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Power Network Digitalization – Impacts on Protection, Automation and Control

Voltage control in distribution systems using deep reinforcement learning in presence of uncertainty

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PSMR

Overview of the presentation

1. Voltage variation problem in distribution systems

2. Uncertainty in distribution system analyses

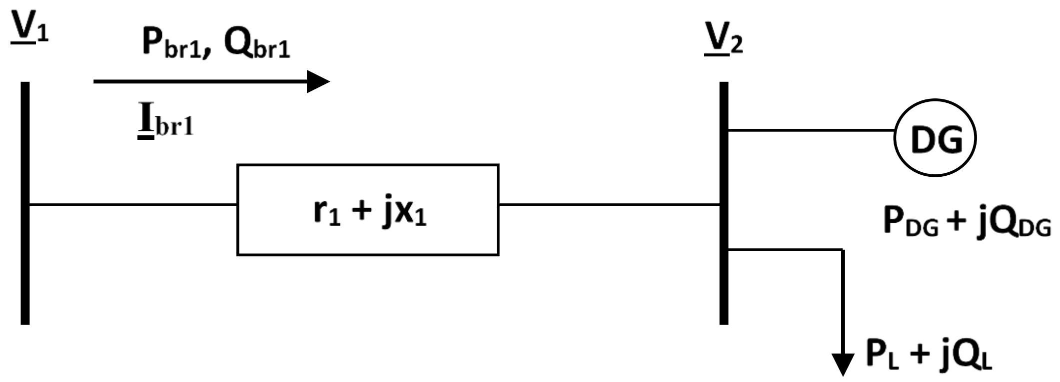
3. Literature review of voltage control methods

4. Proposed reinforcement learning-based voltage control technique

5. Studied distribution network, test cases and obtained results

6. Conclusion

1 Voltage variation in a 2-bus system with Distributed Generation



$$\Delta V_{12} = V_1 - V_2 = r_1 \underbrace{\left(P_L - P_{DG}\right)}_{P_{br1}} + x_1 \underbrace{\left(Q_L \pm Q_{DG}\right)}_{Q_{br1}}$$

Due to <u>load demand changes</u>

and <u>DG active power variations,</u>

<u>both</u> voltage <u>rise</u> and <u>drop</u> violations can occur.

Voltage control measures

Voltage violations can be managed by:

$$\Delta V_{12} = V_1 - V_2 = r_1\left(P_L + P_{DG}\right) + x_1\left(Q_L \pm Q_{DG}\right)$$

1. **On load tap changer (OLTC)** => V_1
2. **Reactive power control of DG** => Q_{DG}
3. **Curtailment of DG active power** => P_{DG}
4. **Load (demand side) management** => P_{L}
5. **Network reconfiguration or reinforcement** => r_1, x_1

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Model uncertainty in distribution systems

Due to **uncertainty**, **unobservability** and **complexity** of distribution **networks**, **simplified models** are **generally** used in the distribution systems:

1. **Loads are voltage independent**
2. **Power factors of loads are known**
3. **Line parameters remain constant**
4. **Network lines are series impedances**
5. **Transformers are pure reactances, …**

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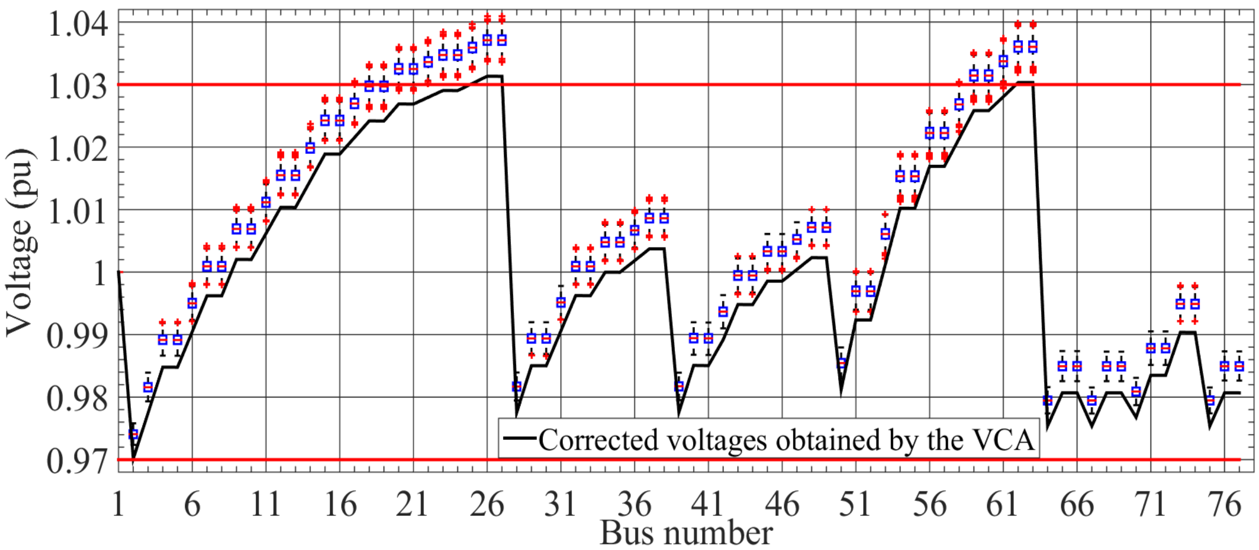
Model uncertainty quantification

