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Ensuring data privacy in AC Optimal Power Flow with a distributed co-simulation framework☆

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ABSTRACT

During the energy transition, the significance of collaborative management among institutions is rising, confronting challenges posed by data privacy concerns. Prevailing research on distributed approaches, as an alternative to centralized management, often lacks numerical convergence guarantees or is limited to single-machine numerical simulation. To address this, we present a distributed approach for solving AC Optimal Power Flow (OPF) problems within a geographically distributed environment. This involves integrating the *e*nergy system *Co-Sim*ulation (eCoSim) module in the eASiMOV framework with the convergence-guaranteed distributed optimization algorithm, i.e., the Augmented Lagrangian based Alternating Direction Inexact Newton method (ALADIN). Comprehensive evaluations across multiple system scenarios reveal a marginal performance slowdown compared to the centralized approach and the distributed approach executed on single machines—a justified trade-off for enhanced data privacy. This investigation serves as empirical validation of the successful execution of distributed AC OPF within a geographically distributed environment, highlighting potential directions for future research.

1. Introduction

The increasing penetrations of distributed energy resources (DERs) has introduced numerous challenges to traditional power system management [1]. These challenges stem from the inherent uncertainties associated with DERs and necessitate effective cooperation among stakeholders [2], including transmission system operators (TSOs) and distribution system operators (DSOs). This is particularly crucial in Germany, where the electric power system comprises 4 TSOs and over 900 DSOs. As a result of new legislation and the undergoing rapid energy transition toward more renewable energies, German TSOs have been driven to establish new vertical cooperation with numerous DSOs and reinforce horizontal cooperation among TSOs [3].

AC Optimal Power Flow (OPF) is a fundamental optimization problem in the field of power systems engineering, playing a crucial role in the efficient and secure operation during energy transition [4–6]. Due to data privacy concerns, traditional centralized management is not favored by system operators or even prohibited by the respective regulations [7]. Addressing this practical issue requires industry-specific solutions that balance coordination efficiency and data privacy, i.e., effectively coordinating while preserving data and model privacy, including detailed grid data and private customer behavior information.

As an alternative to centralized management, distributed management enables different system operators to operate independently and collaborate effectively by sharing limited information with a subset of other operators [8,9], gaining significant attention in recent years. However, due to the inherent NP-hardness [10,11], most existing research on distributed approaches for AC OPF problems either lacks convergence guarantees [12–14] or exhibits a slow convergence rate to a modest accuracy [15]. In contrast, the Augmented Lagrangian based Alternating Direction Inexact Newton method (ALADIN) [16], as

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a recent development in distributed optimization, was tailored for solving the nonconvex AC OPF first in [17]. It offers convergence guarantees and achieves rapid convergence speeds with high accuracy for general nonconvex problems, typically achieving a locally quadratic convergence rate. Unfortunately, a significant focus of these studies has been on optimization algorithms [7,18–22], with numerical simulations typically conducted on single machines, such as desktops, rather than in a distributed computing environment. Consequently, there remains a notable gap in the availability of distributed software architectures capable of solving AC OPF problems utilizing a convergence-guaranteed distributed approach.

To address the research gap, we propose to employ a distributed co-simulation environment for solving distributed AC OPF, which needs to fulfill certain aspects for TSO–DSO cooperation such as data and model privacy within the co-simulation. Additionally, the TSOs and DSOs need methods and tools for flexible collaboration without the need for programming and IT knowledge to setup a co-simulation of the AC OPF. Many co-simulation methods and frameworks do not prioritize the aspects and focus mainly on the multi-modal energy system coupling [23–25]. In light of this gap, the *e*nergy system *Co-Sim*ulation (eCoSim) module within the eASiMOV [26] has been adapted to the aforementioned requirements. It aims for easy setup and usage with a graphical user interface for non-programming experts and enables flexible cooperation among experts from different fields and domains. Distinguishing itself from conventional co-simulation frameworks, we enable the execution of collaborative coupled simulation within a truly geographically distributed context. Originally developed for the multi-modal energy system analysis, there was a necessity to move forward to support the interaction of TSOs and DSOs with the assurance of private and industrial electricity customers' data security and model topology protection.

The present paper investigates AC OPF problems in the context of integrated transmission and distribution systems (ITD) systems, employing the convergence-guaranteed distributed algorithm ALADIN within the geographically distributed eCoSim framework. The main contributions of the present paper are summarized as follows:

(1) We propose a novel distributed approach for solving AC OPF problems by integrating the geographically distributed eCoSim framework with the recently introduced convergence-guaranteed distributed algorithm ALADIN. Within the proposed methodology, local clients and the OPF-coordinator engage in iterative communications to collaboratively solve AC OPF problems while limiting information exchanged to ensure the confidentiality of intricate grid details and private customer behavior.
(2) We evaluate the proposed methodology using an ITD system, simulating the collaboration of TSOs and DSOs. It demonstrates that a distributed algorithm for AC OPF can be effectively implemented within a geographically distributed environment. Comparative analysis involving centralized AC OPF and distributed AC OPF on a single machine reveals that the proposed methodology can maintain high solution accuracy and privacy data preserving at a modest deceleration attributed to communication delays. These results highlight the considerable promise of our strategy for practical implementations in power system operations.

