Forecasting and Decomposition of Distribution Locational Marginal Prices

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Contents

Outline

- Research Question: Can a forecasting architecture be developed which can understand the underlying physical properties of a low-voltage distribution network in the forecasting of Distribution Locational Marginal Prices (DLMPs)?
- Generation of DLMPs using a fixed-point linearization methodology with historic DER generation and load data.
- Decomposition of DLMPs into linear combination of dual variables corresponding to energy balance and physical constraints.
- Development of a forecasting mechanism which utilises Graph Convolution Networks and Long Short-Term Memory to forecast the decomposed elements of the DLMPs using a multi-output, multi-branch approach.

Motivation

- Working towards flexibility and co-ordination at the distribution network level (Review of Electricity Market Arrangements, 2022).
- Rise in number of Distributed Energy Resources.
- Fostering Local energy markets.
- Importance of forecasting pricing signals.
- Pricing signals are hard to forecast due to complexities in physical properties of the distribution network!

What are Distribution Locational Marginal Prices?

- The Price Signal.
- The dual components associated with energy balance constraints between nodes when solving an Optimal Power Flow (OPF) formulation that seeks to optimize for the lowest total cost in the system (Papavasiliou, 2018) (Toubeau, et al., 2021).
- Complicated signals with strong correlations in time and between nodes.
- Challenging to forecast for Day-Ahead and Real-Time Markets.

Challenges Associated with Forecasting DLMPs – Signal Complexity

- OPF is the computation of voltage magnitude and phase angle at each bus in a power system under three-phase steady state conditions.
- Determine cases where there may be physical constraints in the system leading to higher marginal prices.
- Non-linear power flow equations can be solved using numerical methods. Outputs from these form the basis for calculating DLMPs.
- Non-linearities associated with OPF make DLMPs complex signals which are strongly correlated in time and space.

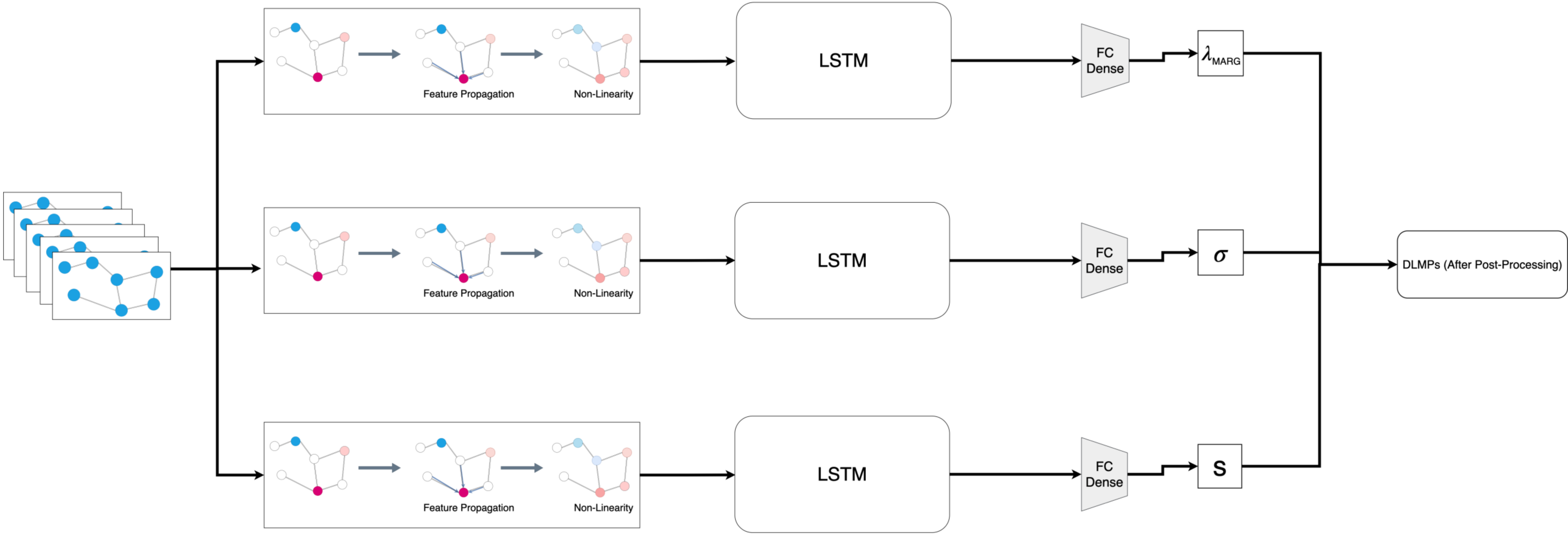
Challenges Associated with Forecasting DLMPs – Model Requirements

- For use in downstream tasks, architecture must allow cold-start forecasting (addition of new nodes in the system).
- Cross-nodal learning will be imperative to understand spatial dependencies.
- Forecasting architecture should be able to capture temporal dependencies in the system.

