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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 large solar thermal systems, are described in this paper. The first procedure concerns the planning phase of the system. The second one considers its operation and should be carried out after about one year of data collecting. The third one examines the daily performance considering predictions of weather and hot water consumption and the actual temperature level in the buffer store. For all three optimization steps the feasibility and the energetic potential have been investigated. For these studies validated system models of two solar domestic hot water systems in Germany have been implemented in TRNSYS. In combination with the simulations, both classical algorithms and Evolutionary Algorithms have been applied for the optimization procedures.

1. INTRODUCTION

To assure good performance of solar thermal systems, both optimization processes and long term monitoring of the solar system are possible approaches. Since monitoring of a system is mandatory to determine whether it and its components work properly, the necessity of an optimization procedure has to be investigated. Such a procedure should lead to the best design and operation of the solar system. The optimization may consist of three different steps described below.

The first step concerns the planning process. Here, the basic design and the component properties of the system have to be optimized in advance. However, even if after the erection of a properly planned system no component shows malfunction, the whole system might not work properly. Since assumptions about the solar radiation and load profile of the hot water consumption are made during the planning process, uncertainties in these assumptions may lead to a system design which yields a non-optimal solar gain in operation.

As a second step, after one year of experience with the system's operation, a further ('static') optimization step can be carried out, now with a measured hot water consumption. However, in contrast to the planning process, only those modifications are allowed which do not incur additional investment. Therefore the optimization is mainly limited to the variation of control parameters and sensor positions.

However, even after the implementation 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 as a third step to find the best parameter configurations for variations in the temperature level in the buffer store, weather conditions and hot water consumption.

To determine which of the three steps are worthwhile to be carried out, the amount of energy saving potential as well as the dependence of this potential on the system properties needs to be calculated. Furthermore, the practicability of each of the three steps has to be investigated.

To identify the influence of the several unknown system parameters on the solar gain, computer simulations with a numerical model of the solar system should be carried out. The task of finding the best values for the optimal performance of the system 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.

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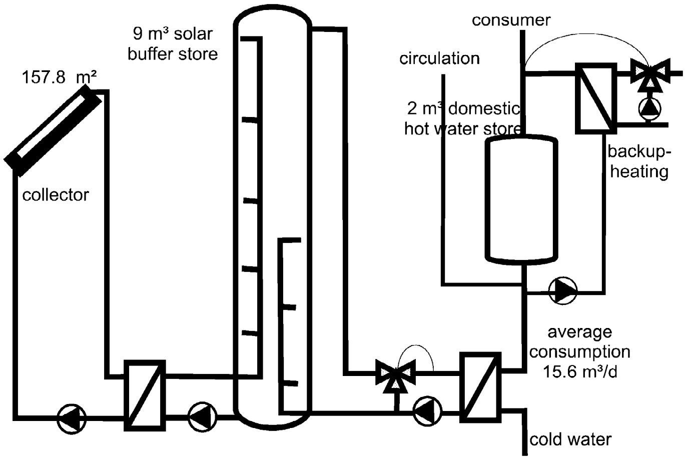

Fig. 1. Design of the SDHW-system of the dormitory in Zwickau. Discharge of the 9 m^3 solar buffer store takes place only during the tapping of hot water.

2. DESCRIPTION OF THE INVESTIGATED SYSTEMS

To reach general conclusions on the problems mentioned above, two different solar domestic hot water (SDHW) systems in Germany have been investigated: a dormitory located in Zwickau and a hospital located in Frankfurt/Main.

Figs. 1 and 2 show the designs of the systems. They differ in the load profiles, collector areas and, consequently, solar fractions. Furthermore, they have different schemes for discharging the buffer store. For both systems validated models have been implemented in TRNSYS (Klein *et al.*, 1994). Input values for the simulations are radiation, ambient temperature and hot water consumption.

