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RANKING OF PARAMETERS INFLUENCING ON POWER OUTPUT OF PHOTOVOLTAIC SYSTEMS BY SENSITIVITY ANALYSIS

Abdul Qayoom Jakhrani*, Saleem Raza Samo** and Shakeel Ahmed Kamboh***

ABSTRACT

This paper aims 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 system. Three sensitivity methods, such as sensitivity index, sensitivity coefficient variance and correlation coefficient were applied for the determination of parameter response by one variable at a time method. A total of seven input variables namely slope, solar azimuth angle, hour angle, ground reflectance, amount of total solar radiation, ambient temperature and wind speed were examined with reference to three output parameters. It was revealed that the most important and sensitive input variable was the amount of total solar radiation and the least important variables was solar azimuth angle and the lowest sensitive variable was wind speed. The higher sensitivity variance is displayed by slope followed by hour angle. Insignificant variance is noted in the results of solar azimuth angle and wind speed for all output parameters. It is concluded that the amount of solar radiation, ambient temperature and slope of the system have significant influence over the model results among all examined variables.

Keywords: parameter ranking, sensitivity analysis, sensitivity index, sensitivity coefficient variance, correlation coefficient, photovoltaic system model.

1. INTRODUCTION

Modern systems and processes are complicated in nature. Their physical investigation is expensive or sometimes even impossible. Therefore, the investigators turned to mathematical or computational models to predict or approximate the behavior of systems and processes [1, 2]. The common problem in the models is that, the role of various parameters is not obvious. Generally, 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. Such knowledge is crucial for the evaluation of model suitability, identification of most influential and sensitive parameters, and for understanding of the systems behavior [3].

The researchers used various terms for describing the influence level of input parameters such as sensitive, important, most influential, major contributor, effective or correlated [4, 5]. The term important was used for those parameters whose uncertainty contributes considerably to the uncertainty in assessment results. The word sensitive referred to those parameters which have a significant influence on output results [6]. However, the main parameter is always sensitive because the parameter changeability will not emerge in the results unless the model is sensitive to the input [7]. A sensitive parameter is not necessarily important because it may have little contribution in the output variability [5]. Different scholars rather used different sensitivity rankings by using different methods according to the nature of analysis and required accuracy.

* Assistant professor, Department of Energy and Environment Engineering, Quaid-e-Awam University of Engineering, Science and Technology (QUEST) Nawabshah

** Professor, Department of Energy and Environment Engineering, Quaid-e-Awam University of Engineering, Science and Technology (QUEST) Nawabshah

*** Lecturer, Department of Mathematics and Statistics, Quaid-e-Awam University of Engineering, Science and Technology (QUEST) Nawabshah

PhD Student, Faculty of Computer Science and Information Technology, Universiti Malaysia Sarawak (UNIMAS), Sarawak, Malaysia

1.1. METHODS OF SENSITIVITY ANALYSIS

Several sensitivity analysis methods could be found in literature from simple to more comprehensive and complicated ones. In brief, these methods includes, one-at-a-time design, differential analysis, factorial design, the derivation of sensitivity and importance indices, subjective analysis, construction of scatter plots, the relative deviation method, relative deviation ratios, correlation coefficients, rank transformation, rank correlation coefficients, partial correlation coefficients, regression techniques, standardized regression techniques, the Smirnov test statistic, the Cramer-von Mises test, Mann-Whitney test, and the squared ranks test [8-12]. Another method for determining parameter sensitivity was given by Hoffman and Gardner [13], which is based on the output % difference by varying one input parameter from its minimum value to its maximum value [14]. Hamby [5] and [14] and Bauer and Hamby [15] conducted a detailed performance of many individual indices relative to a composite index. Their results showed that the model proposed by Hoffman and Gardner [13] performs well for the sensitivity analysis of parameters as compared to ten selected indices. Furthermore, different sensitivity analysis (SA) methods have different characteristics, 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 the sensitivity measure, and the computational cost involved [10, 14].