The classical simplified network models can mislead analyses and lead to unsafe voltage control decisions [1]



The boxplots show the possible deviations of nodal voltages considering the model uncertainty associated with the loads, lines and transformer

3

Review of voltage control methods

1- Based on an Optimal Power Flow (OPF), e.g. [2]

- **OPF** can be used as the **central decision maker** to **define** the optimal **set-point of control variables** that **minimizes an objective function** while **maintaining operational constraints**.
- **OPF** is formulated as a **constrained optimization problem:**

$$\begin{aligned} \textbf{Min:} \quad & f(u,x) \\ \textbf{Subject to:} \quad & g(u,x)=0 \\ & h(u,x)\leq 0 \end{aligned}$$

- **OPF** is a **non-linear non-convex** problem => **difficult to solve.**
- It **relies on a simplified deterministic** network model.
- => it **cannot take into account the uncertainty** associated with the network model and its operating point.

Review of voltage control methods

2- Based on a linearized formulation, e.g. [3-4]

- ❑ **Sensitivity analysis** linearizes the relationships between control variables and node voltages (and branch currents).
- ❑ Linearized voltage control problem can be formulated as:

$$\mathbf{Min:}\ \mathbf{C^T x}$$

$$\mathbf{Ax \le b}$$

$$\mathbf{l_b \le x \le u_b}$$

- $\mathbf{C^T}$: coefficients reflecting costs of control actions,
- $\mathbf{x}$: vector of control variables to remove voltage violations,
- $\mathbf{A}$: sensitivity matrix, $\mathbf{b}$: vector of required voltage changes,
- $\mathbf{l_b, u_b}$: bounds on control variables.

- ❑ It relies on linearized equations => **entails simplification errors**.
- ❑ It **cannot handle the uncertainty** impacts.

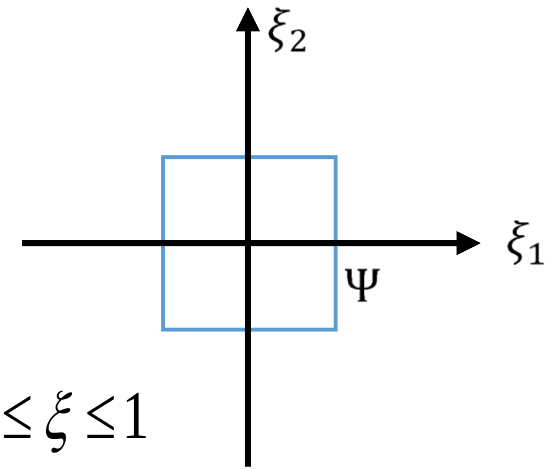
Review of voltage control methods

3- Based on Robust Optimization (RO), e.g. [5]

