Multi-objective investment and operating optimization of energy systems with integer cut constraints and evolutionary algorithm

Samira Fazlollahi [a]***, François Maréchal*** [b]***, and Benoit Beraud*** [c]***,***

[a] *Veolia Environnement Recherche et Innovation (VERI), 291 avenue Dreyfous Ducas, 78520 Limay, France, samira.fazlollahi@epfl.ch, CA*

[b] *Ecole Polytechnique Fédérale de Lausanne, Industrial Energy Systems Laboratory, CH-1015 Lausanne, Switzerland, francois.marechal@epfl.ch*

[c] *Veolia Environnement Recherche & Innovation, Chemin de la Digue, BP 76 Maisons-Laffitte Cedex, France*

Abstract: The design and operating of energy systems are key issues for matching the energy supply and consumption. Several optimization methods based on the Mixed Integer Linear Programming (MILP) have been developed for this purpose. However, due to the uncertainty, analyzing only one optimum solution with mono objective function is not sufficient for sizing the energy system.
In this study, first a multi periods MILP model with Integer Cut Constraints (ICC) is developed. The goal is to systematically generate a set of good solutions rather than one optimum solution. In this step the effect of CO_2 emission is studied by doing the parametric optimization.
In the second step, in order to study the economical and environmental targets simultaneously, the problem is reformulated as a multi-objective optimization model with evolutionary algorithm (QMOO). In this step the model is decomposed into master and slave optimization. Finally both developed models are demonstrated by means of a case study comprises six types of conversion technologies, namely heat pump, boiler, photovoltaics, as well as gas turbine, fuel cell and gas engine. Results shown, QMOO is particularly suited for doing a multi-objective optimization because it works with a population of potential solutions, each presenting a different trade-off between objectives. However MILP with ICC is more suited for generating a set of ordered solutions with a short resolution time. It is not computationally expensive.

Keywords: Energy systems, Mixed Integer Linear Programming, Evolutionary algorithm, CO2 mitigation, Multi-objective optimization

1. Introduction

District energy systems (DES) have the potential to decrease the CO_2 emissions of energy services besides increasing the efficiency of energy supply [1],[2],[3]. A wide range of technologies including: combined heat and power plants (CHP), photovoltaic systems (PV), heat pump, fuel cell and other systems with renewable energy sources [4] could be used in a DES.
However, the use of renewable sources and CHP units usually add more specific issues like the unbalance between energy supply and demand. Consumers' heat and electricity demand are time dependent, while for certain DES technologies the production level can not be varied too much during short periods [5].
Therefore, a systematic procedure is needed to select and size a DES system comprising various technologies. The operation strategy also should be optimized taking into account the variation of electrical and thermal demands [6]. Some researches have been reported on this topic, and mainly focused on the optimal operation of a specific DES technology from the economic point of view [7],[8],[9].

Nowadays, environmental issues are becoming increasingly important and the environmental burdens and costs should be minimized simultaneously. These burdens are usually contradictory objectives. In order to deal with such a difficult problem, mathematical optimization methods are usually employed. Multi objective optimization of energy systems can be achieved through diverse optimization techniques, such as genetic and evolutionary algorithms and linear or non-linear programming [10],[11]. Selection and sizing of technologies in a poly-generation scheme are investigated with the nonlinear programing [12],[13], [14]. Haesen et al.[15] introduced a methodology for long-term planning of DES placement with multi objectives approach.
However through the knowledge of authors, the multi-objective optimization of DES with Integer Cut Constraints (ICC), has never been done.
In the present work first, a MILP mode is developed by adding the integer cut constraints (ICC)(sec.2.1. & sec.3.2.). The goal is to systematically generate ordered set of good solutions. ICC is used to avoid the generation of already known solutions when solving the MILP problem.
Second, the multi-objective optimization with evolutionary algorithm (QMOO), is developed (sec.3.) to study the total cost and CO_2 emission simultaneously by decomposing the model into master and slave optimization. Both methods are used for sizing and operation of energy systems.
Finally developed models are demonstrated by means of a case study (sec.4.), and results are compared to conclude on advantages and disadvantages of each approach (sec.5.).

2. Problem formulation

In energy systems, conversion technologies are used to transform the primary energy sources into useful services. Several technologies may be used simultaneously or in competition in order to satisfy the energy requirement at the minimum cost.
In general, the configuration and operation conditions of a system yielding the best economy are pushed into a range where environmental loads are higher than the least. Multi objective optimization tackle the issue of conflicting objective functions (such as environment and economy), finding a 'balanced' optimal solution.
In this work three techniques; ϵ constraint, integer cut constraints and evolutionary algorithm, have been adapted for multi-objective optimization of the energy system with economical and environmental targets. The common part of these three models is called Energy System Optimization model (ESO). It is a MILP model including several alternative utility systems.
In the following parts, first the Energy System Optimization (ESO) model is described, after that ϵ method and integer cut constraints (ICC) are used to generate systematically a set of good solutions rather than one optimum configuration. Finally, the problem is reformulated as an evolutionary multi-objective optimization model to study the economical and environmental targets simultaneously.

2.1. Energy system optimization (ESO)

Energy System Optimization (ESO) is a Mixed Integer Linear (MILP) model. The configuration and the operating condition of an energy system are optimized in this step. Here, the aim is to minimize the total cost under the technical, the heat and the power cascade constraints.
From the vast set of optimization methods [16], here the problem is formulated as a MILP model. The energy conversion technologies (ECT) in the central station are supplying the energy demand of the region. Main variables and constraints of the model are explained in the next part.
In the present work, energy conversion technologies (ECTs) are denoted by letter s together with an index i. The variations of the power and the heat consumptions are taken into account by dividing the year into periods, denoted by an index t, $t = 1, 2, ..., N_t$. The electrical power is denoted by $\dot{\mathbf{E}}$ and the heat power by $\dot{\mathbf{Q}}$ [kW], the type of resources are denoted by letter r. Beside that, all variables are shown with bold and parameters with normal letters.

