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Investigations on Optimizing Large Solar Thermal Systems

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Abstract

Three different optimization procedures, which are expected to improve the performance of solar thermal systems, have been investigated and described in this paper. The first procedure concerns the planning phase of the solar system. The second one considers the operation of the system and thus can be carried out after about one year. The third one examines the daily performance considering predictions of weather and hot water consumption and the actual temperature level in the buffer storage. For all three optimization steps the feasibility and the energetic potential haven been investigated. For these investigations, measurements at two solar domestic hot water systems in Germany have been carried out and validated system models have been implemented in TRNSYS. In combination with these simulations, both classical algorithms and evolutionary strategies have been used for the optimization procedures.

1. INTRODUCTION

To assure a good performance of solar thermal systems both an optimization process and a long term monitoring of the solar system are conceivable solutions. Since a monitoring of a system is mandatory to control whether all components and thus the whole system works properly, the necessity of an optimization procedure has to be estimated. Such a procedure should lead not only to a good but to the best design and operation of the solar system. The optimization may consist of three different steps described below.

In the first step, the planning process and hereby the design of the system has to be optimized in advance. But even if after the erection of a properly planned system no component does malfunction, the whole system might not work properly. Since assumptions of the radiation and the amount and profile of the hot water consumption had to be made for the planning process, the uncertainties of these assumptions might lead to a system design which yields a non-optimal solar gain under operation.

Thus, for example after one year of experience in the operation of the system, a further ("static") optimization step can be carried out, now with a measured hot water consumption. But in contrast to the planning process, only those modifications are allowed which do not lead to additional investments. Therefore the optimization is mainly limited to the variation of control parameters.

But also after realization of these optimizations the system is possibly not operating in the best configuration for each single day. Consequently, daily ("dynamic") optimizations can be carried out to find the best parameter configurations for all variations of the temperature level in the buffer storage, the weather conditions and the hot water consumption.

To determine which of the three steps are worthwhile to carry out, the amount of the energy saving potential as well as the dependencies of these potentials on the system properties have to be examined. These properties are for example the system design, the solar fraction, the hot water consumption or the site of the solar system.

Besides the energetic potential, the practicability of each of the three steps has to be examined. Depending on the considered step, several system parameters are unknown. To determine their influences on the solar gain, computer simulations with a numerical model of the solar system can be carried out. The task of finding the best values for an optimal performance of the system for all unknown parameters leads to multi-dimensional problems. Thus it is not obvious, which is the best tool or algorithm to solve such problems in combination with system simulations.

2. DESCRIPTION OF THE INVESTIGATED SYSTEMS

To reach some degree of generality concerning the investigations of the problems mentioned above, two different solar domestic hot water (SDHW) systems have been investigated: A dormitory located in Zwickau (Germany) and a hospital in Frankfurt/Main (Germany).
Figure 1 and Figure 2 show the designs of the systems. They have different profiles and different amounts of hot water consumption, different collector areas and hereby different solar fractions. Furthermore they differ in the discharge scheme of the buffer storage. In addition to the measurement equipment at the systems a long-term monitoring advice has been installed at the hospital in Frankfurt.
For both systems validated system models have been implemented in TRNSYS (Klein, S.A. et al, 1994), an established simulation program for solar thermal systems.

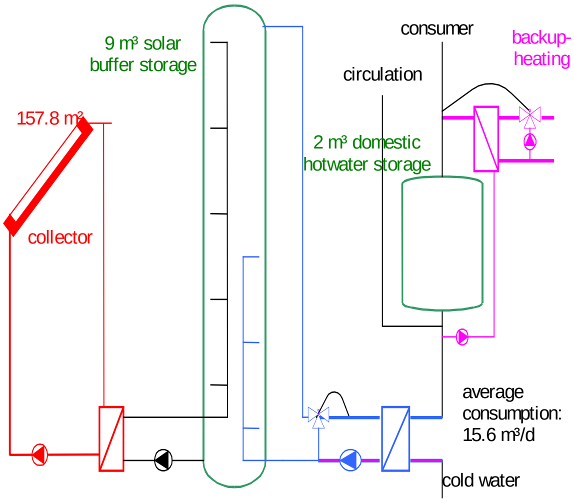

Figure 1: Design of the SDHW-system of the dormitory in Zwickau. A discharge of the solar buffer storage (which is one single 9 m³ storage) takes place only during the tapping of hot water.

