured by the unit, the state s_i can be initialized according to a weighted proportion between the local frequency f_i and the value x_i determined in the previous round as the ratio between the state and weight. Ultimately, x_i represents an estimate of the global average frequency locally available in the unit. The proposed modification follows the principles of reinforcement learning, establishing a premium for the global quantity determined from the previous communication cycles, accelerating a consensus being reached between units, and thus allowing for faster and more accurate determination of the average frequency of the system. Even if, in this case of determining the average frequency, the initialization of the weights is uniform for all nodes, it is important to remark that the underlying communication network must be strongly connected. Like in the previous case of determining the total inertia, this will allow all units to eventually reach a consensus value. Contrarily, if the network is disconnected, a consensus will only be reached within each connected group of units. Real-time knowledge of

the system's average frequency may be of fundamental importance to the system operator, especially if this information is accessible at a local and distributed level. Knowledge of the average frequency can be advantageously utilized for the development of advanced control schemes for damping system oscillations using wide-area control architectures. For these purposes, it is possible to refer to the concept of wide-synchronization control [43], where the average frequency of the system is used to determine a transient change in the active power output of selected actuators. The actuators in the scheme are typically the controllers of non-synchronous generation sources interfaced via power electronic converters. This concept—which relies on the average frequency of the system as a feedback signal for wide-area damping control—has been proven to significantly increase damping and the stability of the system [44,45]. In addition to the technical advantages described, in cases where the provision of damping is regulated by the network code of the system operator and remunerated as a service, the application of the proposed method would also increase the economic benefits for the owners of the plants providing that service.

Algorithm 2 Algorithm #2 for determination of the average frequency

Require: $\mathcal{A}$, set of nodes or agents
Require: $\mathcal{N}_i$, set of neighbors of node i
Ensure: N_A , number of elements in $\mathcal{A}$
Ensure: r_{max} , maximum number of rounds
Ensure: x_i , estimation of the average frequency at node i

- 1: $r \leftarrow 0$
- 2: **for each** node i in $\mathcal{A}$ **do**
- 3: $s_i \leftarrow$ measured local frequency f_i
- 4: $w_i \leftarrow 1$
- 5: Send (s_i, w_i) to i
- 6: $r \leftarrow r + 1$
- 7: **while** $r < r_{max}$ **do**
- 8: **for each** node i in $\mathcal{A}$ **do**
- 9: **for each** node j in $\mathcal{N}_i$ **do**
- 10: Let (s_j, w_j) be the pair received from j at $r - 1$
- 11: $s_i \leftarrow (s_i + s_j)/2$
- 12: $w_i \leftarrow (w_i + w_j)/2$
- 13: Send (s_i, w_i) to j
- 14: $x_i \leftarrow s_i/w_i$
- 15: $r \leftarrow r + 1$

3. The Application Case

The proposed peer-to-peer distributed algorithms are demonstrated taking the European power system as a case study. This system is also known as the Continental Europe Synchronous Area, and it is the largest interconnected electrical grid. The geographical extent of the synchronous area is shown in Figure 3. The European system is examined by referring to the large-scale dynamic model provided by the European Network of Transmission System Operators (ENTSO-E) [46]. This model includes a representation of all areas, with more than 20,000 nodes, and it is capable of replicating the main frequency dynamics of the system [46–48]. For the purposes of this work, the ENTSO-E model has been developed further with some specific additions and modifications. The original simulation model is modified with the integration of a sensor network, by adding several PMUs across the entire system. The integration of the measurement units is performed area-wise with a random selection of nodes, for a total share of 5% over the total number of nodes in the area. This results in the inclusion of approximately 1100 measurement units in the system. This number of PMUs was determined according to the considerations in Section 2

to also assess the effectiveness of this method with a defined number of measurement units, thus demonstrating the potential scalability of the proposed algorithm. Then, for the implementation of the proposed distributed algorithms, a peer-to-peer communication network was implemented in the model. The communication network accounts for the exchange of local information between measurement units. It is worth remarking that the units communicate only with a limited set of neighbors. For a given PMU participating as an agent in the distributed algorithm, the neighboring units have been identified according to the methodology described in Section 2, fixing a connectivity radius of 300 km. The model also takes into account the latencies, which are represented using a strictly second-order Padé approximation, as detailed in [43,44]. The total round-trip delays have been assumed randomly in the range of 100 to 400 ms.

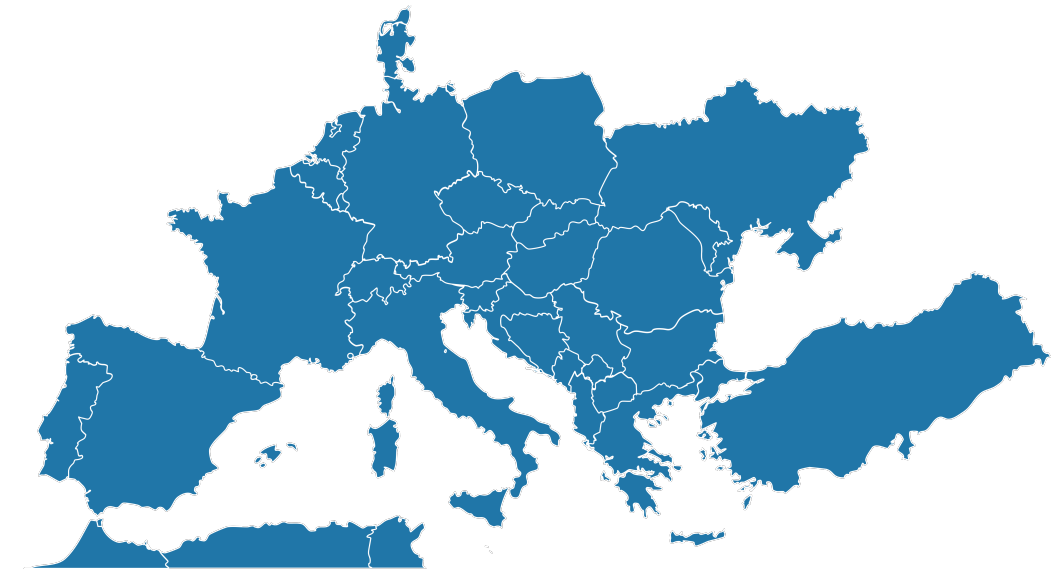


Figure 3. Continental Europe Synchronous Area.

