From Time Series Models to Neural Networks: Predicting Energy Usage in Ontario

Dalla Lana School of Public Health

Amin Kharaghani, Huiyan (Ashley) Mao, Michael Prashad, Shuting Lou

Objectives

- To predict the hourly electricity demand in the residential sector in Ontario
- To explore the key predictors in forecasting hourly electricity usage
- To compare and evaluate the performance of four time series models and a neural network in predicting electricity usage

Methods

Data Source

- Hourly demand data (MW) for all sector (residential, industrial, etc) aggregated (IESO)*
- Annual demand (PJ) for each sector (NRCan)*
- Hourly air temperature and weather data (ETH Zurich and Imperial College London)*

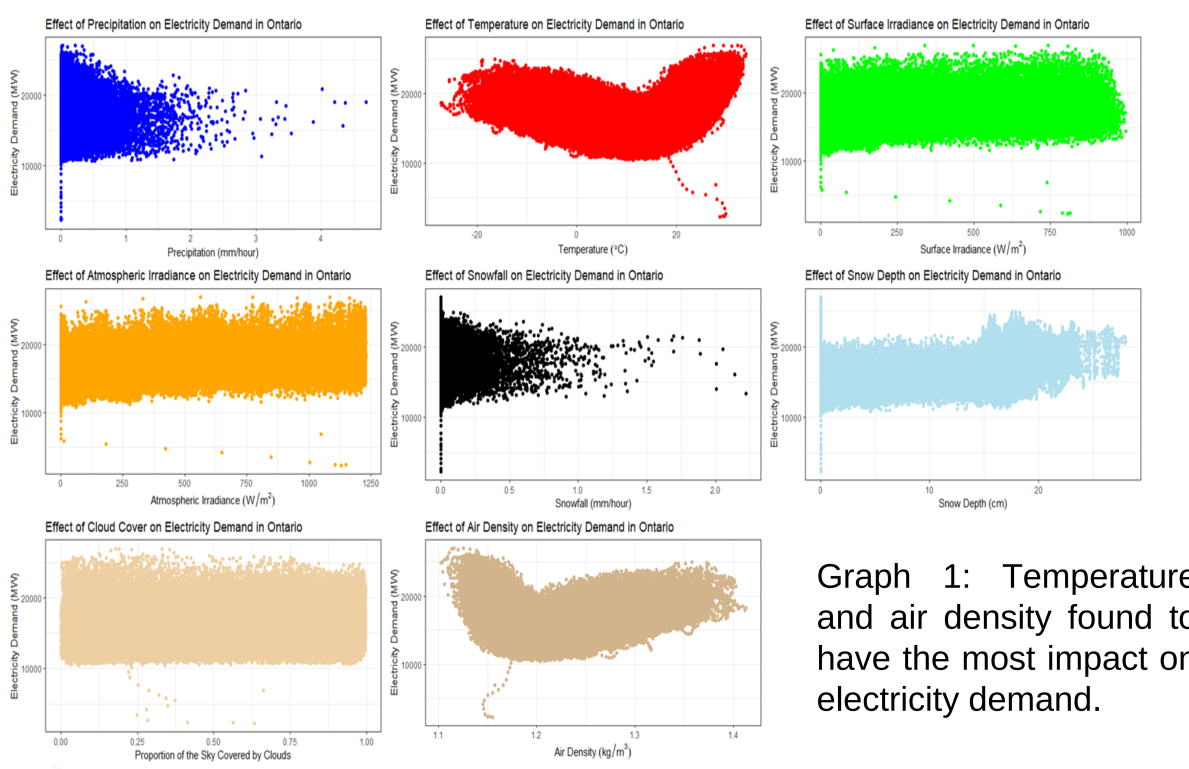
* All data from year 2003-2016

Software

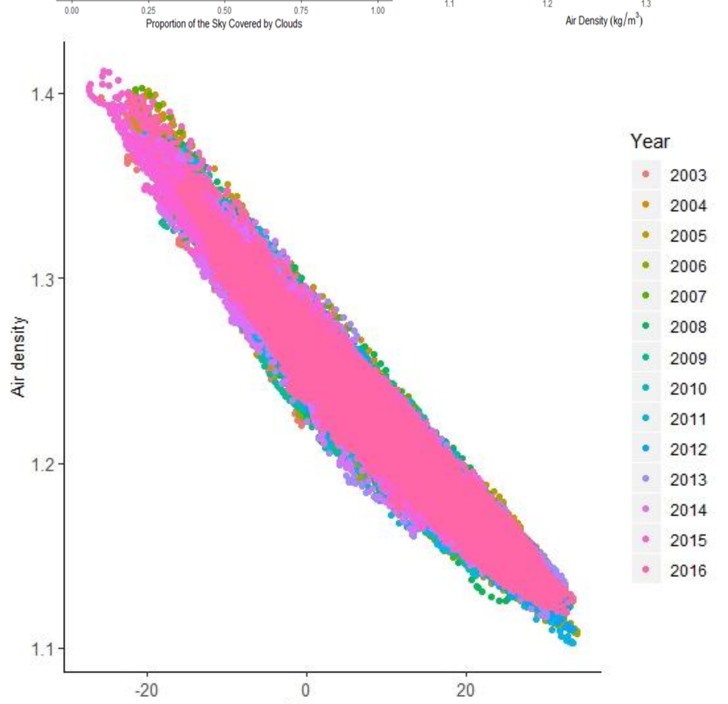
- R & Python

Variable Selection

- Temperature and air density have the most impact on energy usage, but they are highly correlated

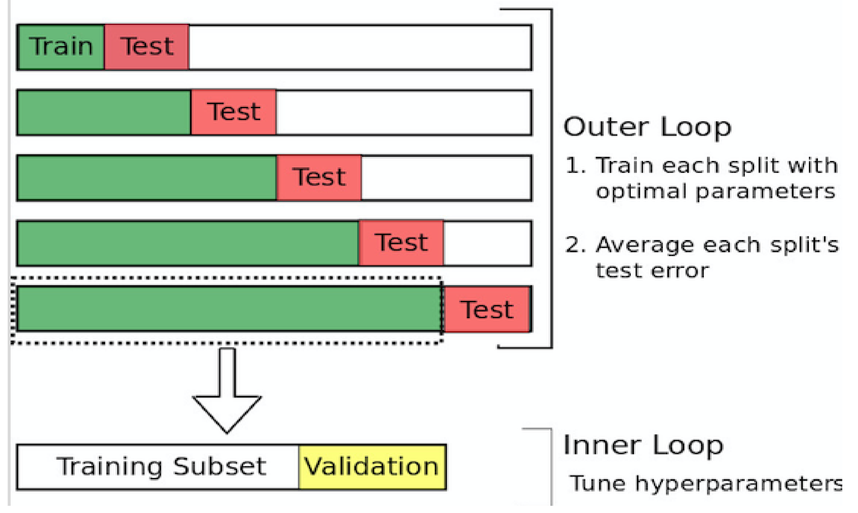


Graph 1: Temperature and air density found to have the most impact on electricity demand.



Graph 2: Temperature and air density found to be highly correlated

Training and Validation



Graph 3: Nested cross-validation was applied to train the model.

Models

1) Baseline

- Uses the average value as the predictor
- As a baseline of how well our other models are doing

2) Dynamic Harmonic Regression (DHR)

- Models the seasonal pattern using Fourier terms with short-term time series dynamics handled by an Autoregressive Moving Average (ARMA) error
- Allows any length seasonality (seasonality assumed fixed)

3) Seasonal Trend decomposition using Loess (STL)

- Decomposes a time series into seasonal trend, and irregular components using loess

4) Multiple Seasonal Trend decomposition using Loess (MSTL) and Exponential Smoothing (ETS)

- Energy demand is decomposed into five components: a trend, a daily seasonal component, a weekly seasonal component, a yearly seasonal component, and residuals
- Forecasts of the seasonally-adjusted data are obtained via exponential smoothing and are seasonalized again, using last year data.

