

# Uncertainties Impact and Mitigation with an Adaptive Model-Based Voltage Controller

**Muhammad Andy PUTRATAMA, Remy RIGO-MARIANI,  
Vincent DEBUSSCHERE, Yvon BESANGER**

*Univ. Grenoble Alpes, CNRS, Grenoble INP, G2Elab*

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TECHNICAL TRACK 3– Control and power management of electrical systems

# Presentation Outline

1. Introduction
2. Model-based voltage controller
3. Simulations & uncertainties impact assessments
4. Proposed model fitting algorithm (impedance estimation)
5. Conclusion

# 1. Introduction

## Technical Challenges of DER integration

- DER integration has been projected to **grow exponentially** in the future
- High integration of DERs present could lead to **voltage violation problems**
  - The DSO shall maintain the quality of grid voltage delivered to the customers
- These highlight the need of proper **control** and **optimization of DERs**

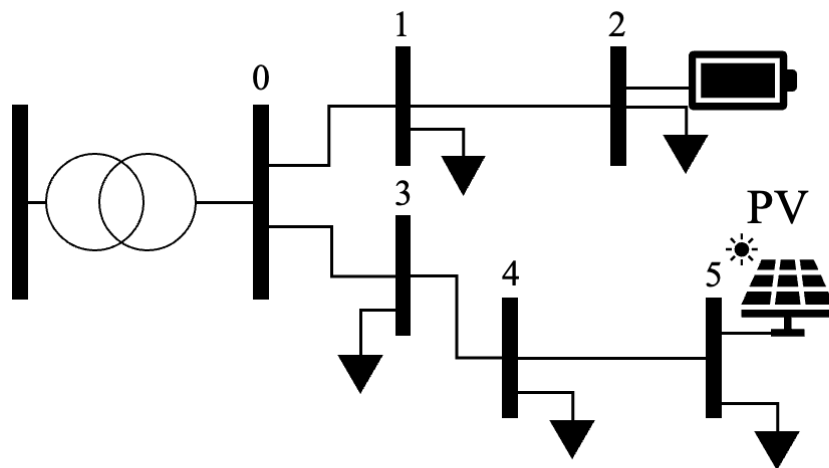
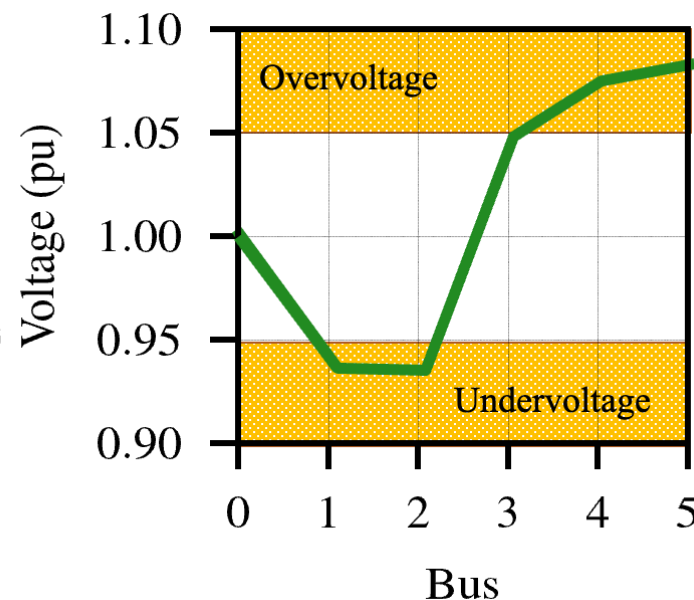


Illustration of distribution grid



Voltage profile at the bus

# 1. Introduction

## Limitations in model-based voltage controller

- A model-based controller is typically formulated as an **optimal power flow (OPF) problem**.

$$\min f(x) \text{ (e.g., Energy cost, losses)}$$

Subject to:

- devices and lines operation constraints
- voltage operating limits

- Most research on model based-controllers incorporate the following ideal assumptions:

