A Survey of Photovoltaic power forecasting approaches in Solar energy Landscape

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ABSTRACT: The integration of solar energy into the modern power grid faces challenges due to its inherent variability. Accurate solar forecasting plays a vital role in mitigating these challenges and enabling the smooth integration of solar resources. This paper presents a comprehensive overview of solar forecasting techniques, classifying them according to their prediction horizons (short-term, medium-term, and long-term). The evolution of forecasting methodologies is explored, ranging from Numerical Weather Prediction (NWP) models and statistical approaches to advanced deep learning techniques like Long Short-Term Memory (LSTM) networks and autoencoders. The suitability of these techniques is discussed in the context of lead time, accuracy requirements, and computational resources. This research paper aims to provide a structured analysis of the current landscape of solar forecasting, highlight strengths and weaknesses of various methods, and guide future research efforts towards even more refined and robust forecasting solutions for promoting renewable energy integration.

Index Terms—Solar forecasting, Time-series analysis, LSTM, ARIMA/SARIMA

I. INTRODUCTION

Renewable energy sources, particularly solar power, are essential for transitioning to a more sustainable energy grid. But grid managers have a great difficulty because of the intrinsic unpredictability of solar power output. Precise solar forecasting techniques are crucial in mitigating these challenges by providing advanced predictions of solar power production. These forecasts enable informed decision-making, optimized scheduling, and effective grid integration of solar resources. This paper explores the evolution of solar forecasting, its different classifications, and the cutting-edge techniques used for reliable and accurate predictions.

Solar forecasting methodologies are broadly categorized based on their prediction horizons. Short-term forecasts spanning minutes to hours ahead support near-real-time decisions for maintaining grid stability, while medium-term forecasts over months or seasons assist in utility planning. Long-term forecasts guide decisions about future capacity expansion and project development. Forecasting methodologies have steadily advanced in complexity, including weather-driven Numerical Weather Prediction models, persistence-based approaches, statistical time-series techniques like ARIMA models, and recent deep learning architectures such as LSTMs and autoencoders. The choice of optimal forecasting techniques depends on several factors, including the lead time desired, the required level of accuracy, and the availability of computational re- sources. In order to propose possible directions for future research, this study will critically assess the benefits and drawbacks of the most recent solar forecasting methods. This systematic investigation provides a comprehensive foundation for continued research and advancement toward even more precise and adaptable solar forecasting models to support the growth of renewable energy and reliable grid operation.

II. CLASSIFICATION OF SOLAR FORECASTS

A. Short-Term Forecasts

1) *Intra-day Forecasts:* Intra-day forecasting provides continuous solar power predictions from minutes to hours ahead, crucial for balancing supply and demand. These near-real- time forecasts on 5 minute to 1 hour timescales use weather modeling, machine learning, and live data to capture short term PV output fluctuations. By factoring in latest cloud cover, irradiance, and panel temperature impacts, intra-day models help operators smoothly ramp other generators to offset solar changes. Intra-day models utilize high resolution, localized weather and PV installation data, unlike day-ahead forecasts relying on regional models. With frequent model updates and granular forecasts, intra-day forecasting enables smooth solar integration despite intermittent output from passing clouds.

2) *Day-ahead Forecasts:* Day-ahead forecasting predicts solar output 24 hours in advance, supporting energy operations like market scheduling and utility load planning. Made each morning, day-ahead models use weather prediction data, statistics, and machine learning to estimate next day hourly PV production. Models incorporate parameters like temperature, humidity, clouds, and wind. Historical data trains machine learning algorithms on daily/seasonal patterns. On-site sensor insights provide current conditions. More accurate day-ahead solar forecasts allow traders to better schedule operations and transmission. Utilities can smooth variable solar generation in next day load forecasts. Improved forecasts also help plant operators schedule maintenance and bidding.

B. Medium-Term Forecasts

1) *Seasonal Forecasts:* Seasonal forecasting predicts solar output over months or a whole season, crucial for utility planning, revenue estimation, and maintenance scheduling. Seasonal models use medium-term weather forecasts, historical averages, and machine learning. Inputs include expected temperature, precipitation, humidity, and cloud cover monthly or seasonally. Historical data trains algorithms on seasonal solar patterns. Understanding expected generation by season helps utilities plan for electricity demand. Grid operators can ramp up other sources if a cloudy/rainy season reduces solar output. Plant owners depend on seasonal forecasts to estimate revenue and schedule maintenance downtime during seasons with lower expected output.

C. Long-term Forecasts

1) *Year-ahead forecasts:* Year-ahead forecasting predicts solar generation one or more years ahead, supporting capacity planning, project development, and strategic decisions. Models use historical averages for typical annual generation, long- term weather projections for irradiation and temperature, and projected solar deployment. Understanding estimated solar generation a year out helps utilities plan long-term capacity needs. Knowing future solar growth helps transmission planners accommodate extra generation. Developers can assess project viability. However, substantial uncertainties in multi- year weather/climate models and solar deployment limit accuracy. Still, even imprecise year-ahead forecasts provide useful information for high-level planning purposes.

III. FORECASTING TECHNIQUES

A. Numerical Weather Prediction Models

This type of models are computer programs that use current weather conditions as inputs to forecast the weather ahead based on mathematical equations of atmospheric physics and motion. NWP models are a key component of many solar fore- casting approaches. They provide predictions of cloud cover, temperature, precipitation and other weather parameters that influence solar irradiance at the earth's surface. By modeling weather systems and patterns, NWP can estimate the solar energy available days or weeks in advance [5].

1) *Weather Forecasting Model:* The WRF is a widely employed mesoscale numerical weather prediction (NWP) system renowned for its versatility and accuracy. It pro- vides various configurations for solar forecasting like precise representation of cloud microphysics, radiation transfer, and aerosol-cloud interactions. National Center for Atmospheric Research's (NCRA) WRF-SOLAR is an augmented version of standard WRF model, a comprehensive solar forecasting system developed with special emphasis on DNI, DIF, GHI[1]. Modifications were made to the radiation schemes to allow input of aerosol optical properties. This enables representing aerosol-radiation interactions and direct effects. Aerosol datasets can be specified, including climatologies or time- varying reanalysis products. This provides atmosphere aerosol representation. Cloud-aerosol feedbacks were introduced by coupling aerosols in microphysics to radiation. This allows aerosol indirect effects on clouds. Shallow cumulus clouds now provide sub-grid cloud fraction feedbacks to radiation. This reduces positive bias in irradiance. Clear-sky validation showed large improvements in irradiance accuracy from the aerosol effects, especially using reanalysis aerosol data. WRF- Solar significantly reduced errors in clear-sky GHI, DNI and DIF compared to standard WRF.
2) *North American Mesoscale Forecast System:* The NAM model provides short-range weather forecasts out to 84 hours over North America at 12km resolution. Developed by the National Centers for Environmental Prediction, it ingests observational data assimilated into initial conditions. With high resolution and frequent updates, the NAM better resolves mesoscale features and incorporates latest observations for improved short-term prediction.

