MULTI-OBJECTIVE OPTIMIZATION OF THE DESIGN AND OPERATION OF AN ENERGY HUB FOR THE EMPA CAMPUS

M. Hohmann[1,2,3], C. Waibel[1,2], R. Evins[1,2], J. Carmeliet[2,4]

1: Laboratory for Urban Energy Systems, Swiss Federal Laboratories for Materials Science and Technology, EMPA, Duebendorf, Switzerland

2: Chair of Building Physics, Swiss Federal Institute of Technology, ETHZ, Zurich, Switzerland

3: Automatic Control Laboratory, Swiss Federal Institute of Technology, ETHZ, Zurich, Switzerland

4: Laboratory for Multiscale Studies in Building Physics, Swiss Federal Laboratories for Materials Science and Technology, EMPA, Duebendorf, Switzerland

ABSTRACT

This paper presents a comparison of two multi-objective optimization processes used to simultaneously select and size the components of an energy hub and to determine their optimal operation according to net present value and carbon emissions. The first is a single-level optimization process that uses a mixed-linear integer programming (MILP) model based on the energy hub concept in which time-varying demands and supply availabilities must be matched using conversion and storage options. The second is a bi-level optimization process composed of a multi-objective genetic algorithm (GA) as the upper level to optimize selection and sizing of components. A linear programme is nested within the GA as the lower level to optimize the operation of each proposed system.

The study uses measured data from the Empa research campus in Dübendorf, Switzerland for the heating, cooling and electricity demands that must be met. Appropriate values for solar availability, energy prices and equipment costs were used. The optimization process is conducted for a whole year, allowing the consideration of seasonal storage. The energy hub includes electricity, gas, solar power, and medium temperature and high temperature thermal networks. The technologies considered include boilers, chillers, photovoltaic panels, combined heat and power plants, heat pumps and storage.

Results presented give trade-off fronts of the competing objectives (carbon emissions and discounted costs) that reveal a set of optimal design solutions, including their optimized hourly operational schedules. The effectiveness of the two approaches is compared, including the convergence of the optimization, necessary computing time and the identification of solution characteristics. It is shown that the single-level optimization finds a better Pareto front in much shorter time than the bi-level approach for this problem instance.

Keywords: Multi-objective, Bi-Level, Optimisation, Energy Hub, Measured data

INTRODUCTION

Research facilities often consume large amounts of energy for heating, cooling and operation. Budget constraints and environmental considerations make it necessary to minimise costs and emissions of the energy consumption. As shown in [1], optimization techniques are increasingly used to design and operate multi-carrier energy systems. The optimization methods are used in combination with modelling frameworks such as the energy hub concept of [2]. District systems that also include cooling and operate on different temperature levels can reduce energy consumption and emissions of buildings [3]. The design of a new energy system is a multi-objective problem as costs and environmental impacts must be considered together.

A single-level optimization process was compared to a bi-level optimization process in order to address the multi-objective problem based on monthly samples in [4]. In [5], a bi-level optimization process in combination with the energy hub model operating on an hourly basis was proposed. The contribution of this paper is the comparison of a single-level optimization process to a bi-level optimization process for a large energy system including short- and long-term storage based on hourly measurement data for a whole year, including time-varying electricity prices.

METHOD

The energy system of the research facility is modelled using the energy hub approach. The model consists of energy streams for electricity, gas, solar power, medium temperature and high temperature thermal networks, and represents their interdependencies via conversion and storage technologies. The model expresses these energy system constraints as a mixed-integer linear programming (MILP) model implemented in Matlab using Yalmip [6] and solved using IBM CPlex.

The optimization process is conducted for a whole year, allowing the consideration of seasonal storage. The temporal resolution is hourly. The objective is to minimize the net present value of the capital and operational costs. A single-level multi-objective optimization process, composed of a mixed-integer linear program, is compared to a bi-level multi-objective optimization process. The single-level optimization process is extended with the ε-constrained technique in order to obtain a multi-objective Pareto front.

