# Making Analysis of Power Systems Scalable through Distributed Computing

Aryan Ritwajeet Jha

# My interest in Distributed Computing

- Have always worked in Power System Control and Stability domain
- Transmission Systems are well-behaved, homogeneous

Illustrations by Pixeltrue on icons8

# The Average Transmission Line.

Illustrations by Pixeltrue on
icons8

# My interest in Distributed Computing

- Have always worked in Power System Control and Stability domain
- Transmission Systems are well-behaved, homogeneous
- Low R/X ratio.
- Good Jacobians
- Easy computations due to low variance in system components.

Illustrations by Pixeltrue on icons8

# My interest in Distributed Computing

- Now have been assigned to work on Distribution Systems.
- These lines are NOT homogeneous!

Illustrations by Pixeltrue on icons8

# The Average Distribution System at a feeder level substation in the subcontinent.

# My interest in Distributed Computing

- Now have been assigned to work on Distribution Systems.
- Highly heterogeneous!
- High R/X ratio
- NOT well-behaved Jacobians, YBus, etc.
- Unbalanced phases
- Our usual analysis methods will NOT work for these systems.
- Distributed Computing might help.

Illustrations by Pixeltrue on icons8

# What do I NOT mean by Distributed Computing?

# Fast Newton-Raphson Power Flow Analysis Based on Sparse Techniques and Parallel Processing

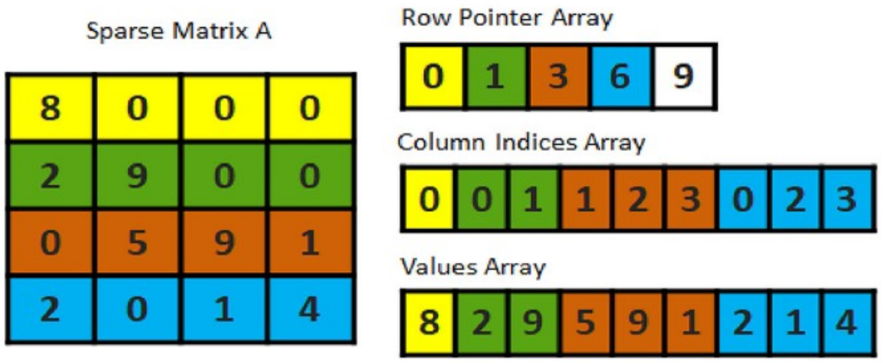
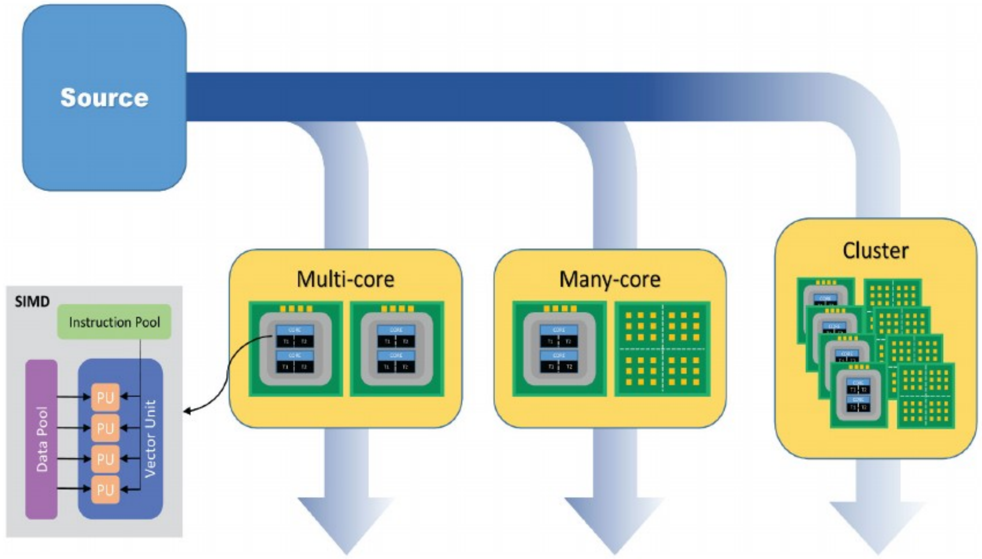



Fig. 1. A Sparse Matrix and its Corresponding CSR Arrays.