   The authors utilized the NAM weather model to generate forecasts of GHI and DNI[2]. They analyzed the NAM model forecasts using FANOVA for a specific weather station lo- cation. According to the study, the NAM model's forecast inaccuracy is influenced by the interplay of several physical elements, including solar zenith angle and GHI. Machine learning techniques were used to combine and correct the NAM model's biases differently in each weather category or subspace. By accounting for localized differences in the NAM model's biases through categorization parameters, the machine learning approach achieved over 30% improvement in forecast accuracy compared to the raw NAM model.
3) *European Centre for Medium-Range Weather Forecasts:* Global atmospheric variable predictions, both deterministic and ensemble, can be procured from the ECMWF model at different resolutions. It solves prognostic equations on a spherical grid with physical parameterizations. The ensemble system perturbs initial conditions to generate forecast scenarios and quantify uncertainty. ECMWF provides guidance worldwide and its ensemble is a leading tool for probabilistic forecasting from short-range to seasonal timescales. In one such study, a short-term probabilistic solar power fore- cast using the ECMWF Ensemble Prediction System (EPS) is presented[3]. The authors test the approach on three solar farms in Italy with distinct climatic conditions. The EPS ensemble of weather forecasts provides uncertainty estimates that feed into a radiative transfer model after bias correction with a neural network. These are compared to a persistence ensemble baseline. Results across the test cases show the calibrated EPS ensembles provide skillful probabilistic forecasts, outperforming persistence.

B. Persistence Forecasts

Persistence forecasts exploit the autocorrelation in time series data by assuming a meteorological variable will remain unchanged over a future period. For solar forecasting, simple persistence assumes irradiance persists, while smart persistence assumes clear sky index persists. Physics-informed variants incorporate specific cloud properties, like cloud fraction or albedo, and assume they persist. Persistence models perform well for short-term solar forecasts under an hour but degrade with longer lead times as persistence assumptions breakdown from sun angle shifts and temporal cloud variations.

A study proposed a new approach called '*Physics based Smart Persistence*' for intra-hour solar power forecasting using only GHI measurements[4]. Firstly, it calculates the extraterrestrial radiation and solar zenith angle, which are fundamental parameters determined by astronomical calculations. Secondly, it employs advanced techniques to predict cloud albedo and cloud fraction, which significantly influence the amount of solar radiation reaching the Earth's surface. The cloud albedo is estimated using a sophisticated two-stream approximation model, while the cloud fraction is forecasted through a weighted moving average method over a 5-minute window, assuming that cloud structures exhibit a certain degree of persistence over short time scales. Experiments using 11 years of 1-min GHI data show PSPI outperforms the baseline models for 5-60 min forecasts, especially under cloudy conditions, without needing additional atmospheric data.

The authors of employed tests using physics-based models and data imputation techniques with data from 15 solar measurement stations across India[5]. Nine data imputation methods are evaluated to fill missing data gaps. The Kalman method is found to perform best overall. The imputed data is used to test a solar forecasting model namely Physics-based Smart Persistence model for Intra-hour forecasting (PSPI). PSPI decomposes solar forecasting into computing solar position and predicting cloud properties. Results show PSPI outperforms Smart Persistence for forecasts up to 150 minutes ahead, with increasing errors at longer time horizons. They utilized MAE for analysis of forecast accuracy and hourly performance plots for hour-hour comparisons

This article developed a new solar forecasting methodology called “stochastic persistence”[6]. It models measured solar irradiation as having a deterministic trend and stochastic noise. Data from two stations used: Ajaccio, Corsica (hourly) and Tilos, Greece (15 min). The additive scheme models the difference between clear sky index and measurements, while the multiplicative scheme models the ratio. Stochastic persistence outperforms classical persistence in accuracy. For hourly data, multiplicative works best with low error. For 15 min data, additive is better, likely due to challenges modeling clear sky at higher frequencies. Normalized RMSE evaluated prediction accuracy against ground truth measurements.

A new approach that incorporates correlations between solar radiation and cloud properties was created and assessed to anticipate global, direct, and diffuse irradiance using four new physics-informed persistence models[7]. Using 15-minute data from 1998-2014, they improved performance over bench- marks, especially at lead times beyond 1.25 hours. The 4th level models performed best overall. Model accuracy related to temporal variability of assumed persistent cloud predictors. Contrasting radiation dependencies on cloud fraction versus albedo explained relative model performance. Various statis- tical performance metrics were used, including skill scores, modified Taylor diagrams, and distribution comparisons.

C. Regressive Techniques

1) Auto-Regressive Integrated Moving Average models: ARIMA, a statistical analysis model which used for time-series based analysis. It leverages historical data on solar power output, meticulously accounting for trends, seasonal variations, and random fluctuations. This model essentially dissects past power generation patterns, adjusts for any long-term trends or seasonal effects, and integrates short-term variations to generate forecasts of future solar power production.

The study developed ARIMA models using 34 years of NASA POWER insolation data to forecast monthly average solar radiation over an area in India[8]. The models were vali- dated with RMSE, MAE, MAPE metrics. Building upon their models, the researchers utilized the marching square algorithm to generate four years’ worth of insolation forecasts in the form of visually descriptive contour plots, enabling spatial analysis of solar radiation patterns. Based on the forecast contours, suitable regions were identified for solar projects having maximum and consistent annual average insolation.

This paper investigates the use of ARMA and ARIMA models for predicting solar radiation one, two, and three hours ahead[9]. The proposed model ARIMA(2,2,2) outperforms both ARMA(1,2) and persistence models in all prediction horizons, with the lowest MAPE and highest improvement percentages compared to the persistence model. The paper concludes that ARIMA models are more accurate for multi- period solar radiation prediction than ARMA or persistence models, and suggests incorporating additional parameters like air temperature and sunshine duration in future studies. Evaluation metrics like MAE, MAPE and improvement percentage are used in this experiments.

This article employed models like ARMA, ARIMA, and various NN architectures, the study analyzed their performance in predicting power output from large-scale photovoltaic (PV) plants[10]. Results demonstrated NNs’ superiority in accuracy and computational efficiency over statistical models for one- hour ahead prediction without direct access to weather data. However, both NNs and statistical models proved reliable only for short-term forecasts. Metrics such as MAE and RMSE were used to evaluate model performance and provide recommendations for the effective grid integration of photovoltaic facilities.

2) Seasonal Auto-Regressive Moving Average models: The SARIMA, a time series forecasting technique, is a tailored model to handle seasonal variations in data. The approach combines autoregressive, differencing, moving average models and their seasonal variants to model complex patterns. SARIMA parameters include nonseasonal and seasonal orders for AR, differencing, and MA terms. By incorporating past observations and seasonal fluctuations, SARIMA can generate accurate forecasts for time series data with periodic patterns, making it particularly useful for applications like predicting photovoltaic (PV) power generation, where seasonal variations due to weather conditions play a significant role in output fluctuations.

