A Spatially Distributed Multi-Period Optimal Power Flow Study with Distributed Battery Units

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***Abstract*—The growing presence of battery-associated distributed energy resources (DERs) in distribution networks necessitates the development of multi-period optimal power flow (MPOPF) strategies. Generally, the MPOPF frameworks are developed as mixed integer non-convex programming (MINCP) and solved centrally. However, the main limitation of centralized MPOPF (MPCOPF) is its longer solution time, a typical solution time is in the order of 10^3 to 10^4 seconds. This article proposes a spatially distributed MPOPF (MPDOPF) to overcome such deficiencies. Initially, the OPF problem is developed as a single-phase MPCOPF for a distribution network consisting of distributed DERs and battery units. Later the original large-scale centralized OPF problem is split into multiple sub-problems, which are solved in parallel by sharing boundary voltage and power data with the neighboring agents by following the directives of the Equivalent Network Approximation method (ENApp). The performance characterization of the proposed MPDOPF framework is conducted using the IEEE 123 bus test system. This analysis offers insights into the superiority of distributed MPOPF frameworks over centralized ones concerning solution time.**

***Index Terms*—Batteries, distribution network, distributed energy resources, equivalent network approximation (ENApp)**

I. Introduction

Optimal power flow (OPF) tools are developed to run the distribution grids in the most economical, reliable, and secure manner. The usefulness of OPF studies is gaining more interest due to the penetration of distributed energy resources (DERs), especially solar panels. Presently, deployment of battery units is becoming more pertinent to mitigate the intermittency of DERs and maintain the power balance by controlling the charging/discharging operations [1]. However, the inclusion of batteries converts the single-period time-decoupled OPF problem into a multi-period time-coupled OPF study.

Traditionally, centralized OPF (COPF) methods were popular where a central controller (CC) is responsible for processing the accumulated grid-edge data, solving the OPF algorithm, and dispatching control signals to the controlling resources [2]. The COPF algorithms are generally developed as a mixed integer non-convex programming (MINCP) problem and then simplified either as a convex problem by adopting second-order cone programming (SOCP) relaxations [3] [4], or as a linear problem by adopting Taylor series expansion [2], polyhedral approximations [5] or linear power flow models [6].

To overcome the scalability issues related to the COPF methods, distributed OPF (DOPF) algorithms are often proposed by decomposing the original COPF problem into multiple sub-problems, solved in parallel by permitting neighborhood communication. In this regard, the Auxiliary Problem Principle (APP) and the Alternating direction method of multipliers (ADMM) are two popular algorithms that are used to solve OPF problems as quadratic convex [7], SOCP relaxed convex [8], semidefinite programming (SDP) relaxed convex [9], [10], and linear programming problems [11]. Previously in [12], the authors' research group developed a DOPF framework based on the Equivalent Network Approximation method (ENApp) for solving DOPF problems with lesser macro iterations compared to ADMM.

The above references [3]- [11] mainly focused on developing single-time step OPF problems by neglecting the grid-edge devices having time-coupled operation, like batteries. The inclusion of battery models transforms a single-time step OPF into a multi-period OPF (MPOPF). Reference [13] propound a nonlinear multi-period centralized OPF (MPCOPF) framework to solve the active-reactive power dispatch from the batteries and DERs in a distribution network. Alizadeh and Capitanescu [14] proposed a stochastic security-constrained MPCOPF which is solved by sequentially solving a specific number of linear approximations of the original problem. Usman and Capitanescu [15] developed three different MPCOPF frameworks. All three approaches start by solving a linear program to fix the binary variables followed by either a linear or non-linear program to determine the continuous variables. Optimal battery schedules are determined in [16] considering uncertain renewable power generation by solving an MPCOPF. A bi-level robust MPCOPF is suggested in [17] for determining active and reactive power dispatches from the grid edge devices. Wu et al. [18] framed a Benders Decomposition (BD) based multi-period distributed OPF (MPDOPF) for a virtual power plant collocated distribution network after decomposing the original centralized multi-parametric quadratic problem into one master and multiple sub-problems.

For the past few years, several pieces of research have been conducted for developing MPOPF portfolios. However, the following research gaps persist.

