Simulation-based Optimization of Solar Combisystem Sensitivity Analysis at Optimum

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Abstract

In this paper, a solar thermal combisystem is optimized for minimal solar energy costs at specified extended fractional energy savings by applying hybrid genetic CHC – binary search optimization algorithm. An optimization potential of around 13% in terms of solar energy costs or 19 percent points in terms of extended fractional energy savings can be achieved when compared to the system configuration planned by experts. A Pareto front is built showing the optimal solar energy costs at desired energy savings of the system, or vice versa. The influence of variations of domestic hot water and space heating demand as well as geographical location on course and position of the Pareto front and optimal combisystem configuration is investigated. To determine the most important parameters and quantify their influence on the solar energy costs, methods of global sensitivity analysis are applied near the optimum.

Keywords: Numerical optimization, hybrid genetic algorithm, Pareto front, sensitivity analysis

1. Introduction

Since operation of a solar thermal combisystem consisting of many interacting components is complex, dynamic system simulations are often required to investigate the system behaviour. Proper dimensioning of the system components as well as efficient controller settings depend on changing boundary conditions as weather, domestic hot water and space heating demand. In addition to the energetic performance, the dimensioning of combisystem must be justified economically. All this makes finding the combisystem configuration optimally designed in terms of cheapest solar energy costs for given location and demand rather challenging. After the optimal configuration is found, further investigation is required showing how sensitive it is to variations of the boundary conditions or single system parameters.

In this paper the reference solar combisystem proposed in the IEA-SHC Task 32 (Heimrath and Haller, 2007) is numerically optimized for minimal solar energy costs by a hybrid genetic CHC – binary search optimization algorithm. It is shown to be reliable and efficient for finding optimal system configuration (Kusyy et al., 2010). As a result of several optimization runs, each with different constraints on extended fractional energy savings of the combisystem, the Pareto front between solar energy costs and fractional energy savings is built. It shows minimal energy costs at desired fractional energy savings or, vice versa, maximal fractional energy savings that are possible to achieve at given energy costs. Further, the influence of boundary conditions on the Pareto front and optimal combisystem configuration is investigated. This allows estimating the performance decrease of the solar combisystem optimized for given initial conditions but operated at changed conditions.

The influence of combisystem parameters and two boundary conditions (DHW demand and collector price) on solar energy costs is accessed by application of global sensitivity methods in the parameter space near the optimum. Parameters having much influence on the solar energy costs must be handled carefully, and less influential parameters may deviate from their optimal values with only insignificant increase of solar energy costs. This might be helpful if, for example, components of particular optimal sizes are not accessible on the market.

All numerical simulations of the solar combisystem are carried out by TRNSYS simulation software (Klein et al., 2007) and the coupling with the optimization algorithm is done by GenOpt generic optimization program (Wetter, 2008)

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2. Optimization problem formulation

2.1. Description of solar combisystem

The reference solar combisystem (Figure 1) proposed in IEA-SHC Task 32 is the object of investigation in the present paper. The combisystem is planned to cover domestic hot water consumption and space heating demand of a single family house. Solar thermal collectors are connected via an external heat exchanger to a store which is the central system component. A conventional heater is intended to heat up an auxiliary volume at the top of the store when the energy supplied by solar collectors is not enough to cover the demand. On the consumption side, the tap water is prepared via fresh water station and space heating is supplied directly from the store.

For simulation of the Task 32 combisystem the locations Stockholm, Zurich and Madrid are chosen representing a wide range of the European climates. The yearly profile for domestic hot water demand with a 6 minute time resolution is generated using the DHWcalc tool (Jordan and Vajen, 2005) as a typical profile for a single family house. According to the profile, the consumption of the domestic hot water is stochastically distributed over the days having main peaks in the morning and late afternoon. Three reference buildings (two-storey, $140\ m^2$ of the living area) with the same architectural design but different wall insulation and window thermal quality resulting in different heating demand (30, 60 and $100\ kWh/m^2a$ for Zurich climatic conditions) are defined in Task 32.

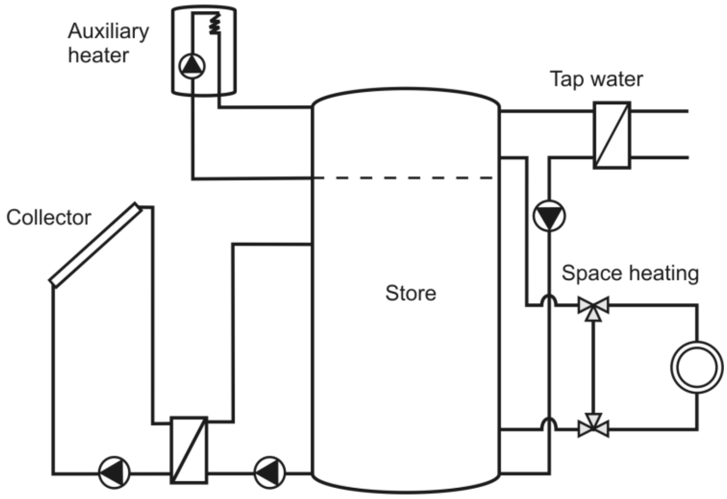

Fig. 1: Schematics of investigated solar combisystem

2.2. Target function

In this study the solar combisystem is optimized for minimum costs per kWh of saved auxiliary final energy. The target function dependent on the set of the optimization parameters $X = \{x_1, \dots, x_N\}$ which are listed in Table 1 below, installer margin m and interest rate r, is constructed as follows:

$$F_{target}(X, c, m, r) = \frac{F_{cost}(X, m, r)}{E_{ref} - E_{sol}(X) + \hat{F}_{penalty}\big(f_{sav,ext}(X), c\big)} \qquad (1)$$

The energetic performance of the combisystem is described by the denominator of the target function, where E_{ref} is the auxiliary final energy consumption of the reference heating system, $E_{sol}(X)$ is the energy consumption of the solar combisystem and $E_{ref} - E_{sol}(X)$ is the amount of auxiliary final energy saved by the solar combisystem over the year. The third term $\hat{F}_{penalty}$ in the denominator of (1) is the penalty added to the target function if the extended fractional energy savings $f_{sav,ext}$ defined as

$$f_{sav,ext}(X) = 1 - \frac{E_{sol}(X) + F_{pen,DHW}(X) + F_{pen,SH}(X)}{E_{ref}} \qquad (2)$$

are less than a given value c. The term $\hat{F}_{penalty}$ is needed only if the extended fractional energy savings $f_{sav,ext}$ of the optimized combisystem must be kept larger than c. It determines how much solar gains are missing in order to reach $f_{sav,ext} = c$. The terms $F_{pen,DHW}$ and $F_{pen,SH}$ in (2) describe the penalties are applied when the required tap hot water temperature ($45\ ℃$) cannot be supplied or the room temperature drops below the desired set temperature (19.5 ℃).

