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Research

Parameter Estimation and Screening of Solar Cells

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The aggregation (sorting) of the individual solar cells into an array is commonly based on a single operating point on the current–voltage (I–V) characteristic curve. An alternative approach for cell performance prediction and cell screening is provided by modelling the cell using an equivalent electrical circuit, in which the parameters involved are related to the physical phenomena in the device. These analytical models may be represented by a double exponential I–V characteristic with seven parameters, by a double exponential model with five parameters or by a single exponential equation with four or five parameters. In this article we address issues concerning methodologies for the determination of solar cell parameters based on measured data points of the I–V characteristic, and introduce a procedure for screening solar cells for arrays. We show that common curve-fitting techniques, e.g. least-squares, may produce many combinations of parameter values while maintaining a good fit between the fitted and measured I–V characteristics of the cell. Therefore, techniques relying on curve-fitting criteria alone cannot be used directly for cell parameterization. We propose a consistent procedure that takes into account the entire set of parameter values for a batch of cells. This procedure is based on a definition of a mean cell representing the batch, and takes into account the relative contribution of each parameter to the overall goodness of fit. The procedure is demonstrated on a batch of 50 silicon cells for Space Station Freedom.

INTRODUCTION

The analysis of the current–voltage (I–V) characteristic of a solar cell is one of the most important diagnostic methods that may be used to characterize the solar cell. The current–voltage equation that models the solar cell by an equivalent electrical circuit contains several parameters related to physical phenomena occurring in the device. Changes in the parameter values may reveal important information about the effects of environmental conditions (e.g. radiation effects on space solar cells) or manufacturing processes on the performance of solar cell. Another application of the I–V equation of solar cells or arrays may be in the area of photovoltaic system design and performance analysis. In this paper we propose still another application of the I–V equation in the area of cell screening and arraying, i.e. the selection of compatible cells for an array from a production batch.

The methods for the determination of solar cell equation parameters from experimental data may be grouped into two types: methods that use selected points of the I–V characteristic[1,2] and methods that

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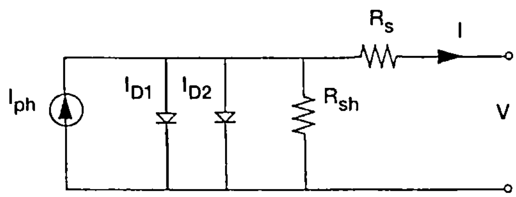

Figure 1. Electrical equivalent circuit of a solar cell

use all the test points.[3–7] By using only selected points, the methods for calculating the cell parameters may be simpler and faster; however, the main deficiency of such procedures lies in the implicit assumption that the selected points are accurately measured and thus faithfully represent the entire characteristic. In practice, measurement errors may be introduced that may result in poor parameter estimation. This effect may be more pronounced for test data taken under uncontrolled conditions. Using all test points for the determination of the cell parameters provides greater accuracy through the increase in the statistical degrees of freedom in the process.

A common technique for cell screening is based on a single operating point. However, the cells in the array may not match at other operating points. In addition, the single-point matching may also be affected by variation in the measurement conditions. Therefore, the screening of cells based on the entire set of test points of the I–V characteristic may ensure the selection of more 'identical' cells for the array.

The solar cell may be modelled with different number of parameters and with either single or double exponents. A model with seven parameters is shown in Figure 1 and its I–V equation is

$$I = I_{ph} - I_{01}\left\{\exp\left[\frac{q(V+IR_s)}{n_1 kT}\right] - 1\right\} - I_{02}\left\{\exp\left[\frac{q(V+IR_s)}{n_2 kT}\right] - 1\right\} - \frac{V+IR_s}{R_{sh}} \tag{1}$$

where I and V are the cell terminal current and voltage, respectively, and I_{ph}, I_{01}, I_{02}, n_1, n_2, R_s and R_{sh} are seven model parameters related to physical phenomena; I_{ph} is the photogenerated current, I_{01} and I_{02} are reverse saturation currents, n_1 and n_2 are ideality factors, R_s is the series resistance and R_{sh} is the shunt resistance. Another model with a double exponent but with five parameters is obtained by setting $n_1 = 1$ and $n_2 = 2$. When a single exponent is used for the cell model, the I–V characteristic is written with five parameters as

$$I = I_{ph} - I_0\left\{\exp\left[\frac{q(V+IR_s)}{nkT}\right] - 1\right\} - \frac{V+IR_s}{R_{sh}} \tag{2}$$

A model with a single exponent but with four parameters is obtained for $R_{sh} \to \infty$. A single exponent model is mainly used for design calculation of photovoltaic systems.

The problem of determination of the solar cell equation parameters when considering all the experimental data points is an optimization problem (known as a curve-fitting problem). The basis for the solution of the problem relies on defining an appropriate error criterion (objective function, OF) for the difference between the experimental and the theoretical characteristic curve of the solar cell, and then minimizing this criterion using optimization algorithms.

