Household Power Consumption Analysis and Forecasting

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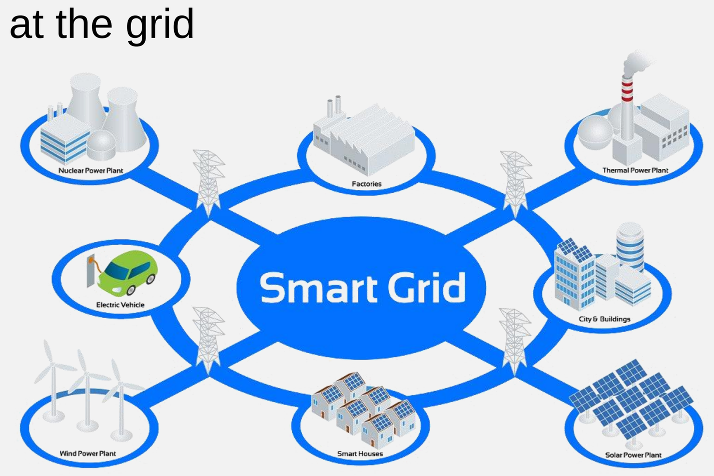
Introduction

What is Demand Response in Smart Grid?

Negotiation with the consumers to shift their electricity usage during peak hours in response to time-based rates or other incentives

Why is it important?

- Balance electric demand and supply at the grid
- Reduce consumer's monthly bill
- Reduce carbon emissions

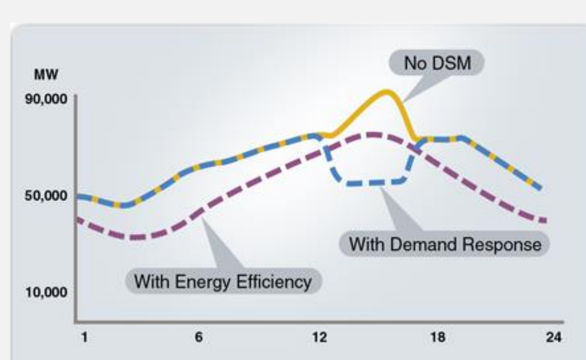


Challenges:

- Accurate prediction of peak hours
- Consumer profiling
- Awareness and understanding of the consumer about his load pattern

Objectives

- Explore the effects of the following on household electricity consumption:
  - Consumer's demographics
  - Static characteristics
  - Weather
  - Dynamic time-of-use (dToU) pricing
- Forecast short term energy consumption
- Make recommendations to the utility and consumer



Dataset

Project:
Low Carbon London Trial (LCL)
Location: London, UK
Time period: 2013
Households: 5567
dToU pricing: 1122

Smart Energy Meter Readings
(half-hourly)

Static characteristics
- Type of house
- Insulation material
- No. of rooms/occupants
- Type and number of appliances etc.

