Multi-objectives, multi-period optimization of district heating networks using evolutionary algorithms and mixed integer linear programming (MILP): Selection of typical days

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Abstract

A systematic procedure, including process design and integration techniques for sizing and operation optimization of a poly-generation plant and design of a district heating network is presented in this paper. In the developed model a simultaneous multi objectives and multi-period optimization are principally investigated. The goal is to simultaneously minimize costs and CO_2 emission using multi-objective evolutionary algorithms (EMOO) and Mixed Integer Linear Programming (MILP). Typical days definition and the extension of the post processing phase are the novelty of this work.
The proposed method helps the decision maker to know; which type and configuration of poly-generation technologies (centralized and decentralized) are best suited for the district? Is it viable to combine these technologies with other technologies (like heat pumps, solar PV)? Where in the district shall these technologies be implemented (geographically)? what are the optimal flow, supply and return temperatures of the distribution networks (heating and cooling) considering the requirements of the district and the technical limitations of the technologies?

Keywords: CO_2 mitigation, Poly-generation systems, Mixed Integer Linear Programming, Evolutionary algorithm, Typical days.

1. Introduction

Poly-generation technologies, joined with the integration of biomass, have a good potential for CO_2 emissions reduction in the district heating networks. A systematic optimization procedure is needed to select and size the equipments and simulate the operation conditions in short periods of time like hour by hour. The energy system analyses could be divided into two major steps; first sizing and design optimization and second, operation optimization.
The optimization of energy systems that include one or more technologies to meet the requirements of energy systems is extensively studied by many authors. It is referred to D.Connolly [2010] for a detailed review. Besides, simulation and modeling of biomass based cogeneration systems are reviewed in Raj et al. [2011]. Most of these publications carried out only simulations, while system design optimization is neglected. Diverse procedures exist to size cogeneration plants, like a structural optimization approach based on the mixed-integer linear programming by Papoulias and Grossmann [1983]. For a detailed overview, the role of optimization modeling techniques in power generation is reviewed in A.Bazmi [2011]. However, most of these optimization mod-

els only consider a mono economic objective function, completed with environmental and energetic targets as constraints, rather than following multi objective optimization. To sum up, energy system analyses are extensively studied by many authors. However, a systematic procedure including process design and energy integration techniques with simultaneous consideration of multi-periods and multi-objectives aspects for energy system designs is still missing. A multi-objective optimization model with evolutionary algorithms (EMOO) and MILP based on the decomposition approach has been developed (S.Fazlollahi [2011]) to deal with this complexity. Besides, in urban systems the design procedure relies on the definition of typical days operation to calculate the annual expected system performance and the optimal size of equipments and storage systems. In this paper, the definition of the typical days in a energy system design is discussed. In addition, a post processing phase is also presented to analyze the results in more details.

2. Methodology

The multi-objective optimization techniques are used in order to investigate sizing and operating effects of poly-generation technologies on CO_2 emissions. The basic concept of the developed model is the decomposition of the problem into several parts, as illustrated in Figure 1. Three major parts (C.Weber [2006]) are; a **Structuring phase** in which required data will be collected and manipulated. Secondly the **Multi-objective nonlinear optimization phase** will solve the system configuration and produce results in the form of a Pareto frontier. In the third section, the **Post-Processing phase**, the Pareto frontier and associated results will be studied in details by doing a more details process operation simulation.