Problem formulation

The energy hub concept [2] allows the modelling of multi-carrier energy systems in terms of power flows. In this paper, a slightly modified representation is used. A carrier node k connects different storage devices, expressed as $q_{t,k}^{store}$ (storing) and $q_{t,k}^{dis}$ (discharging), conversion devices, expressed as $p_{t,k}^{in}$ and $p_{t,k}^{out}$, supply grids $g_{t,k}$ and loads $l_{t,k}$. The power flows of a carrier node must be balanced at every time step t as in equation (1). Conversion devices are represented by a linear input-output relationship determined by the efficiency matrix A, as shown by equation (2). The state-of-charge of storage devices are represented by a dynamic discrete linear equation (3) and characterized by the charging and discharging matrices A_+ and A_- and the loss coefficient a. The operational decision variables are constrained by the design variables (i.e. equipment capacities) (4).

$$p_{t,k}^{out} - p_{t,k}^{in} - q_{t,k}^{store} + q_{t,k}^{dis} - l_{t,k} + g_{t,k} = 0 \ \forall t, k \tag{1}$$

$$p_t^{out} = A\, p_t^{in} \tag{2}$$

$$e_{t+1} = a\, e_t + A_+ q_t^{store} - A_- q_t^{dis} \ \forall t \tag{3}$$

$$0 \le p_t^{out} \le p_{\max},\ 0 \le q_t \le q_{\max},\ 0 \le e_t \le e_{\max} \tag{4}$$

The operational decision variables at every timestep are the inputs and outputs of storage and conversion devices and the grid supply. The design variables are the output capacities of the conversion devices, the input and output capacities of the storage devices, the storage capacities and the binary variables that state if devices are present in the energy hub. Equations (1) to (4) express the constraint set of the optimization problem.

The single-stage optimization process incorporates both the design decision variables and the operational decision variables in the MILP model. In order to conduct a multi-objective optimization, the carbon dioxide emissions are constrained by a maximum amount ε that is consecutively reduced to give a spread of solutions.

In the bi-level optimization process, the design variables are determined by the genetic algorithm NSGA-II [7] and the operation variables by a MILP model. Because the MILP does not contain capacities it solves much faster. The objective functions of the genetic algorithm are the net present value of the total costs and the carbon emissions. The linear program in the inner loop optimizes the operational costs. The GA runs for 50 generations, with a population size of 50.

Case Study

The case study is based on the Empa/Eawag research facility in Dübendorf, near Zürich, Switzerland. The energy demand data used for this study originates from hourly measurements for 2012 of electricity, cooling and heating demand. The annual total demand is found in Table 2. The demand for the medium temperature heating power has been estimated based on the profile from the high temperature grid.

Figure 1 illustrates all possible technology options of the energy hub. The high temperature (HT) grid is at 65°C. The medium temperature (MT) grid is at 38°C. The different temperature gaps of the heat pumps lead to different coefficients of performance (see Table 1). A varying percentage of biogas can be added to the gas consumption of the CHP and the boiler. The cooling towers ensure that excess power in the medium temperature grid is exhausted.

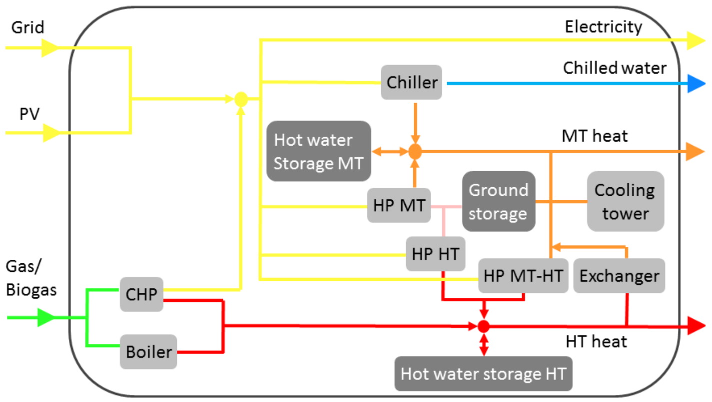


Figure 1: Energy hub of the Empa research facility

The efficiency coefficients, the unit costs and fixed costs of the equipment are listed in Table 1. The costs of the geothermal storage depend only on the input/output capacity and not on the storage capacity. The hot water tank costs depend on both the input/output capacity and the storage capacity. The costs and efficiency values are based on industry estimates. Operational costs of 0.046 CHF/kWh and carbon emissions of 0.099 tCO_2/MWh are added to the objective function for the photovoltaic panels.

