COLLECTOR PARAMETER IDENTIFICATION METHODS AND THEIR UNCERTAINTIES

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Abstract

This paper gives an overview of different methods for collector parameter identification and uncertainty analysis. The parameters for two uncovered collector models have been identified based on measured data of a 50 m^2 solar heating system under continental climate. The model parameters are determined using two different parameter identification methods - a global optimization method and a matrix method (Multi Linear Regression, MLR). For a steady state model according to EN12975, the standard multi linear regression has been implemented based on the least square method. The results are similar to the parameters identified by (Rockendorf et al., 2001) for temperate climate, except for the heat transfer coefficient b_1. For the parameter identification of the iterative, non-linearized model (Frank, 2007) the global optimization algorithm, particle swam optimization with constriction coefficient algorithm (PSOCC), has been implemented in Genopt and coupled with the simulation tool TRNSYS. It runs stable and gives plausible and reproducible results, however, it is more difficult to implement and has a longer running time.

1. INTRODUCTION

The thermal behaviour of solar collectors can be described by mathematical models. With experimentally or theoretically determined model parameters, the model should deliver the thermal power gained by the collector for given boundary conditions. In international standards (EN 12975, ISO 9806 and ASHRAE 93), test procedures and mathematical models are described that establish the collector efficiency under specific boundary conditions. The EN12975 provides three different test procedures, the steady-state test (SST) under outdoor and indoor conditions and the quasi-dynamic test (QDT) under outdoor conditions. (Fischer et al., 2004) and (Kratzenberg et al., 2005) compared the SST and QDT for flat-plate collectors and pointed out, that the QDT offers a much more complete characterisation of the collector. Furthermore, the QDT has the advantage of allowing the execution of more collector tests within the same time period and using the same test equipment. On the other hand, the QDT requires a somewhat more demanding effort for the parameter identification and their uncertainties. (Rojas et al., 2008) found that the three different SST methods according to EN 12975, ISO 9806 and ASHRAE 93 provide similar results for the collector parameters.

The collector parameters are determined based on the experimental test results. The EN12975 prescribes multiple linear regression (MLR) as the parameter identification tool to be used. However, the identification of collector parameters by fitting them to measured data is a mathematical minimization problem in a multidimensional parameter space and can be performed using different methods. Several parameter identification methods of different complexity have been proposed in literature:

- Multiple linear regression (MLR)
    - Least square method (LS)
    - Weighted least square method (WLS)
- Dynamic parameter identification
- Artificial neural networks
- Generic optimization program

(Perers, 1993) remark that the MLR method based on LS can be used to identify collector parameters, but without statements about the uncertainties. A comparison between MLR based on LS and a dynamic parameter identification method using the Levenberg Marquardt Algorithm (implemented in the DF program (Spirkl, 1990)) is presented in (Fischer et al., 2003). The authors of the study show that both methods lead to more or less the same results for the collector parameters.

(Mathioulakis et al., 1999) developed a methodology for the evaluation of uncertainties in the results of solar collectors tests according to the SST method in ISO 9806. This methodology is based on experimental uncertainties and on the implementation of the WLS. (Müller-Schöll and Frei., 2000) and (Sabatelli et al., 2002) remarked that the MLR regression based on the LS is not the most accurate to determine collector parameters and their uncertainties for SST method in ISO 9806. The advantage of the WLS in comparison to the LS method applied for the QDT is shown in (Kratzenberg et al., 2006). (Kalogirou, 2006) reported that artificial neural networks (ANN) can be successfully used for collector parameter identification. For this approach six ANN models for flat-plate collectors have been developed and validated.
In this study parameter identification is presented with the use of measured data gained under continental climate for two different uncovered collector models, the steady-state model according EN12975 and an iterative, non-linearized model (Frank, 2007). The parameters of the steady-state model were identified using the LS method. The results are compared to the parameters obtained under European boundary conditions (Rockendorf et al., 2001). The parameters of the iterative model are determined using particle swam optimization with constriction coefficient algorithm (PSOCC) implemented in the optimization program GenOpt (GenOpt, 2009).
Methods for calculating uncertainties are described, because of their significance for the model validation process.

