Physics-Informed AI for Calculating PV Hosting Capacity in LV Networks

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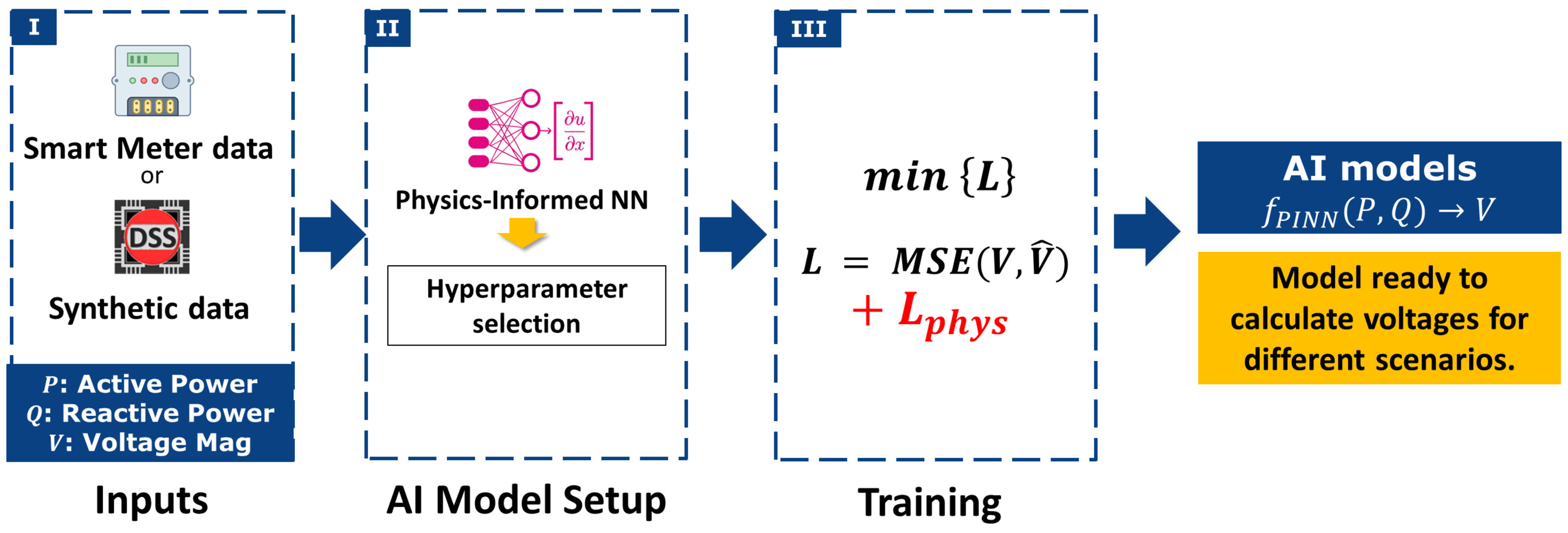
1. Introduction

- **Rooftop PV is rapidly increasing in LV networks, pushing voltages above statutory limits and increasing the risk of thermal overloading.**
- **Distribution companies must know how much PV LV networks can host** without breaching voltage and thermal limits → **PV Hosting Capacity (HC)**.
- However, **most distribution companies lack accurate electrical models**, preventing accurate voltage calculations and leaving them to **rely mainly on thermal limits or simple rules of thumb** when assigning HC.
- Conventional AI on smart-meter data is a promising way to estimate HC, but they struggle to extrapolate, **opening the door to physics-informed AI that embeds physical knowledge for more reliable HC calculations.**

2. Methodology

- ***A. Building the Physics-Informed AI models***



- ***B. Design of Physics Constraints***

Equation	Description
$L_{phys_1} = \sum_{i=1}^{C}\left(\Delta V_i - \sum_{j=1}^{C}\frac{\partial \hat{V}_i}{\partial P_j}\Delta P_j - \sum_{j=1}^{C}\frac{\partial \hat{V}_i}{\partial Q_j}\Delta Q_j\right)^2$	Enforces a first-order Taylor expression linking voltage changes to changes in P and Q through their sensitivities.
$L_{phys_2} = \sum_{i=1}^{C}\sum_{\substack{j=1\\ i\neq j}}^{C}\left(\frac{\partial \hat{V}_i}{\partial P_j} - \frac{\partial \hat{V}_j}{\partial P_i}\right)^2$ $L_{phys_3} = \sum_{i=1}^{C}\sum_{\substack{j=1\\ i\neq j}}^{C}\left(\frac{\partial \hat{V}_i}{\partial Q_j} - \frac{\partial \hat{V}_j}{\partial Q_i}\right)^2$	Symmetry constraints that enforce reciprocal voltage effects between customers, separately for P and Q changes.

