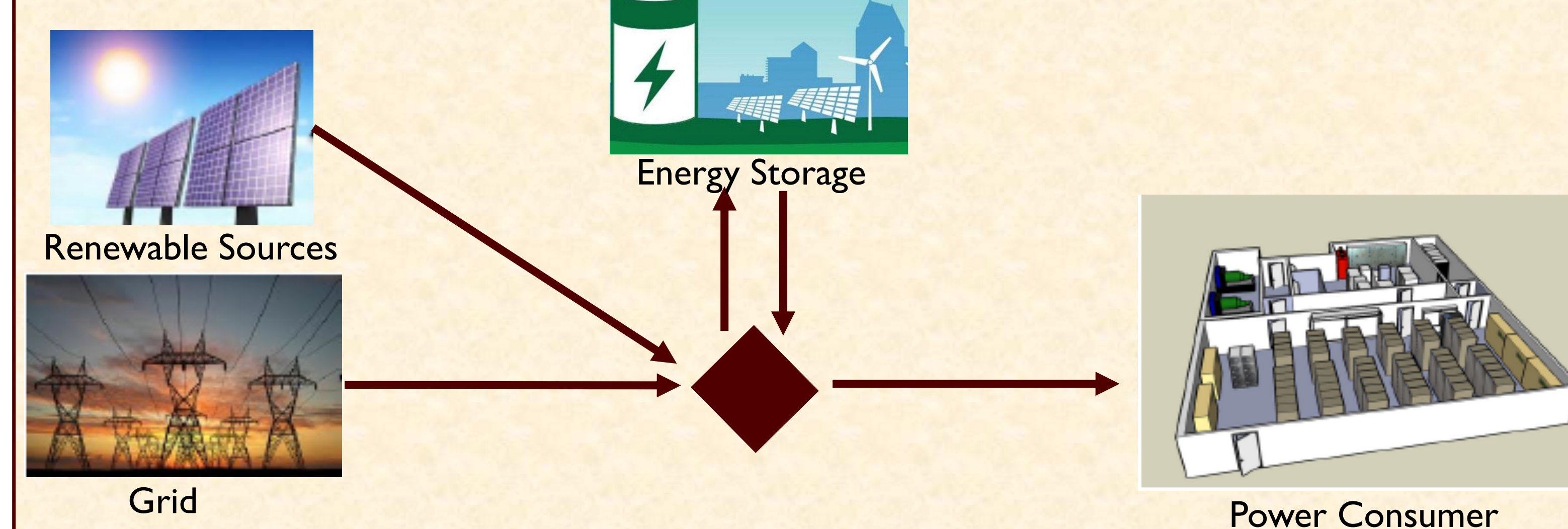


Research PIs

Dr. Natarajan Gautam, Department of Industrial and Systems Engineering
Dr. Katherine Davis, Department of Electrical and Computer Engineering
Dr. Anirban Bhattacharya, Department of Statistics

