



Advancing Power System Resilience through Enhanced Load Forecasting Considering Extreme Weather Conditions

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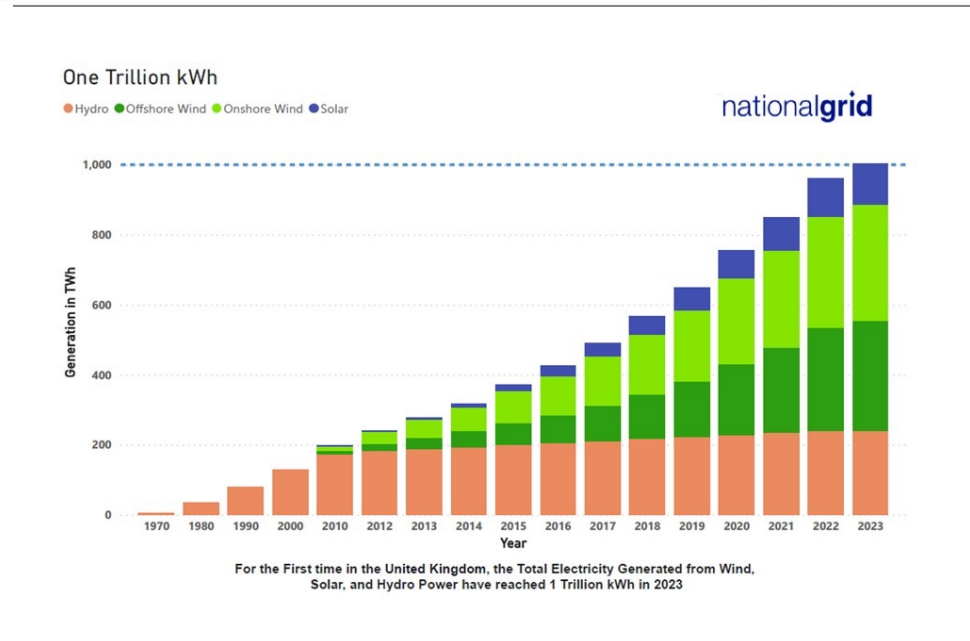
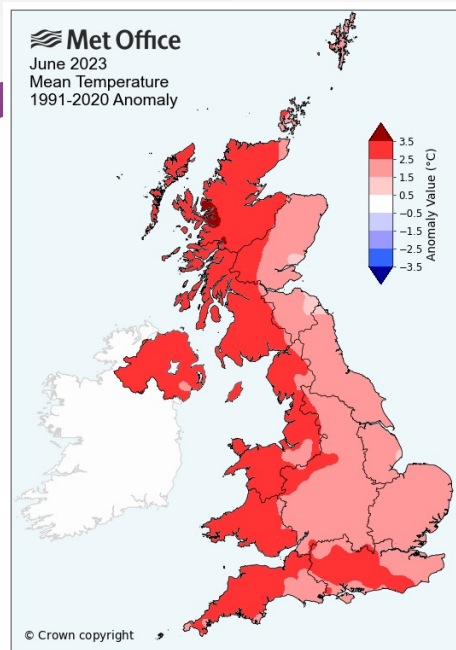




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Background



Climate Change

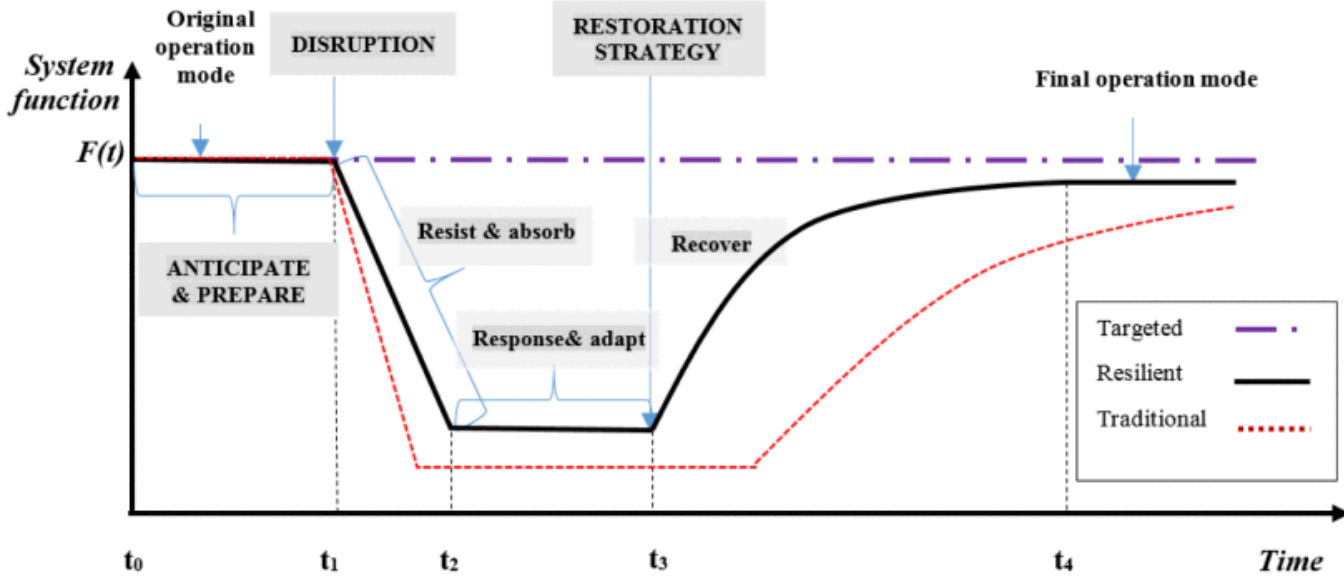
- Extreme weather
- Increasing Frequency and Intensity

