BI-LEVEL OPTIMISATION OF DISTRIBUTED ENERGY SYSTEMS INCORPORATING NON-LINEAR POWER FLOW CONSTRAINTS

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ABSTRACT

This paper presents a bi-level optimisation process for the design and operation of a distributed energy system taking into account non-linear electrical grid constraints. It includes the optimal selection of various distributed energy resources (micro combined heat and power, photovoltaic, air source heat pump, gas boiler and heat storage) and the optimal operation of the selected resources at the neighbourhood level. The objective is to explore the tradeoff between cost and carbon emissions over the lifespan of the selected resources while satisfying the heat and electrical demands of the buildings as well as avoiding the violation of existing electrical grid constraints. This is accomplished by using two optimisation "levels" within one optimisation process. The main level uses a multi-objective genetic algorithm (GA) to optimise a set of design variables (capacities of technologies in each building). The evaluation of each candidate solution of the GA has two steps. First, the optimal operation of all distributed energy resources is determined using the energy hub approach (a mixed integer linear programming model); the results are passed back to the main level where they are summed to give the objective function value. This is followed by a non-linear power flow calculation to check if the proposed operation violates existing electrical grid constraints. The optimisation framework is applied to a case study consisting of several buildings at the low voltage distribution network level. The optimal design and operation of distributed energy system is determined. The impact of the existing electrical grid in limiting integration of distributed energy resources is shown to be highly significant. The effect on the solutions proposed and how limitations can be decreased are also discussed.

Keywords: bi-level optimisation, power flow constraints, MILP, GA, energy hub

INTRODUCTION

The Swiss energy strategy 2030 set a target of at least 50% reduction of greenhouse gas reduction compared to 1990. Distributed energy systems (DES) that satisfy simultaneously various energy demands (heat and electricity) can be a key enabling factor for meeting the targets. They provide potential for large energy savings but with the downside of energy networks becoming more complex to design and operate. Various authors have looked at the optimal design and operation of DES while taking into account building systems [1] [2] [3]. The models used for optimising DES are largely based on mixed-integer linear programming formulations (MILP). However, they all assume that the distribution grid capacity is big enough to integrate any amount of renewables. This is not always a valid assumption since most of the electrical grids were design before renewables were an influencing factor. On the other hand, a number of publications address optimal power flow and/or placement of distributed generation in the distribution grid while assuming building systems as predefined [4] [5] [6]. Such optimisations are mostly based on heuristics such as genetic algorithm.

In this paper, we present a multi-objective bi-level optimisation framework for the optimal design and operation of DES which takes into account building systems and non-linear power flow constraints. We analyse how much the existing electrical grid is limiting integration of distributed energy resources and how this limitation can be decreased.

BI-LEVEL OPTIMISATION FRAMEWORK

A bi-level optimisation framework uses two optimisation "levels" within one optimisation process. An overview is given in Figure 1. Here the main level uses a multi-objective genetic algorithm to optimise a set of design variables (equipment capacities) for each building. The evaluation of each candidate solution has two steps. The first is a MILP model, where optimal operation is determined and the cost and emissions calculated. This is followed by a power flow calculation to check if the proposed operation violates existing electrical grid constraints. If the proposed solution violates a grid constraint, it will be penalised in the constraint function of genetic algorithm.

