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Development of a Prediction Model for Output Power Reduction of PV Solar Panels Based on Environmental Parameters Using Particle Swarm Optimization Technique

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Abstract: Design guidelines for solar panels regarding the environmental parameter's influence over the solar panel power output are limited. This study proposes an output power percentage reduction model for predicting the effect of environmental parameters (ambient temperature, wind speed, relative humidity, dust accumulation and rain amount) using Particle Swarm Optimization (PSO). The PSO technique prevents an exhaustive traditional trial-and-error procedure for obtaining the set of the unknown coefficients of the proposed model. A total of 244 databases were collected from the literature and divided into two parts. The first set which comprises 194 data sets were used to build the proposed model while 50 datasets as the second set were used in the verification process. Three performance measures, namely mean absolute, mean absolute percentage and root mean square errors were used in the proposed model to ensure the accuracy of the study. The design procedure and accuracy of the proposed model are illustrated and analyzed via. simulation tests in MATLAB Software. The results show the applicability of the PSO technique to solve the solar energy problems. This technique can be adopted as an effective tool to explore the optimal solutions for the growth of the power reduction of solar panels with the different environmental parameters and provided a design guideline for solar panel site.

Key words: Environmental parameters, power reduction, Particle Swarm Optimization (PSO), solar panel, PSO technique, MATLAB Software

INTRODUCTION

Fossil fuel which is a non-renewable energy source is decreasing globally and has a negative effect on the environment. This issue requires seeking alternative renewable sources such as wind Photovoltaic (PV), geothermal energy and sea tide. Among these sources, PV power is a common and established technology that is becoming widely used. PV power is one of the potential candidates for green energy which has received considerable attention and the PV system directly converts solar radiation into electricity through the PV effect (Zhang *et al.*, 2015; Shi *et al.*, 2015; Koad *et al.*, 2017; Sawant and Bhattar, 2016; Anagnostos *et al.*, 2017).

Evaluation of PV technology performances can be done based on operating efficiency (Mani and Pillai, 2010; Tzivanidis *et al.*, 2015) while the PV system under the operation of real climatic conditions must be a known receiver of visible solar radiation (Mekhilef *et al.*, 2012). Environmental and climatic conditions have a strong effect on the PV performance (Gupta *et al.*, 2015). Therefore, studies on environmental and climatic conditions, including dust accumulation, precipitation, wind velocity, relative humidity, ambient temperature and other parameters are specific and relevant to the locality of the PV installation (Darwish *et al.*, 2013; El-Azab and Amin, 2015) (Table 1).

Darwish *et al.* (2013) reviewed the effect of some environmental parameters with dust on the PV performance. Relative humidity on the performance of the PV was studied by Kazem *et al.* (2012). Relative humidity increases the adhesion force that connects dust particles to a surface (Paudyal and Shakya, 2016). Shima *et al.* (2015) found that PV output power is affected by the ambient temperature, i.e., clean and cool PV results in high power generation and efficiency. Mejia *et al.* (2014)'s study the performance of PV during the dry seasons

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Table 1: List of symbols

Symbols	Quantity
T_a	Ambient Temperature
D_{acc}	Dust accumulation
RH	Relative Humidity
R_{ain}	Rain amount
N	Number of particles in swarm
W	Inertia Weight factor used to balance the global exploration and local exploitation
$v_{j,g}^{(t)}$	Velocity of particle j at iteration t
$x_{j,g}^{(t)}$	gth components for the position of particle j at iteration t
M	Number of components for the v_j and x_j vectors
t	Number of iterations (generations)
c_1, c_2	Cognitive and social acceleration factors, respectively "acceleration coefficients"
r_1, r_2	Random variables uniformly distributed within range (0, 1)
pbest	Best position found by the ith particle (personal best)
gbest	Best position found by swarm (global best, best of personal best)
y	Actual output value
ý	Predicted output value

period in which 29.76% efficiency reduction is observed but there was a slight improvement due to dew drops at morning. Soiling is the phenomenon of depositing dust on a surface during exposure to the environment. This phenomenon is considered as a major critical issue for PV that causes a decrease in the efficiency of the solar power system (Catelani *et al*., 2013). The deposition rate depends on the season (Chaichan *et al*., 2015). In an experiment conducted by Goossens and Kerschaever (1999) indicated that high wind speeds promote dust accumulation on the surfaces. Meanwhile, Mani and Pillai (2010) reported that dust-related degradation in PV performance is worse in the tropical regions where arrays are installed with lower tilt angles. Even though there are extensive studies about these parameters but there is no real model that can help to identify the relationship between power reduction and aforementioned parameters. Thus this study attempts to establish a novel model to calculate power reduction based on environmental parameters that named: ambient temperature, wind speed, relative humidity, dust accumulation and rain amount , to help the designers who wait from 5-10 years for adequate design efforts (Josephs, 1976), rabidly and randomly variation of parameters during the day and estimates how much Power Percentage Reduction (PPR) of the PV panel according to the variation in these parameters also, depend on the experimental data for sites already established (Touati *et al*., 2013).

The PSO can be a useful tool to generate the PPR model where the key issue related to the optimization techniques in obtaining values for a set of parameters that maximize or minimize objective functions subject to certain constraints (Rardin, 1998; Bergh, 2001). An optimization technique developed as a PSO is described by Hibbit (2005). The development of PSO is inspired by the flocking behavior of birds. Similar to Genetic Algorithm (GA) (Imran *et al*., 2017), PSO is established depending on a population that is initialized randomly. PSO is a heuristic global optimization method that has attracted the attention of many researchers (Pousinho *et al*., 2011; Hussein, 2016) which is applied to solve continuous and discrete optimization problems (Ethaib *et al*., 2016). This method is currently the most commonly used optimization technique (Zhang *et al*., 2015; Khare and Rangnekar, 2013; Pambudi *et al*., 2017). The multi-objective optimization problem can be solved through the PSO simulation (Chen *et al*., 2014a, b). Mansur and Alwis (1984) developed a technique for the reliability-based design of composite structures. The PSO technique is substantially more efficient than the other soft computing tools and this technique requires only a few function evaluations that will lead to an improved or similar quality of output (Ashour and Rishi, 2000). Previously, the PSO technique was applied in many studies and applications in engineering fields (Hanoon *et al*., 2017; Biao *et al*., 2014). Moreover, PSO is a heuristic global optimization method. Therefore, this method has attracted the attention of many researchers and is currently one of the most commonly used optimization techniques (Khare and Rangnekar, 2013; Vijayalekshmy *et al*., 2016).