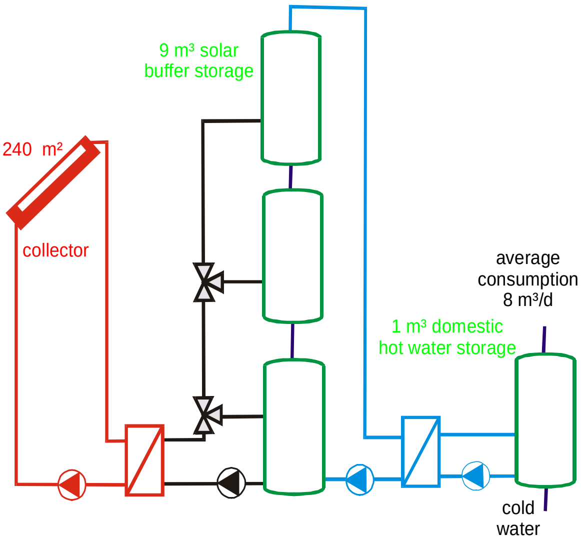

Figure 2: Design of the SDHW-system of the hospital in Frankfurt/Main. A discharge of the solar buffer storage (which consists of six 1.5 m³ storages) takes place, if the temperature level in the DHW storage is below the temperature in the solar buffer storage.

3. DESCRIPTION OF THE INVESTIGATED ALGORITHMS

Validated system models, e.g. implemented in TRNSYS, enable in a sequence of parameter variations the detection of a parameter set which may lead to an optimal performance of a solar system. But since not all possible combinations of the values for all parameters can be tested, a further algorithm is needed to estimate the next parameter set to be tested. This algorithm has to fulfill some requirements:
(a) The algorithm must lead to a parameter set which is the best of all possible sets.
(b) Due to long simulation times the algorithm must find this best parameter set as soon as possible.
But since the dependency of the object function on the parameters is not necessarily monotonous and furthermore because of correlations between the specific parameters, no analytical solution exists for solving such problems in multidimensions. Thus, a compromise between the requirements (a) and (b) has to be accepted. This compromise has to refer to the specific problem, how exact a parameter has to be determined, or in other words, how sensitive the objective function reacts on this parameter. Furthermore, the maximum time period allowed for the total optimization process has to be considered.
In our investigations, seven out of the big amount of algorithms which can be found in literature have been implemented in a Visual C++ program in order to find the most suitable algorithm for the specific solar requirements. Among these algorithms were five “classical” algorithms adopted from Press (1997) as well as two evolutionary algorithms adopted from Wienholt (1996). These algorithms have been combined with TRNSYS-simulations, which are initialized and executed by the program as shown in Figure 3. After the execution, the simulation result is evaluated and with the help of one of the optimization algorithm a new set of parameters for the next simulations is determined. With this set the whole circuit starts again. If a stop criteria is attained, the

whole process stops.

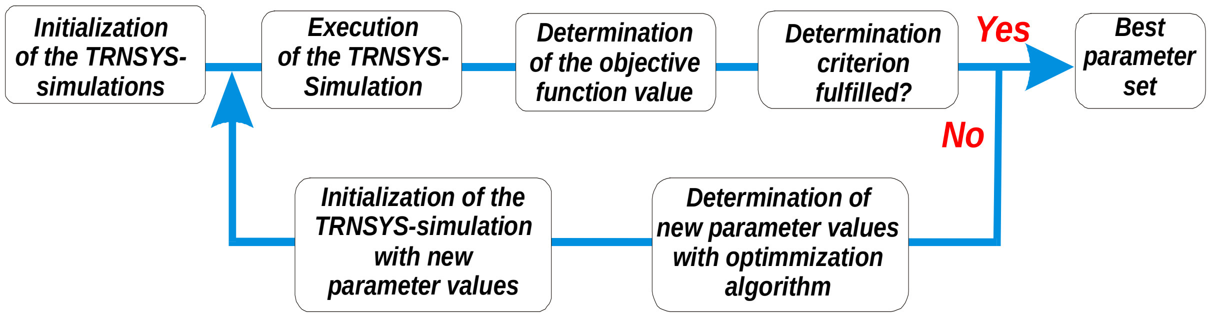

Figure 3: Optimization procedure for the combination of an optimization algorithm and TRNSYS-simulations.