Smart Grid

- Renewable energy integration
- Uncertainty and Intermittency
- Power outage and economic loss

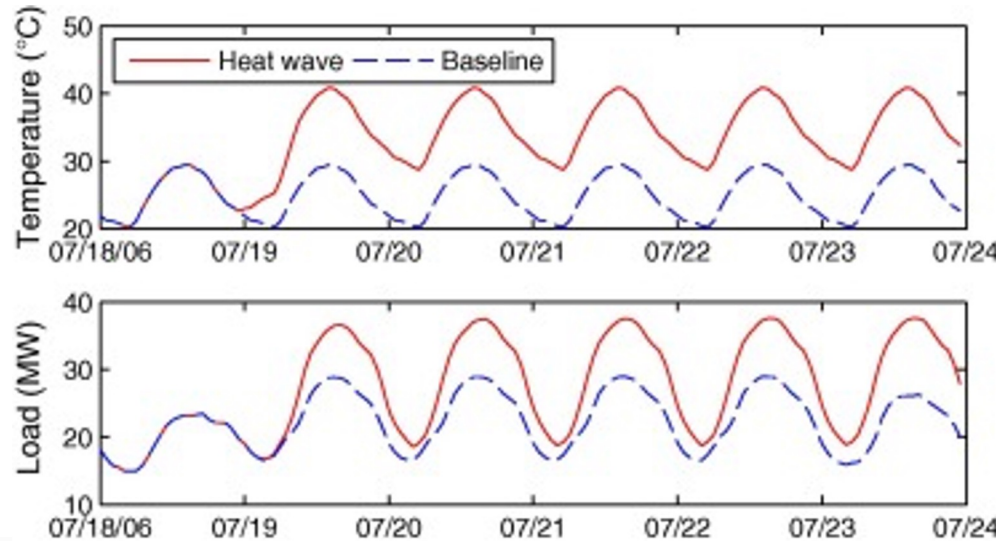
Challenges

Background



Extreme Weather

- Heatwaves, cold waves
- Typhoon, hurricane
- Storms
- Wildfire
- ...



Importance



Prediction and Optimization

- Short-term load forecasting
- Potential demand spikes and drop Prediction
- Generation and storage optimization

Emergency Response Planning

- Short-term load forecasting
- Critical loads prioritize
- Demand response programs determination

Load Forecasting

- Long-term load forecasting
- Infrastructure upgrade and expansion planning

- Renewable energy integration
- Power outages prevention
- Electricity supply stability

Investment and Upgrade Planning

Economy and Sustainability

Challenges



- ❑ Current works on load forecasting:
 - ❑ Mainly focus on **normal** load forecasting
 - ❑ Extreme weather: probabilistic modeling, uncertainty modeling, scenario analysis
 - ❑ Low generality: users, extreme event types
 - ❑ **Lack of relevant public data**

- ❑ Objectives
 - ❑ Studying the **impact of different extreme weather** on the load profile.
 - ❑ Overcoming the challenge of predicting these patterns due to their **infrequent but high-impact nature**.
 - ❑ Developing more sophisticated forecasting models to **manage and mitigate risks**.

