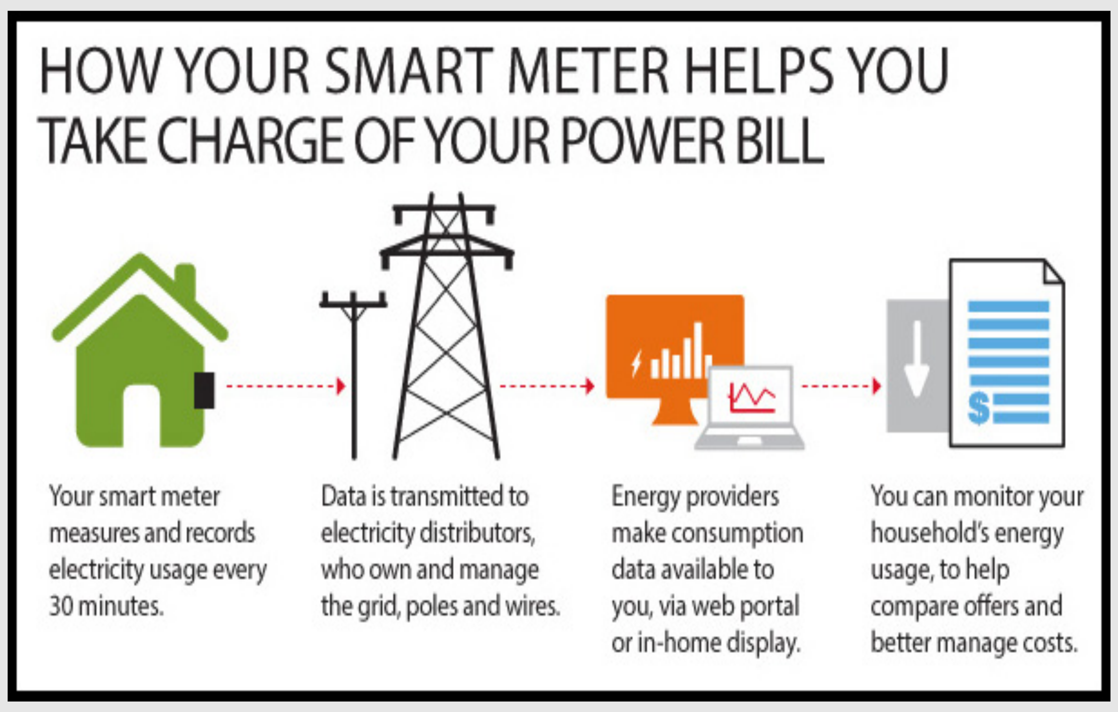
Energy Forecasting using Kalman Filters

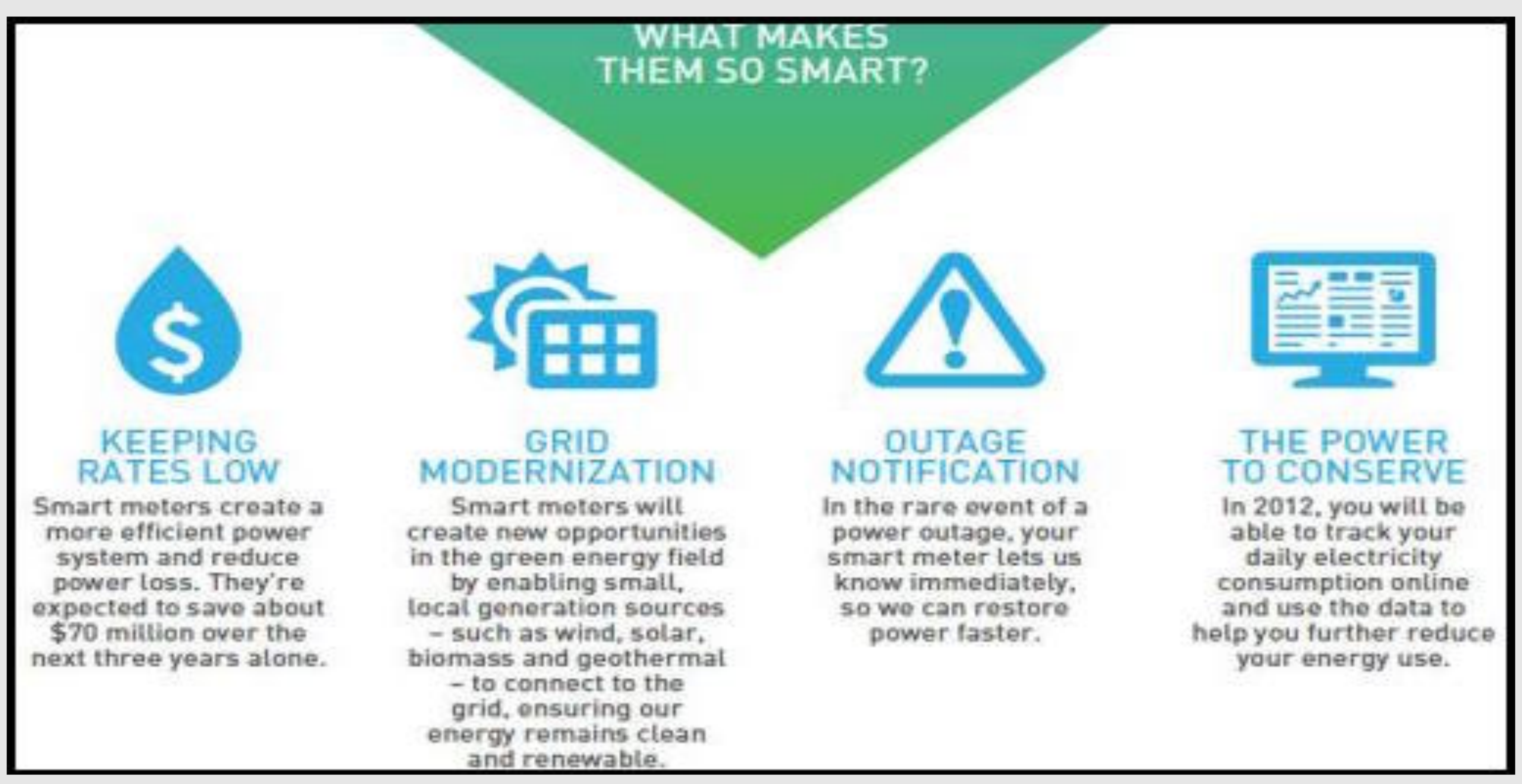
Megha Gupta and Angshul Majumdar
{megha1124, angshul} @iiitd.ac.in

