Scoping Low-Cost Measures to Nowcast Sub-Hourly Solar Radiations for Buildings

L Chen[1], H Du[1] and Y Li[1]
[1] Welsh School of Architecture, Cardiff University, Bute Building, King Edward VII Avenue, Cardiff, CF10 3NB, Wales, UK

Abstract. Solar energy, as a clear, renewable and promising resource, has brought tremendous value for carbon emission reduction in the last three decades. However, the uncertainty of solar radiation brings significant challenges to the renewable heat and electrical system for buildings. Thus, many different solar radiation forecasting methods, such as Numerical Weather Prediction Methods (NWP), Statistical Methods, Top-Down Methods, Bottom-Up Methods and Hybrid Methods have been developed to make the best guess on future solar radiations. Based on the meteorology definition, nowcasting refers to the forecast of the temporal horizon from the next few seconds up to six hours. Predicting solar radiation within this range are extremely challenging, but crucial for solar energy system operation. This paper firstly reviewed the state of art of solar radiation forecasting methods and compared the key features of each method. According to the advantage and costs of each method, this paper then proposed a methodology to generate high accuracy low-cost solar radiation nowcast data for optimising building solar thermal system performance and related control strategies. Note that this paper focused on the scoping study of methodology rather than field experiments, and further research with experiments data will be reported in a journal publication.

1. Introduction

Solar energy, as a clear, renewable and promising resource, has attracted a lot of researchers' interest in the last three decades. A large number of researches have explored the utilisation of solar energy in the built environment. However, the uncertainty of solar energy brings significant challenges to its utilisations. As a result, solar radiation forecasting methods have been developed to achieve a better understanding of solar radiation. Nonetheless, it's worth noting that there are very few pieces of research focusing on near-future forecasting of solar radiation and its significant potentials for building performance optimisation. In the meanwhile, there are increasing opportunities, such as the development of the Internet of Things and 5G internet infrastructure, to enable the development of building optimisation through using real-time solar radiation forecasting.

Therefore, this paper pays attention to study a new nowcasting method of solar radiation, which combines the advantages of various forecasting methods and discuss its application on building performance optimisation. According to the definition of nowcasting in meteorology term, this research aims to explore a nowcasting method with the temporal horizon from the next few minutes up to six hours.

2. The state of art of solar radiation forecasting methods

2.1 *Diversified types of solar radiation forecasting methods*
The first step of studying solar radiation forecasting methods is to explore their classifications. Previous reviews [1], [2], [3] have discussed the classification of solar forecasting methods. Based on previous studies, solar forecasting methods can be classified into five clusters: Numerical Weather Prediction Methods (NWP), Statistical Methods, Top-Down Methods, Bottom-Up Methods and Hybrid Methods.

2.2 *Numerical Weather Prediction Methods (NWP)*
Numerical weather predictions (NWPs) use mathematic models of the atmosphere and oceans to predict the weather in the future. In general, NWPs methods are suitable for the macroscopical and long-term forecast. Representative NWP models involve into two types: global models, such as Global Forecast System (GFS), or regional models including European Centre for Medium-Range Weather Forecasts (ECMWF), Weather Research and Forecasting (WRF) for North America. In recent years, a lot of researchers have expressed their interests in the WRF model because it is open-source and can be configured by the user to a high resolution over a specific region. The representative studies of NWP methods are listed in table 1.

Table 1. NWP Methods for Solar Radiation Forecasting

Article	Parameter	Frequency	Data Source	Method
Mathiesen and Kleissl. [4]	GHI	Intra-day	Public Meteorological Observations	NAM/GFS /ECMWF
Yang and Kleissl. [5]	GHI	Intra-day	Public Meteorological Observations	WRF
Mathiesen et al. [6]	GHI	Day Ahead/Intra-day/Intra-hour	Public Meteorological Observations Meteorological Satellites	WRF-CLDDA
Lara-Fanego et al. [7]	GHI/DNI	Hourly	Public Meteorological Observations	WRF
GHI: Global Horizontal Irradiance, DNI: Direct Normal Irradiance, DHI: Diffuse Horizontal Irradiance				