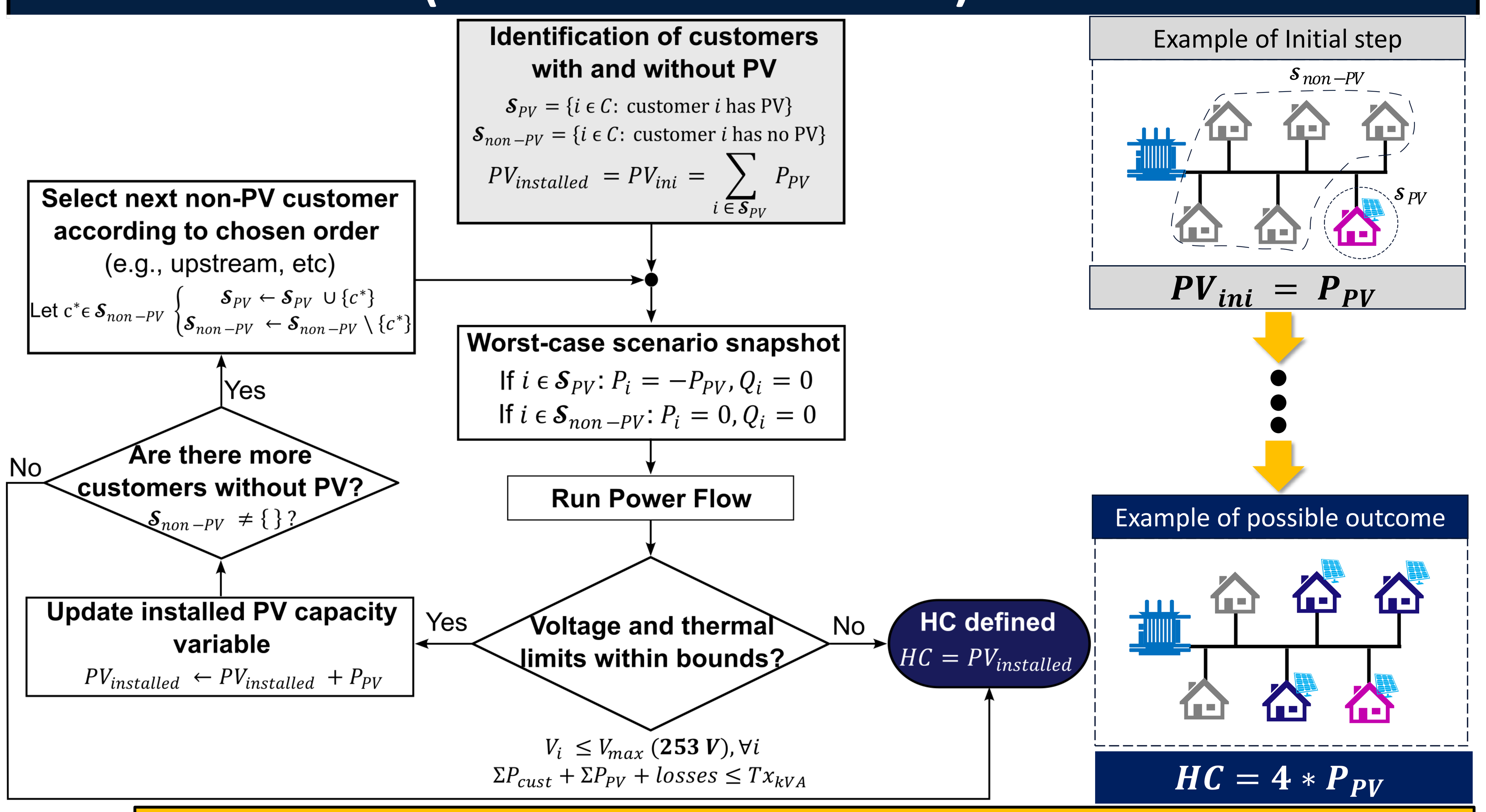
C: Number of customers in the LV network