Methodology

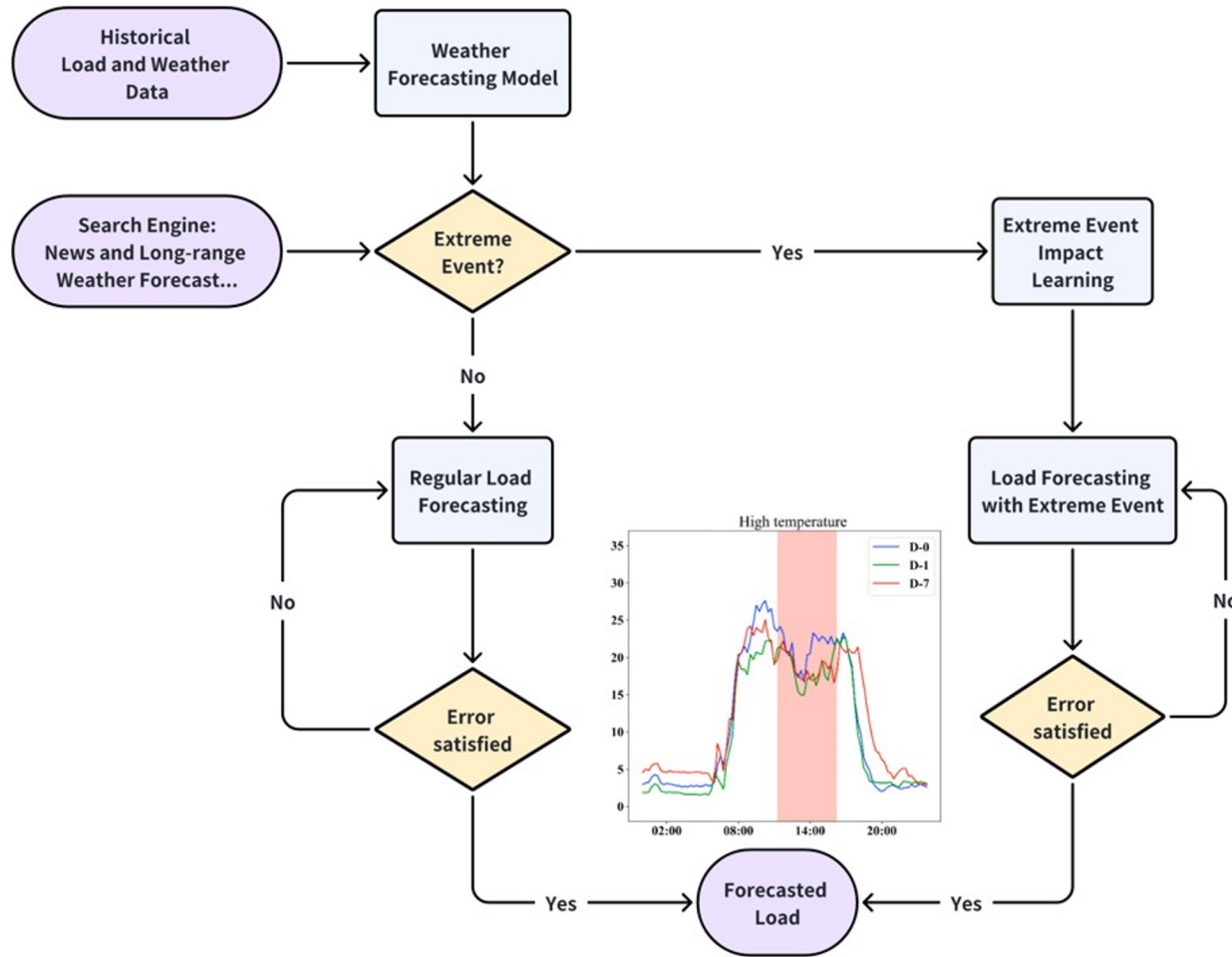


Fig.1 Framework of Enhanced Load Forecasting Considering Extreme Weather



Extreme Weather Events Load Dataset (EWELD)

- ✓ **15-minute** intervals over **6** years
- ✓ **386** industrial and commercial users across **17** different industries in **3** cities
- ✓ A total of **5,741** records of extreme weather events