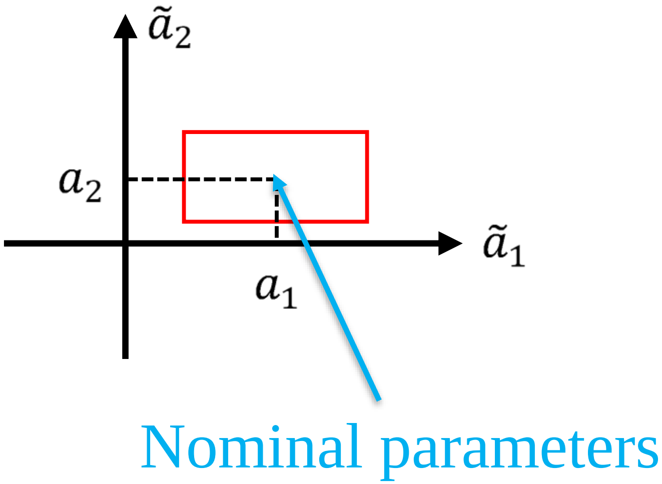
- ❑ The robust optimization can be adopted to deal with the voltage control problem **subject to uncertainty**.

- ❑ RO considers that the entries of matrix A are subject to uncertainty, defined by $a_{ij} = a_{ij} + \xi_{ij} a_{ij}$

- ❑ It finds a solution that is robust against the **worst realization** of uncertainty => could be **too conservative and costly.**



$-1 \leq \xi \leq 1$



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Review of voltage control methods

4- Based on Chance-Constrained Optimization (CCO), e.g., [6]

- CCO aims to immunize the constraint i subject to uncertainty **with a confidence level** $(1-\epsilon_i)$:

$$\mathrm{P}\left(\sum_{j=1}^{n}\tilde{a}_{ij}x_j \leq \tilde{b}_i\right) \geq 1-\epsilon_i$$

- It permits to **adjust the desired level of conservatism** against uncertainty by changing ϵ_i.

- The complexity of CCO formulation increases when there are **several coupled constraints subject to uncertainty**.

- **Difficult** to be applied to **large-scale** distribution networks.

Reinforcement Learning (RL) principles

- RL principles consist in **an agent interacting with an environment** over a number of discrete time steps until the agent reaches a terminal state.
- At each time step, the **agent observes a state from the state space**, and **selects an action** according to its policy.
- The agent ends up in the next state while **receiving a reward** based on its taken action.
- During the training, **the goal of the agent is to learn the best policy** i.e., to select actions that **maximize the future reward**.
- An agent generally starts from an initial (poor) policy.
- It **progressively learns** through many experiences/interactions with the environment **how to maximize its rewards**.
- The performance of the trained agent is evaluated in the test phase on the **unseen new observations**.

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Reinforcement Learning for voltage control problem [7]

In the context of voltage control problem:

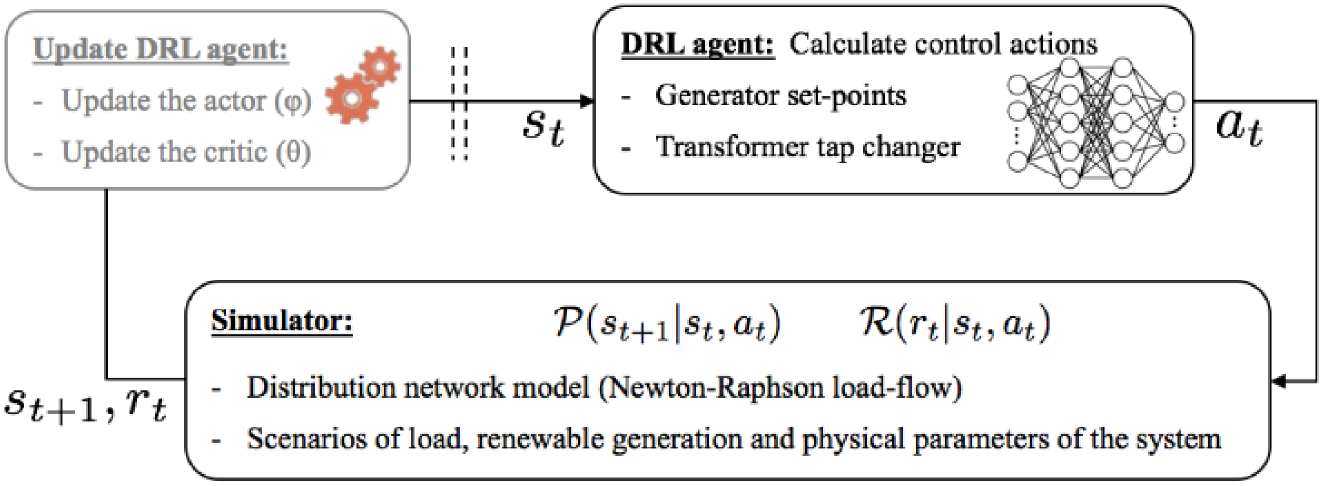
- **Agent** is the central control algorithm that manages the voltage limits;
- **Environment** is the distribution network (subject to the different sources of uncertainty);
- **Action space** includes the control decisions (DG power set-points & OLTC action) to manage the voltage limits;
- **State space** contains the monitored voltages, DG powers and OLTC set-point;
- **Reward function** consists of the voltage violation **costs** as well as the **control decision costs**:

$$r_t = -\sum_{g \in \mathcal{G}} \left(C_Q |\Delta Q_{g,t}| + C_P |\Delta P_{g,t}| \right) - C_{TR} |\Delta Tap_t| + \begin{cases} +R_{pos}, \ \forall V_{n,t} \in [\underline{V}, \overline{V}] \\ -R_{neg}(\underline{V} - V_{n,t}), \ \forall V_{n,t} < \underline{V} \\ -R_{neg}(V_{n,t} - \overline{V}), \ \forall V_{n,t} > \overline{V} \end{cases}$$

Tunning the coefficients of reward function

4 Deep Reinforcement Learning (DRL) for voltage control [7]

- To **boost the learning capabilities** of the RL agent, it is complemented by the **actor-critic architecture**.
- The goal of the actor is **to learn a deterministic policy** which selects the action *a* based on the state *s*.
- The quality of **the action is estimated by the critic**.
- Actor and critic functions are estimated using **deep neural networks**.



Training of the proposed DRL-based voltage control technique

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Studied distribution network and simulation parameters

- The proposed DRL-based voltage control approach is tested on a **real MV distribution system in Benin** [8].
- Vèdoko HV/MV substation alongside **5 representative** MV **feeders** connected to it has been modelled.
- It consists of **100 buses** and feeds an overall demand equal to 26.3 MW and 12.7 Mvar.
- 10 DG units (of 4 MW) are considered (two DGs per feeder).
- The DRL-based agent is **trained on 10000** different working states of **nodal load demands and DG powers**.
- The DRL-based agent is **tested on 2000 unseen new samples**.
- The **environment/simulator is changing** in each sample to consider the **distribution network model uncertainty impacts**.
- A **random error is added to take into account the uncertainty** in **DG power** forecasts.

