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Direct normal irradiance forecasting and its application to concentrated solar thermal output forecasting – A review

Edward W. Law [a,*], Abhnil A. Prasad [a], Merlinde Kay [a], Robert A. Taylor [a,b]

[a] School of Photovoltaic and Renewable Energy Engineering, University of New South Wales, Sydney, New South Wales 2052, Australia
[b] School of Mechanical and Manufacturing Engineering, University of New South Wales, Sydney, New South Wales 2052, Australia

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Abstract

Solar irradiance forecasting can reduce the uncertainty of solar power plant output caused by solar irradiance intermittency. Concentrated solar thermal (CST) plants generate electricity from the direct normal irradiance (DNI) component of solar irradiance. Different forecasting methods have been recommended for a range of forecast horizons relevant to electricity generation. High DNI forecast accuracy is important for achieving accurate forecasts of CST plant output which are shown to increase CST plant profitability. This paper reviews the DNI forecast accuracy of numerical weather prediction models, time series analysis methods, cloud motion vectors, and hybrid methods. The results of the reviewed papers are summarised to identify the best DNI forecast accuracy for particular forecast horizons. The application of DNI forecasts to operate CST plants is also briefly reviewed.

This paper found that additional research is required for time series analysis methods to corroborate current results and for satellite-based cloud motion vectors to establish DNI forecast accuracy. It was also concluded that future research should use the same error metrics to report results to facilitate fair comparison of DNI forecast accuracy from different studies. In addition, the creation of a common high quality DNI data set to evaluate all forecasting methods would also help to verify best forecast accuracy. The review of DNI forecasting for CST plants found that using accurate 2-day ahead DNI forecasts can increase revenue and decrease penalty costs. Future research should investigate benefits from using short-term DNI forecasts from the intra-hour forecast horizon up to the 6-h forecast horizon to determine CST plant operation. Another aspect to research is to determine whether the benefit of DNI forecasts for a CST plant is affected by different regulations in different electricity markets.

Keywords: DNI forecasting; Numerical weather prediction; Time series analysis; Cloud motion vector; Forecast accuracy; Concentrated solar thermal power

1. Introduction

Solar energy is a renewable resource that has established itself in both small-scale and large-scale electricity generation. Electricity can be generated from solar irradiance by either non-concentrated photovoltaic (PV) modules or by concentrated solar thermal (CST). PV output is calculated from global irradiance on the plane of the PV modules which can be derived from global horizontal irradiance (GHI) (Lorenz et al., 2009, 2011). GHI consists of diffuse irradiance and direct normal irradiance (DNI) components. In contrast to PV, CST output calculations only use the DNI component because diffuse irradiance cannot

* Corresponding author. Address: School of Photovoltaic and Renewable Energy Engineering, Tyree Energy Technologies Building, University of New South Wales, Sydney, New South Wales 2052, Australia.
E-mail address: edward.law@unsw.edu.au (E.W. Law).

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Nomenclature

AERONET	Aerosol Robotic Network
AFSOL	Aerosol-based Forecasts of Solar Irradiance for Energy Applications
AI	artificial intelligence
ANN	artificial neural network
AOD	aerosol optical depth
AR	autoregressive
ARIMA	autoregressive integrated moving average
ARMA	autoregressive moving average
ARPS	Advanced Multiscale Regional Prediction System
BOM	Australia Bureau of Meteorology
BRL	Boland–Ridley–Lauret model
CARDS	Coupled AutoRegressive and Dynamical System
CSM	clear sky model
CST	concentrated solar thermal
DNI	direct normal irradiance
ECMWF	European Centre for Medium-range Weather Forecasts
ESRA	European Solar Radiation Atlas
EUMETSAT	European Organisation for the Exploitation of Meteorological Satellites
GFS	Global Forecast System
GHI	global horizontal irradiance
HIRLAM	High-resolution Limited Area Model
JMA	Japan Meteorology Agency
libRadtran	library for radiative transfer
LS-SVM	least squares support vector machine
MA	moving average
MACC	Monitoring Atmospheric Composition and Climate
MAE	mean absolute error
MAPE	mean absolute percentage error
MASS	Mesoscale Atmospheric Simulation System
MBE	mean bias error
MLP	multi-layer perceptron
MM5	Fifth-generation Pennsylvania State University-National Center for Atmospheric Research Mesoscale Model
MOS	Model Output Statistics
MRM	Meteorological Radiation Model
MSG	Meteosat Second Generation
MW h	Megawatt-hour
NAM	North American Model
NDFD	National Digital Forecast Database
NEM	National Electricity Market
NESDIS	NOAA's Satellite and Information Service
nMAE	normalised MAE
nMBE	normalised MBE
NOAA	National Oceanographic and Atmospheric Administration
nRMSE	normalised RMSE
NWP	numerical weather prediction
PV	photovoltaic
REST2	Reference Evaluation of Solar Transmittance – 2 Bands
RMSE	root mean square error
RTM	radiative transfer model
SUNY	State University of New York GOES satellite-based solar model
SVM	support vector machine
SVR	support vector regression
TDNN	time delay neural network
TES	thermal energy storage
THI	time horizon invariant
TSA	time series analysis
TW h	Terawatt-hour
WRF	Weather Research and Forecasting
WRF-CLDDA	high-resolution direct-cloud-assimilating WRF

be effectively concentrated. GHI and DNI are intermittent due to events like clouds temporarily covering the sun, thus causing uncertainty in the electricity supply from solar power plants. High uncertainty in supply increases the risk of an unexpected imbalance in supply and demand occurring, which can result in network voltage and frequency exceeding safe operation limits thereby reducing network reliability and security (NERC, 2009; AEMO, 2010). A network will have ancillary services or operating reserves allocated to correct these imbalances and high supply uncertainty makes it more difficult to ensure that the allocation is both sufficient and economic (Ela et al., 2011). Weather forecasting methods can be applied to forecast solar irradiance, which in turn can be used to forecast solar power plant electricity output and reduce supply uncertainty.

Forecasts can be obtained for various horizons and the relevant forecast horizons are determined by the local electricity market regulations. For example, the Australian National Electricity Market (NEM) requires power plants to submit dispatch offers up to 40 h ahead every day and allows power plants to update dispatch quantities up to 5 min before dispatch orders are made (Elliston and MacGill, 2010). Based on these regulations, it would be useful to have forecast methods that are accurate at the forecast horizons of 40-h and 5-min ahead, in addition to other forecast horizons that are relevant to NEM regulations.

The accuracy of a forecasting method for a particular forecast horizon depends on the method's ability to accurately forecast the atmospheric phenomena that affect solar irradiance intensity and are significant over the time scale of the forecast horizon. For example, numerical weather prediction (NWP) models produce more accurate solar irradiance forecasts beyond 5 h ahead than cloud motion vectors (CMVs) because NWP models consider cloud motion, formation and dissolution in their physical modelling whereas CMVs only account for cloud motion (Kühnert et al., 2013). Suitable solar irradiance forecasting methods across a range of forecast horizons were proposed by Schroedter-Homscheidt et al. (2009). Forecasts for 1-day ahead should be obtained from modelled aerosol optical depth (AOD) input to NWP models with post-processing. Forecasts between 1 and 5-h ahead were recommended to be obtained from satellite-based CMVs, and forecasts from 1 to 10-min ahead should use persistence of ground measurements. Kleissl (2010) supported the proposal and added ground-based CMVs to produce forecasts up to 1-h ahead, which was supported by Schroedter-Homscheidt et al. (2012), Diagne et al. (2013) and Coimbra et al. (2013). Kostylev and Pavlovski (2011) proposed using time series analysis (TSA) methods as another source of up to 1-h ahead forecasts. A summary of the forecast horizons with corresponding applications and forecast methods is presented in Table 1.

Reviews of GHI forecast accuracy have been conducted for TSA methods by Reikard (2009), for NWP models by Perez et al. (2011, 2013) and Lorenz et al. (2009), and for satellite-based methods by Perez et al. (2010) and Polo et al. (2008). All three forecasting methods were reviewed by Kostylev and Pavlovski (2011) and Diagne et al. (2013) and their conclusions supported the matching of forecasting methods to forecast horizons shown in Table 1. In addition, Kostylev and Pavlovski (2011) suggested guidelines for best GHI forecast accuracy in clear sky and cloudy conditions at multiple forecast horizons. Best clear sky GHI forecast normalised root mean square error (nRMSE) was suggested to be about 15% at 1-h ahead and rising to about 25% nRMSE at 3-days ahead. Best cloudy sky GHI forecast nRMSE was suggested to be about 35% at 1-h ahead and rising to about 45% at 3-days ahead. These results allow the accuracy of new GHI forecasting methods to be compared against current best forecasting methods and determine which forecast horizon it is most suitable for. For example, GHI forecast nRMSE of 16.5% in all sky conditions was reported for the Coupled AutoRegressive and Dynamical System (CARDS) by Huang et al., 2013 which further testing in clear sky or cloudy sky only conditions may prove to be more accurate than the suggested best accuracy by Kostylev and Pavlovski (2011). In contrast, DNI forecast accuracy has not been fully reviewed. The lack of a DNI forecast benchmark was noted by Kraas et al. (2013) and a couple of years before that Marquez and Coimbra (2011) claimed an absence of studies to compare DNI forecast accuracy against. The application of GHI forecast information to forecast PV output has received a significant amount of research attention as demonstrated in the review by Inman et al. (2013). On the other hand, studies about forecasting CST output are few in number. The greater interest in GHI and PV output forecasting may be explained by the greater utilisation of PV compared to CST, as shown by an estimated 65 Terawatt-hours (TW h) of energy generated from PV in 2011 whereas for CST it was estimated to be 4 TW h (IEA, 2013).

