CS-2A

Forecasting Energy Demand

Presented by

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What will we cover?

1. Problem statement
2. Background concepts
   2.1. Time Series Data
   2.2. Time Series Forecasting Techniques
   2.3. Load Forecasting approaches
3. Case Study
   3.1. Feature Selection
   3.2. Modeling
   3.3. Results

Problem Statement

What is load forecasting?

Definition

- Load forecasting refers to estimating the future electric load for a given forecast horizon based on available information

Types of Load Forecasting

- Short Term Load Forecasting
  - 1 hour to 1 week forecast horizon
- Medium Term Load Forecasting
  - 1 week to 1 month forecast horizon
- Long Term Load Forecasting
  - months to years forecast horizon

Use Cases

- Operation and planning for entities like ISOs and utilities
- Trading in electricity market
- Load following
- Real time dispatch
- Operating reserves
- Smart-grid automation and control

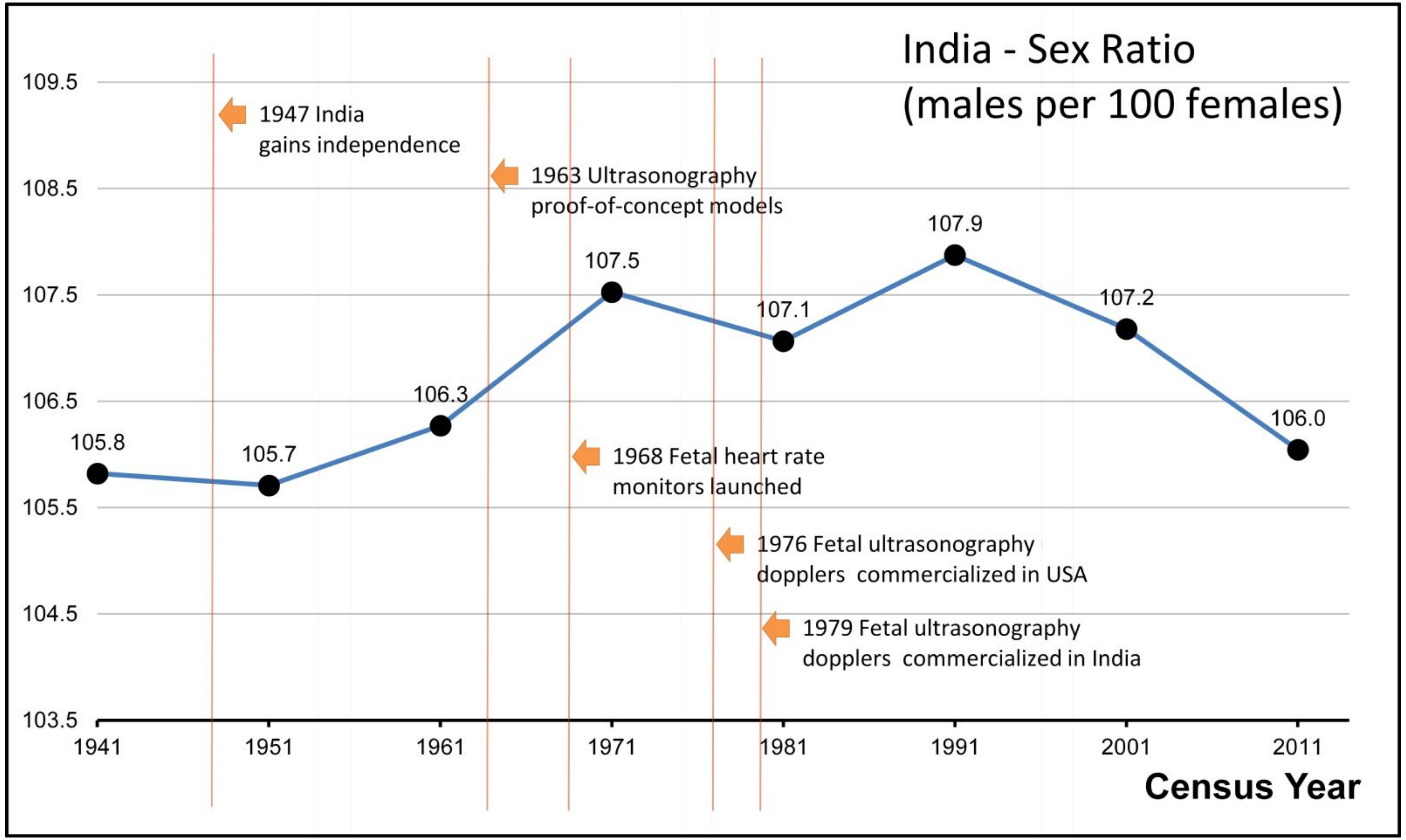
Background Concepts

How to deal with a problem like this?

