# Methods for Multi-Objective Investment and Operating Optimization of Complex Energy Systems

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**Abstract**

The design and operations of energy systems are key issues for matching energy supply and consumption. Several optimization methods based on the mixed integer linear programming (MILP) have been developed for this purpose. However, due to uncertainty of some parameters like market conditions and resource availability, analyzing only one optimal solution with mono objective function is not sufficient for sizing the energy system.
In this study, a multi-period energy system optimization (ESO) model with a mono objective function is first explained. The model is then developed in a multi-objective optimization perspective to systematically generate a good set of solutions by using integer cut constraints (ICC) algorithm and $\epsilon$ constraint. These two methods are discussed and compared.
In the next step, the ESO model is reformulated as a multi-objective optimization model with an evolutionary algorithm (EMOO). In this step the model is decomposed into master and slave optimization.
Finally developed models are demonstrated by means of a case study comprising six types of conversion technologies, namely, a heat pump, boiler, photovoltaics, as well as a gas turbine, fuel cell and gas engine. Results show that, EMOO is particularly suited for multi-objective optimizations, working with a population of potential solutions, each presenting a different trade-off

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between objectives. However, MILP with ICC and $\epsilon$ constraint is more suited for generating a small set of ordered solutions with shorter resolution time.

*Keywords:*
Energy systems, Mixed Integer Linear Programming, Evolutionary algorithm, Multi-objective optimization, $CO_2$ mitigation, Integer Cut Constraints (ICC)

## 1. Introduction

In recent years, the analysis and design tools for energy systems have undergone important developments. The optimal configuration for an energy system in the district sector remains a complex problem throughout the year, due to the wide variety of technology options, volatile energy prices, great diurnal and annual fluctuations in energy consumption [1].

In addition, environmental issues are becoming increasingly important when planning energy systems. 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 employed, in which multi-objective optimization methods tackle the issue of conflicting objective functions (such as thermo economic and environmental impact).
The literature can be divided into two main categories; the first category concerns multi-objective and mono objective optimization models of energy systems, the second category concerns solving techniques of multi-objective optimization models.

The optimization of energy systems in an urban area is extensively studied by many authors. Refer to [2] for a detailed overview. Focusing on purely economic indicators for designing energy systems in the residential-commercial sector, has already been under taken by the majority of optimization studies. E. Cardona [3] used mono-objective linear programing with boundary constraints related to the secondary objectives for energy saving in airports. D.Ziher [4] also used the same approach for analyzing the tri-generation system in a hospital, while P.Arcuri et al [5] used a mixed integer programming model with $\epsilon$ constraint. M.Casisi et al [6] proposed a mixed integer programming model to optimize a distributed cogeneration system with a district heating network. A mixed integer linear programming

(MILP) for optimizing the preliminary design of combined heat, cooling and power systems with thermal storage is presented by M.A.Lozano et al [7].

Selection and sizing of technologies in a poly-generation scheme are investigated with nonlinear programing [8, 9]. Haesen et al [10] introduced a methodology for long-term planning of district energy systems (DES) placement with multi objectives approach.

The second state of the art part of this work is on multi-objectives optimization techniques. 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 [11, 12]. However, these optimizers frequently face questions on their performances [13]. Multi-objective optimization for designing of a small-scale distributed CCHP system has been performed in [14] in which a genetic algorithm has been applied to find the set of Pareto optimal solutions.

A multi-objective optimization model based on the trade-off curve for analyzing the optimal operating strategy of a district energy system is applied in [15]. There the trade-off analysis is performed between the pure environmental optimization and the pure economic optimization, rather than simultaneous optimization of both objectives. A multi-objective optimization model based on the harmony search algorithm (HS) is presented in [16] to design the low-emissions and energy-efficient residential buildings. This algorithm uses stochastic random searches and performs well for global searching, however, since it does not use gradient information it may take a relatively long time to converge to a local optimal.

Integer cuts techniques are applied in MILP and MINLP problem formulation to generate in a systematic manner a set of discrete and organized solutions. The technique is used in global optimization to identify sub-problems and in MINLP mathematical programming techniques when decomposition algorithm are used [17]. To the knowledge of the authors, integer cut constraints has never been applied in the field of multi-objective optimization of complex energy systems.

In the present work firstly, an energy system optimization (ESO) model is explained. It is a mono objective mixed integer linear programming (MILP) model. This model is used to optimize the configuration and the operating conditions of an energy system.

In the second step, the energy system optimization (ESO) model is used with a multi-objective perspective by applying the $\epsilon$ constraint technique (sec.3.1). The $\epsilon$ constraint is used to parametrically optimize $CO_2$ emissions

as a second objective function.
In the next step, the energy system optimization (ESO) model is developed by combining both the integer cut constraints (ICC) algorithm and the $\epsilon$ constraint (sec.3.3). The goal is to systematically generate a good set of ordered solutions. Integer cut constraints (ICC) is used to avoid the generation of already known solutions when solving the mixed integer linear programming (MILP) model.

Subsequently, a multi-objective optimization with evolutionary algorithm (EMOO) is presented (sec.3.4) to study the total cost and $CO_2$ emissions Pareto trade-off. This is done by decomposing the model into a master and slave optimization.

Finally these methods are demonstrated and validated by means of a case study (sec.4), and results are compared to conclude on advantages and disadvantages of each approach (sec.6).

## 2. Problem formulation

In energy systems, conversion technologies are used to transform primary energy into final energy. End-use devices are normally used to convert final energy into useful services. Several technologies may be used simultaneously or in competition in order to provide the energy requirement at the minimum cost.

In general, the configuration and operating conditions of a system yielding the best economy are pushed into a range where environmental loads are high. Multi objective optimization tackles the issue of conflicting objective functions, finding a set, named Pareto set, of 'balanced' optimal solution.

Before explaining the multi objective optimization model, the mono objective energy system optimization (ESO) model is first presented in this part.

### *2.1. Energy system optimization (ESO)*

Energy system optimization (ESO) is a mixed integer linear programming (MILP) model. The configuration and the operating condition of an energy system are main decision variables which are optimized. Here, the aim is to minimize the total cost under the technical, the heat and the power cascade constraints.

