PERFORMANCE OPTIMIZATION OF LARGE CONTROL SYSTEMS – CASE STUDY ON A CONTINUOUS PULP DIGESTER

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Abstract: This paper presents an example application of a novel multivariate control parameter tuning method, called Iterative Regression Tuning (IRT), on a simulator of continuous pulp digester. IRT is a data based method in which multivariate regression and iterative optimization methods are utilized in the parameter tuning. In the test case seven PI controllers and two model based controllers were tuned simultaneously and six user-defined quality measures were set as optimization targets. Encouraging results on the process performance improvement were obtained and the method proved a clear potential for optimization of large industrial systems. *Copyright © 2005 IFAC*

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1. BACKGROUND

The control performance assessment and controller tuning have been intensive research topics during the last decades. Undoubtedly, one reason for this is the fact that as many as about 60 % of the industrial PID controllers are behaving inefficiently or even detrimentally, i.e., far from the optimal achievable control performance, see, e.g., (Harris *et al*., 1999).

Especially the work initiated by Harris (1989) on the minimum variance benchmarking has attracted a lot of interest. Improvements on the original work have been reported, e.g., in (Huang and Shah, 1999). Also, methods for detecting oscillating and sluggish control loops have been published, see, e.g., (Thornhill and Hägglund, 1997) and (Hägglund, 1999). In (Tyler and Morari, 1996) a control performance monitoring method based on likelihood methods was introduced. Various controller tuning techniques have been presented by researchers and many of them have been even applied by the practicing control engineers, particularly those for single loop tuning.

One interesting control tuning method was suggested by Hjalmarsson *et al* (1994). They introduced the Iterative Feedback Tuning (IFT) method that takes a new approach to control performance improvement.

The basic idea is to find the parameters that optimize the LQG type design criterion. IFT is an example of the iterative identification in closed loop methods that are used for controller redesign. These methods and closed loop identification in general are reviewed, e.g., in (Landau, 2001).

A more general approach compared to IFT is the Iterative Regression Tuning (IRT) method, first described in (Hyötyniemi, 2002). A case study, in which the performance of a power plant simulator was optimized using the proposed method, was reported in (Halmevaara and Hyötyniemi, 2004).

This paper gives another successful example of applying IRT to performance optimization. In Chapter 2 the idea of the IRT method is presented. Chapter 3 introduces the model of the pulping process, Chapter 4 presents results of the case study and in Chapter 5 the results are discussed more thoroughly and some conclusions are drawn.

2. IRT METHOD

A dynamical MIMO system (multiple inputs, multiple outputs) with input and output signals, u and y, respectively, is presented in Fig. 1. The parameters θ define how the output signals depend on the inputs.

In general, θ consists of any continuously enumerable parameters, such as, controller parameters, setpoint values or process parameters. In this paper only control parameters are considered, however. The performance of the system can be characterized by means of quality measures, q, that are calculated from the input and output signals. For instance, robustness and accuracy are important concepts in describing the performance of a control system. Such concepts can be measured, e.g., with the variance and the setpoint tracking ability of controlled variables, respectively.

In statistical sense, the quality measures values, q, depend on the system parameters, θ. For example, if all parameters θ affecting the output are properly chosen, the system performance will be satisfactory on the average, regardless of the input signals that are introduced to the system. Viewed on a lower abstraction level the system is dynamic determining the dependency between u and y, whereas the upper level connection between θ and q can be considered static. Although the connection between θ and q involves stochastic uncertainties, q being a function of more or less random realizations of signals u and y, this dependency can be modelled statistically. This model makes it possible to optimize the system performance with respect to its parameters.