All three constraints are combined with the data-fitting term in a weighted loss, with λ₁, λ₂ and λ₃ tuning the influence of each physics term in training.

$$L_{phys}(\lambda_1,\lambda_2,\lambda_3) = \lambda_1 \cdot L_{phys_1} + \lambda_2 \cdot L_{phys_2} + \lambda_3 \cdot L_{phys_3}$$

All three constraints are built *only* from (P, Q, V) data. No LV network model, topology, or line parameters are used.

3. HC Calculation (Low-demand Scenario)



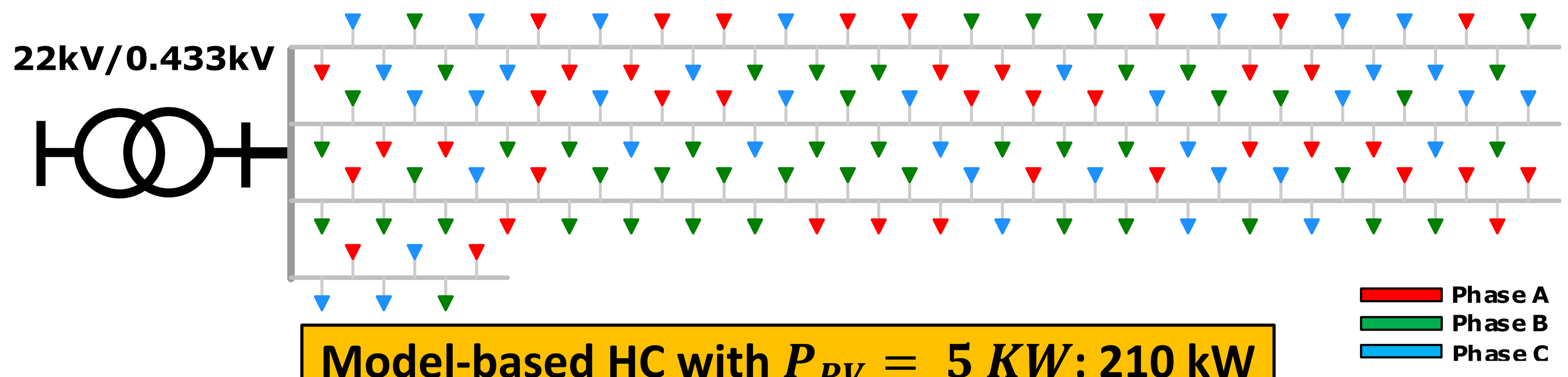
The aim is to compare the HC results against electrical model ($HC_{mismatch} = HC_{MB} - HC_{AI}$) to report how accurate the AI is.

4. Case Study

- Realistic Australian LV network with **126** customers.
- **25%** of PV penetration (**31 customers with PV**).
- **500 kVA transformer**.
- Synthetic data is used for the P, Q, and V datasets.
- Training dataset: **21 days (3 weeks)** of summer season.
- AI models to evaluate:
  - **Ridge Regression.**
  - **Conventional NN.**
  - **Physics-Inspired NN.**

Sensitivity analysis of constraint weights (λ₁, λ₂, λ₃) using 48 combinations.

$\lambda_1 = [0, 1\times10^{-6}, 1\times10^{-5}, 1\times10^{-4}]$
$\lambda_2 = [0, 1\times10^{-5}, 1\times10^{-4}]$
$\lambda_3 = [0, 1\times10^{-5}, 1\times10^{-4}, 1\times10^{-3}]$



Model-based HC with $P_{PV} = 5\,KW$: 210 kW
(+11 customers, 42 in total)

5. Results

A. One PINN Configuration vs Simplified HC Rules (Only thermal)

Taking **one PINN** out of the 48 λ combinations

λ1	Λ2	λ3	Calculated HC [kW]	HC mismatch [kW]	Outcome
1E-05	1E-05	1E-03	200	**10**	Voltages Ok! Thermal Ok!