2.1.1. Technical constraints

In this research, six types of energy conversion technologies (ECT) have been considered, namely heat pump, boiler, photovoltaics (PV), as well as gas turbine, fuel cell and gas engine. Technologies model proposed by F.Maréchal [17],[18] are developed in this study to simulate each energy conversion technologies (ECTs). Main constraints related to the ECTs are:

1. Existence of a subsystem s_i:

$$\dot{Q}min_{s_i} * \mathbf{y_{s_i,t}} \leq \sum_{r}^{N_r} \mathbf{\dot{Q}^-_{s_i,r,t}} \leq \dot{Q}max_{s_i} * \mathbf{y_{s_i,t}} \qquad \forall s_i = 1,...,N_s \quad \text{and} \quad \forall t = 1,...,T \tag{1}$$

2. Electricity production in the subsystem s_i, and the consumption of heat pump hp_j:

$$\mathbf{\dot{E}^-_{s_i,t}} = (\sum_{r}^{N_r} \mathbf{\dot{Q}^-_{s_i,r,t}}/\eta_{th,s_i}) * \eta_{el,s_i} \quad \text{and} \quad \mathbf{\dot{E}^+_{hp_j,t}} = \mathbf{\dot{Q}^-_{hp_j,t}}/COP_{hp_j} \qquad \forall t,i,j \tag{2}$$

3. Fuel consumption of type r in period t and, the CO_2 emission in the subsystem s_i:

$$\mathbf{\dot{Q}_{Fuel,r,t}} = \sum_{s_i}^{N_s} \mathbf{\dot{Q}^-_{s_i,r,t}}/\eta_{th,s_i} \quad \forall r,t \quad (3) \qquad \mathbf{M_{CO_2,s_i}} = \sum_{t}^{T}\sum_{r}^{N_r} \mathbf{\dot{Q}^-_{s_i,r,t}}/\eta_{th,s_i} * d_t * m_{co_2,r} \quad \forall i \quad (4)$$

4. Energy supply in the subsystem s_i:

$$\mathbf{E^-_{s_i,t}} = \mathbf{\dot{E}^-_{s_i,t}} * d_t \quad \forall i,t \quad , \quad \mathbf{Q^-_{s_i,r,t}} = \mathbf{\dot{Q}^-_{s_i,r,t}} * d_t \quad \forall i,t,r \tag{5}$$

5. Maximum utilization of the subsystem s_i and, it existence during whole periods:

$$\mathbf{Y_{s_i}} \geq \mathbf{y_{s_i,t}}, \quad \mathbf{\dot{Q}_{s_i}} \geq \sum_{r}^{N_r} \mathbf{\dot{Q}^-_{s_i,r,t}} \quad \forall i,t \quad (6) \qquad \mathbf{\dot{Q}^-} \geq 0, \quad \mathbf{\dot{E}^-} \geq 0, \quad \mathbf{y} \in \{0,1\}, \quad \mathbf{Y} \geq 0 \quad (7)$$

2.1.2. Heat demand

In order to compute the optimum size and operating strategy of the district energy system, the energy consumption for different energy services is needed. In this work, consumers' heat demand is characterized based on the heating signature, inspired by the work of L.Girardin [19]. The following equations represent the demand constraints:

1. The heat flow to a consumer c_m and, the heat balance in a subsystem s_i:

$$\mathbf{\dot{Q}^+_{c_m,t}} = \sum_{i}^{N_s}\sum_{r}^{N_r} \mathbf{\dot{Q}^-_{s_i,c_m,r,t}} \qquad \forall m,t \quad (8) \qquad \sum_{r}^{N_r} \mathbf{\dot{Q}^-_{s_i,r,t}} \geq \sum_{m}^{N_m}\sum_{r}^{N_r} \mathbf{\dot{Q}^-_{s_i,c_m,r,t}} \qquad \forall t,i \quad (9)$$

2. Overall heat balance:

$$\sum_{m,t}^{N_m,T} \mathbf{\dot{Q}^+_{c_m,t}} * d_t = \sum_{t,i}^{T,N_s}\sum_{r}^{N_r} \mathbf{\dot{Q}^-_{s_i,r,t}} * d_t + \sum_{t}^{T} \mathbf{\dot{Q}_{loss,t}} * d_t \tag{10}$$

2.1.3. Electricity demand

Electricity demand of a consumer in the period t can be satisfied with the direct power from each energy conversion technologies (ECT) or from the main power grid. Different quality levels are considered for electricity and denoted by $l = 1, ..., N_l$. The highest quality is $l = 1$ and the lowest one is $l = N_l$. As an assumption, the electricity export and import from the grid has the lowest quality. There is also a possibility of cascading the residual electricity from the higher quality ($\dot{R}_l^-$) to the lower quality level.

1. Electricity balance:

$$\sum_{l,m} \dot{E}^+_{l,c_m,t} + \sum_j \dot{\mathbf{E}}^+_{hp_j,t} = \sum_{l,i} \dot{\mathbf{E}}^-_{l,s_i,t} + \dot{\mathbf{E}}^+_{grid,t} - \dot{\mathbf{E}}^-_{grid,t} \quad \forall t, \quad \dot{\mathbf{E}}^+_{grid,t} \geqslant 0, \quad \dot{\mathbf{E}}^-_{grid,t} \geqslant 0 \tag{11}$$

2. Electricity cascade:

$$\sum_{m,t} \dot{E}^+_{l,c_m,t} - \sum_t \dot{\mathbf{R}}^-_{l,t} + \sum_t \dot{\mathbf{R}}^-_{l+1,t} = \sum_{i,t} \dot{\mathbf{E}}^-_{l,s_i,t} \quad \forall l \tag{12}$$

$$\dot{\mathbf{R}}^-_{l,t} \geqslant 0 \quad , \quad \dot{\mathbf{R}}^-_{l,t} = 0 \quad \forall l = 1 \quad , \quad \dot{\mathbf{R}}^-_{N_l+1,t} = \dot{\mathbf{E}}^-_{grid,t} - \dot{\mathbf{E}}^+_{grid,t} + \textstyle\sum_j \dot{\mathbf{E}}^+_{hp_j,t}$$

2.1.4. Start up and shut down decision:

Eq.13 defines the start up variable $\mathbf{up_{s_i,t}}$ that has the value 1 at the time t when the technology is started. Eq.14 constraints each technology to run for at least N_{min,s_i} hours [20].

$$\mathbf{up_{s_i,t}} \geq \mathbf{y_{s_i,t+\Delta t}} - \mathbf{y_{s_i,t}} \quad \forall i, t \tag{13}$$

$$\sum_{t+\Delta t}^{t+N_{min,S_i}} \mathbf{y_{s_i,t}} * \Delta t \geq \mathbf{up_{s_i,t}} * N_{min,s_i} \quad \forall i, t \tag{14}$$

This group of constraints is mainly used for analyzing the system in a short period (e.g. daily operation), but in the current work it is used to impose the restriction on the electricity production in the regulated market.

