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Development of an Empirical Coefficient for the Short Circuit Current to Determine Soiling Effect on PV Performance

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Abstract: In this study, the effect of dust accumulation on the performance of photovoltaic (PV) module has been shown. A statistical analysis has been conducted on a medium sized sample data collected from 30 hours of experimental work to obtain an empirical coefficient like temperature coefficients of short circuit current and open circuit voltage usually provided by manufacturers. This coefficient will be named dust coefficient of short circuit current and it will represent a predefined range of environmental conditions and soiling amounts; as the available testing conditions, and the statistical model prediction limits bound the coefficient extent of applicability.

Keywords: *Solar energy*; *Photovoltaic; Soiling; Statistical modelling*

1. INTRODUCTION

The term "Soiling" is normally used to describe the accumulation of dust on the front glass of PV module. Electrical characteristics of PV module, particularly, the short circuit current will be affected by shading due to dust accumulation and a simultaneous decrease in the relevant efficiencies will occur. Al-Shabaan et al. [1] have concluded the same as they found that deposited dust adhered to PV panels' surfaces, which in turn; reduced the amount of solar radiation that reaching PV panels and decreasing the panels 'efficiency significantly. Sulaiman et al. [2] experiments were conducted using dust particles on solar panels with a constant-power light source and found that the accumulated dust on the surface of the photovoltaic solar panel can reduce the system's efficiency by up to 50%.

More technical, shading affects the current provided by a PV panel, but the voltage remains the same as Maghami [3] have approved. Another study made by Ndiaye et al. [4] on a mono crystalline silicon (mc-Si) and a poly crystalline silicon (pc-Si) PV modules put more emphasis on the effect of dust on PV panel electrical characteristics by specifying the maximum power and the short circuit current among others as the most affected performance characteristics by dust depositing on PV modules surfaces with up to 78% recorded loss in the maximum power output for both mono and poly crystalline modules, while the open circuit voltage has not changed for data collected during one operation year without cleaning.

The effect of dust composition has been studied by Kaldellis et al. [5] and they found from their study of different air pollutants a considerable reduction of PVs' energy performance, depending strongly on particles' composition and source. Studying the effect of dust solely or in parallel with other affecting factors was recommended by Mekhilef et al. [6]. Cristaldi et al. [7] worked on a simplified method for evaluating the impact of both aging and dust deposition. Their method allowed distinguishing between aging of PV module losses and presence of dust losses. Hai Jiang et al. [8] have prepared a laboratory setup with Sun simulator and test chamber so to measure the degradation in output efficiency with dust deposition density increasing from 0 to $22\,\mathrm{g\,m^{-2}}$. They found the corresponding reduction of PV output efficiency grew from 0 to 26% and they have noticed linear relationship between reduction of efficiency and dust deposition density. Siddiqui [9] developed an equation between differences in efficiencies of module with respect to thicknesses of dust collected on the module using collected data for all seasons for a certain location. The study of Kumar et al. [10] also analyzed and quantified losses caused by accumulation of dust on surface of photovoltaic modules based on other researchers experiments.

In section 2 a complete description of the test equipment, setup and procedure are presented. Section 3 tackles the statistical model technique used in this study, derives the empirical model, assessing the utility of the model and presents the results in form of a general equation combines the temperature and soiling effect. Section 4 summarizes the results and concludes the study.

2. MATERIALS AND METHODS

To estimate the proposed statistical model parameters, a solar/weather simulation chamber was used (Atlas SEC 1100 Solar Simulator Chamber). Sample data was collected from indoor tests conducted on a mono-crystalline PV module by controlling environmental parameters surrounding it. PV module temperature was maintained within varying manner while irradiation was kept constant. Details of the test environment and test setup are provided next.