In the present work, energy conversion technologies (ECT) in the central station supply the energy demand of the region, denoted by the letter $s$ and index $i$. Variations of the power and the heat consumptions are taken into account by dividing a year into periods, denoted by an index $t$, $t = 1, 2, ..., N_t$. The electrical power is denoted by $\mathbf{\dot{E}}$ and the heat power by $\mathbf{\dot{Q}}$ [kW], the type of resources are denoted by letter $r$. In addition, 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 a heat pump, boiler, photovoltaics (PV), as well as gas turbine, fuel cell and gas engine. Technology models proposed by F.Maréchal [18, 19] are developed in this study to simulate energy conversion technologies (ECTs). The main constraints related to the ECTs are:

1. Existence of a subsystem $s_i$:

$$\begin{aligned} &\dot{Q}min_{s_i} \times \mathbf{y_{s_i,t}} \leq \textstyle\sum_r^{N_r} \mathbf{\dot{Q}^-_{s_i,r,t}} \leq \dot{Q}max_{s_i} \times \mathbf{y_{s_i,t}} \\ &\forall s_i = 1, ..., N_s \quad \text{and} \quad \forall t = 1, ..., T \end{aligned} \tag{1}$$

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

$$\mathbf{\dot{E}^-_{s_i,t}} = (\textstyle\sum_r^{N_r} \mathbf{\dot{Q}^-_{s_i,r,t}}/\eta_{th,s_i}) \times \eta_{el,s_i} \tag{2}$$

$$\mathbf{\dot{E}^+_{hp_j,t}} = \mathbf{\dot{Q}^-_{hp_j,t}}/COP_{hp_j} \quad \forall t, i, j \tag{3}$$

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

$$\mathbf{\dot{Q}_{Fuel,r,t}} = \textstyle\sum_{s_i}^{N_s} \mathbf{\dot{Q}^-_{s_i,r,t}}/\eta_{th,s_i} \quad \forall r, t \tag{4}$$

$$\begin{aligned} \mathbf{M_{CO_2,s_i}} = &\textstyle\sum_t^T \sum_r^{N_r} (\mathbf{\dot{Q}^-_{s_i,r,t}}/\eta_{th,s_i} \times \\ &d_t \times m_{co_2,r}) \quad \forall i \end{aligned} \tag{5}$$

4. Electricity supply in the subsystem $s_i$:

$$\mathbf{E^-_{s_i,t}} = \mathbf{\dot{E}^-_{s_i,t}} \times d_t \quad \forall i, t \tag{6}$$

$$\mathbf{Q^-_{s_i,r,t}} = \mathbf{\dot{Q}^-_{s_i,r,t}} \times d_t \quad \forall i, t, r \tag{7}$$

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

$$\mathbf{Y_{s_i}} \geq \mathbf{y_{s_i,t}}, \quad \dot{\mathbf{Q}}_{\mathbf{s_i}} \geq \sum_{r}^{N_r} \dot{\mathbf{Q}}^{-}_{\mathbf{s_i,r,t}} \quad \forall i, t \tag{8}$$

$$\dot{\mathbf{Q}}^{-} \geq 0, \quad \dot{\mathbf{E}}^{-} \geq 0, \quad \mathbf{y} \in \{0,1\}, \quad \mathbf{Y} \geq 0 \tag{9}$$

*2.1.2. Heat demand*

In order to compute the optimal size and operating strategy of the district energy system, consumption profiles of energy services are needed. In this work, the consumers' heat demand is characterized based on the heating signature, inspired by the work of L.Girardin [20]. The following equations represent demand constraints:

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

$$\dot{\mathbf{Q}}^{+}_{\mathbf{c_m,t}} = \sum_{i}^{N_s} \sum_{r}^{N_r} \dot{\mathbf{Q}}^{-}_{\mathbf{s_i,c_m,r,t}} \qquad \forall m, t \tag{10}$$

$$\sum_{r}^{N_r} \dot{\mathbf{Q}}^{-}_{\mathbf{s_i,r,t}} \geq \sum_{m}^{N_m} \sum_{r}^{N_r} \dot{\mathbf{Q}}^{-}_{\mathbf{s_i,c_m,r,t}} \quad \forall i, t \tag{11}$$

2. Overall heat balance:

$$\sum_{m}^{N_m} \sum_{t}^{T} \dot{\mathbf{Q}}^{+}_{\mathbf{c_m,t}} * d_t = [\sum_{t}^{T} \sum_{i}^{N_s} \sum_{r}^{N_r} (\dot{\mathbf{Q}}^{-}_{\mathbf{s_i,r,t}} \times d_t) - \sum_{t}^{T} \dot{\mathbf{Q}}_{\mathbf{loss,t}} \times d_t] \tag{12}$$

*2.1.3. Electricity demand*

The electricity demand of each consumer in the period $t$ can provide with the direct power from each energy conversion technology (ECT) or from the main power grid. In the present work different quality levels are defined for the electricity production and consumption based on the type of resources, denoted by $l = 1, ..., N_l$. The highest quality level is $l = 1$ and the lowest 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 a higher quality ($\dot{R}_l^-$) to a lower quality level:

1. Electricity balance at time $t$:

$$\sum_l^{N_l} \sum_m^{N_m} \dot{E}^{+}_{l,c_m,t} + \sum_j^{N_j} \dot{\mathbf{E}}^{+}_{hp_j,t} =$$
$$(\sum_l^{N_l} \sum_i^{N_i} \dot{\mathbf{E}}^{-}_{l,s_i,t} + \dot{\mathbf{E}}^{+}_{grid,t} - \dot{\mathbf{E}}^{-}_{grid,t}) \tag{13}$$
$$\forall t, \quad \dot{\mathbf{E}}^{+}_{grid,t} \geqslant 0, \quad \dot{\mathbf{E}}^{-}_{grid,t} \geqslant 0$$

2. Electricity cascade:

$$\sum_m^{N_m} \sum_t^{T} \dot{E}^{+}_{l,c_m,t} - \sum_t^{T} \dot{\mathbf{R}}^{-}_{l,t} + \sum_t^{T} \dot{\mathbf{R}}^{-}_{l+1,t} =$$
$$\sum_i^{N_s} \sum_t^{T} \dot{\mathbf{E}}^{-}_{l,s_i,t} \quad \forall l \tag{14}$$

$$\dot{\mathbf{R}}^{-}_{l,t} \geqslant 0 \quad , \quad \dot{\mathbf{R}}^{-}_{l,t} = 0 \quad \forall l = 1$$
$$\dot{\mathbf{R}}^{-}_{N_{l+1},t} = (\dot{\mathbf{E}}^{-}_{grid,t} - \dot{\mathbf{E}}^{+}_{grid,t} + \sum_j \dot{\mathbf{E}}^{+}_{hp_j,t}) \tag{15}$$

*2.1.4. Start up and shut down decision:*

Equation 16 defines the start up variable $\mathbf{up_{s_i,t}}$ that has the value 1 when the technology $s_i$ is started at time $t$. Eq.17 constraints each technology to run for at least $N_{min,s_i}$ hours [21].

$$\mathbf{up_{s_i,t}} \geq \mathbf{y_{s_i,t+\Delta t}} - \mathbf{y_{s_i,t}} \qquad \forall i, t \tag{16}$$

$$\sum_{t+\Delta t}^{t+N_{min,S_i}} \mathbf{y_{s_i,t}} * \Delta t \geq \mathbf{up_{s_i,t}} \times N_{min,s_i} \qquad \forall i, t \tag{17}$$

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

*2.1.5. Objective function*

In the optimization, the objective function is to minimize the total cost "TC", which is the sum of annual operation and investment costs [22]. Operation and investment costs are denoted by OPEX [€/year] and CAPEX [€/year] respectively. The total annual investment cost is linearized as a function of equipments' capacity, and characterized by two parameters,

