A BI-LEVEL DESIGN AND OPERATION OPTIMISATION PROCESS APPLIED TO AN ENERGY CENTRE

Ralph Evins[1,2], Kristina Orehounig[2]
[1] Empa, Swiss Federal Laboratories for Materials Science and Technology,
Überlandstrasse 129, 8600 Dübendorf, Switzerland
[2] Chair of Building Physics, ETH Zürich,
Stefano-Franscini-Platz 5, 8093 Zürich, Switzerland
ralph.evins@empa.ch

ABSTRACT

This paper presents the methods and results of a bi-level optimisation process used to select and size the components of an energy centre as well as to determine their optimal operation. The optimisation process used a single-objective optimisation of operational control nested within a two-objective optimisation of design parameters to minimise capital costs and carbon emissions.

Results given include the overall trade-off front, trends amongst design variables, and operational schedules for a particular solution. Constraints on roof area were critical at the design level, and complex interactions between demand and supply were identified at the operational level.

INTRODUCTION

Overview

Heuristic optimisation approaches like genetic algorithms provide a powerful way to address problems that are not convex, may have discontinuities, and lack gradient information. They can also handle multi-objective optimisation. This is typical of design problems such as the selection and sizing of plant. However, they rapidly become unmanageable for very large numbers of variables and constraints.

Mixed Integer Linear Programming (MILP) is an optimisation approach that is only suitable for problems without discontinuities or nonlinearities. It can solve problems with very large numbers of variables and constraints very rapidly if the underlying complexity of the problem is not too great.

Bi-level optimisation approaches divide a problem into two levels, where the lower level depends upon variables of the upper level, and the upper level objective(s) depend on the lower level objective(s). In this work we combine a multi-objective genetic algorithm for design optimisation and a MILP for operational optimisation into a bi-level approach. The optimisation process consists of a design level, and nested within it an operational level. An overview is given in Figure 1.

The aims of this research are twofold: to avoid the assumptions regarding control strategies that are common in design level optimisation approaches, and to incorporate design decisions that are often omitted into operational level problems. This is achieved using a combination of two methods (GA and MILP), in order to use the best features of each method as appropriate, rather than applying a single method to both parts of the problem.

Previous work

Many works have applied computational optimisation processes to low-carbon building design: a comprehensive review is given in (Evins, 2013). In relation to energy centres, some works (Abdollahi and Meratizaman, 2011; Evins et al., 2011; Kayo and Ooka, 2009) performed a design optimisation by making assumptions regarding optimal control; others (Shaneb et al., 2012; Vasebi et al., 2007) optimised operational scheduling but not design aspects. Two works (Ooka and Komamura, 2009; Tanaka et al., 2007) addressed both design and operational issues as part of the same optimisation, using a genetic algorithm for both, but this was only practical over a single day.

Deb and Sinha (2008; 2009) have developed the idea of bi-level optimisation using a multi-objective evolutionary algorithm. They adapted the selection procedure of the NSGA-II algorithm (Deb et al., 2002) to account for non-domination rank and crowding distances at the two distinct levels.

There have been very few applications of a bi-level approach to problems concerning low-carbon buildings. Fazlollahi and Maréchal (2013) applied an evolutionary algorithm and mixed-integer linear programming combination to the multi-objective and multi-period optimisation of biomass conversion technologies. They refer to the approach as a master-slave algorithm in which decision variables are partitioned into design and control groups. The design level proposed plant capacities, and the slave level solved the heat cascade, mass balance and energy balances based on the outputs of a thermo-economic model. The process was tailored to investigate the use of conversion units, co-generation units and heat recovery units.

DESIGN LEVEL

The design problem concerned the configuration of the provisional energy centre layout shown in Figure

2. The nine design variables are listed in Table 1, which shows the maximum value and step size for each. They cover discrete choices of plant and storage capacities; a capacity of zero indicates that a particular item was omitted. The number of possible unique design configurations was 5,598,720.

The two objectives of the design optimisation were cost (capital only) and annual carbon emissions. These represent the typical focus of building developers and owners who wish to achieve a given level of environmental certification for minimal construction cost. The capital cost objective consisted of an installation term (only included if the item capacity was above zero) and a proportional term (multiplied by the item capacity) for each item of plant, and was evaluated using price estimates from manufacturers (given in Table 1). A constraint limited the maximum available roof space for renewables (solar thermal and PV) to $50m^2$.