An error criterion σ may be defined as

$$\sigma = \left\{\frac{1}{N}\sum_{j=1}^{N}\left[\frac{(I_{th})_j - (I_{exp})_j}{(I_{exp})_j}\right]^2\right\}^{1/2} \tag{3}$$

where N is the total number of data points, $(I_{th})_j$ is the theoretical generated current at voltage V_j and $(I_{exp})_j$ is the experimentally measured current at the same voltage V_j. This criterion may give unreliable results, mainly because of the emphasis of the error in the low current part of the characteristic. This may be overcome by using the error criterion ε (normalized chi-squared, Chisq)

$$\varepsilon = \frac{\left\{\frac{1}{N}\sum_{j=1}^{N}\left[(I_{\text{th}})_j - (I_{\text{exp}})_j\right]^2\right\}^{1/2}}{I_{\text{ph}}} \tag{4}$$

Another criterion is based on the area difference between the experimental and the theoretical I–V characteristics[5]

$$\Delta A = \sum_{\substack{j=1 \\ j\neq m}}^{N-1} \left|\frac{(\Delta I_j + \Delta I_{j+1})[(V_{\text{exp}})_{j+1} - (V_{\text{exp}})_j]}{2}\right| + \left|\frac{[(V_{\text{exp}})_{m+1} - (V_{\text{exp}})_m]}{2}\frac{(\Delta I_m)^2 + (\Delta I_{m+1})^2}{|\Delta I_m| + |\Delta I_{m+1}|}\right|$$

where $\Delta I_j = (I_{\text{th}})_j - (I_{\text{exp}})_j$, and $(V_{\text{exp}})_j$ is the experimental measured voltage at the jth point. The second term applies for current error ΔI changing sign between the mth and $(m+1)$th point. The parameters obtained by this criterion will be less dependent on the distribution of the experimental points along the I–V characteristic. Normalizing ΔA will give the error of the fit as a percentage, i.e.

$$\frac{\Delta A}{A} = \frac{\Delta A \times 100}{\sum_{j=1}^{N} \frac{[(I_{\text{exp}})_j + (I_{\text{exp}})_{j+1}][(V_{\text{exp}})_{j+1} - (V_{\text{exp}})_j]}{2}} \tag{5}$$

Several minimum-seeking (optimization) algorithms were used in the present study. We report here only on results obtained by two algorithms—a simplex-based procedure E04CCF and a quasi-Newton method E04JAF—both in the NAG Library.[8] Because the I–V mathematical expression forms an implicit relation berween I and V, the optimization procedure must involve a root-finder called iteratively by the minimum-seeking algorithm for the actual curve fitting. A robust root-finder used in this study is the Van Wijngaarden–Dekker–Brent algorithm.[9]

In this work it was found that different choices of initial conditions (i.e. the initial values of the parameters) may result in substantially different sets of parameter values for the same solar cell. This issue is related to the strong non-linearity of the model equations of the solar cell. The two alternatives for the initial conditions examined in this study are based on the measured data points of the I–V characteristic and on the computed data of a 'mean cell' for the batch. A 'mean cell,' which will be defined later, may be considered as a hypothetical cell best representing all the cells in the batch. In both cases, the initial parameter values of the cell were determined by the procedure outlined in Ref. 7.

One aim of this study is to develop a reliable and consistent method for the determination of the solar cell parameters from the measured data points of the I–V characteristics. Another aim is to develop a method for screening solar cells for aggregation into arrays. The study was carried out on a batch of 50 8×8 cm silicon solar cells of the Space Station Freedom of the preliminary design (Figure 2). Figure 3 shows the measured data for all 50 cells at 25°C. Each individual I–V characteristic is composed of 100 measured data points. It is clear that there is some variation in the data that can be attributed to structural differences among the cells as well as to measurement errors. It should be noted that these 50 cells were already pre-screened (for a desired current range) at 0.495 V.

ISSUES IN PARAMETER ESTIMATION

Once a model equation is selected, the problem becomes a mathematical task of finding a set of parameters that result in the least difference between the experimental and theoretical characteristic of the solar cell. As a result, the parameters may obtain values without physical significance, such as a negative series resistance. Negative values for the parameters are avoided by squaring the components of the vector ϕ of the parameters in the I–V equation.

In this work we show that optimization methods for the determination of the cell parameters may