2.1.5. Objective function

In the optimization, the objective function is minimizing the total cost "TC", which is the sum of annual operation and investment costs [21]. Operation and investment costs are denoted by OPEX [€/year] and CAPEX [€/year] respectively. The total annual investment cost is assumed to be a linear function of equipments' capacity, and characterized by two parameters, β_{s_i}[€/kW,year] and α_{s_i}[€/year]:

$$\min \mathbf{TC} = \mathbf{OPEX} + \mathbf{CAPEX} \tag{15}$$

$$\mathbf{CAPEX} = \sum_i^{N_S} (\alpha_{s_i} * \mathbf{Y_{s_i}} + \beta_{s_i} * \dot{\mathbf{Q}}_{\mathbf{s_i}}) \quad \forall s_i \tag{16}$$

The total operation cost is calculated with cumulative fuel consumption during all periods and the net import of electricity:

$$\mathbf{OPEX} = \sum_{t,r,i,l,m} \left(\dot{\mathbf{Q}}_{\mathbf{Fuel,r,t}} * d_t * c_r + \dot{\mathbf{E}}\mathbf{L}_{l,t,c_m} * d_t + (\dot{\mathbf{Q}}_{\mathbf{loss,t}} * d_t * c_{loss}) + \mathbf{M_{CO_2,s_i}} * tax_{co_2} \right) \tag{17}$$

$$\dot{\mathbf{E}}\mathbf{L}_{l,t,c_m} = cel^+_{N_l,t} * (\textstyle\sum_j \dot{\mathbf{E}}^+_{\mathbf{hp_j,t}} + \dot{\mathbf{E}}^+_{\mathbf{grid,t}}) - (cel^-_{N_l,t} * \dot{\mathbf{E}}^-_{\mathbf{grid,t}}) - cel^-_{l,t} * \dot{\mathbf{E}}^+_{\mathbf{l,c_m,t}}$$

3. Multi-objective optimisation

Multi-objective optimization techniques have been introduced in the conceptual design of energy conversion systems in order to provide an enlarged set of candidate solutions for a sizing problem that is characterized by several conflictive objectives such as efficiency, cost and environmental impact (see, for example [22]; [23]; [24] and [25] for CHP plants, [26] for internal gasification combined cycles). Many methods are available for solving multi-objective optimization problem [30-33]. In the present work three different methods namely; ϵ-constraint, integer cut constraints and multi objective evolutionary algorithm are studied.

3.1. $\in$ constraint method

The ϵ-constraint method has been applied by various authors for doing the multi-objective optimization [34-35]. It is based on transferring one of the objectives of the original problem to an additional constraint. This constraint imposes ϵ as an upper or lower limit on the value of secondary objective. The optimization problem is repeatedly solved for different values of ϵ to generate set of solutions. It is computationally intensive [36] and can be mathematically expressed as: [monika]

$$\min f_2(x), \quad f_1(x) \leqslant \epsilon_j \quad with \quad \epsilon_j = \epsilon_1, \epsilon_2, ..., \quad and \quad Lim_{inf} \leqslant \epsilon_j \leqslant Lim_{sup} \tag{18}$$

where $f_1(x)$ is the total cost (eq.15) and $f_2(x)$ is the environmental objective function (eq.4). The extreme points of the interval $[lim_{inf}\ lim_{sup}]$ can be determined by solving each single objective problem separately.

3.2. Integer cut constraints (ICC)

The ICC is used to systematically generate ordered set of solutions. The restriction of the k_{th} solution is obtained by adding the following constraint.

$$\sum_{i}^{N_s}(2 * y_{s_i}^k - 1) * \mathbf{Y_{s_i}} \leq (\sum_{i}^{N_s} y_{s_i}^k) - 1 \quad \forall k = 1, ..., n_{sol} \tag{19}$$

where, $y_{s_i}^k$ is the value of $\mathbf{Y_{s_i}}$ in the solution k and n_{sol} is the number of solutions. The use of ICC could be a good tool when solving utility system integration. The systematic generation of multiple solutions allows the comparison of the proposed solutions using different criteria, which are not accounted in the definition of objective function, and to perform a sensitivity analysis on uncertain parameters like resources cost or the energy price.
Here the ϵ method integrated with integer cut constraints (ICC) is developed to generate a set of solutions and also to consider simultaneously the economic and environmental criteria in the synthesis of district energy systems.

3.3. Multi-objective evolutionary algorithm (QMOO)

Due to the ability of handling non-linear and non-continuous objective functions, evolutionary algorithms have thereby proven as a robust method for solving complex multi objective optimisation problems.
In this paper, multi-objective optimization based on the evolutionary algorithm is performed to investigate the effect of sizing and operation of energy systems on CO_2 emission (Fig.1).
The model is decomposed into master and a slave optimization [1]. The nonlinear master problem is solved using an evolutionary algorithm (QMOO) [11], three objectives being the minimization of

