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Scenario based technique applied to photovoltaic sources uncertainty

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ABSTRACT

There is an increasing need to forecast power generated by photovoltaic sources in day-ahead power system operation. The electrical energy generated by these renewable sources is an uncertain variable and depends on solar irradiance, which is out of control and depends on climate conditions. The stochastic programming based on various scenarios is an efficient way to deal with such uncertainties. In this research paper, the long term hourly recorded irradiance data in 15 past years are applied to generate the next day's irradiance scenarios. Irradiance determines the operating point of PV panel as well as the generated electrical power. Also, the scenario generation method based on autoregressive and moving average time series is proposed. For decreasing the number of scenarios, backward reduction based on Kantorovich distance is applied. The obtained results confirm the accuracy and ability of the proposed method in forecasting the relevant data.

Keywords: Photovoltaic, Uncertainty, Stochastic, Scenario, ARMA.

1. Introduction

In recent years, using renewable energy sources has extensively increased. This is mainly due to reduction of fuel resources and simultaneously low operation costs and environmental impacts as well as less pollution of renewable resources. Solar energy is the most prevalent renewable source because of its availability. There is a need in day-ahead power system operation to forecast the amount of electrical power generated by each source. Uncertainty in the amount of photovoltaic cell output power, makes the power system operation encounter with some challenges. The amount of produced power by photovoltaic source depends on solar irradiance. Prior investigations have implemented diverse approaches to solar irradiance forecasting. They could be divided into two general categories: weather-based (sky conditions) as physical methods [1-3], and methods based on recorded historical data. As a sample ref. [4] applied Markov Switching Model for point estimation irradiance forecast based on historical data.

In another classification, solar forecasting methods are classified into five classes [5] concluding: time series; regression; numerical weather prediction; machine learning; and image-based forecasting.

A method is classified as a time series method if it falls in one of three families of models, namely, autoregressive integrated moving average (ARIMA), exponential smoothing (ETS), and generalized autoregressive conditional heteroskedasticity

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(GARCH)[5]; Regression is a statistical process for estimating the relationships among variables [5]; Numerical Weather Prediction (NWP) models directly simulate the irradiance fluxes at multiple levels in the atmosphere, separately considering the shortwave and longwave parts of the solar spectrum [5]; Machine learning is a branch of artificial intelligence [6]. Artificial Neural Network (ANN) is one of machine learning methods applied to forecast solar irradiance [3,7,8]; In image-based forecasting sky or earth, imagery can add predictive skill because it provides advance warning of approaching clouds at a lead time of several minutes to hours. This lead time far exceeds that of a single ground-based radiometer [5]. Sky image-based forecasting methods suffer from short-time forecast duration up to one hour [9].

In this context, Ref. [10] applied novel semi-empiric models based on Angstrom-Prescott (A-P) equations, and ref. [11] applied the Autoregressive (AR) model based on HelioClim-3 images to forecast irradiance, but both were used for short-time prediction up to one hour.

The literature survey reveals that all of the mentioned references are based on applying the point estimation methods, which are belong to deterministic forecasting category. Regarding stochastic nature of physical phenomena, even the most extreme models can not accurately predict the amount of solar radiation. Stochastic analysis based on scenarios introduced in this study re capable to be applied to day-ahead stochastic forecasting of solar irradiance, based on historical data. They are mainly free from two limitations of the mentioned point estimate deterministic methods: restriction of forecasting duration; and the importance of the precision of forecasted point.

Actual recorded historical amount of irradiance in the same days of the past years are available. Global Horizontal Irradiance (GHI) is the total amount of irradiance received on a horizontal surface is applied. These are datum for forecasting tomorrow's irradiance scenarios in each hour. Monte Carlo simulation method (MCS) can be easily applied for this purpose, but the relevant high amount of calculations is not reasonable for such a problem with high amount of data. In this paper, autoregressive and Moving Average (ARMA) time series based analysis, has been applied for generating scenarios. This scenario generation method will have a lower computational burden at the same high precision.

These scenarios are possible amounts of the uncertain variable with known possibilities. A high number of scenarios brings a high amount of calculations. Certainly there are some scenarios with very low possibility and those relevant scenarios results' will be very close together. Therefore, scenario reduction procedure is needed to eliminate such low effect scenarios to decrease the calculations burden.

Also, we applied the backward reduction based on Kantorovich distance [12] for eliminating same and low probability scenarios. This scenario-based photovoltaic source uncertainty analysis process can be applied in network stochastic programming to fraction of stochastic framework to estimated deterministic parts.