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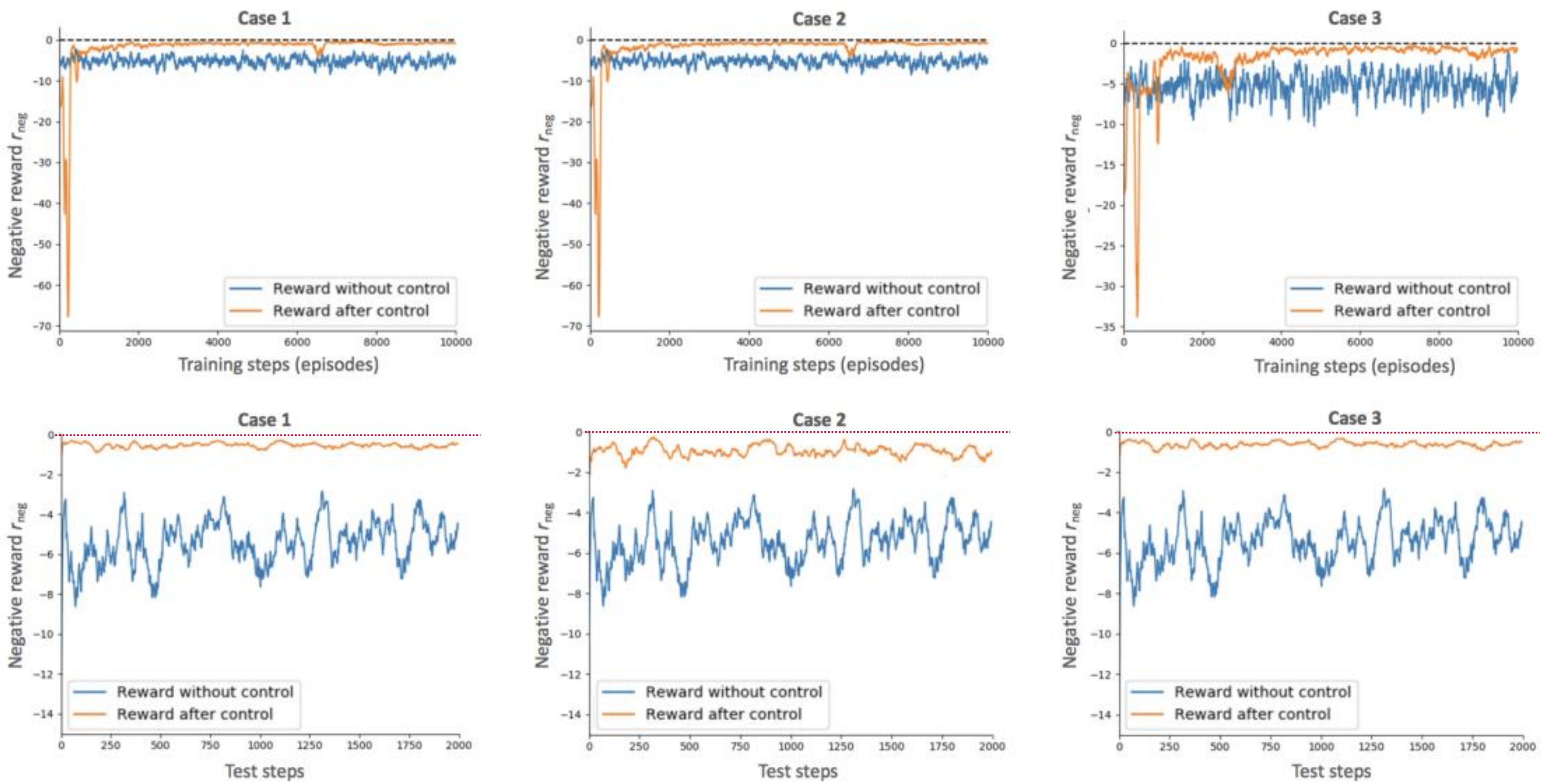
Studied test cases and obtained results

Case 1: Uncertainty sources are **disregarded** in both **training and test phases**;

Case 2: Uncertainty sources are **disregarded during the training**, but **considered in test phase**;

Case 3: Uncertainty sources are **considered in both training and test** phases.



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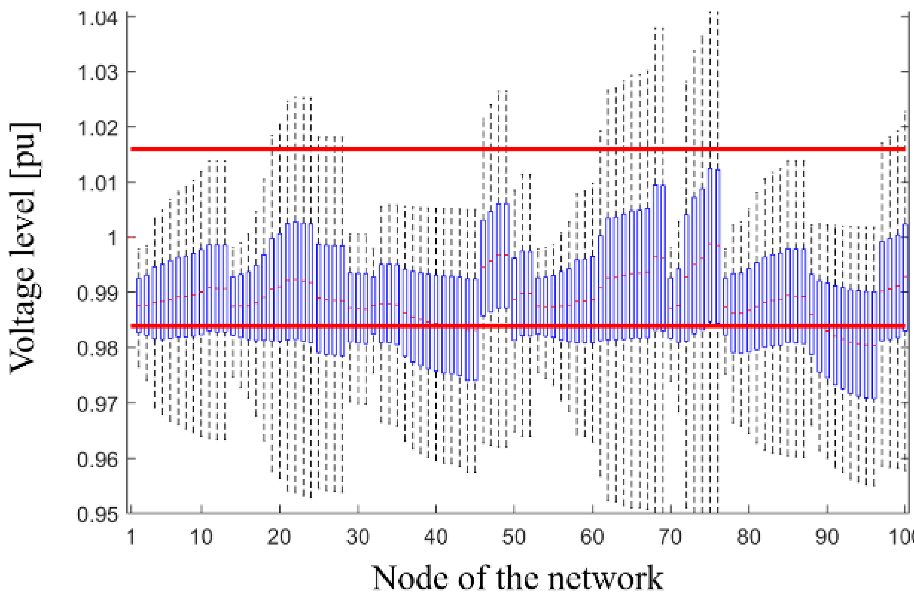
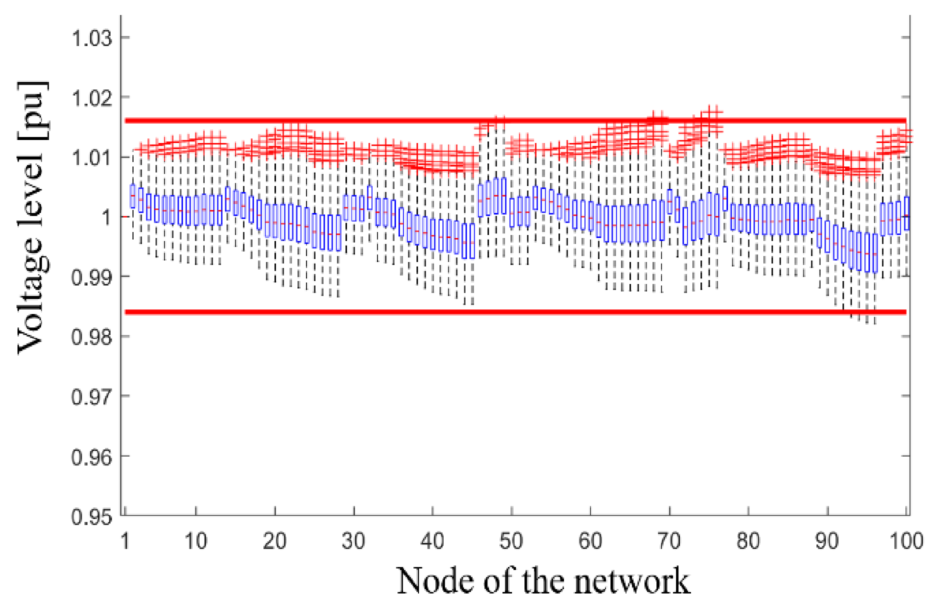
Initial and corrected voltages during test phase (in case 3)