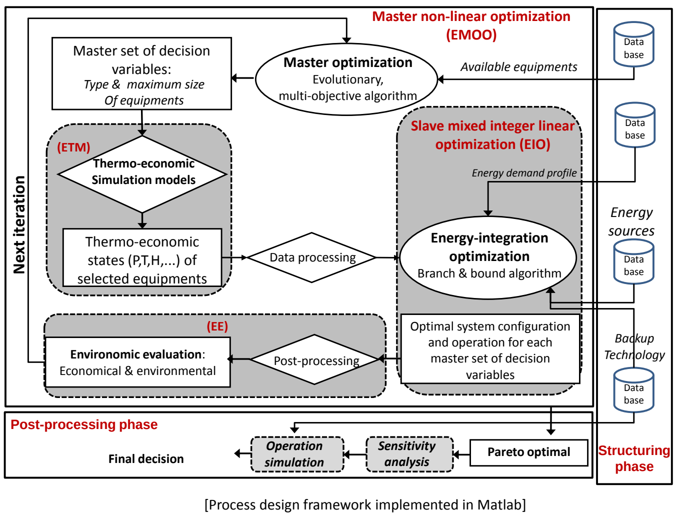

Figure 1: Illustration of the process optimization strategy

2.1. *Structuring phase*

The structuring phase regroups the collection, design and management of all data that will be required to solve the district energy problem. These principally include, the list of available energy sources, simulation models of available and alternative District Energy Conversion Systems (DECS), simulation models of individual backup technologies, the geographical information of a district and the energy consumption profile.

2.1.1. Typical days definition

In an urban system, the demand profile is needed to size the system and optimize its configuration. Due to the complexity of the optimization algorithm, the representation of the annual demand profile by a set of typical days is preferred when doing the system design. While in the post processing phase when the system configuration and its size are known, the use of a yearly operation schedule (hour by hour) allows to calculate performances of the system and verify the feasibility of its configuration. A good data set of typical days should be able to represent every day of the year with a certain degree of accuracy. There will be a better accuracy by increasing the number of typical days but the optimization resolution time will also increase.
In the present work the demand profile for typical days is calculated using a centroid clustering algorithm.The real demand for each day is compared to its typical day using standard deviation of average daily demands (Sigma CDC), standard deviation of hourly demand, standard deviation of load curves (ELDC), as well as more empirical methods such as the difference in maximum of load curve (Delta LDC) and calculating the number of days over or under producing by a pre-defined margin. These performance indicators should allow the manipulator to know the validity of selected typical day. Table.1 shows the comparison between these indicators for different number of typical days and Figure.2 compares 8760 hours of a typical year operation with 8 estimated typical days.

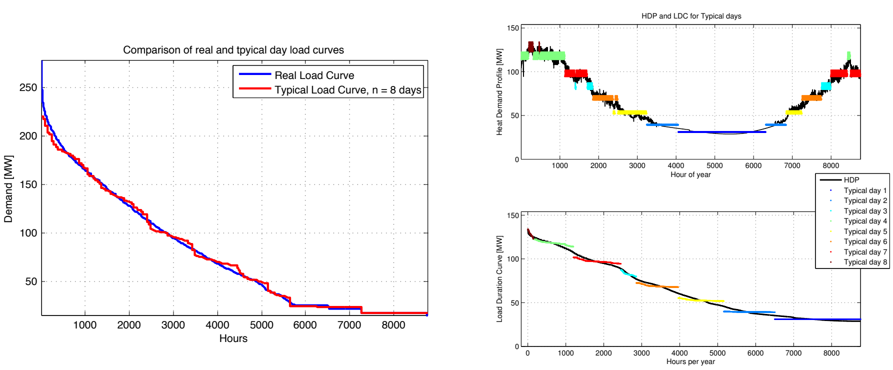

Figure 2: Typical day Load curve

2.2. Multi-objective nonlinear optimization phase

The optimization algorithm has the aim of solving a complex non linear problem consisting of minimizing the investment costs (CAPEX), operational costs (OPEX) and CO_2 emissions simultaneously. The goal of this step is to optimize the system configuration and size the selected equipments. Evolutionary and conventional algorithms are exploited in order to generate a multitude of possible solutions which can be placed on a Pareto frontier. In order to reduce the complexity of this large non linear problem, the optimization phase is decomposed in four major parts (S.Fazlollahi [2011]), a **Master**

Table 1: Comparison between the number of typical days

Number of typical days	5	6	8	10	12	Monthly*
Sigma CDC	0.18	0.13	0.09	0.06	0.05	0.26
Sigma Profile	0.10	0.10	0.09	0.09	0.09	0.11
ELDC	0.12	0.11	0.10	0.09	0.08	0.18
Delta LDC	0.21	0.21	0.20	0.15	0.14	0.05
Delta prod. 15%	131	88	16	8	3	140

*Mean monthly values and one extreme condition

optimization (MOO), a **Thermo-Economic simulation (ETM)**, a **Slave optimization (EIO)** and **Environomic evaluation (EE)**.