The reminder of this paper is organized as follows. Section two describes the applied methods in this work. That contains the scenario generation and reduction methods that applied, and the method of converting irradiance to PV cell output power. the irradiance data from Denver, Centennial measurement station applied to forecast tomorrow irradiance as a case study. The results in part Ⅲ confirm the robustness and accuracy of the proposed method.

2.Mathematical Formulation

2.1 Scenario generation

For generating the scenarios, time-series based method, ARMA, is applied. The importance of ARMA processes is due to the fact that every stationary process can be approximated arbitrarily well by an ARMA process [13]. An ARMA(p, q) process Y is mathematically expressed as [14]:

$$y_t = \sum_{i=1}^{p} \phi_i y_{t-i} + \varepsilon_t - \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \qquad (1)$$

In which the index t shows time step, ε_t stands for an uncorrelated Norma stochastic process with mean zero and variance σ_ε^2, referred as white noise, innovation term, or error term, $WN(0,\sigma^2)$. p and q show the order of $AR(p)$, and $MA(q)$. The procedure to generate a set of scenarios for stochastic process Y is based on the sampling of the error terms from relevant distribution $\varepsilon_t \sim N(0,\sigma^2)$.

This process will be continued until the predefined number of scenarios are generated. The small number of generated scenarios reduces the accuracy of response as well as the final estimation. On the other hand, high number of scenarios bring heavy data computations. In order to achieve the correct answer and reduce the computational burden at the same time, scenarios describing all the circumstances must be screened. That means that scenarios with a very low probability and similar scenarios must be eliminated. This requires defining a correct process to reduction of the same scenarios.

2.2 Scenario Reduction

In the following, the reduction algorithm, which is based on "Kantorovich Distance", is detailed [15]. Let n_T denotes the number of stages in the optimization problem and n_S determines the number of scenarios. It is assumed that all scenarios have a common root in a one-stage tree where branching occurs only after the root node. A scenario, $\xi^{(i)}, i \in \{1,\dots,n_S\}$ is defined as a sequence of nodes of the tree as follows:

$$\xi^{(i)} = (\eta_0, \eta_1^{(i)}, \dots, \eta_{n_T}^{(i)}), i = 1,\dots,n_S \tag{2}$$

$\eta_0 = \eta_0^{(i)}, \forall_i$ denotes the root of all scenarios, and $\eta_j^{(i)}$ determines the leaf of scenario i within the scenario tree on stage $j, j \in \{1,\dots,n_T\}$. For each node, $\eta_j^{(i)}$, a vector $P_j^{(i)} \in R^{n_j^P}$ of parameters is given. Each node on stage j has n_j^p parameters. The probability to get from stage j to stage $j+1$ within the scenario i, from $\eta_j^{(i)}$ to $\eta_{j+1}^{(i)}$, is denoted by $\pi_{j,j+1}^{(i)}$. Thus the probability for the whole scenario $\xi^{(i)}$ is given by:

$$\pi^{(i)} = \prod_{j=0}^{n_T-1} \pi_{j,j+1}^{(i)} = \pi_{0,1}^{(i)} \tag{3}$$

The distance between two scenarios $\xi^{(i)}$ and $\xi^{(i)}$ is defined as:

$$d(\xi^{(i)}, \xi^{(j)}) = \left(\sum_{k=0}^{n_T} (P_k^{(i)} - P_k^{(j)})^2 \right)^{1/2} \tag{4}$$

The relevant algorithm for deleting scenarios is detailed in below. This deleting procedure is applied iteratively, deleting one scenario in each step and consequently changing the probabilities of other scenarios, until a given number of scenarios is remaining.

(a)Determining the scenarios to be deleted: Remove scenario $\xi^{(s^*)}$, $s^* \in \{1,\dots,n_S\}$ satisfying:

$$\pi^{(s^*)}.\min_{s\neq s^*}\{d(\xi^{(s)},\xi^{(s^*)}\} = \min_{m\in\{i,\dots,n_S\}}\{\pi^{(m)}.\min_{n\neq m}[d(\xi^{(n)},\xi^{(m)})]\} \tag{5}$$

According to the defined distance, scenarios that are near to the others will be deleted; also, the scenarios having a small probability are more likely to be deleted than others.

(b) Changing the number of scenarios: $n_S := n_S - 1$

(c) Changing the probability of the scenario $\xi^{(\bar{s})}$, that is the nearest to $\xi^{(s^*)}$:

$$d(\xi^{(\bar{s})}, \xi^{(s^*)}) = \min_{s\neq s^*} d(\xi^{(s)}, \xi^{(s^*)}) \tag{6}$$

Set $\pi_{0,1}^{(\bar{s})} := \pi_{0,1}^{(\bar{s})} + \pi_{0,1}^{(s^*)}$;

This has to be done, as the sum of all probabilities of the remaining scenarios should remain equal to 1 and the only branching occurs at stage 0 at the root node.

