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Using **Electric Vehicles** in a Flexibility Management System: **A Digital Twin** Based Approach

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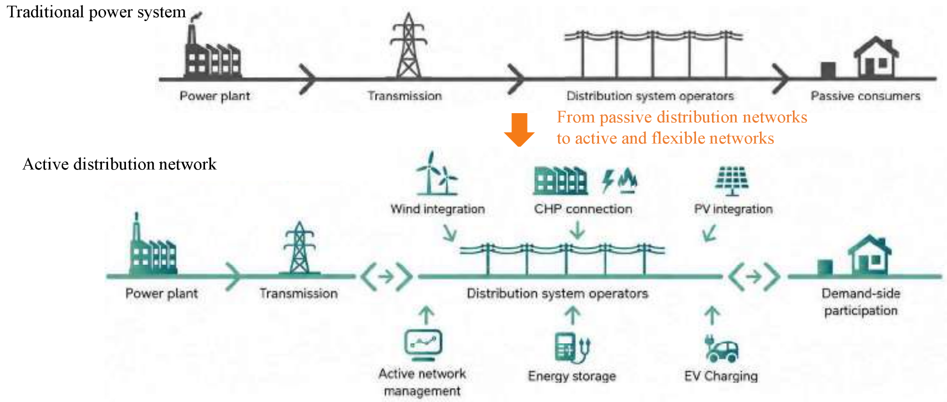
Problem Statement

Context and motivation

The transition from centralized generation to active distribution networks introduces new **flexibility** and new **operational challenges**

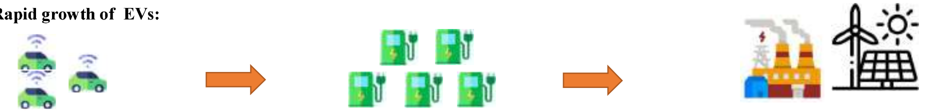


[1] IPCC, \Climate change 2014: synthesis report," IPCC, Geneva, Switzerland, Tech. Rep., 2014, p. 151 (cit. on pp. 1, 2).

Problem Statement

New operational challenges in distribution networks

1 Rapid growth of EVs:



More EVs increase daily electricity demand → More charging stations are required → Higher load demand and peak power consumption

2 Changing Power Flows:

- Bidirectional power flows
- More dynamic grid behavior
- Forecastable, but uncertain

3 Impacts on the electrical networks:

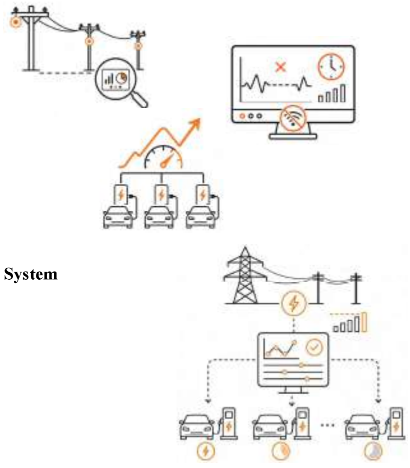
- Voltage variations along the distribution network
- Thermal constraints on cables and lines

Problem Statement

From operational challenges to research needs

Key Issues:

1. Limited observability in low-voltage distribution networks
2. Lack of real-time voltage and current information
3. High EV charging demand during peak hours



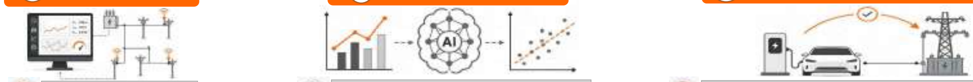
Proposed research direction: Monitoring and Flexibility Management System

1. State estimation from limited measurements
2. Real-time Digital Twin monitoring
3. Grid-aware EV charging management

A **Monitoring and Flexibility Management System** is needed to ensure efficient, and voltage-safe operation of future distribution networks

Problem statement

Scientific positioning



1 Digital Twin	2 State Estimation	3 Flexibility Management System
Real-time monitoring	Classical methods	EV charging optimization
Sparse measurements	Data-driven methods	Voltage-aware constraints
Distribution network	LR/RNN/LSRM/GNN/CANN	SVM-based limits

This Thesis

- **Digital Twin-based monitoring** — Low-voltage distribution networks
- **Data-driven state estimation** — Scalable & data-efficient
- **Grid-aware EV charging management** — Robust & interpretable
- **Real-time validation** — Real-world deployable

Key added value

- Improved observability
- Voltage & current estimation
- Network-constrained EV charging
- Rel-time implementation

An integrated framework that combines Digital Twin monitoring, data-driven state estimation and grid-aware EV charging management for reliable and real-time operation of LV distribution networks

Problem statement

Objectives and Contributions

Network observability

1.1 How can voltage and current states be estimated in low-voltage distribution networks using limited available measurements?

Data-driven estimation

1.2 How can data-driven models complement physics-based estimation to reconstruct unmeasured voltage and current states from limited measurements?

Smart EV charging

2.1 How can EV charging be optimized by balancing peak reduction and user charging requirements?

Grid-aware constraints

2.2 How can voltage and current limits be included in the charging optimization to ensure safe network operation?

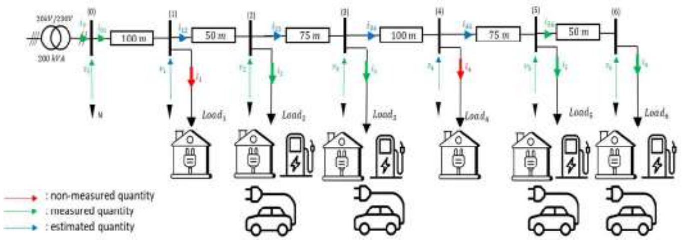
Integrated real-time validation

2.3 How can the complete monitoring and flexibility management framework be implemented and validated in real time?

Part 1: Digital Twin-Based Monitoring for Low-Voltage Distribution Networks

Overview of the proposed methodology

- Study case:



- Radial low-voltage feeder
- Residential loads and EV charging station
- Limited available measurements
- Unmeasured Voltages and currents to be estimated

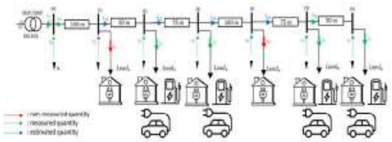
Problem: Limited observability and incomplete knowledge

Objective:
Estimate the **unmeasured voltages and line currents** needed for the **Flexibility Management System (FMS)**

Part 1: Digital Twin-Based Monitoring for Low-Voltage Distribution Networks

Overview of the proposed methodology

1 Study case



- Radial low-voltage feeder
- Not all buses are equipped with sensors
- Network parameters are **not fully known**

Problem: Limited observability and incomplete knowledge

2 Offline development

1. Dataset generation using the physics-based network model
2. Training and comparison of estimation methods
3. Best method selection: CANN

3 Online & Real-time Implementation

1. Real-time measurements
2. CANN-based estimation
3. OPAL-RT / SPHEREA platform
4. SCADA

Estimated voltages & currents
Input for FMS

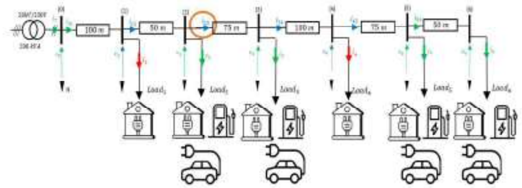
Objective:
Estimate the **unmeasured voltages and line currents** needed for the **Flexibility Management System (FMS)**

