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The influence of the measurement environment on the accuracy of the extraction of the physical parameters of solar cells

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Abstract. This article concerns the influence of measurement conditions on the extraction of a solar cell's equivalent circuit parameters. Influences previously not investigated are considered, thus helping to define suitable measurement strategies. The influences of measurement environments are investigated, as is the influence of the fitting algorithm chosen. It is shown that the number of measurement points for the current–voltage characteristic can have an important effect on the accuracy of the parameters extracted. The stability of the system is of minor importance, as long as the variations in the measurement conditions are monitored. We also show that the Marquardt–Levenberg algorithm using a least squares error criterion and a hybrid algorithm employing an area criterion outperform other choices of fitting algorithm.

Keywords: diode ideality factor, series resistance, shunt resistance, diode-saturation current, solar simulator, fitting, photovoltaic, standard measurement procedure

1. Introduction

Solar cells are conventionally assessed by measuring the current–voltage characteristic of the device under illumination and then extracting a set of semi-physical parameters from the data. The extraction and interpretation has a variety of important applications. These parameters can, for example, be used for quality control during production or to provide insights into the operation of the devices, thereby leading to improvements in devices. Parametric models also supply the most accurate method for calculating the performance of a photovoltaic system, which can be modelled by aggregating the characteristics of single cells [1]. In all cases the quality of the conclusion depends mainly on the appropriateness of the parameters used. It is therefore important to identify the most accurate method of determining such parameters.

This paper concerns the effects of strategy, accuracy and stability of the measurements on the accuracy of the parameters determined. Several different methods for the identification of the parameters have been applied and various measurement environments and procedures have been investigated through simulation.

Several methods for the extraction of parameters have been suggested. Some methods, e.g. the one used by Wolf and Rauschenbach [2], depend on the use of a multiplicity of measurements under different environmental conditions. The disadvantage of this approach is that in certain cases the parameters need not be independent of those environmental conditions, i.e. they vary with temperature and irradiation [3, 4]. Thus, this method can be expected to generate significant error if any of the parameters changes its value due to the variation in measurement conditions.

Simplified, so-called direct, approaches have been suggested [5–8], in which the equivalent circuit parameters are identified from particular features of the data, such as intercepts on the I and V axes and gradients at these points. For the unrealistic case of error-free measurements, direct calculation may appear attractive [9]. The disadvantage of such methods, though, is that they depend on the accuracy of the points chosen for the calculation. Should any of these points be erroneous, this will have a significant effect on the calculated parameters. Thus, such methods were left out of this investigation and instead the focus was on the use of various 'fitting' algorithms for the extraction of parameters, as suggested by many workers [10–14].

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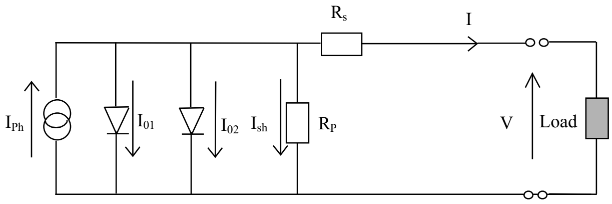

Figure 1. An electrical representation of the two-diode model of a solar cell. The ideal current generator is in parallel with the two diodes and a resistance R_P. This block is then in series with a further resistance R_S.

Fitting algorithms are numerical methods for 'fine tuning' a given set of estimated parameters with respect to a user-defined error function. This definition makes it clear that the quality of the result depends on three things: the estimation of the parameters, the error function and the applied algorithm.

Investigations published so far, e.g. [9, 15], have dealt with the influence of the error criterion used in the fitting process, assuming that all algorithms are equally good and that strategy, accuracy and stability of the measurements do not influence the overall accuracy. To date the influences of the latter factors have not been investigated systematically. It will be shown here that they have important consequences for the accuracy of the model as a predictive tool. The limitations of such a parameter extraction are also investigated and recommendations for an accurate procedure are given.

2. Parametric description of solar cells

Solar cells can be described in terms of a set of parameters that are related to the physical properties of these devices. The parameters are derived from the equivalent circuit which in general consists of an ideal current source in parallel with two diodes and a shunt resistance. These elements are also in series with a resistance (see figure 1). The I–V characteristic is given, implicitly, by [16]

$$I = -I_{ph} + I_{01}\left[\exp\left(\frac{eV_j}{n_1 kT}\right) - 1\right] + I_{02}\left[\exp\left(\frac{eV_j}{n_2 kT}\right) - 1\right] + \frac{V_j}{R_p} \tag{1}$$

with

$$V_j = V - IR_S. \tag{2}$$

Here I is the current through the device in amperes, V is the voltage in volts and T is the temperature of the p–n junction in kelvin. The cell-specific physical parameters describing the behaviour of the device are I_{ph} (the photocurrent in amperes), I_{01} and I_{02} (the diode-saturation currents of the first and second diode in amperes), n_1 and n_2 (the diode-ideality factors of the first and second diode), R_S (the series resistance in ohms) and R_p (the parallel or shunt resistance in ohms). The remaining terms are natural constants, where e is the electronic charge and k is Boltzmann's constant. Variations in the irradiation (G in W m^{-2}) influence only the photocurrent.