2. BASIC CONCEPT OF CALCULATION OF UNCERTAINTY

The ISO "Guide to the Expression of Uncertainty in Measurement " (GUM, 1995) establishes a unified method for evaluating and stating measurement uncertainties. The fundamental idea behind uncertainty is that the value of each measurand can only be determined with an uncertainty due to systematic and random errors. A brief description of the GUM method is given in the following (cf. Adunka, 1998).
Systematic errors are similar values under identical conditions and derive from e.g. a defect measurement instrument. But even if all systematic errors could be quantified exactly and eliminated, the results of repeated measurements would not be the same. The results usually scatter randomly around the true value (of a perfect measurement). The causation of these *random errors* are not correctable with the present measurement equipment. The measurement result is an estimated value and depends on random errors and inadequate corrections of the systematic errors.
The uncertainty gives us an interval around the measurement result in which the true value of the measured quantity lies with a certain probability (Figure1.c). An uncertainty is thus not the same as an error. According to (GUM, 1995), two complementary methods of uncertainty estimation should always be used. These are classified as type A and type B methods (VIM, 2004):

- **Type A:** method of evaluation of a component of measurement uncertainty by a statistical analysis of quantity values obtained by measurements under repeatability conditions
- **Type B:** method of evaluation of a component of measurement uncertainty by means other than a statistical analysis of quantity values obtained by measurement

The type A and type B classifies the method of uncertainty estimation and not the source of the error that causes the uncertainty. Nevertheless, type A uncertainty always deals with uncertainty caused by random errors and type B uncertainty may deal with uncertainty caused by systematic and random errors.

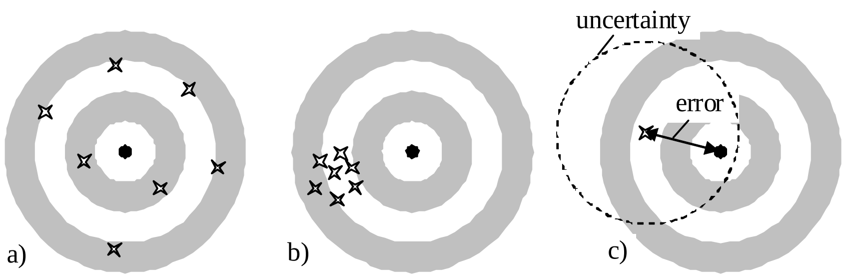


Figure 1. Comparison between systematic and random errors; a) major random error; b) major systematic error; c) Uncertainty is not the same as en error (difference: measurand and true value) (Glembin, 2009)

When a measurement is repeated under the same conditions, the best estimated value for the true value is the arithmetic mean value $\overline{x}$ with the related Type A uncertainty $u_{Type\ A}(\overline{x})$:

$$\overline{x} = \frac{1}{N}\sum_{i=1}^{N}(x_i); \qquad u_{Type\ A}(\overline{x}) = \sqrt{\frac{1}{N(N-1)}\sum_{i=1}^{N}(x_i - \overline{x})^2} \tag{1}$$

As is evident from Eq. 1, the type A uncertainty is the empirical standard deviation of the mean and can be reduced by increasing the number of measurements.
Unlike type A uncertainty estimation, uncertainty estimation of type B uses an assumed probability density (a priori probability) which is connected for example with the used measurement instrument. To compute the type B uncertainty the variance of this probability distribution has to be developed. Usually, sensor specifications furnish the accuracy *a* of the sensor, which is the maximum deviation from the true value *x*. Within the range between the upper limit $a_u=x+a$ and the lower limit $a_l=x-a$ each value has equal probability. So the type B uncertainty can be calculated by the variance of the rectangular distribution:

$$u_{Type\ B}(x) = \sqrt{\frac{a^2}{3}} = \sqrt{\frac{(a_u - a_l)^2}{12}} \tag{2}$$

If a measurand *y* depends on several measured values $x_{1..n}$, with their own uncertainty, then the combined uncertainty $u_c(y)$ is given by:

$$u_c(y) = \sqrt{\sum_{i=1}^{n}\left(\frac{\partial f}{\partial x_i}\right)^2 \cdot (u(x_i))^2 + 2\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\frac{\partial f}{\partial x_i}\frac{\partial f}{\partial x_j}u(x_i)u(x_j)r(x_i,x_j)} \tag{3}$$

The correlation *r(X,Y)* is a common measure of the relationship between two random variables *X* and *Y*, which is defined with the covariance *cov(X,Y)* between the variables (e.g. Montgomery, 2003):

$$r(X,Y) = \rho_{X,Y} = \frac{\sigma_{XY}}{\sigma_X \sigma_Y}; \qquad \mathrm{cov}(X,Y) = \sigma_{XY} = E\left[(X-\mu_X)(Y-\mu_Y)\right] \tag{4}$$

The value of correlation lies between 0 (no correlation) and 1 (strict correlation). If no correlation is present, the second summation term in Eq. 3 will be zero.

$$u_c(y) = \sqrt{\sum_{i=1}^{n}\left(\frac{\partial f}{\partial x_i}\right)^2 \cdot (u(x_i))^2} \tag{5}$$

Assuming a Gaussian distribution of the measurement process, the uncertainty u_c tells us that the true value of the measured quantity lies within $\pm u_c$ around the measurement result with a probability of 68%. However, it has to be noted that most measurement results are usually given the expanded uncertainty *U* by multiplying u_c by a coverage factor *k*:

$$U = k \cdot u_c(y) \tag{6}$$

Preferably, a value of $k = 2$ is to be used. In the case of a Gaussian distribution follows a confidence interval of 95%.

