SCHEDULING OF GAS TURBINE COMPRESSOR WASHING

G. HOVLAND* AND M. ANTOINE**

*School of Information Technology and Electrical Engineering
University of Queensland, Australia
Email: hovland@itee.uq.edu.au

**Plant Optimisation
ABB Power Technology Systems, Switzerland
Email: marc.antoine@ch.abb.com

ABSTRACT—This paper describes an estimation method for gas turbine compressor degradation and an economical optimisation model for determining the optimal compressor washing cycles. The optimisation model aims at minimising fuel consumption and emissions in combined-cycle power plants. The results presented are of significant importance for power plants operators that have the possibility of frequently connecting and disconnecting to the power grid. By optimising power generation periods and levels, downtimes and maintenance scheduling, the operators ensure that the plant operates at a high efficiency level in periods when fuel prices are high. High efficiency levels ensure low fuel consumption and emission levels. The work presented in this paper was implemented as a product prototype at ABB Utility Automation in 2003 and patented in 2005. [1].

Key Words: Compressor washing, mixed-integer optimisation.

1. INTRODUCTION

All power plant components, such as compressors, gas and steam turbines and heat exchangers, deteriorate in performance during operation. The impact of performance deterioration results in loss in power output or increased fuel consumption. Loss in power output reduces revenues for the plant owner. Increase in fuel consumption increases operating costs and emissions. Both these factors increase equipment lifecycle cost. Performance deterioration results in higher firing temperatures, resulting in increased component creep life used for a given power demand. In combined-cycle power generation, even a 1% reduction in fuel consumption can result in reduced operational costs of more than US$1m and reduced CO2 emissions of 50 tons per year for a typical plant.

In this paper the focus is on the economic optimisation of compressors at the air-intake of a combined-cycle power plant. The goal is to keep the compressor efficiency at high levels and hence save fuel for the given operating points. The efficiency degrades during normal operation due to pollutants in the air intake. The pollutants, such as dust, hydrocarbon aerosols, pollen or salts, attach themselves to the compressor blades and cause a reduction of efficiency. The plant operator has four options related to the compressor efficiency: A) Continue normal operation / power production and let efficiency degrade from the current level, B) perform an online washing of the compressor, C) perform an offline washing and D) run the machine in the idle state. The online washing (option B) can be performed without closing down the plant. Chemicals and water are injected into the air-intake of the compressor. The water and chemicals will clean the first stages of the compressor before the water evaporates. An offline washing (option C) requires a plant shutdown. The blades of all compressor stages are soaked with water and chemicals. Since the water and chemicals do not evaporate and stay in contact with the blades much longer compared to an online washing, an offline washing usually restores the efficiency to a higher level. However, since a plant shutdown is required for an offline washing, it may be far more economical to perform online washes at
regular intervals depending on prices of power sold and fuel purchased. The idle state (option D) keeps the gas turbine running without producing power. This mode can be more economical than a plant shutdown when the idle period is short. This paper addresses the scheduling problem (options A, B, C and D) of compressor washing taking maintenance and fuel costs into account.

Figure 1 below shows an overview of the technologies used for the economic scheduling of compressor washing. The complete optimisation solution consists of several parts which will be briefly described in this paper. Section 2 presents a relatively simple dynamic model of a compressor. The compressor is modelled by its input-output behaviour. The model presented relates the state variables (massflow and pressure) to measured temperatures and the unknown parameter (isentropic efficiency). Section 3 briefly describes the Kalman filter approach for estimating the time-varying efficiency level. Section 4 presents a linearised fuel benefit model while section 5 presents the hybrid dynamic model of the compressor. This model is the link between the physical model and the economic model. The model is called hybrid since boolean decision variables are introduced in addition to the physical variables of massflow and pressure. The boolean variables link the economics with the physics. In section 6 a model predictive optimisation is described. The set of boolean variables is duplicated for each time step, in our case the time step is one day. The optimisation computes the optimal sequence of the boolean decision variables from the start to the end of the optimisation period. Section 7 illustrates the economical benefits of the proposed optimisation. A compressor washing scheduling is performed over a time period of one year and potential savings compared to a fixed maintenance approach are calculated. The work presented in this paper is related to the work presented in [3] and [11] where lifetime consumption models and economic mixed-integer optimisation were used to determine production levels of combined-cycle power stations.