$\beta_{s_i}$[€/kW,year] and $\alpha_{s_i}$[€/year]:

$$\min \mathbf{TC} = \mathbf{OPEX} + \mathbf{CAPEX} \tag{18}$$

$$\mathbf{CAPEX} = \sum_{i=1}^{N_S} (\alpha_{s_i} * \mathbf{Y_{s_i}} + \beta_{s_i} * \dot{\mathbf{Q}}_{\mathbf{s_i}}) \tag{19}$$

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

$$\begin{aligned} \mathbf{OPEX} = \textstyle\sum_{t,r,i,l,m} [(&\dot{\mathbf{Q}}_{\mathbf{Fuel,r,t}} \times d_t \times c_r) + (\dot{\mathbf{E}}\mathbf{L}_{l,t,c_m} \\ &\times d_t) + (\dot{\mathbf{Q}}_{\mathbf{loss,t}} \times d_t \times c_{loss}) \\ &+ (\mathbf{M}_{\mathbf{CO_2,s_i}} \times tax_{co_2})] \end{aligned} \tag{20}$$

where:

$$\begin{aligned} \dot{\mathbf{E}}\mathbf{L}_{l,t,c_m} = [&cel^{+}_{N_l,t} \times (\textstyle\sum_j \dot{\mathbf{E}}^{+}_{\mathbf{hp_j,t}} + \dot{\mathbf{E}}^{+}_{\mathbf{grid,t}})] - \\ &(cel^{-}_{N_l,t} \times \dot{\mathbf{E}}^{-}_{\mathbf{grid,t}}) - (cel^{-}_{l,t} \times \dot{\mathbf{E}}^{+}_{\mathbf{l,c_m,t}}) \end{aligned} \tag{21}$$

## 3. Multi-objective optimisation

Multi-objective programming represents a very useful generalization of mono objective approaches for energy systems design problems [23]. It is referred to [24, 25] for more details on theory and application of multi-objective programming.

Multi-objective optimization problems can be found in various fields like energy systems design. An energy system optimization is characterized by several conflictive objectives such as efficiency, cost and environmental impact. Therefore, multi-objective optimization techniques have been introduced in the conceptual design of energy systems in order to generate a set of optimal solutions. For such solutions, called Pareto optimal solutions, no improvement is possible in any objective without sacrificing at least one of the other objective functions. Mavrotas et al. [26] presented a multi-objective optimization framework for energy planning by using $\epsilon$ constraint, while Kavvadias et al. [27] used multi-objective optimization based on the evolutionary algorithm for the design of trigeneration plants.

Many methods are available for solving multi-objective optimization problems [28–31]. In the present work three different methods, namely; $\epsilon$-constraint, integer cut constraints (ICC) and a multi objective evolutionary algorithm (EMOO) are studied.

### *3.1. $\in$ constraint*

The $\epsilon$-constraint, also known as parametric optimization [32], has been applied by various authors for multi-objective optimization of energy systems [33, 34]. It is based on formulating an auxiliary model by defining one of the objectives of the original problem to an additional constraint. This constraint imposes $\epsilon$ as an upper limit on the value of the secondary objective. The optimization problem is repeatedly solved for different values of $\epsilon$ to generate the entire Pareto set. It is computationally intensive and can be mathematically [1] expressed as:

$$\begin{aligned} &\min f_1(x(\epsilon_j)),\\ &subject \quad to: f_2(x(\epsilon_j)) \leqslant \epsilon_j, \quad A \times x(\epsilon_j) \leqslant b \\ &with \quad \epsilon_j = \epsilon_1, \epsilon_2, ..., \epsilon_n \quad and \quad Lim_{inf} \leqslant \epsilon_j \leqslant Lim_{sup} \end{aligned} \tag{22}$$

where $f_1(x(\epsilon_j))$ is the economic objective in terms of the total cost (eq.18), and $f_2(x(\epsilon_j))$ is the environmental objective (eq.5). The extreme points of the interval $[Lim_{inf}\ Lim_{sup}]$ can be determined by solving each single objective problem separately.

In mixed integer linear optimization models, when $\epsilon$ is changed from $\epsilon_i$ to $\epsilon_{i+1}$ a full range of solutions could be missed out on due to the discrete nature of integer variables and the solution space. This set of good solutions may not be the optimal solutions but rather suboptimal ones nearby the Pareto frontier. These solutions mainly shows the different system configurations which are important for engineers and decision makers. Therefore the use of $\epsilon$-constraint could potentially lead to omitting attractive solutions. An illustrative example in sec.4 shows this point. In order to take care of this issue one option could be adjusting the density of the grids in the $\epsilon$-constraint. This may lead to several useless calculations with no guaranty of finding good values for $\epsilon_i$.

### *3.2. Integer cut constraints (ICC)*

The integer cut constraints (ICC) algorithm is used to systematically generate sets of ordered solutions in mixed integer linear optimization models with single objective function. The restriction of the $k_{th}$ solution is obtained by adding the following constraint.

$$\sum_{i=1}^{N_s}(2 \times y_{s_i}^k - 1) \times \mathbf{Y_{s_i}} \leq (\sum_{i=1}^{N_s} y_{s_i}^k) - 1 \quad \forall k = 1, ..., n_{sol} \tag{23}$$

where, $y_{s_i}^k$ is the value of $\mathbf{Y_{s_i}}$ in the solution k and $n_{sol}$ is the number of already obtained solutions. The systematic generation of multiple solutions allows the comparison between solutions by using multi-criteria analysis methods. However this is done using a mono-objective optimization model and there is therefore no guaranty of obtaining a high diversity of solutions for different criteria such as environmental and economic ones.

As mentioned before, the interest of using integer cut constraints (ICC) is to generate a set of good solutions near the optimal solution. These solutions are suboptimal but still interesting for engineers even if they are not optimal respect to the selected objective.

### *3.3. $\in$ constraint combined with integer cut constraints (ICC)*

In the present work a new algorithm based on the combination of the $\epsilon$ constraint, that concern the continuous variables, and the integer cut constraints (ICC), deals with the integer variables, is proposed in order to use the advantages of both methods simultaneously in mixed integer linear optimization models.

The new algorithm consist of two main loops, the outside loop for the integer cut constraints (ICC) and inside loop on the $\epsilon$ constraint. The number of iteration in the outside loop and the number of discretization steps in the parametric optimization ($\epsilon$ constraint) should be defined by the user at the beginning.

In this algorithm after generating the first cut constraints, an $\epsilon$ constraint is imposed on the upper bound of the second objective. The $\epsilon$ is varied inside its interval from $Lim_{inf}$ to $Lim_{sup}$. After analyzing the results of all iterations, the next cut constraint is generated and added to the optimization model (outside loop). The $\epsilon$ constraint is imposed for each new cut constraint. It will continue to generate all cut constraints. The number of cut constraints and the number of iteration on the $\epsilon$ are defined by the user at the beginning. Finally, Pareto optimal solutions and some suboptimal solutions are presented.The algorithm is shown in Fig.1.