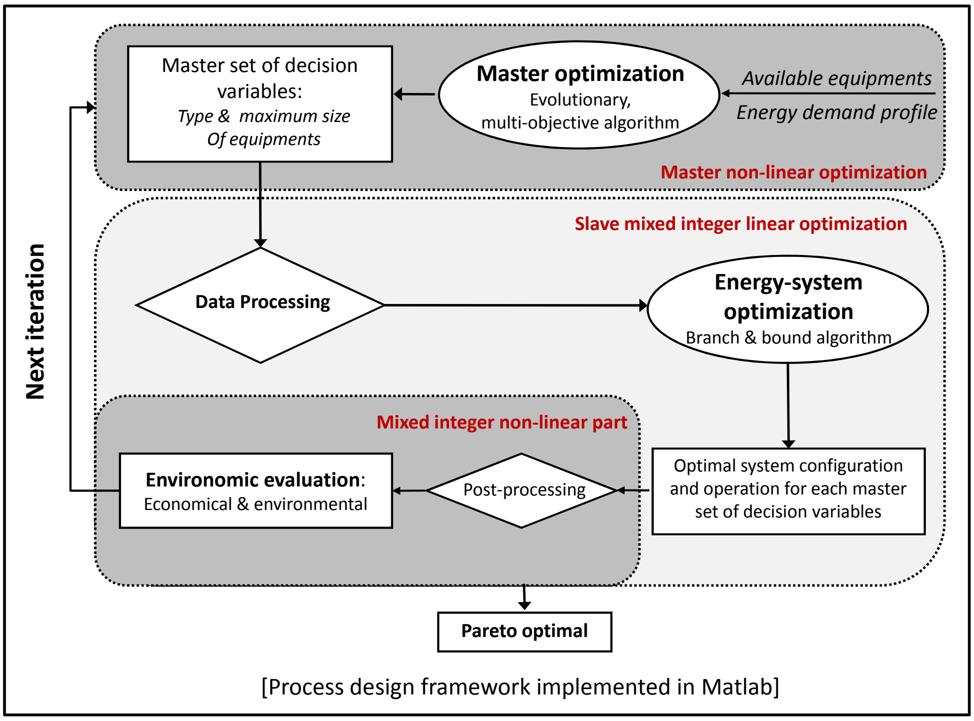

Fig. 1: Overall evolutionary multi objective optimization sequence

annual investment and operation costs, and CO_2 emissions:

$$\min_{\dot{\mathbf{Q}}_{\mathbf{s_i}},\mathbf{Y}_{\mathbf{s_i}}} \left[\mathbf{OPEX} \quad , \quad \mathbf{CAPEX} \quad , \quad \sum_{t}^{T} \sum_{r}^{N_r} \dot{\mathbf{Q}}^{-}_{\mathbf{s_i,r,t}} / \eta_{th,s_i} * d_t * m_{co2,r} \right] \quad , \quad s.t. \quad \min_{\dot{\mathbf{Q}}_{\mathbf{s_i,r,t}},\mathbf{y}_{\mathbf{s_i,t}}} \mathbf{TC} \tag{20}$$

Binary variables, for the choice of the conversion technologies and their maximum available capacity, are decision variables in the master optimization. The slave optimization, min **TC**, is the MILP model described in sec.2.1. $\mathbf{Y}_{\mathbf{s_i}}$, is the decision variable in the master optimization and consequently the input data in the slave optimization.

The minimization of the total cost, including the CO_2 taxes, is the objective function in the slave optimization. The size and the operating condition of each energy conversion technologies (ECT) are main decision variables in the slave optimization. Finally the results of QMOO are presented with the Pareto optimal frontier.

4. Illustrative example

An illustrative example of the model usage is presented in this section. The case comprises six types of energy conversion technologies (ECT), namely heat pump, 3 boilers for heating, solar PV, as well as 4 gas turbines, fuel cell and 4 gas engines for heat and electricity production[18]. Capacity ranges of equipments, are given in Table 1. Any combinations of these ECTs are allowed with six types of available resources (see Table. 2). Economical and technical information were taken from the literature [14],[27], [28]. As an assumption, the efficiency of biomass and biogas are defined 5% [29] less than the other types, with 4 times more maintenance cost. The selling electricity price for solar PV is assumed 4 times more than the co-generation. Besides, the constant CO_2 taxes equal to 0.0001 [€/kg CO_2] [1] is added to the objective function.

The average consumers heat demands are given for twelve periods of a year and one extreme condition, with corresponding duration, in Table 4. Power production is considered as an opportunity for producers. They could sign a contract and sell the electricity with the contract price or sell it directly

Table 1: *Equipments' capacity with the corresponding ranges*

Equipment	Short name	Capacity Ranges: $[MW_{th/el}]$
Boiler1	B1	[0 3]
Boiler2	B2	[0 2]
Boiler3	B3	[0 4.5]
Heat pump	HP	[0 0.2]
Solar PV	PV	[0 0.4]
Gas turbine1	GT1	[0 5.5]
Gas turbine2	GT2	[0 5.3]
Gas turbine3	GT3	[0 10.6]
Gas turbine4	GT4	[0 8]
Gas Engine1	E1	[0 0.5]
Gas Engine2	E2	[0 1.4]
Gas Engine3	E3	[0 1]
Gas Engine4	E4	[0 2]
Fuel cell	FC	[0 0.7]

Table 2: *CO_2 Intensity and Price of resources*

Resource type	CO_2 emission: $[Kg/kWh]$	Price: [€/kWh]
Electricity	0.088	0.08
Natural Gas	0.231	0.031
Light Fuel Oil	0.301	0.033
Heavy Fuel Oil	0.319	0.021
Coal	0.37	0.15
Biomass	0	0.019
Biogas	0	0.03

Table 3: *Three objectives' ranges explored by ICC and QMOO*

	Investment: [k€/year]	Operation: [k€/year]	CO_2 $[tons/year]$
ICC (Fig.1)	[277 537]	[46 308]	[7.6 10.3]
ICC (Fig.3)	[277 495]	[58 344]	[7.2 10.2]
MOO (Fig.6)	[89.4 524]	[46 811]	[6.3 10.2]

to the electricity market with market price. In this example the first situation is considered, where the company has to produce electricity with full capacity of co-generations from October to March, and rest of the year should turn the system off, but there is an interest of high regulated electricity price. This constraint is imposed by using Eq.13 and 14.