Time Series Data

- Time series data is a sequence of data points arranged in time order
- Often the sequence consists of successive equally spaced points in time
- This spacing is known as the sampling interval
- Distinguishing characteristic is that successive records are dependent

Time Series Data Example - 1



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Time Series Data Example - 2

Stock Market Data

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Time Series Forecasting Techniques

- Regression
- Fuzzy time series
- Stochastic time series
- Deep learning

Regression

- Doesn’t care about the time series nature of the problem
- Needs to be fed with lag features to take into account past behaviour
- This approach to regression is called Autoregression

[Detailed Reading]

Fuzzy Time Series

- Models the time series using fuzzy sets
- Identifies rules the time series follows with respect to the fuzzy sets
- Uses these rules to generate predictions

[Detailed Reading]

Stochastic Time Series

- Assumes the time series has 4 components
  - Trend, Seasonality, Cyclical, Residual
- Consists of methods like ARMA, ARIMA, SARIMA etc.
- Combines different techniques to model the components of time series

Detailed Reading

Deep Learning

- Uses neural architectures fed with features to generate predictions
- Sequence to sequence models like RNNs are preferred
- Capable of modeling non-linear behaviour
- Handles sophisticated temporal dependence

Detailed Reading

Load Forecasting : A Brief History

- In the late 19th century, electricity was primarily used for lighting
- Load forecasting was very straightforward
    - Count the number of bulbs installed
    - Use this to estimate the rough load in the evening
- This archaic method is used to this date to forecast street light loads

Load Forecasting : A Brief History

- As variety of electrical appliances grew forecasting became non-trivial
- With HVAC penetration demand was highly affected by weather
- Since software was not ubiquitous manual methods were built
- This led to the rise of HDD, CDD, wind-chill factor etc.
- Similar day method, still used by many utilities, was also developed

Load Forecasting : A Brief History

- In 1980s computer based forecasting methods were first developed
- These were primarily long term load forecasts (years to decades)
- In 1990s short term load forecasting rose to prominence
- The complexity was met by AI based approaches
- Although wide adoption was hindered by black-box nature of models

Load Forecasting : A Brief History

- Today in the era of smart grids load forecasting is very complicated
    - Renewable energy generation
    - Increasing electrification (appliances like EV)
    - Behavioral complexities
- Most utilities operate with ~3% day-ahead load forecast error

Case Study

Load forecasting for Smart Utilities

Feature Selection

- Results are only as good as the information provided to the model
- In forecasting the features selected should adhere to the following
  - Be able to explain some component of the behaviour
  - As a set explain non-overlapping components of the behaviour
- Some models require these explanations to conform to requirements
  - Eg. Autoregression models expect the features to linearly impact the behaviour

Feature Selection

- Some types of features for load forecasting
  - Load features
  - Weather features
  - Time and event features

