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Sensitivity Analysis of a Standalone Photovoltaic System Model Parameters

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Abstract: The values of input variables of any model are cause to undergo changes due to influence of environmental conditions. These changes can be investigated by conducting the sensitivity analysis of input variables with respect to output variables. Sensitivity analysis increases the validity, credibility and assurance of model estimates. The purpose of this study was to identify the most important and sensitive input variables and to prioritize the parameters based on their influence on the model outputs of a standalone photovoltaic (SAPV) system. For that, a normalized local sensitivity analysis and sensitivity index of seven input variables of a SAPV system model with reference to three output parameters namely amount of absorbed solar radiation, maximum photovoltaic (PV) module power output and optimum PV array area has been carried out. It was revealed from the analysis that the most important and sensitive input variable was the amount of total solar radiation and the least important variable was solar azimuth angle and the lowest sensitive variable was wind speed.

Key words: Sensitivity analysis, input variables, output parameters, photovoltaic system, mathematical model

INTRODUCTION

The physical examination of highly complex systems and processes are expensive or sometimes even impossible. Therefore, the investigators turned to use mathematical or computational models to predict or approximate the behavior of systems (Fellin *et al*., 2004; Saltelli *et al*., 2006). The cause of uncertainties in the model inputs are not known which results the ambiguity of model outputs. The role of every input variable in the changing of model outputs is needed for the evaluation of model suitability and understanding of the system behavior (Isukapalli and Georgopoulos, 2001). Various terms could be found in literature for the expression of input parameters such as sensitive, important, most influential, major contributor, effective or correlated (Iman and Helton, 1988). However, the term important is used for those parameters whose uncertainty contributes considerably to the uncertainty in the output results and the word sensitive referred to those variables which have a significant influence over output results (Saltelli *et al*., 2010). The main parameter is always sensitive because the parameter changeability will not appear in the results unless the model is sensitive to the input (Cacuci *et al*., 2005). A sensitive parameter is not necessarily important because it may have little contribution in the output variability (Hamby, 1994). So, the object of the study was to investigate the most important input variable of a standalone photovoltaic system.

METHODS OF SENSITIVITY ANALYSIS

Different scholars rather used different sensitivity methods according to the nature of analysis and required accuracy. In brief, these methods include one-at-a-time design, differential analysis, subjective analysis and factorial design (Hamby, 1994). The sensitivity of parameters can also be examined by the construction of scatter plots, calculation of relative deviation ratios, determination of rank transformation, rank correlation and partial correlation coefficients and also by means of regression techniques (Hamby, 1995). Various statistical tests such as Smirnov statistic, Cramer-von Mises, Mann-Whitney and the squared rank can also be adopted for sensitivity analysis of model parameters (Cukier *et al*., 1978; Iman and Hora, 1990; Bell and Otto, 1992;

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Bekele and Nicklow, 2007). Moreover, another simple method for determining parameter sensitivity was given by Hoffman and Gardner (1983), which is based, on the output percent difference by varying one input parameter from its minimum value to its maximum value. It is very helpful to compare the performance of many individual indices relative to a composite index (Hamby, 1995). It is given as:

$$SI = \frac{y_{max} - y_{min}}{y_{max}} \tag{1}$$

where, SI is the sensitivity index, y_{min} and y_{max} represent the minimum and maximum output values, respectively.

All Sensitivity Analysis (SA) methods have their own characteristic, theories and range of applications. Therefore, the choice of a sensitivity analysis method is generally depends on the sensitivity measure employed, the required precision in the estimates of model predictions and the computational cost involved (Bell and Otto, 1992; Isukapalli and Georgopoulos, 2000). However, the Differential Sensitivity Analysis (DSA) method is a major component of nearly all other sensitivity analysis techniques (Hamby, 1994). DSA method enables a direct examination of the sensitivity of simulation results to input parameter changes (Purdy and Beausoleil-Morrison, 2001). This method requires a base case simulation in which input parameters are set with the basic estimates of the parameters under consideration. It is mostly accomplished by computing partial derivatives of the output functions with respect to the input variables (Saltelli *et al.*, 1993; Zakayo, 2009).

The generalized form of Differential Sensitivity Analysis (DSA) model contains several independent variables such as $X = (X_1 ....X_n)$ and one dependent variable Y, where $Y = f(X)$. The sensitivity analysis can be performed by an explicit arithmetic equation that illustrates the relationship between the independent variables and the dependent variable (Tolsma and Barton, 2002). The sensitivity coefficient (S_i) for a definite independent variable can be determined from the partial derivative of the dependent variable with respect to the independent variable (Saltelli *et al.*, 2006). Such as:

$$S_i = \frac{\partial Y}{\partial X_i}\left(\frac{X_i}{Y}\right) \tag{2}$$

where, the quotient X_i/Y is introduced to normalize the coefficient by removing the influence of units. It was assumed that the higher order partials are insignificant and there was no correlation among input parameters due to the nature of calculations (Christopher and Patil, 2002).

The partial derivative was also approximated as a finite difference for the large set of equations and the output values was calculated for small changes in the input parameter (Ostermann, 2005). The nonlinearities are ignored in the model (Pinjari and Bhat, 2006; Saltelli *et al.*, 2000). Therefore, the partial derivative can be approximated as:

$$S_i = \frac{\%\Delta Y}{\%\Delta X_i} \tag{3}$$

The sensitivity coefficient dy/dx was considered to be a linear estimate of number of units change in the variable y as a result of a unit change in the parameter x. It means that the sensitivity outcomes depend on physical units of variables and parameters. Therefore, normalized sensitivity coefficients ($\tilde{s}$) are used to make the sensitivity results independent of the units of the model parameters.

$$\tilde{S} = \frac{x}{y}\frac{dy}{dx} \tag{4}$$

The derivative in Eq. 4 can be discretized by using forward finite difference scheme as follows:

$$\tilde{S}_i = \frac{x_i}{y_i}\left(\frac{y_{i+1} - y_i}{x_{i+1} - x_i}\right) \tag{5}$$

where, $\tilde{s}_t$ is the local normalized sensitivity coefficient. It represents a linear estimate of the percentage change in the variable y caused by a one percent change in the parameter x.