Because no physical dependency between θ and q is assumed to be known, the modeling is based on observed data. It turns out that, under certain assumptions regarding the data distribution, linear model is optimal for this purpose. First, if the data can be assumed unimodal, meaning it comes from a single multivariate Gaussian distribution, the dependency between θ and q is linear in the maximum likelihood sense (see, e.g., Pindyck and Rubinfeld, 1991). The Gaussianity assumption can be motivated by the central limit theorem stating that if a number of independent variables are added together the resulting distribution approximates Gaussian, no matter what the original distribution of the variables was. However, it must be noted that the Gaussianity assumption holds only locally and therefore the linear models cannot be applied successfully over the whole parameter space but only locally. Not to lose the Gaussianity, the quality measures are assumed to be smooth functions of the parameters. The validity of the above assumptions in practice will be discussed in more details below within the results of the case study.

As was mentioned above, the system under consideration was assumed to be a MIMO system. Consequently, it is reasonable to assume that there exists a large amount of parameters affecting the outputs of the system, and similarly multiple quality measures are required to describe the desirable performance of the overall system. Modeling the dependencies of parameters and quality measures with a linear model has many advantages. First, the

linear model is easy to compute and, second, the numerical problems typically plaguing estimation of high dimensional linear models can be avoided effectively by using multivariate statistical methods, such as Principal Component Analysis (PCA), Partial Least Squares (PLS) and Canonical Correlation Analysis (CCA). These methods are presented more thoroughly, e.g., in (Hyötyniemi 2001).

The required data sets are generated with Markov Chain Monte Carlo (MCMC) simulations, in which the values of θ are randomly varied (locally) and the consequent values of q are calculated. (Notice, that a simulator of the process is used here for the data generation.) If the system involves n parameters and the performance is assessed with m quality measures, the vector representation of a data sample is

$$\theta = \begin{pmatrix} \theta_1 \\ \vdots \\ \theta_n \end{pmatrix}, \quad q = \begin{pmatrix} q_1 \\ \vdots \\ q_m \end{pmatrix}, \qquad (1)$$

and the data set of k samples can be expressed

$$\Theta = \begin{pmatrix} \theta^T(1) \\ \vdots \\ \theta^T(k) \end{pmatrix}, \quad Q = \begin{pmatrix} q^T(1) \\ \vdots \\ q^T(k) \end{pmatrix}. \qquad (2)$$

The multivariate statistical methods assume the data to be appropriately preprocessed. This means that, the data has to be locally centered and scaled to unit variance before modelling. Based on data, a linear model F that describes the dependency between θ and q,

$$q = F^T \cdot \theta, \qquad (3)$$

can be estimated. The same mapping for the data set of k samples in the matrix form can be presented as
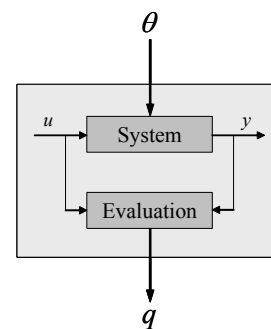
$$Q = \Theta \cdot F. \qquad (4)$$

Fig. 1. A "higher-level" statistical model between parameters, θ, and quality measures, q, describes the relevant properties of the underlying dynamic MIMO system, having inputs u and outputs y. (Hyötyniemi, 2002)
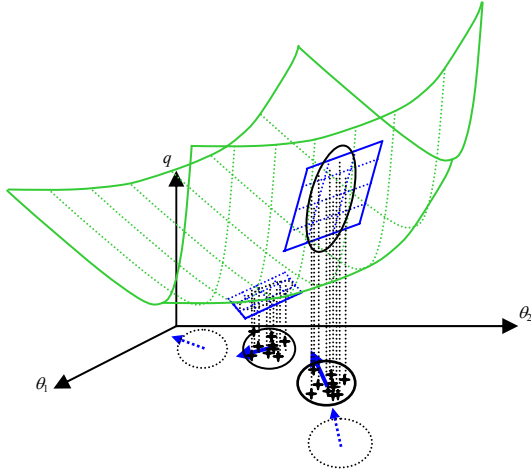
Fig. 2. The dependency of the parameters θ_1 and θ_2 and the quality measure q is modelled based on data in four successive global iteration steps (Halmevaara and Hyötyniemi, 2004).