3.1. Classical algorithms

Five of the "classical" algorithms mentioned in Press *et al* (1997) have been implemented in the optimization program. These are two Modified Gradient Methods (BFGS and CGM), the Powell-Algorithm, the Simplex-Algorithm and the method of Simulated Annealing. The Modified Gradient Methods determine with the gradient of the object function of the actual search step and the steps before the new parameter set to be tested. From a starting point, the Powell-Algorithm executes sequences of linear searches, each in one fixed direction. After a number of linear searches the new search direction has to be determined, but no extensive estimations of the gradient in multi-dimensions are necessary for the choice of the new directions. The Simplex-Algorithm represents a figure with a dimension one more than the number of unknown parameters. This figure moves through the parameter space to the direction of a better object function value, also without an estimation of the gradient. These moves are done by reflection, expansion and contractions of one parameter or the entire set. However, the disadvantages of all these four algorithms is, that they are unable to avoid sticking in local minima. The method of Simulated Annealing tries to provide the latter and is implemented as a sequence of Simplex-Algorithms. In this sequence, also inferior parameter sets will be prosecuted with a decreasing probability. This enables, under certain circumstances, to escape from a local minimum but requires plenty of attempts to converge.

3.2. Evolutionary Algorithms

Evolutionary Algorithms try to adopt the model of natural, biological evolution on optimization problems. Hereby, a non-analytical search algorithm can be formulated with the help of mutation, recombination and especially selection principles, which favors those parameter sets for survival, which are best adapted to the certain problem. A fixed number of the best parameter sets of one generation are selected to form new parameter sets first by recombination and then by mutation. To classify the operators, the selection is a deterministic procedure and mutation and recombination are pure stochastic functions.
Apart from such an Evolution Strategy, a genetic algorithm has been implemented in the optimization tool. This uses a binary coding of the parameter values, so the biological functions act only on this binary string. This has the property that all the possible parameter values have to be digitized and due to this only discrete values can be tested by the system simulations. Furthermore, genetic algorithms use a probabilistic selection procedure for the estimation of a new generation of parameter sets. For all of the evolutionary operators some modes are available which can influence the performance of the whole algorithm.
Because of the probabilistic property of evolutionary algorithms they are expected to be successful in optimizing high dimensional problems as well as in the case that the object function region has many local minima. Problems with only a few unknown parameters and no local minima besides a global minimum are supposed to be solved easier with gradient or non probabilistic methods.

4. OPTIMIZATION OF THE PLANNING PROCESS

Optimizing the solar system design during the planning process strikes for two goals. On the one hand, the energetic output of the systems should be maximized whereas the investment should be minimized and on the other hand, the planning process should be simplified for the planner in order to guarantee a reliable system performance later on and to reduce the planning costs.

For such an optimization, the fixed boundary conditions for the system have to be considered. These are for example the orientation and area for the solar collectors (mostly the roof) or the space in the room for the buffer storage. Furthermore, the weather conditions and an assumed hot water consumption have to be taken into account. But also the demands of the customer (e.g. the desired solar fraction or the investment volume) are important for the planning of the system.

After the determination of these boundary conditions, a great number of free parameters remains. These parameters are related to the system design, the types of all components, the dimensions of all components and all control parameters which include sensor positions as well as flow rates. Some of these parameters can vary continuously within their possible range, for others only discrete values are possible. Due to the latter and the high number of parameters to be determined, a genetic algorithm seems to be suitable for optimizations during the planing process.

4.1. Assumptions

To estimate the practicability and potential of an optimization of the planning process, the planning of the solar system in Frankfurt, originally done by experienced solar engineers with conventional methods, has been repeated. With a weather profile generated with Meteonorm (cp. Meteotest (1997)) and a hot water consumption generated from the measured profile and the former assumed amount of the consumption one-year TRNSYS simulations have been carried out. The aim was the reduction of the solar heat costs in consideration of the annuity of the whole investment calculated by equation (1). For the latter, a 20 year period of operation has been specified with interest rate of 6 % for the investment and the current costs (energy of the pumps, insurance of the system and repair cost).

$$\zeta = \text{solar heat costs} = \frac{\text{annuity per year}}{\text{solar gain per year}} \qquad (1)$$

To calculate the investment for each variation of the system design, cost functions of each component depending on the type and dimension of all these components had to be found. These functions were partly taken from Remmers (1999) and partly from manufacturers information. Due to the high complexity, no basic change in the system design has been undertaken during the optimization and the variations are mainly limited to the variation of the components dimension.

As a main boundary condition, the collector area and the arrangement of the collectors have been fixed to those of the installed system (240 m²). Another possibility to avoid unintentional dimensioned systems would have been to fix the investment sum, but this seemed to be more difficult to realize in the optimization algorithm due to the need of penalty functions.

To optimize all the other components in the solar circuit, a hydraulic modelling of the solar circuit has been made in addition to the thermal simulation of the system. This leads to a number of 20 parameters which seem to be reasonable to optimize concerning practical considerations. In detail there are six control parameters, the flow rates for the charging and discharging of the buffer storage, the volume of the buffer storage, the diameter of the pipes in the collector circuit, the azimuth and the inclination of the collector orientation, UA-values of the charging and discharging heat exchangers, three positions of temperature sensors at the buffer storage and three positions for the inlets of the charging unit.

