Renewable and Sustainable Energy Reviews 147 (2021) 111187

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Applications for solar irradiance nowcasting in the control of microgrids: A review

Remember Samu [a,*], Martina Calais [a], G.M. Shafiullah [a], Moayed Moghbel [b], Md Asaduzzaman Shoeb [a], Bijan Nouri [c], Niklas Blum [c]

[a] Discipline of Engineering and Energy, College of Science, Health, Engineering and Education Murdoch University Australia, Australia
[b] APD Engineering Level 16, 200 St George Perth WA, Australia
[c] German Aerospace Center (DLR), Institute of Solar Research, Ctra de Senes s/n km 4, 04200, Tabernas, Spain

ARTICLE INFO

Keywords:
Control strategies
Distributed energy resources
Microgrids
Sky camera
Solar forecasting
Solar nowcasting
Solar PV

ABSTRACT

The integration of solar photovoltaic (PV) into electricity networks introduces technical challenges due to varying PV output. Rapid ramp events due to cloud movements are of particular concern for the operation of remote islanded microgrids (MGs) with high penetration of solar PV generation. PV plants and optionally controllable distributed energy resources (DERs) in MGs can be operated in an optimized way based on nowcasting, which is also called very short-term solar irradiance forecasting up to 60 min ahead. This study presents an extensive literature review on nowcasting technologies along with their current and future possible applications in the control of MGs. Ramp rates control and scheduling of spinning reserves are found to be the most recognized applications of nowcasting in MGs. An online survey has been conducted to identify the limitations, benefits and challenges of deploying nowcasting in MGs. The survey outcomes show that the incorporation of nowcasting tools in MG operations is still limited, though the possibility of increasing solar PV penetration levels in MGs if nowcasting tools are incorporated is acknowledged. Additionally, recent nowcasting tools, such as sky camera-based tools, require further validation under various conditions for more widespread adaptation by power system operators.

1. Introduction

Close to a billion people worldwide are living in remote areas [1] and electricity generation in these remote areas is heavily dependent on either fossil fuels (mostly diesel), hybrid solar photovoltaic (PV)/battery systems or both fossil fuels and solar PV. Due to the remoteness, low electricity demand and low population densities of these locations, extending grids to supply electricity may be uneconomic. This creates opportunities for microgrids (MGs) [2], small scale power systems that provide the power to a small group of customers [3].

At least 50% of the installed MGs around the world rely heavily on fossil fuels [4]. This heavy reliance on fossil fuels does not only make the generation systems environmentally unsustainable but also more costly due to fuel transportation costs and due to the highly volatile cost of fuel [5]. The world is slowly moving away from utilising these fossil fuel-based generation sources towards environmentally friendly clean energy generation sources. The main motivation of this drift is the need to meet the world's targets of greenhouse gas (GHG) emission reductions [6]. Even though these fossil fuels still dominate the current energy mix with a combined total of 59.4% for electricity generation worldwide [7], an increase in the penetration of renewables is forecast and renewables are expected to dominate the generation mix by 2040 [8]. A significant amount of expected renewables will be from solar PV and the cumulative total global solar PV capacity is expected to reach 1.3 TW by 2023 [9].

Solar PV technology is being deployed into remote areas due to resource availability, rapid reduction in cost and advances in PV technology, thus making it one of the fastest-growing renewable energy technologies [10]. The widespread availability of abundant solar resources makes this technology feasible in most regions of the world [11].

The integration of PV systems into remote electricity networks is challenging, primarily due to the fluctuating PV generation caused by cloud movements which may result in rapid power ramp events. Spinning or operational reserves, which are centrally controlled, are likely to be critically affected by the variability of PV generation [12]. Against this backdrop, utilisation of small scale DERs is rapidly increasing, thus presenting research opportunities for possible ways of integration of

* Corresponding author.
E-mail address: r.samu@murdoch.edu.au (R. Samu).

https://doi.org/10.1016/j.rser.2021.111187
Received 22 December 2020; Received in revised form 16 April 2021; Accepted 4 May 2021
Available online 17 May 2021

Abbreviations

AFLC	audio frequency load control
AI	artificial intelligence
AMFA	adaptive modified firefly algorithm
ANN	artificial neural network
AR	autoregressive
ARIMA	autoregressive integrated moving average
ARMA	autoregressive moving average
ASI	all sky imager
CBH	cloud base height (m)
CNN	convolutional neural network
CSP	concentrated solar power
CSIRO	Commonwealth Scientific and Industrial Research Organisation
DERs	distributed energy resources
DNI	direct normal irradiance (W/m^2)
DRM	demand response management
EA	evolutionary algorithm
ECMWF	European Center for Medium-Range Weather Forecasting
EV	electric vehicles
FNN	fuzzy neural network
GFS	global forecast system
GHG	greenhouse gas
GHI	global horizontal irradiance (W/m^2)
GTI	global tilted irradiance (W/m^2)
LSTM	long short-term memory
LT	long-term
MA	moving average
MAE	mean absolute error (%)
MAPE	mean absolute percentage error (%)
MASE	mean absolute scaled error (%)
MG	microgrid
MILP	mixed-integer linear programming
MLP	multi-layer perception
MPP	maximum power point
MRE	mean relative error (%)
MSE	mean square error (%)
MT	medium-term
NMAE	normalized mean absolute error (%)
NMSE	normalized mean square error (%)
NN	neural network
NOAA	National Oceanic and Atmospheric Administration
NWP	numerical weather prediction
PR	pattern recognition
PSI	probability of successful islanding (%)
PSO	particle swarm optimisation
PV	photovoltaic
RBF	radial basis function
RBPNN	recurrent backpropagation neural network
RF	random forest
RMSE	root mean square error (%)
RNN	recurrent neural network
RPF	renewable power fraction
ST	short-term
SVM	support vector machine
SVR	support vector regression
TSI	total sky imager
USA	United States of America
VPP	virtual power plant
WRF	Weather Research and Forecasting

these DERs in MGs. DERs have been reported to present economical, environmental and socioethical benefits [13]. Nowcasting, in combination with controllable DERs, is one possible method to address power ramp events caused by PV output fluctuations and consequently enable higher PV integration into remote networks. Nowcasting can be defined as very short-term solar irradiance forecasting up to 60 min ahead.

A suggested potential application of nowcasting was the provision of spinning reserves [14]. This study by Ekistica [14] proposed the integration of sky camera-based nowcasting tools. In the absence of a nowcasted significant drop in the next 2 min, it was proposed that the control system would respond to the nowcast by reducing the minimum required spinning reserve, i.e., the capacity to be kept available by a number of online diesel generators. This reduction in spinning reserve requirement would allow a switch to the diesel generator configuration that is more conducive to higher PV penetration thus removing or reducing the need for PV curtailment [19]. These control mechanisms enable increased PV penetration levels and reduce system costs due to reduced use of diesel fuel.

Research publications on nowcasting mainly focus on the characterisation of statistical performance metrics or forecast errors concerning error indices or applications not related to the utilisation of nowcasting tools for MG control [15–19]. Outlined applications of irradiance forecasting in pre-existing literature include forecasting for minimizing system operating costs, power system sizing, energy markets and reliability assessment [15,20–24].

Solar irradiance forecasting topic gained most of its popularity starting from the year 2010, and since then, exponential growth in research on this topic has been observed as shown in Fig. 1. Research on nowcasting and short-term solar irradiance forecasting started to gain attention after the year 2011 as shown in Fig. 2. Figs. 1 and 2 were created by performing a systematic literature review on solar irradiance forecasting from the year 1990. The literature on nowcasting and control of MGs relevant for this study were then selected from this systematic review.

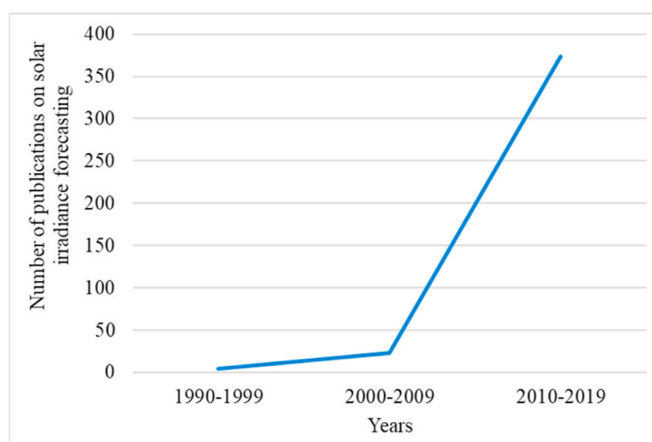

Fig. 1. Solar irradiance forecasting reviewed publications.

The majority of these studies do not focus on applications of nowcasting in the design and control of DERs in MGs. There are few papers on forecasting applications, fewer on nowcasting applications and even fewer on nowcasting applications in MGs. This study, therefore, strives to address this gap, with the main focus on determining the state-of-the-art technology suitable for nowcasting and how it may be applied to intelligently control DERs in MGs and in view of enabling an increase in

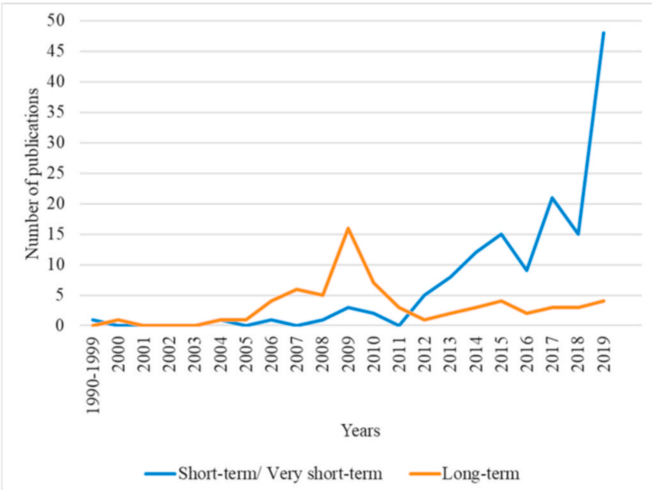

Fig. 2. Relationship between solar forecasting horizons and publication period.

PV hosting capacities in remote MGs. Up to date and recent literature on current technologies available for nowcasting and prospective applications of nowcasting in the control of MGs is reviewed. Additionally, a survey was conducted to collect information about applications of and experience with nowcasting using sky camera-based tools in the control of MGs, thus also serving as a contribution to literature and supporting the reviewed literature. It will assist in improving the understanding of benefits and limitations of using nowcasting in microgrid applications both for central PV plants and DERs. This study will be useful for utilities to make better decisions regarding the applications of nowcasting to improve the operation of MGs.

This paper is divided into seven sections. The background and rationale of this study together with present nowcasting techniques are outlined in Section 2 followed by the methodology applied for this study in Section 3. Section 4 reports the applications of solar irradiance forecasting in MGs whilst Section 5 provides an overview and outcomes of the conducted survey. Recommendations are presented in Section 6 and finally, conclusions and future work are presented in Section 7.

2. Background and rationale

The most significant challenge that the world is currently facing is an anthropogenic climate change, thus driving the development of sustainable energy solutions to reduce the use of fossil fuels. This has led to the increasing utilisation of renewable energy resources mostly solar PV, wind and hydro. However, solar PV power can have short-term variability, mostly due to intermittent cloud cover which presents challenges to MGs with increasing PV penetration levels [25]. This variable nature of solar PV may, especially on intermittent cloudy days, result in ramp events, thus adversely affecting power system management.

Currently, in some MGs, fluctuations in PV output, are being managed by using battery storage systems, dump loads, flywheels, fuel cells, or by operating PV systems below their maximum power point (MPP) [26–29]. To control output power from variable renewable energy generation systems, power ramp limits are also imposed by power utilities [30]. Unfortunately, these methods are either insufficient, costly or limiting the capacity of PV integration. Against this backdrop, a literature review is performed to analyse the possibility of incorporating nowcasting tools in the control of an MG which incorporates solar PV.

Power flow within a traditional electricity grid was unidirectional from the centralized generation to the system loads. However, this is no longer the case as with widespread integration of DERs, power flow can be bi-directional. Consumers can now generate power using renewable energy resources, with or without energy storage, and can export to or import from the grid.

In MGs with a generation mix of fossil fuel-based generation and solar PV, spinning reserve and generator minimum loading requirements heavily influence the operation of the MG. Changes in solar PV output can be beyond the available spinning reserve or the response capability of the control system of the fossil fuel-powered generation system of the MG and can lead to grid stability issues [31]. If the output of PV solar generation exceeds the customer demand, power flows back to the power station, resulting in reverse power operation of generators leading to tripping. On the contrary, in the event of sudden cloud cover that results in a rapid decrease in the solar generation output, generators may become overloaded leading to load shedding or generator tripping and system shutdown. Fig. 3 and Fig. 4 show the scenarios when the generation capacity exceeds customer load (over-generation) and when there is a significant PV output drop due to cloud cover (under--generation), respectively. To overcome these scenarios, if sufficiently reliable, nowcasting could be incorporated into the intelligent control of MGs.

The utilisation of nowcasting tools in the control of PV systems, together with intelligent control of other generation systems and/or storage in MGs can help mitigate the effects of the varying PV output. Nowcasts can minimise the impacts on system management by predicting PV output, which will help in the intelligent provision of the operating reserve to cover for the predicted reduction in PV output.

Typically, electrical power systems do not incorporate nowcasting tools in their operation leading to less than optimum PV penetration into MGs. This also applies to the existing MGs in Australia where nowcasting tools have been trialled but not widely applied [14,32,33]. Nowcasting is, therefore, expected to play an important role in the design of future MGs, which include high levels of solar PV generation. The following section analyses different solar irradiance forecasting methods which can be utilised in MG applications.

2.1. Solar irradiance forecasting

Solar irradiance forecasting can be defined as predicting solar irradiance ahead of time [34]. The history of solar irradiance forecasting can be traced back to the early 20th century or late 19th century following the beginning of the numerical weather prediction (NWP) [35].

2.2. Classification of solar irradiance forecasting

Solar irradiance forecasting can be classified based on the forecast horizons. The forecast horizon is defined as a time span into the future. Table 1 outlines a summary of the classification of solar irradiance forecasting based on the forecast horizons whilst Table 2 is a summary of solar irradiance forecasting based on inputs type [36–40]. In this study, forecasting has been categorised into four types namely; long-term (LT), medium-term (MT), short-term (ST) and very short-term which is called nowcasting.

Forecasting of the next day's generation is of importance for the

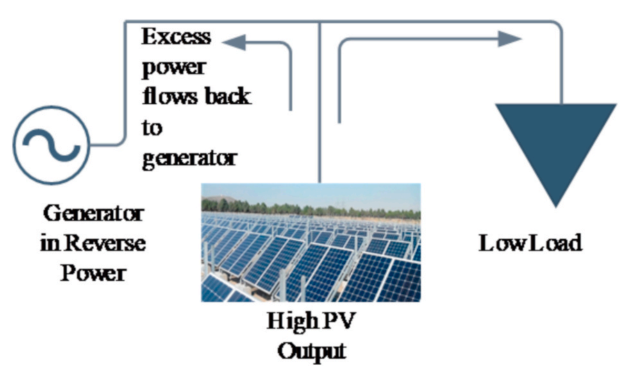

Fig. 3. Overgeneration scenario.

