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Distributed Optimization for the DER-Rich Electric Power Grid

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Distributed Optimization for the DER-Rich Electric Power Grid

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ABSTRACT

Centralized algorithms are widely used for optimization and control in power system applications. These algorithms require all the measurements and data to be accumulated at central location and hence suffer from single-point-of-failure. Additionally, these algorithms lack scalability with an increasing number of sensors and actuators, specially with the increasing integration of distributed energy resources (DERs). As the power system becomes a confluence of a diverse set of decision-making entities with a multitude of objectives, the preservation of privacy and operation of the system with limited information has been a growing concern. Distributed optimization techniques solve these challenges while also ensuring resilient computational solutions for the power system operation in the presence of both natural and man-made adversaries. A detailed discussion of possible applications of distributed optimization in power systems is provided in this work. However, there exist multiple challenges for accurate and computationally efficient distributed solutions.

Commonly-used distributed optimization approaches include Lagrange relaxation, augmented Lagrangian, approximate

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network directions in conjunction with standard Lagrangian, auxiliary problem principle, alternating directions method of multipliers, optimality condition decomposition, proximal atomic coordination, and optimal feedback-based voltage control. A comprehensive classification of the distributed optimization problems has been discussed and detailed in this work. All of these algorithms have displayed efficient identification of global optimum solutions for convex continuous distributed optimization problems. The algorithms discussed so far are predominantly used to manage continuous state variables. Inclusion of integer variables in the decision support are needed for specific power system problems.

Mixed integer programming (MIP) problem arises in a power system operation and control due to tap changing transformers, capacitors and switches. The global optimization techniques for MIPs are Branch and Bound, Branch and Cut, Cutting planes, Adaptive coordinate search, Nelder-Mead, Genetic algorithm etc. Although the above optimization techniques are able to solve NP-hard convexified MIP problems centrally, but are time consuming and do not scale well for large scale distributed problems. Decomposition and solution approach of distributed coordination can resolve the scalability issue. Despite the fact that a large body of work is present on the centralized solution methods for convexified MIP problems, the literature on distributed MIPs is relatively limited. The distributed optimization algorithms applied in power network to solve MIPs are reported here. ML based solutions can help to get faster convergence for distributed optimization or can replace optimization techniques depending on the problem as discussed in this work. Finally, a summary and path forward are provided, and the advancement needed in distributed optimization for the power grid is also presented.

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1

Introduction to Distributed Optimization in Power System

1.1 Optimization Requirements in Power System

Majority of the decision-making tools used in the power system can be classified into (i) rule/heuristic-based approaches, and (ii) optimization-based approaches. Therefore, the scope of power system resource optimization problems, also known as mathematical programming, ranges from tools deployed within the energy management system (EMS) of the power transmission system control center, advanced distribution management system (ADMS), outage management systems, energy market operational problems (economic dispatch and unit commitment) to enterprise asset management. Consequently, optimal power flow (OPF) problems, where power flow equations are considered to be constraints of the optimization problem, is one of the well studied problems in the power engineering literature, since it was introduced by Carpentier (Carpentier, 1962). Typically, power system optimization problems deal with steady-state system operation subject to satisfying system operating conditions, independent of having to worry about how these states would be reached. In this regard, model predictive control (MPC) has also been used in the power engineering context to determine the control action for a dynamical system over a finite,

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receding time horizon. In this case, 'dynamics' of the system is typically captured by the load and generation variability, and hence, it would be wise to classify them as multi-period rolling horizon optimization problems. Additionally, the research community is increasingly concerned about security-/chance-constrained OPF so that the system performs desirably under varying operating conditions. Therefore, the scope of OPF problems is indeed vast, with each of the optimization algorithms having widely varying operational, and infrastructural requirements, depicting their performance.

1.2 Limitations of Centralized Optimization

The underlying physics and system behaviour of a DER-Rich electric grid is substantially different compared to a traditional one. On one hand, DERs including micro turbines, diesel generators or inverter based renewable energy resources have inherent capability of enhancing the reliability of the system in conjunction with providing crucial self-healing support during natural disasters. On the other hand, if not carefully monitored and controlled, they can significantly hamper the stability of the grid. The diverse set of unprecedented as well as unknown possible scenarios emphasizes on strengthening the situational cognizance of the system which has led to advancing sophisticated sensor arrangement, data accumulation and processing technology. But the high volume of data as well as the huge number of control variables drag some serious concerns with the Centralized Controller. As the number of variables increase, the computational burden and the time to find a feasible solution increase exponentially instead of linearly which limit the scalability of the centralized optimization solver. Also, centralized controller suffer from the risk of single point of failure and increased cyber vulnerability. A technical failure or a cyber attack at the central controller can compromise the security of the whole system putting all the decision making at hold. Apart from that, centralized controllers requiring all information to be shared at a central location fall behind in ensuring privacy preferred by many utilities, especially independently owned DERs. Distributed approaches can potentially circumvent the aforementioned challenges and act as a successful alternative with satisfactory performance especially for DER-Rich Electric power grid.

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1.3 Addressing the Limitations by Distributed Optimization

In distributed optimization approach, the control system is divided into multiple local agents each solving its own sub-problem and handling its control variables. The local controllers share limited information only to their neighboring agents and are expected to reach the global optimal solution as would be determined by the central controller. Various aspects of distributed approaches and their impact especially on solving OPF for DER-Rich distribution systems are briefly discussed below.