The m quality measures can be combined into a scalar valued optimization cost function, J, e.g., by calculating a weighted sum,

$$J = w^T q = \sum_{i=1}^{m} w_i \cdot q_i, \qquad (5)$$

where w is an $m \times 1$ weighting vector. Alternatively, various multiobjective optimization methods are also available, see, e.g., (Miettinen, 1999). As was mentioned above, the estimated model, F, is valid only locally, and therefore the optimal solution,

$$\theta^* = \arg \min_{\theta} J\big(q(\theta)\big), \qquad (6)$$

cannot be found with a single calculation and one has to accept the approach of taking short update steps towards this optimum. The easiest way to find the local optimum (here, a minimum) is the Gradient descent algorithm. Other applicable methods are, e.g., Conjugate gradient method, Newton-Rhapson and Scoring algorithms. The gradient, which indicates the direction of the maximal growth of the cost function, J, is obtained by substituting (3) into (5) and by differentiating the equation resulting in

$$\frac{dJ}{d\theta} = \frac{d}{d\theta}\big(w^T F^T \theta\big) = Fw. \qquad (7)$$

To minimize the value of J the parameters are updated to negative gradient direction according to

$$\bar{\bar{\theta}}(K+1) = \bar{\bar{\theta}}(K) - \gamma \cdot \frac{dJ}{d\theta}(K) = \bar{\bar{\theta}}(K) - \gamma \cdot F(K)w. \qquad (8)$$

Above, $\bar{\bar{\theta}}$ refers to prevailing parameter values (the centre of the parameter variation in a local iteration process), K is the global iteration step index and γ is

the length of the parameter update step. The notation $F(K)$ emphasizes the fact that the matrix F is estimated over and over again, in every global iteration step. Also the values of γ and w can vary during the optimization procedure.

In summary, the IRT method can be condensed as follows (see Fig. 2): The procedure consists of K global iteration steps. Through these steps the values of the parameters are gradually tuned towards their optimal values. Each step consists of a local iteration process, i.e., k simulations are run with slightly varied parameter values and the consequent quality measures are calculated. A local linear model is estimated from the data if the Gaussianity assumption is not violated. The subsequent parameter update is based on the calculation of the gradient of the cost criterion. Global iteration steps are taken until the performance of the system meets its objectives or as long as significant improvements on the system performance can be observed.

One of the most important advantages of the IRT method is that it ignores the structure of the underlying control system, i.e., no matter whether a multivariable controller or a multi loop SISO control system is considered. In both cases, the control structure is optimized as a whole including all interdependencies. Optimal performance for large and complex control systems cannot be achieved by tuning controllers one by one. Further, the possibility to use different quality measure definitions makes the method flexible and expressive.

3. PULP DIGESTER CASE STUDY

A model of a Finnish pulp mill was applied in the test case. The process model was constructed with the APROS software that is a professional simulation environment for modeling combustion and nuclear power plants, and pulp and paper mills (see Anon. 2004). APROS provides large libraries of process and automation components, which can be combined into rigorous models of industrial plants. APROS has been used successfully, e.g., in various training simulator and process analysis projects.

In the following, some terminology related to pulp production is first explained. Then, the model of the pulp mill is introduced, after which the tuning targets of the case study are formulated.