Table 1
Forecasting horizon with corresponding application and forecast method, adapted from Kleissl (2010).

Forecast horizon	Application	Forecast method
1–10 min	Baseline	Persistence
10 min to 1 h	Short-term ramps, regulation	Ground-based CMV TSA
1–5 h	Load following	Satellite-based CMV
6 h to 10 days	Unit commitment	NWP

Despite the present relatively low use, annual energy generated from CST is expected to grow and exceed 30 TW h by 2017 (IEA, 2013). This expectation is based on the ability of CST with integrated thermal energy storage (TES) to control its output and thereby provide greater value to an electric network. A study showed the value of CST with TES was $32–40 per Megawatt-hour (MW h) greater when compared against PV and $30–51 per MW h greater when compared against fossil fuel plants (Denholm et al., 2013). The value was evaluated from satisfying base load demand, supplying ancillary services and providing generation that is guaranteed to be available. CST holds an advantage in energy storage because, by directly storing absorbed thermal energy in molten salt tanks, TES is cheaper and more efficient than electrical, chemical and mechanical energy storage options available to PV (Madaeni et al., 2012).

DNI forecast information can be used by CST plants to optimise the TES charge and discharge schedule (Usaola, 2012; Dominguez et al., 2012) which can provide financial benefits such as higher revenue or lower costs as demonstrated by Wittmann et al. (2008) and Kraas et al. (2013) respectively. DNI forecasting can also help CST plants to optimise operation by reducing heat loss thus increasing solar-to-electricity conversion efficiency (Powell et al., 2011). Although GHI forecasts are well researched and DNI can be statistically derived from GHI, the results should not be directly applied to DNI forecasts because sky conditions affect DNI more strongly than GHI (Lara-Fanego et al., 2012a; Marquez and Coimbra, 2011). Hence, a review of DNI forecast accuracy should be conducted.

This paper aims to determine the currently best available DNI forecast accuracy from results published in literature and investigate how DNI forecasting has been applied to CST plants. In the following sections, general information about forecasting DNI is presented. Following that, solo and hybrid forecasting methods are reviewed. After that, the best DNI forecast accuracies for particular forecast horizons are identified and summarised. Then, the application of DNI forecasts to forecasting CST plant output is briefly reviewed before closing with the conclusion.

2. Forecasting direct normal irradiance

Solar irradiance incident on a horizontal plane at the earth's surface is called global horizontal irradiance (GHI). GHI is made up of diffuse irradiance and direct normal irradiance (DNI) components. DNI is the irradiance that arrives directly from the sun and is incident on a surface normal to its path. Diffuse irradiance is the irradiance scattered from that path. The relationship between the three irradiances is shown in Eq. (1).

$$Diffuse + \mathrm{DNI} * \cos\theta_z = \mathrm{GHI} \quad (1)$$

where θ_z is the solar zenith angle.

GHI forecasts are used to predict the performance of non-concentrating solar applications such as photovoltaic (PV) systems and flat plate solar thermal collectors. Most concentrating solar applications are only able to effectively concentrate DNI towards a receiver. Therefore DNI forecasts are required to estimate the future performance of concentrating solar applications such as concentrated solar thermal (CST).

When clouds are present they are the main cause of DNI intensity reduction, whereas aerosols are the main cause when clouds are absent (Wittmann et al., 2008; Gueymard, 2012). Aerosol concentration is usually quantified by aerosol optical depth (AOD). The reduction in DNI intensity due to aerosols ranges from 30% to 100% depending on aerosol concentration whereas for GHI the reduction in intensity is considerably lower at about 10% (Schroedter-Homscheidt and Oumbe, 2013; Lara-Fanego et al., 2012a; Marquez and Coimbra, 2011). The difference in intensity reduction between GHI and DNI is one key reason why GHI forecasting results should not be directly applied to DNI forecasting.

The accuracy of a forecasting method is typically reported using the root mean square error (RMSE), the mean absolute error (MAE) and the mean bias error (MBE). Large errors cause greater increase in RMSE than MAE because RMSE sums the square of errors while MAE sums the absolute value of errors. This characteristic of RMSE can be used to reflect the much greater severity of large forecast errors compared to that of small forecast errors (Perez et al., 2013). This is true for grid regulation at sub-hourly intervals when large forecast errors will require more reserve generation to be obtained at short notice to make up for the difference in electricity supply and demand. As such, RMSE is useful for describing and comparing the accuracy of intra-hour forecasts (Kostylev and Pavlovski, 2011). If forecast values and actual values are plotted against each other, then MAE quantifies the spread of data points around a line passing through the origin with gradient of 1 Perez et al. (2013). MAE is less sensitive to large errors compared to RMSE which is considered appropriate for quantifying uncertainty in intra-day forecasts used for unit commitment because there is more time to organise reserve generation (Kostylev and Pavlovski, 2011). MBE identifies the long-term tendency of a forecast method to over-predict or under-predict, which describes the accuracy of forecasts for horizons longer than a day ahead (Kostylev and Pavlovski, 2011).

The values of these metrics may be divided by a reference irradiance value, such as the mean or maximum irradiance, to obtain normalised RMSE (nRMSE), normalised MAE (nMAE) and normalised MBE (nMBE). The normalised error metrics demonstrate the significance of the error by comparing the magnitude of the error to the magnitude of the reference irradiance. The error from two separate studies may have the same magnitude, but the error will be less significant in the study in which the magnitude of the reference irradiance is larger. The values used to normalise the metrics should be clearly stated, otherwise it may reduce the usefulness of results by making comparisons between studies unhelpful (Kostylev and Pavlovski, 2011).

3. Clear sky models

The solar irradiance at a particular location on the Earth's surface typically follows an annual cycle. Simple clear sky models (CSMs) can model this cycle by using variables which determine solar position and extra-terrestrial solar irradiance (Reno et al., 2012). More complex CSMs can simulate attenuation of solar irradiance after transmission through the atmosphere by including atmospheric variables such as AOD or ozone thickness (Reno et al., 2012). The availability of high quality data for calibrating the model to the location is vital for high modelling accuracy (Reno et al., 2012; Ineichen, 2006; Badescu et al., 2012). When selecting a CSM, modelling accuracy is important and it is equally important to consider ease of use, availability of input data and the ability of the model to output desired irradiance values (Ineichen, 2006).

Some CSMs directly output DNI, such as the Simplified Solis model (Ineichen, 2008), the Reference Evaluation of Solar Transmittance – 2 Bands (REST2) model Gueymard, 2008 and the Bird model (Bird and Hulstrom, 1981). If DNI is not a direct output, then global-to-diffuse models, also called global-to-beam models, may be used to separate the GHI into DNI and diffuse components by statistical means. Examples of such models are the DirInt model (Perez et al., 1991), the Skartveit and Olseth model (Skartveit et al., 1998), and the Boland–Ridley–Lauret (BRL) model Ridley et al., 2010. If either the diffuse or DNI component of GHI is determined, then the other can be calculated due to the relationship described in Eq. (1).

CSMs can assist solar irradiance forecasting by modelling clear sky irradiance based on forecast values of atmospheric composition. For example, Ruiz-Arias et al. (2012) used the Weather and Research Forecasting (WRF) model to forecast pressure, humidity, and AOD to input to the REST2. Besides that, CSMs may be used to interpolate NWP solar irradiance output from 3-h resolution to 1-h resolution as applied in studies by Breitkreuz et al. (2009), Lorenz et al. (2009) and Martin, 2011. Correlations between cloud cover and reduction in clear sky irradiance have been identified by Kasten and Czeplak (1980), Gul et al. (1998), Chen et al. (2007) and Myers (2007). Thus cloud cover data may be added to modify clear sky irradiance and estimate solar irradiance in overcast conditions.

