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10216 – Reactive Power Forecasting At The Transmission-Distribution Interfaces Using Physics-Based Machine Learning

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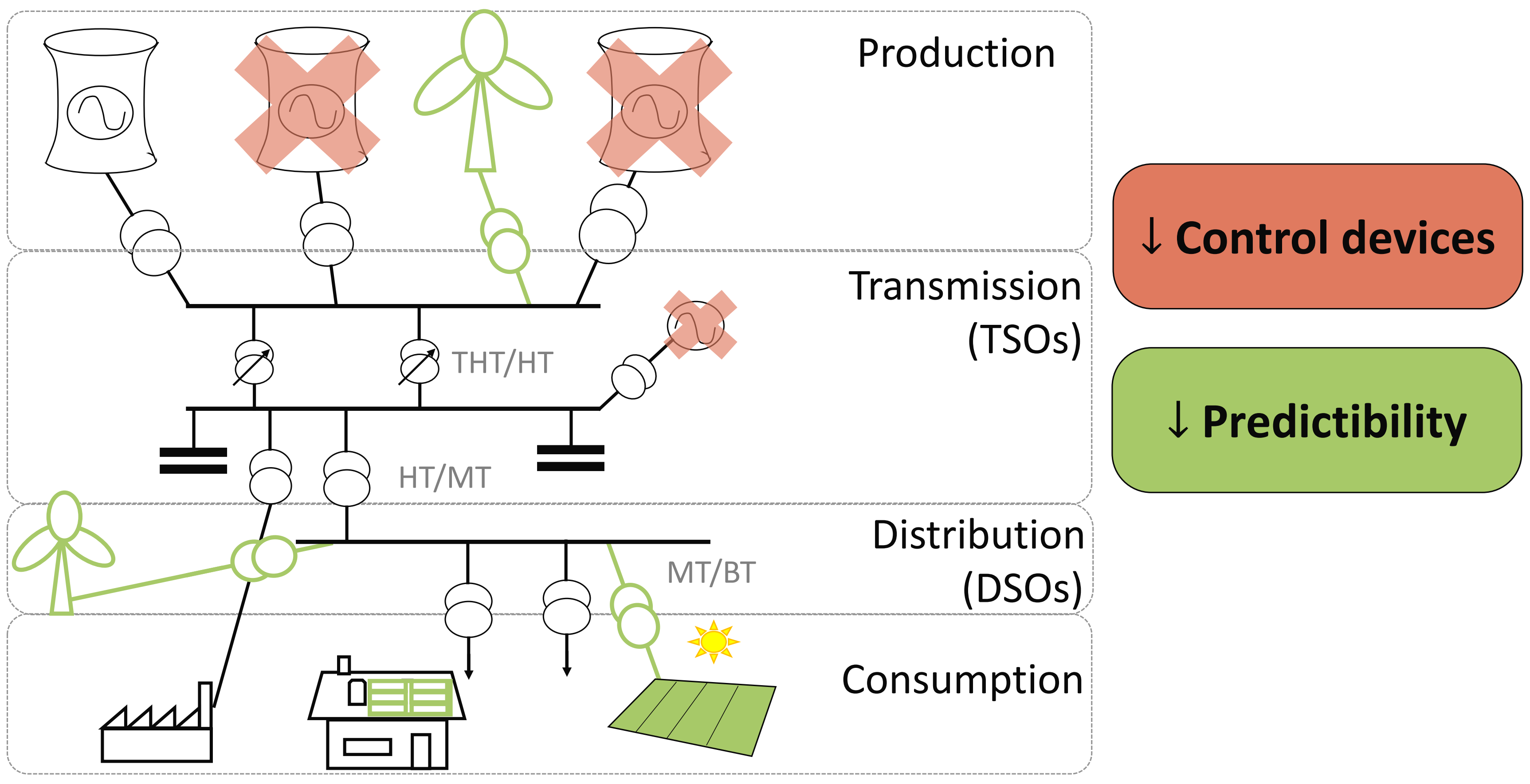
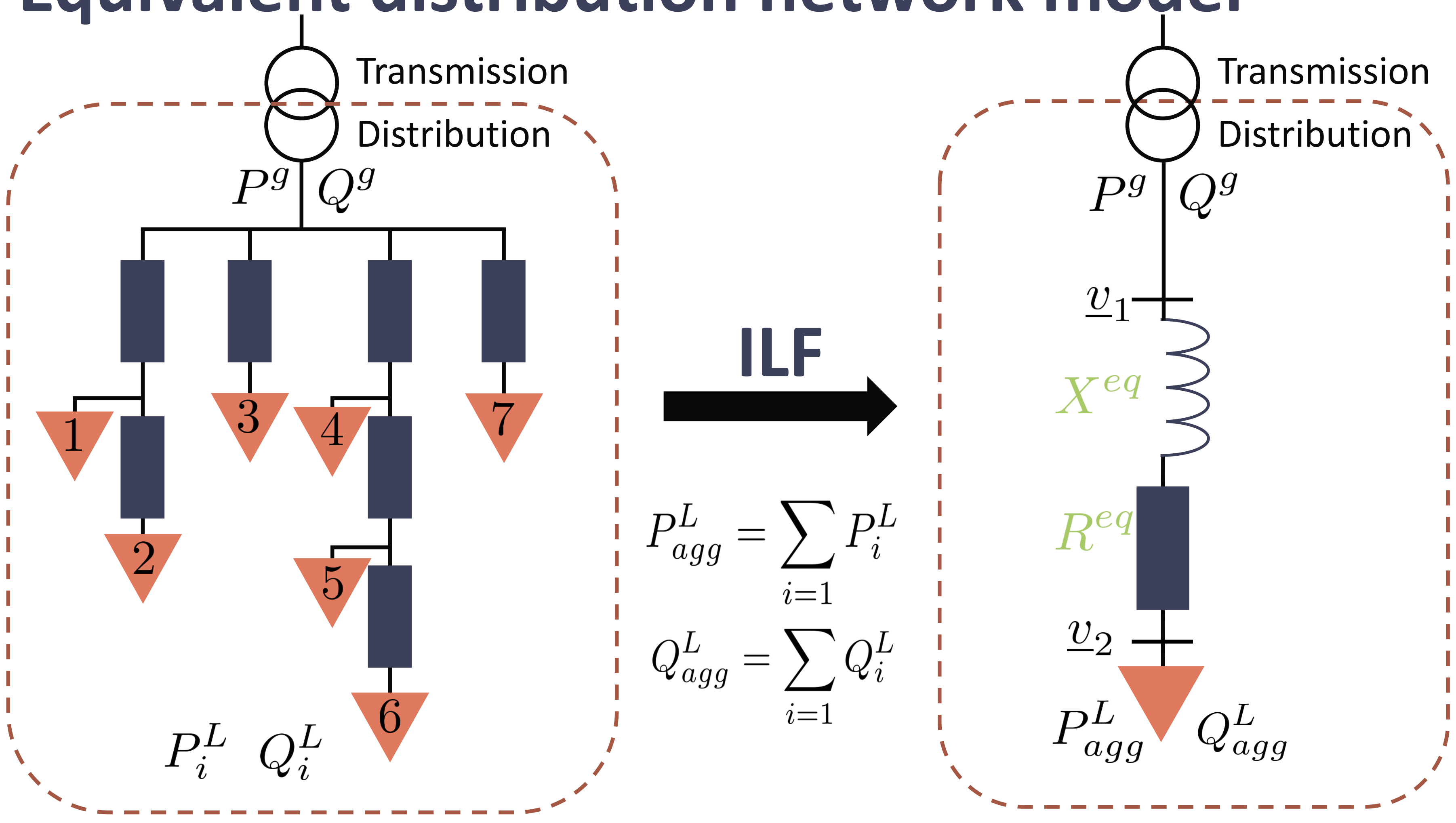
Context