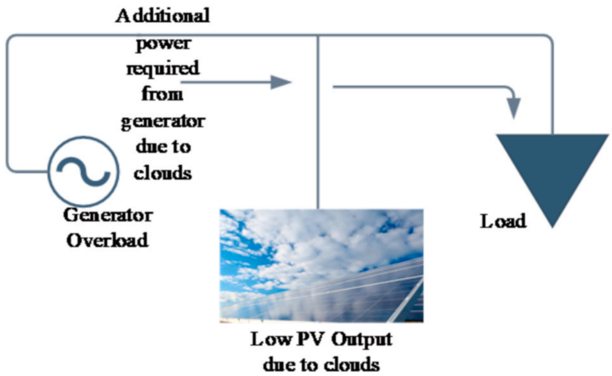

Fig. 4. Under-generation scenario.

Table 1
Classification of solar irradiance forecasting based on the time horizon.

Forecasting type	Time horizon	Utilised models
Long-term	1–10 years ahead	Statistical models with processed data
Medium-term	1 month to 1 year ahead	Statistical models
Short-term	1 h or several hours ahead to 1 day or 1 week ahead	Numerical Weather Prediction (NWP) together with Statistical and Machine Learning Algorithms (AI), Satellite images
Nowcasting	1 min to 60 min ahead	Sky camera-based Imagery

Table 2
Classification of solar irradiance forecasting based on inputs.

Forecasting type	Inputs	Utilised models
Historical solar irradiation and Meteorological parameters based	Historical solar irradiation and weather data such as air temperature, cloud, sunshine duration, clearness index, latitude and longitude	Artificial Neural Network (ANN), Autoregressive Integrated Moving Average (ARIMA), Support Vector Regression, Automatic Regression, Bayesian Neural Network Schemes
Historical data-based	Historical solar irradiation and weather prediction	ARIMA, Recurrent Neural Networks (RNN), Hybrid models and Wavelet Networks
Meteorological Input based	Geographical coordinates, humidity, wind direction, wind speed, air temperature, pressure, clearness index, sunshine duration and cloud	Fuzzy logic, Hybrid models, Radial Basis Function networks (RBF) and Multilayer Perception (MLP) networks
Image-based	Sky images, satellite images	Image Processing Models

pricing of the electricity and the scheduling and planning of power systems operations like load flow analysis, optimum power flow and unit commitment [41–49]. The output parameters that can be predicted are solar irradiance (W/m^2) and PV output (MW). The latter can be used for the evaluation of the system security based on the solar plants' optimum dispatch [50–56].

For intraday and day-ahead forecast horizons, the Global Forecast System (GFS) and the European Centre for Medium-Range Weather Forecasts (ECMWF) models are more reliable than statistical methods, with the spatial resolution being the limiting factor of their outcomes, whilst the Weather Research and Forecasting (WRF) model allows for small temporal resolutions. For intra-day and intra-hour time scales, statistical time-series models are utilised [57,58]. The intra-day and the day ahead forecasting horizons are associated with large grid operation activities [59], whilst 1–60 min ahead forecasting horizons are important for MGs. NWP models are typically used for forecasts of 4–6 h ahead up to 3 days and these models were reported to perform better than the satellite-based forecasts in these time horizons [60,61].

For short-term forecasting, images from satellites can be used to forecast between 1 and 6 h ahead [62]. Nowcasting has been a major focus recently in solar PV forecasting studies. This can be performed by a single sky camera or a network of sky cameras [17,63]. Previously, some authors argued that statistical models still show some level of competency when it comes to nowcasting [64]. Some of the models that Reikard [64] reported were the ARMA, ANNs and the AR models.

Utilisation of satellite images for solar irradiance forecasting involves several complex steps, some of which were explained in detail in the studies by Refs. [65–70]. Deterministic annual and daily solar irradiance patterns do exist, but cloud cover, cloud thickness and cloud base height (CBH) have a significant impact on solar irradiance. Clouds possess strong irregularities in space and time, thus making cloud determination at any time a crucial task in solar irradiance modelling and forecasting. Major satellites like the Himawari 8, together with raw weather data, are employed for the prediction of power output from solar PV, using satellite images [71].

2.3. Solar irradiance forecasting methods

There are three main methods applied for solar irradiance forecasting namely; statistical methods, physical methods and ensemble methods. These major methods comprise sub-models as outlined in

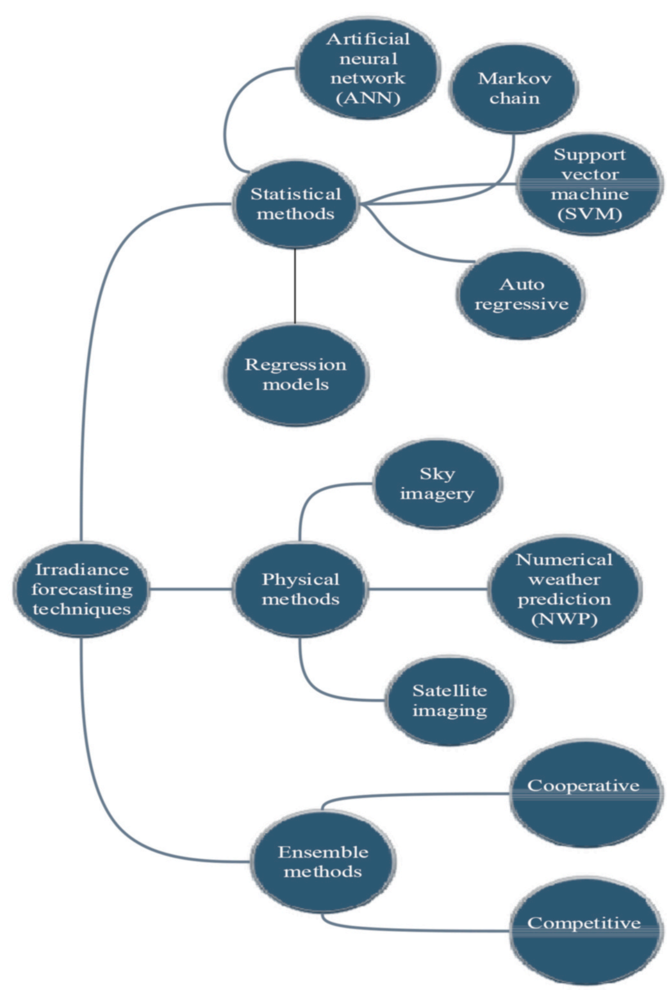

Fig. 5. Physical, ensemble and statistical solar irradiance forecasting methods.

Fig. 5.

2.4. Statistical methods

Statistical methods are mathematical models which recognize a pattern or relationship from historical data [72]. The statistical methods mostly use time series models such as artificial neural networks (ANN), support vector machines (SVM), Markov chain, autoregressive (AR) and regression models [16]. Time-series data can be defined as sequential parameter observations taken at consecutive points in time [73]. Solar irradiance data are time-series data and the relationship between hourly irradiance and the past meteorological parameters can be reconstructed using statistical methods [74,75].

In statistical analyses, the dataset is usually split into training, validation and test datasets [76]. Data that are used to fit the model are called training data (biases and weights in the case of ANN) [77], whilst validation and test dataset are used for the provision of an unbiased evaluation model fit on the training dataset and the performance assessment of a fully-specified classifier respectively [78–80].

In their book, Johnson and Kuhn [77], recommended data splitting using 10-fold cross-validation for both larger and smaller sample sizes. In cross-validation, the dataset is split into test and train first. The test dataset is then reserved and an arbitrary percentage (T%) of the training dataset is then chosen to be the actual training dataset leaving (100-T)% as the validation dataset on which the model will be iteratively trained and validated. Fig. 6 displays the visualisation of these dataset splits.

Most statistical methods assume that the discovered patterns over time are static, but in reality, over time, database patterns evolve [81]. This poses a challenge in detecting when concept drift occurs. Concept drift is the change in the relationships between output and input data over time which may result in degrading and poor predictive performances in statistical models [82]. A summary of statistical methods and their applications is outlined in Table 3.

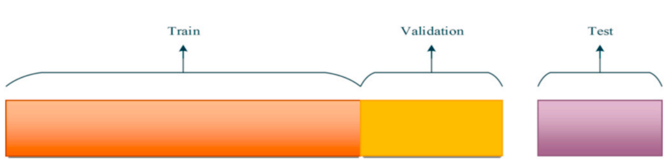

Fig. 6. A visualisation of the dataset splits.

Table 3
Statistical methods.

Method	Description	Application(s)
Artificial Neural Networks (ANN)	• Consists of 3 layers namely input, output and hidden layers [85]. • There are 3 stages of modelling; Stage 1: Definition of the type of ANN and the input and output parameters. Stage 2: Model training Stage 3: Model validation and testing [83].	Commonly applied in optimisation, pattern recognition, data arranging, solving of complex nonlinear data simulations [84].
Support Vector Machine (SVM)	• Consists of a a p dimensional input layer, a hidden layer comprising j kernel inner products and an output layer that is linear [85,86]. The nonlinear radial basis function (RBF) kernel function is defined by: $K = (x_i, x_j) = e^{\gamma\|x_i - x_j^2\|}$ where x_j and x_i are input space vectors, $\gamma = -1/(2\sigma^2)$, where σ is the Gaussian noise level of the standard deviation.	Mainly applied in computing, environmental and hydrology fields [87,88]
Markov Chain	• Consists of a serial dependence between adjoining states [89]	Modelling of discrete-time stochastic processes in various domains such as neuro-linguistic programming (NLP) algorithms, engineering (variable renewable energy resources such as solar and wind), physics, game theory, medicine and finance [90].
Autoregressive (AR)	• Computes correlations between independent and dependent parameters [91]. The general equation for AR is outlined as [52]: $R_t = \varphi_0 + \varphi_1 R_{t-1} + \varphi_2 R_{t-2} + \ldots + \varphi_p t_{t-p} + e_t$ where p is a non-negative integer, φ_i are coefficients and the white noise e_t has a constant variance σ_e^2 and a zero mean.	Statistical time-series data processing and forecasting [92].
Regression	• A technique for functional relationship determination between predictor (independent) and response (dependent) parameters. Multiple linear and simple linear regression analyses are the two widely employed regression analyses depending on the correlation complexities between the parameters [93].	Mainly used in optimisation, model causal effect dependencies between variables, time-series data analysis and forecasting [94,95]

2.5. Physical methods

There are two main types of physical solar irradiance forecasting methods namely the sky image-based and the satellite image-based solar irradiance forecasting models. Physical methods employ a variety of image processing techniques that facilitate and enable usability and validation of the models especially to identify image patterns e.g. identifying clouds or atmospheric conditions and to recognize patterns between images captured in sequence or from different locations in tasks such as cloud tracking or in the estimation of cloud height. Table 4 summarises the commonly used image processing and minimization techniques for both all-sky imagers (ASIs) and satellite-based systems.

2.5.1. Sky imagery

For the prediction of nowcasts with high spatial and temporal resolutions, sky image-based forecasting methods are typically used. Sometimes referred to as total sky imagers (TSIs), ASIs or just sky cameras [105], and modified NWP models [106] are promising forecasting techniques for nowcasting.

Ground-based ASIs can provide much higher temporal and spatial resolutions than satellite data. ASIs can also capture sudden irradiance changes, i.e. ramps at resolutions of less than a minute. The speed of cloud movements highly determines the maximum achievable forecast horizon [107]. In their analysis, West et al. [108], provided a motivation for the application of ground-based sky imagery forecasting with a minimum forecast horizon of 1 min and a maximum of 20 min. This could reduce fossil fuel consumption and network step loads in remote areas where MGs, with PV and fossil fuel generation, are present. It was also reported in the same study that it is possible to utilise sky cameras for forecasting ground distances from 1 m to 1 km from the sky camera. This sky camera-based short-term forecast focuses on local ramp events, local-global horizontal irradiance (GHI) and direct normal irradiance

Table 4
Common image processing techniques for ASIs and satellite bases systems.

Technique	Description	Application
Morphological image processing	A non-linear image processing technique that aims at describing the geometric structure of an image [96].	Non-Gaussian noise suppression, Geometry-based enhancement and feature detection [96].
Image interpolation	A technique of remapping (distorting) or resizing an image from one pixel grid to another by estimating values at unknown points using known data [97].	Image rotation, correcting for lens distortion, increase or decrease the total number of pixels, pixel intensity approximation based on values at surrounding pixels [97].
2-D cross-correlation	Involves movement of a kernel's centre over an image and sum of products computation at each location [98].	Development of spatial filtering algorithms and recognition of patterns between images.
Filtering in the frequency domain	A technique to minimise or suppress waves of certain frequencies [98].	Image sharpening and smoothing.
Image thresholding	Isolation of objects from the background [99].	Image classification based on evaluating the red-blue-ratio, spatial processing, image enhancement, image segmentation,
Convolutional neural network (CNN)	A deep learning algorithm that can take an input image assign importance to various objects in the image to differentiate one from the other.	Classification, image recognition [100].
L0 gradient minimization technique	A minimization technique that detects important edges on an image globally. This is achieved by diminishing insignificant and low amplitude details, whilst preserving salient edges [101].	Removal of rain pixels from images [101].
Alternating minimization method (AMM), total variation (TV) regularisation, L2 norm fidelity model (TV-L2 model), TV-L1 minimization.	Minimization techniques for recovering impulse noise corrupted images. These techniques minimise noise on images without losing corners, other sharp structures and edges of images.	Image reconstruction, image denoising [102–104].

(DNI) resulting in better-informed network operations and disaggregation of local generation and demand.

Nowcasting tools utilising cheap surveillance cameras as sky cameras were believed to be high accuracy nowcasting tools available [108]. These can either be used as a network of 2 or more cameras, or as a single camera depending on the goal, focus and area of the study. Single cameras are normally used together with ceilometers, pyranometers, pyrheliometers and temperature sensors [109]. In this study by Alonso-Montesinos, Batlles and Portillo [109], it was proved that for very short-term forecasting of PV output, sky cameras together with ceilometers, pyranometers and pyrheliometers more accurate than satellite images. Recent studies that made use of a single sky camera were also performed by Refs. [110,111] outlining that in the presence of other parameters and real-time data, a single sky camera will still perform better for nowcasts than satellite images or statistical models.

Cloud base height (CBH), is another very important parameter when using a single sky camera for nowcasting purposes. Unless the forecasts are only focused on the exact location of the camera as outlined by Anagnostos et al. [112], CBH information is a requirement for an accurate forecast [113]. In this study by Anagnostos et al. [112], a single sky camera system together with sensors and neural networks were utilised for energy yield prediction to investigate the output of the PV system which was very close to the camera position.