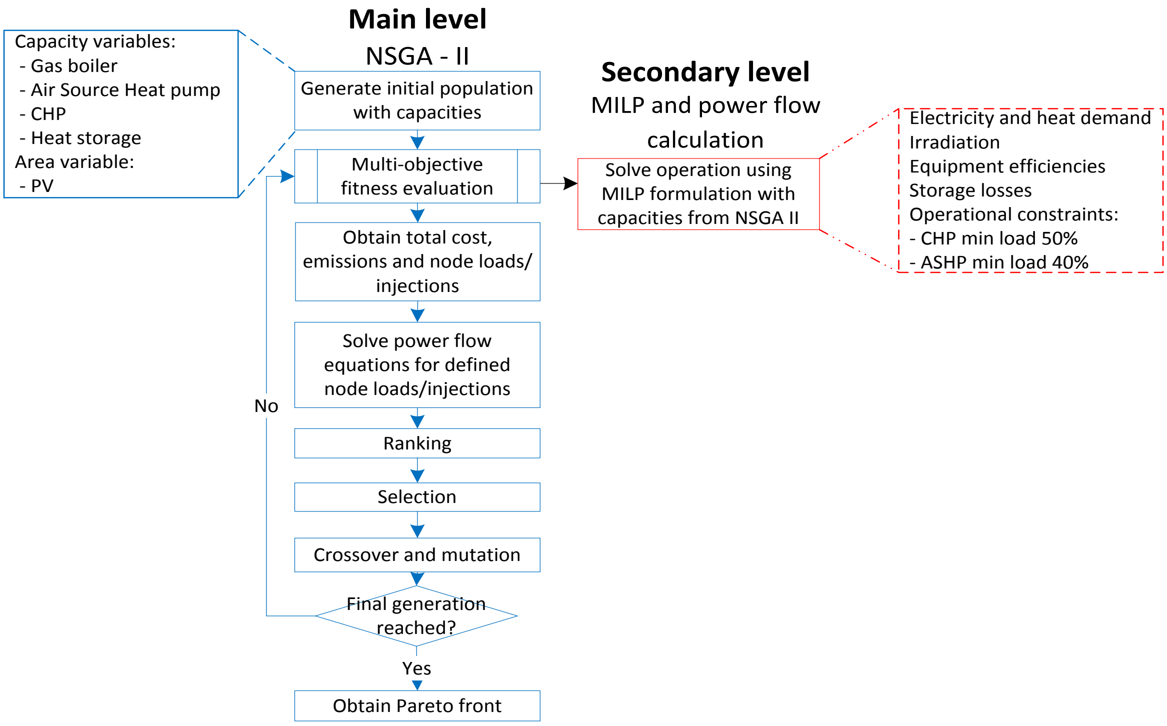


Figure 1: Flowchart of the bi-level optimisation process.

The genetic algorithm – design optimisation

Genetic algorithms are a metaheuristic belonging to the class of evolutionary approaches based on iteratively improving solutions by use of recombination and mutation. Solution population based on their fitness and used to form a new population. In this paper the multi-objective Non-dominated Sorting Genetic Algorithm NSGA II [7] is used. The two objectives used are minimization of total cost and carbon emissions over the lifespan of the technologies. The design variables are the capacities of the considered technologies for each building: combined heat and power (CHP), photovoltaics (PV), air-source heat pump (ASHP), gas boiler and heat storage. There are 5 buildings giving a total of 25 decision variables. If a decision variable is equal to 0 it means that that technology will not be installed. Capacities are passed to the MILP secondary level optimisation model (described below) where optimal operation as well as operating costs and emissions objectives is determined. Proposed

solutions are checked if they violate grid constraint by solving power flow equations (see next section). If they violate grid constraints, they are penalised proportionally by how much limits are exceeded. In the sorting step, solutions without violations are always dominating solutions with violations and solutions with smaller violations dominate solutions with larger violations. This way non-violating solutions are always selected and eventually violating solutions will not be included in the current population.
The optimisation was run for 100 generations with a population size of 100, crossover probability 0.9, mutation probability 0.5 and mutation distribution η_m 10.

Mixed integer linear programming – operational optimisation

Optimal operation for each solution by proposed the main level is solved using a MILP model. The formulation is based on the energy hub framework [8] where each technology is represented by a conversion efficiency between different energy streams. Each building is represented by an energy hub as shown in Figure 2. Additional constraints included are minimum load for CHP (50%) and ASHP (40%), and daily heat storage. For more details about the model, the reader is referred to [9].