2.3 *Statistical methods*
Statistical methods for solar radiation forecasting have been very popular in the past double decades because of the rapid development of computer techniques. Statistical methods can be divided into two categories: model-driven methods and data-driven methods. Model-driven methods utilise statistical model to determine the interdependent quantitative relationship among variables. Typical model-driven methods include an autoregressive integrated moving average (ARIMA), exponential smoothing (ETS), etc. Unlike model-driven methods which tend to require researchers' mastery of empirical models, data-driven methods are based on machine learning (ML) and thus emphasise self-learning of models based on ample data sample, where learning implies classification, regression, and prediction. The most typical data-driven methods include artificial neural network (ANN), support vector machine (SVM). In general, statistical methods have good elasticity in spatial and temporal resolution. However, the main challenges involve the selection of input variables, models, algorithms, and validation methods. Table 2 lists remarkable researches of statistical methods for solar radiation forecasting.

Table 2. Statistical methods for solar radiation forecasting

Article	Parameter	Frequency	Data Source	Model-Driven Method
Al-Alawi and Al-Hinai. [8]	GHI	Monthly	Public Met Observations	ARMA
Yang et al. [9]	GHI/DHI/DNI	Hourly	Public Met Observations	ARIMA
Dorvlo et al. [10]	GHI	Monthly	Public Met Observations	RBF/ ANN (MLP)
Renno et al. [11]	DNI	Daily/Hourly	Privately-owned Measurement	ANN (MLP/BP/LM)
Jiang and Dong. [12]	GHI	Hourly	Public Met Observations	SVM
Chu and Coimbra. [13]	DNI	5/10/15/20 Mins	Privately-owned Measurement	kNN

2.4   Top-Down methods

The principle of top-down methods is to analyse satellite cloud images obtained from the atmosphere above. Through examining two consecutive images captured by the meteorological satellite, cloud motion can be tracked based on statistical algorithms. Cloud motion accompanied by cloud cover information is translated into the solar radiation forecast based on the specific mathematic models. The working features of satellite determine its good performance on regional and middle-term solar radiation forecasting. Typical researches of top-down methods are listed in table 3.

Table 3. Top-Down Methods for Solar Radiation Forecasting

Article	Parameter	Frequency	Data Source	Method
Perez et al. [14]	GHI	6 Hours	Met Satellites	Satellite Image Analysis
Nonnenmacher et al. [15]	GHI	1/2/3 Hours	Met Satellites	Satellite Image Analysis
Lorenz et al. [16]	GHI	30 Mins-6 Hours	Met Satellites	Satellite Image Analysis
Hammer et al. [17]	GHI	30 Mins-2 Hours	Met Satellites	Satellite Image Analysis

2.5 Bottom-Up methods

In recent years, researches of bottom-up forecast methods have presented promising potentials to overcome the limitations induced by the low spatial and temporal resolution of NWP and top-down methods. As similar as top-down methods, the key of the bottom-up method is to analyse advection of clouds through consecutive cloud images observed with ground-based all-sky cameras called "Total Sky Imager" (TSI) for achieving solar radiation forecast. Based on the ability of the ground-based camera, these methods can provide advance cloud information at a lead time of several minutes to hours for forecast solar radiation in the very short-term temporal horizon. Table 4 presents the typical researches of bottom-up methods.

Table 4. Bottom-Up Methods for Solar Radiation Forecasting

Article	Parameter	Frequency	Data Source	Method
Richardson et al. [18]	GHI	Intra-hour	Public Met Observations + Privately-owned Measurement	Ground Cloud Image Analysis
Yang et al. [19]	GHI	30 s-15 Mins	Public Met Observations + Privately-owned Measurement	Ground Cloud Image Analysis
Marquez et al. [20]	DNI	3-15 Mins	Public Met Observations + Privately-owned Measurement	Ground Cloud Image Analysis
Cervantes et al. [21]	DNI	5 Mins	Public Met Observations + Privately-owned Measurement	Ground Cloud Image Analysis
Peng et al. [22]	GHI	1/5/10/15 Mins	Public Met Observations + Privately-owned Measurement	Ground Cloud Image Analysis

2.6 Hybrid methods

Hybrid Methods usually consist of any two or more of the methods described previously. In recent years, several Hybrid Methods have presented their superior performance for forecasting high-quality solar radiation. Through taking advantage of the strengths of each methodology, hybrid methods can increase the forecasting accuracy efficiently. Another reason to develop hybrid methods is to overcome the limitations of each forecasting methods in their specific spatial and temporal horizon. Remarkable researches of hybrid methods are presented in table 5.