Many researchers are fascinated by the use of PSO for various optimization problems in different fields. Specifically in renewable energy, PSO has been successfully applied to solve numerous and diverse optimization problems (Chen *et al*., 2014a, b; Balasankar *et al*., 2017; Mohandes, 2012; Sharafi and ELMekkawy, 2014; Tabet *et al*., 2014).

Thus, the main objective of the current study is to develop a model for PPR in a solar panel system using the PSO technique. Also, this study aims to find a new design guide for selecting a suitable site for the power plant establishment and the procedure will minimize the time consumed for the design process.

The applications of this technique in renewable energy remain limited despite the extensive research on the optimization techniques in modern solar plants such as in the aeronautical, automotive, civil engineering and mechanical industries. The renewable energy optimization does not merely comprise tracking systems or cost reduction. Renewable energy optimization techniques can be used to investigate the effect of environmental parameters on the performance of the power plant.

Despite the extensive studies on the environmental parameter's behavior on the power output of the solar power plant, assessing the power plant output with the different environmental parameters remains difficult to understand because of the rabid and random parameter variation.

The present study shows the capability of the PSO technique to assess the PPR of the PV with the different environmental parameters. Also, this study will aid designers in determining the appropriate site for the solar model.

MATERIALS AND METHODS

Solar energy is the future of alternative energy and the use of solar energy increases the efficiency of the solar power system. The most important factors that affect its efficiency are the environmental conditions for a solar power system excitation site where each site is different from the other. The output energy reduction of the solar panel is studied through experimental testing results. Therefore, this study investigates the prediction of the PPR through the PSO technique.

PSO technique

PSO concept: The PSO technique is a population-based search algorithm with each individual referred to as a particle and represents a candidate solution. Each particle in the PSO flies through the search space with an adaptable velocity that is dynamically modified based on its own and other particle flying experience. In the PSO, each particle aims to improve by imitating the traits of its successful peers. The particle has the capability to remember the best position in the search space that the particle has visited previously. The position matching to the best fitness is known as pbest and the overall best out of all the swarms in the population is called gbest. Two characteristics, namely, position and velocity are assumed to be associated with each particle. The particle moves around to different places in the design space and remembers the best position (in terms of the objective function value or food source) that the particle has determined. The communication of information occurs between particles with regard to good positions in the space. The particle's individual velocities and positions are adjusted accordingly based on the information. For example this study considers the behavior of birds in a flock. Each bird has a limited intelligence independently and therefore behaves in accordance with the following outlined rules:

- The bird aims to not come considerably closer to the other birds
- The bird flies toward the average direction of the other birds
- The bird attempts to adjust the average position between the other birds with minimum spaces in the flock

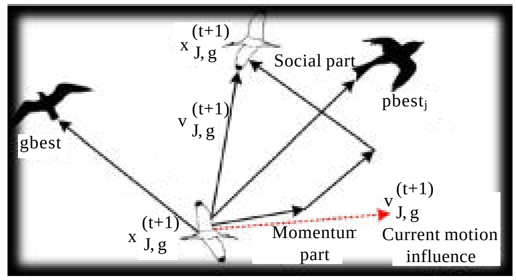

Fig. 1: Description of velocity and position updates in PSO for a 2-dimensional parameter space

The development of the PSO is done based on the following model: If the target (food) is found by one bird that is a maximum of the objective function this bird immediately transfers the information to other birds. With least delay, all other birds will move to the target (food).

Each bird has its own independent thinking and previous memory or experience. Therefore, randomly search is simulated in the design space for the determination of the maximum value of the objective (fitness) function. The birds are able to locate their target (food) over many iterations. The following formulas show that changed the position and velocity of each particle can be computed using the current velocity and the distances from the to the (Mier, 1984; Kratzig and Polling, 2004; Hibbit *et al.*, 2005):

$$v^{(t+1)}_{j,g} = wv^{(t)}_{j,g} + c_1 r_1 \left(pbest_{j,g} - x^{(t)}_{j,g}\right) + c_2 r_2 \left(gbest_g - x^{(t)}_{j,g}\right) \quad (1)$$

$$x^{(t+1)}_{j,g} = x^{(t)}_{j,g} + v^{(t+1)}_{j,g} \quad (2)$$

with j = 1, 2, 3, ..., n and g = 1, 2, 3, ..., m:

- The jth particle position in the swarm is illustrated by d-dimensional vector $x_j = (x_{j,1}, x_{j,2}x_{j,3}, ..., x_{j,d})$
- The jth particle velocity in the swarm is indicated by another vector $v_j = (v_{j,1}, v_{j,2}, v_{j,3}, ..., v_{j,d})$
- The best last location of the jth particle is presented by $pbest_j = (pbest_{j,1}, pbest_{j,2}, ..., pbest_{j,d})$
- The best position determined by the swarm is called global best (i.e., best of personal best) and presented by $gbest_j = (gbest_{j,1}, gbest_{j,2}, ..., gbest_{j,d})$

In PSO search space each particle flies with velocity based on its previous best solution and the best previous solution of its assemblage. Figure 1 shows particle velocity and location updates for 2D parameter space. The velocity consists of three main vectors shown in Fig. 1.