Finally, the model includes the implementation of the two distributed algorithms presented in this work. According to the principle of the proposed algorithms, each unit holds an internal state and weight within a given period of time. For this, the conventional model of the PMU has been extended with the inclusion of this feature. According to the selected algorithm, the ratio between the state and the weight gives at any time an estimate of the total inertia or of the average frequency of the system. The application of the two specific algorithms to the case of the European power system is described in the next subsections.

3.1. Application #1: Total Inertia

The application of the proposed peer-to-peer distributed algorithm for the determination of the total inertia to the European power system was performed according to the following procedure. First, an estimation of the local inertia is assigned to the individual units distributed across the system. The estimation is performed in different steps, according to [49]. The first step is the differentiation of the local inertia's contribution according to the type of generation. Values of the typical inertia constants H_i are provided in [49] per generation type. Then, the individual inertia constants are weighted according to the actual generation mix on an hourly basis. For this, an hourly weighting factor k_i is assigned to each of the generation types as follows $k_i(t) = P_i(t)/P_{tot}(t)$. The values S_i —representing the hourly generation mix per generation technology—are obtained from the ENTSO-E Transparency Platform [50] for an entire year (2023). These values are finally assigned to the local units in the system for the application of the proposed peer-to-peer

distributed algorithm. Each unit will exchange its local estimation E_i with the neighboring units, and the algorithm will aim at the determination of the total inertia of the system. At the beginning, the states s_i receive the local estimations E_i , while the weights w_i are initialized to the inverse of the total number of units for the sake of simplicity. The value P_{tot} represents the sum of all P_i for the given area and period of time. Since the ENTSO-E platform provides the data on the actual generated power, the corresponding rated power S_i required for the computation of the inertia contribution is determined considering the typical loading factors LF_i per generation technology, as $S_i(t) = P_i(t)/LF_i$. The typical loading factors per generation type are also given in [49]. The individual local inertia contributions E_i are therefore computed as $E_i(t) = H_i k_i(t)/LF_i$. These values are shown in Figure 4 for all European countries. The application of the distributed algorithm to determining the total inertia produces the results shown in Figure 5, where the actual value of the total inertia is also reported for comparison. Close-up details are shown in Figure 6 for a more complete assessment of the results. It can easily be observed that the total inertia of the system computed according to the proposed algorithm substantially matches the actual value.

For a better insight into the distributed characteristics of the proposed algorithm, the local estimations of the total inertia—held within each unit as $x_i = s_i/w_i$ —are shown in Figure 7. It can be noticed that the local estimations within all units are very close to the actual values, providing local and distributed availability of the global information represented by the total inertia of the system. For a quantitative assessment of the algorithm's accuracy, the standard error metrics of the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) have been also computed. For the numerical results in Figure 7, the error metrics are a MAE = 1.73×10^{-4} and an RMSE = 2.77×10^{-4} .

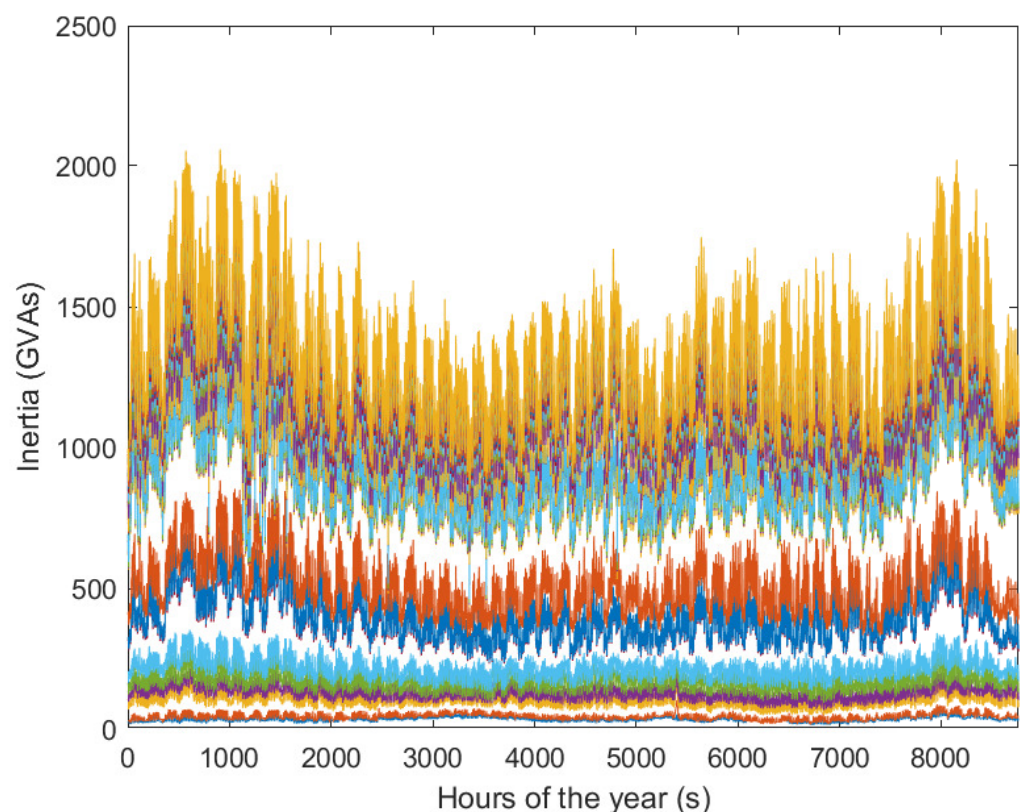


Figure 4. The individual inertia of different areas across the system.