(d) Continuing with step (a) as long as $n_s > N$. Otherwise, STOP.

2.3. Irradiance to PV cell output power

A single-diode PV module model [16] is shown in Fig.1. It consists of a current source, a diode, and series and parallel resistances.

PV cell equivalent circuit output current *I*, can be expressed as a function of the module output voltage *V*, as follows [17]:

$$I_V = I_{sc}\left\{1 - C_1\left[\exp\left(\frac{V + \Delta V}{C_2 \cdot V_{oc}}\right) - 1\right]\right\} + \Delta I \tag{7}$$

where:

$$C_1 = \left(1 - I_{mp}/I_{sc}\right)\cdot\exp\left[-V_{mp}/(C_2 \cdot V_{oc})\right] \tag{8}$$

$$C_2 = \frac{V_{mp}/V_{oc} - 1}{Ln\left(1 - I_{mp}/I_{sc}\right)}$$

$$\Delta I = \alpha\left(S/S_{ref}\right)\Delta T + \left(S/S_{ref} - 1\right)\cdot I_{sc}$$

$$\Delta V = -\beta \cdot \Delta T - R_s \cdot \Delta I$$

$$\Delta T = T - T_{ref}$$

$$T = T_A + 0.02 \cdot S$$

α Current change temperature coefficient at reference insolation (Amps/C°),

β Voltage change temperature coefficient at reference insolation (Volts/C°),

I Module Current (Amps),

I_{mp} Module Maximum Power Current (Amps),

I_{sc} Module Short Circuit Current (Amps),

S Total Tilt Insolation (kWh/m^2),

S_{ref} Reference Insolation (kWh/m^2),

R_s Module Series Resistance (Ohms),

T Cell Temperature (C°),

T_A Ambient Temperature (C°),

T_{ref} Reference Temperature (C°),

ΔT Change in Cell Temperature (C°),

V Module Voltage (Volts),

V_{mp} Module Maximum Power Voltage (Volts),

V_{oc} Module Open Circuit Voltage (Volts).

The average power output from a PV cell is calculated using the following equation in the integral form

$$P_{pv} = \int P(I)\cdot f(I)\cdot dI \tag{9}$$

where $f(I)$ is irradiance probability density function.

2.4.Flowchart

The general proposed flowchart concluding the different steps of generating and reducing scenarios from irradiance historical recorded data is shown in Fig.2. Each step described in the following.

Step 1: Input data

Irradiance historical recorded data for each hour of the day used as input data.

Step 2: Weibulll distribution fitting

For 'a' as scale parameter and 'b' as shape parameter, Weibulll probability density function is defined as:

$$f(x|a,b) = b.a^{-b}.x^{b-1}.e^{-(\frac{x}{a})} = \frac{b}{a}.(\frac{x}{a})^{b-1}.e^{-(\frac{x}{a})} \tag{10}$$

The input historical data for each hour is fitted to Weibulll PDF. The reason for selecting the Weibulll distribution is due to its positive value for positive values of x, and is zero otherwise. Furthermore, it has enough flexibility to match positive irradiance data.

Step 3: The order of ARMA model

The ACF and PACF plots of irradiance historical data for each hour of the day were

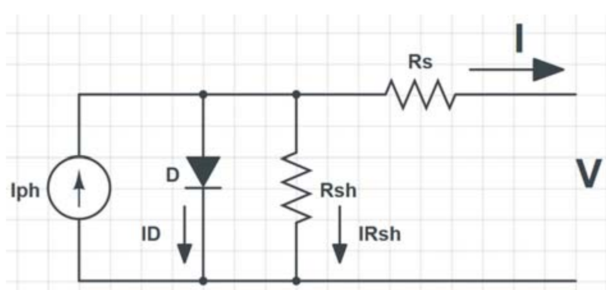

Fig.1. Single-diode model of a PV source including series and parallel resistances