1.1 Physics-Based Linear State Estimation (PLSE)

Design of the PLSE architecture

Red color: non-measured quantity
Green color: measured quantity
Blue color: estimated quantity

- PLSE architecture is derived from the network topology
- The network is divided into electrical cells between neighboring voltage buses
- Each cell is modelled with local voltage and current relations
- Estimated variables are propagated from one cell to the next, following physical causality to estimate other variables
- State 2 is obtained from its local estimation cell



- Current $\tilde{i}_{23}$ is estimated with sensed voltages:

$$\tilde{i}_{23}(s) = \frac{(\hat{v}_2(s)-\hat{v}_3(s))}{R_{23}+L_{23}s}$$

1.1 Physics-Based Linear State Estimation (PLSE)

Design of the PLSE architecture

Red color: non-measured quantity

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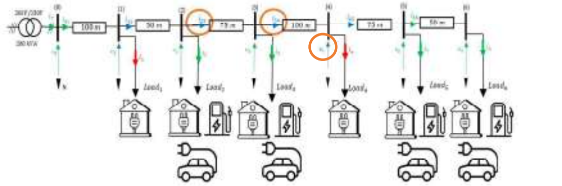
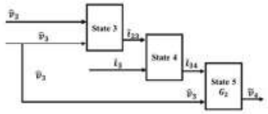




- Estimated variables are propagated from one cell to the next, following physical causality to estimate other variables
- State 3 is obtained from its local estimation cell
- State 4 is then estimated using the output of State 3
- State 5 is then estimated using the output of State 3

- Current $\tilde{\imath}_{23}$ is estimated with sensed voltages:

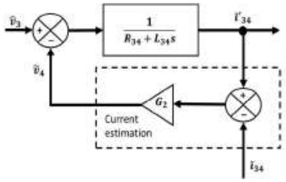
$$\tilde{\imath}_{23}(s) = \frac{(\hat{v}_2(s) - \hat{v}_3(s))}{R_{23} + L_{23}s}$$

- Current $\tilde{\imath}'_{34}$ can be also estimated with voltages:

$$\tilde{\imath}'_{34}(s) = \frac{(\hat{v}_3(s) - \tilde{v}_4(s))}{R_{34} + L_{34}s}$$

- Current $\tilde{\imath}_{34}(s)$ is estimated with sensed current and the previous estimation:

$$\tilde{\imath}_{34}(s) = \tilde{\imath}_{23}(s) - \hat{\imath}_3(s)$$



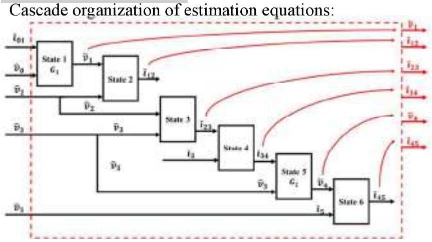
- The voltage $\tilde{v}_4$ is estimated to decrease the estimation error of the current ,

$$\tilde{v}_4(s) = G_2 \times (\tilde{\imath}'_{34}(s) - \tilde{\imath}_{34}(s))$$

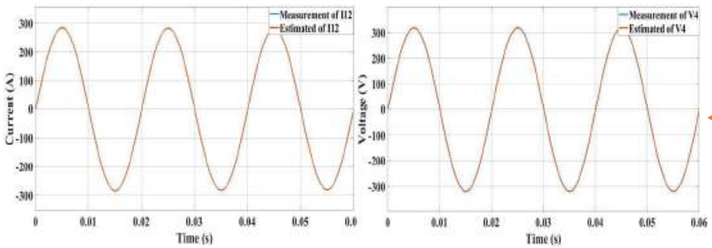
1.1 Physics-Based Linear State Estimation for Distribution Network Monitoring

Results of the PLSE

Cascade organization of estimation equations:



Result: Linear scenario



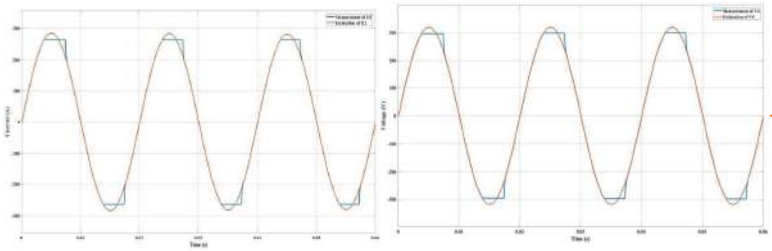
- In this case the inductance and resistance are considered known
- A linear system is suggested
- But in real-world the system is not linear

- The estimation is good and the error is quite small (less than 2%)

1.1 Physics-Based Linear State Estimation for Distribution Network Monitoring

PLSE

- Nonlinear scenario: distribution network with parameter variation
- Nonlinear effects are considered through saturation of the line impedance

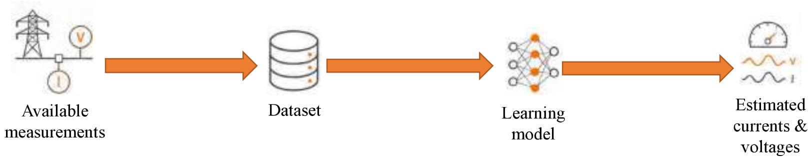


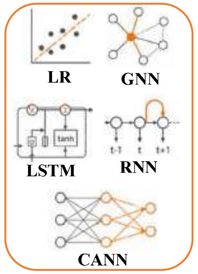
- The estimation does not accurately follow the saturation behavior

- In real network, most of time the characteristics of cable are not known
- The system is nonlinear one
- This result motivates the need for better estimation algorithm that deals with those obstacles

From physics-based insight to learning-based methods

- Data-driven state estimation learns the mapping between available measurements and unmeasured voltage/current states directly from data





Objective: reconstruct unmeasured voltages and currents from limited measurements, while handling nonlinear network behavior

1. Learning the relationship between sparse measurements and unmeasured electrical states
2. Able to deal with nonlinear behavior

Cascaded Artificial Neural Network (CANN)

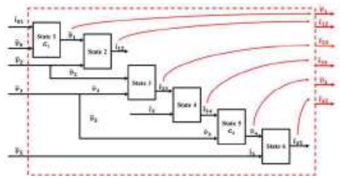
“La physique ne nous donne pas seulement l’occasion de résoudre les problèmes, Elle nous aide à en trouver les moyens.
—Henri Poincaré

[2] H. Poincaré, Science et méthode. Paris, France: Ernest Flammarion, 1908.