For more accurate nowcasts, or in the absence of cloud base height information, two or more cameras could be employed to form a system. The distance between the cameras should be optimized such that the cameras' coverage radii overlap for full coverage. Increasing the distance between the cameras would reduce the overlap or matching, resulting in inaccurate forecasts [114]. In this study, Kuhn et al. [114], used a two 3 megapixel cameras system to determine the optimal distance that should be left between the cameras and they concluded that at cloud heights up to 12,000 m, a distance of 1500 m was the optimal one, with distances less than 1500 m resulting in undersampling of the sky images and those above 1500 m resulting in a reduced overlap. They also concluded that higher resolution cameras are best for shorter distances, for example for distances ranging from 0 to 1000 m, a 6-megapixel camera is better.

A two sky camera system is also a cheaper alternative of determining cloud base height compared to ceilometers, though [113] concluded that the combination of one ASI and a pyranometer network (Time Series Correlations) can estimate CBH more accurately than an ASI-pair. A detailed comparison between a two sky camera system and a four sky camera system for the optimisation of a sky camera nowcasting system that has improved cloud tracking and cloud height detection was performed by Ref. [63]. It was concluded in this study that overall the four-camera system performed better than the two-camera system, but the two-camera system had its advantages such as less CPU memory, lower maintenance costs and less hardware expenditure.

As detailed in the literature, more cameras are better in providing more accurate and more reliable nowcasts. Hence studies are being conducted, utilising more cameras, even though in some cases, a cost-benefit analysis may prove otherwise. A study was performed on the east coast of United States of America at the Long Island Solar Farm using a three-camera system network positioned in a triangular manner, together with 25 pyranometers for validation [115]. This system developed by Peng et al. [115], was also able to determine cloud base height and gave accurate forecasts for up to 15 min ahead. Studies based on a four sky camera system were conducted by Refs. [17,116]. In the four sky camera system, validation analysis by Kuhn et al., and Nouri et al. [17,116], concluded that aggregation reduces forecasting errors and the validation period for the system should represent all weather conditions. This 4-camera system was able to handle frequent multilayer cloud conditions.

The first study to utilise 6 shadow cameras for nowcasting was conducted in Spain [117]. The term 'shadow cameras' was used in this study, since the 6 cameras were facing downwards, taking photos from an 87-m-high tower. They used ground photos of shadows taken by the cameras to nowcast solar irradiance by analysing spatial irradiance distributions over several square kilometres. Additionally, even though many sky camera-based nowcasting studies have been performed for solar PV systems, they can also be used for DNI forecasting for concentrated solar power (CSP) plants [118].

There have been a variety of sky imagery-based systems developed to date, with variations in their cloud detection techniques and cloud tracking functions [119,120]. A number of systems use off-the-shelf security cameras and the Mobotix security camera Q26 developed by a German company called MOBOTIX is an example of cameras used in such systems [121]. Fig. 7(a) shows a Mobotix Q26 sky camera and Fig. 7(b) shows an example of a sky image for solar irradiance forecasting captured at Murdoch University in Western Australia.

A summary of the steps involved in forecasting based on sky images is outlined in Fig. 8. Fig. 8 is limited to approaches similar to those of the WOBAS nowcasting system [122–124], especially the creation of shadow or irradiance maps is rather a rare feature. Most ASI systems will

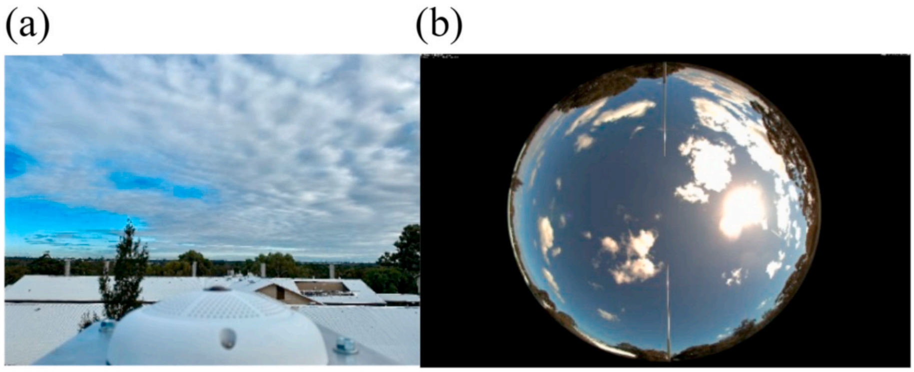

Fig. 7. (a). Mobotix Q26 camera. (b). Captured sky image at MurdochUniversity in Western Australia on 13/04/ 2020.

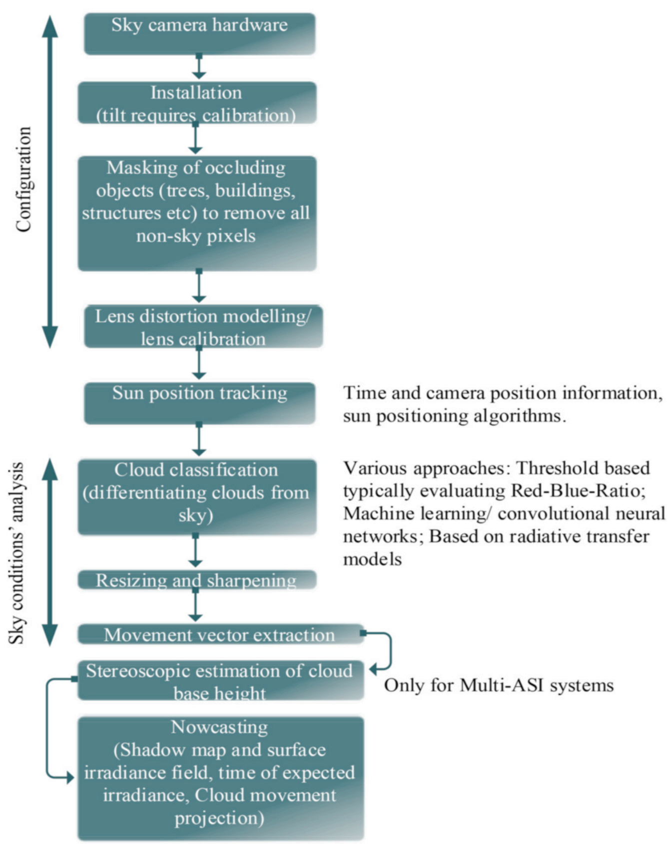

Fig. 8. Example steps involved in sky camera configuration and processing of a sky camera-based nowcasting system.

create nowcasts for the immediate vicinity of the camera (single-camera approaches). In this outlined approach, sky images of or near the forecast site are obtained, followed by an analysis of the sky image data for cloud recognition, then, using consecutive images, a cloud motion vector is developed and finally, nowcasting and cloud cover predictions are developed using the obtained cloud data [125]. It is also important to note that sky cameras are not limited to approaches based on physical methods only. A study conducted by Wanget al., [126], outline the possibility of utilising a sky camera forecasting system based on deep learning methods namely long short-term memory (LSTM) neural network and CNN without cloud detection and modelling.

Table 5 summarises available sky-imagery based forecasting product examples suitable for system-level control applications. However, the review of the outlined products in Table 5 is limited (especially for the Steady Eye by Steadysun and Instacast and SkyInsight by Reuniwatt) as product information and information on the application experiences are primarily based on information provided by the manufacturer [127–130]. A further product for use in PV plants up to 50 kW, the Solar Smoother with Sky Eye Technology, uses a sky camera tool by Magellan Power in combination with a 13.8 kW inverter and three LG RESU65 lithium-ion batteries (19.5 kWh) for solar smoothing of PV system output [131].

2.5.2. *Satellite imaging*

In satellite imaging, overhead flying satellite sensors are used for cloud pattern detection using both infrared and visible images. Geostationary satellites such as the Meteosat network of central Asia, Africa and Europe and the National Oceanic and Atmospheric Administration (NOAA) Geostationary Operational Environmental Satellite network for South and North America, are used to obtain cloud motion data which is then used for solar irradiance forecasts ranging from 1 min to 5 h ahead. Unfortunately, satellite imaging proves to be less efficient in detecting instant cloud pattern changes [133]. However, satellite-based approaches are not limited to imaging only. Lidar and Radar approaches are used for cloud observation [134].

A summary of satellite imaging processing is outlined in Fig. 9 [6]. Brief descriptions of steps 1 and 2 are provided in Fig. 9. Step 3 involves utilisation of statistical methods to forecast GHI using the atmospheric transmission;$k(t)$. The value is defined as $k = 0$ in overcast conditions and $k = 1$ in clear sky conditions. The maximum, minimum and average forecasts of GHI are obtained from the maximum, minimum and average forecasts of k respectively. Unfortunately, systematic errors exist in this forecasting process hence the introduction of the post-processing step for correction.

2.6. *Ensemble methods*

Ensemble methods can also be termed, hybrid models, as they are an integration of two or more models to overcome the weaknesses of individual techniques thus increasing accuracy and strength [91]. The definition can be simplified as any combination of physical and/or statistical methods [135]. There are three ways of integrating ensemble methods which are, non-linear, linear and combination of both [57]. Ensemble methods can be further categorised into cooperative and competitive ensemble forecasting [136].

2.6.1. *Cooperative ensemble forecasting*

Cooperative ensemble forecasting is a technique whereby a forecasting task is divided into fewer sub-tasks which will be individually solved [136].

Table 5
Forecasting tool examples.

Product, Manufacturer	WobaS-4cam by CSP Services	Steady Eye by Steadysun	InstaCast by Reuniwatt	SkyInsight by Reuniwatt	Fulcrum3D-CloudCAM
Product type	Sky camera-based forecasting system	Sky camera-based forecasting system	Sky camera-based forecasting system	Sky camera-based forecasting system	Sky camera-based forecasting system
Forecast parameters	GHI, DNI and global tilted irradiance (GTI)	GHI, DNI, GTI, PV system output (percentiles)	GHI, DNI, GTI, PV system output	GHI, DNI, GTI, PV system output	Irradiance/solar power output
Area of forecast	Up to 8 × 8km^2	Point forecast (site and town level claimed)	2 km radius of camera location	Not stated	An area of 250 m radius around the camera
Image update rate	30 s	10sesond	<1 min	I minute	configurable
Forecast horizon	15 min	Up to 60 min, updated every minute	30 min	10 min	Up to 15 min (depends on local atmospheric conditions)
Spatial resolution	Up to 25m^2	Not stated	10 m^2	Not stated	Not stated
Components	4 all-sky cameras (Mobotix Q24, Q25 or Q26, 3 and 6 MP resolution images respectively) Pyranometer/ Pyrheliometer (if available, otherwise modelled irradiance data for the location is used)	Sky camera and solar irradiance sensor, either stand-alone or Ethernet-based system configurations are available.	Long-wave infrared thermal camera 180-degree angle using Infrared thermal camera with hemispherical mirror, ambient temperature sensor, humidity sensor, irradiance sensor, mini-PC and relay card.	Long-wave infrared thermal camera 180-degree angle using Infrared thermal camera with hemispherical mirror, ambient temperature sensor, humidity sensor, irradiance sensor, mini-PC and relay card.	CloudCAMTM (all-sky camera and processing system), pyranometer, temperature and humidity sensors (other optional sensors are also available)
Application examples and references	Operational at 2 solar research centres and at a commercial 50 MW solar power plant, La Africana in Spain [17].	Hybrid system [129]	Microgrid Example, Brazil [132].	Hybrid PV-Diesel system [128].	Karratha Airport 1 MW Solar Project [33].

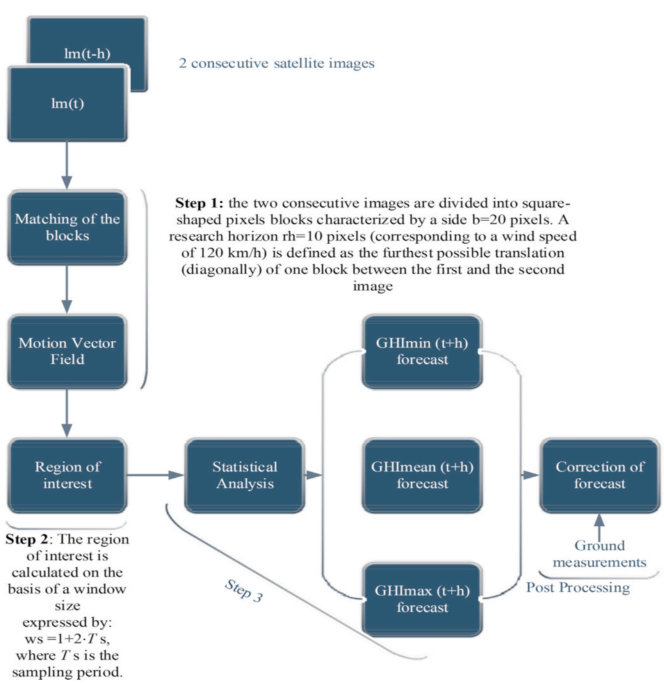

Fig. 9. Steps in satellite imaging forecast process.

2.6.2. *Competitive ensemble forecasting*

Multiple predictors that have different parameters are used in competitive ensemble models to build separate forecast models. A combined average from the individual forecast models is combined resulting in the main forecast [136]. As outlined before, these ensemble methods can be hybrid ANN utilised in speeding up the forecast convergence thus minimizing forecasting errors [137].

A combination of RNN, evolutionary algorithm (EA) and particle swarm optimisation (PSO), was utilised for solar irradiance forecasting in hybrid and stand-alone PV power systems. This model provided more accurate forecasts compared to the individual models [138]. Similar hybrid approaches were employed for solar irradiance forecasting and the prediction accuracies were higher compared to the accuracies of the individual forecast methods [139–149].

2.7. *Performance comparison based on results in the reviewed literature*

A performance comparison between ensemble (both cooperative and competitive) forecasting methods and individual forecasting methods is performed in this section. The error measures used for this performance comparison are mean absolute error (MAE), mean relative error (MRE), mean square error (MSE), mean absolute scaled error (MASE), mean absolute percentage error (MAPE), normalized mean absolute error (NMAE), normalized mean square error (NMSE) and the root mean square error (RMSE). The formulae used to determine these error measures are outlined from Eq. (4) to Eq. (11) [136], where n is the sample size, y is the detected value and $\hat{y}$ is the forecast value.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{4}$$

$$MRE = \frac{1}{n}\sum_{i=1}^{n}\frac{|\hat{y}_i - y_i|}{y_i} \tag{5}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{6}$$

$$MASE = \frac{\sum_{i=1}^{n}|\hat{y}_i - y_i|}{\frac{n}{n-1}\sum_{i=2}^{n}|y_i - y_{i-1}|} \tag{7}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \tag{8}$$

$$NMAE = \frac{1}{n}\sum_{i=1}^{n}\frac{|\hat{y}_i - y_i|}{\max(y_i)} \tag{9}$$

$$NMSE = \frac{1}{n}\sum_{i=1}^{n}\frac{\hat{y}_i - y_i}{y_i - y} \quad (10)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \quad (11)$$

Table 6 outlines a summary of the reviewed benchmark models in comparison to the ensemble methods. According to Table 1, the selected reviewed methods fall into the short-term forecasting horizon. Additionally, these methods include both cooperative [150,151] and competitive [152,153] ensemble forecasting methods. In general, as observed in Table 6, the ensemble forecasting methods outperformed the best alternative methods. The 'improvement' metric presented in Table 6 is calculated using Eq. (12), E_b is the best-performed benchmark method and E_p is the reported method.

$$Improvement = \frac{E_b - E_p}{E_b} \quad (12)$$

3. Methodology

A literature review on the existing solar forecasting methods with a focus on their applications in MGs is presented in this study. The focus of the review is on nowcasting methods and their applications in MG operations. Short term (ST), long-term (LT) and medium-term (MT) solar irradiance forecasting methods with their characteristics were reviewed in brief. For the identification of recent up to date and relevant literature on solar irradiance forecasting methods and applications, previously published papers were collected by searching on international publishers' databases, such as Wiley, IEEE Explore, Taylor & Francis, Hindawi, Springer, ASME and CIGRE and through Google Scholar, Scopus, ScienceDirect, ISI Web of Science, Engineering Village and the Murdoch University Library database. Fig. 10 is a summary of the applied methodology in this study.

