Simulation based Fault Detection for Large Solar Thermal Systems

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Abstract

Solar thermal systems are designed to function for about 25 years, but faults and malfunctions are likely to occur at a certain time, causing energy and economic losses. Fault detection and monitoring during the operation of large solar thermal systems is essential for ensuring a continuous optimal energy yield. This paper describes several aspects of a simulation-based approach to detect faults.

In the simulation based approach, energy yields of large solar thermal systems are simulated with TRNSYS and then compared to measured data. TRNSYS models are developed with a modularized approach, so that the generation of a new model does not consume much time. Uncertainties of both measured and simulated data are taken into consideration for the fault analysis. Two case studies of large solar thermal systems, for which one year of measured data was available, are presented.

1. Introduction

Fault detection and monitoring are important features to ensure an optimal energy yield for a solar thermal system during its whole lifetime. Faults and malfunctions can create energy and economic losses. Several approaches for fault detection have already been proposed [1]; however there is room for improvements. The Austrian project IP-Solar is developing a service for quality assurance and energy yield monitoring for large systems, which includes a thorough analysis of the measured data of the complete system including storage and auxiliary heating. Besides standardizing procedures in data management, the two main components of the method are an algorithm and a simulation based fault detection module. Algorithms look for faults based on measured data. The simulation based method compares simulation results of energy flows with measured energy flows. The focus of this paper will be the simulation based fault detection. Further results of the IP Solar project are discussed in Ohnewein et al. [2].

In the simulation based method, results of TRNSYS simulations are compared to measurements. Confidence intervals for both simulated and measured data are calculated. If the difference is larger than the confidence interval, a fault is found. The advantage of a simulation based approach is that one has a relatively objective base case that is not influenced by measured data. Furthermore one can quantify energy losses caused by certain faults. A potential disadvantage is the time required to generate models and carry out the simulations. Therefore, a critical step is the quick generation of TRNSYS models (section 2.1) and the analysis of uncertainties in measurements and simulations (section 2.2). The first steps of the simulation based fault detection have been applied to a large two-line system and a large system feeding the solar energy into a district heating net, which are described in section 3.1. Results of simulations, measurements and sensitivity analysis are described.

2. Methodology

2.1. Modularized built up TRNSYS models

Sophisticated simulations of solar thermal systems are often carried out in the simulation environment TRNSYS, since it has a high flexibility and reliability. However, a limiting factor for using TRNSYS for automated fault detection is the large time investment that is required to generate an accurate model for the, often complex, solar thermal systems. Therefore, a modular way of building TRNSYS models is used. The model is organised in subsystems, e.g. the solar loop or the storage part are subsystems; these can easily be connected and replaced. To increase the applicability of the subsystems, also several hydraulic options and several control strategies are integrated in the TRNSYS subsystems. These can be set by flags in equations blocks, e.g. one can choose how the storage is charged. This makes it possible to quickly build TRNSYS models for a multitude of hydraulically different solar thermal systems with diverse control strategies. TRNSYS subsystems for typical large solar thermal systems have been developed and tested [3].

2.2. Uncertainty analysis

If one compares measured and simulated energy yields, uncertainties in both, measured data and simulated energy yields, should be taken into account. Measurements are imperfect and give rise to errors, which are often subdivided in random errors and systematic errors. Random errors are caused by unpredictable fluctuations of events. These cannot be corrected, but they can be reduced by increasing the number of observations. Systematic errors can be corrected when they are derived from a recognized effect [4, 5].

In the ‘Guide to the Expression of Uncertainty in Measurement’, uncertainties are grouped in two categories, Type A and Type B uncertainties. For Type A, the uncertainties are evaluated by ‘a statistical analysis of series of observations’, while Type B uncertainties are evaluated by other means, e.g. manufacturer’s specifications [5]. Both Type A and Type B uncertainties are evaluated based on probability distributions.