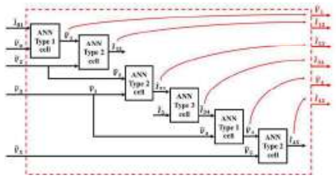
From linear baseline to nonlinear cascaded estimator

CANN

- Use the same methodology of cascaded and equation using in the PLSE method



- This methodology give the following CANN architecture

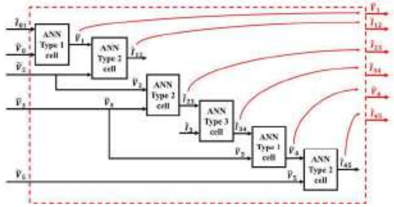


- Estimation equations define the inputs of each ANN
- The CANN is built as a cascade of elementary ANN blocks
- Each ANN estimates one local electrical quantity
- The output of one ANN is used by the next ANN
- The architecture follows the physical causality of the feeder
- Each estimated variable keeps a physical meaning

Goal: Learn the relationship between sparse measurements and unmeasured electrical states while handling nonlinear behavior

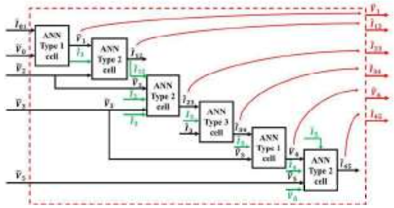
Cascaded Artificial Neural Network (CANN)

CANN architecture



Augmented CANN architecture

- More measured electrical quantities are available in the network
- These quantities are added as additional inputs to enrich the information provided to each ANN
- An augmented CANN architecture is then obtained



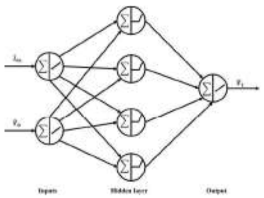
Cascaded Artificial Neural Network (CANN)

- The CANN is composed of several ANN blocks connected in cascade
- Each ANN estimates local electrical quantities for one network section
- The outputs of one ANN are used as inputs for the next ANN

➢ CANN is developed in Python using TensorFlow

Characteristics	Description
Hidden layer	1
Number of hidden neurons	4
Activation function	Rectified Linear Unit (Relu)
Optimizer	Adaptive Moment Estimation (ADAM)
Epochs	Early stopping

- The structure of the ANN:



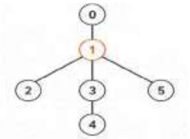
- Simple architecture with fast training and inference
- Able to capture nonlinear relationships between measurements and electrical states

As CANN belongs to the neural network family, it is compared with other data-driven architectures: RNN, LSTM, and GNN

1.2 Data-Driven State Estimation Methods

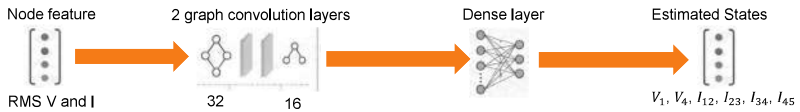
Graph Neural Network: GNN

- The feeder topology is encoded as a graph: buses are nodes, lines are edges, and the adjacency matrix describes their electrical connections.



  - Buses = nodes
  - Lines = edges

- The GNN uses graph convolution layers to learn from both measurements and network topology



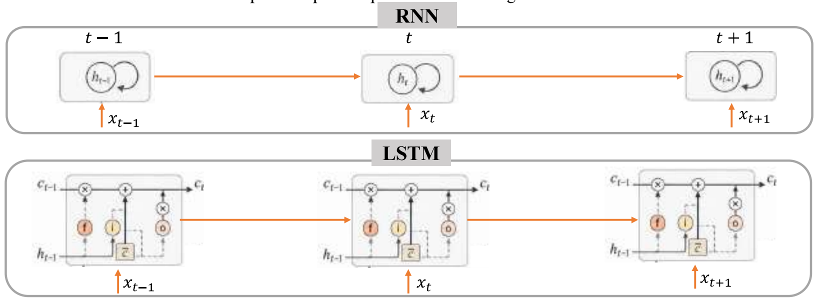
- The main architecture and training parameters of the developed GNN estimator are summarized below

Parameter	Description
Node feature dimension	5 features per node
Graph layers	2 graph convolution layers
Hidden units	32 and 16 (tanh activation)
Output variables	V_1, V_4, I_{12}, I_{23}, I_{34}, and I_{45}
Training strategy	Early stopping on validation loss
Optimizer	Adam
Loss function	Mean Squared error (MSE)

1.2 Data-Driven State Estimation Methods

Recurrent Neural Network (RNN) and Long Short-term Memory (LSTM)

- RNN and LSTM are used to exploit temporal dependencies in voltage and current measurements



- RNN captures short-term dependencies
- LSTM uses memory cells and gates to learn longer-term behavior

- The main architecture and training settings of the RNN/LSTM estimators are summarized below

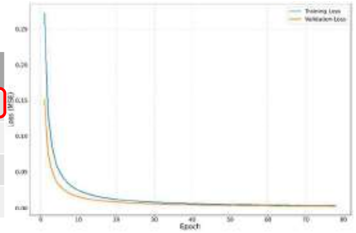
Characteristics	Description for RNN and LSTM
Model architecture	Sequential (linear stack of layers)
Inputs	$I_{01}, V_0, V_2, I_2, V_3, I_3, V_5, I_5, V_6, I_6$
Outputs (targets)	V_1, V_4, I_{12}, I_{23}, I_{34}, and I_{45}
Activation function	Relu (Rectified Linear Unit)
Number of hidden layers	3
Optimizer	Short for Root Mean Square propagation (Rmsprop)
Epochs	Early Stopping Process

1.2 Data-Driven State Estimation Methods

Comparison and Selection of the Best Estimation Method

- Tested multiple algorithms for response time, accuracy, and robustness
- Results with training database (learning process)
- $Error_x(\%) = \frac{|x_{true} - x_{test}|}{x_{true}} \times 100$
- To ensure a fair comparison, the same training and testing datasets are used for all studied algorithms
- The objective is to compare them and choose the most appropriate for the estimation process

Type of algorithm	Number of iterations	Average relative error of voltage (%)	Average relative error of current (%)	Training time on the learning dataset (s)
CANN	78	< 1%	< 6%	61.243
GNN	183	< 1%	> 20%	177.066
RNN	125	< 1%	> 10%	101.029
LSTM	142	< 1%	> 10%	154.424

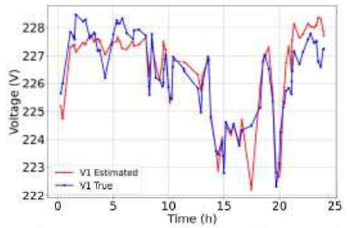


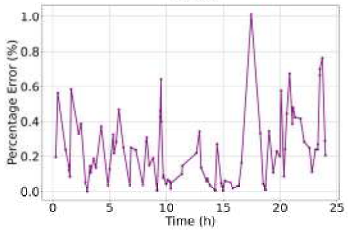
CANN was the best choice due to fast response and high accuracy in current estimation.