Table 5. Hybrid Methods for Solar Radiation Forecasting

Article	Parameter	Frequency	Data Source	Method
Lima et al. [23]	GHI	24 hours	Public Met Observations	ANN + WRF
Marquez et al. [24]	GHI	30/60/90/120 Mins	Public Met Observations + Met Satellite	ANN + Satellite Image
Voyant et al. [25]	GHI	Hourly	Public Met Observations	ANN + ARMA + Time Series
Wu and Chen. [26]	GHI	Hourly	Public Met Observations	ARMA + TDNN
Chu et al. [27]	DNI	5/10 Mins	Public Met Observations + Privately-owned Measurement	ANN + TSI

2.7 Comparative analysis

Table 6 lists various spatial-temporal horizons, where different methods can achieve good performance. All of them have respective advantages and limitations according to their spatial-temporal horizon. In this case, hybrid methods can integrate the strengths of different methods that thus can perform well in widest spatial and temporal horizon once the suitable combination of different methods is utilised. As a result, the spatial and temporal horizon of hybrid methods is contributed to achieving good performance of solar forecasting according to flexible application purposes, such as building simulation.

Table 6. Performance of Different Methods in Various Spatial-Temporal Horizon

Methods	NWP	Statistical	Top-Down	Bottom-Up	Hybrid
Spatial Horizon	5-20 km	1 m-2 km	1-10 km	1 m-2 km	1 m-20 km
Temporal Horizon	4-36 hours	1 second-1 month	30 mins-6 hours	5-30 mins	1 second- 1 month

2.8 Data acquisition for solar radiation forecasting

2.8.1 Public Meteorological Observations. The database of public weather observations, such as National Oceanic and Atmospheric Administration (NOAA) and UK Met Office, which can provide the most comprehensive and long-term meteorological data involving temperature, relative humidity, etc. In general, all solar radiation forecast methods are more or less dependent on this data source.

2.8.2 Privately-owned Measurement. This way of data acquisition usually is conducted by individuals or teams comes from the laboratory of academic and research institution, such as the Welsh School of Architecture. Through utilising *specific equipment for different measuring purposes, such as* BF5 Pyrheliometer for measuring solar radiation, this way can obtain high accurate historical and current data.

2.8.3 Meteorological Satellites. This way can provide the uppermost data – satellite cloud images – for top-down methods. Different meteorological satellites, such as GOES-West Satellite, are operated by various meteorological organisations, such as National Oceanic and Atmospheric Administration (NOAA). The quality of satellites cloud images is dependent on the characters of a specific satellite, such as coverage area, movement orbit, image resolution, and photograph intervals.

2.8.4 Ground-based Total Sky Imagers. The most important data source of bottom-up methods – ground-based cloud image – can be obtained from total sky imager. The performance of different "total sky imagers" are relevant to various characters including equipment composition, resolution, environmental adaption, size, cost and associated software application.

2.8.5 Weather Application Programming Interface (API). Recently, an ascendant approach, which utilises Application Programming Interface (API) to provide meteorological data, has expressed its potentials as an accurate and accessible data resource. Table 2 in the authors' previous study [28] showed the available data types from various APIs.

3. Scoping study into the methodology

According to the comprehensive and comparative analysis of existing solar forecasting methods, this study proposes a mixed nowcasting method based on the representative data-driven model - artificial neural network (ANN) and several significant ways of data acquisition and processing including TSI methods, Privately-owned Measurement and publicly available Weather API. Unlike conventional studies using direct meteorological data from public weather observation or privately-owned measurement as inputs for ANN model without consideration of actual physical conditions, this study
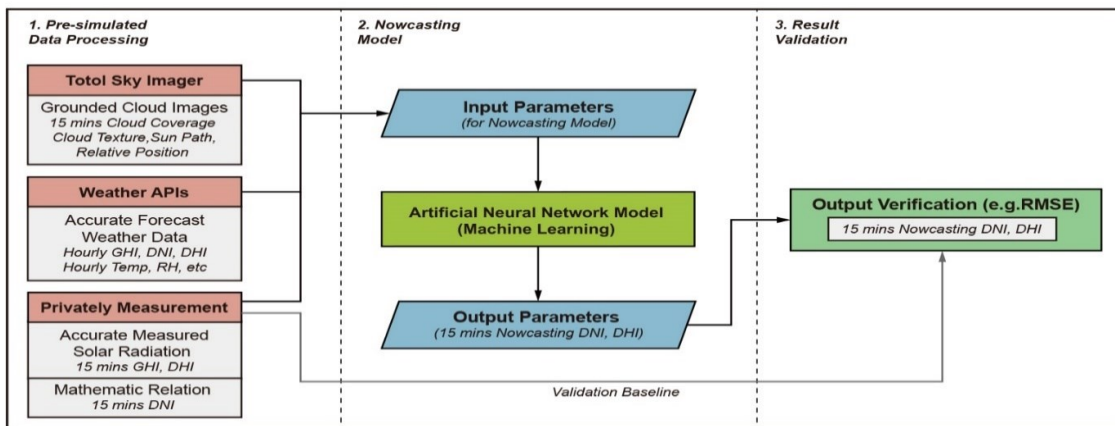
Figure 1. Proposed Nowcasting Method of Solar Radiation