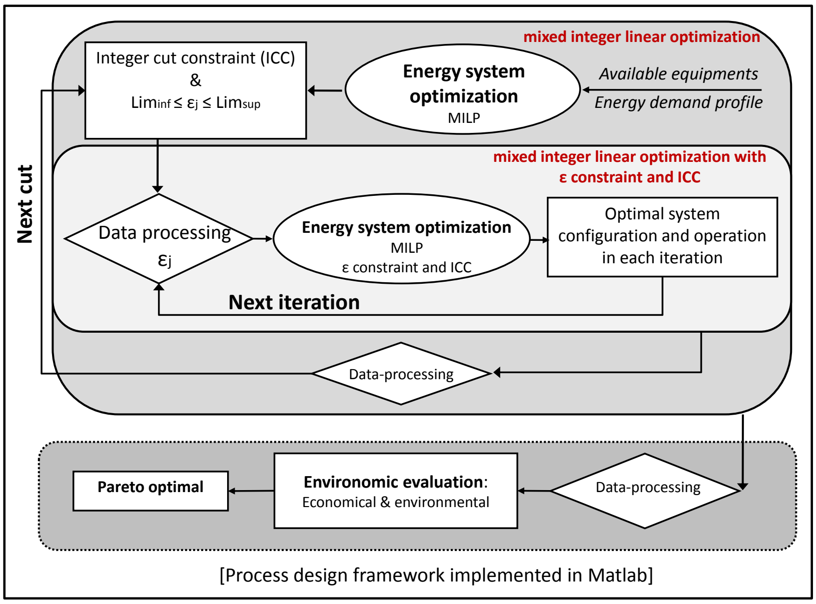


Figure 1: ∈ constraint combined with integer cut constraints (ICC): overall sequence

In the proposed model, the risk of missing good solutions between two $\epsilon$'s values (from $\epsilon_i$ to $\epsilon_{i+1}$) in MILP models is quite low. A set of competing solutions, near the Pareto optimal, is systematically generated and offering not only the Pareto frontier but also a set of suboptimal solutions. Furthermore, high diversities for different selected targets are obtained (Table.4).

### *3.4. Multi-objective evolutionary algorithm (EMOO)*

Due to their ability for handling non-linear and non-continuous objective functions, evolutionary algorithms have proven to be a robust method for solving complex multi objective optimization problems [35, 36]. Several researches have been reported on the application of multi-objective evolutionary algorithm (EMOO) (see, for example [37] for thermal system design; [38] for CHP plants, [39] for internal gasification combined cycles)

In this paper, the multi-objective optimization based on the evolutionary algorithm (EMOO) is performed to investigate the effects of sizing and operations of energy systems on $CO_2$ emissions. The algorithm is shown in Fig.2. The model is decomposed into master and slave optimizations as described in

[40]. The nonlinear master problem is solved using an evolutionary algorithm (EMOO) [12]. Objectives being the minimization of annual investment and operation costs, and $CO_2$ emissions:

$$\min_{\dot{\mathbf{Q}}_{\mathbf{s_i}},\mathbf{Y}_{\mathbf{s_i}}} [\mathbf{OPEX} + \mathbf{CAPEX} \quad , \quad \sum_t^T \sum_r^{N_r} \dot{\mathbf{Q}}^-_{\mathbf{s_i},\mathbf{r},\mathbf{t}} / \eta_{th,s_i} * d_t * m_{co_2,r}] \tag{24}$$

$$s.t. \quad \min_{\dot{\mathbf{Q}}_{\mathbf{s_i},\mathbf{r},\mathbf{t}},\mathbf{y}_{\mathbf{s_i},\mathbf{t}}} \mathbf{TC}$$

Binary variables, for the choice of the conversion technologies and their maximum available capacity, are decision variables in the master optimization. $CO_2$ taxes is also considered as a decision variable in the master level. It is defined in order to study effects of $CO_2$ emissions in the slave optimization with the single objective function. The slave optimization, $\min \mathbf{TC}$, is the MILP model described in sec.2.1. $\mathbf{Y}_{\mathbf{s_i}}$ and $CO_2$ taxes are decision variables in the master optimization and consequently the input data in the slave optimization.

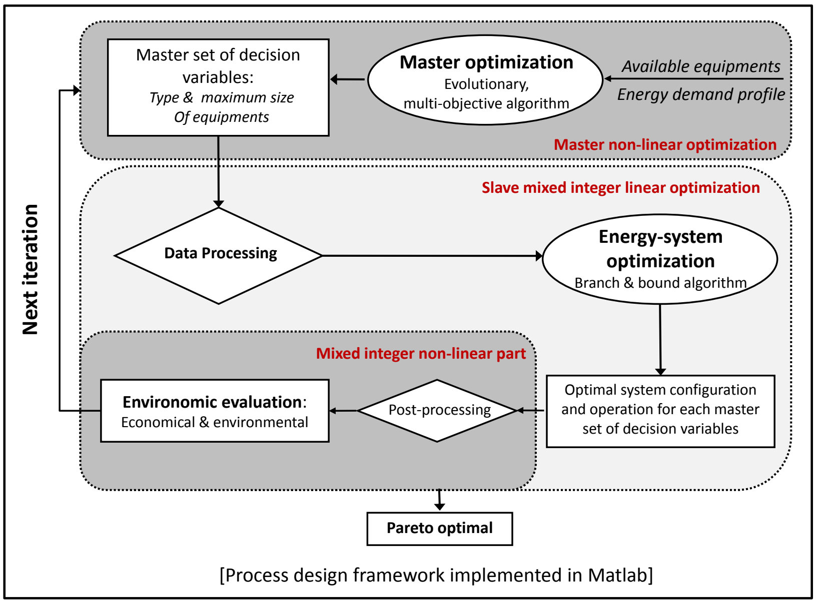


Figure 2: Overall evolutionary multi objective optimization sequence

The minimization of the total cost, including $CO_2$ taxes, is the objective function in the slave optimization. The size and the operating conditions of each energy conversion technology (ECT) are main decision variables in the slave optimization. Finally, Pareto optimal solutions, generated by multi-objective evolutionary algorithm (EMOO), are presented. It is referred to [41] for more explanations.

## 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 a 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 [19]. 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 [9, 42, 43].
As an assumption, the efficiency of biomass and biogas are defined 5% less

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] |

than the other types with 4 times more maintenance cost. The selling electricity price for solar PV is assumed to be 4 times higher than the price of the co-generation.

Table 2: $CO_2$ Intensity and Price of resources

| Resource type | $CO_2$ emissions: $[kg/kWh]$ | 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 |

The average consumers' heat demands are given in Table 3 for twelve periods of a year and one extreme condition with the corresponding duration. 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 to the electricity market with the market price. In this example the first situation is considered. The company has to produce electricity at full capacity of co-generation plants from October to March and rest of the year should turn the system off, but there is an interest of the regulated electricity price. This constraint is imposed by using Eq.16 and Eq.17.

Table 3: 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 of the $\in$ constraint*

In the first step the illustrative example is optimized by using $\epsilon$ constraint (see.3.1) with the economic objective in terms of the total annual cost (€/year), and the environmental objective in terms of the total $CO_2$ emissions. The goal is to identify the type, size and the operating condition of a central plant under these two objectives.

