Simulation-based optimization of a solar water heating system by a hybrid genetic – binary search algorithm

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Abstract

A proper design of a large solar heating system is important to maximize the benefit of the system. The system hydraulics, control parameters and dimensions of single components are usually tried to be optimized towards achieving better system performance at lower costs. The complexity of the target functions, a large number of optimization parameters and boundary conditions imposed on the system require application of advanced numerical optimization techniques and tools as well as additional software.

In this paper, a hybrid genetic algorithm is proposed and applied to optimization of a solar combisystem. The hybrid algorithm couples the CHC genetic algorithm with the binary (*n*-ary) search method. The results of the optimizations show that the proposed algorithm is almost two times faster than the pure CHC genetic algorithm and, in separate cases, more reliable in finding the global optimum.

The parallel version of the algorithm was implemented in GenOpt (generic optimization software) and applied to optimization of a solar combisystem modelled and simulated with the simulation software TRNSYS. Results of the optimization are presented in this paper.

1. Introduction.

As it was shown before [1], the genetic algorithms or evolution strategies should be used for optimization of solar heating systems since they are more likely to find the global optimum. However, as these optimization techniques widely explore the optimization space, they are computationally very expensive. Thousands of simulations are usually needed to approach the global optimum. As a one-year simulation of a typical solar heating system takes around 10 minutes on a modern computer, around one week is needed for the simulation-based optimization of such a system.

In this paper an attempt is made to construct a more efficient optimization algorithm by coupling the CHC genetic algorithm [2], a highly efficient modification of the genetic algorithm, with a local optimization algorithm, the so-called binary (*n*-ary) search method. The resulting hybrid algorithm should take benefits of both algorithms. It should efficiently explore the space as the genetic algorithm does but as soon as it finds the valley of the suspected global optimum it should not waste more time by exploring the surroundings, but localize the optimum with the speed of the binary (*n*-ary) search.

2. Description of the optimization algorithm

Genetic algorithms are inspired by evolution. They are widely used as a tool for optimization. An implementation of a classic genetic algorithm begins with an initial generation of randomly chosen individuals (chromosomes) each of which is a combination of the properly encoded optimization parameters (genes) and is actually a point in the search space. The individuals are being evaluated and those who represent better solutions to the target problem are given more chances to be selected for reproduction than those who are the poorer ones. The selected individuals then undergo the recombination (crossover) and mutation process in order to create the next generation of points in the search space. Application of selection, recombination and mutation operators is repeated until either the algorithm converges or a defined stopping condition is satisfied.

2.1. The CHC algorithm

The CHC genetic algorithm was developed by L. Eshelman [2]. The CHC abbreviation stands for Cross generational elitist selection, Heterogeneous recombination by incest prevention and Cataclysmic mutation.

This algorithm monotonically collects the best strings found so far. It starts with a random parent population. After recombination, the N best individuals are drawn from the parent and offspring populations to create the next parent generation. The recombination is done by the uniform crossover called HUX, which swaps exactly half of the bits between the two individuals chosen randomly from the parent population. Selection of the parent individuals for recombination is random but with the restriction, that their binary encodings must be a certain Hamming distance (number of the bits in which the binary encodings differ one from another) away from one another. Such "incest prevention" is designed to promote diversity in the offspring population. Nevertheless, when the population converges to the point that it begins to reproduce more or less the same individuals, the cataclysmic mutation is performed which mutates heavily all the individuals except for the best one. The CHC algorithm typically uses small population sizes.

2.2. The binary (*n*-ary) search

The binary (n-ary) search is a one-dimensional search. It runs along one parameter at a time, while the other parameters remain fixed. Variation range of the parameter is first divided by n points at which the target function is calculated. The points neighbouring to the best point are then chosen as the boundaries of the new range. The n-ary divisions are repeated until the value of target function does not improve any longer or a given precision is reached. After that, the n-ary search fixes the investigated parameter to the obtained optimal value and moves to the next parameter. This outer parameter cycle repeats until the target function cannot be improved any more.