introduces several data resources to acquire both meteorological data and physical cloud information as the model inputs which have potential to improve the accuracy of ANN forecasting model in very Short temporal horizon. The proposed working flow of this mixed nowcasting method is illustrated in figure 1.

3.1 Data acquisition and processing for nowcasting model

For this scoping study, it is necessary to demonstrate a good understanding of available and reliable data sources for nowcasting model development. This section presents three ways of data acquisition and processing, which generate crucial input parameters for the ANN nowcasting model.

TSI (Total Sky Imager) Method. Through analysing cloud cover information based on consecutive grounded cloud images, TSI methods can generate the forecast of physical sky conditions. The major steps of image processing in TSI method include Exposure Compensation, Undistorted and Cropping, Masking (Removing useless information), Segmentation (Generating grayscale image based on "Red to Blue Ratio") – Filtering (Transforming the grayscale image into a binary image), Optical Flow & Cloud Motion Vectors (Generating associated vectors based on feature points in consecutive images for forecasting cloud motion). The specific content of these steps can refer to the paper by Richardson et al. [18]. Following above steps, this study operates TSI to take cloud image in the very short time interval for cloud image analysis to acquire the nowcasting of cloud physical information involving cloud coverage, cloud texture, sun path, the relative position between cloud and sun, etc.

Privately-owned Measurement. In this study, accurate historical and current data, which are measured by specific equipment, are used as important inputs for nowcasting model and baseline. The typical equipment for solar radiation, such as BF5 Pyrheliometer, are used to measure the precise value of GHI and DHI in the very short time interval and calculate the simultaneous value of DNI.

Weather Application Programming Interface (API). With the development of weather APIs, some APIs, such as Weatherbit and Solcast, have started to provide not only general meteorological data, such as humidity, temperature etc., but also hourly historical, current and forecast solar radiation data. Although the data accuracy of weather APIs still needs to be improved and verified, these data undoubtedly can be used as an essential reference that has significant application potentials. In this study, DNI and DHI obtained from Weatherbit API are used as inputs for nowcasting model.

In summary, TSI methods could provide second/minute-ahead cloud physical information; Privately-owned Equipment provides minutes-ahead accurate value of DNI and DHI; Weather APIs provides the hourly average value of DNI, DHI and other meteorological parameters. All these parameters as inputs will be introduced to train the ANN nowcasting model.

3.2 ANN nowcasting model

The principle of ANN model is to operate classification, regression, and prediction automatically through machine learning. Once the training and testing stages of machine learning are completed, ANN, as a kind of "black box" model, can apply historical data to forecast future data. The basic architecture of ANN model mainly consists of input layers, hidden layer and output layer. In this research, minute-ahead cloud physical information from TSI methods, hourly average value of DNI, DHI and other meteorological parameters from Weather APIs are introduced into input layer; Minute-ahead accurate value of DNI and DHI from Privately-owned Equipment is introduced into output layer. As a result, the training of ANN nowcasting model can establish a connection among physical cloud information, general meteorological data and accurate solar radiation data. Representative researches of ANN model are presented by Renno et al. [11].

3.3 Result Validation

A range of metrics can be used for validating time series data prediction. The commonly used metrics include the Root Mean Square Error (RMSE), the Mean Absolute Error (MAE) and the Mean Absolute Deviation Percent error (MADP). The study plan to test all metrics and make a sensible judgement on

how good they are to suit the validation process for solar radiation forecasting. Crucial comparative data are forecast solar data from nowcasting method and actual solar data from measuring equipment.