Research on nowcasting is still limited and to gather as much literature on the topic, a further search on utility companies' websites for technical reports was performed. Boolean operators, "AND" and "OR" were used in search engines together with search terms to cover substantial plausible combinations. Keywords or phrases such as 'solar irradiance forecasting' or 'irradiance forecasting' or 'nowcasting' or 'applications of solar forecasting' or 'short-term solar forecasting' or 'very short-term solar forecasting' or 'forecasting in MGs' or 'applications of forecasting in MGs', were used as search items.

The research was performed by limiting the database and searching for keywords in the title of the article, abstract and keywords. The main focus was on English peer-reviewed academic journals and technical/industry reports with no restriction applied on the publication date, however, more preferences were given to the recently published articles. Conference papers, technical reports, doctoral and masters theses and other articles which did not have clear publisher information, were excluded from the review process. The majority of the reviewed literature were published between 2011 and 2019 due to the freshness of nowcasting and its applications to MG operations.

Table 6
Performance comparison between ensemble and individual solar forecasting methods.

Ensemble method	Horizon	Benchmark methods	Improvement
Wavelet-recurrent backpropagation neural network (RBPNN) [151]	1 day	RBPNN	77.6% (MRE), 74.5% (MAE)
Non-linear regression and pattern recognition (PR) [153]	3 h, 1 h	Regression, ARIMA, ANN	33.3% (MRE, 3 h), 40.0% (MRE, 1 h)
Multi-stage ANN [150]	1 day	ANN	17.4% (MAE)
Bagging ANN [152]	1 day	RNN, MLP	2.3% (MAPE), 17.4% (MAE)

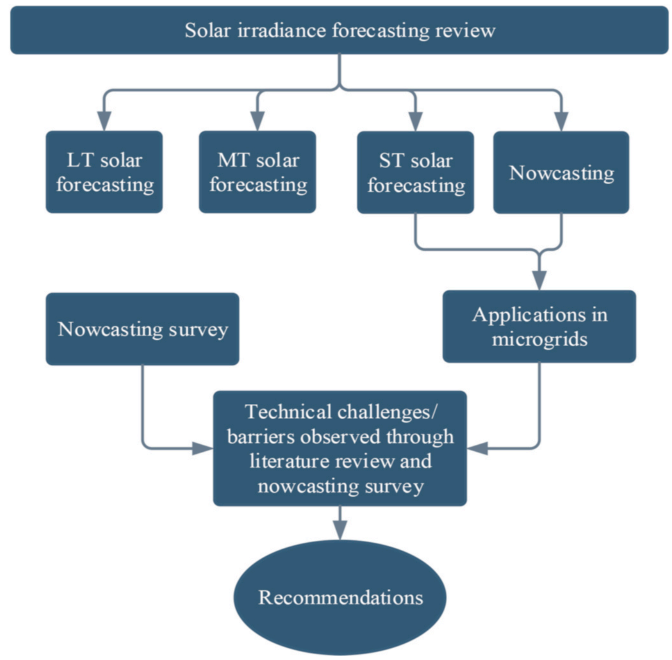

Fig. 10. Methodology summary.

An online survey was also conducted to further investigate the advantages and barriers of integrating nowcasting in the control of MGs. The survey was able to provide feedback on the novel nowcasting tools and current and future possible applications of the tools in the control of MGs. The survey participants were engineers in utility companies, researchers and developers of short-term irradiance forecast tools. Their contacts were obtained mostly from the reviewed literature and companies' websites. Detailed results and lessons learnt from the survey are outlined in section 5 of this paper.

4. Applications in microgrids

Although studies on nowcasting and short-term solar irradiance forecasting methods were performed, their focus remained on the characterisation of forecast errors in terms of performance metrics or error indices. These studies concentrated more on minimizing forecast errors under different forecast horizons and spatial resolutions [6,57,154]. Additionally, the few published works on nowcasting are applied to large power systems with renewable energy rather than MGs [155]. This section strives to bridge this gap by surveying the links between nowcasting and its current and potential applications in MG operations.

4.1. Applications of statistical methods

The commonly utilised statistical nowcasting methods are ARMA, ANN and mixed-integer linear programming (MILP). Prospective MG applications of nowcasting using statistical methods may be found in energy management, dispatch scheduling, provision of spinning reserve, electricity markets clearing, control of energy storage systems, power flow control and performance of peak shaving.

Aslam et al. [156], designed an energy management strategy applying ST solar irradiance in a residential household and found that the peak load was alleviated effectively thus minimizing the energy cost. Additionally, with the recent development of smart appliances and electric vehicles (EVs), nowcasting can be utilised for scheduling smart appliances and charging/discharging of EVs optimally to mitigate energy costs. The utilisation of nowcasting also enables a smart home to interact with the MG and power grid and then make autonomous decisions (purchasing electricity) based on power generation and hourly energy tariff [156].

In electricity market clearing, nowcasting can ensure an optimal integration model of PV systems including demand response, storage devices, and dispatchable distributed generations in MGs or virtual power plants (VPPs) to increase their revenues in the market [157]. Another possible application of statistical nowcasting in MGs is the performance of peak shaving. Peak shaving refers to measures by which a participant of an energy grid reduces the power received quickly and for a short period to avoid a spike of demand in the grid. This is either possible by temporarily scaling down consumption ("load shedding"), activating an on-site power generation system, or relying on a battery. Nowcasting can be integrated into this application power flow control to ensure self-correcting capabilities thus responding to issues of performing peak shaving, utilising locally generated energy respecting grid element constraints [158].

Dispatch scheduling and provision of spinning reserves is another possible application of nowcasting in MGs. An example of the provision of spinning reserves as a nowcasting application was outlined for an islanded MG in Ref. [159]. In this study, the probability of successful islanding (PSI) concept is developed. PSI is the probability of MG maintaining enough spinning reserve to meet local demand and accommodate local renewable generation after promptly islanding from the main grid. The PSI is formulated as MILP utilising multi-interval approximation considering the probability distributions of forecast errors of load, PV and wind. To minimise total operating costs while conserving user-specified PSI, a chance-constrained optimisation problem is formulated for the optimal scheduling of MGs and solved by MILP [159].

Nowcasting and ST solar irradiance forecasting using statistical methods have been utilised mainly in larger power networks as summarised in some selected studies in Table 7. These studies were selected as they show how different statistical methods can be employed for the same applications and how the same statistical method can be employed for different applications. A potential future work would be a performance comparison of these methods for the reported applications and their potential transferability to MGs with smaller temporal/spatial scales.

Table 8 lists possible applications based on forecast horizons. It is observed from Tables 7 and 8 that the majority of possible applications using statistical methods are related to short-term solar irradiance forecasting rather than nowcasting. However, in remote islanded MGs with solar PV, nowcasting is of importance as it can potentially be applied in ramp rates control and spinning reserve scheduling to mitigate the effects of rapidly varying PV output on the distribution network.

Table 7
Solar forecasting in MG applications.

Paper	Year	Prospective MG application	Method used
[156]	2020	Energy management	MILP
[160]	2019	Energy management	Neural network (NN)
[161]	2019	Dispatch scheduling	ARMA, ANN, support vector regression (SVR), random forest (RF)
[162]	2017	Energy management	Persistence technique
[159]	2017	Provision of spinning reserve and dispatch scheduling	MILP
[163]	2016	Energy management	ARMA
[164]	2015	Energy management	Simple moving average SMA
[165]	2014	Energy management	Stochastic programming
[166]	2014	MG management and energy scheduling	Ensemble statistical methods, ARMA
[157]	2014	Electricity markets	Stochastic programming
[167]	2014	Control of battery energy storage system and MG operations of real-time electricity markets	MILP
[158]	2014	Power flow control and performance of peak shaving	MILP
[168]	2014	Energy management	Stochastic method and adaptive modified firefly algorithm (AMFA)

Table 8
Applications based on forecast horizons [6,19,57,59,64,154,169–177].

PV forecasting horizon	Possible applications
Nowcasting	• Scheduling of spinning reserves • Ramp rates control
Short-Term (ST)	• Operational planning • Electricity market transactions • Peak load matching • Load following • Unit commitment

4.2. Applications of physical methods

Physical methods used in solar irradiance nowcasting include NWP, sky imagery and satellite imaging models as outlined in section 2.1.1.2. NWP models were utilised in the Western Wind and Solar Integration Study Phase 2 in the Western United States of America (USA) [155]. In this technical report, it was stated NWP models were used for different solar irradiance forecasting horizons; MT, ST and nowcasting. Comparisons of the performance of NWP models in different forecast horizons proved that more accurate forecasts were observed during nowcasting than MT or ST forecasting.

The USA Western Interconnection grid was simulated with the integration of NWP models for 5-min nowcasts. Ramps experienced in the power system under clear sky conditions were met through unit commitment with the remaining variability met through increased reserves. Similarly, dispatch met the forecasted load ramps and regulation was only used to meet load variations outside the forecasted ramps from one interval to the next. It was concluded from this technical report that reserves were, therefore not needed to cover for known changes in power output because this was considered in unit commitment. It was also reported that more accurate nowcasts ultimately lead to a significant reduction in reserve requirements [155]. Nowcasting applications presented in Ref. [155] can also be employed in MGs for the provision of spinning reserves and ramp rates control.

DigSilent PowerFactory was employed to model a hybrid PV and diesel generation MG system in a study based on Carnarvon data, a remote coastal town in Western Australia [178]. In this study, the authors focused on analysing nowcasts using sky imagers to help manage generation dispatch. Their simulation results proposed a PV integration of up to 30% of the peak load resulting in 8% fuel savings. Furthermore, Peters et al. [179], studied the benefits of nowcasting on a combined setup of PV and battery storage and diesel generation in terms of PV curtailment, required spinning reserve and fuel savings.

A study [180] based on a forecasting system utilising two sky cameras at Murdoch University, Perth Campus, investigated forecasts of clear sky conditions and cloud shading events. Findings from this study outlined that clear sky conditions were predicted with 97% accuracy, indicating high fuel savings and for non-persistent conditions, the accuracy was 90%.

A few published technical reports on applications of nowcasting using sky imagery models in large power systems with PV, which are also relevant to MGs have been reviewed and summarised in Table 9. Table 10 summarises drawbacks and strengths of different nowcasting methods.

A CloudCAM™ cloud recognition camera and analysis software were also integrated into the control of the solar PV battery storage system in Ref. [33]. In this study, in the event of a cloud event nowcast, the controls would enable batteries to be brought online to ensure smooth ramp-downs.

The Commonwealth Scientific and Industrial Research Organisation

Table 9
Projects utilising sky imagery for nowcasting.

Project	Sky imagery nowcasting system/tool	Prospective application for MG	Advantages	Barriers/disadvantages
Sky camera trial at Maningrida in Australia PV-Diesel. (2020) [14].	Sky camera.	• The potential application was the provision of spinning reserves.	• It is outlined that nowcasts would potentially allow the system to operate at a higher renewable power fraction (RPF) in periods of clear weather thus reducing diesel fuel usage. • Reduction in spinning reserve requirements and reduction in PV curtailment are some of the mentioned potential advantages of integrating nowcasts into the control of MGs.	• Camera connectivity, the sky camera experienced some periods of downtime. • Larger drops in available PV power were easier for sky cameras to predict than smaller drops.
Karratha Airport Solar Project in Australia. (1 MW Solar PV, 468 kW battery, grid-connected to the Western Australian North West Interconnected System (2018) [33].	Fulcrum3D Cloudcam.	• Ramp rate control: Pre-emptive reduction of PV array output and battery control to meet a nominal ramp-down rate, where the ramp down time is 720 s. • Minimizing energy curtailment: PV output is only curtailed when the PV output is more than 778 kW, below this level only the battery provides ramp support).	• Battery and nowcasting system performed above expectations presenting smooth ramp up and ramp down generations. • Significant reduction in system capital costs due to a reduction in required batteries. • Without nowcasting, the number of batteries required will be doubled and need to operate at higher rates of discharge to maintain the output within the acceptable ramp rates.	• A build-up of dirt on the cameras impacted nowcasting accuracy.
Voltalia 16 MW PV-Diesel system in Brazil (2018) [132].	Reuniwatt Sky Cam Vision™.	• Ramp rate control.	• Enabled higher PV penetration. • Reduction of system operation costs by reducing the use of diesel.	
Virtual Power Station 2.0 in Australia (2018) [32].	Sky camera.	• Ramp rate control. • Control of energy storage systems. • Demand response management. • Load control.	• The nowcasting system performed as expected. • The system could be used to mitigate network voltage and power swings.	• Delays in communication and transmission of AFLC signals throughout the network and in the air conditioners to respond.
Solar thermal power plant in Spain. 50 MW (2017) [124]	WOBAS nowcasting system.	• Control of the heat transfer fluid in a CSP. • Intra-day and day-ahead electricity markets.	• Increase in power output of the power plant. • Increase in the lifetime of the plant's components due to the reduction in thermal stress.	

(CSIRO) assessed the ability of demand response management (DRM) control of air conditioning load to follow rapid fluctuations in PV output due to cloud events in Ref. [32]. In this study 5 min ahead nowcasts utilising the CSIRO sky imaging system were performed. Upon the reception of nowcasts, a request to activate DRMs was lodged through the phone and the DRM commands were transmitted through the network as audio frequency load control (AFLC) signals. The nowcasting system performed as expected, however, as activation of DRMs was by verbal request using the phone, there were some delays in the drops in aggregate air conditioning load. Additionally, there were some delays in the transmission of AFLC signals and in the response of air conditioners. These drawbacks of this project open opportunities for research and improvements. A similar nowcasting system could be integrated into fully automated intelligent control of MGs. These controllers may be used to manage the balance of generation and controllable loads and support power quality at either a single site or multiple sites with DERs connected in MGs.

It was observed that the applications of nowcasting stated in Table 9 varied from project to project and so were the advantages, lessons learnt, and barriers/disadvantages. As displayed in Table 10 and in Section 4, nowcasting methods have been trialled mostly to optimize the operation of power plants or prosumers connected to large power systems with limited reports or research in MG applications. Against this backdrop, it is therefore of importance to explore the potential or possibility of similar applications of nowcasting in remote MGs.