1) The MPOPF frameworks are mainly solved centrally [13]- [17]. The centralized methods suffer from scalability and computation challenges for bulk distribution grids and require longer solution time (in the range of a few thousand seconds).

TABLE I: TAXONOMY TABLE FOR COMPARISON

References	DERs	Batteries	Single period OPF	Multi-period OPF	Centralized OPF	Distributed OPF	Framework
[3], [4]			✓		✓		Convex
[5]	✓		✓		✓		Linear
[6]			✓		✓		Linear
[7]	✓		✓			✓	Convex (APP)
[8]- [10]	✓		✓			✓	Convex (ADMM)
[11]	✓		✓			✓	Linear (ADMM)
[12]	✓		✓			✓	Non-convex (ENApp)
[13]	✓	✓		✓	✓		Non-convex
[14]–[17]	✓	✓		✓	✓		Linear/convex
[18]	✓	✓		✓		✓	Quadratic (BD)
This paper	✓	✓		✓		✓	Non-convex (ENApp)

2) Reference [18] proposed a MPDOPF framework using BD. However, BD suffers from slow convergence and needs a central controller to solve the master problem.

This article aims to address the above research gaps by developing a spatially distributed MPOPF (MPDOPF) framework. The bulk network is divided into multiple connected areas, each solving its own local MPOPF problem and periodically communicating the values of boundary variables with neighboring areas. The interaction between the areas is modeled by following the principles of the ENApp DOPF algorithm. ENApp outperforms the other DOPF algorithms in terms of convergence speed and requires very few macro iterations [12]. A taxonomy table to compare the existing studies and the present work is provided in Table I. The specific contributions are listed below:

1) A MPOPF framework is proposed for a distribution network consisting of DERs and batteries. The integer variables related to battery charging/discharging are avoided by adding a "Battery Loss" cost term with the objective function. The loss term will ensure the non-occurrence of simultaneous charging/discharging operations.
2) The original MPOPF framework is solved in a distributed manner by following the principles of the ENApp-based distributed OPF. This provides faster convergence and requires less solution time compared to the traditional MPCOPF.
3) Detailed comparative analyses between traditional MPCOPF and the proposed MPDOPF are carried out on the IEEE 123 bus test system and the superiority of MPDOPF is established. ACOPF feasibility validation is also performed by implementing the derived control signals into OpenDSS platform.

II. PROBLEM FORMULATION

A. Notations

In this study, the distribution network is accounted as a tree (connected graph) having N number of buses (indexed with i, j, and k) and the study is conducted for T time steps (indexed by t), each of interval length Δt. The sets of buses with DERs and batteries are D and B respectively, such that $D, B \subseteq N$. A directed edge from bus i to j in the tree is represented by ij and the set for edges is $\mathcal{L}$. Line resistance and reactance are r_{ij} ohm and x_{ij} ohm, respectively. Magnitude of the current flowing through the line at time t is denoted by I_{ij}^t and $l_{ij}^t = \left(I_{ij}^t\right)^2$. The voltage magnitude of bus j at time t is given by V_j^t and $v_j^t = \left(V_j^t\right)^2$. Apparent power demand at a node j at time t is $s_{L_j}^t$ $(= p_{L_j}^t + jq_{L_j}^t)$. The active power generation from the DER present at bus j at time t is denoted by $p_{D_j}^t$ and controlled reactive power dispatch from the DER inverter is $q_{D_j}^t$. DER inverter capacity is $S_{D_{R_j}}$. The apparent power flow through line ij at time t is S_{ij}^t $(= P_{ij}^t + jQ_{ij}^t)$. The real power flowing from the substation into the network is denoted by P_{Subs}^t and the associated cost involved per kWh is C^t. The battery energy level is B_j^t. Charging and discharging active power from battery inverter (of apparent power capacity $S_{R_j}^t$) are denoted by $P_{c_j}^t$ and $P_{d_j}^t$, respectively and their associated efficiencies are η_c and η_d respectively. The energy capacity of the batteries is denoted by B_{R_j}, and the rated battery power is $P_{B_{R_j}}$. soc_{min} and soc_{max} are fractional values for denoting safe soc limits of a battery about its rated soc capacity. The reactive power support of the battery inverter is $q_{B_j}^t$.