Sensitivity of photovoltaic system parameters: El Shatter and Elhagry (2000) conducted Sensitivity Analysis (SA) on unknown parameters such as series resistance (R_s), shunt resistance (R_{sh}), light generated current (I_{ph}), reverse diode saturation current (I_o) and ideality factor (n) with suggested fuzzy input parameter (h) from 0.2 to 0.8 and output parameter (e) around 10%. They found that the PV module parameters were severely affected by temperature variation. Kolhe *et al.* (2002) conducted an economic feasibility of a standalone photovoltaic (SAPV) system and a diesel generator. The fuel consumption rate was compared versus diesel generator rated power capacity at different load factors. They also analyzed PV/diesel life cycle cost ratio against cost of the PV array and diesel with energy demand. Ito *et al*. (2006) carried out a sensitivity analysis of a very large scale PV system in deserts. They compared the PV module efficiency with generation cost, energy payback time and carbon dioxide (CO_2) emissions. Loutzenhiser *et al*. (2007) used Monte Carlo and fitted effects for N-way factorial for uncertainty analysis of total solar radiation on a south-west facade building integrated PV system. Cameron *et al*. (2008) analyzed power outputs of different PV models with different PV module technologies at daily and monthly average yearly basis. Emery (2009) evaluated uncertainties of measured PV power output with rated PV power output and measured current and voltage with junction temperature and solar irradiance. A monthly mean solar radiation with total and beam radiation, PV cell temperature with ambient temperature and energy output for fixed, optimum and tracking PV systems was evaluated by Gang and Ming (2009). Ren *et al*. (2009) conducted sensitivity analysis of levelized cost of energy with capital cost, efficiency, interest rate and electrical sale price. Talavera *et al*. (2010) conducted SA on Internal Rate of Return (IRR) of a grid connected PV system with three scenarios on the parameters of annual yield of PV system, PV module unit price, initial investment and interest rate. The sensitivity of R_s to R_{sh}, R_{sh} to R_s and of current, voltage and power of a single diode PV cell model was conducted by Zhu *et al*. (2011).

Kaabeche *et al*. (2011) carried out a techno-economical valuation of a PV system on hourly solar radiation, wind speed and ambient temperature versus time. The authors compared number of PV modules with storage capacity of different autonomy days and total annualized cost with different deficiencies of power supply probabilities and net present cost with various discount rates, capital cost and project life (Jakhrani *et al*., 2012a). The uncertainty analysis of a double diode model was conducted by Adamo *et al*. (2011). They compared the amount of solar irradiance versus temperature, mean relative estimation error on R_s and R_{sh} and standard deviation on R_s and R_{sh}. The sensitivity analysis on levelized cost of electricity versus interest rate with the inputs of initial installation cost of PV system, energy output and degradation rate was carried out by Branker *et al*. (2011). They compared discount rate versus initial installation cost of PV system with the inputs of lifetime loan term, energy output, degradation rate and zero interest loans. They also evaluated lifetime of PV system versus initial installation cost of PV system with the inputs of discount rate, energy output, degradation rate and zero interest loan. Dufo-Lopez *et al*. (2011) applied Strength Pareto Evolutionary Algorithm to the multi-objective optimization of standalone PV-wind-diesel system with battery storage. They conducted SA on parameters like inflation of diesel cost, acquisition cost and emissions of PV panels. Andrews *et al*. (2012) presented a methodology for fine resolution modeling of a PV system using PV module short circuit current (I_{sc}) at 5 min time-intervals. They identified the pertinent error mechanisms by filtering the data with regressive analysis. Mbaka *et al*. (2010) carried out an economic evaluation among three different power producing systems such as PV hybrid system, standalone PV system and standalone diesel generator system using net present value cost. Sensitivity analysis on diesel prices and the unit cost of PV modules was conducted by Jakhrani *et al*. (2012b, c).

It is revealed from the literature review, that the most of mathematical models used in sensitivity analysis are based on systems of algebraic and differential equations. The common problem in the models is that, the role of various parameters is not obvious. Generally, the important parameters, effects of changing parameters and uncertainties of model results due to uncertainty of model inputs are not known. In many applications, this information is exactly needed. Furthermore, the sensitivity analysis methods are mostly used for the analysis of biological, environmental, water quality parameters and chemical kinetics. However, these are rather new in the analysis of PV system parameters. No complete sensitivity analysis of PV system input variables as a function of output parameters has been found in the literature. Most of sensitivity analysis was conducted on the cost analysis of systems and a few on current-voltage characteristics of PV modules. It was necessary to examine the behavior of most influential input variables of PV model with respect to output parameters. Therefore, this study was conducted using differential sensitivity analysis method along with sensitivity index for the identification and extent of sensitive and important model parameters. These methods are computationally efficient and allow rapid preliminary examination of the model parameters. It also provides the slope of the calculated model output in parameter space at a given set of values. The evaluation of model suitability, identification of most influential and sensitive parameters is identified which are essential for the prediction of system performance.

METHODOLOGY

Normalized local sensitivity analysis of PV system model parameters such as absorbed solar radiation (S_T), PV module maximum power output (P_{max}) and optimum PV array area (A_{opt}) has been carried out by differential sensitivity analysis method. Five input variables namely slope (β), solar azimuth angle (γ), hour angle (ω), ground reflectance (ρ_g) and monthly average daily total solar radiation ($\bar{H}_T$) were used for examination of absorbed solar radiation (S_T). The absorbed solar radiation (S_T) with other two input variables namely ambient temperature (T_a) and wind speed (V_w) were utilized for the estimation of PV module maximum power output (P_{max}) and required optimum PV array area (A_{opt}) as shown in Fig. 1. In Addition, various empirical equations were adopted for the calculation of transitional model parameters. Those transitional estimated values were used as the input of the required models.