3.1. Modelling accuracy

The REST2 model was shown to marginally have the lowest nRMSE of 27% in the comparative study by Ineichen (2006). The European Solar Radiation Atlas (ESRA) model (Rigollier et al., 2000) and the Molineaux model (Molineaux and Ineichen, 1998) shared the same nRMSE as the REST2 model. The nRMSE of 5 other models tested in the study ranged from 28% to 34%. The REST2 model was also shown to have the largest nMBE of −25%. The result of the REST2 model having lowest nRMSE was reproduced in the comparative study by Gueymard (2012). Results averaged over 5 test locations showed that the REST2 model had nRMSE of 1.42% while the nRMSE range for 17 other models in the study was 2.64–43.18%. Gueymard (2012) considered the Simplified Solis model, the Hoyt model (Hoyt, 1978), the Bird model, and the Iqbal-C model (Iqbal, 1983) to also have good DNI modelling accuracy. The comparative study by Badescu et al. (2012) tested 54 CSMs using a variety of methods that analysed model sensitivity to inputs and seasons. No single CSM clearly outperformed the others. However the shortlist of best models for global and diffuse irradiance listed the (ASHRAE 1972) model (ASHRAE, 1972), the Biga model (Biga and Rosa, 1979), the ESRA model, and the REST2 model. In all of the studies, the normalised error values were calculated through division by the mean DNI of the test data for a particular location. The REST2 model was also found to be the most accurate at modelling GHI in a comparative study by Reno et al. (2012).

3.2. Global-to-diffuse models

A comparison of 17 global-to-diffuse models was conducted by Torres et al. (2010) and the models most able to match the measured diffuse irradiance data were the Skartveit and Olseth model, the DirInt model, and the BRL model. The RMSE were 46.57 W/m^2, 45.53 W/m^2, and 48.12 W/m^2 respectively for the 3 models. The other 14 models had RMSE larger than 53 W/m^2. The Erbs model (Erbs et al., 1982) was found to have similar nRMSE and nMBE to the DirInt model and the Skarveit and Olseth model in a study by Ineichen (2008). Vick et al. (2012) compared the DirInt model against measured DNI and found that the annual percentage difference was at most ±4.28%. This was better than the Direct Insolation Simulation Code (DISC) model (Maxwell, 1987) which had annual percentage difference of ±6.46% and worse than the DirIndex model (Perez et al., 2002) which had the result of ±2.41%.

A study by Ridley et al. (2010) showed that the BRL model had an average median absolute percentage error of 19.55% which outperformed 27.02% achieved by the Reindl model (Reindl et al., 1990), 21.96% achieved by the Skartveit and Olseth model, and 32.63% achieved by the Perez model (Perez et al., 1992) in the Southern Hemisphere. In the Northern Hemisphere the difference in performance was smaller with average median absolute percentage error of 8.22% for the BRL model, 9.24% for the Reindl model, 9.13% for the Skartveit and Olseth model, and 11.30% for the Perez model. The BRL model was found by Copper and Sproul (2012) to have an average RMSE of 113 W/m^2 which was less than 118 W/m^2, 121 W/m^2, and 115 W/m^2 achieved by the Skartveit and Olseth model, the Watanabe model (Watanabe et al., 1983) and the Zhang model (Zhang et al., 2002) respectively for Australian locations. The MBE of the BRL model (−27 W/m^2) was neither the minimum nor the maximum value among all the MBE values.

Overall, the BRL model is shown to perform better than other global-to-diffuse models in Spain by Torres et al. (2010), in Australia by Copper and Sproul (2012), and in both hemispheres by Ridley et al. (2010). The Skarveit and Olseth model is also a good global-to-diffuse model because it had slightly lower RMSE than the BRL model in the study by Torres et al. (2010) and came second to the BRL model and ahead of other models in the studies by Ridley et al. (2010) and Copper and Sproul (2012). The DirInt model is another model that may be good because it was shown to have similar performance to the Skartveit and Olseth model by Torres et al. (2010) and Ineichen (2008).

4. Numerical weather prediction

Solar irradiance forecasts may be obtained from the use of numerical weather prediction (NWP) models. A description of the atmosphere at a given time is used as a starting point for NWP models. Equations that physically describe horizontal momentum, vertical momentum, hydrostatic continuity and conservation of energy are used to calculate changes in the state of the atmosphere across fixed time steps. Thus NWPs model are able to forecast atmospheric variables by evaluating the equations over the necessary number of time steps to arrive at the desired forecast horizon.

NWP models may be generally separated into two categories according to the modelling domain spatial extent. Models in the first category cover the entire globe and are called global models. Examples of global models are the European Centre for Medium-Range Weather Forecasts (ECMWF) model (ECMWF, 2012) and the Global Forecast System (GFS) (EMC, 2013). Models in the other category cover only a region of the globe and are called regional or mesoscale models. Examples of mesoscale models are the Weather and Research Forecasting (WRF) model (Skamarock et al., 2008), the Mesoscale Atmospheric Simulation System (MASS) model (Manobianco et al., 1996), the Advanced Multiscale Regional Prediction System (ARPS) (Xue et al., 2000), the North American Model (NAM) (Janjic et al., 2010), and the Fifth-generation Pennsylvania State University – National Center for Atmospheric Research Mesoscale Model (MM5) (Grell et al., 2008). Mesoscale models depend on global models for defining boundary conditions of the modelling domain. However, the smaller modelling domain allows the topography to be described at higher resolution in mesoscale models compared to global models and thus forecasts can be obtained at higher resolution (Perez et al., 2013). The typical time resolution of output for regional NWP models is 1 h or 3 h for global models (Diagne et al., 2013; Perez et al., 2013). NWP models are recommended to be used when the forecast horizon exceeds 5 h (Perez et al., 2010; Kleissl, 2010), due to the "spin up" time required to assimilate data and initialise (Coimbra et al., 2013).

Within each category, NWP models can vary according to design parameters such as horizontal spatial resolution, vertical spatial resolution, forecast horizon, output time step and parameterization to model atmospheric processes. Due to the different configurations, forecast accuracy for a particular location will vary among the NWP models as demonstrated for GHI forecast accuracy in the review by Perez et al. (2013) for sites in the US, Canada and Europe using several global and regional NWP models. The nRMSE normalised by mean GHI for 1-day ahead forecasts ranged from 20% to 69% in US sites, 29% to 44% in Canadian sites, and 40% to 64% in central European sites.

NWP use radiative transfer models (RTMs) to calculate solar irradiance and they typically predict GHI not DNI (Larson et al., 2013; Ruiz-Arias et al., 2012). There are several methods to obtain DNI from NWP model outputs. Breitkreuz et al. (2009) used a global-to-diffuse model and the ratio of forecasted GHI to GHI from a clear sky model (CSM) to derive DNI forecasts at 1 h resolution from the 3 h resolution output from the ECMWF. In the same study, hourly DNI forecasts were also obtained from a forecasting system called the Aerosol-based Forecasts of Solar Irradiance for Energy Applications (AFSOL). AFSOL was made from the MM5, an emission database, a chemical transport model and the library for radiative transfer (libRadtran). Lara-Fanego et al. (2012a) combined satellite measurements of aerosol and ozone with outputs from a WRF model initialised with GFS boundary conditions to derive DNI forecasts. Lara-Fanego et al. (2012b) derived DNI forecasts from a WRF model initialised with ECMWF boundary conditions by using WRF outputs and a global-to-diffuse model. Ruiz-Arias et al. (2011) used WRF outputs, a broadband CSM and satellite measurements of ozone and AOD to obtain DNI forecasts. González et al. (2010) used the Meteorological Radiation Model (MRM) to derive DNI from the WRF model initialised with GFS boundary conditions.

As cloud cover and aerosols strongly affect DNI intensity, the ability of NWP to model their presence and effects is vital for accurate forecasting. When clouds are present, forecast error can be caused by inaccurate modelling of the vertical and horizontal distribution of clouds as well as inaccurate modelling of cloud layer thickness (Larson et al., 2013). For aerosols, forecast error can be due to inaccurate parameterization of the scattering and absorption by water vapour, ozone and aerosols molecules (Larson et al., 2013). In general, NWP models usually fail to predict the presence of clouds and thus forecast accuracy is biased towards over-predicting available DNI (Larson et al., 2013; Mathiesen et al., 2013). General factors which cause errors in NWP model forecasts include inaccurate initial values, coarse spatial resolution, and large calculation time steps.

4.1. Forecast accuracy

A summary of DNI forecast accuracy from NWP is presented in Table 2. The annual average DNI forecast accuracy in all sky conditions from the WRF model was shown to outperform persistence by Lara-Fanego et al. (2012a, 2012b). However, persistence can sometimes outperform NWP. For example, when the daily clearness index was 0.5, the annual nRMSE for persistence was about 125% while it was about 150% for the WRF model (Lara-Fanego et al., 2012a).

The results presented in Table 2 from Lara-Fanego et al. (2012a, 2012b), Wittmann et al. (2008) and González et al. (2010) are for all sky conditions. They suggest that in any sky condition, the DNI forecast nRMSE for 1-day ahead forecasts would be about 60% and for 2-days ahead forecasts it would be between 40% and 60% depending on the NWP model used. The results from Lara-Fanego et al. (2012a) suggest that DNI forecast accuracy may increase slightly when forecast horizon is extended from 1 to 3 days ahead.