Department of Computer Science, IIIT Delhi

Motivation

- Smart meters consists of real time sensors provide a host of benefits like energy efficiency and savings, improved retail competition, better demand, response actions, improved tariffs, accurate billing.





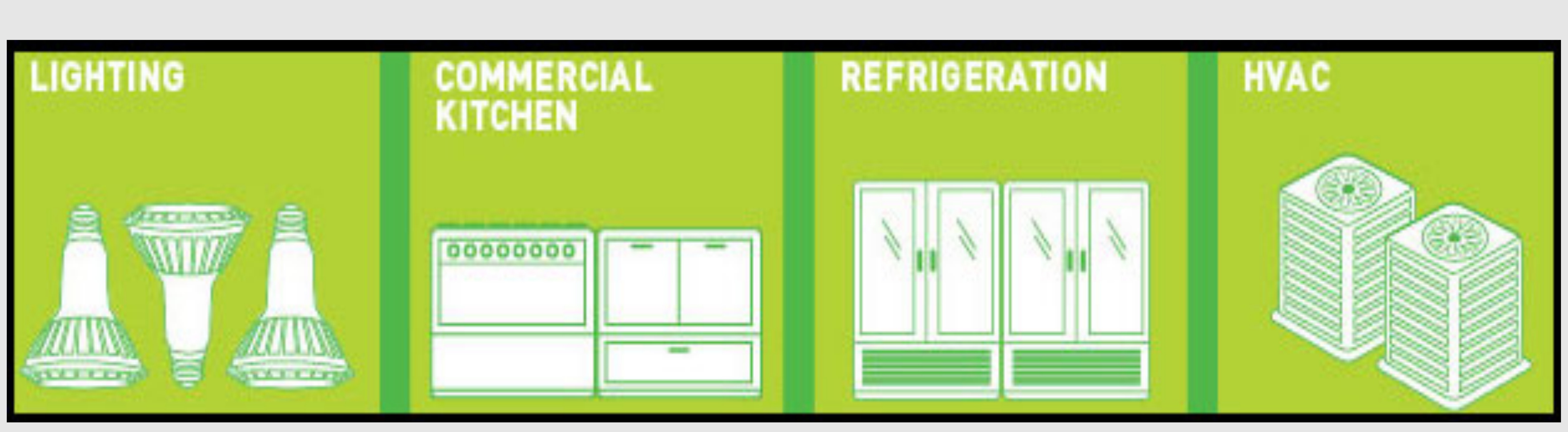
- They generate huge amount of time-series data that is used to gain meaningful insights. Machine learning has been applied to the problem of energy consumption and demand forecasting analysis.
- Energy forecast is usually divided into three classes, short term load forecast which ranges from 1 hour to 1 week (STLF), medium term forecast (MTLF) which ranges from 1 week to 1 year and long term forecast (LTLF) which is mostly more than a year.

Objective

- The problem concerns the prediction of future values of time–series (TS) data of electric load, leveraging previously observed history.

