Optimal scheduling of Energy Hubs and CCHP systems

The future development of electric and thermal energy generation, transport and distribution relies on the exploitation of both conventional and renewable energy sources via a wide variety of energy conversion technologies; on the top of that electric and thermal energy storage could be utilized in order to match the demand with response exploiting more effectively the possible synergies between the installed units.

In this context Combined Heat and Power (hereafter CHP) power plants and engines are particularly attractive due to the higher efficiency when compared to conventional units generating only one energy commodity. CHP units can be classified into two main categories:

- one-degree-of-freedom units feature a single independent operating variable, the load (defined as the current fuel input rate divided by the maximum one), which controls the two energy outputs (e.g., electric and thermal power). As a result, for a certain power plant or engine load, it is not possible to vary the share of the two energy outputs according to customer needs. Examples of one-degree-of-freedom CHP units are internal combustion engines and gas turbines with waste heat boiler, backpressure steam cycles, and combined cycles with back-pressure steam turbine.
- Two-degree-of-freedom units feature two independent operating variables, the load and another one (such as a steam extraction valve) adjusting the share of the two energy outputs. Although these systems are more complex and typically more costly, the second control variable increase the operational flexibility of the unit. Examples are steam cycles with extraction condensing steam turbine (a steam extraction valve controls the steam bled from the turbine and used to provide heat to the customer).

It is worth noting that also more sophisticated units featuring three independent variables exist (e.g. CHP natural gas combined cycle with post firing and extraction-condensing steam turbine). Moreover, looking at the energy outputs, some units can be configured so as to cogenerate cooling power in addition to electricity and heat. Such units are called Combined, Cooling, Heat and Power (CCHP). Examples are units made by an internal combustion engine, a waste heat boiler and an absorption chiller (converting heat into chilling power).

Systems featuring several CCHP or CHP units may be integrated with other units such as boilers, heat pumps, and energy storage systems within so-called Energy Hubs. The sizes may range from few hundreds of kW for buildings to hundreds of MW for industrial users and or district heating networks.

Three main types of challenging optimization problems arise when dealing with such integrated systems:

- short-term scheduling, also called unit commitment,
- long-term operation planning,
- design or retrofit of the energy hub (see Section 3.1.1.5).

The short-term unit commitment problem can be stated as follows:

Given:

- the considered time horizon (e.g., one day, two days, one week) and an appropriate discretization into time periods (e.g., 1 h, 15 min),
- forecast of electricity demand profile,
- forecast of heating and cooling demand profile,
- forecast of ambient temperature,
- forecast of time-dependent price of electricity (sold and purchased),
- performance maps of the installed units,
- operational limitations (start-up rate, ramp-up, etc.) of units,
- efficiency and Maximum capacity of storage systems;

optimize the following independent variables:

- on/off of units,
- load of units,
- share among heat and power (only for two-degree-of-freedom units),
- energy storage level (hence charge/discharge rate) in each time period (for each energy storage system);

so as to minimize the operating costs (fuel + operation and maintenance + electricity purchase) minus the revenues from electricity sale for the given time horizon while fulfilling the following constraints:

- energy balance constraints for each time interval, e.g. electric energy, thermal energy, etc.,
- start-up constraints for each time unit, for each unit,
- ramp-up constraints for each time unit, for each unit,
- performance maps relating the independent control variables of the units with their energy outputs (e.g. output thermal power as a function of the load),
- a number of case-specific side constraints, e.g. maximum number of daily turns-on/off, for each unit; precedence constraints between units; minimum time unit permanence in on/off states, for each unit etc.

All constraints, except the performance maps of the units, can be easily formulated as linear equalities or inequalities. Performance maps of units are generally nonlinear and often not convex functions yielding to a nonconvex Mixed Integer NonLinear Program.

Due to the large number of variables, both integer and continuous, commercially available global MINLP solvers are not capable of finding the global optimum within reasonable time limits [1-Taccari 2015]. Besides genetic algorithms [2-Kazarlis,1996] or Tabu search [3-Mantawy,1998] from late nineties or other solutions going from Lagrangian relaxation [4-Borgetti et al 2003] to heuristic algorithms based on engineering practice for simple problems [5-Bischi 2016], the most effective approaches are based on the linearization of performance maps so as to obtain a Mixed Integer Linear Program (MILP) [6-Mitra 2013]. This allows to use efficient MILP solvers, such as Cplex [7] and Gurobi [8], and have better guarantees on the quality of the returned solution [1-Taccari 2015]. The performance maps of the machines can be linearized using either the convex hull representation [9-Ladhelma] or classic piecewise linear approximations [10-D'Ambrosio 2010] of 1D [11-Zhou 2013] and 2D functions [12-Bischi 2014]; the latter kept into account also daily storage facing an large increase of computational effort, ranging from two to three orders of magnitude.

The so described problem assumes that forecasts of energy demands and prices are accurate and their uncertainty is limited. If data uncertainty needs to be considered, the short-term scheduling problem can be extended and reformulated either as a two-stage stochastic program [13-Alipour 2014, 14-Cardoso 2016] or a robust optimization problem with recourse [15-Zugno 2016].

As an additional challenge, when determining the optimal scheduling of CHP units, it is necessary to take into account of the European Union regulation for high efficiency CHP units [16-EU regulation]. If a CHP unit achieves throughout the whole year a primary energy saving index above a threshold value, incentives are granted. Being a yearly-basis constraint, it poses the need of considering the whole operating year as time horizon when determining the optimal scheduling of CHP units. The same requirement concerns energy hubs featuring seasonal storage systems [17-Gabrielli et al. 2017] capable of efficiently storing energy for several months. Since tackling the scheduling problem for the whole year as a single MILP is impracticable, metaheuristics based on time decomposition to reach near optimal solutions in a reasonable amount of time have been proposed. [18-Bischi et al. 2017] proposed a rolling horizon algorithm in which the time horizon is partitioned into weeks. The extension of the MILP model from one day to seven days may imply an increase of computational time from few sec for a single day to tens of minutes for the week (with MILP gap below 0,1%) but it allows to better manage the thermal storage system accounting for the weekly periodicity of the users' demand. Within the rolling-horizon algorithm, the weekly MILP subproblems are solved in sequence from the current week till the end of the year. The yearly-basis constraints related to the CHP incentives are included in each weekly MILP subproblem by estimating the energy consumption and production of the future weeks of the year with the corresponding typical operating weeks (previously determined and optimized). If the yearly basis CHP incentive constraints are not met, the rolling horizon algorithm is repeated considering a higher (less optimistic) energy consumption for the future weeks. Thanks to the decomposition of the operating year into weekly subproblems, the computational time required to optimize the whole year of operation with a tight relative MILP gap (0.1%) ranges from 1 day to 3 days, making the algorithm an effective scheduling and control tool for energy hubs featuring CHP units.

Finally it is worth pointing out that, due to growing industrial interest in the optimal operation of complex energy systems for providing cooling, heating and power (e.g., energy service companies, multi-utilities managing district heating networks as well as power plant operators), several tools are already available on the market [19-Bettinelli et al. 2016].

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