No.	Extreme Weather	Criterion
EW1	Low temperature	Temperature below lower bounds of the 95% confidence interval of temperatures between 2015 to 2022 in the city, e.g, 50°F (Fahrenheit) for City 1
EW2	High temperature	Temperature above upper bounds of the 95% confidence interval of temperatures between 2015 to 2022 in the city, e.g, 95°F for City 1
EW3	High humidity	Relative humidity(%) above upper bounds of the 95% confidence interval of humidity between 2015 to 2022 in the city, e.g, 97.85% for City 1
EW4	High heat and humidity	Temperature larger than 95°F and relative humidity larger than 60%
EW5	Severe thunderstorm - Damaging Wind Gusts	Wind gust larger than 58 mph and smaller than 74 mph (miles per hour)
EW6	Severe thunderstorm -Very Damaging Wind Gusts	Wind gust larger than 74 mph and smaller than 91 mph
EW7	Severe thunderstorm -Violent Wind Gusts	Wind gust larger than 91 mph
EW8	Tropical Storm	Wind speed larger than 39 mph and smaller than 54 mph
EW9	Severe Tropical Storm	Wind speed larger than 54 mph and smaller than 73 mph
EW10	Typhoon	Wind speed larger than 73 mph and smaller than 93 mph
EW11	Strong Typhoon	Wind speed larger than 93 mph and smaller than 114 mph
EW12	Super Typhoon	Wind speed larger than 114 mph
EW13	Heavy Rain	Weather condition equals 'Heavy Rain'
EW14	Heavy Rain/Windy	Weather condition equals 'Heavy Rain/Windy'
EW15	Heavy Rain Shower	Weather condition equals 'Heavy Rain Shower'
EW16	Heavy Rain Shower/Windy	Weather condition equals 'Heavy Rain Shower/Windy'
EW17	Heavy T-Storm	Weather condition equals 'Heavy T-Storm'
EW18	Heavy T-Storm/Windy	Weather condition equals 'Heavy T-Storm/Windy'
EW19	Light Sleet	Weather condition equals 'Light Sleet'
EW20	Light Sleet/Windy	Weather condition equals 'Light Sleet/Windy'

Datasets



- ✓ **Diverse Effects:** Different extreme weather events have varying impacts on load.
- ✓ **Load Type Dependency:** The specific impact is dependent on the type of load (e.g., residential, commercial, industrial).
- ✓ **User Categories:** User categories (such as households, businesses, and industries) experience these impacts differently.
- ✓ **Location Characteristics:** The geographic and climatic characteristics of the location also play a critical role.