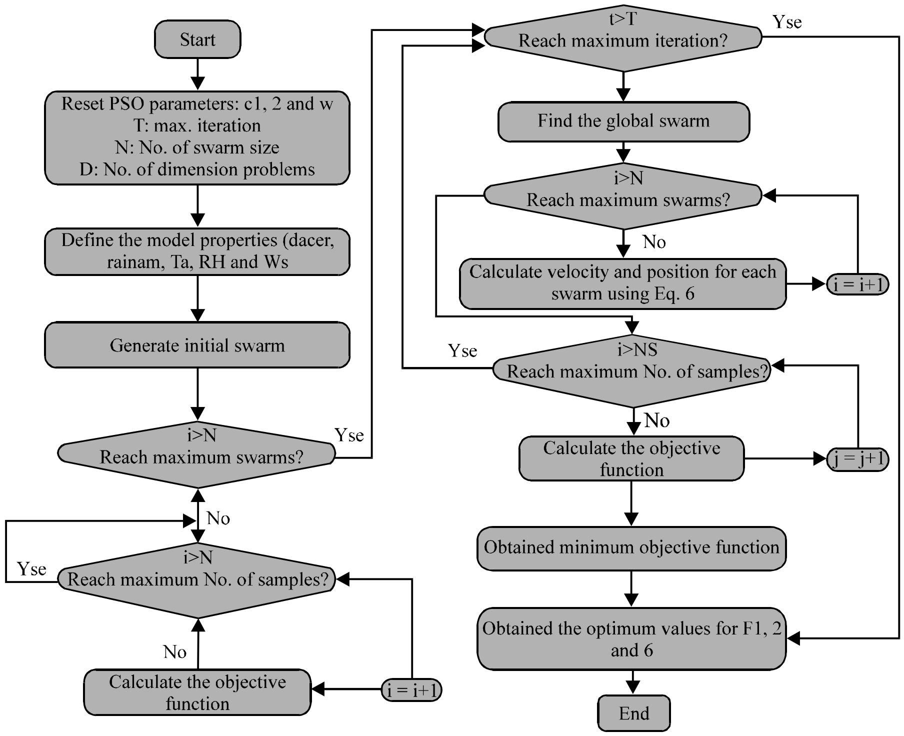

Fig. 2: Flowchart of PSO of proposed PPR Model

Vectors are momentum or inertia, cognitive or memory and social or swarm. The momentum or inertia element of the vector is based on particle velocity in the previous time step. This component provides the trend for particle persistence in its current path. The cognitive component or memory is derived from the best particle position during each iteration. This component attracts particles to its better position in its former space solution. In the final vector, a social element or swarm, the particles are attracted towards the best position in the swarm. Figure 2 shows the computational flow chart of the PSO algorithm used in the present study. The accurate selection of the PSO parameters has a marked effect on the performance of the algorithm. The neighborhood size is also required for the local best algorithm. For the PSO implementation, several parameters need to be carefully selected for its efficient performance. The parameters include swarm size, initial inertia weights (w) and stopping criteria. Other parameters are cognitive and social acceleration factors which are denoted as c_1 and c_2, respectively.

The weighting of the stochastic acceleration terms are represented by the two constants, namely, c_1 and c_2 that pull each particle toward the pbest and gbest positions. Low values will allow the particles to depart from the target position in space before being pulled back. However, high values result in an abrupt movement toward (or past) the target regions. The suitable selection of inertia weight (w) provides a balance between the global and local explorations thereby requiring limited iteration on average to determine a sufficiently, optimal solution. As originally developed, w often decreases linearly from approximately 0.9-0.4 during a run (Mier, 1984).

Performance measures: Three statistical performance measures, namely RMSE, MAE and MAPE were used to evaluate the prediction accuracy of the proposed models. Equations 3-5 showed the formulas for each of the performance measures enumerated. These performance measures are:

Root Mean Square Error (RMSE): To determine the square error of the prediction compared with the actual values, RMSE is a frequently used performance measure that is computed to obtain the square root of the summation value. Thus, the average distance of a data point from the fitted line measured along a vertical line is called RMSE. In other words, the difference between the values predicted by the model and the actual observed

Table 2: Main PSO parameters

Description	Details
Number of particles (N)	A typical range is 10-40 while for some difficulty or special problems the number can be increased to the range of 50-100
Dimension of particles (D)	It is determined by the problem to be optimized
Inertia weight (w)	Usually is set to a value <1 and for faster convergence, w = 0.7 is considered (Lavanya and Udgata, 2011) It can also be updated during iterations
Vectors containing the lower and upper bounds of the n design variables, respectively, x^L, x^U	They are determined by the problem to be optimized. Different ranges for different dimensions of the particles can be applied in general
Cognitive and social parameters	Usually $C_1 = C_2 = 1.494$ (Lavanya and Udgata, 2011) or other values can also be used provided that $0<C_1+C_2\leq 4$

Table 3: PSO convergence parameters

Description	Details
Maximum number of iterations (T_{max}) for the termination criterion	Determined by the complexity of the problem to be optimized in conjunction with other PSO parameters (D, N)
Number of iterations for which the relative improvement of the objective function satisfies the convergence check. Minimum relative improvement of the value of the objective function	If the relative improvement of the objective function over the last number of iterations (including the current iteration) is less or equal to the minimum relative improvement, convergence has been achieved

values from the system is RMSE measurements. With this statistical performance measure, the undesirable large differences can be identified efficiently. The formula is presented in Eq. 3:

$$\text{RMSE} = \sqrt{\frac{1}{NS}\sum_{i=1}^{NS}\left(y\text{-}\acute{y}\right)^2} \tag{3}$$

