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Optimal cogeneration in an integrated kraft mill

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An optimal control system designed to minimize the consumption of high pressure steam (and thus minimizing energy costs) while meeting the paper mill's demand for process steam and electric power is developed. An installation example is described and system performance and benefits are discussed. It should be noted that the theories developed in this paper can be readily extended to the design of an optimal control system which maximizes the electric generation under the given inlet steam flow.

1 Introduction

Optimization of cogeneration of process steam and electric power represents a significant potential for energy cost reduction in an integrated kraft mill. The optimal loading pattern and process steam extraction flows depend upon the time-varying demand for steam and electric power in the mill, and represents an interesting case for cost minimization by optimization.

The economic benefits from such optimization have been increasing with the increasing fuel costs. Another motivation should be the growing concern about available energy resources. The theory needed to solve the optimization problems is by now well established. The practical implementation does, however, pose several problems which must be overcome in order to commission an industrial optimal control system.

The paper covers modeling, identification, man–machine considerations, and implementation of a computer-based control system for optimization of process steam and electricity in one of St. Regis' paper mills. Emphasis is placed on problems arising from the use of industrial plant measurements as inputs to the identification and optimization algorithms as opposed to well designed experimental inputs, and on system design in order to achieve operator acceptance.

The total cogeneration optimization problem involves boiler load allocation, boiler efficiency improvement, turbine extraction flow allocation, tieline demand control, and load shedding. This problem is illustrated in Fig. 1, where it is broken down into two sub-problems: boiler optimization and optimization of turbine generators.

This paper is limited to the turbine flow allocation problem. The problem may be defined in several ways. Referring to Fig. 1, one specification would be to determine

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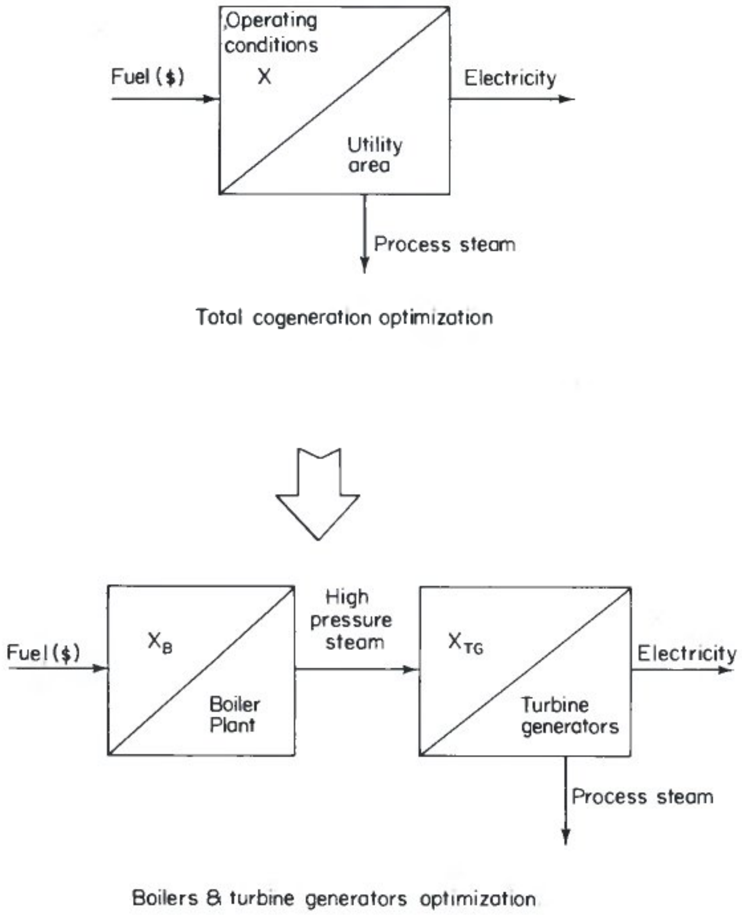

Figure 1.

turbine operating conditions so that high-pressure input steam flow is minimized subject to a specified production of electric power and process steam. In a plant with a utility tieline, the criterion could be to minimize purchased power subject to constraints on desired process steam. More sophisticated criteria could be used to involve high-pressure steam generating costs. The choice of criterion is not critical for the optimal allocation system described in the sequel.