A study, which found the optimal SARIMA model selected for solar radiation forecasting was SARIMA(4,0,18)(0,1,1) based on comparing AIC values[11]. This means a seasonal MA term was included to capture seasonality. The model was fit on 9 years of weekly solar radiation data. It was then used to forecast for 2 years and compared to actual values. The SARIMA model performed well for solar forecasting, with low MAPE values around 7% for the LA data. This indicates it accurately captured the seasonal patterns. The model fit the data better than for wind speed forecasting. The confidence intervals were wider, indicating higher variability/uncertainty in wind predictions.

The paper suggests using a hybrid SARIMA-SVM model to predict a small-scale grid-connected solar plant's electricity output[12]. The model uses a blend of SARIMA method to estimate the linear components and SVM model to find nonlinear patterns. The authors used experimental data from a 20 kW plant to develop and validate the model. Statistical tests showed the hybrid model outperformed SARIMA and SVM alone for hourly power forecasts over several days. The approach does not require forecasted weather data and utilizes accessible MATLAB functions. The hybrid approach exhibits satisfactory precision for forecasting photovoltaic power out- put over short time horizons.

The paper presents a combined approach for short-term forecasting of solar power output, utilizing both a SARIMA model and an artificial neural network model[13]. The models run in parallel and their outputs are combined using optimized weighting factors. The authors evaluated various SARIMA and ANN model structures using actual PV system data. The hybrid approach reduced forecast error by 10% during periods of high PV power volatility compared to the individual models. Overall, the parallel architecture and periodic recomputation of weighting factors allows the hybrid model to dynamically adapt based on forecast accuracy of the individual models. The method shows good performance for prediction time frame from 15 minutes to 1 day.

3) Exogenous variable models: Exogenous variable models like ARIMAX, SARIMAX, and ARMAX extend traditional time series models by integrating external factors (exogenous variables) into the forecasting process. In these models, along- side the endogenous variables (the variables being forecasted), exogenous variables, such as weather data or economic indicators, are included. By incorporating these external factors, the models capture additional information that influences the behavior of the time series. This integration enables more accurate and robust forecasts, as the models can account for external influences beyond the historical data alone.

The study compared SARIMA and SARIMAX models for PV generation forecasting[14]. SARIMA struggled in variable weather but performed better in stable conditions, while SARIMAX, incorporating solar radiation forecasts, im- proved accuracy during irregular patterns. SARIMA adapted well in intra-day forecasting, capturing short-term variations effectively. However, SARIMAX's inclusion of exogenous factors significantly enhanced day-ahead predictions overall. The findings highlight the importance of considering external factors like solar radiation for robust PV generation forecasts, particularly in fluctuating weather. While SARIMA showed promise in certain conditions, SARIMAX's use of additional variables proved essential for optimizing accuracy across di- verse scenarios.

The paper describes a method based on system identification approaches for predicting solar radiation components using linear ARX and ARMAX models[15]. Hourly meteorological data from 2005-2015 was used, including variables like air temperature, humidity, radiation components, etc. Performance was evaluated using RMSE and FIT metrics. The proposed models demonstrated robust performance in forecasting extraterrestrial normal radiation, infrared horizontal radiation, and extraterrestrial horizontal radiation, exhibiting low root mean square error (RMSE) and high goodness-of-fit (FIT) values. However, the models had very high errors and low FIT for direct normal and diffuse horizontal radiation. The authors conclude linear modeling works better for cyclical/sinusoidal data, which was not the case for direct and diffuse radiation.

D. Deep Learning Approaches

1) ANN Approach: Artificial Neural Networks are a cate- gory of machine learning techniques that draw inspiration from the intricate neural networks present in the human brain. These networks are composed of interconnected processing units, analogous to neurons, systematically arranged into layered structures. Each neuron processes input data by applying a weighted sum and an activation function, producing an output signal that serves as input to subsequent neurons. During training, ANNs tune connection weights to reduce prediction errors, allowing them to learn complex data patterns and relationships. ANNs are versatile tools employed for classification, pattern recognition and regression across various fields like image processing, natural language, and financial forecasting. This study develops an ANN model to predict hourly solar radiation in Tamil Nadu, India using meteorological data from 6 locations[16]. Different ANN architectures with 3 learning algorithms (Levenberg-Marquardt, Resilient Propagation, Scaled Conjugate Gradient) were compared. The model with Levenberg-Marquardt algorithm and 12 hidden neurons showed the best performance based on statistical error analysis. With the MAPE of 0.48% also shows the high accuracy of the model, with the predictions deviating less than 0.5% from the real values on average.

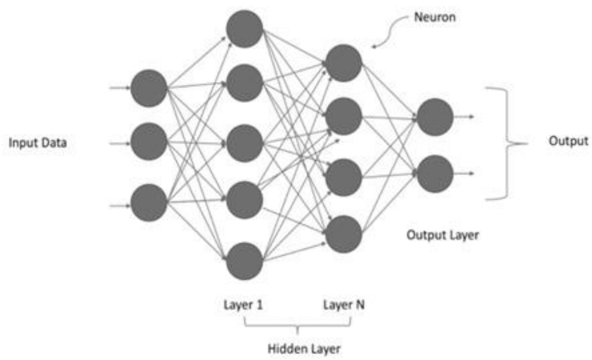

Fig. 1: Artificial Neural Network[36]

Another article presents an artificial neural network model for solar power estimation[17]. A sensitivity analysis identified the most relevant input variables, including solar irradiance and temperature. The ANN model outperformed multiple linear regression and persistence models in two test cases, with lower RMSE and higher correlation between forecasts and actual values. The results show ANNs can effectively forecast solar power using weather variables. The ANN approach achieved a RMSE score of 0.0554 which is highest compared to multi-linear regression and persistent approaches.

This paper forecasts solar radiation in India using feed forward, backpropagation, deep learning on 1 year of Gorakhpur data[18]. The model averaged network achieved the best performance with an average RMSE of 75.36% across 12 months. Backpropagation performed worst at 313.64% RMSE. Nine weather and time inputs were used. Data preprocessing converted minute to hourly averages. The model averaging approach combines multiple separately trained models, boosting performance over individual models.

This article proposes Artificial Neural Networks (ANNs) to forecast solar photovoltaic (PV) power output in Jordan on historical solar irradiance data[19]. The model uses 5 inputs of past irradiance to predict next day PV output. Trained on over 19,000 samples of irradiance and PV power from a 264KWp system, an optimized 22-layer ANN achieved excellent test results with Root Mean Square Error of 0.0721 in 24 hour PV power prediction. This demonstrates machine learning's promise for accurately forecasting solar power based on weather, helping integrate solar PV systems. The model uses real-world irradiance and power data, with preprocessing to ensure matched data pairs.