The $CO_2$ emissions interval $[Lim_{inf},\ Lim_{sup}]$ was partitioned into 50 sub-intervals.
Fig.3 shows the Pareto optimal solutions and Fig.4 represents results based

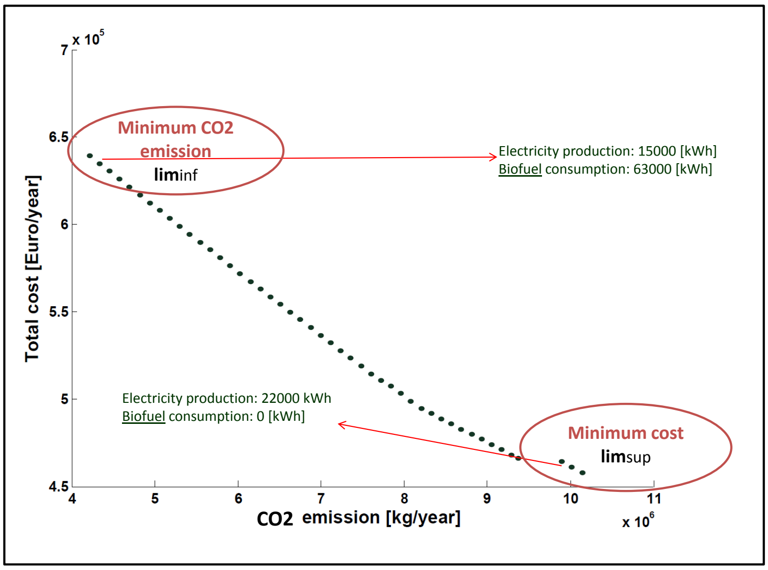


Figure 3: $\epsilon$ constraint: Pareto frontier

on three indicators; the operation cost, the annual investment cost and the $CO_2$ emissions. In this approach, the operating conditions are mainly affected by $\epsilon$ constraint, while only 3 different system configurations are identified in these 50 solutions (Fig.4). The results indicate that when $\epsilon$ is changed from $\epsilon_i$ to $\epsilon_{i+1}$ some configurations are neglected due to the discrete definition of integer variables.

### *4.2. Results of the integer cut constraints (ICC) method*

The integer cut constraints (ICC) are used (see.3.2) to generate a wide range of system configuration with 120 cuts. The Pareto set and some other solutions of this step is shown in Fig.5, and Fig.6 represents results based on three indicators; the operation cost, the annual investment cost and the $CO_2$ emissions. In each iteration a new configuration is generated by using cut constraints. Here, multi criteria analysis methods [24] can be used to compare solutions by using different criteria. However, a high diversity of

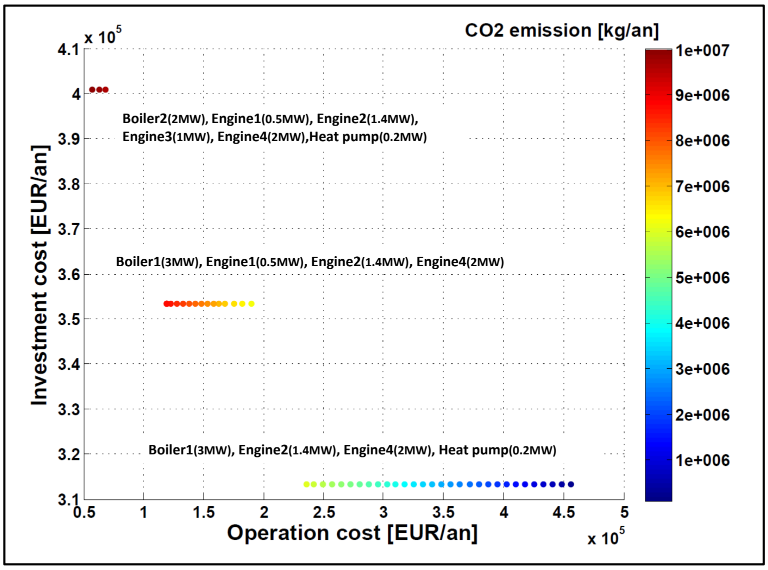


Figure 4: $\epsilon$ constraint: economical and environmental indicators

solutions for the environmental target is not obtained.

The resolution time for each additional solution (Fig.7) and the accumulated resolution time of first 120 solutions (Fig.8) are measured. Adding a new cut constraint in each iteration, makes the MILP more difficult to solve, thus explaining why the Fig.8 shows exponential behavior.

To sum up, regarding the resolution time, the integer cut constraints (ICC) are efficient for limited numbers of cuts; while for high numbers of cuts the resolution time will increase significantly. However, a set of good solutions near the optimal solution is generated. These solutions are suboptimal but still interesting for engineers even if they are not optimal.

### *4.3. Results of $\in$ constraint combined with the integer cut constraints (ICC) method*

In the first optimization model with only the $\epsilon$ constraint, results covered a wide range of the environmental objective, while the diversity of system configurations was quite low. The contrary is found in the optimization with the integer cut constraints (ICC).

In order to have a high diversity of system configurations and to cover a wide range of the environmental objective simultaneously, both techniques

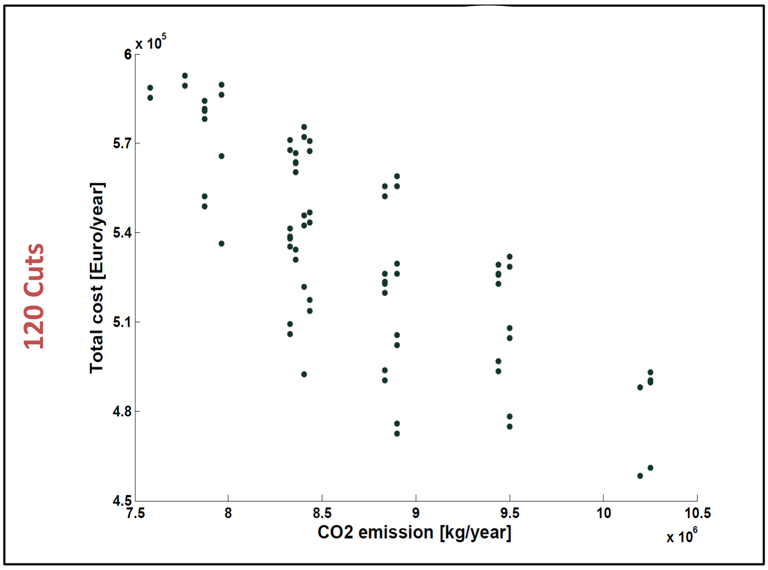


Figure 5: Integer cut constraints (ICC) method: Pareto frontier and nearby solutions

are combined (see.3.3).
The Pareto frontier and nearby solutions for 120 cuts and 30 iterations over the $CO_2$ emissions interval is shown in Fig.9. Fig.10 represents the operation cost, the annual investment cost and the $CO_2$ emissions of results.
Wide ranges of both objectives are covered by the new algorithm, but the resolution time increases significantly (Table.4).