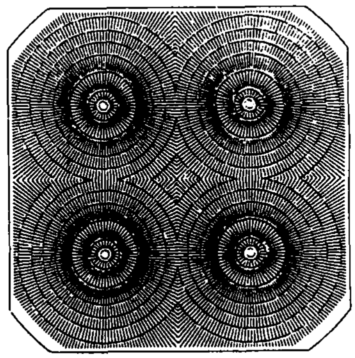

Figure 2. An 8 × 8 cm silicon solar cell of Space Station Freedom

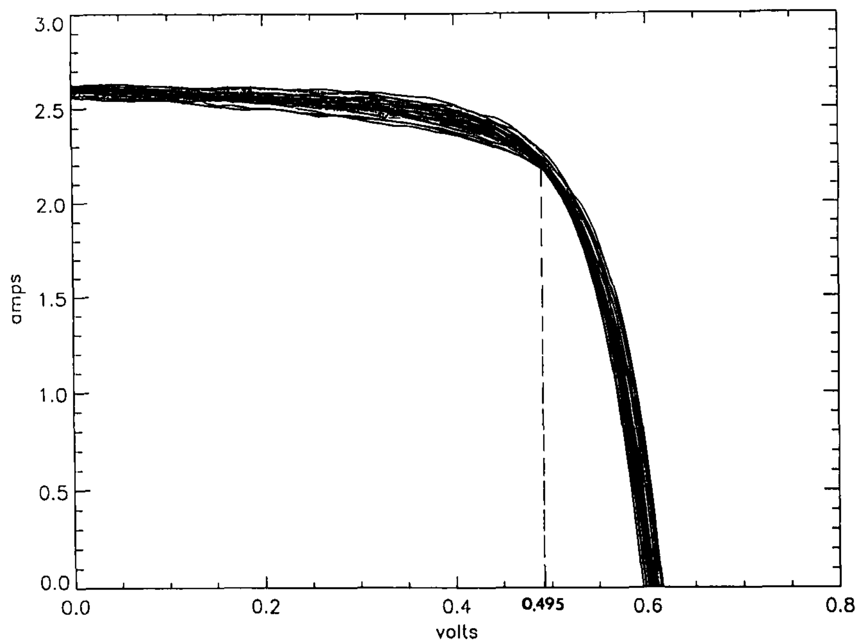

Figure 3. Distribution of the measured I–V characteristics of 50 cells

give misleading or inconsistent results. The reasons for this are numerous: the incompleteness of the solar cell model and the non-linearity of its equation; the optimization and root-finding algorithms and error criteria; machine (computer) and compiler accuracy; measurements conditions; accuracy of instrumentation; and the number and distribution of the measured points along the I–V characteristic.

The I–V equation is described by an implicit function and is highly non-linear. The parameter values are typically of different orders of magnitude. This leads to a solution with a very flat optimum (curve-fit error criterion) in most of the parameters and is therefore insensitive to large variations in certain parameter values. For the same reason, the solution may converge to different parameter sets starting from different initial conditions.

In spite of the above-mentioned issues, it is possible to obtain a good fit between the theoretical I–V equation and the experimental I–V data with an arbitrary low fitting error using different fitting methods.

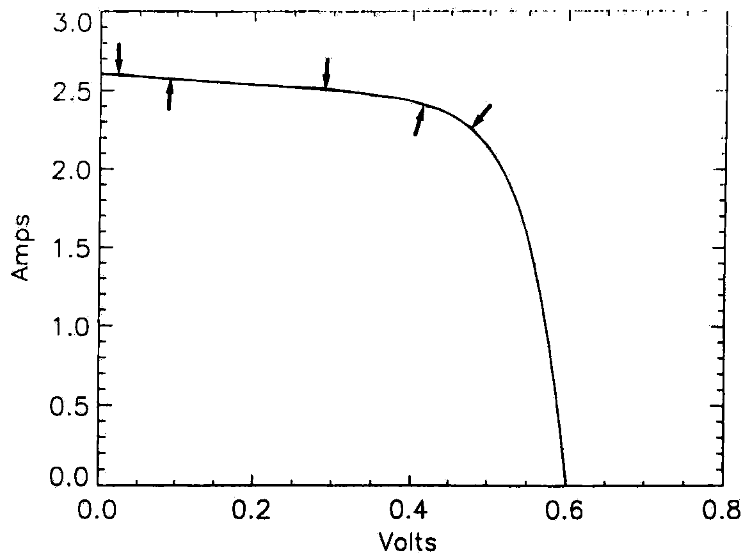

Figure 4. Experimental and fitted I–V characteristics of cell ss01

However, different fitting methods with the same error tolerance may lead to widely varying sets of solar cell parameters. This general observation is referred to in this study as the consistency problem. To obtain a consistent solution to the solar cell parameters we developed a 'consistent method,' defined as a method that consistently converges to 'similar' parameter values for 'similar' cells obtained from the same batch. In other words, our proposed method is founded on the expectation that similar cells of the batch should produce similar parameter sets.

The issues discussed above are illustrated in the following graphs and tables for a randomly selected solar cell of the batch. Figure 4 shows good visual agreement between the theoretical curve and the measured data, which include some humps as indicated by arrows. The particular method used combines a seven-parameter double exponential model, a simplex-based optimization algorithm, a normalized-area error criterion and the measured data as initial conditions. Figure 5 shows the variation of the objective function $\Delta A/A$ (Equation (5)) with the photocurrent I_{ph} and the reverse saturation current I_{02}. It is clear that the error criterion is insensitive to the parameter I_{02} and its optimal value is therefore poorly defined. A better-defined optimum is shown in Figure 6 for the series resistance R_s and the reverse saturation current I_{01}. Also in this case the optimum is flat, indicating the possibility of obtaining different parameter values.

The fact that acceptable curve fits may be obtained with different sets of parameter values for the same cell, using different optimization algorithms and initial conditions with the same objective function, is shown in Table I. The algorithms compared are Newton and simplex-based techniques; the initial conditions are based on the experimental and the mean cell data (to be defined in the next section), and the error criterion is $<0.5\%$. The full range of the I–V characteristic was considered in this comparison.