A quantification of uncertainties in the measured energy yields is necessary. Since measurements are not made under steady-state but under dynamic conditions, a Type A analysis cannot be made, therefore, only Type B uncertainties are considered. These are dealt with via normal error propagation, so for heat flows (Equation 1), the uncertainty is calculated with Equation 2.

$$\dot{Q} = \dot{V} \cdot \rho \cdot c_p \cdot (T_2 - T_1) \qquad \text{(Eq. 1)}$$

$$\frac{u(\dot{Q})}{\dot{Q}} = \sqrt{\left(\frac{u(\dot{V})}{\dot{V}}\right)^2 + \left(\frac{u(\rho)}{\rho}\right)^2 + \left(\frac{u(c_p)}{c_p}\right)^2 + \left(\frac{u(T_2 - T_1)}{T_2 - T_1}\right)^2} \qquad \text{(Eq. 2)}$$

Uncertainties in the simulation are caused by different factors:

- uncertainty in simulation parameters (e.g. collector efficiency)
- uncertainty of measured input data (e.g. irradiance)
- uncertainty in the model, its components and their combination

Uncertainties in the first two categories can be estimated based on available literature and datasheets of sensors, for the third category of uncertainties this is not possible. To deal with these first two uncertainty categories the authors have used the following approach. A simple sensitivity analysis has been carried out to estimate which parameters are sensitive and need to be included in the uncertainty analysis for the system simulations. For the sensitivity analysis, potential sensitive parameters and all the measured input data points have been varied; one parameter at a time, and the change in output energy was studied. A more detailed description for the individual systems follows in chapter 3.2.

The confidence interval of the simulation is, in this first step, calculated with a classical minimum/maximum analysis. That means that all the sensitive parameters and sensitive measured input data are set to their highest or lowest value so that the output is maximized. This basically means that the confidence interval is overestimated, however since the uncertainties of the third category are not taken into account this can match well with reality. In a later stage this will be followed up by a Monte Carlo analysis.

Several simulations are made every day for each investigated system. Next to the whole system, also individual subsystems are simulated for localisation of faults. Fault detection is carried out on a daily basis by comparing measured and simulated energy yields at different locations in the system.

3. Test plants

3.1. Description of Systems and TRNSYS decks

At the moment four field tests are carried out, for two of these systems enough data is available for analysis. System 1 is a large solar thermal system feeding the solar heat directly to a district heating net; it has a collector aperture area of 1287 m^2 and is located in Graz, Austria. The second system is feeding its heat into a two-line network; this system has 139 m^2 collector area and 14 m^3 storage and is also located in Graz. The other two are solar combi systems of about 15 m^2 collector area and they are located near Kassel, Germany.

Two simplified hydraulics are shown in Figure 1 and 2. Temperature sensors, volume flow sensors and heat flow meters are installed. Furthermore, one irradiance sensor (SP Lite) is installed in the collector plane of system 1. Measured data for system 1 and 2 has been available since June 2009.

A schematic view of the TRNSYS subsystems can be found (blue boxes) in Figures 1 and 2. The parameters required for the simulation have been made available by the installers of the system (SOLID) or are based on datasheet information. The storage temperatures in the nodes of the storage are initialised at the start of the day, based on the measured data from the 5 temperature sensors in the storage. The decks have been verified against measured data. However parameters are not fitted against measured data.

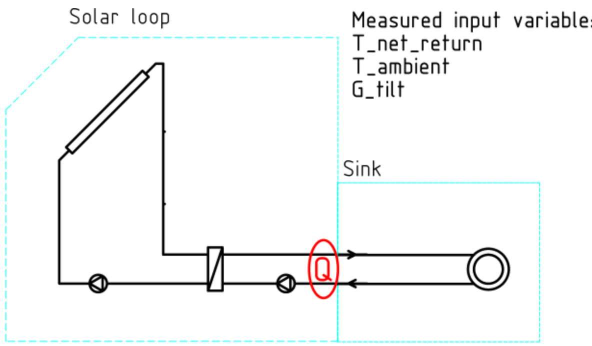

Fig. 1. System 1: Solar heating fed-in to district heating network, the measured input variables that are used as inputs are listed, the Q in the red ellipse is the location where the heat flows are compared.