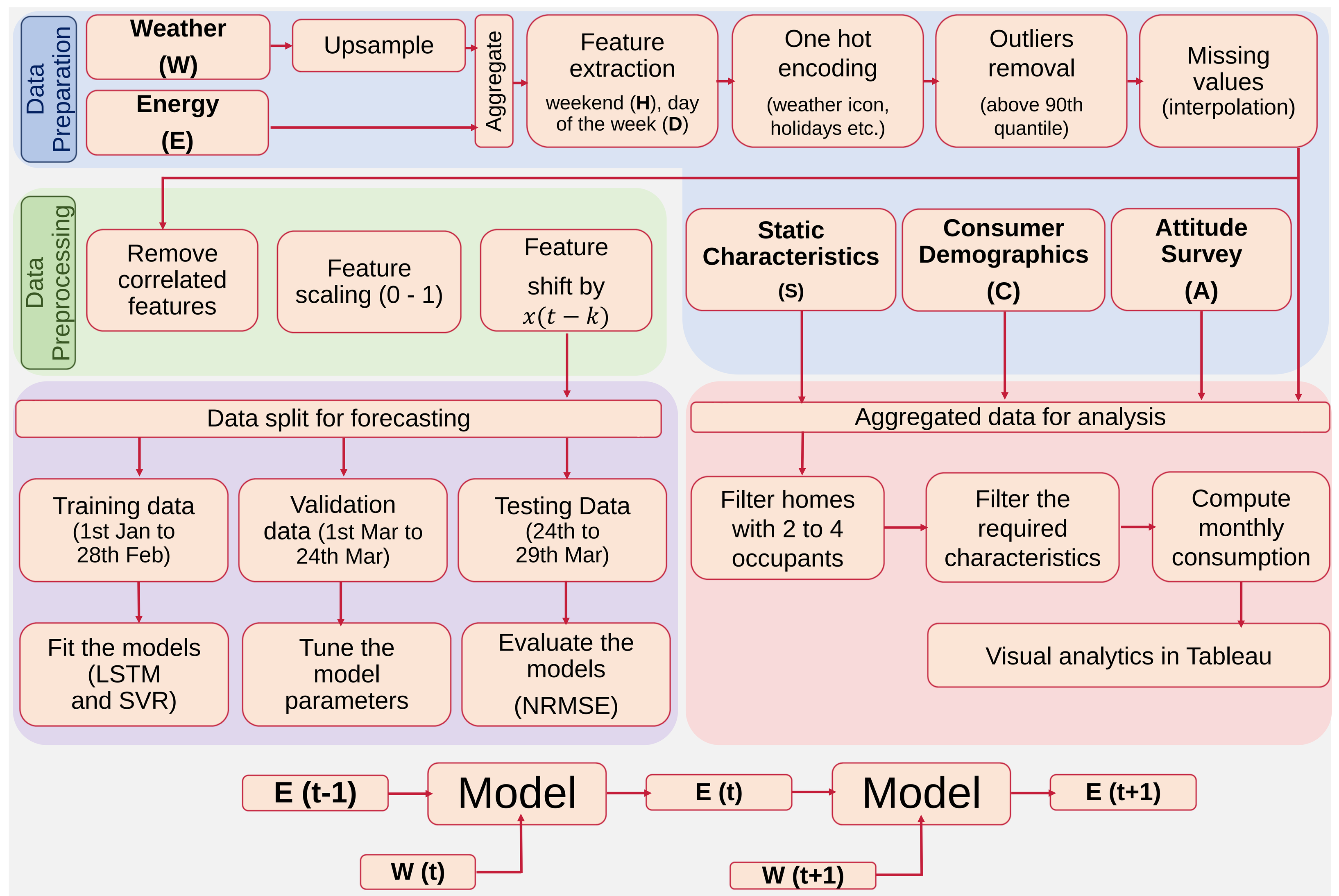
Consumer demographics
- Age category
- Income level
- Gender etc.

Survey data
- Attitude of consumers towards dToU

Hourly weather data
- Source: Dark Sky API
- Temperature
- Pressure
- Humidity
- Visibility
- Wind-speed

Limitations:
- Bulk of Missing categorical data for static characteristics and demographics
- Frequently changing weather data of London

Methodology



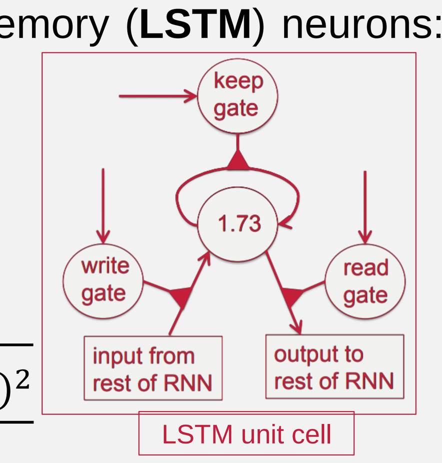
Techniques

- Recurrent Neural Networks (**RNN**) with Long-Short-Term-Memory (**LSTM**) neurons: 2 hidden layers, Adam Optimizer
- Support Vector Regression (**SVR**) with Gaussian Kernel