The rest of this paper is organized as follows: Section 2 presents the distributed AC OPF. Section 3 introduces the integration of distributed AC OPF into a co-simulation environment. The evaluation of a use case with four different setups is shown in Section 4, and Section 5 concludes this paper.

2. Distributed AC optimal power flow

This section introduces the distributed approach for the coordinated dispatch operation challenge across various systems. This applies to universal configurations of power systems, including those with only transmission or distribution systems.

2.1. Conventional formulation

Consider a power system $\mathcal{S} = (\mathcal{N}, \mathcal{L})$, where $\mathcal{N}$ denotes the set of buses and $\mathcal{L}$ denotes the set of branches. Additionally, let $\mathcal{R}$ be the set of all regions, and let $\mathcal{L}^{\text{tie}} \in \mathcal{L}$ be the set of connecting tie-lines between neighboring regions. The cardinality of the corresponding sets are

$$n^{\text{bus}} = |\mathcal{N}|,\ n^{\text{line}} = |\mathcal{L}|,\ n^{\text{reg}} = |\mathcal{R}|,\ n^{\text{tie}} = |\mathcal{L}^{\text{tie}}|.$$

In the present paper, the complex voltage at a bus is expressed in polar coordinates, i.e., $V_i = v_i e^{\theta_i}$, where v_i and θ_i are the magnitude and angle of the complex voltage V_i at the bus $i \in \mathcal{N}$. Thereby, the classic AC OPF problem can be written as follows

$$\min_x\ f(x) = \sum_{i\in\mathcal{N}} \left\{ a_{i,2} \left(p_i^g\right)^2 + a_{i,1}\, p_i^g + a_{i,0} \right\} \tag{1a}$$

subject to $\forall i \in \mathcal{N}$

$$p_i^g - p_i^l = v_i \sum_{k\in\mathcal{N}} v_k \left(G_{ik} \cos\theta_{ik} + B_{ik} \sin\theta_{ik} \right), \tag{1b}$$

$$q_i^g - q_i^l = v_i \sum_{k\in\mathcal{N}} v_k \left(G_{ik} \sin\theta_{ik} - B_{ik} \cos\theta_{ik} \right), \tag{1c}$$

$$\underline{v}_i \le v_i \le \overline{v}_i,\ \ \underline{p}_i^g \le p_i^g \le \overline{q}_i^g,\ \ \underline{q}_i^g \le q_i^g \le \overline{q}_i^g, \tag{1d}$$

and

$$|s_{ij}| = \sqrt{p_{ij}^2 + q_{ij}^2} \le \overline{s}_{ij},\ \forall (i,j) \in \mathcal{L} \tag{1e}$$

with

$$p_{ij} = v_i^2 g_{ij} - v_i v_j \left(g_{ij} \cos\theta_{ij} + b_{ij} \sin\theta_{ij} \right), \tag{2a}$$

$$q_{ij} = -v_i^2 b_{ij} - v_i v_j \left(g_{ij} \sin\theta_{ij} - b_{ij} \cos\theta_{ij} \right), \tag{2b}$$

where $a_{i,2}$, $a_{i,1}$, and $a_{i,0}$ denote the polynomial coefficients of operation cost of power generations at bus i. p_i^g, q_i^g (resp. p_i^l, q_i^l) denote the real and reactive power produced by generators (resp. loads) at bus i the state vector x includes all the voltage angle and magnitude, as well as active and reactive generator injections, i.e., $x = (\theta, v, p^g, q^g)$; these variables are set to 0 if there is no generator (resp. load) connected to a bus i. G, B denote the real and imaginary part of the complex nodal admittance matrix Y, $\underline{\cdot}$ and $\bar{\cdot}$ denote upper and lower bounds for the corresponding state variables.

2.2. Distributed reformulation

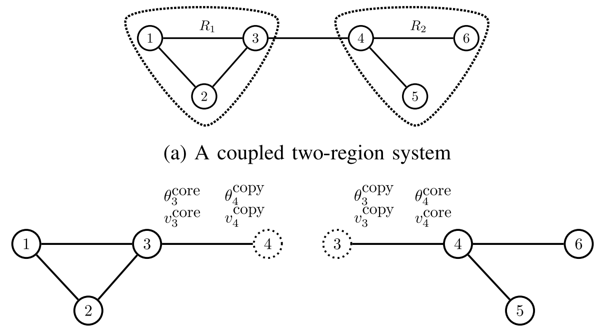
Regarding the distributed problem formulation, we share components with neighboring regions to ensure physical consistency, following [3,27]. Thereby, in a specific region $\ell \in \mathcal{R}$, $\mathcal{N}_\ell^{\text{core}}$ denotes the set of core buses that are entirely local, $\mathcal{N}_\ell^{\text{copy}}$ denotes the set of copy buses shared by neighboring regions, and thus the set of all buses in the region ℓ can be represented as $\mathcal{N}_\ell = \mathcal{N}_\ell^{\text{core}} \cup \mathcal{N}_\ell^{\text{copy}}$. Moreover, let $\mathcal{L}_\ell$ denote the set of all regional branches.