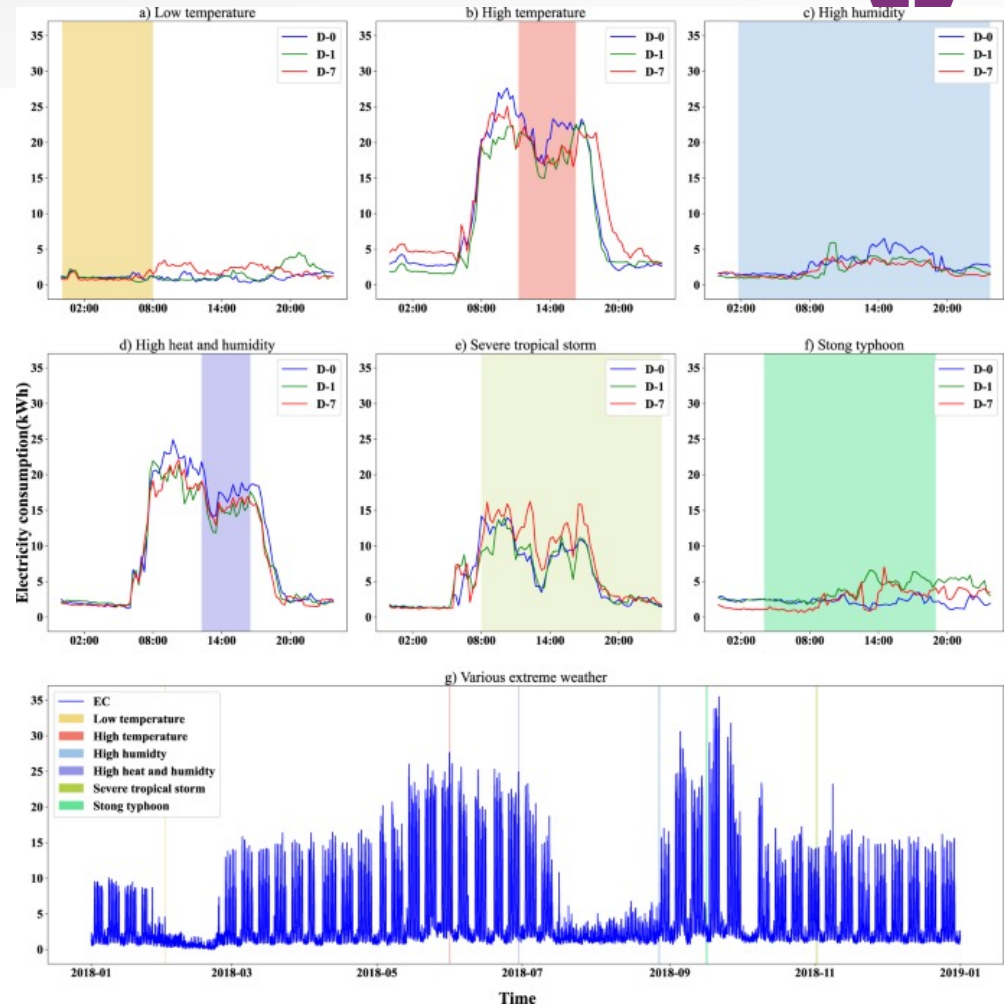
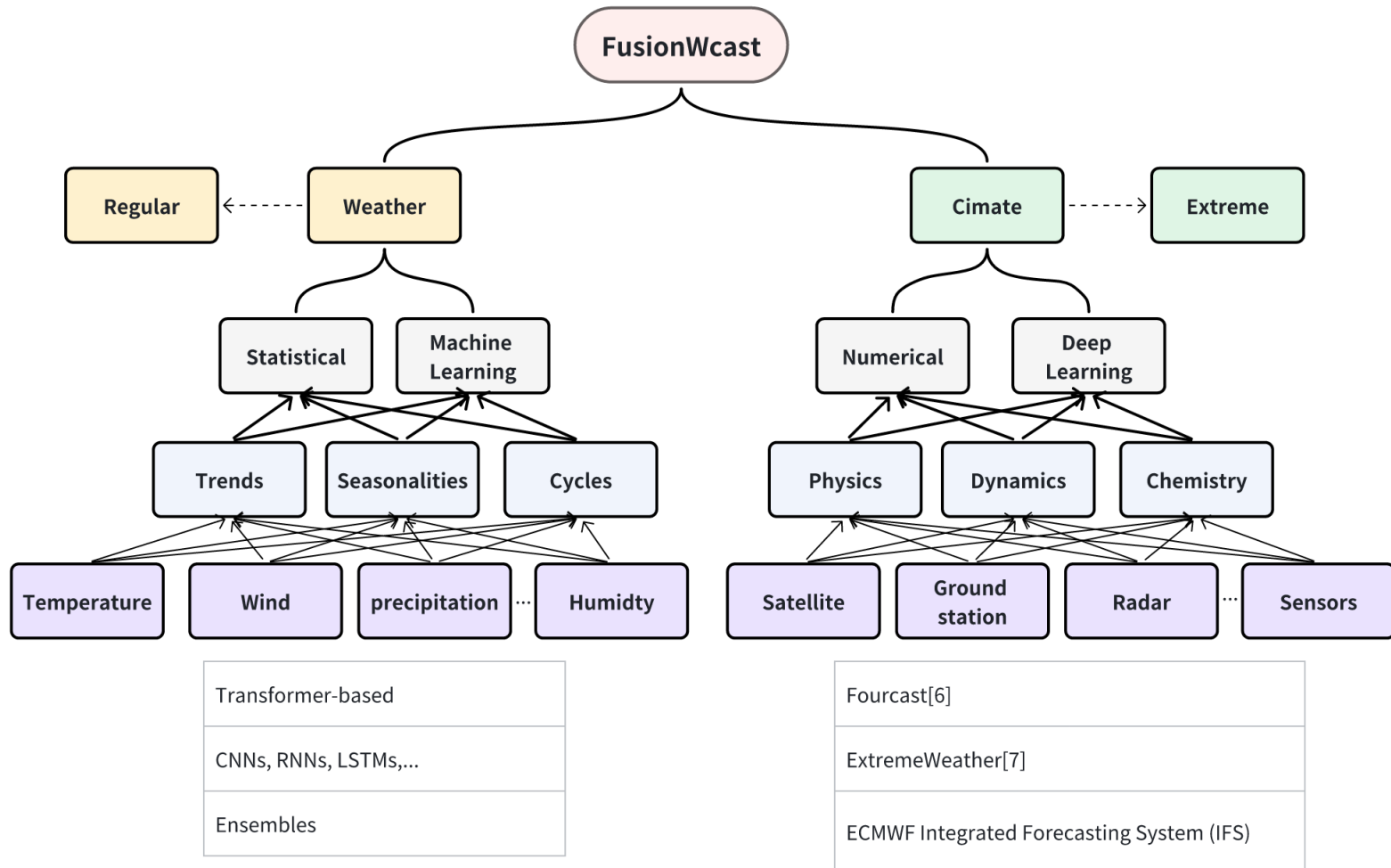


Fig.2 Impacts of various extreme weather events on the electricity consumption of U380 in 2018. (a) Low temperature; (b) High temperature; (c) High humidity; (d) High heat and humidity; (e) Severe tropical storm; (f) Strong typhoon; (g) The time of different types of extreme weather in 2018. Shaded areas show the period of different extreme weather events. Different color lines represent daily electricity consumption curves of the different days: the day extreme weather happened (D-0) in the blue line, the previous day in the green line, and the same day of the last week in the red line.

