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Planning of Large Solar Thermal Systems: Automatic Optimizations

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Abstract

Automatic parameter optimizations during the planing process of large solar domestic hot water systems carried out with a combination of TRNSYS-simulations and an optimization algorithm are supposed to improve the performance of the systems. To investigate the potential and reliability of such a procedure and to gain information about the dependency of the best system design on the boundary conditions (hot water consumption, investment volume, hydraulic scheme, etc.), optimizations of two different solar thermal systems have been carried out. The optimized systems have been compared with the installed systems, which were conventionally planned by experienced engineers. The matter of fact that many parameters have to be fixed during the planning process leads to multidimensional problems. For these problems it is not clear which optimization algorithm suites best. Thus, two classical algorithms and two Evolutionary Strategies have been investigated concerning convergence speed and quality of the resulting parameter vector.

1. INTRODUCTION

A good system design and the proper dimensions of all its components are a prerequisite for a good performance of solar systems. Suitable design and dimension depend on the location of the system (especially climate), the amount and profile of domestic hot water consumption and other boundary conditions such as size and orientation of the roof for the solar collectors. Furthermore, the intentions of the customer and maximum investment have to be considered. Taking all these requirements into account, automatic optimizations using computer simulation programs like TRNSYS (Klein, S.A. et al, 1994), an established simulation program for solar thermal systems, could be one possible solution for the planning process.
The present paper focuses on the detection of the feasibility and the energy saving potential of automatic optimization processes and tries to find out, whether such processes are worthwhile to carry out. Furthermore, the dependencies of these potentials on the system properties like system design, solar fraction, hot water consumption or site of the solar system were investigated.
Besides the energetic potential, practicability and reliability of the optimization process were investigated. Before the construction of the system, many parameters such as buffer store volume or heat-transfer-coefficients of the heat-exchangers have to be set. The task of finding the best parameter sets to guarantee an optimal performance of the system leads to multidimensional problems. Because it is not obvious which is the best tool or algorithm to solve such problems in combination with solar system simulations, the usability of four different optimization algorithms have been investigated regarding convergence speed and feasibility.

2. INVESTIGATED SYSTEMS

To reach some degree of generality, two different solar hot water (SHW) systems have been investigated which are both installed at hospitals in Frankfurt/Main (Germany).
Figure 1 shows the design of the larger SHW-system, in the following referred to as “System A”. Measurement equipment which has been installed at this system enables a long-term monitoring and delivers information about the hot water consumption and the operation of the system. Using these information, a validated system model was implemented in TRNSYS.
Figure 2 shows the design of the smaller system, later on referred to as “System B”. At this system, no measurement equipment has been installed. Due to this, information is only available about the estimated amount of the daily hot water consumption before the construction of the system. As System A and B are both installed at hospitals, they were assumed to have similar load profiles. Thus, to implement a TRNSYS-model for this system as well, the distribution of the consumption over the day and furthermore over the year is taken from measured values of System A.
The systems differ in the hot water load (but with similar distributions over the day), the collector area and hereby in the solar fractions. Furthermore, the discharge schemes of the solar buffer store are different.

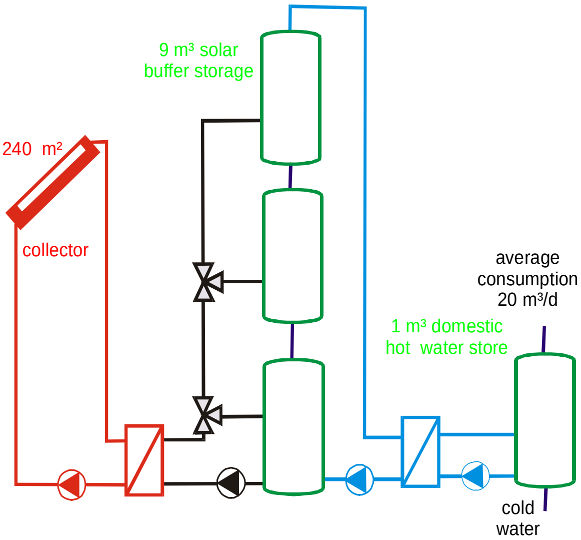

Figure 1: Design of the larger SHW-system ("System A", $f_{sol} \approx 30\%$). A discharge of the solar buffer store takes place if the temperature level in the DHW store is below the temperature in the upper solar buffer store.