For these optimizations a genetic algorithm has been used with a number of 10 individuals in the parent generation and 60 individuals in the offspring generation. The algorithm uses a gray coding instead of a simple binary coding, which leads together with the applied resolution of the 20 parameters to a coding string length of 126. With this, the mutation probability has been set to $\frac{1}{126}$. The number of crossover points for the recombination has been set to 2 with a recombination probability of 0.6. To select a new parent generation, a rank based selection algorithm has been used. For each of the 20 parameters a certain resolution has been chosen, whereas for the diameter of the pipes and for the buffer storage volume, standard values are allowed which are not necessarily equidistant.

In a second optimization run the number of unknown parameters has been reduced to 14 (6 parameter values have been set to values, which have been supposed to be best) to determine the dependency of the performance of the genetic algorithm on the number of parameter.

4.2. Results

Figure 4 shows the results of the two optimization procedures for the solar system in Frankfurt. It can be seen, that both optimizations converge to the same solar heat cost value and that their convergence speed does not differ significantly. At the beginning of the process, the optimization with 14 parameters seems to be marginally faster, but later the optimization with 20 parameters results in a better optimization value due to the optimization of the additional parameters. This indicates, that for genetic algorithms a reduction of the number of unknown parameters is not as important as it is supposed to be for the classic algorithms.

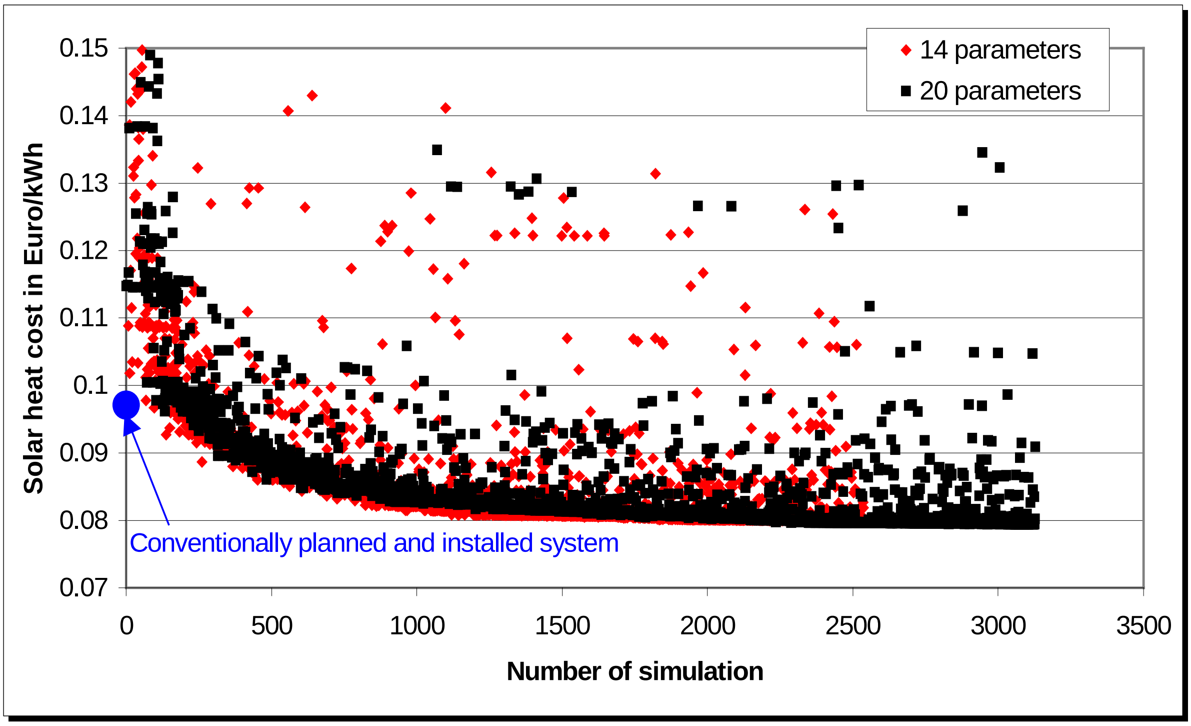

Figure 4: Optimization of the planning of the solar system in Frankfurt with a genetic algorithm. Black dots represent the optimization with all 20 parameters, red dots the optimization with the reduced set of 14 parameters. Plotted are the optimization results of the solar heat costs during the progress, the blue dot represents the appreciated solar heat cost of the installed system.