For the sake of clarity, we take a 6-bus system, shown in Fig. 1, as an example. The system is partitioned into two regions, i.e., R_1 and R_2. To establish a self-contained AC OPF sub-problem for region R_1, the nodal power balance at the core buses $\{1,2,3\}$ should be added as constraints. Besides, the complex voltage of the copy bus $\{4\}$, shared by the neighboring region R_2, is also required for the nodal balance at core bus 3. Similarly, an AC Optimal Power Flow can be established for region R_2. Finally, an additional affine consensus constraint should be added to ensure physical consistency between core and copy buses, i.e.,

$$v_3^{\text{copy}} = v_3^{\text{core}}, v_4^{\text{copy}} = v_4^{\text{core}}, \theta_3^{\text{copy}} = \theta_3^{\text{core}}, \theta_4^{\text{copy}} = \theta_4^{\text{core}} \tag{3}$$

In this way, the problem (1) can be reformulated in the standard affinely coupled distributed form:

$$\min_{x\in\mathcal{X}}\quad f(x) := \sum_{\ell\in\mathcal{R}} f_\ell(x_\ell) \tag{4a}$$



(a) A coupled two-region system

(b) Decoupled region R_1 (c) Decoupled region R_2

Fig. 1. Decomposition by sharing components between neighboring regions.

$$\text{s.t.} \quad h_\ell(x_\ell) = 0 \qquad | \, \kappa_\ell, \quad \forall \ell \in \mathcal{R} \tag{4b}$$

$$\sum_{\ell \in \mathcal{R}} A_\ell x_\ell = b \qquad | \, \lambda \tag{4c}$$

where local state x_ℓ includes the voltage angle and magnitude θ_i, v_i for all bus $i \in \mathcal{N}_\ell$, and the generator injections p_i^g, q_i^g for all core bus $i \in \mathcal{N}_\ell^{\text{core}}$. f_ℓ denotes the local cost function with respect to core generators in the region ℓ, while h_ℓ collects the nodal power balance (1b)(1c) for all core bus $i \in \mathcal{N}_\ell^{\text{core}}$. The consensus constraint (4c) ensures consistency of core and copy variables between neighboring regions. Throughout this paper, we write down the Lagrangian multipliers right after the corresponding constraints, e.g., κ_ℓ, γ_ℓ and λ in the problem (4).

Remark 1. In the present paper, the distributed problem (4) is initialized with a flat start, where the voltage angles and magnitudes are set to zero and 1.0 p.u. respectively [4]. For this initialization strategy it is demonstrated numerically that it can provide a good initial guess for distributed AC OPF [15,17,28].

2.3. Distributed optimization algorithm

Inspired by Sequential Quadratic Programming (SQP), Augmented Lagrangian based Alternating Direction Inexact Newton method (ALADIN) was first proposed in [16] to handle generic distributed optimization problems and tailored for nonconvex AC OPF in [17], where the active set method is used for handling inequality constraint. Under the mild assumption that the iterate is sufficiently close to the optimizer so that the active set can settle at its final optimal value, the ALADIN algorithm is general convergence guaranteed with locally quadratic convergence rate; for detailed proof for dispatch problems of ITD systems, we refer to [7]. However, the assumption does not always hold, and the optimal active set may not be found due to nonlinearity [29]. The issue becomes more critical when the problem size becomes large.

To improve the scalability, the ALADIN for AC OPF problems is outlined in Algorithm 1. Following the idea of augmented Lagrangian, the separated local problem is formulated as (5) in step (i), where ρ is the penalty parameter, and Σ_ℓ is the positive-definite weighted matrix for state variables x_ℓ in the region ℓ. Based on curvature information (6), ALADIN builds a coupled quadratic program (QP) (7) in step (iii) to coordinate the results of the decoupled step from all regions. The original ALADIN algorithm applies the active set method to impose active inequalities as equalities, and thus, only the resulting KKT system-based linear equations need to be solved. In contrast, we add bounds on the step δ in the coupled problem (7) to keep the feasibility of the next iterate $x + \delta$. At the cost of complexity of the coupled problem (7), the combinatorial difficulty by the active set is avoided, and the scalability of ALADIN for AC OPF is thus improved. Practically, the dual condition is sufficient to ensure a small violation of the condition, when the predefined tolerance ϵ is small enough [30,31].