Background

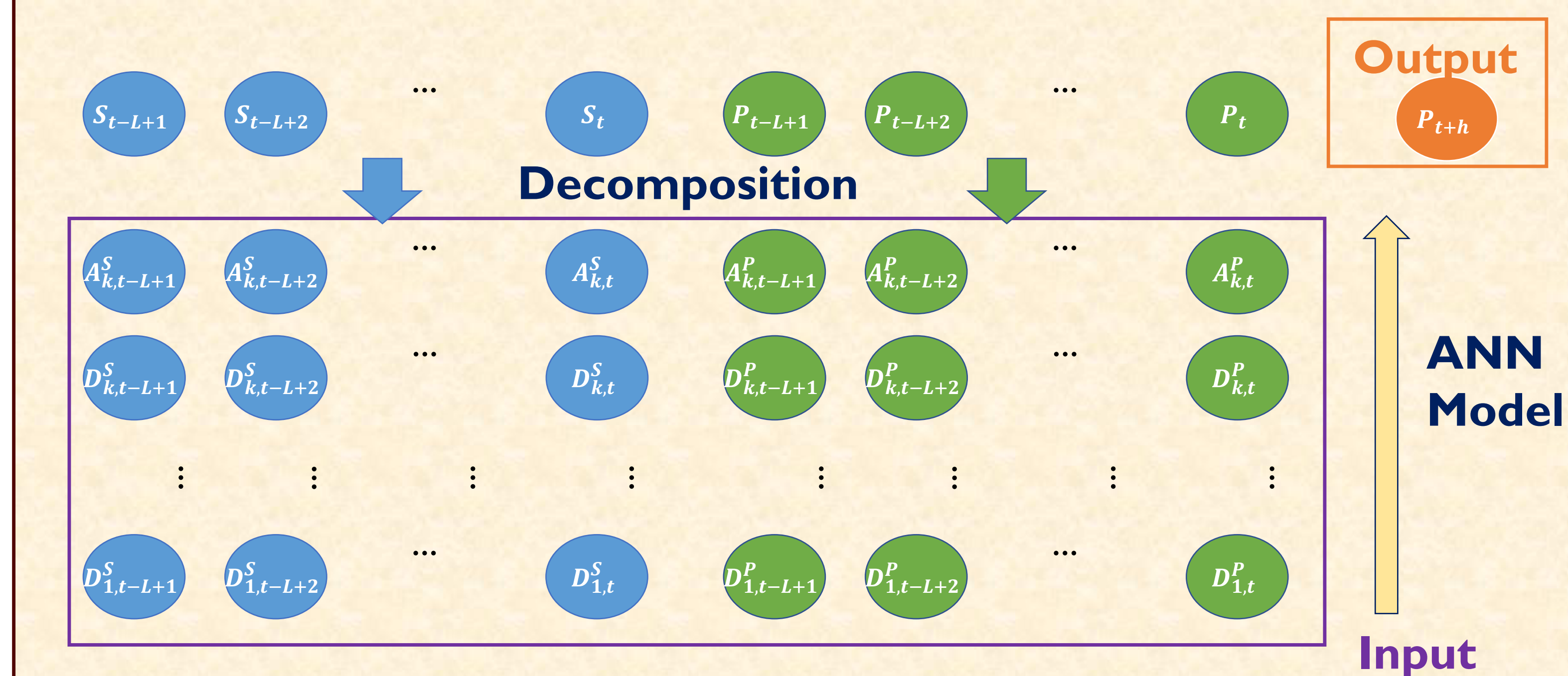
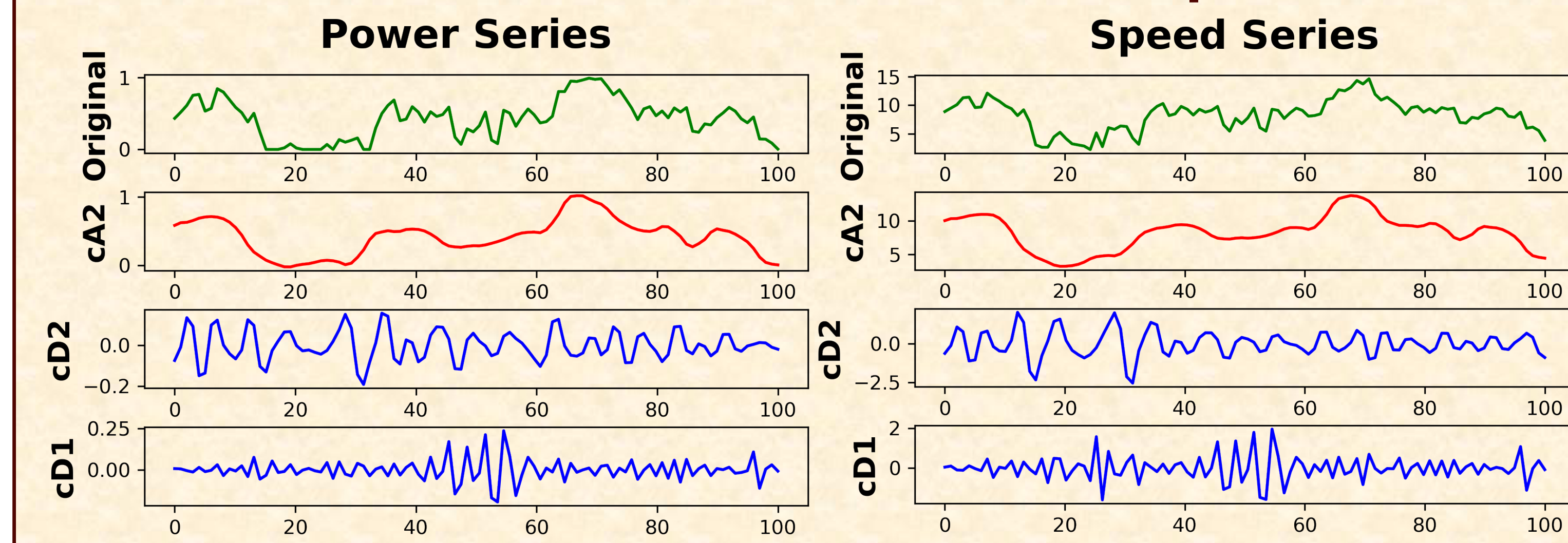