To determine the costs of the combisystem described by the function F_{cost} in (1), a comprehensive market study is required. It is connected with large uncertainties due to the variety of solar thermal components of different quality on the market. Furthermore, the prices of the system components, transportation costs, interest rates, etc., are noticeably time dependent, different special offers may influence the cost function. All this together with non-transparency of the installer price margins makes an exact determination of the costs quite difficult.

In this study a simple calculation of the prices of individual system components is attempted. If any optimization parameters from Table 1 below have an impact on the price of a certain system component, then the price function for this component is built which is a dependency of the component market price from the magnitude of these parameters. The price functions are built for each component based on the offers of online discounters. Dependency of the price from the optimization parameters is chosen as a polynomial up to the second degree and the unknown coefficients of the polynomial are determined by performing linear or multilinear regression. Offers of the online discounters, taken as the regression data, seem to be the cheapest retail prices on the market accessible for the end user and probably they are the best approximate for the wholesaler prices. The component prices offered by the installers most likely already include their margins which might be different for different components and also vary from installer to installer. For example, one installer might add 30% to the price of collectors and 50% to the store price offered by the wholesaler whereas another installer might do vice versa. From this reason the component prices offered by the discounters and not the installer prices are chosen to be appropriate for building the cost function of the solar combisystem.

On the other hand, however, it seems unlikely that the end user will be able to hire the installer to build up the combisystem out of the user's own components bought by the discounter. Therefore, to estimate the final price for each component $C_i, i = 1, \ldots, N$ for the end user, the discounter prices $F_{cost,disc}(C_i)$ are corrected by the factor m representing expected installer margin, supposed to be the same for all components. To get the final capital costs $F_{cost,cap}$ the installation costs equal to 20% of the price for solar combisystem are added.

$$F_{cost,cap}(X, m) = 1.2 \cdot m \cdot \sum_{i=1}^{N} F_{cost,disc}(C_i) \quad (3)$$

The final capital costs $F_{cost,cap}$ depend implicitly (through the functions $F_{cost,disc}(C_i)$) on at least some of the optimization parameters X. In the present implementation the capital costs include German value added tax equal to 19%

Following the annuity method, the annual payments due each year over the lifetime of the solar combisystem at the given interest rate r are calculated as follows:

$$F_{cost}(X, m, r) = \frac{(1+r)^{20} \cdot r}{(1+r)^{20} - 1} \cdot F_{cost,cap}(X, m) + 0.007 \cdot F_{cost,cap}(X, m) \quad (4)$$

The lifetime of the combisystem is set to 20 years and it is not varied in any of the following optimizations. Second term in (4) describes annual maintenance and insurance costs. These costs discounted to the installation year, are taken to be equal around 11% of the capital costs $F_{cost,cap}$ for the lifetime of the combisystem and the interest rate of 2.5% ($r = 0.025$).

The cost function $F_{cost}(X)$ with interest rate of 2.5% and $m = 1.5$, meaning that 50% is added to the discount component prices as an installer margin, is used in the target function $F_{target}(X, c)$ from (1) in the following optimizations. Other annuities $F_{cost,contr}(X) = F_{cost}(X, 1, 0.025)$ and $F^0_{cost,contr}(X) = F_{cost}(X, 1, 0)$ both representing the costs with different interest rates of 2,5% and 0%, respectively, for the company which installs the solar thermal systems ($m = 1$), are calculated as well. After subtracting the added value tax, the costs $\hat{F}^0_{cost,contr}(X)$ for the installation company doing, for example, an energy contracting are obtained. The cost function $F^0_{cost}(X) = F_{cost}(X, 1.5, 0)$, that is the cost function for the end user ($m = 1.5$) investing its own savings ($r = 0$) in a solar combisystem, is presented in the results below as well.

After substituting the annuity cost functions into (1) the corresponding target functions, are obtained. Since all the cost functions derived here do not change the weighting of the capital costs $F_{cost,disc}(C_i)$ of single components under the sum sign in (3) but only modify the sum as the whole, the optimal system configuration $X = X_{opt}$ received for one of the functions is also the optimum for all others.

2.3. Optimization parameters

Before the optimization algorithm may start, the parameters of the system must be specified, especially values of which are believed to be not optimal and should be adjusted in order to improve the existing system. Not only the parameters themselves, but also the variation ranges in which the parameter values can be varied during the optimization are to be chosen. Too wide variation ranges will most likely slow down the optimization whereas too narrow ranges may cause missing the optimum when the optimal parameter value lies beyond the specified variation range. For any two parameters which are involved in interactions with regard to the target function (f.e. flow rate and pipe diameter), the variation ranges should be chosen such that none configuration of the values (f.e. flow rate chosen large and pipe diameter - small) will cause the system simulation to fail.

In this study, 18 parameters of the solar heating combisystem are adjusted in the process of optimization in order to get the optimal value of the target function (1). All optimization parameters with their variation ranges are listed in Table 1. In several optimizations below, the variation ranges of certain parameters are modified so that the optimum lies within the variations ranges.