1.2. SENSITIVITY ANALYSIS OF PHOTOVOLTAIC SYSTEM PARAMETERS

Jakhrani et al [16] conducted sensitivity analysis of model input variables upon output parameters for a standalone photovoltaic system. The input variable includes amount of solar radiation, hour angle, solar azimuth angle, ground reflectance, slope of solar modules, wind speed and ambient temperature. The output parameters were absorbed solar radiation, maximum power output of a PV module and the required area of PV module. El Shatter and Elhagry [17] carried out sensitivity analysis (SA) of 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. [18] 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 photovoltaic (PV) array and diesel with energy demand. Ito et al. [19] 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 CO_2 emissions. Loutzenhiser et al. [20] 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. [21] analyzed power outputs of different PV models with different PV module technologies at daily and monthly average yearly basis.

Emery [22] 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 [23]. Ren et al. [24] conducted sensitivity analysis of levelized cost of energy with capital cost, efficiency, interest rate and electrical sale price. Talavera et al. [25] carried out 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. [26]. Kaabeche et al. [27] 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. The uncertainty analysis of a double diode model was conducted by Adamo et al. [28]. 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. [29]. 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. [30] 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. [31] presented a methodology for fine resolution modeling of a PV system using PV module short circuit current (I_{sc}) at 5-min time-scales. They identified the pertinent error mechanisms by filtering the data with regressive analysis. Mbaka et al. [32] 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. SA was conducted on diesel prices and the unit cost of PV modules.

It is revealed from the literature review that the most of the sensitivity analysis methods are used for the analysis of biological, environmental, water quality parameters and chemical kinetics. 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 the sensitivity analysis was conducted on the cost analysis of the systems and a few on the parameters of equivalent electrical circuit characteristics of PV modules. Equivalent electrical circuit (I-V characteristic curve) parameters are implicit in nature and their performance itself depends upon the values of other input variables such as slope, solar azimuth angle, hour angle, ground reflectance, monthly average daily total solar radiation, ambient temperature and wind speed. The influence of these input variables is not studied by the former researchers. Therefore, the assessment of their effect is crucial for the evaluation of model suitability, identification of the most influential and sensitive parameters for the system design and performance prediction. Thus a sensitivity analysis is carried out to understand the system behavior and to investigate the response of PV system models with respect to the variation in input variables. In this study, sensitivity index has been used, which is computationally efficient technique that allows rapid preliminary examination of the model. It also provides the slope of the calculated model output in parameter space at a given set of values. Furthermore, sensitivity coefficient variance and correlation coefficients have been determined for the analysis of parameters variation due to the changing of input variables.

2. METHODOLOGY

Kuching with latitude (ϕ) of 1.48^{o} N was selected for this analysis due to availability of recorded solar radiation data of the area. Worst (lowest radiation) month method was used for this study. Since, January is the lowest solar radiation month in Kuching. The long term average value of a single day i.e. 17th day of January $(n = 17)$, which characterizes similar monthly average values were used for this analysis as adopted by Jakhrani et al. [33]. Five input variables namely slope (β), solar azimuth angle (γ), hour angle (ω), ground reflectance or albedo (ρ_g) and monthly average daily total solar radiation $(\overline{H}_T)$ with three constants such as solar constant $(G_{sc} = 1367\ W/m^2)$ were used for calculation of absorbed solar radiation (S_T). The absorbed solar radiation (S_T) with two other variables namely ambient temperature (T_a) and wind speed (V_w) were used as input for the estimation and assessment of PV module maximum power output $(P_{\max})$ and optimum PV array area (A_{opt}) as shown in Figure 1.