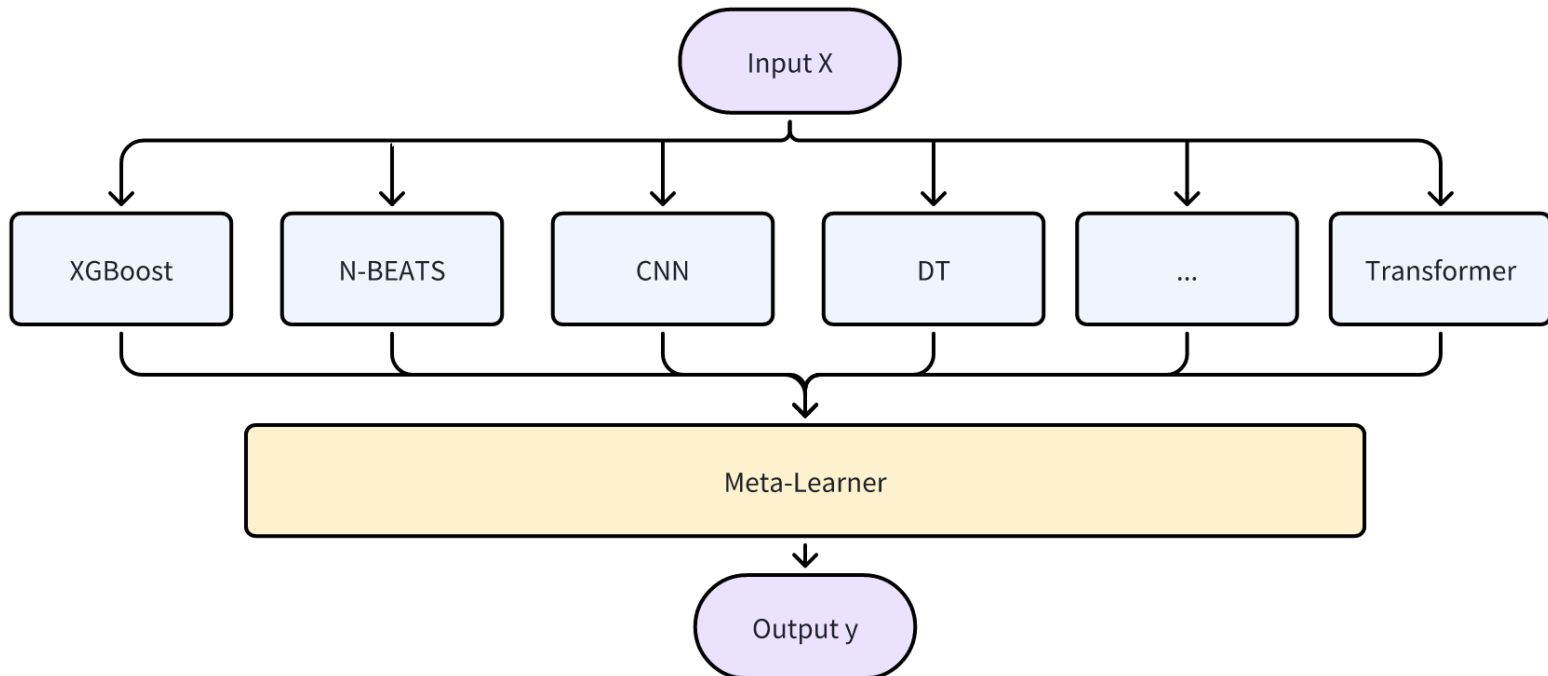
Weather Forecasting



Load Forecasting



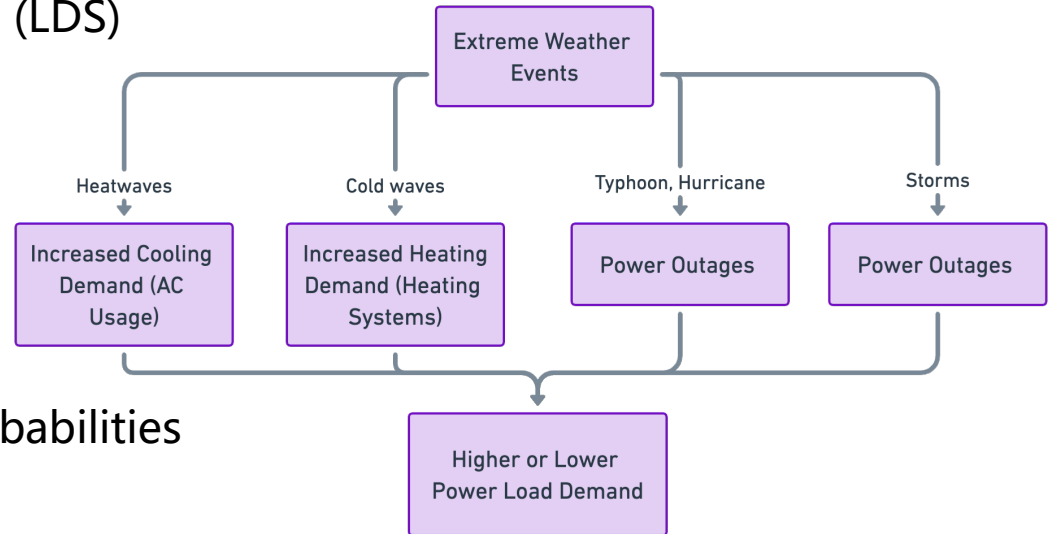
- ✓ Stacked Ensemble Learning
- ✓ Base Models for Diversity
- ✓ Meta-Learner Integration



Extreme Weather Learning



- **Extreme Weather Detection**
 - Feature Engineering and Threshold Setting
 - Generalized Extreme Value (GEV)