- **Relaxed OPF formulation**

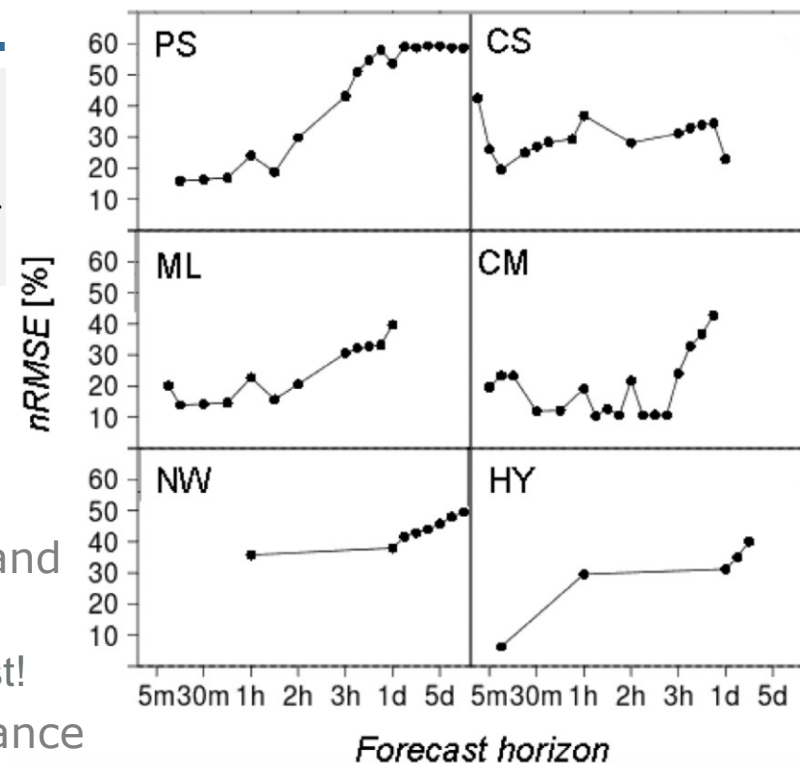
- The solution/relaxation may not be accurate

- **Deterministic model:** Perfect forecast of PV and loads

- It is almost **impossible** to have a precise forecast!

- **Knowledge of grid parameters** (i.e., impedance values)

- In real life, distribution grid data is usually **not available/inaccurate**, especially in LV grid



Accuracy of different forecast methodologies

(R.Blaga et al., 2019)

# 1. Introduction

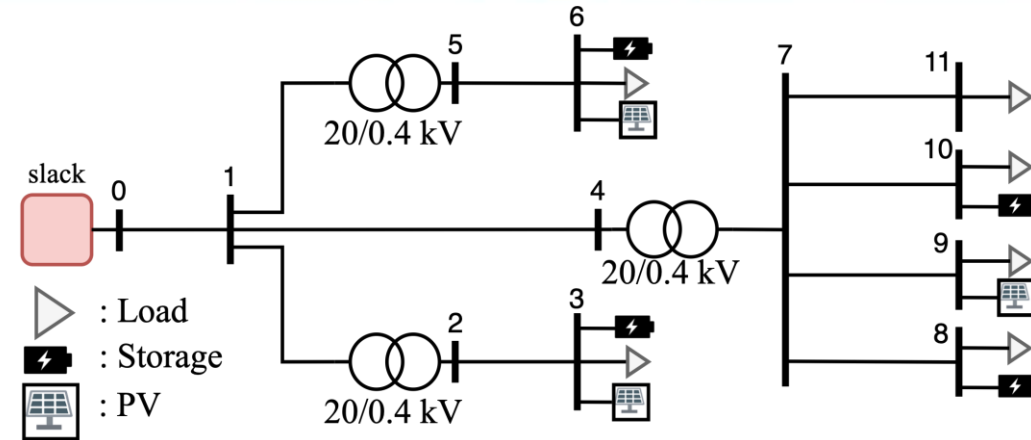
## Research Objectives & Contributions

- In this study, we aim to investigate the impact of three different uncertainties to the performance of a model-based voltage controller:
  1. *Controller Model (i.e., different OPF relaxation techniques)*
  2. *Forecast*
  3. *Grid parameter data (i.e., impedance values)*
  
- Furthermore, the contribution of the work also consist of:
  - A model-based voltage controller to minimize the total number of voltage deviation
  - An adaptive controller with updated model data based on local measurements index.

