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Energy conception of an integrated system – II. Alternative solutions and optimization

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An optimum choice of a technology for effective utilization of biomass and/or alternative fuel integrated into complex energy producing systems is subjected not only to economic requirements but it is strongly influenced by environmental constraints and targets. This paper is a continuation of the contribution Drápela et al., where the principles of renewable and alternative fuel integration into complex systems are described in general terms. In this paper, the key part of the integration procedure, i.e. the selection of potential arrangements and optimization of the most promising one is discussed in details. The focus is given on mathematical model building and the following points are discussed: classification of indices, decision variables, parameters, and used terms; choice of appropriate model elements i.e. bounds, constraints (more and more sweeping environmental legislation, support on green energy production, etc.), and objective function (investment, payback, environmental targets).

Introduction

The key challenge is to build a general mathematical model that will allow us to find optimal decisions about the use of fuel of various types (fossil coal and renewable biomass) with respect to the different time horizons, various demands and uncertain future with respect to technology considered, and the existing equipment design. Step by step, we will build a general mathematical program and introduce several its simplifications that will be approximately solvable by the selected optimization software. For the detail discussion on particular instance of the studied problem, see Drápela et al. It is also important to mention the recent experience of the authors from Brno University of Technology with similar optimization related problems, see Pavlas et al. (2006) and (2008).
At first, we shortly review some useful reference to the optimization models for similar problems. The key paper by Salagado and Pedrero presents a survey of the studied problems related to cogeneration systems during the period from 1983 up to 2006. They found that polynomial terms have been often used to model dependencies described in models. Both types of convex and non-convex optimization models have been utilized. From the objective function point of view, multiple criteria have been frequently tested. The studied problems have been modeled by linear programming, nonlinear, mixed

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integer, multiperiod and multi-criteria programming. Various solution methods to these problems have been tested. The classical methods as the simplex, dynamic programming, generalized network programming, Lagrangian relaxation, sequential linear and quadratic programming, Newton's method, dual linear or separable programming have been either enriched or replaced by artificial intelligence methods like genetic algorithms, Tabu search, evolutionary programming, and ant colony algorithm. Optimization related software like MATLAB and GAMS with included solvers has been used.

At the end of our short review we have to emphasize that the use of stochastic elements is not common in the optimization problems for cogeneration systems. The aforementioned paper refers to the case where randomness of the electricity and heat demand is assumed, besides using the mean values for variables related to electric power and heat. Other papers consider the uncertainty of: the heat demand, the electricity prices and CO2 emission permits prices, etc.

The last paragraph mentions that stochastic elements have not been combined with optimization models very often for the studied class of problems. We must notice that the combined models have been discussed for the problems in the neighborhood areas. For example, there are several stochastic programming models related to general energy consumption and distribution problems, see, e.g., Wallace and Fleten and references therein.

We deal with the actual problem of fossil fuels substitution with renewables. Therefore, from the modeling point of view, the challenge is to use the ideas of the abovementioned stochastic programming models to apply the experience in the suitable way to the studied problem.

Model building

The building of the optimization model follows the discussion in the related paper Drapela et al. The considered plant processes are described in Drapela et al. in details. For simplicity we utilize Fig. 1 that shows a block diagram of real system – heating plant. The important heat fluxes are also denoted by symbols used later in the text. The model is introduced through its elements.

