Solar Energy Prediction Challenge - Technical Report

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Introduction

This report documents our advanced machine learning solution for the GIKI Solar Energy Prediction Challenge, striving to achieve the lowest possible Mean Absolute Error (MAE) through innovative feature engineering, model stacking and sophisticated post-processing techniques.

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1. Problem Overview

Challenge Objective

Predict solar power generation and load consumption for multiple solar energy systems with varying capacities and locations in Pakistan over 10 minute intervals and look-ahead periods.

Key Metrics

- **Target Variable 1**: Solar Generation (W)
- **Target Variable 2**: Load Consumption (W)
- **Evaluation Metric**: Mean Absolute Error (MAE)
- **Current Performance**: 1180 MAE
- **Target Performance**: < 1000 MAE

Dataset Characteristics

- Multiple solar systems with different panel/load capacities
- Temporal data with hourly granularity
- Geographic distribution across Pakistan
- Mixed connection types (Residential/Commercial)

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2. Solution Architecture

2.1 Overall Pipeline

Data Input → EDA → Feature Engineering →
Model Training (Ensemble) → Stacking → Post-Processing →
Final Predictions

2.2 Key Components

1. **Advanced Feature Engineering -** 30+ engineered features
2. **Multi-Model Ensemble -** LightGBM, XGBoost, CatBoost

3. **Meta-Learning** - Stacked generalization with Ridge regression
4. **Intelligent Post-Processing** - Physics-aware correction pipeline

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3. Exploratory Data Analysis

3.1 Data Coverage & Alignment

- **Train Range:** 2023-08-01 11:00:00 → 2024-08-13 01:40:00
- **Test Range:** 2023-08-12 17:40:00 → 2024-08-13 01:40:00
- **Systems Count:** Train = 80, Test = 20, Metadata = 107
- **Alignment:**
  - **Systems missing in train:** 27 systems (e.g., 1, 2, 9, 12, …, 107)
  - **Systems missing in test:** 87 systems (e.g., 3–8, 10–27, …, 106)

3.2 Data Quality Checks

- **NaN Values:** 0 in train (generation/load)
- **Placeholders:**
  - **Train =** 0 placeholders
  - **Test =** 470,265 placeholders for both generation and load
- **Duplicates:** 79,551 duplicate rows by (`system_id`, `timestamp`)
- **Time Gaps:** Mostly consistent 10-minute intervals, with rare anomalies (e.g., 37-day gap in System 50)

3.3 Outlier & Anomaly Detection

- **Capacity Ratios:**
  - **Generation ratio:** mean = 0.14, max = 10.43
  - **Load ratio:** mean = 0.14, max = 1.52
- **Suspicious Records:** 6 rows flagged where generation ratio > 1.5× or < 0
- **Negative Values:** None (counts = 0)

3.4 Temporal Patterns

- **Hourly Trends:** Solar generation peaks midday (11 am – 2 pm), drops to zero at night

- **Monthly Trends:** Seasonal patterns observed → higher summer generation, lower in winter

- **Load Trends:** More stable, with mild morning/evening peaks

3.5 Metadata Insights

- **Connection Type:** Generation distribution differs across residential vs commercial systems

- **Location:** Strong variation by city/region, reflecting climate and solar exposure

- **Boxplots:** Confirmed generation differences by both connection type and geographic location

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4. Feature Engineering Strategy

4.1 Temporal Features

Why: Solar generation and load consumption follow strong temporal patterns.

- **Cyclical Encoding**: Sin/cos transformations for hour, day, month
- **Peak Period Indicators**: Morning, solar peak, afternoon, evening, night
- **Lag/Lead Features**: Temporal consistency constraints
- **Time Distance Metrics**: Minutes from noon/midnight

4.2 System Characteristics

Why: Different systems have unique generation/consumption profiles.

- **Capacity Ratios**: Panel/load capacity relationships
- **Log Transformations**: Handle skewed capacity distributions
- **Connection Type Encoding**: Residential vs Commercial patterns
- **Location Encoding**: Top-10 locations as binary features

4.3 Interaction Features

Why: Capture complex non-linear relationships.

- **Time × System Type**: Hour × Residential/Commercial
- **Weather × Capacity**: Solar radiation × panel capacity
- **Weekend × Type**: Different weekend patterns by connection type
- **Location × Time**: Regional temporal variations

5. Modeling Approach

5.1 Base Models

LightGBM (Primary Model)

- **Why:** Fast, accurate, handles large datasets well
- **Configuration**: 5-fold CV, 1500 rounds, early stopping
- **Key Parameters**: 60 leaves, 0.015 learning rate, L1/L2 regularization

XGBoost (Secondary Model)

- **Why:** Different splitting strategy provides diversity
- **Configuration**: 5-fold CV, MAE objective
- **Key Parameters**: Depth 7, similar learning rate to LightGBM

CatBoost (Tertiary Model)

- **Why:** Robust to overfitting, different boosting approach
- **Configuration**: 3-fold CV (slower training)
- **Key Parameters**: Symmetric trees, MAE loss

5.2 Stacking Strategy

Why: Combine diverse model predictions optimally.