Only clear sky conditions were used by Breitkreuz et al. (2009) and Ruiz-Arias et al. (2012) which are shown in Table 2. Results from clear sky conditions only were also reported by Lara-Fanego et al. (2012a) and Wittmann et al. (2008). Lara-Fanego et al. (2012a) showed 1-day ahead clear sky DNI forecast nRMSE of 21–22% whereas Ruiz-Arias et al. (2012) showed a range of 6–20% depending on the availability of aerosol data to input. The lower nRMSE was achieved by using aerosol data.

For 2-days ahead clear sky DNI forecast nRMSE, Wittmann et al. (2008) reported 17.4% for the AFSOL and 28.6% for the ECMWF which is similar to the results of Breitkreuz et al. (2009) which were 18.8% and 31.2% respectively. Lara-Fanego et al. (2012a) reported 22–24% for 2-days ahead clear sky DNI forecast nRMSE. The

Table 2
Summary of DNI forecast accuracy from NWP.

Author(s)	NWP description	Forecast horizon	nRMSE (%)	RMSE (W/m^2)	nMAE (%)	MAE (W/m^2)	nMBE (%)	MBE (W/m^2)
Gala et al. (2013)	ECMWF – use a CSM to derive DNI	1 h				30.22		
						23.21		
		3 h				65.92		
						45.30		
		1 day				243.09		
						205.03		
Lara-Fanego et al. (2012a)	WRF initialised with GFS – use satellite measured aerosol and ozone to derive DNI	1 day	61	304			22	109
			60	294			35	172
		2 days	62	311			24	117
			58	290			36	178
		3 days	63	319			25	119
			62	305			38	182
Lara-Fanego et al. (2012b)	WRF initialised with ECMWF – use a RTM to derive DNI	1 day	60				35	
Ruiz-Arias et al. (2012)	WRF initialised with ECMWF – no aerosol input	1 day	18.5	143			17.3	134
			19.3	163			18.8	159
			12.8	113			12.2	108
	WRF initialised with ECMWF – aerosol input from satellite measurements	1 day	8.5	66			7.9	61
			9.7	82			9.3	79
			7	62			6.6	58
			7	54			6.2	48
			7.6	64			7.1	60
			5.9	52			5.4	48
Breitkreuz et al. (2009)	AFSOL	2 days	18.8	96			11.2	57
	ECMWF – use Skarveit and Olseth CSM to derive DNI	2 days	31.2	159			−26	−134
Wittmann et al. (2008)	AFSOL	2 days	47	208.6			15.6	69.4
	ECMWF – use Skarveit and Olseth CSM to derive DNI	2 days	41.7	184.9			−23	−103.2
González et al. (2010)	WRF initialised with GFS – use MRM to derive DNI	Not stated			18.23	87.28		

errors reported by Wittmann et al. (2008) are slightly smaller but less data was used for testing so Lara-Fanego et al. (2012a) may be considered more representative of expected forecast error.

Seasonal separation of results was done by Lara-Fanego et al. (2012a) and González et al. (2010). Both showed that the WRF initialised with GFS boundary conditions would have better DNI forecast accuracy in summer compared to the annual average forecast accuracy while the other seasons were likely be worse. This could be explained by cloudy conditions being less common during summer, thus forecasts for summer are generally more accurate (Lara-Fanego et al., 2012a). The nRMSE for 1–3 days ahead DNI forecasts was 33–48% in summer, 66–102% in autumn, 69–86% in winter, and 53–59% in spring (Lara-Fanego et al., 2012a). The nMAE was 13.11% in summer, 19.4% in autumn, 19.82% in winter, and 20.63% in spring (González et al., 2010).

4.2. Improving forecast accuracy

Breitkreuz et al. (2009) suggested that the ECMWF should use AOD values that are more accurate than those in climatology databases whereas the AFSOL should use better cloud modelling to increase DNI forecast accuracy. As part of the Monitoring Atmospheric Composition and Climate (MACC) project, AOD forecasts were integrated into the ECMWF (ECMWF/MACC) by adding a chemical weather prediction suite. Using data from the aerosol robotic network (AERONET), it was found that hourly AOD forecasts from the ECMWF/MACC were more accurate or equal to a 2-day persistence method in Europe and America but not in eastern Asia and western Africa (Schroedter-Homscheidt et al., 2013). This was explained by the ECMWF/MACC emissions database lacking data about the rapid industrialisation in Asia and Africa. Ruiz-Arias et al. (2012) demonstrated that additional aerosol data input to WRF initialised with ECMWF boundary conditions increased the clear sky DNI forecast accuracy. As shown in Table 2, the nMBE and nRMSE were almost halved when aerosol data was used.

Mathiesen et al. (2013) assimilated cloud cover in the initial conditions of a high-resolution, direct-cloud-assimilating WRF (WRF-CLDDA) by altering the water vapour mixing ratio. Testing showed the WRF-CLDDA had better GHI forecast accuracy than the NAM during overcast or partially cloudy conditions but not during clear sky conditions. It was suspected that this was due to WRF-CLDDA failing to model cloud dissipation accurately. The improvement in GHI forecast accuracy may also be achieved by DNI forecast accuracy.

The spatial resolution of a NWP model affects its ability to resolve the presence of clouds (Diagne et al., 2013). It may be expected that higher resolution would improve the ability to resolve clouds and thus increase forecast accuracy. Lara-Fanego et al. (2012b) found that higher spatial resolution did not improve DNI forecast accuracy from the WRF when sky conditions were cloudy or overcast, but there was an improvement for clear sky conditions. An improvement in WRF clear sky global irradiance forecast accuracy was observed by Ruiz-Arias et al. (2011) when spatial resolution was increased. This suggests that higher spatial resolution improve the ability to resolve the effects of topography on clear sky solar irradiance but do not improve the ability to resolve the presence of clouds (Lara-Fanego et al., 2012b). Mathiesen et al. (2013) reported that increasing resolution usually reduces forecast accuracy and noted that spatial averaging can increase forecast accuracy by reducing random error. Lara-Fanego et al. (2012b) showed that spatial averaging could significantly reduce 2-day ahead DNI forecast nRMSE and nMBE by the WRF, particularly during cloudy conditions. The best results were obtained for a horizontal resolution of 27 km and spatial averaging over 100 km $\times$ 100 km, which is similar to the findings of Lorenz et al. (2009) for GHI forecasts using the ECMWF.

5. Time series analysis

Time series analysis (TSA) methods produce forecasts by statistically analysing trends in historical time series of either the forecast variable or other variables, named exogenous variables, which influence the forecast variable. Clearness index and relative air mass were identified as the most relevant exogenous variables for predicting DNI (López et al., 2005). Solar irradiance data that has been collected for a long period of time relative to the temporal resolution, such as over several days at 1 min resolution or several months at 1 h resolution, may be used to produce forecasts using TSA methods.

The simplest TSA model is the persistence model which assumes that conditions in the future will be exactly the same as those in a previous time. Forecasting models are often compared against the persistence model to demonstrate better forecast accuracy and thus justify the higher complexity. Regressive TSA models analyse recent time series behaviour to produce forecasts. Regressive models are usually divided into autoregressive (AR) models, moving average (MA) models, or a combination of both terms in either autoregressive moving average (ARMA) models or autoregressive integrated moving average (ARIMA) models. A description of the differences between these models and the time series behaviour suited to each one is in the text by Box et al. (1994). Artificial intelligence (AI) TSA models are able to identify recurring patterns in the historical time series and use the information to produce better forecasts. These models may be created using either an artificial neural network (ANN) or a support vector machine (SVM). An ANN model may adopt one of several different structures defined by the number of layers or the presence of feedback loops. General use of AI models is detailed for ANN by Haykin (1999) and for SVM by Vapnik (1998).

ANN models are usually favoured over ARMA-based models because ANN models can be directly applied to nonlinear time series and can be made without detailed knowledge or assumptions regarding the behaviour of the time series (Tymvios et al., 2008; Zhang et al., 1998). It has been speculated that ANN models are more suited than ARMA-based models to forecast solar irradiance time series because of non-linearity in the time series (Ji and Chee, 2011; Sfetsos and Coonick, 2000), however evidence to show non-linearity in the deseasonalised solar irradiance time series has not been provided. In addition, ANN models have the ability to adapt by changing the magnitudes of weights and biases which optimises them to model new changes in a time series (Haykin, 1999). A review of 32 studies that used ANN to forecast GHI or diffuse irradiance conducted by Mellit (2008) concluded that ANN can be generalised and applied to any location even if the location has incomplete data.

A disadvantage in using ANN models is that the model training process may result in a poor ANN model which is more likely to occur if the model structure is complicated or the data has a lot of noise (Reikard, 2009; Mellit et al., 2013). To overcome this problem, the available time series data may be separated into a training set, a validation set and a testing set (Tymvios et al., 2008). The training set and validation set are jointly used during the training process to ensure that the ANN model ignores most of the noise. After the training process is completed, the testing set is used to evaluate the ANN model. This allows differently structured ANN models to be compared against each other to determine which has the best performance. However, this solution requires significantly more data to be available.