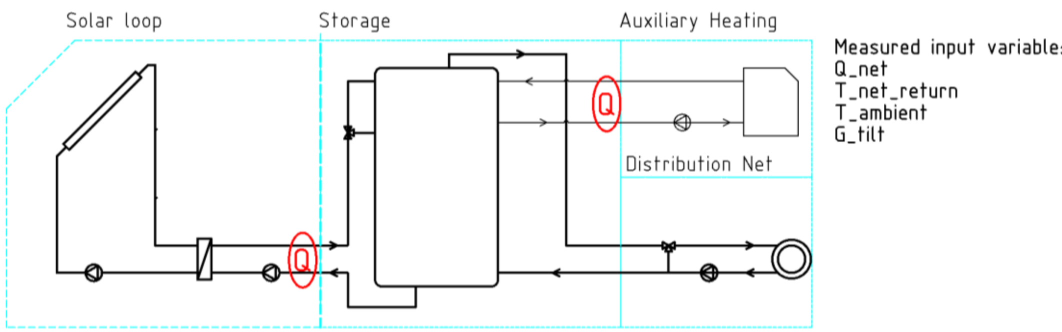

Fig. 2. System 2: Solar heat fed into two-line system the measured input variables that are used for the simulation inputs are listed, the Q in the red ellipse is the location where the heat flows are compared.

3.2. Sensitivity analysis of system 1 and 2

A sensitivity analysis has been carried out for system 1 and 2. This has been done for a one year period. Since no irradiation information was available for system 1, a standard weather profile (Meteonorm) for Graz has been used as input for the simulation. A profile for the return temperature of the net has been generated based on the available measured data. For system 2, the analysis has been carried out with measured input data for irradiance, ambient temperature and heat demand. Since data was not available for all days, a selection of 182 days was made, evenly spread across the months.

The parameters and input variables that have been altered in the sensitivity analysis are listed in Table 1, including the maximum and minimum change and the steps between the parameter changes. All parameters and input variables have been varied up to at least twice the expected uncertainty values, one parameter at a time. The results for the sensitivity scenarios for system 1 are shown in Figure 4, the x-axis shows the change in input parameter or variable, while on the y-axis the change in yearly solar energy production (secondary loop) is shown. The parameters/variables with a steep line are very sensitive to changes. An example of a very sensitive input variable is irradiance, of which the yearly solar energy yield increases relatively about twice as much as the relative change in input. This is caused by higher efficiencies of the collector at higher irradiance values and by the high return temperature (about 55 °C) of the district heating net. The change in daily solar energy yield is relevant for the fault detection as well. This change is usually smaller for days with a large daily energy production, while for days with a low daily energy production the relative change may be much larger than the relative yearly change, shown in Table 1. This suggests that it is wise to have part of the uncertainty as an absolute value.