The electricity prices are varying on a daily, weekly and seasonal basis. All pricing data is taken from the local distribution company. Carbon emissions are based on the European UCTE electricity mix. The time frame of the total net present costs is 20 years. The discount rate is 2.5%. Energy costs are assumed to increase by 2.5% per year.

Equipment	Efficiency/COP	Unit costs [CHF/kW]	Fixed costs [CHF]
CHP	ε_{el} : 0.3, ε_{th} : 0.4	500	500000
PV	0.18	300 [CHF/m^2]	100000
Boiler	0.7	200	50000
Chiller	ε_{cool} : 4.9, ε_{th} : 5.8	400	100000
HP MT-HT	5	550	120000
HP Ground-HT	3	550	120000
HP Ground-MT	4.5	550	120000
Heat exchanger	0.9	200	-
Pump MT-Ground	45	10	5000
Cooling tower	-	240	-
Ground storage	0.003%/hour	2000	-
MT storage	0.5%/hour	10 [CHF/kW], 4 [CHF/kWh]	10000
HT storage	0.5%/hour	10 [CHF/kW], 2 [CHF/kWh]	10000

Table 1: Parameters of the devices in the energy hub

Carrier	Price [CHF/MWh]	Carbon emissions [tCO_2/MWh]	Load [MWh/yr]
Electricity	0.0951-0.1361	0.594	10204
Natural gas	0.0632	0.237	-
Biogas	0.1452	0.125	-
MT heat	-	-	1369
HT heat	-	-	5627
Cooling	-	-	3899

Table 2: Parameters of the carriers, including loads to be met.

RESULTS AND DISCUSSION

The single-level optimization requires two optimization runs (one minimising emissions, the other costs) to determine the minimum and maximum emissions to use as bounds for the ε-constraints. The single-level outperforms the bi-level optimization for this type of problem, as seen in Figure 2. The computation time for the single-level problem with 16 ε points was 2.15 hours, whereas the bi-level algorithm took 28 hours for 50 generations. From the evolution of the hypervolume shown in Figure 3, it appears that the bi-level algorithm has not yet fully converged. The solutions obtained by the bi-level method after 5 generations are also shown, as this corresponds to the same runtime as the single-level case. It is clear that the optimisation has not progressed at all by this point.

Figure 4 presents the design variables of the single-level optimization solutions. The dominant mitigation measure to reduce the carbon emissions is the use of biogas in combination with the CHP. The UCTE electricity mix includes a lot of power generated by coal plants, giving very high carbon emissions for electricity. The installation of storage and heat pumps results in only a limited reduction of emissions because the heat pumps increase the electricity demand to some degree. Hence, only the use of biogas and electricity production through the CHP can reduce the emissions further. Lots of heat is wasted for very low levels emissions due to the overproduction of heat by the CHP. This mode of operation is not permitted in many countries. High capacities of the heat exchanger and the cooling tower are good indicators that excess heat from the CHP is wasted. These points on the Pareto fronts should not be considered for the implementation of the energy system. The high electricity base load and the high electricity prices favour the use of photovoltaics panels, which are installed at the maximum capacity for all solutions (even the cheapest, since the capital cost is easily paid back through lower electricity bills within the timeframe considered).