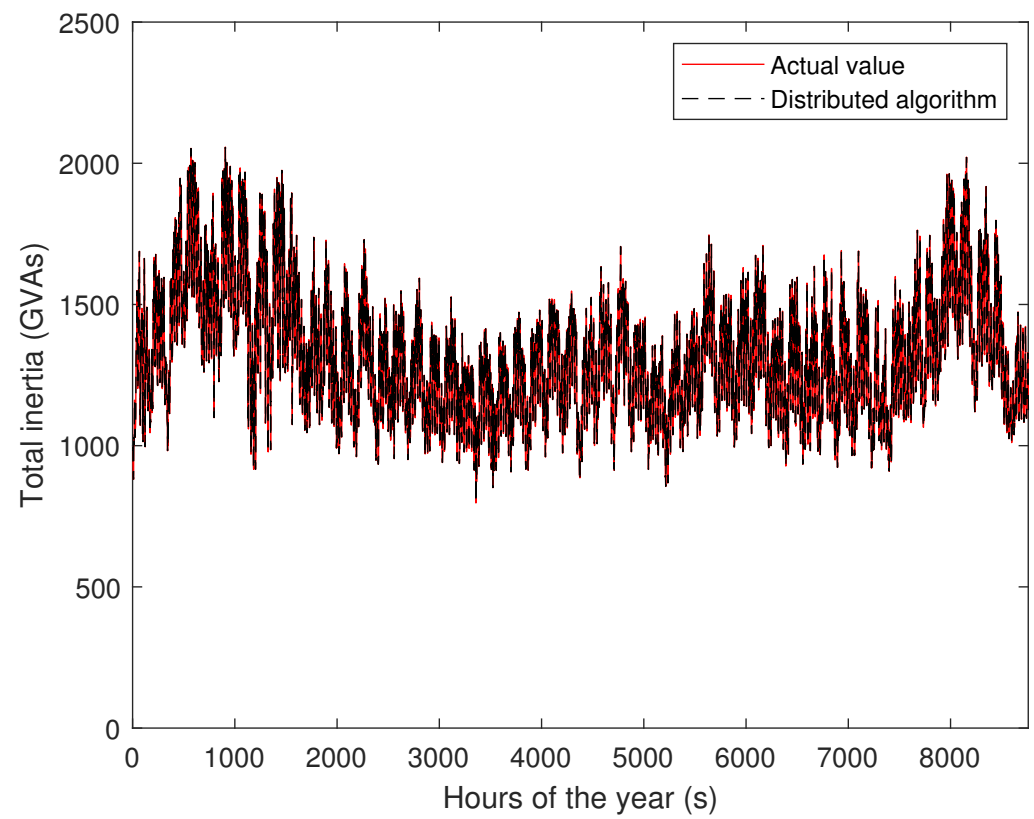


Figure 5. Determination of the total inertia with the proposed algorithm.

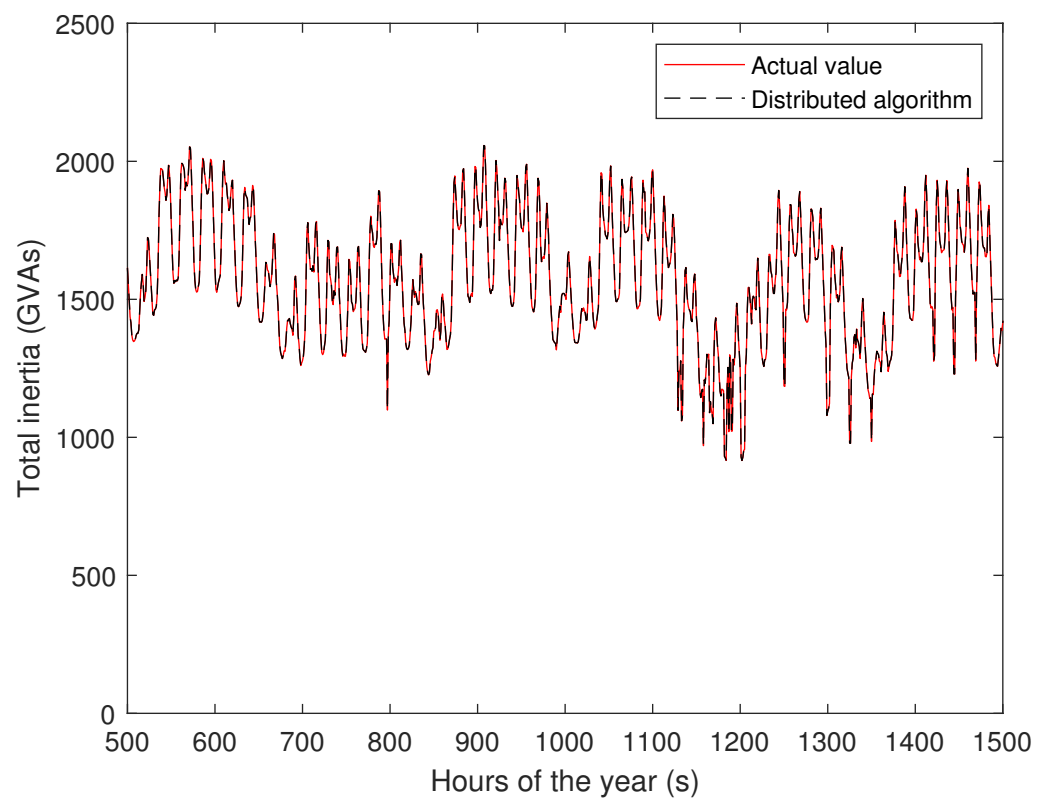


Figure 6. Determination of the total inertia with the proposed algorithm—time detail.