- Voltage levels in power systems are strongly tied to reactive power, requiring appropriate management.
- Reactive power exchanges at T-D interfaces are crucial for TSO and DSO.
- Predicting reactive power exchanges is complicated due to renewable generation, increasing replacement of overhead lines with underground cables, and lack of detailed information (mainly at the distribution level.
- Existing model-based approaches rely on simulations but face limitations in network topology data, while data-driven approaches may lack interpretability and anticipation of topology changes.
- Prediction is conducted using a limited feature set due to the constrained observability of the distribution network, particularly for the TSO.

This work proposes a hybrid approach that combines Inverse Load Flow method to reconstruct the equivalent line parameters of the studied distribution network and traditional Machine learning algorithms to predict reactive power at T-D (Transmission-Distribution) interface.

Equivalent distribution network model



$$P_{agg}^L = \sum_{i=1} P_i^L$$

$$Q_{agg}^L = \sum_{i=1} Q_i^L$$

Inverse Load Flow (ILF)

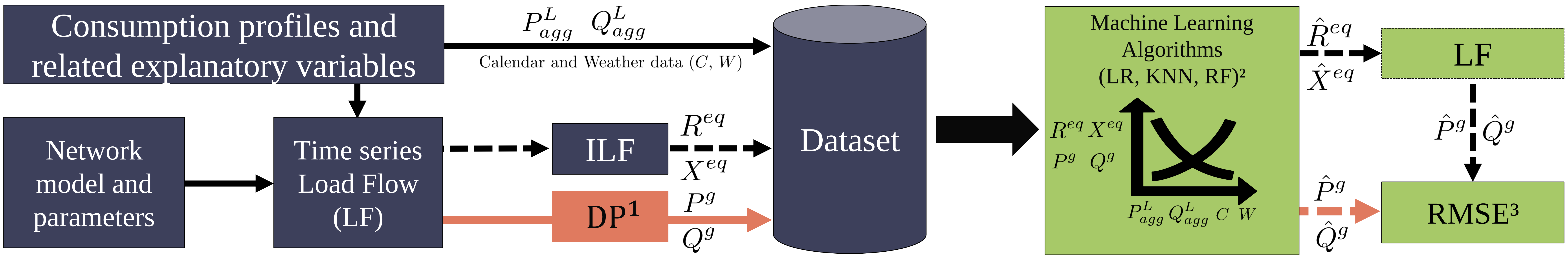
$$P^g \longrightarrow \quad P^g = g - gv_2\cos(\theta_2) + bv_2\sin(\theta_2) \quad \longrightarrow R^{eq}$$

$$Q^g \longrightarrow \quad Q^g = -b + bv_2\cos(\theta_2) + gv_2\sin(\theta_2) \quad \longrightarrow X^{eq}$$

$$P_{agg}^L \longrightarrow \quad P_{agg}^L = gv_2^2 - gv_2\cos(\theta_2) - bv_2\sin(\theta_2) \quad \longrightarrow v_2$$

$$Q_{agg}^L \longrightarrow \quad Q_{agg}^L = -bv_2^2 + bv_2\cos(\theta_2) - gv_2\sin(\theta_2) \quad \longrightarrow \theta_2$$

Hybrid Reactive Power Prediction Methodology at the T-D interface



Consumption profiles and related explanatory variables

P_{agg}^L Q_{agg}^L

Calendar and Weather data (C, W)

Network model and parameters

Time series Load Flow (LF)

ILF

R^{eq} X^{eq}

DP[1]

P^g Q^g

Dataset

Machine Learning Algorithms (LR, KNN, RF)[2]

R^{eq} X^{eq} P^g Q^g

P_{agg}^L Q_{agg}^L C W

$\hat{R}^{eq}$ $\hat{X}^{eq}$

LF

$\hat{P}^g$ $\hat{Q}^g$

RMSE[3]

$\hat{P}^g$ $\hat{Q}^g$

[1] The proposed physics-based machine learning model is benchmarked against the classical data-driven prediction methods (DP = Direct Prediction) implemented by eliminating both ILF and LF steps