Modeling

- Traditional models are unable to model complex behaviour well

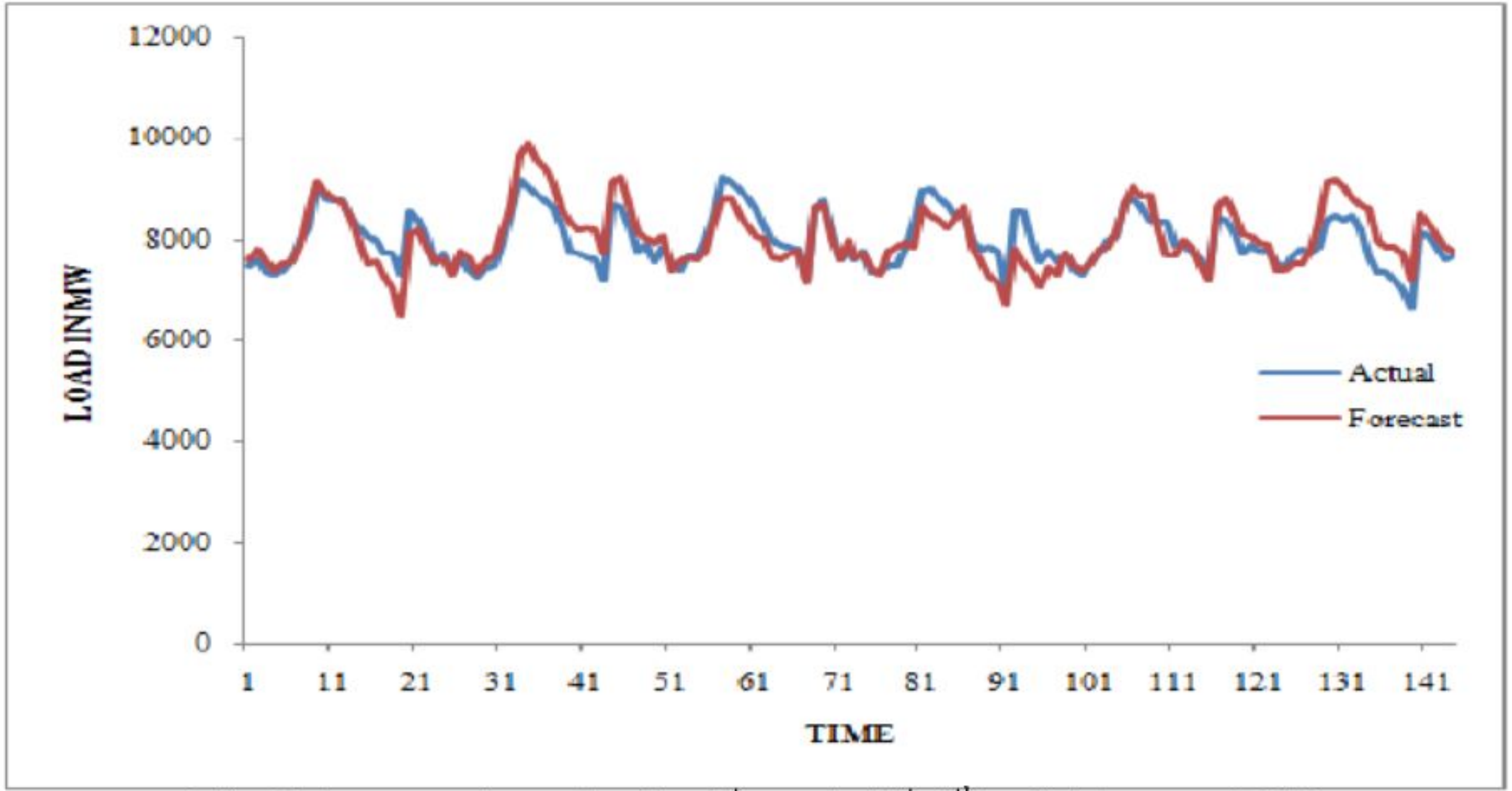
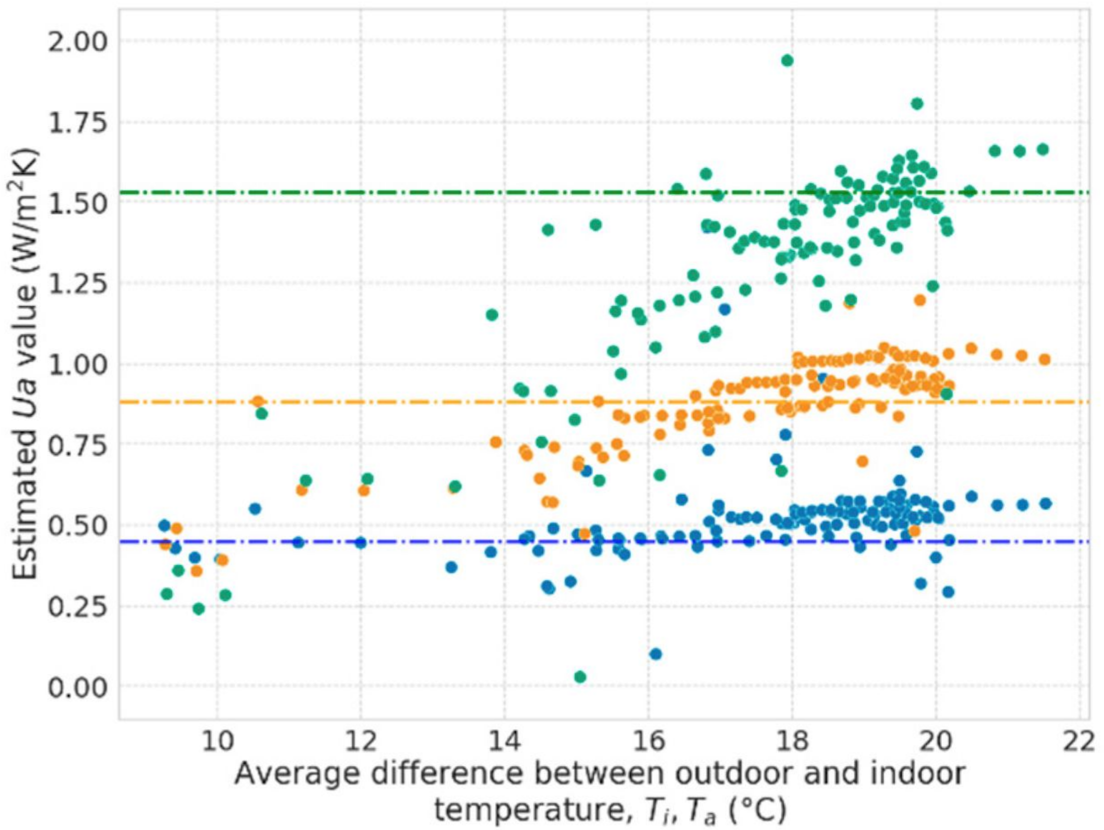