B. MPCOPF with Batteries

The OPF problem aims to minimize two objectives as shown in (1). The first term in (1) aims to minimize the total energy cost for the entire horizon. The incorporation of 'Battery Loss' cost as the second term ($\alpha > 0$) helps to avoid the usage of binary (integer) variables generally used to refrain from simultaneous charging/discharging. This is done to make the OPF problem a simple non-convex problem but not a MINCP. The term still ensures the complementarity of charging and discharging operations during a particular time [19].

$$\min \sum_{t=1}^{T} \Bigg[C^t P_{Subs}^t \Delta t + \alpha \sum_{j \in \mathcal{B}} \Big\{ (1-\eta_C) P_{C_j}^t + \left(\frac{1}{\eta_D} - 1\right) P_{D_j}^t \Big\} \Bigg] \tag{1}$$

Subject to the constraints (2) to (13) as given below:

$$0 = \sum_{(j,k)\in\mathcal{L}} \left\{P_{jk}^t\right\} - \left(P_{ij}^t - r_{ij} l_{ij}^t\right) - \left(P_{d_j}^t - P_{c_j}^t\right) - p_{D_j}^t + p_{L_j}^t \tag{2}$$

$$0 = \sum_{(j,k)\in\mathcal{L}} \left\{Q_{jk}^t\right\} - \left(Q_{ij}^t - x_{ij} l_{ij}^t\right) - q_{D_j}^t - q_{B_j}^t + q_{L_j}^t \tag{3}$$

$$0 = v_i^t - v_j^t - 2(r_{ij} P_{ij}^t + x_{ij} Q_{ij}^t) + \left\{r_{ij}^2 + x_{ij}^2\right\} l_{ij}^t \tag{4}$$

$$0 = (P_{ij}^t)^2 + (Q_{ij}^t)^2 - l_{ij}^t v_i^t \tag{5}$$

$$P_{Subs}^t \geq 0 \tag{6}$$

$$l_{ij}^t \in \left[0, I_{R,ij}^2\right] \tag{7}$$

$$v_j^t \in \left[V_{min}^2, V_{max}^2\right] \tag{8}$$

$$q_{D_j}^t \in \left[-\sqrt{{S_{D_{R,j}}}^2 - {p_{D_j}^t}^2}, \sqrt{{S_{D_{R,j}}}^2 - {p_{D_j}^t}^2}\right] \tag{9}$$

$$0 = B_j^t - \left\{B_j^{t-1} + \Delta t \eta_c P_{c_j}^t - \Delta t \frac{1}{\eta_d} P_{d_j}^t\right\} \tag{10}$$

$$P_{c_j}^t, P_{d_j}^t \in \left[0, P_{B_{R_j}}\right] \tag{11}$$

$$q_{B_j}^t \in \left[-0.44 P_{B_{R,j}}, 0.44 P_{B_{R,j}}\right] \tag{12}$$

$$B_j^t \in \left[soc_{min} B_{R,j}, soc_{max} B_{R,j}\right] \tag{13}$$

The distribution network is represented with the help of the branch power flow equations (2) to (5). Constraints (2) and (3) signify the active and reactive power balance at node j, including contributions from any attached DERs ($p_{D_j}^t, q_{D_j}^t$) and/or batteries ($P_{c_j}^t, P_{d_j}^t, q_{B_j}^t$). The KVL equation for branch (i, j) is represented by (4), while the equation describing the relationship between current magnitude, voltage magnitude and apparent power magnitude for nodes i and j is (5). Backflow of real power into the substation from the distribution system is avoided using the constraint (6).The box limits for squared branch current and squared node voltage are enforced via (7) and (8). (9) describes the reactive power limits of DER inverters. The trajectory of the state of charge of batteries versus time is given by (10) and is the only class of constraints in this paper coupling the optimal power flow problem in time. Battery charging and discharging powers are non-negative valued variables which should not exceed the battery's rated power capacity, as given by (11). Every battery's reactive power is also constrained based on the associated inverter's rated capacity, as described by (12). For safe and sustainable operation of the batteries, the state of charge B_j^t is constrained to be within some percentage limits of the rated battery soc capacity, as given in (13)