3.1. Terminology

The *kappa number* is a measure of lignin content in the cooked pulp. It is measured with the amount of potassium permanganate consumption in an acid pulp dilution. The remaining lignin content of the pulp has a strong effect on the colour of the produced fibres. It also affects the strength properties of pulp, which makes it an important controlled variable.
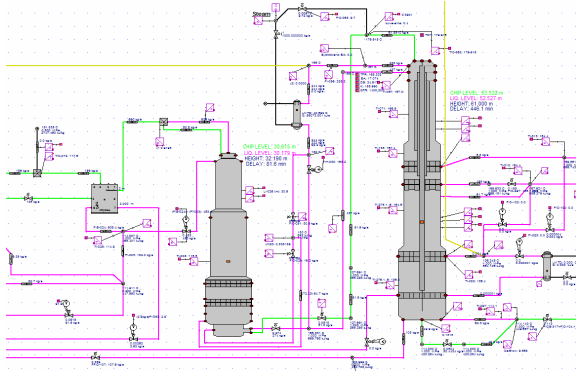
Fig. 3. The model of the pulp mill: The chip feed
    screw conveyor (left), the impregnation vessel
    (in the middle), and the pulp digester (right).

The kappa number is controlled by adjusting the *H
factor*. H factor is an experimental combination of
the cooking time *t* and the temperature *T*. One H
factor unit denotes the effect of one hour cooking in
100 °C. The H factor is defined as follows

$$H = \int_0^t e^{(43,2 - 16115/T)} dt \ . \tag{9}$$

After cooking the pulp is washed in several
successive washing stages before bleaching. The
cooking chemicals are recycled, and thus the
washing losses are tried to minimize. The washing
starts at the bottom of the digester with a counter
current washing. The efficiency of the washing is
measured with the *washing coefficient* that is defined
as ratio of used washing liquor to the amount of
washed pulp. To ensure uniform pulp properties
constant washing coefficient is desirable.

3.2. Model and problem description

A general overview of the model is presented in Fig.
3. First, the woodchips and the impregnation liquor
are mixed, after which the mixture is fed into the
impregnation vessel. The flow continues to the top of
the digester, where the mixture is heated with steam
to the cooking temperature. Wood was modelled to
consist of several cellulose, carbohydrate and lignin
components, and the liquor was assumed to contain
sodium hydroxide and sodium sulphide in addition to
the organic compounds dissolved from the
woodchips. Chemical reactions during the cooking
phase were modelled according to (Gustafson *et al.*
1983). Several circulation streams of used black
liquor to the preceding parts of the process were
modelled. The subsequent washing and bleaching
operations were excluded from the model.

In the case study, the production of pulp in a steady
state operation was considered, i.e., changes of
neither production rate nor quality targets of the pulp
were simulated. In the initial state of the test case,
several control loops were behaving poorly. The

level controllers in the impregnation and the digester
vessels were oscillating heavily due to their
inappropriate tuning. Due to unsatisfactory level
control, also the washing coefficient control failed to
meet its targets. The two model-based controllers
were behaving even more detrimentally. The other
one predicts the kappa number of the produced pulp
based on the digester top temperature measurement.
There is a five hour time delay in the cooking
process which makes this prediction essential for the
process control. The other model calculates the
setpoint value for the H factor based on the measured
temperature profile of the digester, the amount of
applied alkali and the kappa number of the produced
pulp. Both models were giving strongly biased
predictions, causing naturally serious problems. Due
to the improper controller tuning the process was
producing continuously out of specification pulp.

3.3. Optimization targets

Cost function of the optimization was formulated
according to equation (5) with $m = 6$ and $w_i = 1$, $\forall i =$
1…6. All quality measures were defined with the
same mathematical expression,

$$q_i = \frac{1}{T} \sum_{t=1}^T \left| y_i(t) - y_{i,sp}(t) \right|, \tag{10}$$

in which $i = 1…6$, t is the time series sample index, T
is the length of the simulated time series, y_i is the
measured process variable and $y_{i,sp}$ is the setpoint
value for y_i (except for $i = 6$, for which y_i is the
predicted H factor and $y_{i,sp}$ is the true H factor
calculated from the digester temperature profiles).
The six considered variables were:

y_1: kappa number in the digester blow,
y_2: washing coefficient,
y_3: liquor level in the digester,
y_4: chip level in the digester,
y_5: chip level in the impregnation vessel, and
y_6: H factor prediction.

