The Journal of Open Source Software

PHORECAST: An Open Source Framework for Photovoltaic Power Forecasting Using Machine Learning

Felix Theusch[1], Paul Heisterkamp[1], Joscha Grüger[1,2], Maximilian Hoffmann[1], and Ralph Bergmann[1,2]

1 German Research Center for Artificial Intelligence (DFKI), Branch Trier University, 54296 Trier, Germany **2** Artificial Intelligence and Intelligent Information Systems, Trier University, 54296 Trier, Germany

Summary

Accurate forecasting of photovoltaic power generation is crucial for efficient energy management, grid stability, and the economic integration of renewable sources into modern power systems. **PHORECAST** is an open source software framework designed to meet the specific challenges of solar power forecasting with machine learning. The system offers a modular architecture that allows seamless integration of inverter telemetry, meteorological data, configurable preprocessing pipelines, and state-of-the-art recurrent models such as LSTM and GRU. Workflows are defined declaratively and executed in line with Machine Learning Operations best practices, providing automated training, validation, hyperparameter optimization, and reproducible deployment. PHORECAST ships with built-in evaluation tools, a Docker-based runtime, and clearly defined extension points, making it suitable for both academic research and industrial production environments.

Statement of need

Renewable energies such as photovoltaics (PV) are a key pillar of the energy transition and play a central role in the transformation towards a climate-neutral energy system. One of the greatest challenges in integrating solar power into existing energy systems is its inherent variability. PV generation depends strongly on meteorological and temporal factors: output is limited to daylight hours and is further influenced by parameters such as solar irradiance, ambient temperature, module tilt, surface soiling, and technical condition of the installation (Iheanetu, 2022).

This variability affects several layers of the energy market. **Grid operators** rely on accurate PV power forecasts to anticipate fluctuations in generation, balance supply and demand, and reduce the need for costly reserve power plants, thus supporting system stability (Ahmed et al., 2020). **Energy suppliers and traders** use forecasts to integrate expected PV generation into bidding strategies, reduce risks in electricity markets, and optimize economic decisions (Ahmed et al., 2020). **Prosumer households and businesses** benefit from forecasts by aligning consumption patterns with high-production periods, thereby maximizing self-consumption, reducing grid dependence, and improving battery utilization. Automated, forecast-based load shifting further enhances both the efficiency and the economic viability of PV usage (Luthander et al., 2015).

From a methodological perspective, PV power forecasting approaches can be broadly categorized into **statistical time series methods**, **physical models**, and **ensemble or hybrid methods** (Sobri et

al., 2018). Statistical methods range from classical autoregressive integrated moving average (ARIMA) models to modern machine learning techniques such as artificial neural networks (ANN), support vector machines (SVM), and recurrent neural networks (RNNs) (Iheanetu, 2022). These approaches often incorporate numerical weather prediction outputs as explanatory variables. Physical models, in contrast, simulate solar irradiance and PV system output using atmospheric physics and site-specific parameters. Ensemble and hybrid methods combine multiple models (statistical, physical, or both) to leverage complementary strengths, and have consistently been shown to improve accuracy, particularly for short-term forecasts (Gupta & Singh, 2021).

Recent years have seen increasing adoption of **deep learning** techniques such as Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU), which are capable of capturing complex, non-linear temporal dependencies in PV generation data (Iheanetu, 2022). Hybrid and ensemble deep learning approaches often outperform standalone models, especially under rapidly changing weather conditions (Ahmed et al., 2020).