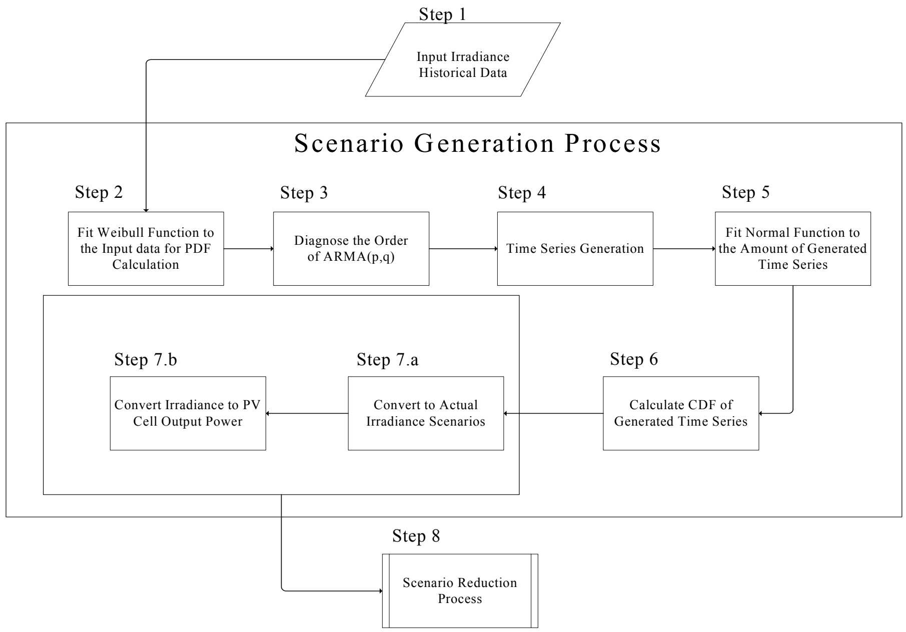

Fig. 2. Flowchart of the generating scenarios from historical data

used to diagnose the order of ARMA(p,q) for each hour.

Step 4:

Ns random samples from white noise as an error term generates Ns time-series amounts as scenarios for each hour.

Step 5: Fitting generated time series

When time-series amounts as scenarios generated, Norma function is fitted as PDF of them. As ARMA time series have Norma distribution.

Step 6: Time series CDF

CDF of generated scenarios is being calculated, based on the PDF calculated in the previous step.

Step 7.a: Scenario transformation

Random irradiance scenarios are transformed into actual solar irradiances by distribution transformation. CDF calculated in step 6, came from a Norma distributed PDF of generated time-series amounts. That must be transformed into actual irradiance amounts. Scale and shape parameters in step 2 are applied to take inverse from this CDF. The results are actual irradiance scenarios with Weibulll probability distribution.

Transfer function is:

$$Irradiance = \Phi^{-1}[F_y(Y)] \tag{11}$$

In this transformation $F_y^{(Y)}$ is CDF of generated scenarios from time-series with Norma PDF, and $\Phi\,(\cdot)$ is CDF of actual irradiance historical data with Weibulll PDF. This process is done for each hour of day.

Step 7.b: Irradiance to power

If $E(\frac{W}{m^2})$ be the solar irradiance, since $\frac{E}{E_{ref}} = \frac{S}{S_{ref}}$, it can be applied in Eq.(8). Since based on Table (1), E_{ref}equals to 800(W/m^2), for one hour period S_{ref} will be equal to 0.8(kWh/m^2). That is applied for calculation of T in Eq.(8). Using Eqs. (7), (8), and (9) irradiance scenarios were converted to PV cell output power scenarios.

Step 8: Scenario Reduction

Based on the process described in part Ⅱ.B, scenarios are reduced from 1000# to 10#.

3.Case study simulation

The recorded solar irradiance data as historical data for all days of the year, in all day hours, from 1999 to 2005, is available to the public at the measurement station, Denver/Centennial [18]. So, in this research a special day of 2005 is considered here. August 10, 2005 is selected as the sample day. Due to the dependence of solar irradiance on season and month of the year, applied historical data are based on Table 1. So, there are 159 recorded historical data for each hour of tomorrow to generate scenarios.

Thereafter, generation and reduction of scenarios for day-ahead PV cell output power stochastic programming is done based on available actual historical data.

Parameters of the solar module, supposed to be installed in a microgrid are proposed in Table 2.

Table 1. Historical data

August 5, 1991 until August 15, 1991	11 data for each hour
August 5, 1992 until August 15, 1992	11 data for each hour
August 5, 1993, until August 15, 1993	11 data for each hour
August 5, 1994 until August 15, 1994	11 data for each hour
August 5, 1995 until August 15, 1995	11 data for each hour
August 5, 1996 until August 15, 1996	11 data for each hour
August 5, 1997 until August 15, 1997	11 data for each hour
August 5, 1998 until August 15, 1998	11 data for each hour
August 5, 1999 until August 15, 1999	11 data for each hour
August 5, 2000 until August 15, 2000	11 data for each hour
August 5, 2001 until August 15, 2001	11 data for each hour
August 5, 2002 until August 15, 2002	11 data for each hour
August 5, 2003 until August 15, 2003	11 data for each hour
August 5, 2004 until August 15, 2004	11 data for each hour
August 5, 2005 until August 9, 2005	5 data for each hour

Table 2. Parameters of the solar module, Siemens SM110 [20]