5. Applications of nowcasting in microgrids: A survey

As observed from the reviewed literature, there is a limited number of publications on nowcasting and its applications in MG operations. Against this backdrop, a survey was conducted to explore further on advantages, barriers, current and future possible applications of nowcasting in MG control.

5.1. Survey methodology

A web-based survey was conducted from March to May 2020 to collect information about applications of and experience with nowcasting mostly utilising sky camera-based tools in the control of MGs. This survey aimed to assist in improving the understanding of the benefits and limitations of using this novel technology in MG applications.

Fig. 11 summarises the methodology followed for the survey. A Qualtrics online platform was used for the distribution of the survey. Qualtrics is a web-based application used to conduct online surveys for evaluation, research and other data collection activities [181]. This survey consisted of fifteen questions. The questions were a mix of multiple-choice, pull-down menu selection, and open text questions which took, on average, between 15 and 17 min to complete. A total of 268 prospective participants worldwide were contacted by email and the distribution of the prospective participants according to organisation activity and according to geographical location is displayed in Table 11 and Fig. 12 respectively. This survey was approved by the Murdoch University Human Research Ethics Committee (Approval 2020/004).

5.2. Survey participants

This survey was designed for academics/researchers working on/are familiar with solar irradiance forecasting, engineers at utility companies

Table 10
Strengths and drawbacks of nowcasting methods.

Nowcasting method	Strengths	Drawbacks
Sky imagery	• Excellent spatial and temporal resolution thus increasing nowcasting accuracy and reducing forecast errors.	• As a novel technology, there is still a need for validation under different conditions until the technology is commercially adopted. • Connectivity issues existed in some performed trials. • Expert knowledge is required for deriving cloud motion vectors. • Larger drops in available PV power were easier for sky cameras to predict than smaller drops [14]. • The availability of a trade-off between efficiency and reliability of sky camera nowcasts. The cameras with higher reliability had lower efficiency and vice versa [14].
NWP	• Modified NWP models have increased forecast accuracy.	• Presence of coarse spatial and temporal resolution • Calculations involved are complex and require a significant amount of time and computational resources. • It can be difficult to acquire large volumes of physical input data.
Statistical models	• Models have a basic structure; hence no expert knowledge is required. • Use of readily available meteorological data. • ANNs can model solar irradiance nonlinear behaviour and knowledge of data to be forecasted is obtained through training the models.	• A large volume of historical data is required for increased accuracies in nowcasting. • ANNs require a significant amount of time and computational resources. • To enhance nowcast accuracies, a large amount of training data is required

that operate MGs and developers of nowcasting tools. The survey was undertaken anonymously, and responses were recorded within composite data in Qualtrics.

5.3. Survey results and discussion

The contacted participants and the recorded responses are shown in Fig. 13. As shown in Fig. 13, a total of 34 responses were received out of 268 contacted prospective participants. Respondents referred to as 'Other,' are from participants in government national meteorology offices, product development, design and retail sectors. On average, all the respondents had 12 years of experience. Differences and trends in responses may be observed in the respondents' answers depending on their years of experience and organisation activity. Fig. 14 shows the distribution of the respondents' years of experience.

It is seen from Fig. 13 that the distribution of the survey respondents is directly proportional to the contacted prospective participants. The highest percentage of contacted prospective participants (46%) were from research (institutes and academia), followed by utility companies and lastly solar nowcasting tools developers and others. The same distribution is observed in the recorded responses as well, the highest responses (56%) were from research (institutes and academia) and the lowest (15%) from solar nowcasting tools developers and others. Additionally, the survey results showed a clear correlation between the geographical location of the prospective survey participants and the recorded responses as shown in Fig. 15.

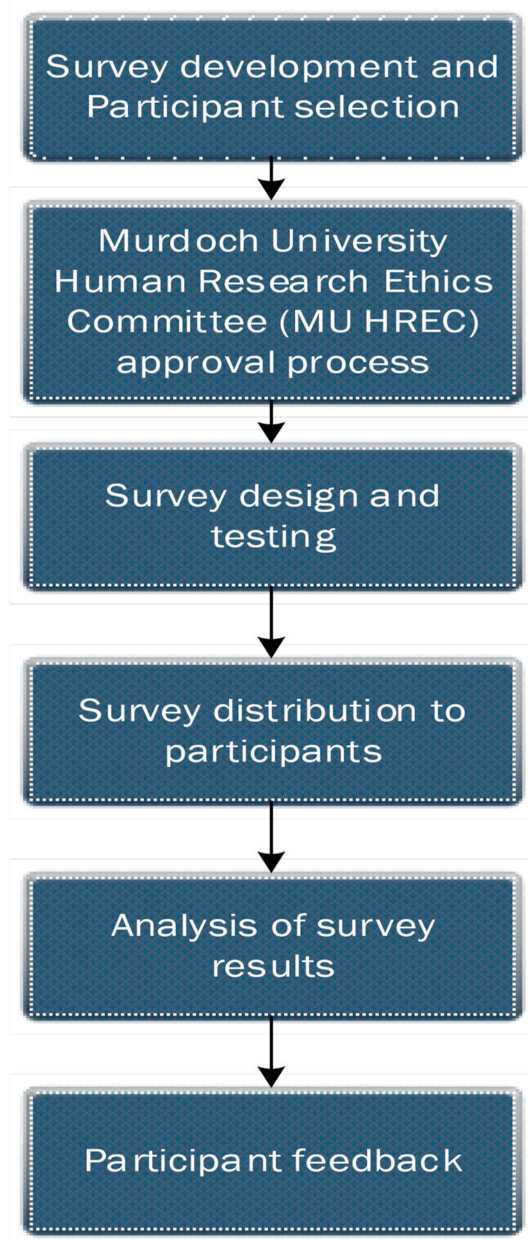

Fig. 11. Survey methodology.

Table 11
Prospective participants.

Organisation Activity	Contacted prospective contacts
Research (Institute and academia)	123
Utility Company	111
Solar nowcasting tools developers and others	34

It was observed that 19 out of 34 respondents either incorporated or developed tools for nowcasting that can be used in MG applications. Furthermore, 10 of these 19 respondents either had experience with or utilised sky camera technology whilst the other 9 employed machine learning, NWP and other statistical methods for nowcasting.

The choice of utilising sky camera technology by some organisations was mainly because of the novelty of the technology as opposed to other technologies which were chosen due to affordability, availability and validated acceptable reliability of the methods. Moreover, some organisations reported that solar variability is mainly due to cloud

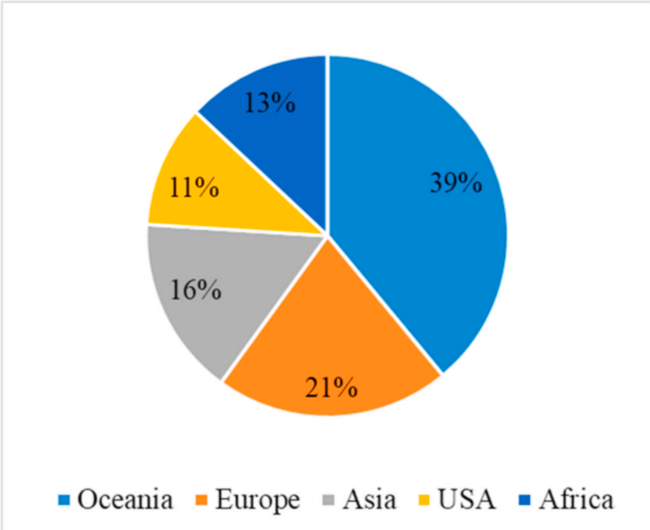

Fig. 12. Location distribution of prospective participants.

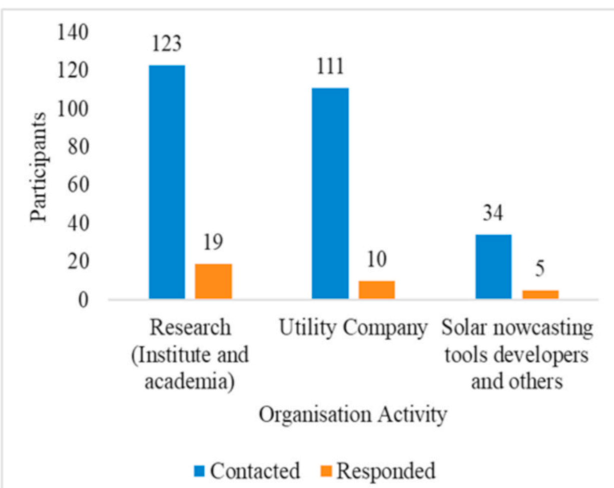

Fig. 13. Survey responses.

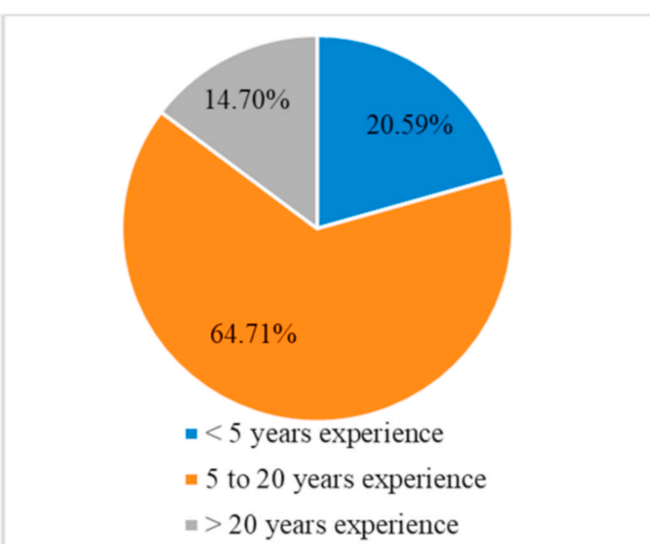

Fig. 14. Respondents' years of experience.

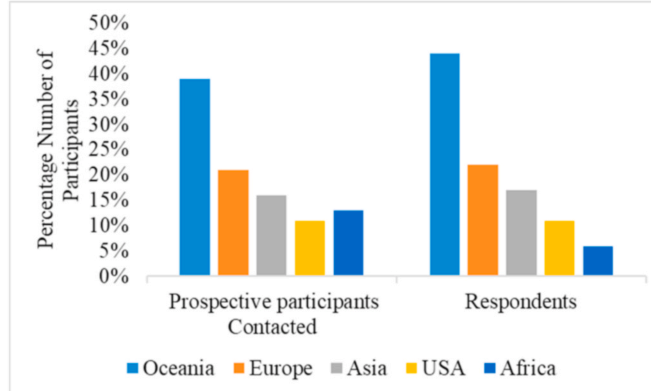

Fig. 15. Relationship between contacted prospective participants and the respondents.

movement and one of the best ways to detect and monitor this is by using sky camera technology. Others reported that nowcasting was complicated in their application by complexities such as the existence of forecast errors and internet connectivity issues.

However, of the respondents who either incorporated or developed tools for nowcasting that can be used in MG applications, only 2 had incorporated sky camera technology in real-life MG operations. These 2 respondents were both from the Oceania region, both had 25 years of experience and both from utility companies; one was a manager in energy strategy and one was a principal planning engineer. Moreover, both of them reported that sky camera technology is still expensive to be adopted by many utility companies, the manager in energy strategy recommended replacing sky-camera based nowcasting with batteries since battery technologies have been validated and the costs of batteries are decreasing.

Furthermore, some utility companies' main interests were in the forecast accuracy for potential inclusion into diesel-PV hybrid MGs. They intended to operate the power system with low spinning reserve when clear sky conditions exist (or a minimum amount of time until a cloud shading event occurs). Due to the significant decrease in battery costs, they believed that the value of nowcasting in this application is limited since, in the presence of battery storage, cloud events will be of much less concern. A total of 5 out of the 34 responses proposed replacing sky camera technology with batteries in microgrid operations. These 5 respondents had 11–25 years of experience.

As concluded from the provided responses, majority of utility companies are not yet using sky camera technology because it is still a new technology and there are not enough results for utilities to be confident in their capabilities. Additionally, as with any other new technology, the respondents outlined a possibility of a high initial cost of this technology and there is still a need to validate sky camera technology, though almost all respondents believed that there is still a potential for this technology's applications in MG operations.

The reported applications of nowcasting in MGs included control of storage and diesel back up, operation optimisation in CSP and PV plants with storage and provision of ramp rates. Table 12 summarises benefits and challenges of incorporating nowcasting in MG operations and possible ways of overcoming these challenges as concluded from the survey feedback. Fig. 16 displays the percentages of responses to one of the survey questions which asked whether or not the participants thought incorporation of sky camera-based nowcasting tools in MG operations would enable to increase PV penetration levels in MGs. As observed in Fig. 16, the majority of respondents believe PV penetration levels in MGs can be increased by incorporating nowcasting tools. Additionally, depending on the forecast accuracy, solar irradiance forecasting in MGs may also result in cost savings of up to 7% [182].

Table 12
Benefits, challenges and how to overcome challenges.

Benefits	• Reduction of battery sizes and curtailment to stay within ramp limits. • Reduction of fast ramps in solar PV output to maintain the required power quality and reliability. • Efficient system management and optimal dispatch scheduling as well as intelligent control of storage or diesel back up. • Provision of stability in MGs.
Challenges	• Existence of forecast errors. • Internet connectivity related to sky camera technology in remote MGs. • Lack of experience and lack of demonstrated reliability • System maintenance (both hardware and software) can be difficult especially if a failure occurs in a remote location.
Possible ways to overcome challenges	• Validation of technology under different conditions. • Collaboration between forecast providers, network operators and grid experts. • Hybridization of methods. • Complementing sky camera-based nowcasting technology with batteries. • Forecasting the variability of (solar irradiance/PV system output) signals rather than forecasting the signals themselves.

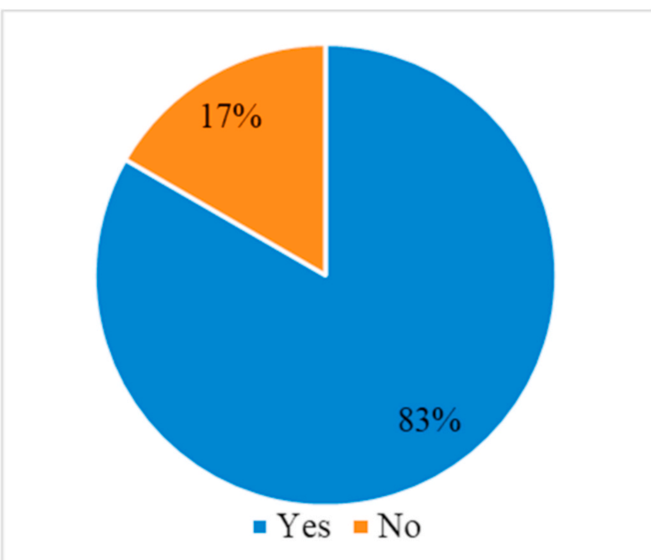

Fig. 16. Responses to the question, "In your view, does very short-term solar irradiance forecasting enable an increase in PV penetration in a microgrid?"