3. DESCRIPTION OF THE INVESTIGATED ALGORITHMS

With validated system models a parameter set which may deliver optimal performance of a solar system can be found through the use of a sequence of parameter variations. However, since

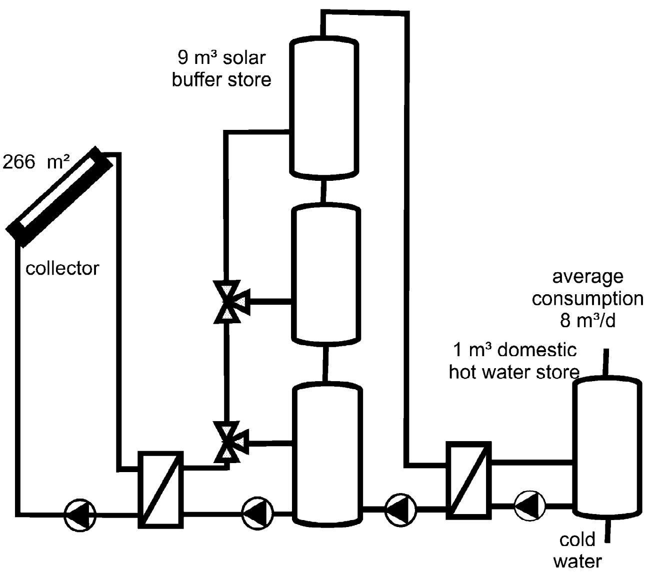

Fig. 2. Design of the SDHW-system of the hospital in Frankfurt/Main. Discharge of the six 1.5 m^3 solar buffer stores takes place depending on the temperature levels in the storage units.

not all possible parameter sets can be tested, another algorithm is needed to estimate which is the next most promising parameter set to be tested. This algorithm has to fulfill the following requirements:

(a) The algorithm has to lead to a parameter set which is nearly the best of all possible sets.
(b) Due to long simulation times the algorithm should find this best parameter set as quick as possible.

However, since the dependency of the objective function on the parameters is not necessarily monotonic and there may be correlations between specific parameters, no analytical solution exists for solving such problems in multi-dimensions. Thus, a compromise between the requirements (a) and (b) has to be accepted. This compromise depends upon the specific problem, how exactly a parameter has to be determined, or in other words, how sensitively the objective function reacts to this parameter. Furthermore, the maximum time period allowed for the total optimization process has to be considered.

In our investigations, seven out of the large number of algorithms which can be found in literature have been implemented in order to find a preferred algorithm for the specific solar requirements. Among these were five ‘classical’ algorithms (two gradient methods (CGS, BFGS), the Powell Algorithm, the Simplex Algorithm and the algorithm of Simulated Annealing) adopted from Press *et al*. (1997) as well as two Evolutionary Algorithms (Evolution Strategy and Genetic Algorithm) adopted from Wienholt (1996). The algorithms have been combined with TRNSYS-simulations, which are initialized and executed by a control program.

4. OPTIMIZATION DURING THE PLANNING PROCESS

Optimizing the solar system design during the planning process has two benefits: The ratio of investment and energetic output of the systems can be minimized, and the planning process can be simplified. This simplification can lead to a reduction of the planning costs and may avoid planning mistakes.

For such an optimization, certain fixed boundary conditions for the system have to be considered. These may be, for example, orientation and area of the solar collectors. Furthermore, the local weather conditions and an assumed hot water consumption have to be taken into account. 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 remain. These parameters are related to the system design, types and sizes of components and to control parameters which include sensor settings and positions as well as flow rates. Some of these parameters can vary continuously within their permissible range; for others only discrete values are possible. These discrete parameter values can be considered by a Genetic Algorithm because of its binary coding of the parameter values. Since Evolutionary Algorithms in general are assumed to be advantageous dealing with complex and high dimensional problems, a Genetic Algorithm seems to be suitable for optimizations during the planning process. A similar approach was made in Loomans and Visser (2002).

4.1. Assumptions

To estimate the practicability and potential of an automated optimization during the planning process, the planning of the solar system in Frankfurt, originally carried out with conventional methods by experienced solar engineers, has been repeated. With a weather profile (time resolution 1 h) generated with Meteonorm (cp. Meteotest, 1997) and a load profile generated from former assumptions of the expected hot water consumption (time resolution 1/2 h), one-year TRNSYS simulations with a simulation time step of 7.5 min were carried out. The aim was the reduction of the solar heat costs in consideration of the annuity of the whole investment (20 year period of operation, interest rate of 6%) calculated by Eq. (1).