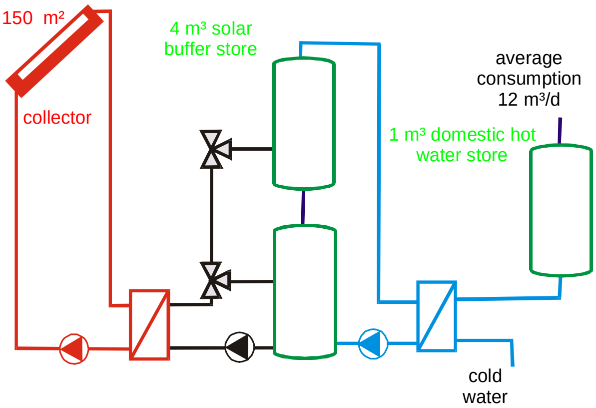

Figure 2: Design of the smaller SHW-system ("System B", $f_{sol} \approx 28\%$). A discharge of the solar buffer store takes place only during the tapping of hot water.

3. DESCRIPTION OF THE INVESTIGATED ALGORITHMS

Validated numerical system models, e.g. implemented in TRNSYS, enable in a sequence of parameter variations the detection of a parameter set which leads to an optimal performance of a solar system. However, since not all possible combinations of all parameter values can be tested, an algorithm is needed to determine the next parameter set to be tested. This algorithm has to fulfill some requirements to show a good performance:

(a) The algorithm should finally lead to a parameter set which is the best of all possible sets.
(b) Due to long simulation run times the algorithm should find this best parameter set with a minimum number of simulation calls.

However, since the dependency of the objective function on the parameters is not necessarily monotonous and correlation exists between the specific parameters, no straightforward solution for solving such problems in multidimensional search spaces can be found. 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.
Because optimizing solar thermal systems during the planing process is a very complex multidimensional problem, not all algorithms seem to be useful for solving such problems. Thus, from the seven algorithms which were tested in Krause (2001) concerning their applicability in a complete optimization procedure only the four most promising algorithms were investigated in the present work. These algorithms are on the one hand Simplex Algorithm and Powell Algorithm from the group of the "classical" algorithms and on the other hand a Genetic Algorithm and an Evolutionary Strategy from the group of the Evolutionary Algorithms. The classical algorithms have been adopted from Press (1997), the Evolutionary Algorithms were implemented considering the descriptions of Wienholt (1996). All algorithms have been combined with TRNSYS-simulations in an optimization program (implemented in C++), which initializes and executes the system simulations.

4. OPTIMIZATION DURING THE PLANNING PROCESS

Optimizing the solar system design during the planning process strikes for two goals. Firstly, the ratio of investment and operating costs (for instance the electric power consumption of the pumps) and the energetic output of the systems should be minimized. Secondly, the planning process should be simplified for the planner in order to increase the reliability of the system performance later on and to reduce the planning costs.
For the optimizations, the boundary conditions for the system have to be fixed. These are e.g. orientation and area available for the solar collectors. Furthermore, climate and hot water consumption have to be assumed. However, also the demands of the customer (e.g. the desired solar fraction or the investment volume) are important for the planning.
After the determination of these boundary conditions, a large number of free parameters remains. These parameters are related to the system design, the types and 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 reasonable range, for others only discrete values are possible. Due to the latter and the high number of parameters to be fixed, a Genetic Algorithm seems to be suitable for optimizations during the planing process.
Besides this Genetic Algorithm, the applicability of the other algorithms has been investigated as well and compared concerning their performance. Furthermore, investigations regarding the dependence of this performance on the system design and the hot water consumption have been undertaken.