Where
y = Actual value
ý = Predicted value
NS = Number of data samples

Mean Absolute Error (MAE): MAE is frequently used to measure the accuracy of continuous variables. This statistical performance measure tests the closeness between eventual outcome and the forecast. In this case, the errors between the predicted and actual value are measured and the mean of the magnitude is computed thereby disregarding the direction of errors. Equation 4 shows the mathematical formula for MAE:

$$\text{MAE} = \frac{1}{NS}\sum_{i=1}^{NS}\left|y\text{-}\acute{y}\right| \tag{4}$$

Mean Absolute Percentage Error (MAPE): MAPE measures the accuracy of the model. This is very useful and important measure because it gives the size of the error in terms of percentage. It also comes with the added advantage of interpretability and scale-independency. MAPE can be evaluated using Eq. 5:

$$\text{MAPE} = \frac{1}{NS}\sum_{i=1}^{NS}\left|\frac{y\text{-}\acute{y}}{y}\right| \tag{5}$$

Convergence criteria: Looking at the iterative nature of the PSO search, the optimization procedure can be stopped by applying convergence criteria. In PSO algorithm, two most prominent and widely adopted convergence criteria are used. The first criterion is the maximum number of iterations while the second one is the minimum error needed for calculating the optimum value of the objective function. The maximum number of iterations is applied based on the difficulty of the optimization issues whereas the second criterion assumes previous knowledge of the global optimum value. In a situation where the optimum value is known a priori, it is possible to test or fine tune the algorithm in mathematical problems. However, this does not apply to optimal structural process problems where optimization is not previously known. A list of the main PSO parameters is given in Table 2 while Table 3 lists and clarifies the convergence parameters of the PSO utilized in the current study.

The following highlights show how the PSO algorithm can be implemented to search for the optimum PPR of PV:

Algorithm 1; PSO algorithm:
Step 1: The initialization of the swarm of each particle is done by the assignment of a random position in the problem hyperspace
Step 2: The objective function of the proposed PPR for each particle is evaluated
Step 3: The comparison of objective function value of each individual particle with its pbest. If the current value is better than the pbest value this value is set as the pbest and the current particle position, Xi is set as pbest
Step 4: The best objective function for each particle is identified. The value of its objective function is determined to be gbest and its position is pbest
Step 5: The velocities and positions of all the particles are updated based on Eq. 1 and 2
Step 6: Steps 2-5 are repeated until one of the convergence criteria (i.e., the maximum number of iterations or a sufficiently good objective function value is reached) are met

(a) (b)

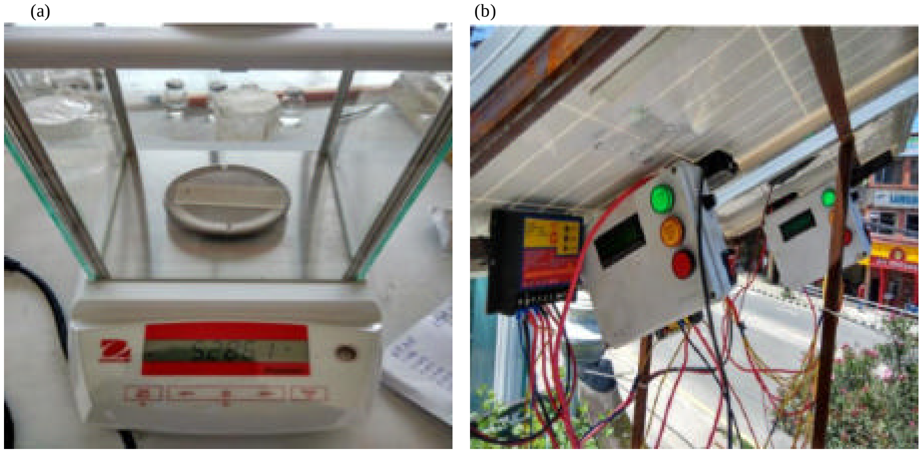

Fig. 3: a, b) Experimental setup data collection (Paudyal and Shakya, 2016)

Fig. 4: Data collection techniques (Paudyal and Shakya, 2016)

Experimental data: For the purpose of the analysis, the database was divided into two sets, i.e., training and verification set and testing set. The testing set was not seen during model development, rather it usage was restricted to model testing after training. In order to ensure database division is consistent, different types of combinations of the training and testing sets were considered. In that case, the minimum, maximum, mean and standard deviation of the power percentage reduction values should be consistent amongst the training and the testing datasets. A total of 244 experimental data from various published studies (Paudyal and Shakya, 2016; Elminir *et al*., 2006) were collected to establish the database of the proposed model. Out of the 244 data sets, 194 data which represent 80% are considered for training process while the remaining 20%, i.e., 50 data were used for verification of the PPR.

Frank and Todeschini, proposed that for a model to be acceptable, a minimum ratio of 3 for the number of datasets records over the number of input variables is needed. Furthermore, the researchers recommended the use of ratio values higher than five. For the current study, this ratio for the training set was 194/5 = 38.8. Looking at the ratio, the ratio exceeded the suggested value. The factors selected as inputs for training in this study are ambient temperature, wind speed, relative humidity, dust accumulation and rain amount. Figure 3-5 shows the geometrical details of the case studies. The database was compiled in a patterned format. Each pattern comprises an input vector that contains the environmental parameters of PV and an output vector that contains the corresponding PPR. Table 4 provides the range, mean, median and standard deviation values of all basic design parameters used in the database.