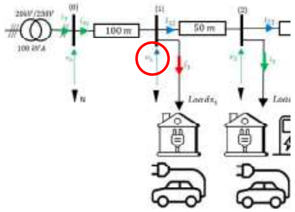
1.2 Data-Driven State Estimation Methods

Obtained results with the testing database

- Results from the CANN:

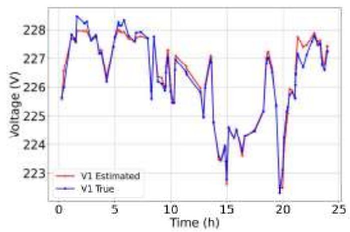


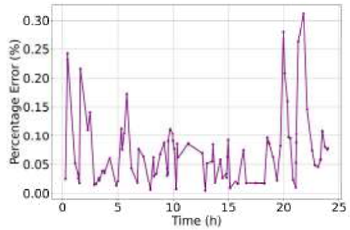




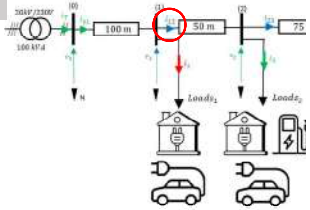
- The error is acceptable

- Results from the GNN:

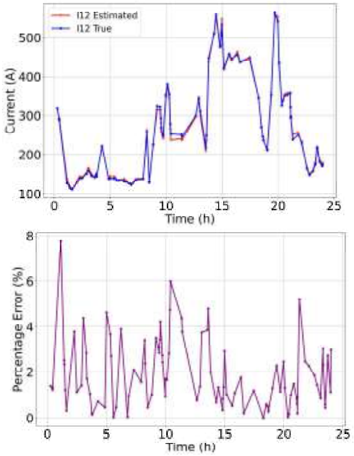




Obtained results with the testing database

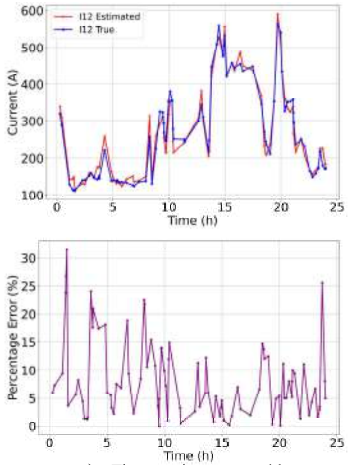


- Results from the CANN:



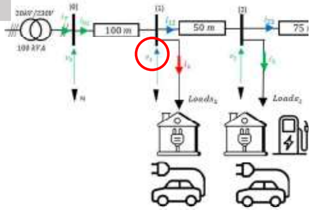
➢ The error is acceptable

- Results from the GNN:

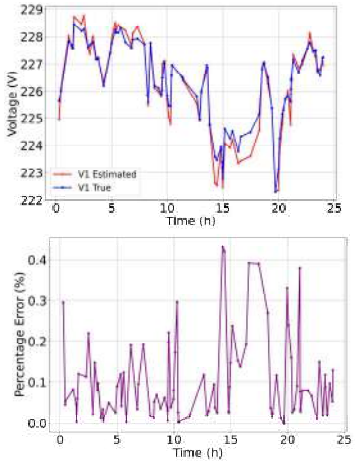


➢ The error is unacceptable

Obtained results with the testing database

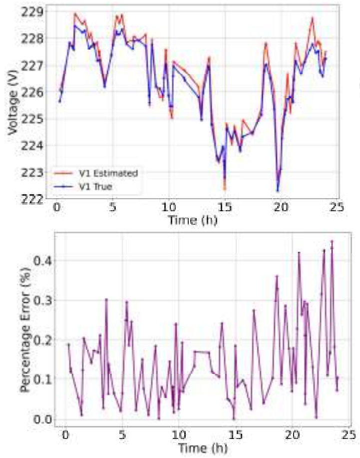


- Results from the RNN:

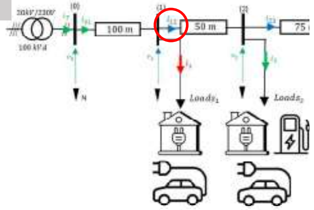


➢ The error is acceptable

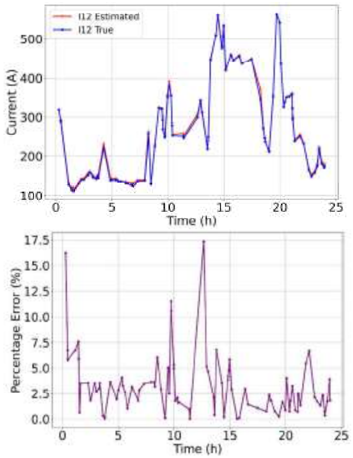
- Results from the LSTM:



Obtained results with the testing database

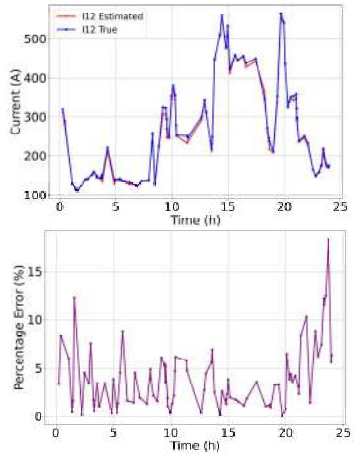


- Results from the RNN:



➢ The error is unacceptable

- Results from the LSTM:



0 **Problem Statement**

1 **Part 1: Digital Twin-Based Monitoring for Low-Voltage Distribution Networks**

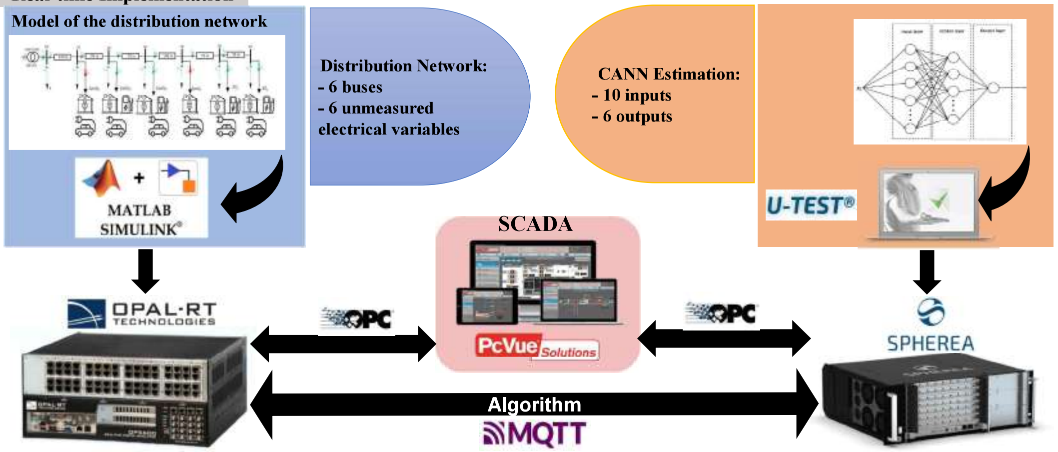
- 1.1 Physics-Based Linear State Estimation
- 1.2 Data-Driven State Estimation Methods
- 1.3 Real-time Implementation of the Monitoring System