2. COMPRESSOR EFFICIENCY MODEL

The model used consists of two nonlinear ordinary-differential-equations (ODEs) and a static relationship between isentropic (or polytropic) efficiency, ambient conditions and temperature after the compressor, see [5]. The model has the following form:

$$\frac{df}{dt} = \frac{A}{L_c} (P_{\infty} - p)$$  (1)
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\[ \frac{dp}{dt} = \frac{a_0^2}{V_p} \left( f - k_x \sqrt{p - P_{amb}^2} \right) \]  

\[ T_{ac} = T_{amb} \left( \frac{p}{P_{amb}} \right) \exp \left( \frac{\kappa - 1}{\kappa} \right) \]  

\[ T_{ac} = \frac{1}{\eta_{ac}} (T_{a} - \eta_{ac} P_{amb}^2) + P_{amb} \]  

where \( A_1 \) (cross-sectional area), \( L_c \) (length), \( V_p \) (volume) and \( k_i \) (friction flow coefficient) are constant parameters of the compressor. \( a_0 \) and \( \kappa \) are the sonic air velocity and ratio of specific heats for air, respectively. The dynamic states \( f \) and \( p \) are the compressor massflow and pressure, \( P'_{amb} \) and \( T'_{amb} \) are ambient pressure and temperature, \( P'_{ac} \) and \( T'_{ac} \) are pressure and temperature at the compressor outlet. \( T_a \) and \( \eta_{ac} \) are the compressor’s isentropic temperature and efficiency.

The superscripts ‘ indicate that the measured pressure or temperature has been corrected for ambient conditions. In order to compare efficiency for different days and reliably evaluate degradation, the measured temperatures and pressures must be normalised to a reference condition. This reference condition is usually selected as standard conditions for dry air, see for example [10]. The following variables are introduced for the standard conditions:

\[
\begin{align*}
T_0 &= 287.15 \text{ (K)} \\
P_0 &= 101325 \text{ (Pa)} \\
\kappa_0 &= 1.4
\end{align*}
\]

where \( T_0 \) is standard temperature, \( P_0 \) is standard pressure and \( \kappa_0 \) is the standard ratio of specific heats. The following correction procedure is suggested in [10]: First the temperature ratio \( \theta \) and the pressure ratio \( \delta \) are defined.

\[
\begin{align*}
\theta &= \frac{T_{amb}}{T_0} \\
\delta &= \frac{P_{amb}}{P_0}
\end{align*}
\]

The corrected temperatures and pressures are then given by:

\[
\begin{align*}
T_{amb}' &= \frac{T_{amb}}{\theta} = T_0 \\
P_{amb}' &= \frac{P_{amb}}{\delta} = P_0 \\
T_{ac}' &= \frac{T_{ac}}{\theta} \\
P_{ac}' &= 1 + \frac{\kappa - 1}{\kappa_0 - 1} \left[ \frac{P_{ac}}{\theta^{(\kappa - 1)/\kappa}} \right]^{3.5}
\end{align*}
\]

\( \kappa \) at the compressor outlet is computed from a standard gas table from measured temperature, pressure and the weight fraction of vapour in the intake air.
The goal of the Kalman filter to be presented in the next section, is to accurately estimate the compressor isentropic efficiency $\eta_i$, given the dynamic compressor model and corrected measurements of temperature and pressure after the compressor.

3. PARAMETER ESTIMATION VIA KALMAN FILTERING

It should be noted that given measurements of temperature and pressure both before and after the compressor, it is possible to calculate the compressor efficiency directly. However, any noise present in these measurements will directly influence the efficiency. The Kalman filter significantly reduces the noise in the efficiency estimate by calculating the isentropic efficiency from the estimated pressure state. Moreover, the efficiency estimate can be further improved if additional dynamics are introduced for combustion and turbine stages. Such models would link additional plant measurements with the states (massflow and pressure) of the compressor.

In order to use the Kalman filter, the model described in section 2 must first be converted to the following form:

$$\frac{dX}{dt} = F(X,U,P)$$  \hspace{1cm} (9) \\
$$Y = H(X,U,P)$$  \hspace{1cm} (10)

where $X = (f,p)$ is the state vector, $U = (T_{amb}^*, P_{amb}^*, P_{ac}^*)$ is the input vector, $Y = (T_{ac}^*)$ is the measurement vector and $P = (\eta_i)$ is the vector of unknown time-varying parameters. Given $U$ and $Y$, the different variants of the Kalman filter simultaneously estimate the state vector $X$ and the parameter vector $P$.