Compared to the estimated solar heat cost of the installed system of 9.7 European Cent per kWh, the best configuration leads to an improvement of about 18 %, caused both by an increase of the solar gain and a decrease of the investment. However, the estimation of the real optimization potential is more difficult. For this, the knowledge of the assumptions of the former planer of the solar systems is necessary. On the one hand, the assumptions refer to the former cost functions for every component, which might differ from the assumptions made in this investigations. On the other hand, possibly not every request of the owner of the solar system has been considered for the optimization. This means, that in our investigations the collector area has been set to a constant value of 240 m², but if the request of the owner for instance was a constant amount of investigation, the best design of the system could differ significantly.

Especially since the cost functions of the solar components are dependent on time and manufacturer, rules for the dimensioning of the system are difficult to derive from our optimizations. But due to high costs of the buffer storage, this component should be designed as small as possible. Besides the decrease of the solar gain with a small buffer storage volume, a further limit of a small dimensioning is the reliability of the system, which has not been considered in the optimizations. For example a small buffer storage volume can possibly lead to frequent stagnation periods of the solar system, which may cause overheating of the collector field that may reduce the life-time of the field.

5. "STATIC" OPTIMIZATION OF THE OPERATION OF A SOLAR SYSTEM

Despite the optimization of the planning of a solar system, the build system might not work optimally because of inaccuracies of the assumed weather conditions and especially the hot water consumption which eventually necessitate changes of some system parameters. An installed long-term monitoring can provide the amount and profile of the real hot water consumption. Thus, after for instance one year of experience in the operation of the system, a further optimization step can possibly improve its performance. But in this step, only those variations of the system are allowed, which do not lead to additional costs. Only in extreme cases, a replacement of a poorly dimensioned component will be reasonable.
Due to this, the number of parameters to be optimized decreases to the number of control parameters and flow rates. Thus two fields of interest occur:

(a) What is the best algorithm to carry out this step concerning the convergence speed and reliability of the determined parameter set?
(b) What is the potential of this optimization step?

5.1. Assumptions

To answer these questions, optimizations of the two investigated solar thermal systems have been carried out. For both, one year TRNSYS-simulations have been implemented with a time step of 7.5 minutes. For the system in Zwickau, measured data of weather and hot water consumption (resolution: 1/2 h) from 1999 have been used as input data for the simulations. For the optimization of the system in Frankfurt, weather data have been taken from Meteonorm, whereas the hot water consumption has been determined and extrapolated from a measured period of three weeks in 2000.
After the construction of the system not the investment but the solar gain (or the back-up heat demand) and the electricity consumption of the pumps are of interest. Therefore, the maximization of the solar gain at the heat exchanger for the discharge of the buffer storage less the primary energy consumption of the pumps is the objective function ζ of the optimizations (cp. (2)). The mean efficiency of the power plants in Germany (grid losses included) can be assumed as about 33%.

$$\zeta = Q_{sol} - \eta_{power\ plant} \cdot Q_{electric} \tag{2}$$

Equation (3) shows the assumed dependency of the electricity consumption of the pumps on the flow rate in the pipes, collectors and heat exchangers.

$$Q_{electric} \sim \left\{ \begin{array}{l} \dot{V}^2 \text{ for laminar flow} \\ \dot{V}^3 \text{ for turbulent flow} \end{array} \right\} \tag{3}$$

At the system in Zwickau, all seven optimization algorithms have been applied, for Frankfurt only four of them.

5.2. Results

Figure 5 shows the result of the optimization of the solar gain less the electricity consumption of the solar domestic hot water system of the dormitory in Zwickau. In this example, the classical algorithms seem to converge much faster to an optimum than the evolutionary and genetic algorithms, even if the latter find a marginal "better optimum". The comparison between the evolutionary and the genetic algorithms affirm the opinion mentioned in literature, e.g. Bäck (1996), that evolutionary algorithms are better suited to problems, where the parameters can assume continuous values. To adapt also genetic algorithm to problems with continuous parameter values, a high resolution is necessary for the binary coding which complicates the optimization problem. Additional investigations on the performance of these two algorithms concerning the different modes of mutation, recombination and selection operators have not been carried out in our work. Here we only used those modes which are recommended in literature, but other modes can possibly improve the performance of these algorithms. The latter point makes it difficult for a planner to use such an evolutionary or genetic algorithm, because apart from the optimization of the solar system, also an optimization of the optimization algorithm itself might be necessary.
Comparing the five classical algorithms only small differences in their performance occur. Here, the Simplex-algorithm seems to be the fastest algorithm, whereas the Simulated Annealing algorithm finds the parameter set with the best value of the objective function. But even the simple Powell algorithm provides a fast performance

with a good parameter set. But for all these algorithm, especially for the Simplex and the Simulated Annealing algorithm (which also uses the Simplex algorithm), the performance has a high dependency on the initial starting point of the optimization. That means, a smart choice of the first parameter sets to be tested can improve the performance of the algorithms significantly. This performance refers both to the convergence speed and to the quality of the resulting best parameter set.