The article presents a novel solar power forecasting method- ology integrating genetic algorithms and artificial neural net- works (ANNs), crucial for optimizing solar photovoltaic (PV) systems' performance under varying weather conditions[20]. Utilizing real-time data from Odisha, India, the model exhibited significant advancements over traditional methods. By employing ANN-based temperature forecasting and Genetic Algorithm optimization, it achieved remarkable accuracy in predicting solar PV output. The study highlights the importance of accurate forecasting for grid stability and renewable energy integration. Additionally, statistical analyses such as regression and ANOVA underscored the method's robustness.

2) ***LSTM****:* Long Short Term Memory is a type of recurrent neural network design specifically developed to tackle the issue of the vanishing gradient problem commonly encountered in conventional RNNs. It uses memory cells with self- connections to maintain information over long sequences via selective retaining or forgetting. LSTM cells contain input, forget, and output gates controlled by sigmoid functions that regulate information flow. A tanh function also regulates cell state updates. The inclusion of gating mechanisms in LSTMs allows them to effectively capture long-range dependencies and manage diverse time lags. Consequently, LSTMs are highly suitable for tasks such as speech recognition, language modeling, and predicting time series data.

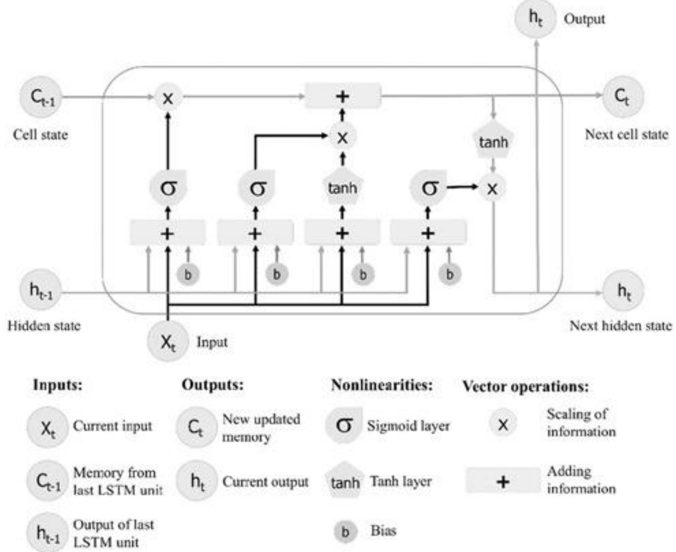

Fig. 2: Long Short Term Memory[37]

This article proposes a simplified LSTM approach for one day ahead solar power forecasting[21]. It compares LSTM and MLP models trained on datasets from PV systems in Thailand and Taiwan. The LSTM model with 50 hidden nodes and Tanh activation function performed best, achieving a test RMSE of 0.497 on the Thailand dataset. Data preprocessing included fixing missing values, feature selection using correlation analysis, normalization and dimensionality reduction. The LSTM model successfully captured intra-hour ramping and performed well on different weather conditions like sunny, cloudy and rainy days.

This article proposes a forecasting mechanism using LSTM neural networks with the Nadam optimizer[22]. Tested on a 250kW India plant with 366 days of data, LSTM-Nadam achieved significantly lower RMSE of 86.19 compared to

164.12 for SARIMA and 124.126 for ARIMA. It outperformed LSTM with other optimizers. This demonstrates LSTM- Nadam's efficacy for long-term forecasting, crucial for grid integration and planning of large solar PV systems. Preprocessing involved data cleaning, imputing missing values, and normalization. The model uses meteorological factors like temperature and solar radiation as inputs.

In this article, two LSTM models for short-term solar power forecasting are presented. Time of day, month, weather, and historical power statistics are used as input elements in these models.[23]. Data is from a Florida solar farm. The single-step model predicts the next time step, with performance degrading beyond 12 hour input sequences. It achieved 0.5-0.75 MW MAE across seasons. The multi-step model predicts up to 24 hour horizons. Adding time and month indices improved intraday performance. It achieved 0.58-0.99 MW MAE. The LSTM models outperformed regression and NARX networks and captured weather effects well with half-hourly data across multiple years.

The article proposes an LSTM-fully connected layer for short-term solar power generation forecasting[24]. The model combines LSTM layers to capture time continuity and periodicity and FC layers to learn feature mappings. Experiments on real PV power data show the model with all three input types achieves the best performance. Compared to GRNN, GBDT, SVM, FFNN and LSTM models, the proposed LSTM- FC model optimizes and lowers the RMSE by 11.79%, 7.77%, 9.1%, 11.33%, and 9.16% respectively. The model demonstrates effectively capturing temporal correlations and incorporating multiple relevant data sources can improve photovoltaic power forecasting accuracy.

The article proposes a hybrid LSTM and Gaussian process regression (GPR) model for short-term solar power forecasting[25]. It uses weather data and time features as inputs. The results on two datasets show LSTM outperforms a basic neural network for point forecasting accuracy. The novel LSTM-GPR model achieves slightly better point forecast accuracy than LSTM alone and significantly outperforms GPR alone. The hybrid model also provides reliable prediction intervals, unlike LSTM alone. Overall, the article demonstrates the LSTM-GPR hybrid model achieves high performance on both point and interval forecasting for solar power prediction using standard datasets. The methodology combines the strengths of deep learning via LSTM and probabilistic modeling via GPR.

The study employs LSTM network to forecast hourly solar irradiance in Johannesburg[26]. Utilizing historical meteorological data from Meteoblue, the LSTM model outperforms Support Vector Regression (SVR), achieving a nRMSE of 3.2%, significantly better than SVR's performance with the same dataset. The LSTM architecture, designed to address vanishing and exploding gradient issues, exhibits superior accuracy in predicting solar irradiance, crucial for efficient power generation. The study underscores LSTM's potential for enhancing solar energy forecasting and suggests its application for stable power generation in solar farms.

3) Auto-Encoders: Autoencoders are used for dimensionality reduction and unsupervised learning. They are made up of a decoder that reconstructs the original input and an encoder that compresses input data into a latent form. By minimizing reconstruction error, autoencoders learn to capture salient data features in the latent space. As a result, high- dimensional data may be represented compactly, which is advantageous for processes like anomaly detection, denoising, and data compression. Variants like variational and denoising autoencoders offer additional capabilities. Autoencoders have diverse applications including image processing, language understanding, and recommendation systems.

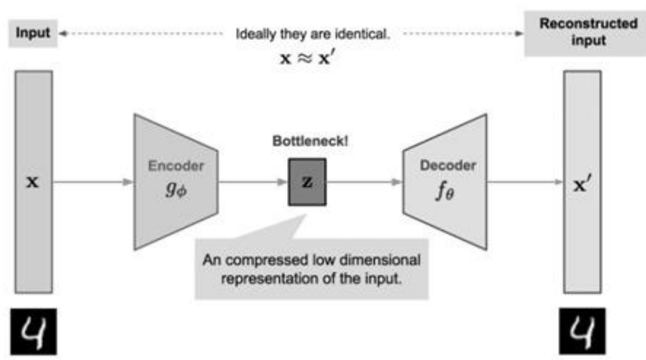

Fig. 3: Auto Encoder[35]

The article proposes a variational autoencoder (VAE) approach for short-term forecasting of photovoltaic (PV) solar power production[27]. The method is evaluated on two real- world PV system datasets. The VAE model consistently out- performs seven other deep learning models (RNN, LSTM, GRU, etc.) and two machine learning baseline models (logistic regression and SVM) in terms of statistical performance metrics like RMSE, MAE, R2. In the PV power time series data, the VAE model may identify both linear and nonlinear characteristics. The research also looks at the models' ability to foresee one or more steps ahead. As a preprocessing step, the PV power data is standardized using min-max normalization between 0 and 1.