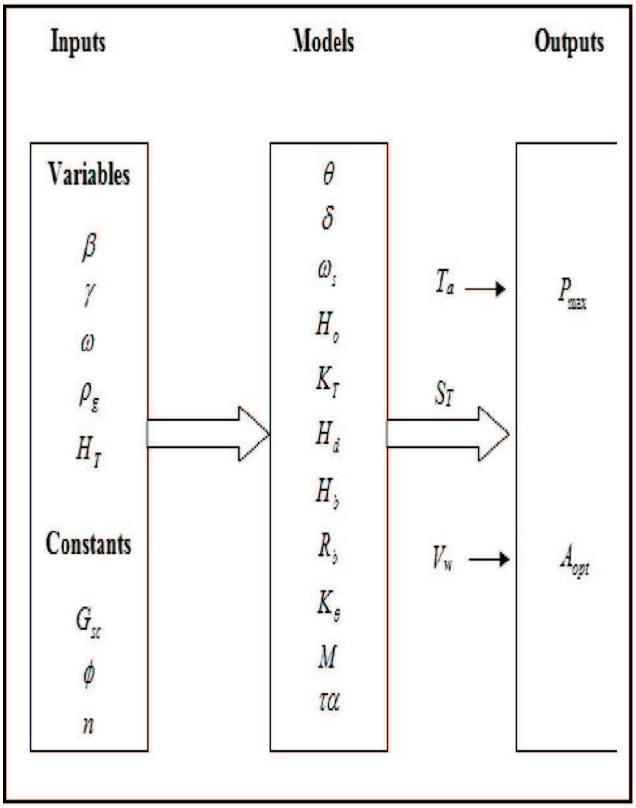

Figure 1. Model for sensitivity analysis of photovoltaic system parameters

Sensitivity analysis results were validated using different models for estimation of power output with various input values of solar radiation ambient temperatures. The models used for this study were Evans [34], Borowy BS, Salameh [35], Hove [36], Jie et al. [37] and Jakhrani et al. [38]. Sensitivity analysis of model parameters was carried out by means of differential analysis method. In first step of 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 [39]. Three sensitivity analysis methods such as sensitivity variance, sensitivity index and correlation coefficients have been adopted for the evaluation of three output parameters such as absorbed solar radiation (S_T), PV module maximum power output $(P_{\max})$ and optimum PV array area (A_{opt}). The algorithm proposed by Hoffman and Gardner [13] is used for the determination of sensitivity index of parameters. It is given as:

$$SI = \frac{y_{\max} - y_{\min}}{y_{\max}} \qquad (1)$$

where SI is the sensitivity index, $y_{\min}$ and $y_{\max}$ represent the minimum and maximum output values, respectively. The changes in the results of output parameters with respect to changes in input variables are calculated by means of parameter variance (V) [6].

$$V = \frac{1}{n}\sum_{i=1}^{n} (\tilde{S}_i - \bar{\tilde{S}})^2 \qquad (2)$$

where $\tilde{S}_i$ is the local normalized coefficient and represents a linear estimate of the percentage change in the variable y caused by a one percent change in the parameter x. $\bar{\tilde{S}}$ is the arithmetic mean of $\tilde{S}_i$ and n is the number of data points in $\tilde{S}_i$. Moreover, the strength and significance of the linear relationship between the input variable x and output variable y in the regression equation is measured by correlation coefficient (r). Its values are always between -1 and 1. Therefore, the dependence of output parameter y on a single input variable x is determined by Pearson correlation coefficient and is defined as [2, 14]:

$$r_{xy} = \frac{\sum_{i=1}^{n}(y_i - \bar{y})(x_i - \bar{x})}{\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2 \sum_{i=1}^{n}(x_i - \bar{x})^2}} \qquad (3)$$

3. RESULTS AND DISCUSSIONS

The values of input parameters were varied around the base values of parameters. The slope (β) was changed with an interval of five degrees from 0° to 90°. The comparative values of sensitivity coefficient variance, sensitivity index and correlation coefficient of output parameters at various slopes are shown in Figure 2.