Electrical Parameter	**Value**
Rated power, P_{max} (W)	110
Rated current , I_{mp} (A)	6.3
Rated voltage, V_{mp} (V)	17.5
Short circuit current, I_{SC} (A)	6.9
Open circuit voltage, V_{OC} (V)	21.7
Temp. coefficient of the short-circuit current, (Change of I_{SC} with temperature), α (mA/°C)	+1.2 (+0.04%/°K)
Temp. coefficient of the open-circuit voltage, (Change of V_{OC} with temperature), β (Volts/ C°)	-0.0775 (-0.34%/ K°)
Reference Irradiance, E_{ref} (W/m^2)	1000
Reference temperature, T_{ref} (C°)	25
Ambient temperature, T_A (C°)	20

3.1. Results

Step 1: Input data

Step 2:

Figure 3 shows the histogram of fitting historical data at 12 pm to Weibulll distribution. Here, scale and shape parameters are 856.1658 and 6.0644, respectively. That was done for each hour of the day, and shape parameters extracted.

Step 3: The order of ARMA model

The ACF and PACF for irradiance historical data are plotted to diagnose the order of ARMA(p,q) for each hour of day. That is shown in Fig.4 for 12 pm.

ACF and PACF plot shape changes for each hour of the day is reviewed in Table (3).

Because, the ACF plot shape is geometric and PACF is being zero after 'p' lags, AR model is applied to generate time-series.

for AR (P) model, Eq. (1) will be as:

$$y_t = \sum_{i=1}^{p} \phi_i y_{t-i} + \varepsilon_t \tag{12}$$

Step 4: Time series generation

For simplicity of the problem, AR(4) model is applied. For 12 pm, Φ_1, Φ_2, Φ_3 and Φ_4 are 0.5084, 0.1670, 0.0099 and 0.3022, respectively. MATLAB 'ar' function with the forward-backward approach is applied to estimate the model. The model white noise variance is 9.3091e+3. That was done for each hour of day. AR coefficients and white noise variance extracted for each hour. By taking 1000 random samples from white noise as error term, 1000 time-series amount as scenarios are generated for each hour.