$$\zeta = \text{solar heat costs} = \frac{\text{annuity}}{\text{annual solar heat delivery to the domestic hot water storage}} \tag{1}$$

To calculate the investment for each variation of the system design, cost functions depending on the type and size of all components had to be found. These functions were taken from Remmers (1999) and from manufacturers’ information. Due to the multitude of possible system designs, for instance the discharge strategy of the buffer store or the choice of external or internal heat exchangers, no basic change in the system design was made during the optimization and the varia-

Table 1. Settings of the Genetic Algorithm used for the optimization during the planning process for the two examples of 20 and 14 parameters

Number of parameters	20	14
Individuals in parent generation	10	10
Individuals in offspring generation	60	60
Coding of individuals	Gray-coding	Gray-coding
Coding string length	126	87
Mutation probability	1/126	1/87
Crossover points for recombination	2	2
Recombination probability	0.6	0.6
Selection algorithm	Rank based	Rank based

tions were mainly limited to the variation of the components' size.

As a major boundary condition, the collector area and the hydraulic connection of the collectors were fixed to those of the installed system ($240\ m^2$). Another possibility to avoid oversized 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 model of the solar circuit has been implemented in addition to the thermal simulation of the system. This hydraulic model allows to calculate the electricity consumption of the pumps depending on the flow rates and pressure losses in the circuits. Altogether, this leads to a number of 20 parameters which seem to be reasonable for a practicable optimization. These parameters include control parameters, flow rates, buffer storage volume, pipe diameters, collector orientation, UA-values of the heat-exchangers and sensor and inlet positions at the buffer store as listed in Table A1 (see Appendix).

For these optimizations a Genetic Algorithm has been used with the settings listed in Table 1. 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, only standard values were allowed whose resolutions are not necessarily constant over their entire range.

In a second optimization run the number of unknown parameters has been reduced to 14 (6 parameter values with little influence on the objective function have been fixed according to former optimizations and practical experience) to determine how the efficiency of the Genetic Algorithm depends on the number of parameters.

4.2. Results

Fig. 3 shows the results of the two optimization runs for the solar system in Frankfurt. It can be seen that both runs 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

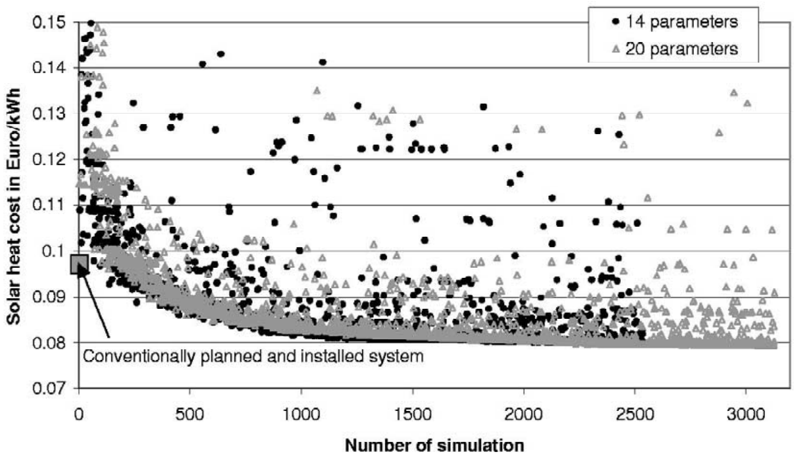

Fig. 3. Optimization of the planning of the solar system in Frankfurt with a Genetic Algorithm. Grey triangular dots represent the optimization with 20 parameters, black dots the optimization with the reduced set of 14 parameters. The results for the solar heat costs during the optimization process are plotted in the figure; the big gray rectangular dot represents the estimated solar heat cost of the installed system.

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 classic algorithms.

Compared to the estimated solar heat cost of the installed system of 9.7 Euro Cent per kWh, the best configuration leads to an improvement of about 18%, caused both by an increase in the solar gain and a decrease in the investment. However, estimation of the real optimization potential is more difficult. For this, knowledge of the assumptions of the original planner of the solar systems is necessary. On the one hand, the assumptions refer to costs of every component prior to the construction of the system. These might differ from the assumptions made in these investigations. On the other hand, not every request of the owner of the solar system may have been considered in the optimization. Thus, the best design of the system could differ significantly from the design which results from the former assumptions.