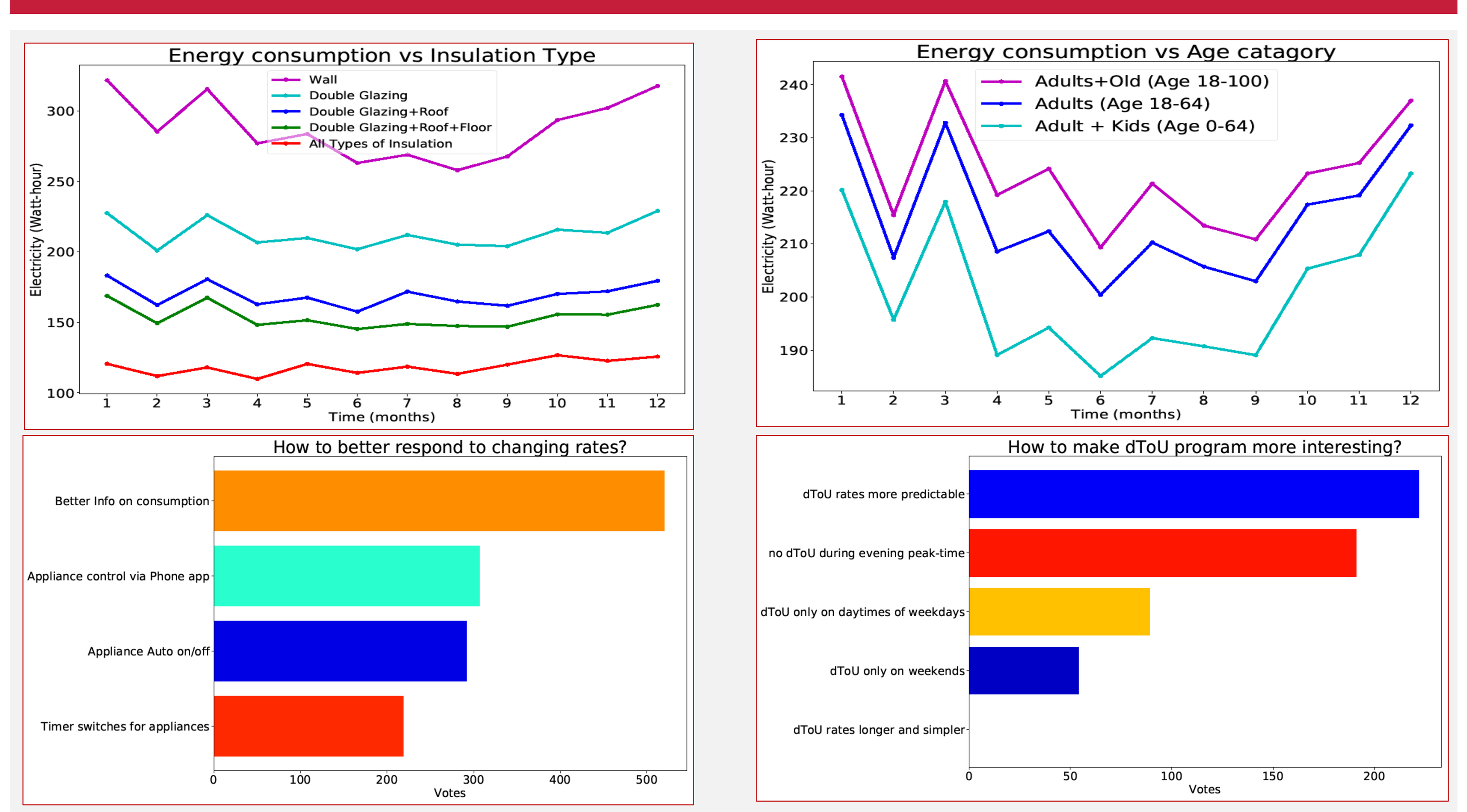
$$K(x,y) = exp(-\frac{||x-y||^2}{2\sigma^2})$$

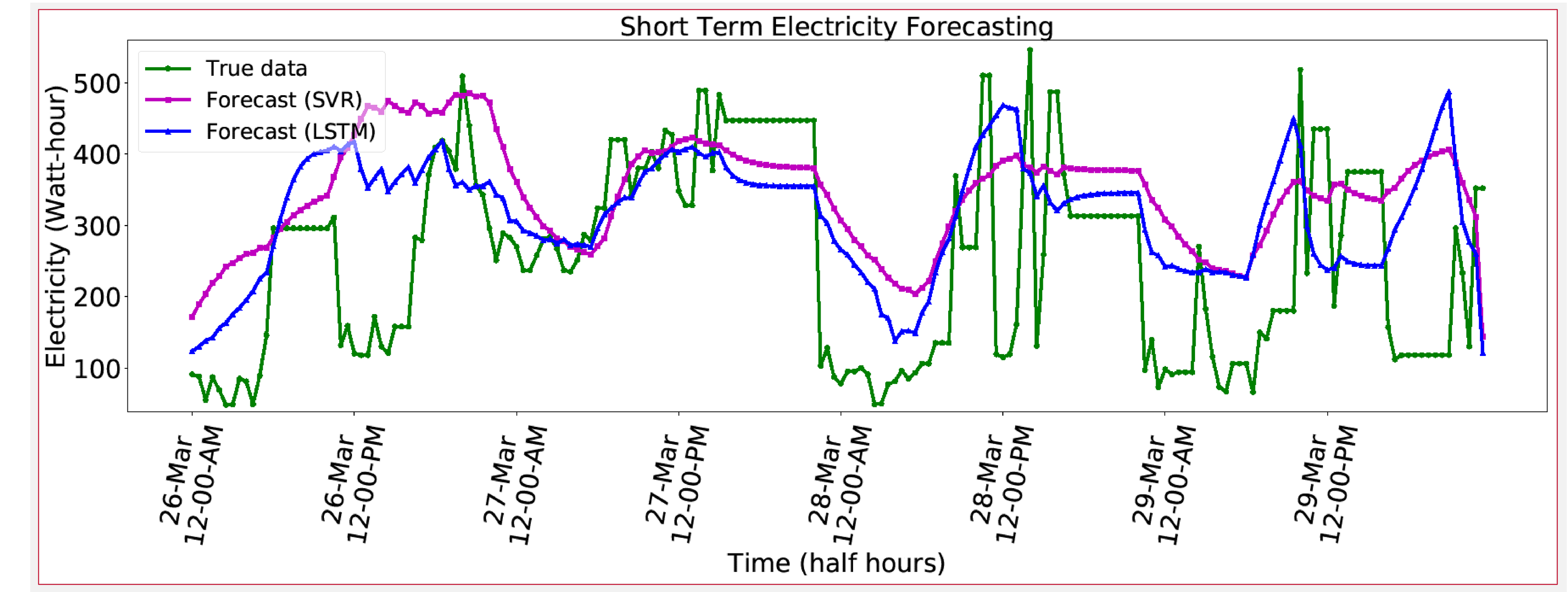
- **Evaluation metric**: Normalized Root Mean Square Error

