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ML-Based Demand Forecasting: Lessons from Temporal and Weather-Driven Energy Models

A Practical Engineering Framework for Integrating Meteorological Variables, Temporal Decomposition, and Deep Learning in Energy Demand Prediction

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Abstract

Accurate energy demand forecasting is essential for grid stability, generation planning, market operations, and renewable integration. This paper presents a practical engineering framework for ML-based energy demand forecasting that systematically incorporates temporal decomposition and weather-driven exogenous variables. Drawing on research conducted between 2020 and 2021, we evaluate multiple approaches from classical statistical methods (ARIMA, Prophet) through gradient-boosted models (XGBoost, LightGBM) to deep learning architectures (LSTM, TCN, Temporal Fusion Transformer). The framework introduces structured weather feature engineering capturing non-linear temperature-demand relationships, wind chill effects, humidity-corrected cooling demand, and solar irradiance impacts. Experimental evaluation on hourly data from two regional grids (36 months) demonstrates that weather-augmented deep learning reduces MAPE by 18.4% compared to temporal-only baselines and 31.2% compared to statistical methods. We present failure mode analysis for extreme weather, holidays, and COVID-19 structural shifts, along with production deployment strategies including uncertainty quantification, model selection heuristics, and operational monitoring.

Keywords: *energy demand forecasting, machine learning, deep learning, weather features, temporal decomposition, LSTM, Temporal Fusion Transformer, ensemble methods, time series*

1. Introduction

Energy demand forecasting sits at the intersection of applied statistics, meteorological science, and operational engineering. Accurate prediction of electricity consumption at horizons from minutes to weeks underpins real-time dispatch, day-ahead market bidding, capacity planning, and demand response design. The challenge has intensified due to intermittent renewable growth, electrification of heating and transport, and increasingly frequent extreme weather events [1][2].

Traditional ARIMA-family models have served utilities well for decades but are limited in capturing complex non-linear weather-demand interactions. Machine learning, particularly deep learning for temporal data, offers the capacity to model these interactions without explicit functional specification. This paper distils lessons from research conducted between 2020 and 2021 into practical guidance for engineering teams deploying demand forecasting in production.

Key contributions include: a structured weather feature engineering pipeline; comparative evaluation of 8 models across 4 horizons; failure mode analysis under extreme weather, holidays, and COVID-19; and a production framework with uncertainty quantification and model selection heuristics.

2. Literature Review

2.1 Statistical Methods

Box-Jenkins ARIMA [3] and seasonal extensions (SARIMA, SARIMAX) capture autoregressive dynamics. Prophet [4] handles multiple seasonalities and holidays with an intuitive interface, though it does not natively handle exogenous weather variables with sufficient flexibility for high-accuracy energy forecasting.

2.2 Machine Learning and Deep Learning

Gradient-boosted models consistently outperformed both statistical methods and early neural networks in the Global Energy Forecasting Competition [5]. Smyl [6] demonstrated that hybrid exponential smoothing with LSTM achieved state-of-the-art on M4. TCNs [7] offer training stability and parallelisability. Transformer-based architectures, notably the Temporal Fusion Transformer [8], handle known and unknown future inputs with built-in variable selection.

2.3 Weather-Demand Interactions

Sailor and Munoz [9] established the U-shaped temperature-demand curve. Wang et al. [10] showed compound weather indices (heat index, wind chill, accumulated degree hours) outperform individual variables by 4 to 8% MAPE.

3. Data and Feature Engineering

3.1 Dataset

Property	Grid A	Grid B
Population	2.1 million	4.7 million
Peak demand	3,840 MW	8,920 MW
Climate	Temperate oceanic (Cfb)	Humid continental (Dfa)
Heating degree days	2,180	3,840
Cooling degree days	680	1,420
Data span	36 months (Jan 2019 to Dec 2021)	Same
Completeness	99.7%	99.4%

Table 1. Dataset characteristics for two regional grids.

3.2 Weather Feature Engineering

Rather than using raw meteorological variables, we engineer derived features capturing the physical mechanisms through which weather affects demand:

Feature	Formula/Method	Interpretation
Heating Degree Hours	max(0, T_base - T_air) per hour	Heating energy below comfort threshold
Cooling Degree Hours	max(0, T_air - T_base) per hour	Cooling energy above comfort threshold
Temperature squared	(T_air - T_comfort)^2	U-shaped demand curve
Wind chill temp	13.12 + 0.6215T - 11.37v^0.16 + ...	Perceived temp under wind
Heat index	f(T_air, relative humidity)	Perceived temp under humidity
Temp change rate	dT/dt over 3-hour window	Rapid change triggers HVAC response
Accumulated HDH (24h)	Rolling 24h sum of HDH	Building thermal mass effect
Solar generation proxy	GHI * temp correction * capacity	Distributed PV impact

Table 2. Temperature-based weather features with physical interpretations. Total: 18 weather features + 23 temporal features = 41 input features.