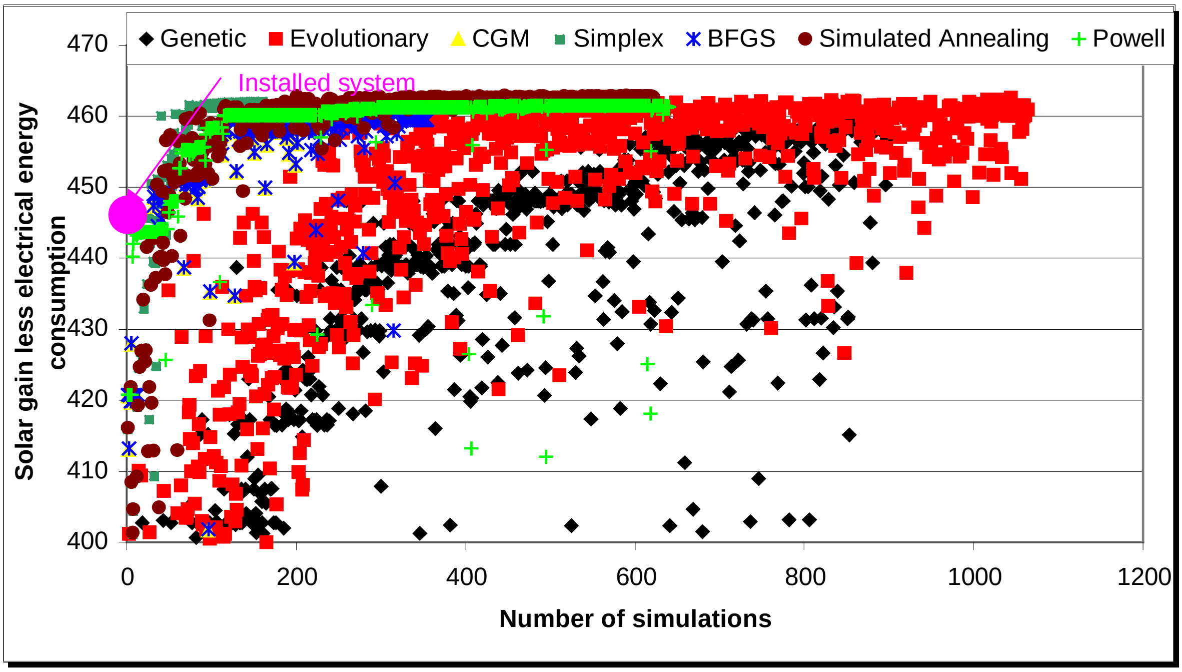

Figure 5: Optimization of the solar gain less the primary energy consumption of the pumps of the domestic hot water system in Zwickau (Germany) with seven of the implemented optimization algorithms. Seven parameters (two flow rates and five regulation parameters) have been chosen for the variations during the optimization. It can be seen, that the classical algorithms are much faster in solving this special problem than the evolutionary and genetic algorithms. Also can be seen, that the energetic potential for this system is only in the range of 4 %.

A sensitivity analysis of the objective function on the parameter values indicate that only the primary and the secondary volume flows of the solar circuit have a great effect on the objective whereas the regulation parameters have only small effects. Only if the regulation parameters are shifted out of the reasonable range, they have a distinct influence. Thus, only two parameters and not all seven are important for the optimization of the system, which reduces the investigated problem to a quasi two-dimensional problem. Thus, it is obvious that simple search algorithms show a good performance and that evolutionary and genetic algorithms are oversized for such problems.

To answer the second question concerning the optimization potential of such a static optimization, Figure 5 additionally shows the objective function value of the installed system. Compared to this value the best optimization leads to an improvement of 3.8 %. This value seems to be rather small, especially considering, that only approximations of the determined best parameter values can be used at the real system. The approximations are necessary because of the resolution of the solar controller and discrete stages of the possible flow rates the pumps can provide. Further optimization with variations of the amount of the hot water consumption indicate that the solar gain at the system in Zwickau with its special design and dimensioning depends only marginally on the parameter values.