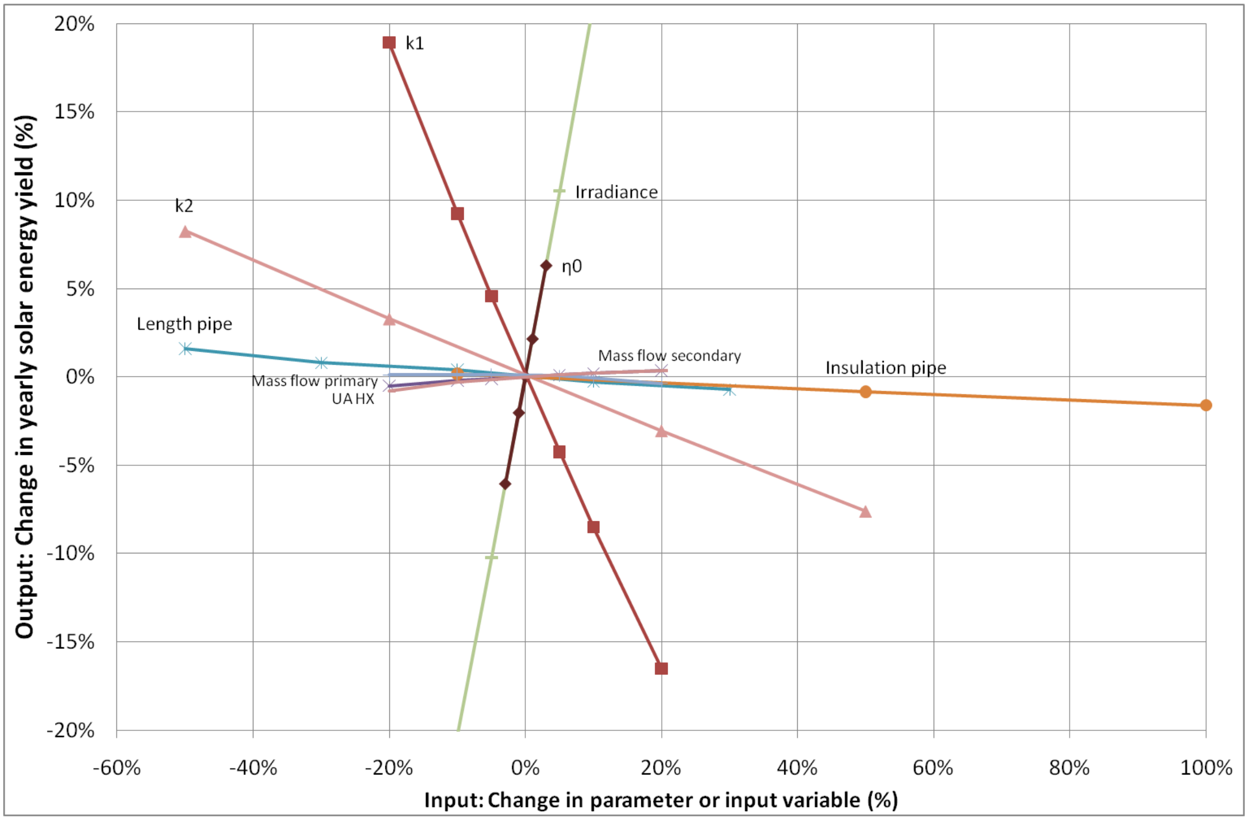

Fig. 4. Sensitivity analysis of system 1

Table 1 shows in its last column the uncertainty margins of the parameters and input variables that are used in the simulation. The assumptions for the measurement sensors are based on the type of sensors used. In literature large uncertainties for the collector parameters have been found [6], however these assume that the different parameters are totally independent from each other. This leads to very large uncertainties for large values of the reduced temperature difference. Furthermore for the derivation of the collector parameters, these are not independent and therefore the lower uncertainties for the collector parameters have been applied.

Tab. 1, Scenarios in and results of sensitivity analysis for 2 systems, one year simulations

Parameter or input variable	**Max / Min**	**Step**	**System1 Sens (%/%)***	**System 2 Sens (%/%)***	**Uncertainty for simulation**
η_0	6%	3/6 %	2.08	1.4	2%
k1	20%	5/10/20 %	0.88	0.5	3%
k2	50%	20/50 %	0.16	0.1	-
Heat capacity collector	20%	10/20 %	-	0.02	-
UA value of solar heat exchanger	20%	5/10/20 %	0.02	0.03	-
Length of pipes in solar loop	50%	10/30/50 %	0.02	0.04	-
Thermal conductivity pipe insulation	100%	-10/50/100%	0.02	0.02	-
Nominal mass flow primary loop	20%	5/10/20 %	0.01	0.01	-
Nominal mass flow secondary loop	20%	5/10/20 %	0.03	0	-
Store volume	5%	2/5 %	-	0.05	-
Store heat loss factor	50%	20/50 %	-	0	-
Irradiance	20%	5/10/20 %	2.06	1.4	5% +10 W
Ambient temperature (°C)	2 K	0.5/1/2 K	2.5 %/K	1.6%/K	0.5 % + 0.6°C
Return temperature net (°C)	2 K	0.5/1/2 K	1.1 %/K	1.1 %/K	0.5 % + 0.6°C
Heat demand net	10%	2/5/10 %	-	0.05	3.2% (only S2)