# 2. Model-based Controller Test System

## Test system specification:

- 11-bus system
- 3x 250 kW PVs (non dispatchable)
- 4x 0.5 MWh/300 kW Storage



Considered test system

A Radial distribution Grid can be modelled using **DistFlow** equations:

$$P_{ij,t} = \sum_{k:(j,k) \in E} P_{jk,t} + r_{ij} \ell_{ij,t} + p_{j,t}^{ld} - p_{j,t}^{PV} + p_{j,t}^{ESS}$$

$$Q_{ij,t} = \sum_{k:(j,k) \in E} Q_{jk,t} + x_{ij} \ell_{ij,t} + q_{j,t}^{ld} + q_{j,t}^{ESS}$$

$$v_{j,t} = v_{i,t} - 2(r_{ij} P_{ij,t} + x_{ij} Q_{ij,t}) + (r_{ij}^2 + x_{ij}^2) \ell_{ij,t}$$

Where:

$$\ell_{ij,t} = \frac{P_{ij,t}^2 + Q_{ij,t}^2}{v_{i,t}}$$

**Non-linear!**

# 2. Model-based Controller

## Generic Voltage control formulation

■ **Objective Function:** 
$$\min_{\mathbf{p}^{ESS}, \mathbf{q}^{ESS}} \underbrace{\sum_{t \in T} \sum_{i \in N} (\vartheta_{i,t}^+ + \vartheta_{i,t}^-)}_{\text{Voltage Deviation}} + \underbrace{C_{loss} \sum_{t \in T} \sum_{(i,j) \in E} \ell_{ij,t} r_{ij}}_{\text{Grid Losses}}$$

■ **Subject to:**

- Grid model (DistFlow Es)
- ESS Operation constraints
- Voltage relaxation:

$$0 \leq V_{i,t}^+, \vartheta_{i,t}^+ \leq 0.05\alpha_{i,t}$$

$$0 \leq V_{i,t}^-, \vartheta_{i,t}^- \leq 0.05(1 - \alpha_{i,t})$$

$$\alpha_{i,t} \in \{0, 1\}$$

$$V_{i,t} = 1 + V_{i,t}^+ + \vartheta_{i,t}^+ - (V_{i,t}^- + \vartheta_{i,t}^-)$$

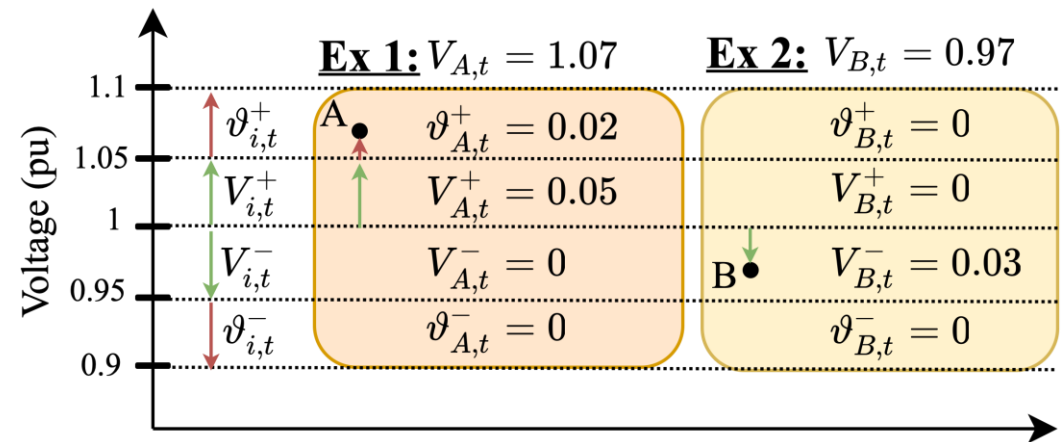


Illustration of linear voltage Relaxation

The OPF problem is still **non-convex** due to the branch current relation

# 2. Model-based Controller

## Convex relaxation

Three relaxation techniques considered:

### 1. SOCP Relaxation:

$$\ell_{ij,t} = \frac{P_{ij,t}^2 + Q_{ij,t}^2}{v_{i,t}} \quad \Rightarrow \quad \ell_{ij,t} \geq \frac{P_{ij,t}^2 + Q_{ij,t}^2}{v_{i,t}} \quad \text{or} \quad \ell_{ij,t} + v_{i,t} \geq \left\| \begin{array}{c} 2P_{ij,t} \\ 2Q_{ij,t} \\ \ell_{ij,t} - v_{i,t} \end{array} \right\|_2$$

### 2. Quadratic Relaxation

$$\ell_{ij,t} = \frac{P_{ij,t}^2 + Q_{ij,t}^2}{v_{i,t}} \quad \Rightarrow \quad \ell_{ij,t} \geq \frac{P_{ij,t}^2 + Q_{ij,t}^2}{v_{0,t}}$$

Voltage at the slack bus

### 3. Linear Relaxation

$$P_{ij,t} = \sum_{k:(j,k) \in E} P_{jk,t} + \cancel{x_{ij}\ell_{ij,t}} + p_{j,t}^{ld} - p_{j,t}^{PV} + p_{j,t}^{ESS}$$

$$Q_{ij,t} = \sum_{k:(j,k) \in E} Q_{jk,t} + \cancel{x_{ij}\ell_{ij,t}} + q_{j,t}^{ld} + q_{j,t}^{ESS}$$

$$v_{j,t} = v_{i,t} - 2(r_{ij}P_{ij,t} + x_{ij}Q_{ij,t}) + \cancel{(r_{ij}^2 + x_{ij}^2)\ell_{ij,t}}$$

and

$$\ell_{ij,t} = \frac{P_{ij,t}^2 + Q_{ij,t}^2}{v_{0,t}}$$

Non-linear terms are neglected

# 3. Simulations

## Voltage Performance Index

- All the conducted simulations consider **one-day simulation** horizon with **30 min** time step.
- A Voltage performance index (VPI) in [0%, 100%] is proposed to quantify controller performance.

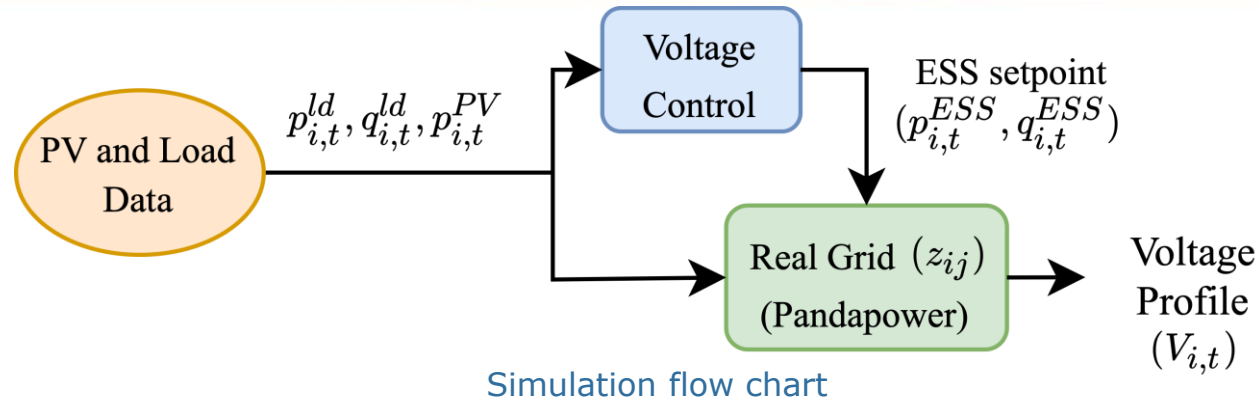
$$VPI(\%) = \frac{\sum_{t \in T} \sum_{i \in N \setminus \{0\}} \delta_{i,t}}{(|N| - 1)|T|} \times 100$$
$$\delta_{i,t} = \begin{cases} 0, & \text{if } 0.95 \leq V_{i,t} \leq 1.05 \\ 1, & \text{otherwise} \end{cases}$$

Our primary objective is to maintain the voltage between [0.95, 1.05]