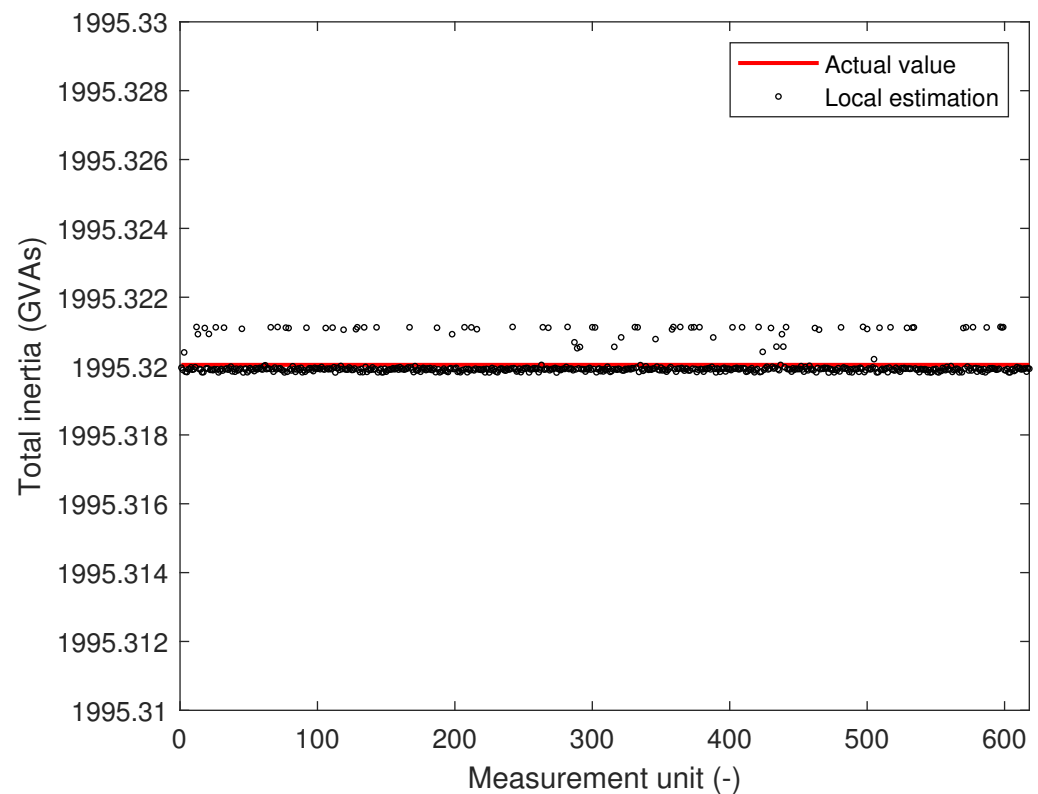


Figure 7. Determination of the total inertia with the proposed algorithm—round detail.

The results show that the units are able to reach a consensus on the sum, determining a local estimate substantially close to the actual total inertia of the system.

3.2. Application #2: Average Frequency

The proposed peer-to-peer distributed algorithm for the determination of the average frequency was applied to the European power system according to the following procedure. The European power system is simulated for a dynamic analysis considering a disturbance of a 1 GW generation imbalance on the western side of the system. This event corresponds to an actual incident that occurred in the system, and it was used to validate the original ENTSO-E model [47]. The frequencies in the different parts of the system are recorded by the distributed PMUs which have been integrated into the simulation model. During the solution of the model, at the end of each integration step, the PMUs exchange the local frequency measurements with neighboring units and update their state s and weight w with the received pairs, according to the proposed algorithm and for a given number of rounds of communication. Once this process is completed, the simulation moves on to the next integration interval, and the procedure starts over. At any instant of operation, the algorithm aims to determine the average frequency of the system. At the beginning, the states s_i receive local measurements of the frequency f_i , while the weights w_i are all initialized to 1. The application of the distributed algorithm to determining the average frequency produces the results shown in Figure 8, where the actual value of the average frequency is also reported for comparison. A plot with only the actual average frequency and the estimations computed locally within the units is shown in Figure 9 for a more complete assessment of the results. It can easily be observed that the average frequency of the system computed according to the proposed algorithm substantially matches the actual value. Also, in this case, the algorithm's accuracy was quantitatively assessed by computing the standard error metrics of the RMSE and MAE. For the numerical results in Figure 9, the error metrics are a $\text{MAE} = 6.10 \times 10^{-4}$ and an $\text{RMSE} = 6.10 \times 10^{-4}$. The two metrics

differ only in some irrelevant digits because in the case of the average consensus, all individual estimations are basically of the same magnitude.

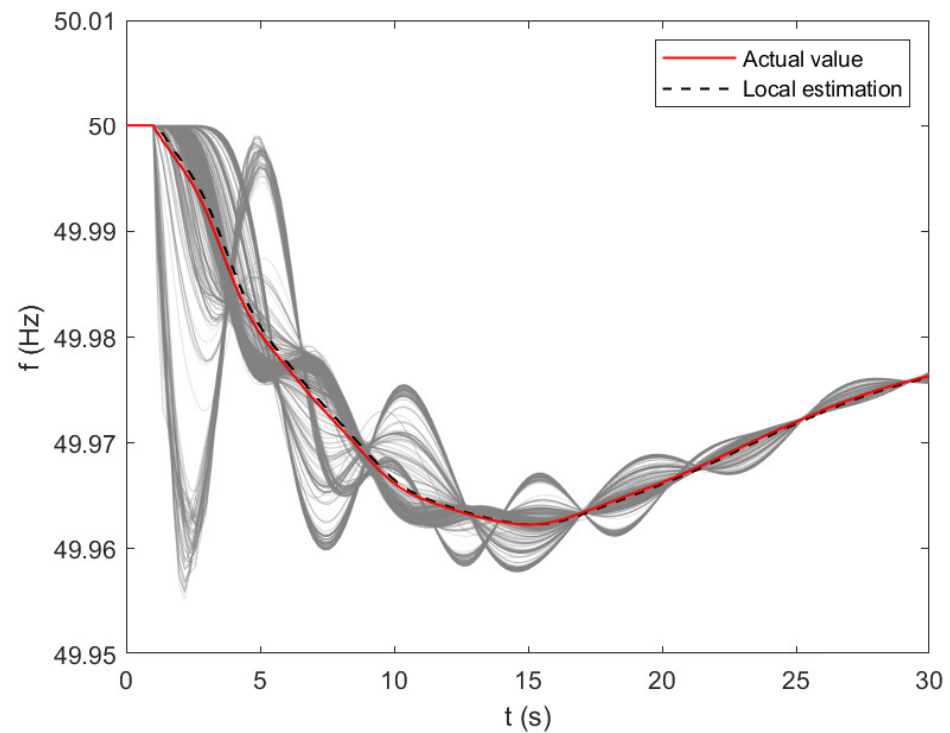


Figure 8. Determination of the average frequency with the proposed algorithm.

