

Master Thesis Defense

# Systematic Analysis of Impact of Aggregation On Time Series Forecasting

by:

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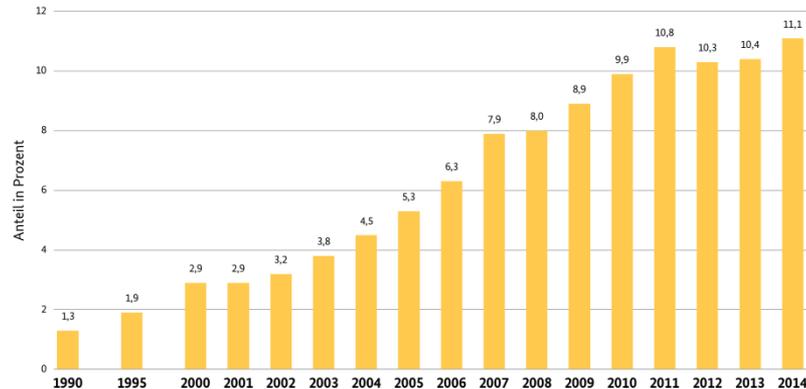
Supervised by:

Prof. Dr.-Ing. Wolfgang Lehner

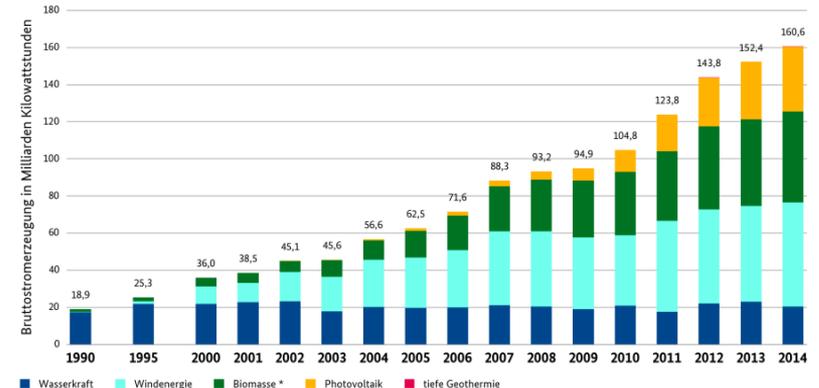
## NEED FOR RENEWABLE ENERGY FORECASTING

- Renewable energy source as major source of energy
- Wind and Solar are major contributors
- Fluctuation in Production
- Need for Renewable Energy forecast model

Entwicklung des Anteils erneuerbarer Energien am Primärenergieverbrauch in Deutschland \*



Entwicklung der Stromerzeugung aus erneuerbaren Energien in Deutschland



# Motivation

## GOAL

- Development of a reusable forecast model
- Data Preprocessing and reduction of input space
- Improved Forecast Results and Performance

## ISSUES

- Issues with Wind Energy Forecasting
  - Nonlinear relation b/n Power output and wind
  - Individual site forecast errors are amplified
- Aggregation of output from Ensemble of sites



## RESEARCH QUESTION

- Can Aggregation of Power Time Series with high similarity leads to better forecast result
  - If yes, what is the criteria for finding the Time Series with high similarity
- Clustering and Aggregation of Time Series lead to better forecast results along with better performance

# Approach

## AGGREGATION

- Analyze the behavior of Time Series Forecast results on Aggregation
- Choose a small subset of Time Series
- Aggregate them at different sizes from lowest to highest
- Find the *Similarity Measure* between Time Series in each aggregate
- Perform forecasting of each aggregate and calculate the error
- Analyze the relationship between the *Similarity Measure* and *Forecast Error*

Time Series Subset



## CLUSTERING

- Analyze the behavior of a set of Time Series upon clustering
- Apply standard clustering algorithm on a small subset
- Aggregate Time Series in each cluster and perform forecasting.
- Compare it with the Forecast result of Individual Time Series in the Subset