5) Multiple Seasonal Trend decomposition using Loess Autoregressive Moving Average (MSTL-ARIMA)

- Identical to Model 4), except ARIMA is used in place of ETS

6) Long Short-Term Memory (LSTM)

- A powerful recurrent neural network that overcomes vanishing gradient problem for long sequence
- Conditional gates to decide what to carry onto the next memory block

Model Evaluation

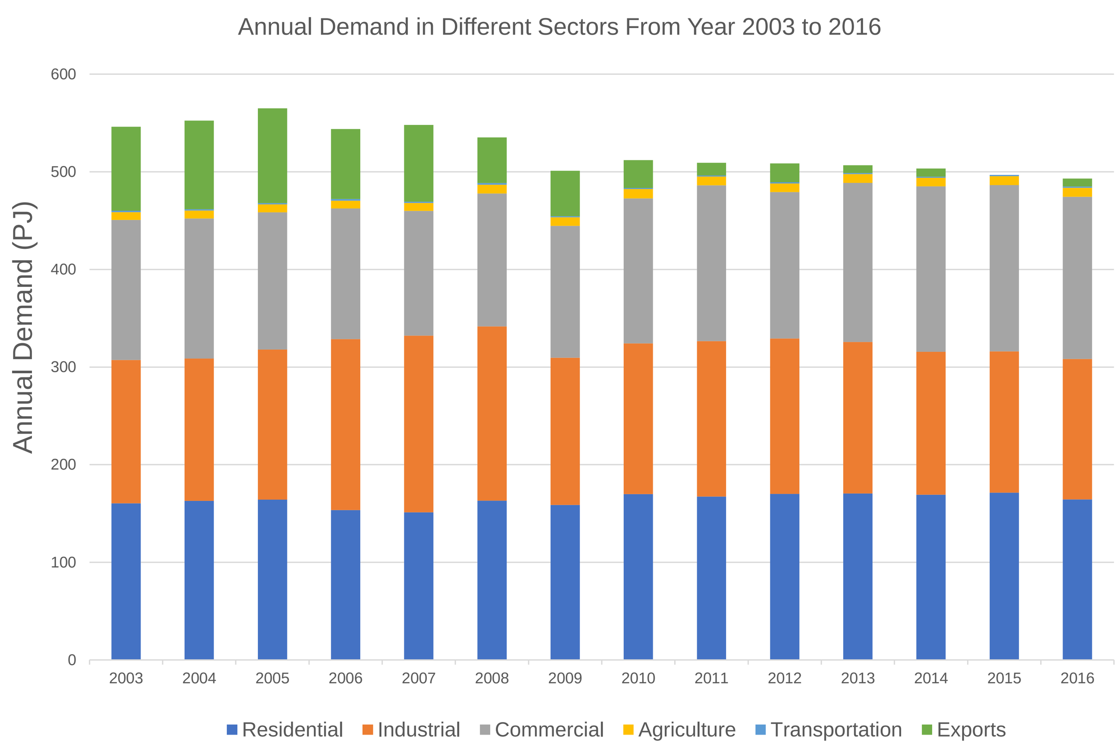
- Mean absolute error (MAE)