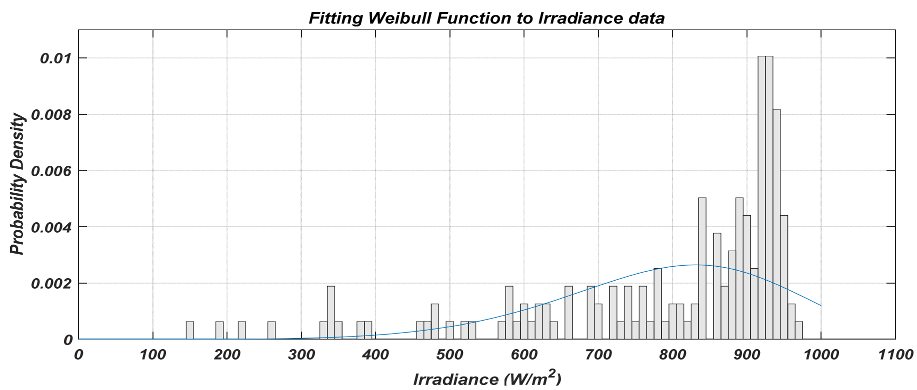

Fig.3. Fitting Weibulll PDF to irradiance historical recorded data at 12 pm

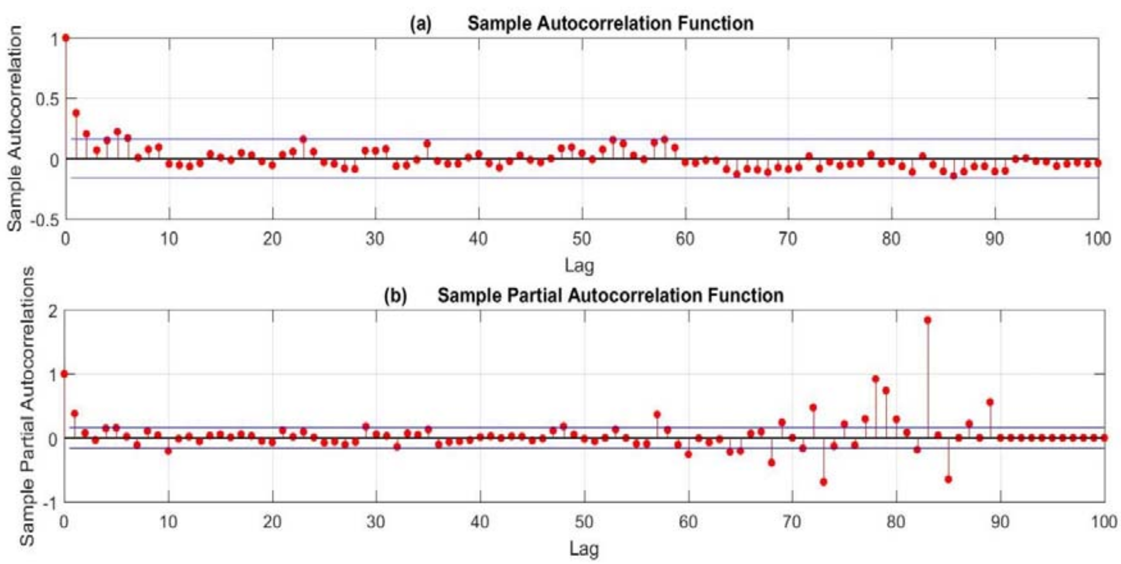

Fig.4. ACF and PACF plot of historical data at 12 pm. (a) ACF, (b) PACF

Table 3. Irradiance historical data ACF and PACF plot shape for each hour of day

PACF significant up to 'p' lags	ACF plot shape	Data for 'H' o'clock
'72'	Geometric	'6'
'86' (79th is dominant)	Geometric	'7'
'87'	Geometric	'8'
'137'	Geometric	'9'
'79' (only 79)	Geometric	'10'
'91'	Geometric	'11'
'89'	Geometric	'12'
'91'	Geometric	'13'
'93'	Geometric	'14'
'84'	Geometric	'15'
'92'	Geometric	'16'
'85'	Geometric	'17'
'93'	Geometric	'18'
'90'	Geometric	'19'

Step 5: Fitting generated time series

After generating time-series amounts as scenarios, Norma function is fitted as PDF of them. For 12 pm, mean and standard deviation are 916.9663 and 180.8115, respectively. That was done for each hour.

Step 6: Time series CDF

Based on the PDF calculated in step 5, CDF of generated scenarios is being calculated.

Step 7.a: Actual irradiance scenarios is shown in Fig.5.

Step 7.b:

PV cell output power generated scenarios is shown in Fig.6.