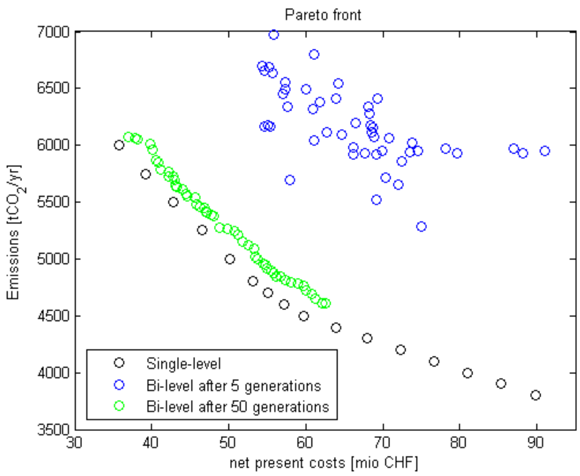


Figure 2: Pareto front for the single and bi-level optimizations

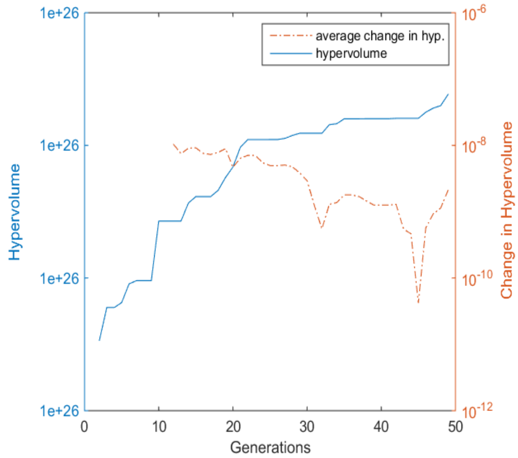
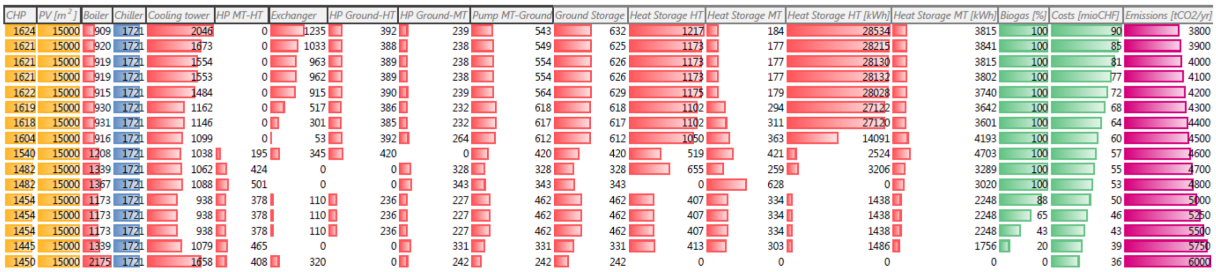


Figure 3: Hypervolume of the Pareto front and the change in hypervolume for the bi-level optimisation



CHP	PV [m²]	Boiler	Chiller	Cooling tower	HP MT-HT	Exchanger	HP Ground-HT	HP Ground-MT	Pump MT-Ground	Ground Storage	Heat Storage HT	Heat Storage MT	Heat Storage HT [kWh]	Heat Storage MT [kWh]	Biogas [%]	Costs [mioCHF]	Emissions [tCO2/yr]
1624	15000	909	1721	2046	0	1235	392	239	543	632	1217	184	28534	3815	100	90	3800
1621	15000	920	1721	1673	0	1033	388	238	549	625	1173	177	28215	3841	100	85	3900
1621	15000	919	1721	1554	0	963	389	238	554	626	1173	177	28130	3815	100	81	4000
1621	15000	919	1721	1553	0	962	389	238	554	626	1173	177	28132	3802	100	77	4100
1622	15000	915	1721	1484	0	915	390	239	564	629	1175	179	28028	3740	100	72	4200
1619	15000	930	1721	1162	0	517	386	232	618	618	1102	294	27122	3642	100	68	4300
1618	15000	931	1721	1146	0	301	385	232	617	617	1102	311	27120	3601	100	64	4400
1604	15000	916	1721	1099	0	53	392	264	612	612	1050	363	14091	4193	100	60	4500
1540	15000	1208	1721	1038	195	345	420	0	420	420	519	421	2524	4703	100	57	4600
1482	15000	1339	1721	1062	424	0	0	328	328	328	655	259	3206	3289	100	55	4700
1482	15000	1367	1721	1088	501	0	0	343	343	343	0	628	0	3020	100	53	4800
1454	15000	1173	1721	938	378	110	236	227	462	462	407	334	1438	2248	88	50	5000
1454	15000	1173	1721	938	378	110	236	227	462	462	407	334	1438	2248	65	46	5250
1454	15000	1173	1721	938	378	110	236	227	462	462	407	334	1438	2248	43	43	5500
1445	15000	1339	1721	1079	465	0	0	331	331	331	413	303	1486	1756	20	39	5750
1450	15000	2175	1721	1658	408	320	0	242	242	242	0	0	0	0	0	36	6000