Tab. 1: List of parameters with variation ranges for optimization ("optimization range") and for calculation of parameter influence on solar energy costs F_{target} near optimum ("sensitivity range"). Resolution N for optimization parameters is given in bits meaning that each parameter may take any of 2^N values equidistantly distributed between endpoints of its optimization range

Parameter	Notation	Optimization range	Resolution	Sensitivity range
Optimization parameters				
1. Collector area, m^2	A_{col}	$[5; 36]$	5	$[14; 21]$
2. Store volume, m^3	V_{store}	$[0.5; 2.0]$	4	$[1.2; 1.8]$
3. Number of auxiliary nodes	N_{aux}	$[5; 20]$	4	$[8; 12]$
4. Store insulation thickness, m	D_{iso}	$[0.05; 0.8]$	4	$[0.2; 0.3]$
5. Pipe inner diameter, mm	D_{pipe}	$[10; 40]$	4	$[10; 15]$
6. Specific collector flow rate, kg/m^2h	m_{flow}	$[5; 36]$	5	$[11; 16.5]$
7. ΔT controller upper dead band, K	$\Delta T_{col,up}$	$[4; 11.5]$	4	$[4; 6]$
8. ΔT controller lower dead band, K	$\Delta T_{col,low}$	$[0.1; 4.0]$	4	$[4; 6]$
9. ΔT controller sensor pos. in store	$H_{col,sens}$	$[0.01; 0.3]$	4	$[0.14; 0.21]$
10. UA value of solar hx, W/K	UA_{col}	$[1000; 5500]$	4	$[1000; 1500]$
11. UA value of DHW hx, W/K	UA_{DHW}	$1000; 10300]$	4	$[0.4; 0.8]$
12. Collector inlet position in store	$H_{col,in}$	$[0; 1]$	5	$[0.07; 0.105]$
13. SH outlet position in store	$H_{SH,out}$	$[1 - V_{aux}/V_{store}; 1]$	4	$[0.15; 0.3]$
14. SH inlet position in store	$H_{SH,in}$	$[0.07; 0.3]$	4	$[6580; 9870]$
15. Set temperature of aux. heater, °C	$T_{aux,set}$	$[50; 70]$	4	$[52; 78]$
16. Aux. controller upper dead band, K	$\Delta T_{aux,up}$	$[4; 16]$	4	$[7.2; 10.8]$
17. Aux. controller lower dead band, K	$\Delta T_{aux,low}$	$[0.5; 4]$	4	$[2.1; 3.2]$
18. Collector slope,°	sl	$[40; 71]$	5	$[53; 79]$
Boundary condition parameters				
19. DHW demand multiplier	DHW			$[1.0; 1.5]$
20. Collector price, Eur/m^2	$Price_{col}$			$[300; 450]$

2.4. Optimization algorithm

The algorithm solving the optimization problem is a sequence of operations, usually repeated iteratively, which are performed on the set of optimization parameters. The solution found by the optimization algorithm is the system configuration optimal with regards to a chosen target function. Whether the found solution is really the optimal one and how efficient the performed operations are, are the questions of reliability and efficiency of the algorithm. In this study, the solar combisystem is optimized by the hybrid genetic CHC – binary search optimization algorithm. It belongs to hybrid optimization algorithms which are an attempt to make the reliable global optimization algorithms faster by coupling them with computationally less expensive local algorithms.

To speed up the optimization, the proposed hybrid algorithm is parallelized for simultaneous solar combisystem simulations on multi-core CPUs or in the computer network using HTC Condor (High Throughput Computing) distributed computing software. The hybrid CHC – binary search algorithm was started 6 times in a row for chosen optimizations in order to test its reliability. All the optima found by the algorithm differed less than $1-2\%$ from their mean value, depending on the number of optimization parameters, boundary conditions and system configurations. This means that most probably the global optimum was found each time and the algorithm might be seen as a reliable one.

The parallelized version of the hybrid genetic CHC – binary search optimization algorithm is implemented in GenOpt (Generic Optimization software) which is the open source framework for the numerical optimization. For more details on the hybrid algorithm refer to (Kusyy et al., 2010).

3. Optimization results

3.1. Pareto front

The proposed hybrid CHC – binary search optimization algorithm is applied to optimization of the solar combisystem (Figure 1) located in Zürich, Switzerland. The single family house has space heating demand of $60\,kWh/m^2a$ $(8{,}4\,MWh/a)$ and domestic hot water consumption is set to $200\,l/d$ $(2{,}93\,MWh/a)$. Optimization parameters varied during the optimization are listed in Table 1 and the target function F_{target} is defined by (1).

The solar combisystem is optimized for different extended fractional energy savings $f_{sav,ext}$. Seven optimizations are carried out with respect to F_{target} with corresponding constraints c with $c = 0.3, 0.35, \ldots, 0.6$ on the $f_{sav,ext}$, and one optimization is started without any constraint, that is, with $c = 0$. Optimal values of F_{target} plotted versus $f_{sav,ext}$ build the Pareto front, that is, the minimal costs per saved auxiliary energy for each given extended fractional energy savings $f_{sav,ext}$ (Figure 2).

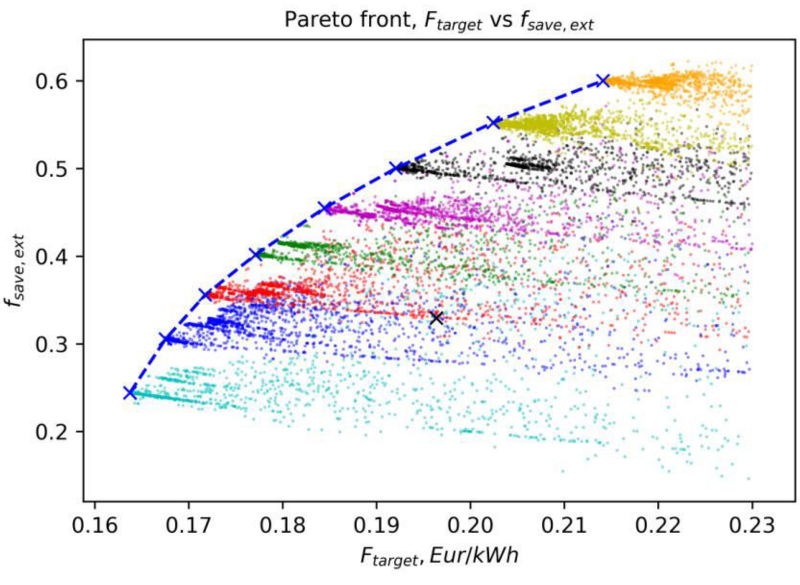

Fig. 2: Interpolation of Pareto front: optimal F_{target} versus $f_{sav,ext}$ for combisystem with DHW consumption $200\ l/d$ and SH demand $60\ kWh/m^2a$, located in Zürich. Results of 8 optimizations are shown by blue crosses. Colored points depict non-optimal configurations (F_{target}, $f_{sav,ext}$) calculated in progress of optimizations. Each color represents different optimization. Black cross shows properties (F_{target}, $f_{sav,ext}$) of base combisystem. The turnkey-cost on the x-axis include 19% VAT, but no subsidies