## NREL WIND INTEGRAION DATASETS

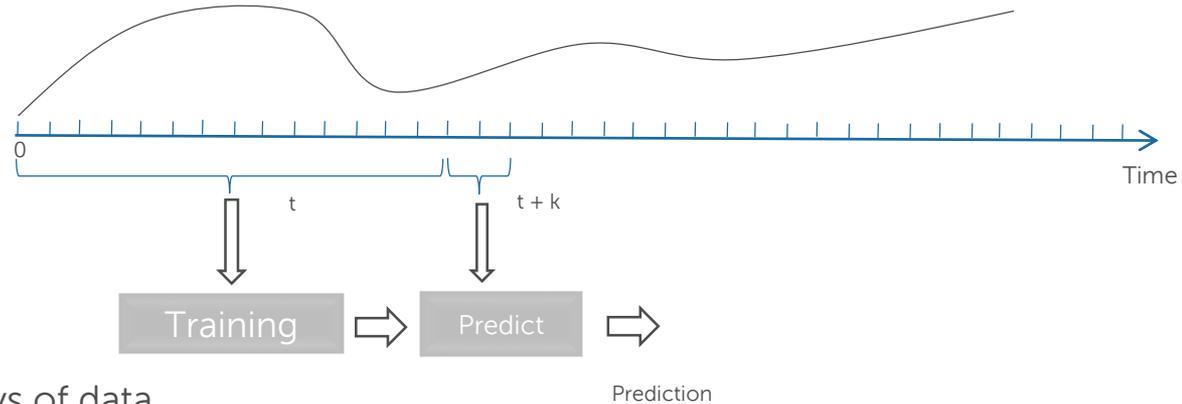
- Eastern & Western Integration Dataset
- Eastern Dataset contains data from ~1300 sites
- Modelled using mesoscale Numerical Weather Prediction(NWP) Model
- Data of 3 years from 2004 to 2006 of 10 minutes
- Wind Speed(m/s) and Power(MW)
- Geographic Coordinates of each site given

## TOOLS

- R statistical environment
- Models were built using standard R packages
- MySQL used for data storage

## METHODOLOGY

- Sliding window approach
  - Window Size = 24 hours
- Very Short forecasting
  - Model Training
  - Prediction
- Prediction in steps of 1 hour
- Total Length of 10 days and 50 days of data



## MODELS USED

- Gradient Boosted Model (gbm)
  - Multivariate Adaptive Regression Splines (MARS)
  - Multi Layered Feed Forward Neural Network (MLP)
  - Bayesian Regularization of Neural Network (BRNN)
- Regeression Based
- Neural Network Based

# Experiments Overview

## AGGREGATION EXPERIMENTS

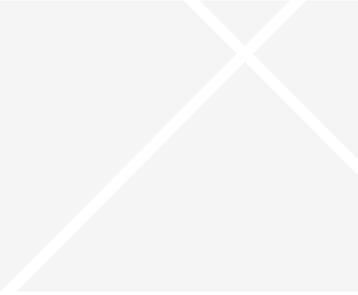
- Aggregation of Subset of Time Series
- Deduce the Correlation between Similarity Measure and Forecast error

## CLUSTERING EXPERIMENTS

- Hierarchical Clustering
- Clustering & Aggregation at different levels
- Application on datasets of different sizes
- Performance Analysis



# Aggregation Experiments



## GOAL

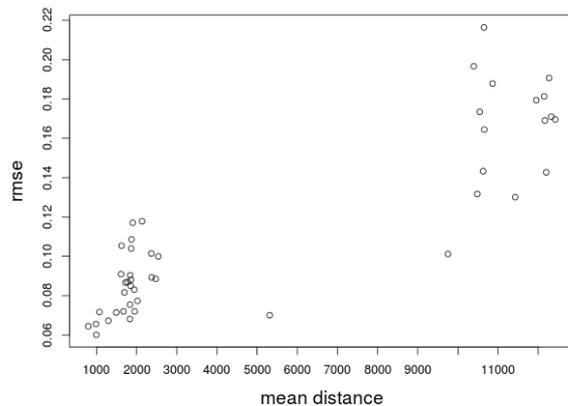
- Analyze the relationship between Time Series *Similarity Measure* and *Forecast Error*
- Idea: Lower the Similarity Measure then lower the Forecast Error
- Analyze this behavior using different Standard Similarity Measures