2.2.1. Master optimization

The set of decision variables in the master optimization include the type and the maximum available size of equipments. These variables are used to define possible superstructures for a district energy system. Here, a list of available and alternative equipments is the main input data from the structuring phase. The master optimization is solved by an evolutionary algorithm (EMOO) [25] with three objectives: the minimization of the annual investment cost (CAPEX), the operating cost including incomes (OPIN), and the overall CO_2 emissions of a system (Eq.1).

$$\min_{\mathbf{\dot{Q}_{s_i}},\mathbf{Y_{s_i}}} [\mathbf{OPIN}, \quad \mathbf{CAPEX}, \quad \mathbf{M_{CO_2}}], \quad s.t.\{\mathbf{ETM},\mathbf{EIO},\mathbf{EE}\} \tag{1}$$

2.2.2. Thermo-Economic simulation (ETM)

Subsequently, in the second step the thermodynamic and economic state of the selected equipments in the superstructure is calculated by using thermo-economic simulation models (ETM). Here, the goal is to calculate the investment turnkey cost, the heat load of the heat transfer requirement, the temperatures, the enthalpy and the power of selected equipments in nominal and part loads conditions. These values, the list of available energy sources and the energy consumption profiles (including the temperature and power levels) are the main input parameters for the slave optimization.

2.2.3. Slave optimization (EIO)

The next step is the slave optimization. It solves the energy integration problem (EIO) as a mixed integer linear model (MILP). It will calculate the best usage of equipments in the selected superstructure in order to supply the requirements of the system. It is solved by robust linear programming methods. Here the aim is to minimize the total cost under the energy balance, the heat and power cascade constraints (Eq.2). The input data and parameters used in the slave optimization include the values of the master decision variables, the thermodynamic parameters which are outputs resulting from thermo-economic simulation models, energy consumption profiles and the resources' availability. The optimization includes the model of an optimal management strategy that assumes a cyclic operation over each day.

$$\begin{aligned}\min_{\mathbf{\dot{R}e_{l,p,t_p}},\mathbf{\dot{R}_{r,p,t_p}},\mathbf{y_{s,p,t_p}},\mathbf{f_{s,p,t_p}}} \sum_{s,p,t_p} \mathbf{f}_{s,p,t_p}([\sum_i \dot{Q}^+_{s_i,p,t_p} c^+_{i,p,t_p} - \sum_j \dot{Q}^-_{s_j,p,t_p} c^-_{j,p,t_p} + \sum_l (cel^+_{l,p,t_p} * \dot{E}^+_{s,l,p,t_p} - cel^-_{l,p,t_p} * \dot{E}^-_{s,l,p,t_p})] * d_{t_p}) \\ +[(\textstyle\sum_{s,p,t_p} \mathbf{f}_{s,p,t_p} * \mathbf{\dot{M}_{CO_2,s,p,t_p}} * tax_{co_2}) + cel^+_{N_l,p,t_p} * \mathbf{\dot{E}^+_{grid,p,p_t}} - cel^-_{N_l,p,t_p} * \mathbf{\dot{E}^-_{grid,p,t_p}}] d_{t_p}\end{aligned} \tag{2}$$

2.2.4. Environomic evaluation (EE)

The selected superstructure in the master level and the result of the slave optimization are used in the environomic evaluation (EE) phase to calculate objective functions of the master optimization, namely CAPEX, OPIN and M_{CO_2}. After all iterations are completed the results will be presented by the Pareto optimal frontier.

2.3. Post-processing phase

The result of the data processing and optimization will be a Pareto optimal configuration. Several key performance indicators will be calculated for weighting solutions. Weighted solutions are presented to stakeholders and engineers for selecting the most interesting configurations. The feasibility of interesting configurations will be calculated by simulating a typical operating year. The size of back up technologies and the operation of the storage system are also studied with the simulation model.

2.3.1. Sensitivity analysis

A sensitivity analysis will 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 simulation.

3. Conclusion

A systematic procedure including process design and energy integration techniques with simultaneous consideration of multi-periods and multi-objective aspects, economic and environment targets, for energy system design and operation is proposed. A decomposition approach is used to deal with this complexity. In order to do so, a method has been developed in three main phases; structuring phase, optimization phase and post processing phase. It combines the use of typical day definitions and the operation evaluation in the post processing phase by doing the simulation of a typical operating year.

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