# 3. Simulations

## Impact of Controller Models

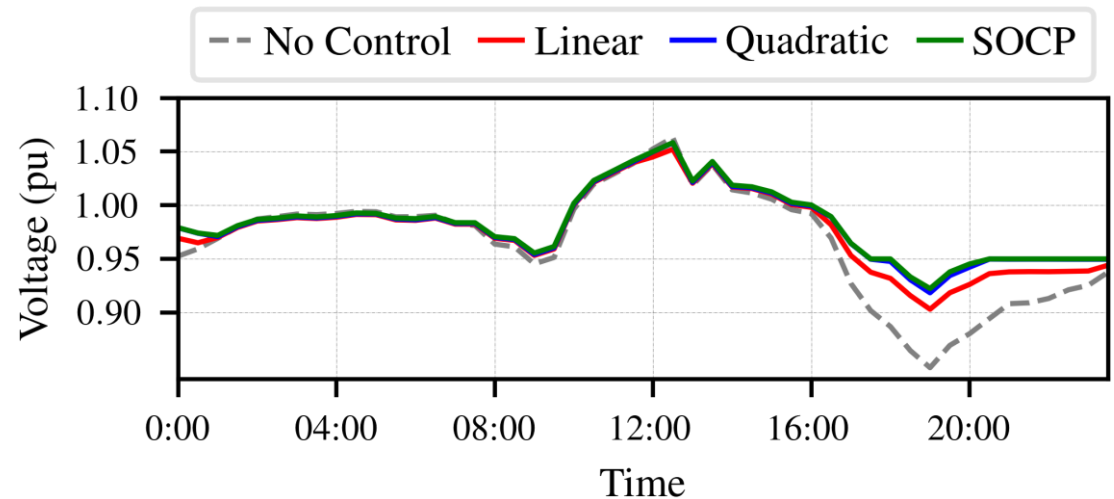
- Simulation Scheme
  - Pandapower** is utilized to simulate real grid



## Results

Relaxation Method	VPI
No control	15.53
Linear	6.33
Quadratic	4.93
<b>SOCP</b>	<b>0.94</b>