In opposite to this small potential, the static optimizations of the solar system in Frankfurt lead to an energetic potential of about 13 %. The reason for this high potential can be found in the rather different dimensioning of this system compared to that in Zwickau as well as in bugs in the regulation concept of the system. The dimensioning in Frankfurt has resulted in a much higher solar fraction, than it was intended by the planner. This increase is caused by a much smaller hot water profile than it has been assumed from the planner. This leads to flow rates that are inappropriate for the real conditions. But in contrast to this, the detection of the bugs in the regulation concept which can also be done by the optimizations is actually the task of a long-term monitoring. Therefore, the remaining potential of the static optimization would be much smaller.

6. "DYNAMIC" OPTIMIZATION OF THE OPERATION OF A SOLAR SYSTEM

To react on the daily variations of the weather conditions, the hot water consumption and the temperature level in the buffer storage, it could be reasonable to operate the solar system with specific control parameters and flow rates for each day. Thus daily optimizations can be carried out to determine the best parameter set for each condition. Hereby all those parameters can be varied which can be changed automatically by the controller. To do such a dynamic optimization, a long term monitoring with a bidirectional communication between the controller and the optimization unit is necessary. Furthermore, information about the weather forecast and prediction of the hot water consumption for the following day are essential to estimate an optimal parameter set.
But uncertainties in these predictions lead to inaccuracies in the determined parameter set for the certain day. This parameter set might even results in a reduction of the solar gain instead of an improvement. Thus, both the potential of the optimization step and the accuracy of the predictions have to be investigated to determine whether such an optimization step is reasonable.

6.1. Assumptions

For a dynamic optimization of the solar system the same parameters have to be determined as for static optimizations. To estimate the potential of this optimization step, the best value of each parameter has to be determined for every day of the year. Thus, the optimization potential is the improvement of the objective function due to special values of every parameter for every single day compared to the result with one constant value for each parameter for the whole year. Regarding the seven unknown parameters for example at the system in Zwickau this leads to $365 \cdot 7 = 2555$ unknown parameters, which is impossible to solve by any optimization algorithm in a reasonable time. Also reducing the problem to a sequence of 365 optimizations for just one day each with nightly new initialization of the buffer storage temperature distribution, cannot reduce the effort to a suitable size, not to mention that for the optimization of the parameters of one day, it could be necessary to regard the boundary conditions of the following days.
Thus a reduction of the considered days and parameters has to be made. The highest potential could be expected, when the variation of the boundary conditions of the system are high as well, therefor eight days of measured data at the solar system in Zwickau from 1999 have been selected for the investigations. These days include all variations of high and low values of the irradiation, water consumption and temperature level in the buffer storage. Since the volume flow in the collector circuit has the highest effect on the objective function, only this parameter (with a constant capacity rate between primary and secondary circuit) has been selected for the dynamic optimizations. Together with the eight days also eight unknown parameters have to be considered. Again the solar system of the dormitory in Zwickau with the solar gain less the electricity consumption of the pumps has been chosen as the objective function for the TRNSYS simulations. The implementation and execution has been done with the Simplex-algorithm.
First, a static optimization of the volume flow for these eight days has been carried out. That means, one constant value for the whole period has been determined to maximize the solar gain, that has been chosen as the reference value. After that, a dynamic optimization of the eight flow rates at these days has been carried out.

6.2. Results

Figure 6 shows the flow rates in the collector circuit determined for every investigated day by the optimization to be best at these special days with the corresponding global irradiation in the collector plane and the hot water consumption. Additionally, the corresponding global irradiation in the collector plane and the hot water consumption, which together give an impression of the temperature level in the buffer storage, can be found in the figure. With these three values, the value of the flow rate can be interpreted. The values of the fifth and the eighth day have to be neglected due to the marginal irradiation. From the other days it can be concluded, that the flow rate has to decrease with increasing temperature level in the buffer storage.
But even if for every day different best values for the flow rate have been determined, the corresponding improvement of the solar energy gain of the eight days is with 0.6 % rather small. One of the results of the static optimization, that the dependency of the solar gain on the parameter values is very small for well dimensioned systems, corroborates the statement that the potential of the dynamic optimizations must be small. The parameter value that has been found to be the best for an investigated period is particularly determined by those "types of days" that occur frequently and/or are marked by high solar gain. Thus, the improvement can only be gained from those days, which have low solar gains or occur seldom. Consequently the improvement should be small. Only in

those cases an improvement could be higher, if there are some special conditions for which very different parameter values are best, but the resulting "average" parameter value is a mean value of these different values, that is not optimal at all stages. Therefore it is possible, that the selected eight days do not represent the perfect time period to determine the energetic potential but only an approximation.
But with the consideration that the uncertainties in the weather and hot water consumption predictions reduce the expected the solar gain the potential remains at a low value. The uncertainties in the predictions of the global radiation turned out to be smaller than 1 kWh/m²d for 79 % of the days for the prediction of the actual day but for only 61 % for the prediction of the third day after. Since the hot water consumption of a dormitory or a hospital has significant profiles, the standard deviation of the water consumption can be reduced to under 10 % of the certain amount if all weekends, official holidays and semester holidays have been considered.