In first step of differential sensitivity analysis, the base values, ranges and distributions were selected for each input variable. Secondly, a Taylor series approximation to the model output was developed close to the base values of the model inputs. The first order Taylor series was preferred. Thirdly, the variance propagation techniques were used for the estimation of the uncertainty in model output in terms of its projected values and variance, because these values changes according to the order of approximation. Finally, the first order Taylor series was used to estimate the magnitude of each input parameter (Helton and Davis, 2003; Helton *et al*., 2005). The sensitivity information by differential analysis methods was carried out by changing the values of one parameter on a single variable, because of its simplicity. Furthermore, the results of various output parameters are also examined by conducting the sensitivity index of input variables.

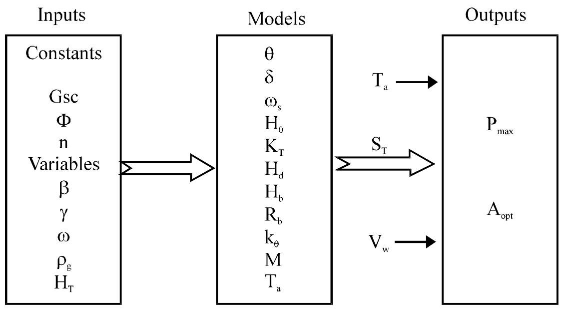

Fig. 1: Model for sensitivity analysis of SAPV system parameters

RESULTS AND DISCUSSION

The values of input parameters were varied around the base values of parameters. The values of slope (β) were changed with an interval of five degrees from zero degree to 90° as shown in Fig. 2. The estimated results, differential change, percentage change and normalized local sensitivity coefficient values of output parameters such as S_T, P_{max} and A_{opt} are illustrated in Fig. 2a-d, respectively. It was observed that the amount of absorbed solar radiation (S_T), maximum power output (P_{max}) at zero degree were 12. 8 MJ m^{-2} and 93.4 W, at 25° the values were 13.6 MJ/m^2 and 99.4 W and at 90° of slope these values were 8.5 MJ m^{-2} and 61.2 W, respectively. The positive change was found up to 20° and then the change became negative up to 90°. The results of absorbed solar radiation (S_T) and maximum PV module power output (P_{max}) were observed as 2.3% at 0°, 0% around 25° and 10% at 90° of slope. The estimated optimum PV array area (A_{opt}) was found to be 16.5 m^2 at 90° and minimum area of 10.2 m^2 was noted around 25° of slope. Negative change in the optimum PV array area were observed from 0 to 25° of slope and positive from 25 to 90° of slope. A maximum of 12% change was observed at 90° of slope and minimum around 25°. It was found that the optimum area of PV modules is inversely proportional to the absorbed solar radiation and maximum PV module power output. As power output from PV modules decreases the requirement of PV array area increases for the system installation.

The input values of the solar azimuth angle (γ) was varied with an interval of 10° from -90 to +90° as shown in Fig. 3. The estimated values, differential change, percentage change and normalized local sensitivity values of output parameters are shown in Fig. 3a-d, respectively. The maximum results of S_T and P_{max} was found at the solar azimuth angle of 0° with 13.3 MJ m^{-2} and 97.2 W, respectively and minimum results were observed at ±90°. Both the amount of absorbed solar radiation and PV module power output showed positive change from -90 to 0°and negative change from 0° to +90°. The change of 10° solar azimuth angle results 0.0043% change in the output values at 0° of solar azimuth angle and 0.06% were observed at +90°. At zero degree of solar azimuth angle, the normalized coefficients were zero but negative up to +90° of solar azimuth angle. In contrary to the results of S_T and P_{max}, A_{opt} displayed negative change from -90° to 0° and positive change from 0° to +90°. The normalized coefficients of sensitivity analysis for A_{opt} were found positive with almost same values of S_T and P_{max}.

