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A Comprehensive Review of Vision-Based and Data-Driven Solar Power Forecasting Techniques

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Abstract: The increasing penetration of large-scale photovoltaic power plants has intensified the challenge of managing power variability caused by rapid changes in solar irradiance. Short term and ultra short-term power fluctuations, mainly driven by cloud movement, can lead to severe ramp rate violations and grid instability, particularly in weak and island power systems. This review critically examines existing solar power forecasting approaches with a focus on short-term forecasting methods relevant to ramp rate control. Conventional physical and statistical models are discussed alongside machine learning and deep learning techniques, highlighting their strengths and limitations across different time horizons. Special emphasis is placed on vision-based forecasting methods using satellite imagery and ground-based sky imagers, which have demonstrated superior capability in capturing fast irradiance transients. The review further analyses commonly used input parameters, forecasting horizons, and cloud motion prediction techniques. Based on comparative assessment, the paper identifies key research gaps related to real-time deployment, data integration, and model generalization. The findings provide a structured foundation for developing accurate and practical forecasting frameworks to support grid stability in high solar penetration environments.

Index Terms: Solar power forecasting, Ramp rate mitigation, Sky imager, Cloud motion prediction, Renewable energy integration

1 Introduction

Globally, the countries of the world are gradually moving towards renewable energy, aiming to reduce the carbon footprint. In according to that, renewable energy sources are clean and unlimited [1], [2]. Most common renewable energy sources technologies include hydro power, solar energy (photovoltaic and solar thermal), wind energy, biogas, geothermal, biomass, wave and tidal power etc. With the shift to renewable energy sources, solar power has emerged as a major trend which is freely available [3], [4], [5], [6], [7], [8].

Sri Lanka electricity generation is primarily based on thermal and hydropower plants. In order to meet future demand for electricity, Sri Lanka is moving toward using renewable energy sources. According to the CEB (Ceylon Electricity Board) "Long Term Generation Expansion Plan 2022-2041", their goal is to achieve 70% renewable energy in electricity generation by 2030 [9]. The target is to meet all energy demands through renewable energy sources and other indigenous sources. In Sri Lankan flat dry zone, solar radiation ranges from 4.0 to 4.5 kWh/m2/day, while the high plains receive an average of 2.0 to 3.5

kWh/m2/day. Accordingly, it has been estimated that with its huge solar energy potential, specified by its tropical climate and sunshine prevailing throughout the year, there could be a rapid growth of large and medium scale solar implementations in Sri Lanka. This renewable resource not only provides huge opportunities for the augmentation of solar power generation but also for fulfilling the requirements of energy. It can reduce the dependency on fossil fuels by exploiting its sunshine throughout the year and accelerate sustainable development in Sri Lanka. Results Large-scale solar projects in Sri Lanka have already been proposed in order to help the country realize its goals of renewable energy and, therefore, provide eco-friendly solutions to the surging energy demand in the country [10][11].

However, the intermittent and unpredictable irradiance transients cause fluctuations in photovoltaic (PV) power generation which can negatively affect grid stability when injected into the grid in PV systems that are connected to the national power grid. So, to ensure the stability of the grid in the presence of high PV penetration, It is essential to smooth out the fluctuations in solar power generation before integrating it into the grid [12]. In smaller power systems like islands, due to its intermittent nature, photovoltaic power may cause harmonic distortion in the waveforms of voltage and current, which may cause blackouts [13]. In addition, sudden fluctuations in PV power can result in significant voltage deviations, power fluctuations, frequency deviations, power quality issues, unintentional islanding, and grid frequency effects causing grid stability difficult to maintain, especially in weak distribution grids where PV penetration is high [14].

For grid stability, generation and load should always be balanced, which can cause significant ramp rate issues in power plants. By sudden drops or surges in grid may cause instability of network leading to power generation demand imbalances. PV power ramp rate fluctuations are the main reason for stability variations. When large PV generation increases or decreases significantly, problems arise while injecting PV power into the grid. This PV power ramping causes significant power quality issues and voltage fluctuations. The way these fluctuations affect the size of the PV system [15]. According to this, ramp rate limitations are imposed by utilities in some countries. So, PV plant owners and operators impose a maximum standard power ramp rate, as examples in Germany ramp rate is 10% of the maximum capacity of the plant per minute, in Denmark 11%, In Ireland, Hawaii the ramp rate is limited to 30MW per minute [13], [12], [15].

In Sri Lankan context research, which is done from the perspective of grid integration to determine the main variability features of a distributed solar PV generation include that, in a single solar PV plant, there is a high probability that the maximum power output variation, approximately around 70% of the plant's installed capacity, which can occur within a period of 6 minutes. Also, they observed that 38% per minute in their sites [16]. In generally it is important to maintain a ramp rate at least 10% considering global context.