Fig.3 Forecasted results for 1st week (1st-7th) of February 2016

ARIMA Model
Error - 4.74% MAPE
Source

Modeling

- Introduction of renewable energy and EVs are increasing complexity
- Deep learning models are capable of modeling non-linear relations



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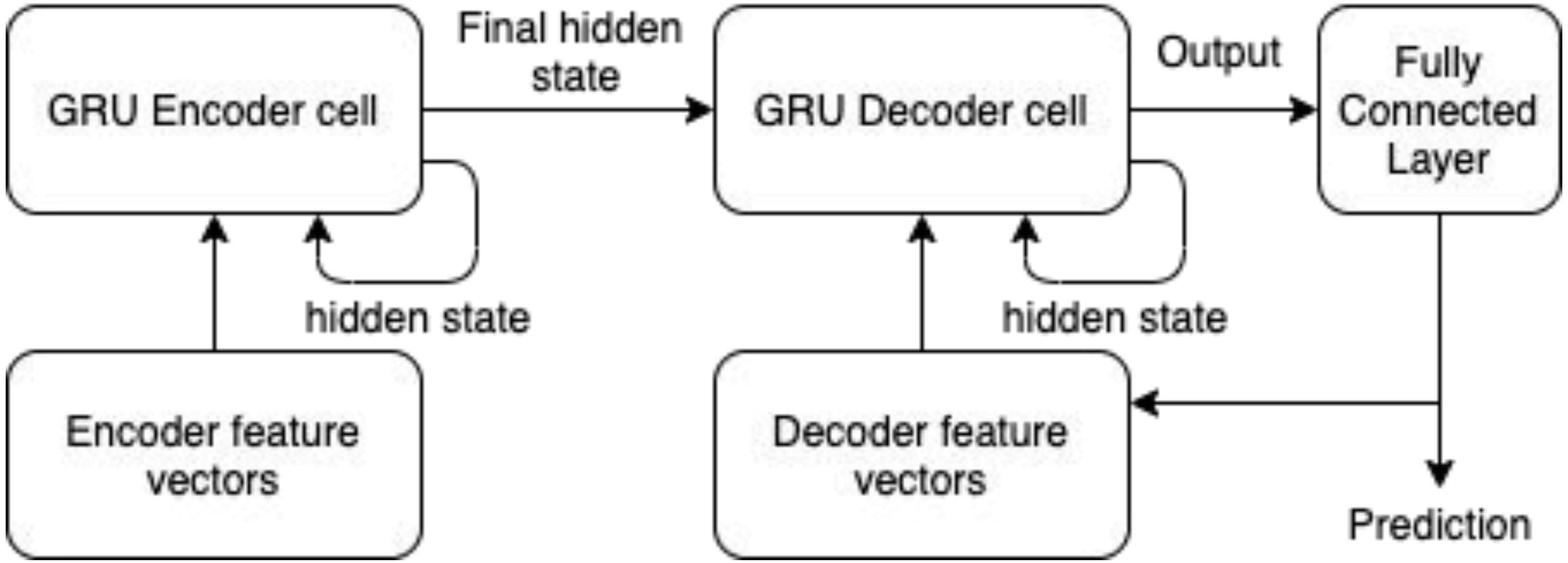
Modeling : Our Approach