The papers and patents [1], [4], [6], [7] and [8] describe four different variants of the Kalman filter for continuous tracking of unknown variables, such as the isentropic efficiency, based on nonlinear ODEs. The four variants are the Extended Kalman Filter (EKF), two Unscented Kalman Filters (UKF) and the Adaptive Extended Kalman Filter (AEKF). Each of these filters has benefits in different situations. For the work presented in this paper we have used the EKF. We have found the UKF versions to be better suited for strong nonlinear models, but the drawback is a higher computational effort compared to the EKF. See our paper [7] for an extensive comparison of these filters on power plant models. The output of the parameter estimation is a complete mapping of compressor efficiency (estimated parameter) vs. massflow and pressure ratios (estimated states). This information is used to find the benefits of online and offline washes as measured by the efficiency. In addition, the Kalman filters are used to estimate the degradation of the efficiency during normal plant operation.

Figure 2 shows two different corrected estimates of isentropic efficiency vs. the compressor ratio $P_{ac}^* / P_{amb}^*$ for a 300MW combined-cycle power plant. The upper curve was estimated one week after the lower curve. During the week between the two estimates, the power plant was down for maintenance. The estimated improvement in isentropic efficiency is about 2% over the entire range of pressure ratios.
4. FUEL BENEFIT MODEL

The optimisation algorithm requires a model of the potential fuel benefits of a washing as a function of the current compressor efficiency. To compute the benefit in fuel savings after a washing, we derive the following relations based on the power and isentropic efficiency equations.

\[
f_{\text{fuel}} = \frac{1}{C_x} (P_c + P_o)
\]

\[
P_c = (T_{\text{amb}} - T_{\text{amb}}) f_a C_g
\]

\[
T_{\text{amb}} = \frac{1}{\eta_{\text{is}}} (T_{\text{is}} - T_{\text{amb}})
\]

where \(P_c\) is the power consumed by the compressor, \(P_o\) is the power output from the plant, \(C_g\) is the heat value of the fuel, \(f_a\) is the airflow, \(T_{\text{is}}\) is the isentropic temperature and \(\eta_{\text{is}}\) is the isentropic efficiency.

If an offline washing is made, the efficiency increases from \(\eta\) to \(\eta_2\) with the following factor.

\[
k_1 = \frac{\eta_2}{\eta}
\]

Then, the following fuel benefit can be shown from the equations above.

\[
\Delta f_{\text{fuel}} = \frac{P_c}{C_g} \left( \frac{1}{k_1} - 1 \right)
\]

Since \(k_1\) is a non-linear function of the state variables \(\eta\) and \(\eta_2\), we cannot implement this benefit function directly. Instead, we make the following approximations.
\[
\frac{1}{k_1} = \frac{\eta}{\eta^2} = 1 + \left(\frac{\eta - 1}{\eta^2}\right) = 1 + \frac{\eta - \eta^2}{\eta^2} \approx 1 + \frac{1}{\eta_0} (\eta - \eta^2) \quad (16)
\]

\[
\frac{1}{k_2} = 1 + \frac{\gamma}{\eta_0} (\eta - \eta^2) \quad (17)
\]

where \(1/k_1\) and \(1/k_2\) are the approximated efficiency benefits for offline and online washings, respectively. The approximations above are valid when \(\eta^2 \approx \eta_0\), where \(\eta_0\) is the nominal compressor efficiency level. The fuel benefit function for online washing \((k_2)\) is shown in Figure 3. Note that after an offline wash, the efficiency level is restored to the maximum level and the fuel benefit is reduced to zero.