The n-ary search is the local optimization method as it optimizes only one parameter in a turn. However, on the contrary to the path-oriented methods which start from the initial point and move in the direction where the target function is improved, it is more robust and can avoid local optima.

2.3. The hybrid CHC-binary (*n*-ary) search algorithm

Genetic algorithms are sometimes coupled with the computationally less expensive local optimization algorithms in order to accelerate convergence to the global optimum. All such combinations, however, increase risk that the optimization ends somewhere at a local optimum far from the thought global one.

The application range of such hybrid algorithms should be first carefully investigated. When the surface of the target function has no sharp and deep global optimum but rather a broad one (many ripple-like local optima are not a problem), then the proposed algorithm might be applied with more chances on success

In the investigations for this paper, the CHC genetic algorithm is coupled with the *n*-ary search method. Switching from the CHC algorithm to the *n*-ary search occurs when the best individual of the CHC is not improved for a given number of generations. If the target function is supposed to have not a very complex surface and the CHC algorithm hits the basin of the global optimum relatively fast, then it could be beneficial to switch to the *n*-ary search before the cataclysmic mutation of the CHC algorithm takes place. Otherwise it is better to sacrifice more computational time to the CHC algorithm and switch to the *n*-ary search after mutation.

It is believed that the pure CHC algorithm should be more reliable in finding the global optimum as it widely explores the searching space. However, it might stuck in the local optimum especially if the population size is chosen too small or restriction on the Hamming distance between two mating individuals is too weak. It is possible in these cases that the *n*-ary search hits out of the local optimum and reaches if not the global optimum then at least a better local one. The results below show exactly such a case.

The proposed hybrid algorithm should be carefully tuned with a closer look onto the complexity of the target function. To be on the safe side, it is recommended to run the same optimization several times. If the optimization results are (nearly) the same in all runs, then it is more likely that the global optimum has been found.

3. Description of the solar combisystem

The proposed hybrid genetic algorithm was applied to optimization of the reference solar combisystem of IEA SHC Task 32 [2] (Fig. 1). Besides the collector and storage tank, the system has an auxiliary heating loop with a heated volume inside the tank. The system is used for tap water preparation as well as for space heating. The demand profile of the tap water was stochastically generated (around 200 l/day) as a typical profile for a one-family house. The weather data for Zurich (Switzerland) were taken for simulation and time resolution of the calculations was 6 minutes. The system was simulated for a whole year.

The solar combisystem is optimized for minimum cost per kWh of saved auxiliary energy. The target function F_{target} is constructed as

$$F_{\text{target}} = \frac{F_{\text{cost}}}{E_{\text{ref}} - E_{\text{aux}}} + F_{\text{penalty}}(f_{\text{save, therm}}, c) \qquad (1)$$

The first term describes the costs per kWh of saved auxiliary energy. The cost function F_{cost} covers costs of the investment in solar components (collector, store, pumps, heat exchangers, etc.), installation costs (10% of the component costs), interest rate (6% for a twenty-year credit for all investment and installation costs) as well as the operational (electricity demand) and maintain costs of the system (1%

of the investment costs per year). The second term F_{penalty} in (1) is the penalty added to the target function if the fractional thermal savings $f_{\text{save,therm}}$ of the system, defined as

$$f_{\text{save,therm}} = 1 - \frac{E_{\text{aux}}}{E_{\text{ref}}}, \tag{2}$$

are less than a given value c.