To maintain this grid stability there are several methods that can be achieve ramp rate control. They are, use Energy Storage Systems (ESS), active power curtailment, ESS-MPPT (Energy Storage Systems -Maximum Power point Tracking) hybrid systems, ESS-FPPT (Energy Storage Systems -Flexible Power point Tracking), Short-Term PV forecasting models etc [12], [13], [17],[18]. Among this an energy storage system (ESS) can effectively smooth out these fluctuations by charging redundant generated power and discharging when output power drops unexpectedly. However, this ESS method is too expensive for utility-level real power compensation to control both increasing and decreasing ramp rates and have a limited life for batteries [13]. active power curtailment, ESS-MPPT, ESS-FPPT methods are feasible for small generation variations, these cannot be deployed for large scale PV power plants. Therefore, it is not possible to get a solution for sudden fluctuations only by using an external device [12], [17].

Short term PV generation forecasting is an optimal method for utility level ramp rate control, providing accurate power variation estimates based on weather data, cloud tracking, and historical patterns [13], [15]. To effectively address the challenges posed by fluctuations in solar power generation, it is imperative to maintain desired ramp rates in power plants. Accurate solar irradiance forecasting is essential for mitigating the variability of PV output, and the success of mitigation methods is dependent on the accuracy of these forecasts. By incorporating precise forecasts into power plant control systems, operators can proactively adjust generation output. This proactive adjustment enables power plants to smoothly ramp up or down in response to predicted changes in solar power, avoiding sudden and potentially disruptive shifts that could stress equipment and destabilize the grid. Furthermore, the integration of fast response energy storage technologies, such as batteries and capacitors, complements accurate forecasts by facilitating swift power injection or absorption [14]. This capability is essential in compensating for short term fluctuations, maintaining grid stability, and, ultimately, reducing ramp rates. The combination of accurate forecasting and advanced energy storage helps to optimize battery charging and discharging processes, resulting in a more stable and efficient integration of renewable energy into the power grid [15].

According to above, Solar power forecasting is necessary for mitigating fluctuations in power systems, particularly in regions like Sri Lanka with high solar potential. The intermittent nature of solar power, influenced by cloud movement and weather changes, requires accurate solar radiation forecasts. Integrating precise forecasts enables efficient energy storage management, smoothing out fluctuations and enhancing grid stability while maximizing renewable energy integration.

2 CLASSIFICATION OF PV FORECASTING

PV energy forecasts are classified in various ways based on key variables such as prediction horizon, variable under prediction, spatial scale, forecast methodology, and forecast type [19]. Below figure 01 shows a general classification of PV power forecasting,

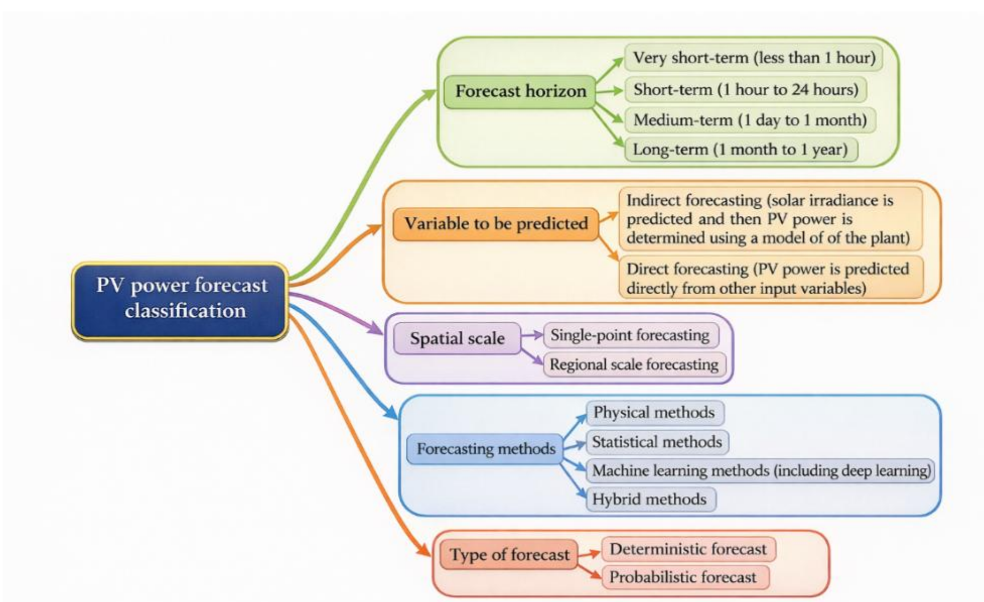

Fig. 1 General Classification of PV power Forecasting

2.1 PV Forecasting Methods

Several methods and algorithms have been developed for PV forecasting. There are three major categories: physical methods, statistical methods, and Hybrid methods. The methods of PV forecasts are summarized in Figure 02.