The photocurrent can be modelled as [17]

$$I_{ph} = (C_0 + C_1 T)G. \tag{3}$$

Here C_0 and C_1 are empirical constants modelling the temperature and the irradiation dependence. The temperature dependence is neglected in this paper because we want to deal with single I–V characteristics only and a thermal dependence of I_{ph} could not be observed in the given case of a single measurement anyway.

The above-mentioned model applies for all photovoltaic cells which use diffusion for the separation of charge carriers, i.e. for all commonly available materials with the exception of amorphous silicon. The first diode describes recombination within the bulk and the second diode describes the recombination in the space-charge region. In some materials, mainly heterojunctions, the second diode dominates completely and the first diode can be neglected. These materials still follow this description, though, so that equation (1) can be taken as a general model for diffusion-driven devices.

The physical parameters for a given cell are extracted from measurements of the I–V characteristics. The implicit definition of equation (1) makes the task of parameter extraction difficult and very often only one diode is considered in order to simplify this procedure. However, doing so results in a loss of information and is thus not desirable. In the following the full two-diode model is considered.

Plotting the terms of equation (1) as a function of V shows that the partial currents dominate in different regions of the I–V characteristic, as shown in figure 2. The parameters assumed in this case were chosen in order to represent an arbitrarily chosen crystalline-silicon cell (in this case one manufactured at the University of Erlangen, Germany). The implicit equation (1) was solved for each I–V point by an iteration process. The method used is the van Wijngaarden–Dekker–Brent method given by Press *et al* [18]. The parameters used in this plot are used throughout this paper. The model parameters used are $C_0 = 2.19 \times 10^{-3}$ A m^2 W^{-1}, $C_1 = 0$ A m^2 W^{-1} K^{-1}, $G = 1000$ W m^{-2}, $T = 328$ K, $R_S = 2.5 \times 10^{-2}$ Ω, $n_1 = 0.99$, $I_{01} = 2.4 \times 10^{-9}$ A, $n_2 = 1.9$, $I_{02} = 5.5 \times 10^{-5}$ A and $R_P = 200$ Ω. It is obvious from figure 2 that the contribution of the current through the shunt is very small and one might decide to ignore it completely. However, under certain operating conditions (e.g. when parts of a module are shaded) the shunt resistance is very important to the overall device behaviour. Thus it is included in what follows, although it proved difficult to keep it within the desired range when fitting. The photocurrent is assumed to be voltage independent, as is the case for devices manufactured from polycrystalline or crystalline silicon. The onset of the influence of the diodes depends very much on the diode-ideality factors and the magnitudes of the diode-saturation currents. The series resistance becomes very important for higher current levels. Its impact is perhaps most noticeable in the plot of the partial current through the shunt resistance. When this is plotted on an expanded scale, as on the right-hand axis in figure 2, the resulting curve can be seen to exhibit 'non-ohmic' behaviour, due to the influence of the series resistance.

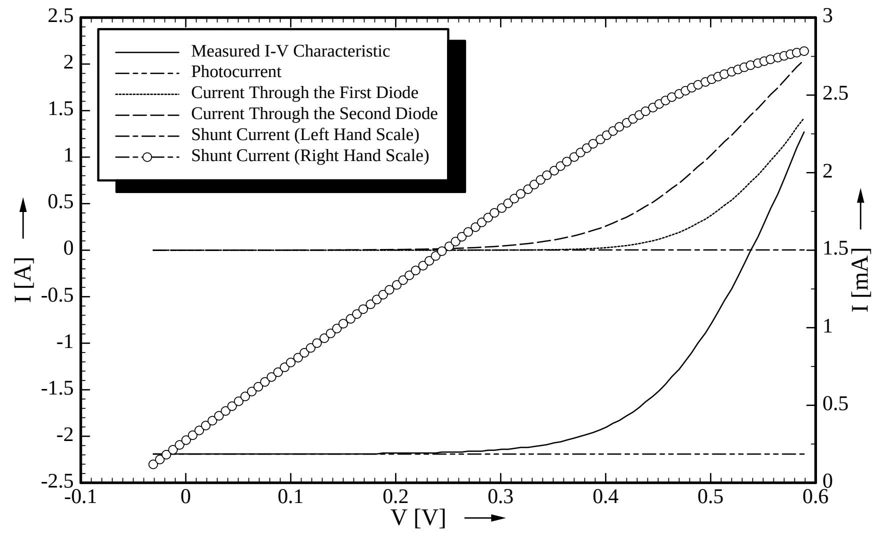

Figure 2. Contributions of the partial currents to the overall I–V characteristic. The graph shows the partial currents through the electrical devices representing the equivalent circuit, which are calculated as described in the text. The contribution of the shunt is diminishingly small, thus it was plotted a second time on another scale.