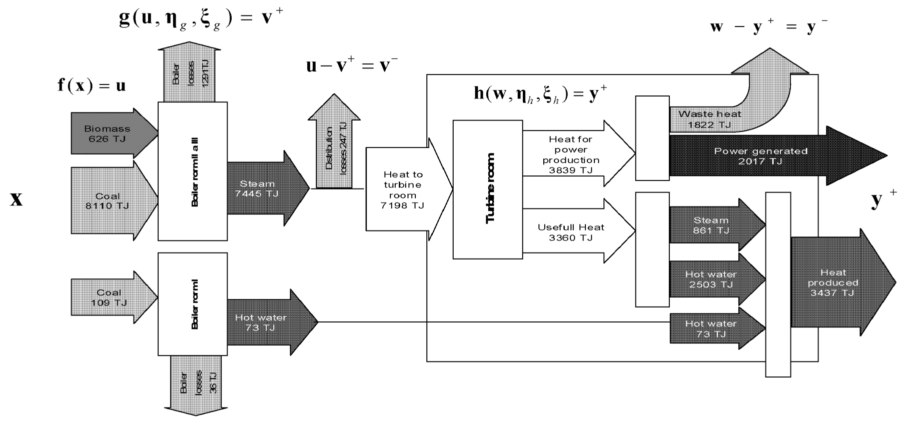

Fig. 1: Model elements depicted within the block diagram of the plant

Periods: We consider several time periods defined by the specific calendar and we denote the actual period by $t = \tau,...,T$. Time periods can be of various lengths and they can be defined in months and years. To be able to incorporate historical data in the model we denote the initial time period where the first decision should be made as τ and the past data is related to the periods $t = 1,...,\tau - 1$. This allows modeling in mid-time and long-time period. To simplify notation, we do not include time related subscripts in symbols below.

Boilers: To identify the boiler (or group of boiler of the same type and parameters), we use index $k = 1,...,K$. For the considered case, we assume three groups of boilers used (see Drápela et al.). Two of them are producing superheated steam. The steam is then led to the turbine room for cogeneration. The heat from turbine covers base load, whereas the third one covers only peak load, and its output does not enter the power generation stage and is consumed directly to satisfy the part of the demand.

Fuel feeding rates: For varying fuel types (inputs in the model), we utilize index $j = 1,...,J$. We consider two fuel types i.e. lignite as a representative of fossils and some biomass-based alternative fuel (for examples see Drapela et al.) as a renewable. The amounts of input fuels are denoted by nonnegative vector $\mathbf{x}$. In case of more time periods considered, we use a subscript t e.g. $\mathbf{x}_t$. However, while introducing basic model elements, we focus on one actual period, and hence, omit subscripts. When we refer to the vector component, we follow common mathematical rules and write e.g. $x_{t,jk}$ as it identifies the amount of input j in the boiler k. Therefore, the vector dimension is specified by $\mathbf{x} \in \Re^{J \times K}$. For certain purposes, e.g. to reduce the size of the model, we may consider aggregated values of various variables, e.g., inputs $\mathbf{x}$. To identify the aggregated vector or even the scalar value with specific definition of aggregation, we index the type of aggregation by index $l = 1,...,L$. For better understanding, these subscripts are coded by explanatory letters. For example, we define overall input as x_O and $x_O = \sum_{j=1}^{J}\sum_{k=1}^{K} x_{jk} = \mathbf{1}^T\mathbf{x}$. Similarly, for the given boiler k, we define sum of all inputs of various fuel types as $x_{Ek} = \sum_{j=1}^{J} x_{jk}$ and for the given fuel of type j we define sum of all inputs for various boilers as $x_{Fj} = \sum_{k=1}^{K} x_{jk}$.

Fuel input and steam generation in boilers: The input amounts are transformed in to the equivalent nonnegative amounts $\mathbf{u} \in \Re^{J \times K}$ of thermal energy in TJ (transformed input fuel to the boiler). Transformation is written as $\mathbf{f}(\mathbf{x}, \boldsymbol{\xi}_g) = \mathbf{u}$ where needed computations are realized by components of separable vector function $\mathbf{f} :\in \Re^{J \times K \times J \times K} \to \in \Re^{J \times K}$. The values of $\mathbf{u}$ are then transformed again through the process of combustion into utilizable energy (steam or hot water) by vector transformation $\mathbf{g}(\mathbf{u}, \boldsymbol{\eta}_g) = \mathbf{v}^+$. All functions considered through the text are also verified by statistical methods applied to proposed formulas and valid data.