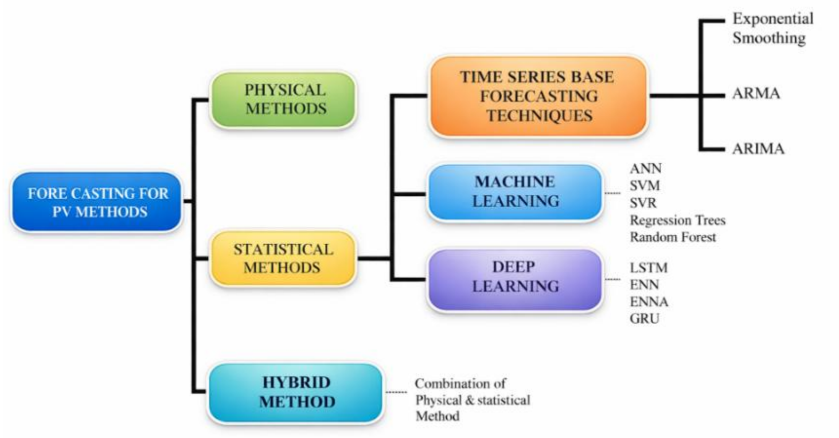

Fig. 2 Forecasting methods of PV Generation

2.1.1 Physical Methods

In physical forecasting techniques, forecast solar power generation using atmospheric variables such as air pressure, surface roughness, and temperature, based on meteorological data from Numerical Weather Prediction (NWP) models. These data include solar irradiance, temperature, humidity, and air pressure. NWP models, which can be divided into mesoscale and global models, use atmospheric data and equations to make predictions. Significant NWP models include the Global Forecast System (GFS), Climate Forecast System (CFS), and Global Data Assimilation System (GDAS), which allowing long term predictions of more than 15 days of range [20].

Furthermore, various NWP forecasting modes, like Weather Research and Forecasting Ensemble Prediction System (WEPS), Deterministic Weather Research and Forecasting (WRFD), and Radar Weather Research and Forecasting (RWRF), are provide short-term to medium-term forecasting data (from hours to days) without requirement of historical data. However, accuracy of these NWP forecasts is dependent on meteorological stability, which have challenges in developing physical models for NWP [21].

2.1.2 Statistical Methods

Statistical forecasting techniques that are used for predicting PV power generation uses historical time series and real-time data, which require few inputs than deep learning (DL) methods. They can perform short-term prediction, outperforming Numerical Weather Prediction (NWP) models. These methods use mathematical equations like curve fitting, moving average (MA), and autoregressive (AR) models to extract patterns and to build correlations from previous input data. Prediction accuracy is determined by the data quality and dimensions. Statistical approaches can be classified into two categories as Machine learning and Time series-based forecast models [21]. While statistical methodologies have been around for a while and offer benefits such as interpretability, they can be challenging to train because they depend on explanatory variables [22].

- **Time Series Based**

Time series analysis is the examination of historical data patterns to forecast future values utilizing statistical methods such as exponential smoothing, autoregressive moving average (ARMA), and autoregressive integrated moving average (ARIMA). These methods seek to identify regular patterns in data without being influenced by external factors, but they may produce larger forecast errors when applied to unstable data. Exponential smoothing involves giving more weight to recent historical data while gradually decreasing weights for distant data points. ARIMA, a hybrid of autoregressive (AR) and moving average (MA) models, converts non-constant sequences to constant ones using differential processing before using ARMA for prediction. The AR model computes a weighted average of past data based on its relationship to real time data, while the MA model addresses random errors by averaging them [23].

- **Exponential Smoothing**

The exponential smoothing method, also known as exponentially weighted moving average (EWMA), uses the exponential window function to analyse historical time series data and predict future outcomes. The algorithm assigns unequal weights to historical observations, resulting in an exponential reduction of data from recent to distant points. However, it can easily learn and make decisions based on assumptions [23].

- **ARMA (Auto Regressive Moving Average)**

ARMA, a time series analysis tool, is valued for its forecasting capabilities, particularly in fields such as solar and wind energy. ARMA uses autoregressive (AR) and moving average (MA) components to generate predictive models from historical data. Its adaptability and ability to recognize cyclical patterns are significant advantages. However, ARMA's reliance on static time series data has limitations. Despite this drawback, its simplicity and interpretability make it popular for short-term forecasting. However, ARMA may face difficulties with nonlinear relationships and long-term forecasting [23].

- **ARIMA (Auto Regressive Integrated Moving Average)**

The ARIMA model, which is an extended version of ARMA, is recognized for its flexibility and interpretability in time series forecasting. ARIMA, which includes autoregressive (AR), integration (I), and moving average (MA) components, excels at capturing various time series patterns and ensuring a consistent level of forecast accuracy for short-term horizons [23]. Notably, it can handle non-stationary values in the analysed data. Despite its benefits, ARIMA's linear assumption, sensitivity to parameter selection, and limitation in capturing long-term dependencies are all important considerations. However, ARIMA's robustness to outliers, ability to manage missing data, and statistical soundness make it an invaluable tool for practical forecasting applications in a wide range of domains.