The testing was conducted in an Atlas SEC 1100 Solar Simulator Chamber in Gulf Organization for Research and Development, Techno-hub facility at Doha, Fig. 1. The parameters that can be controlled in the chamber includes air (ambient) temperature, irradiance, relative humidity via a touch screen control panel located on the front of the chamber. The used PV module is RNG-50D (50W Mono crystalline Solar Panel) manufactured by Renogy. Electrical characteristics of the PV module are provided in **Table 1**. The irradiance was set fixed at 1000 W/m2 inside the chamber, while the actual working value was in the range of 900 W/m2 to 930 W/m2. The temperature of the chamber was set to vary increasingly from (30 ºC to 60 ºC). A fixed soil quantity was repeatedly added at every run of the chamber, which is uniformly distributed over the module surface, **Fig. 2**. The uniform distribution of the soil was maintained manually by using cloth as a sieve to spread soil fine particles over the module front glass. The soil was weighed by weight scale with a precision of 1 g. Plaster sand was used for the soiling and the test started with quantity of 1g per module area till 59g per module area. Each run consisted of measuring the short circuit current I_{sc} , which was measured by Pro's Kit MT-1280 3 1/2 Digital Multimeter. The temperature of the PV was monitored at 6 different points of the PV backside and its average was considered as the PV temperature. The measurement was done by Class B PT100 temperature sensors connected to the monitoring system of the Atlas SEC 1100 solar simulator chamber logger which gave out real time outputs of the parameters being monitored except the power output of the PVs. The relative humidity was set constant at 0% so to avoid any effects of its variation. The irradiance at the PV module's plane was measured using an ISO 9060 First class compliant Kipp & Zonen CMP 6 pyranometer (in the SEC1100) which can measure up to 2000W/m2 in a spectral range of 285 to 2800 nanometers with a sensitivity of 12.29x10-6 µV/Wm-2 and a 180° field of view.

Table 1. Renogy's RNG-50D module electrical characteristics

Maximum power at STC	50 W
Optimum operating voltage (V_mp)	18.5 V
Optimum operating current (I_mp)	2.7 A
Open circuit voltage (V_oc)	22.7 V
Short circuit voltage (I_sc)	2.84 A
Module efficiency	14.67%
Maximum system voltage	600 VDC UL
Maximum series fuse rating	15 A

