Aggregation and Prediction of Energy Consumption Data

What is the Aggregation Level at which a Graph Neural Network Performs Optimally?

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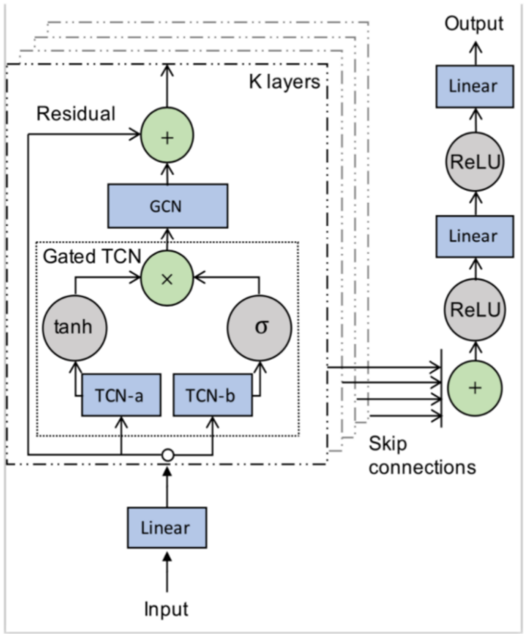
INTRODUCTION

With an increase in renewable energy sources, which are stochastic in their power supply, accurate demand predictions are needed to provide the optimal supply. Different types of methods have been proposed in the short-term load forecasting (STLF) problem, such as statistical and machine learning methods [1-2]. Recently, a new Graph Neural Network (GNN) has shown great improvement over other forecasting algorithms [3].

METHOD



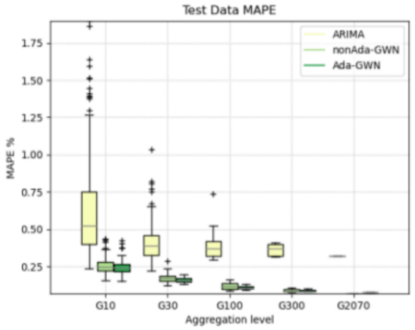
The framework for Graph WaveNet [3].

RESULTS

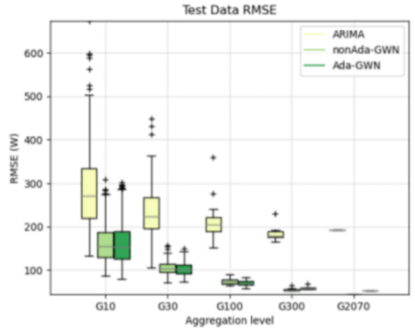
Both Ada-GWN and nonAda-GWN perform significantly better than ARIMA on all aggregation levels. Ada-GWN slightly outperforms nonAda-GWN.

At low aggregation levels, volatility in data makes it difficult for all models.

Both GWN models show improvement between two adjacent aggregation levels.



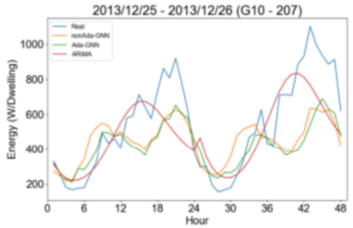
(a) The MAPE errors



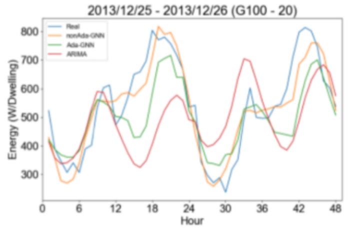
(b) The RMSE errors

Figure 1. The MAPE and RMSE errors of the models trained on all aggregation levels.

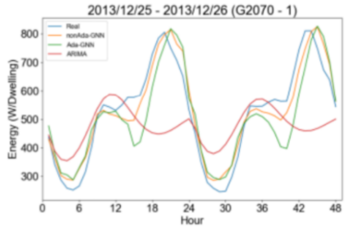
RESULTS



(a) Aggregation level 10



(b) Aggregation level 100



(c) Aggregation level 2070

Figure 2. Detailed prediction results of 25-26 December for different aggregation levels.

Model	MAE	MAPE	RMSE
Ada-GWN	22,2%	23,6%	22,63%
ARIMA	9,3%	15,1%	9,4%
nonAda-GWN	27,7%	28,71%	28,15%

Table1. Average percentage increase between adjacent aggregation levels.

CONCLUSION

This paper showed very low MAPE errors of 6,60 % and 7,89% at the highest aggregation level, comparable to country-level predictions.

Besides, although non-adaptive Graph WaveNet outperformed the baseline, self-adaptive Graph WaveNet was consistently and significantly better than non-adaptive Graph WaveNet. This shows that the spatial relationship between houses needs to be adaptively learned to improve the performance of spatial-temporal electric load forecasting.

Furthermore, we saw a consistent improvement in performance as the aggregation levels increased. This indicates that to achieve high STLF performances, we need to look at higher aggregation levels. We also observed a sharp increase in errors at lower aggregation levels.

The Graph WaveNet model also has limitations, including the need for a lot of training data without missing values and the requirement for consistent historical data length across all units. These challenges could be overcome with transfer learning.

REFERENCES

[1] Shyh-Jier Huang and Kuang-Rong Shih. "Short-term load forecasting via ARMA model identification including non-Gaussian process considerations". In: IEEE Transactions on Power Systems 18.2 (2003), pp. 673–679. doi: 10.1109/TPWRS.2003.811010.

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