3. COLLECTOR PARAMETER IDENTIFICATION METHODS

Identification of parameters in a model by fitting them to measured data is a well established process. The methodology to determine the regression coefficients is always the same (Adunka, 1998). An objective function is defined to quantify the difference between measured data and the model. Afterwards, the regression coefficients are determined so that the value of the objective function is minimized.
Thus, the identification of collector parameters by matching them to measured data is a mathematical minimization problem in a multidimensional parameter space and can be performed using different

methods. Nevertheless, the quality of parameter determination critically depends on the quality of measured input data. Hence, the international standards prescribe the operation points of the collector as well as the boundary conditions regarding the requirements of the evaluation model and the data analysis algorithm (e.g. MLR). Consequently, the SST has many more restrictions concerning the boundary conditions than the QDT. If an investigation (e.g. validation of a model) differs in this boundary conditions, a detailed analysis of measurement data using statistical methods is essential. With this analysis it is possible to estimate the quality of the parameters before the real parameter identification procedure for the MLR.

- **Multiple linear regression (MLR)**

The basic assumption of the adjustment theory is the total disorder of the measurements, their normal distribution and the maximum likelihood principle. The target of parameter identification is to locate a model with k parameters p_j to represent an array of N observations $\left(z_{i1}, z_{i2}, ..., z_{im}, y_i\right)$ with the largest accuracy:

$$y(z_1,...,z_m) = y\left(f_1\left(z_1,...,z_q\right),... f_k\left(z_1,...,z_w\right), p_1,..., p_k\right) \tag{7}$$

If each observation can be described by Eq. (8) the relationship is called a multiple linear regression (MLR) model. The response y is related to k regressor variables $x_j = f_j\left(z_1,...,z_w\right)$ and the parameter p_j are called the regression coefficients, representing the expected change in response y per unit change in x_j. ε is a random error term.

$$\begin{aligned} y_i &= p_0 + p_1 \cdot x_{i1} + p_2 \cdot x_{i2} + ... + p_k x_{ik} + \varepsilon_i \\ &= p_0 + \sum_{j=1}^{n} p_j x_{ij} + \varepsilon_i \qquad i = 1, 2, ..., n \end{aligned} \tag{8}$$

The model specifies a hyperplane in the k-dimensional space, which has generally non-linear shape. In other words: The equations $f_j\left(z_1,...,z_w\right) = x_j$ behind the regressor variables x_j can be highly non-linear. The least square (LS) method provides an objective function L, which must be minimized with respect to p_0,, p_1,..,p_k to estimate the regression coefficients in the MLR model:

$$L = \sum_{i=1}^{n} \varepsilon_i^2 = \sum_{i=1}^{n} \left(\mathrm{y_i} - p_0 - \sum_{j=1}^{k} p_j x_{ij} \right)^2 = \sum_{i=1}^{n} \left(\mathrm{y_i} - \mathrm{\hat{y}_i}\right)^2 \rightarrow \min \tag{9}$$

The residual is defined as the difference between observation $\mathrm{y_i}$ and the fitted value $\mathrm{\hat{y}_i}$. The residual mean square error (MSE) as well as the standard deviation of the regression coefficients is given by (Kratzenberg, 2005):

$$MSE = \frac{\sum_{i=1}^{n} \left(\mathrm{y_i} - \mathrm{\hat{y}_i}\right)^2}{n-k}, \qquad s\left(p_j\right) = \sqrt{\mathrm{var}\left(p_j\right)} \tag{10}$$

For the steady state solar collector test model the efficiency of the collector is expressed by (Rockendorf et al., 2001 and prEN 12975-2, 1997):

$$\eta_{mo} = \eta_0 \left(1 - b_u \cdot v_w\right) - \left(b_1 + b_2 \cdot v_w\right) \frac{\left(T_f - T_a\right)}{G^*} \tag{11}$$

with the net irradiation G^*

$$G^* = G + \left(\varepsilon / \alpha\right)\left(E_L - \sigma T_a^4\right) \tag{12}$$

In the LS method, the parameters η_0, b_u, b_1 and b_2 are fitted in a way that the sum of the square deviations between the model results η_{mo} and measured results η_{me} is minimized (cf. Eq. 9):

$$L = \sum_{i=1}^{n} \left(\eta_{me,i} - \eta_{mo,i}\right)^2 \rightarrow \min \tag{13}$$