### *4.4. Results of evolutionary algorithms (EMOO)*

The multi objective evolutionary algorithm (EMOO) (see.3.4), is also used as on illustrative example to optimize total annual costs and $CO_2$ emissions simultaneously and draw the Pareto set of solutions.
Two objectives, total costs and $CO_2$ emissions, together with fourteen integer variables are defined in the master optimization to select the type and the 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 activated in the slave optimization to cover the remaining heat demand.

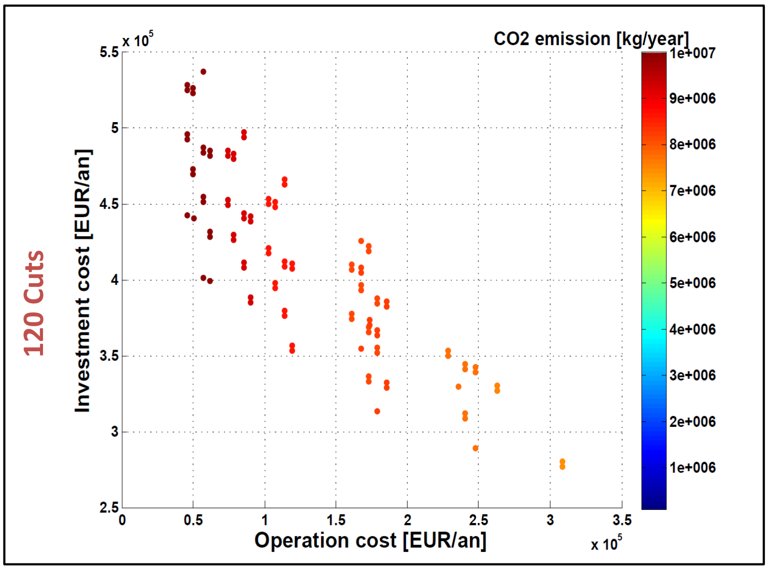


Figure 6: Integer cut constraints (ICC) method: economical and environmental indicators

Fig.11 shows the Pareto set of 120 plant configurations. To generate these sets of solutions, 1800 iterations of the master optimizer have been carried out with 13500 [*sec*] resolution time. The operation cost (operation expenses - incomes), the investment cost and the $CO_2$ emissions of these 120 solutions are also presented in Fig.12.

### *4.5. Discussion*

An optimal solution of three methods in terms of the total annual cost are exactly the same and featuring B2, E1, E2, E3, E4 together with HP. The production levels in this optimal configuration, during 12 typical days are shown in Fig.13. Due to the attractive electricity price, the heat production level during December and March is more than the heat demand.
The minimum and the maximum values of three indicators, explored by each algorithm, are presented in Table.4.
Fig.14 and Fig.15 represent the results of the evolutionary algorithm (EMOO) and integer cut constraints (ICC) combined with the $\epsilon$ constraint in the same scale. Wide ranges of both objectives are covered by the evolutionary algorithm (EMOO). The advantages of the $\epsilon$ constraint or the integer cut con-

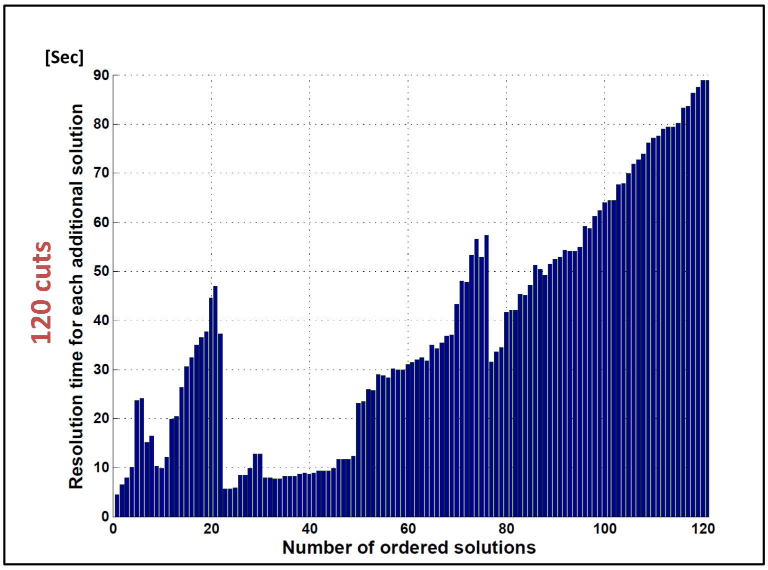


Figure 7: ICC: Resolution time for each additional point

straints (ICC) is their short resolution time for generating limited number of solutions. The computation time of the evolutionary algorithm (EMOO) for generating 120 Pareto points, is equal to 13500 [$sec$], which is longer than integer cut constraints (ICC). The $\epsilon$ constraint combined with the integer cut constraints (ICC) also has a higher resolution time than the $\epsilon$ constraint or the integer cut constraints (ICC) alone.
In conclusion, the integer cut constraints (ICC) and $\epsilon$ constraint are quicker to execute than EMOO.

Table 4: Three objectives' ranges explored by ICC, $\epsilon$ constraint and EMOO

| | Investment: [k€/year] | Operation: [k€/year] | $CO_2$ [$tons/year$] | Time [Sec] |
|---|---|---|---|---|
| ICC | [277 537] | [46 308] | [7.6 10.2] | 2700 |
| $\epsilon$-ICC | [277 470] | [46 411] | [4.2 10.2] | 12400 |
| EMOO | [89 524] | [46 811] | [6.3 10.2] | 13500 |

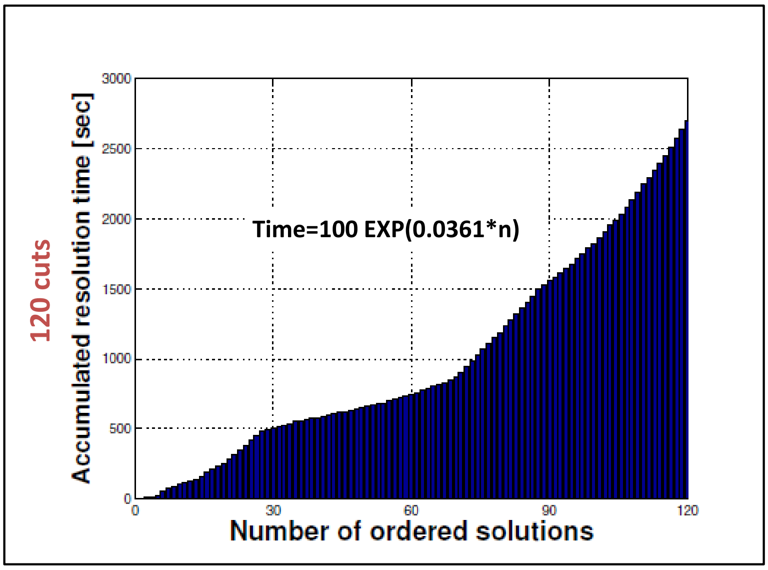


Figure 8: ICC: Accumulated resolution time

## 5. Post-processing phase

After generating a Pareto optimal configuration with the set of good solutions, several key performance indicators are calculated for each solution. The stakeholders' preferences can then be used to define the weighting factors to sort solutions. Weighed solutions are presented to stakeholders and engineers for selecting the most interesting configurations.
A sensitivity analysis can also be performed on uncertain parameters like market conditions (costs, electrical costs, heat costs, $CO_2$ emissions taxes) and resource availability. A distribution functions of performance indicators will be generated for selected members of the Pareto frontier by using MonteCarlo simulations. The results of this sensitivity analysis will also help the deception makers to pick an optimal solution from the solution pool.