(a)

(b)

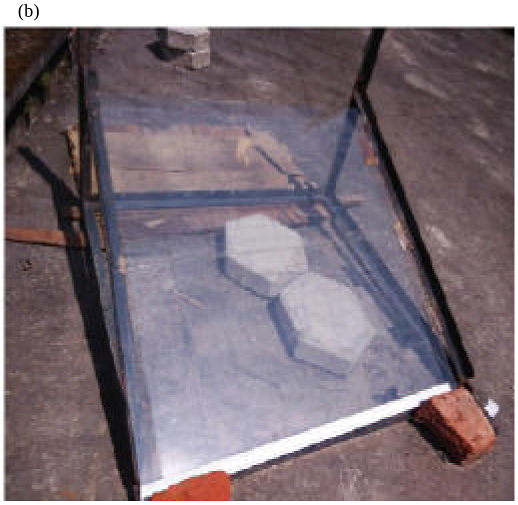

Fig. 5: a, b) Wooden frames covered by glass samples exposed to environment (Elminir *et al*., 2006)

Table 4: Range of PPR parameters for PV used in database

Factors	Min	Max	Mean	SD
Ambient Temperature (T_a)	8.93	26.16	19.55	4.82
Wind speed (W_s)	0.5	4	1.497	0.871
Relative Humidity (RH)	30.28	77.04	58.12	8.60
Dust accumulation (D_{acc})	0.148	9.896	3.799	2.456
Rain amount (R_{ain})	0	67.046	8.193	12.403

Objective function: A good agreement was attained between the experimentally, measured PPRs that were accounted for via. the final model obtained from PSO. The proposed model was simulated using a MATLAB code to optimize the PPR Model for the PV. The proposed model to be optimized is as follows:

$$P_{red} \quad F_1+F_2T_a+F_3D_{acc}+F_4R_{ain}+F_5\log RH+F_6\log W_s \qquad (6)$$

Where:

P_{red} = The Predicted PPR
T_a = Ambient Temperature
D_{acc} = Dust accumulation
R_{ain} = Rain amount
RH = Relative Humidity
W_s = Wind speed
F_1-F_6 = Unknown coefficients

The use of PSO is to primarily optimize the PPR Model by searching for an optimum set of coefficients from within the solution space. Accordingly, the difference between the measured PPR of the PV and that calculated using the final form of the optimized equations is minimal.

The objective function for each PSO Model was constructed to measure the agreement between experimentally measured data and the predicted output of the model. Furthermore, the convergence of a particular model was determined based on terminating the search process but this happened when a set of coefficients was achieved that minimize the objective function.

RESULTS AND DISCUSSION

Three PSO Models were adopted to optimize the PPR that corresponded to the three different performance measures. These models have been proposed to analyze the effects of the performance measures and the number of particles in a swarm on the results of the PSO Model.

The primary task of the objective function in a PSO technique is to minimize the variance between the predicted and measured PPR. By definition, PSO provides models that are capable of assessing the maximum PPR with the experimental results.

The PSO algorithm updates its process until either an appropriate gbest is completed or the pre-defined number of maximum iterations is reached. The number of iterations is fixed at 1,000 because the variances in the objective functions become constant after 400-700 iterations as shown in Fig. 6. The swarm size was varied to analyze the particle number that provided the best performance for convergence and processing time. In the current study, 10-50 particles were used to investigate the effect of the particle number on the accuracy of the proposed model. Figuer 6 shows that the swarm sizes of 10-50 for MAE, MAPE and RMSE, effectively estimate between the predicted and measured PPR. Figuer 6 also shows the variation of the performance measure values of the objective function for the different particle

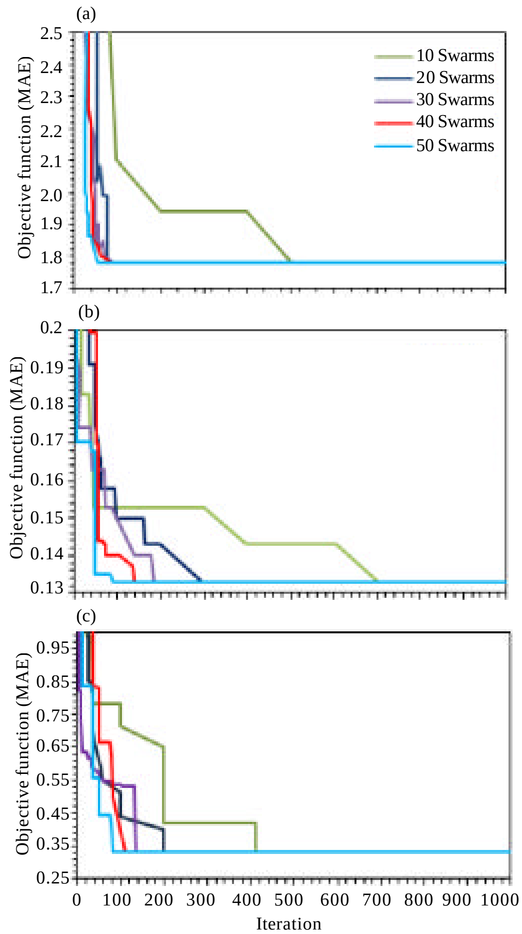

Fig. 6: Convergence process for different swarm sizes

Table 5: Parameters used in PSO algorithm model setting

	Objective function		
Factors	RMSE	MAE	MAPE
F1	3.3800	4.7511	1.1425
F2	-0.3614	-0.0996	-0.0440
F3	1.8282	2.3781	2.5343
F4	-0.0306	-0.0424	-0.0394
F5	2.6928	1.1053	1.5191
F6	-1.1938	-2.9290	-2.7262
Iteration	1000.0	1000.0	1000.0
Upper bound	5.0000	5.0000	5.0000
Lower bound	-5.0000	-5.0000	-5.0000
Swarm size	20.0	20.0	20.0

populations. Figuer 6 shows that the 20 swarms provide the best solution for the PSO algorithm because they achieve the minimum objective function of approximately 1.78 for MAE, 0.33 for RMSE and 0.133 for MAPE. For the other swarms, 10 swarms exhibit high errors while 30-50 swarms are more time-consuming than 20 swarms. Table 5 presents the optimum values of the coefficient factors that are suggested in the proposed model for the different performance measures. Bland and Altman (2007), Igelstrom *et al.* (2013) and Stralen *et al.* (2008) analysis is used to study the agreement between the models and to find which objective function (MAE, RMSE and MAPE) is suitable for the proposed PPR Model. The advantage of Bland-Altman plot also has shown the variation in the results and it is a scatter plot. In the Bland-Altman plot, the mean +1.96 and -1.96 SD are shown in the graph 7, namely, the "limits of agreement". Based on the limits of agreement, the range of values can be easily identified as either large or small. A refers to the measured value; B is the predicted value and Standard Deviation (SD) of the differences. From this plot, estimating the level of (methodical) difference, scattering the values and showing whether a relation between the measured and predicted error exists is much easier. Figuer 7 shows, a reasonable agreement occurs between the different testing methods. The data distributed between the limits of agreement is 96.4% for MAE and RMSE (Fig. 7a and c) and 93.8% for MAPE (Fig. 7b).