In order to evaluate the carbon emissions objective, it is necessary to know how the proposed plant design will be operated in order for hourly energy consumption to be calculated; this is determined by the sub-optimisation process detailed below.

The design optimisation was performed using the `gamultiobj` multi-objective genetic algorithm in MatLab[1], which is loosely based on NSGA-II (Deb et al., 2002). Briefly, genetic algorithms manipulate a population of solutions using operators for mutation and crossover. Individuals are selected to continue to the next generation based on their performance against objective function(s). For multiple objectives, this is often based on the degree of non-domination, i.e. how many solutions are better in all objectives than the one under consideration. NSGA-II is a very widely used choice because it is robust to many different problem types whilst still being reasonably efficient.

The optimisation was run for 50 generations with a population size of 50 and the following parameters and options: linear feasible seeding; crossover fraction 0.8; single point crossover; adaptive feasible mutation; tournament selection; elite count 5; pareto fraction 0.5. An archiving system was added to avoid re-evaluating old solutions and to allow the final overall Pareto front of all solutions visited to be collated.

OPERATIONAL LEVEL

The ‘energy hub’ concept originally proposed by Geidl and Andersson (2005) was used to solve the energy flow scheduling problem for each design proposed by the genetic algorithm (i.e. this sub-optimisation acted as the simulator for the master optimisation). This model formulates a linear programme to represent the dynamic conversion of different energy streams. A mixed integer formulation was used based on that of Parisio et al. (2012) in order to include storage terms. To briefly describe the model (the reader is referred to the above papers for a more comprehensive description):

- A conversion matrix (see Table 2) describes the relationship between input I_x to output O_y (see Figure 2).
- Varying the coefficients P_z of the conversion terms determines the schedule of operation that meets the demands, within the constraints on the inputs, whilst minimising an objective function.
- A multi time-period formulation is obtained by solving for different values of P for each time step, for which there are different demand and supply constraints.
- This allows storage terms to be implemented that transfer energy from one timestep to another, based on conservation and loss equations.

The energy hub model used the design parameters (plant and storage capacities) proposed by the genetic algorithm as capacity constraints, and gave as an output the optimal operational schedule that minimises carbon emissions. These were calculated by applying the following carbon factors to the energy demands obtained: grid electricity $0.47kgCO_2/kWh$; natural gas $0.18kgCO_2/kWh$. The optimisation was performed three times using demand profiles for a winter week, mid-season week and summer week. The carbon emissions were then averaged and scaled to an annual value to be used by the design level optimisation.

The core constraint at the operational level concerned plant energy conversion performance, forming the main matrix of the energy hub model, given in Table 2. Negative values indicate that one energy stream is used as an input for conversion another stream. Where this is not the case (grid electricity; gas for boiler, CHP and fuel cell), the above carbon factors were applied. The other terms in the matrix indicate conversion efficiencies (e.g. 80% for gas boiler), between multiple energy streams if applicable (e.g. fuel cell has an electrical efficiency of 35% and a heat efficiency of 30%).

Temporally-varying constraints (i.e. time series giving a different constraint value for each timestep) governed the energy demands to be met (for electricity, cooling and heat) and the availability of solar gain for PV and solar thermal. Thermal comfort was ensured since the building energy demands were pre-calculated to meet the desired set point temperatures. These were obtained from an EnergyPlus model of a $500m^2$ office building using a Zurich weather file. The solar availability was calculated from the same weather file for a south-facing panel at 30 degree inclination. In addition to the space heating, cooling and lighting loads, a base load of 5kW heat and 3kW electricity were also

[1] It is worth noting that a limitation of the Matlab implementation is the lack of nonlinear constraints.

included, representing domestic hot water and background parasitic electricity use respectively.

Constraints also governed the minimum loads permitted for some plant (10% for ground source heat pump (GSHP) and air source heat pump (ASHP); 50% for combined heat and power (CHP); only on or off for fuel cell (FC)) and the performance of storage (battery: 95% input efficiency; 95% output efficiency; 1% loss per timestep; hot water tank: 100% input efficiency; 95% output efficiency; 2% loss per timestep).