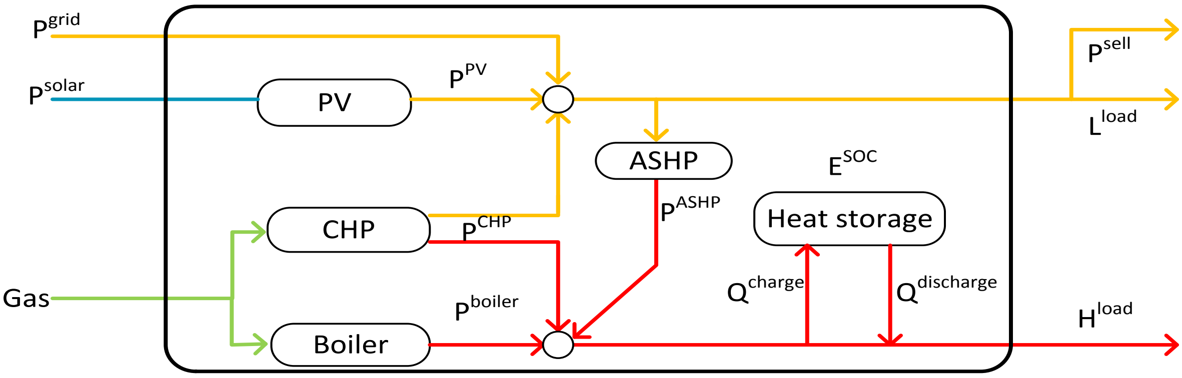


Figure 2: Representation of conversions between various energy streams within one building.

The buildings were modelled in EnergyPlus and simulation was run using weather data for Zürich, Switzerland in order to obtain hourly heating and electricity demand. In the MILP model, electricity and heat demand are represented by 24 hourly demand curves for each month in order to decrease computational time (in total 288 timesteps). The model uses the design variables proposed by NSGA as capacity constraint and aims to minimise total costs (investment and operational cost) while satisfying the electricity and heat demand of each building. Carbon emissions are calculated by applying the following carbon factors: grid electricity 0.5 kgCO_2/kWh and natural gas 0.2 kgCO_2/kWh. It is assumed that carbon is accounted for electricity exported to the grid with the same grid carbon factor. This is the reason why negative net carbon emissions can be obtained in the result section. Operational cost and carbon emissions were calculated for 20 years (the assumed lifespan of the equipment). The efficiency, capacity bounds and cost of each technology is shown in Table 1 based on data from [1] [2] [3].

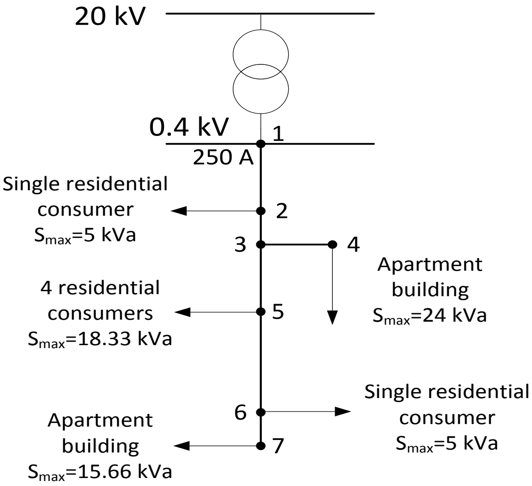
Technology	Efficiency	Capacity bounds	Cost
CHP	η_{el}: 25%. HER: 2	0 -100 kW	500 €/kW
Gas boiler	80%	0-150 kW	70 €/kW
PV	15%	0-150 kWp	600 €/m^2
ASHP	COP: 2.8	0 -100 kW	400 €/m^2
Thermal storage	99% per timestep	0-60 kWh	70 €/kWh

