A Comparison of Hybrid and Statistical Time Series Forecasting Techniques for Short-Term Energy Demand Forecasting

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1. Introduction and Motivation

- The aim of this project is to compare the performance of a state-of-the-art *hybrid* forecasting model - winner of the M4 Competition **[1]** - with traditional statistical forecasting techniques, to assess the suitability of the model for short term energy demand forecasting
- Improvements in short-term energy demand forecasting can reduce the reliance on highly-polluting coal plants, thus reducing carbon emissions significantly
- Our primary contribution is including *contemporaneous* weather information as additional features in the LSTM

2. Statistical Benchmark Methodology

ARIMA Family

- **A**uto-**r**egressive **I**ntegrated **M**oving **A**verage models combine previous values of the time series $\boldsymbol{x_{t-p}}$, previous errors of the model $\boldsymbol{\epsilon_{t-q}}$, and optional differencing $\boldsymbol{x_t'}$ to generate forecasts:

$$x_t' = c + \phi_1 x_{t-1}' + \ldots + \phi_p x_{t-p}' + \theta_1 \epsilon_{t-1} + \ldots + \theta_q \epsilon_{t-q}$$

Exponential Smoothing Family

- Exponential Smoothing models attempt to decompose the time series $\boldsymbol{x_t}$ into multiple components: such as the level $\boldsymbol{l_t}$ and seasonality $\boldsymbol{s_t}$, and apply smoothing to these values in order to generate a forecast:

$$Level: \quad l_t = \alpha \frac{x_t}{s_t} + (1-\alpha) l_{t-1}$$

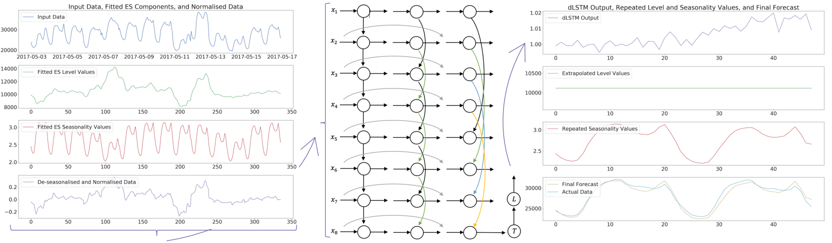
$$Seasonality: \quad s_{t+m} = \gamma \frac{x_t}{l_{t-1}} + (1-\gamma) s_t$$

Other Models

- These include naïve models that replicate recent (seasonal or non-seasonal) observations, and the *Theta method*

3. Hybrid Methodology

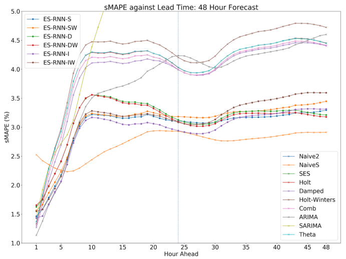
- The hybrid *ES-RNN* model, developed by Slawek Smyl of Uber Technologies **[2]**, uses multiple time series, representing energy generation, pricing, and demand, in order to generate a prediction for future demand
- The model is hierarchical, as it combines a global machine-learning component - a **dilated Long Short-Term Memory (LSTM)** neural network - that cross-learns across all the time series, with a local statistical component - an **Exponential Smoothing (ES) model** - whose parameters are individual to each time series



1. A simplified version of Holt-Winters' ES model is fitted to each time series in the dataset.
2. This generates a *level* and *seasonality* component for each point in the series, which are used to normalise the series.
3. The series are then individually inputted into the LSTM, which has *dilated* connections to help learn the seasonality
4. The dLSTM output then passes through non-linear and linear layers to give a vector of the correct length
5. This is re-seasonalised and de-normalised using saved seasonality and level values, giving the final forecast

4. Experiments and Results

- We tested the models on four years of Spanish system-level hourly energy demand data. We split the data by year and by season, giving 16 series across which we averaged the models' performance
- In the short-term, the ARIMA model performed optimally. For longer-term forecasts, the seasonal naïve model (*NaiveS*) was superior.
- The hybrid models were found to be able to accurately generate both short-term and long-term forecasts



Method	OWA
NaiveS	0.790
ES-RNN-DW	0.802
ES-RNN-D	0.810
ES-RNN-I	0.832
ES-RNN-S	0.867
ES-RNN-SW	0.916
ES-RNN-IW	0.921
Comb	0.992
Holt	0.999
SES	1.000
Naive2	1.000
Theta	1.000
Damped	1.002
Holt-Winters	1.073
ARIMA	1.171
SARIMA	2.196
Naive1	3.811

The OWA measures the relative improvement over the seasonally-adjusted naïve method (*Naive2*)

5. Conclusions and Future Work

- In this project, we used four years of hourly energy demand data to compare empirically the short-term forecasting accuracy of six variants of the hybrid ES-RNN model to eleven statistical forecasting models
- We found that for forecast horizons of up to 6 hours, the ARIMA model performs optimally. When forecasting at longer horizons, the naive seasonal method is dominant. For consistent forecasts across all lead times, the novel hybrid models introduced in this project are shown to be preferable
- In future work, we wish to include *forecasted* weather information, as we believe this likely holds the key to generating more accurate long-term forecasts

6. References

[1] S. Makridakis, E. Spiliotis, and V. Assimakopoulos, "The m4 com- petition: 100,000 time series and 61 forecasting methods", Inter- national Journal of Forecasting, vol. 36, no. 1, pp. 54–74, 2020.

[2] S. Smyl, "A hybrid method of exponential smoothing and recur- rent neural networks for time series forecasting", International Journal of Forecasting, vol. 36, no. 1, pp. 75–85, 2020.