Therefore Eq. (11) must be transforme into the design of Eq. (8):

$$\eta_{mo} = \underbrace{\eta_0}_{p_0} - \underbrace{\eta_0 b_u}_{p_1} \cdot \overbrace{v_w}^{x_1} - \underbrace{b_1}_{p_2} \overbrace{\frac{\left(T_f - T_a\right)}{G^*}}^{x_2} - \underbrace{b_2}_{p_3} \cdot \overbrace{v_w \frac{\left(T_f - T_a\right)}{G^*}}^{x_3} \tag{14}$$

It must be noted that the LS method is correct only with the assumption that the uncertainty of η_{me} is the same for all data points. The problem with this approach is that, in reality, the uncertainty for η_{me} measured at low radiation e.g. is larger than the uncertainty of those measured at high radiation.

That is why an alternate algorithm, the weighted least square (WLS) method, will be discussed. The WLS method calculates a minimum based on measured values and their uncertainties as well as on the model parameters and their uncertainties. Thus the objective function changes to:

$$\chi^2 = \sum_{i=1}^{n} \frac{\varepsilon_i^2}{u_c^2\left(\varepsilon_i\right)} = \sum_{i=1}^{n} \frac{\left[\eta_{me,i} - \eta_{mo,i}\right]^2}{u_c^2(\varepsilon_i)} \tag{15}$$

In this function, each square difference is divided by the square of the uncertainty of the corresponding data point i (Kratzenberg et a., 2006):

$$u_c^{\,2}(\varepsilon_i) = \left(\frac{\delta\left(\varepsilon_i\right)}{\delta\left(\eta_{me,i}\right)} \cdot u\left(\eta_{me,i}\right)\right)^2 + \sum_{j=1}^{k}\left(\frac{\delta\left(\varepsilon_i\right)}{\delta\left(x_{j,i}\right)} \cdot u\left(x_{j,i}\right)\right)^2 \tag{16}$$

The uncertainty analysis for the SST is described in (Müller-Schöll and Frei., 2000) and for QDT in (Kratzenberg et a., 2006).

- **Dynamic parameter identification (DF program)**

(Spirkl, 1990) has developed a dynamic parameter identification method and implemented in the DF program. This iterative search method uses the Levenberg Marquardt Algorithm, which has become the standard of non-linear least square routines. Detailed description of the algorithm can be found in (Press, 1992). A comparison between the MLR based on LS and the dynamic parameter identification method has been made in (Fischer et al., 2003). The authors of the study reported that both methods lead to nearly the same results for the collector parameters. Furthermore, the DF program has the advantage of high flexibility with respect to the input data as well as to the collector model.

- **Generic optimization program (GenOpt) and PSO algorithm**

GenOpt is a generic optimization program, which minimizes an objective function with respect to multiple parameters. The objective function is determined by a simulation program (e.g. TRNSYS) that is iteratively called by GenOpt. The program has a library including local and global multi-dimensional as well as one-dimensional optimization algorithms. Furthermore, users can easily add their own minimization algorithms to GenOpt's library. The general working methodology of GenOpt has been described in detail by (Wetter, 2001).

The PSO algorithms are population-based probabilistic optimization algorithms first proposed by (Kennedy and Eberhart, 1995). The PSO uses a simple mechanism that mimics swarm behaviour in birds flocking and fish schooling to guid the particles to search for global optimal solutions. A detailed description of the algorithm can be found in (Poli et al., 2007).

It must be noted that the PSO does not provide specifications concerning the uncertainty of the located optimum. To calculate the uncertainty the following methodology is performed. After locating the assumed optimum using the PSO, a local minimization method (Hooke-Jeeves algorithm) with the initial values of the assumed optimum is applied. The Hooke-Jeeves algorithm works with a given increment z, which is comparable to the accuracy of a measurement instrument. With Eq. (2) the uncertainty is given by:

$$u_{GenOpt} = \sqrt{z^2/3} \tag{17}$$

In this study the particle swam optimization with constriction coefficient algorithm (PSOCC) is used to identify the collector parameters of an iterative, non-linearzised model for uncovered collector given by (Frank, 2007):

$$\dot{q}_{use,mo} = \alpha\left(K_b(\Theta)\cdot G_{b,t} + K_d \cdot G_{d,t}\right) - \left(U_{c0} + U_{c1}\cdot v_w\right)\left(T_p - T_a\right) - \varepsilon_{eff}\sigma\left(T_p^4 - T_{sky}^4\right) - U_b\left(T_f - T_a\right) - c_{eff}\frac{\partial T_f}{\partial t} \tag{18}$$