Table 4: *Twelve period data set for the heating demand*

	January	February	March	April	May	June	
Duration $[h]$	744	672	744	720	604	424	
$T_{mean}[C]$	1.87	4.93	7.78	11.4	14.05	15.76	
$Q_{mean}[kW]$	5	4	3	2	1	0.7	
	July	August	September	October	November	December	-10
Duration $[h]$	285	160	492	658	719	744	1
$T_{mean}[C]$	16.7	16.69	15.61	12.8	10.38	5.09	-10
$Q_{mean}[kW]$	0.6	0.5	0.8	2	2.5	4	8

4.1. Results with $\in$ constraint

In the first step the illustrative example is optimized by using ϵ method with economic and environmental objectives. The economic objective considered the economic aspect of energy system in terms of total annual cost (in e/year). The environmental objective function minimized the total annual CO_2 emission. The goal is to identify the type, size and the operating condition of a central plant under these two objectives.
The CO_2 emission interval $[Lim_{inf}, Lim_{sup}]$ was partitioned in to ?? sub-intervals, and the model was solved for each of the limits of these sub-intervals.
Fig.2 and 3 show the Pareto frontier and three corresponding configurations. In the optimization model the operation condition and the fuel type are mainly effected by ϵ constraint and the environmental target, while the three group of configurations (Fig.3) are quite similar.

4.2. Results with Integer cut constraints

The multi-periods investment and operation optimization model with ICC (see.2.1.) is used for illustrative example to identify the type, size and the operating condition of technologies in order to satisfy all heat demands. The first 120 ordered solutions are generated by using integer cut constraints.The

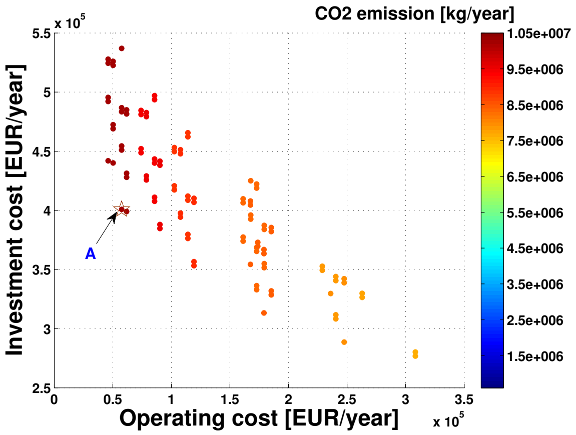

Fig. 2: Set of ordered solutions with mono objective function: ICC:

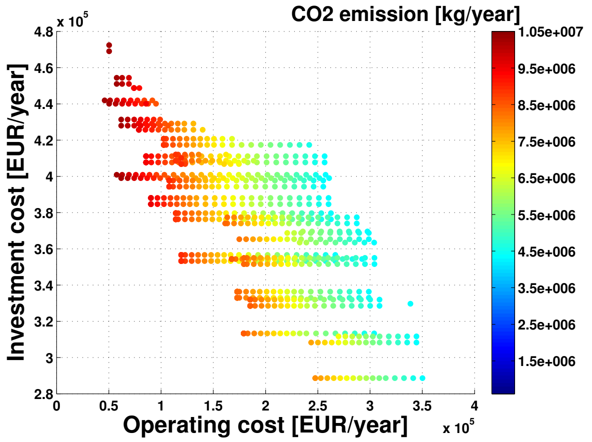

Fig. 3: Parametric optimization results on CO_2 emission: ICC

operation cost [1], investment cost and CO_2 emissions for these 120 solutions are presented in Figure4. The installed capacity in most of the solutions with the high investment cost and the low operation cost (top-left side of figure 4) is high. These configurations are mainly future engines and gas turbine with natural gas resources, that is why they have the highest CO_2 emission level.
Between these 120 solutions the optimum configuration, in terms of the total annual cost including CO_2 taxes (point A in Figure 4), features B2, E1, E2, E3, E4 together with HP. It emits 10197 [$tons - CO_2/year$], with the operation cost of 57.5 [k€/year] and investment cost arround 400 [k€/year].
The 32^{nd} ordered solution has the minimum heat losses and is equal to 0.9 MWh, while there is 5 MWh heat losses in the solution A (Figure 4). However, the total annual cost of this solution is 13% more than the solution A, and with 27% less electricity production.
The electricity price is attractive for the system, that is why four engines are selected in the configuration A. Engines have to be cool down. Part of this available heat is used for heating demand and rest is losses.

In order to analyze these solutions and make a strategic decision, a set of performance indicators (e.g. environmental indicators, exergy efficiency, primary energy saving) are needed.

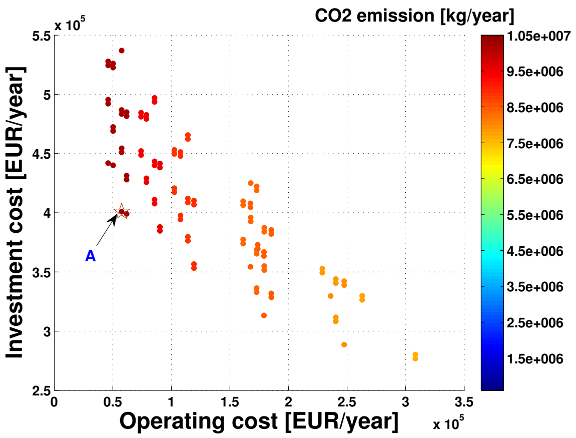

Fig. 4: Set of ordered solutions with mono objective function: ICC:

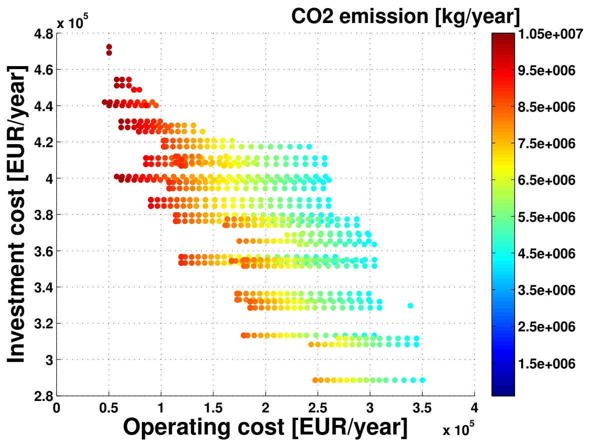

Fig. 5: Parametric optimization results on CO_2 emission: ICC

4.2.1. Emission effects

In order to study the effect of CO_2 emissions on total cost, a new constraint is imposed on the upper bound of the system's emission. When the CO_2 emission is limited, the optimizer is reducing the

