Long-Term Operations Planning in Combined Heat and Power Supply Systems

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Abstract: This paper reports on a method for long-term operations planning in combined heat and power supply systems with a planning horizon of up to 15 months. Solutions to the special problems of modelling either energy supply contracts and electrical and thermal loads within a Mixed-Integer-Linear Programming approach are suggested. Additionally a method is proposed, which controls the optimization procedure and reduces the CPU-time spent in the applied MILP-program. Based on data of two actual cogeneration systems exemplary results of load representations and of the optimization algorithm are presented.

Keywords: operations planning, fuel scheduling, mixed-integer linear programming

1 Introduction

The operation of cogeneration systems is characterized by a simultaneous heat and power production meeting actual load demands. This and different types of electric power-, heat- and cogeneration-units with various technical restrictions to be considered make operations planning more difficult. Additionally energy supply contracts for primary and secondary energy are incorporated into the system. Due to the fact that cogeneration systems must be operated according to minimal operational costs with respect to technical, contractual and legal constraints operations planning is a complex problem.

The complexity of the planning problem requires a subdivision into tasks with different study periods. A typical hierarchy for an overall operations planning is presented in [1]. Additionally this paper reports on solution methods, which are mainly used to solve deterministic operations planning problems: Dynamic Programming (DP), Lagrangian Relaxation (LR) and Mixed-Integer-Linear-Programming (MILP). Examples for early approaches using DP, LR and MILP are suggested in [2], [3] and [4]. They propose solution methods for the short-term unit commitment of thermal power systems.

Following works in the field of unit commitment concentrate on various aspects. So the application of LR is extended to large thermal [5] and hydro-thermal systems [6]. Important preconditions applying LR to the unit commitment problem are the decomposable structure and the convexity of mathematical optimization problems. In order to manage non-convex mathematical problems finding absolute optimal solutions Ref. [12] applies MILP to cogeneration systems.

Beside these research efforts some proposals solving the long-term operations planning problem have been discussed in the literature. A survey of the methodologies and constraints is given in [7], also discussing the influence of randomness in long-term operations planning. In agreement with this guideline the approaches [8] and [9] propose stochastic solution methods for hydro-thermal systems and a deterministic approach [10] is applied to purely thermal power systems. To the authors knowledge only a few proposals report on optimal operations planning of cogeneration systems. The most of them suggest approaches for the unit commitment problem, such as example [11] and [12]. Valuable mathematical models of HPC-units are proposed in [12]. In this paper a deterministic approach is presented to solve the long-term operations planning problem of cogeneration systems.

2 System modelling

2.1 Problem analysis

Long-term operations planning becomes necessary, whenever an overall planning problem includes constraints coupling periods of several months or one year (e. g. a fuel constrained contract with yearly max. limits). In that case the long-term problem has to be solved in order to determine input data for the short-term unit commitment (e. g. weekly or daily energy amounts). Depending on the constraints of the actual long-term problem the study period varies between one month and 15 month. This is also influenced by the maintenance schedule, which is part of the input data in long-term operations planning.

An approach to system modelling must be designed in order to involve all technical, contractual and load depending constraints. With respect to the complexity of the problem the system modelling is subdivided into different models of system components. Figure 1 illustrates the abstract structure of an actual cogeneration system introducing four different kinds of components each represented by the
2.2 Load representation

In opposite to the short-term unit commitment, where electrical and thermal load curves can be forecasted with considerable accuracy, load curve forecasts for long-term horizons are not feasible. However, long-term operations planning for cogeneration systems requires a load representation in the form of simultaneous electrical and thermal load curves. Assuming only singular values of energy consumption and load maxima are predicted (e.g., values per month), these singular values have to be linked with load curve data of the past to obtain a load representation matching the requirements of long-term operations planning. The algorithm, which is applied to generate a load representation, includes four steps.

In the first step a period in the past comparable to the actual study period is chosen. It is assumed, that electrical and thermal load curves of this period are known and are representative for the cogeneration system. The load curve data of the past are suited to the singular forecasted energy and load maxima data by linear transformation. As a result a quasi load curve forecast exists divided into time intervals of one hour length. The aim of the next steps is a reduction of time intervals by extracting characteristic load and peak load curves leaving electrical and thermal energy demands unchanged.