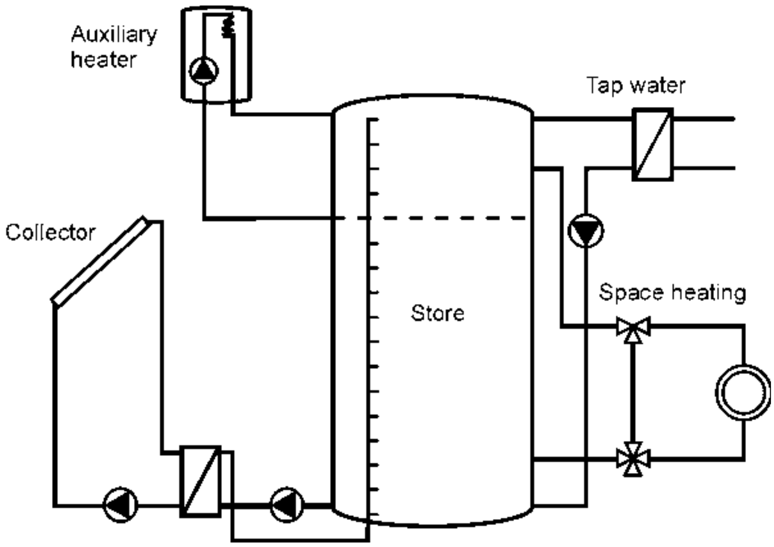

Fig. 1. Scheme of reference solar combisystem with auxiliary heating loop

All in all, sixteen parameters were chosen as optimization parameters that could have influence on the target function. They comprise the design parameters as collector area, store volume, insulation thickness, UA values of the heat exchangers, pipe diameter, inlet/outlet positions, etc. and such operational parameters as mass flow rate, set temperature of the auxiliary heater, dead bands of the control of collector and auxiliary heater. The operational parameters were set constant for the simulation period.

4. Optimization results and discussion

First, the solar combisystem was optimized without any requirement to the fractional energy savings $f_{\text{save,therm}}$ and then with $f_{\text{save,therm}}$ not less than 35 and 45%, respectively. The cost per kWh of saved auxiliary energy, corresponding $f_{\text{save,therm}}$ as well as the optimal values of the five most important optimization parameters are given in Table 1 for the base case and three optimization cases. It is seen that either the fractional savings can be improved by around 10% at the same cost or the cost per kWh of saved auxiliary energy can be reduced by around 10% at the same $f_{\text{save,therm}}$.

Table 1. Results of optimizations of the solar combisystem. The base case stands for the standard configuration of the IEA SHC Task 32 system. The solar heat costs include interest of 10 to 12 €ct/kWh for a credit for all investment and installation costs.

Optimization case	F_{target}, €ct/kWh	$f_{\text{save,therm}}$, %	Collector area, m^2	Store volume, m^3	Insulation thickness, m	Solar HX UA, W/m$^2_{\text{col}}$ K
0. base case	30.7	34	20	1.0	0.15	105
1. no constraints on $f_{\text{save,therm}}$	25.5	26	11	0.7	0.4	118
2. $f_{\text{save,therm}} \geq 35\%$	27.1	35	17	1.1	0.3	147
3. $f_{\text{save,therm}} \geq 45\%$	30.2	45	26	1.9	0.3	130

In Fig. 2, the best value of the target function obtained so far by the proposed hybrid CHC-binary(*n*-ary) search (dashed lines) and by the pure CHC genetic algorithm (solid lines) versus the number of simulations are given for the third optimization case ($f_{\text{save,therm}} \geq$ 45%). Two typical independent optimization runs are shown for both algorithms. The results are the same up to the point when the *n*-ary search is launched. In the first run, it is seen that the *n*-ary search can noticeably accelerate the convergence and ended up at the optimum almost twice as fast as the pure CHC algorithm does. In the second run, the CHC algorithm stuck in a local minimum, whereas the *n*-ary search improved the solution up to the (likely) global minimum. Although the hybrid algorithm needed in the second run almost as many calculations as the pure CHC algorithm in the first run, it is more reliable. In this example, the *n*-ary search ran with $n = 5$, the population size of the CHC algorithm was taken as $N = 30$. Switching from the CHC algorithm to the *n*-ary search was done before the cataclysmic mutation of the CHC algorithm, because the study of the target function surface showed that it is quite shallow and relatively smooth in the basin of expected optimum.

