Data-driven decentralised control design in Active Distribution Networks

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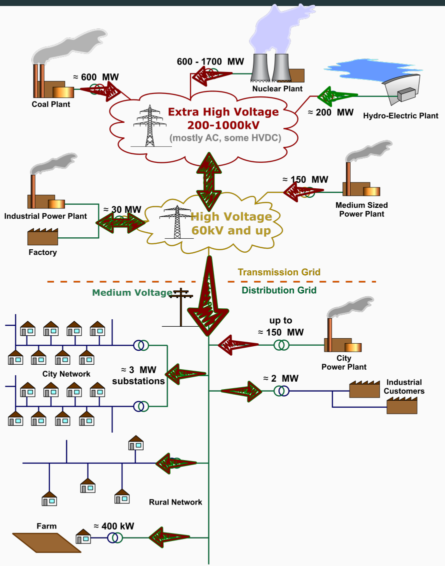
Sustainable Power Systems Lab

Cyprus University of Technology

Motivation

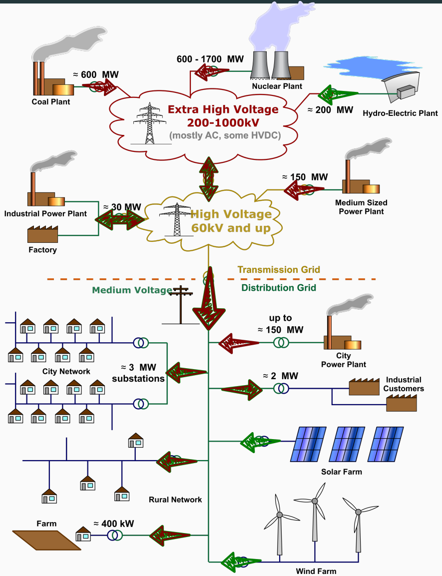
New developments in distribution grids



Transformation of power systems

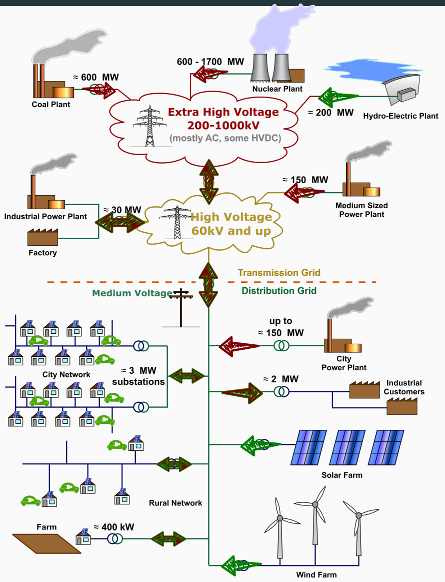
New developments in distribution grids

- Introduction of large distributed generators (renewable energy sources, etc.)



New developments in distribution grids

- Introduction of large distributed generators (renewable energy sources, etc.)
- Introduction of small distributed generators and energy storage systems
- Electrification of transportation (plug-in hybrid, battery electric, etc.)



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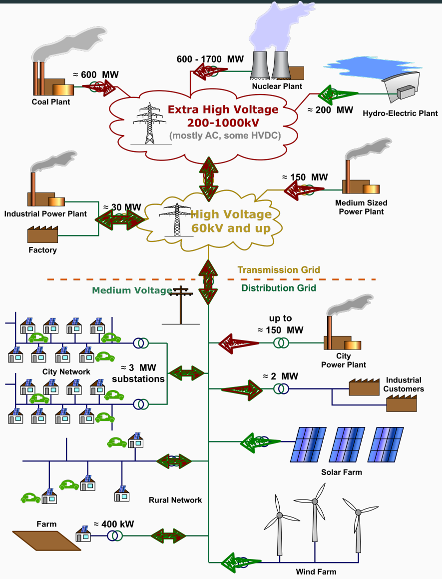
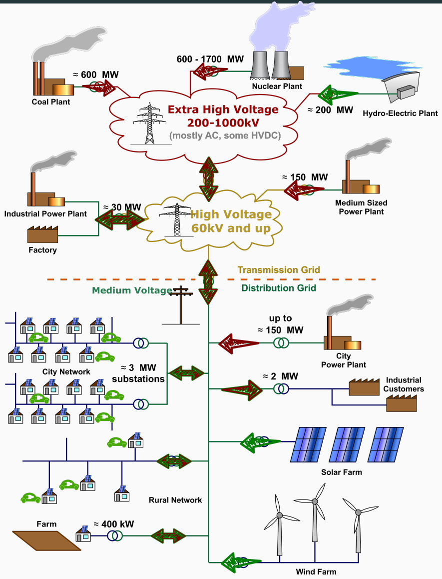
- Introduction of large distributed generators (renewable energy sources, etc.)
- Introduction of small distributed generators and energy storage systems
- Electrification of transportation (plug-in hybrid, battery electric, etc.)
- Demand response schemes (reaction to price signals, emergency load reduction, peak shaving, etc.)



New challenges

- **Operation of the distribution grids close or above the physical limits and hosting capacity.** *Distribution grids were not designed to host generation.*



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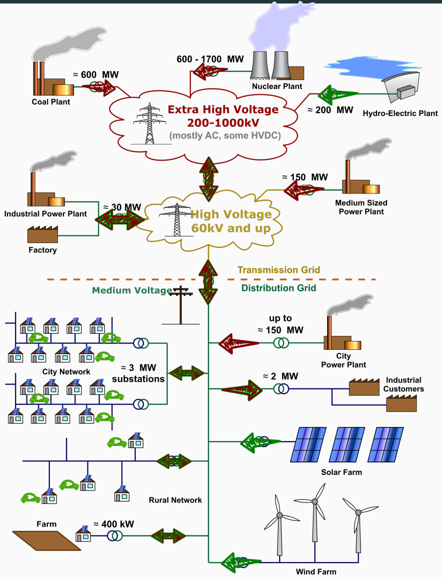

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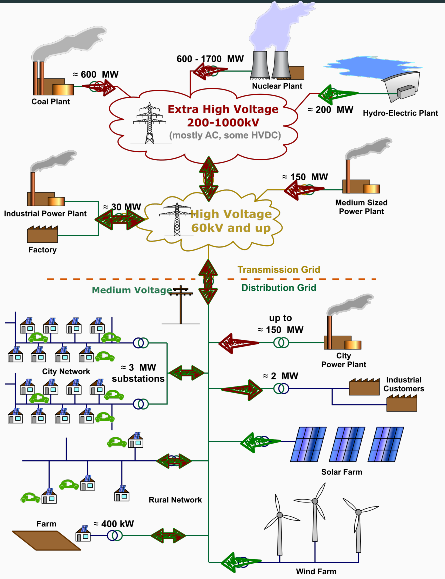