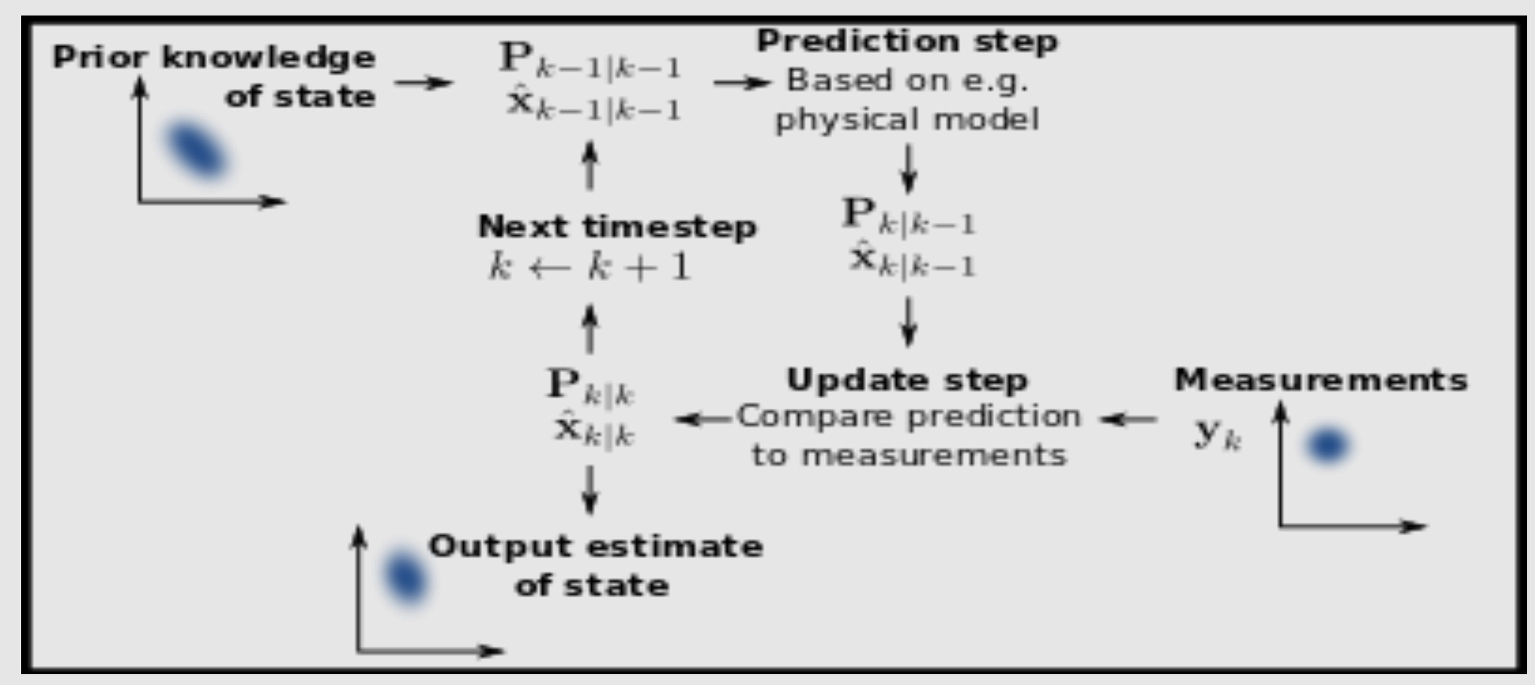
Dataset

We have used Reference Energy Disaggregation dataset (REDD) [1] that contains power consumption data from 6 real homes, for the whole house (channel 1 & 2) as well as the individual circuit (other channels) in the house. We perform experiments on 'house 2' and 'channel 1' data from REDD. The dataset has 31859 records and 2 columns.



Methodology

Given the past few days energy consumption data, we predict the consumption for the next day using Kalman Filters. Kalman Filtering is an algorithm that uses measurements obtained over a period of time containing noise and inaccuracies and produces estimates of unknown variables that happen to be more precise than those based on single measurements alone.
This algorithm works on two steps, prediction step and update step [2].



- We aggregate every 2 hours data per day for n days and predict the consumption for the (n+1)th day. The prediction is done over four phases in the day, that is morning, afternoon, evening and night.

Results

- The comparison is made across the no. of days learning takes place and across different phases in the day.

No.of days, n	Error % Phase 3, 7-9 am	Error % Phase 3, 12-2 pm	Error % Phase 2, 6-8 pm	Error % Phase 3, 9-11pm
3	85.67	85.79	95.18	86.22
5	85.66	85.73	61.13	77.2
7	37.98	14.98	98.73	53.23
9	85.61	60.46	85.68	59.73
11	61.61	62.37	36.25	99.4

Fig. 1 Experiment Results

Future Work

- Use other algorithms to compare like ARIMA, ESN for better comparison of the existing technique.
- Find better parameters in order to get better performance.
- Should be able to use this technique on long range forecasts as well.

References

1. http://redd.csail.mit.edu/
2. https://en.wikipedia.org/wiki/Kalman_filter