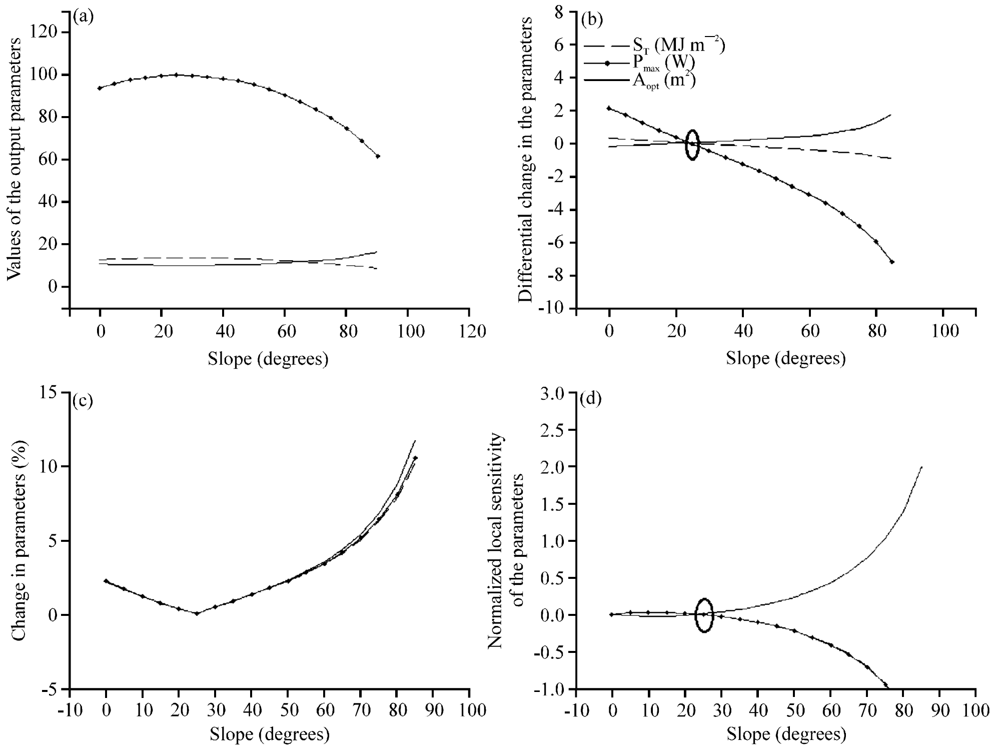

Fig. 2(a-d): Sensitivity analysis of output parameters with respect to slope, (a) Values of output parameters, (b) Differential change in parameter values, (c) Percentage change in parameter values and (d) Normalized local SA values of parameters

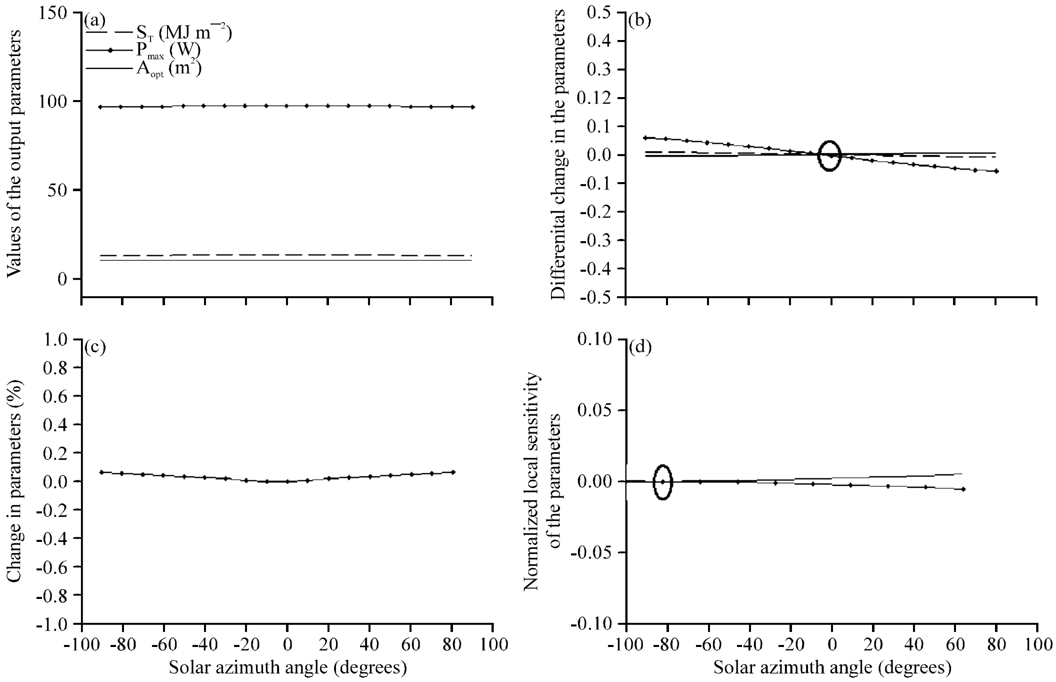

Fig. 3(a-d): Sensitivity analysis of output parameters with respect to solar azimuth angle, (a) Values of output parameters, (b) Differential change in parameter values, (c) Percentage change in parameter values and (d) Normalized local SA values of parameters