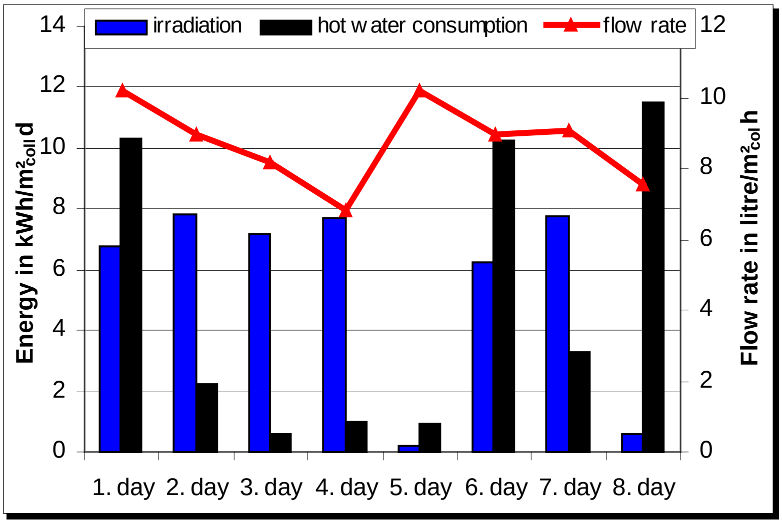

Figure 6: Best determined flow rates in the collector circuit for the eight investigated days with the corresponding global irradiation in the collector plane and tap water energy, both referred to the collector area. It can be seen that the flow rate should decrease with an increase of the temperature in the storage due to a high global radiation and a low hot water consumption. The value of day five and eight are not meaningful because of the poor irradiation.

7. SUMMARY AND CONCLUSIONS

Three different optimization steps that are expected to improve the performance of SDHW-systems have been investigated concerning their feasibility and energetic potential. Firstly, an optimization of the planning of a SDHW-system has been carried out. Hereby, 20 parameters have been determined with a genetic algorithm in combination with the simulation program TRNSYS. With this optimization, the solar heat cost can be reduced for about 18 % compared with the conventionally planned and installed system. This procedure shows, that an automatic optimization of the planning process is possible, if the cost functions for all components of the system are known, whereas the real potential of such a system is difficult to determine and differs from one planning process to the other.
Secondly, a static optimization of flow rates and regulation parameters has been carried out. This static optimization is supposed to react on variations of the real hot water consumption compared with the consumption assumed for the planning process. A sensitivity analysis showed that only the flow rates have a significant influence on the objective (solar gain less the electricity consumption of the pumps), whereas the influence on the regulation parameters is marginal. During this process, a comparison of seven optimization algorithms has been carried out. For this certain problem, the classical algorithms like the Simplex-algorithm or the method of Simulated Annealing converge much faster to an optimum parameter vector than the evolutionary strategies. At well functioning systems the energetic potential seems to be rather small, whereas at badly designed and/or installed systems, there is possibly a distinct potential. But a great part of this potential can be made accessible by a long term monitoring, which should be installed anyway.
Thirdly, a dynamic optimization of flow rates and regulation parameters has been carried out. Here, daily optimization with the consideration of predicted weather conditions, hot water consumption and temperature levels in the buffer storage should lead to an optimal operation for all states of the system. But since the solar gain at a well functioning system does not dependent strongly on the flow rates and the regulation parameters, the potential of using every day a different optimal parameter vector seems to be very small, too. Moreover, the uncertainties in the weather forecast and the prediction of the hot water consumption have to be considered. These uncertainties probably reduce the determined potential.
Thus, the investigations showed that all optimization steps can be carried out with different search algorithms and objective functions. But for all steps, the determination of the energetic potential is very difficult and somehow

arbitrary, for the optimization of the operation (step two and three), it seems to be very small at well designed and installed systems. Therefore, it has to be concluded, that an optimization process like it is presented here is feasible, but the potential of a long term monitoring is regarding to the experience, e.g. Peuser et al. (1997), much higher. Only when a long-term monitoring is implemented, an optimization of the operation of a SDHW-system could be a further step. In contrast to this, the use of optimization procedures in the planning process seems to be more promising.

8. ACKNOWLEDGMENTS

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