Algorithm 1 ALADIN

Input: z, λ, $\rho > 0$, $\mu > 0$ and symmetric matrices $\Sigma_\ell > 0$
Repeat:

(i) solve the following decoupled NLPs for all $\ell \in \mathcal{R}$

$$\min_{x \in \mathcal{X}} \quad f_\ell(x_\ell) + \lambda^\top A_\ell x_\ell + \frac{\rho}{2} \left\| x_\ell - z_\ell \right\|^2_{\Sigma_\ell} \tag{5a}$$

$$\text{s.t.} \quad h_\ell(x_\ell) = 0 \qquad | \, \kappa_\ell \tag{5b}$$

(ii) compute the gradient g_ℓ, the Jacobian matrix J_ℓ of equality constraints h_ℓ^{act} and the approximated Hessian H_ℓ at the local solution x_ℓ by

$$\begin{aligned} g_\ell &= \nabla f_\ell(x_\ell), \; J_\ell = \nabla h_\ell(x_\ell), \\ H_\ell &= \nabla^2 \left\{ f_\ell(x_\ell) + \kappa_\ell^\top h_\ell(x_\ell) \right\} \end{aligned} \tag{6}$$

(iii) obtain $(\delta, \lambda^{\text{QP}})$ by solving coupled QP

$$\min_{x+\delta \in \mathcal{X}} \quad \sum_{\ell \in \mathcal{R}} \frac{1}{2} \left(\delta_\ell\right)^\top H_\ell \, \delta_\ell + g_\ell^\top \delta_\ell \tag{7a}$$

$$\text{s.t.} \quad \sum_{\ell \in \mathcal{R}} A_\ell (x_\ell + \delta_\ell) = b \qquad | \, \lambda^{\text{QP}} \tag{7b}$$

$$J_\ell \, \delta_\ell = 0, \quad \forall \ell \in \mathcal{R} \tag{7c}$$

(iv) update the primal and the dual variables with full step

$$z = x + \delta \quad \text{and} \quad \lambda = \lambda^{\text{QP}} \tag{8}$$

Remark 2. The excellent technical note [32] provides the Jacobian and the Hessian of the power flow constraints (1b)(1c) computed efficiently using sparse matrix manipulations.

3. Distributed AC OPF with co-simulation

The framework introduced herein is developed for distributed co-simulation of multimodal energy systems and has been generalized to address the distributed AC OPF problems. We begin by offering a concise overview of the framework, followed by an elaborate discussion on its adaptation to the specific problem.

3.1. Co-simulation framework description

The main aim of the co-simulation approach is enabling the coupling of different solvers by employing distinct tools or frameworks to model individual systems. This approach facilitates interaction and communication among systems modeled using different methodologies [33] and technologies. The main challenges in contrast to classical simulation are adequate high performances of simulation runtime, easy configuration of the set-up procedure, and compatibility of simulation tools [34]. Nevertheless, data privacy presents a significant challenge where the co-simulation environment involves the coupling of geographically distributed simulations. The module eCoSim - *e*nergy system Co-Simulation which is part of the modular framework eASiMOV - *e*nergy system *A*nalysis, *Si*mulation, *M*odeling and *O*ptimization, described in [26], aims to couple and analyze multimodal energy systems [35]. It enables co-simulation in geographically distributed environments while preserving the data privacy of models. Furthermore, experts can work in suitable environments and still contribute to complex system co-simulation. In this way, we ensure a high degree of flexibility for cooperation, where experts do not need to adjust their models to one environment. Regarding the structure of the *e*nergy system *Co-Sim*ulation (eCoSim) module, we refer to [34] and it is outlined as follows:

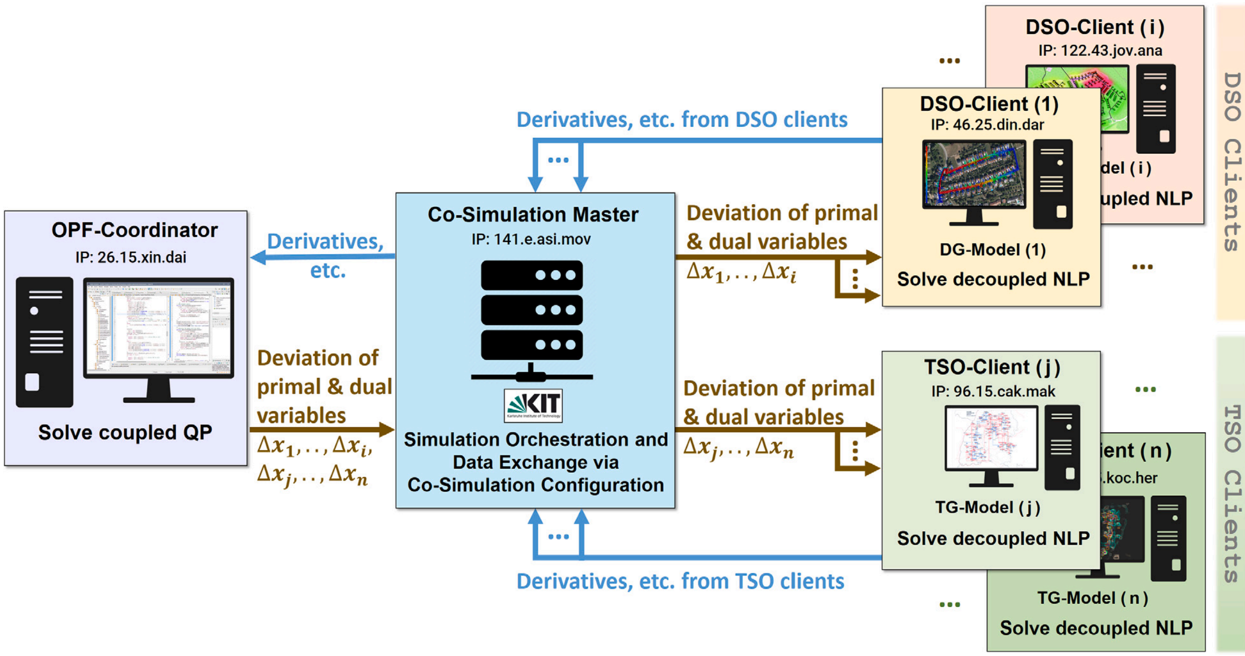


Fig. 2. The eASiMOV-eCoSim co-simulation architecture enables geographically distributed AC OPF calculation with respect to data and model privacy.

– *Simulation Module* is considered as a stand-alone simulator, which is composed of a model and corresponding solver.
– *Simulation Master* is an orchestrator that manages the data exchange between the modules.

Communication between corresponding modules is done through the simulation master, i.e. there is no direct communication between the modules. Furthermore, the simulation master initiates time steps and coordinates the simulation set-up. Transmission Control Protocol (TCP) is used for communication between the master and modules, where the master initiates a simulation process by sending commands to each module, receives results, and transmits them to corresponding modules. To enable synchronization and to solve the algebraic loop, so-called Logical Delay Block (LDB) elements are nested into the metamodel that describes the dependency of individual simulation modules, which can be set up via a graphical user interface. Simulation modules have the so-called black box structure, where the topology of each module is neither known to other modules nor to the simulation master, [36]. In each module, the input–output interface must be precisely defined. This interface is later, in case of a geographically distributed co-simulation, only visible to the simulation master. A database linked to the simulation master records all simulation results, statistics regarding data transfer and client status as CPU and memory loading.

3.2. Adaptation to distributed AC OPF

Since the co-simulation framework was originally developed to enable energy system analysis by coupling simulators on an FMU definition basis, an adaptation is needed to support source code-based simulators. In this paper, we present a solution for distributed AC OPF based on a MATLAB implementation. Nonetheless, the proposed method can be easily transferred to other implementations in other programming languages. The proposed architecture to combine eCoSim with the OPF calculation is shown in Fig. 2. The eCoSim co-simulation platform is adapted to support the simulation orchestration and the synchronization for the distributed OPF problem. To use these concepts of eCoSim the existing OPF code has been modularized and consists of separate clients for the DSOs/TSOs that solve decoupled NLP (5) and a coordinator which solves a coupled QP (7). The coordinator does neither have any further knowledge about the other clients' models nor does it share additional information about its own model. Thus, the presented method ensures the data privacy. Therefore, it is not critical to assign the coordinator's task to a TSO. The following subsection shows the implementation details for a distributed AC OPF calculation, also with support for coupled remote simulations with geographical distance.

3.3. Implementation details

The co-simulation framework eCoSim provides a wrapper for the MATLAB code to initialize, run a single step, and stop the MATLAB execution by using standardized function names. By standardizing the interfaces, any MATLAB code that allows for parallelization can be executed in a distributed manner on this platform.

The eCoSim wrapper code is shown in the algorithms 2 and 3 from the perspective of a single simulation module — either a client or a coordinator. The inputs for the simulation module are eCoSim commands, a Boolean *sim_running* indicating the current status of a simulation module, and a pre-defined error margin ε for the local clients as a threshold to stop the OPF calculation of the respective module.

When the eCoSim master setup is accomplished, a *sim_setup* command is sent to each connected client. This initializes the clients as shown in lines 3-5 in both algorithms by executing corresponding MATLAB code, containing the initial settings for the TSOs and DSOs.

The execution of one simulation step for the clients (simulation modules) is initiated via a *sim_step* command sent by eCoSim master. The execution order depends on the co-simulation configuration and guarantees the correct orchestration of the simulation modules. The LDB stops the execution of certain simulation modules until other simulations finish their simulation step and provide their output as an input to the depending simulators. A single simulation step for a local client is shown in lines 7-15. It executes `run_localClient_i.m` where the decoupled NLP (5) is solved. After each simulation step, the error of the local client is calculated and compared to the threshold ε, which signals eCoSim master to stop the local client. A single simulation step for the coordinator is shown in lines 7-11. In contrast to the local client, the coordinator changes in the second iteration to *sim_running* = `True` since it waits for the first results from the clients and executes