3. The methodology applied

A common approach for testing the quality of the parameters extracted is to compare selected measured points with points calculated on the basis of the parameters extracted. Points commonly chosen for this task are the open-circuit voltage (V_{OC}), maximum-power point (MPP) and short-circuit current (I_{SC}). This approach has two distinct disadvantages. First, it does not consider explicitly any inaccuracies in the measurements and can thus be misleading. Second, it is possible to obtain an excellent description of these particular points despite there being significant flaws in the sets of fitted parameters. Thus the measurement of distinct points on the I–V characteristic and recalculating them with the extracted parameters is not necessarily a good measure of the accuracy of the extracted parameters.

In order to avoid these problems, simulated data were used in this study. Data were generated by specifying the desired voltage (or current) and iteratively calculating the corresponding current (or voltage) from equations (1) and (2). These data were used as inputs to commonly used fitting algorithms.

Two examples of the main classes of fitting algorithms were chosen, in order to give a representative picture. The simplex algorithm (SI) is taken as an example of a fitting algorithm that does not compute the first derivative of an error function, whilst the Marquardt–Levenberg algorithm (ML) is selected as an example of an algorithm that does. Additionally, an unconventional hybrid algorithm was evaluated. The simplex algorithm and the Marquardt–Levenberg algorithms are implemented in the ways given by Press *et al* [18]. The initial vertex needed for the simplex algorithm is calculated according to the suggestion of Caceci and Cacheris [19]. All parameters in these algorithms (e.g. the step width and the stopping criterion) were carefully adjusted in order to give optimum results. The hybrid algorithm is our own development. It uses a simplex algorithm for fitting the 'non-linear' parameters (R_s, n_1 and n_2) and a singular-value decomposition for fitting the remaining 'linear' parameters (I_{ph}, I_{01}, I_{02} and R_p). It is described in more detail in [20].

These three methods cover the most common ways for parameter identification. For each of these the influence of the measurement conditions on the accuracy of the parameters yielded has been investigated.

Most fitting algorithms require starting values for all the parameters to be fitted. The potential influence of this choice on the final values is illustrated in figure 3, in which the simplex algorithm is started with values which are ideal for all parameters except for the series resistance which is given a known error. (The ε value used for the evaluation of the effectiveness of the parameter extraction is described in equation (4) below.) It is clear that, for the simplex algorithm, even small variations of the initial value of the series resistance can lead to poor performance regarding the accuracy of the parameters extracted. This is discussed in more detail in section 4.1.

It is obviously not realistic to use the ideal parameters as inputs. In order to represent real situations, the initial values were estimated using available techniques. In this work a mixture of the methods given by Craparo and Thacher [7] and by Sharma *et al* [21] has been applied, as described in more detail in a previous work [20].

It appears from the literature that the error criterion applied for fitting the I–V curve is about the only factor considered so far for improving the quality of the fitting procedure, see e.g. the work of Appelbaum *et al* [15]. This is extended in this work to a search for combinations of algorithms and fitting-error criteria because it was felt that this could make a significant difference. Standard approaches are used here for the fitting error criteria and we examine two in particular: the weighed least squares method after Araujo *et al* [11] (LS) and the area method of Phang and Chan [13], in which the area between the 'real' and estimated I–V curves is minimized.

The three algorithms tested in this work (namely the simplex, Marquardt–Levenberg and hybrid algorithms) fit

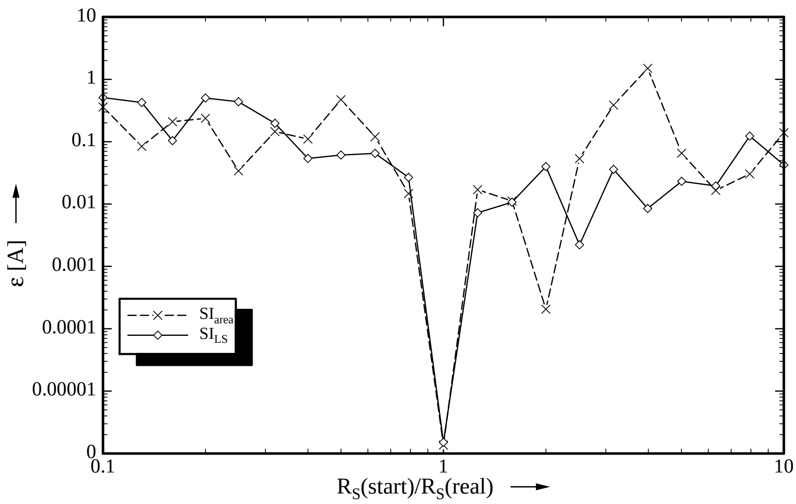

Figure 3. The dependency of the accuracy of the simplex algorithm on the starting value. It is obvious that, in order to deliver good results, the simplex algorithm needs starting values that are better than usually estimated for both tested error criteria (least squares (LS) and area).