Each point (F_{target} , $f_{sav,ext}$) located to the left of the Pareto front is not reachable, that means, under the given boundary conditions, no combisystem can be built having such properties. On the other hand, each combisystem with the properties (F_{target} , $f_{sav,ext}$) to the right of the Pareto front is realizable but not optimal.

The optimum of each optimization corresponding to a given constraint c with $c = 0.3, 0.35, \ldots, 0.6$ is marked by a blue cross. Colored points depict the properties (F_{target} , $f_{sav,ext}$) of intermediate non-optimal system configurations which are calculated by the algorithm before the optimum is reached. Colors of the points correspond to the values of constraint c, for example, red color means $c = 0.35$, black - $c = 0.5$, etc. Higher density of the points is observed near optimum, where the algorithm converges and performs more calculations. Only the points corresponding to combisystem configurations with $F_{target} < 0.23\ Eur/kWh$ are shown for better visibility. Blue dashed line connecting the optima shows interpolation of the Pareto front.

3.2. Optimization potential. Comparison to Task 32 reference combisystem

The base configuration of the solar combisystem from IEA Task 32 has extended fractional energy savings $f_{sav,ext} \approx 0.33$ and solar energy costs of $0.196\ Eur$ per kWh of saved final auxiliary energy. This point is depicted by the black cross in Figure 2. The minimal costs for the combisystem with the same fixed $f_{sav,ext}$ are nearly $0.17\ Eur/kWh$ what is around 13.5% cheaper than those for the base configuration. On the other hand at nearly the same F_{target} as for the base system, it is possible to construct the combisystem with noticeably higher fractional energy savings $f_{sav,ext} = 0.52$.

Optimal values of optimization parameters, target function F_{target}, corresponding $f_{sav,ext}$, energy amounts such as solar yield, auxiliary energy Q_{aux}, measured at the store doubleports, store losses, various capital and annuity costs for end user and installer / energy contractor both with interest rate of 2.5% and when investing own capital, are listed in Table 2 for all eight optimized combisystems along with the base case.

It is seen from Table 2 that the Task 32 reference combisystem is more expensive than the optimal combisystem with approximately the same fractional energy savings. It is mostly due to larger collector area and store volume. The auxiliary heating volume is also slightly larger but the store insulation is thinner. The store losses are with 2.3 MWh/a noticeably larger than those for the optimal combisystem (only around 1.3 MWh/a). The systems significantly differ also in specific flow rates, set temperatures of the auxiliary heater, collector inlet positions, etc. However it is not obvious which parameters except, probably, collector area and store volume, make the most contribution to the deviation between target functions of the both combisystems. The results of sensitivity analysis from Section 5 below might be used for a rough estimation.

The optimal combisystem with similar solar energy costs F_{target} as the reference system reaches almost 19% higher $f_{sav,ext}$. It has significantly larger solar collectors ($38m^2$ vs $20m^2$) and therefore higher solar yield. The store volume remains nearly the same; the store losses are still smaller due to better store insulation and lower auxiliary set temperature.

Tab. 2: Properties of solar combisystem optimized for different target extended energy savings $c = 0, 0.3, 0.35, \ldots, 0.6$. Optimal values of parameters being varied, energy demands, solar yield and store losses for both reference heating system and optimized solar combisystems followed by differently defined capital and annuity costs and resulting target functions are showed together with reached fractional energy savings. First column shows properties of base case combisystem defined in framework of Task 32

	base case Task 32	opt1, $c = 0$	opt2, $c = 0.3$	opt3, $c = 0.35$	opt4, $c = 0.4$	opt5, $c = 0.45$	opt6, $c = 0.5$	opt7, $c = 0.55$	opt8, $c = 0.6$
Optimization parameters									
Collector area, m^2	20	10	14	19	24	30	38	45	54
Store volume, m^3	2	0.8	1.2	1.5	1.9	2	2.1	2.5	3.1
Aux. volume, m^3	0.2	0.14	0.16	0.14	0.12	0.2	0.12	0.16	0.18
Store insulation, m	0.15	0.2	0.2	0.2	0.15	0.25	0.2	0.25	0.25
Pipe diameter, mm	13	14	10	12	12	14	14	14	16
Flow rate, kg/m^2h	15	36	11	10	10	9	10	9	8
ΔT upper db, K	7	4.5	4.0	4.0	4.0	4.5	9.5	5.5	6.5
ΔT lower db, K	4	0.7	4.0	1.9	2.1	1.0	2.1	0.7	1.7
ΔT sensor pos., %	0.1	0.15	0.15	0.15	0.15	0.15	0.07	0.13	0.07