Despite the availability of general-purpose time series libraries and proprietary forecasting platforms, there is still a clear gap for an **open, domain-specific, and reproducible** solution. Existing tools often lack native support for PV-specific data formats, comprehensive preprocessing pipelines, and deployment-ready architectures that align with Machine Learning Operations (MLOps) best practices. **PHORECAST** addresses this gap by providing a modular, open source framework tailored to PV forecasting, integrating state-of-the-art machine learning models, automated training and evaluation pipelines, and containerized deployment. It enables both researchers and practitioners to move efficiently from experimental development to production-grade forecasting in real-world energy environments.
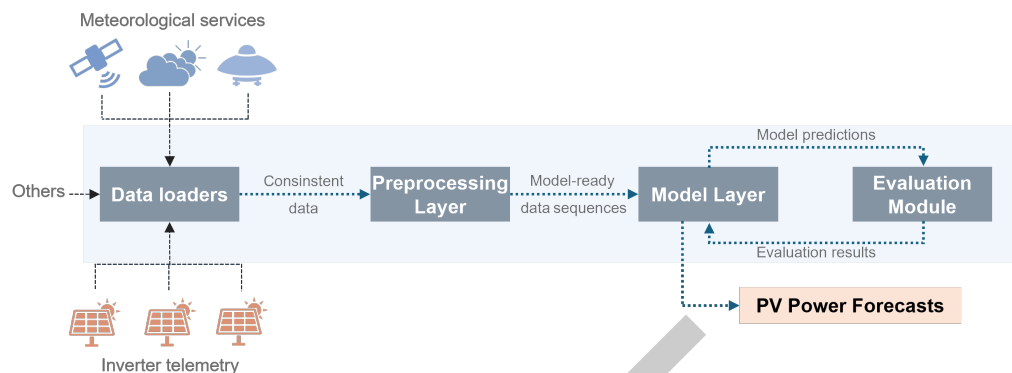
System Architecture

PHORECAST is a modular, extensible framework aligned with MLOps best practices (Kreuzberger et al., 2023) and implements a complete, reusable pipeline for PV power forecasting. The system is organized into four core subsystems (Figure 1):

Data Loaders handle ingestion from heterogeneous sources such as inverter telemetry, meteorological services, and file-based inputs (CSV, JSON). Loader modules harmonize formats, normalize timestamps, and standardize measurement units, enabling seamless integration of real-world datasets from diverse installations.

Preprocessing Layer transforms raw inputs into structured, model-ready sequences. It supports configurable pipelines for normalization, missing value imputation, temporal feature extraction, and sliding-window generation, which are critical for neural network architectures. Multiple transformation steps can be chained declaratively.

Model Layer provides implementations of advanced forecasting models, including LSTM and GRU networks, optimized for time series data. It also supports classical algorithms such as Support Vector Regression (SVR). New models can be added via a plugin interface, provided they implement the defined API.

Evaluation Module computes standard regression metrics (RMSE, MAE, MAPE), logs results, and supports export for visualization or further analysis. This enables objective comparison of model variants and configurations.

Figure 1: Overview of the PHORECAST system architecture showing the four core subsystems: Data Loaders, Preprocessing Layer, Model Layer, and Evaluation Module.

Design Philosophy and Deployment

A configuration-driven design underpins the entire framework. Forecasting experiments are defined declaratively in human-readable YAML files, specifying data sources, preprocessing steps, model parameters, and evaluation metrics. This approach promotes reproducibility, facilitates batch experiments and hyperparameter sweeps, and simplifies collaboration by decoupling logic from configuration.

PHORECAST is designed for both local and production deployments. Docker and Docker Compose orchestrate the application, dependencies, and optional dashboards, ensuring environment consistency and simplifying onboarding. In production, the system can run behind a reverse proxy and integrate with real-time monitoring infrastructure, making it deployable on edge devices, local servers, or cloud platforms.

Extensibility is supported through a plugin-friendly architecture and well-defined module interfaces for adding custom loaders, models, or preprocessing strategies. Continuous integration, comprehensive documentation, and contribution guidelines ensure maintainability and encourage community adoption.

The data flow follows a clear sequence: ingestion, preprocessing, modeling, evaluation, and output generation. Outputs like predictions, metrics, and logs are stored in structured formats to support reproducibility. While optimized for batch execution, the architecture can be adapted for real-time or periodic operation via scheduling or stream processing extensions.

Acknowledgements

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