the I–V characteristics, adjusting the model parameters in order to minimize the given error criterion. At the end of the process, we are not really interested in how good the fit to the particular I–V curve is (in fact, it is always excellent). What we are interested in is how accurately the model parameters are extracted, compared with the actual answers which we know *a priori*. For solar-cell-modelling purposes one needs all these parameters to be accurate, not just to find a set that fits one particular I–V curve well, but need not work so well in other circumstances. One way to discuss the accuracy of the parameter extraction would be, of course, to quote the relative errors in each and every case, but this would produce a very large amount of data and would not really provide the most useful feedback. Below we choose to define in equation (4) an independent and global quality-of-fit indicator for the parameters extracted. The motivation for this quality-of-fit indicator is that (i) it is independent of any fitting-error-minimization criterion, (ii) it emphasizes the fact that all errors have impacts on current measurements, (iii) it allows one to appreciate that the maximum power point (MPP) is of special importance under normal operating condition and (iv) in situations in which all parameters are very accurate except perhaps one parameter which is very inaccurate, it will tend to give a better result than if, say, all the parameters are out to a modest degree. Experience tells us that the former situation is preferable to the latter in most practical situations. In summary, the quality-of-fit indicator for the parameter extraction is heuristic but works very well as a guide in practice.

Following on from the above, the quality of fit associated with a given set of parameters is defined to be

$$\varepsilon = \sum_{i=1}^{7} |(P_{i,fit} - P_{i,real})w_i| \qquad (4)$$

where P_i represents the seven parameters to be extracted. The subscripts 'fit' and 'real' indicate the extracted and the real (i.e. simulated) values, respectively. We have chosen to define a weighting factor w_i in relation to the maximum power point as

$$w_i = \left.\frac{\partial I}{\partial P_i}\right|_{MPP}. \qquad (5)$$

This means that ε has the units of amperes. In this work ε values of less then 0.01 A correspond to good parameter extraction; ε values of less than 0.001 A correspond to nearly perfect parameter extraction. The relative errors between the extracted and modelled parameters are typically well below 1% for ε values less than 0.001 A.

4. Tests and results

It was stated above that there is no reliable method for the investigation of the validity of the extracted parameters. All parameters depend on a variety of semiconductor properties. This can be illustrated in the case of the series resistance which is conventionally taken as the lumped resistance for the entire path of the charge carriers and is thus a semi-empirical value. Minor inaccuracies in the determination of the separate contributions could lead to a significant shift in the real value and hence lead to uncertainties in the absolute lumped values. In order to avoid these difficulties, tests were conducted exclusively with simulated data.

The graphs presented throughout this paper were generated by using the same set of data as that given in section 2. The reason for doing so is for the sake of consistency. The results are comparable with those obtained from other sets of data and illustrate some typical idiosyncracies.

The normal approach is to assume that the diode-ideality factors are constant at the theoretical values of $n_1 = 1$ and $n_2 = 2$. The values used for the results reported in this study are chosen to represent data typical of a 75 cm^2 silicon solar cell. The first diode-ideality factor is derived from Shockley's theory for diodes [22]; the second assumes that the recombination happens only via traps in the middle of the band gap. This is certainly not true for thin-film solar cells, for which the second diode is normally dominated by other effects, such as recombination at grain boundaries or due to impurities. Even in the fundamental work of Wolf *et al* [23], deviations from the theoretical values were observed for both diode-ideality factors. Hence, it was felt that varying this ideality factor is necessary in order to achieve a broad applicability. Other sets of data were tested as well, revealing no significant differences; thus the decision to present results using these values is purely arbitrary. Only when a diode-ideality factor was given unrealistic values, thus diminishing the influence of that particular diode or making the two diodes mathematically indistinguishable from each other (i.e. their contributions to the overall current had a similar shape), was a decrease in the accuracy of the extraction of the parameters observable.

The environmental conditions assumed are an operating temperature of 328 K and an irradiation level of 1000 W m^{-2}. The irradiation relates to standard measurement conditions while the temperature was chosen to represent a realistic operating temperature. Variations in these external constants have no significant effect on the accuracy of the process.

4.1. The influence of the number of measurement points

The first investigation carried out was to assess the influence of the number of measurement points. Certain parameters dominate the characteristic in particular regions, as discussed in section 3. Hence it is necessary to identify sufficient data to cover all regions adequately.