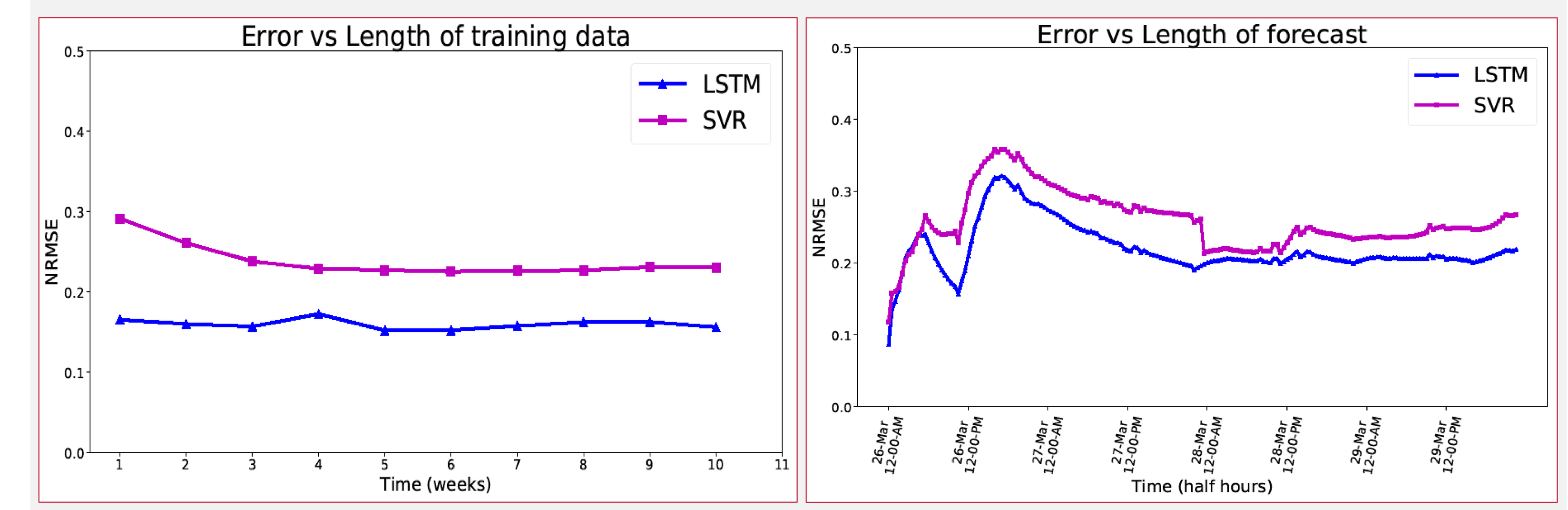
$$NRMSE = \frac{1}{y_{max} - y_{min}} \times \sqrt{\frac{\sum_{t=1}^{n}(y_p - y)^2}{n}}$$



Results







$NRMSE_{LSTM}$: 0.21 $NRMSE_{SVM}$: 0.28

Conclusions

- For short term forecasting:
  - LSTM networks perform slightly better than SVR
  - Small amount of training data is well sufficient
  - Error increases upon increasing the forecasting period
  - Weather parameters are not highly weighted
- Consumers can save up to 30.5% energy by using full insulations instead of the commonly used double glazing insulation
- Utilities can get better result out of dToU program by keeping the consumers well-informed about their consumption, and making the dToU more predictable e.g. every Sunday

Future Work

- Discover unique patterns in each house for real time personalized dynamic energy pricing

References

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