The parameter values obtained from the fitting process may depend on the initial conditions for the reasons mentioned above. Table II lists the parameter values of cell number ss01 obtained using 10 randomly selected (different) initial conditions, designated as ss01.01–ss01.10. The last row shows the standard deviation of each parameter. The largest deviations are observed in I_{01} and I_{02}, representing the two most insensitive parameters. All of the parameter sets produce good fits to the experimental data, as shown in Figure 7.

The variation of parameter I_{01}, measured in standard deviations, for the batch of 50 cells is shown in Figure 8. Similar distributions are obtained for other parameters.

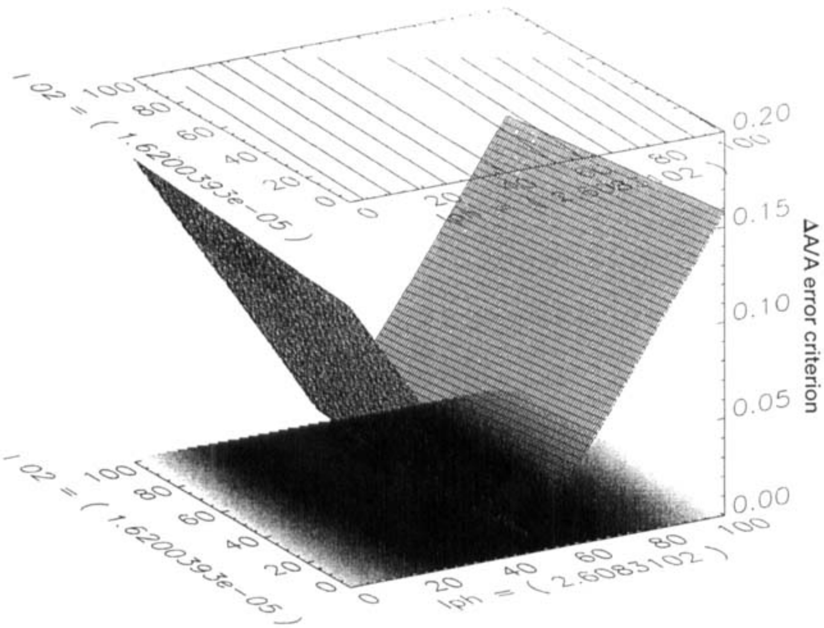

Figure 5. Variation of the photocurrent I_{ph} and reverse saturation current I_{02} at the optimum ($\pm 50\%$ variation around optimal I_{ph} and I_{02})

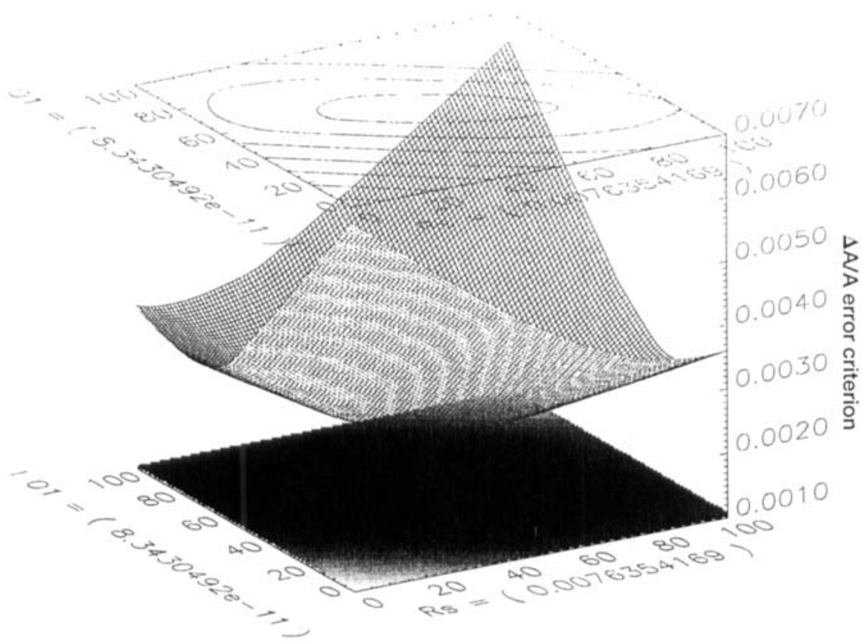

Figure 6. Variation of the series resistance R_s and the reverse saturation current I_{01} at the optimum ($\pm 50\%$ variation around optimal R_s and I_{01})

Table I. Different set of parameters for the same cell (Seven-parameter model, error criterion $\Delta A/A$, full I–V range.)