4.1. Assumptions

To estimate the practicability and potential of an automated optimization, the planning of the two solar system mentioned above, originally carried out with conventional methods by experienced solar engineers, has been repeated. With a weather profile generated with Meteonorm (cp. Meteotest (1997)) and a load profile generated from former assumptions of the expected hot water consumption (resolution of the data: 1/2 h) one-year TRNSYS simulations with a simulation time step of 7.5 minutes have been carried out for System A. However, because of the differing discharge system of System B compared with System A, the profile of the hot water consumption was needed with a higher resolution for System B. This profile was generated from measured values of System A with a resolution of 6 minutes (which is equal to the simulation time step for System B). To implement the discharging strategy of System B, a new TRNSYS controller-type was developed.

The aim of the optimizations was the reduction of the solar heat costs in consideration of the annuity of the whole investment, the electricity consumption of the pumps and the maintenance costs (20 year period of operation, interest rate of 6 %) calculated by equation eqn(1).

$$\zeta = \textit{solar heat cost} = \frac{\textit{annuity}}{\textit{annual solar heat delivery to the domestic hot water storage}} \quad (1)$$

To calculate the investment for each variation of the system design, cost functions for each component, depending on type and dimension, had to be found. These functions were taken from Remmers (1999) and 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 components dimensions and control parameters.

As a major boundary condition, the collector areas and the hydraulic connections of the collectors have been set to those of the installed systems (240 m² and 150 m², respectively). Another possibility to avoid unintentional dimensioned systems would have been to fix the investment. However, because the investment varies with the dimension of the components, penalty functions as an additional term to the solar heat cost would be necessary to guarantee, that the optimized system would meet the desired investment as well.

To take the pumping energy into account, a hydraulic modeling of the solar circuit has been made in addition to the thermal simulation of the system. Altogether, this leads to a number of 20 parameters respectively which seem to be reasonable to optimize concerning practical considerations. Table 1 contains a complete list of these parameters.

Parameter	**System A**	**System B**
	(20 parameters)	**(20 parameters)**
Flow rates	2	2
Buffer store volume	1	1
Sensor positions at buffer store	3	3
Inlet positions of buffer store	3	3
UA-values of heat-exchangers	2	1
Dependency of the heat-exchanger UA-value on flow rate	-	1
Orientation of collector field	2	2
Control parameters for the primary solar circuit	2	2
Control parameters for the secondary solar circuit	2	2
Control parameters for the discharge of buffer store	2	2
Diameter of pipe	1	1

Table 1: Listing of parameters which have been optimized in the planning process. The control parameters include both, set and hysteresis values.

Mainly a Genetic Algorithm has been used for the optimizations. In addition also an Evolutionary Strategy and the Simplex and Powell algorithms were investigated to get an impression of their performance. For the two classical algorithms are no possibilities to improve the performance of the algorithms except for the choice of the starting points. For the Evolutionary Strategy and the Genetic Algorithm many settings have to be chosen. No investigations of the performance depending on these settings have been made, thus, the standard settings recommended in Bäck (1996) were taken. These settings are listed in Table 2. Because of the necessity to use discrete parameter values with a Genetic Algorithm, a certain resolution has been chosen for each of the 20 parameters, whereas for the diameter of the pipes and for the buffer storage volumes, only standard values were allowed which are not necessarily equidistant.

	Genetic	**Evolutionary**
Number of parameters	**20**	**20**
Individuals in parent generation	10	10
Individuals in offspring generation	60	60
Coding of individuals	Gray-Coding	-
Coding string length	126	-
Mutation	Probability: 1/126	Standard deviations for all parameters
Crossover points for recombination	2	-
Recombination	Probability: 0.6	Discrete, sexual
Selection algorithm	Rank based	Deterministic, only from offspring generation

Table 2: Algorithm-parameter settings of the Genetic Algorithm and the Evolutionary Strategy.