The objective function is defined as the sum over the squares of the difference between measured thermal output $\dot{q}_{use,me,i}$ and the model prediction $\dot{q}_{use,mo,i}$ divided by the uncertainty of the measurand $u\left(\dot{q}_{use,me,i}\right)$ for each time step:

$$L = \sum_{i=1}^{n} \frac{\left[\dot{q}_{use,me,i} - \dot{q}_{use,mo,i}\right]^2}{u_c^2\left(\dot{q}_{use,me,i}\right)} \tag{19}$$

The thermal output of the collector is calculated with the following well known equation:

$$\dot{q}_{use,me} = \dot{V}\rho c_p\left(T_{out} - T_{in}\right) \tag{20}$$

If the measured input data (flow rate, density, specific heat capacity and temperature difference) are independent from each other, the uncertainty of the measured thermal output can be calculated by:

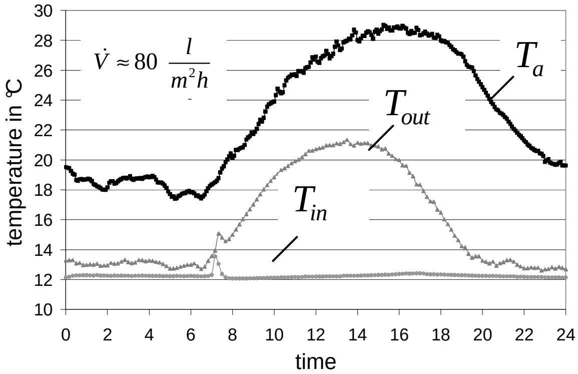
$$u_c(\dot{q}_{use,me}) = \sqrt{\left(\frac{\partial \dot{q}_{use,me}}{\partial \dot{V}}\cdot u\left(\dot{V}\right)\right)^2 + \left(\frac{\partial \dot{q}_{use,me}}{\partial \rho}\cdot u\left(\rho\right)\right)^2 + \left(\frac{\partial \dot{q}_{use,me}}{\partial c_p}\cdot u\left(c_p\right)\right)^2 + \left(\frac{\partial \dot{q}_{use,me}}{\partial \Delta T}\cdot u\left(\Delta T\right)\right)^2}$$
$$\Rightarrow\ u_c(\dot{q}_{use,me}) = \sqrt{\left(\rho c_p \Delta T\cdot u\left(\dot{V}\right)\right)^2 + \left(\dot{V}c_p\Delta T\cdot u\left(\rho\right)\right)^2 + \left(\dot{V}\rho\Delta T\cdot u\left(c_p\right)\right)^2 + \left(\dot{V}c_p\rho\cdot u\left(\Delta T\right)\right)^2} \tag{21}$$

4. MEASUREMENTS

A test plant with 50 m^2 uncovered collector (Solar-Flex) is operating connected to a district heating net in Bishkek (Kyrgyzstan). The following measurement data have been recorded as one minute average values: global-, diffuse-, and long wave irradiance, flow-, return- and ambient temperature, absorber flow rate, air humidity and wind speed. In the present study the period between 11.08.2008 and 30.09.2008 is analysed. All calculations are made with 10-minute average values.

For the SST method only data vectors are considered that fulfil the conditions of EN12975. However, the wind speed does not fulfil the norm, but varies between 1 and 2 m/s. For the parameter identification with GenOpt all data are used.

Figure 1 shows a day in August 2008 with a typical ambient temperature and irradiation profile. The water inlet temperature of the uncovered collector is far below the ambient temperature level. Due to the unusual operating conditions, the useful power gain of the collector can be larger than the irradiance resulting an “efficiency” above one.



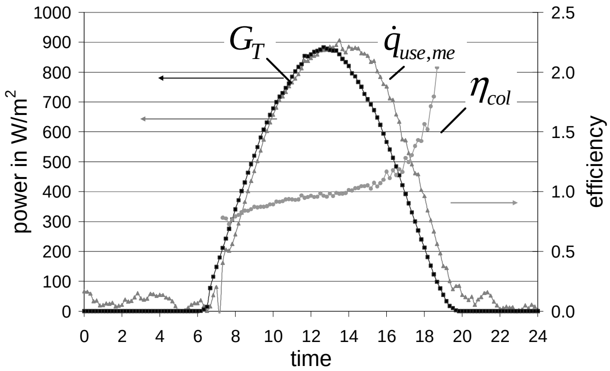


Figure 1. Typical day in August (Bishkek, Kyrgyzstan): Ambient as well as collector temperatures profile (left). Irradiance, useful power gain and efficiency of the collector (right)

5. RESULTS

In the next subsection a multi linear regression based on the least square method will be applied for determining the parameters of the steady state model. In the second subsection the parameters of the iterative, non-linearized model are identified with GenOpt.