Leffler (1978) uses as a model curves of producing power versus throttle flow, and allocates an increase in process steam demand to the turbine with the highest incremental power generation (a decrease in load to the lowest). He assumes that continuous load demand changes causes this iterative allocation scheme to tend to optimal (i.e. maximizing electric power output at a given process steam demand).

The approach taken in the present paper uses a simple model relating input steam flow to intermediate and low pressure steam extractions and to electric power produced. The model parameters are estimated on line, and the estimated model is used to compute the optimum operating conditions for the turbines. The system is implemented with a man-in-the-loop. The optimal operating conditions are thus presented to the turbine operator, who adjusts the steam flows manually. Two important reasons for this arrangement were easier and cheaper installation (DDC equipment can be installed later when the optimal control system has been justified), and the desire to get operator acceptance of the computer control system, which is believed to be important for the evaluation of overall system performance.

2 Control system structure

The control system structure will be explained by the use of Fig. 2. The turbine-generators are used to extract the process steam, which is then fed to headers LP1 and LP2. The high pressure steam flow to turbine no. i is y_i. The extraction steam flows (including condensing steam flows) are $u_1{}^i$ to $u_{m-1}{}^i$. The variable $u_m{}^i$ denotes the electric power generated by the turbine-generator. Process steam demands are q_1 and q_2.

The optimization problem is formulated as follows:

Minimize

$$J = \sum_{i=1}^{p} y_i \tag{1}$$

subject to constructional constraints (i.e. maximum and minimum values for steam flows and generated power for all turbines) and

$$\left.\begin{aligned} q_1 &\geqslant q_{10} \\ q_2 &\geqslant q_{20} \\ \sum_{j=1}^{p} u_m{}^j &\geqslant S \end{aligned}\right\} \tag{2}$$

where q_{10}, q_{20} are the process steam demands and S is the mill's electric power demand. Using mathematical models in the form $y_i = f_i(u_1{}^i \ldots u_m{}^i)$ the optimum operating conditions are computed. The optimal values are presented to the operator who then adjusts the flows accordingly.

We have been using a turbine model where f_i is a linear function of $u_i{}^i$. The minimization of the function (1) is done by linear programming. The turbine generator model is derived by Nagaranjan and Suh (1976). Its application to the present problem is discussed in the following section.

The optimal operating conditions are computed periodically. The period was chosen by considering the operators situation. To get operator acceptance the period should not be too short. On the other hand, the system should not be too slow in responding to any changes in steam demands in the plant. A control interval of 30 minutes was chosen as a good compromise for the relatively steady state operations. During the emergency and upset conditions which may occur from time to time, the operators are privileged to ask for the optimal loading reports as often as they wish.

3. Process model

The time constants of the turbine system were found to be much smaller than the chosen control interval of thirty minutes. They were in fact less than thirty seconds. Therefore it was sufficient to use a steady-state turbine model in the optimization.

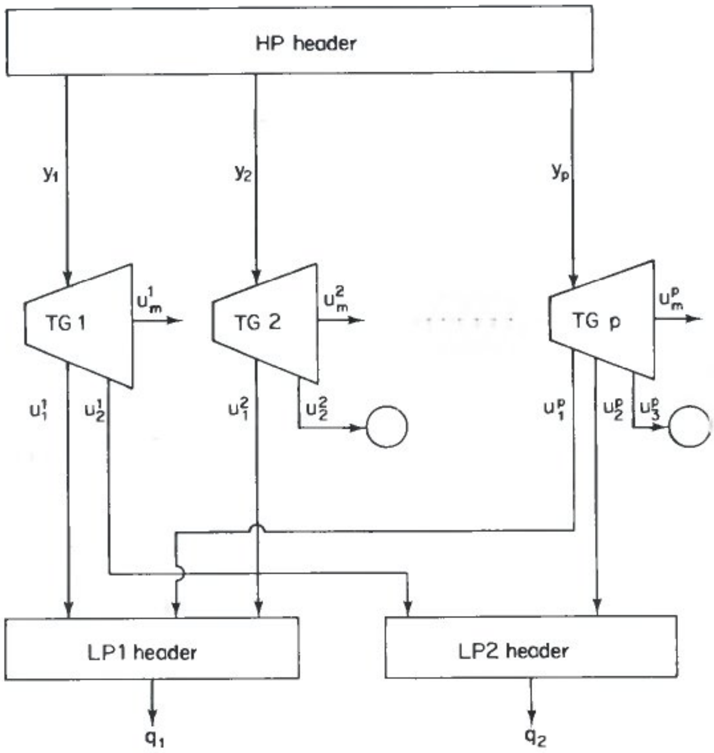

Figure 2.