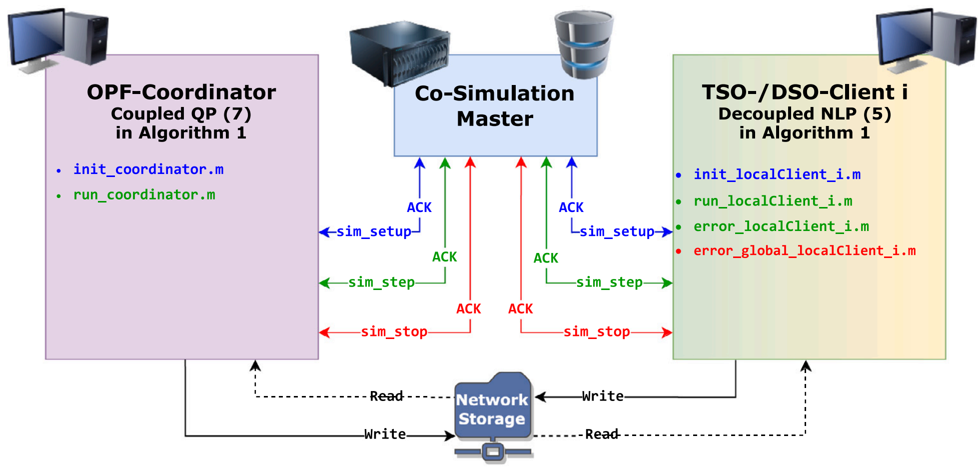


Fig. 3. Integration of MATLAB OPF code (Algorithm 1) into the eCoSim control code (Algorithm 2 and 3).

`run_coordinator.m` where the coupled QP (7) problem is solved. As soon as all local clients signal the end of their computations for one iteration step, all simulation modules (local clients and the coordinator) are stopped via the *sim_stop* command sent by eCoSim master (lines 17-20 and lines 13-15 respectively). The configuration of the integration of MATLAB OPF code into eCoSim is shown in Fig. 3 depicting the TSO-/DSO-clients as the local clients and one coordinator in general. The OPF coordinator is responsible for solving the coupled QP (7) while the TSO and DSO local clients solve the decoupled NLP (5). The communication between eCoSim master and the simulation modules is achieved via the three introduced commands. For data exchange, a network storage is used: for N simulation modules, there are $2N$ files kept inside the network storage holding deviation data of primal and dual variables as an output of the coordinator and derivatives data as an output of the clients (see Fig. 2). During a *sim_step* the local clients first read from the storage, calculate their simulation step, and then write their results into their file for the coordinator to read. The coordinator has the same procedure but writes and reads from the opposite files than the local client, i.e. it writes into the file a local client reads from and reads from the file a local client writes to. As no sensitive data is exchanged during these read-and-write processes, data privacy is always ensured.

Algorithm 2 Control of TSO-/DSO-Client

Input: eCoSim *command*, *sim_running*, *sim_step*, error margin ε
Output: *sim_running*

```
1: // Process Control Message
2: switch (command)
3: // Initialize Client
4: case sim_setup:
5:   init_localClient_i.m
6: // Perform Simulation Step
7: case sim_step:
8:   if sim_running then
9:     // Solve decoupled NLP (5) in Algorithm 1
10:    run_localClient_i.m
11:    error = error_localClient_i.m
12:    if error < ε then
13:      return sim_running = FALSE
14:    end if
15:  end if
16: // Stop Client
17: case sim_stop:
18:   error_global_localClient_i.m
19:   STOP_SIMULATION_MODULE
20: end switch
```

Algorithm 3 Control of OPF-Coordinator

Input: eCoSim *command*, *sim_running*, *sim_step*

```
1: // Process Control Message
2: switch (command)
3: // Initialize Coordinator
4: case sim_setup:
5:   init_coordinator.m
6: // Perform Simulation Step
7: case sim_step:
8:   if sim_running then
9:     // Solve Coupled QP (7) in Algorithm 1
10:    run_coordinator.m
11:  end if
12: // Stop Coordinator
13: case sim_stop:
14:   STOP_SIMULATION_MODULE
15: end switch
```

4. Case study

This chapter introduces a case study on distributed AC OPF using the co-simulation platform eCoSim and demonstrates the simulation results by four different approaches.

4.1. Distributed AC OPF co-simulation setting

The OPF framework is built on MATLAB-R2020b, the ITD systems are merged based on the open-source toolbox rapidPF [3][2] and power systems model is built with the assistance of MATPOWER toolbox [37]. The case study is carried out on a standard laptop computer with `Intel® Core™ i7-8850H CPU @ 2.60 GHz` and `16 GB` installed RAM. CASADI toolbox [38] is used for modeling optimization problems and IPOPT [39] are used as nonlinear solver. For tuning parameters in the proposed method, an adaptive heuristics approach is adopted, as discussed in [17]. The numerical test case is built upon the IEEE benchmarks, where the TSO model uses a 57-bus transmission system from PGLib [40] and two DSO models use 33-bus distribution systems from

[2] The code is available on https://github.com/xinliang-dai/rapidPF.