✅ ***10 kW mismatch translates to two fewer PV customers → Very good accuracy!***

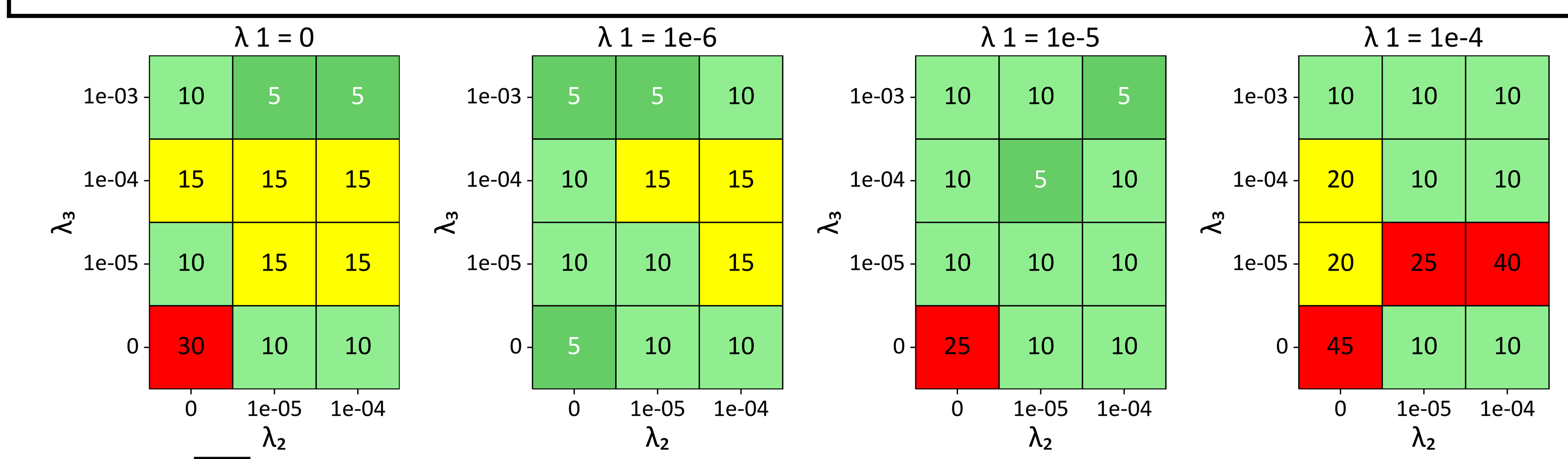
HC based on Transformer Capacity (TX_{kVA})

Limit (% of TX_{kVA})	Customers with PV	Assigned HC [kW]	HC mismatch [kW]	Max V (Model-based) [V]	Outcome
100	100	500	**290**	**271.19**	> 253 V
75	75	375	**165**	**268.80**	> 253 V
50	50	250	**40**	**261.91**	> 253 V

❌ ***When LV models are unavailable, relying on thermal-limit rules alone can hide voltage issues → Bad for the network!***

For distribution companies, this means it's possible to use physics-informed AI in top of thermal rules to safely allow PV connections on LV networks.

B. HC mismatch report and λ sensitivity analysis



✅ ***Very accurate calculations:* 7 models with HC mismatch ≤ 5 kW, and 33 of 48 models below 10 kW mismatch.**

✅ ***Best model* ($\lambda_1 = 1e-6, \lambda_2 = 0, \lambda_3 = 0$), RMSE = 2.91 V**

C. Performance against conventional AI models

ID	λ1	λ2	λ3	HC mismatch [kW]	RMSE [V]
Ridge Regression				5	3.82
Conventional NN				30	9.15
Best Physics-Informed NN	0	1E-05	1E-03	**5**	**2.91**

✅ ***Better HC calculation and voltage metrics than conventional AI models.***

6. Key Remarks

- **Physics-informed AI models give hosting capacity results that are consistently closer to the electrical-model benchmark than conventional AI (e.g. Ridge Regression, Conventional NNs).**
- **They offer a voltage-aware alternative to common thermal-only planning rules when detailed LV network models are unavailable.**

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