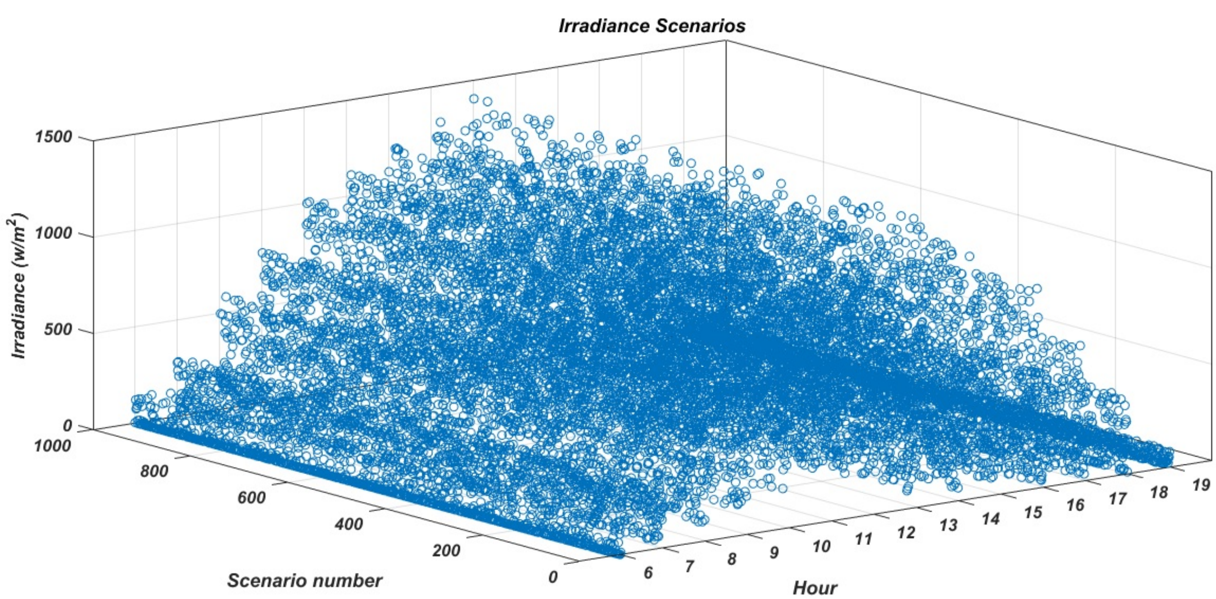

Fig.5. Generated Irradiance scenarios

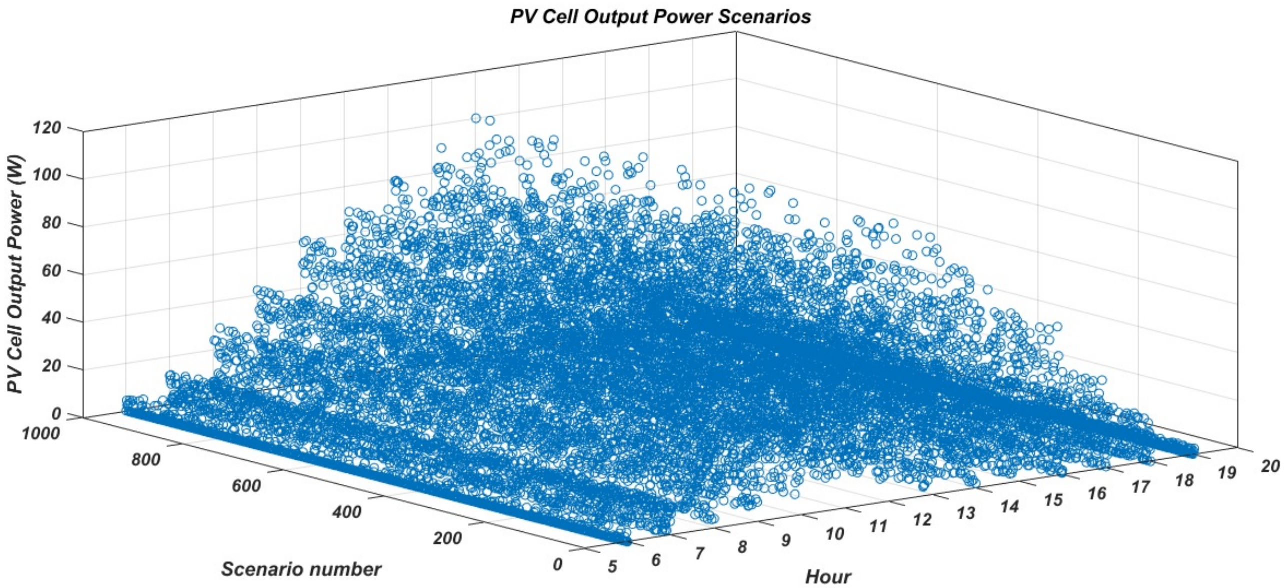

Fig.6. PV cell output power scenarios

Step 8: Scenario Reduction

Irradiance and PV cell output power reduced scenarios are shown in Figs.7 and 8, respectively.

August 10, 2005 actual irradiance amounts are as Table (4). Figure 9 shows irradiance scenarios generated from historical data, and actual hourly measured irradiance amounts in August 10, 2005. It can be seen that there is great accuracy in the method proposed and described in this research.