Consider one of the turbine generators in Fig. 2. An energy balance gives

$$h_y y = \sum_{i=1}^{m-1} h_i u_i + u_m + \Delta \tag{3}$$

where h_y is the enthalpy of the inlet steam, h_i ($i=[1, m-1]$) is the enthalpy of the extraction steam flows and Δ is the energy losses. Equation (3) is linear in y and u_i. The parameters are constant for constant steam temperatures and pressures. Equation (3) rewritten in terms of steam flows and electric power is

$$y = \theta_0 + \sum_{i=1}^{m} \theta_i u_i \tag{4}$$

where the parameter vector is

$$\theta = [\theta_0 \theta_1 \ldots \theta_m]^t \tag{5}$$

Since (3) and (4) are equivalent representations it follows that

$$\left.\begin{aligned} \theta_0 &= \frac{\Delta}{h_y} \\ \theta_i &= \frac{h_i}{h_y}, \quad i=[1, m-1] \\ \theta_m &= h_y^{-1} \end{aligned}\right\} \tag{6}$$

The reason for writing the turbine model in the form (4) is the optimization problem where the plant's demand of low pressure steam and electricity are considered as inputs and the task of the control system is to minimize the sum of system outputs, namely high pressure steam consumption.

Using eqn. (4) for each turbine generator, and a mass balance for steam flows to the different low pressure headers, a model for the total process is obtained. This process model is linear in the parameters. The parameters depend on the operating condition. They are functions of steam temperatures and pressures. In addition the loss term Δ seems also to vary. Data collection in the plant showed that the parameter values differed significantly from those determined from turbine construction data. All these factors contributed to the decision to estimate the model parameters on-line.

If eqn. (4) is interpreted in terms of energy flows, θ_0 should be the only variable parameter. If such a model is used for the parameter estimation, the parameters must be recalculated using actual temperatures and pressures in order to present the optimal operating conditions to the operator in terms of steam flows.

4. Parameter estimation

A much smaller sampling interval can be used for the estimation algorithm than that of the optimization. For the present application a three minute interval was chosen as the sampling period. This appeared to be reasonable in terms of CPU utilization. Another reason for selecting the three minute sampling period was that the critical frequency for the process was determined to 10 cycles per hour.

Several least squares algorithms were considered for the parameter estimation. In order to track the time-varying parameters, a limited-memory algorithm or an algorithm with time-weighted residuals was necessary.

To eliminate errors due to variations in temperature and pressure within the memory period, all measurements were transformed to nominal conditions. Comparisons with results obtained without normalization gave only marginally different parameter values.

The limited-memory algorithm was implemented as a batch algorithm. The parameter estimate is then obtained as the ordinary least squares estimate using the $N+1$ last samples (k denotes the present sample):

$$\hat{\theta}=\left\{\theta \,\middle|\, \min_{\theta} \sum_{i=0}^{N} (y(k-i)-u^T(k-i)\theta)^2\right\} \tag{7}$$

The solution is well-known

$$\hat{\theta}=(U^TU)^{-1}U^TY)$$

where

$$\left.\begin{aligned} u&=[u_1 \; \dots \; u_m]^T \\ U&=\begin{bmatrix} 1 & u^T(k) \\ \vdots & \vdots \\ 1 & u^T(k-N) \end{bmatrix} \\ Y&=\begin{bmatrix} y(k) \\ \vdots \\ y(k-N) \end{bmatrix} \end{aligned}\right\} \tag{9}$$

Trying this algorithm on turbine operating data, it was found that the parameter estimates often fluctuated strongly from one set of data to another. Negative (non-physical) parameter values were obtained in several cases. It should be mentioned that better accuracy in the estimates may be obtained by transforming to zero mean variables before doing the estimation. However, results obtained in this way were also subject to the same noise sensitivity.

The main reason for the fluctuation in the estimates was the fact that some of the inputs u_i were nearly constant over long periods. This shows up in near singularity of the matrix $U^T U$. Constant u_i is of course due to the attempt to run the plant smooth and steady (e.g. baseloading some turbines). It is disadvantageous to the parameter estimation only. It is thus not desirable to try to excite the process. Instead it was decided to try another estimation method.