There were 18 variables per timestep (of which 5 were binary, the rest continuous): the 10 conversions, and four each for the two stores (charging quantity, discharging quantity, charging state and discharging state). The optimisation was conducted for three periods each containing 120 timesteps, giving 6,480 variables overall. For each timestep there were 3 equality constraints (the three energy demands to be met) and 12 inequality constraints (PV availability, solar thermal availability, and five for each store governing storage losses and continuity), giving 5,400 constraints overall.

RESULTS AND DISCUSSION

Design level

Figure 3(a) shows the objective space of the design level optimisation: the points in blue indicate all solutions evaluated. The total number of function evaluations was 810, each of which performed 3 operational level optimisations (winter, mid-season, summer). The final population contained 18 Pareto-optimal solutions; the archive of all solutions contained 69 Pareto-optimal solutions. These are shown in red in Figure3(a). Figure 3(b) shows a plot of hypervolume against generation. Hypervolume is a measure of the area enclosed by the Pareto front. It clearly shows that the Pareto front is not advancing, and thus it is reasonable to assume that the optimisation is complete.

Figure 4 uses the graphical approach of Brownlee and Wright (2012) to analyse the design level results. It shows the variation in design level variable values amongst the 69 optimal solutions using a colour scale. The key at the bottom shows the variable value each colour corresponds to. The objective function values for each are also indicated as bar graphs; these correspond to the axes of Figure 3(a). This method of plotting solutions makes it easy to identify trends amongst design variables.

The most obvious feature of the design variables is that the battery storage is never specified, presumably since it is so expensive and the large thermal store available is sufficient. There are some straightforward trends, where the variable is added more or less linearly in proportion to one of the objectives. The CHP is added almost exclusively for only the most expensive, lowest carbon solutions; the fuel cell and absorption chiller options are only used for those in the more expensive half of the solution set. PV is added gradually when progressing through the lower cost solutions, rapidly reaching its maximum; 53 out of 69 solutions have the full capacity of 50m^2 PV installed.

Other variables exhibit more complex behaviour. Solar thermal is added in small amounts (10m^2) periodically, frequently being exchanged for other options. Air source and ground source heat pumps are added in alternate bands. The hot water tank capacity is also periodic, alternating in response to other changes. This is surprising since storage is often understood to be an essential feature, but there are solutions with zero storage in the upper (lower emissions) half of the solution set.

Operational level

An example of the results of one of the operational level optimisations is given in Figure 5, showing the optimal schedules for a design solution from the middle of the range, which is highlighted in black in Figure 4. This is indicative of the sort of operational result obtained for every design level evaluation. The electricity, heat and cooling balances are presented for the winter, mid-season and summer periods used. In each case the black line shows the building energy demand (as negative), and the other contributions are shown for each technology. Where energy is subtracted for conversion to another form, this is shown as negative. For heat, storage input and output is also shown (with input as negative).

For electricity, demand reaches a maximum of 66kW during the day in winter (which reduces on sunny days), and a maximum of 30kW most days in summer. To supply this there is a balance between the fuel cell (which runs most of the time, but has a small capacity), PV (for which there are big gaps in availability, particularly in winter) and import from the grid.

Cooling is not required in winter. In the mid-season period the absorption chiller (30kW for this particular design solution) is big enough to meet almost all of the required load. Conversely in summer almost all the load is supplied by electric chiller, which forms the majority of the electricity demand. The absorption chiller supplies around 10% of the cooling demand, and forms the majority of the heat demand in summer.

Heating demands are very sporadic in both the winter and mid-season periods; in the summer period only the base load is present. Solar thermal provides very little heat in winter and mid-season, but more in summer. The ground source heat pump is used to meet peak demands in winter. The fuel cell, which runs almost all the time, provides around half the base heat load. The storage is used in all periods. In the summer it is charged during the day and discharged in morning and evening; in other periods it is less regular.

The majority of the carbon emission come from grid electricity (winter: 1,251kgCO_2/week; mid-season: 1,057kgCO_2/week; summer: 2,275kgCO_2/week). The emission from gas for the fuel cell were very low and constant across all periods at around 20kgCO_2/week; in winter only, the gas boiler had emissions of 136kgCO_2/week. Total emissions are highest in summer (2,297kgCO_2/week), and lower in winter (1,408kgCO_2/week) and mid-season (1,079kgCO_2/week). These values averaged over the whole year[2] gives 116,391kgCO_2/a, the objective function value for the design level optimisation.