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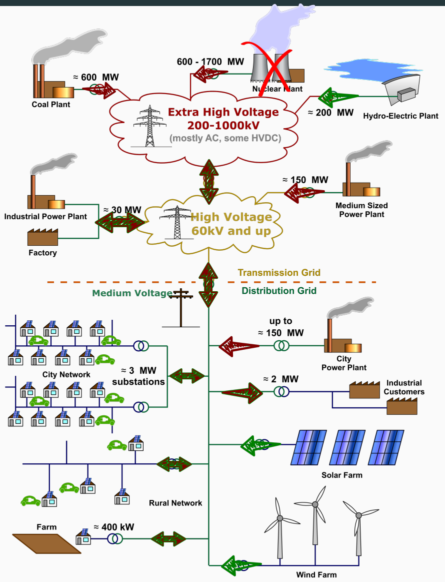
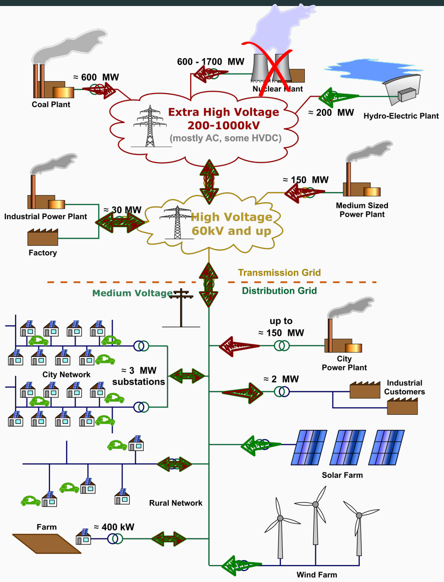
- **Bi-directional flows.** *Most of system protections and operation practices were not designed for this.*
- **Increased uncertainty.** *Intermittent generation, new consumption profiles and patterns, unknown consumer response.*
- **Decommission of conventional units.** *Loss of traditional "dispatchable" generation and control.*



New challenges

Need for Active Distribution Networks with real-time control



Approaches

Real-time operation of distribution grids

Approaches

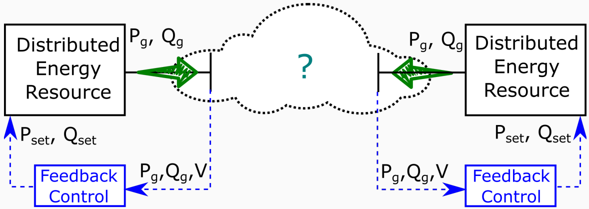
Local

Only local measurements and decisions

No communication

Lower cost and more robust

"One size fits all"



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Distributed
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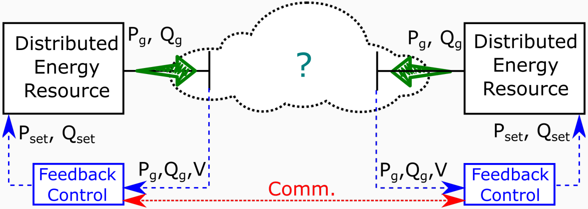

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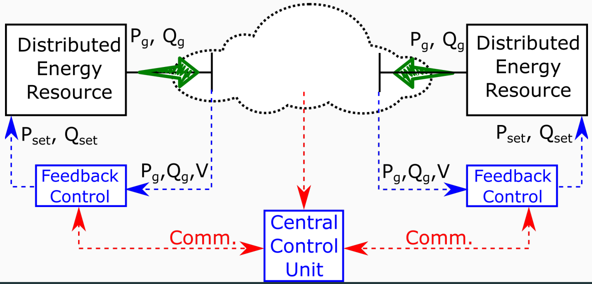

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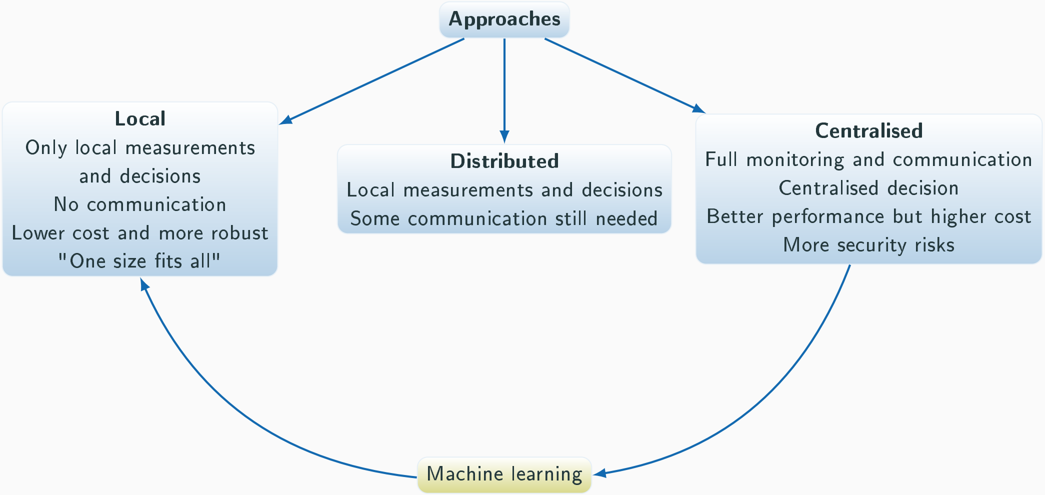
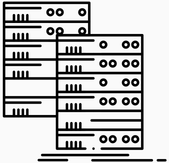
Can we design local controls that can mimic the optimal behavior?

Real-time operation of distribution grids



Data-driven local control design

Historical timeseries data



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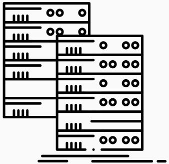

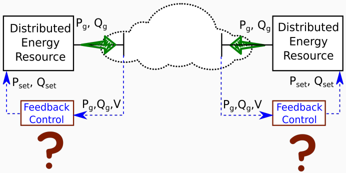

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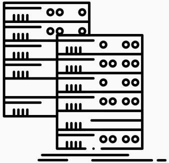
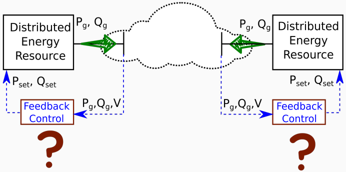
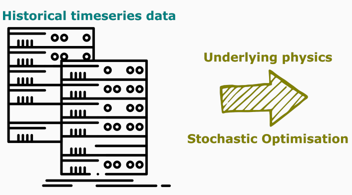
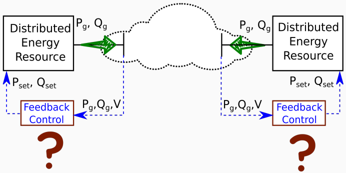




Two-stage process

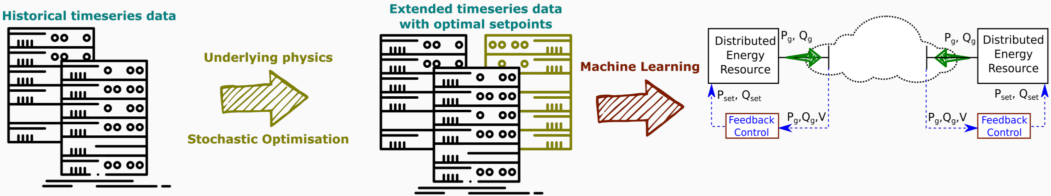
Data-driven local control design





Two-stage process

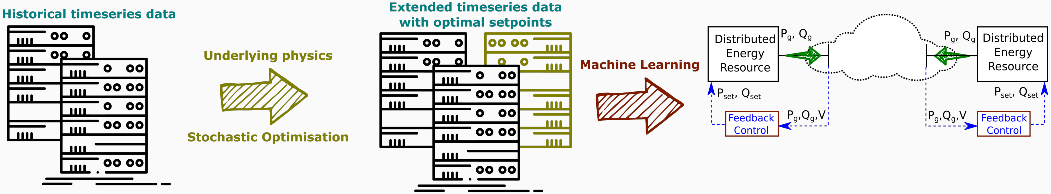
- **Step 1**: Process historical data and extend with optimal setpoints