The article proposes a LSTM-AE model for photovoltaic (PV) power forecasting[28]. Using a real-world PV system dataset from Australia, the LSTM-AE model is shown to outperform benchmark methods like BPNN, RNN, LSTM and GRU in terms of RMSE, MAE and R2 performance metrics. Specifically, the LSTM-AE model achieved average RMSE of 0.0762 kW, MAE of 0.0389 kW, and R2 of 0.9993 across different test periods. Data preprocessing included missing value imputation, outlier removal, and normalization. The methodology uses encoder-decoder LSTM architecture for feature learning and reconstruction.

This article introduces a novel approach for forecasting day- ahead photovoltaic (PV) power, which merges a generative adversarial network (GAN) with a convolutional autoencoder (CAE)[29]. Real PV plant data and weather data from China are used. The data is first categorized into sunny, cloudy and rainy days using self-organizing map for weather clustering. The CAE-GAN model is then trained for each weather type. Testing on 73 test days shows the model achieves a mean absolute error of 0.92MW, 16.73% MAPE and 19.87% RMSE across weather types, outperforming LSTM, CNN, and other GAN variants. The CAE enhances feature extraction from inputs while GAN leverages adversarial training for accuracy.

This article proposes a multi-task temporal convolutional autoencoder approach for day-ahead wind and solar power forecasting using numerical weather prediction data[30]. The method combines multi-task learning to leverage data from multiple parks and temporal convolutions to capture time dependencies. Compared to single-task and MLP-based autoencoders, the proposed approach reduces trainable parameters by up to 202 times while improving reconstruction error by up to 300% on 117 PV parks and 445 wind parks. For power forecasting, fine-tuning two encoder layers yields up to 18.3% and 1.5% error reductions for PV and wind, respectively.

4) Hybrid Models: Hybrid solar forecasting models like CNN-LSTM blend distinct deep learning components to exploit their respective advantages. CNNs extract spatial features while LSTMs capture temporal dynamics, handling complex interactions between weather, geography, and other factors affecting solar generation. This enhances accuracy. Other hybrids could integrate RNN variants like GRUs or Bi-LSTMs with CNNs, autoencoders, or sequence-to-sequence models, allowing comprehensive data processing. By capturing diverse information, these hybrid approaches enable robust, reliable solar predictions.

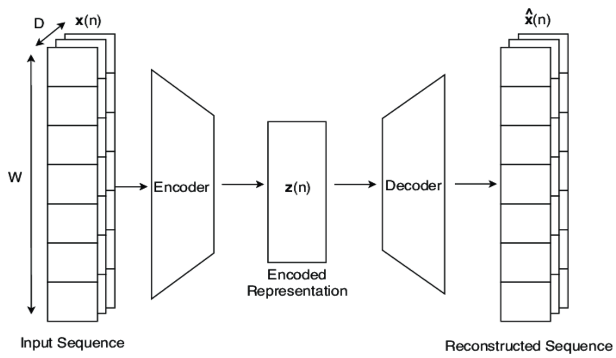

Fig. 4: LSTM Autoencoder[38]

This research suggests a hybrid model, combining CNN and LSTM architectures within an autoencoder framework, for forecasting short-term photovoltaic (PV) power genera- tion[31]. They used CNN for spatial feature extraction and LSTM autoencoders for temporal feature learning. Using real PV farm data from the UK along with weather data, the model is tested for 0.5h, 1h and 2h ahead forecasting. Compared to LSTM, CNN-LSTM, GRU, CNN-GRU models, the proposed hybrid model reduces errors by 5-25% in RMSE and MAE metrics while significantly decreasing training time by 70%. It also outperforms recent methods in literature by 40-80% across time horizons. Preprocessing includes normalization of the PV generation data.

The authors proposed LSTM, Bi-LSTM, and GRU for very short-term solar energy forecasting using weather data from Amherst station[32]. It compares machine learning regressors like Ridge, LASSO, ElasticNet, and SVR as baselines, with SVR giving best results. The deep learning models outperform these with Bi-LSTM giving lowest error metrics - RMSE of 0.0356, MSE of 0.0012, MAE of 0.0124 and MAPE of 12.2%.

The models are robust as evident from consistent performance of variants. Hybrid models of Bi-LSTM, LSTM and GRU are also tested for multi-step ahead predictions. LSTMs and GRU prove effective for accurate and reliable solar forecasting based on the weather dataset with minimal preprocessing like feature correlation analysis.

The paper introduces a new deep learning model named Bi- LSTM-based deep stacked sequence-to-sequence autoencoder (S2SAE) for forecasting solar irradiation and wind speed[33]. Real-world datasets from NREL were used for training and testing. Data preprocessing included handling missing values and normalization. The suggested model combines the dimensionality reduction of stacked autoencoders with the capabilities of bidirectional long short-term memory (Bi-LSTM) networks. It was compared to LSTM, GRU, and shallow S2SAE models. The Bi-LSTM S2SAE model achieved the highest accuracy of 99.7% for solar forecasting and 98.42% for wind speed, the lowest MAPE of 0.2763% and 1.58%, and lowest RMSE of 0.0358, outperforming the other methods.

This literature proposes a novel GRU-CNN for short-term solar power forecasting[34]. The model combines a GRU to extract temporal features and a CNN to extract spatial features from the PV dataset. The dataset covers 5 years with a 5-minute resolution from the Desert Knowledge Australia Solar Centre. Results show the GRU-CNN model achieves superior performance over individual GRU, LSTM, and CNN models, with average error metrics of 0.0813 for MAE, 0.0194 for MSE and 0.1359 for RMSE. The key novelty is fusing temporal and spatial features through the integrated GRU- CNN architecture.

Lastly, the authors developed an hour-ahead photovoltaic (PV) power forecasting method using RNN-LSTM model[35]. It uses actual field data from three PV plants over 2016-2019, including weather data like temperature, solar irradiation and wind speed. Data preprocessing techniques like normalization are used. The proposed RNN-LSTM model is compared to regression, machine learning and hybrid models. It achieves superior test performance with the lowest RMSE of 26.85 W/m2, 19.78 W/m2, 39.2 W/m2 and highest r of 0.998 for monocrystalline, polycrystalline film PV plants respectively, demonstrating robustness across PV technologies. Different LSTM architectures are also analyzed, with the single-layered RNN-LSTM performing the best.