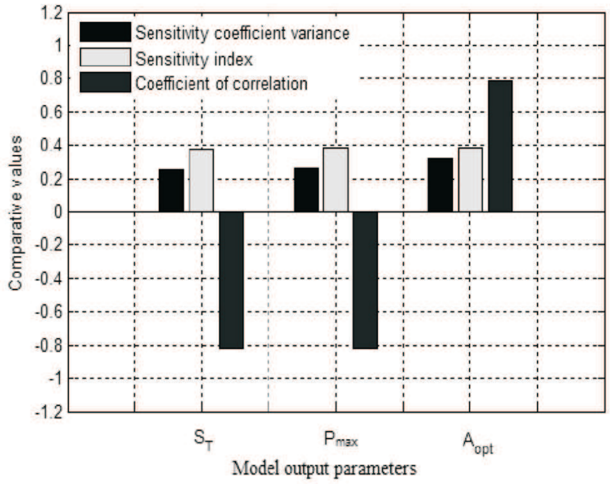

Figure 2. Values of output parameters by different sensitivity methods at various slopes (β)

The obtained sensitivity coefficient variance was 0.2518, 0.2658 and 0.3216, the sensitivity index was 0.3794, 0.3847 and 0.3847, and the correlation coefficient was -0.8219, -0.8211 and 0.7891 for output values of S_T, $P_{\max}$ and A_{opt} respectively. The higher sensitivity variance and sensitivity index was observed in optimum PV array area (A_{opt}) as compared to absorbed solar radiation (S_T) and maximum PV module power output $(P_{\max})$. Negative correlation coefficient was noted in both absorbed solar radiation and maximum PV power output, whereas, the positive correlation was observed in optimum PV array area.

The input values of the solar azimuth angle (γ) were varied with an interval of 10° from -90° to +90°. The *-comparative results of sensitivity coefficient variance, sensitivity index and correlation coefficient of output parameters at various solar azimuth angles are shown in Figure 3. It is discovered from the analysis that variance and correlation coefficient in the results of solar azimuth angle was found to be zero and one respectively. However, the sensitivity index of all output parameters were approximately 0.38.

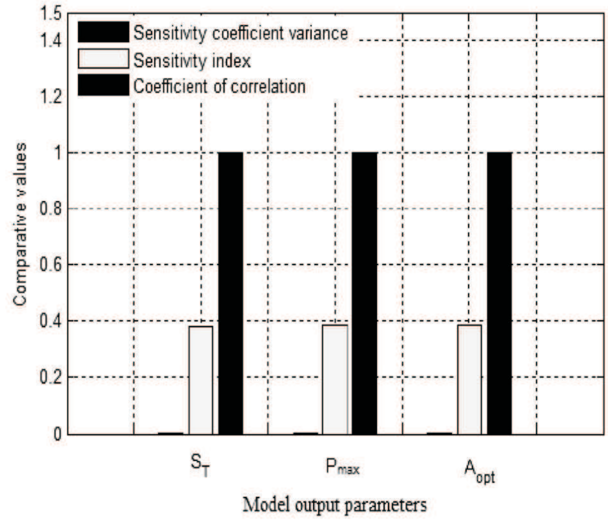

Figure 3. Values of output parameters by different sensitivity methods at various solar azimuth angles (γ)

The input values of the hour angle (ω) were varied with an interval of 15° from -75° to +75 °. The comparative values of sensitivity coefficient variance, sensitivity index and correlation coefficient of output parameters at various hour angles are shown in Figure 4. The variance of S_T was almost zero, whereas, the variance in the results of $P_{\max}$ and A_{opt} were 0.11 and 0.09 respectively. The sensitivity index and correlation coefficient of all three output variables were 0.17 and 1.0 respectively.