5.1. Forecast accuracy

As shown in Table 3, there are few results to use for drawing conclusions about DNI forecast accuracy using TSA methods. All of the studies used ANN with feed-forward structure as part of their analysis. Mellit et al. (2010) showed that the feed-forward ANN had a higher correlation coefficient than an adaptive alpha model. Mishra et al. (2008) showed that the feed-forward structure had lower nRMSE than the radial basis function structure. The nRMSE results from Alam et al. (2006) fall in the same range for a feed-forward ANN. Neither study specified what value was used to normalise the RMSE.

Table 3
Summary of DNI forecast accuracy from TSA methods.

Author(s)	TSA description	Forecast horizon	nRMSE (%)	RMSE (W/m^2)	nMBE (%)	MBE (W/m^2)	Correlation coefficient
Mellit et al. (2010)	Feed-forward ANN	1 h					0.9834
	Adaptive alpha model	1 h		2.74		0.751	0.9754
Mishra et al. (2008)	Feed-forward ANN	Not stated	0.8				
			5.4				
	Radial basis function ANN	Not stated	7				
			29				
Alam et al. (2006)	Feed-forward ANN	Not stated	2.75		−0.55		
			2.13		−0.76		
			2.79		−1.28		
			1.85		−0.26		
			1.65		−0.67		

Reported trends in GHI forecasting from TSA methods may be used to estimate the relative performances of TSA methods in DNI forecasting. A comparative study by Reikard (2009) investigated GHI forecasting accuracy from a regression model, a regression model with added sinusoids, an ARIMA model without exogenous inputs, an ARIMA model with exogenous inputs, an ANN model and a hybrid ARIMA-ANN. The ARIMA model with no exogenous inputs was best at 1–4-h forecast horizons with mean absolute percentage error (MAPE) ranging from 35.2% to 54.0% (Reikard, 2009). The ARIMA model with exogenous inputs and the ARIMA-ANN model had very similar performance with MAPE ranging from 35.3% to 54.4% and 35.3% to 54.1% respectively (Reikard, 2009). The performances of these models were better than the ANN model which had MAPE ranging from 41.4% to 56.2%. This was attributed to the ARIMA model being best at following the diurnal solar irradiance cycle by using 24 h differencing and at modelling nonlinear variability by using time varying coefficients. The same three models also had the best forecast accuracy when sub-hourly forecast horizons of 5 min, 15 min, and 30 min were used (Reikard, 2009). This was explained by the dominance of the diurnal cycle being replaced by sub-hourly patterns which these models were able to reproduce better than the other models (Reikard, 2009).

A comparison of GHI forecast accuracy by a least-squares SVM (LS-SVM) model and a radial basis function ANN model was made by Zeng and Qiao (2013). The average MAPE for the LS-SVM model was about 22–33% for 1–3-h ahead forecasts which was better than the average MAPE of about 24–35% for the ANN model (Zeng and Qiao, 2013). The lower forecast error of the LS-SVM was explained by its better ability to model nonlinear and time-varying time series.

The results from Reikard (2009) and Zeng and Qiao (2013) respectively suggest that an ARIMA model or a SVM model may be preferable to an ANN model to forecast DNI when the forecast horizon is less than 4 h. However, each of the studies only evaluated a single ANN model. There are different structures that may be used to make an ANN model (Haykin, 1999) and a review by Mellit (2008) did not find any one structure to be best at solar irradiance forecasting. Therefore, future investigations in DNI forecast accuracy using TSA methods should consider ARIMA models, SVM models and ANN models.

6. Cloud motion vectors

The cloud motion vector (CMV) method uses satellite or ground-based imaging instruments to remotely track the motion of clouds. Fujita (1968) pioneered the CMV method by successfully tracking cloud motion from geosynchronous satellite pictures. He also developed a stereoscopic technique to track cloud features using ground-based sky cameras (Bradbury and Fujita, 1968). Most of the pioneering work and the operational status of cloud tracking with satellite imagery was documented by Menzel (2001).

The process for deriving CMVs from satellite images begins with using known features which remain stationary within a tolerance limit between successive images to correct for consistency (Menzel and Purdom, 1994). Next, a tracer is selected within the target image. Tracers usually correspond to cloud features that are easily traceable, such as locations with highest pixel brightness and the computed local gradients around these locations. Tracers must be consistent and all prospective tracers are checked by spatial coherence analysis checks for consistency (Coakley and Bretherton, 1982). After that, the tracers are assigned an altitude based on either the infrared window sampling method (Fritz and Winston, 1962), the CO_2-slicing method (Menzel et al., 1983) or the H_2O-intercept method (Schmetz et al., 1993). Finally, the tracers are tracked using a pattern matching algorithm which matches a feature from the target area in one image to a search area in the following image.

Three basic pattern matching procedures used for tracking cloud motion are cross-correlation, the sum of absolute differences, and the sum of squared differences (Marcello et al., 2009). The most commonly used algorithm is the maximum cross-correlation technique (Leese et al., 1970, 1971; Merril, 1989). This algorithm determines the maximum cross-correlation coefficient from successive images to calculate the displacement vector of a chosen feature. It performs well for single clouds with unique patterns but fails to discriminate between motions in multiple cloud layers. Fourier transforms can increase the algorithm computation speed.

Another technique is the automatic cloud tracking algorithm which applies the standard pattern correlation coefficient to images from geostationary satellites (Schmetz et al., 1993). This technique allows correlation of more displacements due to the segmentation of target and search area. It has faster computation speed and detects more features. Errors in pattern matching can produce poor results and therefore quality control is performed using automated editing algorithms (Hayden and Velden, 1991; Hayden and Nieman, 1996), manual checks, and comparative climatology from radiosondes (Schmetz et al., 1993). The final CMVs are reported as averages of two to three component vectors calculated from a sequence of images (Nieman et al., 1997; Schmetz et al., 1993).

Other pattern matching methods include correlation–relaxation labelling (Evans, 2006), Bayesian estimation (Konrad and Dubois, 1992), neural-network (Cote and Tatnall, 1995), functional-analytic (Bannehr et al., 1996), hierarchical method using simulated annealing and fuzzy reasoning (Mandal et al., 2005) and scale space classification (Mukherjee and Acton, 2002) methods. Most of these techniques show improvement in cloud classification but are computationally expensive for calculating CMVs.

Solar irradiance forecasting can use CMVs to describe advection of present clouds and predict images of future cloud cover. In this method, cloud images are converted to solar irradiance forecasts using statistical or physical models. Statistical models are created from regression of satellite measurements and corresponding ground measured solar irradiance for a given area. These models are computationally efficient and require neither meteorological data nor calibration, but lack generality due to shortage of ground-based measurements (Noia et al., 1993a). Physical models use radiative transfer equations that describe transmission, absorption and scattering in the earth-atmosphere system to reduce clear sky irradiance (Noia et al., 1993b). These models do not need ground-based measurements and are frequently applicable depending on available meteorological data. The HELIOSAT method (Hammer et al., 2003) is most commonly used for short-term global irradiance forecasts using satellite-based CMVs (Hammer et al., 1999; Heinemann et al., 2006a, 2006b; Lorenz et al., 2004).

Ground-based imaging instruments to forecast solar irradiance using cloud cover indices (Marquez et al., 2013; Yang et al., 2012; Crispim et al., 2008), automated cloud classifications (Tapakis and Charalambides, 2013), and CMVs (Bosch et al., 2013; Chow et al., 2011; Marquez and Coimbra, 2013; Stefferud et al., 2012) were found to work well for specific sites and lack spatial coverage. In contrast, satellite images have greater spatial and temporal resolution that ensures cloud structures are easily detectable (Zelenka et al., 1999).

CMVs are used for weather forecasting by several meteorological centres, including the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) (Holmlund et al., 2010), the National Oceanographic and Atmospheric Administration's Satellite and Information Service (NOAA/NESDIS) (Daniels et al., 2004), the Japan Meteorology Agency (JMA) (Oyama and Shimoji, 2008) and the Australia Bureau of Meteorology (BOM) (Marshall et al., 2012).

6.1. Forecast accuracy

The DNI forecast accuracy from CMVs is summarised in Table 4. Only the 5 min and 10 min forecast results from Marquez and Coimbra (2013) and Quesada-Ruiz et al. (2014) are included to compare against the results of Chu et al. (2013). Marquez and Coimbra (2013) evaluated DNI forecast accuracy from ground-based CMV using forecast horizons from 3 min to 15 min and found CMVs to outperform persistence at all forecast horizons. The method used by Marquez and Coimbra (2013) divided sky images into sectors with fixed sizes. This method was modified by Quesada-Ruiz et al. (2014) to vary the size of sectors to increase the accuracy of estimating DNI for each sector. Both methods were tested and the RMSE results showed that the modified method performed better than the original method in all sky conditions and forecast

Table 4
Summary of DNI forecast accuracy from CMV.