## METHODOLOGY

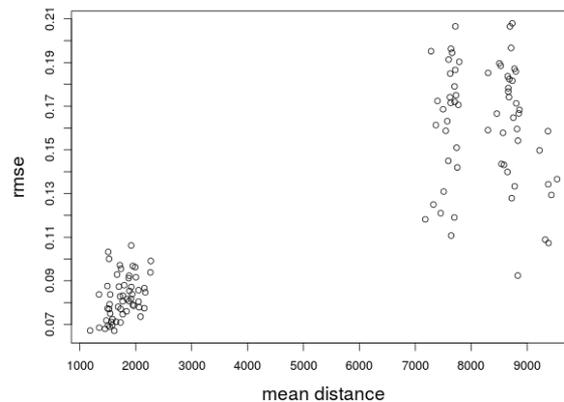
- 10 different subset of Time Series of size 10 is chosen
  - 5 subsets are randomly chosen
  - 5 subsets belong to a specific geographic location
- Each subset is aggregated at different sizes from 1 to 10
- Forecasting is done on all the *combinations* of aggregates of each size
  - RMSE is calculated
  - Lengths = 10 days & 50 days
- Different standard Similarity Measures are used
  - Like Euclidean Distance, Fourier Distance and Principal Components
  - Weighted mean of Similarity Measure