3.4   Software choices

The study has considered a range of software environment to implement data capturing, data and image processing, algorithm development. Python 3.4 and OpenCV 4.0 are cost-free open-sources software that could act as crucial roles for data classification, function calculation, and image processing because its flexibility to link hardware equipment with software programs. In further, Python can also be integrated with building simulation engines, such as Modelica, to implement optimisation and control.

### 3.5   Hardware requirement

Research equipment of Conventional TSI methods tends to be very professional and expensive, such as the European Union's Seventh Programme DNICAST project (€3m, 2013-2017). The costs of such equipment are in a range of £25k-30k per set which is not affordable for general application at a domestic scale. Therefore, this study proposed alternative equipment considering middle/low-cost option. Table 7 listed the cost, major equipment and key features of recommended hardware option.

Table 7. Options of hardware for nowcasting

Cost options	Combination Types	Parameters	Camera Resolution	Camera View	Environmental Adaption	Built-in Software
High (~£25k)	ASI-16 All Sky Imager SPN1 Sunshine Sensor	Cloud Image GHI/DHI	5 Mega Pixels	180°	Strong (Case + V&H System)	√
Middle (~£3.5k)	ASI183MC Pro Camera BF5 Sunshine Sensor	Cloud Image GHI/DHI	20 Mega Pixels	180°	Middle (Case + V&H System)	√
Low (~£50)	Raspberry Pi Camera Weather API	Cloud Image GHI/DNI/DHI	5 Mega Pixels	175°	Weak (Case Only)	X

3.6   Future work - nowcasting application

This research will focus on building simulation & control once the solar radiation nowcasting is completed. A simulation engine, such as Modelica, can be used to construct a Model Predictive Control (MPC) model for building system optimisation. By introducing DNI and DHI generated from nowcasting methods and other weather data obtained from measurement as input parameters, the MPC model can conduct self-adjustment of indoor environmental parameters including temperature, relative humidity, etc. to optimise the solar thermal system. Potential control units of the MPC model includes thermal storage, valves, switches, etc. The specific content of these steps will be based on the work conducted by Oldewurtel et al. [29]. The proposed nowcasting application method is illustrated in figure 2.
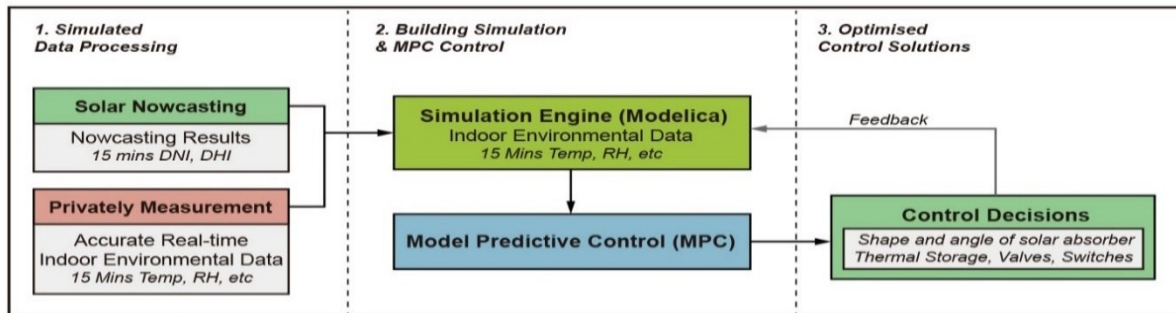
Figure 2. Proposed Nowcasting Application Method

4. Conclusion and discussion

Through reviewing previous solar forecasting methods, this study proposed a new nowcasting method of solar radiation with consideration of its practice and future work. Significant contributions of this research include four parts. Firstly, this study presents a comprehensive and comparative analysis of various solar forecasting methods. Secondly, a mixed nowcasting method is constructed by combining the advantages of various forecasting methods and various way of data acquisition that thus can provide the nowcasting of both DNI and DHI. Thirdly, lower-cost hardware and software are discussed which will be welcomed by further researchers. Finally, this study presents the plan to use nowcasting solar data to operate building simulation and control for optimising building performance.

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