Two-stage process

- **Step 1**: Process historical data and extend with optimal setpoints
- **Step 2**: Use ML on the extended dataset to design local controls

Data-driven local control design



Two-stage process

- **Step 1**: Process historical data and extend with optimal setpoints
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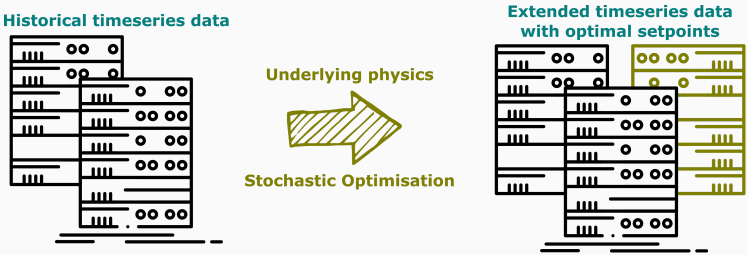
- Testing and validation

Data-driven local control design

Extending historical data with optimal setpoints



Multi-period OPF problem formulation

$$\min_{\boldsymbol{u}} \sum_{t} (c_{op}^T \boldsymbol{u} + c_{el}^T\, losses)$$

OPF-based data processing

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Controls ($\boldsymbol{u}$):

- Active power curtailment (APC)
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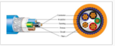

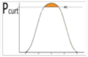

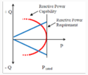

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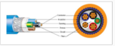

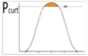

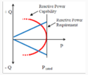

OPF-based data processing

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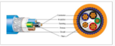

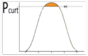

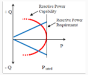

OPF-based data processing

AC power-flow constraints

- Non-convex and non-linear

OPF-based data processing

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  - **Backward/Forward Sweep (BFS) power flow (Fortenbacher et al. 2016)**
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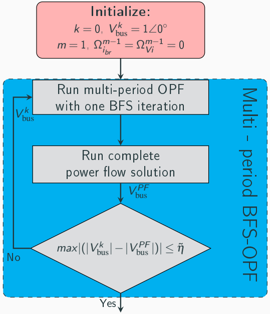
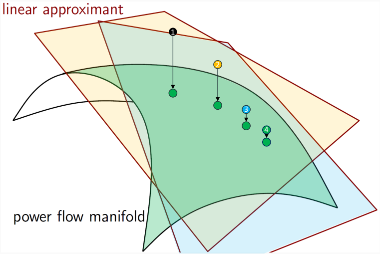
- **Use a single BFS iteration for the OPF problem**

OPF-based data processing





Qualitative illustration of the iterative BFS-OPF scheme

OPF-based data processing

Tackling Uncertainty

- Branch current flows and voltages are functions of the power injections and are hence influenced by **renewable generator & load power uncertainty**

OPF-based data processing

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OPF-based data processing

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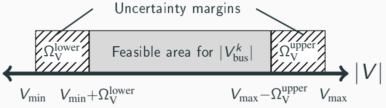

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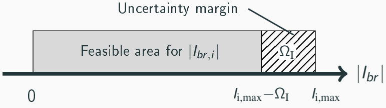


OPF-based data processing

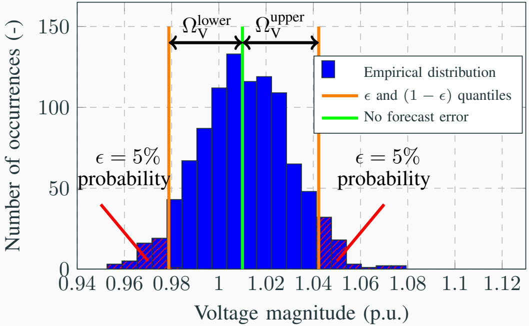
Uncertainty margins evaluation

- Analytical approach $\rightarrow$ Need to know the probability distribution

OPF-based data processing

Uncertainty margins evaluation

- Analytical approach → Need to know the probability distribution
- Monte Carlo simulation using historical data from forecast errors
  - No assumptions about the uncertainty distribution
- Quantile ε calculation



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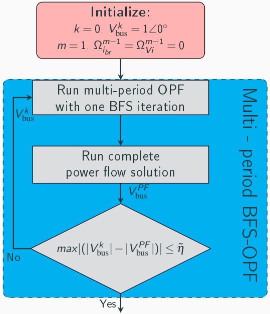

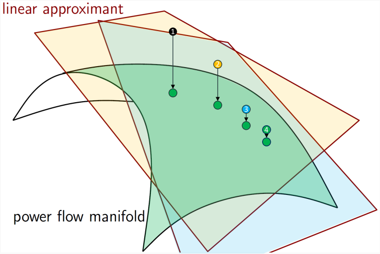

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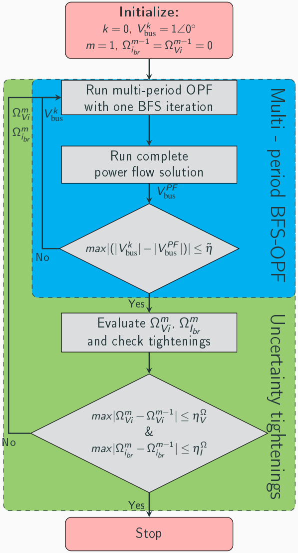
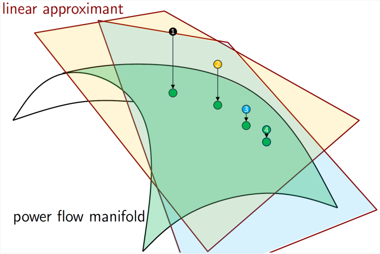
OPF-based data processing





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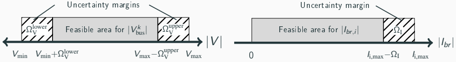
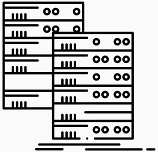
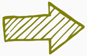


Extending historical data with optimal setpoints

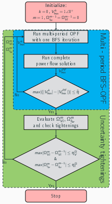
Historical timeseries data



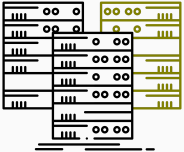
Underlying physics



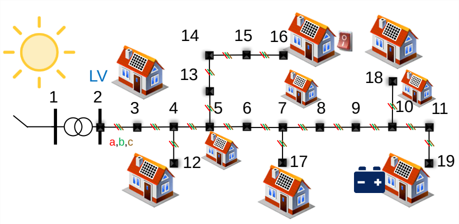
Stochastic Optimisation



Extended timeseries data with optimal setpoints



Test system



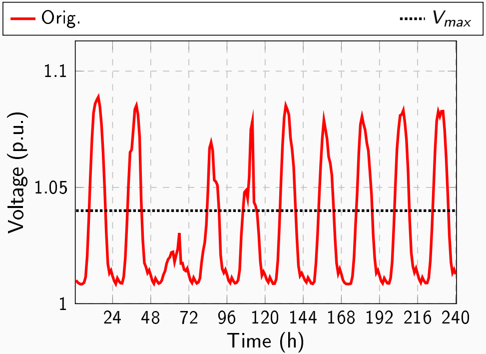
Control actions

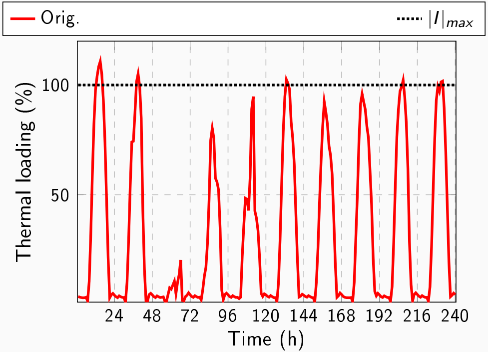
- Active Power Curtailment (APC)
- Reactive Power Control (RPC)
- Battery Energy Storage System (BESS)
- Controllable load (CL)
- On Load Tap Changers (OLTC)