Proposed Framework

- The proposed framework exploits the graphical structure of the distribution network using Graph Convolution Networks (GCN) coupled with LSTM to forecast DLMPs.
- Inputs: PV generation, Load, physical constraint component, price for marginal units and a binary marginal unit indicator.
- Outputs: physical constraint component (σ), price for marginal units (λ_{MARG}) and binary marginal unit indicator (s) which are converted to DLMPs (λ) in post-processing.

Proposed Framework - Diagram



Where σ represents the physical constraint component, λ_{MARG} represents the price for marginal units and s represents a binary marginal unit indicator

Proposed Framework – GCN

- A variant of the Convolutional Neural Network which learns graph representations of the system.
- Acts as a message passing system between nodes and has been used in other similar use cases such as traffic forecasting and precipitation forecasting.
- At the beginning of each layer, features of each node are aggregated by some aggregation function with feature vectors in its local neighborhood. These feature vectors are propagated locally (Wu, et al., 2019).
- Simultaneous update of all nodes in the system smooths hidden representations of the system and encourages cross nodal learning among locally connected nodes.

Proposed Framework – LSTM

- A type of Recurrent Neural Network which has previously given SOTA results for speech recognition and natural language processing tasks.
- Ability to use backwards context for forecasting using gated units (forget gate, input gate and output gate).
- Can leverage long-term information from past inputs for forecasting via a memory cell.
- Holds an internal representation of past events and outputs values based on relevant past information.

Proposed Framework – Calculating DLMPs

- The forecasting system outputs the physical constraint component, Forecasted price for marginal units and a binary marginal unit indicator.
- To calculate DLMPs (λ) for all nodes in the system the following equation is used:

$$\lambda_{NONMARG} = A * \lambda_{MARG} + B * \sigma \quad (1)$$

$$\lambda = \lambda_{MARG} \bigcup \lambda_{NONMARG} \quad (2)$$

$$Where\ A, B\ are\ matrices\ that\ represent\ the\ network,$$
$$\sigma\ corresponds\ to\ the\ dual\ variable\ that\ represents\ physical\ contraints$$

Marginal units are the units that operate between their minimum and maximum limits

- Custom loss function defined as follows:

$$Overall\ Loss = 1 \cdot loss_{\lambda MARG} + 10 \cdot loss_{\sigma} + 100 \cdot loss_{MARG\ UNIT} \quad (3)$$

Case Study

- 33 Bus system.
- Unit types: PV Generation, PV with Storage, Storage Only and Load Only.
- 491 days of data split into 48 settlement periods.
- 70:20:10 train/validation/test split.
- 65,990 data points when considering every node at every timestep.
- Ablation study looking at the MLP, GCN, LSTM and GCN+LSTM architectures.