6. Recommendations

A comprehensive literature review on different nowcasting methods and their applications in MGs was performed. A survey was conducted to gather more information from solar nowcasting tools' developers, engineers working in utility companies and researchers, on the limitations and benefits of nowcasting in MGs. As reported in sections 2 to 5 of this study, various drawbacks and barriers/disadvantages were identified. The following recommendations could mitigate or eliminate the effects of the outlined drawbacks and barriers:

- Development of fully automated intelligent control of MGs using VPP concepts as opposed to the system that was developed in Ref. [32].
- Validation of sky camera-based nowcasting models under different conditions and different geographical locations.
- Conducting a comparative analysis between nowcasting techniques to determine parameters such as forecast errors, efficiencies and reliability.
- The hybridisation of nowcasting techniques.
- Nowcasting the variability of solar irradiance/PV system output signals rather than nowcasting the signals themselves.

7. Conclusion and future work

Solar irradiance forecasting methods to date and their applications have been explored. Different methods in terms of model input and output variables, time horizon and forecast were reviewed. This study categorised irradiance forecasting methods into ensemble, time-series statistical and physical methods. Further analysis was performed through a survey to determine current and future possible applications of nowcasting in MG operations. Prospective MG applications of nowcasting include ramp rates control and scheduling of spinning reserves.

The promising novel technology to date for nowcasting purposes is the sky camera-based method and its benefits and limitations in MG applications have been presented. Barriers such as the existence of forecast errors, lack of experience and demonstrated reliability and system maintenance issues in remote MGs still inhibit the utilisation of sky camera-based nowcasting technology. To date, incorporation of sky camera-based nowcasting tools in MG operations is still minimal due to the novelty of the technology as concluded from the obtained survey feedback. Based on both the reviewed literature and the conducted survey, it was evident that sky camera-based nowcasting technology has a great potential in MG applications and proved to be a better technology in terms of prediction accuracy than statistical and NWP methods.

Nowcasting has been employed for different applications in large power systems with renewables. However, possible future works can include research on the possibility of integrating nowcasting in MGs for similar applications as the ones in large power systems, specifically provision of spinning reserves and ramp rates control. In remote MGs, nowcasting would possibly reduce system costs due to reduced fuel usage and hopefully enable an increase in PV penetration levels.

Due to the possible accumulation of dirt and debris on sky cameras under different environments, research should be performed to determine optimum heights to place the sky cameras or cleaning mechanisms to reduce impacts on nowcasts. As extracted from the survey feedback, some engineers suggested replacing sky camera-based nowcasting with battery storage systems in MGs, future studies could be performed on the techno-economic comparative analysis between utilisation of battery storage systems and sky camera-based nowcasting in MGs to determine their strengths and drawbacks/limitations. This most recent review provided in this study can be useful for engineers working in utility companies, researchers and solar nowcasting tools' developers to assess the capabilities and practical requirements for these tools to mitigate impacts on power system management due to PV fluctuations.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We would like to thank all the survey participants worldwide from various organisations for the provision of very useful input.

References

[1] International Energy Agency. World energy outlook. 2018. 2018.
[2] Xu D, Mumata M, Mogi G. Economic comparison of microgrid systems for rural electrification in Myanmar. Energy Procedia 2019;159:309–14. https://doi.org/10.1016/j.egypro.2019.01.010. Elsevier Ltd.

[3] Adelfang Osie. HOMER microgrid news. 2019. https://microgridnews.com/what-is-a-microgrid/.
[4] Akinyele D, Rayudu RB R. Sustainable microgrids for energy-poor communities: a spotlight on the planning dimensions. IEEE Smart Grid Newsl 2016:5–7.
[5] Bunker Kaitlyn, Stephen Doig, Kate Hawley JM. Renewable Microgrids: profiles from islands and remote communities across the globe. 2015.
[6] Barbieri F, Rajakaruna S, Ghosh A. Very short-term photovoltaic power forecasting with cloud modeling: a review. Renew Sustain Energy Rev 2017;75: 242–63. https://doi.org/10.1016/j.rser.2016.10.068.
[7] International energy agency I. Electricity statistics. 2019. https://www.iea.org/statistics/electricity/.
[8] Emma Foehringer Merchant. BP and McKinsey agree renewables will Be the dominant power source by 2040, but diverge on numbers. 2019.
[9] Bellini E. PV magazine 2019.
[10] Adam Wentworth. Growth in solar is bringing power to millions in remote communities. Clim Action 2018.
[11] Cader C, Bertheau P, Blechinger P, Huyskens H, Breyer C. Global cost advantages of autonomous solar-battery-diesel systems compared to diesel-only systems. Energy Sustain Dev 2016:14–23. https://doi.org/10.1016/j.esd.2015.12.007.
[12] Karimi M, Mokhlis H, Naidu K, Uddin S, Bakar AHA. Photovoltaic penetration issues and impacts in distribution network – a review. Renew Sustain Energy Rev 2016;53:594–605. https://doi.org/10.1016/j.rser.2015.08.042.
[13] Vezzoli C, Ceschin F, Osanjo L, M'Rithaa MK, Moalosi R, Nakazibwe V, et al. Distributed/Decentralised renewable energy systems. Green Energy Technol. Springer Verlag; 2018. p. 23–39. https://doi.org/10.1007/978-3-319-70223-0_2.
[14] SETuP Ekistica. Skycamera trial. 2020.
[15] Zhang J, Hodge BM, Lu S, Hamann HF, Lehman B, Simmons J, et al. Baseline and target values for regional and point PV power forecasts: toward improved solar forecasting. Sol Energy 2015;122:804–19. https://doi.org/10.1016/j.solener.2015.09.047.
[16] Ahmed A, Khalid M. A review on the selected applications of forecasting models in renewable power systems. Renew Sustain Energy Rev 2019;100:9–21. https://doi.org/10.1016/j.rser.2018.09.046.
[17] Kuhn P, Nouri B, Wilbert S, Prahl C, Kozonek N, Schmidt T, et al. Validation of an all-sky imager-based nowcasting system for industrial PV plants. Prog Photovoltaics Res Appl 2018;26:608–21. https://doi.org/10.1002/pip.2968.
[18] Nouri B, Wilbert S, Kuhn P, Hanrieder N, Schroedter-Homscheidt M, Kazantzidis A, et al. Real-time uncertainty specification of all sky imager derived irradiance nowcasts. Rem Sens 2019;11:1059. https://doi.org/10.3390/rs11091059.
[19] Stefferud K, Kleissl J, Schoene J. Solar forecasting and variability analyses using sky camera cloud detection & motion vectors. IEEE Power Energy Soc. Gen. Meet. 2012:1–6. https://doi.org/10.1109/PESGM.2012.6345434.
[20] Hanna R, Kleissl J, Nottrott A, Ferry M. Energy dispatch schedule optimization for demand charge reduction using a photovoltaic-battery storage system with solar forecasting. Sol Energy 2014;103:269–87. https://doi.org/10.1016/j.solener.2014.02.020.
[21] Mammoli A, Ellis A, Menicucci A, Willard S, Caudell TSJ. Low-cost solar micro-forecasts for pv smoothing. In: 2013 1st IEEE Conf. Technol. Sustain.; 2013. p. 238–43.
[22] Cui M, Zhang J, Hodge B-M, Lu HFH S. A methodology for quantifying reliability benefits from improved solar power forecasting in multi-timescale power system operations. IEEE Trans Smart Grid 2017;99:12.
[23] Law EW, Kay M, Taylor RA. Evaluating the benefits of using short-term direct normal irradiance forecasts to operate a concentrated solar thermal plant. Sol Energy 2016;140:93–108. https://doi.org/10.1016/j.solener.2016.10.037.
[24] Husein M, Chung IY. Day-ahead solar irradiance forecasting for microgrids using a long short-term memory recurrent neural network: a deep learning approach. Energies 2019;12. https://doi.org/10.3390/en12101856.
[25] Jamal T, Urmee T, Calais M, Shafiullah G, Carter C. Technical challenges of PV deployment into remote Australian electricity networks: a review. Renew Sustain Energy Rev 2017;77:1309–25. https://doi.org/10.1016/J.RSER.2017.02.080.
[26] Tsikalakis AG, Hatziargyriou ND. Centralized control for optimizing microgrids operation. In: 2011 IEEE power energy Soc. Gen. Meet., IEEE; 2011. p. 1–8. https://doi.org/10.1109/PES.2011.6039737.
[27] Sukumar S, Mokhlis H, Mekhilef S, Karimi M, Raza S. Ramp-rate control approach based on dynamic smoothing parameter to mitigate solar PV output fluctuations. Int J Electr Power Energy Syst 2018;96:296–305. https://doi.org/10.1016/j.ijepes.2017.10.015.
[28] Lonij VPA, Jayadevan VT, Brooks AE, Rodriguez JJ, Koch K, Leuthold M, et al. Forecasts of PV power output using power measurements of 80 residential PV installs. Conf Rec IEEE Photovolt Spec Conf 2012:3300–5. https://doi.org/10.1109/PVSC.2012.6318280.
[29] Byrnes L, Brown C, Wagner L, Foster J. Reviewing the viability of renewable energy in community electrification: the case of remote Western Australian communities. Renew Sustain Energy Rev 2016;59:470–81. https://doi.org/10.1016/j.rser.2015.12.273.
[30] Shivashankar S, Mekhilef S, Mokhlis H, Karimi M. Mitigating methods of power fluctuation of photovoltaic (PV) sources - a review. Renew Sustain Energy Rev 2016;59:1170–84. https://doi.org/10.1016/j.rser.2016.01.059.
[31] Power, Corporation Water. Solar/diesel mini-grid handbook. 2019.
[32] Knight Chris. Virtual power station 2.0. Australian Renewable Energy Agency (ARENA); 2018. accessed July 7, 2020, https://arena.gov.au/knowledge-bank/virtual-power-station-2-0/.
[33] Russell Harris. Karratha airport solar project 1 MWp solar PV system. 2018.
[34] Alzahrani A, Shamsi P, Dagli C, Ferdowsi M. Solar irradiance forecasting using deep neural networks. Procedia Comput. Sci., vol. 114. Elsevier B.V.; 2017. p. 304–13. https://doi.org/10.1016/j.procs.2017.09.045.
[35] Gueymard CA, Pedro HTC, Coimbra CFM. History and trends in solar irradiance and PV power forecasting: a preliminary assessment and review using text mining. Sol Energy 2018;168:60–101. https://doi.org/10.1016/J.SOLENER.2017.11.023.
[36] Coimbra CFM, Kleissl J, Marquez R. Overview of solar-forecasting methods and a metric for accuracy evaluation. Sol. Energy Forecast. Resour. Assess. 2013: 171–94. https://doi.org/10.1016/B978-0-12-397177-7.00008-5.
[37] International Energy Agency. Photovoltaic and solar forecasting: state of the art report IEA PVPS T14-01:2013 forecast PV power actual PV power forecast PV power actual PV power. 2013.
[38] ARENA. Australian Solar Energy Forecasting System Final report: project results and lessons learnt-solar-energy-forecasting-system-asefs-phase-1. 2013.
[39] Sreenu Sreekumar, Bhakar Rohit. Solar power prediction models: classification based on time horizon, input, output and application. Proc. Int. Conf. Inven. Res. Comput. Appl. (ICIRCA 2018:67–71. IEEE; 2018.
[40] Raza MQ, Nadarajah M, Ekanayake C. On recent advances in PV output power forecast. Sol Energy 2016;136:125–44. https://doi.org/10.1016/j.solener.2016.06.073.
[41] Bessa RJ, Trindade A, Miranda V. Spatial-temporal solar power forecasting for smart grids. IEEE Trans Ind Informatics 2015;11:232–41. https://doi.org/10.1109/TII.2014.2365703.
[42] Fernandez-Jimenez LA, Muñoz-Jimenez A, Falces A, Mendoza-Villena M, Garcia-Garrido E, Lara-Santillan PM, et al. Short-term power forecasting system for photovoltaic plants. Renew Energy 2012;44:311–7. https://doi.org/10.1016/j.renene.2012.01.108.
[43] Hugo TC, Pedro CFMC. Assessment of forecasting techniques for solar power production with no exogenous inputs. Sol Energy 2012;86. https://doi.org/10.1016/J.SOLENER.2012.04.004. 2017–28.
[44] Mathiesen P, Kleissl J. Evaluation of numerical weather prediction for intra-day solar forecasting in the continental United States. Sol Energy 2011;85:967–77. https://doi.org/10.1016/j.solener.2011.02.013.
[45] Zeng J, Qiao W. Short-term solar power prediction using a support vector machine. Renew Energy 2013;52:118–27. https://doi.org/10.1016/j.renene.2012.10.009.
[46] Mazorra Aguiar L, Pereira B, David M, Díaz F, Lauret P. Use of satellite data to improve solar radiation forecasting with Bayesian Artificial Neural Networks. Sol Energy 2015;122:1309–24. https://doi.org/10.1016/j.solener.2015.10.041.
[47] Bernecker D, Riess C, Angelopoulou E, Hornegger J. Continuous short-term irradiance forecasts using sky images. Sol Energy 2014;110:303–15. https://doi.org/10.1016/J.SOLENER.2014.09.005.
[48] Rana M, Koprinska I, Agelidis VG. 2D-interval forecasts for solar power production. Sol Energy 2015;122:191–203. https://doi.org/10.1016/j.solener.2015.08.018.
[49] Marquez R, Coimbra CFM. Intra-hour DNI forecasting based on cloud tracking image analysis. Sol Energy 2013;91:327–36. https://doi.org/10.1016/j.solener.2012.09.018.
[50] Lorenz E, Hurka J, Heinemann D, Beyer HG. Irradiance forecasting for the power prediction of grid-connected photovoltaic systems. IEEE J Sel Top Appl Earth Obs Remote Sens 2009;2:2–10. https://doi.org/10.1109/JSTARS.2009.2020300.
[51] Perez E, Beltran H, Aparicio N, Rodriguez P. Predictive power control for PV plants with energy storage. IEEE Trans Sustain Energy 2013;4:482–90. https://doi.org/10.1109/TSTE.2012.2210255.
[52] Huang J, Korolkiewicz M, Agrawal M, Boland J. Forecasting solar radiation on an hourly time scale using a Coupled AutoRegressive and Dynamical System (CARDS) model. Sol Energy 2013;87:136–49. https://doi.org/10.1016/j.solener.2012.10.012.
[53] Bhardwaj S, Sharma V, Srivastava S, Sastry OS, Bandyopadhyay B, Chandel SS, et al. Estimation of solar radiation using a combination of Hidden Markov Model and generalized Fuzzy model. Sol Energy 2013;93:43–54. https://doi.org/10.1016/j.solener.2013.03.020.
[54] Kraas B, Schroedter-Homscheidt M, Madlener R. Economic merits of a state-of-the-art concentrating solar power forecasting system for participation in the Spanish electricity market. Sol Energy 2013;93:244–55. https://doi.org/10.1016/j.solener.2013.04.012.
[55] Lonij VPA, Brooks AE, Cronin AD, Leuthold M, Koch K. Intra-hour forecasts of solar power production using measurements from a network of irradiance sensors. Sol Energy 2013;97:58–66. https://doi.org/10.1016/j.solener.2013.08.002.
[56] Fernández EF, Almonacid F, Sarmah N, Rodrigo P, Mallick TK, Pérez-Higueras P. A model based on artificial neuronal network for the prediction of the maximum power of a low concentration photovoltaic module for building integration. Sol Energy 2014;100:148–58. https://doi.org/10.1016/j.solener.2013.11.036.
[57] Diagne M, David M, Lauret P, Boland J, Schmutz N. Review of solar irradiance forecasting methods and a proposition for small-scale insular grids. Renew Sustain Energy Rev 2013;27:65–76. https://doi.org/10.1016/j.rser.2013.06.042.
[58] Diagne HM, Lauret P, David M. Solar irradiation forecasting: state-of-the-art and proposition for future developments for small-scale insular grids. 2012.
[59] Kostylev VV, Pavlovski A. Solar power forecasting performance – towards industry standards. 2011.
[60] Heinemann D, Lorenz E, Girodo M. Forecasting of solar radiation. 2006.
[61] Perez R, Kivalov S, Schlemmer J, Hemker K, Renné D, Hoff TE. Validation of short and medium term operational solar radiation forecasts in the US. Sol Energy 2010;84:2161–72. https://doi.org/10.1016/J.SOLENER.2010.08.014.