Network description

- Based on European CIGRE LV grid
- Normalized profiles
  - PV & forecasts: Real data from Zurich
  - Load: Typical profiles based on CIGRE
- Summer day simulations
  - High solar radiation
- Acceptable limits:
  - Voltage: $\pm 4\%$
  - Current: up to 1 $p.u.$
  - VUF: up to 2%

Some results





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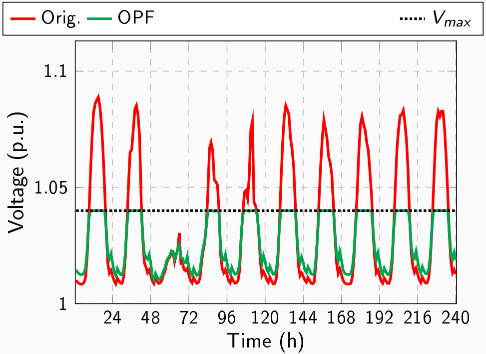

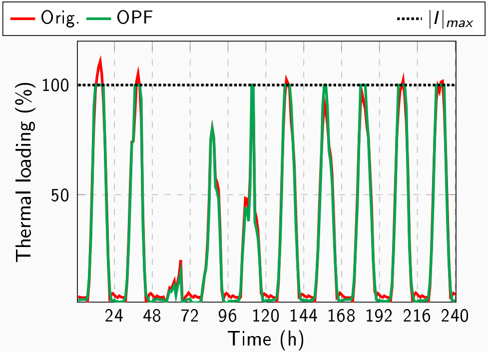

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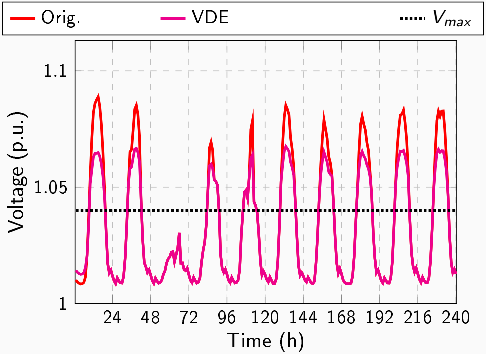
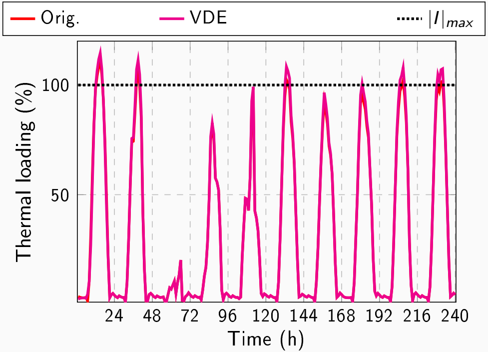
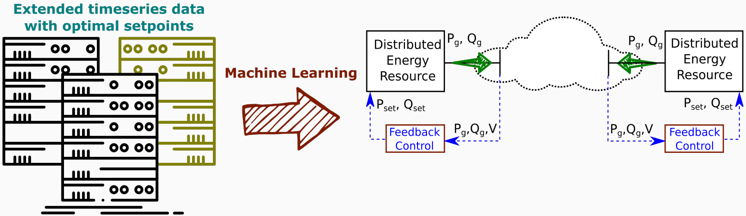




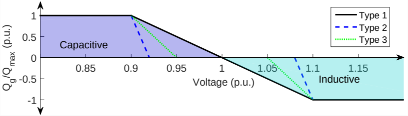
Optimised local control schemes

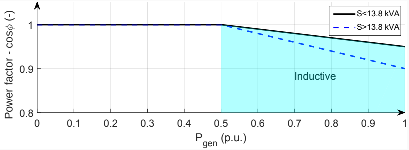


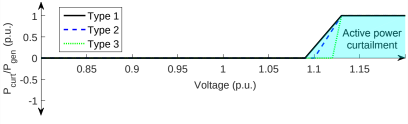
Optimised local control schemes

Existing local control schemes

- Usually all distributed generators of same type and similar size have the same curve
- Several types, usually: $Q = f(V)$, $cos\phi = f(P)$, $P_{curt} = f(V)$
- "Open" loop or "closed" loop







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Optimised local control schemes

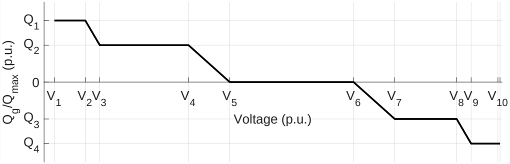
- Data-driven local controls based on processed data from the previous step
- Candidate DERs
  - Distributed Generators (DGs)
  - Basttery Energy Storage Systems (BESS)
  - Controlable Loads (CLs)

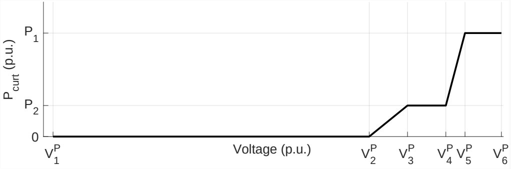
Karagiannopoulos et al., "Data-driven Local Control Design for Active Distribution Grids using off-line Optimal Power Flow and Machine Learning Techniques", IEEE Transactions on Smart Grids, 2019

Optimised local control schemes

DGs: Piece-wise (segmented) linear fitting

- Simple and efficient (R, sklearn, MATLAB, etc.)
  - Breakpoint selection
  - Nonlinear least squares regression
- Modified to impose stability-related monotonicity and slope constraints





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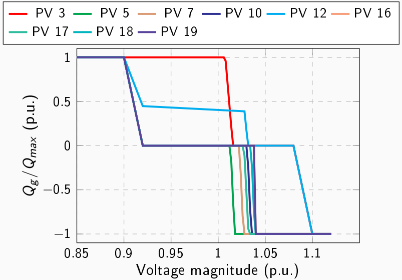
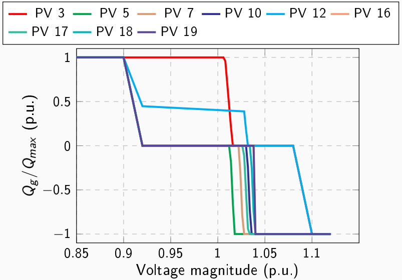


Optimised local control schemes

Unique characteristic curve per DG

- Need to program a different curve for each agent
- Large number of inverter-based DGs