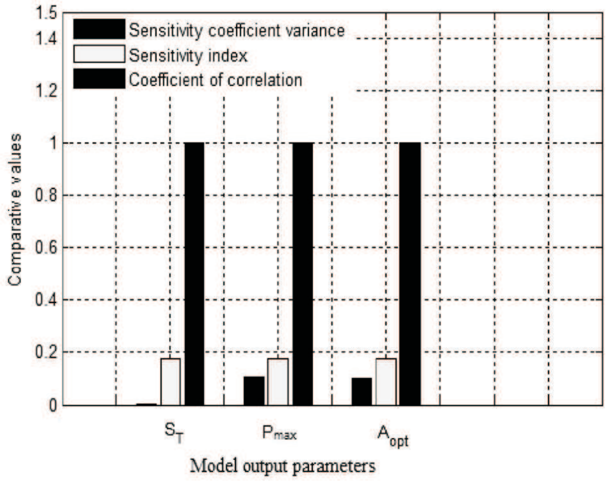

Figure 4. Values of output parameters by different sensitivity methods at various hour angles (ω)

The input values of ground reflectance (ρ_g) were varied by an interval of 0.1 from 0.0 to 0.7. The relative values of sensitivity coefficient variance, sensitivity index and correlation coefficient of output parameters at various ground reflectance (ρ_g) inputs are shown in Figure 5. The variance in the results of S_T, P_{max} and A_{opt} were 0.0064, 0.0061 and 0.0057, and sensitivity index were 0.251, 0.2492 and 0.2492 respectively. The correlation coefficient of all three output parameters with respect to input variables was unity.

The input values of monthly mean daily total solar radiation on horizontal surface $(\overline{H})$ were changed with an interval of 1.0MJ/m^2 from 5.0 to 25.0MJ/m^2. The results of sensitivity coefficient variance, sensitivity index and correlation coefficient of output parameters at monthly mean daily total solar radiation are shown in Figure 6. The variance in the results of S_T, P_{max} and A_{opt} were 0.0, 0.0035 and 0.0007, and sensitivity index were 0.8071, 0.8069 and 0.8069 respectively. The correlation coefficient were found to be unity, in all three output variables such as S_T, P_{max} and A_{opt}.

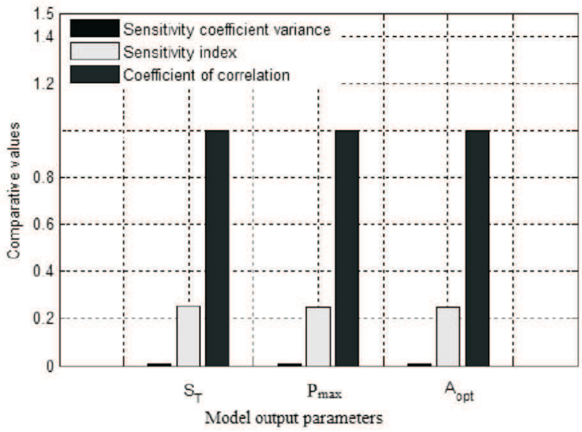

Figure 5. Values of output parameters by different sensitivity methods at various input values of ground reflectance (ρ_g)

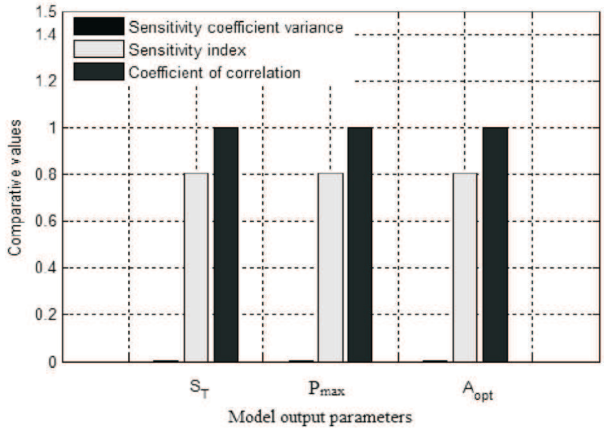

Figure 6. Values of output parameters by different sensitivity methods at various levels of total solar radiation $(\overline{H})$