C. ENApp based Distributed Multi-Period OPF with Batteries

Solving a nonlinear nonconvex OPF problem is computationally intensive. In the ENApp paradigm, the original OPF problem is divided into several subproblems, based on physically connected 'parent-child' area relationships in the radial distribution network. ENApp primiarly requires three classes of operations. The first is of course solving for the OPF of each individual subproblem, the second is checking for 'boundary convergence' between related areas to check if further improvement iterations are needed and the third and last operation is exchange of variables between related areas for subsequent iterations. Out of these three operations, only solving the OPF is computationally intensive.

The key advantage of using ENApp in preference to MPCOPF is its efficient division of the OPF problem into several smaller problems via efficient exploitation of power flow physics in a radial network [12]. Typically, Nonlinear Programming problems grow superlinearly in complexity with increase in problem size, and thus division of the OPF problem into smaller, more manageable chunks greatly speeds up the solution process.

The solution process for each subproblem can then be parallelized, saving computation time even further.

Additionally, on paper it might appear that ENApp requires solving of the subproblems across multiple iterations, potentially nullifying the benefit from reduction in problem size. However in practice, once the first OPF iteration is completed for each area, the results can be used to 'warm-start' subsequent iterations with significant speedups in solution times.

Thus, in essence, the 'computational bottleneck' for ENApp is computing the OPF solution of its biggest subproblem, which typically translates to the single biggest area as part of the spatial decomposition of the radial distribution grid (assuming the number of DERs and Batteries is not significantly higher in another area).

The advantage of this smaller computational bottleneck will be readily seen in Sections III-C and III-D when compared against MPCOPF on the Test System.

For the rest of this paper, we'll be addressing ENAPpp based Distributed Multi-Period OPF simply as MPDOPF for brevity.

III. Case Study Demonstration

A. Simulation Data: IEEE 123 Bus Test System

We're using a Balanced Three-Phase version of the IEEE 123 Bus Test System, which has 85 Load Nodes. Additionally, $20\% \, (17)$ and $30\% \, (26)$ of these load nodes also contain reactive power controllable Solar photovolatics (PVs) and Batteries respectively. Their ratings are as per Table II. To demonstrate the effectiveness of the proposed algorithm, the Test System has been divided into four areas on similar lines as [12]. The full test system along with the area-wise division is shown in Figure 1.

It is assumed that a horizon-wide forecast for loads p_L^t, solar power output p_D^t and cost of substation power C^t is available to the distribution grid operator. Figure 2 shows the forecasted profiles for load, solar irradiance and cost of substation power over a 5 time-period horizon.

To showcase the workflow of the proposed algorithm, simulations were run for a 5 time-period horizon.

B. Simulation Workflow

All simulations were set up in MATLAB 2023a including both the high level algorithms as well as calls to the optimization solver. MATLAB's `fmincon` function was used to parse the nonlinear nonconvex optimization problem described by (1) to (13) in tandem with the SQP optimization algorithm to solve it. From the completed simulations, the resultant optimal control variables were obtained, and were passed through an OpenDSS engine (already configured with system data and