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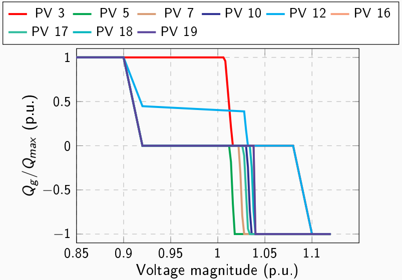
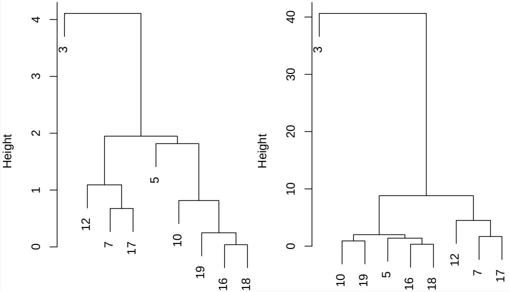


Clustering of the curves

- Assign DGs to clustered curves based on "distance" with hierarchical clustering



a. Euclidean distance b. DTW distance

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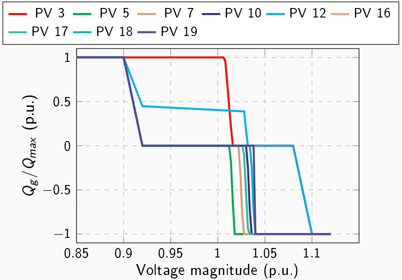

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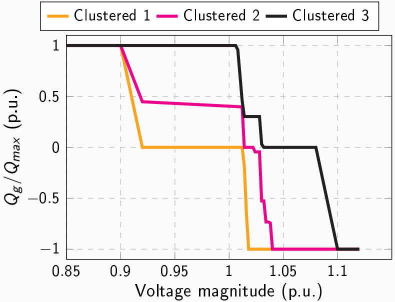
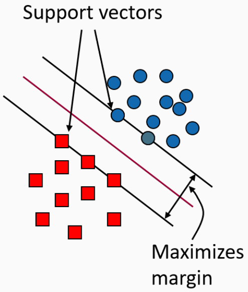


BESS: Support Vector Machine (regression)

- Maximize the margin around the separating hyperplane
- Simple and efficient (R, sklearn, MATLAB, etc.)
  - quadratic programming problem



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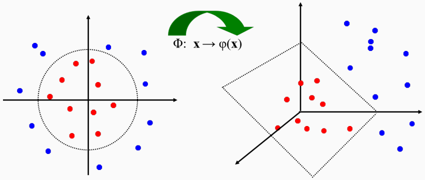
  - Map the original feature space to some higher-dimensional feature space where the training set is separable



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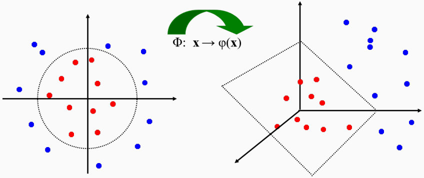
- Modified to impose stability-related impose monotonicity and slope constraints (e.g., monotone kernel regression methods)



Optimised local control schemes

CLs: Support Vector Machines (classification)

- Easy to implement (Python, MATLAB)
- Apply SVM with different kernel functions using the following features:
  - Voltage
  - Active power consumption
  - Reactive power consumption
  - Active PV power injection

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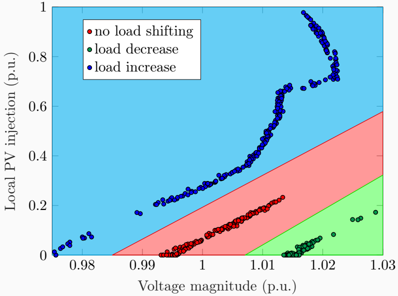


Karagiannopoulos et al., "Data-driven Local Control Design for Active Distribution Grids using off-line Optimal Power Flow and Machine Learning Techniques", IEEE Transactions on Smart Grids, 2019

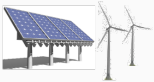
Optimised local control schemes

Summary of methods

Distributed Generators

- Segmented regression with unknown breakpoints

- Monotonicity & slope constraints
- Volt/Var & Volt/Watt curves

$\mathbf{\Phi}_1 = [V]^T \longrightarrow$  $\longrightarrow P_g, Q_g$

BESS

- Support Vector Machine (SVM) regression

- Various kernel functions
- Energy constraints

$\mathbf{\Phi}_2 = [V, P_d, Q_d, P_g,]^T \longrightarrow$ 

$\longrightarrow P_B, Q_B$

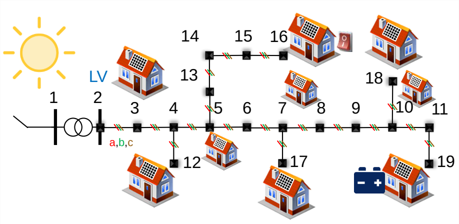
CLs

- Support Vector Machine (SVM) classification

- Various kernel functions
- 3 classes: load decrease, increase, or no shifting

$\mathbf{\Phi}_3 = [V, P_g,]^T \longrightarrow$  $\longrightarrow P_{CL}$

Test system



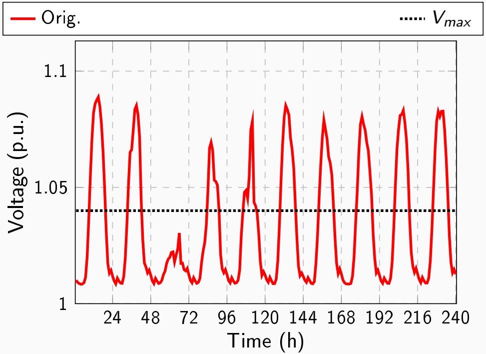
Control actions

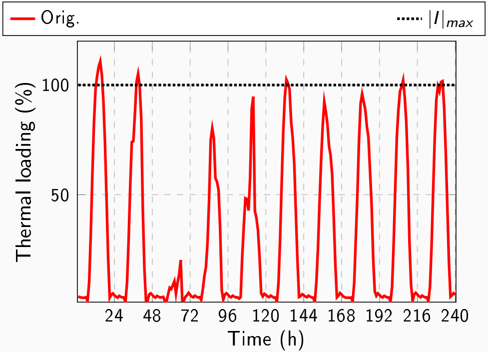
- Active Power Curtailment (APC)
- Reactive Power Control (RPC)
- Battery Energy Storage System (BESS)
- Controllable load (CL)
- On Load Tap Changers (OLTC)

Network description

- Based on European CIGRE LV grid
- Normalized profiles
  - PV & forecasts: Real data from Zurich
  - Load: Typical profiles based on CIGRE
- Summer day simulations
  - High solar radiation
- Acceptable limits:
  - Voltage: $\pm 4\%$
  - Current: up to 1 $p.u.$
  - VUF: up to 2%

Some results





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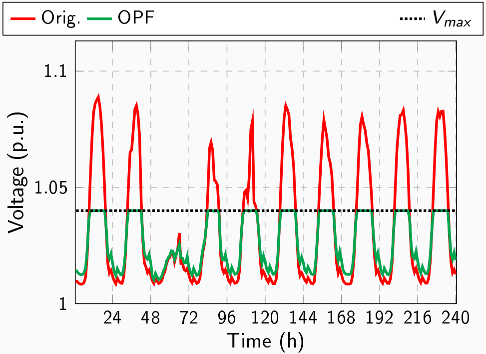