Randomness: Hence, random vector $\boldsymbol{\eta}_g \in \Re^{J \times K}$ is used to represent statistically identified uncertainties in the boiler efficiency (c.f nonlinear regression analysis) with components for specific input j and boiler k, vector $\boldsymbol{\xi}_g \in \Re^{J \times K}$ identifies further aggregated random influences involving lower heating value (LHV), and $\mathbf{v}^+$ represents the amount of energy in TJ that is further used through the process controlled to satisfy existing demands. The separable vector function $\mathbf{g}$ maps the domain set into the image set, i.e. $\mathbf{g} :\in \Re^{J\times K \times J\times K \times J\times K} \rightarrow \in \Re^{J\times K}$. In addition, we denote lost heat as $\mathbf{v}^-$ where $\mathbf{u} - \mathbf{v}^+ = \mathbf{v}^-$. Quite naturally, we assume that $\mathbf{v}^+, \mathbf{v}^- \geq \mathbf{0}$. It involves lost heat in boilers and partial heat losses (distribution losses) through distribution between boiler-house and turbine house (about 3.3%). As above, we introduce $v_O^+ = \sum_{j=1}^{J}\sum_{k=1}^{K} v_{jk}^+$, $v_{Ek}^+ = \sum_{j=1}^{J} v_{jk}^+$, and $v_{Fj}^+ = \sum_{k=1}^{K} v_{jk}^+$. In addition, for the purpose of precise identification of input from boilers to generators, we introduce the subset of indices $k \in \Im \subseteq \{1,...,K\}$, and then $v_{\Im}^+ = \sum_{j=1}^{J}\sum_{k\in\Im} v_{jk}^+$. The alternative description may deal with identity transformation of heat through the turbine house stage (see below).

Scenarios: Regarding further information about random vectors, we will deal with finite discrete probability distributions derived from historical measurements and balance data coming from real plant (see Wallace and Fleten for scenario techniques). To identify various realizations of these random vectors, we introduce superscript $s = 1,...,S$, i.e., for random vector $\boldsymbol{\eta}_g$, its s-th realization is denoted by $\boldsymbol{\eta}_g^s$, and similarly, for random vector $\boldsymbol{\xi}_g$, its s-th realization is denoted by $\boldsymbol{\xi}_g^s$. We do not differ between various set of scenarios here, however, in case of necessity it is explicitly emphasized by further indices. The realization will be further called a scenario. Sometimes, for simplicity purposes we will also talk about index of realization as about the scenario. As a result, values of $\mathbf{v}^+$ must be indexed by scenario superscript, as well.

Scenario identification and reduction: These scenarios can be visualized as points in $\Re^{J\times K}$ forming a cluster of points. We may introduce its convex hull bounded by piece-wise linear boundary curves. Instead of considering all points, an expert, who studies this cluster and its hull, taking into the account transforming functions $\mathbf{f}$ and $\mathbf{g}$, can select a reduced set of important scenarios and can specify piece-wise linear functional lower and upper bounds $\mathbf{b}_{\mathbf{g}L}(\mathbf{u}), \mathbf{b}_{\mathbf{g}U}(\mathbf{u})$ respectively (even convex for the lower case and concave for the upper case) for values of $\mathbf{v}^+$. Precisely, $\mathbf{b}_{\mathbf{g}L}(\mathbf{u}) \leq \mathbf{v}^{+s} \leq \mathbf{b}_{\mathbf{g}U}(\mathbf{u}), s = 1,...,S$ where scenarios involve all scenarios from the selected reduced representative set.

Turbine room: The next stage of the current time period deals with power generating units. We index them by $i = 1,...,I$. For the considered case, we consider two units. It is important to emphasize that the total energy output from the boiler house is less or equal to the input for the turbine house. Therefore, we denote the amount of energy input in these units by nonnegative vector $\mathbf{w} \in \Re^I$ that may serve as another control variable after the variables describing inputs. So, components are related to units and we do not make a difference between inputs by the indices j and k from the previous stage. As above, we introduce $w_O = \sum_{i=1}^{I} w_i$, and hence, the following balance equation $w_O = v_{\Im}^+$ should be satisfied (additional identity equation can be introduced for the direct heat