- We use a GRU-cell based encoder-decoder architecture



Modeling : Key Decisions

- Why a deep learning model?
  - Capable of modeling complex non-linear relationships
  - In such scenarios, Traditional models require massive and sometimes impossible levels of feature engineering to achieve barely comparable results
  - Flexibility allows for wide applicability

Modeling : Key Decisions

- Why a GRU-RNN model?
  - Time series is sequential data and RNNs are designed to model sequential data
  - GRU vs LSTM
    - Unlike an NLP task (typical LSTM use case) here memory based context is much simpler
    - Choosing a less complex cell saves training time and requires significantly lesser data
  - RNN provides the flexibility for variable length of context

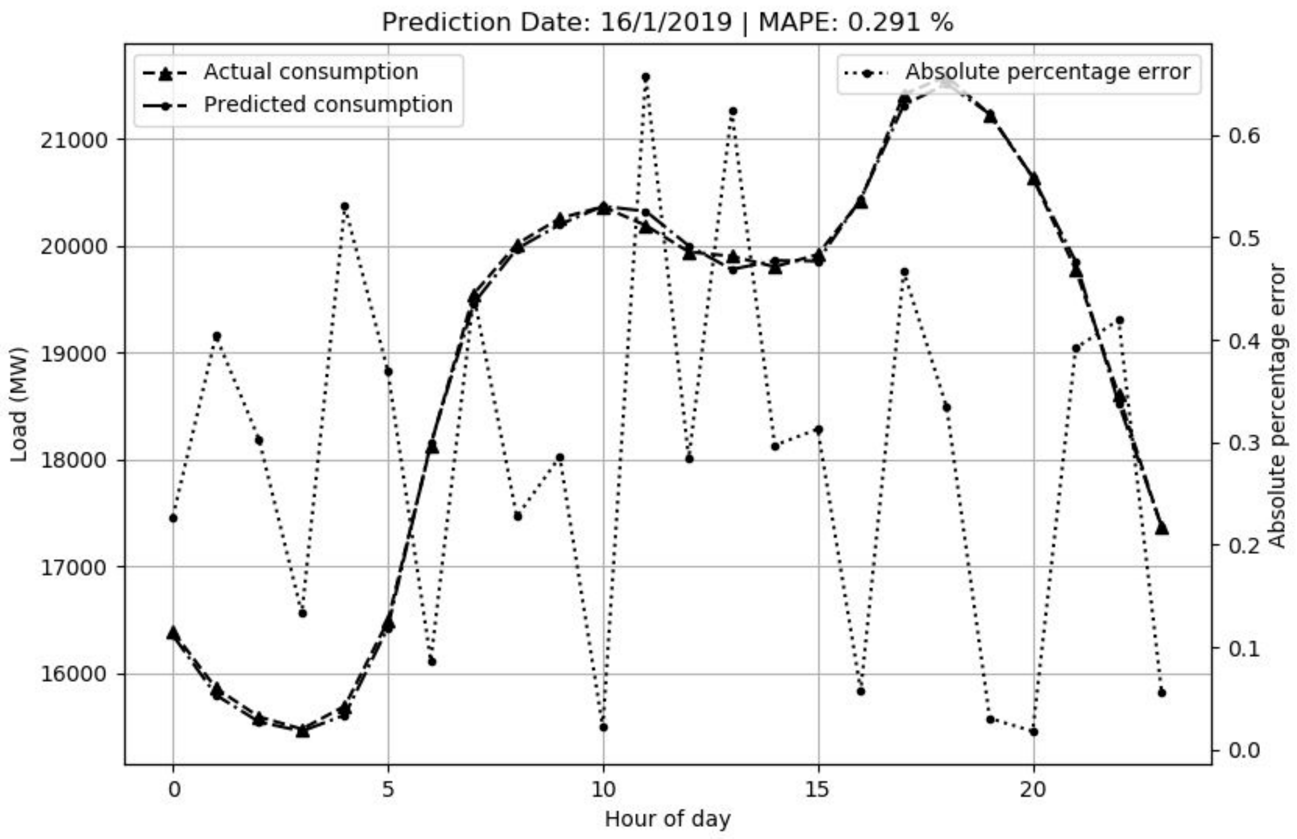
Model : Capabilities

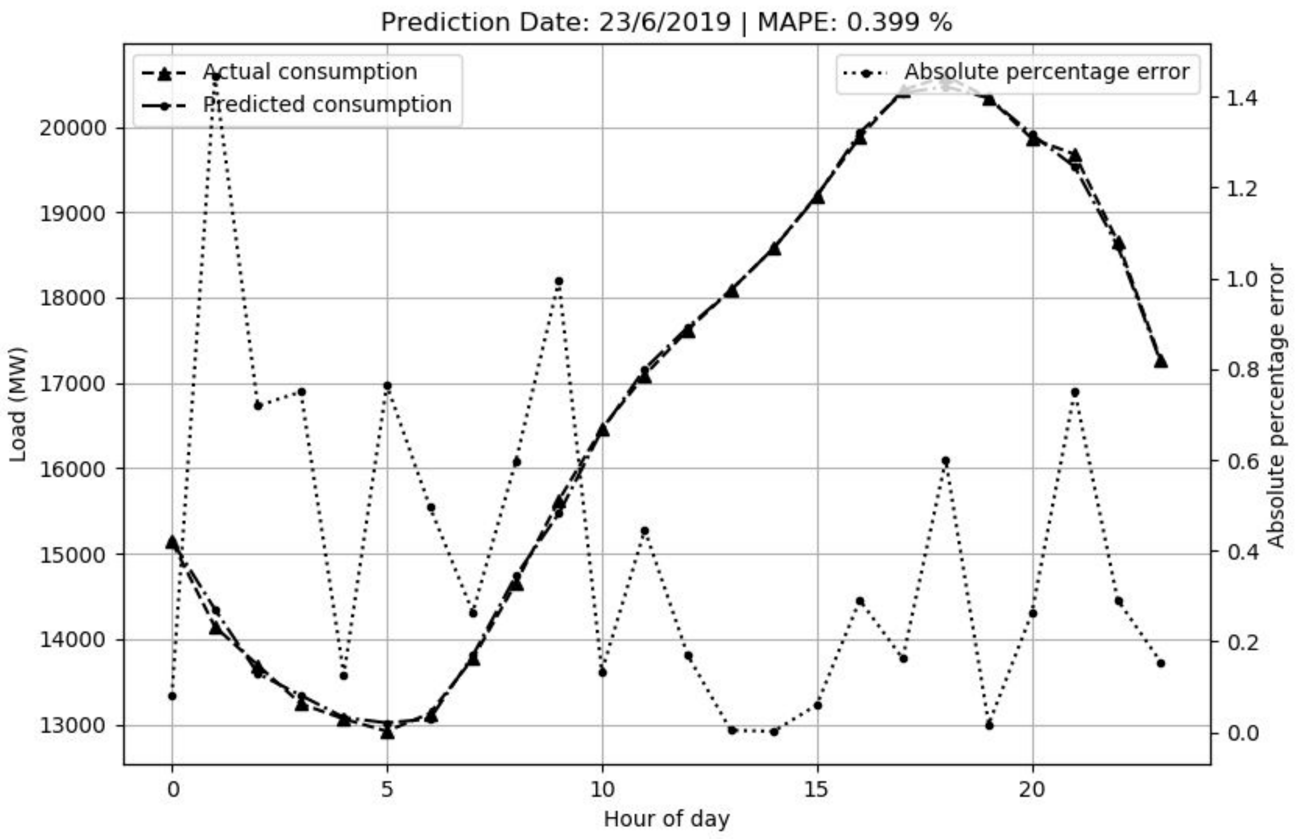
- Prediction at hourly frequency for n-days ahead
- Can use however many days of context available
  - For evaluation we use n-days before context for a n-days ahead prediction
- Even with less training data a base model can use transfer learning
- Adapts quickly to change in behaviour using the context
- Can be used for a single house to complete grid