$$\text{MAE} = \frac{1}{n}\sum_{j=1}^{n}\left|y_j - \hat{y}_j\right|$$

Results

Hourly Usage on Residential Sector

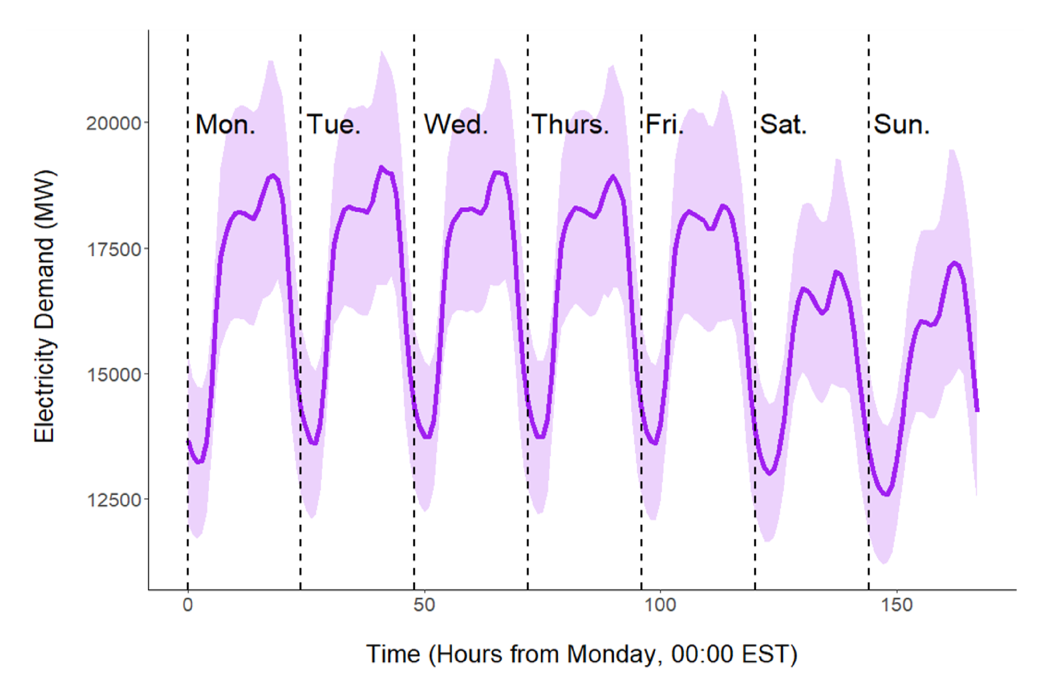
- The hourly electricity demand provided by the organizers well as exported energy
- Residential-specific usage was calculated using proportion (blue)



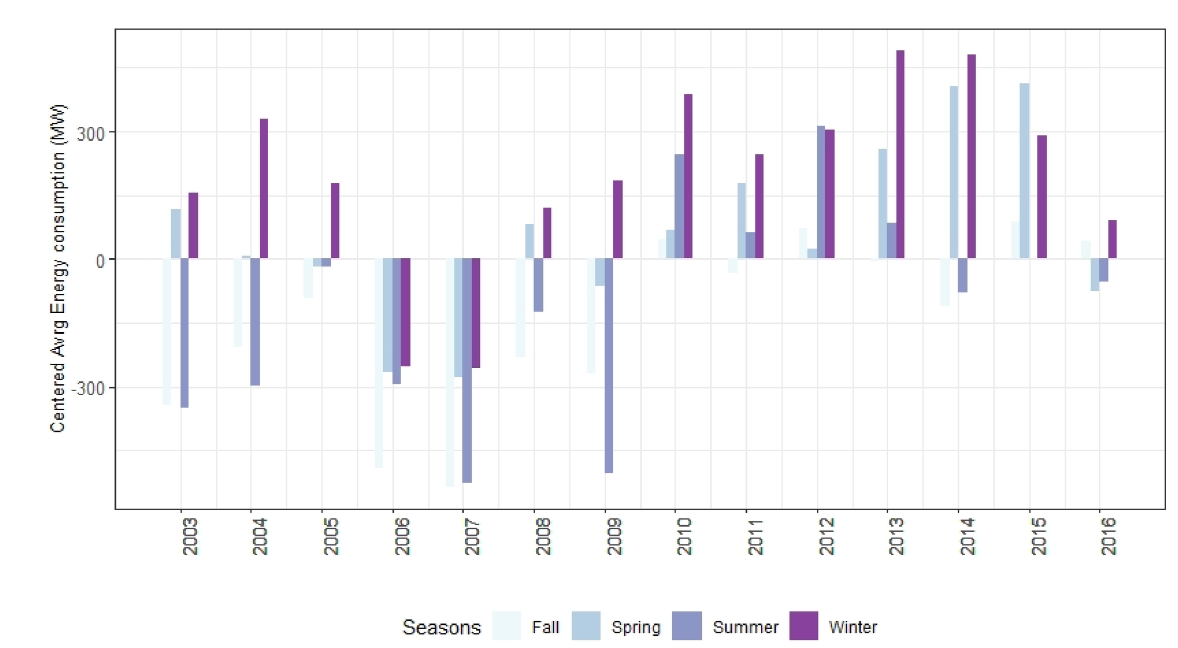
Graph 4: Annual energy production broken into all sections.