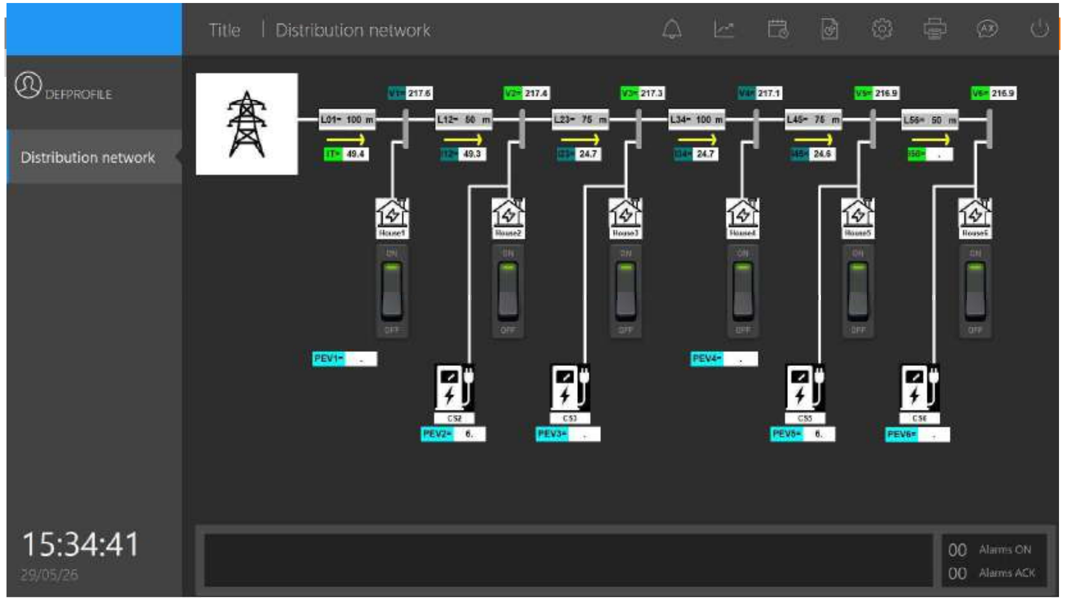
2 **Part 2: Flexibility Management System for Smart EV Charging**

- 2.1 Optimization Framework for Flexible and Grid-Aware EV Charging
- 2.2 Multi-objective optimization including load hosting capacity
- 2.3 Real-Time Flexibility Management System

3 **Conclusion**

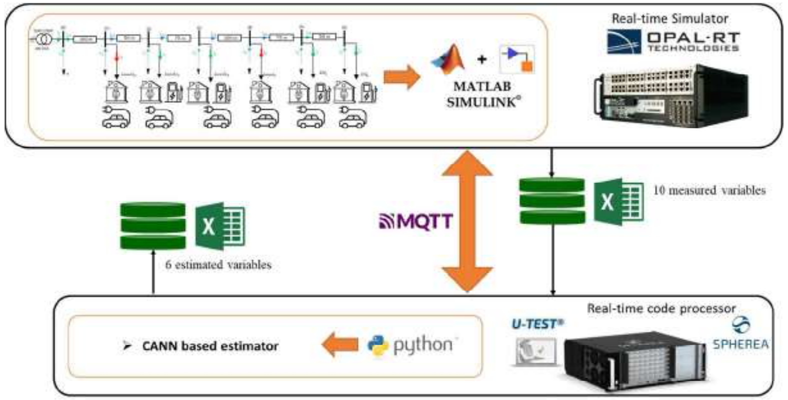
Real-time Implementation





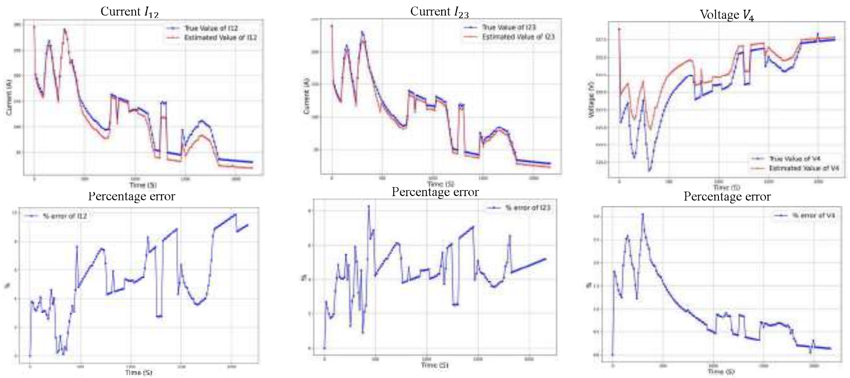
Methodology

- Offline Training: Determine weights and biases for CANN
- Real-Time Deployment: Implement CANN in a real-time system
- Tools Used: Opal RT and Spherea (2 calculators)



Real-time implementation results

- Objective: validate that the CANN estimator can provide real-time voltage and current states required by the Flexibility Management System



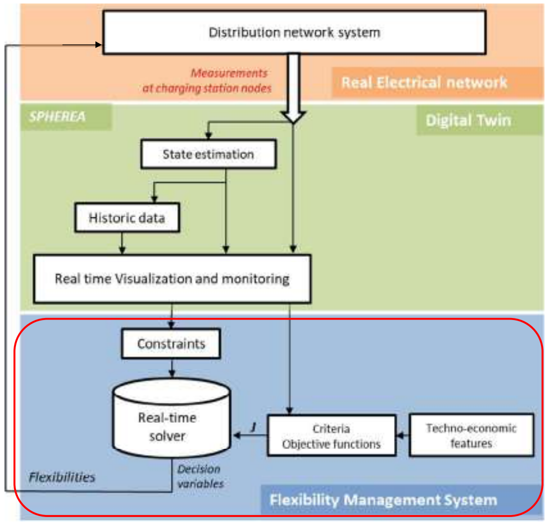
Main observation:

- Voltage estimation is more accurate than current estimation
- Current estimation is more sensitive to load variations and EV charging events
- More available inputs improve CANN accuracy. I_{23} (more inputs) shows lower error than I_{12} (fewer inputs)

The augmented CANN estimator provides reliable real-time voltage and current estimates. More input information leads to higher accuracy, which is essential for effective monitoring and FMS operation

Part 2: Flexibility Management System for Smart EV Charging

Overview of the proposed methodology



Objective
Enable smart EV charging while preserving safe distribution network operation

Operational Perspective
Considering distribution network operational constraints

Optimization objectives

1. **Objective 1:** Shift charging to-off-peak periods
2. **Objective 2:** Fast charging as soon as possible

Subject to grid and user constraints

Expected benefits

- Avoid network overload and instability
- Maintain a stable demand profile
- Support reliable EV charging decision

2.1 Optimization Framework for Flexible and Grid-Aware EV Charging

General framework

Coordinate EV charging while respecting user needs and distribution network constraints

Inputs

- Monitoring data: Measured and estimated V and I
- EV data: SOC, arrival / departure time
- Load forecast / historical data
- Grid limits: Transformer, voltage, current

Optimization engine

- **Objective 1:** Load smoothing / peak reduction
- Grid-safe EV charging schedule
- **Objective 2:** Fast charging / user satisfaction
- **Vehicle + grid constraints**

Outputs

- Charging power setpoints $P_{EV}(k)$
- Updated SOC

Sequential update every 15 min: k → k+1 → k+2 …

2.1 Optimization Framework for Flexible and Grid-Aware EV Charging

Unified Formulation of EV and Grid Power Constraints

Constraints

Charging power limits

$$0 \leq P_{EV,v}(k\Delta t) \leq P_{EV,v}^{max} (= 6.6kW)$$

SOC dynamics charging

$$SOC_v(k\Delta t) = SOC_v((k-1)\Delta t) + \frac{P_{EV}(k\Delta t)}{E_{EV,v}^{nom}} \times \Delta t \times \eta$$

SOC limits constraint

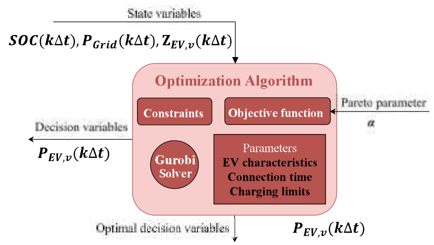
$$SOC_v^{min}(20\%) \leq SOC_v(k\Delta t) \leq SOC_v^{max}(100\%)$$

SOC deficit constraint

$$Z_{EV,v} = SOC_v^{Target} - SOC_v(K_{dep,v}\Delta t) \geq 0$$

Grid power limits

$$P_{Grid}(k\Delta t) \leq P_{Grid}^{max}$$



Design optimization

PYOMO GUROBI

The optimization problem is formulated in a linear/convex form to be efficiently solved by Pyomo–Gurobi in real time.