Therefore, the MAE and RMSE showed a high level of accuracy for the measured PPR with the MAPE Model. Where m is the mean of the differences between the predicted PPR and measured; m -1.96 SD and m +1.96 SD are the upper and lower limits of the interval of the agreement, respectively.

The results show demonstrates that the statistical analysis of the PPR predicted by the proposed model matches the experimental results well. The RMSE, MAE and MAPE result in mean = 1.03, SD = 0.164 and COV = 0.159; mean = 1.01, SD = 0.157 and COV = 0.155 and mean = 1.03, SD = 0.164 and COV = 0.158, respectively. These results indicate that the proposed model is generally reliable.

The mean value of the MAE Model is considered very close to 1.0 (i.e., 1.01). The coefficient of the variation obtained from the results for MAE (i.e., 0.155) indicated good accuracy and consistency of the values obtained. This result was sufficient to consider the proposed model properly to assess the PPR of the PV under different environmental parameters. Moreover, further research is necessary to increase the accuracy of the proposed model considering the wide range of parameters. Figuer 8 shows a comparison of the model predictions with the experiment performed for the three models of the aforementioned performance measures.

The efficiency of the proposed model is shown Fig. 8 which is optimized via. in the PSO Model of the PV using the PPR results of the 194 environmental parameters collected from the published studies. The performance of the proposed model for RMSE, MAE and MAPE is

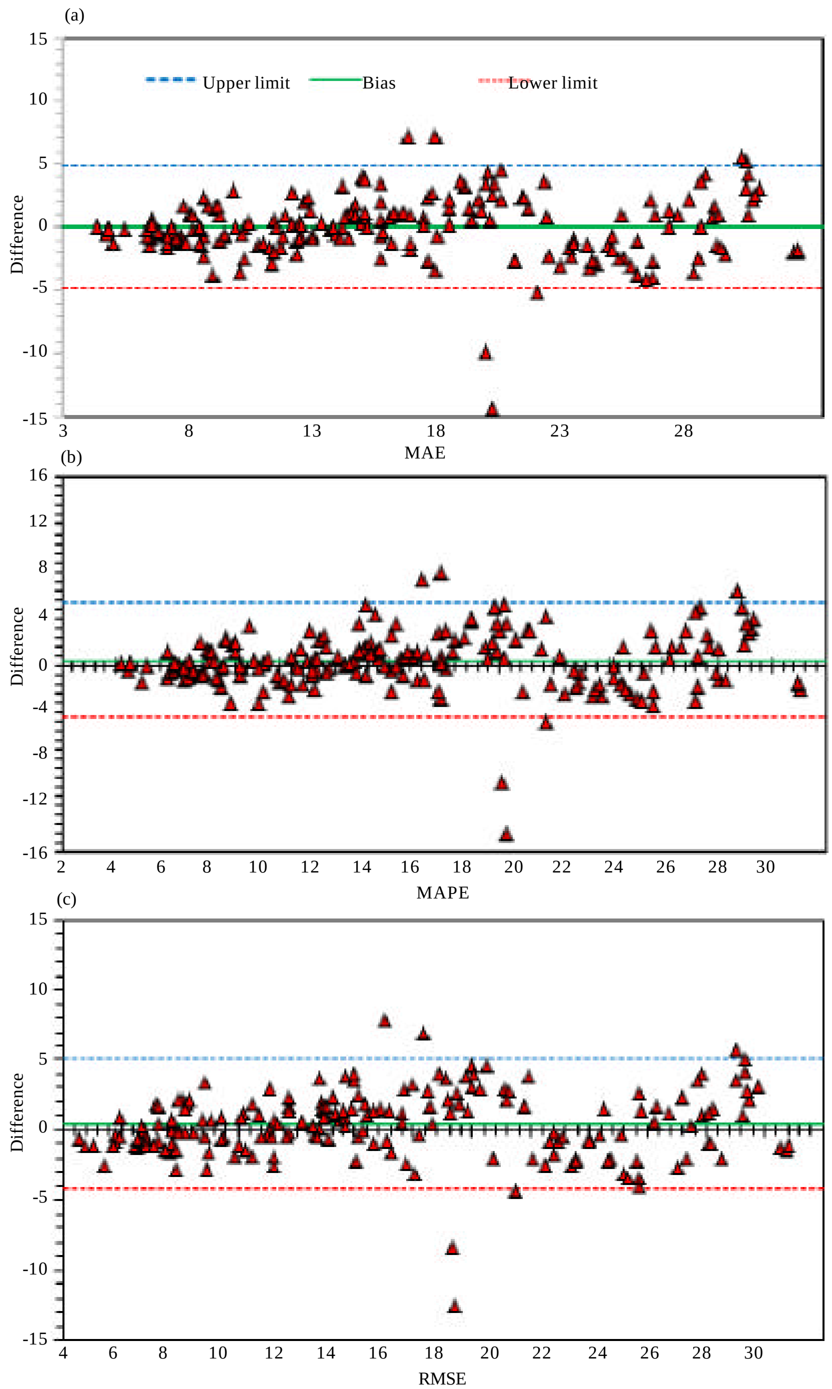

Fig. 7: Bland-Altman plot of relation between measured and predicted PPR: a) Mean absolute error; b) Mean absolute percentage error and c) Root mean square error

illustrated in this Fig. 8. Moreover, Fig. 8 indicates the ratio of the experimental to the predicted PPR for all PV in the database. The model provided by MAE is considered as a better-estimated model compared with MAPE; the former is slightly different from the latter with an average, standard deviation and coefficient of variation of 1.01, 0.26 and 0.264, respectively and shows the output quantities predicted by the proposed model. The results show that the swarm size has a minimal influence on the results of the proposed model.