[1] operation cost= operation expenses - incomes

electricity production besides increasing the biofuel consumption to satisfy the upper bound of the new constraint. Two techniques are developed to generate a set of ordered solutions including CO_2 constraint.
In the first technique, the upper bound of CO_2 constraint is changed, during arbitrary steps, from the maximum to the minimum feasible levels. In addition, set of ordered solutions are generated in each emission level. Figure.5 shows the variation of operation and investment costs by changing the upper bound of CO_2 emission from $10.5*10^6$ to $3*10^6$ [kg/year CO_2] in the current example. Besides, the first 20 ordered solutions in each emission level are generated.
In the second technique, the arbitrary number of ordered solutions are generated. In each iteration the minimum level of CO_2 emission during the previous iterations is considered for the upper bound of CO_2 constraint. Figure.6 shows 120 solutions generated by this technique. In order to do the comparison between ICC and QMOO, the accumulated resolution time of these 120 solutions are measured (Figure.7).
This way of parametric optimization is used for doing the multi objective optimization together with ICC.

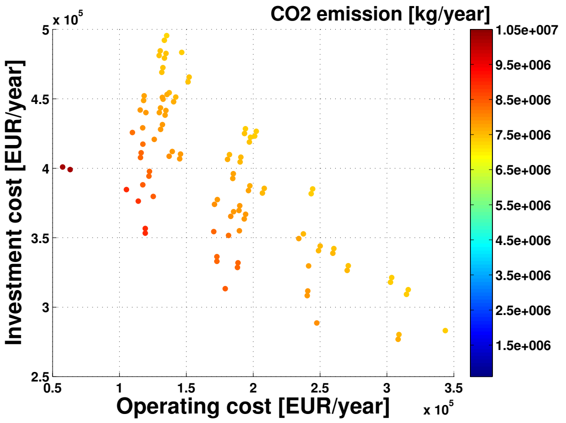

Fig. 6: Multi objective optimisation results: ICC

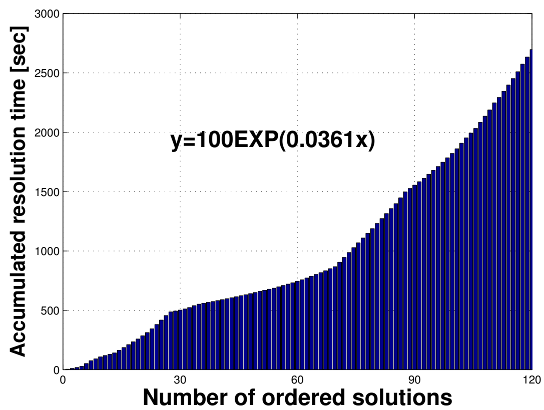

Fig. 7: Accumulated resolution time: ICC

4.3. Results with evolutionary algorithm (QMOO)

The multi objective evolutionary algorithm (QMOO) (see.3.), is also used for illustrative example to optimize investment cost, operation cost and CO_2 emission simultaneously and draw the Pareto frontier for different possibility of a power plant configuration.
Three objectives, investment and operation costs and CO_2 emission, together with fourteen integer variables are defined in the master optimization to select the type and maximum size of energy conversion technologies (ECTs), while the fuel choice and the utilization level of selected equipments are left to the slave MILP optimization. If the selected capacity in the master optimization is underestimated, then a back up boiler, is defined in the slave optimization to cover all heat demand.
Several researches have been reported on QMOO (see, for example [11];[22]; [23]; [24] and [25] for CHP plants, [26] for internal gasification combined cycles).
To make the optimization of the test case, 1800 iterations of the master optimizer have been carried out with13500 [*sec*] resolution time. Figure 9 shows the result in a population of 150 plant configurations.

4.4. Results and discussion

An optimum solution of QMOO and MILP model, in terms of the total annual operation and investment costs including incomes, are exactly the same. Both optimum solutions feature B2, E1, E2, E3, E4 together with HP. The production levels for this optimum configuration, during 12 typical days, are shown in Figure 8. Due to the attractive electricity price, the heat production level during December

and March is more than the heat demand.
The minimum and maximum values of three objectives, explored by QMOO and ICC, are presented in Table.3. Wide ranges of three objectives are covered by QMOO. It works with a population of potential solutions, each presenting a different trade-off between objectives. That is why it is suited for doing a multi-objective optimization.
The advantages of MILP model with ICC is its short resolution time for generating limited number of solutions. Figure 7 shows the ICC computation time for first 120 solutions of illustrative example with CO_2 constraint. In each iteration, for generating a new solution, an additional ICC constraint (Eq.19) is added based on the previous solutions. Adding a new constraint makes the MILP more complicated and difficult to solve. That is why the Figure 7 shows more or less an exponential behavior. However, the computation time of QMOO for generating150 population, in the current case study (sec.4.), is equal to 13500 [*sec*], much more longer than ICC.
In conclusion, due to the well known solvers (e.g. Cplex) the developed MILP model with ICC is quicker (see figure 7) than QMOO.

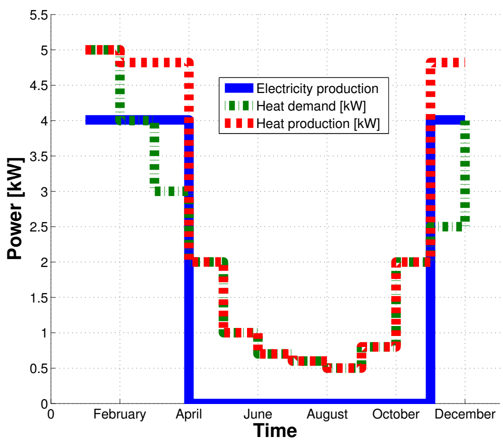

Fig. 8: Heat and power production

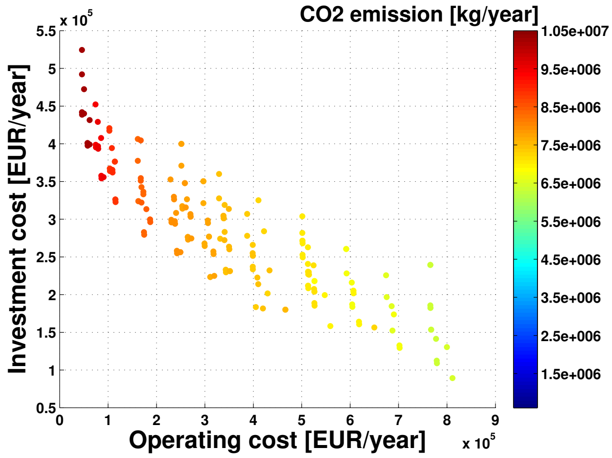

Fig. 9: Multi objective optimisation results: MOO

QMOO is particularly suited for doing a multi-objective optimization [11]. In the recent example both methods generate the same optimum solution, in terms of the total annual cost, which is not always true because of the heuristic approach of evolutionary algorithm.