- **Machine Learning**

The introduction highlights machine learning (ML) as an AI field where machines autonomously discern patterns in historical and current data to make predictions with minimal loss. ML forecasting algorithms offer advanced patterns and approaches, primarily aimed at improving forecast accuracy while minimizing loss. Unlike conventional methods, which rely on explainable linear processes, ML methods utilize nonlinear approaches to minimize loss functions, optimizing prediction accuracy [24].

Machine learning models establish relationships between input and output variables in datasets, essential for forecasting tasks [25]. ML employs algorithms that learn from training data, uncovering complex patterns and insights without explicit programming. However, challenges arise from the training process and the volume of data required.

ML automates large-scale data such as categorization, regression, and clustering. In addition to that, ML is more accurate for medium and long term forecasting than time series generation techniques, which struggle to estimate nonlinear models with high precision [26].

These are some examples for ML algorithms which used for forecasting models, Artificial Neural Network (ANN), Support Vector Machines (SVM), Support Vector Regression (SVR), Regression Trees, Random Forest etc.

- **Deep Learning**

The introduction to Deep Learning (DL) as an AI subset in which neural networks autonomously identify complex patterns in data, improving prediction accuracy with minimal loss and leaving from traditional methods by using nonlinear approaches to optimize outcomes.

DL is a novel approach to ML that employs a deep architecture to generate precise and efficient models. DL techniques efficiently analyse time-series data by turning input data through multiple linear or non-linear processes and extracting the output from deep architecture [25].

DL is capable of overcoming the limitations of shallow models in feature extraction and hyperparameter over-tuning. It is capable of learning from large amounts of data, including imbalanced and heterogeneous datasets with high dimension. Complexity and difficulty of renewable energy data, changing weather patterns must always be taken into account when extracting the data relationship from high-dimensional data [27].

2.1.3 Hybrid Methods

The hybrid technique combines physical and statistical methods to make predictions. The physical model provided by the PV module manufacturers is first applied, and the result is then analysed statistically to improve accuracy. Combining two different physical or statistical techniques is also a type of hybrid. A drawback of the hybrid method is that it is more complex because it employs more than one technique and requires considerably greater machine resources [28].

As an example, Ensemble forecasting is a method of hybrid approach, which combines multiple predictions from various models or methods, is a combination of statistical and physical models. It leverages the strengths and minimizes the weaknesses of individual approaches to produce a more accurate forecast. The core idea of ensemble technique involves training multiple base learners, then they combine their predictions to improve model performance with a unified output [29].

3 Input Parameters of Solar Power Generation Forecasting

According to my literature review, several input parameters have been identified in previous works. Solar irradiance, sourced from Numerical Weather Prediction (NWP) models, Thermopile pyranometers data, solar irradiance maps and satellite data, stands out as the most pivotal parameter, directly dictating the quantity of solar energy received. Cloud cover and motion, obtained from satellites, ground-based observations, or NWP models, provide essential insights into future cloud cover changes, influencing solar irradiance dynamics. Historical weather parameters such as relative humidity, precipitation, temperature, dew point, wind speed, and snow cover, with their impact varying across countries, locations, and seasons. Through techniques like Pearson correlation, researchers have discerned the specific factors influencing solar irradiance. Additionally, historical PV generation data is incorporated to further refine solar energy forecasting models.

In a recent study, researchers analysed historical weather data from a weather station to predict solar generation. They found strong correlations between sky cover, relative humidity, precipitation, and solar intensity, while temperature, dew point, and wind speed showed partial correlations with each other and solar intensity. This insight highlights the complex relationship between weather parameters and solar energy generation, providing valuable guidance for improving predictive models in renewable energy research [30].

In recent Korean research, a comprehensive dataset was employed, comprising historical PV power generation data, solar irradiance maps, and diverse weather parameters such as temperature, sunlight duration, insolation, cloudiness, cloud height, fine dust levels, snowfall, and rainfall. Researchers conducted a thorough analysis using three distinct methods: monthly, seasonal, and a revised seasonal approach considering global warming. This comprehensive analysis, which took historical trends and potential climate change influences into account [31].

A recent study in Illinois, USA, aimed to improve daily solar radiation predictions using a hybrid deep learning model and various climatic data combinations from two stations. Parameters like relative humidity, temperature, precipitation, and wind speed were considered. This research sought to enhance the accuracy of solar radiation forecasts, providing insights into better prediction models by integrating climatic data [32].

In a recent paper, researchers introduced a dual-stream network for accurate PV forecasting. Their input data comprised active power, wind speed, temperature, humidity, global radiation, diffuse radiation, wind direction, and rainfall. This approach aimed to improve PV forecasting accuracy by integrating diverse parameters into a dual-stream network framework [33].

A study in Sri Lanka focused on predicting daily solar power generation using weather forecasts from Hambantota. Input parameters included daily power generation, average GHI, temperature, humidity, precipitation, and wind speed. Researchers suggested enhancing the model by considering additional meteorological parameters and emphasized the importance of cloud cover in improving predictive accuracy [34], [35].