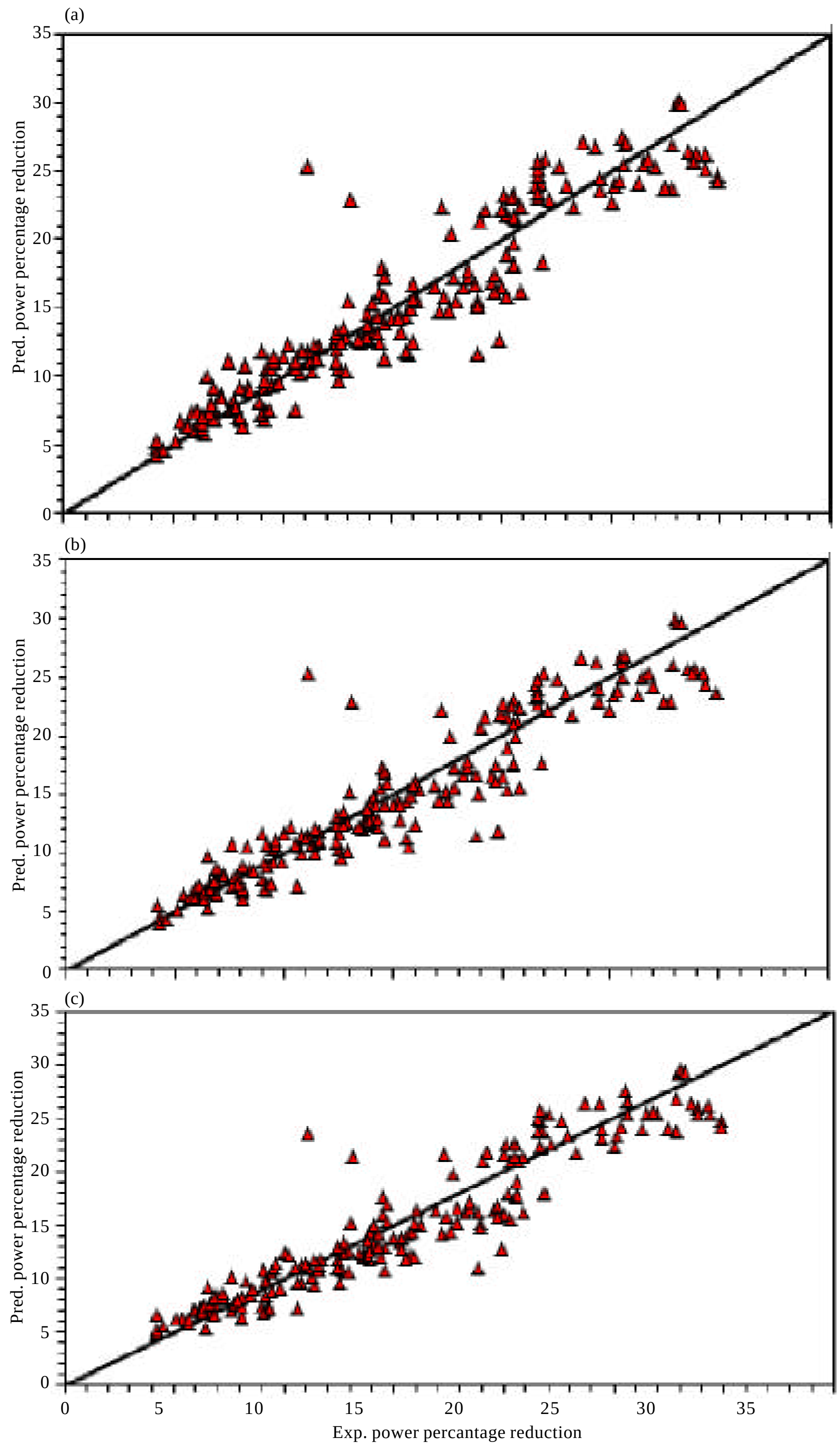

Fig. 8: Comparison between experimental and predicted PPR of proposed model: a) Mean absolute error ($R^2 = 0.8952$); b) Mean absolute percentage error ($R^2 = 0.8922$) and c) Root mean square error ($R^2 = 0.8911$)

Parametric study: The evaluation of the environmental parameters for a new solar power plant requires a large survey data set. Therefore, the site should be as close as possible to the load center to minimize the power transmission losses. A case study was conducted to evaluate the ability of the proposed model to assess the