The input values of ambient temperature (T_a) were changed with an interval of 5°C from 15°C to 50°C. The comparative values of sensitivity coefficient variance, sensitivity index and correlation coefficient of output parameters namely P_{max} and A_{opt} at various ambient temperature (T_a) levels are shown in **Figure 7**. The variance in P_{max} and A_{opt} were found to be 0.0068 and 0.0074. The sensitivity index and the correlation coefficient for both output parameters (P_{max} and A_{opt}) were 0.21 and 1.0 respectively.

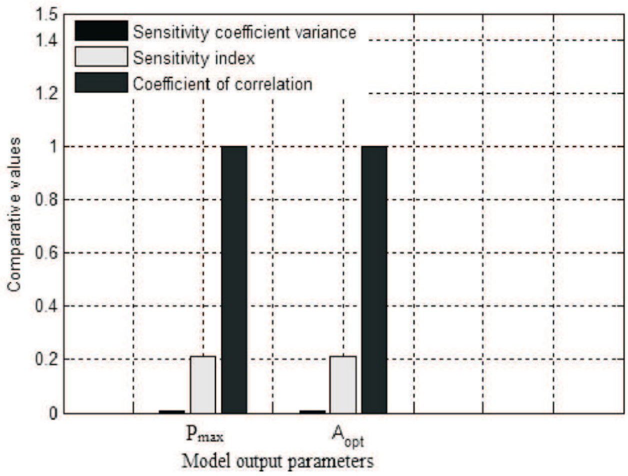

Figure 7. Values of output parameters by different sensitivity methods at various levels of ambient temperature (T_a)

The input values of wind speed (V_w) were changed with an interval of 1m/s from zero to 10m/s. The comparative values of sensitivity coefficient variance, sensitivity index and correlation coefficient of output parameters such as P_{max} and A_{opt} at various wind speed levels are shown in Figure 8. The variance, the sensitivity index and the correlation coefficient for both output parameters were found to be 0.0001, 0.033 and 1.0 respectively.

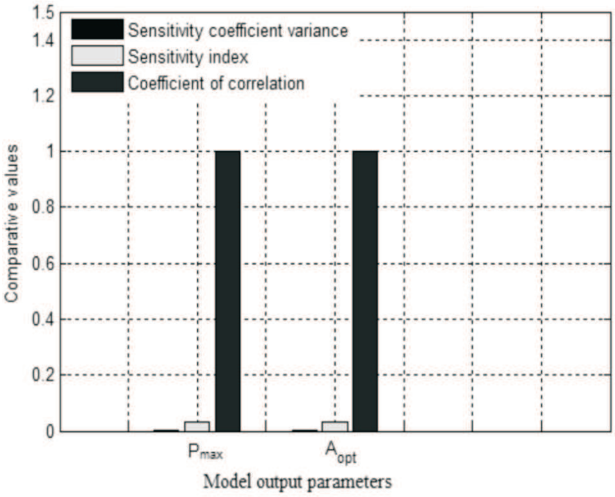

Figure 8. Values of output parameters by different sensitivity methods at various wind speed (V_w)

The overall sensitivity coefficient of variance of output parameters such as S_T, P_{max} and A_{opt} with respect to input variables namely slope (β), solar azimuth angle (γ), hour angle (ω), ground reflectance (ρ_g), total solar radiation $(\overline{H})$, ambient temperature (T_a) and wind speed (V_w) are given in **Figure 9**. The higher sensitivity variance is displayed by slope (β) with more than 0.25 for all output parameters followed by hour angle (ω) with the variance of 0.1. Less variance is observed for the input variable of ground reflectance (ρ_g), total solar radiation $(\overline{H})$ and ambient temperature (T_a). Negligible variance is noted in the results of solar azimuth angle (γ) and wind speed (V_w) for all output parameters.