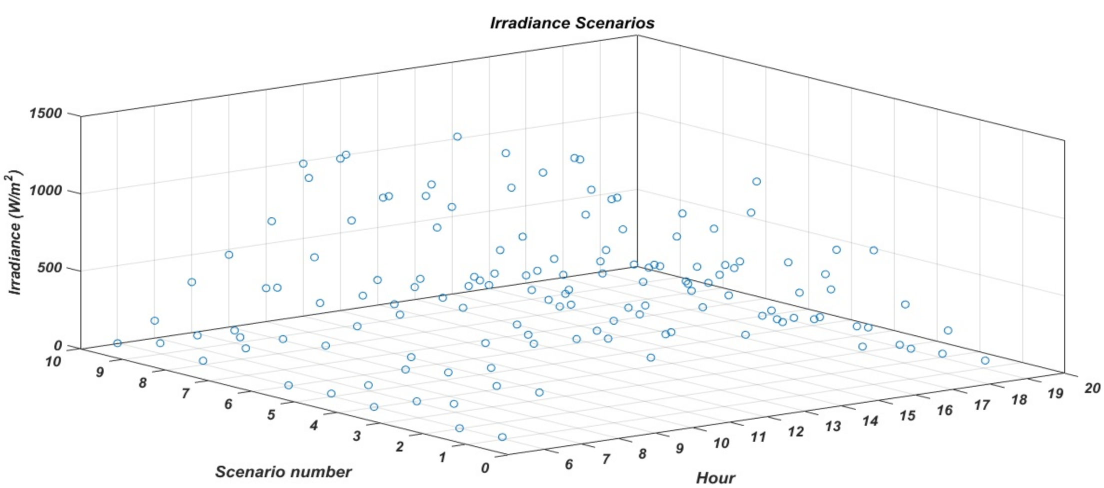

Fig.7. Reduced irradiance scenarios

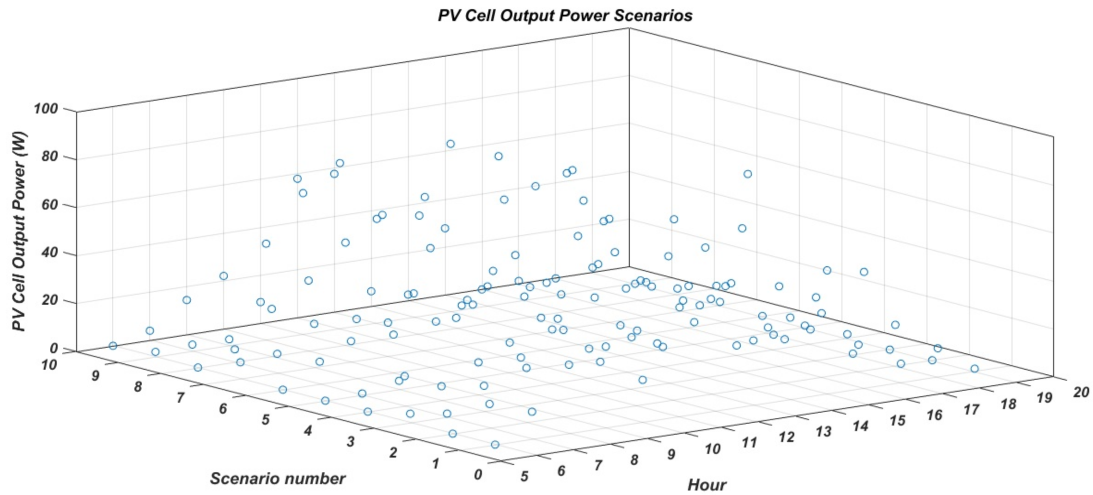

Fig.8. Reduced PV cell output power scenarios

Table 4. August 10,2005 actual irradiance amount at each hour of day

Hour	Actual measured irradiance
6	0
7	182
8	348
9	445
10	709
11	841
12	559
13	454
14	141
15	196
16	101
17	134
18	58
19	12

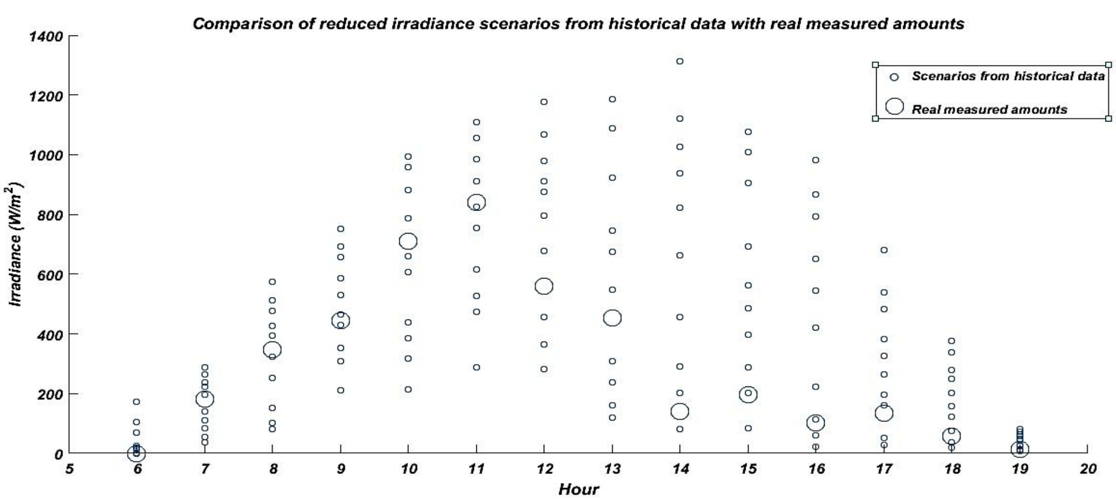

Fig. 9. Comparison between actual irradiance and predicted amounts with generated scenarios distribution

4.Conclusion

Previous studies reported on solar irradiance forecasting, are mainly based on applying deterministic methods (point estimation). This is despite the fact that due to the out of control sky condition changes, exact forecasting is impossible. The purpose of this study is to present a comprehensive method to meet irradiance and PV power forecast problem as a stochastic problem. In this paper generating irradiance scenarios based on ARMA time-series is proposed. Reducing scenarios method based on Kantorovich distance is applied. The suggested technique is applied to recorded irradiance historical data, for forecasting next day. Converting irradiance amounts to PV cell output power was described, too. Comparing the results with the actual values demonstrated the ability of the proposed method inaccurate forecasting. The method can be applied for any number of parallel or series PV cells that contributes to PV module or PV array. The described method of generating and reducing scenarios in this paper can be easily applied to day-ahead stochastic programming with other uncertain sources like wind energy.

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