 - Label Distribution Smooth (LDS)
- **Extreme Weather Impact**
 - Regression
 - Correlation Analysis
- **Post-processing Strategy**
 - Threshold Optimization
 - Calibration of forecast probabilities
 - Bias Correction
- **Adjustment on the Sample Weights**



Results

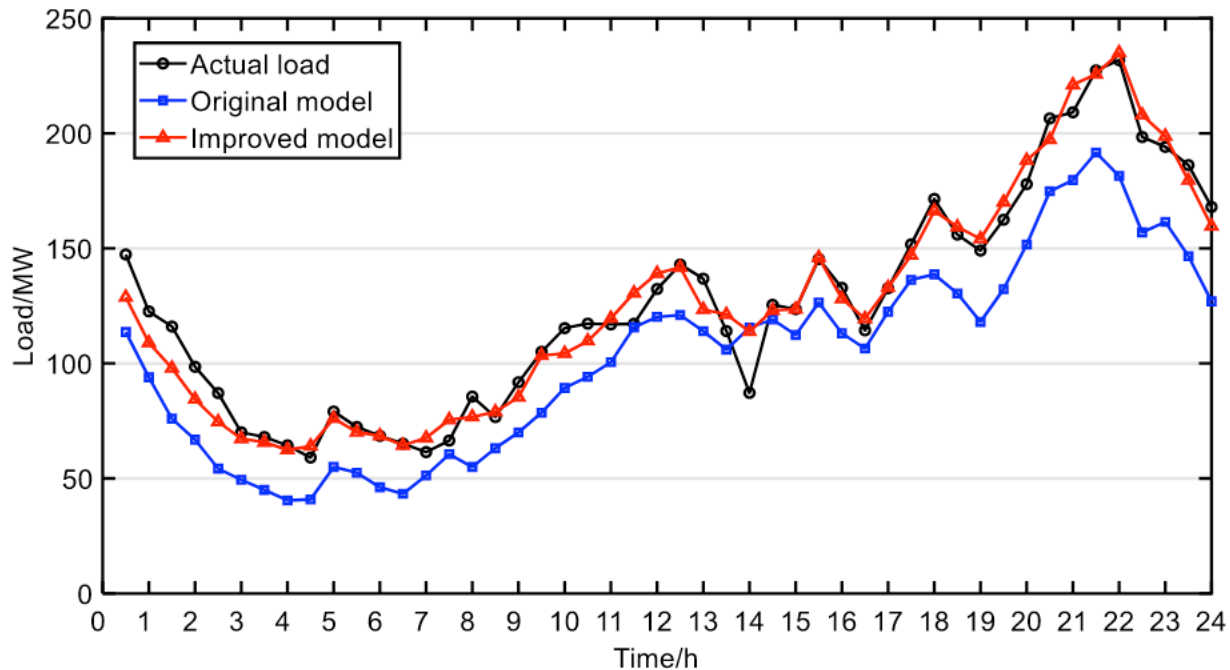


- Mean Absolute Percentage Error (MAPE)