It is believed that difficulties like these may be experienced frequently in combined estimation and control of industrial processes.

In order to avoid the strong noise sensitivity in the parameter estimates a recursive estimation algorithm was chosen. The recursive parameter estimates are given by

$$\hat{\theta}(k+1)=\hat{\theta}(k)+K(k+1)\epsilon(k+1) \tag{10}$$

The innovations process is

$$\epsilon(k+1)=y(k+1)-u^T(K+1)\hat{\theta}(k)$$

The algorithm's forgetting factor is included in the computation of K. It is expected that the recursive algorithm will just keep the present estimate when the innovation process contains no information of changes in some of the parameters, as will be the case when corresponding inputs are constant over some time.

The limited memory algorithm is available in recursive form too, see, e.g. Goodwin and Paine (1977). It requires storage of the last N samples. Other recursive least squares algorithms, e.g. exponentially window, do not require storage of any old samples. In order to take full advantage of the recursive estimation approach and avoid storing old values, an exponentially window algorithm was chosen.

The exponential window least squares algorithm can be obtained in at least two ways. One approach is to emphasize the effect of current data by giving past data less weight. Another is to model the time variation of the parameters, and use a Kalman filter for the estimation. We found by testing both methods that the latter was very well suited for the present problem.

The parameters were modeled by the stochastic difference equation

$$\theta(k+1)=\theta(k)+v(k) \tag{12}$$

while the data are modeled as

$$y(k)=u^T(k)\theta(k)+w(k) \tag{13}$$

Assuming that the independent, stationary stochastic sequences $v(k)$ and $w(k)$ have zero mean values and covariance matrices V and W, respectively, the best linear unbiased estimate of θ is given by the Kalman filter equations. The values of W and V were used as tuning variables to make the estimation response satisfactory. It should be mentioned that thorough comparison of the two exponential window estimates was not done since the Kalman filter approach was found to be easy to apply.

The problems of noise sensitivity and strongly fluctuating estimated parameter values were completely eliminated when the recursive estimator was used.

5. An application

The combined parameter estimation and linear programming optimization system was implemented at a St. Regis kraft mill. The actual turbine-generator system is shown in Fig. 3. Process steam to two low-pressure headers is extracted from three turbines, two of which are condensing turbines. The papermaking process requires steam at two different pressures, 165 and 65 psi. From Fig. 3 it is seen that 165 psi steam is extracted from turbines 1 and/or 3, while 65 psi steam can be extracted from all three turbines.

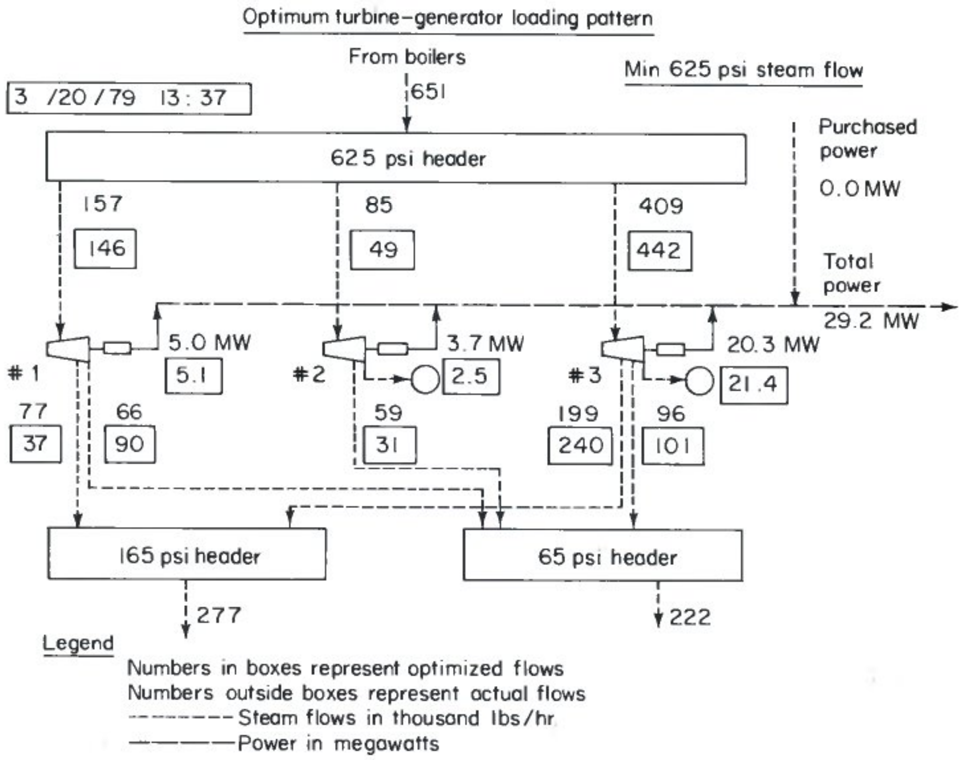

Figure 3.