UA solar hx, W/K	2100	1000	1000	1300	1900	2200	2500	3100	3400
UA DHW hx, W/K	5333	5340	6580	5340	6580	5960	7200	7200	6580
Coll. inlet pos., %	0.4	0.65	0.81	0.84	0.81	0.84	0.87	0.84	0.68
SH outlet pos., %	0.96	0.85	0.88	0.91	0.94	0.91	0.95	0.94	0.95
SH inlet pos., %	0.15	0.28	0.30	0.30	0.27	0.27	0.27	0.26	0.18
T_{set} aux. heater, $°C$	63	55	52	55	55	54	54	51	51
Aux. upper db, K	8	9.6	7.2	7.2	10.4	11.2	10.4	8.0	8.8
Aux. lower db, K	2	2.6	2.1	2.8	3.8	2.6	3.8	2.6	3.5
Collector slope,°	45	51	53	56	57	61	60	60	61
Energy quantities, MWh/a									
Aux. demand, Q_{aux}	7.82	8.84	8.08	7.45	6.89	6.24	5.68	5.02	4.43
Solar yield (spec.)	5.89(294)	3.54(353)	4.51(322)	5.34(281)	6.50(270)	6.68(222)	7.58(199)	8.17(181)	9.09(168)
Store losses	2.30	1,00	1.22	1.41	1.99	1.50	1.82	1.74	2.05
Ref. demand, E_{ref}	14.72	14.7	14.7	14.7	14.71	14.71	14.72	14.72	14.72
Solar demand, E_{sol}	9.88	11.11	10.21	9.47	8.80	8.02	7.36	6.59	5.88
Capital costs, $kEur$ (Eur/m^2)									
End user $F_{cost,cap}$	13.3(663)	8.2(819)	10.5(749)	12.5(659)	14.6(608)	17.2(573)	19.7(519)	23.0(510)	26.4(488)
Contractor $F_{cost,cap}$	8.9(442)	5.5(546)	7.0(499)	8.4(439)	9.7(405)	11.5(382)	13.2(346)	15.3(340)	17.6(325)
Solar energy costs (Annuity costs), Eur/kWh (Eur/a)									
End user, rate 2.5% F_{target} (F_{cost})	**0.196** (951)	**0.164** (587)	**0.168** (752)	**0.172** (898)	**0.177** (1046)	**0.184** (1234)	**0.192** (1414)	**0.202** (1645)	**0.214** (1891)
End user, own cap. F^0_{target} (F^0_{cost})	0.158 (763)	0.131 (471)	0.134 (603)	0.138 (721)	0.142 (840)	0.148 (990)	0.154 (1134)	0.162 (1320)	0.172 (1517)
Contractor, rate 2.5% $F_{target,contr}$, $(F_{cost,contr})$	0.131 (634)	0.109 (391)	0.112 (501)	0.115 (598)	0.118 (697)	0.123 (822)	0.128 (942)	0.135 (1096)	0.143 (1260)
Contractor, own cap. $F^0_{target,contr}$, $(F^0_{cost,contr})$	0.105 (509)	0.088 (314)	0.090 (402)	0.092 (480)	0.095 (560)	0.099 (660)	0.103 (756)	0.108 (880)	0.115 (1011)
Extended fractional energy savings									
$f_{sav,ext}$	**0.329**	**0.244**	**0.305**	**0.356**	**0.402**	**0.455**	**0.500**	**0.552**	**0.600**

3.3. Profitability of optimized solar combisystem

Any solar combisystem lying on the Pareto front is optimal with respect to the pair (F_{target} , $f_{sav,ext}$). However, only one configuration might be optimal when taking into account its profit over the lifetime. To calculate the profitability of the solar combisystem solar energy costs and reference fuel price, for example gas price, should be at hand for the lifetime period of the system. In Figure 3 profit over 20 years compared to reference fuel price taken constant at 0.10 Eur/kWh is shown versus extended fractional savings of the system for five different solar energy costs functions. The reference fuel price is chosen constant for simplicity, any price trend can be taken as well. According to the figure, different size (fractional energy savings) of the combisystem is optimal for each solar energy costs. For example, for the private person investing its own capital (curve in magenta) solar combisystem of any size would be unprofitable. Only for the contractor investing own money (no tax) the solar combisystem remains bringing small profit of maximally around 2.4 $kEur$ at $f_{sav,ext} = 0.40$.

It is obvious that the profit calculation and consequently the best size of the solar combisystem depends on the the reference fuel price to much extent. Changing this price to 0.16 Eur/kWh makes the combisystem profitable for four out of five cost calculations. For the private person investing its own capital the solar combisystem with $f_{sav,ext} = 0.35$ would be the most profitable and it would bring around 2.3 $kEur$ over 20 years. For the contractor investing own capital and paying no tax, the solar combisystem with $f_{sav,ext} = 0.55$ would be the best, bringing 11.2 $kEur$ profit.

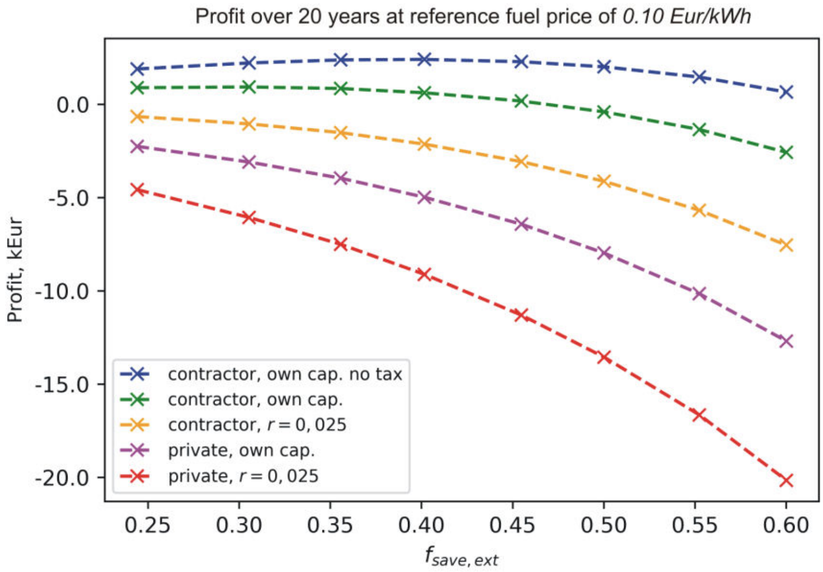

Fig. 3: Profit calculation over 20 years versus extended fractional savings (system size) for five variations of the cost function. Reference fuel price is set constant to $0.10\ Eur/kWh$ for the whole lifetime period

4. Influence of boundary conditions on optimization results

4.1. Influence of domestic hot water demand

To estimate the influence of DHW demand, the demand is changed proportionally - the DHW profile is multiplied by a factor. The combisystem is optimized for $\pm 50\%$ change in DHW consumption, that is, for $100l/d$ and $300l/d$ at 45°C. The corresponding Pareto fronts are shown in Figure 4. Light blue dashed lines show $-10\%, +10\%$ and $+20\%$ with respect to F_{target} of the Pareto front for the combisystem with the base DHW demand of $200l/d$ (blue curve).

