Grey-Box Modeling for Photo-voltaic Power Systems using Dynamic Neural-Networks

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***Abstract*—There exists various ways of modeling and forecasting photo-voltaic (PV) systems. These methods can be categorized, in board-way, under either definite equations models (white or clear-box) or heuristic data-driven artificial intelligence models (black-box). The two directions of modeling pose a number of drawbacks. To benefit from both worlds, this paper proposes a novel method where clear-box model is extended to a grey-box model by modeling uncertainities using focused time-delay neural network models. The grey-box or semi-definite model was shown to exhibit enhanced forecasting capabilities.**

Keywords – Photovoltaic, renewable energy, neural networks, grey-box modelling

I. Introduction

Photovoltaic (PV) energy is now positioned amongst the top three new power generation means installed in Europe and is expected to remain so [1]. Nonetheless, like other RES, PV sources pose a number of integration challenges such as the impact on voltage profile, impact on operational costs of the grid, regulation and load-following requirements [2]. Advance knowledge of the expected yield from PV sources will help tackle these challenges, to allow for proper planning of available generation sources and provide insights into the impact of PVs on the power network. However, the forecasting task requires non-primitive techniques, as power yield from PVs is intermittent in nature. The intermittent and non-linear characteristics of PV data is due to an interplay of various factors such as the variability in sunrise and the amount of sunshine, sudden changes in atmospheric conditions, cloud movements and dust [3][3]. The PV power data can thus be viewed as consisting of two parts: the deterministic and the stochastic parts.

Various mathematical models that capture physics of PVs or clear-box models are possible but are inaccurate or impractical for large systems [4][4]. However, clear-box models possess various strengths such as that their structures are of physical meaning and usually have fewer parameters to estimate [5].

On the other hand, data-driven or black-box models based on statistics or artificial-intelligence are popular methods as they are simple and easy to use. Dynamic Neural Networks (DNNs) such as the 'Focused Time-Delay Neural Networks' (FTDNN) and the 'Distributed Time-Delay Neural Networks' (DTDNN) [6] have been studied for PV forecasting. These methods can handle nonlinear time-series data that are dynamic in nature. However, black-box models require good data for proper modeling – both quality and quantity. It is also difficult to design due to large number of parameters and lack of a systematic way to arrive at an optimal structure.

This paper proposes novel grey-box model for photovoltaic power forecasting. Clear-box models are enhanced by modeling forecasting error using black-box dynamic neural networks; hence grey-box model resulting. The grey-box approach was shown to enhance the forecasting accuracy compared with definite clear-box model.

II. Background

There are various physical principle based models developed for PV modules [7],[8]. However, these equations require numerical solution and thus are sometimes replaced with simplified equations that relate the power output with the efficiency of the system and variation in radiation and temperature [9], [10]. These equations are basically a translation of performance measurement from standard test measurements (STC; Air Mass 1.5 spectrum with global irradiance (G=1000W/m^2 and module temperature = 25^{o}C). One famous simple method is that of Osterwarld [9] which can be described as follows:

$$P_m = P_{mo}.\frac{G}{G_o}[1-\gamma.(T-25)] \quad (1)$$

Where P_m is the cell/module maximum power (W), P_{mo} is the cell/module maximum power in STC (W), γ is the cell maximum power coefficient (^{o}C^{-1}) which ranges from -0.005 to -0.003 ^{o}C^{-1} in crystalline silicon and can be assumed to be -0.0035^{o}C^{-1} with good accuracy.

Another version of equation (1) is given below [9][10]:

$$P_{MPP} = G_t.A_a.\eta.[1+K_T(T_C-T_{ao})] \quad (2)$$

$$\eta = \eta_m \eta_{dust} \eta_{mis} \eta_{DCloss} \eta_{MPPT}$$

G_t is the global irradiance on the titled surface in W/m^2, K_T is thermal derating coefficient of the PV module in %/^{o}C, A_a area of the PV array in m^2, η_m is the module efficiency, η_{dust} is 1-the fractional power loss due to dust on the PV array, η_{mis} is 1-the fractional power loss due module mismatch, η_{DCloss} is 1-the fractional power loss in the dc side, η_{MPPT} is 1-fractional power loss due to the MPPT algorithm, T_C is the cell temperature in ^{o}C, T_{ao} is the ambient temperature at STC conditions in ^{o}C. The ac power of the PV system is then estimated by using manufacturer's efficiency curve of three phase inverter.