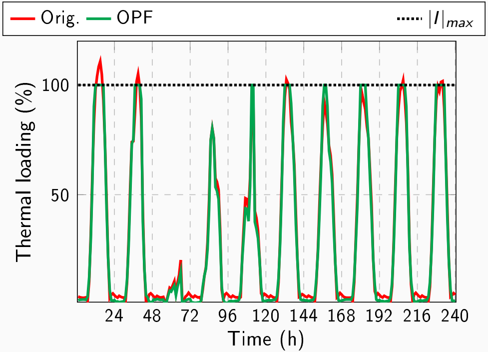

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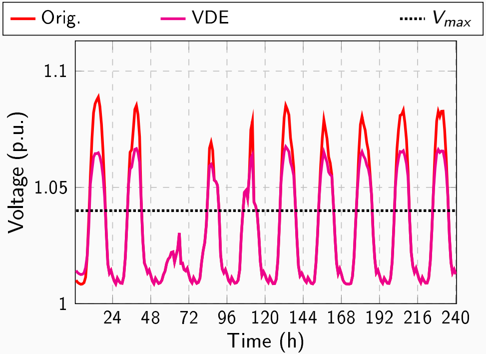

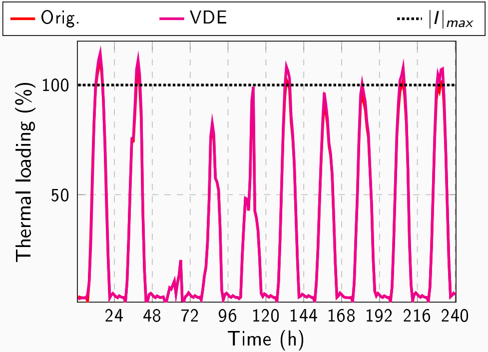

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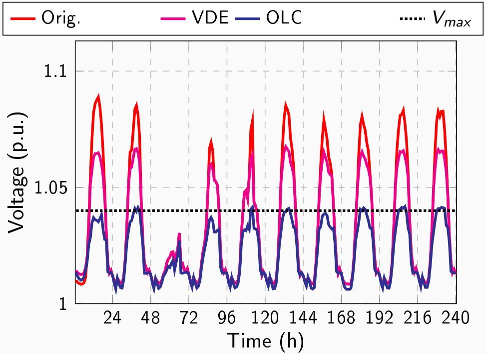

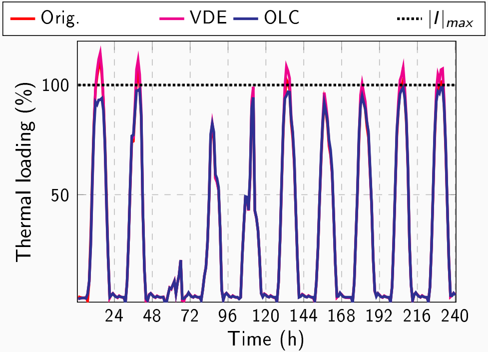

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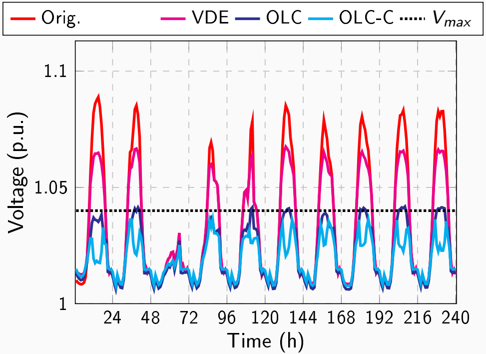
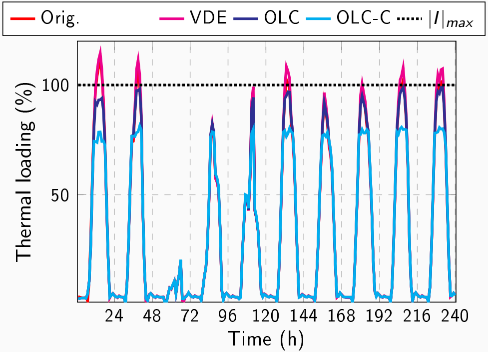
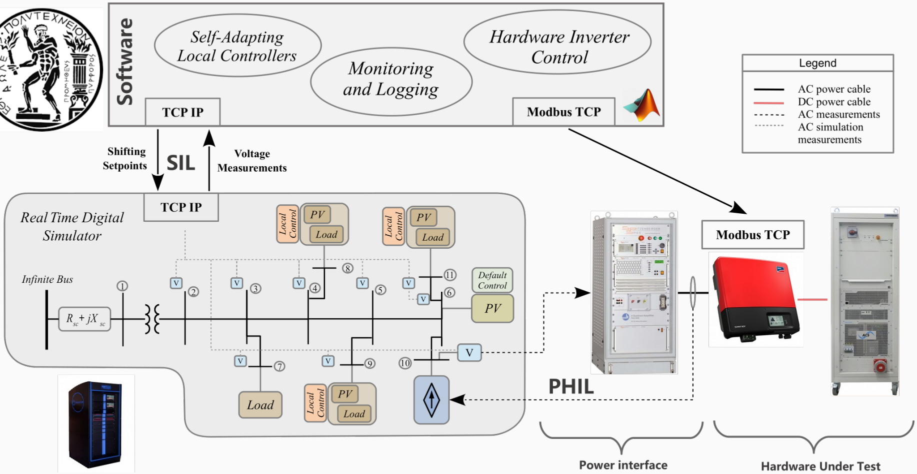




How about a hardware validation?



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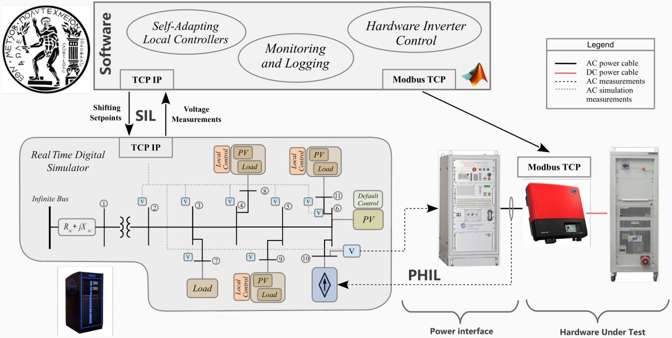

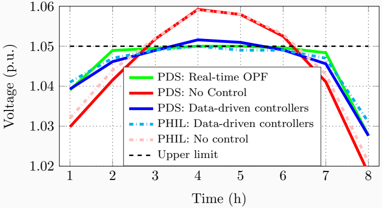

Concluding remarks

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Summary

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- Lack *monitoring*, *communication*, and *remote control* infrastructure

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Data-driven optimised local controllers can bridge the gap

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Data-driven optimised local controllers can bridge the gap

Future steps

- Extend to different types of controls and embed grid-supporting services.
- Single-stage data-driven control design $\rightarrow$ distributionally robust optimisation?
- Self-adapting controls through online learning to handle changing conditions $\rightarrow$ (Deep)RL?

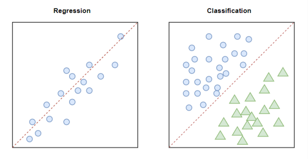

SPS
Sustainable Power Systems Lab
Cyprus University of Technology
Questions?