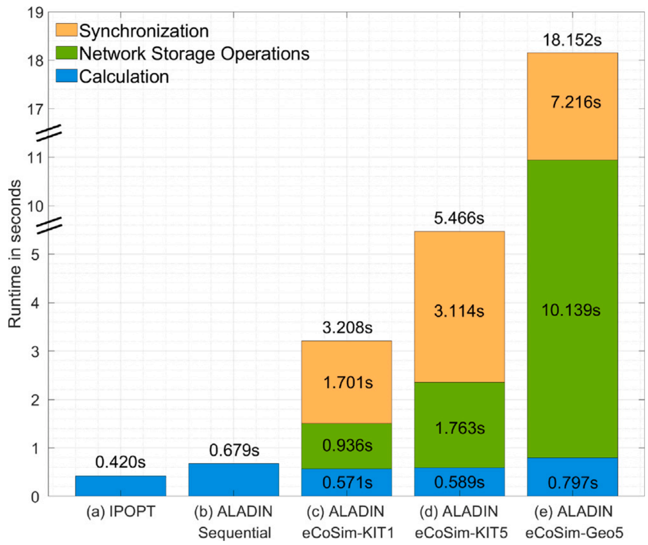


Fig. 4. Runtime comparison for the use cases with a serial MATLAB implementation in (a) IPOPT and (b) ALADIN, a distributed execution with eCoSim on one computer in the KIT network in (c) eCoSim-KIT1, on five computers in the KIT network in (d) eCoSim-KIT5 and a geographically distributed co-simulation with access to the network storage located at KIT over a VPN connection in (e) eCoSim-Geo5. The clients are distributed over three cities with a geographical distance of up to 15 km to KIT (the internet routing Runtimes are measured at the coordinator software module located at KIT).

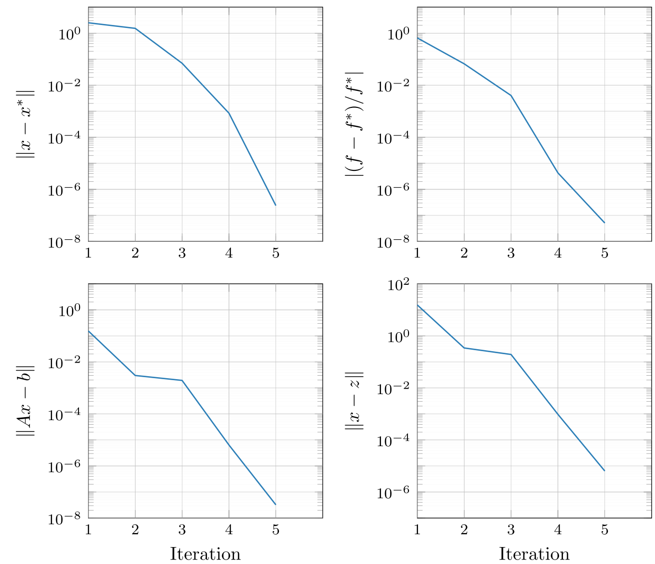


Fig. 5. Numerical Results by proposed distributed algorithm.

the MATPOWER package [37]. For both the local and the truly distributed setups using eCoSim, the same configuration is used for the integration. The configuration inside eCoSim consists of three local clients, one coordinator, and one LDB. The local clients are connected to the coordinator via the LDB, and the coordinator is connected to the local clients in return. The LDB ensures the correct data exchange between the local clients and the coordinator inside the storage network.

The simulation is conducted in five distinct setups, as depicted in Fig. 4. The first setup, shown in Fig. 4(a), employs IPOPT for centralized optimization on a single computer. The next two configurations utilize ALADIN for distributed optimization, also on a single computer, differing in their approach to coordination and communication; specifically, eCoSim-KIT1 introduces geographically distributed co-simulation and utilize network storage at KIT for data exchanges. The last two setups demonstrate true distributed execution by distributing the eCoSim master module and simulation modules across multiple computers. The distinction lies in that eCoSim-Geo5 is configured similarly to eCoSim-KIT5 but incorporates a geographical distance among the computers, all located within a 15 km radius of KIT, exploring of distributed computing effects over short geographical distances.