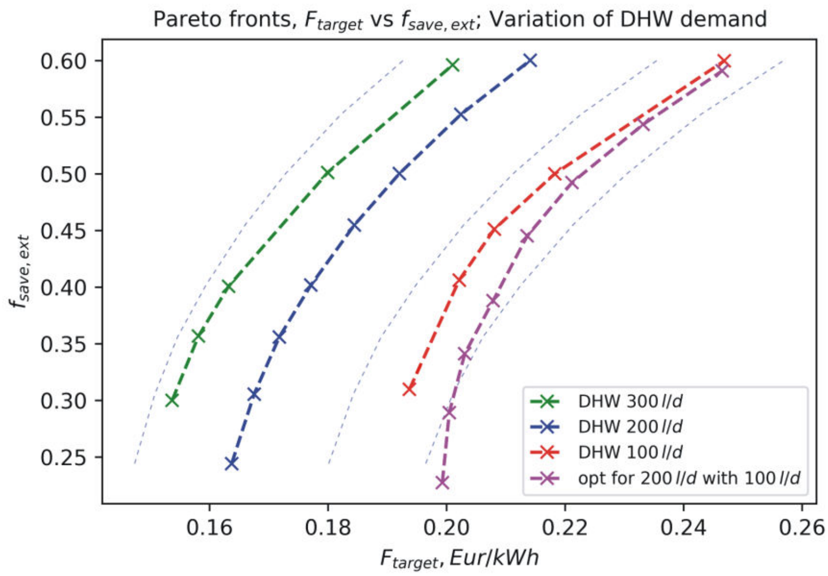

Fig. Fehler! Verweisquelle konnte nicht gefunden werden.**: Pareto fronts for combisystem with $\pm 50\%$ changed DHW demand. Light blue dashed lines show $-10\%, +10\%, +20\%$ solar costs levels with respect to combisystem with base DHW demand of $200l/d$ (blue line). Pareto front for combisystem optimized for DHW demand of $200l/d$, but then used with $100l/d$, is shown in magenta**

If the DHW consumption decreases by 50% to $100l/d$, then the solar costs of the combisystem optimized for this consumption increase by around 15% depending on the point on the Pareto front. The solar heat from the combisystem optimized for 50% larger DHW demand will be around $5-8\%$ cheaper.

The quality of the solar combisystem optimized for the base DHW demand of $200l/d$ but used with reduced demand of $100l/d$ is shown by the magenta curve in Figure 4. It is seen that although the energy costs are increased by around $18-20\%$ in comparison to the base demand, the combisystem optimized for the base demand but used with the reduced demand is not significantly worse (only around $1-5\%$) than the combisystem optimized for the reduced demand.

4.2. Influence of space heating demand

The influence of the space heating demand is estimated in a similar way. Three building envelopes are defined within IEA Task 32 having space heating demand of $30, 60$ and $100\ kWh/m^2a$. Pareto fronts for the optimal combisystems for all three buildings located in Zurich are shown in Figure 5. The curves lie close to each other, differing in less than 5%. A closer look at the data behind the curves shows more distinctions. For example, to reach $f_{sav,ext} = 0.50$ by the combisystem optimized for the SH demand of $30\ kWh/m^2a$, collector area of $20\ m^2$ is required, for $60\ kWh/m^2a$ - $38\ m^2$ and for $100\ kWh/m^2a$ - $57\ m^2$. The fact that the green curve corresponding to SH demand of $30\ kWh/m^2a$ lies to the right of the blue one can be explained by good house insulation – SH demand is shifted to the colder months with less solar yield.

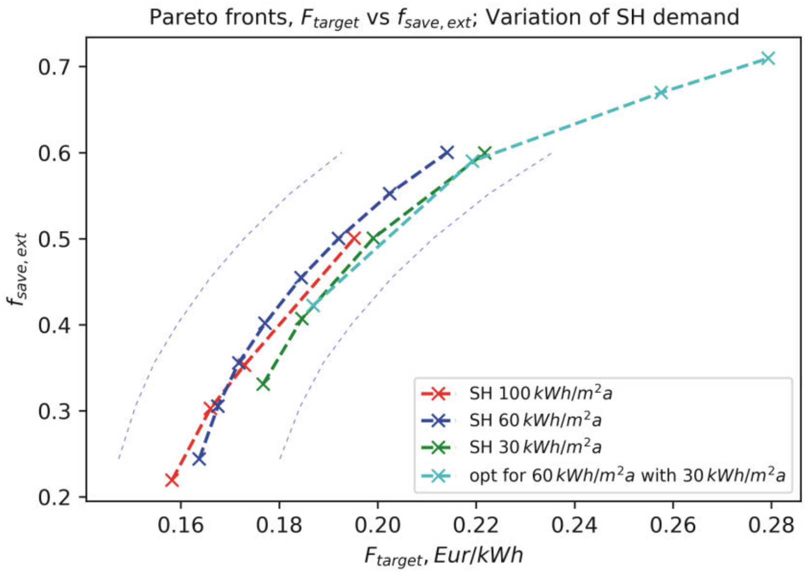

Fig. 5: Pareto fronts for combisystem with changed SH demand. Light blue dashed lines show $-10\%, +10\%$ with respect to combisystem with SH demand of $60\ kWh/m^2a$ (blue line). Pareto fronts for combisystems with changed SH demand lie close to each other but system configurations differ significantly. Combisystem optimized for SH demand of $60\ kWh/m^2a$ and then applied to better insulated house with $30\ kWh/m^2a$ (in cyan) remains optimal but each point on base Pareto front is shifted to a point located higher on this line.