General rules for the sizing of the system are difficult to derive from our optimizations because costs depend on date of purchase and which manufacturer is used. One rule could be that due to high costs of the buffer store, this component should be designed as small as possible without a decrease of the solar gain. Besides this decrease with a small buffer storage volume, a further compromise due to a small dimensioning is the reliability of the system (e.g. avoidance of overheating of the collector field). This has not been considered in the optimizations.

5. STATIC OPTIMIZATION OF THE OPERATION OF A SOLAR SYSTEM

Despite having performed optimization during the planning of a solar system, the built system might not work optimally because of inaccuracies in the assumed weather conditions and especially the hot water consumption. Therefore, changes of the parameter configuration might be necessary. For example, after one year of operational experience, a further optimization step may improve the performance. However, in this step, only those parameter variations of the system are allowed that do not lead to additional investments. In extreme cases, replacement of a poorly dimensioned component might be reasonable.

Due to this, the number of parameters to be optimized reduces to the number of control parameters and flow rates. Thus two fields of interest emerge:

(a) What is the best algorithm to maximize the convergence speed and reliability of the determined parameter set?

(b) What is the improvement potential of this optimization step?

5.1. Assumptions

To answer these questions, optimizations of the two considered solar thermal systems have been carried out. For both systems, one year TRNSYS-simulations were performed with a simulation time step of 7.5 min. For the system in Zwickau, measured data of weather and hot water consumption (resolution: 1/2 h) from 1999 were used as input data for the simulations. For the system in Frankfurt, weather data that were generated with Meteonorm were used. Hot water consumption was extrapolated from a measured period of 3 weeks in 2000. Taking just this short period as representative seems sufficient, because the main differences in the hot water consumption of large hospitals are between week-day and week-end with only small variations over the year.

After the construction of the system, the solar gain (or the back-up heat demand) and the electricity consumption of the pumps are of interest, not the investment cost. Therefore, the maximization of the solar gain at the heat exchanger on the discharge side of the buffer store less the primary energy consumption of the pumps (the mean efficiency of the power plants in Germany (grid losses included) was assumed as about 33%) was considered as the objective function κ of the optimizations given by Eq. (2). For a post installation optimization, the number of parameters decreases to those parameters which lead to no additional costs. Thus, seven parameters, which are flow rates and control parameters (like set temperatures or sensor positions) were varied as listed in Table A1.

$$\kappa = Q_{\text{sol}} - \frac{1}{\eta_{\text{power plant}}} \cdot Q_{\text{electric,pump}} \tag{2}$$

The electricity consumption of the pumps is assumed to be dependent on the flow rate like Eq. (3).

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

5.2. Results

Fig. 4 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

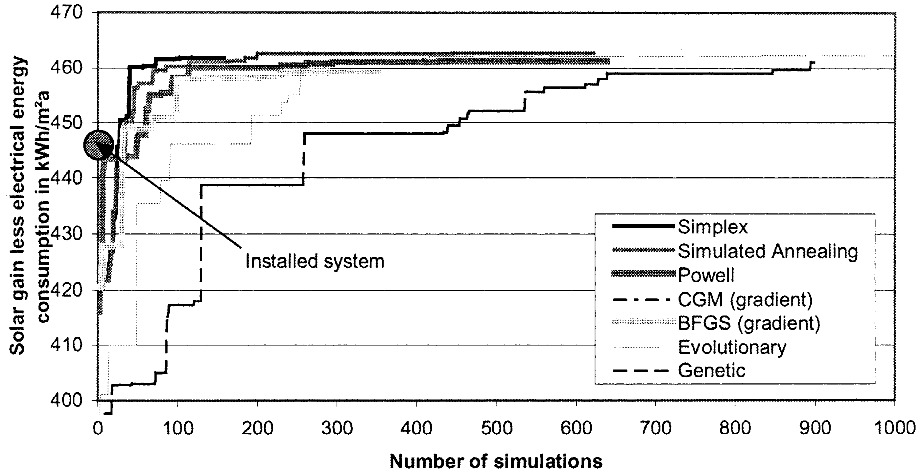

Fig. 4. Optimization of the solar gain less the primary energy consumption of the pumps for the domestic hot water system in Zwickau (Germany), carried out with seven different optimization algorithms. Seven parameters (two flow rates and five regulation parameters) were chosen for the variations during the optimization. It can be seen that the classical algorithms are much faster in solving this special problem than the Evolutionary Algorithms. Furthermore, the energetic optimization potential for this system is only in the range of 4%.

