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EABOT – Energetic analysis as a basis for robust optimization of trigeneration systems by linear programming

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ABSTRACT

The optimization of synthesis, design and operation in trigeneration systems for building applications is a quite complex task, due to the high number of decision variables, the presence of irregular heat, cooling and electric load profiles and the variable electricity price. Consequently, computer-aided techniques are usually adopted to achieve the optimal solution, based either on iterative techniques, linear or non-linear programming or evolutionary search. Large efforts have been made in improving algorithm efficiency, which have resulted in an increasingly rapid convergence to the optimal solution and in reduced calculation time; robust algorithm have also been formulated, assuming stochastic behaviour for energy loads and prices. This paper is based on the assumption that margins for improvements in the optimization of trigeneration systems still exist, which require an in-depth understanding of plant's energetic behaviour. Robustness in the optimization of trigeneration systems has more to do with a "correct and comprehensive" than with an "efficient" modelling, being larger efforts required to energy specialists rather than to experts in efficient algorithms. With reference to a mixed integer linear programming model implemented in MatLab for a trigeneration system including a pressurized (medium temperature) heat storage, the relevant contribute of thermoeconomics and energo-environmental analysis in the phase of mathematical modelling and code testing are shown.

1. Introduction

In the last decade, a growing interest has been observed for combined heat and power (CHP) or combined heat, cooling and power (CHCP) applications in buildings. This is obviously due to the high conversion efficiency of polygeneration systems and the consequent energy and pollutant-emissions savings, but also due to favourable external conditions, like the new opportunities existing in the liberalised energy market and the growth of a "small scale CHP" market, which has gradually reduced the purchase and installation cost of CHP units (typically, in the order of 600–800 €/kW$_e$).

These promising perspectives have stimulated the efforts of scientists towards the definition of criteria for the optimization of CHCP design and operation for applications in the civil sector. Several analyses have been oriented to assess the potential benefits in terms of energy and pollutant-emissions savings [1,2] and, in some cases, some peculiar aspects were examined adopting thermoeconomic cost-accounting methods [3] or pinch analysis [4]. In order to understand the complexity of the optimization problem, the following aspects can be remarked:

- Safety of supply and flexibility are usually ensured by redundancy, i.e. the system is designed as a "facility of systems of a same product", where different components may alternatively contribute to cover the demand of a specific energy vector.
- The problem is time-dependent: the variability in energy loads and prices requires the adoption of flexible plant operation strategies; in the civil sector, discretization on hourly basis is usually pursued, resulting in a high number of decision variables as concerns plant operation. Discussions have arisen on the possibility to adopt a reduced set of "standard days" (typically defined on seasonal and "working–non-working" bases) without loss of reliability, but this is a controversial argument which needs *ad hoc* considerations for each case.
- The decision variables have a non-homogeneous nature, both as concerns the way they affect the objective function and the values they can assume. Either in case of profit, energy or pollutant-emission saving-oriented optimizations, the objective function depends on annual results, calculated

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Nomenclature

a, b	constants in linearized equations
B	generic flux (energy or exergy terms)
C	cooling demand or production
CHCP	combined heat, cooling and power
CHP	combined heat and power
CONS	energy consumption
COP	coefficient of performance
D	energy load, on hourly basis
E	electricity demand or production
FOR	feasible operation range
GA	genetic algorithms
H	heat demand or production
i^*	interest rate
LL	load level
LP, NLP	linear and non-linear programming
LR	Lagrangian relaxation
m	mass of hot water stored
MP	market price
NPV	net present value
PES	primary energy saving
PHR	power to heat ratio
STOR	stored energy (kWh)
T	temperature
TES	thermal energy storage
Z, z	total and specific capital cost

Superscripts

abs	absolute
conv	conventional
dir	for direct uses
rel	relative

Subscripts

Abs	absorption chiller
boilmax	corresponding to boiler capacity (heat peak load)
del	delivering
el.ch.	electric chiller
Exch	exchanged with the grid
inv	investment
pow.plant	power plant
ret	return

Greek symbols

δ	0–1 binary variable
η	efficiency

as sum of single values obtained for each time-step. The optimization problem can be divided into three different sub-problems:

(a) *Synthesis*: in order to optimize the plant configuration, i.e. to select what components should be installed, a starting redundant "superconfiguration" is usually adopted, that is a general CHCP scheme where several components are included and a high level of interconnections among them is assumed. The decision variables at synthesis level are 0–1 variables, each indicating the decision to include/not include a certain component.

(b) *Design*: CHCP systems for buildings applications are usually made up by highly standardised components (gas turbines, reciprocate engines, water–lithium bromide absorption chillers, etc.), which can be regarded as black boxes and modelled by defining their part load behaviour. The absence of variables involving the thermodynamic state of working fluids (the optimization of heat exchangers represents a 2nd refinement level, not considered in this paper) makes the design optimization easier than usual. Only a relatively small number of design variables representing the size of plant components is included.

(c) *Operation*: the optimization of plant operation is more complex than usual; in fact, CHCP systems offer several possibilities of loading the different components to cover energy requests, the optimal solution depending on efficiency figures, energy loads and prices. This optimization level involves both 0–1 variables (the on/off state for each component) and continue variables (the load level of each component). Also, the optimization routine must be applied on hourly basis, because both energy load and prices are time-dependent.

The variables of the different sub-problems are not of a "same rank"; for instance, operational variables could be optimized only once fixed values for the decision variables at synthesis and design level have been assumed. This aspect heavily influences the choice of the most appropriate resolution technique. Evolutionary search, for instance, which has been extensively used in the optimization of energy systems by genetic algorithms (GA), is not suitable for our problem because of the deficiency in handling highly constrained problems; also, GA could be preferably adopted to optimize plant operation as internal routine of an iterative synthesis-design optimization [5] and this approach is not suitable for the examined problem due to the huge number of different operating conditions. Several heuristic approaches have been proposed, oriented to determine near-optimal solutions basing on "aggregate thermal load" duration curves [6] or thermoeconomics [7]; most of them, however, do not include an "integrated" optimization process, but assume a priori a sub-optimal management strategy (either "heat tracking" or "electricity tracking" operation modes). More recently, linear programming (LP) techniques have been extensively used [8,9], due to the possibility to solve large scale problems with thousands variables approaching the "multi-level" optimization problem by an "horizontal algorithm", where synthesis, design and operational variables are threaten similarly. More refined approaches have been proposed in [10], where a robust optimization included a sensitivity analysis in LP to consider stochastic energy loads, and in [11], where an efficient algorithm was proposed, which resulted much faster than an efficient sparse simplex code.

The fact that the production of the three energy vectors follows a joints characteristic makes often convenient to include thermal energy storages (TESs, i.e. hot water and/or chilled water tanks); usually, the TES is used to maximise power production during peak hours (where high value electricity is produced), storing eventual surplus heat/cooling energy to reuse it during off-peak hours. The inclusion of a TES significantly varies the structure of the optimization problem, introducing dynamic constraints; a clear overview of the techniques proposed in the literature to deal with *storage constraints* was provided in [12]. Let us here briefly resume the two main currencies:

– Decoupling the time-dependent storage constraint, a set of small-size single-period sub-problems may be solved. In [12,13] Lagrangian relaxation (LR) methods were used,