The control system consists of a PDP 11/34 CPU with 48K words memory and 5M bytes bulk memory, operating under RSX 11M. Peripherals are a Textronix graphic CRT and a hardcopier for operator's use, and a programmer's CRT and a line printer supplied by DEC. Application programming was done in Fortran.

6. Man–machine communication

Communication from the computer to the operator is done by a graphical display. The operator uses designated keys on the keyboard to call up the desired process information.

The specification of optimal operating variables is done in a process diagram as shown in Fig. 3. The optimal values are given in boxes. The operator adjusts the valves until he obtains near agreement between values inside and outside the boxes. In this way the process computer is introduced as an aid for the operator when running the plant, and not as a competitor. Through the illustrative graphical display he is given an easy overview of the state of operation of the turbine-generators. In addition, on request several other reports and graphics can be presented, e.g. daily and shift reports, and process trend reports as shown in Fig. 4. These have contributed to give the operator better understanding of the process.

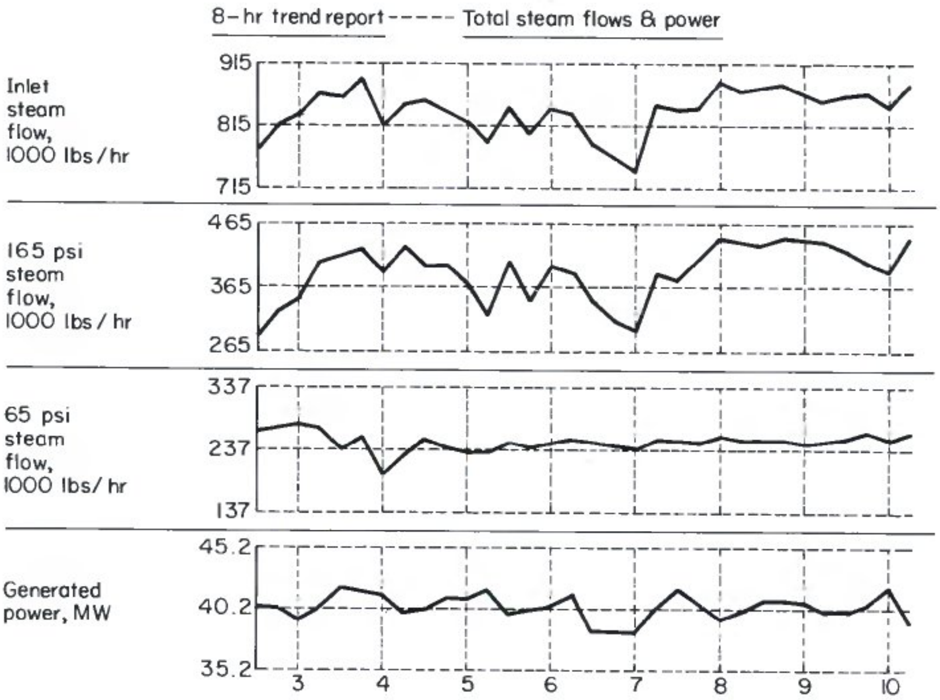

Figure 4.

7. Benefits, justification of the system

A favorable return on investment due to the computer system has been reported. Other tangible benefits include quicker and better operator response to major process upsets, smoother start-up, better understanding of his process, etc. Most of all, the operators have accepted the system as a production tool which they rely on heavily.

8. Conclusion

A real time optimal control system for cogeneration of process steam and electricity in a paper mill power house has been described. The control system consists of on-line estimation of turbine-generator parameters and determination of optimal operating conditions by linear programming. The use of a recursive estimation algorithm for tracking the turbine generator parameters was found to be well suited for the practical application.

At this writing another control system is being installed at a St. Regis kraft mill.

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