# High Correlation

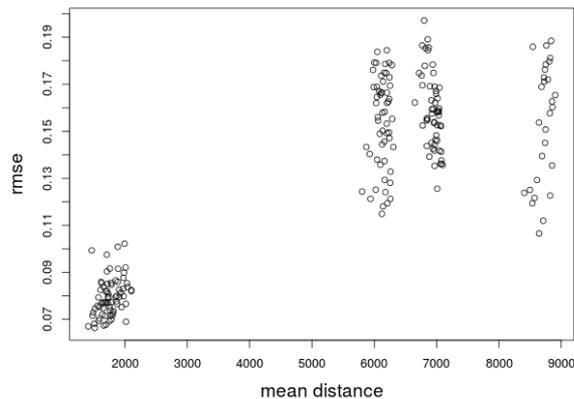
Cluster Size= 2 , Correlation= 0.8823



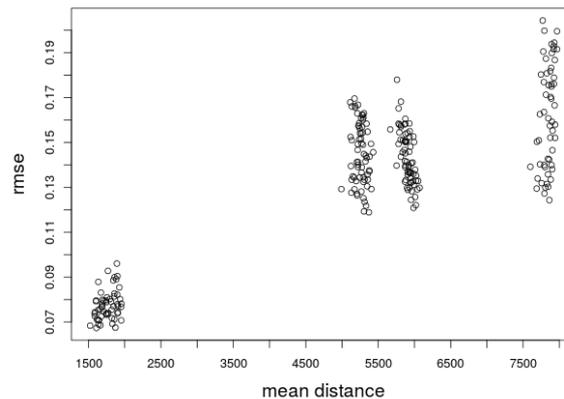
Cluster Size= 3 , Correlation= 0.86733



Cluster Size= 4 , Correlation= 0.86384

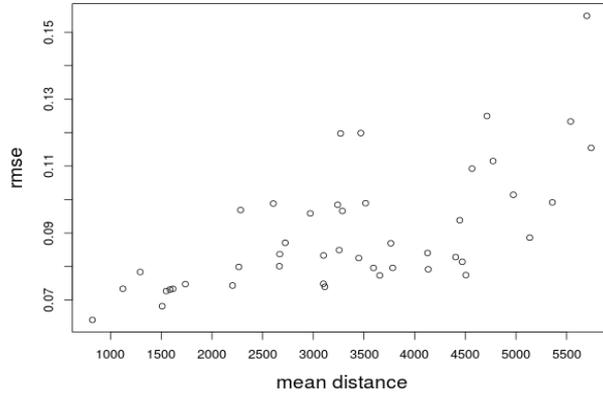


Cluster Size= 5 , Correlation= 0.87161

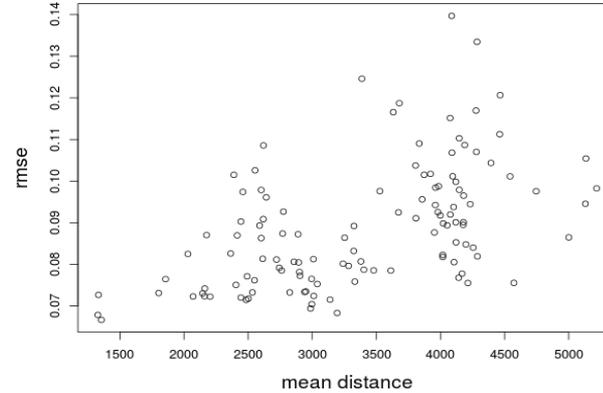


# Diluting Correlation

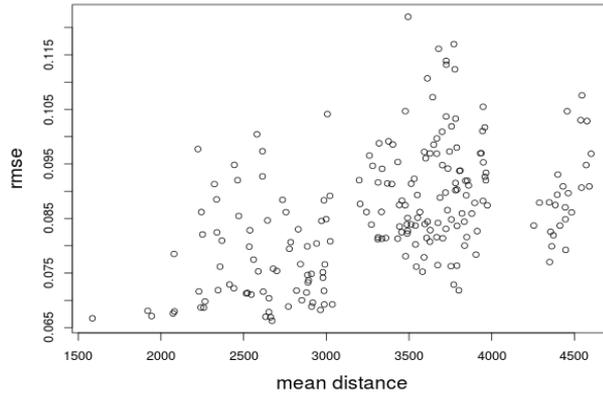
Cluster Size= 2 , Correlation= 0.64913



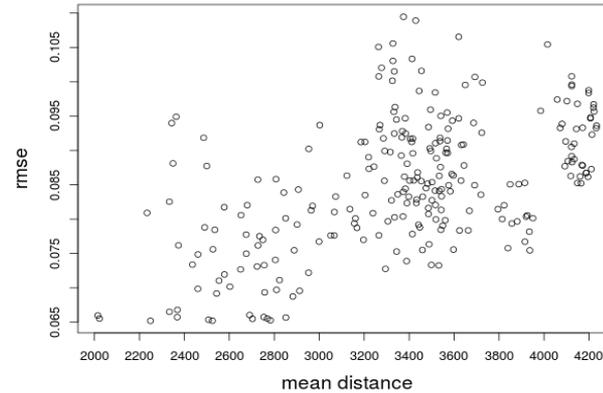
Cluster Size= 3 , Correlation= 0.52409



Cluster Size= 4 , Correlation= 0.49195

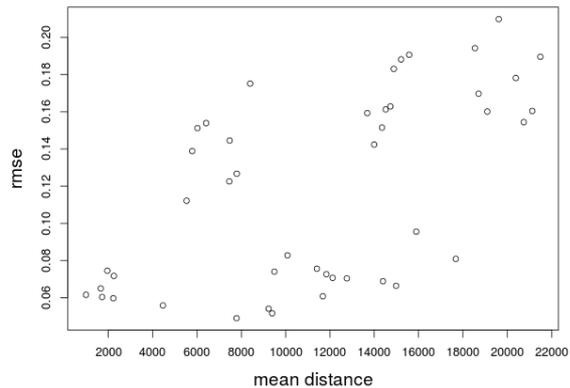


Cluster Size= 5 , Correlation= 0.53786

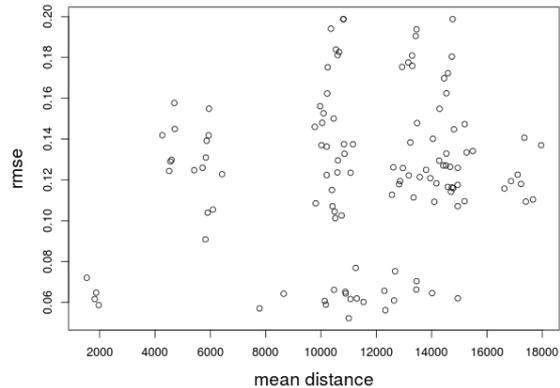


# Poor Correlation

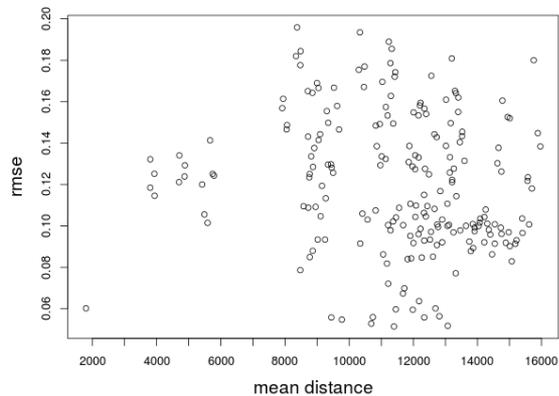
Cluster Size= 2 , Correlation= 0.58894



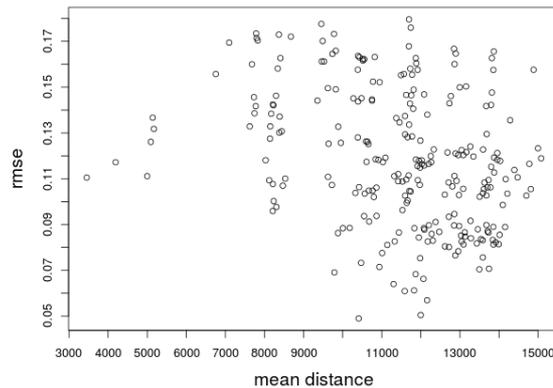
Cluster Size= 3 , Correlation= 0.15634



Cluster Size= 4 , Correlation= -0.14483



Cluster Size= 5 , Correlation= -0.31156

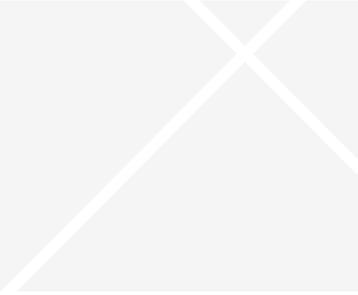


# Results

- High Correlation is obtained with average similarity measure  $< 2500$