IV. SUMMARY OF STUDIES

With thorough review of existing approaches, we found that most physical methods like NAM, ECMWF, WRF, perform best when combined with machine learning deep learning approaches. Most of the studies carried out had the time- ahead approaches. Most of the studies carried out had the time-ahead duration of 24-hours, with some experiments in long-term forecasting. Commonly used evalutation metrics include RMSE(Root Mean Square Error), MAE(Mean Ab- solute Error), MAD(Mean Absolute Deviation), MAPE(Mean Absolute Percentage Error), r2(Coefficient of determination). By observations, we found that Auto-regressive methods like ARIMA SARIMA exceeded the performance of the physical methods. By capturing analysis of the historical data, they were accurately able to generate power generation forecasts.

A. Key parameters

The task of the power prediction is dependent on the region of study, therefore data pertained to a region such as the weather parameters like solar irradiance, temperature, cloud cover, wind speed, and are all considered in these studies. Seasonal and diurnal patterns allow for the identification of trends and patterns that can be used to train forecasting models. Most of the forecasted variables include DIF,DNI,GHI[29].

B. *Best performing approaches*

Hybrid models like CNN-LSTM, Bi-LSTM, and GRU-CNN outperform traditional methods in solar power forecasting due to their ability to capture both spatial and temporal dependencies. CNN-LSTM model trained on historical data, achieved and RMSE score of 0.081 in 1-h forecast duration[31]. The Bi-LSTM based approach also achieved higher RMSE score of 0.99 among other architectures[33]. The GRU-CNN model outperformed vanilla LSTM with a high score of RMSE 0.1359

C. Challenges

Solar power forecasting faces challenges including weather uncertainty, data limitations, modeling diffuse/direct irradiance, optimizing model structure and parameters, capturing short-term variability, effectively handling multiple timescales, integrating real-time plant data, accounting for spatial variations, and managing computational complexity.

D. Future Works

As the adoption of solar energy continues to grow rapidly, the demand for more accurate and reliable forecasting will intensify. Moreover, as the solar energy industry expands globally, region-specific forecasting models that account for local weather patterns and environmental factors will become increasingly important. Ultimately, continued innovation in solar forecasting will not only enhance the efficiency and reliability of solar power systems but also accelerate the transition towards a sustainable energy future.

TABLE I: Summary of Investigated Studies

Ref	Year	Methodology	Output	Metrics
[1]	2016	Augmented WRF + aerosol-cloud-radiation feedbacks	GHI, DIF, DNI	RMSE (Improvements) GHI: 46% DNI: 60% DIF: 70%
[2]	2016	Blending of NAM and ML models	GHI, DNI	MAE: 119 W/m2 MAPE: 11.93% RMSE: 173 W/m2 NMAE%: 14.3%
[3]	2016	ECMWF EPS forecasts inputted to NN, Post processing- VD, EMOS Persistence Ensemble (PE)	Power output(kW)	MRE (PE): (8.91%, 7.65%, 4.99%) (VD): (8.02% , 8.92% , 10.72%) EMOS: (9.41% , 7.60% , 7.47%)
[4]	2018	Physics-based Smart persistence model for Intra-hour Solar forecasting (PSPI)	GHI	MBE = 9.03 W/m^2 $FS = 0.05 MAE = 105.8 W/m^2 r = 0.78, RMSD = 189.1 W/m^2$
[5]	2021	PSPI + Kalman Data Imputation	GHI	For 15 min Ahead MAE: 65.92 for 150 min Ahead MAE : 130.1
[6]	2018	Stochastic persistence	GHI	Ajaccio: Additive nRMSE: 0.3873 Multiplicative nRMSE: 0.3844 Tilos: Additive nRMSE: 0.2902 Multiplicative nRMSE: 0.3194
[7]	2020	4 Level Hierarchical - PSPI	GHI, DNI, DIF	Percent Error (PE) for GHI: 7% at 1 hour ahead
[8]	2020	ARIMA	Avg Solar Insolation	R2 = 0.9293 RMSE = 0.3529 MAE = 0.2659 MAPE = 6.556
[9]	2015	ARMA & ARIMA (Persistence forecast as baseline)	Solar Radiation	Imrovement percentage 1- hour ahead: MAPE : 18.11% ARMA & 7.87% for ARIMA 3-hour ahead MAPE : 32.07% for ARMA and 71.67% for ARIMA
[10]	2019	ARIMA & Bi-LSTM	Power output(kW)	ARIMA: R=0.912 RMSE=1.318 (Poor) Bi-LSTM: R=0.98 RMSE=0.791(Best)
[11]	2020	SARIMA + Akaike Information crtieria for model selection	Solar radiation	MAPE = 7% for Los Angeles and 15.6% for Chicago
[12]	2019	Hybrid Model : SARIMA + ANN	Solar power output	Hybrid model - 96 step ahead: 233.3 W (10% improvement over SARIMA) Sarima : 259.0 W
[13]	2013	SARIMA + SVM	Power Output(kW)	Hybrid: NRMSE 9.4%, NMBE 0.18%, MPE 2.74%, R 0.99 &SARIMA: NRMSE 9.57%, NMBE -0.36%, MPE 5.2%, R 0.99
[14]	2016	SARIMAX - exogenous from solar radiation forecasts	Power Output(kW)	Day-Ahead NRMSE of 10.93%. Intra-day NRMSE of 9.11%.
[15]	2022	ARX and ARMAX	DNI,DHI, ETR,ETH,IHR	DNI (ARMAX) RMSE = 59.43 FIT = 51.22% EHR (ARX): RMSE = 7.15% FIT = 91.34%
[16]	2021	ANN + Levenberg-Marquardt Algo	Solar Radiation	MAD: 0.0456 MSE: 0.00578 RMSE: 0.0763 MAPE: 0.4846
[17]	2015	ANN	Solar Power output	RMSE = 0.08-0.1 and R = 0.94 - 0.96
[18]	2018	ANN, Back Propogation, Model Averaged ANN	Global Solar radiation	RMSE 75.36%
[19]	2017	ANN	Solar Power output	RMSE = 0.0721 and R values of 0.9983 and 0.9965
[20]	2020	ANN + Genetic Algorithm	Solar power output(kW)	RMSE = 1.11952 to 2.282671 ((12 Months) MAE = 0.428703704 to 1.829259259 (12Months) MAPE = 1% to 5% (12 Months)
[21]	2021	LSTM - 200 nodes + tanh activation	Solar Power output	RMSE = 0.497
[22]	2022	LSTM neural network with Nadam optimizer	Solar Power output	RMSE = 86.19 MAE = 69.976
[23]	2020	LSTM	Solar Power output (kW)	MAE = 1.14, RMSE = 1.92, MBE = -0.09
[24]	2021	LSTM- Fully Connected	Solar Power output	$R^2 = 0.96, nRMSE = 0.1743, RMSE = 2.5605.$
[25]	2021	LSTM and Gaussian Process Regression (GPR)	Solar Power output	RMSE = 264.98, MAE= 201.77, MAPE =9.43%
[26]	2020	LSTM	Solar Irradiance	nRMSE 4-month data =0.04 (1-year data)=0.036 (10 year data)= 0.032
[27]	2020	VAE	Solar Power output	R2= 0.995 RMSE= 199.645 MAE = 99.838 EV= 0.995
[28]	2023	LSTM-AE	Solar Power output	MAE: 0.0389 kW MSE: 0.0064 RMSE: 0.0762 kW R2: 0.9993
[29]	2023	GAN + Convolutional Autoencoder (CAE)	Solar Power output	MAE = 0.9215, avg MAPE = 16.73% and avg RMSE = 19.87%.
[30]	2022	Temporal Convolution based multi-task autoencoders	Solar Power output	nRMSE = 0.098(18.3% reduction from Baseline)
[31]	2023	CNN- LSTM	Solar Power output	RMSE= 0.081 MAE=0.038
[32]	2023	LSTM, Bi-LSTM, and GRU	Solar Power output	Bi-LSTM model: MSE: 0.0012 MAE: 0.013 RMSE: 0.0359 MAPE: 12.050% GRU model: MSE: 0.0012 MAE: 0.0138 RMSE: 0.0354 MAPE: 12.564%
[33]	2023	Bi-LSTM-based deep stacked Seq2Seq Auto Encoder	Solar Power output	MAPE: 0.2763 RMSE: 0.99 R2: 3.03
[34]	2022	RNN-LSTM	Solar Power output	(MAE, RMSE for 3 plants) (19.43, 32.72) (17.13, 25.4) (49.54, 63.93)
[35]	2021	GRU-CNN	Solar Power output	MAE: 0.0813 MSE: 0.0194 RMSE: 0.1359 R2: 0.9989