Formulation of the load-smoothing objective function

Objective function — ***Load smoothing / peak reduction***

Compute the average demand level from the forecasted base load

$$P_{avg} = \frac{1}{K}\sum_{k=1}^{K}\left(\sum_{b=1}^{B}\tilde{P}_{load,b}(k\Delta t)\right) = \frac{1}{K}\sum_{k=1}^{K}\tilde{P}_{feeder}(k\Delta t)$$

Compute the total grid demand including PEV charging

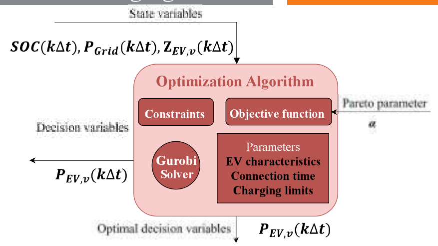
$$P_{Grid}(k\Delta t) = \tilde{P}_{feder}(k\Delta t) + \sum_{v=1}^{V} P_{PEV,v}(k\Delta t)$$

Define the upward deviation above the average demand

$$P_{pen}(k\Delta t) \geq P_{Grid}(k\Delta t) - P_{avg}$$
$$P_{pen}(k\Delta t) \geq 0$$

Minimize demand peaks above the average level

$$\boxed{J_1 = \sum_{k=1}^{K}\left(P_{pen}(k\Delta t)\right)^2}$$



P_{avg}: average load demand

$\tilde{P}_{feeder}$: power at each feeder (in other word power at each bus)

P_{pen}: penalized power above the average demand level

P_{Grid}: the total grid power drawn from the upstream network

We assume that arrival and departure time of EVs are known

Fast charging and bi-objective formulation

Objective function — ***Fast charging / user satisfaction***

Define the SOC deficit at the departure time

$$z_{EV,v} \geq SOC_v^{target} - SOC_v\left(k_{dep,v}\Delta t\right)$$

Minimize the total SOC deficit of connected PEVs

$$J_2 = \sum_{v=1}^{V} z_{EV,v}$$

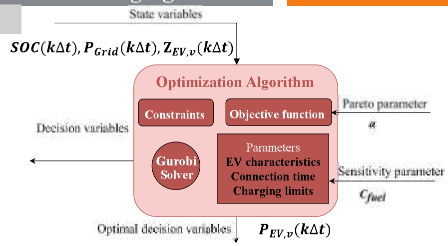
Normalize both objectives to avoid scale dominance

$$\frac{J_1}{J_1^{max}} \text{ and } \frac{J_2}{J_2^{max}}$$

J_1^{max} and J_2^{max} are obtained by solving each objective separately under the same conditions.

Combine grid-oriented and user-oriented objectives

$$\boxed{Objective\ Function:\ min\ OF = \alpha\frac{J_1}{J_1^{max}} + (1-\alpha)\frac{J_2}{J_2^{max}}}$$



Z_{EV}: deficit of SOC level

$\alpha \in [0,1]$

P_{pen}: panelized power above the average demand level

We assume that arrival and departure time of EVs are known

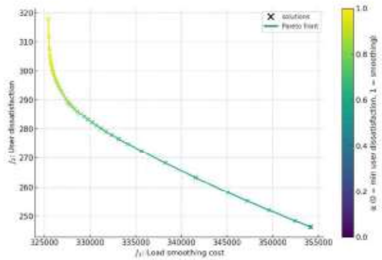
Pareto analysis

Varying α allows the evaluation of the trade-off between grid-oriented load smoothing and user-oriented fast charging

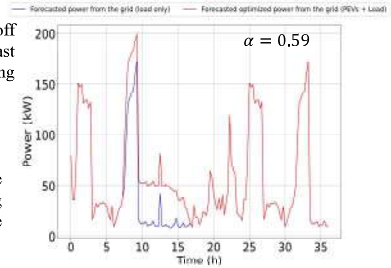
Results and analysis

- Six PEVs are connected at different buses with different arrival times, departure times, and initial SOC levels.

PEV location [P_{PEV_v}]	Arrival time [$t_{arr_{PEV_v}}$]	SOC at arrival [$SOC^{initial}_{PEV_v}$]	Target SOC [$SOC^{final}_{PEV_v}$]	Departure time [$t_{dep_{PEV_v}}$]
PEV 1 at bus 1	07:00 pm	35%	100%	08:30 am (next day)
PEV 2 at bus 2	08:00 am	35%	100%	08:30 pm
PEV 3 at bus 3	08:00 pm	40%	100%	07:30 am (next day)
PEV 4 at bus 4	09:00 pm	35%	100%	09:00 am (next day)
PEV 5 at bus 5	09:00 am	50%	100%	08:00 pm
PEV 6 at bus 6	10:00 am	45%	100%	11:00 pm

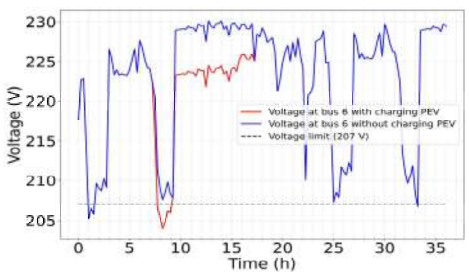


- The Pareto front shows the trade-off between load smoothing and fast charging, depending on the weighting factor α
- The optimized charging profile reduces demand peaks by shifting charging power over the available connection windows

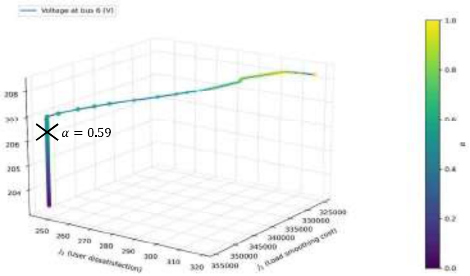


Results and analysis

- Study the impact of optimized PEV charging on the voltage profile



$\alpha = 0.59$



- PEV charging may create voltage drops at the end of the feeder, especially at bus 6
- This motivates the integration of voltage and current constraints into the charging optimization

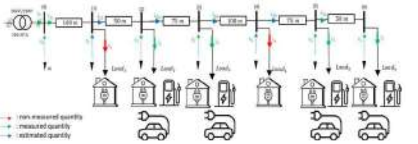
2.2 Multi-objective optimization including load hosting capacity

Voltage impact without nonlinear power-flow equations

- Voltage constraints are described by nonlinear power-flow equations, which makes their direct integration into the EV charging optimization computationally challenging.