algorithms seem to converge much faster to an optimum than Evolution Strategy and Genetic Algorithm, even if the latter found a slightly 'better optimum'. The comparison between the Evolution Strategy and the Genetic Algorithms affirm the results stated in literature, e.g. Bäck (1996), that Evolution Strategies are better suited to problems in which the parameters can be assumed to be continuous values. In order to adapt Genetic Algorithms to problems with continuous parameter values, a high resolution is necessary for the binary coding, which increases the complexity of the optimization problem. Additional investigations of the performance of these two algorithms, with regard to the different modes of mutation, recombination, and selection operators, have not been carried out in our work. The variety of the different modes makes it difficult for a planner to use such an Evolution Strategy or Genetic Algorithm, because apart from the energetic optimization of the solar system, also an optimization of the Evolutionary Algorithm itself might be necessary to reduce the required simulation runs.

Comparing the five classical algorithms only small differences occur in their performance. Here, Simplex seems to be the fastest algorithm, whereas Simulated Annealing finds the parameter set with the best value of the objective function. However, even the simple Powell Algorithm provides a fast performance with a good parameter set. However, for all these algorithms, especially for Simplex and Simulated Annealing (which also uses Simplex), the performance depends strongly on the initial parameter vectors. 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.

A sensitivity analysis of the objective function of the parameter values indicates that only the primary and secondary volume flows of the solar circuit have a major impact on the objective function whereas the control parameters have only small effects. Only if the regulation parameters are shifted out of the reasonable range, they influence the objective function distinctly. Thus, only two parameters and not all seven are important for the optimization, which reduces the investigated problem to a quasi two-dimensional problem. This simplifies the optimization problem and explains why simple search algorithms show a good performance and why Evolution Strategy and Genetic Algorithm are oversized for such problems.

To answer the second question concerning the optimization potential of such a static optimization, Fig. 4 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, given that only approximations of the determined best parameter values can be used in the real system. The approximations are necessary because of the limited resolution of the solar controller and because there are discrete steps in the possible flow rates the pumps can provide. Further optimizations with variations in the amount of the hot water consumption indicate that the solar gain at the system in Zwickau, with its special design and sizing, depends only slightly on most of the parameter values.

In contrast to this small potential, the static optimizations of the solar system in Frankfurt lead to an energetic improvement potential of about 13%. The reason for this high potential can be found in the rather different sizing of this system compared to that in Zwickau as well as in bugs in the control strategy of the system, for example the poor co-ordination of the trigger of the two pumps in the primary and secondary collector circuit. Due to significantly smaller hot water consumption, the dimensioning of the system in Frankfurt resulted in a much higher solar fraction than was intended by the planner. This leads to implemented flow rates that are too high for the real conditions. Furthermore, even if bugs in the control strategy can also be detected by the optimizations, it should actually be the task of long-term monitoring. Therefore, the remaining potential for static optimization would be much smaller.

6. DYNAMIC OPTIMIZATION OF THE OPERATION OF A SOLAR SYSTEM

To react to daily variations of the weather conditions, hot water consumption and the temperature level in the buffer store, it might be reasonable to operate the solar system with specific control parameters and flow rates for each day. If so, daily optimizations can be carried out to determine the best parameter set for every condition. Only such parameters that can be changed automatically by the controller are varied. To perform such a dynamic optimization, information about the weather forecast and a prediction of the hot water consumption for the following day are essential to estimate an optimal parameter set.

However, uncertainties in these predictions lead to inaccuracies in the determined parameter set for the certain day. This parameter set might even result in a reduction instead of an improvement of the solar gain. 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 would be reasonable.