- **Parameter identification for the SST model using MLR method based on LS**

Probability plots are extremely useful and are often the first technique used in an effort to determine which probability distribution is likely to provide a reasonable model for the data. The observations do not even approximately lie along a straight line, giving a clear indication that the data do not follow a normal distribution.

Figure 2 shows a normal probability plot as well as a histogram of the residuals, indicating a normal distribution of the residuals. Thus, the MLR based on LS can be used according to the objective function that is given in Eq. (13).

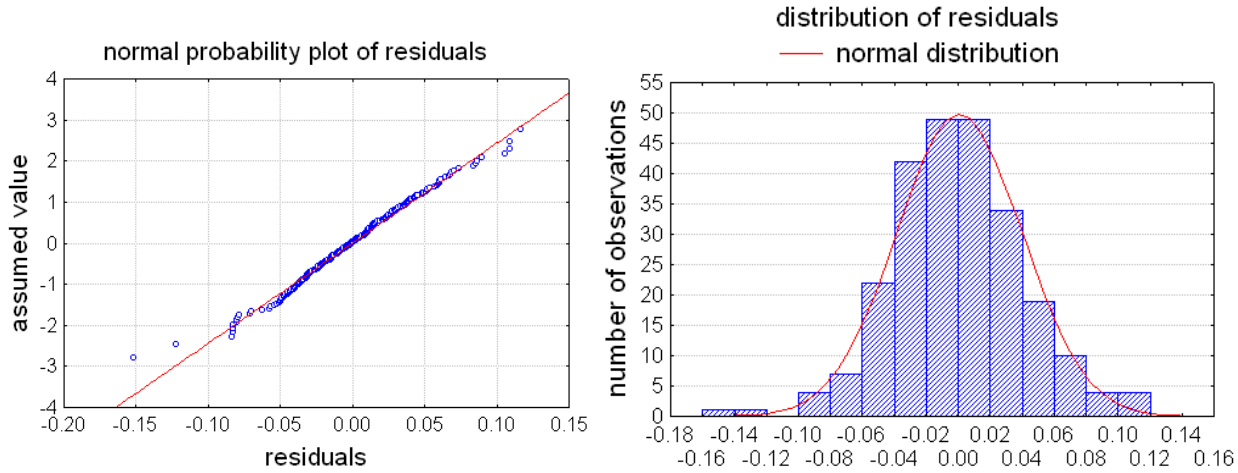


Figure 2. Normal probability plot of residuals (left) and histogram of residuals (right). Period under review: 11.08.2008 - 30.09.2008 (only data vectors are considered that fulfil the conditions of EN12975)

Table 1 presents the collector parameters of the steady state collector model (cf. Eq. 11) under continental and temperate climate obtained by the MLR method based on LS. Eq. (10) was used to determine the standard deviation of each collector parameter. The results are compared to results from extensive tests carried out by Rockendorf (2001). The parameters are found to be of a similar order of magnitude, except for b1. B1 refers to the heat loss coefficient, so the heat transfer is smaller for the energy gain (situation under continental climate) and larger for the energy losses (under temperate climate). A possible cause is that if the collector is warmer than the ambient, the collector heats the overlying air layer, which becomes warmer and goes up. If the collector is colder than the ambient, the air layer heats up the collector and relatively cools down and the colder air stays down, therefore the heat transfer rate could be lower.

Table 1. Collector parameters obtained by SST under continental and temperate climate. The standard deviation of each parameter is given in brackets

	continental climate	temperate climate (Rockendorf et al., 2001)
η_0	0,823 (0,032)	0,843
b_u in s/m	0,036 (0,028)	0,028
b_1 in W/(m^{2}K)	5,91 (1,79)	16,49
b_2 in J/(m^{3}K)	5,53 (1,28)	4,07

The resulting efficiency curve is shown in Figure 3. On the left side of Figure 3, it can be seen that a large share of the efficiency values are higher than 1. This is caused by the fact that also the enthalpy of the ambient air is used for heating the fluid. The average efficiency for the considered timeframe is 0.99. On the right side of Figure 3 a comparison of modelled and measured efficiencies is shown, and correspond reasonably well.