[62] Lorenz Elke, Annette Hammer DH. Short term forecasting of solar radiation based on satellite data. EUROSUN2004 (ISES Eur. Sol. Congr. 2004:841–8.
[63] Nouri B, Kuhn P, Wilbert S, Hanrieder N, Prahl C, Zarzalejo L, et al. Cloud height and tracking accuracy of three all sky imager systems for individual clouds. Sol Energy 2019;177:213–28. https://doi.org/10.1016/J.SOLENER.2018.10.079.
[64] Reikard G. Predicting solar radiation at high resolutions: a comparison of time series forecasts. Sol Energy 2009;83:342–9. https://doi.org/10.1016/J.SOLENER.2008.08.007.
[65] Lorenz Elke, Heinemann Detlev. 1.13—prediction of solar irradiance and photovoltaic power. In: Ali Sayigh E, editor. Compr. Renew. energy. Oxford: Elsevier; 2012. p. 239–92.
[66] Rigollier C, Lefèvre M, Wald L. The method Heliosat-2 for deriving shortwave solar radiation from satellite images. Sol Energy 2004;77:159–69. https://doi.org/10.1016/j.solener.2004.04.017.
[67] Olseth JA, Skartveit A. Solar irradiance, sunshine duration and daylight illuminance derived from METEOSAT data for some European sites. Theor Appl Climatol 2001;69:239–52. https://doi.org/10.1007/s007040170029.
[68] Perez R, Ineichen P, Moore K, Kmiecik M, Chain C, George R, et al. A new operational model for satellite-derived irradiances: description and validation. Sol Energy 2002;73:307–17. https://doi.org/10.1016/S0038-092X(02)00122-6.
[69] Rigollier C, Bauer O, Wald L. On the clear sky model of the ESRA — European Solar Radiation Atlas — with respect to the heliosat method. Sol Energy 2000;68:33–48. https://doi.org/10.1016/S0038-092X(99)00055-9.
[70] Rigollier C, Lefèvre M, Blanc P, Wald L. The operational calibration of images taken in the visible channel of the Meteosat series of satellites. J Atmos Ocean Technol 2002;19:1285–93. https://doi.org/10.1175/1520-0426(2002)019<1285:TOCOIT>2.0.CO. 2.
[71] Jones R. Document information project PV forecasting for DNSPs client ARENA status project overview report prepared. 2018.
[72] Jung J, Broadwater RP. Current status and future advances for wind speed and power forecasting. Renew Sustain Energy Rev 2014;31:762–77. https://doi.org/10.1016/j.rser.2013.12.054.
[73] Montgomery Douglas C, Cheryl L, Jennings MK. Introduction to time series analysis and forecasting. John Wiley & Sons.; 2015.
[74] Cornaro C, Pierro M, Bucci F. Master optimization process based on neural networks ensemble for 24-h solar irradiance forecast. Sol Energy 2015;111:297–312. https://doi.org/10.1016/j.solener.2014.10.036.
[75] Guermoui M, Melgani F, Danilo C. Multi-step ahead forecasting of daily global and direct solar radiation: a review and case study of Ghardaia region. J Clean Prod 2018;201:716–34. https://doi.org/10.1016/j.jclepro.2018.08.006.
[76] Xu Y, Goodacre R. On splitting training and validation set: a comparative study of cross-validation, bootstrap and systematic sampling for estimating the generalization performance of supervised learning. J Anal Test 2018;2:249–62. https://doi.org/10.1007/s41664-018-0068-2.
[77] Max Kuhn, Kjell J. Applied predictive modeling. first ed. Springer; 2013.
[78] James Gareth, Witten Daniela, Hastie Trevor, Tibshirani R. An introduction to statistical learning: with applications in R. first ed. Springer; 2013.
[79] Stuart Russell, Peter Norvig. Artificial intelligence: a modern approach. third ed. Pearson; 2009.
[80] Ripley BD. Pattern recognition and neural networks. 1996.
[81] Maimon Oded, Rokach L. Data mining and knowledge discovery handbook. second ed. Springer; 2010.
[82] Wang H, Abraham Z. Concept drift detection for streaming data. Proc Int Jt Conf Neural Networks 2015;2015-Septe. accessed March 21, 2021, http://arxiv.org/abs/1504.01044.
[83] Amrouche B, Le Pivert X. Artificial neural network based daily local forecasting for global solar radiation. Appl Energy 2014;130:333–41. https://doi.org/10.1016/j.apenergy.2014.05.055.
[84] Voyant C, Notton G, Kalogirou S, Nivet ML, Paoli C, Motte F, et al. Machine learning methods for solar radiation forecasting: a review. Renew Energy 2017;105:569–82. https://doi.org/10.1016/j.renene.2016.12.095.
[85] Shamshirband S, Petković D, Saboohi H, Anuar NB, Inayat I, Akib S, et al. Wind turbine power coefficient estimation by soft computing methodologies: comparative study. Energy Convers Manag 2014;81:520–6. https://doi.org/10.1016/j.enconman.2014.02.055.
[86] Mellit A, Pavan AM, Benghanem M. Least squares support vector machine for short-term prediction of meteorological time series. Theor Appl Climatol 2013;111:297–307. https://doi.org/10.1007/s00704-012-0661-7.
[87] Mohammadi K, Shamshirband S, Tong CW, Arif M, Petković D, Sudheer C. A new hybrid support vector machine-wavelet transform approach for estimation of horizontal global solar radiation. Energy Convers Manag 2015;92:162–71. https://doi.org/10.1016/j.enconman.2014.12.050.
[88] Olatomiwa L, Mekhilef S, Shamshirband S, Mohammadi K, Petković D, Sudheer C. A support vector machine-firefly algorithm-based model for global solar radiation prediction. Sol Energy 2015;115:632–44. https://doi.org/10.1016/j.solener.2015.03.015.
[89] Hocaoglu FO, Serttas F. A novel hybrid (Mycielski-Markov) model for hourly solar radiation forecasting. Renew Energy 2017;108:635–43. https://doi.org/10.1016/j.renene.2016.08.058.
[90] Vidhya Analytics. Markov chain | characteristics & applications of Markov chain. 2021 (accessed March 30, 2021), https://www.analyticsvidhya.com/blog/2021/02/markov-chain-mathematical-formulation-intuitive-explanation-applications/.
[91] Antonanzas J, Osorio N, Escobar R, Urraca R, Martinez-de-Pison FJ, Antonanzas-Torres F. Review of photovoltaic power forecasting. Sol Energy 2016;136:78–111. https://doi.org/10.1016/j.solener.2016.06.069.
[92] Dai X, Liu J, Zhang H. Application of AR model in the analysis of preearthquake ionospheric anomalies. Math Probl Eng 2015;2015. https://doi.org/10.1155/2015/157184.
[93] Fumo N, Rafe Biswas MA. Regression analysis for prediction of residential energy consumption. Renew Sustain Energy Rev 2015;47:332–43. https://doi.org/10.1016/j.rser.2015.03.035.
[94] Pal M, Bharati P. Applications of regression techniques. Springer Singapore; 2019. https://doi.org/10.1007/978-981-13-9314-3.
[95] Linear builtin. Regression: applications with TensorFlow 2.0 | built in. 2021 (accessed March 30, 2021), https://builtin.com/data-science/linear-regression-tensorflow.
[96] Maragos P. Morphological filtering. Essent. Guid. To image process. Elsevier Inc.; 2009. p. 293–321. https://doi.org/10.1016/B978-0-12-374457-9.00013-5.
[97] Fadnavis S. Image interpolation techniques in digital image processing: an overview, vol. 4; 2014.
[98] Gonzalez Rafael C, Woods RE. Digital image processing. Pearson; 2018. accessed April 11, 2021, https://b-ok.global/book/5062366/8e48ba.
[99] McAndrew Alasdair. A computational introduction to digital image processing. 2015.
[100] Ryu A, Ito M, Ishii H, Hayashi Y. Preliminary analysis of short-term solar irradiance forecasting by using total-sky imager and convolutional neural network. In: 2019 IEEE PES GTD Gd. Int. Conf. Expo. Asia (GTD ASIA); 2019.
[101] Manu BN. Rain removal from still images using L0 gradient minimization technique. In: Proc. - 2015 7th Int. Conf. Inf. Technol. Electr. Eng. Envisioning trend Comput. Inf. Eng. ICITEE 2015, institute of electrical and electronics engineers Inc.; 2015. p. 263–8. https://doi.org/10.1109/ICITEED.2015.7408953.
[102] Liu X. Alternating minimization method for image restoration corrupted by impulse noise. Multimed Tool Appl 2017;76:12505–16. https://doi.org/10.1007/s11042-016-3631-8.
[103] Zhang W, Cao Y, Zhang R, Li L, Wen Y. Image denoising via L 0 gradient minimization with effective fidelity term. Math Probl Eng 2015;2015. https://doi.org/10.1155/2015/712801.
[104] Fan L, Zhang F, Fan H, Zhang C. Brief review of image denoising techniques. Vis Comput Ind Biomed Art 2019;2:7. https://doi.org/10.1186/s42492-019-0016-7.
[105] Scolari E, Sossan F, Paolone M. Irradiance prediction intervals for PV stochastic generation in microgrid applications. Sol Energy 2016;139:116–29. https://doi.org/10.1016/j.solener.2016.09.030.
[106] Lee JA, Haupt SE, Jiménez PA, Rogers MA, Miller SD, McCandless TC. Solar irradiance nowcasting case studies near sacramento. J Appl Meteorol Climatol 2017;56:85–108. https://doi.org/10.1175/JAMC-D-16-0183.1.
[107] Chow CW, Urquhart B, Lave M, Dominguez A, Kleissl J, Shields J, et al. Intra-hour forecasting with a total sky imager at the UC San Diego solar energy testbed. Sol Energy 2011;85:2881–93. https://doi.org/10.1016/j.solener.2011.08.025.
[108] West SR, Rowe D, Sayeef S, Berry A. Short-term irradiance forecasting using skycams: motivation and development. Sol Energy 2014;110:188–207. https://doi.org/10.1016/J.SOLENER.2014.08.038.
[109] Alonso-Montesinos J, Batlles FJ, Portillo C. Solar irradiance forecasting at one-minute intervals for different sky conditions using sky camera images. Energy Convers Manag 2015;105:1166–77. https://doi.org/10.1016/J.ENCONMAN.2015.09.001.
[110] Paulescu M, Paulescu E. Short-term forecasting of solar irradiance. Renew Energy 2019;143:985–94. https://doi.org/10.1016/j.renene.2019.05.075.
[111] Caldas M, Alonso-Suárez R. Very short-term solar irradiance forecast using all-sky imaging and real-time irradiance measurements. Renew Energy 2019;143:1643–58. https://doi.org/10.1016/J.RENENE.2019.05.069.
[112] Anagnostos D, Schmidt T, Cavadias S, Soudris D, Poortmans J, Catthoor F. A method for detailed, short-term energy yield forecasting of photovoltaic installations. Renew Energy 2019;130:122–9. https://doi.org/10.1016/J.RENENE.2018.06.058.
[113] Wang GC, Urquhart B, Kleissl J. Cloud base height estimates from sky imagery and a network of pyranometers. Sol Energy 2019;184:594–609. https://doi.org/10.1016/J.SOLENER.2019.03.101.
[114] Kuhn P, Nouri B, Wilbert S, Hanrieder N, Prahl C, Ramirez L, et al. Determination of the optimal camera distance for cloud height measurements with two all-sky imagers. Sol Energy 2019;179:74–88. https://doi.org/10.1016/J.SOLENER.2018.12.038.
[115] Peng Z, Yu D, Huang D, Heiser J, Yoo S, Kalb P. 3D cloud detection and tracking system for solar forecast using multiple sky imagers. Sol Energy 2015;118:496–519. https://doi.org/10.1016/J.SOLENER.2015.05.037.
[116] Nouri B, Kuhn P, Wilbert S, Prahl C, Pitz-Paal R, Blanc P, et al. Nowcasting of DNI maps for the solar field based on voxel carving and individual 3D cloud objects from all sky images. AIP Conf Proc 2018;2033:190011. https://doi.org/10.1063/1.5067196.
[117] Kuhn P, Wilbert S, Prahl C, Schüler D, Haase T, Hirsch T, et al. Shadow camera system for the generation of solar irradiance maps. Sol Energy 2017;157:157–70. https://doi.org/10.1016/J.SOLENER.2017.05.074.
[118] Nou J, Chauvin R, Eynard J, Thil S, Grieu S. Towards the short-term forecasting of direct normal irradiance using a sky imager. IFAC-PapersOnLine 2017;50:14137–42. https://doi.org/10.1016/J.IFACOL.2017.08.1856.
[119] Urquhart B, Kurtz B, Dahlin E, Ghonima M, Shields JE, Kleissl J. Development of a sky imaging system for short-term solar power forecasting. Atmos Meas Tech 2015;8:875–90. https://doi.org/10.5194/amt-8-875-2015.
[120] Yang H, Kurtz B, Nguyen D, Urquhart B, Chow CW, Ghonima M, et al. Solar irradiance forecasting using a ground-based sky imager developed at UC San Diego. Sol Energy 2014;103:502–24. https://doi.org/10.1016/j.solener.2014.02.044.