The formulation of optimization problems requires consideration of some input data influencing the subdivision of the study period. Maintenance schedules or dates of changing energy prices are only two examples splitting the study period into a minimal number of subperiods with fixed limits. Within each subperiod load curve data of characteristic days will represent the calendar days. If any subperiod is too long to find representative load curves of characteristic days, an additional splitting of such a period may be inevitable. As a result of the second step the study period is divided into subperiods.

In the third step the number of characteristic days is determined. Usually four characteristic days (i.e., one for each Monday, working day, Saturday, and Sunday) are selected, any different choice of the number of characteristic days is also possible. The algorithm assigns calendar days to characteristic days including a special assignment of extraordinary days like holidays. The load curve of each characteristic day in each subperiod is calculated by averaging the actual loads of assigned calendar days. A peak load curve also generated is determined as follows: Those simultaneously existing electrical and thermal load demands, which yield maximal weighted addition, are inserted into electrical and thermal peak load curves. The weighting factors depend on heuristic choice defined by subjective assessment.

In the fourth step each subperiod is considered as a closed-loop load curve of characteristic days. The procedure achieves a reduction of the number of time intervals changing the already existing load representation as less as possible. The interval number is decreased during an iterative procedure. First, a weighted addition of electrical and thermal load differences between neighbouring time intervals is determined. Time intervals indicated by minimal weight-
In addition are connected by calculating new electrical and thermal load and peak load curve values leaving the energy demands unchanged. This procedure repeats until a previously fixed interval number is reached. Now the load representation consists of simultaneous electrical and thermal load and peak load curves with a drastically reduced interval number. While the load curves characterize the average load demands, the peak load curves describe the stochastic nature of loads.

In addition to the procedure preparing the load representation a detailed statistical analysis is performed and documented. This enables a tuning of the load representation before using it within the optimization procedure. Results obtained from load curve data of two real cogeneration systems will be presented in this paper.

2.3 Energy supply contracts

Energy supply contracts, which include time coupling constraints covering periods of several months or a year, are of special interest in long-term operations planning. Although almost every contract differs from each other, the objective of modelling is to develop a flexible approach applicable either to simple and to complex contracts. Therefore the following costs have to be taken into account:

- costs depending on the amount of energy:
  Figure 2 shows a more complex example of a contract with two energy price zones. During the period the contract is valid a price change occurs. Assuming the energy demand before/after the price change is \( E(p = 1) / E(p = 2) \) the costs \( C_t \) are determined by the illustrated piecewise linear function. The other piecewise linear functions "1st-price" and "2nd-price" are lower and upper bounds for the costs \( C_t \). Either the lower bound or the upper bound is reached, if the energy is consumed completely before or after the price change.

- costs per time depending on fuel, electric power or heat demand:
  Figure 3 shows an example of a contract with two price zones and different on-peak and off-peak tariffs. Assuming the actual power demand is \( P \) the costs per time \( C' \) are determined by a tariff, which is valid in the actual time interval.

Both of the cost terms will seldom appear together in the same energy supply contract, although it could be from a mathematical point of view. Additional costs have to be regarded facing a special kind of electric power supply contract, which is available to meet demands in times of electrical peak loads. Additional costs depending on the number of contract utilizations occur, if a certain number of free utilizations is exceeded. Beside the costs contract modeling has to consider either minimal or maximal limits of energy consumption and upper or lower bounds of fuel, electric power or heat demands.

3 Mathematical formulation

Notation:

- \( c \) : energy supply contract
- \( C \) : costs in \([\text{DM}, \$]\)
- \( \dot{C} \) : costs per time in \([\text{DM/h}, \$/h]\)
- \( E \) : energy in \([\text{TJ}]\)
- \( F(t) \) : frequency of time interval \( t \)
- \( l \) : load (electrical or thermal)
- \( N_{\text{max}} \) : maximal number of permitted utilizations
- \( N_f \) : number of free utilizations
- \( N_p \) : number of price periods
- \( p \) : price period
- \( P \) : power (in general, i.e., electric or thermal power or fuel) in \([\text{MW, MJ/s}]\)
- \( \hat{P} \) : peak load demand/contribution
- \( P_{el} \) : electric power in \([\text{MW}]\)
- \( P_{th} \) : heat, thermal power in \([\text{MJ/s}]\)
- \( s \) : a set of connections with a certain node
- \( t \) : time interval
- \( t_{1/2} \) : first/last time interval of a price period
The third cost term includes additional costs, if the number of free utilizations defined in electric power supply contracts is exceeded. Costs and number of utilizations are determined by:

\[ C_3(c) = C(c) \cdot (N_{\text{max}} - N_f) \cdot Y(c) \]  

\[ \sum_t F(t) \cdot X(c,t) - (N_{\text{max}} - N_f) \cdot Y(c) \leq N_f \]  