4.2. Results and discussions

We first compare the runtime behavior of the five different setups explained in the previous subsection, as shown in Fig. 4. The y-axis shows the runtime in seconds for the introduced setups. The two MATLAB-based setups IPOPT and ALADIN have a total runtime of 0.420 and 0.679 s, respectively. Both of them are executed sequentially on a single machine without communication effort. The other three setups for ALADIN-eCoSim are divided into the time for the OPF (calculation), writing-/reading the network storage (network storage operations) and the eCoSim synchronization-/overhead time (synchronization). For each of these three cases, the runtime consists of an average of ten runs. The coordinator is chosen as the reference for the runtimes evaluation. It represents the best runtime, as it needs to interact with each local client's network storage. The calculation runtime of the locally distributed AC OPF is about the same as the MATLAB implementations. The differences in the calculation runtime can be attributed to the different execution environments and, therefore, resulting in different measuring methods. The averaged total runtime for the ALADIN-eCoSim-KIT1 case is 3.208 s, whereas the calculation time is 0.571, the synchronization time is 1.701 and the time for network storage operations is 0.936 s. In the distributed case ALADIN eCoSim-KIT5 with five computers, the time for calculation is 0.589 s, the time for the network storage operations is 1.763 s, and the time for the synchronization is 3.114 s. In the ALADIN-eCoSim-KIT5 solution, the total runtime is 5.466 s. The calculation time is 0.589 s, the synchronization takes 3.114 s, and the time for the network storage operations is 1.763 s. Compared to the eCoSim-KIT1 solution, distributing the modules onto different computers raises the time effort for the synchronization and network storage operations. For the geographically distributed computing over the VPN at the KIT (ALADIN-eCoSim-Geo), the total time is 18.152 s, whereas the calculation time is 0.797, the synchronization time is 7.216 and the time for network storage operations is 10.139 s. The communication over the VPN is significantly higher, which in turn, is compensated by data security and privacy. One reason for this is the network storage location at the KIT and thus the additional time needed to access the network storage from outside the KIT over a VPN. Another reason for this could be the amount of concurrent users in the KIT VPN.

The numerical convergence performance of Alg. 1 is illustrated in Fig. 5, for which the centralized approach (IPOPT) is used as the reference solution. After five iterations, the ALADIN algorithm can approach the reference solution with very high accuracy with respect to state deviation $\|x - x^*\|$ and objective value $|(f - f^*)/f^*|$. Meanwhile, the primal residuals $\|Ax - b\|$ and dual residuals $\|x - z\|$ approach zeros, indicating the algorithm converges to a very small neighborhood of the reference solution with negligible violation of coupling constraints. The solution accuracy by applying ALADIN is demonstrated in Table 1, affirming that all three approaches by applying ALADIN converge to the same reference solution computed by IPOPT.

The proposed distributed framework can maintain data privacy and decision-making independence. The case study shows that the distributed co-simulation environment effectively keeps model topology private in exchange for higher runtime, which might be significantly reduced in the future with a direct data exchange without the use of network storage.

5. Conclusion and outlook

The present paper introduces a novel distributed approach for solving distributed AC Optimal Power Flow (OPF) using the convergence-guaranteed Augmented Lagrangian based Alternating Direction Inexact

Table 1
Comparison numerical results.

	IPOPT	ALADIN		
		Sequential	eCoSim-1	eCoSim-5
Cost	34 210.54	34 210.55	34 210.55	34 210.55
Optimality Gap	–	5.07×10^{-8}	2.46×10^{-8}	2.46×10^{-8}
Primal Res.	–	3.22×10^{-8}	8.70×10^{-8}	8.70×10^{-8}
Dual Res.	–	6.41×10^{-6}	4.64×10^{-7}	4.64×10^{-7}
$\|x - x^*\|$	–	7.21×10^{-7}	2.88×10^{-7}	2.88×10^{-7}

Newton method (ALADIN) that guarantees convergence by the *e*nergy system *Co-Sim*ulation (eCoSim) module within the eCoSim software framework. Furthermore, the methodology has been extensively evaluated, and comparative analysis is conducted between the proposed method, centralized OPF, and distributed OPF executed on a single machine.

Our proposed approach has demonstrated highly successful numerical results while maintaining an acceptable level of computational deceleration. Notably, it distinguishes itself by being a geographically distributed solution for AC OPF, in contrast to existing studies focusing solely on numerical performance but conducted on a single machine. Within this distributed co-simulation setup, each simulation module, including the OPF-coordinator and co-simulation master, cannot access sensitive data from other modules, ensuring strict data privacy. This characteristic makes our distributed algorithms well-suited for execution in geographically distributed environments, offering practical applicability in real-world industrial scenarios. Furthermore, the introduced platform's universal nature, facilitated by a unified interface, enables the conversion of any parallelizable code into a distributed application with minimal effort.

This research leads to many interesting questions for further investigation, including further scaling up the problem size, simulating based on grid datasets, improving the efficiency of eCoSim, investigating alternatives to the network storage and other applications based on real-world scenarios.

CRediT authorship contribution statement

Xinliang Dai: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Supervision, Visualization, Writing – original draft, Writing – review & editing. **Alexander Kocher:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Jovana Kovačević:** Conceptualization, Investigation, Methodology, Software, Writing – original draft, Writing – review & editing. **Burak Dindar:** Investigation, Visualization, Writing – original draft, Writing – review & editing. **Yuning Jiang:** Conceptualization, Methodology, Validation, Writing – original draft. **Colin Jones:** Methodology, Validation, Supervision. **Hüseyin K. Çakmak:** Conceptualization, Investigation, Methodology, Project administration, Resources, Software, Supervision, Visualization, Writing – original draft, Writing – review & editing. **Veit Hagenmeyer:** Conceptualization, Supervision, Validation, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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