The total number of data points obviously depends on their distribution as well. Here we investigate only measurements taken at regular voltage intervals. Other measurement strategies are investigated in section 4.2.

It appears from figure 4 that the total number of points has only a minor impact on the overall accuracy of the parameter extraction. Apart from one bad fit in the Marquardt–Levenberg algorithm using the area criterion, all extracted values are more or less ideal. This one bad fit is surprising and was further investigated. It relates to an intrinsic problem of the Marquardt–Levenberg algorithm which utilizes a Gauss–Jordan elimination in order to calculate the eigenvalues. During this process a matrix may come close to being singular, causing difficulties with rounding-off errors. This typically happens with the values describing the shunt resistance, when the corrected values lead to a very large increase in the parameter, driving it to unrealistically high values. Graphically, one could imagine the algorithm following a winding valley to its minimum. At some stage it would reduce the affected values again but, due to the rounding-off error during the calculation, the new values calculated do not create a sufficient improvement. The main effect of the rounding-off error is then essentially to prevent the final ‘homing in’ of the algorithm. The other parameters tend to be close to their ideal values in such a case.

Minor variations are due to the selected stopping criterion. The accuracy can generally be improved by reducing the tolerable variation of the parameters yielded between each optimizing step. This would, however, significantly increase the calculation time. It appears that all algorithms are very robust for total point numbers above 150.

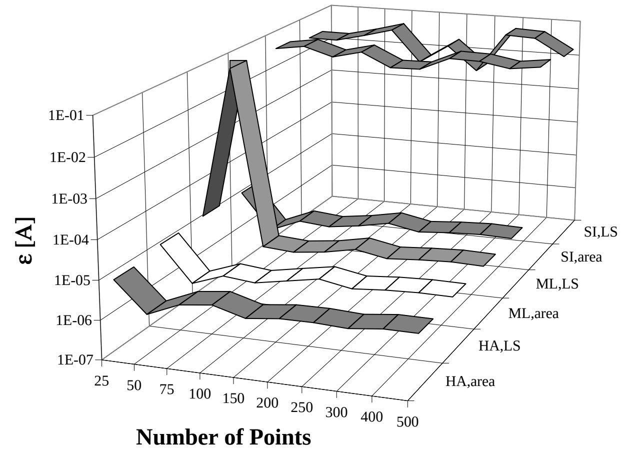

Figure 4. Accuracies for measurements with evenly distributed voltage steps. It appears that in this case the point number has only a minor influence. The hybrid algorithm and the Marquardt–Levenberg algorithm recover the parameters very well whereas the simplex algorithm struggles for all numbers of measurement points.

The simplex algorithm seems to have the most difficulty in recovering the real values. This is somewhat surprising insofar as this algorithm is the one most commonly used and should be able to identify the minimum correctly. Because this was generally observed it was investigated in detail. It turned out that the explanation lies with the specification of the starting value. The simplex algorithm delivered very good values for nearly ideal starting values but as soon as the starting values were less ideal it soon deteriorated. This is shown clearly in figure 3 for the case of varying series resistance. This graph concerns variations in a single parameter; the situation deteriorates as soon as more parameters are varied. The problem is due to premature stopping, i.e. stopping at non-ideal values. Premature stopping is due to the high number of local minima. Beier [24] showed in her work that there are many local minima due to the implicit definition of equation (1). The variation in the quality of the results presented in figure 4 is due to frequent restarting of the algorithm, which were performed following the recommendation given by Press *et al* [18]. This introduces an arbitrary element which allows a significant increase in accuracy of the overall algorithm, but is still far from ideal.

It can be concluded that, for this particular measurement procedure, the number of measurements does not significantly influence the accuracy as long as it is greater than 25. Increasing the number of points above 150 results in only a minor improvement.

4.2. The influence of the measurement procedure

There are three standard measurement strategies for measuring the I–V characteristics of solar cells. One can apply the voltage in regularly distributed steps (as in section 4.1), control the current in regularly distributed steps or measure with a variable resistance load. All three strategies have been simulated. The simulated measurement strategies with equal current steps and with a passive load lead to a

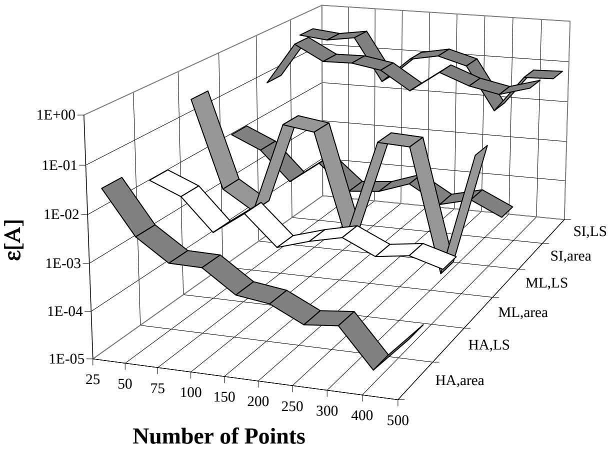

Figure 5. Accuracies for measurements with evenly distributed current steps. It is obvious that a higher point density leads in most cases to a higher accuracy. The simplex algorithm is inaccurate, just like in the other simulations. The idiosyncracies of the Marquardt–Levenberg algorithm employing the area criterion are explained in the text.