Sparsification reduces the data computation overhead and makes our analysis more scalable.

# Fast Newton-Raphson Power Flow Analysis Based on Sparse Techniques and Parallel Processing




Parallel Processing of Data using mutli-core CPUs, GPUs and SMIDs is also referred to as distributed computing.

# Fast Newton-Raphson Power Flow Analysis Based on Sparse Techniques and Parallel Processing

TABLE VII
PERFORMANCE COMPARISON OF IMPLEMENTED NEWTON-RAPHSON POWER FLOW WITH OTHER REFERENCES

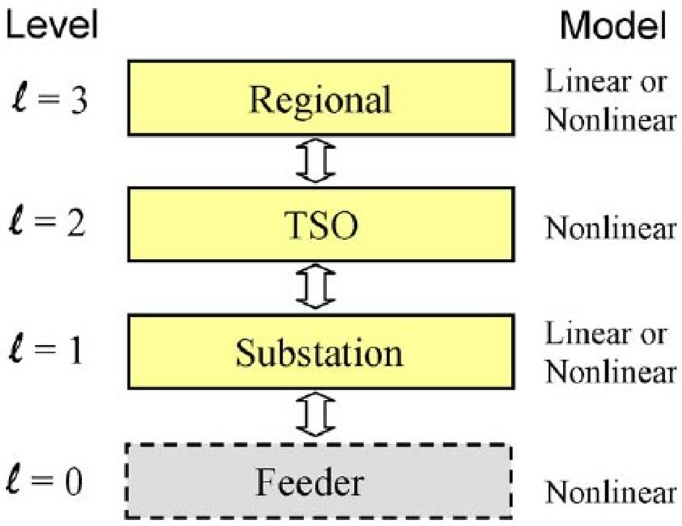
| Number of Buses | Reference | Platform | Runtime (Seconds) |
|---|---|---|---|
| 82,000 | Proposed | CPU-Sparse | **1.87** |
| | MATPOWER-NR | CPU-Sparse | 3.91 |
| | MATPOWER-NR-Qlim | CPU-Sparse | Diverged |
| | MATPOWER-FD | CPU-Sparse | 12.1 |

A speedier execution of data processing is certainly a desired output for a scalable algorithm.

But none of these methods refer to the usage of Distributed Computing here.

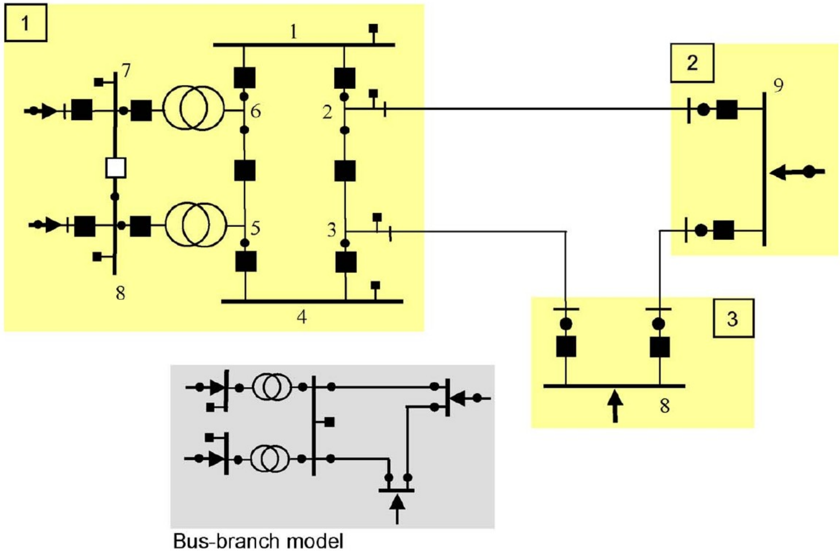
# Alright.. then what do I mean by Distributed Computing?