Electricity Usage Behaviour

- A clear daily trend, and a weekly trend as well as an annual trend behaviour is seen with energy usage, shown below.

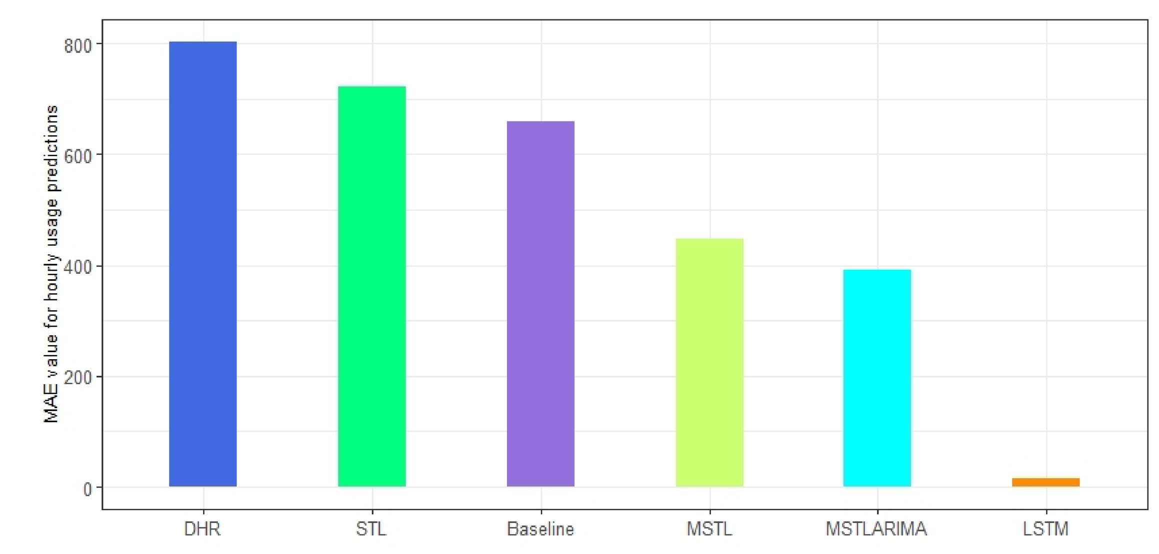


Graph 5: Weekly energy usage behaviour.