With regard to the nodes introduced into the system model a balance equation for each node and each time interval has to be formulated. The equation varies with the components connected with a node. If only units and contracts are connected and no link to a load exists, the equation is given by:

\[ \sum_{u \in S} P(u,t) + \sum_{c \in S} P(c,t) = 0 \]  

If a load (electrical or thermal) is connected with a node, two equations for each time interval describing load and peak load have to be considered:

\[ \sum_{u \in S} P(u,t) + \sum_{c \in S} P(c,t) = P(l,t) \]  

\[ \sum_{u \in S} \hat{P}(u,t) + \sum_{c \in S} \hat{P}(c,t) \geq \hat{P}(l,t) \]  

The equations describing the modelling of power-, heat- and HPC-units including input/output relations, minimum-up/-down times, startup-losses etc. are presented in [12].

Concerning the units this paper concentrates on the problem of matching the requirements of both electrical and thermal peak load demands. Figure 4 illustrates the problem. While the contributions of power- or heating-stations to peak load demands are determined by a maximal output of each station, an operating point of simultaneous maximal electrical power and maximal heat production seldom exists in HPC-units. Therefore peak load modelling of HPC-units has to be formulated as follows:

\[ \ldots (\hat{P}_{el}(u) - \hat{P}_{el}(u)) \cdot Y(u,t) + \hat{P}_{el}(u) \cdot X(u,t) \ldots \geq \hat{P}_{el}(l,t) \]  

\[ \ldots (\hat{P}_{th}(u) - \hat{P}_{th}(u)) \cdot Y(u,t) + \hat{P}_{th}(u) \cdot X(u,t) \ldots \geq \hat{P}_{th}(l,t) \]  

\[ X(u,t) - Y(u,t) \geq 0 \]  

While equations (11) and (12) describe the contribution to the electrical and thermal peak load demands, the equation (13) is necessary to enable a contribution only, if the HPC-unit is in operation. With respect to the physical interpretation the equations permit a flexible adjustment of an electric power and heat contribution along the line of maximal boiler output.
4 Optimization procedure

Solving long-term operations planning problems with MILP requires three steps of performance. First, the mathematical optimization problem is prepared in the form of objective function and constraints in accordance with the mathematical formulations already presented. In the second step a standard MILP-program solves the mathematical problem. The optimal solution assigns values to the optimization variables. The third step is performed to derive from the optimization variables meaningful tables and graphics of the results.

Beside the undisputed advantages of MILP measures are required to reduce CPU-time. They have to concentrate on monitoring and controlling the mathematical optimization algorithm. First of all standard MILP-programs solve a relaxed problem (i.e. all binary variables are considered to be continuous) finding the so called continuous solution (CNT), which is also a lower bound for the optimal solution. In general more than one integer solution is found until the optimal one is reached. Although an improvement of the objective function value is often little, the mathematical optimization algorithm spends considerable CPU-time to find such integer solutions or to prove that no additional integer solution exists.

Besides some control parameters to adjust the algorithm the applied MILP-program offers the opportunity to define a target of the objective function (TGT). By default the optimization procedure defines no upper bound for the first integer solution. The objective function value of the latest integer solution (INT) is introduced as the objective target of the next integer solution. In Figure 5 a functional relation between \( y = (TGT/CNT) \) and \( x = (INT/CNT) \) is illustrated. The proposed procedure defines:

- an upper bound for the first integer solution by introducing \( \epsilon_1 \)
- a minimal difference between the objective function values of \( INT/CNT \) and \( TGT/CNT \) by introducing \( \epsilon_2 \)
- a parameter defining large or small differences between \( INT/CNT \) and \( TGT/CNT \), if the continuous objective function value (1) is at a large or small distance by introducing \( \epsilon_3 \)

The presented procedure offers an automatic calculation of objective targets depending on the latest integer solution. An introduction of parameters supports a tuning of the procedure adapting it to various optimization problems. CPU-time intensive searches for insignificant solutions are avoided.