Backup slides

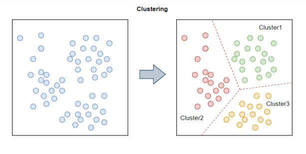
Machine learning in power systems

Basic categories

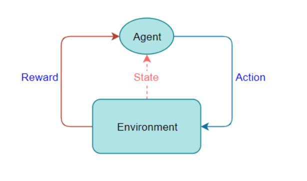
Supervised
Data with labels
Regression & Classification



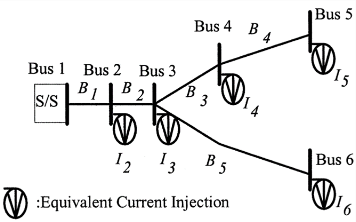
Unsupervised
Data without labels
Clustering



Reinforcement
States and Actions
Classification & Control



Backward/Forward Sweep (BFS) power flow



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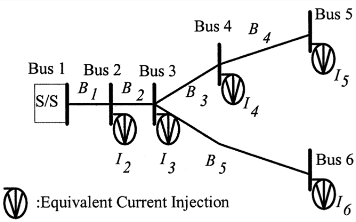

- Bus-injection to branch-current (BIBC)
- Branch-current to bus-voltage (BCBV)

Input: BIBC, BCBV, P_{inj}, Q_{inj}, V_{slack}

initialize: $k = 1$, $V_{\text{bus}}^{k} = 1\angle 0^{\circ}$

do

Backward sweep: $I_{\text{inj}}^{k} = \left(\frac{(P_{\text{inj}}+jQ_{\text{inj}})^{*}}{V_{\text{bus}}^{k*}}\right)$

$I_{\text{br}}^{k} = BIBC \cdot I_{\text{inj}}^{k}$

Forward sweep: $\Delta V^{k+1} = BCBV \cdot I_{\text{br}}^{k}$

$V_{\text{bus}}^{k+1} = V_{\text{slack}} - \Delta V_{\text{tap}} \cdot \rho_{\text{t}} + \Delta V^{k+1}$

Update iteration: $k+ = 1$

while $max|(|V_{\text{bus}}^{k}| - |V_{\text{bus}}^{k-1}|)| \geq \bar{\eta}$

Output: I_{br}^{k}, V_{bus}^{k+1}

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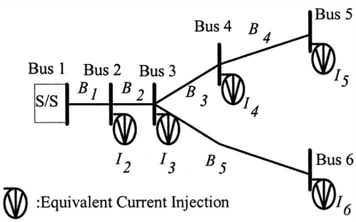

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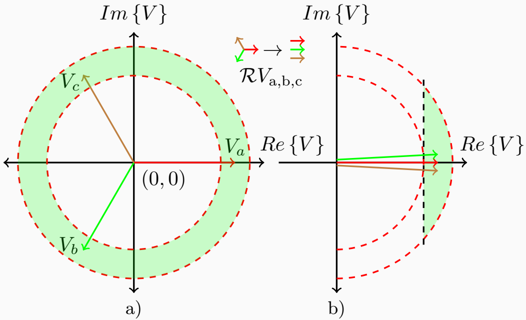
OPF voltage constraints relaxation



Computational time of deterministic OPF solutions

Methods

1. BFS-OPF using YALMIP and Gurobi as the interface platform and solver.
2. Standard AC OPF using the nonlinear and non-convex power flow equations, and IPOPT as the solver of the non-convex problem.
3. Standard AC OPF similar to the previous case plus providing functions for the gradient and hessian of the objective function, the Jacobian of the nonlinear constraints, and the Hessian of the Lagrangian.

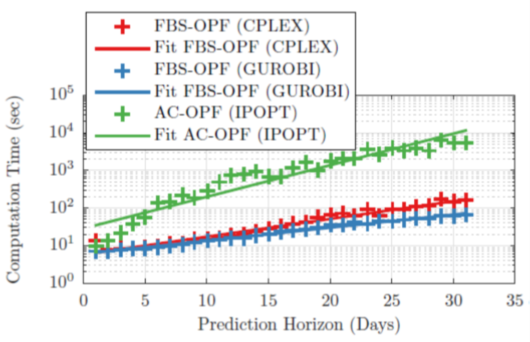
Solving Time (sec)	APC	+RPC	+BESS	+CL
Method 1	2.03	2.47	1.55	2.68
Method 2	9.47	12.53	18.04	16.99
Method 3	0.86	2.61	1.65	1.21

Solving time for the Cigre LV grid.

Solving Time (sec)	APC	+RPC	+BESS	+CL
Method 1	2.59	1.48	1.51	1.57
Method 2	21.41	41.63	41.56	34.61
Method 3	1.92	2.15	2.72	2.75

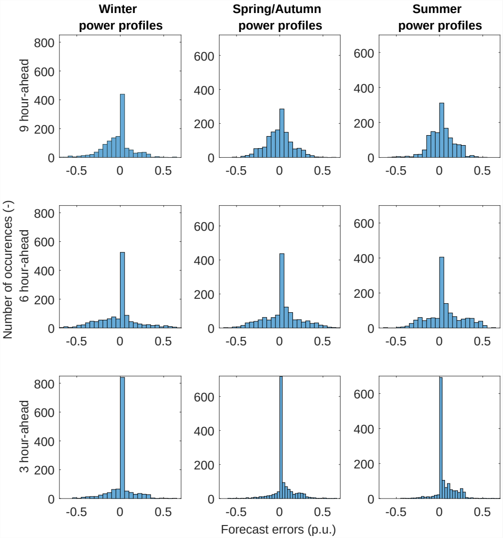
Solving time for the MV-LV grid.

Computational time of deterministic OPF solutions

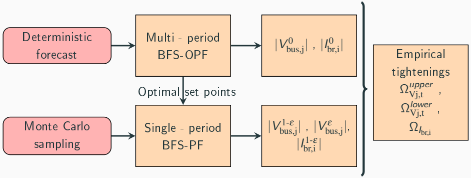


Computation time grows polynomially

Forecast errors of PV generation in Zurich data (EWZ)



Uncertainty tightening procedure



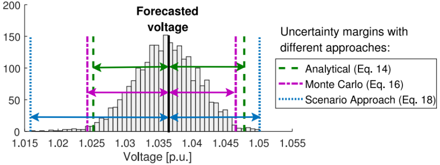
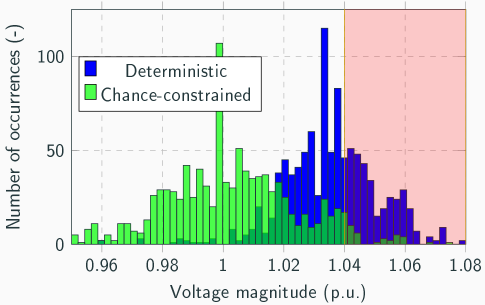
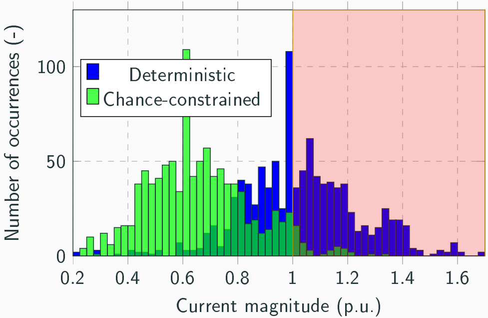


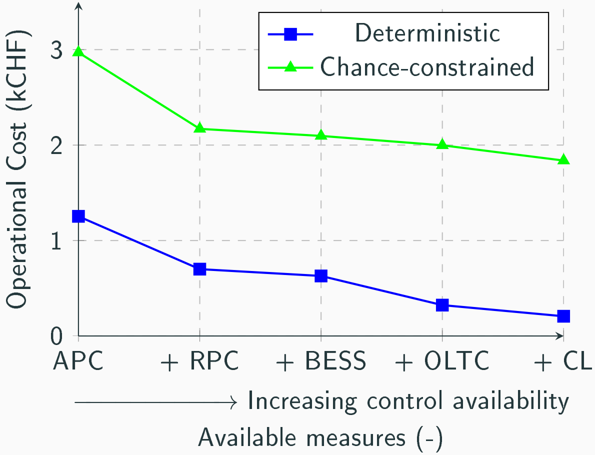
Fig. 1. Uncertainty margins $\lambda^u_{V,j}$, $\lambda^l_{V,j}$ for an example voltage constraint, as obtained with a given set of samples. The black line represents the forecasted voltage, and the histogram shows the empirical voltage distribution for the given sample set. The uncertainty margins are given by the distance between the black line and the corresponding coloured lines: Analytical reformulation (green), Monte Carlo simulation (purple) and Scenario approach (blue).