Table 1: Efficiency, capacity bounds and linear cost of technologies used

Non-linear power flow calculation – electrical grid constraint

After solving the optimal operation in the MILP model, it is calculated how much electricity each building is producing or consuming for each timestep. The values are passed to the electric grid model where buildings are represented as nodes with known loads or injections. The network comprises a single 20/0.4 kV distribution transformer with a single one phase feeder supplying the five residential buildings. The data for the network is based on [10] along with cable data shown in Figure 3. The power factor for all consumers was assumed to be 0.85 lagging and for distributed generation 1. For each timestep, steady-state power flow calculation using the Newton-Raphson method is performed in MATPOWER[11]. The solutions are checked to see if they violate grid constraints – voltage higher than ±10% of the nominal voltage and/or line current higher than 250 A. If they violate, a penalty value of difference between calculated value and the needed one is assigned to the solution in the main level.

Grid layout



Line data

Sbase	100 kVA		
Vbase	0,4 kV		
Send node	Receive node	Resistance (p.u.)	Reactance (p.u.)
1	2	0,012425	0,00363125
2	3	0,0062125	0,001815625
3	4	0,02174375	0,0037625
3	5	0,012425	0,00363125
5	6	0,0186375	0,005446875
6	7	0,0062125	0,001815625

Figure 3: Electricity grid characteristics and line data.

RESULTS

Figure 4 shows the Pareto front obtained, consisting of 28 solutions (blue dots). In addition, grey dots show all evaluated solutions and red crosses solutions that violated either voltage or current constraints. In total there were 10,000 function evaluations. Looking at solutions that violated grid constraint, they are clustered at the lower part of the Pareto front. Lower carbon emissions optimal designs are not possible without upgrading the electrical grid in order that more distributed generation can be integrated. Also, it shows it is very important to include grid constraints in the optimisation of distributed energy systems.

Variable and objective functions values for all 28 optimal solutions are shown in Figure 5. Variables for each building are summed per solution and solutions are sorted by objective function. An increase of cost by 23% can give savings of 47% in carbon emissions when the cheapest solution (1550 k€, 5201 tCO_2) is compared to the most expensive (1916 k€, 2799 tCO_2). It can be clearly seen that PV capacity influences the objective functions the most. Looking at gas boiler, CHP and HP capacities, a small pattern can be observed. In the solutions where sum of CHP and HP capacity is higher than 140 kW, boiler capacity is lower than 300 kW. The reason is that boiler is not used anymore to cover the peak demand but only demand below the minimum part load of CHP and ASHP. Further decrease in carbon emissions is possible by installing more PV and CHP, but these solutions violate grid constraints. If decreasing emissions is imperative, installing batteries or upgrading the electrical grid is needed.