$$\cancel{|\Delta V_{b,b+1}(k\Delta t)| \approx \frac{\sqrt{\left(P_{b+1}(k\Delta t)R_{b,b+1} - Q_{b+1}(k\Delta t)X_{b,b+1}\right)^2 + \left(P_{b+1}(k\Delta t)X_{b,b+1} + Q_{b+1}(k\Delta t)R_{b,b+1}\right)^2}}{|V_b(k\Delta t)|}}$$

- The voltage-drop equation is nonlinear; the challenge is to include its effect in the charging optimization without directly solving nonlinear power-flow equations
- Gurobi also is a linear solving that is not able to solve nonlinear constraints



Constraints to prevent voltage drops

$$\sum_{b=1}^{6} P_b \leq P_{max1}$$
$$\sum_{b=2}^{6} P_b \leq P_{max2}$$
$$\vdots$$
$$P_6 \leq P_{max6}$$
$$P_{max,B}(k\Delta t) \leq \cdots \leq P_{max,2}(k\Delta t) \leq P_{max,1}(k\Delta t)$$

- The admissible power limit decreases along the feeder because voltage drops become more critical downstream

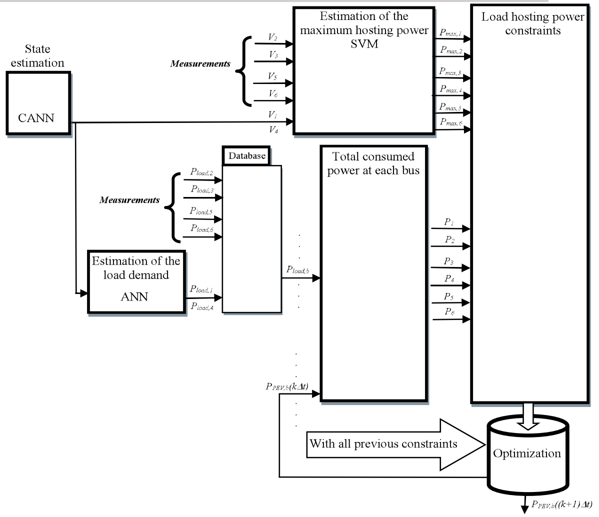
$$P_b(k\Delta t) = \tilde{P}_{load,b}(k\Delta t) + P_{PEV,b}(k\Delta t$$

- These limits are integrated as cumulative downstream power constraints in the optimization problem.

How can these voltage-aware power limits be calculated and integrated into the EV charging optimization algorithm?

2.2 Multi-objective optimization including load hosting capacity

Integration of voltage-aware constraints into the optimization



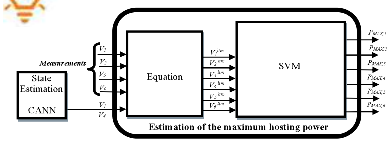
- CANN-based monitoring estimates the unmeasured electrical states of the network
- ANN-based load estimation provides the forecasted demand at each bus
- The total consumed power at each bus is computed by combining base load and PEV charging power
- The admissible limits $P_{max,b}$ are introduced as hosting power constraints in the optimizer
- These constraints keep EV charging within voltage-safe operating limits without solving nonlinear power-flow equations.

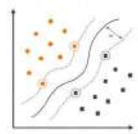
Next step: learn the admissible limits $P_{max,b}$ from data

2.2 Multi-objective optimization including load hosting capacity

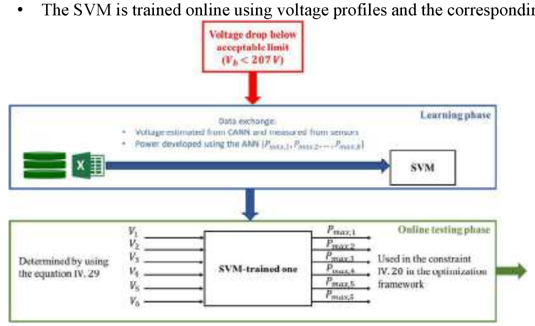
Support Vector Machine-based estimation and integration of hosting power limits

The SVM model is used to estimate the admissible hosting power limits Pmax,b from the voltage profile at each bus.





- The SVM is trained online using voltage profiles and the corresponding hosting power limits



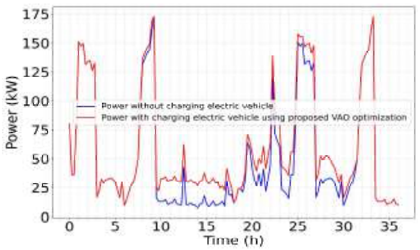
Advantages of online learning:
- Captures nonlinear voltage–power relationships
- Fast estimation of admissible power limits
- Enables voltage-safe EV charging optimization

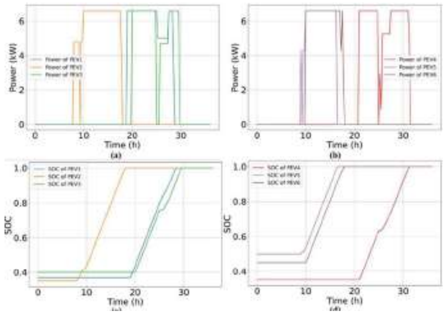
2.2 Multi-objective optimization including load hosting capacity

Results and analysis

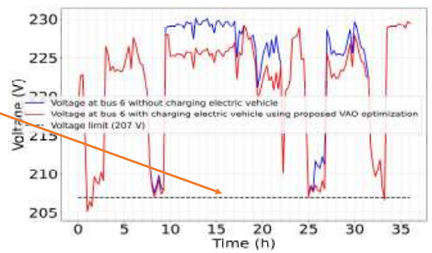
- Same scenario used in the previous slide
- The results from the SVM

Constraints of equation (20)	Value in kW
$\sum_{b=1}^{6} P_b$	$\leq 130.7\ kW$
$\sum_{b=2}^{6} P_b$	$\leq 102.3\ kW$
$\sum_{b=3}^{6} P_b$	$\leq 64.7\ kW$
$\sum_{b=4}^{6} P_b$	$\leq 48.1\ kW$
$\sum_{b=5}^{6} P_b$	$\leq 33.5\ kW$
P_6	$\leq 26.7\ kW$





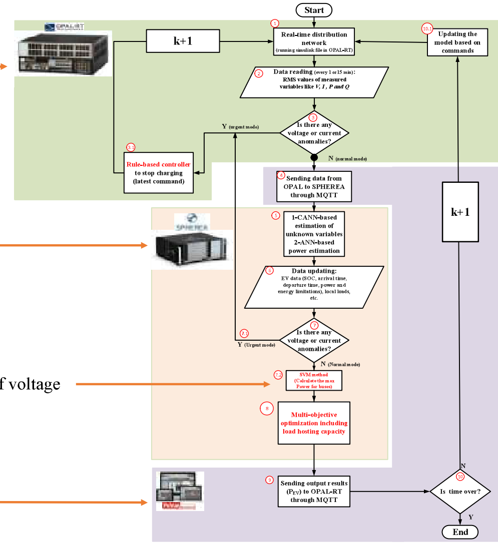
The voltage is in the acceptable limit



2.2 Real-Time Flexibility Management System

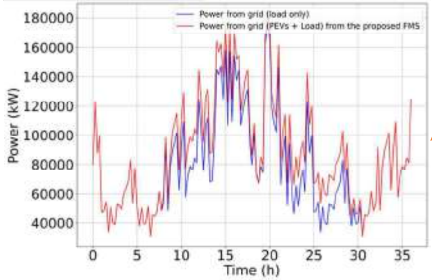
Methodology

- The network is implemented in the OPAL-RT
- The estimation and optimization are developed in SPHEREA
- The SVM is implemented to force the charging in the acceptable range of voltage
- A PcVue is used for visualization