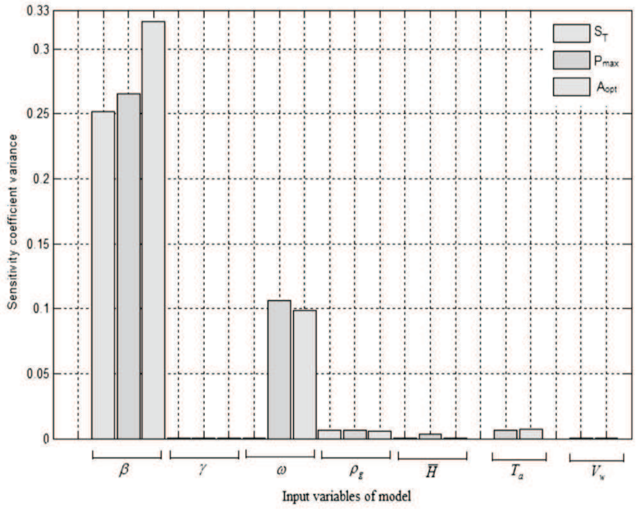

Figure 9. Sensitivity coefficient variance of output parameters versus different input variables

The sensitivity index of all output parameters with respect to input variables are illustrated in **Figure 10**. The highest sensitivity index is shown by total solar radiation $(\overline{H})$ 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.

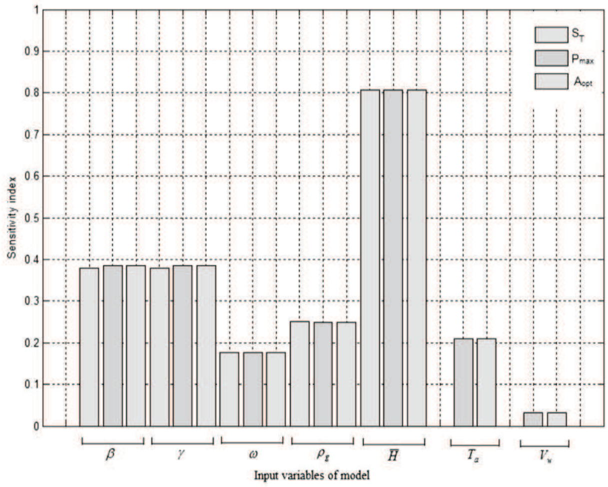

Figure 10. Sensitivity indices of output parameters versus different input variables

The results of correlation coefficient of input variables and output parameters are given in Figure 11. It is found that almost all output parameters displayed higher correlation with input variables except the slope (β). The negative correlation is observed by the input variable of slope (β) for the amount of absorbed solar radiation (S_T) and maximum PV module power output $(P_{\max})$ and positive correlation with optimum PV array area (A_{opt}) with the index of 0.8.

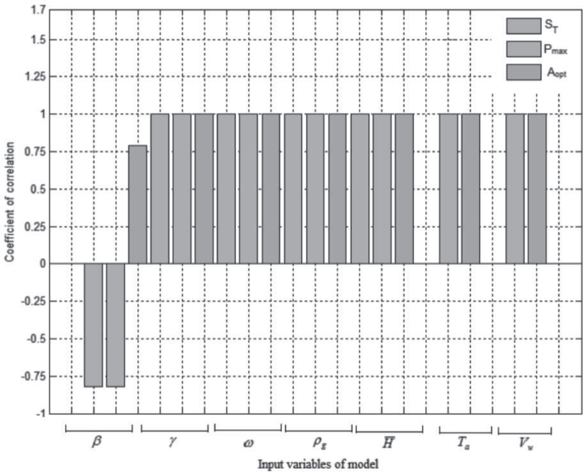

Figure 11. Correlation coefficient of output parameters versus different input variables

The comparison of PV module power out estimations with respect to solar radiation and ambient temperature by various models are given in Figures 12 and 13. It was observed that all model results are mutually consistent and the tendency of model variations was same. Therefore, it was deduced that sensitivity of parameters will be identical due to similar mode of model estimated values.