[121] MOBOTIX. Company. MOBOTIX AG; 2020. accessed January 19, 2020, https://www.mobotix.com/en/whymobotix.
[122] DLR., CSP Services. WobaS-nowcasting system. 2019.
[123] (DLR) I for SR of the GAC. DLR - institute of Solar Research - cloud camera system WobaS provides solar power plants with reliable radiation nowcasts. 2019. accessed February 14, 2020, https://www.dlr.de/sf/en/desktopdefault.aspx/tabid-10436/23661_read-58604/.
[124] (DLR) I for SR of the GAC. DLR - institute of Solar Research - solar irradiance nowcasting system, solar thermal power plant, solar research. 2017. accessed July 7, 2020, https://www.dlr.de/sf/en/desktopdefault.aspx/tabid-10436/12676_read-48274/.
[125] Pelland S, Remund J, Kleissl J, Oozeki KDB T. Photovoltaic and solar forecasting: state of the art. IEA PVPS; 2013. p. 1–36.
[126] Wang F, Zhang Z, Chai H, Yu Y, Lu X, Wang T, et al. Deep learning based irradiance mapping model for solar PV power forecasting using sky image. In: 2019 IEEE Ind. Appl. Soc. Annu. Meet. IAS. Institute of Electrical and Electronics Engineers Inc.; 2019; 2019. https://doi.org/10.1109/IAS.2019.8912348.
[127] Reuniwatt. Intra-hour solar forecasts with InstaCast - Reuniwatt | Solar energy forecasting. 2020. accessed October 26, 2020, http://reuniwatt.com/en/intrahour-solar-forecasts-instacast/.
[128] Boudreault L-É, Liandrat O, Braun A, É Buessler, Lafuma M, Cros S, et al. Sky-imager forecasting for improved management of a hybrid photovoltaic-diesel system. 2018.
[129] Steadysun. SteadyEye - next minutes solar power forecasting. 2020. accessed October 26, 2020, https://www.steady-sun.com/technology/steadyeye/.
[130] Melly NK. Short-term solar forecasting for microgrids. 2019.
[131] Saleh M, Meek L, Masoum MAS, Abshar M. Battery-less short-term smoothing of photovoltaic generation using sky camera. IEEE Trans Ind Informatics 2018;14: 403–14. https://doi.org/10.1109/TII.2017.2767038.
[132] Reuniwatt. New partnership for a solar microgrid in Brazil - voltalia and Reuniwatt. 2018. accessed July 7, 2020, http://reuniwatt.com/en/2018/02/28/voltalia-partners-reuniwatt-first-solar-plant-brazil/.
[133] Tuohy A, Zack J, Haupt SE, Sharp J, Ahlstrom M, Dise S, et al. Solar forecasting: methods, challenges, and performance. IEEE Power Energy Mag 2015;13:50–9. https://doi.org/10.1109/MPE.2015.2461351.
[134] Sassen K, Wang Z, Liu D. Global distribution of cirrus clouds from CloudSat/cloud-aerosol lidar and infrared pathfinder satellite observations (CALIPSO) measurements. J Geophys Res Atmos 2009;114. https://doi.org/10.1029/2008JD009972.
[135] Leva S, Dolara A, Grimaccia F, Mussetta M, Ogliari E. Analysis and validation of 24 hours ahead neural network forecasting of photovoltaic output power. Math Comput Simulat 2017;131:88–100. https://doi.org/10.1016/j.matcom.2015.05.010.
[136] Ren Y, Suganthan PN, Srikanth N. Ensemble methods for wind and solar power forecasting - a state-of-the-art review. Renew Sustain Energy Rev 2015;50:82–91. https://doi.org/10.1016/j.rser.2015.04.081.
[137] Quan DM, Ogliari E, Grimaccia F, Leva SMM. Hybrid model for hourly forecast of photovoltaic and wind power. In: Fuzzy systems (FUZZ). Fuzzy Syst. (FUZZ). IEEE Int. Conf.; 2013. p. 1–6. 2013.
[138] Zhang N, Behera PKWC. Solar radiation prediction based on particle swarm optimization and evolutionary algorithm using recurrent neural networks. In: Syst. Conf. (SysCon). IEEE Int.; 2013. p. 280–6. 2013.
[139] Bouzerdoum M, Mellit A, Massi Pavan A. A hybrid model (SARIMA-SVM) for short-term power forecasting of a small-scale grid-connected photovoltaic plant. Sol Energy 2013;98:226–35. https://doi.org/10.1016/j.solener.2013.10.002.
[140] Yang HT, Huang CM, Huang YC, Pai YS. A weather-based hybrid method for 1-day ahead hourly forecasting of PV power output. IEEE Trans Sustain Energy 2014;5:917–26. https://doi.org/10.1109/TSTE.2014.2313600.
[141] Wang H, Yi H, Peng J, Wang G, Liu Y, Jiang H, et al. Deterministic and probabilistic forecasting of photovoltaic power based on deep convolutional neural network. Energy Convers Manag 2017;153:409–22. https://doi.org/10.1016/j.enconman.2017.10.008.
[142] Dong J, Olama MM, Kuruganti T, Melin AM, Djouadi SM, Zhang Y, et al. Novel stochastic methods to predict short-term solar radiation and photovoltaic power. Renew Energy 2020;145:333–46. https://doi.org/10.1016/j.renene.2019.05.073.
[143] Dong Z, Yang D, Reindl T, Walsh WM. A novel hybrid approach based on self-organizing maps, support vector regression and particle swarm optimization to forecast solar irradiance. Energy 2015;82:570–7. https://doi.org/10.1016/j.energy.2015.01.066.
[144] Wang J, Jiang H, Wu Y, Dong Y. Forecasting solar radiation using an optimized hybrid model by Cuckoo Search algorithm. Energy 2015;81:627–44. https://doi.org/10.1016/j.energy.2015.01.006.
[145] Dolara A, Grimaccia F, Leva S, Mussetta M, Ogliari E. A physical hybrid artificial neural network for short term forecasting of PV plant power output. Energies 2015;8:1138–53. https://doi.org/10.3390/en8021138.
[146] Azimi R, Ghayekhloo M, Ghofrani M. A hybrid method based on a new clustering technique and multilayer perceptron neural networks for hourly solar radiation forecasting. Energy Convers Manag 2016;118:331–44. https://doi.org/10.1016/j.enconman.2016.04.009.
[147] Do MT, Soubdhan T, Robyns Benoît. A study on the minimum duration of training data to provide a high accuracy forecast for PV generation between two different climatic zones. Renew Energy 2016;85:959–64. https://doi.org/10.1016/j.renene.2015.07.057.
[148] Malvoni M, De Giorgi MG, Congedo PM. Forecasting of PV Power Generation using weather input data-preprocessing techniques. Energy Procedia 2017;126: 651–8. https://doi.org/10.1016/j.egypro.2017.08.293. Elsevier Ltd.
[149] Cervone G, Clemente-Harding L, Alessandrini S, Delle Monache L. Short-term photovoltaic power forecasting using artificial neural networks and an analog ensemble. Renew Energy 2017;108:274–86. https://doi.org/10.1016/j.renene.2017.02.052.
[150] Kemmoku Y, Orita S, Nakagawa S, Sakakibara T. Daily insolation forecasting using a multi-stage neural network. Sol Energy 1999;66:193–9. https://doi.org/10.1016/S0038-092X(99)00017-1.
[151] Cao JC, Cao SH. Study of forecasting solar irradiance using neural networks with preprocessing sample data by wavelet analysis. Energy 2006;31:3435–45. https://doi.org/10.1016/j.energy.2006.04.001.
[152] Chaouachi A, Kamel RM, Ichikawa R, Hayashi H, Nagasaka K. Neural network ensemble-based solar power generation short-term forecasting. World Acad Sci Eng Technol 2009;54:54–9.
[153] Hall J. Forecasting solar radiation for the Los Angeles basin-Phase II report. Soc. Am. Sol. Energy, Boulder, Colo.: American Solar Energy Society 2011:141–6.
[154] Ssekulima EB, Anwar MB, Al Hinai A, El Moursi MS. Wind speed and solar irradiance forecasting techniques for enhanced renewable energy integration with the grid: a review. IET Renew Power Gener 2016;10:885–98. https://doi.org/10.1049/iet-rpg.2015.0477.
[155] Lew D, Brinkman G, Ibanez AF E, Heaney M, Hodge B-M, Hummon G M, Stark, King J, Lefton SA, Kumar N, Agan D, Jordan SV G. The western wind and solar integration study phase 2. 2013.
[156] Aslam S, Khalid A, Javaid N. Towards efficient energy management in smart grids considering microgrids with day-ahead energy forecasting. Elec Power Syst Res 2020;182:106232. https://doi.org/10.1016/j.epsr.2020.106232.
[157] Shayeghi H, Sobhani B. Integrated offering strategy for profit enhancement of distributed resources and demand response in microgrids considering system uncertainties. Energy Convers Manag 2014;87:765–77. https://doi.org/10.1016/j.enconman.2014.07.068.
[158] Sechilariu M, Wang BC, Locment F, Jouglet A. DC microgrid power flow optimization by multi-layer supervision control. Design and experimental validation. Energy Convers Manag 2014;82:1–10. https://doi.org/10.1016/j.enconman.2014.03.010.
[159] Liu G, Starke M, Xiao B, Zhang X, Tomsovic K. Microgrid optimal scheduling with chance-constrained islanding capability. Elec Power Syst Res 2017;145:197–206. https://doi.org/10.1016/j.epsr.2017.01.014.
[160] Heydari A, Astiaso Garcia D, Keynia F, Bisegna F, De Santoli L. A novel composite neural network based method for wind and solar power forecasting in microgrids. Appl Energy 2019;251:113353. https://doi.org/10.1016/j.apenergy.2019.113353.
[161] Alamo DH, Medina RN, Ruano SD, García SS, Moustris KP, Kavadias KK, et al. An advanced forecasting system for the optimum energy management of Island microgrids. Energy procedia, vol. 159. Elsevier Ltd; 2019. p. 111–6. https://doi.org/10.1016/j.egypro.2018.12.027.
[162] Dutta S, Li Y, Venkataraman A, Costa LM, Jiang T, Plana R, et al. Load and renewable energy forecasting for a microgrid using persistence technique. Energy procedia, vol. 143. Elsevier Ltd; 2017. p. 617–22. https://doi.org/10.1016/j.egypro.2017.12.736.
[163] Bogaraj T, Kanakaraj J. Intelligent energy management control for independent microgrid. Sadhana - Acad Proc Eng Sci 2016;41:755–69. https://doi.org/10.1007/s12046-016-0515-6.
[164] Pascual J, Barricarte J, Sanchis P, Marroyo L. Energy management strategy for a renewable-based residential microgrid with generation and demand forecasting. Appl Energy 2015;158:12–25. https://doi.org/10.1016/j.apenergy.2015.08.040.
[165] Olivares DE, Mehrizi-Sani A, Etemadi AH, Cañizares CA, Iravani R, Kazerani M, et al. Trends in microgrid control. IEEE Trans Smart Grid 2014;5. https://doi.org/10.1109/TSG.2013.2295514. 1905–19.
[166] Shi W, Lee E-K, Yao D, Huang R, Chu C-C, Gadh R. Evaluating microgrid management and control with an implementable energy management system. In: Ieee Int. Conf. Smart grid Commun., IEEE; 2014. p. 272–7. https://doi.org/10.1109/SmartGridComm.2014.7007658. 2014.
[167] Zhang Y, Liu B, Zhang T, Guo B. An intelligent control strategy of battery energy storage system for microgrid energy management under forecast uncertainties, vol. 9; 2014.
[168] Mohammadi S, Soleymani S, Mozafari B. Scenario-based stochastic operation management of MicroGrid including wind, photovoltaic, micro-turbine, fuel cell and energy storage devices. Int J Electr Power Energy Syst 2014;54:525–35. https://doi.org/10.1016/j.ijepes.2013.08.004.
[169] Reikard G, Hansen C. Forecasting solar irradiance at short horizons: frequency and time domain models. Renew Energy 2019:1270–90. https://doi.org/10.1016/j.renene.2018.08.081.
[170] Alzahrani A, Kimball JW, Dagli C. Predicting solar irradiance using time series neural networks. Procedia Comput. Sci., vol. 36. Elsevier B.V.; 2014. p. 623–8. https://doi.org/10.1016/j.procs.2014.09.065.
[171] Alzahrani A, Ferdowsi M, Shamsi P, Dagli CH. Modeling and simulation of microgrid. Procedia Comput. Sci., vol. 114. Elsevier B.V.; 2017. p. 392–400. https://doi.org/10.1016/j.procs.2017.09.053.
[172] Neves D, Brito MC, Silva CA. Impact of solar and wind forecast uncertainties on demand response of isolated microgrids. Renew Energy 2016;87:1003–15. https://doi.org/10.1016/j.renene.2015.08.075.
[173] El Hendouzi A, Bourouhou A. Forecasting of PV power application to PV power penetration in a microgrid. In: Proc. 2016 Int. Conf. Electr. Inf. Technol. ICEIT 2016, institute of electrical and electronics engineers Inc.; 2016. p. 468–73. https://doi.org/10.1109/EITech.2016.7519644.
[174] Huang Y, Lu J, Liu C, Xu X, Wang W, Zhou X. Comparative study of power forecasting methods for PV stations. Int. Conf. Power Syst. Technol. Technol.

Innov. Mak. Power Grid Smarter, POWERCON2010, 2010 2010:1–6. https://doi.org/10.1109/POWERCON.2010.5666688.
[175] Bacher P, Madsen H, Nielsen HA. Online short-term solar power forecasting. Sol Energy 2009;83:1772–83. https://doi.org/10.1016/j.solener.2009.05.016.
[176] Hassanzadeh M, Etezadi-Amoli M, Fadali MS. Practical approach for sub-hourly and hourly prediction of PV power output. North Am. Power Symp. 2010;2010: 2010. https://doi.org/10.1109/NAPS.2010.5618944. NAPS.
[177] Mellit A, Pavan AM. A 24-h forecast of solar irradiance using artificial neural network: application for performance prediction of a grid-connected PV plant at Trieste, Italy. Sol Energy 2010;84:807–21. https://doi.org/10.1016/j.solener.2010.02.006.
[178] Peters D, Völker R, Kilper T, Calais M, Schmidt T, Carter C, von Maydell CA K. Model-based design and simulation of control strategies to maximize the PV hosting capacity in isolated diesel networks - using solar short-term forecasts for predictive control of diesel generation. In: 32nd eur. Photovolt. Sol. Energy Conf. Exhib., oldenburg: EU PVSEC; 2016.
[179] Peters D, Kilper T, Calais M, Jamal T, Maydell K von. Solar short-term forecasts for predictive control of battery storage capacities in remote PV diesel networks, vols. 325–33; 2018. https://doi.org/10.1007/978-3-319-69844-1_29.
[180] Schmidt T, Calais M, Roy E, Burton A, Heinemann D, Kilper T, et al. Short-term solar forecasting based on sky images to enable higher PV generation in remote electricity networks. Renew Energy Environ Sustain 2017;2:23. https://doi.org/10.1051/REES/2017028.
[181] My Qualtrics. Projects | Qualtrics survey software. 2020. accessed May 13, 2020, https://murdochuni.au1.qualtrics.com/Q/MyProjectsSection.
[182] Mazzola S, Vergara C, Astolfi M, Li V, Perez-Arriaga I, Macchi E. Assessing the value of forecast-based dispatch in the operation of off-grid rural microgrids. Renew Energy 2017;108:116–25. https://doi.org/10.1016/j.renene.2017.02.040.