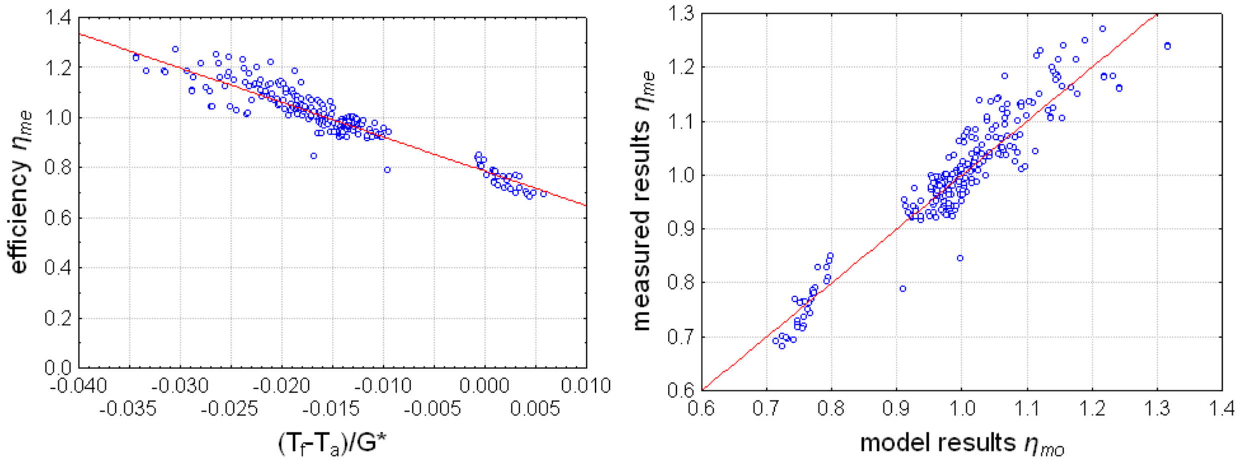


Figure 3. Collector efficiency curve (left) and comparison between measured and model collector efficiency (right). Period under review: 11.08.2008 - 30.09.2008 (only data vectors are considered that fulfil the conditions of EN12975)

- **Parameter identification for the iterative, non-linearized model used GenOpt**

The following section describes the results of the parameter identification with GenOpt for the iterative, non-linearized model. First, the global optimization method PSOCC is applied, followed by the local optimization algorithm Hooke-Jeeves. The Hooke-Jeeves algorithm starts with the global optimized PSOCC parameter values and leads to a slightly better optimum, because of the smaller steps. The objective function improves with 0,4 %. The uncertainty is calculated with Eq (17). The results are shown in Table 2.

Table 2. Collector parameters obtained by iterative, non-linearzied model under continental climate

	PSOCC	Hooke-Jeeves
U_b in W/(m^{2}K)	0,488	0,010
U_{co} in W/(m^{2}K)	9,056	9,775
U_{c1} in J/(m^{3}K)	6,856	6,860
L in W/m^2	1,598 E8	1,592 E8
Time of simulation in sec	700	50

In Figure 4 a multi dimensional parameter space is presented with the objective function in dependence only of U_{c0} and U_{c1}. This is a global optimisation with the PSOCC method. Although there is a concentration of points near the optimum, the algorithm still tries to find an optimum outside this concentration as can be seen in the Figure.

The measured and modelled collector output on a daily basis are shown in Figure 5 for the total considered period. It is clear from the graph that the model matches the measurements well on the majority of the days. As can be seen in Figure 5, the major difference between measurements and simulations is at night. During the day the values correspond well.

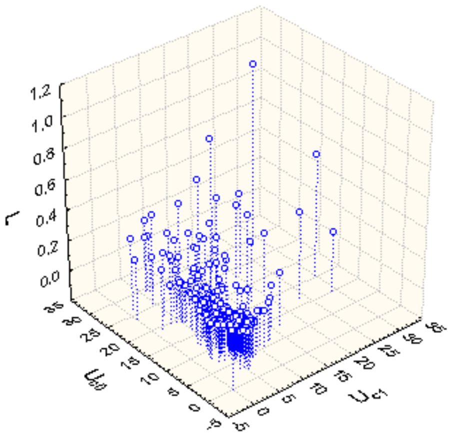


Figure 4. Identification of collector parameters is a minimization problem in a multidimensional parameter space. The diagram shows the objective function in dependence of U_{c0} and U_{c1}

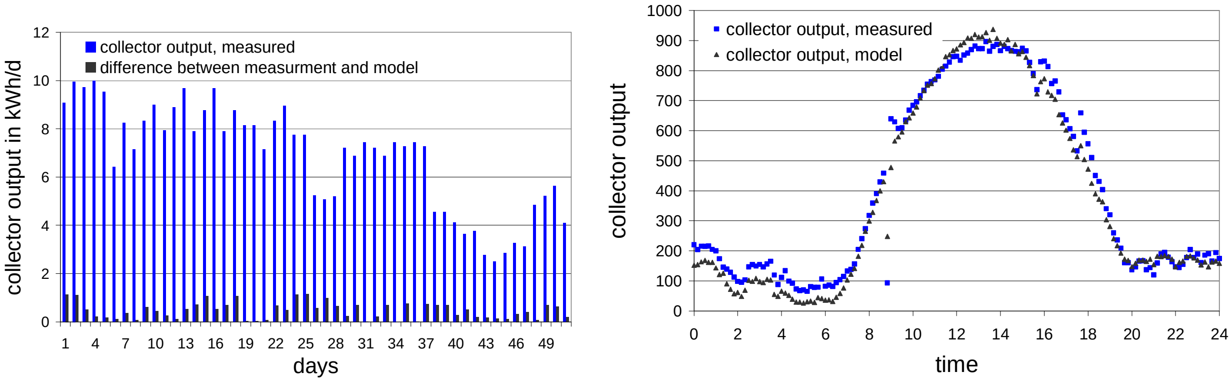


Figure 5. Comparison between modeled and measurement data. Period under review: 11.08.2008 - 30.09.2008 (left) and a typical day in August (right)