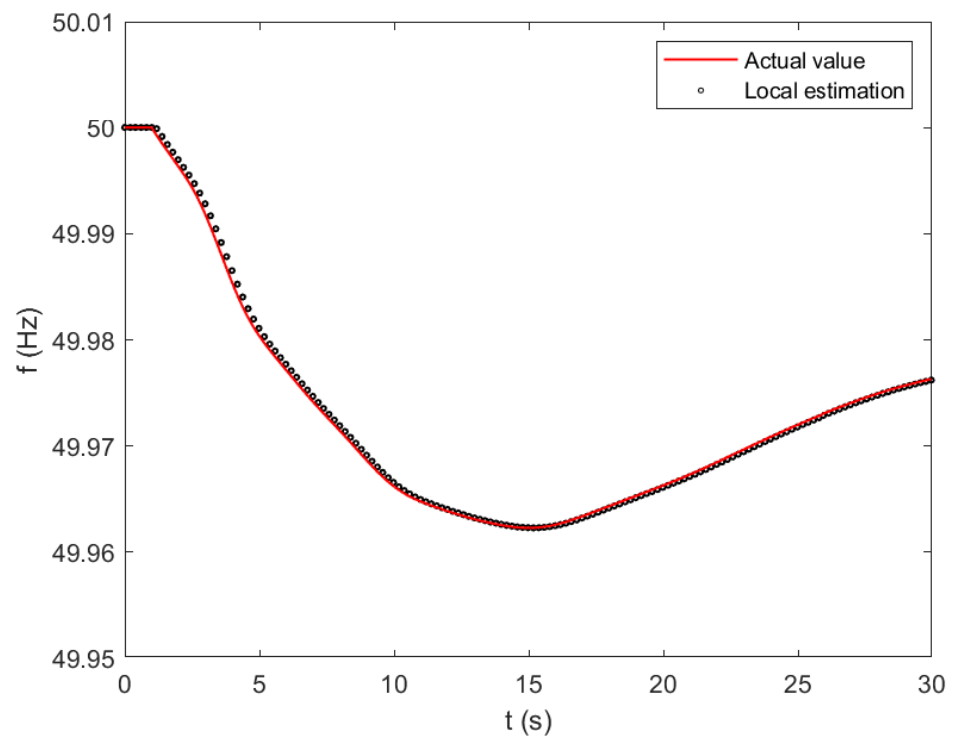


Figure 9. Determination of the average frequency with the proposed algorithm—detail.

For deeper insight into the updating process between units, a snapshot of the initialization and communication rounds during the execution of the algorithm is provided in Figures 10 and 11. The plots show the internal estimations $x = s/w$ of all units for two snapshots taken at time $t = 2$ s and time $t = 5$ s, respectively. The snapshots are taken

just a few seconds after the occurrence of the disturbance, therefore representing critical moments during the transient response of the system, where significant local differences in the frequency are likely to be experienced. The results show the speed of convergence of the implemented algorithm: in just a few rounds of communications, the units are able to reach a consensus on the average, determining a local estimate very close to the actual average frequency of the system. It should be noted that the implemented algorithm works continuously, providing the average frequency of the entire system at any time of operation, even during critical transients characterized by significant frequency excursions.

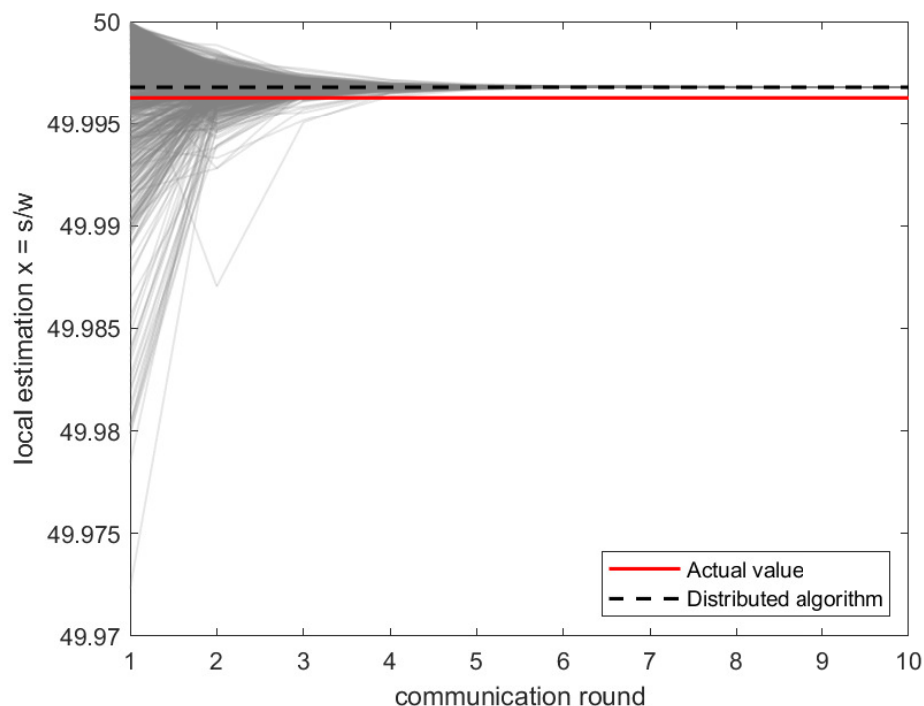


Figure 10. Peer-to-peer communication rounds at $t = 2$ s snapshot.