Figure 4: Design variables (Input/output capacities of conversion and storage devices, storage capacities and biogas use) of selected Pareto solutions.

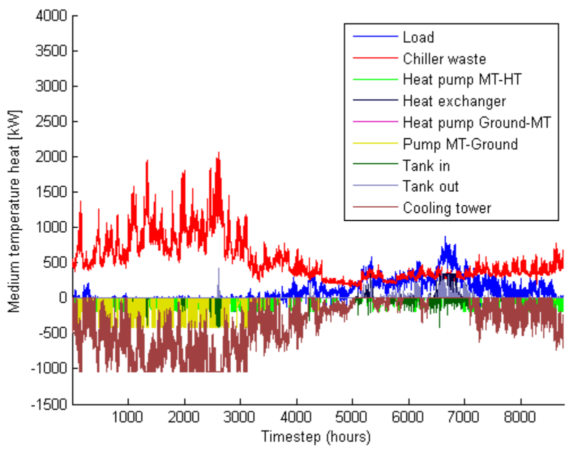


Figure 5:Operation of the medium temperature grid

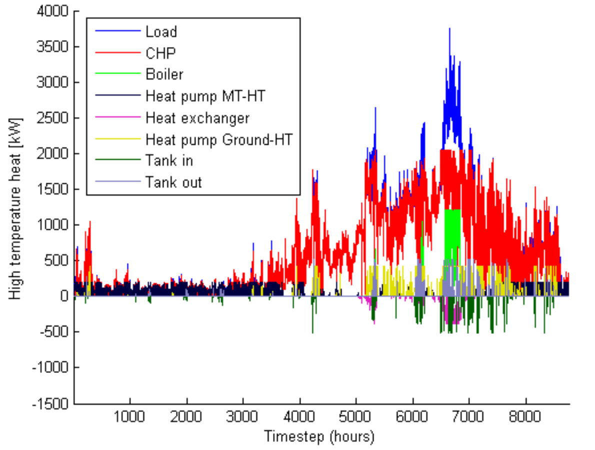


Figure 6: Operation of the high temperature grid

Figures 5 and 6 illustrate a year of operation of the medium temperature grid and the high temperature grid for the single-level solution with emissions of 4600 tCO_2/yr. The low level of high temperature heat needed in summer is supplied by a heat pump using the waste heat from the chiller as a source. The boiler and a small heat pump using the ground as a source are switched on to meet peak demands. The necessity of reducing the emissions of the UCTE electricity mix does not allow the replacement of CHP by large heat pumps. Hence, a lot of waste heat of the chiller is exhausted via the cooling towers.

CONCLUSION

The single-level optimization finds a better Pareto front in much shorter time than the bi-level approach for this problem instance. Further investigation is needed to establish whether this is true for many types of problem (e.g. if the runtime of the MILP with sizing is higher), or if improvements to the bi-level process can overcome this (e.g. seeding with good solutions).

The case study illustrates the importance of a multi-carrier perspective on the reduction of carbon emissions. The high carbon emissions of the European electricity mix lead to high biogas consumption and costly operational solutions. PV is installed at the maximum permitted level of 15,000m^2 in all cases due to high energy prices.

Further research that considers scenarios with different electricity generation mixes is required. A more accurate modelling of the geothermal and short-term storages using temperature nodes is suggested, along with constraints on dumping excess heat from CHP if applicable.

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