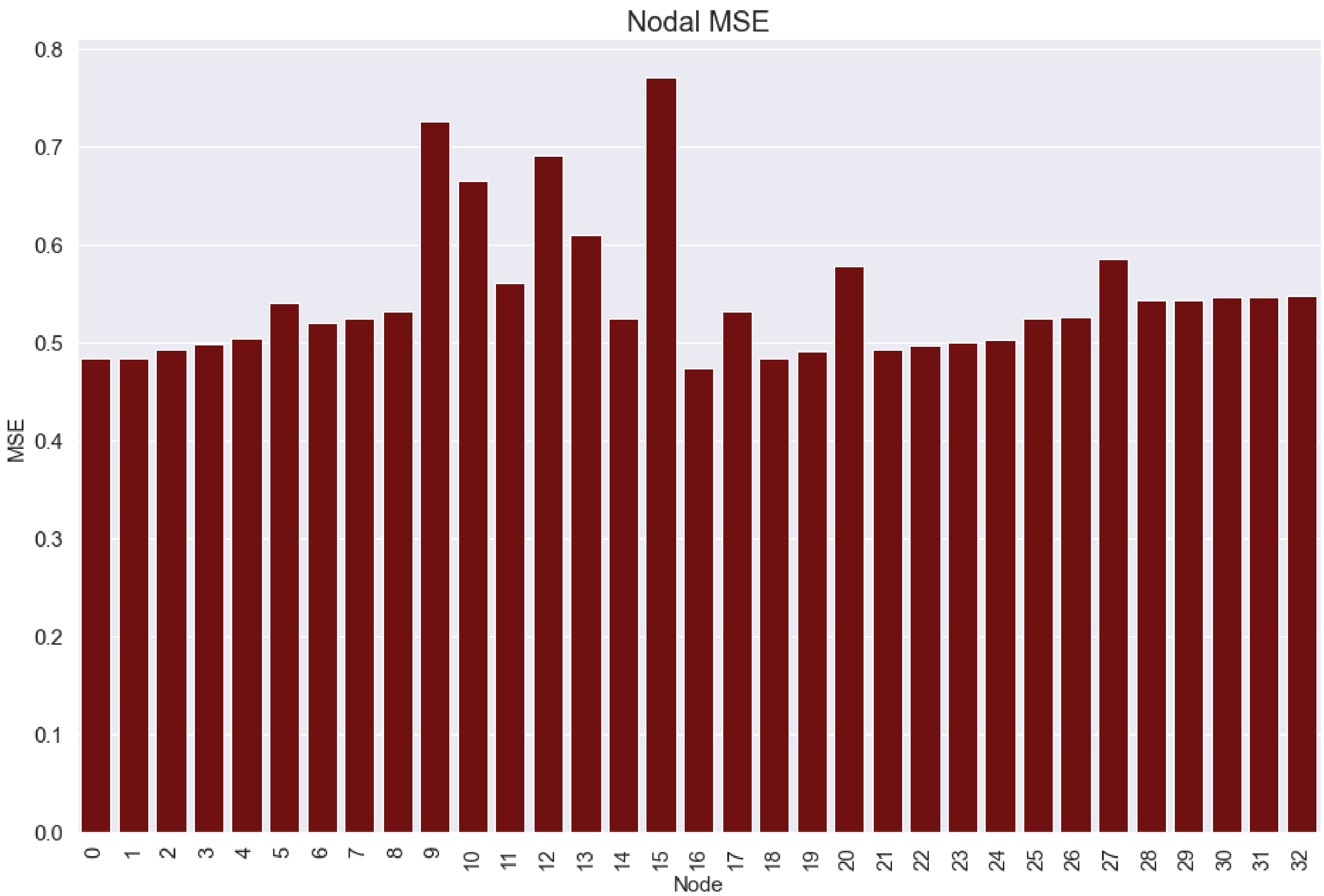
Case Study – Results

Table 1: Model results after final training using optimal parameters

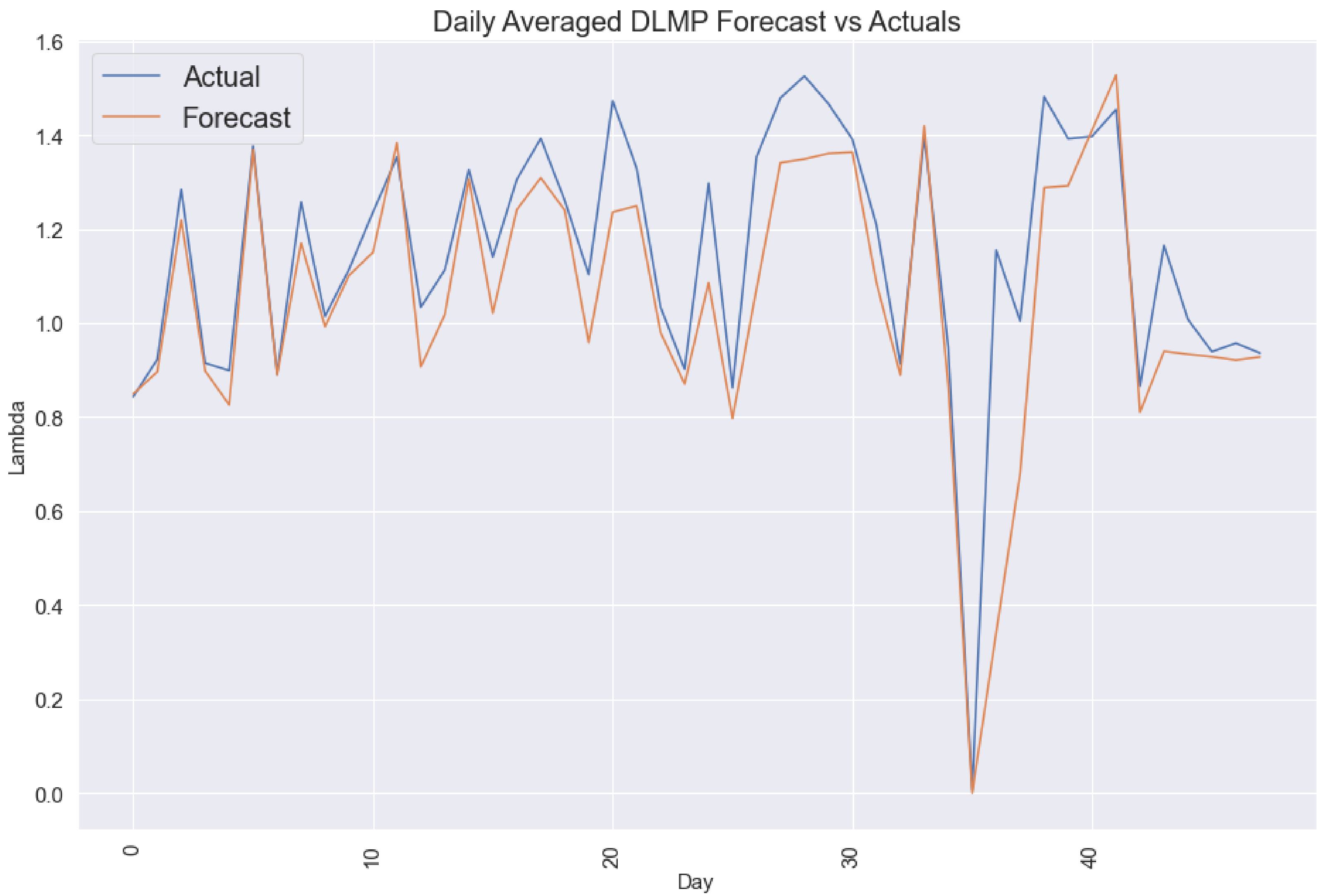
Model	MAPE	MAE	MSE
MLP	23.9598	0.5565	0.5921
LSTM	7.2037	0.6898	0.7453
GCN	13.6905	0.8807	1.1680
LSTM+GCN	**4.5668**	**0.4890**	**0.5465**