The combisystem optimized for the SH demand of $60\ kWh/m^2a$ but operated with $30\ kWh/m^2a$ is almost as good as the combisystem optimized for $30\ kWh/m^2a$. This is shown by the cyan curve in Figure 5 built through only the selected points (cyan crosses) which do not induce large DHW penalty. The curve is shifted up with respect to the base Pareto front, meaning that, for example, the combisystem with $f_{sav,ext} = 0.30$ optimized for the base SH demand of $60\ kWh/m^2a$ obviously has significantly higher $f_{sav,ext} = 0.42$ when applied to better insulated house with only $30\ kWh/m^2a$ heating demand.

4.3. Influence of weather conditions

To estimate the influence of weather conditions, the combisystem is optimized for two additional locations, Stockholm and Madrid. The corresponding Pareto fronts are shown in Figure 6. The combisystem in Madrid is optimized with a less insulated house having larger space heating demand of $100\ kWh/m^2a$ if located in Zurich, but still needs only around $42\ kWh/m^2a$ in Madrid. The minimal solar energy costs are nearly equal for the combisystems built in Stockholm and Zurich for $f_{sav,ext} < 0.35$; For higher $f_{sav,ext}$ (up to 0.50) the comibsystem in Stockholm is up to 12% more expensive whereas the combisystem built in Madrid is around 40% cheaper than in Zurich. Similarly as for variation of space heating demand, the combisystem remains to be nearly optimal when its location is changed (simultaneous variation of solar gain and space heating demand), at least when moving the combisystem from Stockholm to Zurich as it is shown by cyan curve in Figure 6.

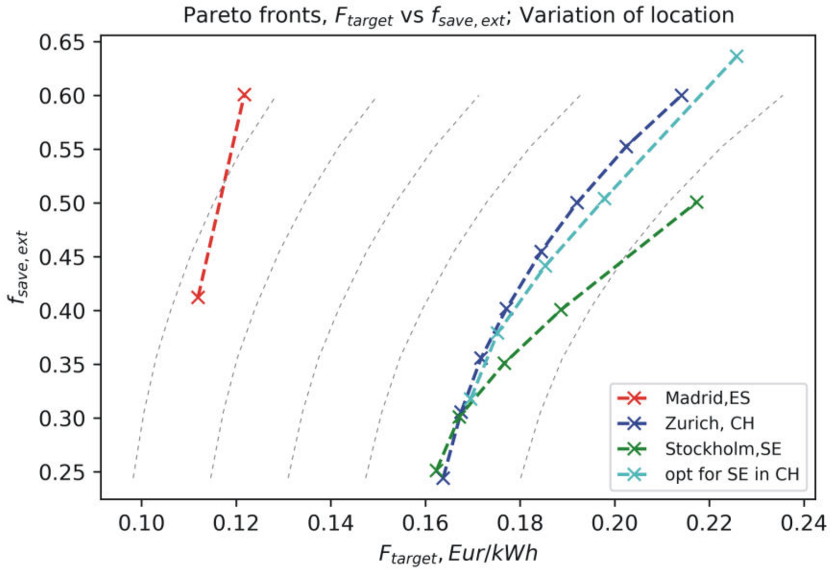

Fig. 6: Pareto fronts for combisystems optimized for different locations. Gray dashed lines show in 10% steps solar costs levels with respect to Zurich location. Combisystem built in Madrid is around 40% cheaper. For $f_{sav,ext} < 0.35$, combisystem built in Stockholm is comparably expensive as that located in Zurich but it is more expensive for larger $f_{sav,ext}$. Combisystem optimized for Stockholm location and then built in Zurich is almost optimal but with similar shift as for variation of SH demand

5. Parameter influence near optimum

The estimation of the sensitivity of the solar energy costs F_{target} upon single parameters varied in a larger parameter space containing the optimum point is carried out by global sensitivity analysis: Multiple Linear Regression (MLR) and Morris methods. The sensitivity analysis is applied to the solar combisystem already optimized for the reference boundary conditions defined above in subsection 2.1. No constraints are applied to $f_{sav,ext}$ in the calculations.

The influence of all 18 optimization parameters together with 2 boundary conditions is investigated. Since the sensitivity analysis requires many simulations with parameter values independently varying near the optimum point, the probability is large that the DHW and SH demands cannot be fully covered by certain combisystem configurations and the respective penalties apply. Thus, the variation range for each parameter is defined as either $[-50\% ; 0\%]$ or $[0\% ; +50\%]$ depending on where less penalty is anticipated due to not meeting DHW or SH comfort requirements. In this way, the sensitivity of the optimization parameters in a “half space” with the optimum lying on the boundary is to be investigated. The optimization and boundary condition parameters with corresponding sensitivity ranges are listed in Table 1.

5.1. MLR Method

The MLR method attempts to model the relationship between k independent variables $x_j, j = 1,..,k$ (parameters) and dependent variable y (target function) in the linear form:

$$y_i = \beta_0 + \sum_{j=1}^{k} \beta_j x_{ij} + \varepsilon_i , \qquad i = 1,..,n, \tag{5}$$

where y_i are n measurements of the target function for corresponding parameter vectors $(x_{i1}, \dots x_{ik})$, that is, system configurations x_i; ε_i denote the model errors. The estimates of the coefficients β_j, denoted as $b_j, j = 0, \dots, k$, are calculated by minimizing the least-squares error, that is, from $\sum_{i=1}^{n} \varepsilon_i^2 \rightarrow min$. The coefficients b_j are the influence measures for corresponding parameters over the variation space. They represent the averaged change of the target function y due to the unit increase in the corresponding parameters x_j when all other parameters are fixed. To determine the quality of the model, that is, to check how well the measured values y_i are described by the fit, the determination coefficient R^2 is used.

The "measured" data required as an input for the MLR are obtained as follows. First $n = 500$ parameter sets (combisystem configurations) are chosen by random sampling of the Latin Hypercube what gives the uniform distribution with respect to each parameter, and then the "measured" F_{target} is calculated for each combisystem configuration. The size n of the "measured" data has influence on the accuracy of the model, $n = 500$ is turned out to be fairly enough.