Algorithm	Initial condition	I_{ph} (A)	R_s (Ω)	R_{sh} (Ω)	I_{01} (A)	I_{02} (A)	n_1	n_2	$\Delta A/A$
Newton	Experimental data	2.61	7.39×10^{-3}	2.98	7.95×10^{-11}	1.15×10^{-5}	1.00	2.00	1.60×10^{-3}
Newton	Mean	2.61	6.12×10^{-3}	3.24	6.50×10^{-11}	1.76×10^{-5}	1.00	2.06	1.79×10^{-3}
Simplex	Experimental data	2.60	8.24×10^{-4}	3.22	3.64×10^{-11}	1.33×10^{-5}	1.05	1.94	2.17×10^{-3}
Simplex	Mean	2.60	1.26×10^{-5}	3.33	6.77×10^{-11}	1.67×10^{-5}	0.99	1.97	2.35×10^{-3}

Table II. Different set of parameters for different initial conditions

I_{ph} (A)	R_s (Ω)	R_{sh} (Ω)	I_{01} (A)	I_{02} (A)	n_1	n_2	$\Delta A/A$	Cell
2.609	7.59×10^{-03}	3.10	2.16×10^{-10}	2.01×10^{-05}	1.04	2.13	1.59×10^{-03}	ss01.01
2.610	7.28×10^{-03}	2.98	8.29×10^{-11}	1.18×10^{-05}	1.01	2.00	1.59×10^{-03}	ss01.02
2.606	4.18×10^{-03}	3.04	3.19×10^{-11}	8.55×10^{-06}	0.99	1.90	1.91×10^{-03}	ss01.03
2.609	7.76×10^{-03}	3.12	1.54×10^{-10}	2.07×10^{-05}	1.03	2.13	1.59×10^{-03}	ss01.04
2.609	6.44×10^{-03}	2.98	2.86×10^{-10}	1.14×10^{-05}	1.06	1.99	1.61×10^{-03}	ss01.05
2.612	8.27×10^{-03}	3.04	1.26×10^{-10}	2.03×10^{-05}	1.02	2.14	1.58×10^{-03}	ss01.06
2.607	7.96×10^{-03}	3.21	3.05×10^{-11}	1.60×10^{-05}	0.96	2.06	1.64×10^{-03}	ss01.07
2.610	7.23×10^{-03}	2.97	3.65×10^{-11}	1.01×10^{-05}	0.97	1.97	1.61×10^{-03}	ss01.08
2.605	4.84×10^{-03}	3.12	1.45×10^{-11}	1.18×10^{-05}	0.95	1.96	1.90×10^{-03}	ss01.09
2.609	8.56×10^{-03}	3.15	8.05×10^{-11}	2.23×10^{-05}	1.00	2.15	1.60×10^{-03}	ss01.10
2.609	7.04×10^{-03}	3.07	1.17×10^{-10}	1.47×10^{-05}	1.02	2.04	4.56×10^{-06}	ss01.mean
2.03×10^{-3}	1.45×10^{-03}	8.36×10^{-02}	9.06×10^{-11}	5.20×10^{-06}	3.95×10^{-2}	2.19×10^{-2}	Standard deviation	

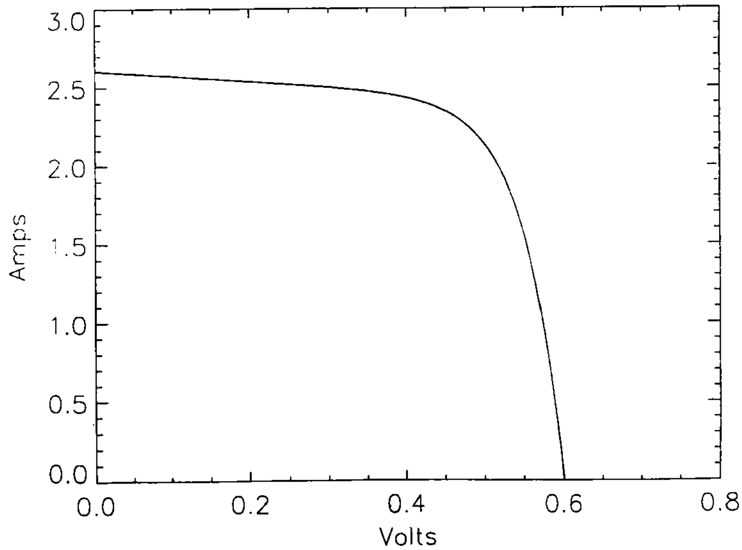

Figure 7. The I–V characteristics of 10 cells produced from cell ss01 by varying the initial conditions