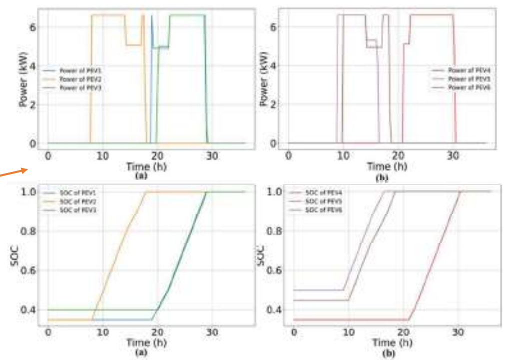


2.2 Real-Time Flexibility Management System

Results



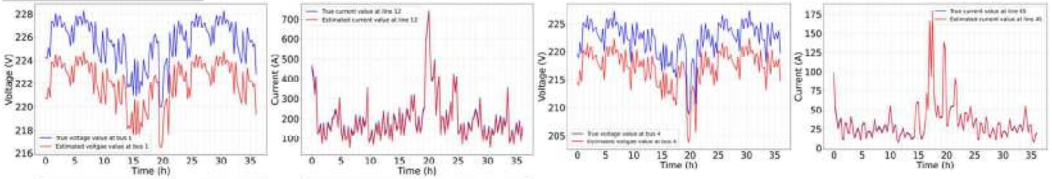
- The objective function is conserved

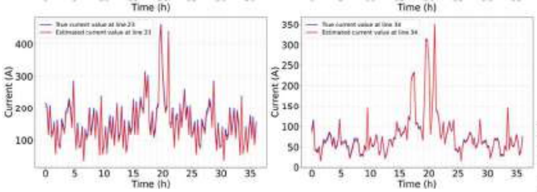


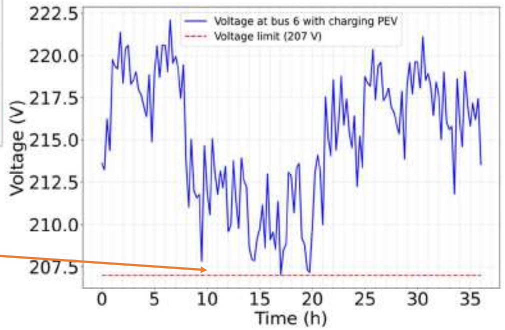
- All SOC target are respected and satisfied

2.2 Real-Time Flexibility Management System

Results







- The voltage limit is respected

5. Conclusion

Conclusion

- Developed real-time monitoring for LV distribution networks
- Estimated voltages and currents using CANN and limited measurements
- Designed a grid-aware FMS with voltage-safe EV charging constraints

Limitations

- Validated mainly in simulation and real-time emulation
- Accuracy depends on measurement quality and availability
- SVM limits depend on training data and network topology

Future Work

- Validation with real field measurements
- Extension to larger networks with PV, storage, and V2G
- Integration of uncertainty, forecast errors, and distributed optimization

Publications

Papers presented at international conferences:

M. EL IAALI, R. RAZI, A. BRUYERE, B. FRANCOIS, and J. SOARES, “Distribution Network Digital Twin: A Basic Machine Learning-Based Voltage Estimator,” **IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm),** 2023.

M. EL IAALI, R. RAZI, A. BRUYERE, B. FRANCOIS, and J. SOARES, “A Novel Cascading Artificial Neural Networks for Enhanced Distribution Network State Estimation,” **IEEE 22nd Mediterranean Electrotechnical Conference (MELECON)**,2024.

M. EL IAALI, R. RAZI, A. BRUYERE, B. FRANCOIS, J. SOARES, and Z. VALE, “Machine Learning Methods for State Estimation in Sparse Distribution Networks,” **IEEE Conference on Artificial Intelligence (CAI)**, 2025.

M. EL IAALI, R. RAZI, A. BRUYERE, B. FRANCOIS, J. SOARES, and Z. VALE, “Machine Learning Approach for Predictive Voltage-Constrained Power Capacity in Distribution Networks with Electric Vehicles,” **IEEE 23rd Mediterranean Electrotechnical Conference (MELECON)**, 2026.

M. EL IAALI, R. RAZI, A. BRUYERE, B. FRANCOIS, J. SOARES, and Z. VALE, “Estimation of Electrical Quantities in Distribution Networks Using GNN and Cascaded ANN: A Performance Comparison,” **the 16th International Conference of the IMACS TC ELECTRIMACS (ELECTRIMACS)**, 2026.

M. EL IAALI, J. SOARES, S. LIMMER, A. BRUYERE, B. FRANCOIS, and Z. VALE, “A Multi-Objective Optimization Approach for Load Smoothing and Rapid PEV Charging in Low-Voltage Networks,” submitted to **the 8th International Conference on Smart Energy Systems and Technologies (SEST)**, Ciudad Real, Spain, 2026.

Poster presentation:

M. EL IAALI et al., “A Digital Twin for Flexibility Management in Distribution Network,” accepted as a Late-Breaking Paper for poster presentation at the **IEEE Symposium Series on Computational Intelligence (SSCI 2025)**, Trondheim, Norway, 2025.

Papers presented at national conferences:

M. EL IAALI, R. RAZI, A. BRUYERE, B. FRANCOIS, and J. SOARES, “Un réseau de neurones artificiels pour l’estimation rapide de l’état d’un réseau de distribution de basse tension,” **Conférence des Jeunes Chercheurs en Génie Électrique (JCGE)**, 2024.

Journal paper suggestion and submitted:

The paper accepted at ELECTRIMACS 2026 may be considered for an extended post-conference publication, subject to the conference selection process and an additional review procedure. **M. EL IAALI**, R. RAZI, A. BRUYERE, B. FRANCOIS, J. SOARES, and Z. VALE, "Estimation of Electrical Quantities in Distribution Networks Using GNN and Cascaded ANN: A Performance Comparison," **the 16th International Conference of the IMACS TC ELECTRIMACS (ELECTRIMACS)**, 2026.

The paper submitted to SEST 2026 may also be eligible for an extended journal publication if accepted and presented, depending on its ranking in the conference review process and the scope of the associated journals.

M. EL IAALI, R. RAZI, A. BRUYERE, B. FRANCOIS, J. SOARES, and Z. VALE, "Real-Time Optimization of Plug-In Electric Vehicle Charging in Distribution Networks: A Flexibility Management System," **will be submitted soon**

M. EL IAALI, R. RAZI, A. BRUYERE, B. FRANCOIS, J. SOARES, and Z. VALE, "Real-Time Flexibility Management System for Smart Charging of Plug-in Electric Vehicles with Machine Learning Integration," **will be submitted soon**

R. RAZI, **M. EL IAALI,** A. BRUYERE, B. FRANCOIS, J. SOARES, and Z. VALE, "State Estimation in Low-Voltage Distribution Networks: A Comparison of Model-Based and AI-Based Approaches," **will be submitted soon**

Thank you for your attention !