Objective

- Predictive analytics: Forecasts of demand and supply
- Prescriptive analytics:
 - Manage power generation
 - Sell or buy power from energy market
 - Perform demand response

Rolling Horizon Predictive Model

ANN Model Based on Wavelet Decomposition



Rolling Horizon Predictive Model (continued)

- **Data Source**
 - NREL hourly wind speed and power data for a specific site
 - From January 1st 2007 to January 31st 2012
- **Forecasting Results**

Hour-ahead	PER	ANN	HMC	Our Model	Hour-ahead	PER	ANN	HMC	Our Model
1	3.9122	4.6726	4.0756	3.3114	1	1.2307	1.3738	1.3641	1.1909
2	9.4628	11.2724	8.8771	7.5258	2	1.9985	2.3131	2.1217	1.9526
3	14.9313	16.6970	13.1483	10.5257	3	2.6226	2.9201	2.7115	2.3856
4	20.3395	23.2260	16.9544	13.5997	4	3.1676	3.5045	3.1998	2.8282
5	25.6180	27.6655	20.3686	15.4361	5	3.6630	3.9317	3.6051	3.0429
6	30.6119	34.8077	23.3255	18.0406	6	4.1029	4.4775	3.9392	3.3648

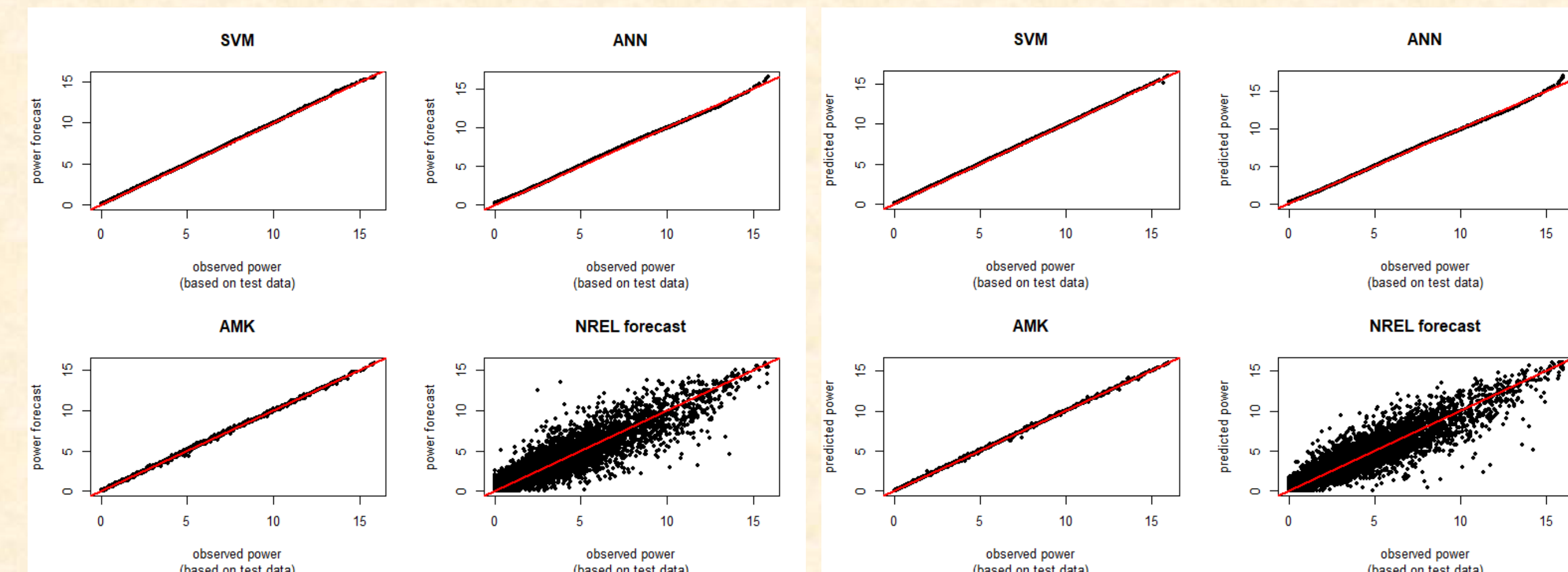
MSE Comparison

MAE Comparison

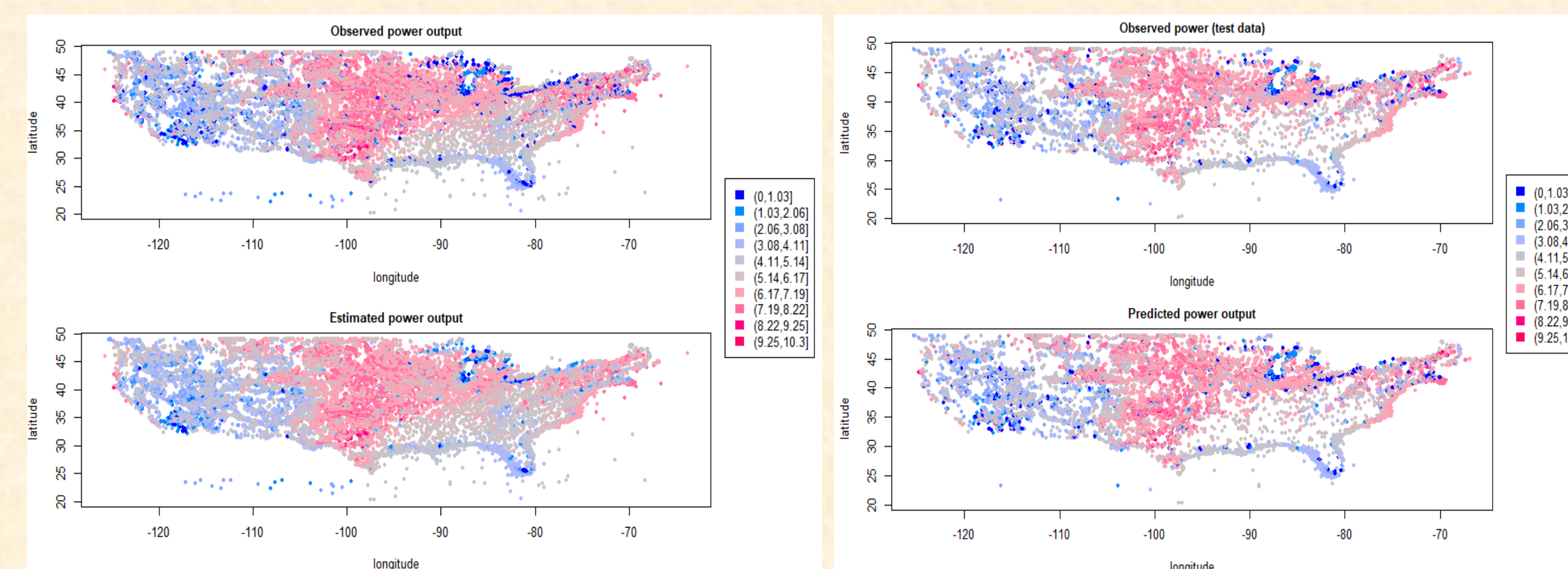
Covariates Based Wind Power Forecasting

- **Part I: Forecast and prediction for a specific site in or near California (latitude: 23.51041, longitude: -117.1473)**
- **Comparative Analysis: Three competing methods**

Scenario	Error Measures	SVM	ANN	AMK	NREL forecast
Forecast	RMSPE	0.020	0.063	0.020	1.043
	MAPE	0.016	0.047	0.016	0.670
Prediction	RMSPE	0.019	0.067	0.029	0.992
	MAPE	0.015	0.047	0.011	0.644



- Both SVM and AMK were preferred over ANN.
- **Part II: Estimation and prediction of wind power (on an average) over different sites**
- Spatial modeling: LatticeKrig method