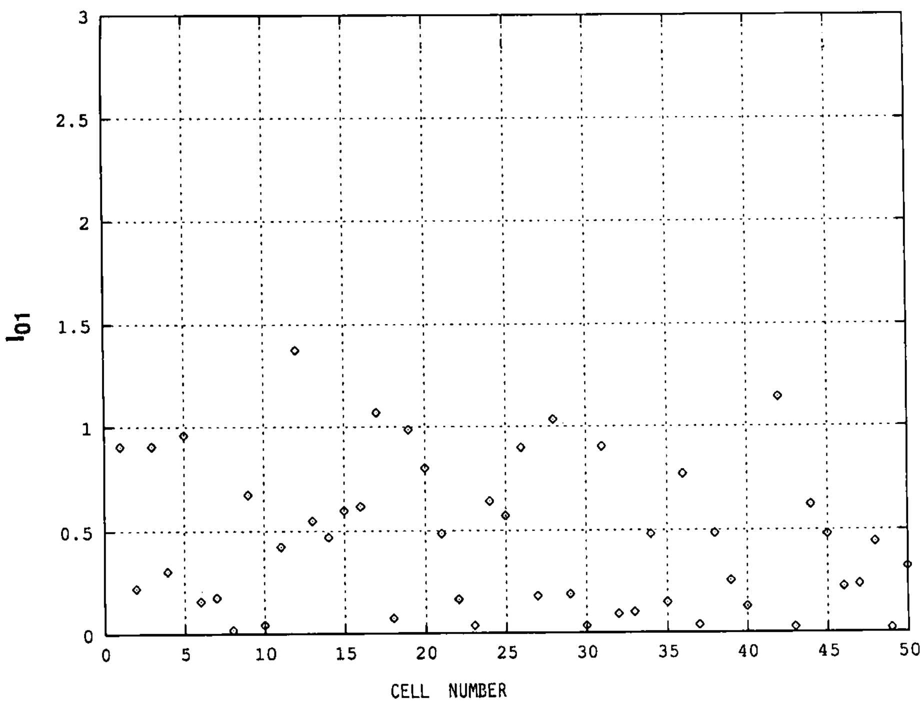

Figure 8. Distribution of the reverse saturation current I_{01}, in standard deviation, for the 50 cells

A CONSISTENT METHOD FOR PARAMETER ESTIMATION

As defined in the preceding section, a consistent method is defined as a method that consistently converges to 'similar' parameter values for 'similar' cells from the same production batch. But since the values obtained from various fitting algorithms are different, even for arbitrary small curve-fit errors, an additional examination of the parameter values is required in order to select the best (or consistent) method for cell parameterization. The consistent method then defines the combination of an optimization algorithm, an error criterion, type of initial conditions and cell model equation. The procedure for selecting the consistent method requires the definition and determination of several new concepts: mean cell, parameter sensitivity, cell frequency and figure of merit.

A mean cell

A mean cell is defined as a cell 'best' representing all the cells in a batch from an overall performance viewpoint. The procedure for determining the mean cell is as follows:

(i) For a given optimization algorithm, error criterion and cell model equation, perform a curve fit for each cell to find the cell parameters.
(ii) Compute the currents (for the given cell model equation) for each cell using its parameters at the same voltage. Repeat at other voltages covering the entire I–V curve at equal intervals.
(iii) Compute the average for all currents (at each particular voltage), thereby generating new data points for the I–V characteristic of a hypothetical 'mean cell'.
(iv) Perform a fit for the mean cell.

Note that if all the experimental data points were sampled at identical voltages, the step of dividing the voltage range may be omitted. As the mean cell represents all cells in the batch, its characteristics may be used for cell and system performance analysis.

Parameter sensitivity (PS)

The values of certain parameters of different cells obtained from the fitting process by various methods may be widely dispersed. This observation applies to single cells for different starting conditions as well as for cells in a production batch. The implication of this observation is that these parameters are less sensitive to the fitting error criterion whereas other parameters are more sensitive. In other words, a large change in a particular parameter value may have only a small effect on the shape of the I–V characteristic (insensitive parameter) while a large change in another parameter value may considerably affect (a sensitive parameter) the I–V characteristic. Therefore, the parameter sensitivity is important as a measure for selecting a consistent method. The 'parameter sensitivity' is defined as the effect of change in parameter value on the cell performance

$$(\mathrm{PS})_j = \frac{\partial(\mathrm{OF})}{\partial P_j} \Bigg/ \max\left[\frac{\partial(\mathrm{OF})}{\partial P_j}\right] \tag{6}$$

i.e. the parameter sensitivity $(\mathrm{PS})_j$ of each parameter j is defined as the normalized partial derivative of the objective function, OF, with respect to the parameter in question, j, having values between zero and unity. The parameter sensitivity ranking was found to be slightly dependent on the fitting method. The ranking of the parameters, in terms of their relative effect on the I–V characteristic, was found to be I_{ph}, n_2, n_1, I_{02}, R_{sh}, I_{01} and R_s, where I_{ph} and R_s are the most and least sensitive parameter, respectively.

Cell frequency (CF)

Further important information that may be used in determining a consistent method is provided by the dispersion of individual parameters. For some fitting methods, the parameter values are more dispersed, while for others the variation is small. The cell frequency (CF) is computed for each parameter and is the count of cells whose parameter value does not deviate from the mean cell parameter value by more than a predetermined amount (in terms of standard deviation SD of the parameter): CF = count of all cells i for parameter j such that

$$m(\mathrm{SD}) > |P_{ij} - P_{mj}| \tag{7}$$

where m is the desired number of standard deviations, P_{ij} is the parameter j of cell i and P_{mj} is the parameter j of the mean cell. The standard deviation of parameter j of each cell is computed from all the N fitted cells, i.e.

$$\mathrm{SD} = \left\{\frac{1}{N-1}\sum_{i=1}^{N}[P_{ij} - P_{mj}]^2\right\}^{1/2} \tag{8}$$

Figure of merit (FM)