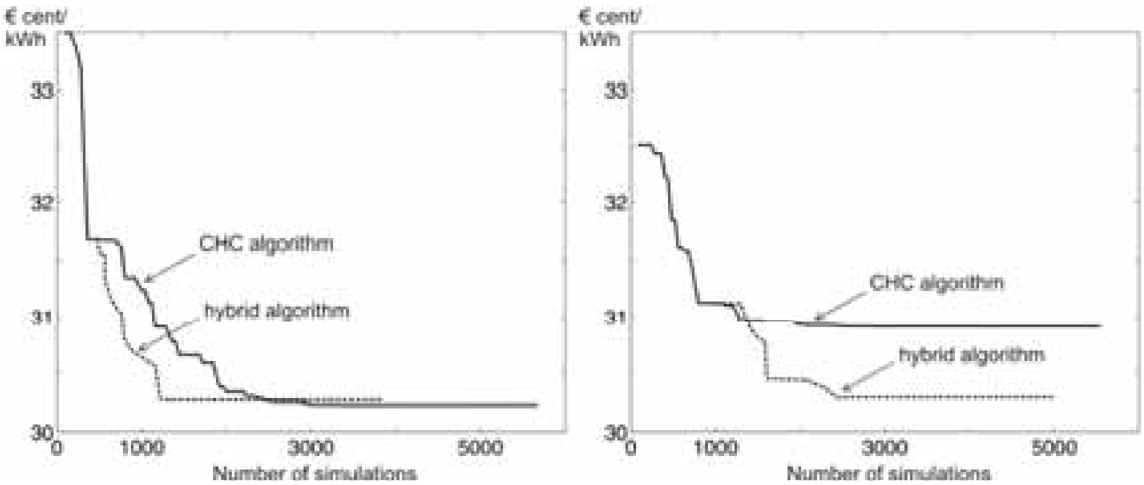

Fig.2. Optimization results (best value of the target function) of two independent optimization runs (left and right) for the solar combisystem with the fractional energy savings ≥ 45%. Solid lines correspond to the standard CHC algorithm and dashed lines to the hybrid CHC – *n*-ary search algorithm.

The proposed hybrid algorithm decreases the computation time from around one week (3000 simulations on the dual core computer, each 7 minutes) to 3 days and up to around 24 hours (on 12 CPUs), when using the parallelized version of the algorithm.

5. Conclusion

The optimization potential for the investigated solar combisystem is either 10% higher fractional savings of the system at the same costs per kWh of saved auxiliary energy, or 10% cheaper energy costs at the same fractional savings. The optimization potential is expected to be even higher if the operational parameters are dynamically optimized and not assumed to be constant over the simulation period as in the present results.

Applied to the optimization of the solar combisystem, the proposed hybrid genetic algorithm shows higher reliability and better efficiency than the pure genetic CHC algorithm, furthermore it is almost two times faster. Therefore, the hybrid algorithm is attractive for resolving computationally expensive and complicated problems as optimizations of the solar heating systems.

Nomenclature

F_{target}	€ct/kWh	target function, cost per kWh of saved auxiliary energy
F_{cost}	€ct	costs of the solar combisystem
E_{aux}	kWh	auxiliary final energy consumption of the solar combisystem
E_{ref}	kWh	final energy consumption of the reference system
$f_{save, therm}$	-	fractional thermal energy savings
$F_{penalty}$	€ct/kWh	penalty function
c	-	constrain on the fractional thermal energy savings

References

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[2] L. Eshelman. Foundations of Genetic Algorithms. Morgan – Kaufmann (1991) 256-283.

[3] IEA SHC Task 32 at http://www.iea-shc.org/task32/index.html.