# A Multilevel State Estimation Paradigm for Smart Grids



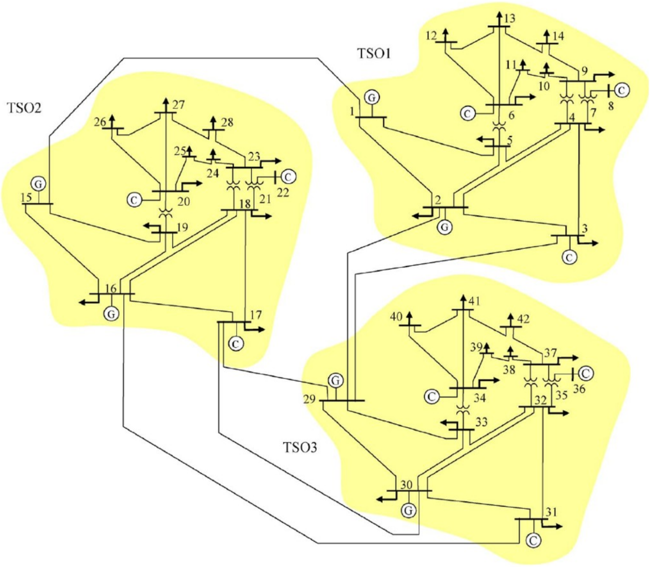

Heirarchial data computation and data reporting

# A Multilevel State Estimation Paradigm for Smart Grids




Dividing a central system into several subsystems and analyzing them all in parallel.

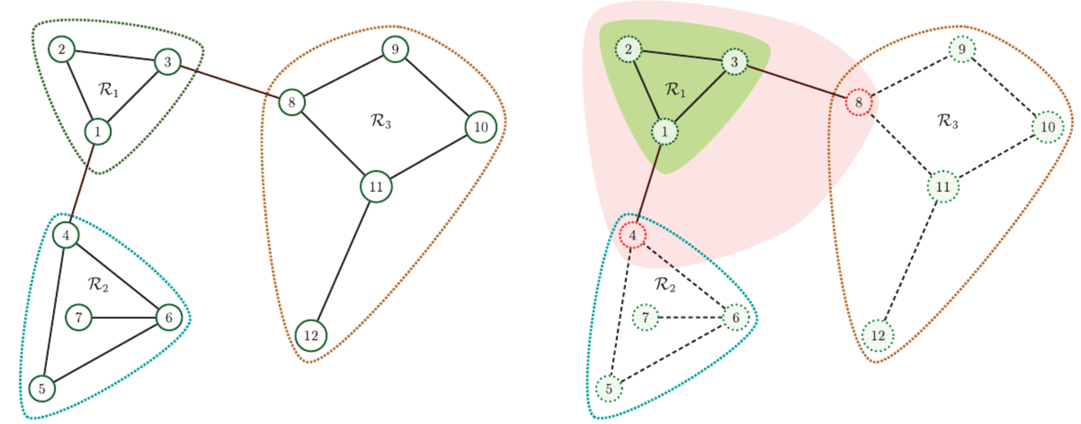
# A Multilevel State Estimation Paradigm for Smart Grids




Dividing a central system into several subsystems and analyzing them all in parallel. Here: Transmission Systems.

# Use Distributed Computing because you should.

# Distributed power flow and distributed optimization—Formulation, solution, and open source implementation




a) Example how to decompose a power grid into three regions $\{1, 2, 3\}$, $\{4, 5, 6, 7\}$, and $\{8, 9, 10, 11, 12\}$.

b) From the perspective of region $\mathcal{R}_1$, the core buses are buses $\{1, 2, 3\}$, and the copy buses are buses $\{4, 8\}$.

**Fig. 1.** Graphical depiction of nomenclature for distributed power flow problems, see Section 2.1.

Data privacy issues due to oversharing between different TSOs. How to counter that?