V. CONCLUSION

In summary, this study underscores the critical importance of diverse solar forecasting methodologies, spanning short-term to long-term predictions, and underscores the necessity of harnessing sophisticated models and data-driven strategies to enhance forecast precision and dependability. By employing numerical weather prediction models like the Numerical Weather Prediction models, in conjunction with innovative approaches such as smart persistence and physics-based models, substantial progress has been achieved in forecasting solar irradiance and power generation. These methodologies furnish invaluable insights for energy planning, grid management, and operational decision-making, thereby facilitating the seamless integration of solar energy into the broader energy framework. With solar power assuming an increasingly pivotal role in the transition toward sustainable energy systems, sustained research and development efforts in solar forecasting techniques stand poised to maximize its efficacy and ensure the realization of a dependable and resilient renewable energy landscape.

VI. REFERENCES

[1] Jimenez, P. A., and Coauthors, 2016: WRF-Solar: Description and Clear-Sky Assessment of an Augmented NWP Model for So- lar Power Prediction. Bull. Amer. Meteor. Soc., 97, 1249–1264, https://doi.org/10.1175/BAMS-D-14-00279.1.

[2] X. Shao, S. Lu and H. F. Hamann, ”Solar radiation forecast with machine learning,” 2016 23rd International Workshop on Active-Matrix Flatpanel Displays and Devices (AM-FPD), Kyoto, Japan, 2016, pp. 19-22, https://doi: 10.1109/AM-FPD.2016.7543604.

[3] Simone Sperati, Stefano Alessandrini, Luca Delle Monache, An appli- cation of the ECMWF Ensemble Prediction System for short-term solar power forecasting, Solar Energy, Volume 133, 2016, 437-450, https://doi.org/10.1016/j.solener.2016.04.016.

[4] Kumler, Andrew. (2019). A Physics-based Smart Persistence model for Intra-hour forecasting of solar radiation (PSPI) using GHI measure- ments and a cloud retrieval technique. Solar Energy. 177. 494-500. 10.1016/j.solener.2018.11.046.

[5] Yelchuri, Srinath, Rangaraj, A. G., Xie, Yu, Habte, Aron, Joshi, Mohit Chandra, Boopathi, K., Sengupta, Manajit, and Balara- man, K.. 2021. ”A Short-Term Solar Forecasting Platform Us- ing a Physics-Based Smart Persistence Model and Data Im- putation Method”. United States. https://doi.org/10.2172/1837967. https://www.osti.gov/servlets/purl/1837967.

[6] Cyril Voyant, Gilles Notton, Solar irradiation nowcasting by stochastic persistence: A new parsimonious, simple and efficient forecasting tool, Renewable and Sustainable Energy Reviews, Volume 92, 2018, Pages 343-352, ISSN 1364-0321, https://doi.org/10.1016/j.rser.2018.04.116.

[7] Weijia Liu, Yangang Liu, Xin Zhou, Yu Xie, Yongxiang Han, Shinjae Yoo, Manajit Sengupta, Use of physics to improve solar forecast: Physics-informed persistence models for simultaneously forecasting GHI, DNI, and DHI, Solar Energy, Volume 215, 2021, Pages 252-265, https://doi.org/10.1016/j.solener.2020.12.045.

[8] Shadab, A., Ahmad, S., Said, S. (2020). Spatial forecasting of solar radiation using ARIMA model. Remote Sensing Applications: Society and Environment, 20. https://doi.org/10.1016/j.rsase.2020.100427

[9] Colak, I., Yesilbudak, M., Genc, N., Bayindir, R. (2016). Multi- period prediction of solar radiation using ARMA and ARIMA models. Proceedings - 2015 IEEE 14th International Confer- ence on Machine Learning and Applications, ICMLA 2015. https://doi.org/10.1109/ICMLA.2015.33

[10] Sharadga, H., Hajimirza, S., Balog, R. S. (2020). Time series forecasting of solar power generation for large-scale photovoltaic plants. Renewable Energy, 150. https://doi.org/10.1016/j.renene.2019.12.131

[11] Maroua Haddad, Jean Nicod, Yacouba Boubacar Mainassara, Landy Rabehasaina, Zeina Al Masry, et al.. Wind and Solar Forecasting for Renewable Energy System using SARIMA-based Model. International conference on Time Series and Forecasting, Sep 2019, Gran Canaria, Spain.