The simplified PV equation adopted for this work is given below [11]:

$$P_{pv} = G_t\ .\ A.\eta_{PV}\ .\ \eta_{loss}\ .\ \eta_{inv}\ [1-\gamma.(T_m-25)] \quad (3)$$

In this equation, miscellaneous losses including dust were lumped together in η_{loss}; PV cell efficiency η_{PV} and MPPT or

inverter efficiency η_{inv} are kept separate. T_m is the module temperature.
The aforementioned equations require detailed modeling of the global irradiance falling on a tilted surface G_t as outlined in the next section.

A. *Irradiance Falling on a Tilted Surface: Hottel's equations*

There exist various models for calculating irradiance on a tilted panel. However, some of these models rely on other meteorological data such as total irradiance on horizontal surface, diffuse irradiance on horizontal surface, beam normal irradiance. Models of this type include those of Perez [12] and Klucher [13]. Others are not accurate in cloudy conditions, Temps and Coulson [14], or in clear skies, Liu and Jordan [15]. Simple models that require no additional solar measurements were proposed by Hottel [4][16],[17] and are adopted in this work. Description of this model is outlined below:
To explain irradiance equations, it is important first to present equations of solar angles as they are a pre-requisite to calculate solar equations.
The derivation of irradiance on tilted surfaces requires the calculation of different solar angles. These equations are mainly based on [17] Solar angles that define the position of the sun with respect to a PV plane are illustrated in Fig. 1.

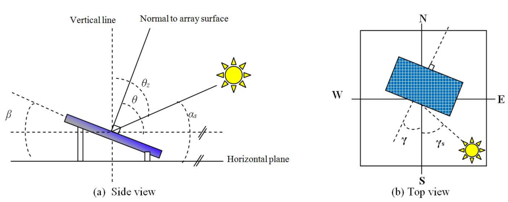

Figure 1. Solar angles of a PV plane

β = Tilt angle of array.

A_s = Solar elevation (altitude): the angle between the horizontal and line to the sun.

θ = Angle of incidence: the angle between normal to array surface and direct irradiance on a tilted surface (or line to the sun).
θ_z = Zenith angle: the angle between vertical line to earth and line to the sun.
γ_s = Solar azimuth angle: the angular displacement from south of the projection of beam radiation on the horizontal plane. Displacements east of south are negative and west of south are positive.
γ = Surface azimuth angle: the deviation of the projection on a horizontal plane of the normal to the surface from the local meridian, with zero due to south, east negative, and west positive; $-180^{o} \leq \gamma \leq 180^{o}$.
The zenith angle θ_z can be written as follows:

$$cos\theta_z = cos\varphi . cos\delta . cos\omega + sin\varphi . \sin\delta \tag{4}$$

Where
δ is the declination angle given by

$$\delta = 23.45 . sin\left(360 . \frac{284+n}{365}\right) \tag{5}$$

φ is the latitude in degrees is the angular location north or south of the equator, north positive; $-90^{o} \leq \varphi \leq 90^{o}$.
ω is the hour angle which is the angular displacement of the sun east or west of the local meridian due to rotation of the earth on its axis at 15^{o} per hour; morning negative, afternoon positive. The hour angle can be calculated by first calculating the solar time given by:

$$\text{Solar time} = \text{standard time} + 4.(L_{st} - L_{loc}) + E \tag{6}$$

Where L_{st} is the standard meridian for the local time zone, L_{loc} is the longitude of the location in question, and longitudes are in degrees west. The parameter E is the equation of time in minutes and is given by:

$$\begin{aligned} E = 22.92(0.000075 &+ 0.001868 \cos B \\ &- 0.032077 \sin B \\ &- 0.014615 \cos 2B \\ &- 0.04089 \sin 2\ B) \end{aligned} \tag{7}$$

Where B is calculated as follows:

$$B = (n-1)\frac{360}{365} \tag{8}$$

The hour angle ω can then be written as:

$$\omega = (Solar\ time - 12).15 \tag{9}$$

Furthermore, the incidence angle θ can be calculated using the following formula:

$$\begin{aligned} \cos\theta = sin\delta\ sin\varphi\ cos\beta &- sin\delta\ cos\varphi\ sin\beta\ cos\gamma \\ &+ cos\delta\ cos\varphi\ cos\beta\ cos\omega \\ &+ cos\delta\ sin\varphi\ sin\beta\ cos\gamma\ cos\omega \\ &+ cos\delta\ sin\beta\ sin\gamma\ sin\omega \end{aligned} \tag{10}$$

The solar irradiance falling on a tilted surface, G_t (W/m^2) is composed of three parts: the direct irradiance G_{tb} (W/m^2), the diffuse irradiance G_{td} (W/m^2) and reflected irradiance G_{tr} (W/m^2), i.e.