*Sens = sensitivity is defined as % change in solar energy yield in the secondary (charging) loop per % change in input

3.3. Results

Results of the simulation of the system with uncertain parameters are shown in Figure 5 for system 2. In total, the energy balances of 219 days have been analysed. There is a pretty good match between measured and simulated values for system 2, however there are still a few days where the measured energy yield is not within the uncertainty margins. At approximately half of these days the measured energy yield was lower than 0.3 kWh/m^{2}day. At a few other days, snow can be a likely cause. In Fig. 6 the measured and simulated energy yields are shown for a day in June 2009.

The average uncertainty margin of the simulated values is plus 12 to minus 19 %, therefore, larger faults causing a daily loss of 25 % should be discovered for system 2. When a fault causes a daily energy loss smaller than the uncertainty margin, the fault cannot be found. The uncertainty margin is slightly lower for larger energy yields. The uncertainty margin for system 1 is approximately plus and minus 24 %. A minimum daily irradiation level for fault detection should be defined.

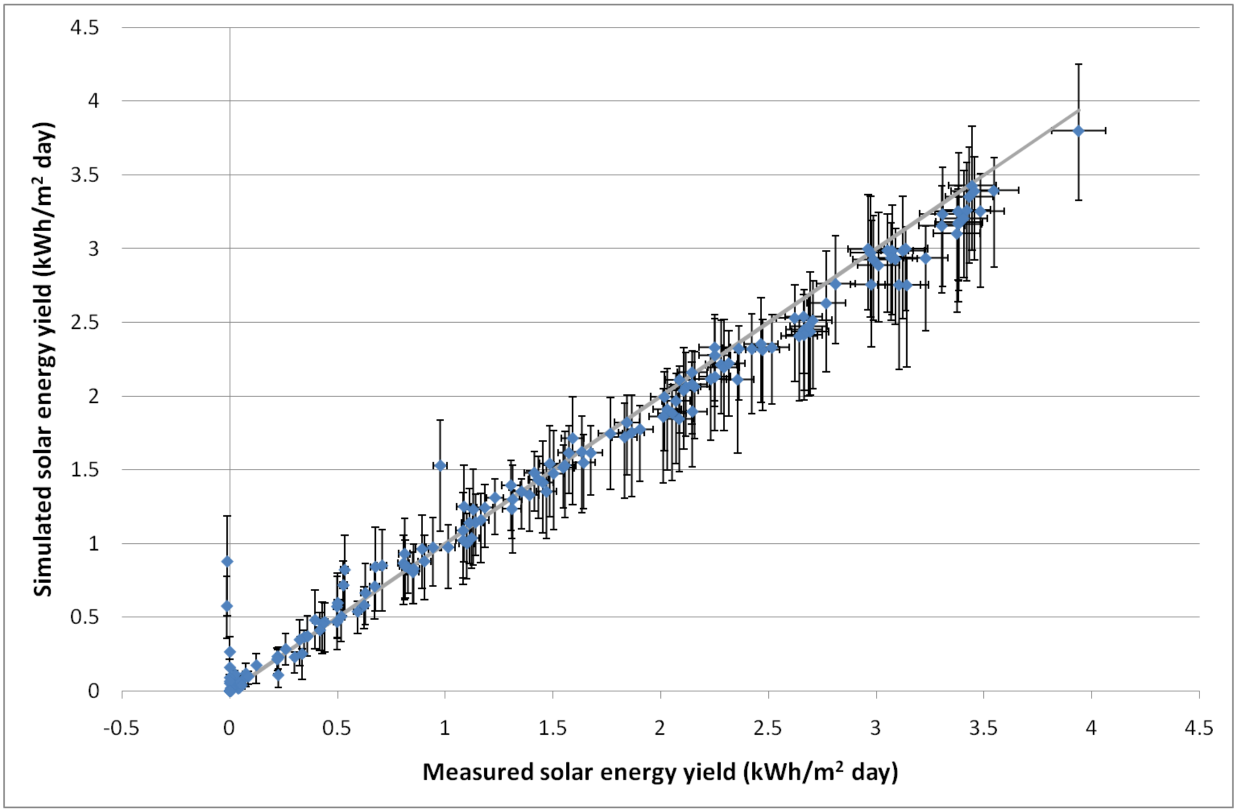

Fig. 5, Daily measured versus simulated solar energy yields for system 2 in the secondary solar loop in Figure 2 with uncertainty boundaries.

