RESIDENTIAL PHOTOVOLTAIC GENERATION FORECAST VIA LONG SHORT-TERM MEMORY AND TRANSFORMER

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Motivation

The deployment of decentralized photovoltaic (PV) systems continues to progress rapidly in Germany. Installed system numbers have risen markedly in recent years, primarily driven by the uptake of small-scale plug-in balcony PV units [1]. This development indicates that PV systems are both economically attractive and widely accepted by the public. However, the ongoing capacity expansion is accompanied by tightening legal and regulatory constraints. For instance, feed-in remuneration is suspended during periods of negative electricity spot market prices [2]. Consequently, the efficient on-site use of self-generated PV energy gains further importance [3]. To enable this, accurate and reliable short-term PV generation forecasts are essential.

Methodology

Selection of Forecasting Method

The choice of forecasting method is driven by the objective of generating short-term PV power forecasts with high accuracy and robust generalization capability. Against this background, a recurrent Long Short-Term Memory (LSTM) network and a Transformer-based model were selected, as both approaches are identified in recent studies being effective for complex time series forecasting. The choice of LSTM and Transformer models enables a systematic comparison between two representative and complementary architecture families reflecting methodological advances in recent years. LSTM provides a well-understood and widely validated standard in the PV literature, while the Transformer represents state-of-the-art in modelling global dependencies and scalable time series processing. [3–6]

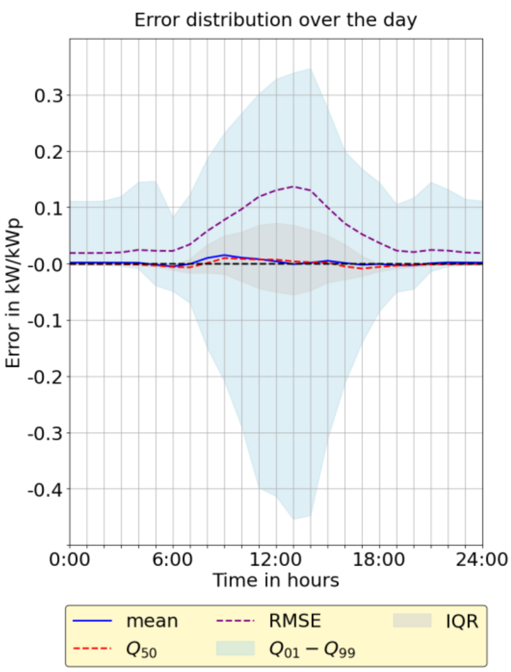

Figure 1: Error Distribution over the day - LSTM

Data Selection and Preprocessing

The data used in this research combines PV power [7–11] and weather datasets [12, 13] from various cities around the world, with a focus on representing different climate zones. The dataset consists of several years in 15-minute resolution for the cities of Gaithersburg [7], Melbourne [8], Istanbul [9], Hongkong [10], and Bielefeld [11].

In the preprocessing, outliers and missing values were removed to ensure a higher data quality. NAN- values were identified and replaced by zeros. Afterwards, zeros were interpolated.

Feature Selection

For assessing the relevance of commonly used features, correlation analysis and scatter plots were used. In addition, simple LSTM models were trained and assessed, where different feature combinations were applied. Used features are e.g. the shortwave radiation, temperature, angel of incidence, cloud coverage, relative humidity, wind speed and lagged values.

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Model Training and Hyperparameter Tuning

The data of each profile were split into a 75% training, 10% validation, and 15% test ratio. The training dataset was employed for model learning. In contrast, the validation dataset monitored the training process and utilized potential termination criteria like early stopping [14]. The test dataset was reserved for model evaluation. Since the dataset comprised data from nine different solar power plants, a 9-group cross-validation approach was applied, where each group corresponds to one plant. This method ensures that the model’s performance is robustly evaluated and generalizes well across different locations [15]. To reduce the risk of overfitting, the models hyperparameter were optimized through Bayesian Optimization. The mean squared error (MSE) was used as the error metric for the loss function, as it assigns greater weight to larger prediction errors.

Forecast Assessment

For assessing forecast accuracy, the average error course over a day was illustrated in Figure 1 for the LSTM model, showing normalized values due to normalisation by the system peak power. It is evident that there is a tendency to underestimate rather than overestimate particularly around noon. Despite this, the LSTM model's average MSE of 0.0057 is higher than that of the Transformer model, which achieves a lower average MSE of 0.0038. This indicates that the Transformer model exhibits superior prediction accuracy in this evaluation, especially in reducing error during critical daytime periods when PV output is highest.

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