4.2. Results

Figure 3 shows optimization results received with Powell, Simplex and Genetic algorithm. For Powell and Simplex algorithms, two additional runs have been undertaken, where the feasible range of each parameter was restricted to more reasonable values. The comparison shows that the Genetic Algorithm achieves the lowest solar heat, even if it needs many simulations to reach the optimum. Because of the discrete property of the parameters in the Genetic Algorithm, many simulation calls were initialized with the same parameter vector and hereby redundant. In the present case, the effective number of simulation calls can be reduced by about 30 %. Without any restrictions concerning the initial values and the parameter ranges for the optimization, Powell and Simplex algorithm show a poor performance, which means that the algorithm stick in local minima without a chance to escape from there. By restricting the search space they reach similar optima as the Genetic Algorithm, but much faster. If much information can be delivered in advance, the classical algorithms show a better performance than the Genetic Algorithm, but the Genetic Algorithm seems to be more reliable and works even properly if nearly no information is available. Furthermore, it is not always clear if the available information is sufficient for the classical algorithms to show a good performance. Only a trial with a Genetic Algorithm might show this afterwards.

A significant improvement of the performance of the Genetic Algorithm by means of changing the starting vector is in opposite to the classical algorithms not possible. In Krause (2001) was shown, that even a reduction of the number of parameters from 20 to 14 only leads to a marginal faster search progress.

The best parameter vector of the optimizations leads to a 20 % reduction of the solar heat cost of the system compared to the conventionally planned and installed system. But because possibly not all assumptions concerning system design, cost functions and boundary conditions made within the optimizations have been considered by the planning engineers in the same way, the real potential of the optimization procedure itself could be different.

Since the cost functions of the solar components depend on time and manufacturer, general rules for the dimensioning of the system are difficult to derive from our optimizations. One could be that due to high costs of the buffer store, 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 (e.g. avoiding of overheating of the collector field), which has not been considered in the optimizations.