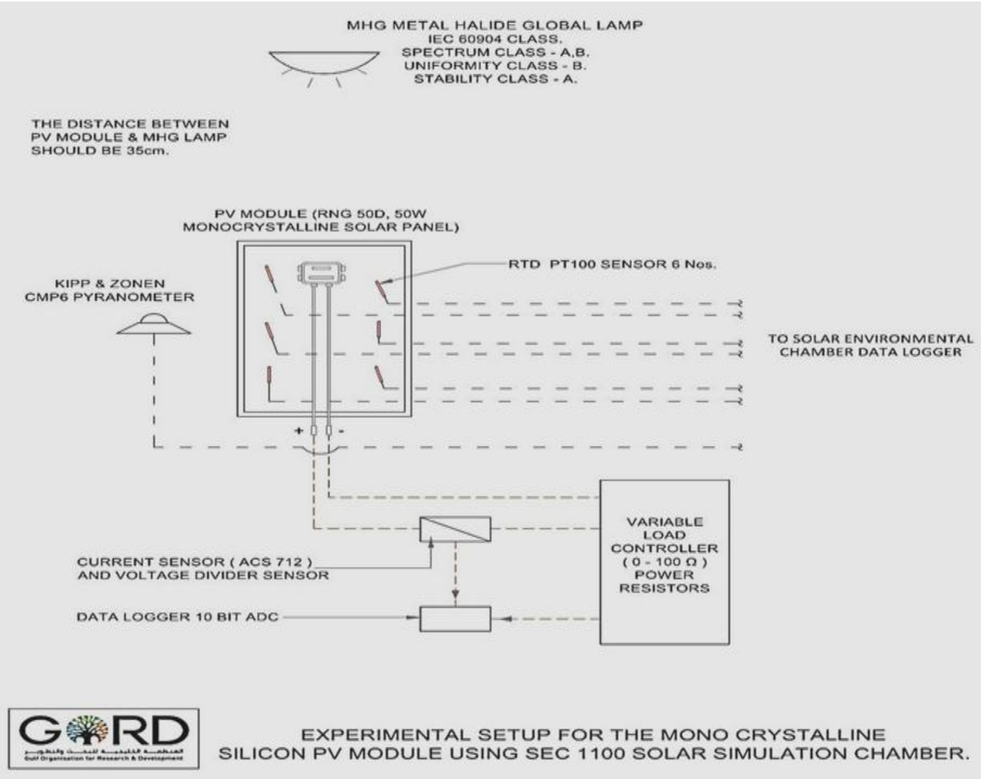

Fig. 1. Experimental Setup diagram for the mono crystalline PV module Soiling test using SEC1100 solar simulator chamber located in GORD's Techno Hub research facility, Qatar.

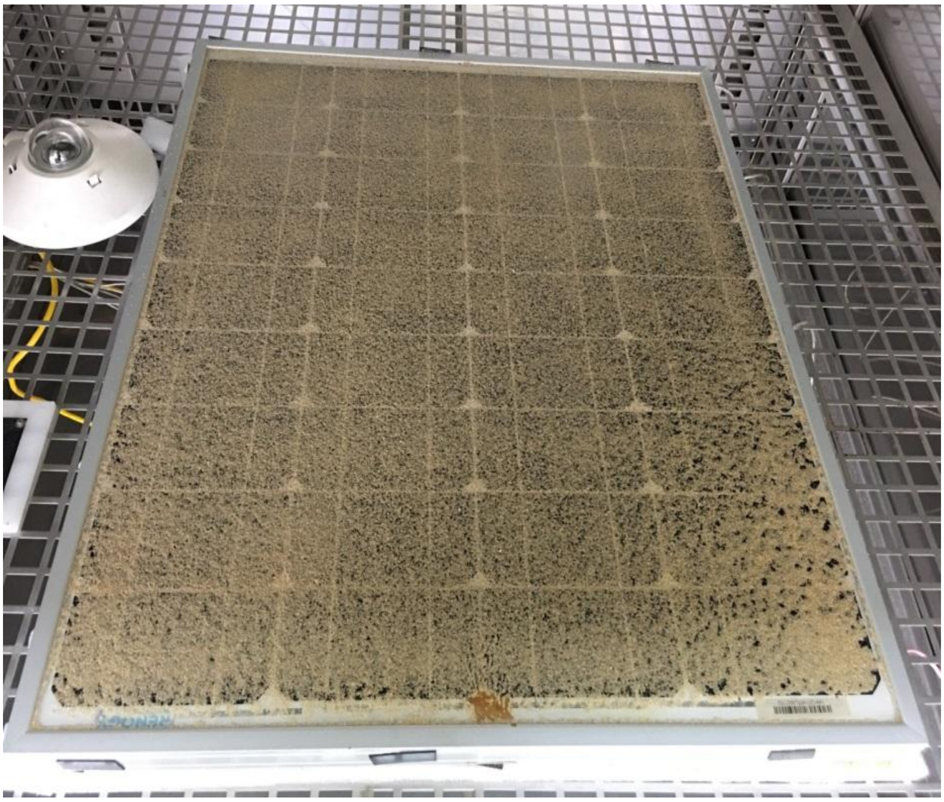

Fig. 2. Photographic view of PV module inside the chamber with 59g of plaster soil uniformly distributed on its top

3. RESULTS AND DISCUSSIONS

3.1 Statistical modeling

It is very crucial to decide how big the sample should be. Then statistical method has been used to determine the demanded sample size, hence the multiple times needed to run the experiment. Among all available statistical sample size determination techniques, power based sample size calculation method was selected as it depends on the degree of certainty, which is set by IEC 61215 standards (P_{max} degradation shall not be more than 5%).