A Figure of Merit (FM) for a particular parameter must take into account the sensitivity of the characteristic to variation in that parameter, together with its dispersion level. An overall FM adds the partial contributions of all parameters

$$\mathrm{FM} = \sum_{j=1}^{M} (\mathrm{PS})_j \times (\mathrm{CF})_j \tag{9}$$

The best or most consistent fitting method is the method resulting in the highest FM value

$$\max[\mathrm{FM}] \tag{10}$$

An example of calculation of the FM values for the 50 fitted cells is provided in Table III for one method (quasi-Newton, $\Delta A/A$ error criterion and a seven-parameter double exponent model). The most sensitive parameter is I_{ph}, whose normalized sensitivity is 1.00. The CF and the FM for predetermined levels of dispersion in terms of standard deviations around the mean cell are also computed. As an example, for one standard deviation the cell frequency is 38 (out of 50) cells for parameter I_{ph}, 34 cells for R_s, etc. and the FM is 91.73. A comparison of different methods, using one standard deviation and initial conditions computed from the measured data, is shown in Table IV. The most consistent method (FM = 91.73) is provided by using a quasi-Newton procedure, with $\Delta A/A$ error criterion and a seven-parameter double exponent model.

Table III. Parameter sensitivity and cell frequency

	I_{ph}	R_s	R_{sh}	I_{01}	I_{02}	n_1	n_2	SD	FM
PS	1.00	9.60×10^{-03}	2.91×10^{-02}	1.25×10^{-02}	6.21×10^{-02}	1.01×10^{-02}	1.90×10^{-02}		
CF	24	27	23	30	45	33	32	0.50	64.76
	38	34	42	45	48	39	45	1.00	91.73
	44	42	44	49	48	42	48	1.50	101.32
	46	49	45	49	48	45	48	2.00	104.60
	48	49	48	49	48	48	48	2.50	107.87

CELL PARAMETERS

The determination of the cell parameters may be required for cells in a production batch and for individual cells. Even by using the method with the highest FM a variation in parameter values is still obtained. Therefore, an alternative concept of a representive cell must be defined for cells in a production

Table IV. Order of methods for Figure of Merit, max[FM] (Measured points as initial conditions, one standard deviation)

Optimization algorithm	Cell model equation	Error criterion	FM
Newton	7 parameters, 2 exponents	$\Delta A/A$	91.73
Simplex	7 parameters, 2 exponents	Chisq	78.94
Simplex	7 parameters, 2 exponents	$\Delta A/A$	72.52
Newton	7 parameters, 2 exponents	Chisq	42.20
Newton	5 parameters, 2 exponents	Chisq	37.87
Simplex	5 parameters, 2 exponents	$\Delta A/A$	32.48

Table V. Mean cell parameters of 50 solar cell batch

$I_{ph} = 2.614$ A
$R_s = 6.13 \times 10^{-3}\ \Omega$
$R_{sh} = 3.49 \times 10^{0}\ \Omega$
$I_{01} = 4.09 \times 10^{-11}$ A
$I_{02} = 1.77 \times 10^{-5}$ A
$n_1 = 0.99$
$n_2 = 2.06$

batch. Such a hypothetical cell, best representing the entire batch, was defined earlier as the 'mean cell'. Using the most consistent method, the values of the mean cell parameters for the batch of 50 silicon cells used in this paper and their variations, in one standard deviation, are tabulated in Table V.

The concept of a representative cell for a production batch may be used also for a single cell. By randomly varying N times the initial conditions during the fitting process and using single-cell experimental data, one obtains a batch of N fitted cells with N sets of parameter values. Since all the sets of parameters correspond to the same physical cell, a mean cell may be defined properly from these sets. The parameter values of this mean cell for $N = 10$ are provided in Table II, and a composite plot of all 10 curve fits is shown in Figure 7. As discussed earlier, no distinguishable differences can be found among the individual fits, even though their individual parameter values are quite different.

CELL SCREENING

The selection of compatible solar cells for an array from a production batch is commonly done on the basis of a single operating point, e.g. the maximum power point. To screen cells based on an approach more faithful to their entire performance characteristics necessitates the determination of model parameters. Because of the difficulties in obtaining unique parameter values, methods that explicitly screen cells by comparing parameter values are not warranted. However, the concept of the mean cell as the cell best representing the entire batch may be used for cell screening. The requirement of similar performance from the cells in the array can be expressed in terms of a similarity of the overall I–V characteristic of individual cells in the batch to the mean cell. A comparison of each cell to the mean cell may be computed by subtracting their respective total area under the I–V characteristic. When normalized, this $\Delta A/A$ ratio represents the overall deviation, from a performance viewpoint, of each cell from the average performance of the batch. Alternatively, one may compare each cell to the mean cell by computing the chi-squared error. Once a comparison is made, a ranking of the cells in terms of their similarity to the mean cell may be done, as shown in Table VI, for the 50 cells used in the study. To