Initial voltages



Corrected voltages



Initial voltage violations are effectively removed while addressing the considered uncertainty sources

Conclusion

- ➢ A **centralized** approach for voltage constraints management in distribution networks based on **deep reinforcement learning** is proposed.
- ➢ It considers the **uncertainties relating to the network parameters/models** as well as the **network operating points** while taking its corrective control decisions.
- ➢ The proposed method is tested on a **real MV distribution feeders** in Benin.
- ✓ Simulation results demonstrate that the proposed DRL-based method can **effectively manage the voltage constraints subject to different sources of uncertainty**.
- ✓ The DRL agent **trained in off-line** mode can **take control decisions in real time**.
- ✓ The **DRL-agent progressively learns the optimal control policy** through interactions with the environment in a **model-free fashion**: without relying on the analytical network models.

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[2] Capitanescu, F.; Bilibin, I.; Ramos, E. R. "A comprehensive centralized approach for voltage constraints management in active distribution grid, IEEE Trans. Power Syst. 2013, 29, 933–942.

[3] Bakhshideh Zad, B.; Hasanvand, H.; Lobry, J.; Vallée, F. "Optimal reactive power control of DGs for voltage regulation of MV distribution systems using sensitivity analysis method and PSO algorithm", Int. J. Electr. Power Energy Syst. 2015, 68, 52–60.

[4] Valverde, G.; Van Cutsem, T. "Model predictive control of voltages in active distribution networks", IEEE Trans. Smart Grid 2013, 4, 2152–2161.

[5] Bakhshideh Zad, B.; Toubeau, J.-F.; Lobry, J.; Vallée, F. "Robust voltage control algorithm incorporating model uncertainty impacts", IET Gener. Transm. Distrib. 2019, 13, 3921–3931.

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[6] Bakhshideh Zad, B.; Toubeau, J.-F.; Vallée, F. “Chance-constrained based voltage control framework to deal with model uncertainties in MV distribution systems”, Energies 2021, 14.

[7] Toubeau, J.-F.; Bakhshideh Zad, B.; Hupez, M.; De Grève, Z.; Vallée, F. “Deep reinforcement learning-based voltage control to deal with model uncertainties in distribution networks”, Energies 2020, 13.

[8] Bakhshideh Zad, B.; Toubeau, J.-F.; Acclassato, O.; Durieux, O.; Vallée, F. “An innovative centralized voltage control method for MV distribution systems based on deep reinforcement learning: application on a real test case in Benin”, CIRED 2021.

Thanks for your attention

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