6.1. Assumptions

For a dynamic optimization of the solar system the same parameters as for static optimizations have to be determined. 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 each 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 $365\times7=2555$ unknown parameters, which is impossible to solve by any optimization algorithm in a reasonable time. Even reducing the problem to a sequence of 365 optimizations for just 1 day, each with nightly re-initialization of the buffer storage temperature distribution, cannot reduce the effort to a suitable size. These considerations apply only for the determination of the improvement potential. For the practical realization of the optimization, only the optimum parameter values for the following day would be of interest. However, for the optimization of the parameters of 1 day, it could be necessary to take account of the boundary conditions of following days.

Thus, for the determination of the potential, a reduction of the considered days and parameters has to be made. The highest potential could be expected, if the variation of the boundary conditions of the system is high as well. Therefore eight particular selected 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 irradiation and water consumption. Due to these variations, the temperature level in the buffer store has high variations, too. Since the volume flow rate in the collector circuit is of dominant influence on the objective function whereas the control parameters are less important (as mentioned in 5.2), only this parameter (with a constant capacity rate between primary and secondary circuit) has been selected for the dynamic optimizations. Thus, for the 8 days also eight unknown parameters have to be considered (cp. Table A1). Again the solar system of the dormitory in Zwickau with the solar gain less the primary operational energy consumption of the pumps was chosen as the objective function for the TRNSYS simulations. The implementation and execution was done with the Simplex Algorithm.

First, one optimal constant flow rate for the whole period of these 8 days was determined in a one-dimensional optimization run. This value and the resulting maximized solar gain (less the primary energy consumption of the pumps) can be chosen as a reference value. After that, a dynamic optimization of the solar flow rate on these 8 days was carried out, leading to eight different values of the flow rate for the period of the 8 days.

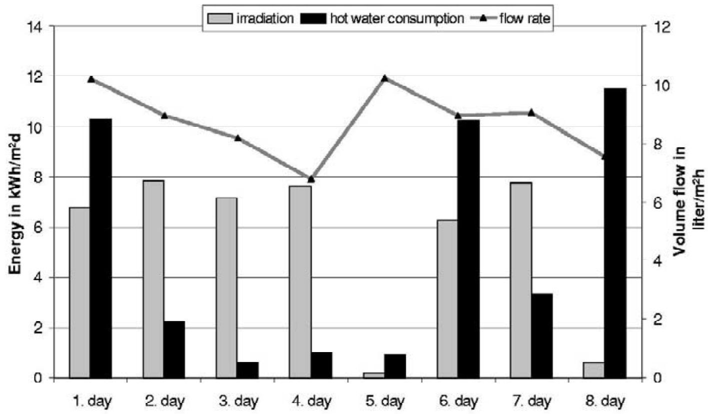

Fig. 5. Optimum flow rates in the collector circuit for the eight investigated days with the corresponding global irradiation in the collector plane and tap water energy both referred to the collector area. It is shown that the flow rate should decrease with an increase of the temperature in the store due to a high global radiation and a low hot water consumption. The values of day five and day eight are not meaningful because of the poor irradiation.

6.2. Results

Fig. 5 shows the optimized flow rates in the collector circuit determined for each investigated day together with the corresponding global irradiation in the collector plane and the hot water consumption. From the irradiation and the water consumption, the temperature level in the buffer store can be derived. With these three values, the value of the flow rate can be interpreted. The values on the fifth and the eighth day can be neglected due to the low irradiation. As expected, it can be concluded that the flow rate should decrease with increasing temperature level in the buffer store.

However, even though different best values for the flow rate have been determined for every day, the corresponding improvement of the solar energy gain of 0.6% during the 8 days is rather small. One of the results of the static optimization, that the dependency of the solar gain on the parameter values is rather small for well-dimensioned systems (cp. Section 5), suggests that the potential of the dynamic optimizations should be small as well. 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 gains. Thus, the improvement can only be gained from those days that have low solar gains or occur seldom. Consequently the improvement can only be small. With the additional assumption that uncertainties in the weather forecast and hot water consumption predictions reduce the expected value of the solar gain, the potential decreases even further.

7. SUMMARY AND CONCLUSIONS

Three different optimization steps that are expected to improve the performance of large SDHW-systems have been investigated with regard to their feasibility and energetic potential. First, an optimization during the planning of a SDHW-system has been carried out. For this, 20 parameters have been determined with a Genetic Algorithm in combination with the simulation program TRNSYS. With this optimization, the solar heat cost could be reduced by about 18% compared with the conventionally planned and installed system. This procedure shows that an automatic optimization during the planning process is possible and might be worth considering, if the cost functions for all components of the system are known. The real energetic improvement potential of such a system is difficult to determine and differs from one planning process to the other.