Table VI. Cell screening

$\Delta A/A$	Cell number	Percentage deviation	Number of cells
0.003515	ss33	1	
0.003626	ss40		
0.004049	ss04		
0.005013	ss34		
0.005042	ss37		
0.005342	ss10		
0.005488	ss32		
0.005907	ss44		
0.007099	ss24		
0.007243	ss25		
0.008173	ss07		
0.008818	ss08		
0.009260	ss20		
0.009412	ss27		14
0.010099	ss14	2	
0.010205	ss49		
0.010275	ss31		
0.010364	ss29		
0.010623	ss18		
0.010754	ss02		
0.011106	ss16		
0.011852	ss36		
0.011885	ss45		
0.011973	ss48		
0.012832	ss42		
0.013513	ss50		
0.014422	ss26		
0.014787	ss01		
0.015070	ss19		
0.015277	ss30		
0.016281	ss47		
0.017097	ss28		
0.017269	ss03		
0.018430	ss22		
0.018609	ss15		35
0.020316	ss09	3	
0.021644	ss06		
0.022172	ss41		
0.023247	ss39		
0.023364	ss38		
0.023542	ss11		
0.024410	ss12		
0.024429	ss35		
0.024841	ss17		
0.025179	ss13		
0.026600	ss46		46
0.030859	ss43	4	
0.032218	ss21		
0.034946	ss05		
0.035750	ss23		50

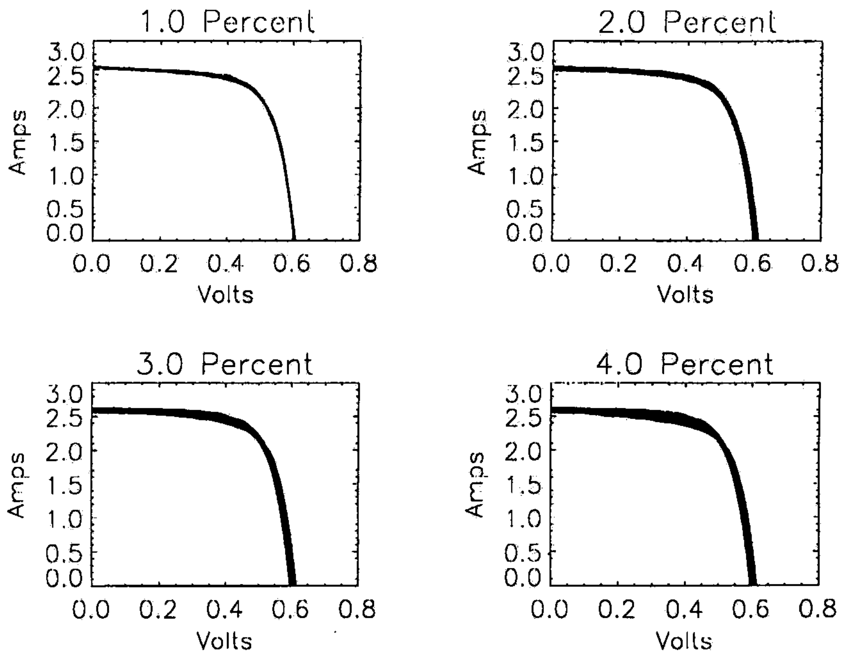

Figure 9. Cell screening according to percentage deviation from the mean cell

chose K cells for an array from the given production batch, one simply selected the top K cells in the list. Table VI shows that the most similar cell to the mean cell is number 33; 14 cells deviate by $<1\%$ from the mean cell; 35 cells deviate by $<2\%$, etc. The distribution of the measured I–V characteristics of the 50 cells for a given percentage deviation from the mean cell is shown in Figure 9. It is visually evident that the selection rule proposed results in cells whose characteristic curves are similar.

DISCUSSION

The parameters of the solar cell I–V equation are related to physical phenomena occurring in the device. Changes in the parameter values may reveal important information about the operating environment or manufacturing processes of the cell. The solar cell parameters are also needed for cell or photovoltaic system analysis. In this study we proposed another application of the cell parameters, namely, screening of solar cells for aggregation into arrays. For all of these applications, the determination of the cell parameters may be based on a small number of selected points. However, ignoring the overall I–V characteristic may lead to erroneous values for the parameters and to a mismatch among the cells in the array at different operating points. Using test points representing the entire I–V characteristic for the determination of the cell parameters may give more reliable values for the parameters.

The estimation of cell parameters based on a set of test points resorts to optimization techniques where the difference between experimental and the theoretical fitted characteristic of the cell is minimized. As such, the solution (i.e. the parameter values) is shown in this study to be non-unique and is subjected to non-trivial computational issues. To obtain a consistent solution to the cell parameters we proposed an additional requirement from the solution. We identified a 'consistent method,' which was defined as a method that consistently converges to 'similar parameters' for 'similar' cells. Identifying a consistent method necessitated the introduction of several new concepts: a mean cell; parameter sensitivity; cell frequency; and a Figure of Merit. These concepts were incorporated into a 'Figure of Merit' resulting in a recommended fitting method and error criterion for the determination of the solar cell parameter values. The 'mean cell' is defined as a hypothetical cell 'best' representing all the cells in the batch from the total performance viewpoint. The mean cell concept may also be used for cell and array performance analysis. The 'parameter sensitivity,' which determines the effect of change in parameter value on the objective function (or cell performance), may be useful also for cell design and manufacturing. Finally, screening of cells for arrays in a consistent manner based on the entire I–V characteristic was also proposed in this study using the mean cell concept.

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