Comparison of violations due to forecast errors

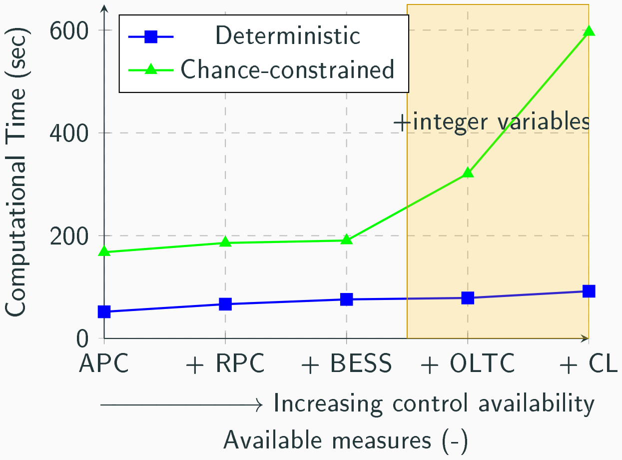




Objective function cost



Computational time of OPF solutions



Some results

Method	VDE	OPF	OLC
Losses (%)	4.60	4.42	4.45
$\lvert V\rvert_{\max}$ (p.u.)	1.069	1.04	1.045
$\lvert I\rvert_{\max}$ (%)	119.94	100	99.49
$VUF_{\max}$ (%)	1.81	1.98	2.33
P_{curt} (%)	0	1.08	2.03

Karagiannopoulos et al., "Data-driven Control Design Schemes in Active Distribution Grids: Capabilities and Challenges", arxiv preprint, submitted to PowerTech 2019

Linear SVR

Given the training data

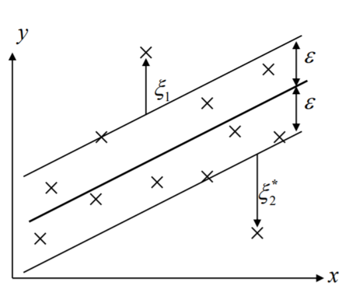
$$(\boldsymbol{x}_i, y_i) \;\; i = 1, \ldots, m$$

Minimise:

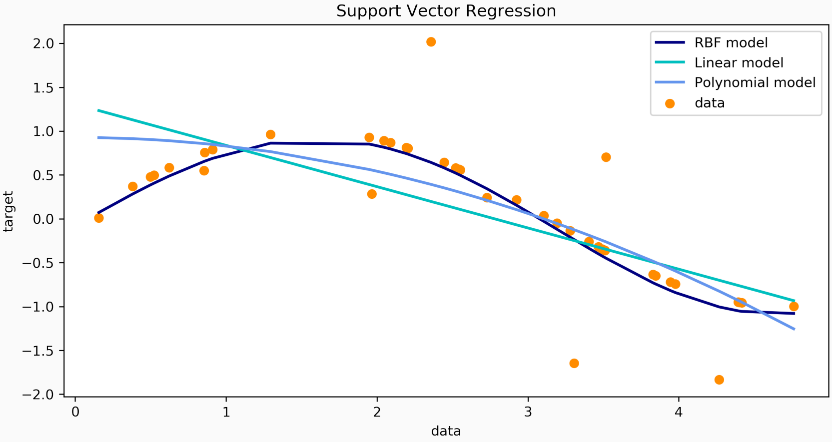
$$\frac{1}{2}\|\boldsymbol{w}\|^2 + C\sum_{i=1}^{m}(\xi_i + \xi_i^*)$$

Subject to:

$$\begin{aligned} y_i - (\boldsymbol{w}\cdot\boldsymbol{x}_i) - b &\leq \varepsilon + \xi_i \\ (\boldsymbol{w}\cdot\boldsymbol{x}_i) + b - y_i &\leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \quad i &= 1, \ldots, m \end{aligned}$$



SVR Kernels

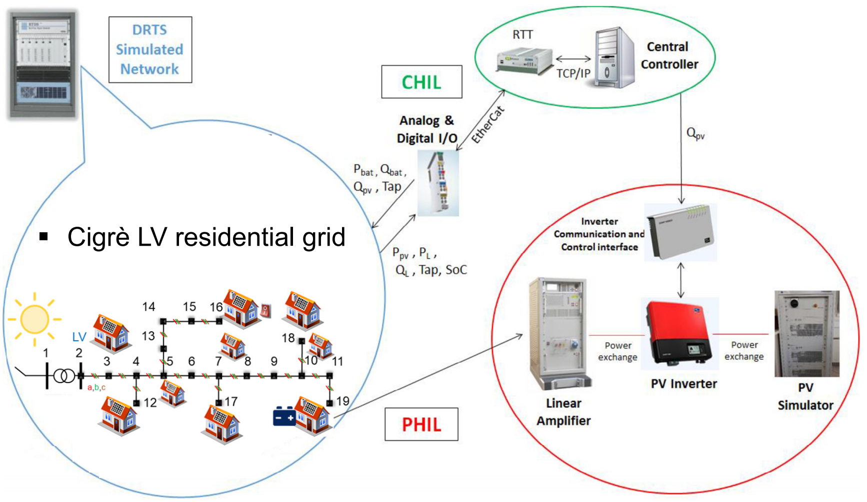


Support Vector Regression
RBF model
Linear model
Polynomial model
data
target
data
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
0
1
2
3
4

SVR Kernels

Node	C	Kernel Type	γ	Polynomial Order
12	4.742	RBF	0.046	—
16	710.250	polynomial	-	4
18	36.243	RBF	0.002	—
19	682.37	polynomial	—	2

Planned testing



- Cigrè LV residential grid

Results comparison

10 sum. days	Orig.	OPF	VDE	OLC	OLC-C
losses (%)	6.49	6.17	7.07	6.59	6.45
V_{max} (p.u.)	1.1073	1.04	1.0808	1.0412	1.0403
V_{MSE} (-)	9.73E-05	0	5.68E-05	6.65E-06	1.88E-05
V_{MAE} (-)	0.0041	0	0.0035	0.0013	0.0023
P_{curt} (%)	0	5.74	0	4.61	4.34

Hierarchical agglomerative clustering algorithm

Input: $\boldsymbol{X}^{\mathrm{j}}$, d

1: Define each voltage series $\boldsymbol{X}^{\mathrm{j}}$ as its own cluster.
2: Calculate the pair-wise distances between the clusters (based on d).
3: Merge the closest 2 clusters based on the minimum average linkage value.
4: Repeat Steps 2-3 until there is only one cluster, comprising all the voltage series

Output: Dendrogram structure of the input data