Then the statistical formula to calculate sample size **n** is given by Cornish et al. [11]:

$$\mathrm{n} = f(\alpha, \beta) \cdot \frac{2\mathrm{s}^2}{\delta^2} \tag{1}$$

where **α** is the significance level (using a two sided test). As it is always 95% significance interval for regression analysis, consequently **α** is 0.05. (1-β) is the power of the test which is determined by the IEC 61215 standard, and f(α, β) is the magnitude of t-variable function in t-Test for means, which its value is calculated with aid of **α** and **β**. **δ** is the smallest reading that is regarded as being important to be able to detect the short circuit current and its value is 0.01. **s** is the standard deviation of short circuit current.

In order to work out sample size, it is important to know standard deviation **s** , or at least to estimate it properly. Within this study a theoretical pilot study based on mathematical equation has been used to estimate standard deviation of short circuit current at the same temperature range of the experiment.

The effect of temperature on short circuit current is represented by the following equation:

$$I_{sc} = I_{sc,ref} \times \left(1 + \mu_{sc} \times \left(T_c - T_{c,ref}\right)\right) \tag{2}$$

where values of short circuit current at standard testing conditions $I_{sc,ref}$ and short circuit current temperature coefficient μ_{sc} are always provided by the manufacturer data sheet, in this study values are 2.84 A and 0.0005 A/g, respectively. T_c is the module temperature, which for the purpose of experimental work for this study, it was taken from 30 ºC to 60 ºC The reference temperature$T_{c,ref} = 25$℃ .
Then the calculated standard deviation of the short circuit current while varying the temperature within the mentioned range is 0.0135.

As it has been set by the IEC standards, an accuracy of 95% is required while testing PV modules to determine the short circuit current temperature coefficient, then taking the same value as the power for the proposed coefficient; β is 0.05 and f(α, β) is 13 by Cornish et al. [11]. Substituting all the known values in equation (1) the predetermined sample size would be 47.

The major disadvantage of using pilot studies is it often underestimates the true variance or is less than the eventual estimate from the full study according to R Core Team [12]. Then arbitrarily increasing standard deviation to 0.015 just to reduce the underestimation effect, the new number of runs will be 59.

3.2 Data Presentation

A sixteen set of varying short circuit current in response of differing soiling quantities is obtained. Each set contains of 59 readings of short circuit current for each 59g of soil. The sets differ according to change in temperature. Starting from 30 ºC and for every 2 ºC a new set is obtained till 60 ºC. To make general perception on the approximate values of the statistical model parameters, it is helpful to plot the sample data in what is called scatter plot. **Figs 3** and **4** show scatter plots of short circuit current against soiling quantity per panel area for temperatures of 30 ºC , and 60 ºC , respectively.