5 Results

The aim of the method presented in section 2.2 is to prepare load representations adapted to the optimization problem. First it is necessary to analyse the influence of different parameters (e.g. number of subperiods, number of time intervals per subperiod). Taking into account the results of this analysis an appropriate load representation can be determined.

Data of two actual cogeneration systems describing load curves over a year in the past have been

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Figure 4: contribution to peak load demands of HPC-units

Figure 6: influence of the parameter "No of subperiods"
analyzed in order to define the above mentioned parameters. A statistical evaluation of the parameters "No of subperiods" and "No of time intervals per subperiod" is performed by calculating average value (AV) and standard deviation (SD) of relative differences between electric power demands of the calendar days and the assigned values in the resulting load representation (s. Figure 6 and 7).

Figure 7: influence of the parameter "No of time intervals per subperiod"

Figure 6 and 7 show similar results for both cogeneration systems. A number of subperiods between 9 and 12 seems to be sufficient. The interval number per subperiod can be limited to 10–20 percent of the original number with little effect on the accuracy of the resulting load representation.

Based on the proposed optimization procedure the long-term operations planning task of system 2 (s. Figure 1) is solved. The study period of one year is divided into 9 subperiods consisting of 40 time intervals each. The size of the entire optimization problem is characterized by approximately 18,000 constraints, 9,500 variables including 1,300 binary one's and 100,000 coefficient matrix entries. Besides time coupling constraints within each subperiod the following constraints covering the entire study period cause a long-term planning task:

- a coal supply contract including two energy price zones
- a min./max. energy amount of gas with a limited delivery per hour
- an electric power supply contract with a fixed price of any additional utilization, if the number of free utilisations is exceeded

Solutions of the long-term planning task are determined in four different stages. In case 1 and 2 the optimization problem of each subperiod is solved one after the other. Case 1 regards none of the overall time coupling constraints. Based on the results of case 1, which includes a certain distribution

<table>
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<th>OBJ in 10^6 DM</th>
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<td>1</td>
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Table 1: objective function values (OBJ) and required CPU-time

of the energy amount of gas and the utilization of the peak load contract, a heuristic distribution of the permitted energy amount of gas and utilization of the contract is calculated and introduced into the input data of case 2. Case 3 solves the entire operations planning problem over the whole study period taking into account none of the time coupling constraints. In case 4 a real overall long-term operations planning problem including all relevant constraints is regarded.

Table 1 shows objective function values and the required CPU-times on a DEC VAXstation 4000/60 computer. Although the mathematical optimization problem is identical, which is also documented by the same objective function value, the required CPU-time in case 1 and 3 differs widely. The comparison between case 1 and 4 shows the influence of the overall time coupling constraints on the objective function value. The difference between objective function values of case 2 and 4 indicates that an optimal solution of the long-term operations planning problem including all relevant constraints can be reached only by an entire approach.

Table 2 contains the allocation of the energy amount of gas (GAS) and the number of utilisations of the peak load contract (UTI) (s. Figure 1 and 8: "pwr 2") among the subperiods. While in case 1 and 3 the sum of both constraints exceeds the permitted

<table>
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Table 2: allocation of GAS and UTI
value of 100%, case 2 and 4 fulfill these constraints.

As a part of the results of case 4 Figure 8 illustrates the distribution of energy demand among the energy supply contracts within each subperiod. Similar graphics could be derived from the results of the optimization algorithm for example containing the energy consumption of each characteristic day in a subperiod. These and other results serve as input data for the short-term unit commitment problem.

![Figure 8: distribution of the energy demands among the energy supply contracts](image)

6 Conclusion

A method to solve the long-term operations planning problem in combined heat and power supply systems has been proposed. In the system modelling attention is given either to electrical and thermal load representation and to the modelling of energy supply contracts. The applied standard MILP-program is controlled by an advanced procedure to reduce the required CPU-time.

Results obtained from an analysis of load data of two actual cogeneration systems confirm the flexibility of the presented method to derive a load representation to be used in the optimization procedure. Furthermore the optimisation results prove the applicability of the presented procedure to long-term operations planning of cogeneration systems.

Future research effort will focus on the integration of long-term operations planning and unit commitment, an advanced monitoring and controlling of the applied MILP-program and on the use of already existing optimisation results to accelerate a solution for future optimizations problems.

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References