# Distributed power flow and distributed optimization—Formulation, solution, and open source implementation

### 2.3. *Distributed optimization problem*

The distributed power flow problem from (4) is a system of nonlinear equations—in a form amenable to distributed optimization. We propose to solve Problem (4) either as a *distributed feasibility problem*

$$\min_{\substack{x_i, z_i \\ \forall i \in \{1,\dots,n^{\text{reg}}\}}} \quad 0 \quad \text{s.t.} \tag{6a}$$

$$g_i^{\text{pf}}(x_i, z_i) = 0 \tag{6b}$$

$$g_i^{\text{bus}}(x_i) = 0 \tag{6c}$$

$$\sum_{i=1}^{n^{\text{reg}}} A_i \begin{bmatrix} x_i \\ z_i \end{bmatrix} = 0, \tag{6d}$$

or as a *distributed least-squares problem*[10]

$$\min_{\substack{x_i, z_i \\ \forall i \in \{1,\dots,n^{\text{reg}}\}}} \sum_{i=1}^{n^{\text{reg}}} \left\| \begin{bmatrix} g_i^{\text{pf}}(x_i, z_i) \\ g_i^{\text{bus}}(x_i) \end{bmatrix} \right\|^2 \quad \text{s.t.} \quad \sum_{i=1}^{n^{\text{reg}}} A_i \begin{bmatrix} x_i \\ z_i \end{bmatrix} = 0. \tag{7}$$

Solve for OPF separately for every single sub-system.

**Algorithm 1** ADMM for problem (8)

**Initialization:** $\zeta_i^0, \lambda_i^0$ **for all** $i \in \mathcal{R}$, $\rho$
**Repeat:**

1) $\chi_i^{k+1} = \underset{g_i(\chi_i)=0}{\operatorname{argmin}} f_i(\chi_i) + \lambda_i^{k\top} A_i \chi_i + \frac{\rho}{2} \|A_i(\chi_i - \zeta_i^k)\|_2^2, \quad i \in \mathcal{R}$ (parallel)
2) $\zeta^{k+1} = \underset{A\zeta=0}{\operatorname{argmin}} \sum_{i \in \mathcal{R}} -\lambda_i^{k\top} A_i \zeta_i + \frac{\rho}{2} \|A_i(\chi_i^{k+1} - \zeta_i)\|_2^2$ (centralized)
3) $\lambda_i^{k+1} = \lambda_i^k + \rho A_i(\chi_i^{k+1} - \zeta_i^{k+1}), \quad i \in \mathcal{R}$ (parallel)

**Algorithm 2** ALADIN for problem (8)

**Initialization:** $\zeta_i^0, \lambda^0, \Sigma_i \succ 0$ **for all** $i \in \mathcal{R}$, $\nu, \rho$
**Repeat:**

1) Solve for all $i \in \mathcal{R}$

$$\chi_i^k = \underset{g_i(\chi_i)=0}{\operatorname{argmin}} f_i(\chi_i) + \lambda^{k\top} A_i \chi_i + \frac{\nu}{2} \|\chi_i - \zeta_i^k\|_{\Sigma_i}^2, \quad \text{(parallel)}$$

2) Compute $\nabla f_i(\chi_i^k)$, $B_i^k \approx \nabla_{\chi_i}^2 \left(f_i(\chi_i^k) + \gamma_i^\top g_i(\chi_i^k)\right)$, $\nabla g_i(\chi_i^k)$.
3) Solve the coordination QP

$$\Delta\chi^k = \underset{\Delta\chi}{\operatorname{argmin}} \sum_{i \in \mathcal{R}} \tfrac{1}{2} \Delta\chi_i^\top B_i^k \Delta\chi_i + \nabla f_i^\top(\chi_i^k) \Delta\chi_i \quad \text{(centralized)}$$
$$+ \lambda^{k\top} \left(\textstyle\sum_{i \in \mathcal{R}} A_i(\chi_i^k + \Delta\chi_i) - b\right) + \frac{\rho}{2} \|\textstyle\sum_{i \in \mathcal{R}} A_i(\chi_i^k + \Delta\chi_i) - b\|_2^2$$
$$\text{subject to } \nabla g(\chi^k)\Delta\chi = 0.$$