CONCLUSIONS

We present the results of a bi-level design and operational optimisation process in which plant capacities and operational scheduling are simultaneously examined, using the operational level process as the evaluation step within the design level algorithm.

Results are presented for the overall optimisation process, giving the trade-off front of solutions obtained and a detailed graphical analysis of the trends amongst the design variables. Operational schedules are also shown for a selected solution. A wide diversity of solutions were found, showing that the method can effectively explore the design space. They ranged from the zero-additional-cost solution with emissions of 173tCO_2/a to the low carbon solution costing £139,200 but emitting only 101tCO_2/a.

It is clear from both the design and operational level results that the constraint on roof area is critical, in particular the impact on PV capacity. There are also obvious sensitivities regarding cost effectiveness of certain technologies (e.g. battery storage), and regarding the precise nature of complex conversion systems (e.g. the heat/power ratio of fuel cells and CHP).

Examining the operational level solutions highlights the complex interactions between demand profiles and plant operational constraints. It would be useful in future to assess the robustness of different designs to variations in demand, perhaps using a stochastic approach. Future work will also extend the process to include a link to the building energy model to allow fabric properties to be optimised alongside plant design and control. It would also be useful to explore ways of coupling two multi-objective processes to explore different operational level strategies.

The bi-level process used here provides a powerful means of assessing design level choices when there are significant operational constraints to be negotiated. This is likely to be the case in any situation with multiple energy streams, multiple convertors, storage options and detailed demand and supply profiles to be respected. This appears to be a fruitful line of future research, bridging the design and control optimisation fields.

[2] (2297+1408+1079)/3 *(365/5), since there were 5 days per period.

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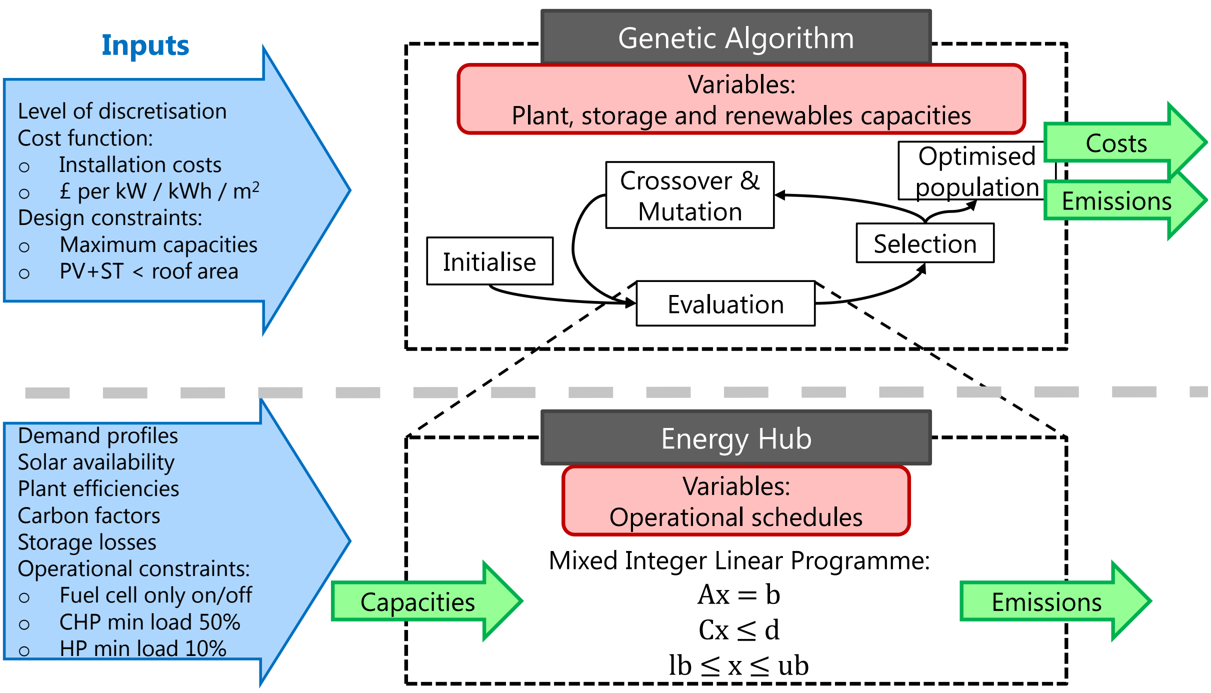

Figure 1. Schematic of the bi-level design and operational optimisation process.