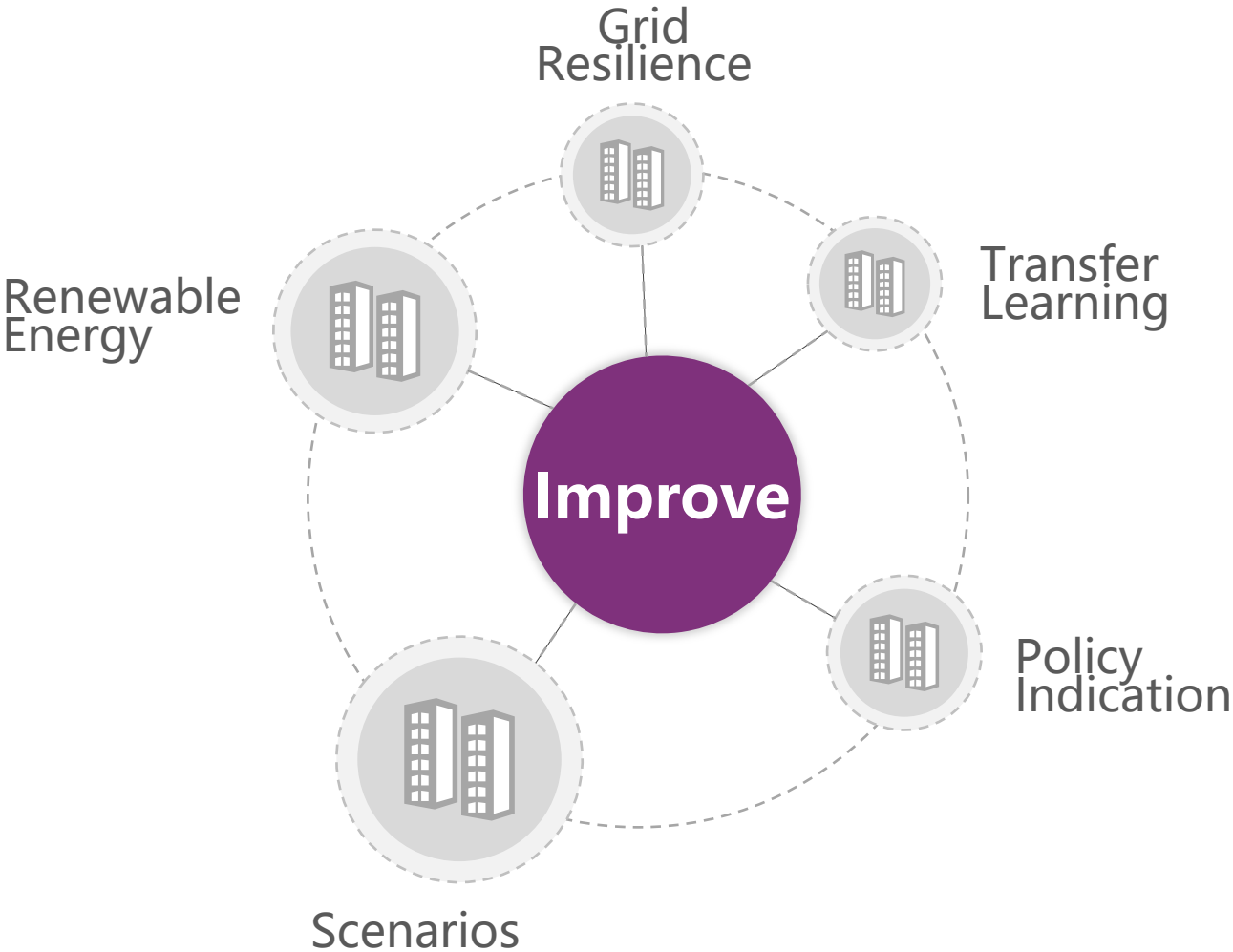
$$\text{MAPE} = \left(\frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \right) \times 100\%$$

- Root Mean Squared Error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$



Future Work



Acknowledgments



This work was supported by the Engineering and Physical Sciences Research Council (EPSRC) for the project “Virtual Power Plant with Artificial Intelligence for Resilience and Decarbonisation” (**VPP-WARD**, EP/Y005376/1).



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Thanks
For Your Listening