Evaluation: NY-ISO dataset

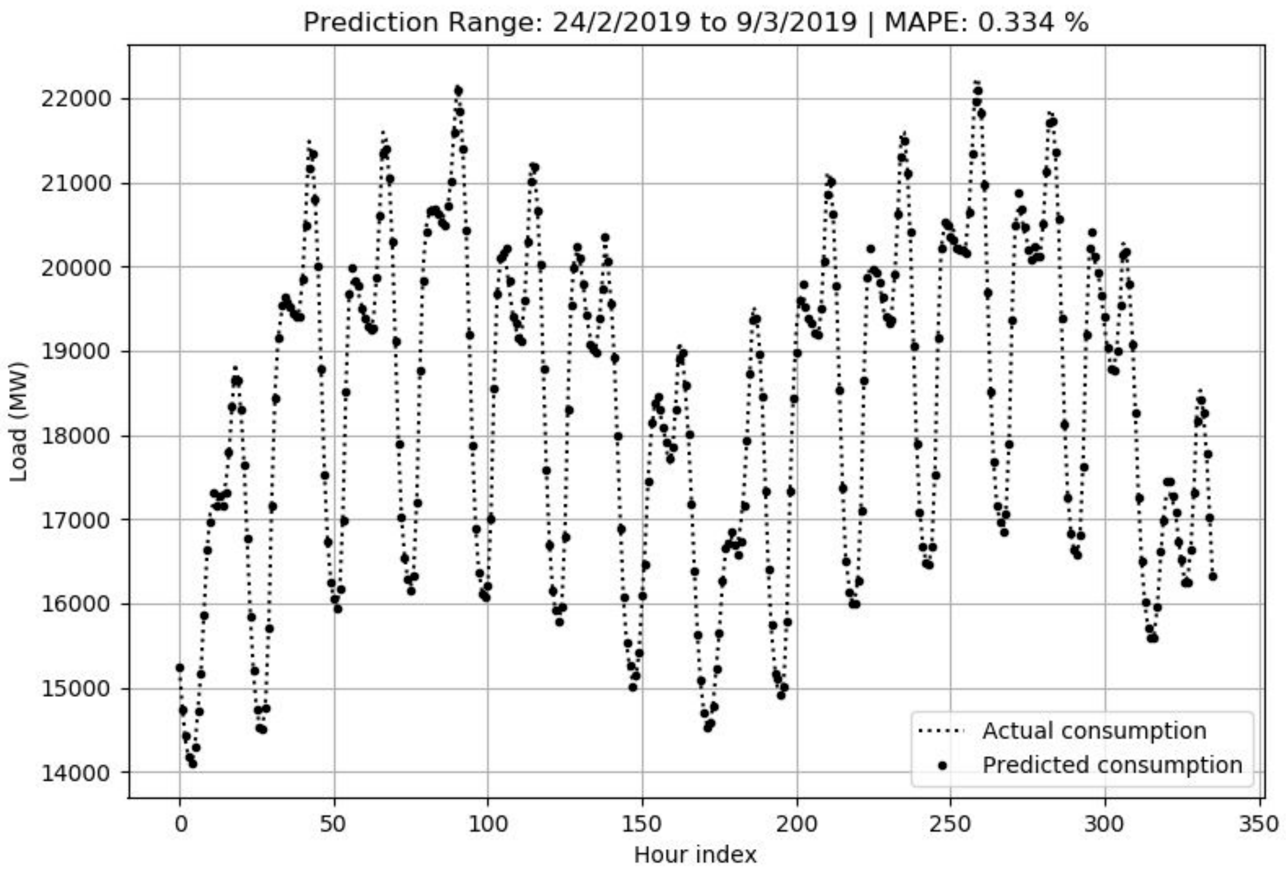
- For standardised results we evaluated the model on NY-ISO dataset
- Metric used was Mean Absolute Percentage Error (MAPE)
- NYISO currently uses a model with 1-day ahead error of 1-2%
- SoTA is currently at 0.61% MAPE for 1-day ahead forecast
- We used data from 2015 to 2018 to train and data from 2019 to test
- 1-day ahead and 14-day ahead predictions were evaluated
    - Context of n days was provided for an n-day ahead prediction