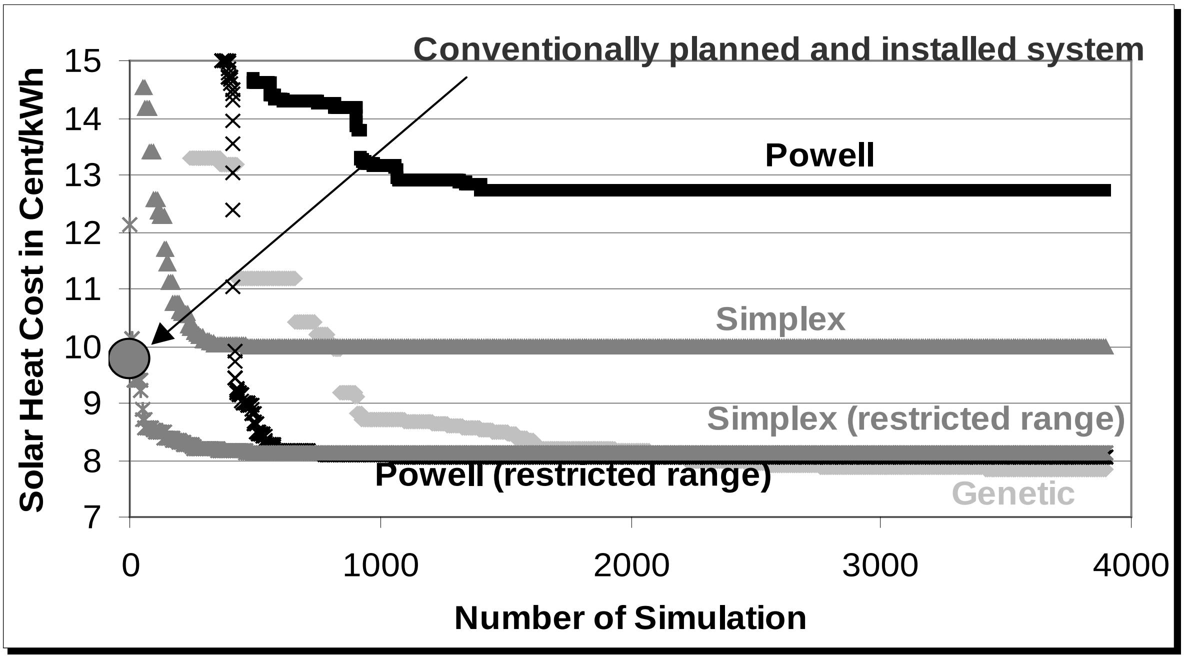

Figure 3: Development of the simulated solar heat costs of System A for three different optimization algorithms. Plotted is the progress of the optimization (defined as the lowest solar heat cost of the system after X simulations) dependent on the number of simulations carried out with Powell, Simplex and Genetic algorithm. For the Powell and Simplex algorithm, two additional runs have been undertaken with restrictions of the allowed parameter ranges. These restrictions means also that the starting values are closer to the optimum than for the normal runs. Additionally, the value of the solar heat cost of the conventionally planned and installed system is plotted.

Before the construction of a solar system, the assumed load profile is known only with great uncertainties. Due to this, system designs are required, which show even with differing load profiles a good performance. Figure 4 shows the dependency of the optimization results on the hot water consumption. The optimizations have been carried out with System A with a fixed collector area of 240 m² but three different loads: The planned load, one-third and triple of this. With the determined best parameter vectors for each consumption cross-predictions have been carried out. As expected, the system with the highest consumption achieves the lowest solar heat cost (about 6.6 Euro Cent/kWh), whereas with the lowest consumption, the solar heat cost is in the range of 11.5 Euro Cent/kWh. The parameter vectors differ mainly in the size of the solar buffer storage (the higher the consumption the smaller the storage volume) and the flow rates for charging and discharging of the buffer store (the smaller the consumption the smaller the flow rates).

The cross-predictions show that large solar thermal systems are good-natured, which means that optimizing with an inaccurately assumed hot water consumption leads only to a bearable deterioration of the solar heat costs. Only if the system has been optimized under extremely exceptional assumptions, for instance if the hot water consumption is not suited to the chosen collector area, some components might have a critical dimension, which could lead to a poor performance under differing conditions. However, for usual proportions, even different (optimized) system designs lead to similar solar heat costs.