Table 1. Design level variable bounds, step sizes and cost function coefficients.

	PV	GSHP	ASHP	CHP	FC	ST	Abs. chiller	Battery	Hot water
Max	$50m^2$	25kW	25kW	25kW	10kW	$50m^2$	30kW	15kWh	50kWh
Step size	$10m^2$	10kW	5kW	5kW	2kW	$10m^2$	7.5kW	5kWh	10kWh
£	£500	£2000	£500	£2000	£1000	£1000	£5000	£8000	£200
£/unit	£500/m^2	£1000/kW	£700/kW	£1000/kW	£2000/kW	£250/m^2	-	£2500/kWh	£40

Table 2. Operational level energy conversion matrix.

	Grid	PV	GSHP	ASHP	Boiler	CHP	FC	ST	Chiller	Abs. chiller
Electricity	1	0.2	-1	-1	0	0.49	0.35	0	-1	0
Cooling	0	0	0	0	0	0	0	0	2.5	0.7
Heat	0	0	4.5	3.5	0.8	0.3	0.3	0.6	0	-1

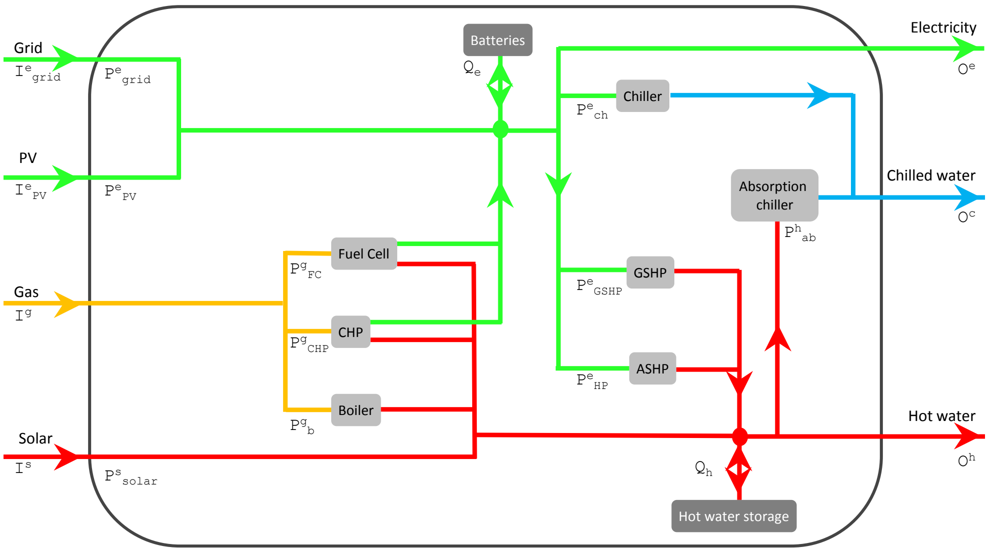

Figure 2. Schematic of the plant layout options considered in the energy centre. Inputs I, conversions P, storage Q and outputs O are indicated.

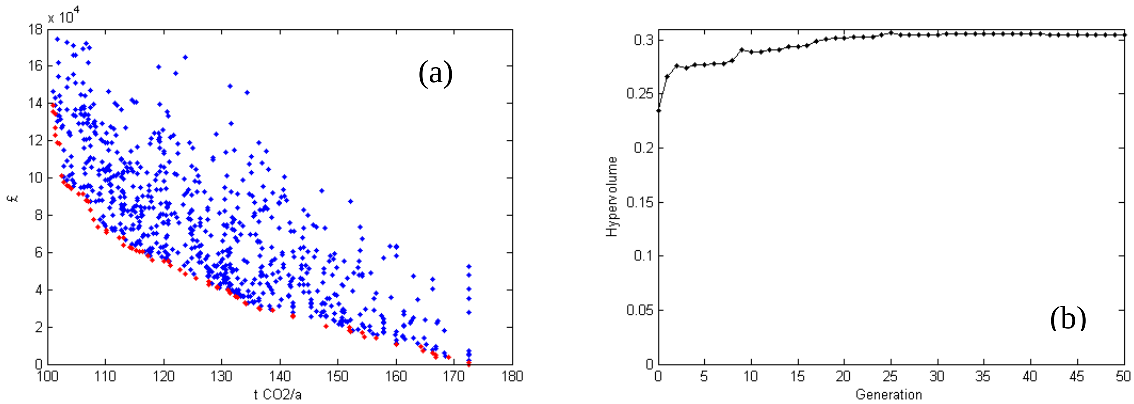

Figure 3. Results of the design level optimisation. (a) All solutions evaluated (blue) and Pareto front (red). (b) Hypervolume against generation.