$$G_t = G_{tb} + G_{td} + G_{tr} \tag{11}$$

The three components of irradiance can be calculated as follows:

$$G_{tb} = G_{on}\ \tau_b \cos\theta \tag{12}$$

$$G_{td} = G_{on} \cos\theta_z\ \tau_d . \frac{(1+\cos\beta)}{2} \tag{13}$$

$$G_{tr} = \rho . G_{on} \cos\theta_z\ \tau_r . \frac{(1+\cos\beta)}{2} \tag{14}$$

Where G_{on} is the extraterrestrial radiation (W/m^2), τ_b is the beam atmospheric transmittance, τ_d is the diffuse atmospheric transmittance, and τ_r is the reflected atmospheric transmittance. G_{on} can be calculated as follows:

$$G_{on} = G_{sc} . \left(1 + 0.033 . cos\left(\frac{360.d}{365}\right)\right) \tag{15}$$

Where G_{sc} is 1367±5 W/m2 and d is the day of the year.
Details of the atmospheric transmittances τ_b, τ_d, and τ_r calculations and formulas can be found in [4][17][18].

III. Proposed Idea: Grey Box PV model

The idea proposed in this paper is to model uncertainties or forecasting errors, due to sudden atmospheric changes, using black-box models. Owing to the capability to handle nonlinearity and time-series data and absence of requirement for transformation to stationary data [19], Dynamic Neural Networks (DNNs) were used; specifically 'Focused Time-Delay Neural Networks' (FTDNN) was explored [6]. This is demonstrated in the Fig. 2 where clear box past power values are compared with actual PV power to find the error or uncertainties in modeling. The overall strucuture of the model includes clear and black box model thus resulting in a novel grey-box model.

The black-box FTDNN part was trained using past PV power error for days 5-20 in July 2010 (summer) and 5 days 5-20 in January 2011 (winter). The PV power of masdar is of an hourly interval resolution. A similar earlier approach [6] to was used in building a global PV FTDNN model. Delayed error inputs of D = [1 : 10] are fed to the network, i.e.,

$$y(n) = f(\,u(n\text{-}1), u(n\text{-}2), .., u(n\text{-}10))$$

Eight neurons were chosen for the hidden layer. The network was tested for one to several steps ahead for the entire system. Five consecutive days in both July 2010 and January 2011 were used to test the models and to compute the average forecasting *RMSE* ($RMSE_{test}$). Future errors forecasted by FTDNN are deducted from future PV power forecasted by clear-box model to produce final grey-box future forecasts.

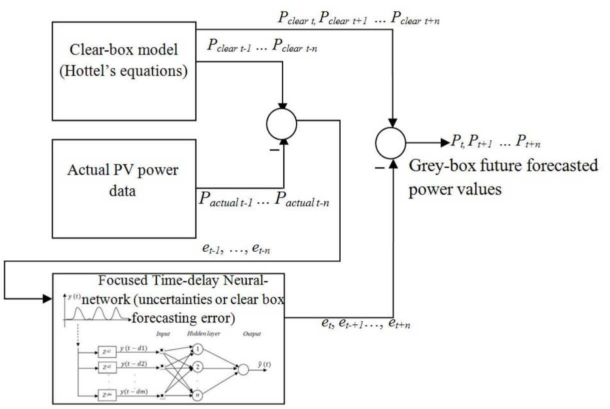

Figure 2. Grey-box PV forecaster

IV. Tested PV System: Clear Box Parameters

The test-bed system, located in Masdar city close to Abu Dhabi airport, is a 220,000 m^2, 10MW PV plant [20][20], [21][21]. The plant consists of around 87,777 panels: 17,777 are polycrystalline and 70,000 are thin-film from Suntech and First Solar respectively. The parameters for the model were taken from data sheets of panels [22][23] and from engineers in Masdar and are given in Table I. These are the parameters with best engineering values taken from data sheet and engineers of the PV system. The model with these values will be referred to as the *clear-box* model.