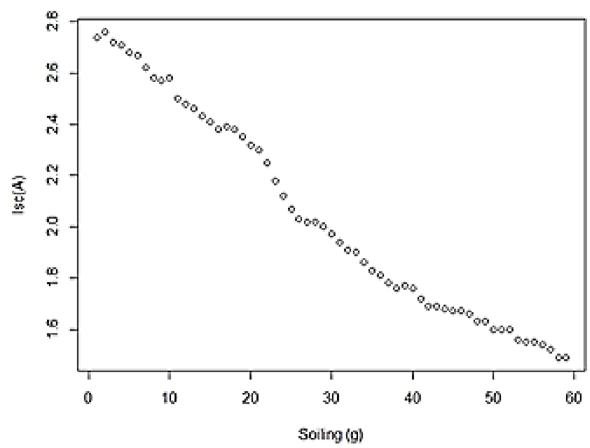

Fig. 3. Short circuit current Vs soiling quantity per panel area at 30℃

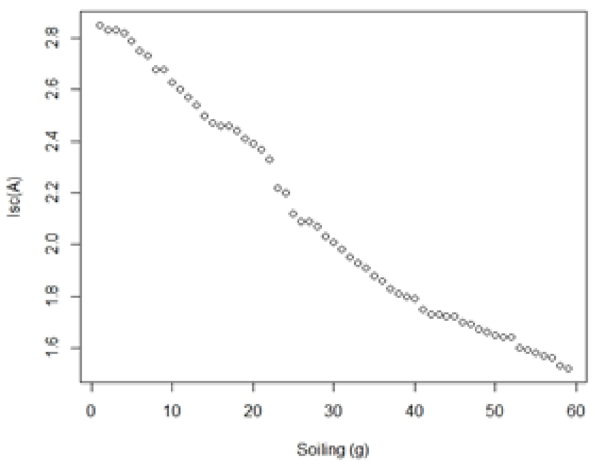

Fig. 4.Short circuit current Vs soiling quantity per panel area at 60℃

If a ruler is placed over the plots, it will show a straight line drawn through most of the points, then in the next subsection, statistical techniques will be used to determine the best fit line and to estimate the parameters of straight line model. A sample of the data at module surface temperature of 30 ℃is used for demonstration purposes in this study.

3.3 Regression Analysis

The simplest graphical model for relating a response variable (short circuit current I_{sc}) to a single independent variable (soiling quantity per panel area *x*) is the straight line model or simple linear model. From the visual fitting of the data demonstrated by the previous scatter plots, it is quite clear that this linear model decently suits sets of data available from the experiment, then the modeling steps would be firstly fitting the model to the data, that is estimating the model parameters (intercept and slope) using the least square method. Then judging whether a relationship exists between I_{sc} and *x*, in other words statistically checking the usefulness of the model. The totality of these methods is called a simple linear regression analysis.

Empirical model

The case of simple linear regression considers a single regressor variable or predictor variable x and a dependent or response variable Y. Then usingthe least squares estimates of the intercept and slope in the simple linear regression model, the fitted or estimated regression line is therefore

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x \tag{3}$$

where $\hat{\beta}_0$ is the intercept and $\hat{\beta}_1$ is the slope and the targeted coefficient of this study. Table (3) presents magnitudes of $\hat{\beta}_0$ and $\hat{\beta}_1$ as obtained for each data set using **R** software for the analysis[13]

Analysis of variance approach to test significance of regression (ANOVA)

An important part of assessing the adequacy of a linear regression model is testing statistical hypotheses about the model parameters and constructing certain confidence intervals. A method called the analysis of variance can be used to test for significance of regression. The procedure partitions the total variability in the response variable into meaningful components as the basis for the test. **Table 2** arranges the test procedure for the sample data at module temperature 30 ºC using **R** software to conduct ANOVA test. From **Table 2** the P-value is 2×10^{-16} , and then the conclusion is β_1 is not zero.

Residual analysis

Analysis of the residuals is frequently helpful in checking the assumption that the errors are approximately normally distributed with constant variance and in determining whether additional terms in the model would be useful. As an approximate check of normality, a normal probability plot of residuals has been constructed. It requires judgment to assess the abnormality of such plots. A probability plot is a graphical method for determining whether sample data conform to a hypothesized distribution based on a subjective visual examination of the data. If the hypothesized distribution adequately describes the data, the plotted points will fall approximately along a straight line; if the plotted points deviate significantly from the straight line, the hypothesized model is not appropriate. Usually, the determination of whether or not the data plot is a straight line is subjective. As while drawing, the one should be influenced more by the points near the middle of the plot than by the extreme points. In assessing the closeness of points to straight line, a "fat pencil" is imagined lying along the line. If all points are covered by this imaginary pencil, a normal distribution adequately describes the data.

Because the points in **Figs 5** and **6** would pass the fat pencil test, the conclusion is the normal distribution is an appropriate model. Notice that the mentioned figures are produced using R software. It is also frequently helpful to plot the residuals: (1) against the fitted values$\hat{y}_i$, (2) against the independent variable$x$. These graphs will usually look like one of four general patterns mention by Vickers [13], where pattern represents the ideal situation, while others represent anomalies, and in such a case either a data transformation is required, or it indicates model inadequacy, which means higher order term should be added, a transformation, or other regressors should be considered. The following **Figs 7** and **8** are made for residuals of model derived from data set at panel temperature of 30 ºC model using R software, which shows weak matching with ideal pattern. A justification to this phenomenon shall be discussed later from the authors' point of view.