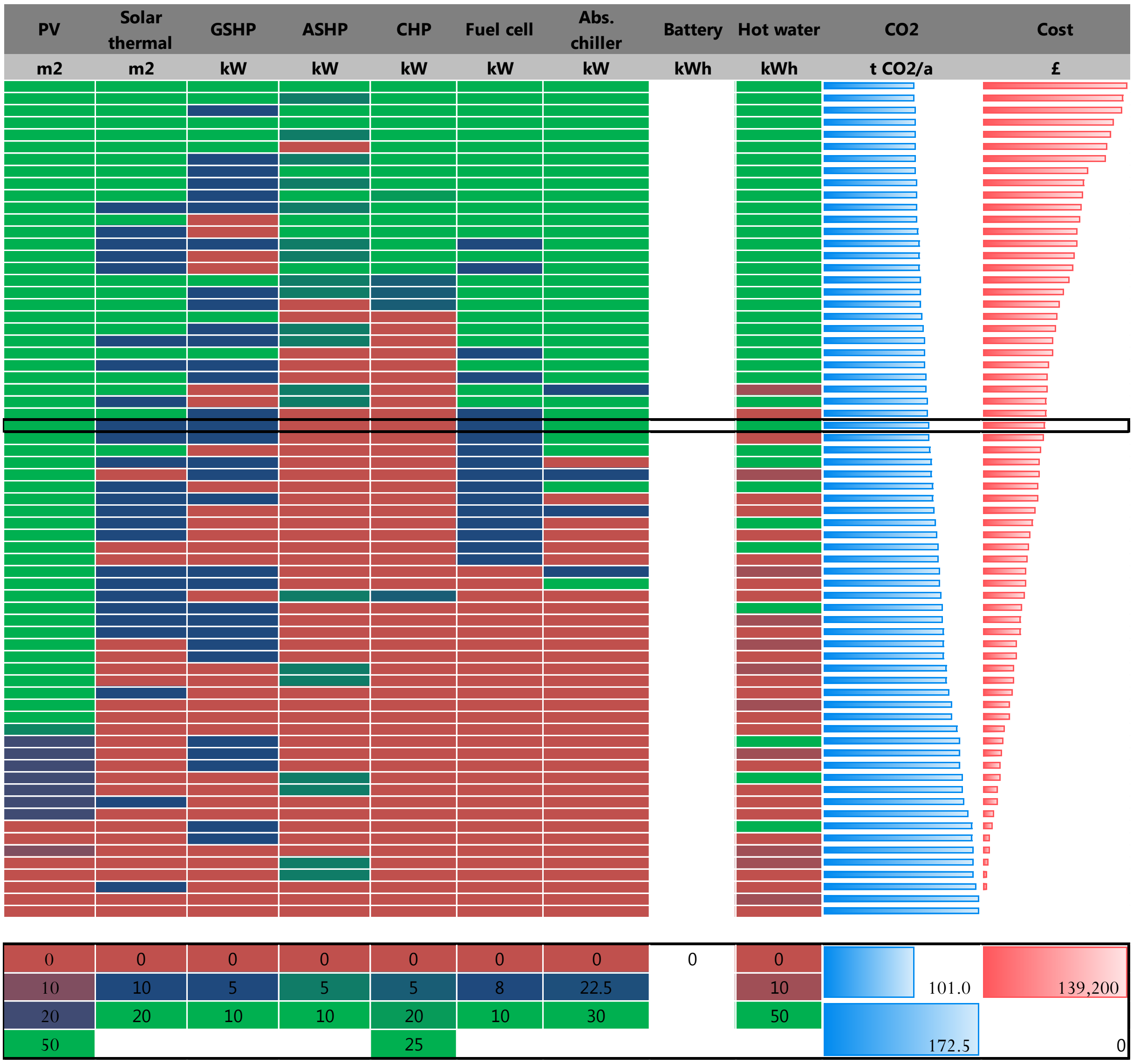

Figure 4. Variations in variable values amongst the solutions to the design level optimisation. Objective function values are also indicated. The key gives the numerical value of each colour for each column.