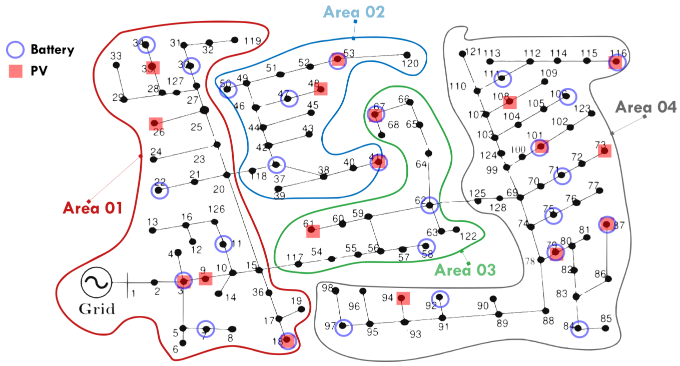

Fig. 1: IEEE 123 Node System Divided Into Four Areas

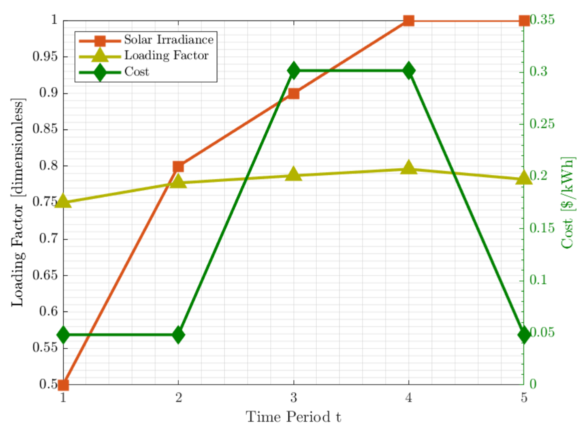

Fig. 2: Forecasts for Demand Power, Irradiance and Cost of Substation Power over a 5 Hour Horizon

TABLE II: Parameter Values

Parameter	Value
V_{min}, V_{max}	0.95, 1.05
$p_{D_{R_j}}$	$0.33 p_{L_{R_j}}$
$S_{D_{R_j}}$	$1.2 p_{D_{R_j}}$
$P_{B_{R_j}}$	$0.33 p_{L_{R_j}}$
B_{R_j}	$T_{fullCharge} \times P_{B_{R_j}}$
$T_{fullCharge}$	4 h
Δt	1 h
η_c, η_d	0.95, 0.95
soc_{min}, soc_{max}	0.30, 0.95
α	0.001

forecast values) in order to check for the feasiblity of the results. The associated code may be found here.

In the following subsections, the proposed algorithm is compared against the centralized (MPCOPF) algorithm in terms of resultant optimal control variables, optimality gap in objective function and computational performance. Secondly, the resultant control variables are tested for ACOPF feasiblity against OpenDSS. Section III-C describes the comparison over a 5 time-period horizon with an additional focus on describing the workflow of the MPDOPF algorithm. Section III-D describes the comparsion over a 10 time-period horizon to test for the scalability of the MPDOPF algorithm.

C. Simulation Results

Table III represents a comparsion between MPCOPF and MPDOPF in their problem scope, results and computational performance.

1) Biggest Subproblem vs Computational Performance: This first section of the table, 'Biggest subproblem' provides specifics of the 'computational bottleneck' encountered by either algorithm during its course. As described in Section II-C, the bottleneck represents the OPF subproblem which is computationally the most intensive, and thus is a key indicator of the expected time the algorithm will take to complete. As can be seen in the third section 'Computation', there is more than a 10x speedup in computation time with MPDOPF, despite the fact that 5 such iterations were performed, totalling to 20 OPF calls over the 4 areas of the Test System.

2) Optimality of Objective Function and Control Values: The second section of the table 'Simulation results' showcases that MPDOPF provides virtually zero optimality gap (same values for Substation Power Cost, the objective function). Interestingly, the values of the control variable themselves, prominently, there is a significant difference in the suggested optimal reactive power control values for inverters associated with DERs and Batteries (results aggregated over all components over the horizon for conciseness), and the substation. This highlights the fact that for a nonconvex nonlinear optimization problem may not necessarily have a unique global optimal point.

TABLE III: Comparative analyses between MPCOPF and MPDOPF - 5 time-period horizon

Metric	MPCOPF	MPDOPF
Biggest subproblem		
Decision variables	3150	1320
Linear constraints	5831	2451
Nonlinear constraints	635	265
Simulation results		
Substation power cost ($)	576.31	576.30
Substation real power (kW)	4308.28	4308.14
Line loss (kW)	75.99	76.12
Substation reactive power (kVAR)	574.18	656.24
PV reactive power (kVAR)	116.92	160.64
Battery reactive power (kVAR)	202.73	76.01
Computation		
Number of Iterations	-	5
Total Simulation Time (s)	521.25	49.87

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Boundary Variable Plots are too tall, make them slightly shorter, like 25% of the page only.

D. Scalability Analysis

To demonstrate the effectiveness of the proposed algorithm over a bigger horizon to demonstrate scalability, simulations were run for a 10 time-period horizon. Figure 6 shows the forecasted profiles for load, solar irradiance and cost of substation power over the horizon.

