Literature review

Antonanzas et al. (2016) provided a comprehensive review of photovoltaic power forecasting methods, underlining the importance of precise energy forecasts for grid management and cost optimization. They argued that meteorological inputs, including solar irradiance, temperature, humidity, and wind speed, are vital for enhancing the predictive capabilities of models. Their study highlighted that the incorporation of environmental data significantly improves the accuracy of power output predictions compared to models relying solely on historical energy production.

Voyant et al. (2017) conducted an extensive examination of various machine learning methodologies for solar radiation forecasting. Their research found that machine learning approaches, such as decision trees, ensemble learning, support vector machines, and deep learning, consistently outperformed traditional statistical models like ARIMA and simple regression models. They stressed that solar irradiance and temperature were the most influential meteorological factors for predicting solar energy production, while humidity and wind speed also played significant supporting roles.

Wan et al. (2015) explored the application of deep learning models, with a particular focus on Long Short-Term Memory (LSTM) networks, for renewable energy time-series forecasting. Their findings indicated that LSTM networks are exceptionally capable of learning long-term temporal dependencies, making them highly suitable for solar forecasting where historical patterns significantly impact future outcomes. Unlike shallow models, LSTMs can manage sequential dependencies effectively, accounting for the cyclical nature of solar energy production over daily and seasonal scales.