LOAD AND SOLAR POWER FORECASTING IN A RESIDENTIAL DISTRIBUTED ENERGY SYSTEM

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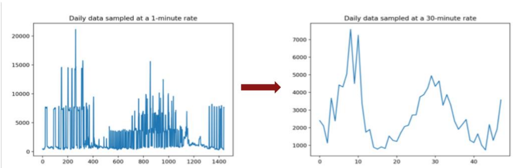
Introduction

Load forecasting is the predicting of electrical power required to meet the demand of the users in the grid.
Electrical load helps the electrical generating and distribution companies:

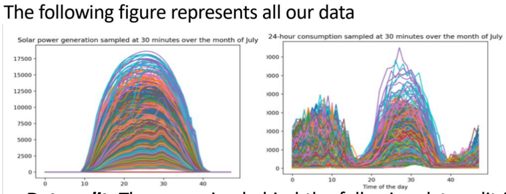
- Plan their capacity and operations in order to reliably supply all consumers with the required energy so that there are no under generation or over generation.
- Helps in deciding and planning for maintenance of the power systems with least impact on users.

Data

- ***Data presentation:*** We have obtained data for the month of July 2015 sampled at a rate of 1 minute for 95 houses. It starts on a Wednesday.
- ***Data preprocessing:*** The data sampled at 1-minute rate has very high variance and unclear pattern. So, we down sampled the data to a rate of 30 minutes where a fathomable pattern starts to form.



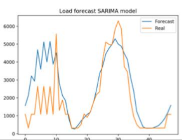
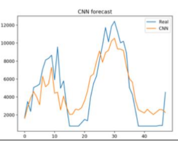
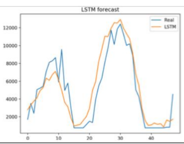
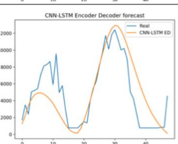
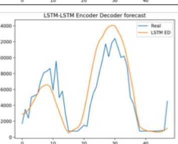
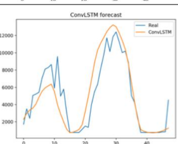
The following figure represents all our data



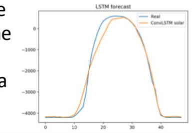
- ***Data split:*** The reasoning behind the following data split is that we wanted to train, develop, test our model on both weekdays and weekends. Therefore, training is first 21 days, development and testing are the next 10 days split equally, resulting in roughly a 70-15-15 split.

Models and Results

The input is a week worth of data and the output is the next day as a 48-step sequence. The metric used is NRMSE (Normalized Root Mean Squared Error)

SARIMAX		(1, 0, 1) (1, 0, 7, 48)	*RMSE*: 1170 kWh *NRMSE*: 33.45%
CNN		Conv1D Maxpooling Dropout Dense Dense	*RMSE*: 440 kWh *NRMSE*: 13.62%
LSTM		LSTM LSTM Dropout Dense Dense	*RMSE*: 376 kWh *NRMSE*: 11.64%
ENCODER-DECODER CNN-LSTM		Conv1D (Encoder) Maxpooling LSTM (Decoder) Dense Dense	*RMSE*: 487 kWh *NRMSE*: 15.09%
ENCODER-DECODER LSTM-LSTM		LSTM (Encoder) LSTM (Decoder) Dense Dense	*RMSE*: 366 kWh *NRMSE*: 11.36%
ConvLSTM		**ConvLSTM2D** **LSTM** **Dense** **Dense**	***RMSE*: 364 kWh** ***NRMSE*: 11.29%**

We have used the same ConvLSTM model on the solar data. We got an RMSE of 124 kWh and a NRMSE of 7.32%



Discussion

- The results were good and equivalent, in some cases an improvement of what is seen in the literature.
- The best performance is the one of the ConvLSTM model. It is also the second fastest model to train after the CNN. It is fast because unlike a traditional LSTM model, it relies on parameter sharing.
- The fastest model to train is the CNN model. However it tends to overfit easily. Therefore we used Dropout and early stopping to achieve better performance on the test set.
- The LSTM-LSTM Encoder-Decoder model performs better than the CNN-LSTM Encoder-Decoder model because the encoding part of the first model is an LSTM which is particularly better at capturing and keeping time-series information even at further LSTM cells.

Future work

Future work is focused on integrating a battery (e.g. Tesla Powerwall) within the house, and trying to minimize spending on electricity making use of the battery to charge from PV panels and to adapt to the fluctuations of the price of electricity every day and season, and use solar.

References

[1] H. Shi et al., "Deep Learning for Household Load Forecasting—A Novel Pooling Deep RNN," in *IEEE Transactions on Smart Grid*, vol. 9, no. 5, pp. 5271-5280, Sept. 2018.
[2] S. Humeau et al. "Electricity load forecasting for residential customers: Exploiting aggregation and correlation between households," *2013 Sustainable Internet and ICT for Sustainability (SustainIT)*, Palermo, 2013, pp. 1-6.
[3] Xingjian Shi et al., "Convolutional LSTM Network: A Machine Learning Approach for Precipitation Nowcasting"
[4] Air quality forecasting using Convolutional LSTM (CS230) Shuo Sun, Gaoxiang Liu
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