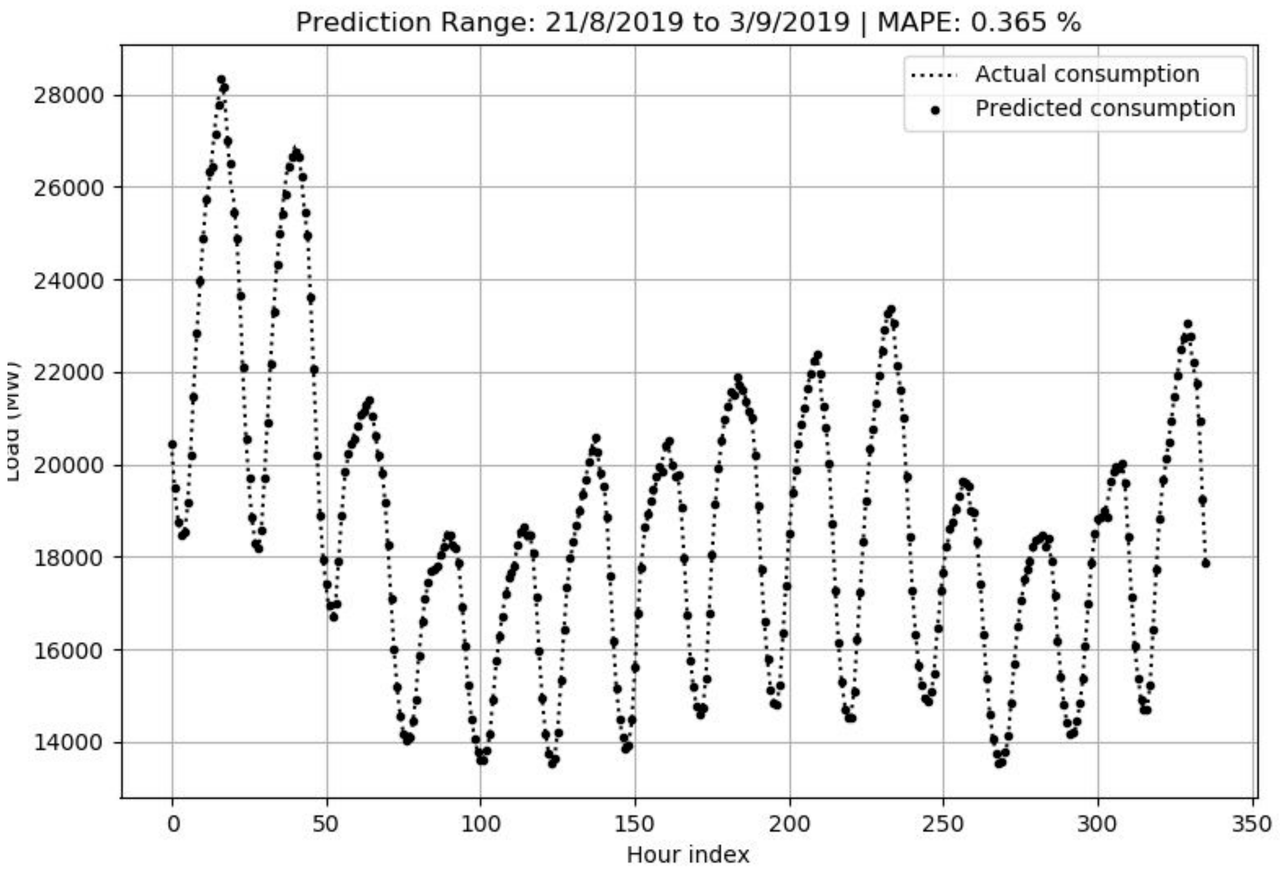
Examples: 1-day ahead forecast





Examples: 14-day ahead forecast





Results

1-day ahead prediction (MAPE)

Average	Min	Max
0.392	0.187	0.839

14-day ahead prediction (MAPE)

Average	Min	Max
0.370	0.295	0.412

Thank You

For discussions/suggestions/queries email: [www.indiasmartgrid.org]
Reference 1
Reference 2

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