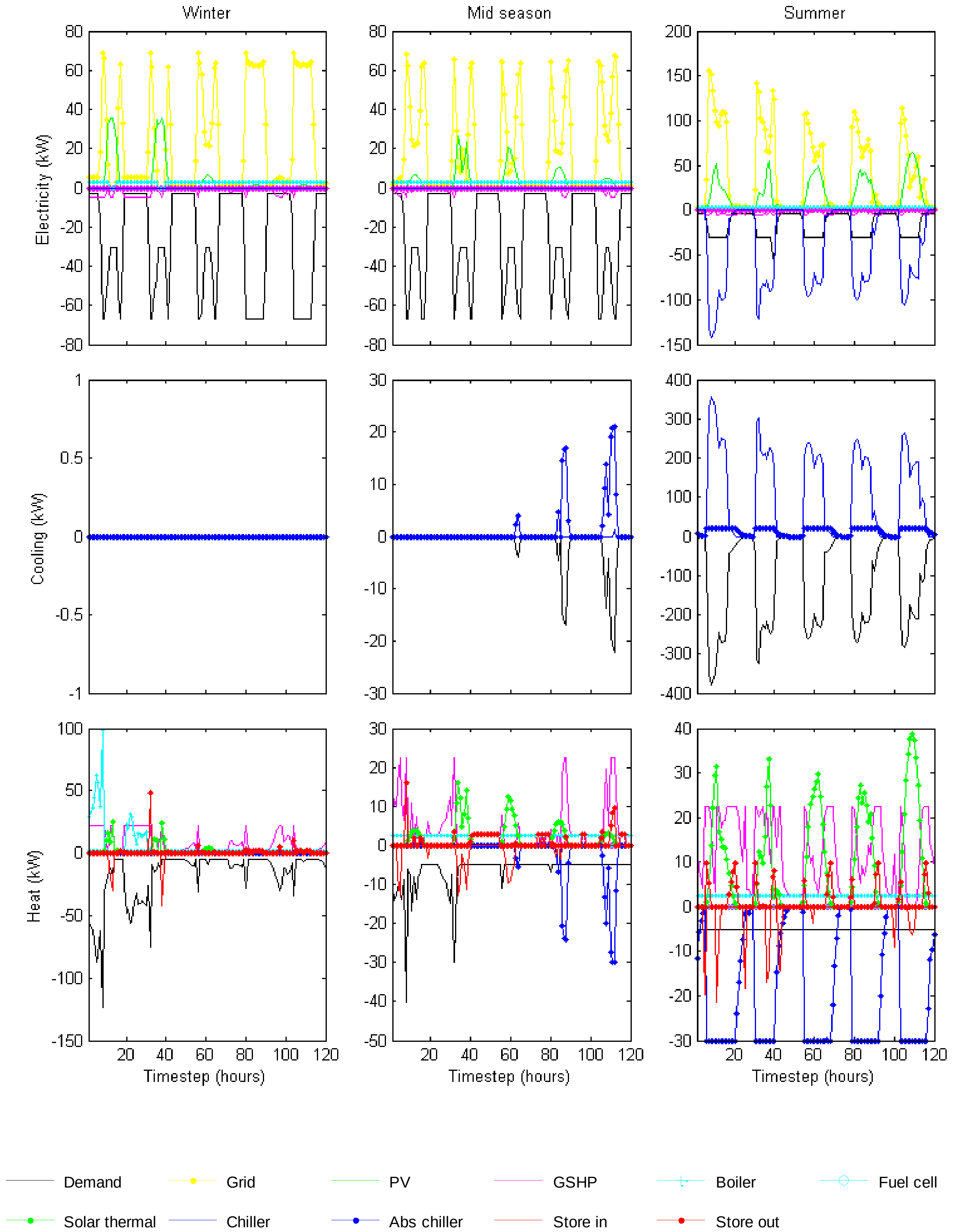

Figure 5. Results of the operational optimisation for an example design solution (highlighted in Figure 4). Energy balances are shown for electricity, cooling and heating for the winter, mid-season and summer periods.