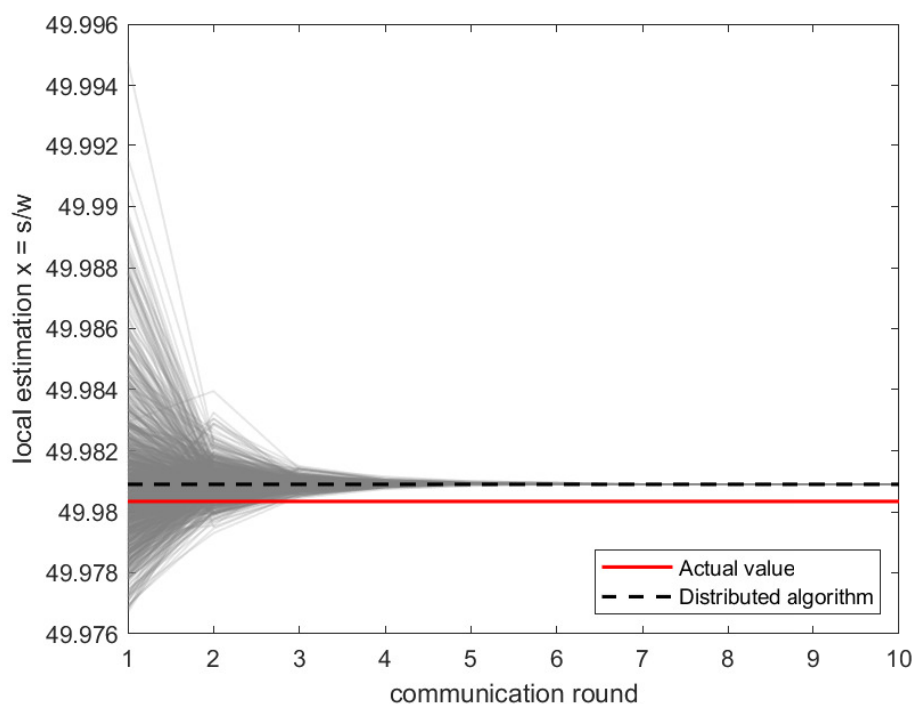


Figure 11. Peer-to-peer communication rounds at $t = 5$ s snapshot.

4. Conclusions

This article presents an innovative use of peer-to-peer distributed algorithms for wide-area monitoring and control in power systems. These algorithms enable each measurement unit to locally estimate global quantities—such as the total inertia and average frequency—through continuous pairwise communication within a network. Based on the push-sum gossip protocol, each unit updates a pair of values (sum and weight) during communication rounds with neighboring units. Over time, this leads to a distributed consensus, allowing every unit to estimate the global power system values. The approach is validated on the large-scale European power system, demonstrating that the algorithms quickly converge to accurate estimates across various time scales and operating conditions, confirming their effectiveness and scalability. The proposed peer-to-peer distributed algorithms enable local estimation of global power system quantities like the total inertia and average frequency, enhancing situational awareness for wide-area monitoring and control. At the same time, they also provide key benefits of decentralized approaches, including flexibility, security, robustness, resilience, and efficiency.

Real-world implementations of the proposed algorithms will undoubtedly encounter technical and regulatory challenges. From a technical point of view, a key challenge lies in establishing a reliable and extensive communication infrastructure. From a regulatory point of view, securing agreement and coordination among various system operators for real-time data exchange will be critical. Building on the algorithms presented in this article, future works will then focus on developing advanced architectures for wide-area monitoring and control, addressing cybersecurity aspects, and optimizing the selection of the measurement units. The future research directions outlined will serve as fundamental points for addressing the challenges and limitations associated with the real-world deployment of the proposed concept.

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References

1. Boyd, S.; Parikh, N.; Chu, E.; Peleato, B.; Eckstein, J. *Distributed Optimization and Statistical Learning via the Alternating Direction Method of Multipliers*; Now Foundations and Trends: Hanover, MA, USA, 2011. [[CrossRef](#)]
2. Olfati-Saber, R.; Fax, J.A.; Murray, R.M. Consensus and Cooperation in Networked Multi-Agent Systems. *Proc. IEEE* **2007**, *95*, 215–233. [[CrossRef](#)]
3. Zhang, B.; Tse, D. Geometry of feasible injection region of power networks. In Proceedings of the 2011 49th Annual Allerton Conference on Communication, Control, and Computing (Allerton), Monticello, IL, USA, 28–30 September 2011; pp. 1508–1515. [[CrossRef](#)]
4. Mengelkamp, E.; Notheisen, B.; Beer, C.; Dauer, D.; Weinhardt, C. A blockchain-based smart grid: Towards sustainable local energy markets. *Comput. Sci.—Res. Dev.* **2018**, *33*, 207–214. [[CrossRef](#)]
5. Suthar, S.; Cherukuri, S.H.C.; Pindoriya, N.M. Peer-to-peer energy trading in smart grid: Frameworks, implementation methodologies, and demonstration projects. *Electr. Power Syst. Res.* **2023**, *214*, 108907. [[CrossRef](#)]