TABLE I. PARAMETERS OF **CLEAR BOX PV MODEL**

Longitude	54.45°
Latitude	24.43°
Altitude	1 m
Area of SunTech panels, A_{Sun}	30,911 m^2
Area of First Solar Panels, A_{First}	72,500 m^2
Miscellaneous losses (Suntech group), η_{loss_Sun}	5% (i.e. η_{loss_Sun} = 95%)
Miscellaneous losses (Firstsolar group), η_{loss_First}	6% (i.e. η_{loss_First}= 94%)
Efficiency of PV panel (Suntech), η_{PV_Sun}	11%
Efficiency of PV panel (Firstsolar), η_{PV_First}	10%
Efficiency of Inverter (Suntech panels), η_{inv_Sun}	95%
Efficiency of Inverter (Firstsolar), η_{inv_First}	94%
Temperature coefficient (%/C°), γ	0.5%
r_o	0.27
r_1	0.29
r_2	0.32
Albedo, ρ	0.35

The clear irradiance model based on Hottel's equations (4)-(15) was simulated; one year irradiance values are plotted in Fig. 3. These values represent clear-sky values expected to fall on Masdar PV panels.

To measure the accuracy of all models, the Root Mean Square Error (*RMSE*) between actual and identified model in terms of PV power output was calculated. The *RMSE* is calculated as follows:

$$RMSE = \sqrt[2]{\frac{\sum_{i=1}^{i=n}(P_a{}^i - P_p{}^i)^2}{n}} \qquad (16)$$

Where P_i^a is the i^{th} actual output power, P_i^p is the i^{th} predicted power by model, and n is number of data points.

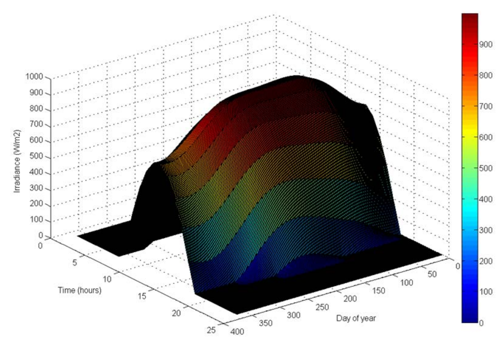

Figure 3. Clear-day irradiance model for one year

V. Results and Discussion

The proposed novel gre-box approach, Fig. 2, was applied to forecast the power yield of Masdar PV system, section IV. Comparison between the accuracy of the clear-box model versus grey-box models is given in table II and Figs. 4 – 5. RMSE values and the plots show how the grey-box approach has produced forecasts that depict closer the actual power yield. The adaptive black-box inserted in the model has enhanced the adapatation of the model toward sudden changes in the environment. The step-ahead forecasts are more accurate using grey-box are more accurate than day ahead however can exihibit some oscillatory behavior with sudden changes in historical values of power, Fig. 5.

TABLE II. Average RMSE values for testing the models (5 days ahead in Winter (January) and Summer (July)

Model	$RMSE_{test}$ (kW)	Imporvement (%)
Clear-box	1633	-
Grey-box (hour (step) ahead)	670	59%
Grey-box (day ahead)	1066	35%

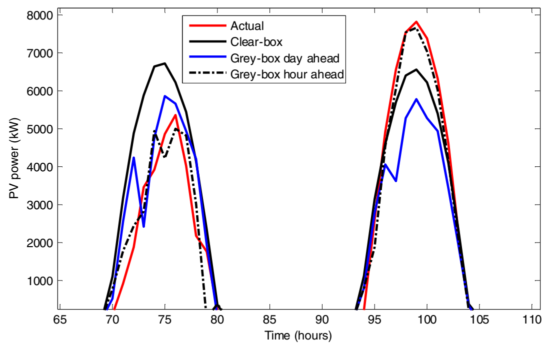

Figure 4. PV power forecasts, January 2011: Sample two days 23-24 January 2011.

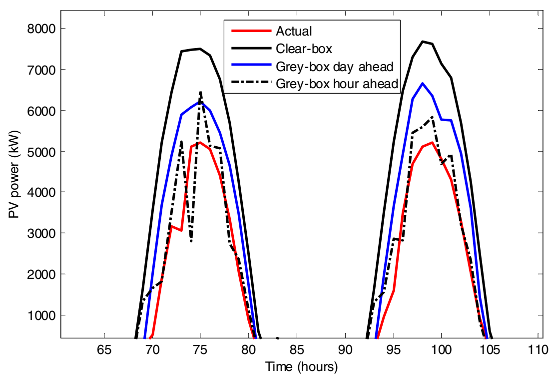

Figure 5. PV power forecasts, July 2010: Sample two days 23-24 July 2010.

VI. CONCLUSION

The enhancement of PV power forecasts using grey-box models was discussed in this paper. Dynamic neural networks were inserted in definite equations of PV power to handle error in forecasts. These errors usually are resulting from sudden atmospheric changes. The grey-box showed improved adaptation to changes and the results confirmed the validity of the approach for both step ahead and several steps ahead forecasts.

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