## 6. Conclusion

The sizing and operations of energy systems are key issues for matching energy supply and consumption. Analyzing one optimal solution for energy system design with a mono objective function is efficient but limiting, as

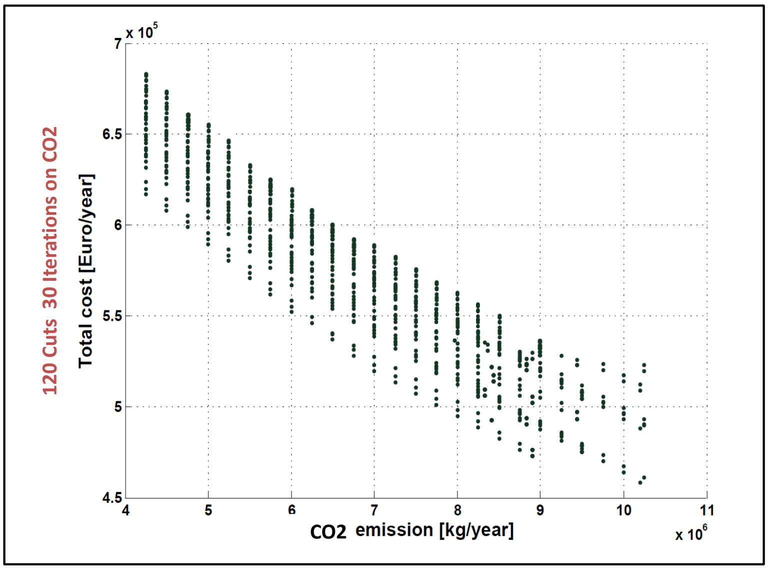


Figure 9: $\epsilon$ constraint with ICC method: Pareto frontier and nearby solutions

it does not allow for the systematic variation of decision variables and the identification of their optimal ranges. Moreover, it is necessary to account the interactions between different decision variables, and also the trade-offs between conflicting objectives.

The issue of multi-objective optimization was addressed in this paper, where two main optimization techniques (integer cut constraints (ICC) combined with the $\epsilon$ constraint, and the multi objective optimization with an evolutionary algorithm (EMOO)) were carried out.

In the first step, a multi periods energy system optimization (ESO) model is explained. It is a mixed integer linear programming (MILP) model with mono objective function. After that, It is developed by adding integer cut constraints (ICC) and $\epsilon$ constraint. The goal is to systematically generate a good set of ordered solutions rather than just one optimal solution. In this step the effect of $CO_2$ emissions is studied by using $\epsilon$ constraint.

In the next step, the problem is reformulated as a multi-objective optimization model with an evolutionary algorithm (EMOO) to study total costs and $CO_2$ emissions, by decomposing the model into master and a slave optimization.

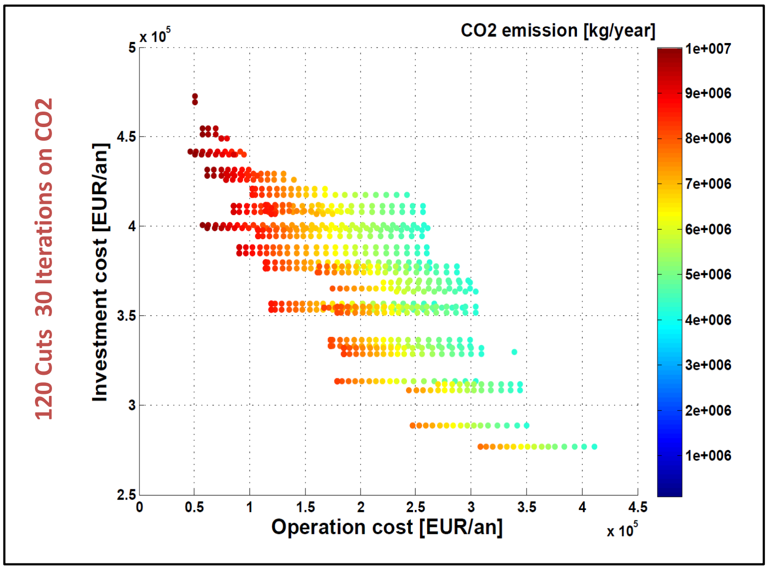


Figure 10: $\epsilon$ constraint with ICC method: economical and environmental indicators

Developed models are demonstrated by means of a case study. The case comprises six types of energy technologies, namely a heat pump and boiler, solar PV, as well as a 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, the mixed integer linear programming (MILP) model with the integer cut constraints (ICC) requires less computational effort than the evolutionary algorithms (EMOO).
- Several powerful mathematical algorithms are developed for solving the mixed integer linear programming (MILP) model with the integer cut constraints (ICC) and the $\epsilon$ constraint, while evolutionary algorithms are a heuristic method without any guarantee for finding the optimal solution.
- The evolutionary algorithm (EMOO) is more effective in obtaining a Pareto optimal set and nearby solutions (see Fig.14 and Fig.15), while the integer cut constraints (ICC) combined with the $\epsilon$ constraint needs

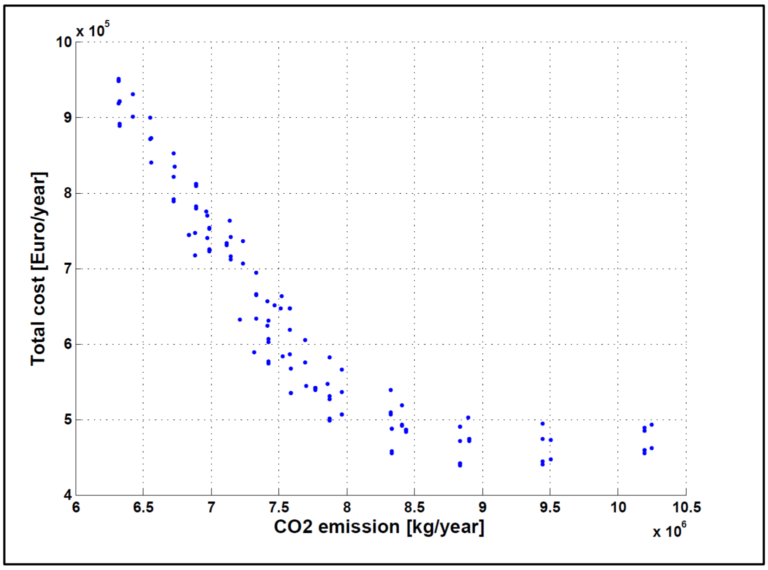


Figure 11: Evolutionary algorithm: Pareto frontier and nearby solutions

to generate most solutions in the feasible space for drawing Pareto frontier which is very time consuming.