The MLR-LS method has several advantages compere to GenOpt. It is relatively simple, fast and easily applicable, since it has been integrated into most spreadsheet programs. However, it is restricted to linear and non-iterative methods. Furthermore the regressors in Eq. (14) should not be correlated. Also, the uncertainty should be the same for all data points, that condition is generally not satisfied in solar heating systems.

GenOpt is much more flexible regarding measured data and models. In contrast to MLR-LS, uncertainties can be included. Furthermore the coupling of TRNSYS with GenOpt runs stable and the results are reproducible. A disadvantage is that the optimisation process requires more time, minutes for GenOpt compared to seconds for MLR-LS.

6. SUMMARY AND OUTLOOK

The parameters for two uncovered collector models have been identified based on measured data of a 50 m^2 system under continental climate. For a steady state model according to EN12975 the standard multi linear regression based on the least square method has been implemented. The results are similar to the parameters identified by Rockendorf for temperate climate, except for the heat transfer coefficient b1.

For the parameter identification of the iterative non-linearized model a global optimization algorithm implemented in Genopt has been coupled with the simulation tool TRNSYS. It runs stable and gives plausible and reproducible results, however, it is more difficult to implement and has a longer running time.

It is planned to analyse the sensitivities of the identified parameters by applying the Morris algorithm which is integrated in GenOpt (Kusyy, 2008)

7. ACKNOWLEGEMENTS

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8. NOMENCLATURE

a	accuracy of a sensor, different units
a_l	accuracy of a sensor (lower limit), different units
a_u	accuracy of a sensor (upper limit), different units
b_1	heat loss coefficient, W/(m²K)
b_2	wind speed dependence of the heat loss coefficient, J/(m³K)
b_u	wind speed dependence of the zero heat loss efficiency, s/m
c_{eff}	effective heat capacity of the collector, J/(m²K)
c_p	specific heat capacity of the fluid, J/(m²K)
E_L	long wave irradiance, W/m²
G	hemispherical irradiance in the collector plane, W/m²
G^*	net irradiance, W/m²
$G_{b,t}$	hemispherical beam irradiance in collector plane, W/m²
$G_{d,t}$	hemispherical diffuse irradiance in collector plane, W/m²
k	coverage factor
$K_b(\Theta)$	incident angle modifier function for beam radiation
K_d	incident angle modifier function for diffuse radiation
L	objective function (MLR based LS, Genopt), different units
$\dot{q}_{use,me}$	useful power gain (measured), W/m²
$\dot{q}_{use,mo}$	useful power gain (modelled), W/m²
T_a	ambient temperature, °C
T_f	average fluid temperature, °C
T_{in}	inlet temperature of the collector, °C
T_{out}	outlet temperature of the collector, °C
T_p	average temperature of the collector surface, °C
T_{sky}	sky temperature, K
p_j	regression coefficient ($j = 1..k$), different units
u	standard uncertainty (type A or type B), different units
u_c	combined uncertainty, different units
U	expanded uncertainty, different units
U_b	heat transfer coefficient on the back side of the collector, W/(m²K)
U_{c0}	wind independent part of the convection heat transfer coefficient, W/(m²K)
U_{c1}	wind dependent part of the convection heat transfer coefficient, J/(m³K)
v_w	wind speed, m/s
$x_{i,j}$	regressor variables, different units
$z_{1..m}$	measured data, different units
z	increment Hooke-Jeeves Algorithm
α	absorption coefficient
χ	objective function (MLR based on WLS), different units
ρ	density, kg/m³
ε	emission coefficient of the absorber surface
ε_i	random error (MLR)
ε_{eff}	effective emission coefficient of the absorber surface
η_0	zero heat loss efficiency
η_{me}	collector efficiency (measured)
η_{mo}	collector efficiency (modelled)
σ	Stefan-Boltzmann constant, W/m²K⁴
LS	Least square method
MLR	Multiple lineare regression
QDT	Quasi-dynamic test
SST	Steady state test
PSO	Particle swam optimization
WLS	Weighted least square method

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