Second, a one year static optimization of flow rates and regulation parameters was carried out. This static optimization is supposed to react to variations of the real hot water consumption from the values assumed for the planning process. A sensitivity analysis showed that only the flow rates have a significant influence on the objective function (solar gain less the primary energy consumption of the pumps), whereas the influence of the control parameters is marginal. During this process, a comparison of seven optimization algorithms was carried out. For this certain problem, the classical algorithms like the Simplex Algorithm or the method of Simulated Annealing converge much faster to an optimal parameter vector than the Evolutionary Algorithms. For well-working systems, the energetic improvement potential seems to be rather small, whereas for badly designed and/or installed systems, there is useful potential for improvement on the basis of variations of control parameters and flow rates alone. On the other hand a great part of this potential can be made accessible by long term monitoring, which should be installed anyway.

Third, a dynamic optimization of flow rates and regulation parameters has been carried out. Here, daily optimization with consideration of predicted weather conditions, hot water consumption and temperature levels in the buffer store should lead to optimal operation for all states of the system. Since the solar gain of a well functioning system does not depend strongly on its flow rates and control parameters, the potential of using a different optimal parameter vector every day seems to be very small. Moreover, uncertainties in the weather forecast and the prediction of the hot water consumption have to be considered. These uncertainties probably reduce the determined potential further.

The investigations show that all optimization steps can be carried out with different search algorithms and objective functions. However, for all these steps, the energetic potential is very difficult to determine and somewhat arbitrary, and for the optimization of the operation (steps two and three), it seems to be very small for well designed and installed systems. Therefore, it is concluded that an optimization process such as is presented here is feasible, but the improvement potential of long term monitoring is much higher considering for example the poor performance of systems mentioned in Peuser *et al*. (1997). If long-term monitoring is implemented, a further optimization of the operation of a SDHW-system might be a useful step. In contrast to post installation optimizations, the use of optimization procedures in the planning process seems to be promising.

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APPENDIX A

Table A1. Listing of kind and numbers of the parameters which have been optimized during the three different optimization procedures. The control parameters include both set and dead spot values

Parameter	Optimization: Planning process		Static optimization	Dynamic optimization
	(20 parameters)	(14 parameters)		
Flow rates	2	2	2	8 (for each day one solar flow rate)
Sensor positions at buffer store	3	3	–	–
Inlet positions of buffer store	3	–	–	–
UA-values of heat-exchangers	2	2	–	–
Orientation of collector field	2	2	–	–
Volume of buffer store	1	1	–	–
Control parameters for the primary solar circuit	2	1	2	–
Control parameters for the secondary solar circuit	2	1	2	–
Control parameters for the discharge of buffer store	2	1	1	–
Diameter of pipe insulation	1	1	–	–

REFERENCES

Bäck T. (1996). *Evolutionary Algorithms in Theory and Practice*, Oxford University Press, Oxford.

Klein S. A. et al. (1994). *TRNSYS—A Transient System Simulation Program, Version 14.1*, Solar Energy Laboratory, University of Wisconsin-Madison, Madison.

Loomans M. and Visser H. (2002) Application of the genetic algorithm for optimisation of large solar hot water systems. *Solar Energy* **72**, 427–439.

Peuser F. A. et al. (1997). *Langzeiterfahrungen mit thermischen Solaranlagen*, ZfS-Rationelle Energietechnik GmbH, Hilden.

Press W. H., Teukolsky S. A., Vetterling W. T. and Flannery B. P. (1997). *Numerical Recipes in C: The Art of Scientific Computing*, Cambridge University Press, Cambridge.

Remmers K. -H. (1999). *Große Solaranlagen, Einstieg in Planung und Praxis*, Solarpraxis, Berlin.

Remund J., Lang R. and Kunz S. (1997). *Meteonorm Version 3.0*, Meteotest, Bern.

Wienholt W. (1996). *Entwurf neuronaler Netze*, Verlag Harri Deutsch, Frankfurt.