Author(s)	CMV type	Forecast horizon (min)	RMSE (W/m^2)	MBE (W/m^2)
Marquez and Coimbra (2013)	Ground-based	5	226	
			208	
			267	
			257	
		10	341	
			317	
			303	
			283	
		15	360	
			392	
			332	
			299	
Chu et al. (2013)	Ground-based	5	150.5	−10.7
		10	144	−8.3
Quesada-Ruiz et al. (2014)	Ground-based, variable sector size	5	∼10	
			∼290	
		10	∼10	
			∼300	
	Ground based, fixed sector size	5	∼11	
			∼370	
		10	∼11	
			∼350	

horizons. The values in Table 4 were approximated from a graph and the lower RMSE is for low variability clear sky conditions whereas the higher RMSE is for high variability broken cloud conditions. Chu et al. (2013) used ground-based CMV to forecast DNI at 5 min and 10 min horizons.

Results from Chu et al. (2013) and Quesada-Ruiz et al. (2014) found that ground-based CMV forecasts of DNI up to 10-min ahead achieved better forecast accuracy than persistence when sky conditions had high variability and worse forecast accuracy than persistence when sky conditions had low variability. This suggests that sky conditions should be considered together with forecast horizon when choosing an appropriate DNI forecasting method, at least for very short-term forecasts up to 10-min ahead.

The RMSE values reported by Chu et al. (2013) are lower most likely because their testing period of 15 September 2011–15 October 2011 contained days with both low and high variability in sky conditions whereas Marquez and Coimbra (2013) used 4 days with only highly variable sky conditions for testing. It is easier to forecast DNI when sky conditions have low variability compared to when sky conditions have high variability. This is reflected in the results from Quesada-Ruiz et al. (2014) which show RMSE to be an order of magnitude lower in clear sky conditions with low variability compared to broken cloud conditions with high variability. Marquez and Coimbra (2013) also acknowledged that uniform sky conditions reduce error averages.

In the absence of papers published about the use of satellite-based CMVs for DNI forecasting, results of GHI forecasting from satellite-based CMVs will be used to indicate potential forecast accuracy. Hammer et al. (2001) found that the nRMSE of 1-h ahead GHI forecasts in north Germany was about 28–35% depending on the number of pixels in the satellite image used to produce the forecast. Perez et al. (2010) found that 1 h ahead GHI forecast RMSE from satellite-based CMV had a range of 68–120 W/m^2 across 7 locations in the US. A slightly lower RMSE of about 60 W/m^2 averaged from 274 locations in Germany was reported by Kühnert et al. (2013). RMSE was calculated for up to 5-h ahead forecasts and the 5-h ahead RMSE values were again close: 116–175 W/m^2 (Perez et al., 2010) and about 110 W/m^2 (Kühnert et al., 2013). Both studies also showed that 1–5-h ahead GHI forecasts from satellite-based CMV had lower RMSE than persistence. In 1-h ahead forecasts the RMSE of satellite-based CMV up to 14 W/m^2 lower than that of persistence and in 5-h ahead forecasts the RMSE of satellite-based CMV was up to 40 W/m^2 lower.

6.2. Improving forecast accuracy

Increasing solar irradiance forecast accuracy from ground and satellite imagery may be achieved by minimising the errors associated with parameters that influence the number and quality of CMVs. Such parameters include the size of the target and search windows (Lunnon and Lowe, 1992; Wade et al., 1992), the time interval between successive images (Purdom, 1996), the position of the vector on the earth disk and rotational motion (Kamachi, 1989).

Another crucial factor is the pattern matching algorithm used for cloud tracking. Area-based approaches, such as cross-correlation, compare and match the intensity patterns of the block-wise areas and are unable to accurately detect when the shape of a cloud changes. Local-feature approaches outperform correlation methods due to enhanced sensitivity of changes in shape and brightness. However, local features are non-uniform and biased in spatial location. Huang et al. (2012) proposed a robust hybrid approach using both area and feature-based techniques with ground-based sky imagers. This approach performed better for variable intensity patterns, multilayer clouds and different cloud shapes.

Forecast accuracy may also be increased by improving solar irradiance models. Better forecasts from the HELIOSAT-2 model (Rigollier et al., 2004) may be obtained by including cloud index median and air mass (Polo et al., 2011; Zarzalejo et al., 2009), improving the algorithm for calculating the cloud index (Dagestad and Olseth, 2007), and enhancing clear sky modules (Mueller et al., 2004).

6.3. Satellite-to-irradiance conversion

The process of converting satellite images to solar irradiance contributes to the overall forecast error from satellite-based CMVs (Kühnert et al., 2013). Thus the satellite-to-irradiance conversion accuracy for DNI is reviewed. The satellite-to-irradiance methods reviewed are briefly described in the paragraph below and their conversion accuracies are summarised in Table 5.

The DLR-SOLEMI method is described in detail by Schillings et al. (2004). It uses visible and infrared images from Meteosat-7 to derive cloud index for input to a CSM and accounts for ozone, aerosols and water vapour. The Perez method, described by Perez et al. (2002), processes GOES 8 (now GOES-East) visible images for cloud cover as input to CSM and accounts for snow cover, aerosol, ozone and water vapour. The HELIOSAT-MSG method is described by Hammer et al. (2009) as a combination of the HELIOSAT method (Hammer et al., 2003), the SOLIS clear sky model, and an exponential parameterisation for direct irradiance. The Eissa method, described and evaluated by Eissa et al. (2013), uses 6 thermal channels of the Meteosat Second Generation (MSG) to detect dust, clouds, and water vapour. These are input to an ANN ensemble along with solar zenith angle, solar time, day number and eccentricity correction to derive atmospheric optical depth. The atmospheric optical depth is input to the Beer–Bouguer–Lambert law to calculate DNI. The State University of New York GOES satellite-based solar model (SUNY) version 1 method was developed from work by Perez et al. (2002, 2004). It operates similarly to the Perez method with 3 major differences. Firstly, visible images from GOES-West are used in addi-

Table 5
Summary of performance of methods which convert satellite images to DNI.

Author(s)	Method description	nRMSE (%)	RMSE (W/m^2)	nMAE (%)	MAE (W/m^2)	nMBE (%)	MBE (W/m^2)
Nonnenmacher et al. (2014)	SUNY version 3	21.67	137.9	10.5	97.7	10.5	66.8
		30.29	151.2	14.21	108.3	14.21	71
		29.79	119.9	8.75	75.1	8.75	35.2
		42.24	161.9	−6.39	92.4	−6.39	−24.5
Eissa et al. (2013)	Eissa method	26.1				−6	
Djebbar et al. (2012)	SUNY version 1	82.3	164.3			2.5	4.6
	SUNY version 3	67.2	133.7			14.3	28.5
Hammer et al. (2009)	HELIOSAT-MSG method	31.3				1.1	
Vignola et al. (2007)	Perez method	40.9	200			2	
Schillings et al. (2004)	DLR-SOLEMI method	36.1					

tion to those from GOES-East. Secondly, the solar irradiance time series is calibrated. Thirdly, anomalous pixel-to-pixel variation is corrected. The SUNY version 3 method is upgraded from SUNY version 1 to use infrared images from GOES-West and GOES-East. A detailed description of the upgrade is provided by Perez et al. (2010). In brief, the infrared images are used to obtain empirical thresholds for deriving solar irradiance over snow covered regions.

Polo et al. (2008) reviewed most of the common methods to predict solar irradiance from satellite images and concluded that the nRMSE of satellite-to-GHI conversion has a range of 17–25%. It is seen in Table 5 that the nRMSE range for satellite-to-DNI conversion is about 21.7–82.3%. Only the Eissa method and SUNY version 3 are able to match satellite-to-GHI conversion accuracy. Both of these methods were evaluated in the most recently published papers in Table 5, suggesting that the latest satellite-to-DNI conversion methods may enable DNI forecast accuracy from satellite-based CMVs to be similar to GHI forecast accuracy in terms of nRMSE.

7. Hybrid forecasting methods

There are advantages and disadvantages associated with each individual forecasting method. Besides improving the forecast method algorithm, poor forecast accuracy by a method may be overcome by using another method that does not share the same disadvantages. This combination forms a hybrid method that may achieve higher forecast accuracy than either method could achieve alone. Although widely studied for GHI, the design and evaluation of hybrid methods is sparsely studied for DNI. The results of studies of hybrid GHI forecasting methods are included to indicate the possible effectiveness of hybrid DNI forecasting methods.

7.1. Hybrid direct normal irradiance forecasting methods

A summary of hybrid methods applied to forecasting DNI and their reported accuracies are presented in Table 6. One common hybrid method is using Model Output Statistics (MOS), which is the use of statistical methods to post-process NWP outputs for the purpose of calculating outputs not directly provided by the NWP (e.g. deriving DNI) or correcting systematic biases in the output by comparing NWP output against historical ground measurements (Heinemann et al., 2006a). MOS has been shown to improve GHI forecast accuracy by the WRF, MASS and ARPS mesoscale NWP models in the US (Perez et al., 2011, 2013). However, the DNI forecast accuracy of the ECMWF without MOS has been found to be more accurate in Spain compared to commercial MOS systems (Schroedter-Homscheidt et al., 2012). NWP with MOS was shown to produce more accurate DNI forecasts than persistence for 2-days ahead forecasts (Kraas et al., 2013). Gerstmaier et al. (2012) compared DNI forecast accuracy from 4 different forecast providers that used NWP with MOS. The RMSE and MBE results from Gerstmaier et al. (2012) were mostly larger than those from Kraas et al. (2013). This may be explained by the preference of forecast providers to use probability of overestimation or underestimation to describe their forecast accuracy (Gerstmaier et al., 2012) and thus the MOS was not designed to minimise RMSE and MBE.