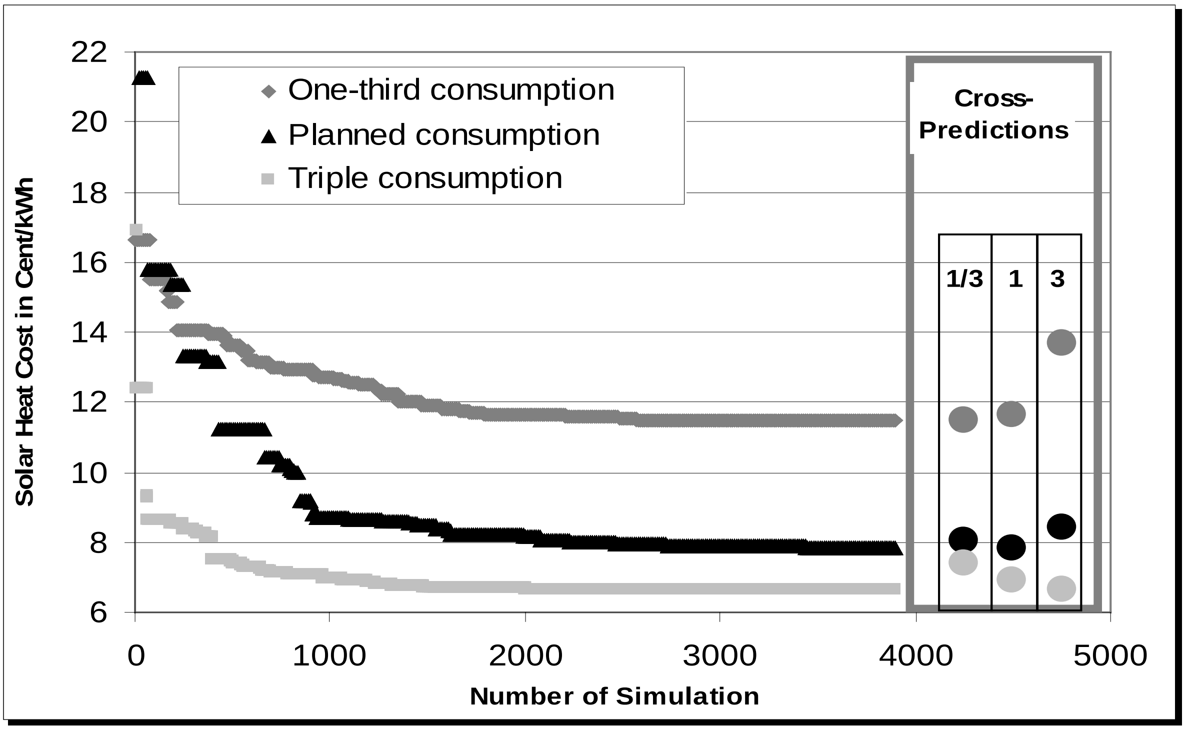

Figure 4: Dependency of the optimization result on the hot water consumption at System A carried out with a Genetic Algorithm. The dots in the rectangle on the right hand side of the diagram represent the cross-predictions, which are carried out with the parameter vectors determined from the optimization with the other amounts of consumption.

Figure 5 shows the result of the optimization of System B carried out with a Genetic Algorithm and with an Evolutionary Strategy. Compared with the values for System A (Figure 3 and Figure 4), the resulting solar heat cost is higher for System B. This results from distribution of the fix costs due to the different collector areas (System A: 240 m², System B: 150 m²) and is no hint whether one system hydraulic (especially the discharge scheme) is better in principle. The optimization of System B leads to an improvement of the solar heat cost of about 38 % compared to the system planned by experienced engineers. This shows, that also for this hydraulic an automatic optimizations works properly.

The comparison of a Genetic Algorithm and an Evolutionary Strategy shows no significant difference in their performance concerning convergence speed and optimization result. At first view, it seems that the Evolutionary Strategy converges a little bit faster, but considering, that with the Genetic Algorithm, many simulations were initialized with the same parameter vector and are therefore redundant, the number of simulations is reduced to the third curve in Figure 5. Because this curve is similar to the curve of the Evolutionary Strategy, the Genetic Algorithm can be recommended because of its possibility to optimize parameters for which only discrete (and not equidistant) values are allowed.