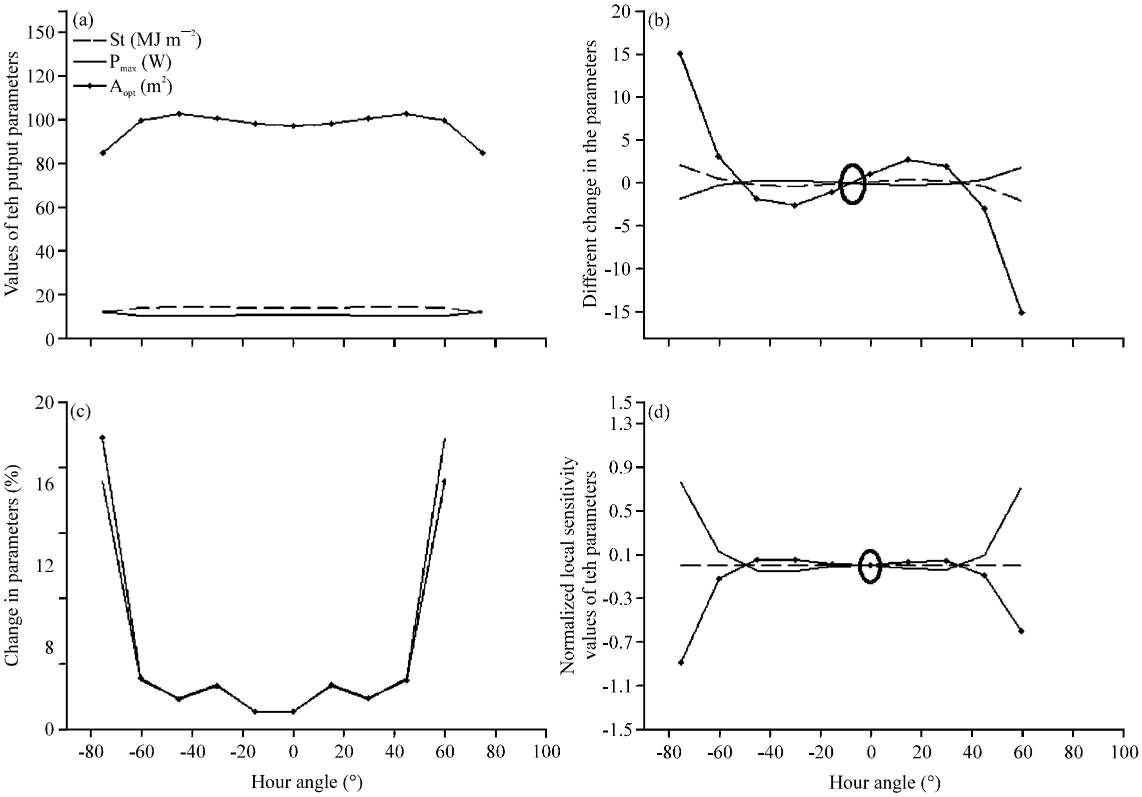

Fig. 4(a-d): Sensitivity analysis of output parameters with respect to hour angle, (a) Values of output parameters, (b) Differential change in parameter values, (c) Percentage change in parameter values and (d) Normalized local SA values of parameters

The input values of the hour angle (ω) was varied with an interval of 15° from -75 to +75 ° as shown in Fig. 4. The estimated results, differential change, percentage change and normalized local sensitivity values of output parameters for the hour angle (ω) are shown in Fig. 4a-d, respectively. It was observed that the amount of solar radiation and maximum PV module power output at zero degree hour angle was 113.3 MJ m^{-2} and 97.0 W and at ±75° hour angle the values were 11.6 MJ m^{-2} and 84.5 W, respectively. Only 2.0 M J m^{-2} and 15.0 W change with 17.7% variation were observed in the results of absorbed solar radiation and maximum PV module power output, respectively at ±75° of the hour angle. The normalized sensitivity coefficient was minus 0.88 at -75° and minus 0.60 at +75° of the hour angle. The optimum PV array area values were approximately 12.0 m^2 at ±75° of the hour angle and 10.4 m^2 at zero degree of the hour angle. Negative change was observed in the values from ±45 to ±75° and positive change from zero degree to ±45° of the hour angle. Fifteen percent change in the output results was observed at ±75° and no change in the results was found at zero degree of the hour angle. Normalized sensitivity results were +0.76 at ±75°, whereas, negative sensitivity coefficients were seen from zero degree to ±45° of the hour angle values.

The input values of ground reflectance (ρ_g) were varied by an interval of 0.1 from 0.0 to 0.7 as shown in Fig. 5. The estimated results, differential change, percentage change and normalized local sensitivity values of output parameters with respect to ground reflectance (ρ_g) are illustrated in Fig. 5a-d, respectively. The maximum amount of S_T and P_{max} was found at higher ground reflectance (ρ_g) inputs and minimum at low levels of ground reflectance (ρ_g). At 0.0 ρ_g the values of S_T and P_{max} were 12.1 MJ m^{-2} and 88.6 W, whereas, at 0.7 ρ_g, the values of S_T and P_{max} were 16.3 MJ m^{-2} and 118.0 W, respectively. The change of 0.6 MJ m^{-2} and 4.0 W were found with the increment of 0.1 variation of ground reflectance. The higher percentage changes were observed at lower levels of ρ_g and vice versa. Around 5% changes were found at zero value of ρ_g and 3.6% change was observed at the value of 0.7 ρ_g.

The input values of monthly mean daily total solar radiation on horizontal surface ($\overline{H}$) were changed with an interval of 1.0 MJ m^{-2} from 5.0 to 25.0 MJ m^{-2} as shown in Fig. 6. The estimated results, differential change,

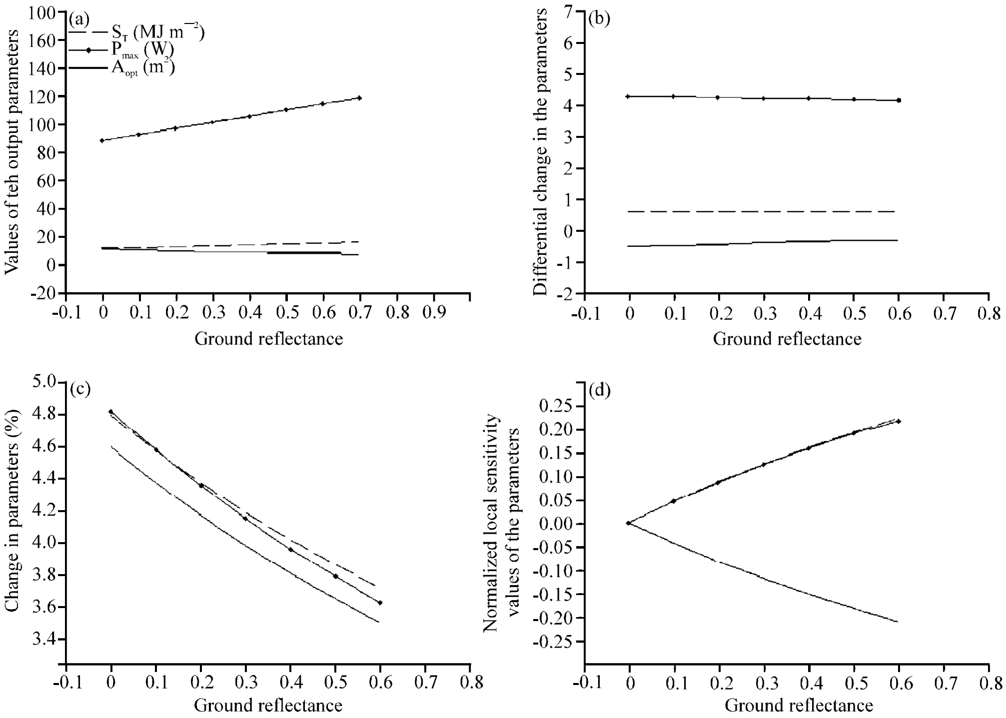

Fig. 5(a-d): Sensitivity analysis of output parameters with respect to ground reflectance, (a) Values of output parameters, (b) Differential change in parameter values, (c) Percentage change in parameter values and (d) Normalized local SA values of parameters