Methods other than MOS can be used for post-processing NWP outputs. The National Digital Forecast Database (NDFD) is an NWP based on the GFS (Perez et al., 2010). Meteorological data from the NDFD was post-processed by ANN to forecast DNI and shown to outperform persistence (Marquez and Coimbra, 2011) for 1-day ahead forecasts. For 2-day ahead to 6-day ahead forecasts, only nRMSE was calculated and results showed that nRMSE increased with longer forecast horizon (Marquez and Coimbra, 2011). For 2-days ahead forecasts, nRMSE was between 35% and 45% which is less than that from Kraas et al. (2013). When compared against the 1–3-days ahead forecast accuracy of an NWP without post-processing in all seasons and sky conditions (Lara-Fanego et al., 2012a), the results from Kraas et al. (2013) do not show any significant forecast accuracy improvement whereas those from Marquez and Coimbra (2011) do.

González et al. (2010) used ANN to post-process WRF outputs and results suggest that forecast accuracy is good but comparisons are difficult to make because RMSE and MBE were not calculated and the forecast horizon was

Table 6
Summary of DNI forecast accuracy from hybrid methods.

Author(s)	Method description	Forecast horizon	nRMSE (%)	RMSE (W/m^2)	nMAE (%)	MAE (W/m^2)	nMBE (%)	MBE (W/m^2)
Chu et al. (2013)	CMV input to ANN	5 min		88.6				−0.2
		10 min		103.3				−1.9
Gala et al. (2013)	ECMWF with SVR post-processed at 3 h resolution then interpolated to 1 h resolution using CSM	1 h				28.00		
						22.77		
		3 h				59.21		
						44.15		
		1 day				203.89		
						179.79		
	ECMWF with SVR post-processed at daily resolution than interpolated to 1 h resolution using CSM	1 h				27.71		
						22.57		
		3 h				58.76		
						43.89		
		1 day				218.05		
						176.02		
Kraas et al. (2013)	ECMWF and HIRLAM with MOS post-processing	2 days	56	257				0.2
			77	347				−33
			58	266				−38
Marquez and Coimbra (2011)	NDFD with ANN post-processing	1 day	32.3	162			−0.5	−2.4
			31.2	156			−1.3	−3.4
			33.2	161			−10.3	−7.1
			32	158			−8.3	−4.2
Gerstmaier et al. (2012)	NWP with MOS post-processing	1 day		363				153
				312				−32
				352				136
				316				104
González et al. (2010)	WRF with ANN post-processing	Not stated			16.61	79.52		

not stated. The study showed that ANN post-processing improved DNI forecast accuracy in both all sky conditions and seasons compared to WRF forecasts without post-processing (González et al., 2010).

SVM was used by Gala et al. (2013) to post-process outputs from the ECMWF at temporal resolutions of either 3 h or 1 day to produce hourly direct horizontal irradiance forecasts. The difference in forecast accuracy from varying the ECMWF output temporal resolution was insignificant. However, SVM post-processing did produce lower MAE compared to ECMWF forecasts without post-processing (Gala et al., 2013). A greater reduction in MAE may be achieved if the algorithm used to derive direct horizontal irradiance from GHI output was optimised to the location (Gala et al., 2013). Again, the lack of reporting results in RMSE and MBE makes comparisons against other forecast results difficult.

Post-processing can also be applied to non-NWP methods. The use of ANN to post-process ground-based CMV outputs was evaluated by Chu et al. (2013) for 5-min and 10-min ahead forecasts. The hybrid model outperformed persistence and CMV without post-processing during periods of very low to intermediate variability in sky conditions, but CMV without post-processing was most accurate for periods of high variability (Chu et al., 2013).

7.2. Other hybrid forecasting methods applied to global irradiance

A successful hybrid method that improved GHI forecast accuracy and may improve DNI forecast accuracy is ensemble modelling, i.e. averaging the results obtained from more than one NWP model initialised with the same inputs. Each NWP model may produce a slightly different forecast from the same inputs because of variation in model design. This is true for DNI forecasting as shown by Breitkreuz et al. (2009) for the AFSOL and the ECMWF, and by Gerstmaier et al. (2012) for a group of 4 NWP with MOS. The different forecast information from each NWP can be averaged to obtain an overall more accurate forecast, as shown by Perez et al. (2013) for GHI forecasting. The success of ensemble modelling depends on the extent to which forecast errors of each NWP offset one another (Perez et al., 2013).

Another approach using multiple forecast methods would be to apply each forecasting method to conditions for which it is most accurate. Forecast conditions were separated into clear sky for ARMA modelling and cloudy sky conditions for ANN modelling in the study by Voyant et al. (2013). Comparisons against solo ARMA and solo ANN models showed an improvement of 0.9–3% in forecast accuracy which was considered insufficient to justify the hybrid model's complexity (Voyant et al., 2013). Further improvement may be achieved by using geographical features and forecast data as inputs instead of only historical time series data (Voyant et al., 2013).

Alternatively, the different methods may be used to model the linear and non-linear components in solar irradiance time series data separately before being combined to make the forecast. Ji and Chee (2011) demonstrated that using ARMA to model the linear component and time delay neural network (TDNN) to model the nonlinear component would produce more accurate forecasts than either an individual ARMA model or TDNN model for most of the time.

Benmouiza and Cheknane (2013) produced hourly GHI forecasts by using a hybrid of a MLP ANN and a k-means clustering method that divided data into groups for preprocessing before input to the ANN. The hybrid method was better when compared against an ARMA model (Benmouiza and Cheknane, 2013), but there was no comparison against a solo MLP ANN. The latter comparison would have been useful for indicating any improvement in forecast accuracy caused by adding the clustering method.

Some studies have proposed combining satellite-based CMVs with other methods to forecast GHI. Miller et al. (2012) proposed combining geostationary satellite-based cloud images with wind field data from the GFS to forecast the motion of clouds up to 3 h ahead. The cloud image forecasts could be made from using individual pixels or from a group of pixels. Neither approach had its forecast accuracy evaluated. Lorenz et al. (2012) combined GHI forecasts from satellite-based CMVs and two NWP models in a linear regression model to produce forecasts up to 6 h ahead. Using data from 290 weather stations in Germany, results showed that the hybrid model had the lowest RMSE for all forecasts between 1 and 6 h ahead. At the 3 h ahead forecast horizon, the hybrid model performed 40% better than using only the ECMWF and 27% better than using only satellite-based CMVs. Marquez et al. (2013) proposed using satellite-based CMVs and ground measurements as input to an ANN model to forecast GHI up to 2 h ahead. Using data from a period of mostly cloudy days in the US, the RMSE of the hybrid method was shown to be 50–80% lower than that of a persistence model.

8. DNI forecast accuracy summary

This paper reviewed the reported accuracy of different DNI forecasting methods at various forecast horizons and sky conditions. Based on the results of the reviewed papers, the current best DNI forecast accuracy of each forecast method for appropriate forecast horizons is summarised in Table 7. Different metrics are used to describe the forecast accuracy in Table 7 because not all studies used the same metrics as shown by the gaps in Tables 2–4 and 6. The nRMSE was the most common forecast accuracy metric reported for NWP models whereas for ground-based CMV methods it was RMSE. The DNI forecasting methods most accurate for each forecast horizon are in line with forecasting methods suggested in Table 1.

The robustness of this summary is limited by the following reasons. Firstly, the use of different metrics in different studies causes difficulty in fairly comparing all the results from different studies. Hence, not all studies reviewed are able to be considered for inclusion in the summary. Secondly, there are few studies about the DNI forecast accuracy of TSA-based methods as shown in Table 3. This makes it difficult to verify the best DNI forecast accuracy. Thirdly, the distribution of weather conditions in the testing data of different studies may vary. All DNI forecasting methods have higher forecast accuracy in clear sky conditions compared to cloudy conditions. Therefore a testing data set with a high proportion of clear sky days will show higher average DNI forecast accuracy compared to a set with a high proportion of cloudy days.