transfer satisfying the peak demands). Although there are principal differences from the boiler stage detailed above, mathematically we will treat this stage in the similar way.
Cogeneration – simultaneous production of heat and power: Therefore, vector function $\mathbf{h}(\mathbf{w}, \boldsymbol{\eta}_h, \xi_h) = \mathbf{y}^+$ represents power generation stage energy transformation. We must emphasize that we make difference between outputs i.e. heat and power because of demands. We index them by $m = 1,\dots, M$. There is random vector $\boldsymbol{\eta}_h \in \Re^{I\times M}$ that represents varying efficiency of transformation of steam into power and useful heat with components for specific unit i and vector $\xi_h \in \Re^{I\times M}$ identifies further aggregated random influences.
Used and waste heat: Then, $\mathbf{y}^+ \in \Re^{I\times M}$ components represent the amounts of energy in TJ that are further used to satisfy existing demands. The separable vector function $\mathbf{h}$ maps the domain set into the image set, i.e. $\mathbf{h} :\in \Re^{I\times I\times M\times I\times M} \to\in \Re^{I\times M}$. In addition, we denote waste heat (lost through cooling tower) as $\mathbf{y}^-$ where $\mathbf{A}_w\mathbf{w} - \mathbf{A}_+\mathbf{y}^+ = \mathbf{A}_-\mathbf{y}^-$ and matrices in the equation serve to balance dimensions of related vectors by the sums and copies of vector components. Quite naturally, we assume that $\mathbf{y}^+, \mathbf{y}^- \geq \mathbf{0}$. The data analysis has shown the need to further study relation between heat and energy outputs, this relation is modeled by additional constraints in the form $\mathbf{y}^+ \in Y$, (or $\mathbf{w} \in W$).
Scenarios and bounds: The scenarios for this stage can be again visualized as points but in $\Re^{I\times M}$ forming another cluster of points. We may again introduce its convex hull bounded by piece-wise linear boundary curves. Instead of considering all points, the expert can select a reduced set of important scenarios and can specify piece-wise linear functional lower and upper bounds $\mathbf{b}_{hL}(\mathbf{w}), \mathbf{b}_{hU}(\mathbf{w})$ respectively (again even convex for the lower case and concave for the upper case) for values of $\mathbf{y}^+$. Precisely, $\mathbf{b}_{hL}(\mathbf{w}) \leq \mathbf{y}^{+s} \leq \mathbf{b}_{hU}(\mathbf{w}), s = 1,\dots, S$ where scenarios involve all scenarios from the selected reduced representative set. Let us note that DEA (decision envelopment analysis) techniques may inspire us for building of bounding functions above.
Demand: At the end, we must consider demand bounds $\mathbf{b}_L, \mathbf{b}_U$ that are not functionally dependent on the stage input, however, they may change randomly, especially when we consider the future. Precisely, $\mathbf{b}_L \leq \mathbf{y}^{+s} \leq \mathbf{b}_U, s = 1,\dots, S$ where scenarios involve again all scenarios from the selected reduced representative set. The lower bound represents power and heat, which must be supplied by contracts. It is usually fixed as the upper bound for the heat because of long contracts. The upper bound represents the chance to sell more, especially green electrical power and may vary randomly. Separate bounds can be similarly specified for the direct heat transfer from the boilers to satisfy peak demands, e.g., by $\mathbf{v}^+ \in V$.
Objective – profits and expenses: There are various expenses through the energy transformation process that we want to sum and optimize. The related cost functions are denoted by $\mathbf{c}(.)$ with a suitable subscript identifying the process stage in the energy production. In particular, $\mathbf{c}_g(.)$ defines costs related to the boiler house stage. This cost includes set up cost and operation cost, etc. The components of the vector cost function are related to the inputs and they are specified by indices j and k . Similarly, $\mathbf{c}_h(.)$ defines costs related to the turbine house stage. The components of the vector cost function are related to the inputs and they are specified by index i . In the case of linear

cost terms in the objective function, the cost vectors are denoted as usually by $\mathbf{c}$ vector with the subscript as discussed above. This linearity is suitable to represent buying inputs. At the end, we consider profit coming from selling power to consumers. Vector $\mathbf{d}(.)$ defines profits related to the turbine house stage. The components of the vector are related to the outputs and they are specified by index i and m.

Randomly varying costs: It is important to emphasize that most of cost parameters must be taken into account as uncertain, because time value of money and inflation should be considered.

Model: The built model belongs among multi-period scenario-based stochastic nonlinear programs. We assume that 0-1 variables will be used in the cost related terms.

Conclusion and further research

Computations: The proposed model is implemented in GAMS and tested for real data. Used amount of scenarios vary between 100 and 3000 in the mid size multiperiod model. It leads to instances of size at most 150 000 variables that can be solved by GAMS/CONOPT/CPLEX/BARON solvers. The key modeling restriction that is tested is the reduction of the amount of possible integer variables that are as usually linked to set up costs and strategical investment decisions.

More periods and decision stages: In the case of more time periods, the cost function values are principal variables that link various time periods, otherwise the model could be efficiently decomposed in the sequence of separable models. This is true because for the future significant change of proportion of inputs, actual technological changes and related investments must be realized (see Drápela et al. for the discussion).

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