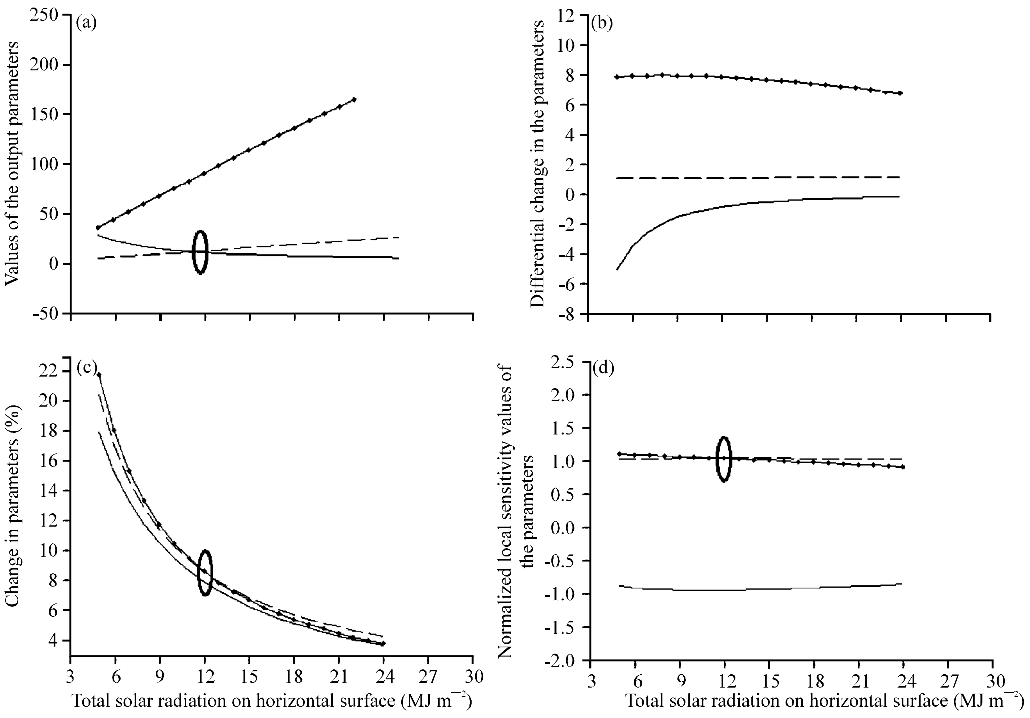

Fig. 6(a-d): Sensitivity analysis of output parameters with respect to total solar radiation, (a) Values of output parameters, (b) Differential change in parameter values, (c) Percentage change in parameter values and (d) Normalized local SA values of parameters percentage change and normalized local sensitivity values of output parameters are illustrated in Fig. 6a-d, respectively. The maximum values of S_T and P_{max} were 26.4 MJ m^{-2} and 185.8 W found at the highest value of $\bar{H}$. The change in S_T and P_{max} values were 1.03 to 1.07 MJ m^{-2} and 7.8 to 6.7 W at the value of 5 to 25 MJ m^{-2} of total solar radiation ($\bar{H}$), respectively. Higher change in the output values of S_T, P_{max} and A_{opt} values were found in the lower level of $\bar{H}$, with 20.4, 22 and 17.8% and minimum percentage change were observed in higher level of $\bar{H}$, around 4% in all output parameters, respectively. Normalized sensitivity coefficient were noted at all data points of S_T and P_{max}. The maximum and minimum value of A_{opt} were 28.2 and 5.4 m^2 found at 5 and 25.0 MJ m^{-2} of $\bar{H}$ respectively. Almost minus 5 m^2 changes in solar radiation were found at low level of solar radiation values and minus 0.2 m^2 was found at higher level of solar radiation.

The input values of ambient temperature (T_a) were changed with an interval of 5°C from 15 to 50°C as shown in Fig. 7. The estimated results, differential change, percentage change and normalized local sensitivity values of output parameters namely P_{max} and A_{opt} are illustrated in Fig. 7a-d, respectively. The optimum values of P_{max} were found at low level of ambient temperatures and the lower results of P_{max} were found at higher temperatures. At 15°C of ambient temperature, the value of P_{max} was 104 W and at 50°C its output value was found to be 82 W. The change in output of P_{max} values per 5°C was found to be around minus 3 W. The percentage change at low level of ambient temperatures was 3.0 and at higher levels of ambient temperatures were 3.6. Normalized local sensitivity coefficient was found negative, because, the increase of ambient temperature was responsible for the decrease in power output. The values of sensitivity coefficients were minus 0.09 at the lower level of ambient temperature and minus 0.3 at the higher levels. The A_{opt} at 15 and 50°C of ambient temperature were 9.2 and 11.6 m^2, respectively. The variation in A_{opt} was 0.3 and 0.4 m^2 and the change in percentage of A_{opt} was 3.2 and 3.7 found at 15 and 50°C of T_a, respectively. The normalized sensitivity coefficients were positive due to increase of A_{opt} with the increase of ambient temperature.