4) Set $\zeta_i^{k+1} = \chi_i^k + \Delta\chi_i^k$ and $\lambda^{k+1} = \lambda^k + \rho\left(\sum_{i \in \mathcal{R}} A_i \chi_i - b\right)$. (parallel)

# Distributed power flow and distributed optimization—Formulation, solution, and open source implementation

**Table 4**
Computing times for different test cases and different solvers when solving the distributed least-squares problem (7) with ALADIN and sensitivities from rapidPF .

| Buses | $n^{reg}$ | MATPOWER case files | $n^{conn}$ | Solution time in s for | | | ALADIN iterations |
|---|---|---|---|---|---|---|---|
| | | | | fminunc | fmincon | worhp | |
| 53 | 3 | 9, 14, 30 | 3 | 2.5 | 2.2 | 2.4 | 4 |
| 354 | 3 | 3 × 118 | 5 | 2.5 | 3.1 | 4.8 | 5 |
| 418 | 2 | 118, 300 | 2 | 4.5 | 5.2 | 7.0 | 5 |
| 826 | 7 | 7 × 118 | 7 | 3.7 | 5.3 | 7.2 | 5 |
| 1180 | 10 | 10 × 118 | 11 | 4.9 | 6.7 | 9.8 | 6 |
| 2708 | 2 | 2 × 1354 | 1 | 212.7 | 41.9 | 53.6 | 4 |
| 4662 | 5 | 3 × 1354, 2 × 300 | 4 | 387.9 | 90.1 | 113.8 | 5 |

The authors designed an in-house algorithm acronymized ALADIN which performed

# Use Distributed Computing because you MUST.

# Distributed Optimization Using Reduced Network Equivalents for Radial Power Distribution Systems

## Distributed Computing for Scalable Optimal Power Flow in Large Radial Electric Power Distribution Systems with Distributed Energy Resources

**Algorithm 1:** Distributed Algorithm for Scaled OPFs

1 Decompose the network into $N$ areas, so that each area has a maximum specified node numbers
2 Initialize complicating variables, $\mathbf{Y}^0 \in \mathcal{S}$; error, $e = 1$; and macro-iteration count $n = 0$
3 If $|e| \leq \epsilon_{tol}$, stop iteration count, and go to step 10
4 Else, increase iteration count $n$: $n \leftarrow n + 1$
5 Solve $\Phi_m$ in parallel using **Algorithm 2**, for all decomposed areas $A_m$, where, $\Phi_m$ depicts the sub-problem –
$$\Phi_m : \; X_m^{(n)} := \underset{X_m \in S_m}{\text{argmin/argmax}} \; f_m\left(X_m, y_{m'}^{(n-1)}\right)$$
6 Update all the complicating variables, $\mathbf{Y}$, using (9), where $\alpha$ can be constant or adaptive
7 Check residual vector $\mathcal{R}^{(n)} = \left[\; \mathbf{Y}^{(n)} - \mathbf{Y}^{(n-1)} \;\right]$
8 $e = \max\, |\mathcal{R}^{(n)}|$
9 Go to step 2
10 Return Global Minimizer:
$X^* = \{X_m^{(n)} \mid m = 1, 2, ..., N\}$

The authors wanted to test Distributed algorithms against Centralized algorithms for Optimal Power Flow for large distribution system with significant renewable penetration.

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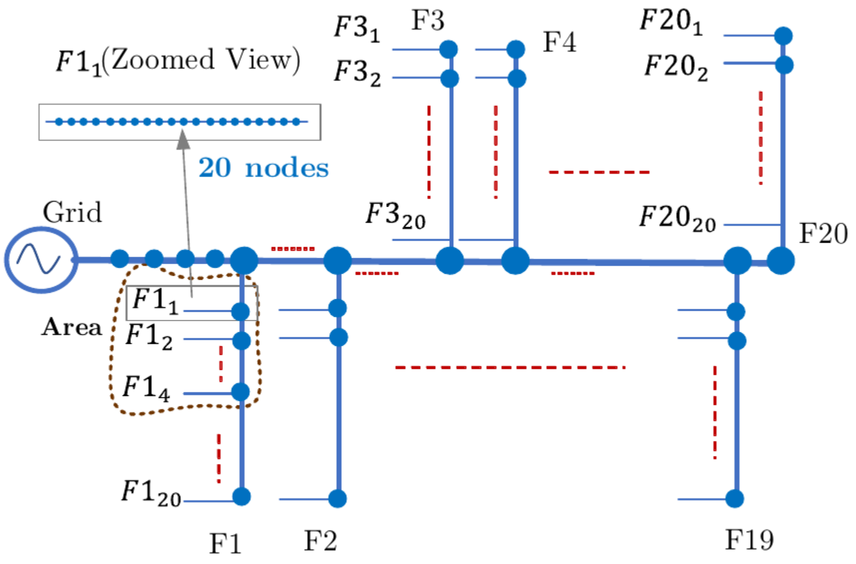