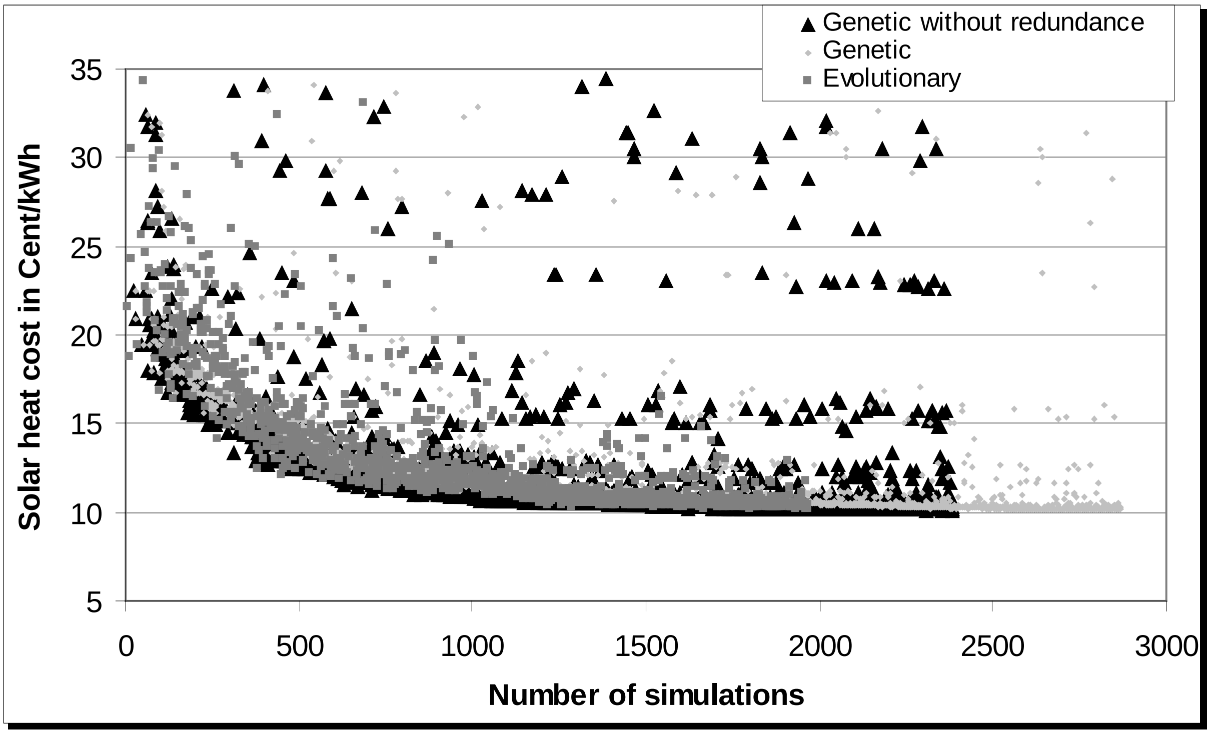

Figure 5: Optimization of System B, carried out with a Genetic Algorithm and with an Evolutionary Strategy. The third curve represents the development of the Genetic Algorithm without the redundant simulations.

5. SUMMARY AND CONCLUSIONS

Supplementary planning optimizations were carried out for two different solar domestic hot water systems, which are both installed at hospitals in Frankfurt (Germany). These systems have different system designs, different collector areas and store volumes and differ in the hot water load. To investigate the potential and reliability of the optimizations based on TRNSYS-simulations, four different optimization algorithms were tested.

Even if the classical algorithms showed a better performance under very special circumstances, Evolutionary Strategy and Genetic Algorithm seem to be more reliable and need nearly no information concerning the parameters to be considered in advance. Between the Evolutionary Strategy and the Genetic Algorithm, no significant difference is noticeable if all redundant simulations can be suppressed.

Both investigated systems could be optimized with the presented procedure. At the larger system, an improvement concerning the solar heat costs of about 20 % could be reached compared to the conventionally planned and installed system, at the smaller system with the special discharging scheme of the solar buffer store, the improvement is in the range of 38 %. Hereby it has to be considered that possibly not all assumptions made within the optimizations concerning boundary conditions, cost functions of components and wishes of customers are equal to the circumstances, which have been taken into account by the planning engineers. Thus, the real potential could be much smaller.

Furthermore it could be shown that large solar thermal systems are good-natured concerning the assumed hot water consumption. Only for unusual proportions between water consumption and collector area, optimizing with the wrong hot water load could result in a poor system performance. Even if for normal proportions the optimizations of systems with different loads yield different system designs, both system designs would lead to similar solar heat costs.

6. ACKNOWLEDGMENTS

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