The input values of wind speed (V_w) were changed with an interval of 1 m sec^{-1} from zero to 10 m sec^{-1} as shown in Fig. 8. The estimated results, differential change, percentage change and normalized local sensitivity values of output parameters namely P_{max} and A_{opt} are illustrated in Fig. 8a-d, respectively. It was found from the results that

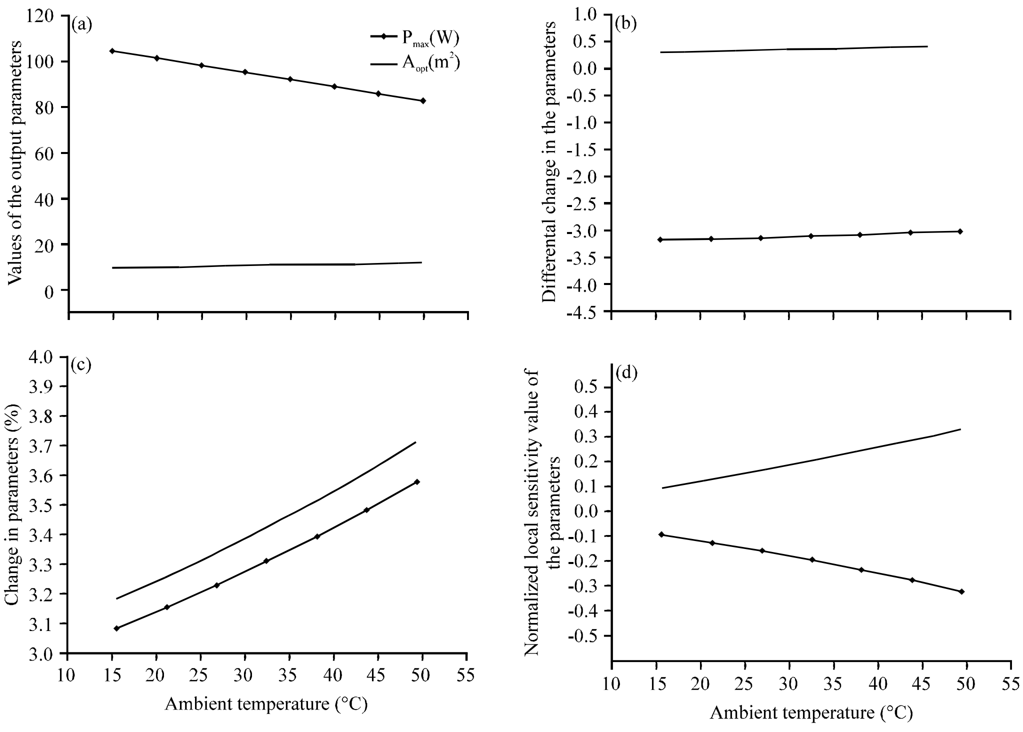

Fig. 7(a-d): Sensitivity analysis of output parameters with respect to ambient temperature, (a) Values of output parameters, (b) Differential change in parameter values, (c) Percentage change in parameter values and (d) Normalized local SA values of parameters

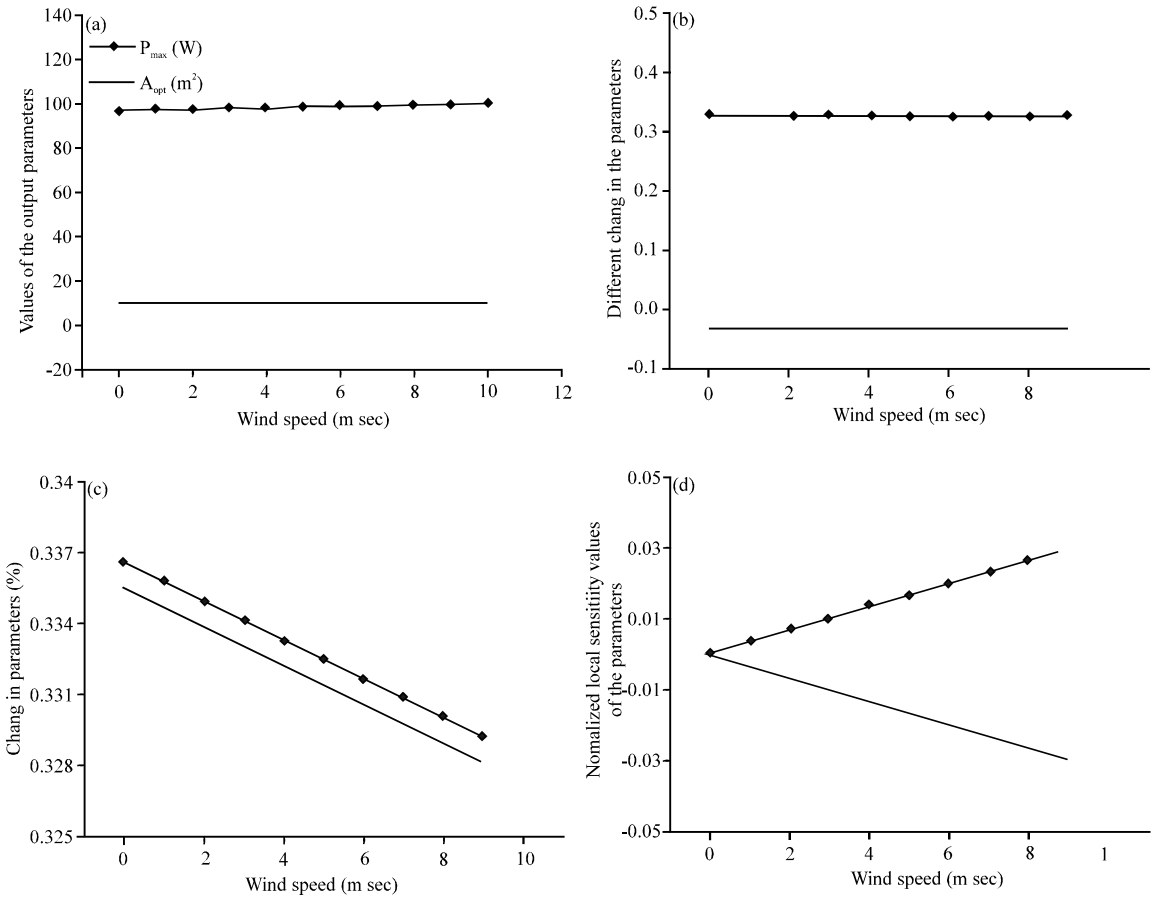

Fig. 8(a-d): Sensitivity analysis of output parameters with respect to wind speed, (a) Values of output parameters, (b) Differential change in parameter values, (c) Percentage change in parameter values and (d) Normalized local SA values of parameters