A study focused on cloud cover nowcasting using satellite images from EUMETSAT's "Geostationary Nowcasting Cloud Type" product, which classifies clouds into 16 categories based on height and type. Nowcasting, a short-term weather forecasting method, was the primary objective. The research aimed to enhance cloud cover prediction accuracy using advanced satellite imagery and classification [36].

In a study, researchers employed an Enhanced Convolutional Neural Network to predict Global Horizontal Irradiance (GHI) on short time horizons. They utilized sequences of infrared images from an All-Sky

Imager, with solar radiation measurements encoded as coloured pixels in the images. The study aimed to improve the accuracy of very short-term GHI forecasts by integrating infrared imagery and encoded solar radiation data [37].

In a study on short-term solar radiation forecasting, researchers combined ground-based sky camera images capturing hemispherical views with data from the Atmospheric Radiation Measurement (ARM) dataset. By integrating these datasets, the study aimed to enhance the accuracy of short-term solar radiation predictions [38].

In research, all-sky images were incorporated into a short-term solar irradiance forecasting model. This model aimed to enhance accuracy by integrating data such as solar irradiance and solar power output alongside the all-sky images. By combining these inputs, the study aimed to improve short-term solar irradiance predictions [39].

Recent research on ultra short-term PV generation forecasting utilized ground-based whole sky cameras (Sky-Imagers) for spatial data and incorporated weather/timestamps data alongside PV generation data for temporal context. This comprehensive approach aimed to improve the accuracy of ultra-short-term PV generation forecasts by considering spatial and temporal factors alongside historical generation data [40]. In recent research, both satellite observations and all-sky cameras were utilized to predict short-term fluctuations in solar energy production caused by occluding clouds. The study aimed to provide forecasts for different time scales, with all-sky cameras predicting up to 30 minutes ahead and satellite observations extending forecasts up to 6 hours ahead [41].

4 Forecasting Time Horizons

Solar radiation forecasting is important for managing solar power within the electricity grid due to the challenges posed by meteorological variability. Accurate forecasts aid grid operators in balancing supply and demand, enhancing system dependability, and reducing the need for large energy storage backups. These forecasts are categorized based on various time horizons, such as intra hour, intraday, and day-ahead cycles, each serving different end user applications in the energy sector [42][43]. While there are no standardized parameters for classification, recent research suggests categorizing forecasting methods based on time horizons, data availability, and type into four main groups. This classification assists researchers and energy suppliers in effectively managing solar energy production based on forecasted horizons and applications [44]. So, for real-time forecasting method related with minutes/seconds category because the main objective of my approach is to maintain ramp rate. Figure 03 shows Predictive scale of grid energy management.

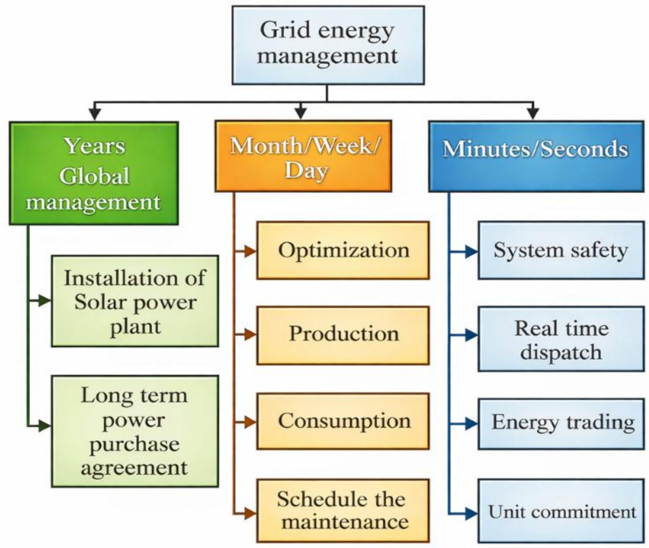

Fig. 3 Predictive Time Scales of Energy Management

5 Total Sky Cover prediction

Even if large scale solar power plants are installed to meet the electricity energy needs Due to the intermittent and unpredictable nature of the solar source accurate solar radiation prediction is becoming increasingly important for grid connections and standalone networks [37]. In according to that cloud cover is one of the factors affecting solar power generation because it poses a significant challenge for stable power grids relying on solar energy from PV plants due to rapid fluctuations in solar irradiance, known as solar ramping. These fluctuations can lead to a sudden drop in power output, sometimes exceeding 60% at specific locations, when clouds pass over PV installations [38]. To overcome this challenge an effective strategy to integrate solar energy into the grid involves anticipating energy supply variability and adjusting grid responses accordingly. This includes predicting short-term fluctuations in electricity production caused by cloud cover at various time scales, such as nowcasting for 5, 10, and 15-minute intervals [41]. By assessing solar radiation at these short interval's aids in power smoothing, real-time dispatch monitoring, and PV storage management, ultimately enhancing grid stability and reliability amidst rapid changes in solar irradiance [37].