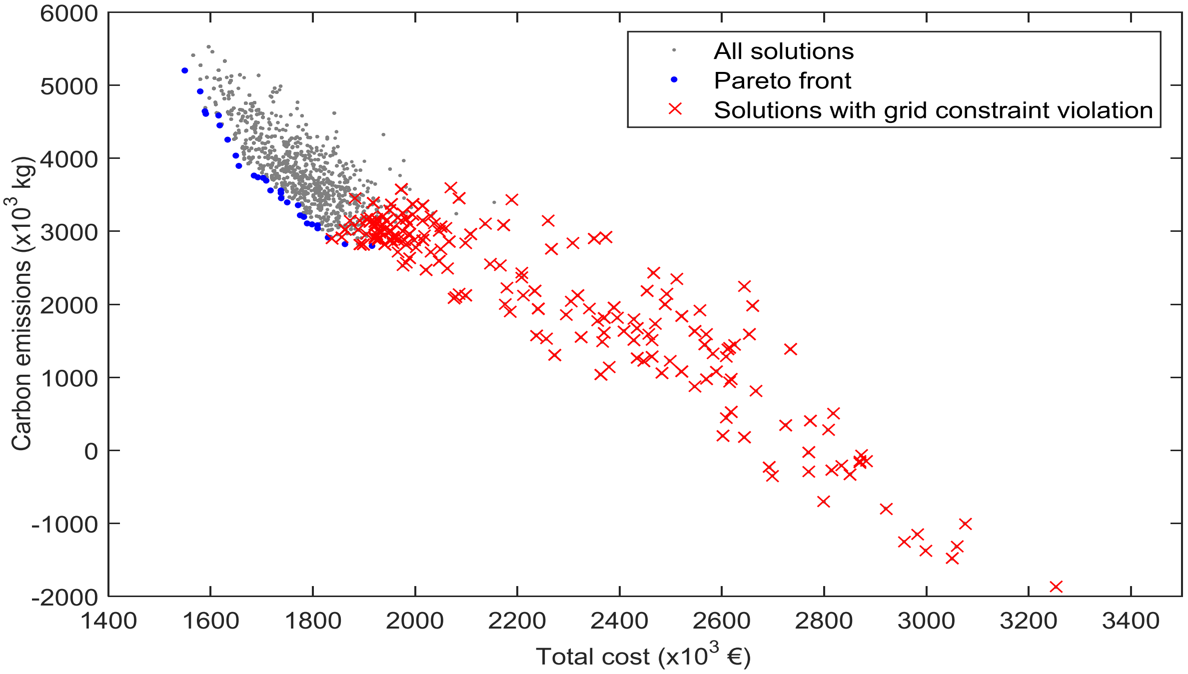


Figure 4: Results of the optimisation showing Pareto front, all solutions evaluated and solutions that violated grid constraint.

Solution	Boiler (kW)	PV (kWp)	CHP (kW)	ASHP (kW)	Heat storage (kWh)	Cost (k€)	Emissions (tCO2)
1	258	195	126	102	142	1916	2799
2	254	192	74	94	131	1863	2824
3	320	189	54	64	82	1830	2915
4	328	176	73	58	127	1809	3040
5	342	177	63	47	178	1809	3082
6	318	177	58	65	117	1798	3094
7	322	173	46	74	88	1789	3108
8	299	167	56	82	52	1782	3197
9	284	164	51	104	96	1775	3219
10	278	154	68	119	92	1771	3357
11	345	152	49	65	60	1750	3396
12	278	145	68	85	122	1738	3452
13	327	142	69	48	124	1738	3525
14	334	141	65	81	128	1737	3558
15	277	136	57	111	114	1717	3559
16	340	135	41	55	157	1709	3694
17	327	129	43	67	159	1703	3731
18	296	127	63	61	109	1692	3739
19	290	122	74	76	121	1685	3763
20	344	111	52	81	167	1655	3895
21	322	102	52	57	123	1649	4036
22	342	85	62	49	123	1633	4255
23	310	69	48	90	92	1618	4450
24	340	63	56	44	109	1616	4585
25	279	51	62	126	137	1591	4609
26	328	56	54	59	71	1589	4643
27	318	32	75	65	75	1580	4915
28	346	10	62	47	167	1550	5201

Figure 5: Capacity breakdown for each technology and objective functions.

CONCLUSIONS

A bi-level optimisation framework for distributed energy systems with the inclusion of non-linear power flow for grid constraints is presented. The framework consists of three interconnected parts: the NSGA-II algorithm for design, a MILP formulation for the optimal operation and steady-state power flow calculations for checking violation of grid constraints.

The results showed that it is important to include grid constraints when optimising DES, especially of low net emissions are targeted. Optimal solutions without violation of grid constraints are possible only down to value of 2799 tCO_2 compared to the overall possible minimum carbon emissions of -1980 tCO_2. Compared to the cheapest, emissions can be decreased by 47% with an increase of cost by 23%, with PV capacity being the most influential parameter. Further decrease in emissions is not possible without grid upgrades or inclusion of batteries.

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