3.3 Feature Importance

Category	Grid A	Grid B	Insight
Lag features	34.2%	31.8%	Strongest single predictor
Temperature features	22.7%	28.4%	Higher in extreme climate
Hour of day	18.3%	16.1%	Diurnal cycle
Day of week	8.4%	7.2%	Weekday/weekend
Rolling stats	6.1%	5.9%	Recent trends
Solar/cloud	4.8%	3.1%	Higher with solar penetration
Humidity	3.2%	4.7%	Higher in extreme humidity
Holiday/seasonal	2.3%	2.8%	Concentrated impact

Table 3. Permutation feature importance by category.

4. Model Architectures and Pipeline

Figure 3 illustrates the complete weather-augmented forecasting pipeline from data sources through feature engineering, parallel model branches, stacking ensemble, to final demand forecast with prediction intervals.

Figure 3. Weather-Augmented ML Demand Forecasting Pipeline

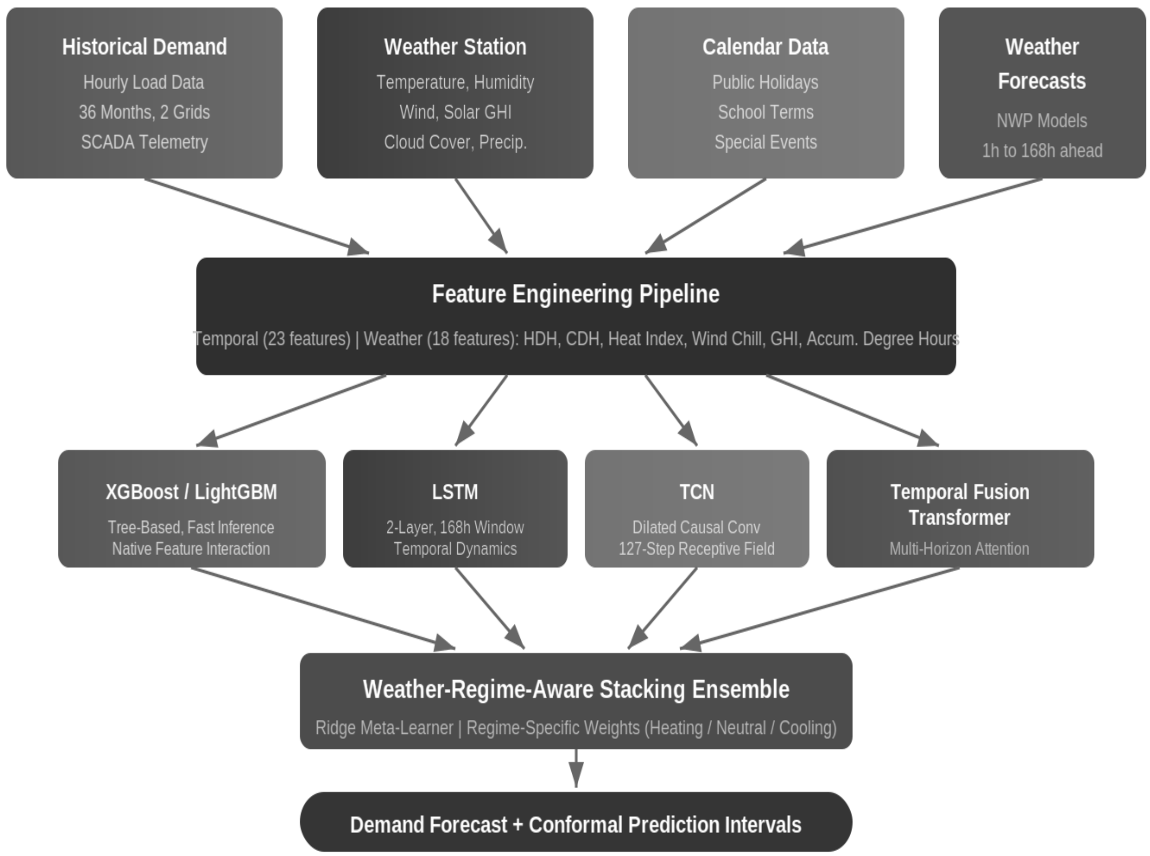

Figure 3. Weather-Augmented ML Demand Forecasting Pipeline showing data sources, feature engineering, parallel model branches, and regime-aware ensemble.