The tuning involved seven PI controllers and two
models that were applied in prediction and setpoint
calculation, i.e., $n = 20$. The PI controllers were
responsible for regulation of the chip and liquor
levels, washing coefficient, production rate, H factor,
and the digester steam chamber temperature.

4. RESULTS

This chapter presents the results of $K = 30$ global
steps. The fairly great number of global steps is due
to the crude gradient method. Also, since the initial
performance was purposefully set to extremely poor,
long tuning time was understandable. In simulations
$k = 50$ on the average and $T = 8h$. Simulations were
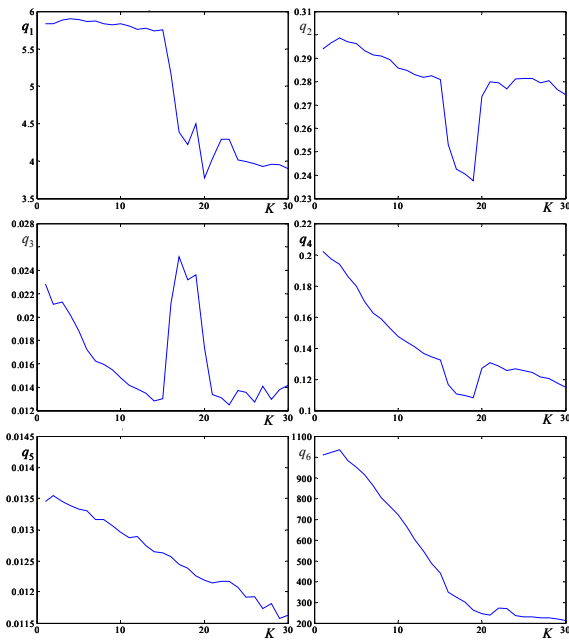run about 25 times faster than real time.

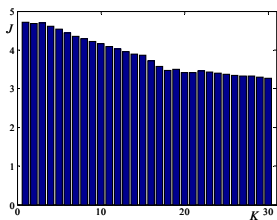Fig. 4. The quality measure values, q_i, $i = 1…6$, in the global optimization steps, $K = 1…30$.

Fig. 5. The values of the cost function, J, during the iterative optimization, $K = 30$.

The IRT method succeeded in improving the process performance regarding the six quality measures (see Fig. 4). For example, the kappa number deviation, q_1, diminished from about 6 to 4 units, and the absolute value of the H factor prediction error, q_6, was reduced from about 1000 to 200 units. For softwood pulp the kappa number is tried to keep within ±2-3 units range from the target. In that sense the control is not yet satisfactory but the tuning succeeded to improve its performance notably. The quality measure values include some stochastic variation and therefore the trends are not monotonically descending. Also occasional "outliers" can be perceived in the values of the quality measures in the global iteration steps 15-20. The causes behind these observations are discussed below.

The success of the optimization can be followed also from the values of J (see Fig. 5). It can be seen how the conflicting targets finally start to slow down the tuning procedure. If the objectives are not met at the end, one has to reconsider the weighting of q_i. It is the only way to continue the optimization among Pareto optimal solutions. Examples of the improved performance are presented in Fig. 6. The fluctuation