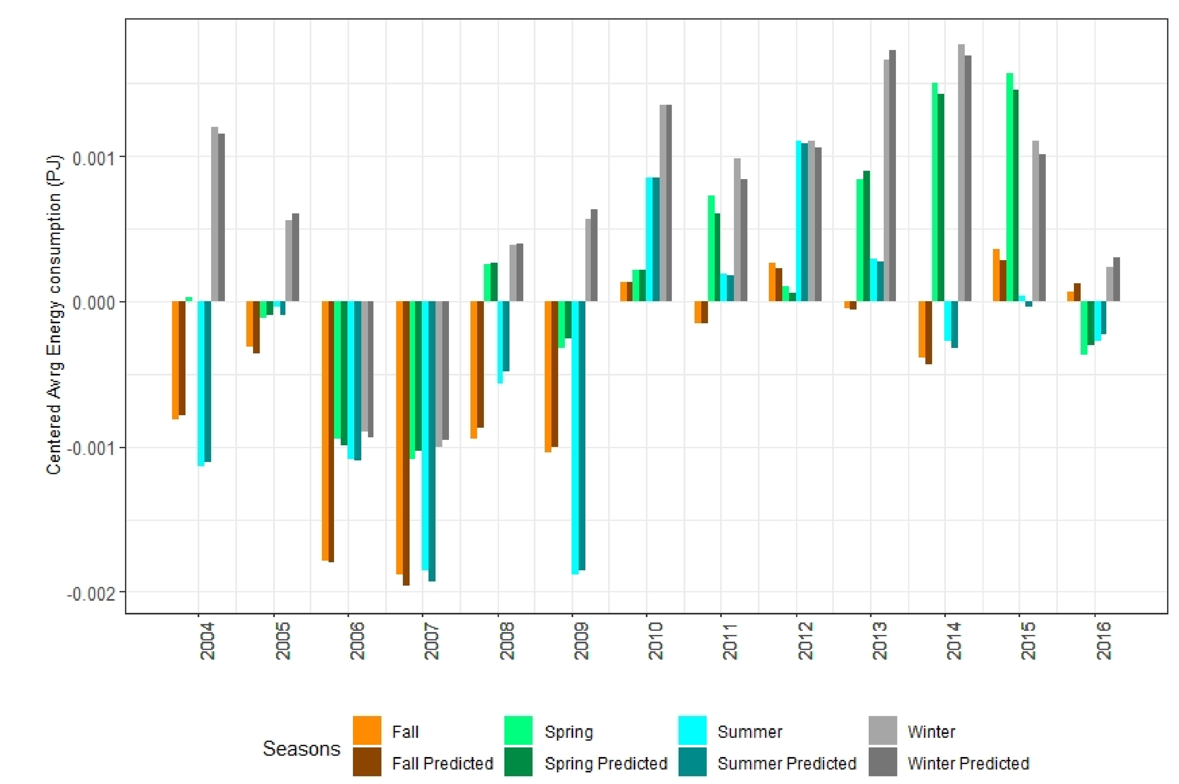


Graph 6: Daily, Weekly and annual energy usage behaviour.

Model Performance Evaluation



Graph 7: A comparison of the different methods we used, based on their MAE values in PJ. Predictions from LSTM had the lowest MAE value.



Graph 8: A seasonal comparison of predicted and actual energy demand for the residential sector, using LSTM model. The predicted demand closely followed the true energy usage,

Conclusion

- LSTM outcompeted the other models based on its minimized MAE value (14.62)
- Temperature and air-density are the important predictors for electricity usage
- This analysis prompts the possibility of using LSTM model in electricity demand forecast

References

De Livera, A. M., Hyndman, R. J., & Snyder, R. D. (2011). Forecasting time series with complex seasonal patterns using exponential smoothing. *J American Statistical Association*, *106*(496), 1513–1527.

Fan, S., & Hyndman, R. J. (2012). Short-term load forecasting based on a semi-parametric additive model. *IEEE Transactions on Power Systems*, *27*(1), 134–141.

Hyndman, R. J., & Fan, S. (2010). Density forecasting for long-term peak electricity demand. *IEEE Transactions on Power Systems*, *25*(2), 1142–1153.

Lee, Seunghui & Jung, Sungwon & Lee, Jaewook. (2019). Prediction Model Based on an Artificial Neural Network for User-Based Building Energy Consumption in South Korea. Energies. 12. 608. 10.3390/en12040608.

Song, K., Kwon, N., Anderson, K., Park, M., Lee, H.S. and Lee, S., 2017. Predicting hourly energy consumption in buildings using occupancy-related characteristics of end-user groups. *Energy and Buildings*, *156*, pp.121-133.

Edwards, Richard & New, Joshua & Parker, Lynne. (2012). Predicting Future Hourly Residential Electrical Consumption: A Machine Learning Case Study. Energy and Buildings - ENERG BLDG. 49. 591-603. 10.1016/j.enbuild.2012.03.010.

Brownlee, J., 2020. *Multivariate Time Series Forecasting With Lstms In Keras*. [online] Machine Learning Mastery. Available at: https://machinelearningmastery.com/multivariate-time-series-forecasting-lstms-keras/ [Accessed 23 May 2020].

UNIVERSITY OF TORONTO
DALLA LANA SCHOOL OF PUBLIC HEALTH