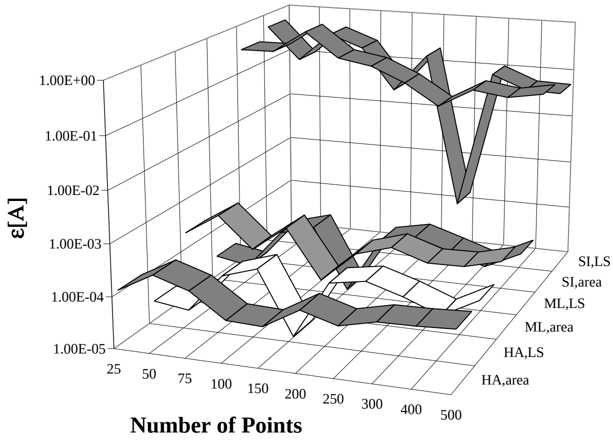

Figure 6. Accuracies for measurements for the passive-loading strategy. No clear trend is obvious. The simplex algorithm is just as inaccurate, as it is in other simulations, with the single exception of using the least squares criterion in the case of 200 measurement points. It can be assumed to be fortuitous that the simplex algorithm had extremely good starting values in one of the restarts.

lower concentration of points around short-circuit conditions and a higher point density towards higher voltages. The equal-current-step strategy yields a point distribution which is more biased towards higher voltages than is the case with the resistive load. Employing the resistive-load strategy restricts the measurements to the fourth quadrant only, i.e. between open-circuit and short-circuit conditions.

The results of the tests using the equal-current-step strategy, shown in figure 5, exhibit a clear trend: increasing the number of points improves the accuracy in most cases. The simplex algorithm still has problems regarding the starting values, whereas the hybrid algorithm and the Marquardt–Levenberg algorithm perform quite well for measurements with more than 150 points. The sub-optimal fits of the Marquardt–Levenberg algorithm using the area criterion may be caused by difficulties in calculating the first derivative of the area criterion for a given point. Thus they cannot be attributed to influences of the measurement conditions. The sub-optimal fits are mainly produced by faulty fitting of the shunt resistance which could probably be controlled by penalizing extreme values within the error criterion.

The passive-load strategy, as shown in figure 6, yields much better results. There is no obvious trend in the graph, except that minor deviations are possible for measurements with less than 75 points. Once again the simplex algorithm suffers from the variations in the input values.

Comparing the different measurement strategies clearly shows that it is preferable to measure devices with constant voltage steps. The passive method yields reliable results as well, but in general the errors are slightly higher than those for the constant-voltage-step strategy. The constant-current strategy performs quite badly in comparison. This is mainly due to the fact that the region around the short-circuit condition is dominated by the shunt resistance and the influence of this parameter is underestimated due to the measurement procedure.

4.3. The influence of the measurement error

Questioning the influence of the measurement error could appear to be quite unnecessary because it is obvious that better measurement accuracy will yield better results. However, solar simulators are quite costly and the question should therefore be phrased as ‘what inaccuracies can be tolerated’. In this section we used sets of data with 200 points and the preferred constant-voltage measurement procedure. Three levels of random measurement errors were generated, which can be attributed to good (level 1), average (level 2) and cheap (level 3) systems. Systematic errors were not investigated because these have a very predictable influence, e.g. systematic measurement errors in the current will lead to a different photocurrent.

In its most general set-up, a solar simulator measures, for a large number of I–V points, the current, voltage, temperature and irradiation at each point. To model the measurement errors we took our simulated values of I, V, T and G at a given point (which are obviously ‘exact’) and added errors drawn from a Gaussian distribution of a given variance (depending on the quality of the solar simulator being modelled). The Gaussian errors were generated using the Box–Muller method given by Press *et al* [18]. The process was then repeated for the next point, with the errors between points being completely uncorrelated. A complete set of points (a ‘measured I–V curve’) was then used for parameter extraction. The following error levels were assumed: for G 1, 5 and 10 W m^{-2}; for T 0.1, 0.5 and 1 K; for I 0.1, 1 and 10 mA; and for V 0.1, 1 and 10 mV. In the first instance the error was added to one measurement only, yielding the sets $G1$, $G5$, $G10$, $T01$, $T05$, $T1$, $V01$, $V1$, $V10$, $I01$, $I1$ and $I10$ which are used in figure 7 (the set name corresponds to the previously given error level). Additionally sets called $L1$, $L2$ and $L3$ were created, in which all four measurements were affected by errors simultaneously. These are also shown in figure 7.