6. Ma, Z.; Callaway, D.S.; Hiskens, I.A. Decentralized Charging Control of Large Populations of Plug-in Electric Vehicles. *IEEE Trans. Control Syst. Technol.* **2013**, *21*, 67–78. [\[CrossRef\]](#)
7. Simpson-Porco, J.W.; Dörfler, F.; Bullo, F. Synchronization and power sharing for droop-controlled inverters in islanded microgrids. *Automatica* **2013**, *49*, 2603–2611. [\[CrossRef\]](#)
8. Doostinia, M.; Beheshti, M.T.H.; Alavi, S.A.; Guerrero, J.M. Distributed control strategy for DC microgrids based on average consensus and fractional-order local controllers. *IET Smart Grid* **2021**, *4*, 549–560. [\[CrossRef\]](#)
9. Li, Y.; Zhang, Z.; Dragičević, T.; Rodriguez, J. A Unified Distributed Cooperative Control of DC Microgrids Using Consensus Protocol. *IEEE Trans. Smart Grid* **2021**, *12*, 1880–1892. [\[CrossRef\]](#)
10. Wu, Z.G.; Xu, Y.; Lu, R.; Wu, Y.; Huang, T. Event-Triggered Control for Consensus of Multiagent Systems With Fixed/Switching Topologies. *IEEE Trans. Syst. Man Cybern. Syst.* **2018**, *48*, 1736–1746. [\[CrossRef\]](#)
11. Zhang, J.; Zhang, H.; Lu, Y.; Sun, S. Event self-triggered leader-following consensus of multi-agent systems with general dynamics. *IET Control Theory Appl.* **2020**, *14*, 1209–1219. [\[CrossRef\]](#)
12. Huang, J.; Chen, L.; Xie, X.; Wang, M.; Xu, B. Distributed Event-triggered Consensus Control for Heterogeneous Multi-agent Systems under Fixed and Switching Topologies. *Int. J. Control. Autom. Syst.* **2019**, *17*, 1945–1956. [\[CrossRef\]](#)
13. Trip, S.; De Persis, C. Frequency Regulation in Power Grids by Optimal Load and Generation Control. In *Smart Grids from a Global Perspective: Bridging Old and New Energy Systems*; Springer International Publishing: Cham, Switzerland, 2016; pp. 129–146. [\[CrossRef\]](#)
14. Andreasson, M.; Dimarogonas, D.V.; Sandberg, H.; Johansson, K.H. Distributed Control of Networked Dynamical Systems: Static Feedback, Integral Action and Consensus. *IEEE Trans. Autom. Control* **2014**, *59*, 1750–1764. [\[CrossRef\]](#)
15. Jin, M. Reinforcement Learning Meets the Power Grid: A Contemporary Survey with Emphasis on Safety and Multi-agent Challenges. *Found. Trends Electr. Energy Syst.* **2025**, *8*, 169–316. [\[CrossRef\]](#)
16. Gómez-Luna, E.; Marlés-Sáenz, E.; Candelo-Becerra, J. A comprehensive review of distributed control techniques for the operation of modern electrical distribution networks. *Math. Model. Eng. Probl.* **2023**, *10*, 1537–1547. [\[CrossRef\]](#)
17. Zhen, F.; Zhenghong, T.; Wenxin, L. Online multi-agent deep reinforcement learning platform for distributed real-time dynamic control of power systems. *Neural Comput. Appl.* **2025**. [\[CrossRef\]](#)
18. Zhang, L.; Yang, F.; Yan, D.; Qian, G.; Li, J.; Shi, X.; Xu, J.; Wei, M.; Ji, H.; Yu, H. Multi-Agent Deep Reinforcement Learning-Based Distributed Voltage Control of Flexible Distribution Networks with Soft Open Points. *Energies* **2024**, *17*, 5244. [\[CrossRef\]](#)
19. Chai, J.; Wang, M.; Xu, Z. A Distributed Event-Triggered Fixed-Time Secondary Control for DC Microgrids Without Continuous Signal Transmission. *IEEE J. Emerg. Sel. Top. Power Electron.* **2024**, *12*, 5123–5138. [\[CrossRef\]](#)
20. Hossain, M.J.; Naeini, M. Multi-Area Distributed State Estimation in Smart Grids Using Data-Driven Kalman Filters. *Energies* **2022**, *15*, 7105. [\[CrossRef\]](#)
21. Gotti, D.; Bizzarri, F.; Brambilla, A.; Giudice, D.d.; Grillo, S.; Linaro, D.; Ledesma, P.; Amaris, H. Inertia Estimation of a Power System Area Based on Iterative Equation Error System Identification. *IEEE Trans. Power Syst.* **2024**, *39*, 6469–6481. [\[CrossRef\]](#)
22. Bof, N.; Carli, R.; Schenato, L. Average Consensus with Asynchronous Updates and Unreliable Communication. *IFAC-PapersOnLine* **2017**, *50*, 601–606. [\[CrossRef\]](#)
23. Quan, R.; Guo, H.; Liu, D.; Chang, Y.; Wan, H. Performance optimization of a thermoelectric generator for automotive application using an improved whale optimization algorithm. *Sustain. Energy Fuels* **2023**, *7*, 5528–5545. [\[CrossRef\]](#)
24. Wang, Z.; Hou, H.; Wei, R.; Li, Z. A Distributed Market-Aided Restoration Approach of Multi-Energy Distribution Systems Considering Comprehensive Uncertainties from Typhoon Disaster. *IEEE Trans. Smart Grid* **2025**, early access. [\[CrossRef\]](#)
25. Li, X.; Scaglione, A. Robust Decentralized State Estimation and Tracking for Power Systems via Network Gossiping. *arXiv* **2013**, arXiv:1303.4153. [\[CrossRef\]](#)
26. Lu, Y.; Yuan, C.; Zhang, X.; Huang, H.; Liu, G.; Dai, R.; Wang, Z. Graph Computing based Distributed State Estimation with PMUs. *arXiv* **2020**, arXiv:2002.09477. [\[CrossRef\]](#)
27. Kekatos, V.; Giannakis, G.B. Distributed Robust Power System State Estimation. *arXiv* **2012**, arXiv:1204.0991. [\[CrossRef\]](#)
28. Parede, V.T.; Aoki, A.R.; Teixeira, M.D.; Fernandes, T.S.P.; Barreto, N.E.M.; Grando, F.L.; da Silva, V.A.; Guerra, F.A.; Ramos, M.P.; da Costa, C.H.; et al. Electrical Event Detection and Monitoring Data Storage from Wide Area Measurement System. *Energies* **2023**, *16*, 1713. [\[CrossRef\]](#)
29. Han, F.; Ashton, P.M.; Li, M.; Pisica, I.; Taylor, G.; Rawn, B.; Ding, Y. A Data Driven Approach to Robust Event Detection in Smart Grids Based on Random Matrix Theory and Kalman Filtering. *Energies* **2021**, *14*, 2166. [\[CrossRef\]](#)
30. Husnoo, M.A.; Anwar, A.; Haque, M.E.; Mahmood, A.N. Decentralized Federated Anomaly Detection in Smart Grids: A P2P Gossip Approach. *arXiv* **2025**, arXiv:2407.15879. [\[CrossRef\]](#)
31. Musca, R.; Riva Sanseverino, E. Metodo per L'interazione tra Elementi di Misura nei Sistemi Elettrici di Potenza. *Italian* 102025000010371, 8 May 2025.
32. Kempe, D.; Dobra, A.; Gehrke, J. Gossip-based computation of aggregate information. In Proceedings of the 44th Annual IEEE Symposium on Foundations of Computer Science, Cambridge, MA, USA, 11–14 October 2003; pp. 482–491. [\[CrossRef\]](#)