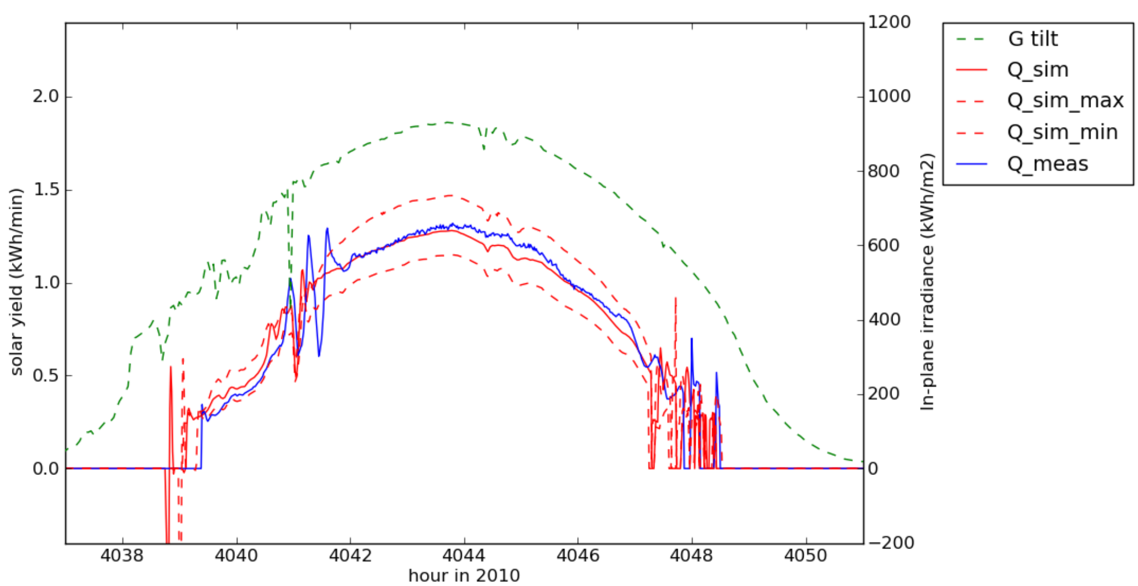

Fig. 6, Measured versus simulated solar energy yields for system 2 secondary solar loop for a day in June 2009.

4. Conclusion and discussion

The results of steps leading up to a simulation-based fault detection method have been presented. A sensitivity analysis has been carried out for two test systems to determine sensitive parameters and input variables. For both systems these are the collector parameters and the input variables (weather, heat demand and return temperatures) used in the simulation. These should be included in an uncertainty analysis to establish a confidence interval for simulated energy yields. The confidence bounds for the two systems are on average in the range of plus and minus 20 %, this is derived with a minimum-maximum analysis. These uncertainty ranges show a good match to measured data above a certain daily irradiation level. A Monte-Carlo Analysis is planned, since it is methodologically better and might lead to better results; but this is not applicable for continuous fault detection. Uncertainties could potentially be reduced by fitting the simulation parameters for the measured data, however than one would assume an initial fault-free operation.

5. Acknowledgements

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