- Integer cut constraints (ICC) is powerful and quick for generating limited number of ordered solutions.
- The evolutionary algorithm (EMOO) is more suited for handling the multi-objective optimization. It provides the information needed for detailed analyses of design trade-offs between conflicting objectives, while the mixed integer linear programming (MILP) model with integer cut constraints (ICC) is a mono objective model and the effect of second objective is studied by adding a new constraint.
- There is a possibility of using parallel computation for solving the evolutionary algorithm (EMOO) and decreasing the resolution time, but in integer cut constraints (ICC) generating a new solution totally depends on previous ones consequently no possibility of using parallel computation.

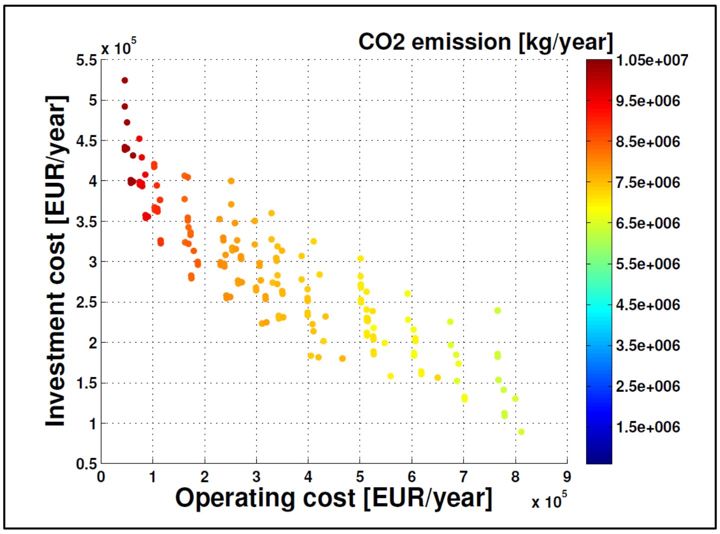


Figure 12: Evolutionary algorithm: economical and environmental indicators

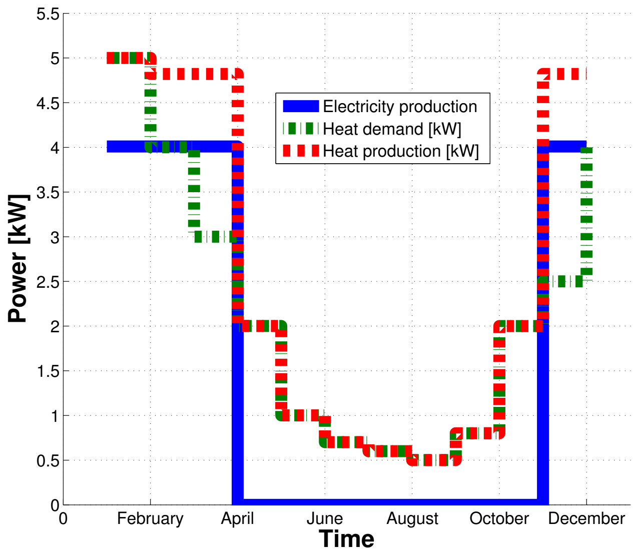


Figure 13: Heat and power production during 12 time periods

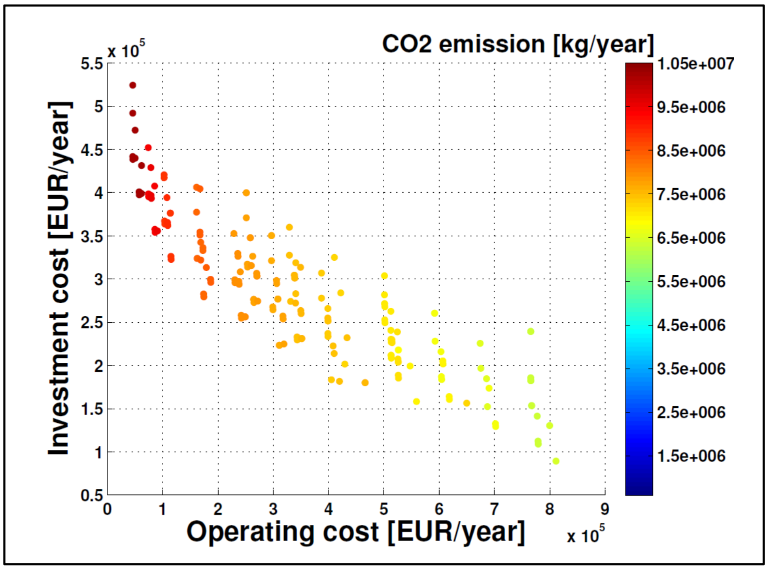


Figure 14: Multi objective optimisation results: EMOO

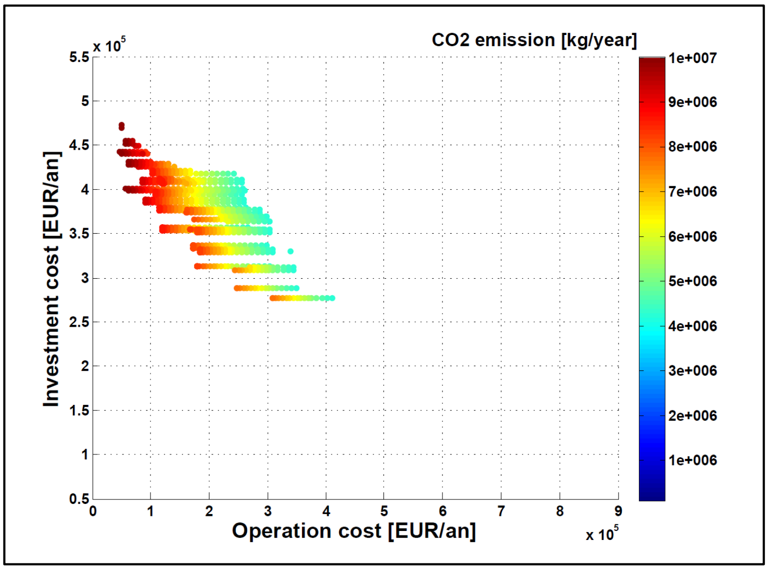


Figure 15: Multi objective optimization results: ICC with *epsilon* constraint

**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 |
| $\eta_{th,s_i}$ | thermal efficiency of subsystem $s_i$ |
| $\eta_{th,s_i}$ | electrical efficiency of subsystem $s_i$ |

| | |
|---|---|
| $\dot{fuel}_{r,t}$ | fuel consumption of type $r$ in time $t$, kWh |
| $CO_{s_i}$ | CO2 emissions in subsystem $s_i$, kg |
| $d_t$ | duration of time interval $t$, h |
| $CO_r$ | CO2 emissions 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 |
| $\epsilon_d$ | the conversion efficiency from the grid |
| $\epsilon_g$ | the conversion efficiency to the grid |
| $\Delta_t$ | 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, € |
| $\alpha_{s_i}$,$\beta_{s_i}$ | 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 |

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