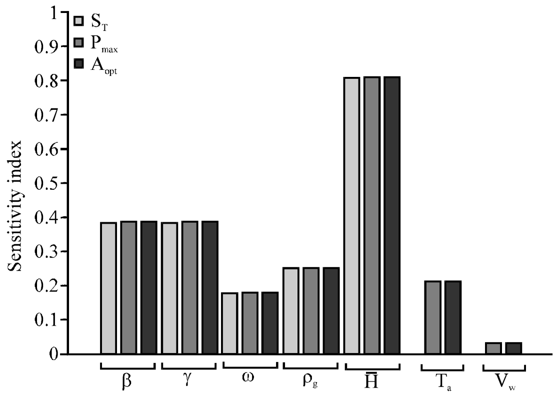

Fig. 9: Sensitivity index of output parameters versus different input variables

the increase of wind speed from zero to 10 m sec^{-1} results the increase of P_{max} from 96.6 to 100.0 W and decrease of A_{opt} from 9.88 to 9.56 m^2, respectively. The increase of 1 m sec^{-1} wind speed results change in 0.3 W power increase and 0.03 m^2 decrease of A_{opt}. The average percentage change in P_{max} values were 0.34 and in A_{opt} 0.33 per 1 m sec^{-1} change of wind speed.

The sensitivity index of all output parameters with respect to input variables are illustrated in Fig. 9. The highest sensitivity index was shown by total solar radiation ($\bar{H}$) with the sensitivity index of 0.8 in all output parameters. The second and third most sensitive variables were found to be slope (β) and solar azimuth angle (γ), both with the sensitivity index of approximately 0.4. The sensitivity index of ground reflectance (ρ_g) was approximately 0.25, the ambient temperature (T_a) with 0.20 and the hour angle (ω) with 0.18. The lowest sensitive variable was found to be wind speed (V_w) with the index less than 0.1.

It was established from the sensitivity analysis of input variables and output parameters that the most important input variable was the amount of total solar radiation ($\bar{H}$) because of its higher contribution in changing the amount of absorbed solar radiation (S_T) level. Consequently, it results the maximum PV module power output (P_{max}) and the less requirement of optimum PV array area (A_{opt}). The changes contributed by amount of total solar radiation ($\bar{H}$) in the output variables is approximately 2.5 times when its amount was varied around its typical ranges, followed by slope (β) with 61%, ground reflectance (ρ_g) 33%, ambient temperature (T_a) 23% and hour angle (ω) 20%. The less important variables were found to be wind speed (V_w) 4% and solar azimuth angle (γ) less than one percent as per one-at-a-time (OAT) method. The highest sensitive input variable was found to be total solar radiation ($\bar{H}$) with the index of 0.8, followed by slope (β), solar azimuth angle (γ), ground reflectance (ρ_g), the ambient temperature (T_a) and the hour angle (ω). The lowest sensitive variable was found to be wind speed (V_w) with the index less than 0.1.

CONCLUSIONS

It was revealed from the sensitivity analysis of input variables and output parameters of a standalone photovoltaic system that the most important input variable was the amount of total solar radiation ($\bar{H}$) because of its high contribution in changing the amount of absorbed solar radiation (S_T) level, the maximum PV module power output (P_{max}) and optimum PV array area (A_{opt}).

The changes contributed by amount of total solar radiation ($\bar{H}$) in the output variables was approximately 2.5 times when its amount was varied around its typical ranges, followed by slope (β) with 61%, ground reflectance (ρ_g) 33%, ambient temperature (T_a) 23% and hour angle (ω) 20%. The less important variables were found to be wind speed (V_w) with 4% variation in the results and solar azimuth angle (γ) less than one percent as per one-at-a-time (OAT) method.

The highest sensitive input variable was found to be total solar radiation ($\bar{H}$) with the index of 0.8, followed by slope (β), solar azimuth angle (γ), ground reflectance (ρ_g), the ambient temperature (T_a) and the hour angle (ω). The lowest sensitive variable was found to be wind speed (V_w) with the index less than 0.1.

NOMENCLATURE

S_T = Monthly average total absorbed solar radiation on a tilted surface (MJ m^{-2})
H_T = Monthly average total solar radiation on a tilted surface (MJ m^{-2})
H_b = Monthly average daily beam radiation on horizontal surface for a month (MJ m^{-2})
H_d = Monthly average daily diffuse radiation on horizontal surface for a month (MJ m^{-2})
R_b = Ratio of beam radiation on a tilted surface to the beam radiation on horizontal surface
ρ_g = Hemispherical ground reflectance or albedo
ϕ = Latitude of location (°)
δ = Declination angle (position of sun in the sky) (°)
β = Slope (surface tilt angle from horizon) (°)
γ = Surface azimuth angle (°)
ω = Hour angle (°)
θ = Angle of incidence (°)
ω_s = Sunset hour angle (°)
G_{sc} = Solar constant = 1367 W/m^2
n = nth day of the year, starting from 1st January (n = 1 on 1st Jan. and n = 365 on 31st Dec.)
H_0 = Extraterrestrial solar radiation on a horizontal surface for a day (MJ m^{-2})
K_T = Clearness index
K_θ = Incident angle modifier
M = Air mass modifier
T_a = Ambient temperature (°C)
V_w = Wind speed (m sec^{-1})
P_{max} = Maximum power output (W)
A_{opt} = Optimum PV array area (m^2)

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