[12] Vrettos, E., Gehbauer, C. (2019). A hybrid approach for short-term PV power forecasting in predictive control applications. 2019 IEEE Milan PowerTech, PowerTech 2019. https://doi.org/10.1109/PTC.2019.8810672

[13] Bouzerdoum, M., Mellit, A., Massi Pavan, A. (2013). A hy- brid model (SARIMA-SVM) for short-term power forecasting of a small-scale grid-connected photovoltaic plant. Solar Energy, 98(PC). https://doi.org/10.1016/j.solener.2013.10.002

[14] Vagropoulos, S. I., Chouliaras, G. I., Kardakos, E. G., Simoglou, C. K., Bakirtzis, A. G. (2016). Comparison of SARIMAX, SARIMA, modified SARIMA and ANN-based models for short-term PV generation forecast- ing. 2016 IEEE International Energy Conference, ENERGYCON 2016. https://doi.org/10.1109/ENERGYCON.2016.7514029

[15] Silva, V. L. G. da, Oliveira Filho, D., Carlo, J. C., Vaz, P. N. (2022). An Approach to Solar Radiation Prediction Using ARX and ARMAX Models. Frontiers in Energy Research, 10. https://doi.org/10.3389/fenrg.2022.822555

[16] Geetha, A., Santhakumar, J., Sundaram, K. M., Usha, S., Then- tral, T. M. T., Boopathi, C. S., Ramya, R., Sathyamurthy, R. (2022). Prediction of hourly solar radiation in Tamil Nadu using ANN model with different learning algorithms. Energy Reports, 8. https://doi.org/10.1016/j.egyr.2021.11.190

[17] Abuella, M., Chowdhury, B. (2015). Solar power forecasting using artificial neural networks. 2015 North American Power Symposium, NAPS 2015. https://doi.org/10.1109/NAPS.2015.7335176

[18] Srivastava, R., Tiwari, A. N., Giri, V. K. (2018). Forecast- ing of Solar Radiation in India Using Various ANN Models. 2018 5th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering, UPCON 2018. https://doi.org/10.1109/UPCON.2018.8597170

[19] Alomari, M. H., Adeeb, J., Younis, O. (2018). Solar photovoltaic power forecasting in Jordan using artificial neural networks. International Journal of Electrical and Computer Engineering, 8(1). https://doi.org/10.11591/ijece.v8i1.pp497-504

[20] Pattanaik, D., Mishra, S., Khuntia, G. P., Dash, R., Swain, S. C. (2020). An innovative learning approach for solar power forecasting using genetic algorithm and artificial neural network. Open Engineering, 10(1). https://doi.org/10.1515/eng-2020-0073

[21] Liu, C. H., Gu, J. C., Yang, M. T. (2021). A Simplified LSTM Neural Networks for One Day-Ahead Solar Power Forecasting. IEEE Access,

9. https://doi.org/10.1109/ACCESS.2021.3053638
[22] Sharma, Jatin Soni, Sameer Paliwal, Priyanka Shaik, Saboor Chaurasiya, Prem Sharifpur, Mohsen Khalilpoor, Nima Afzal, Asif. (2022). A novel long term solar photovoltaic power forecasting approach using LSTM with Nadam optimizer: A case study of India. Energy Science Engineering. 10. 10.1002/ese3.1178.
[23] Hossain, M. S., Mahmood, H. (2020). Short-term photovoltaic power forecasting using an LSTM neural network and synthetic weather fore- cast. IEEE Access, 8. https://doi.org/10.1109/ACCESS.2020.3024901
[24] Li, Y., Ye, F., Liu, Z., Wang, Z., Mao, Y. (2021). A Short-Term Photovoltaic Power Generation Forecast Method Based on LSTM. Mathematical Problems in Engineering, 2021. https://doi.org/10.1155/2021/6613123
[25] Wang, Y., Feng, B., Hua, Q. S., Sun, L. (2021). Short-term solar power forecasting: A combined long short-term memory and gaus- sian process regression method. Sustainability (Switzerland), 13(7). https://doi.org/10.3390/su13073665
[26] Obiora, C. N., Ali, A., Hasan, A. N. (2020). Forecasting Hourly Solar Irradiance Using Long Short-Term Memory (LSTM) Net- work. 11th International Renewable Energy Congress, IREC 2020. https://doi.org/10.1109/IREC48820.2020.9310449
[27] Dairi, A., Harrou, F., Sun, Y., Khadraoui, S. (2020). Short-term fore- casting of photovoltaic solar power production using variational auto- encoder driven deep learning approach. Applied Sciences (Switzerland), 10(23). https://doi.org/10.3390/app10238400
[28] Sabri, M., el Hassouni, M. (2023). Photovoltaic power forecasting with a long short-term memory autoencoder networks. Soft Computing, 27(15). https://doi.org/10.1007/s00500-023-08497-y
[29] Pan, X., Zhou, J., Sun, X., Cao, Y., Cheng, X., Farahmand, H. (2023). A hybrid method for day-ahead photovoltaic power fore- casting based on generative adversarial network combined with con- volutional autoencoder. IET Renewable Power Generation, 17(3). https://doi.org/10.1049/rpg2.12619
[30] Schreiber, J., Sick, B. (2022). Multi-Task Autoencoders and Transfer Learning for Day-Ahead Wind and Photovoltaic Power Forecasts. En- ergies, 15(21). https://doi.org/10.3390/en15218062
[31] Ibrahim, M.S., Gharghory, S.M. Kamal, H.A. A hybrid model of CNN and LSTM autoencoder-based short-term PV power generation forecast- ing. Electr Eng (2024). https://doi.org/10.1007/s00202-023-02220-
[32] Zameer, A., Jaffar, F., Shahid, F., Muneeb, M., Khan, R., Nasir, R. (2023). Short-term solar energy forecasting: Integrated computa- tional intelligence of LSTMs and GRU. PLoS ONE, 18(10 October). https://doi.org/10.1371/journal.pone.0285410
[33] Mughees, N., Jaffery, M. H., Mughees, A., Mughees, A., Ejsmont, K. (2023). Bi-LSTM-Based Deep Stacked Sequence-to-Sequence Autoen- coder for Forecasting Solar Irradiation and Wind Speed. Computers, Ma- terials and Continua, 75(3). https://doi.org/10.32604/cmc.2023.038564
[34] Akhter, M. N., Mekhilef, S., Mokhlis, H., Almohaimeed, Z. M., Muham- mad, M. A., Khairuddin, A. S. M., Akram, R., Hussain, M. M. (2022). An Hour-Ahead PV Power Forecasting Method Based on an RNN-LSTM Model for Three Different PV Plants. Energies, 15(6). https://doi.org/10.3390/en15062243
[35] Sabri, M., el Hassouni, M. (2022). A Novel Deep Learn- ing Approach for Short Term Photovoltaic Power Forecasting Based on GRU-CNN Model. E3S Web of Conferences, 336. https://doi.org/10.1051/e3sconf/202233600064
[36] Lesort, Timothée. (2020). Continual Learning: Tackling Catastrophic Forgetting in Deep Neural Networks with Replay Processes.
[37] Le, Xuan Hien Ho, Hung Lee, Giha Jung, Sungho. (2019). Ap- plication of Long Short-Term Memory (LSTM) Neural Network for Flood Forecasting. Water. 11. 1387. 10.3390/w11071387. 22Sharma, Dilip Kumar, Bhuvanesh Singh, Saurabh Agarwal, Hyunsung Kim, and Raj Sharma. 2022. ”Sarcasm Detection over Social Media Platforms Using Hybrid Auto-Encoder-Based Model” Electronics 11, no. 18: 2844. https://doi.org/10.3390/electronics1118284