  - Correlation starts diluting with average similarity measure  $\approx 5000$
  - No correlation with average similarity measure  $> 10000$
  - Similar results were obtained by experiments with different History Lengths
- 
- High Similarity  $\Rightarrow$  Low Forecast error
  - High Dissimilarity  $\Rightarrow$  Ambiguous results



# Clustering Experiments

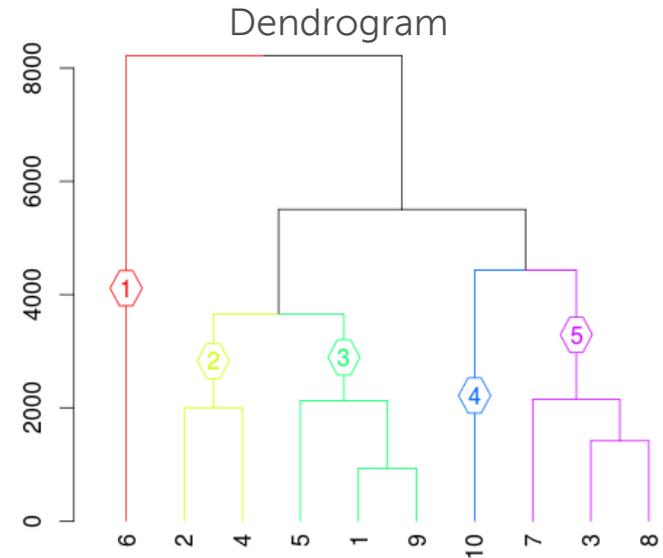


## GOAL

- Analyze the effect of Clustering and Aggregation on a small subset of Time Series
- Perform the analysis using different Standard Time Series Similarity Measures

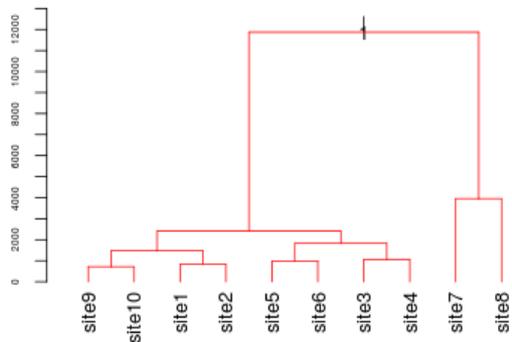
## METHODOLOGY

- Apply Hierarchical Clustering on a smaller subset
- Cut the Dendrogram tree at different levels
  - At each level different number of clusters are formed
- Time Series in each cluster is aggregated and subjected to forecasting
- Overall error is calculated at each level

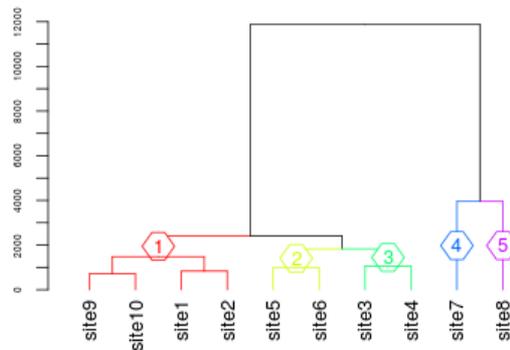


# Results

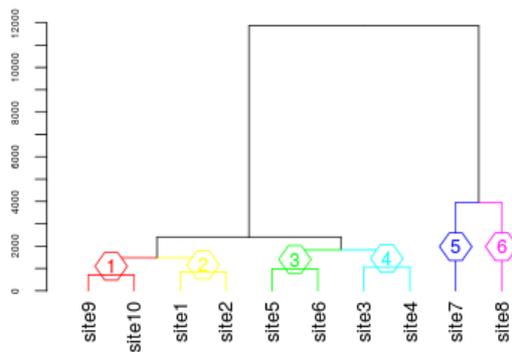
Forecast Error= 0.145383 , Cluster Count= 1