TABLE IV: ACOPF feasibility analyses - 5 time-period horizon

Metric	MPDOPF	OpenDSS
Full horizon		
Substation real power (kW)	4308.14	4308.35
Line loss (kW)	76.12	76.09
Substation reactive power (kVAR)	656.24	652.49
Max. all-time discrepancy		
Voltage (pu)	0.0002	
Line loss (kW)	0.0139	
Substation power (kW)	0.3431	

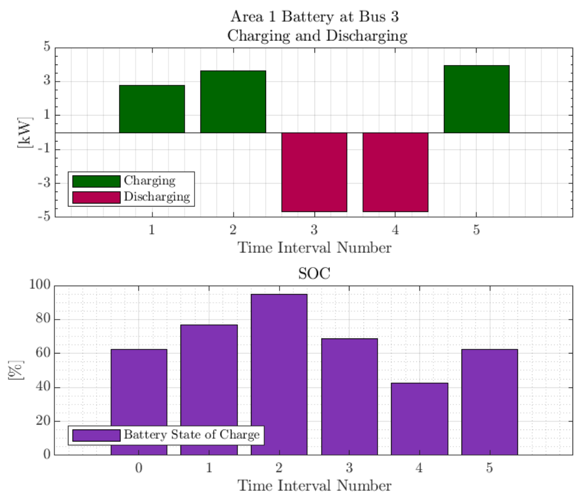

Fig. 3: Charging-Discharging and SOC graphs for Battery at Bus 3 located in Area 1 obtained by MPDOPF

1) Comparison between MPCOPF and MPDOPF: In this section, comparative analyses are carried out between MPCOPF and MPDOPF considering 10-hour time steps with 20% PV penetration and 30% battery penetration.

TABLE V: Comparative analyses between MPCOPF and MPDOPF - 10 time-period horizon

Metric	MPCOPF	MPDOPF
Biggest subproblem		
Decision variables	6300	2640
Linear constraints	11636	4891
Nonlinear constraints	1270	530
Simulation results		
Substation power cost ($)	1197.87	1197.87
Substation real power (kW)	8544.28	8544.04
Line loss (kW)	148.67	148.94
Substation reactive power (kVAR)	1092.39	1252.03
PV reactive power (kVAR)	222.59	139.81
Battery reactive power (kVAR)	388.52	310.94
Computation		
Number of Iterations	-	5
Total Simulation Time (s)	4620.73	358.69

Further, here the

IV. Conclusions

[20]–[24]

TABLE VI: ACOPF feasibility analyses - 10 time-period horizon

Metric	MPDOPF	OpenDSS
Full horizon		
Substation real power (kW)	8544.04	8544.40
Line loss (kW)	148.94	148.87
Substation reactive power (kVAR)	1252.03	1243.36
Max. all-time discrepancy		
Voltage (pu)	0.0002	
Line loss (kW)	0.0132	
Substation power (kW)	0.4002	

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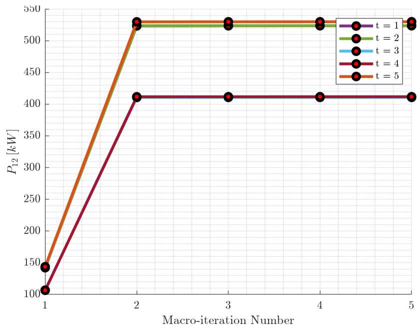
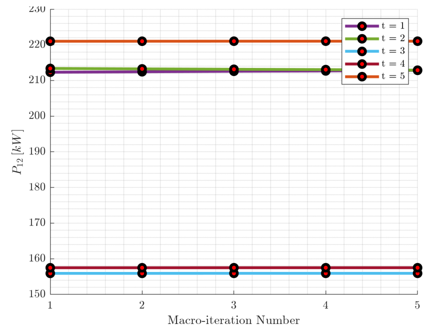
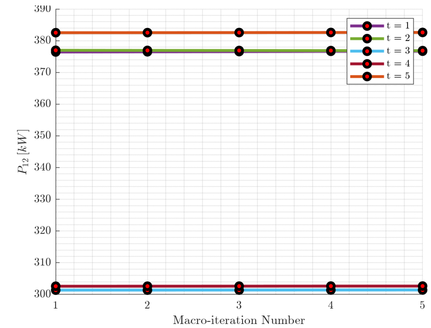