5.1 Data Acquisition

According to the review of input parameters of solar power generation forecasting, this cloud imaginary-based prediction mainly under two categories as: Satellite Image approach and Total Sky imagers approach. Research used these satellite images, total sky imagers as well as exogenous data to input weather parameters, hybrid approaches by combining satellite images and total sky images, and also infrared images utilized [36], [37], [39], [41], [45]. According to my background review, the motivation for selecting the All-Sky Imager method stems from the necessity for real-time forecasting in the context of solar power generation. With the imperative to forecast within a narrow time horizon of 5 to 15 minutes to accurate predictions to mitigate the effects of power generation ramp down. However, the All-Sky Imager method offers a unique advantage by providing comprehensive views of the sky in real-time, capturing vital data on cloud cover, movement, and speed. Below figure 04 shows the predictive methods according to the time horizon and temporal resolution.

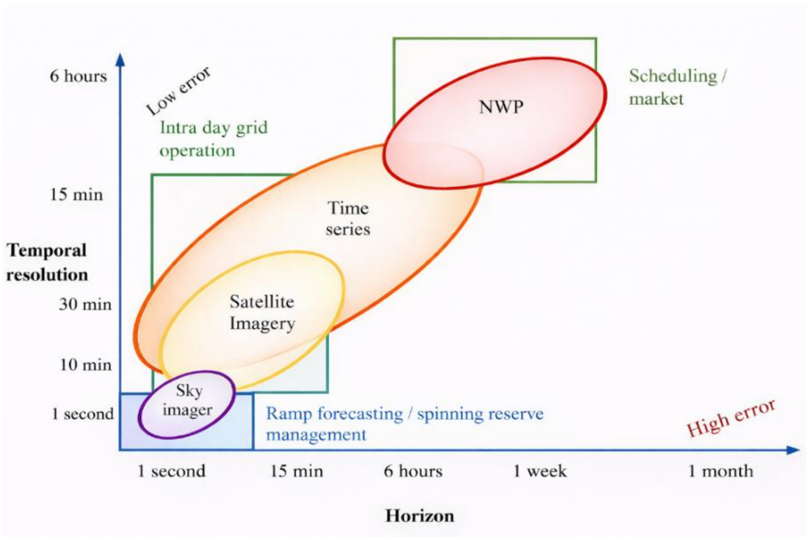

Fig. 4 Solar PV Predictive Methods, Time Horizons vs Temporal Resolution

The reason for selecting this as the most appropriate method is, according to the World Meteorological Organization, satellite-based data is used to forecast solar radiation, with the optimal prediction window ranging from 30 minutes to 6 hours ahead. The technique involves capturing multiple images within an hour to cover extensive areas with both spatial and temporal precision. Satellites offer continuous monitoring of cloud movement over an extended period, enabling more accurate predictions of solar radiation levels. The Total Sky Imager (TSI) could do high-resolution and short-term forecasting over the satellite imagery approach. So, for real time forecasting the most suitable input data is total sky imager [44]. Also, there was a method which was done by using sequence of IR images, they mentioned that there is a drawback which IR image do not have ability to distinguish overcast sky any sunny day sky separately [37]. So, to achieve this objective I will deploy a 170-degree video capturing camera to obtain comprehensive images of the entire sky. Simultaneously, I will integrate a small photovoltaic (PV) panel to collect data on PV generation and solar irradiance. This dual approach allows for the concurrent observation of sky conditions and the corresponding changes in PV generation and solar irradiance. By correlating the cloud details captured by the sky images with the irradiance data and PV generation data, to develop a forecasting model to predict future power generation enabling more accurate forecasts of power generation potential.

5.2 Methodologies Based on Sky Cover Prediction

An Enhanced Convolutional Neural Networks (ECNN) for very short-term solar radiation forecasting in recent study. Here, thorough pre-processing of infrared sky images to eliminate unfavorable weather conditions and enhance efficiency by converting them to grayscale. Additionally, essential data such as Global Horizontal Irradiation (GHI) are integrated into pre-processed images. The ECNN, inspired by the

VGG architecture, is trained to analyses sequences of three consecutive images to capture cloud movement dynamics. [37].

In a recent study utilizing pre-trained prediction algorithms, researchers explored short-term solar radiation forecasting with Total Sky images and deep learning. They employed transfer learning with pre-trained architectures like AlexNet and ResNet-101 to extract features efficiently, reducing training time. The extracted features were fed into an ensemble of 100 decision trees, trained separately for morning, day, and evening scenarios[38].

In a study they proposed an ultra-short-term PV generation forecasting utilizes sky image sequences and a Convolutional Neural Network (CNN) enhanced with exogenous data. Pre-processing involves filtering out unfavorable weather conditions and converting images to grayscale. The CNN captures cloud movement dynamics through consecutive three-image sequences, with an Enhanced CNN (ECNN) further improving accuracy by directly embedding GHI information [45].