5. Conclusion

The sizing and operating of energy systems are key issues for matching the energy supply and consumption. Analyses of one optimum solution of energy system design with mono objective function is efficient but limiting, becouse it does not allow for the systematic variation of decision variables and the identification of their optimum ranges. Moreover, it is necessary to account the interactions between the different decision variables, and also the trade-offs between conflicting objectives.
In this study two different optimization methods, integer cut constraints (ICC) and evolutionary algorithm (QMOO), are studied for sizing and operating of energy systems.
In the first step a MILP model is developed by adding the integer cut constraints. The goal is to systematically generate ordered set of good solutions rather than just one optimum solution.
In the second step, the problem is reformulated as a multi-objective optimization model (MOO) with evolutionary algorithm to study the total cost and CO_2 emission simultaneously, by decomposing the model into master and a slave optimization.
Developed models are demonstrated by means of a case study. The case comprises six types of energy technologies, namely heat pump and boiler, solar PV, as well as gas turbine, fuel cell and gas engine with the integration of biomass and biogas resources.
After analyzing the results obtained by both methods, the following conclusions can be deduced:

- In general, MILP model with ICC requires less computational effort than MOO.
- Several powerful mathematical algorithms are developed for solving MILP, while evolutionary algorithm is a heuristic method without any guarantee for finding the optimum solution.
- MOO is more effective in obtaining the Pareto optimal set (see Fig.9 and Fig.4), while the ICC needs to generate most solutions in the feasible space for drawing Pareto frontier which is very time consuming.
- ICC is powerful and quick for generating limited number of ordered solutions.
- MOO is very powerful for handling the multi-objective optimization. It provides the information needed for detailed analyses of design trade-offs between conflicting objectives, while MILP with ICC is a mono objective model.
- There is a possibility of using parallel computation for solving QMOO and decreasing the resolution time, but in ICC generating a new solution totally depends on previous ones consequently no possibility of using parallel computation.

District energy systems together with networks have a high potential for increasing the efficiency of energy supply and decreasing CO2 emission problems [1]. In the future study, beside the investment and operation optimization of central station, the district networks, as well as storage system will be integrated in the optimization model to investigate the whole district energy system.

Acknowledgments: The authors would like to acknowledge Veolia Environnement Recherche et Innovation (VERI) for the financial support.

Nomenclature

$MILP$	mixed integer linear programming
ECT	energy conversion technologies
DES	distributed energy system
S	ECT as a subsystem
N_{S_i}	Number of subsystems
R	Number of available resources
t	time intervals
C_m	Number of cunsumers
$y_{S_i,t}$	binary variables for existence of subsystem S_i in time t
$fmin_{S_i}$	minimum available capacity of S_i, kW
$fmax_{S_i}$	maximum available capacity of S_i, kW
$\dot{Q}^{-}_{S_i,r,t}$	net heat production of subsystem S_i in time t by using resources of type r, kWh
$\dot{E}^{-}_{s_i,c_m,t}$	electricity export from subsystem s_i in time t to consumer c_m, kWh
$\dot{E}^{-}_{s_i,t}$	electricity production of subsystem S_i in time t, kWh
$\dot{E}_{S_i,t}$	electricity exportation of subsystem S_i in time t, kWh
$\dot{E}_{c_m,t}$	electricity import from consumer c_m in time t, kWh

$\dot{E}^{+}_{C_m,t}$ electricity consumption of consumer C_m in time t, kWh

$\dot{E}^{+}_{,t}$ the consumption of electricity from the grid in time t, kWh

$\dot{Q}^{-}_{S_i,C_m,r,t}$ heat flow from subsystem S_i to a consumer C_m in time t, kWh

$\dot{Q}^{+}_{C_m,r,t}$ consumers heat demand in time t, kWh

$\dot{w}aste_t$ waste heat in time t, kWh

$Q^{-}_{S_i,r,t}$ net heat energy supply of subsystem S_i in time t by using resources of type r, kW

$E^{-}_{S_i,t}$ electricity energy supply of subsystem S_i in time t, kW

η_{th,S_i} thermal efficiency of subsystem S_i

η_{th,S_i} electrical efficiency of subsystem S_i

$\dot{f}uel_{r,t}$ fuel consumption of type r in time t, kWh

CO_{S_i} CO2 emission in subsystem S_i, kg

d_t duration of time interval t, h

CO_r CO2 emission of each resources, kg/kWh

Q_{max,S_i} Maximum utilization of subsystem S_i, kW

Y_{S_i} existence of subsystem S_i during whole periods

ϵ_d the conversion efficiency from the grid

ϵ_g the conversion efficiency to the grid

Δ_t time step, h

N_{min,S_i} minimum number of hours the subsystem S_i has to run once it has been started

$UP_{S_i,t}$ start up decision variables of subsystem S_i in time t, binary

CT total annual cost, €

$OPEX$ annual operation cost, €

$CAPEX$ annual investment cost, €

α_{S_i},β_{S_i} investment linear function's parameters

c_r resource cost, €/kWh

cel^{+}_{t} import electricity price in time t, €/kWh

$cel^{-}_{s_i,t}$ export electricity price of each subsystem s_i in time t , €/kWh

References

[1] Weber celine. *Multi-objective design and optimization of district energy systems including polygeneration energy conversion technologies*. PhD thesis, Ecole Polytechnique Federale de Lausanne., 2008.