of the kappa number has stopped, variance of the digester liquor level has diminished and the H factor prediction has improved tremendously.
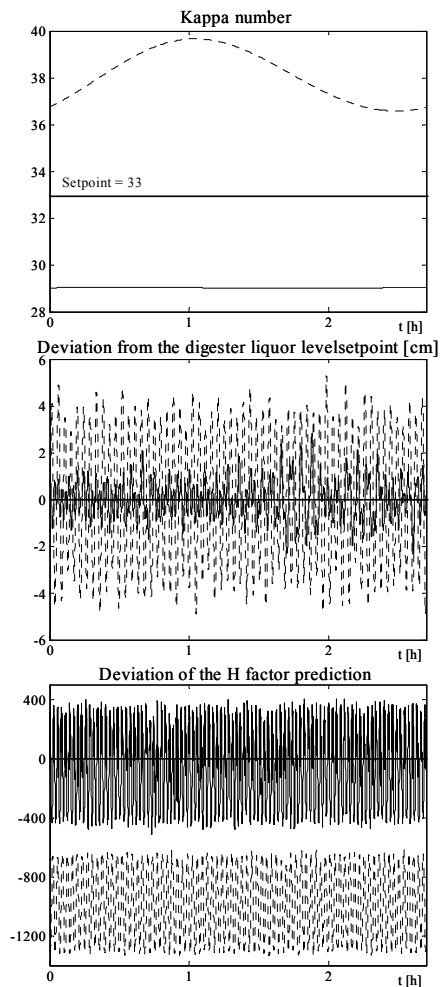

Fig. 6. Simulation results with initial and tuned parameters, $K = 1$ (dotted) and $K = 30$ (solid).
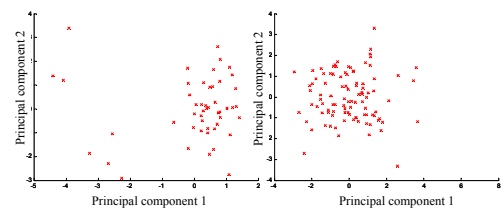

Fig. 7. Distributions of q values projected to the plane spanned by the two major principal components, $K = 18$ (left) and $K = 30$ (right).

The convenient linear model was justified with the assumption of Gaussian data. The distributions of the quality measure data in global steps $K = 18$ and $K = 30$ are shown in Fig. 7. Obviously the distribution in the left figure does not fulfil the Gaussianity assumption. The same can be seen also from Fig. 8 in which the empirical cumulative distribution functions (ECDF) of the distributions are compared to the theoretical CDF of the (0,1) Gaussian

distribution. This comparison is known as the Kolmogorov-Smirnov test. It is evident that at some points in the parameter space the true unknown cost function may be strongly nonlinear, and therefore Gaussianity testing is recommended.

5. CONCLUSIONS

Grasping the general view of a large and complex system, like an industrial process and its control system, is a demanding task. The underlying interdependencies are difficult to comprehend as the size of a system increases. Advanced multivariate statistical methods are required to capture the emerging higher abstraction level concepts.

The IRT method makes it possible to optimize the performance of large systems, and helps the domain area experts to refine their intuition concerning the process and the goals of its performance. As long as the distribution of the quality measures stays close to Gaussian, the IRT method proceeds convincingly. Therefore, defining q should be done carefully. Departures from Gaussianity can be due to nonlinear behaviour of the quality measure or too large local variation of the parameters.

The application of IRT method to controller tuning assumes that a rigorous simulation model of the process is available. It is also assumed that the available computational power enables one to run simulations notably faster than in real time. In that case the IRT method opens up new possibilities: Different control structures can be tuned to their maximum performance and compared with each others before implementation, and, e.g., start-ups of new process plants can be hastened by finding reasonable initial values for controller parameters. In future, implementation of IRT to a semantic mill model design environment will be studied.
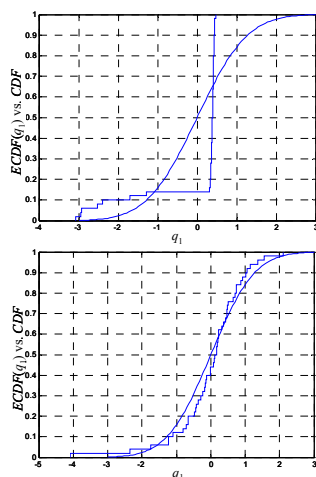

Fig. 8. ECDF of q_1 vs. theoretical CDF of the (0,1) Gaussian distribution, $K = 18$ (top) and $K = 30$ (below).

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