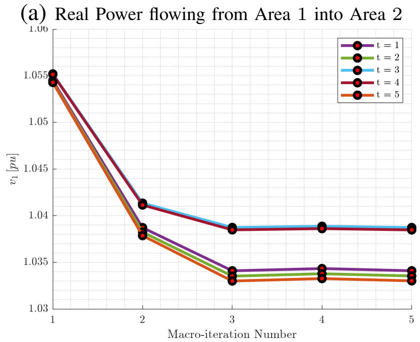
(a) Real Power flowing from Area 1 into Area 2



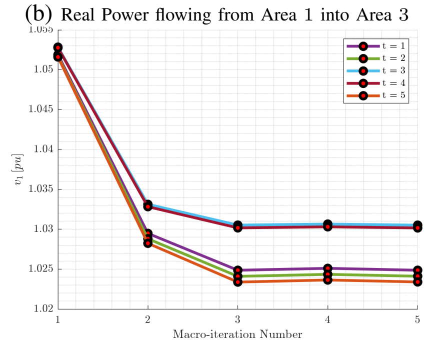
(b) Real Power flowing from Area 1 into Area 3



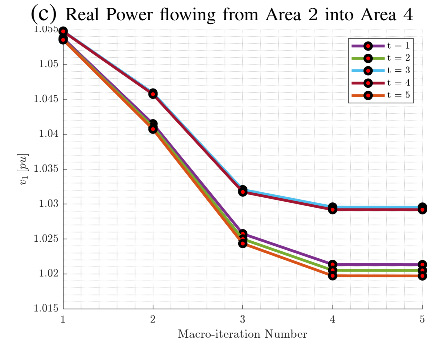
(c) Real Power flowing from Area 2 into Area 4



(d) Voltage at the PoI of Area 1 and Area 2



(e) Voltage at the PoI of Area 1 and Area 3



(f) Voltage at the PoI of Area 2 and Area 4

Fig. 4: Convergence of Boundary variables with every iteration. Each plot represents a particular variable exchanged between a pair of connected areas. Each line graph within a plot represents a particular time period.

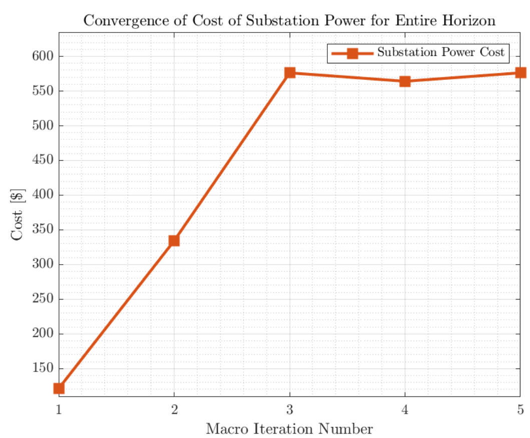


Fig. 5: Convergence of Objective Function Value with each MPDOPF iteration

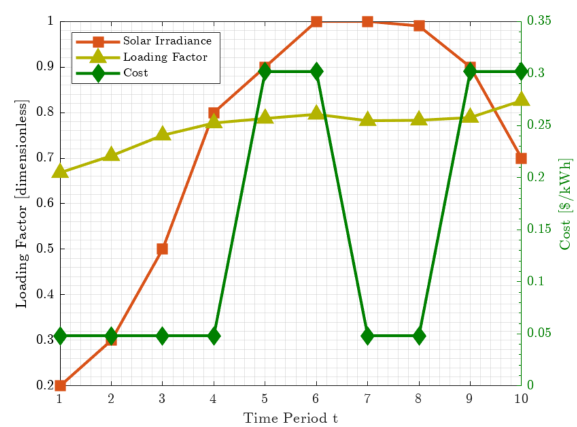


Fig. 6: Forecasts for Demand Power, Irradiance and Cost of Substation Power over a 10 Hour Horizon

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