The measurement error has, as shown in figure 7, a major influence on the accuracy of the extracted parameters.

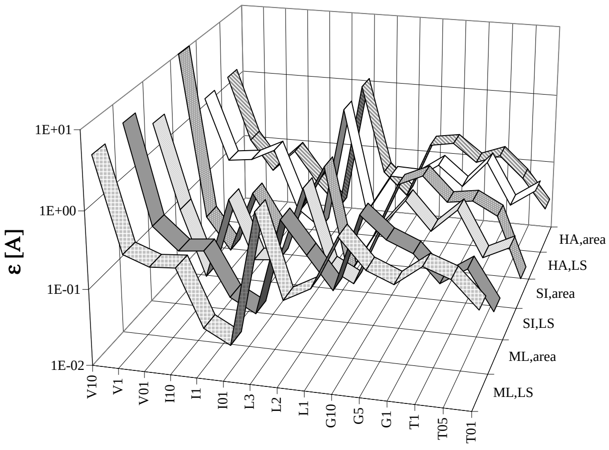

Figure 7. The influence of the measurement error on the accuracy of the extracted parameters. The letter indicates the measurement affected and the number gives the level in millivolts for V, milli-amperes for I, W m^{-2} for G and kelvins for T. The sets marked with L contain errors in all measurements to the same extent as the corresponding level for the single measurements. The result that a higher measurement accuracy yields more accurate parameters is somewhat predictable. However, the difference between the average and the good systems is surprisingly small.

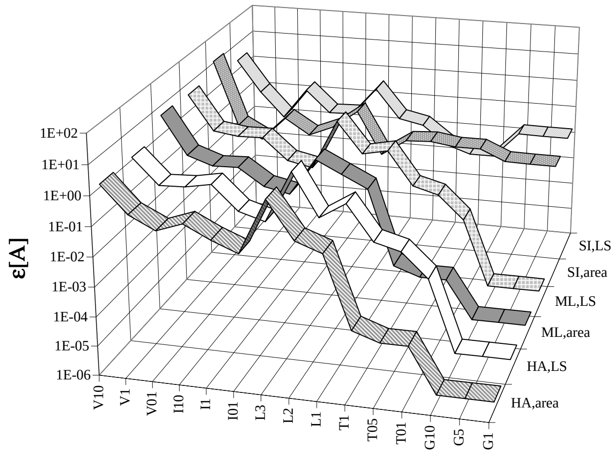

Figure 8. The influence of measurement error when the G and T values are averaged. It is apparent that the results are much more accurate than for unaveraged values (figure 7). This indicates that fast measurements with small thermal drifts are advisable.

The results shown in figure 7 are 'typical', i.e. they have not been averaged in any way. However, we have checked by repeating the process several times that they are also truly representative in that all experiments exhibited the same trends. It appears that the self-averaging over 200 points used in the parameter-extraction process plays a role here. The set-up that allows the most accurate extraction of the parameters is the good system, as could be expected. However, the difference between the good system and the average system is surprisingly low. The slight decrease in the accuracy on going from the error level 2 to error level 3 in the fits using the least squares criterion for the hybrid algorithm and Marquardt–Levenberg algorithm can be reasoned to arise from unusual contributions of the simulated errors. It is quite possible that a random error has by chance only a minor impact on the overall results. If e.g. the voltage has a strong variation at values close to short circuit, it will lead to hardly any error in the current, whereas around the open-voltage condition it would have a significant impact. Following this approach allows the construction of data sets with the same error width, but having different impacts on the extraction process. Additionally, it is possible that errors in two different variables cancel out (e.g. a high current is offset by too high an irradiation reading).

The results of this experiment are idiosyncratic in the case of simplex algorithm. Values delivered can be closer to the original (i.e. simulated) values than those of the otherwise more efficient fitting algorithms, although the value of the internal error criterion used in the fitting process is larger than the values yielded by the otherwise more efficient algorithms. This can be explained as follows: a general problem for the simplex algorithm in the previous experiments was being prone to premature stopping; but this can become beneficial when large errors in the measurements occur. In these apparently paradoxical cases, the simplex algorithm starts with good initial values and merely performs minor adjustments. It thus stays close to the original values, whereas the other algorithms find the minimum according to the chosen internal error criterion which is mathematically better, but in this instance less effective in terms of the heuristic error norm ε.

It is obvious that errors in different variables have different influences on the overall accuracy. The voltage has the most influence, while the impact of the current is surprisingly moderate. The influences of measurement accuracies for the temperature and the irradiation are somewhere in between. The magnitude of the inaccuracy of the sets of data when all measurements are distorted is dominated by the influence of the voltage. This suggests that it is very important to measure the devices using a four-probe measurement, because it was shown by Heidler [25] that measuring with two wires introduces a significant error.

