LONG TERM FORECASTING OF PV PLANT PRODUCTION

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Abstract. This poster outlines a research plan to compare LSTM and Transformer architectures for multi-day photovoltaic (PV) power forecasting. Meteorological data (solar irradiance, temperature, humidity, wind speed, cloud coverage) will be integrated with PV output to train the models. We will assess performance using MAPE, RMSE, and R^2, focusing on varying weather conditions and trends over multi-day horizons. Findings aim to enhance long-term forecast accuracy, thereby improving stability and supporting reliable integration of solar energy into modern power grids.

INTRODUCTION

The integration of photovoltaic (PV) systems into global energy infrastructure continues to expand rapidly, with the International Energy Agency projecting growth from 640 GW in 2022 to over 1,200 GW in the medium term [1]. While this growth presents significant opportunities for renewable energy adoption, it also highlights critical challenges in making forecasting accessible to communities. Although current PV forecasting tools serve industry needs, they often remain inaccessible to citizens and community groups who could benefit from understanding their local renewable energy potential. This research evaluates machine learning approaches for creating intuitive, publicly accessible PV production forecasting tools, examining methods to translate complex technical data into actionable insights for community-led renewable energy initiatives. Our goal is to democratize forecasting technology to empower sustainable energy planning at the grassroots level.

LITERATURE REVIEW

Recent research has demonstrated the effectiveness of Transformer networks for photovoltaic power forecasting. While traditional approaches like artificial neural networks (ANNs) and recurrent neural networks (RNNs) have shown promise [2], Transformers offer unique advantages through their attention mechanism that captures complex spatiotemporal relationships in the data. Pospíchal et al. (2022) achieved impressive results using a Transformer model, obtaining a mean absolute percentage error of just 3.45% for one-day-ahead predictions [3] [6]. Their approach leveraged the model's ability to process both temporal patterns in weather data and spatial relationships across different geographical regions. The multi-head attention mechanism proved particularly effective at identifying relevant correlations between meteorological parameters and solar output across different locations.

A key strength of Transformer architectures is their capability to handle multiple input streams simultaneously while learning meaningful interactions between different types of data. The attention mechanism allows the model to dynamically focus on the most relevant features for prediction, whether they are temporal patterns in historical data or spatial relationships across monitoring stations.

The success of Transformer models in this domain suggests they may become increasingly important for renewable energy forecasting. Their ability to process complex spatiotemporal data while maintaining computational efficiency makes them a promising direction for future research and practical applications in solar power prediction.

RESEARCH METHODOLOGY

This research will evaluate and compare Long Short-Term Memory (LSTM) networks and Transformer models for photovoltaic power forecasting. The models will be trained using historical meteorological data, including solar irradiance, temperature, humidity, wind speed, and cloud coverage, alongside corresponding PV power output measurements. Both architectures will be implemented using Python with PyTorch, trained on data spanning multiple years with an 80-20 train-test split. Performance will be assessed using standard metrics including Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and R-squared values [4]. The evaluation will focus particularly on day-ahead forecasting capabilities, with predictions meticulously made at hourly intervals, ensuring more robust performance evaluation. Special attention will be paid to the models' ability to handle varying weather conditions and seasonal patterns, with separate analysis of performance during highly variable days. The results will provide valuable insights into the comparative strengths of each architecture for solar power prediction.

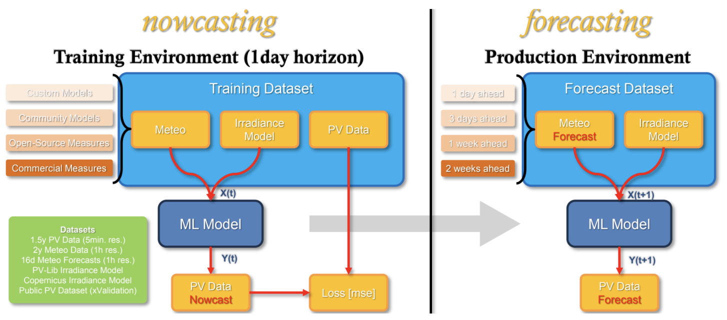

Fig. 1. PV production nowcasting and forecasting workflow

PRELIMINARY CONSIDERATIONS

Several key considerations must be addressed before implementing the forecasting models. These include data quality and preprocessing requirements, the selection of appropriate input features, the handling of missing values, and the determination of optimal sequence lengths for both LSTM and Transformer architectures.

CONCLUSIONS

While current nowcasting methods achieve impressive accuracy with error rates under 1% [6], extending such precision to longer-term forecasting presents significant challenges. Nevertheless, this research aims to leverage the advanced capabilities of LSTM and Transformer architectures to approach comparable accuracy levels for day-ahead predictions. The findings should contribute valuable insights for improving long-term PV power forecasting reliability, ultimately supporting more efficient grid integration of solar energy resources.

References.

[1]. Iea (11 January 2024) *Massive expansion of renewable power opens door to achieving global tripling goal set at COP28 - News, IEA*. Available at: https://www.iea.org/news/massive-expansion-of-renewable-power-opens-door-to-achieving-global-tripling-goal-set-at-cop28

[2] Ogliari, E., Grimaccia, F., Leva, S., & Mussetta, M. (2013). Hybrid predictive models for accurate forecasting in PV systems. *Energies*, *6*(4), 1918-1929.

[3] Pospíchal, J., Kubovčík, M., & Dirgová Luptáková, I. (2022). Solar irradiance forecasting with transformer model. *Applied Sciences*, *12*(17), 8852.

[4] Zhang, J., Florita, A., Hodge, B. M., Lu, S., Hamann, H. F., Banunarayanan, V., & Brockway, A. M. (2015). A suite of metrics for assessing the performance of solar power forecasting. *Solar Energy*, *111*, 157-175.

[5] Tuohy, A., Zack, J., Haupt, S. E., Sharp, J., Ahlstrom, M., Dise, S., ... & Collier, C. (2015). Solar forecasting: methods, challenges, and performance. *IEEE Power and Energy Magazine*, *13*(6), 50-59.

[6] Piantadosi, G., Dutto, S., Galli, A., De Vito, S., Sansone, C., & Di Francia, G. (2024). Photovoltaic power forecasting: A Transformer based framework. *Energy and AI*, *18*, 100444.

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