Coefficient of determination (R^2)

A widely used measure for a regression model is the ratio of sum of squares or coefficient of determination R^2. This coefficient is often used to judge the adequacy of a regression model. Table 3 shows values of R^2 for the data sets at different temperatures, the values are obtained using **R** software.R^2 magnitude shows the variability in the data, hence the accuracy margin of the parameters or the model.

Most of the statistical tests which are done here showed a very good matching with the linear model while more than 97% for the coefficient of determination R2 is obtained. Regardless, it is necessary to present a formula that combines the two governing variables (temperature and soiling) with the response variable (short current):

$$I_{sc} = I_{sc}(T_c) + \beta_{I_{sc}} \times x \tag{4}$$

where $\beta_{I_{sc}}$ is short circuit current dust coefficient per panel area (A/g per panel area), and x is soiling amount (g per panel area). Values of $\beta_{I_{sc}}$ for each corresponding experimental data set are shown in **Table 3**. A convenient estimation is that the intercept parameter shown in Table 3 as β_0 is to be approximated as effect of temperature on the short circuit current $I_{sc}(T_c)$ which is mentioned above in equation (4).

Table 2: ANOVA test results for data set at panel temperature 30℃

	Degree of freedom	Sum Squared	Mean squared	F value	Pr(>F)
x	1	9.348	9.348	2185	<2e-16
residuals	57	0.244	0.004		

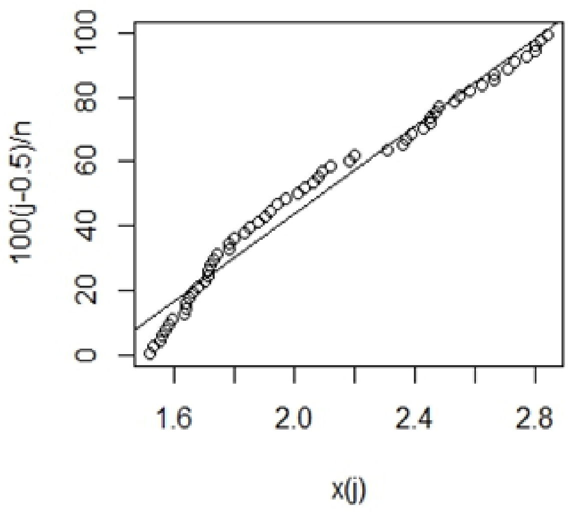

Fig. 5. Normal probability plot of 30℃ data set model residuals*

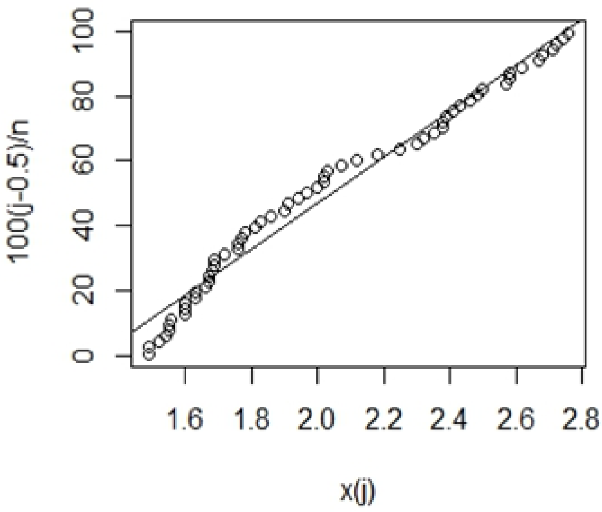

Fig. 6. Normal probability plot of 60℃ data set model residuals

Table 3. Parameters of linear regression model for each data set at different PVpanel surface temperature and