The computer vision-based study integrates ground-based sky images, single-frame RGB images, and historical GHI and meteorological data. It employs the Cuboid descriptor on grayscale sequences for spatiotemporal cloud features and uses Spatial Pyramid Pooling for scale refinement. Additionally, a Dense Convolutional Network (DenseNet) extracts static features from RGB images, which are fused with GHI and meteorological data to create a comprehensive feature map for forecasting [46].

In a research study they improve short-term solar irradiance forecasting by merging sky and satellite images using computer vision and Deep Learning. An ECLIPSE architecture extracts features from both image types and combines them for forecasting [41]. A study on Transformer-based multimodal-learning framework. Initially, Informer encodes historical and empirically estimated clear-sky GHI. Then, ground-based sky images are transformed into optical flow maps, which are processed by Vision Transformer [47].

One study introduces a novel Multi-Layer Cloud Motion Vector (3D-CMV) forecasting technique. It is combined with the fast radiative transfer model (FRTM) to produce forecasts up to 3 hours ahead at 15-minute intervals over 5km × 5km grids across Europe and North Africa. The cloud microphysics data are obtained from the Support to Nowcasting and Very Short-Range Forecasting [48].

Most of the papers data undergo pre-processing to align, filter, sample, and format it for deep learning model training. Subsequently, the trained model's performance is evaluated by predicting sky cover on new data and comparing it against ground truth data [49] [50] .

A study on computer vision and object detection-based cloud and sun detection presents a methodology involving several key steps. Firstly, a Convolutional Neural Network (CNN) model using EfficientDet-D2 is employed to identify and locate the Sun and clouds within the sky image. Subsequently, an algorithm analyses consecutive images to assign unique IDs to clouds and tracks their movement, capturing information on speed and direction. Finally, utilizing the distance and movement data, the study calculates the "Transient Remaining Time," indicating the time until a cloud covers the Sun. They mentioned that this is the firstly implemented methodology offers a comprehensive approach to forecasting solar energy fluctuations by effectively analysing cloud movement dynamics and predicting their impact on solar irradiance [51]. A deep neural network which is based on the two stage R-CNN architecture has been trained for object detection and implemented by CloudSegNet and also has been compared with the U-net segmentation approach [52].

As basic implementations ground based short term cloud coverage predictions also done by using Harris features detection and Lukas-kanade optical flow method for fin velocity vectors have been employed [53].

5.3 Irradiance or PV Generation Forecasting Techniques

To forecast the irradiance or PV generation, most of the research is done by using Long-Short Term Memory (LSTM) algorithm [54]. LSTM serves as a training model, with the weights utilized as inputs to estimate solar irradiance. The estimated solar irradiance, along with the solar power output, is then employed to construct the power curve, facilitating the estimation of solar power[39]. Also, hybrid models integrate both CNN and LSTM utilized [55]and algorithm like kernel learning methods, with the clear sky index serving as the response variable and cloud features as covariates [56].

6 Object Detection and Tracking Techniques

6.1 Object Detection Techniques

Due to a smaller amount of research are gone through machine vision approach, I have gone through deep leaning based real time object detection techniques that can utilized for similar cases.

In a review spanning 2004-2018, cloud detection methods in satellite imagery were explored. Techniques included shape analysis, colour transformation, density analysis, cloud shadow detection, comparison with clear-sky images, and feature extraction. These methods collectively enable scientists to uncover valuable insights from the concealed world beneath the clouds [57]. A study on cloud detection, The WDCD method uses a deep neural network to learn features autonomously from data, saving effort by requiring only block-level cloud labels. By employing special techniques and comparing results to clear sky references, WDCD achieves precise cloud detection, outperforming traditional methods [58].

There are studies related to cloud cover detection by the above object detection, but recently there is a lack of research done on cloud cover detection-based object detection. But in the study on 2023, cloud detection and tracking has been successfully done with object detection [51].

So, gone through a review of trending object detection methods in the world which can use to detect and track cloud movements. Stacking convolutional layers in CNNs makes them excellent at capturing spatial features, which makes them perfect for identifying cloud patterns in satellite imagery. [59], [60]. Also, RNNs, designed to process data sequentially, offer potential advantages for analyzing temporal changes in oud cover. Despite this, standard RNNs encounter challenges with long-range dependencies, limiting their effectiveness in capturing complex temporal relationships within cloud data [61].