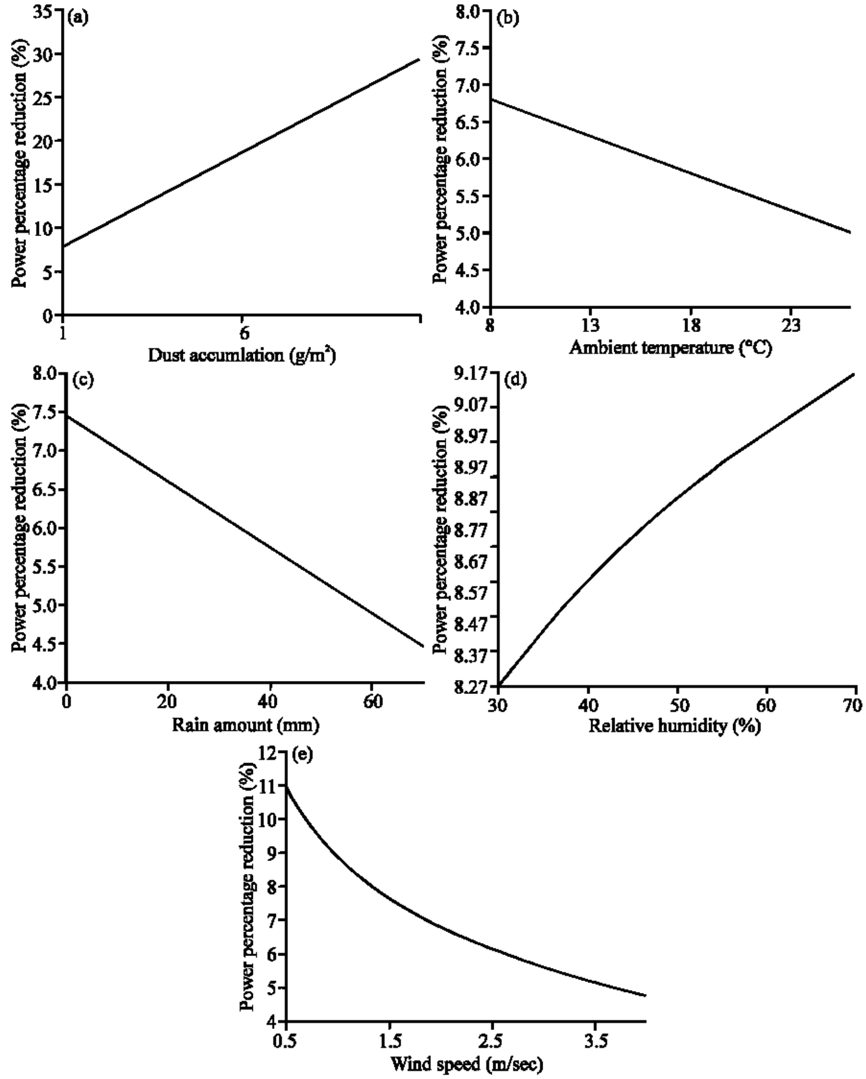

Fig. 9: Variation of predicted PPR with dust accumulation, ambient temperature, rain amount, relative humidity and wind speed: a) Dust accumulation ($y = 2.3781x+5.612$, $R^2 = 1$); b) Ambient temperature ($y = -0.0996x+7.5979$, $R^2 = 1$); c) Rain amount ($y = -0.0424x+7.4371$, $R^2 = 1$); d) Relative humidity ($t = 1.105\ln(x)+4.5087$, $R^2 = 1$) and e)Wind speed ($y = -2.929\ln(x)+8.8313R^2 = 1$)

effect of the various parameters on the PPR. Figuer 9a shows the effect of the dust accumulation on the PPR in which an increase in PPR increases the dust accumulation amount according to a linear relation (Chaichan *et al*., 2015; Klugmann-Radziemska, 2015). Figuer 9a, b decrease in the PPR increases the ambient temperature (Inman *et al*., 2016). Figuer 9c shows, a decrease in PPR increases the rain amount according to a linear relation (Weber *et al*., 2014). According to the logarithmic relation between the PPR and relative humidity, Fig. 9d shows an increase in PPR with an increase in relative humidity (Mekhilef *et al*., 2012; Elbreki *et al*., 2016) while Fig. 9e provides a decrease in the PPR with an increase in wind speed (Sayyah *et al*., 2014).

Proposed model verification: The verification of the built PSO Model was done with 50 experimental data records. This set of data was not used for the construction and optimization of the model. The PSO Model showed a mean of 1.005, an SD of 0.090 and a CoV of 8.98%. This result indicates that this model shows a better interconnection between the experimental and predicted PPR values. Thus, the proposed PSO Model can efficiently estimate the

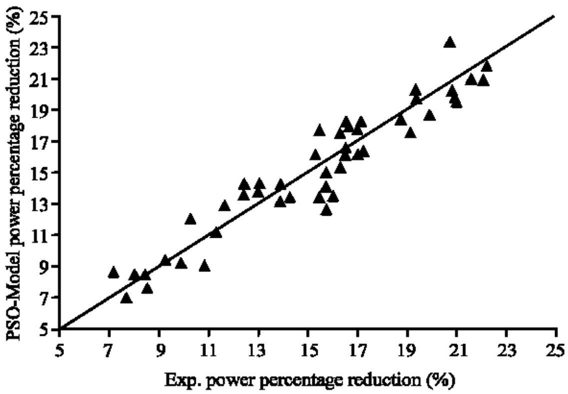

Fig. 10: Comparison between experimental and predicted PPR values for the PSO Model (R^2 = 0.9182)

values of PPR for the various environmental parameters values. For high accuracy, the CoV values should be less than 10%. While CoV value between 10% and 20% indicate a good prediction and values ranging between 20% and 30% indicate low accuracy. Lastly, CoV values above 30% show a significantly, lower precision value. Figuer 10 presents the predicted PPR values as per the PSO Model.

CONCLUSION

This study used the PSO technique to propose a model for PPR in a solar panel. The results of the model show the applicability of the PSO technique to assess the solar energy problems, minimal influence on the processing time and convergence of the PSO algorithm where this technique can be adopted as an effective tool to explore the optimal solutions for the growth of the PPR of the PV with the different environmental parameters such as ambient temperature, dust accumulation, rain amount, relative humidity and wind speed which have a significant effect on the predicted PPR of the PV. This model minimized time consumption in the design process and provides a guideline for selecting the suitable site for the power plant with the consideration of the environmental parameters. In this model, three performance measures, namely, MAE, MAPE and RMSE were analyzed and the result provided a high accuracy of MAE according to it.

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