A Review of State-of-the-art and Short-Term Forecasting Models for Solar PV Power Generation

Wen-Chang et al provides a comprehensive overview [1] of various predictive models for solar radiation and solar photovoltaic (PV) power generation forecasting. They discuss the growing importance of solar renewable energy and the rapid increase in installed solar energy capacity globally, emphasising the need for accurate forecasting models to support efficient energy management.

The review categorises forecasting methods into traditional physics and statistics-based approaches, machine learning models, optimization algorithms, deep learning methods, and hybrid models. It covers a wide range of short-term forecasting models, including those based on Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), Support Vector Machines (SVM), Extreme Learning Machines (ELM), Gradient Boosting Decision Trees (GBDT), and others. They also highlights recent advancements in AI and neural network approaches, such as models utilising dynamic artificial neural networks, adaptive topology based on Portfolio Theory, and deep learning techniques like Long Short-Term Memory (LSTM), Convolutional LSTM, and multi-step CNN stacked LSTM models.

CT-NET: A Novel Convolutional Transformer-Based Network for Short-Term Solar Energy Forecasting Using Climatic Information

Munsif et al proposes a novel approach, CT-NET [2], for short-term solar power generation forecasting by integrating convolutional neural networks (CNN) and transformer-based models.They highlight the limitations of sequential modelling in traditional deep learning approaches and emphasise the advantages of attention-based models, particularly transformers, in processing data in parallel, offering abstract architectures, strong correlations, lower complexity, and universal fitting abilities. The CT-NET comprises an encoder and decoder blocks, with the encoder utilising 1D CNN layers to extract spatial features and a multi-head attention (MHA) mechanism to focus on influential features in the data sequence, resulting in high efficiency and accuracy. The decoder, consisting of an MHA and a feed-forward dense layer, facilitates accurate short-term solar power generation forecasting by considering only the meteorological data of the corresponding PV.

Munsif et al emphasises the need for efficient hardware utilisation and parallel processing, which the attention-based model achieves, leading to faster training and prediction stages. The integration of CNN with MHA layers is highlighted as a unique feature, considering both local and contextual discriminative features in short sequences of solar power generation data. Empirical results using PVP data from Eco-Kinetics demonstrate the superiority of CT-NET over state-of-the-art methods, showcasing lower error rates based on mean squared error (MSE), root mean squared error (RMSE), and mean absolute percentage error (MAPE).

Solar Energy Production Forecasting Based on a Hybrid CNN-LSTM-Transformer Model

Elham et al introduces an approach to solar energy production forecasting by combining Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and Transformer models [3]. While CNN, LSTM, and autoencoders have been successfully applied in solar energy forecasting, they introduce Transformers, originally designed for natural language processing, to address forecasting challenges. However, the paper identifies limitations in the original Transformer model, including quadratic time computation, large memory requirements, and low processing speed, which hinder its application in time-series forecasting.

To overcome these limitations, they propose improvements to the Transformer structure, incorporating new components and modifying the self-attention block. They integrate convolutional layers into the Transformer encoder structure and complement the model with an LSTM network to enhance prediction performance. The proposed forecasting method involves a preprocessing stage based on a clustering technique using the self-organising map algorithm. This clustering, based on seasons, enhances the learning capacity of the model. Experiments using the Fingrid open dataset demonstrate the superior performance of the hybrid CNN-LSTM-Transformer model compared to existing state-of-the-art models and other combinations like LSTM-Transformer and CNN-Transformer.

Application of Temporal Fusion Transformer for Day-Ahead PV Power Forecasting

Miguel et al explores the utilisation of the Temporal Fusion Transformer (TFT) [4], an attention-based deep neural network, for day-ahead photovoltaic (PV) power forecasting. The motivation for employing TFT lies in its ability to capture long-term dependencies in time series data using the attention mechanism, offering advantages in interpretability over other time series methods. The TFT model is specifically designed for multi-horizon time series forecasting, making it well-suited for predicting hourly day-ahead PV power generation.

Traditional recurrent networks, such as LSTM, struggle with determining long-term dependencies, but TFT addresses this limitation by directly learning patterns during training. One notable feature of TFT is its use of a quantile loss function, enabling the generation of probabilistic forecasts with confidence intervals.

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[2] Munsif, M., Ullah, M., Fath, U., Khan, S. U., Khan, N., & Baik, S. W. (2023). CT-NET: A Novel Convolutional Transformer-Based Network for Short-Term Solar Energy Forecasting Using Climatic Information. *Computer Systems Science & Engineering*, *47*(2).
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