One solution to increasing the robustness of this summary would be to create a standardised set of high quality data to fairly compare DNI forecast accuracy from different methods. An approach to develop a high quality DNI data set from ground and satellite measurements has been suggested by Meyer et al. (2011). The DNI data set was proposed for judging CST plant development feasibility and potentially could also be used to evaluate DNI forecasting methods. Besides that, it is recommended that a uniform set of metrics be adopted to evaluate forecast accuracy. The use of RMSE, MAE and MBE is proposed by Kostylev and Pavlovski (2011). However, the MBE of forecasts can mostly be corrected by post-processing and the RMSE and MAE are criticised for being unable to relate the spread of forecast error to the variability of the test data (Coimbra et al., 2013). To replace them, a time horizon invariant (THI) metric calculated from forecast accuracy uncertainty and test data variability is proposed (Coimbra et al., 2013). Describing DNI forecast performance in terms of test data variability would also allow the results from different test sets to be compared more fairly.

9. Concentrated solar thermal output forecasting

Forecasts of DNI can be converted into forecasts of CST output by using a CST plant model. This forecast information at different forecast horizons can be used by a CST plant operator to optimise plant operation. For example, forecasts up to 2-days ahead may be used to determine whether revenue can be increased by storing energy for use during a later period of higher electricity prices and lower DNI intensity. Alternatively, the stored energy may be used to maintain output during unexpected drops in DNI which prevents the CST plant detrimentally affecting grid reliability and avoids the subsequent penalty. Besides that, forecasts up to 5-min ahead may be used to predict possible sharp increases or decreases in incident

Table 7
Summary of best DNI forecast accuracy for appropriate forecast horizons.

Forecast method	Best DNI forecast accuracy for given horizon						Notes	References
	5 m	10 m	1 h	1 d	2 d	3 d		
Persistence	~3 W/m^2 RMSE	~3 W/m^2 RMSE					Clear sky conditions only	Quesada-Ruiz et al. (2014)
Ground-based CMV	~10–~370 W/m^2 RMSE	~10–~350 W/m^2 RMSE					All sky conditions	Quesada-Ruiz et al. (2014)
Ground-based CMV input to ANN	88.6 W/m^2 RMSE	103.3 W/m^2 RMSE					All sky conditions	Chu et al. (2013)
Feed-forward ANN			0.9834 correlation coefficient				All sky conditions	Mellit et al. (2010)
Satellite image to DNI conversion			21.67–42.24% nRMSE				Depends on conversion process	Nonnenmacher et al. (2014), Eissa et al. (2013), Vignola et al. (2007) and Schillings et al. (2004)
NWP				60–61% nRMSE	41.7–62% nRMSE	62–63% nRMSE	All sky conditions and depends of NWP model	Lara-Fanego et al. (2012a, 2012b) and Wittmann et al. (2008)
NWP				5.9–31.2% nRMSE	17.4–31.2% nRMSE		Clear sky conditions only and depends on NWP model	Lara-Fanego et al. (2012a), Ruiz-Arias et al. (2012), Breitkreuz et al. (2009) and Wittmann et al. (2008)
NWP with post-processing				31.2–33.2% nRMSE	56–77% nRMSE		All sky conditions and depends of NWP model and post-processing method	Marquez and Coimbra (2011) and Kraas et al. (2013)

DNI so that CST plant operation can be adjusted to minimise or mitigate the effect of potential thermal shock.

This paper will review the application of DNI forecasting to forecast CST output and optimise CST plant operation. This was tested by Wittmann et al. (2008) who used a small sample of data from July 2003 and Kraas et al. (2013) who used more data covering the period July 2007–December 2009. Both research papers used NWP models and persistence to obtain DNI forecasts 2-days ahead at hourly resolution. Wittmann et al. (2008) used 2 separate NWP models which were the AFSOL and the ECMWF combined with the Skartveit and Olseth global-to-diffuse model to obtain DNI. The ECMWF was combined with the High-resolution Limited Area Model (HIRLAM) by Kraas et al. (2013) and MOS was used to post-process the output from both NWP models to obtain DNI. Both used physical models of parabolic trough CST plants to convert the DNI forecasts to CST output forecasts (Andasol-1 by Wittmann et al. (2008) and Andasol-3 by Kraas et al. (2013)).

Kraas et al. (2013) calculated penalties incurred from generating electricity above or below the amount committed to the day-ahead market as determined by CST output forecasts. The total penalty amount from NWP-based forecasts was 47.6% less than that from persistence-based forecasts (Kraas et al., 2013). This is consistent with the verification results in the same paper that showed the DNI forecast accuracy of ECMWF-HIRLAM-MOS was better than 2-day persistence (Kraas et al., 2013). Wittmann et al. (2008) used CST output forecasts to maximise revenue by favouring electricity sales during periods of high prices. The results showed that during 2 consecutive clear sky days the AFSOL-based and persistence-based CST output forecasts produced similar maximum revenue, whereas during 3 consecutive cloudy days the ECMWF-based and persistence-based CST output forecasts produced similar maximum revenue (Wittmann et al., 2008). The good performance of the persistence forecast was explained by the similar solar irradiance profiles for the consecutive clear sky and cloudy days. If more testing days were used, then results would most likely show the NWP-based forecasts provide higher revenue than the persistence forecast because DNI forecast accuracy has been shown to be higher for NWP models compared to persistence (Kraas et al., 2013; Lara-Fanego et al., 2012a, 2012b). The results were reported in economic units because the investigations were about the use of CST output forecasts to operate the CST plant in an electricity market. The results show that higher forecast accuracies achieve better economic outcomes because the TES will be used more effectively to increase revenue and fewer penalties will be paid for generation deviations.

Sky conditions affect DNI forecast accuracy and the effect on CST output forecast accuracy was shown in the results of the studies. DNI forecasts from AFSOL were shown to be more accurate than the ECMWF in clear sky conditions (Breitkreuz et al., 2009). This correlated with higher revenue being earned by using AFSOL-based forecasts in clear sky conditions whereas in cloudy conditions higher revenue was earned by using ECMWF-based forecasts (Wittmann et al., 2008). The highest DNI forecast accuracy was achieved on days with high irradiation levels and uniform sky conditions which was when the greatest penalty amount reductions occurred (Kraas et al., 2013).

Besides identifying methods to improve forecast accuracy, further research in CST output forecasting should investigate the use of CST output forecasts in different electricity markets. This is because different market regulations may affect the value of information at different forecast horizons. For example, generation bids placed in the day-ahead market may be changed every 5 min in the Australian NEM whereas there are only 6 chances per day to make changes in the Spanish electricity market (Elliston and MacGill, 2010). CST output forecasts at shorter horizons, such as 5–10-min ahead or 1-h ahead, may prove to have higher value in the Australian market than the Spanish market. This also shows that using CST output forecasts at shorter horizons to update generation bids in the day-ahead market should be considered in future studies. It would be useful for evaluations of validated CST plant models to be published so that the effects of modelling accuracy, if any, on CST output forecast accuracy can be identified.

10. Conclusion

Papers about DNI forecast accuracy were reviewed and the results were summarised to show the best accuracy that could be achieved by individual forecasting methods for appropriate forecast horizons. The results partially supported the recommended forecasting methods for each forecast horizon shown in Table 1 when applied to DNI forecasts. When forecasts are up to 10 min ahead, a persistence forecast is best during clear sky conditions whereas ground-based CMVs should be used if it is cloudy or overcast. NWP models should be used to produce forecasts more than 5 h ahead. The application of TSA methods and satellite-based CMVs for 1-h ahead DNI forecasts had no support because the former had a single result and the latter had no results of forecast accuracy.

Future research in DNI forecasting should investigate the use of post-processing because it was shown to improve accuracy of DNI forecasts from ground-based CMVs and NWP models. Besides post-processing, combinations of other forecasting methods have been shown to improve GHI forecast accuracy. Therefore other hybrid models should also be researched for DNI forecasting. The DNI forecast accuracy from TSA methods and satellite-based CMVs should be evaluated. As both methods are recommended for 1-h ahead forecasts, research should also determine conditions under which either method is more accurate. To help improve the robustness of the summary, studies should use the same metrics to report DNI forecast accuracy because it will allow results from different studies to be fairly compared. Possible metrics are the THI metric as well as the currently common RMSE, MAE and MBE. The THI metric considers the variability of the test data which allows results evaluated from different test data sets to be compared fairly. If the THI metric is not used, then using a common high quality test data set to evaluate forecast accuracy would similarly allow results to be fairly compared.

DNI forecast information can be used by a CST plant to pre-empt possible imminent thermal shocks and sudden losses in generation and make plans to reduce their negative impacts instead of reacting to them. The DNI forecasts can also be used with CST plant models to forecast the CST plant output. These forecasts can be used to determine an operation strategy that maximises profit from increased sales at higher prices or minimising penalty charges by reducing the difference between actual output and forecast output. The application of CST output forecasting can help make CST plants more financially attractive to deploy and the network benefits of CST plants relative to PV plants can be achieved. However, there are few papers about using CST output forecasting to determine CST plant operation and more research is required. Future research should also consider the value of CST output forecast information in different markets because market regulations may affect the value. In addition, the use of shorter term forecasts should be considered especially in markets that allow dispatch offers to be frequently updated. The evaluation of CST plant models may help identify any effects that CST plant modelling accuracy has on CST output forecast accuracy.

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