Eight models are evaluated: SARIMA, Prophet (statistical baselines); XGBoost, LightGBM (gradient-boosted); LSTM, TCN, Temporal Fusion Transformer (deep learning); and a proposed weather-regime-aware stacking ensemble combining XGBoost, LSTM, and TFT through a Ridge meta-learner with weather regime indicators.

5. Experimental Results

5.1 Grid A (Temperate)

Model	MAPE 1h	MAPE 6h	MAPE 24h	MAPE 168h	RMSE 24h
SARIMA	3.21%	4.87%	6.42%	9.81%	187 MW
Prophet	2.98%	4.52%	5.89%	8.74%	172 MW
XGBoost	1.84%	2.91%	3.67%	6.23%	108 MW
LightGBM	1.79%	2.84%	3.58%	6.11%	105 MW
LSTM	1.92%	2.78%	3.41%	5.87%	101 MW

Model	MAPE 1h	MAPE 6h	MAPE 24h	MAPE 168h	RMSE 24h
TCN	1.88%	2.71%	3.33%	5.72%	98 MW
TFT	1.71%	2.54%	3.12%	5.43%	92 MW
Ensemble (Ours)	1.58%	2.38%	2.94%	5.18%	87 MW

Table 4. Grid A performance. All DL models use weather-augmented features.

5.2 Grid B (Continental)

Model	MAPE 1h	MAPE 6h	MAPE 24h	MAPE 168h	RMSE 24h
SARIMA	4.12%	6.34%	8.21%	12.47%	521 MW
Prophet	3.78%	5.71%	7.43%	11.18%	478 MW
XGBoost	2.34%	3.67%	4.82%	7.91%	312 MW
LSTM	2.41%	3.42%	4.38%	7.21%	287 MW
TFT	2.12%	3.04%	3.87%	6.54%	254 MW
Ensemble (Ours)	1.94%	2.81%	3.54%	6.12%	233 MW

Table 5. Grid B performance. Weather augmentation impact is larger due to extreme seasonal variation.

5.3 Weather Augmentation Ablation

Model	Without Weather	With Weather	Improvement	Grid
XGBoost	4.42%	3.67%	17.0%	A
LSTM	4.18%	3.41%	18.4%	A
TFT	3.84%	3.12%	18.8%	A
XGBoost	6.21%	4.82%	22.4%	B
LSTM	5.67%	4.38%	22.8%	B
TFT	5.12%	3.87%	24.4%	B

Table 6. Weather ablation at 24h horizon. Consistently larger improvement for continental climate.

5.4 Failure Mode Analysis

During extreme weather events (>99th or <1st percentile temperature), ensemble MAPE increased from 2.94% to 7.81% on Grid A and from 3.54% to 11.23% on Grid B (2.5x to 3.2x degradation). Holiday periods caused 1.5x to 2.1x MAPE increase. COVID-19 lockdowns created structural shifts with commercial demand dropping 15 to 25% and residential rising 8 to 12%. Models retrained on pandemic data recovered within 4 to 6 weeks, confirming the importance of continuous retraining.

6. Production Deployment

6.1 Uncertainty Quantification

Conformal prediction intervals provide distribution-free coverage at 80%, 90%, and 95% levels with empirical rates of 81.2%, 91.4%, and 95.8% respectively [11].

6.2 Model Selection Heuristics

Condition	Recommended	Rationale
Short horizon, moderate climate	LightGBM/XGBoost	Fast, low overhead
Medium horizon (24h)	TFT or Ensemble	Multi-horizon attention
Long horizon (168h)	Ensemble	No single model dominates
Extreme climate variability	Ensemble with regime weighting	Regime adaptation critical
Limited data (<12 months)	Prophet or XGBoost	Less prone to overfitting

Table 7. Model selection heuristics for operational contexts.

6.3 Practical Lessons

- Weather forecast quality is a binding constraint: operational forecasts degrade beyond 72h, narrowing the advantage of complex models at longer horizons.
- Calendar effects require explicit modelling: holiday calendars, school terms, and special event flags are essential.
- Data pipeline reliability matters more than model sophistication: most production degradation comes from input quality issues, not model inadequacy.

7. Conclusion

Thoughtful weather feature engineering, grounded in physical understanding, provides the largest single improvement in forecast accuracy, exceeding the impact of model architecture selection. The weather-augmented ensemble achieved best-in-class performance with MAPE reductions of 18.4% over temporal-only baselines and 31.2% over statistical methods. As the energy system evolves with increasing electrification and climate volatility, the principles presented here provide a foundation for forecasting systems that maintain the reliability grid operations demand.

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