

TEXAS A&M UNIVERSITY Engineering



Problem Definition

The rapid growth of weather-dependent renewable energy generation and fluctuating loads is posing an increasing challenge to maintaining grid stability.



Figure 1. ERCOT past 10-year renewable generation. Many traditional forecasting methods heavily rely on historical data and lack the ability to adapt to real-time changes in installation capacity and evolving weather patterns. This limitation often results in inaccurate forecast of renewable generation and load.

Methodology

To address these challenges, we conducted a data analysis of the relationship between weather and the power grid. Leveraging these insights, we developed an adaptive predictive model inspired by biological systems and validated its performance using the latest data.

Dynamic Systems Analysis

Analyze the relationship between weather conditions and grid system.

- Conducting long-term temporal analysis of renewable energy patterns and load variations.
- Exploring the **spatial correlation** between weather conditions and different zones.
- Apply latent space analysis to examine the evolution of spatial-temporal system relationships

Predictive model design

Based on the data analysis, we selected the most relevant weather features and developed a model incorporating the concept of representational drift. The model was then validated using the most recent data.

Weather-Informed Bio-Inspired Prediction Models for **Enhancing Grid Stability Thomas Chen**

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Engineering Analysis & Design

The data analysis results reveal the relationship between

weather features, temperature characteristics, and grid dynamics.

- a. The spatial correlation region with large solar generation.
- **b.** The correlation heap map show most correlation between weather and generation.
- c. The scatter plot show the relationship between temperature and load throughout the day
- d. The correlation heat map shows that most load zones share similar characteristics.
- e. The latent space reveals the system dynamic evolution throughout the year, with solar generation show noticeable changes.



Figure 2. Renewable correlation heatmaps.



Figure 3. Temperature vs load at time of day

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	Correlation Matrix of Weather Features and Load 2018-01-01 to 2024-01-01													
CUASI	0.74	0.54	0.48	0.02	-0.10	1.00	0.88	0.38	0.73	0.86	0.94	0.92	0.82	
LCA3	0.48	0.28	0.40	-0.00	-0.09	0.88	1.00	0.42	0.85	0.94	0.86	0.94	0.89	
rwesi	0.17	0.11	0.09	-0.01	-0.13	0.38	0.42	1.00	0.63	0.28	0.37	0.45	0.27	
	0.35	0.19	0.29	0.01	-0.07	0.73	0.85	0.63	1.00	0.84	0.72	0.85	0.81	
	0.52	0.34	0.39	0.01	-0.05	0.86	0.94	0.28	0.84	1.00	0.84	0.93	0.95	
uinos	0.69	0.46	0.47	0.06	-0.07	0.94	0.86	0.37	0.72	0.84	1.00	0.93	0.82	
SCENT	0.59	0.40	0.37	0.00	-0.08	0.92	0.94	0.45	0.85	0.93	0.93	1.00	0.91	
ME01	0.45	0.27	0.36	0.02	-0.03	0.82	0.89	0.27	0.81	0.95	0.82	0.91	1.00	
	temp	dew	sun	wind	cloud	COAST	EAST	FWEST	NORTH	NCENT	SOUTH	SCENT	WEST	

Figure 4. Load correlation heatmap.



Figure 5. Renewable generation latent space(UMAP).

Predictive model

The renewable predictive model implement Convolutional Neural Network (CNN) layer to extract weather features, utilize Long Short-Term Memory (LSTM) networks to interpolate the weather flow, and employ an attention mechanism to identify the regions of interest. A fully connected layers (FC) are applied to estimate the installation capacity factor and integrate it with temporal features for the final predictions.



Figure 6. Renewable predictive model.

The load predictive model integrates the previous model with an MLP autoregressive model to predict load based on historical patterns and weather conditions.



Figure 7. Load predictive model

The model was trained using two years from 2021 to 2023 and then fine-tuned and evaluated using data from 2024 onward data.

Renewable predictive model result

The results show adaptability to system changes and provide accurate forecast for renewable generation output.

Load predictive model result

The results indicate that the model successfully predicted

The predictive insights from this approach can be applied

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Outcomes



Figure 8. Forecast results of the renewable predictive model

the mid-term load with an acceptable error margin. Predicted vs Actual Load for ERCOT



Figure 9. Forecast results of the load predictive model

Future direction

to improve smart grid optimization, stability analysis, and

evaluations of extreme weather scenarios

References

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