1. **Scalability**:

   Through the decomposition of the root optimization problem, distributed approaches have a notable effect on the scalability of the system. Since each controller deals with a subset of the original set of decision variables, their computational requirement become way less than the central controller. Furthermore, if a new component such as a new DER or regulator is added to the system, it would necessitate only the corresponding local controller to reorganize its sub-problem to incorporate the new set of variables associated with it. As with the increasing penetration of DERs, number of decision variables to be optimized multiplies substantially. In such a case, the development and implementation of suitable distributed approaches can be a timely adaptation to improve the scalability for DER-Rich distribution systems.

2. **Privacy**:

   Distributed approaches do not require all the information from local agents including critical data related to the privately owned DERs to be sent to the central coordinator ensuring much needed privacy to the private utilities.

3. **Computation Requirement**:

   In a centralized approach, the central controller handles all the variables which are part of the non-convex OPF problem requiring the central controller to have a sophisticated computation capability. But with distributed controller, each agent handles a subset of variables which can reduce their computational requirements.

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4. **Communication Requirement**:

   In centralized manner, every local agent communicates with the central controller via a communication link. So if there are n local agents, there will at least be n communication links from each agent to the central controller which may increase with presence of backup communication links. For distributed approach, n agents will at least need n-1 number of communication links which usually increases if agents are more densely connected. To decrease the number of communication links and hence communication burden, some researchers propose suitable partitioning techniques to ensure weak coupling requirements (Wang *et al.*, 2017; Guo *et al.*, 2017). Furthermore, some researchers share concerns about an agent participating in a distributed optimization algorithm failing to share the data at the end of an iteration will cause other agents to wait and not move to the next iteration. Hence, some works have been reported to enable asynchronous update among the subsystems to address the aforementioned problem (Mohammadi *et al.*, 2018; Mohammadi and Kargarian, 2022).

5. **Cyber Resiliency**:

   One concern with distributed approaches is that agents repetitively share data during the iterative process of distributed algorithms, and in case of unauthorized access to any controller, the shared data can be used to infer information about the local systems. But distributed approaches have provisions to improve the privacy by choosing a modified set of variables to be broadcasted to neighbors rather than the raw measurements which prevents the adversaries to directly extract useful information even if they get access to the shared data. The work proposed in Wu *et al.* (2021), Dvorkin *et al.* (2021), and Ryu and Kim (2022) discusses different encryption or modification techniques to ensure the privacy of the shared variables. Furthermore, the impact of distributed optimization on the propagation of a cyber attack is another important parameter to assess the cyber resiliency. An adversary getting access to one agent may result in compromising itself and its neighbors. But in the case of centralized approach, since every local agent directly

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communicates with the central controller, the central controller may directly get exposed through compromising a local agent which increases the vulnerability of the controller. In addition to that, distributed approaches are more robust to single point of failure. Even if one local controller undergoes some technical problem and fails to operate, the rest of the system can continue their decision-making, keeping the rest of the system unaffected. But a centralized controller will put all the decision making at a halt if it fails to operate. Vosughi *et al.* (2022) provides a detailed comparative analysis on the performance and characteristics of centralized and distributed approaches along with local and decentralized techniques. Nonetheless, Augmenting the robustness and resiliency of distributed approaches is an imperative field of research. Research works including Alkhraijah *et al.* (2022a) and Zhao *et al.* (2017) analyze the effect of cyber attacks in the operation of distributed optimization and provides insight for improving it. Further discussion on this topic is added in Section 5.

Observing the aforementioned advantages, distributed optimization techniques have begun to gain peak attention from the researchers and essentially proving to achieve much importance onto solving power system optimization problems specially for DER-Rich environments.

1.4 Example Applications of Distributed Optimization

OPF is a fundamental problem in power system operation which searches for an operating point that optimizes a certain cost while ensuring various security constraints of the network and satisfying network physics. OPF problems can be single or multi-objective constrained optimization problem. Some common use-cases of the OPF problem include:

- **Voltage Regulation** seeks to minimize the voltage deviation of the overall system usually by utilizing VAR support from inverter based DERs or through Volt-Watt optimization.
- **Generation Cost Minimization** decides optimal generation from traditional and distributed energy resources that minimizes the cost of generation while ensuring power balance between loads and generation.

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- **Loss Minimization** decides optimal power flow through the lines and from generators so that total network loss is minimized.
- **Unit Commitment** as part of OPF tries to determine when and which power plants at each generating station should be shut down or started up so that cumulative generating cost is minimized whilst generation-load demand equilibrium is met.
- **Service Restoration** is the process of gradually restoring the network after partial or complete black-out. DERs can help in providing the emergency power supply to critical loads. Service restoration often entails network reconfiguration and co-ordination of distributed generators to maximize the restored load.
- **Market Pricing and Social Welfare** is, on the contrary to economic load dispatch, enabling load and generation to get matched through a competitive electricity market to determine the marginal price of electricity. Market clearing involves both buyers and sellers to provide bids to be cleared, ensuring maximization of social welfare.
- **Active Power Curtailment** cost of a generating unit represents the opportunity cost of supplying real power that is lost due to allocating reactive power from that unit. Active power curtailment may also include minimizing the active power to meet the demand or to reduce loading on distribution lines during peak demand periods.

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