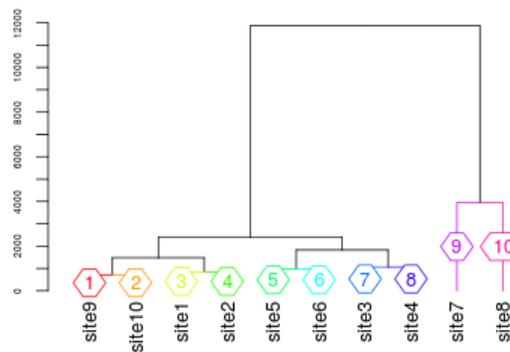
Forecast Error= 0.040642 , Cluster Count= 5



Forecast Error= 0.038223 , Cluster Count= 6



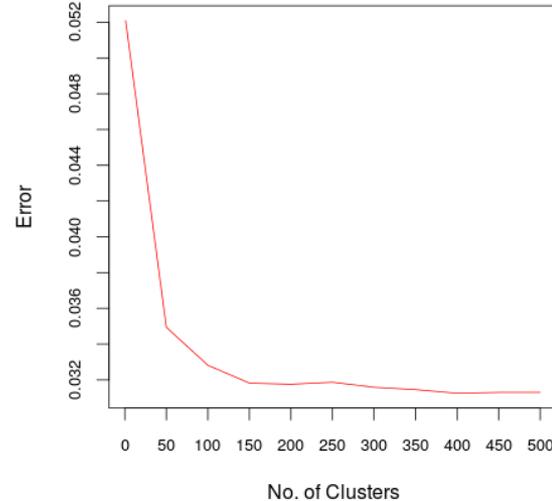
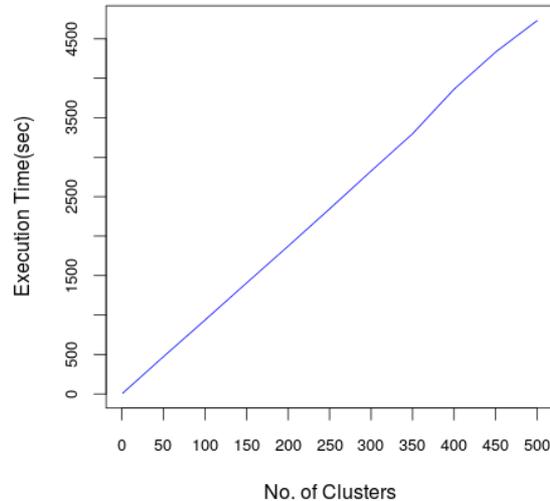
Forecast Error= 0.037806 , Cluster Count= 10



## PERFORMANCE MEASURE

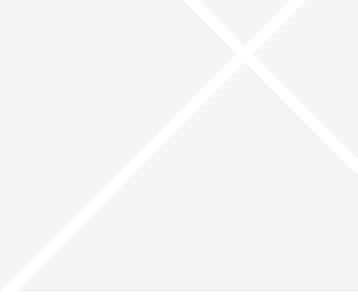
- Apply Hierarchical Clustering on a bigger data subset
- Similar procedure is followed
- Calculate the computation time as performance measure

## RESULTS





# Further Experiments



## SOLAR DATASET

- NREL Solar Power Dataset
- Contains data from ~6000 PV plants
- Hourly data of Power(MW) generated from each plant
- Solar Radiation information obtained from SolarAnywhere
- Dataset is prepared by taking radiation information nearest to the site