Obtained VPI using different relaxation method

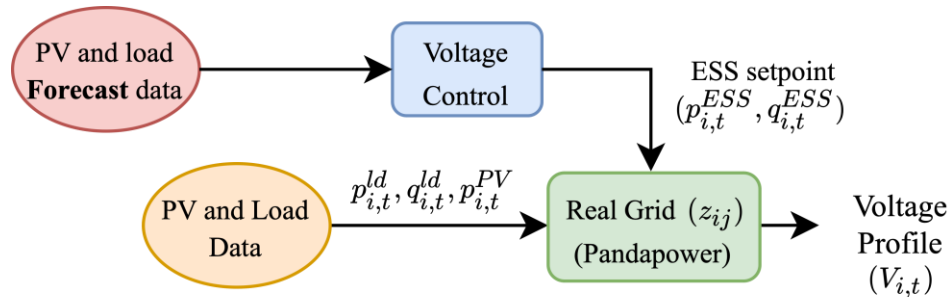


Voltage profile of a particular bus

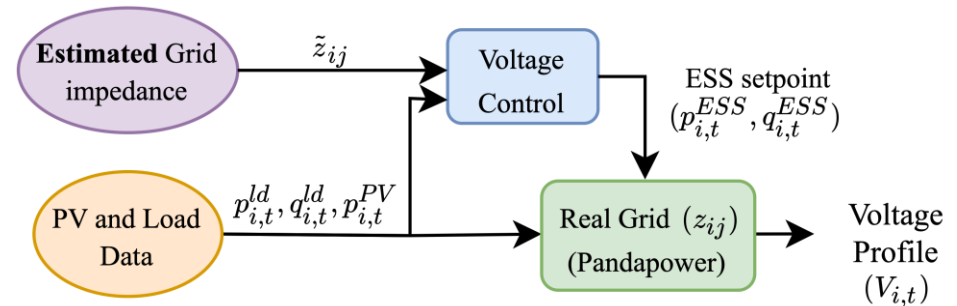
# 3. Simulations

## Impact of Forecast and Model uncertainties

### Simulation Scheme

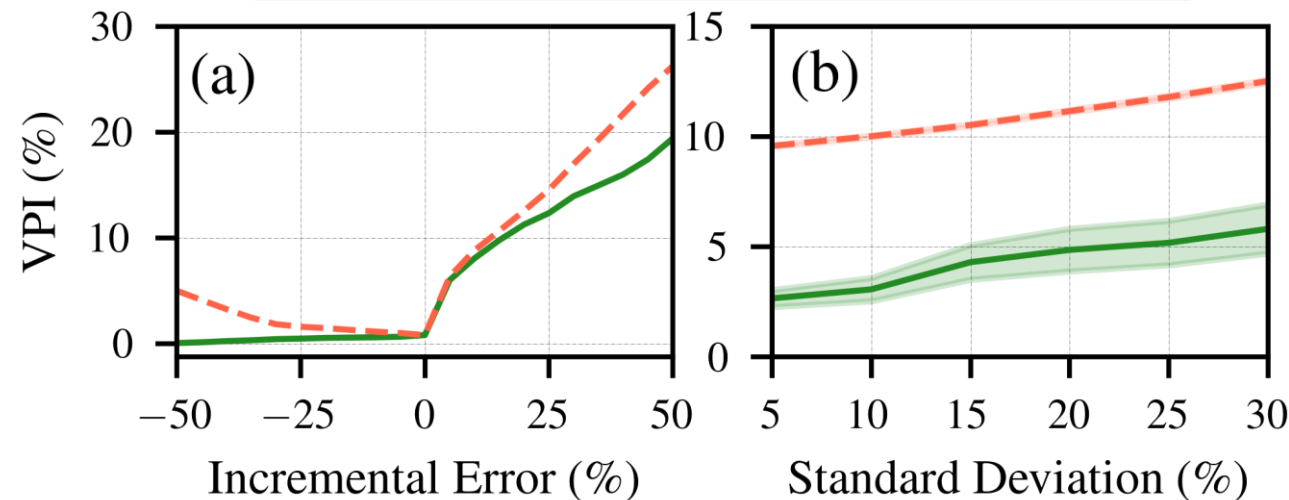


Simulation scheme for investigating **forecast** uncertainty



Simulation scheme for investigating **impedance** uncertainty

— Impact of  $\tilde{z}_{ij}$       - - - Impact of forecast



### Results

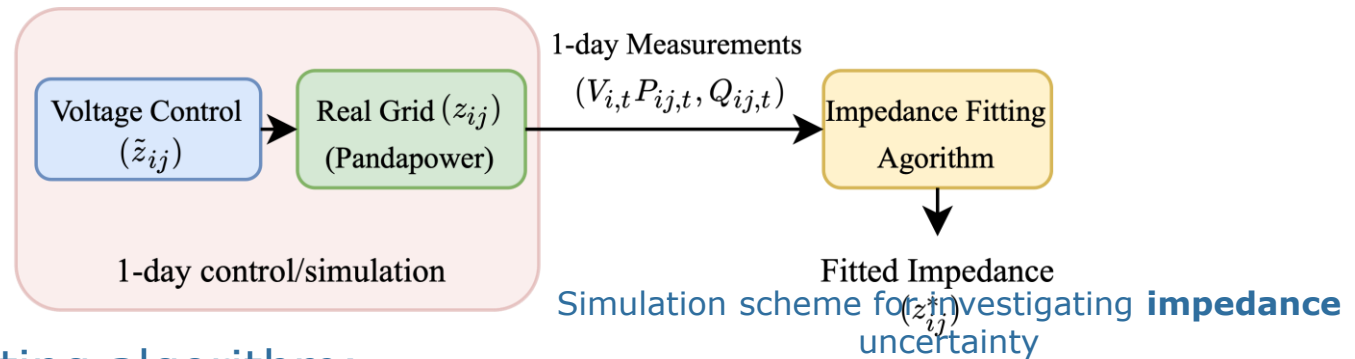
#### Two tests were conducted:

- Incremental error of forecast & estimated impedance data
- Monte Carlo** simulations to generate randomness in forecast & estimated impedance

# 4. Impedance Estimation Formulation

■ **Objective:** to estimate  $r$  and  $x$  using measurement data

■ Simulation flow:



■ Proposed model fitting algorithm:

$$\min_{\mathbf{R}^*, \mathbf{X}^*} \sum_{i \in N} \text{std}(\mathbf{R}_{i,:}^*) + \text{std}(\mathbf{X}_{i,:}^*)$$

Subject to 3<sup>rd</sup> linear DistFlow equation:

$$v_{j,t} = v_{i,t} - 2(r_{ij,t}P_{ij,t} + x_{ij,t}Q_{ij,t})$$

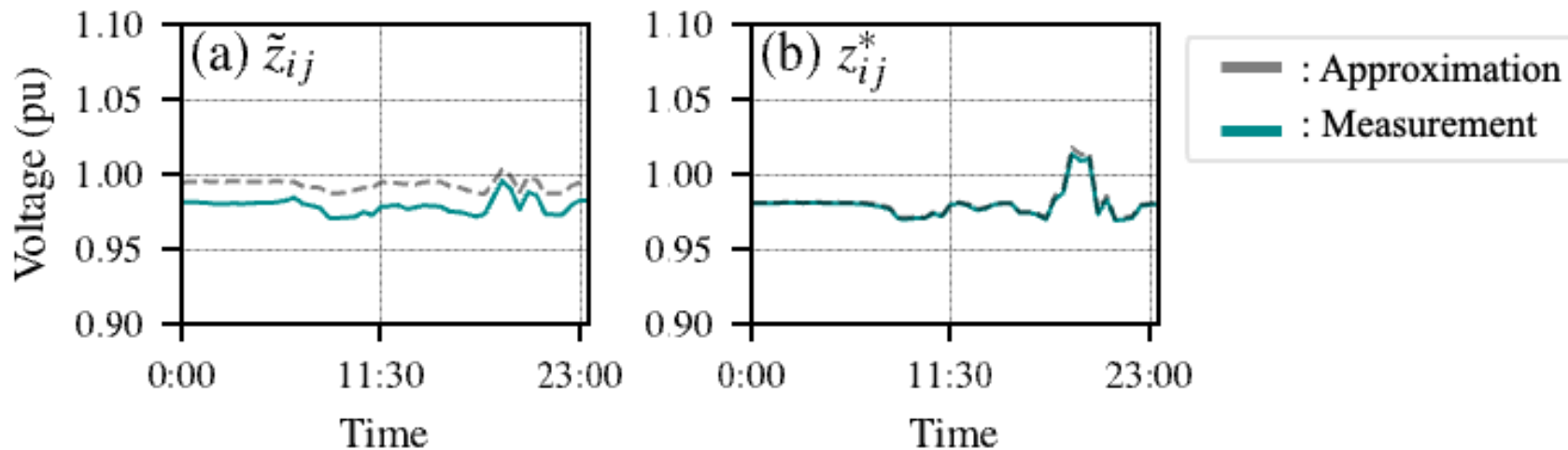
- $R$  and  $x$  are firstly assumed to be **dynamic**.
- The Final  $r$  and  $x$  can be computed by taking the average of  $\mathbf{R}_i$  and  $\mathbf{X}_i$

# 4. Impedance Estimation Results

- The proposed methodology can increase the precision of impedance estimation → Closer VPI as the result with actual impedance

Impedance	No control	Actual impedance	Intial estimated impedance	Fitted impedance
VPI	15.53	0.94	4.22	1.31

VPI Obtained with different impedances



Comparison of voltage profile a particular day using a) initial estimated impedance and b) fitted impedance

# Conclusion & Further Investigation

## ■ Conclusion

1. Three uncertainties (Model, Forecast, Impedance) are considered and their impact to controller performance are observed.
2. The proposed model fitting algorithm is able to significantly improve the accuracy of the impedance estimation

## ■ Further Investigation

1. Improvement of the fitting algorithm with less available measurement data
2. Investigation to observe the optimal number of data required for the fitting algorithm
3. Conduct real-time experimental validation of the algorithm

# Thank you for your Attention!

**Question:**

[Muhammad-andy.putratama@g2elab.grenoble-inp.fr](mailto:Muhammad-andy.putratama@g2elab.grenoble-inp.fr)