33. Wang, H.; Liao, X.; Huang, T. Average consensus in sensor networks via broadcast multi-gossip algorithms. *Neurocomputing* **2013**, *117*, 150–160. [\[CrossRef\]](#)
34. Dimakis, A.G.; Sarwate, A.D.; Wainwright, M.J. Geographic Gossip: Efficient Averaging for Sensor Networks. *IEEE Trans. Signal Process.* **2007**, *56*, 1205–1216. [\[CrossRef\]](#)
35. Kenyeres, M.; Kenyeres, J.; Skorpil, V. The analysis of the push-sum protocol in various distributed systems. *Eur. Sci. J.* **2016**, *12*, 64–80. [\[CrossRef\]](#)
36. Lin, M.J.; Marzullo, K. Directional Gossip: Gossip in a Wide Area Network. In Proceedings of the Third European Dependable Computing Conference EDCC-3, Prague, Czech Republic, 15–17 September 1999.
37. Rezaeinia, P.; Ghareisifard, B.; Linder, T.; Touri, B. Push-Sum on Random Graphs: Almost Sure Convergence and Convergence Rate. *IEEE Trans. Autom. Control* **2020**, *65*, 1295–1302. [\[CrossRef\]](#)
38. Tsianos, K.I.; Rabbat, M.G. Distributed consensus and optimization under communication delays. In Proceedings of the 2011 49th Annual Allerton Conference on Communication, Control, and Computing (Allerton), Monticello, IL, USA, 28–30 September 2011; pp. 974–982. [\[CrossRef\]](#)
39. Tsianos, K.I.; Rabbat, M.G. The Impact of Communication Delays on Distributed Consensus Algorithms. *arXiv* **2012**, arXiv:1207.5839. [\[CrossRef\]](#)
40. Brambilla, A.M.; del Giudice, D.; Linaro, D.; Bizzarri, F. Electric power-system’s global-inertia estimation. *Int. J. Electr. Power Energy Syst.* **2024**, *160*, 110135. [\[CrossRef\]](#)
41. Prabhakar, K.; Jain, S.K.; Padhy, P.K. Inertia estimation in modern power system: A comprehensive review. *Electr. Power Syst. Res.* **2022**, *211*, 108222. [\[CrossRef\]](#)
42. Schiffer, J.; Aristidou, P.; Ortega, R. Online Estimation of Power System Inertia Using Dynamic Regressor Extension and Mixing. *IEEE Trans. Power Syst.* **2019**, *34*, 4993–5001. [\[CrossRef\]](#)
43. Musca, R.; Riva Sanseverino, E.; Zizzo, G.; Giannuzzi, G.; Pisani, C. Wide-Synchronization Control for Power Systems with Grid-Forming Converters. *IEEE Trans. Power Syst.* **2024**, *39*, 4998–5007. [\[CrossRef\]](#)
44. Ippolito, M.G.; Musca, R. A novel wide-area control for general application to inverter-based resources in power systems. *Int. J. Electr. Power Energy Syst.* **2024**, *160*, 110086. [\[CrossRef\]](#)
45. Musca, R.; Riva Sanseverino, E.; Guerrero, J.M.; Vasquez, J.C. Wide-Area Damping Control for Clustered Microgrids. *Energies* **2025**, *18*, 1632. [\[CrossRef\]](#)
46. ENTSO-E SPD (System Protection & Dynamics) Subgroup. Dynamic Model of Continental Europe V2. Available online: https://eepublicdownloads.blob.core.windows.net/public-cdn-container/clean-documents/SOC%20documents/CE_Dynamic_Model_v2_user_s_manual.pdf (accessed on 4 June 2024).
47. Semerow, A.; Höhn, S.; Luther, M.; Sattinger, W.; Abildgaard, H.; Garcia, A.D.; Giannuzzi, G.M. Dynamic Study Model for the Interconnected Power System of Continental Europe in Different Simulation Tools. In Proceedings of the 2015 IEEE Eindhoven PowerTech, Eindhoven, The Netherlands, 29 June–2 July 2015.
48. Busarello, L.; Musca, R. Impact of high share of converter-interfaced generation on electromechanical oscillations in Continental Europe power system. *IET Renew. Power Gener.* **2020**, *14*, 3918–3926. [\[CrossRef\]](#)
49. ENTSO-E. Inertia and Rate of Change of Frequency (RoCoF), Brussels. Available online: https://www.entsoe.eu/Documents/SOC%20documents/Inertia%20and%20RoCoF_v17_clean.pdf (accessed on 16 December 2020).
50. ENTSO-E. Transparency Platform. Available online: <https://transparency.entsoe.eu/> (accessed on 24 July 2025).

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