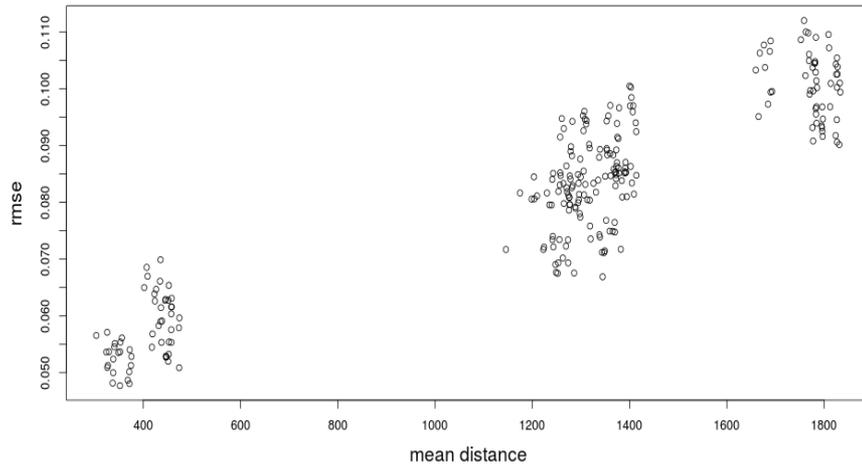
## METHODOLOGY

- 6 different subset of Time Series of size 10 is chosen
  - 3 subsets are randomly chosen
  - 3 subsets belong to a specific geographic location
- Similar Forecasting method was followed
- History Length of whole year
  - Presence of Seasonality

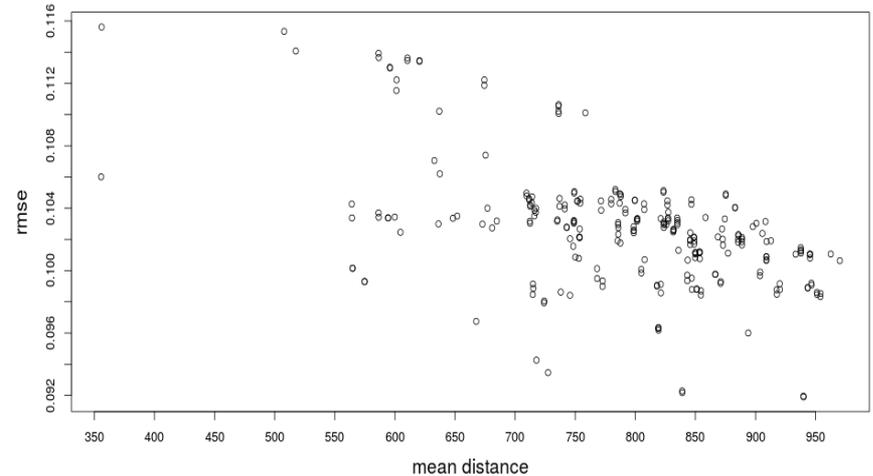
# Results

- Obtained results were not conclusive
- Difference between positive and negative results not clear
- Model Chosen was not complex
- Solar Data contains seasonality

Cluster Size= 5 , Correlation= 0.91083956402638

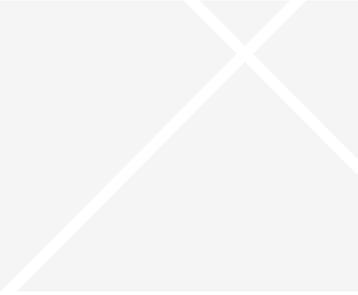


Cluster Size= 5 , Correlation= -0.552332645797715





## Conclusion & Future Work



# Conclusion

## AGGREGATION EXPERIMENTS

- Lower Similarity Measure leads to better Forecast results

## CLUSTERING EXPERIMENTS

- Hierarchical clustering gives better results than simple aggregation
- Not better than Forecasting individual Time Series
- But, forecasting individual Time Series is slower in case of Large Dataset
  - Reduction of input space
  - Improves performance

# Future Work

## CLUSTERING

- Deriving the Threshold for identifying best clusters
- Analyze the performance on very large datasets

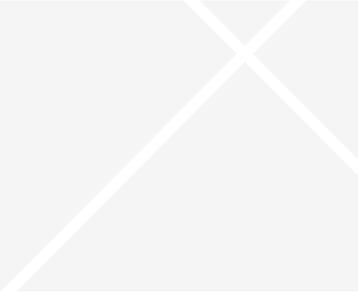
## DATASET

- Work on Solar Dataset by creating better forecast model
- Different datasets other than renewable energy

## ECAST FRAMEWORK



# Questions





Thank You