[2] Kari Alanne and Arto Saari. Distributed energy generation and sustainable development. *Renewable and Sustainable Energy Reviews*, 10(6):539 – 558, 2006.

[3] S.R. Allen, G.P. Hammond, and M.C. McManus. Prospects for and barriers to domestic microgeneration: A united kingdom perspective. *Applied Energy*, 85(6):528 – 544, 2008.

[4] Hongbo Ren and Weijun Gao. A milp model for integrated plan and evaluation of distributed energy systems. *Applied Energy*, 87(3):1001 – 1014, 2010.

[5] Weisheng Zhou Hongbo Ren. Multi-objective optimization for the operation of distributed energy systems considering economic and environmental aspects. *Applied Energy*, 2010.

[6] Yingjun Ruan, Qingrong Liu, Weiguo Zhou, Ryan Firestone, Weijun Gao, and Toshiyuki Watanabe. Optimal option of distributed generation technologies for various commercial buildings. *Applied Energy*, 86(9):1641 – 1653, 2009. ISSN 0306-2619.

[7] Michiel Houwing, Austin N. Ajah, Petra W. Heijnen, Ivo Bouwmans, and Paulien M. Herder. Uncertainties in the design and operation of distributed energy resources: The case of micro-chp systems. *Energy*, 33(10):1518 – 1536, 2008. ISSN 0360-5442.

[8] Tetsuya Wakui, Ryohei Yokoyama, and Ken ichi Shimizu. Suitable operational strategy for power interchange operation using multiple residential sofc (solid oxide fuel cell) cogeneration systems. *Energy*, 35(2):740 – 750, 2010. ISSN 0360-5442.

[9] Pierluigi Mancarella and Gianfranco Chicco. Global and local emission impact assessment of distributed cogeneration systems with partial-load models. *Applied Energy*, 86(10):2096 – 2106, 2009. ISSN 0306-2619.

[10] Gianfranco Chicco and Pierluigi Mancarella. Distributed multi-generation: A comprehensive view. *Renewable and Sustainable Energy Reviews*, 13(3):535 – 551, 2009. ISSN 1364-0321.

[11] G.B. Leyland. *Multi-objective optimization applied to industrial energy problems*. PhD thesis, Ecole Polytechnique Federale de Lausanne., 2002.

[12] Rubio c, c. feasibility analysis of a combined cooling heating-power and desalted water plant in a non-residential building. in: Proceedings of ecos 2008, vol. 3. cracow, poland; 2008. .

[13] Rubio-maya c. combined production of electricity, heat, cold and fresh water, in a sustainable mode for the tourist sector, phd thesis. department of mechanical engineering, university of zaragoza; 2009 (in spanish). .

[14] Gracia A Rubio C, Uche J. Design optimization of a polygeneration plant fuelled by natural gas and renewable energy sources. *Applied Energy*, 88(2):449 – 458, 2011.

[15] Haesen e, driesen j, belmans r. a long-term multi-objective planning tool for distributed energy resources. in: Proceedings of ieee pes power systems conference and exposition, usa; 2006. p. 741 7.

[16] Lorenz T. Biegler and Ignacio E. Grossmann. Retrospective on optimization. *Computers and Chemical Engineering*, 28(8):1169 – 1192, 2004. ISSN 0098-1354.

[17] Francois Marechal and Boris Kalitventzeff. Targeting the integration of multi-period utility systems for site scale process integration. *Applied Thermal Engineering*, 23(14):1763 – 1784, 2003. ISSN 1359-4311.

[18] Francois Marechal and Boris Kalitventzeff. Process integration: Selection of the optimal utility system. *Computers and Chemical Engineering*, 22(Supplement 1):S149 – S156, 1998.

[19] Luc Girardin, Francois Marechal, Matthias Dubuis, Nicole Calame-Darbellay, and Daniel Favrat. Energis: A geographical information based system for the evaluation of integrated energy conversion systems in urban areas. *Energy*, 35(2):830 – 840, 2010. ISSN 0360-5442.

[20] Andres Collazos, Francois Marechal, and Conrad Gahler. Predictive optimal management method for the control of polygeneration systems. *Computers and Chemical Engineering*, 33 (10):1584 – 1592, 2009. ISSN 0098-1354.

[21] Martin Gassner, Renato Baciocchi, Francois Marechal, and Marco Mazzotti. Integrated design of a gas separation system for the upgrade of crude sng with membranes. *Chemical Engineering and Processing: Process Intensification*, 48(9):1391 – 1404, 2009. ISSN 0255-2701.

[22] A. Toffolo and A. Lazzaretto. Evolutionary algorithms for multi-objective energetic and economic optimization in thermal system design. *Energy*, 27(6):549 – 567, 2002. ISSN 0360-5442.

[23] A. Lazzaretto and A. Toffolo. Energy, economy and environment as objectives in multi-criterion optimization of thermal systems design. *Energy*, 29(8):1139 – 1157, 2004. ISSN 0360-5442.

[24] Hongtao Li, Francois Marechal, Meinrad Burer, and Daniel Favrat. Multi-objective optimization of an advanced combined cycle power plant including co2 separation options. *Energy*, 31(15): 3117 – 3134, 2006. ISSN 0360-5442.

[25] Hoseyn Sayyaadi. Multi-objective approach in thermoenvironomic optimization of a benchmark cogeneration system. *Applied Energy*, 86(6):867 – 879, 2009. ISSN 0306-2619.

[26] David Brown, Martin Gassner, Tetsuo Fuchino, and Francois Marechal. Thermo-economic analysis for the optimal conceptual design of biomass gasification energy conversion systems. *Applied Thermal Engineering*, 29(11-12):2137 – 2152, 2009. ISSN 1359-4311.

[27] Ugursal VI Onovwiona HI. Residential cogeneration systems: review of the current technology. *Renew Sustain Energy Rev*, 10(5):389–431, 2006.

[28] Wang RZ Wu DW. Combined cooling, heating and power: a review. *Progress in Energy and Combustion Science*, 32:459–495, 2006.

[29] *http://www.gepower.com/prod_serv/products/recip_engines/en/index.htm*.