The MLR model is built using the simulated "measured" data for the solar combisystem described above. The determination coefficient R^2 for the model with all parameters from Table 1 equals 0.97 meaning that 97% of the variance in measured data is explained by the MLR model. It justifies application of the MLR. If only the optimization parameters are taken as independent variables, then $R^2 = 0.93$. It can be explained by large linear impact of the two boundary conditions – DHW demand and collector price. Influence of single parameters on the solar energy costs F_{target} is shown in Figure 7.

5.2. Morris Method

In contrast to the MLR, the Morris method (Morris, 1991) can be successfully applied to the problems having significantly non-linear relationships between the target function and parameters. However, the Morris method can identify the parameter importance only qualitatively providing no reliable quantification of its influence. Another drawback is lack of the self-verification indicator similar to the MLRs coefficient of determination R^2.

In the Morris method two quantities are used as sensitivity measures for each parameter; the measure μ^* estimates the overall, linear effect of the parameter on the target function, and the measure σ accounts for the second and higher order effects, including interaction effects in which the parameter is involved. The Morris method varies one parameter at a time. Each parameter may take only a set of discrete values, the so-called levels, fixed within the parameter variation range. The elementary effects are calculated for each parameter by changing it over 55% of its variation range defined in Table 1. Number of trajectories, that is, at how many points elementary effects are evaluated for each parameter is set to 80.

In Figure 7 the investigated parameters are presented in descending order regarding their Morris sensitivity measures μ^*. The larger μ^* for the parameter the more linear influence it has on F_{target}. The values of μ^* can be recalculated into mean values of absolute change of F_{target} by simple relation $\overline{|\Delta F_{target}|} = \mu^* \cdot 0.55$ or in its relative change with respect to the optimal F_{target} which is shown on the left y - axis in Figure 7. The 95% confidence intervals of the mean values μ^* are shown by black lines for each parameter. It is seen that the both boundary condition parameters - collector price and domestic hot water demand have large influence followed by the optimization parameters as boiler set temperature, slope, collector area, collector input height, auxiliary volume, etc.

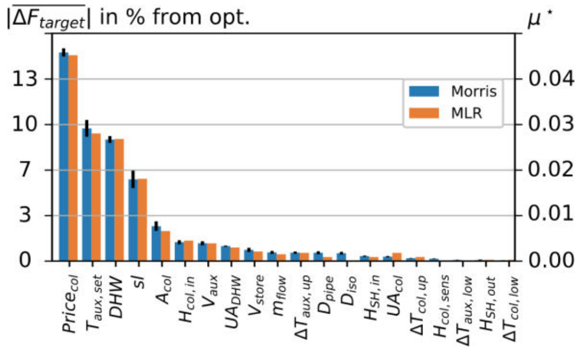

Fig. 7: Results of sensitivity methods applied in parameter variation space as from Table 1. Morris measure μ^* and recalculated $\overline{|\Delta F_{target}|}$ are shown along with results obtained by MLR. Black lines denote 95% confidence interval

Besides the Morris sensitivity measure, similar sensitivities calculated from estimates of the regression coefficients of the MLR method are shown in orange. Although being completely different, the both methods deliver very similar results. It might be considered as a kind of justification of both of them.

6. Conclusions

In the presented paper, the IEA Task 32 solar combisystem is optimized with the hybrid genetic CHC - binary search algorithm for several extended fractional savings and the Pareto front - optimal solar energy costs vs. extended fractional savings - is obtained. It is shown that improvement of either by around 13% in terms of solar costs or 19 percent points in terms of energy savings is reachable compared to the parametrization of the standard IEA Task 32 solar combisystem.

The influence of the domestic hot water and space heating demands as well as the climate conditions (location of the combisystem) on the Pareto front is investigated showing much impact of the DHW demand. It is shown that the combisystem optimized for the base conditions but operated under the changed conditions is not significantly worse than the combisystem optimized for the changed conditions.

The influence of variations of each optimization parameter as well as two boundary condition parameters on the solar energy costs is accessed near the optimum point by application of MLR and Morris methods. Good coincidence of the results of both methods and large value of the determination coefficient of the MLR justify their application.

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8. Nomenclature

Quantity	Symbol	Unit
Collector area	A_{col}	m^2
Store volume	V_{store}	m^3
Auxiliary volume	V_{aux}	m^3
Number of aux. nodes	N_{aux}	-
Store insulation	D_{iso}	m
Pipe inner diameter	D_{pipe}	mm
Spec. coll. flow rate	m_{flow}	kg/m^2h
ΔT controller upper db.	$\Delta T_{col,up}$	K
ΔT controller lower db.	$\Delta T_{col,low}$	K
ΔT controller sensor pos.	$H_{col,sens}$	-
UA value of solar hx.	UA_{col}	W/K
UA value of DHW hx,	UA_{DHW}	W/K
Coll. inlet pos. in store	$H_{col,in}$	-
SH outlet pos. in store	$H_{SH,out}$	-
SH inlet pos. in store	$H_{SH,in}$	-
Set temp. of aux. heater,	$T_{aux,set}$	$°C$
Aux. controller upper db.	$\Delta T_{aux,up}$	K
Aux. controller lower db.	$\Delta T_{aux,low}$	K
Collector slope	sl	°

DHW demand multiplier	DHW	-
Collector price	$Price_{col}$	Eur/m^2
Solar energy costs	F_{target}	Eur/kWh
Aux. energy, ref. combisystem	E_{ref}	kWh
Aux. energy, solar combisystem	E_{sol}	kWh
Extended fractional energy savings	$f_{sav,ext}$	kWh
Penalty function	$\hat{F}_{penalty}$	kWh
Penalty function, DHW	$F_{pen,DHW}$	kWh
Penalty function, SH	$F_{pen,SH}$	kWh
Cost function	F_{cost}	Eur
Capital costs	$F_{cost,cap}$	Eur
Discount component price	$F_{cost,disc}$	Eur
Contractor costs	$F_{cost,contr}$	Eur
Component	C_i	-
Installer margin	m	-
Interest rate	r	-
Vector of opt. parameters	X	-
Constrain on $f_{sav,ext}$	c	-
Measurements of F_{target}	y_i	Eur/kWh