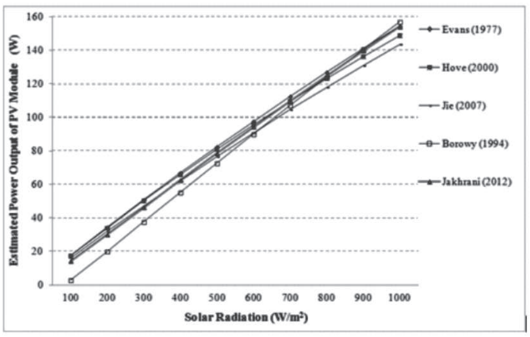

Figure 12. Comparative results of PV module power output versus monthly mean daily solar radiation at constant ambient temperature

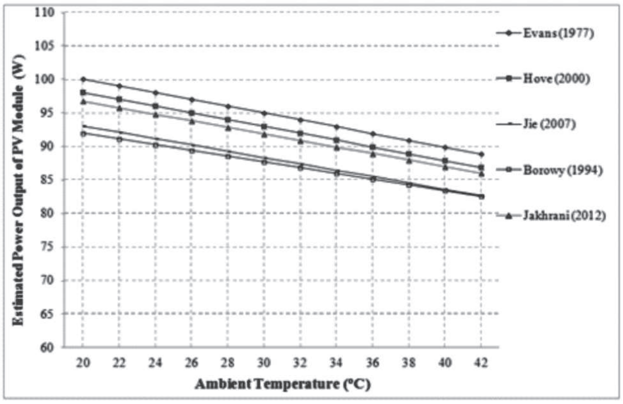

Figure 13. Comparative results of PV module power output versus ambient temperature at a constant solar radiation

It is revealed 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 high contribution in changing the amount of absorbed solar radiation (S_T) level. The changes took place by amount of total solar radiation $(\bar{H})$ in the output variables were 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 or albedo (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.

4. CONCLUSIONS

The results of sensitivity analysis parameters revealed that the most important input variable was the amount of total solar radiation $(\bar{H})$ because of its high contribution in modifying the amount of absorbed solar radiation (S_T) level, PV module power output $(P_{\max})$ and optimum PV array area (A_{opt}). The changes contributed by amount of total solar radiation $(\overline{H})$ in the output variables are approximately 2.5 times when its amount was varied around its typical ranges. The second most important parameters were slope (β) with 61% and the less important important variable was found to be solar azimuth angle (γ) with less than one percent influence over the output results as per one-at-a-time (OAT) method. Similarly, the highest sensitive input variable was found to be total solar radiation $(\overline{H})$ with the index of 0.8. The second sensitive variable was slope (β) with 0.38 and the lowest sensitive variable was found to be wind speed (V_w) with the index less than 0.1.

The higher sensitivity variance is displayed by slope (β) with more than 0.25 for all output parameters followed by hour angle (ω) with the variance of 0.1. The negligible variance is noted in the results of solar azimuth angle (γ) and wind speed (V_w) for all output parameters.

All output parameters displayed higher correlation with input variables except the slope (β). It displayed negative correlation for the amount of absorbed solar radiation (S_T) and maximum PV module power output $(P_{\max})$ and positive correlation with optimum PV array area (A_{opt}) with the index of 0.8.

The following conclusions were drawn from this study:

- The most important and sensitive variable was found to be solar radiation and least important variable was solar azimuth angle and the least sensitive variable was wind speed.
- The higher coefficient variance was displayed by slope followed by hour angle and insignificant variance is displayed by solar azimuth angle and wind speed.
- Almost all output parameters displayed higher correlation with input variables except slope of PV modules.
- Three input variables namely the amount of solar radiation, ambient temperature and slope have governing influence over the model results.

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