[2] Linear Regression, K-Nearest-Neighbors, Random Forest

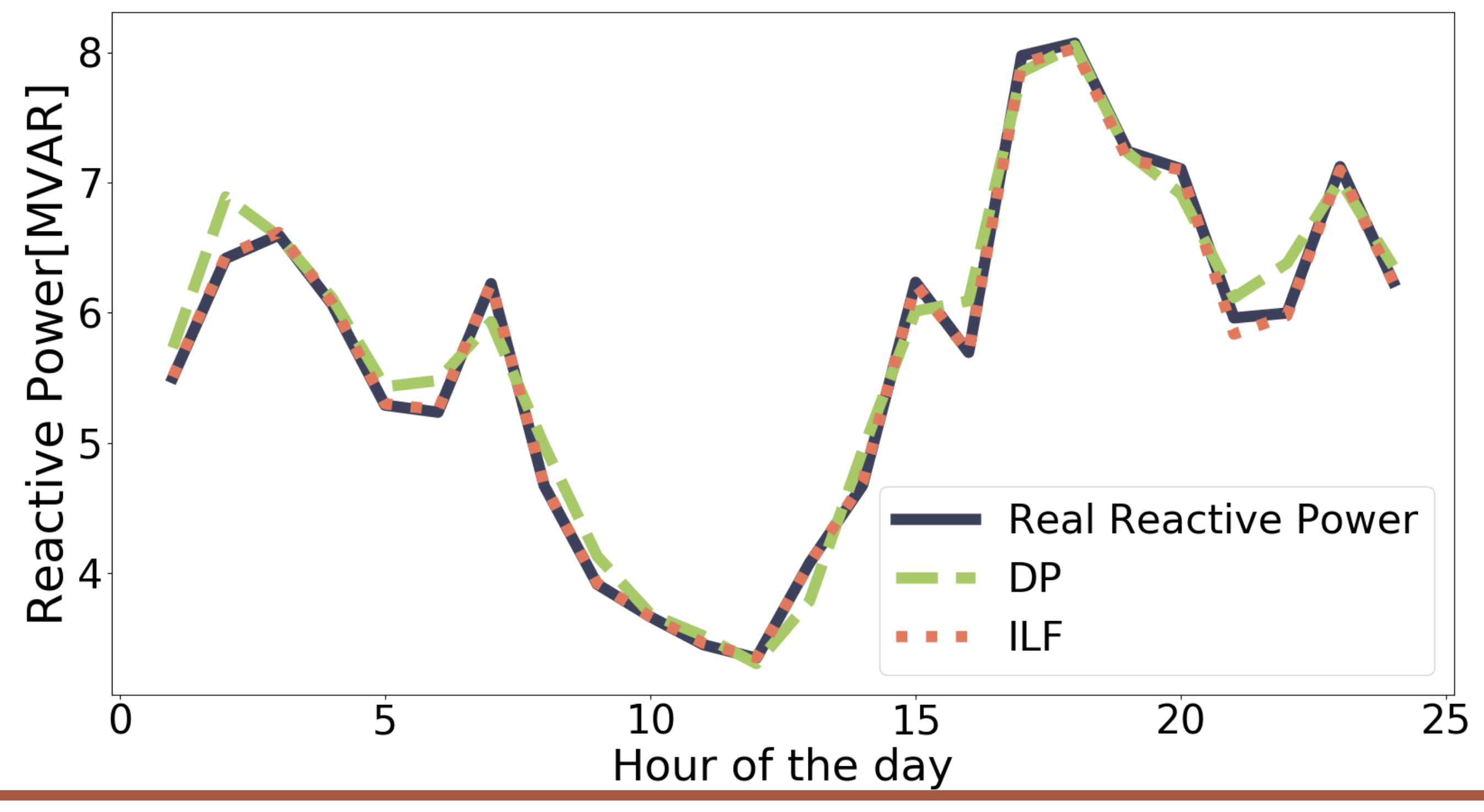
[3] Root Mean Square Error

Short-term Prediction Results

	P^g [%]		Q^g [%]	
	DP	**ILF**	**DP**	**ILF**
LR	*1.710*	*1.508*	*6.545*	*5.870*
KNN	*13.464*	*0.921*	*20.628*	*3.565*
RF	*2.303*	*1.055*	*6.410*	*4.038*

Table – Relative RMSE of power predictions at T-D interface obtained by the proposed ILF-based model and the classical DP using different ML algorithms

Figure – Reactive Power prediction using K-Nearest-Neighbors for Direct Prediction and Inverse Load Flow methods to actual reactive power values for a 24 hours day



Conclusion

- A novel physics-based machine learning model is proposed for accurate T-D interface power prediction.
- The model uses ILF calculation to compute equivalent resistance and reactance of the network.
- The model shows improved accuracy compared to classical data-driven methods by passing through the obtained equivalent resistance and reactance.
- Future work will focus on adding PV production and extending the model to real-life distribution grids.

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