SSD, which Single Shot Multibox Detector, merges feature extraction from various image scales with streamlined prediction, striking a favourable balance between accuracy and speed. This technique enables efficient and accurate detection of objects, including cloud cover, within satellite imagery, making it suitable for real-time applications [62]. YOLO, is renowned for its ability to swiftly predict bounding boxes and object class probabilities simultaneously, facilitating rapid detection. Widely adopted in real-time applications such as drone imagery and video action recognition, YOLO excels in efficiently identifying objects, including cloud cover, within images and videos[63] [64]. These SSD and YOLO are CNN based deep leaning models for object detection technologies.Research on multi-object detection and tracking (MODT) method which is a combination of techniques. they first separate objects from the background using morphological operations and then, a grasshopper optimization algorithm fine-tunes a Kalman filter

Figure 04. Solar PV Predictive Methods, Time Horizons vs Temporal Resolution

for accurate object tracking across video frames. Finally, a similar measure ensures consistent object identification in each frame. This is done for a video surveillance application [65]. The N-YOLO system divides video frames into smaller pieces, runs a fast object detector on each piece, and combines the results for real-time object detection and tracking on low-power devices [66].

The use of deep learning for object detection and tracking is expanding quickly because of the ongoing development of powerful computing technology. Object tracking comes after object detection. Consequently, the accuracy of object detection across video frames is the primary determinant of tracking accuracy [67].

Based on the reviewed literature, it is evident that short-term and ultra-short-term solar power forecasting has evolved from conventional statistical models toward data-driven and vision-based approaches, driven primarily by the need to mitigate rapid power fluctuations and ramp-rate violations in high PV penetration grids. While numerical weather prediction and time-series models remain effective for longer horizons, their limitations in capturing fast irradiance transients restrict their suitability for real-time grid support. Recent studies demonstrate that integrating sky-imager data with deep learning architectures enables more accurate characterization of cloud dynamics and short-term irradiance variability. However, challenges persist in terms of real-time deployment, model generalization across locations, and computational efficiency. These gaps highlight the need for forecasting frameworks that balance prediction accuracy, response time, and implementation feasibility, particularly for islanded and weak grids such as those in Sri Lanka.

7 DISCUSSION

The reviewed studies indicate a clear shift in solar power forecasting research from traditional time-series and physical models toward data-driven and vision-based approaches. Statistical and machine learning methods have shown strong performance in short-term forecasting; however, their reliance on historical numerical data limits their responsiveness to sudden irradiance changes caused by cloud movement. Deep learning models, particularly convolutional and recurrent architectures, have improved prediction accuracy by capturing nonlinear relationships and temporal dependencies in solar data.

Vision based forecasting using satellite images and total sky imagers has emerged as a promising solution for ultra short term prediction. Ground-based sky imagers provide high temporal and spatial resolution, making them suitable for forecasting within minutes. These methods enable direct observation of cloud motion and structure, which are critical factors in solar ramp events. Nevertheless, many existing studies focus on controlled experimental environments, and their performance under real time operational constraints remains insufficiently explored.

Another key observation is the lack of consistency in input parameter selection and evaluation metrics across studies. While solar irradiance and cloud related features are widely used, the contribution of additional meteorological variables varies significantly by location. Furthermore, many approaches prioritize prediction accuracy without adequately addressing computational efficiency, latency, or scalability. These limitations restrict the practical deployment of advanced forecasting models for real-time grid control.

Overall, the literature demonstrates strong methodological progress but also reveals a gap between algorithmic development and field-level implementation. Addressing this gap is essential for translating forecasting accuracy into effective ramp-rate mitigation and grid stability enhancement.

8 Conclusions

This review examined short-term and ultra short term solar power forecasting techniques with a specific focus on mitigating photovoltaic power ramp rate fluctuations. Traditional physical and statistical models were found to be effective for longer forecasting horizons but insufficient for real-time grid support. Machine learning and deep learning approaches have improved forecasting performance by capturing omplex temporal patterns, yet their effectiveness depends heavily on data quality and model design.

Vision-based methods using satellite imagery and total sky imagers demonstrate strong potential for real-time forecasting due to their ability to directly capture cloud dynamics. Among these, ground-based sky imagers offer superior resolution for minute-level prediction, making them well suited for ramp-rate control applications. Despite these advantages, challenges remain in achieving reliable real-time deployment, ensuring model robustness across different climatic conditions, and balancing accuracy with computational efficiency.

The review highlights the need for forecasting frameworks that integrate accurate cloud motion analysis with fast response prediction models. Such frameworks are particularly important for power systems with high solar penetration and limited flexibility, including islanded grids. The insights presented in this paper provide a structured basis for advancing solar forecasting research toward practical grid-support applications.

9 Future Work

Future research should focus on developing real-time forecasting systems that combine sky-imager data with lightweight deep learning models capable of operating under practical computational constraints. Greater attention is required to improve model generalization across different geographic locations and weather conditions, especially in tropical regions with high cloud variability.

Further studies should also explore the integration of forecasting outputs with grid control strategies, such as dynamic ramp rate limiting and coordinated energy storage operation. Standardized evaluation metrics and benchmark datasets would support fair comparison of forecasting methods and accelerate practical adoption. Additionally, long-term field validation of vision-based forecasting systems in operational solar power plants is essential to assess reliability, scalability, and economic feasibility. Addressing these research directions will be critical for enabling stable and efficient integration of large-scale solar power into future electricity grids.

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