its corresponding R^2 values

Surface Temperature (C˚)	Intercept ($\boldsymbol{\beta_0}$)	Dust short circuit coefficient ($\boldsymbol{\beta_1}$)	R squared
30	2.74445938	-0.02337463	0.9746
32	2.76290473	-0.02366745	0.9746
34	2.77625365	-0.02384687	0.9744
36	2.78494448	-0.02396143	0.9746
38	2.79245470	-0.02406487	0.9747
40	2.80169492	-0.02420339	0.9745
42	2.80656926	-0.02426417	0.9734
44	2.80970193	-0.02426125	0.9738
46	2.81624781	-0.02436645	0.9740
48	2.81846289	-0.02437814	0.9736
50	2.82174752	-0.02439158	0.9731
52	2.82569258	-0.02447224	0.9733
54	2.83096435	-0.02454062	0.9735
56	2.83210403	-0.02454471	0.974
58	2.83421975	-0.02452484	0.9733
60	2.83918761	-0.02461134	0.9722

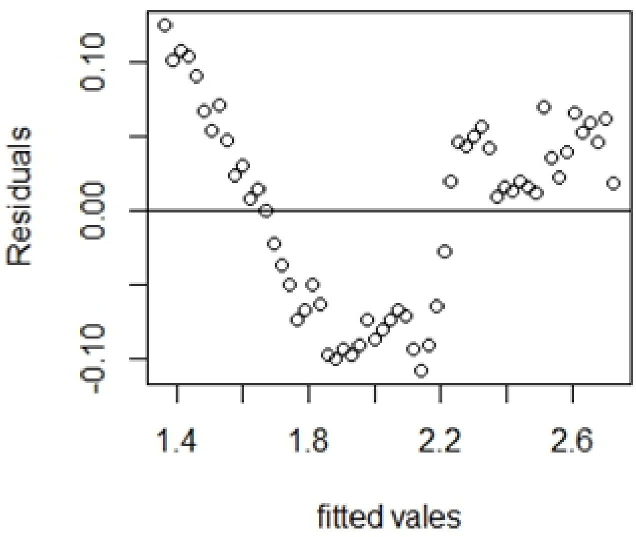

Fig. 7. Residuals Vs fitted values at 30 ºC data set

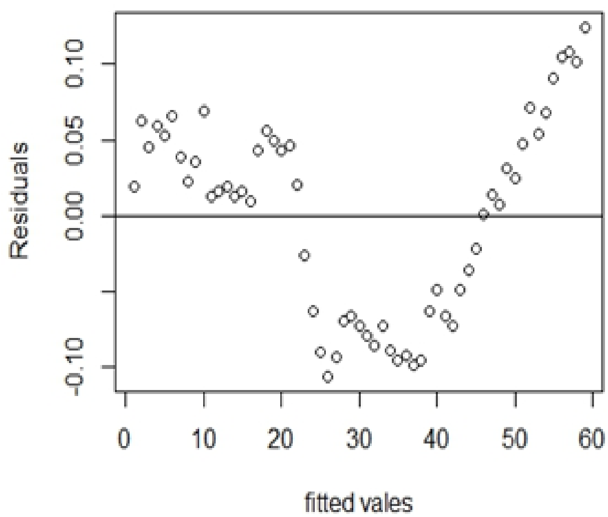

Fig. 8. Residuals Vs independent variable x at 30℃

4. CONCLUSIONS

The targeted short circuit current dust coefficient per panel area $\beta_{I_{sc}}$ (A/g per panel area) was obtained for narrow predefined working conditions, and its values were presented in Table 3. Due to irradiance fluctuation (900W\/m2 to 930W\/m2) while trying to maintain a fixed solar insulation environment for the experiment, and also due to minor but still present effect of temperature on collected data (short circuit current)-though the fixed temperature data collection technique was applied to eliminate its effect- this obvious inequality in variance of collected data normally is to be solved either by transformation, adding more regressor, or even adding a higher order term. No modifications to the model is recommended as reasons mentioned above are thought to be responsible of this inequality, and the expected more accurate model would add a neglectable accuracy to the predicted short circuit current magnitude.

The followings recommendations can be drawn:

- For large scale system design, it would be very practical to consider soiling effect on the net power output, and then obtaining such coefficient would be of great interest.
- Merging this coefficient after conducting more research, just to check accuracy of the model, in the specialized international standards is of considerable feasible benefits.

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