The influence of errors in the temperature and irradiation measurements can, however, be minimized by averaging over all measured values, as shown in figure 8. Here it was assumed that the set of data was measured effectively instantaneously, so that drift in the measurement conditions could be neglected. This approach has the advantage that the measurement errors tend to cancel out. The results for the sets for which the error was introduced in the temperature and the irradiation are nearly ideal, as could be expected from the nature of the added error.

4.4. The influence of the stability of the measurement conditions

In a final test the influence of unstable measurement conditions was investigated. In real measurements, it is often found that the irradiation is not completely stable, mainly due to instabilities in the power supply used to power the solar-simulator lamps or due to weather changes in the case of outdoor measurements. This can significantly change the applicability of various extraction methods, especially when only selected points are used for the extraction of the parameters. This is because typical time constants for changes in reaction are a few microseconds. Commercial simulators are classified according to the size of variations

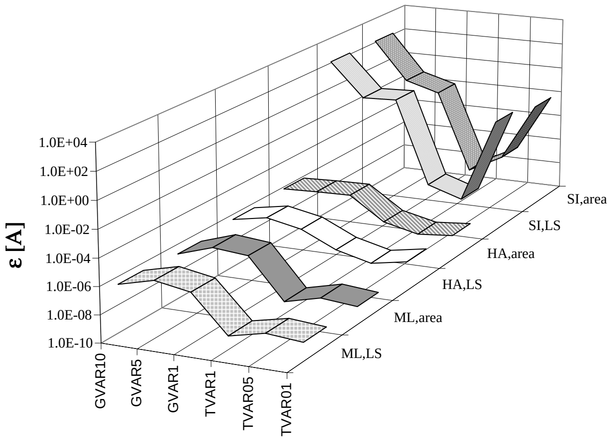

Figure 9. The influence of unstable measurement conditions. Neither the hybrid algorithm nor the Marquardt–Levenberg algorithm has problems with unstable measurement conditions. In contrast, the simplex algorithm does have significantly more problems than it does in the constant case.

around an average irradiation level. For internationally agreed classes, there are three categories of instability: ±2, ±5 and ±10% [26].

Temperature will also vary in practice, particularly if the device is kept in the dark prior to measurement (e.g. to avoid degradation of the sample or excessive heat loads on the cooling equipment). In order to simulate common experimental arrangements, the thermal drift was chosen as 0.1, 0.5 and 1 K over the measurement. Only positive drifts were considered because, under normal conditions of operation, the device temperature will increase.

The data used in this section do not have any added measurement error. The results from these tests are shown in figure 9. It appears that the overall accuracy is hardly influenced by unstable measurement conditions provided that one allows for the drift. The behaviours of the various algorithms are not significantly affected, compared with the case of stable conditions. If the variability is not accounted for, e.g. when the averaged, starting or end value is used, it does have a significant influence on the overall accuracy, as could be expected.

5. Conclusions

The use of synthetic data permits an unambiguous assessment of parameter accuracy and circumvents the problem that measurements could be subject to systematic or random error. Thus it is possible to identify measurement conditions that facilitate reliable parameter extraction. In doing so it is possible to investigate the influence of possible error contributions. Although previous work focused on the use of an ideal error criterion, it is shown clearly that the algorithm also has a significant influence on the overall accuracy. This study showed that the Marquardt–Levenberg algorithm using the least squares criterion and the hybrid algorithm using the area criterion generally performed best, but it also showed that, in the presence of a significant error, such as that typically generated by low-quality measurement systems, the simplex algorithm has the advantage of making only minor adjustments to the guessed starting values.

The number of data points has a varying influence, depending on the measurement procedure. It has been demonstrated that the common method of collecting data at equal current intervals has a negative effect on the accuracy of parameter identification. An extremely high number of measurements is needed to achieve a satisfactory result. Applying equal-voltage steps is a much more effective strategy. The number of points should not be below 150–200 for any measurement procedure.

Investigation of the influence of the measurement error yielded the expected result that even small measurement errors have pronounced effects on the overall accuracy. It is surprising to note that the difference between the simulated top-quality system and the average-quality system is limited and both deliver acceptable results as long as the voltage measurement is of sufficient accuracy. Thus it is extremely important to conduct a four-probe measurement. In general, it does pay off to conduct measurements quickly, so that drift in ambient conditions can be neglected, for then the error in some measurements can be averaged out.

The stability of the measurement conditions does not have a significant impact on the accuracy of the determination of the parameters, as long as the measurements are considered for each point, i.e. one does not rely on starting, average or end values of the environmental conditions. Thus, if it is not possible to conduct the measurement quickly, e.g. due to the integration time for the voltmeter, all environmental conditions should be measured for each point separately.

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