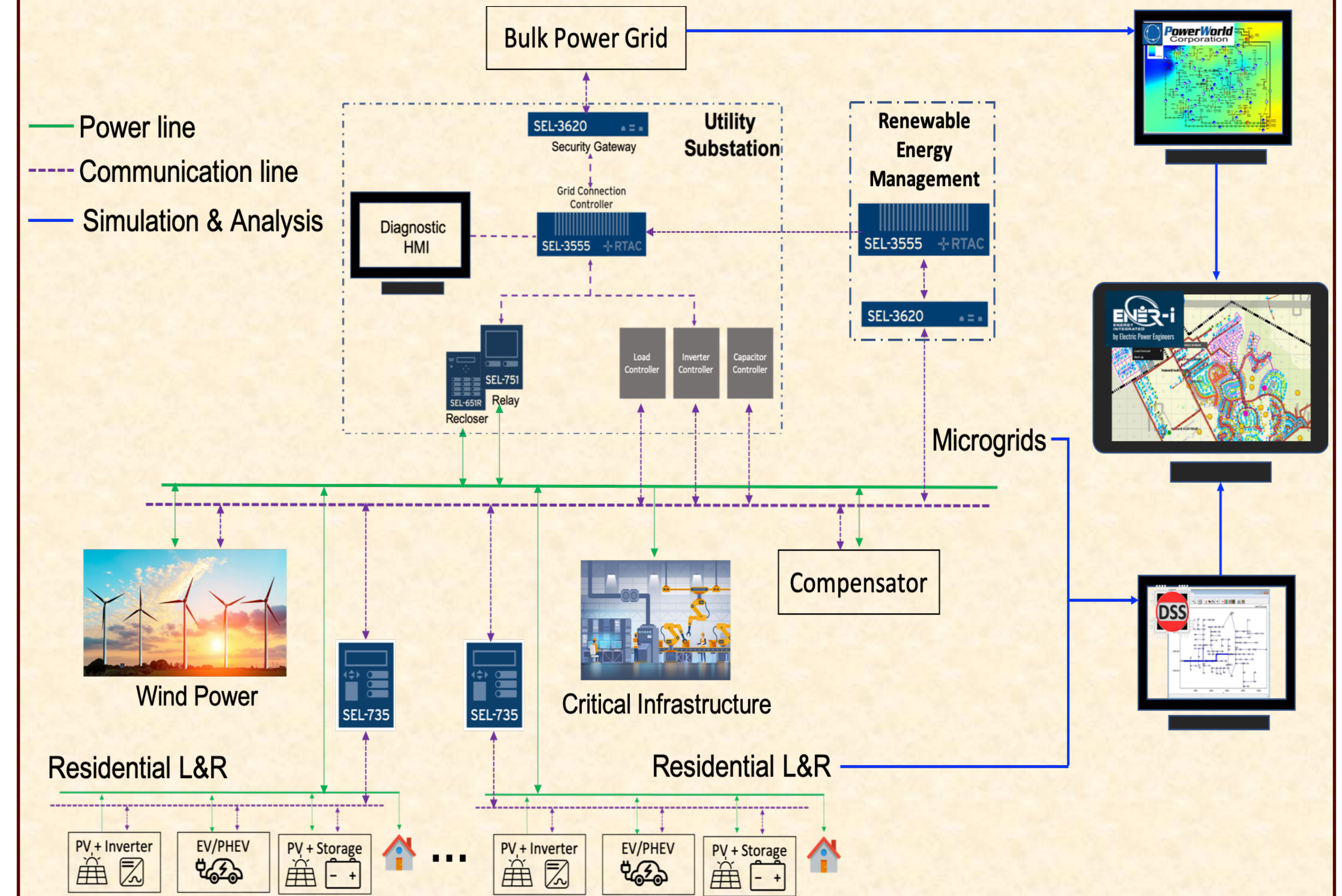


RMSE = 0.86 and MAE = 0.53

RMSPE = 0.92 and MAPE = 0.57

Hardware-in-the-Loop Testbed Design

- **Integrating Renewables, Microgrids, Bulk Power Grid and Power System Control and Protective Devices**



- Analyze how renewable energies impact Microgrids and Bulk Power Grid operation and management with uncertainties
- Validate predictive models and demand response algorithms in a realistic environment
- Generate realistic power system cyber and physical data sets based on historical renewable energy data
- Develop data-driven model to manage renewables, microgrids, and bulk grids securely and economically

Conclusion

- We developed a data-driven model to predict 1-6 hours ahead wind power generation with high accuracy
- We presented a site specific comparative analysis of 3 existing methods, and proposed a spatial method that predicts the wind power with high accuracy.
- We developed a hardware-in-the-loop testbed architecture that combines models, data sources, and data-driven approaches to study how renewable energies impact power systems

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