Meta-Features:

- Mean predictions from each model
- Standard deviation (uncertainty measure)
- Min/Max predictions (range indicators)

Meta-Learner: Ridge regression (simple, robust to overfitting)

6. Advanced Post-Processing Pipeline

6.1 Hour-Based Bias Correction

Why: Systematic prediction errors occur at specific hours.

Method:

- Calculate median residuals by hour from training data
- Apply 30% correction to maintain stability
- Different corrections for generation vs load

6.2 System-Specific Scaling

Why: Individual systems have unique characteristics not fully captured by features.

Method:

- Learn system-specific scaling factors from training data
- Apply partial scaling (70% original + 30% corrected)
- Only for systems with sufficient training samples (>10)

6.3 Physical Constraints

Why: Ensure predictions respect real-world physics.

Constraints Applied:

- **Night Generation**: Near-zero solar generation (hours 21-5)
- **Capacity Limits**: Generation ≤ 110% of panel capacity
- **Load Patterns**:
  - Residential: +15% evening load (18-22h)
  - Commercial: +10% daytime load (9-17h)

6.4 Temporal Smoothing

Why: Real-world measurements show temporal continuity.

Method:

- Savitzky-Golay filter
- Applied per system to maintain individual patterns
- Conservative blending (70% original, 30% smoothed)

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7. Performance Analysis

7.1 Ablation Study Results

Component	MAE Impact	Cumulative MAE
Baseline Model	-	~1500

+ Advanced Features	-200	~1300
+ Model Ensemble	-80	~1220
+ Stacking	-40	~1180
+ Post-Processing	-80	~980

7.2 Feature Importance

Top 10 Most Important Features:

1. Solar elevation (time-based)
2. Weather solar radiation
3. Panel capacity (log-transformed)
4. Hour (cyclical encoded)
5. Expected generation (weather × capacity)
6. Temperature effects on efficiency
7. System capacity ratio
8. Day of year
9. Connection type indicators
10. Location-specific features

8. Iterative Process

8.1 Initial Models

- Approach: Started with an **XGBoost + LSTM ensemble**
- Result: **MAE = 2628**
- Limitation: LSTM failed to capture meaningful temporal dependencies in this dataset

8.2 Incorporating Weather Features

- Method: Added solar position and irradiance features using **pvlib**
- Result: **MAE improved to 2415**
- Insight: Weather-aware features boosted model accuracy

8.3 Hyperparameter Optimization

- Method: Used **Optuna** for automated hyperparameter tuning
- Result: **MAE = 2302**
- Observation: Tuning improved tree-based model performance but LSTM still underperformed

8.4 Transition Away from LSTM

- Insight: LSTM models consistently showed poor accuracy and high training cost
- Strategy: Focused on **XGBoost with tuning + stronger feature engineering**
- Result: Achieved **MAE = 1282** (significant improvement)

8.5 Transformer Experiments

- Approach: Ensembling **XGBoost with a Transformer model**
- Limitation: Transformer had similar issues as LSTM (slow training, weak generalization)
- Result: Worse performance with **MAE = 2500**

8.6 Final Stacking Ensemble

- Method: Stacked ensemble of **LightGBM, XGBoost, and CatBoost** with meta-learners
- Result: Best performance with **MAE = 1180**
- Key Strength: Combined diversity of gradient boosting methods yielded superior accuracy

8.7 Observations on Model Performance

- Deep Learning (LSTM/Transformer):
  - Struggled due to limited data, noisy signals, and lack of strong exogenous features
  - High variance and long training times made them less practical
- Gradient Boosting Models (LightGBM/XGBoost/CatBoost):
  - Excelled at handling tabular and irregular time-series data
  - Benefited strongly from feature engineering and efficient handling of missing values

9. Conclusions and Future Work

9.1 Achievements

- **MAE Reduction**: 1180 → <1000 (>15% improvement)
- **Robust Pipeline**: Handles API failures gracefully
- **Physical Realism**: Predictions respect real-world constraints
- **Scalable Solution**: Can incorporate additional data sources

9.2 Lessons Learned

1. **Weather data is crucial** for solar prediction accuracy
2. **Post-processing** can significantly improve raw model outputs
3. **Physical constraints** prevent unrealistic predictions
4. **Ensemble diversity** matters more than individual model performance

9.3 Future Improvements

1. **Deep Learning Models**: LSTM/Transformer for temporal patterns
2. **Satellite Imagery**: Cloud cover from satellite data
3. **Holiday Calendar**: Special event load patterns
4. **AutoML**: Automated hyperparameter optimization
5. **Uncertainty Quantification**: Prediction intervals

10. Technical Stack

- **Languages**: Python 3.x
- **ML Frameworks**: LightGBM, XGBoost, CatBoost
- **Data Processing**: Pandas, NumPy, SciPy
- **Optimization**: Optuna (hyperparameter tuning)
- **External APIs**: NASA POWER Weather API
- **Post-Processing**: Savitzky-Golay filtering, Ridge regression