Figure 1: Synthetic 10,000 Node System

They used synthetic feeder-level distribution systems with significant DER penetration and applied their grid decomposition algorithm before applying their Distributed OPF algorithm.

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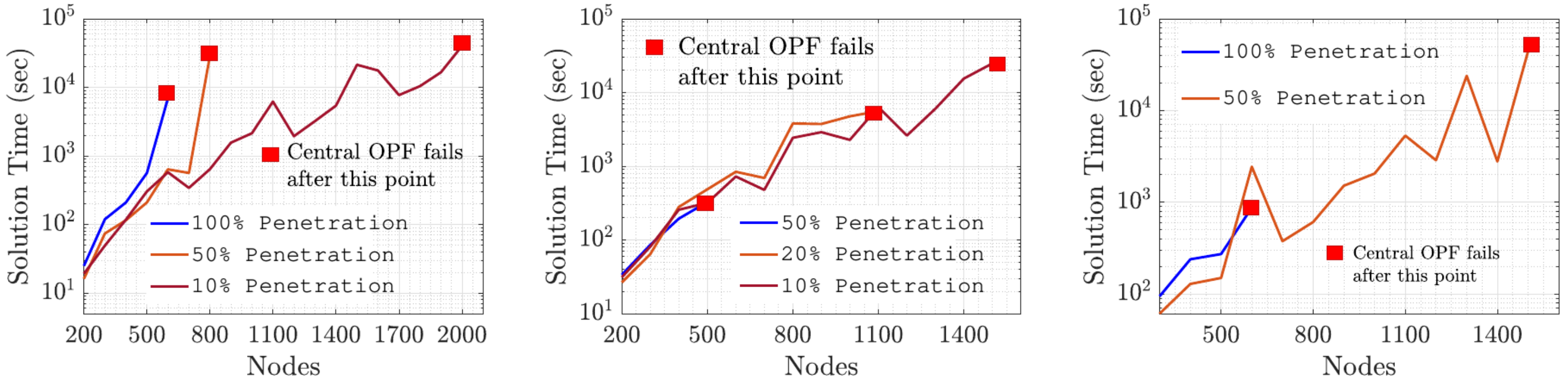


(a) Loss minimization objective (b) DER maximization objective (c) ΔV minimization objective

Figure 5: Solution Time for Central OPF (C-OPF) Problems for Different Sizes of Networks

Centralized OPF algorithms are not only being slower, they are failing to converge!

# What did we do today? A super short summary of the contents of the papers.

01

**Paper 1: Clarification on the term Distributed Computing**

Parallel processing is a part of Distributed Computing, but NOT the concept itself!

02

**Papers 2 and 3: Need for Distributed Computing**

Privacy.
Computational attractiveness.

03

**Papers 4 and 5: A dire need for Distributed Computing**

Larger systems with significant DER penetrations would simply NOT converge for Centralized OPF algorithms. Must use Distributed OPF algorithms.

# Where does all of this fit with the course work?

# In our EE 521 Classes, we learnt..

**Course work covered algorithms designed for Centralized Computation.**

Very effective for homogeneous systems which are NOT large. Robust control.

Lagrangian and Dual Problem Formulation

LP
Simplex Method
Interior Point Method
NLP
Quadratic Programming

**All of these methods are JUST as valid in Distributed Computing .. provided some adjustments are made.**

# Thank you.

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