Where MAPE is the Mean Absolute Percentile Error, MAE is the Mean Absolute Error and MSE is the Mean Square Error

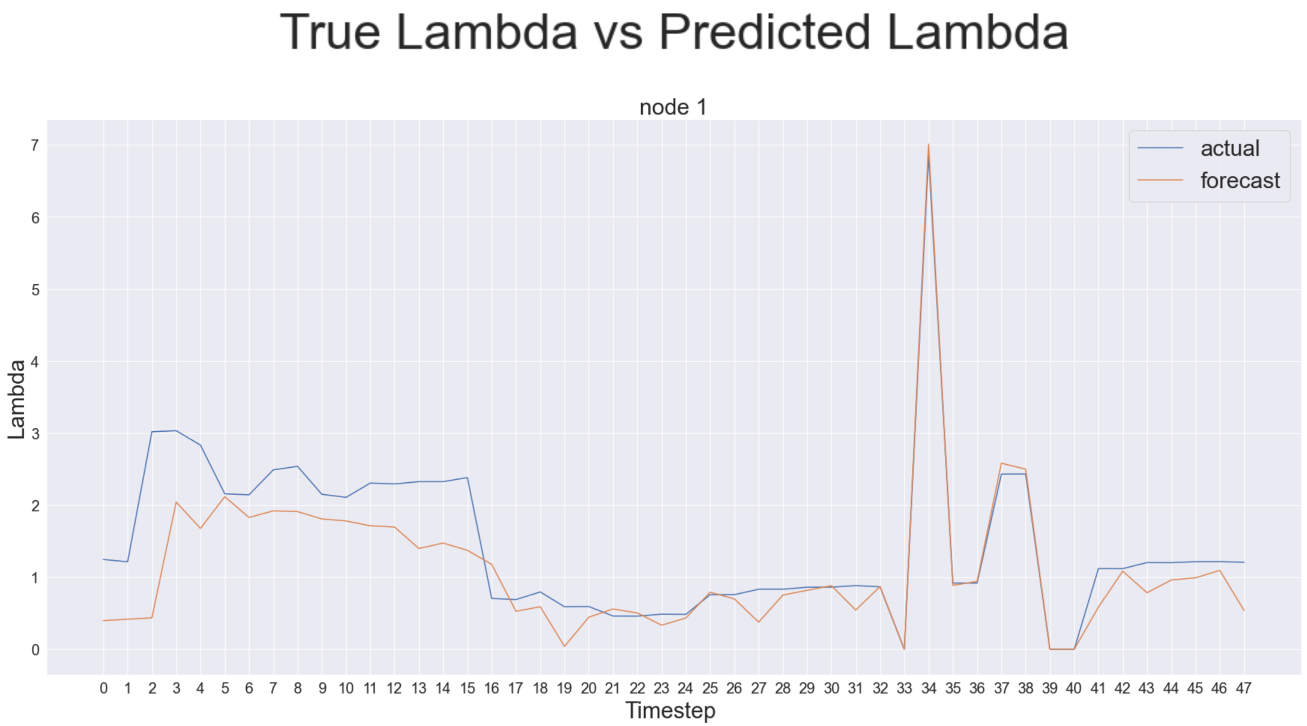
Case Study – Results



Case Study – Results



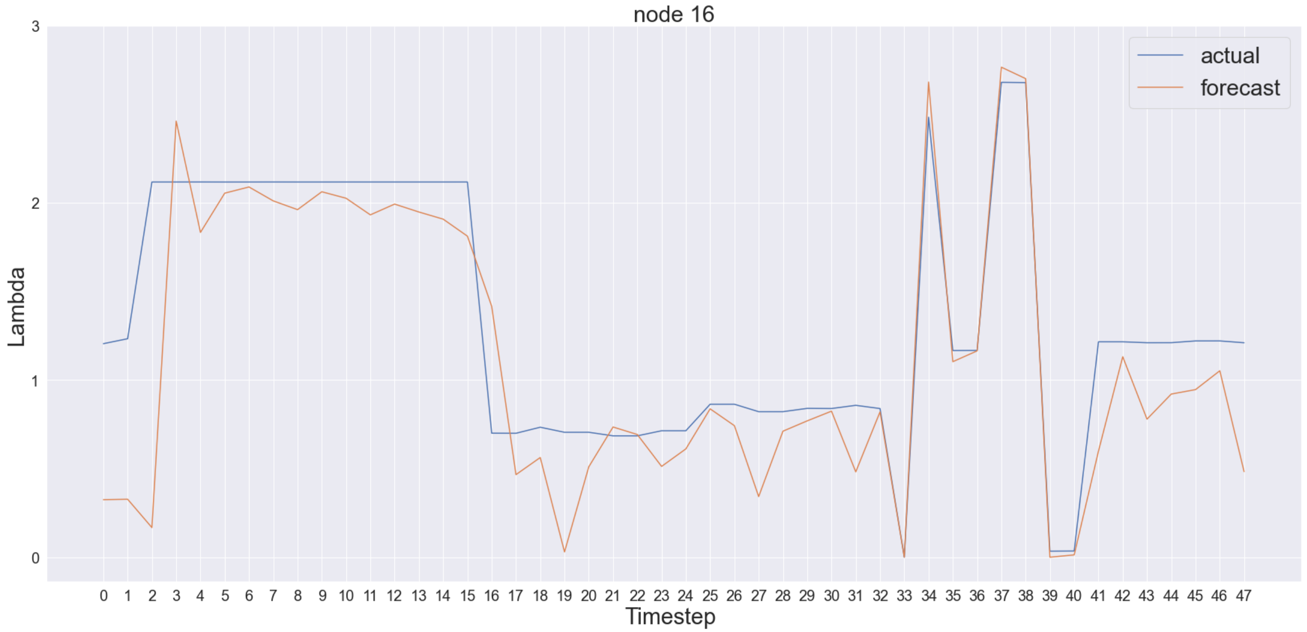
Case Study – Results



Actual vs Forecasted Lambda between timesteps 576-624 of the test dataset

Case Study – Results

True Lambda vs Predicted Lambda



Actual vs Forecasted Lambda between timesteps 576-624 of the test dataset

Conclusions

- The GCN+LSTM outperforms GCN and LSTM only models indicating that the combination of the two allows for effective spatio-temporal learning.
- Our use of the custom loss function is justified as there is correlation between the accuracy of the binary marginal unit indicator and the performance in predicting DLMPs.
- Model can successfully predict spikes in DLMP which indicates that the model can learn some information about the physical properties of the distribution network that cause these spikes.
- The model still struggles to predict in periods of peak generation and low consumption which could be due to actual voltage violation rates being highly uncertain and difficult to predict.

Future Work

- Comparison to other SOTA algorithms for spatio-temporal learning such as bi-LSTM, Attention-LSTM or Attention-GCN.
- Looking at forecasting with bi-directional units and V2G systems.
- Turning deterministic forecasts into probabilistic forecasts using a quantile loss function.
- Continued investigation into cold-start forecasting and changes to input graph structure.

References

- Thank you for your attention, please feel free to ask questions.
- Email: arman.sarjou@city.ac.uk

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