![Figure 3: Efficiency (Top) and Fuel Benefit Model (Bottom).](image)

5. HYBRID DYNAMIC MODEL

The hybrid dynamic model consists of the 14 boolean and continuous variables described below:

- \(\delta_1\) Boolean: Online washing state (0 or 1)
- \(\delta_2\) Boolean: Offline washing state (0 or 1)
- \(\delta_3\) Boolean: Normal operation (0 or 1)
- \(\delta_4\) Boolean: Idle state (0 or 1)
- \(\delta_5\) Boolean: Help state 1 (0 or 1)
- \(\delta_6\) Boolean: Help state 2 (0 or 1)
- \(\eta\) Continuous: Compressor efficiency (0 to 1)
- \(\eta_2\) Continuous: Recoverable efficiency (0 to 1)
- \(\alpha\) Continuous: Degradation rate of \(\eta\)
- \(\alpha_2\) Continuous: Degradation rate of \(\eta_2\)
- \(z_1\) Continuous: Cost of online washing
- \(z_2\) Continuous: Cost of offline washing
- \(z_3\) Continuous: Help variable for \(\alpha\)
z_4 \quad \text{Continuous: Fuel cost due to degradation}

In addition to the 14 states, the model consists of a set of linear constraints and an optimisation criterion. By using only linear constraints, the optimisation problem can be solved by a Mixed-Integer-Linear-Program (MILP) solver. Examples of efficient commercial solvers for MILP problems are CPLEX and Xpress-MP. Nonlinear constraints can often be converted to linear constraints by introducing help variables, such as \( \delta_i \) and \( \delta_6 \).

The model has a state machine of 4 main boolean states (\( \delta_1, \delta_2, \delta_3, \delta_4 \)). The system will always be in only one of these 4 states. The linear constraint describing this behaviour, is simply \( \delta_1 + \delta_2 + \delta_3 + \delta_4 = 1 \). In addition to this constraint, the hybrid model consists of the following 22 logical constraints:

1. IF \( \alpha \leq 0 \) THEN \( \delta_{i}=0 \) ELSE \( \delta_{i}=1 \)
2. IF \( \alpha \leq 0 \) THEN \( \delta_{i}=0 \) ELSE \( \delta_{i}=1 \)
   These two constraints relate the boolean variables \( \delta_i \) and \( \delta_6 \) to the continuous variables \( \alpha \) and \( \alpha_2 \).

3. IF \( \delta_{i}=1 \) THEN \( \alpha_{i+1} = \alpha_0 \)
4. IF \( \delta_{i}=1 \) THEN \( \alpha_2_{i+1} = \alpha_2_i - \epsilon_2 \delta_6 \)
5. IF \( \delta_{i}=1 \) THEN \( \eta_{i+1} = \eta_i + \gamma (\eta_2_{i+1} - \eta_i) \)
6. IF \( \delta_{i}=1 \) THEN \( \eta_2_{i+1} = \eta_2_i - \alpha_2_i \)
   These four constraints describe the system after an online wash. The variable \( \alpha \) which describes the degradation rate of the compressor efficiency \( \eta \), is reset to its initial value. The variables \( \eta_2 \) and \( \alpha_2 \) describe the non-recoverable degradation of a compressor. These variables always decrease, except when the compressor is in the idle state. The non-recoverable efficiency can be thought of as the efficiency level of a perfectly clean but ageing compressor. Constraint 5 models the increase in efficiency after an online wash. The constant parameter \( \gamma \) (between 0 and 1) models the effectiveness of an online wash. Online washes usually only clean the first rows of compressor blades before the water and chemicals evaporate. Hence, the blades at the compressor outlet will not be clean and the compressor efficiency is not restored to the maximum value. As will be seen from the next set of constraints, the maximum efficiency that can be restored, is given by the recoverable level \( \eta_2 \).

7. IF \( \delta_{i}=1 \) THEN \( \alpha_{i+1} = \alpha_0 \)
8. IF \( \delta_{i}=1 \) THEN \( \alpha_2_{i+1} = \alpha_2_i - \epsilon_2 \delta_6 \)
9. IF \( \delta_{i}=1 \) THEN \( \eta_{i+1} = \eta_2_{i+1} \)
10. IF \( \delta_{i}=1 \) THEN \( \eta_2_{i+1} = \eta_2_i - \alpha_2_i \)
    These four constraints describe the system after an offline wash and look very similar to the equations for the online wash. The only difference is the behaviour of \( \eta \) which is restored to the maximum level given by the recoverable efficiency \( \eta_2 \).

11. IF \( \delta_{i}=1 \) THEN \( \alpha_{i+1} = \alpha_i - \epsilon \delta_5 \)
12. IF \( \delta_{i}=1 \) THEN \( \alpha_2_{i+1} = \alpha_2_i - \epsilon_2 \delta_6 \)
13. IF \( \delta_{i}=1 \) THEN \( \eta_{i+1} = \eta_i - z_3 \)
14. IF \( \delta_{i}=1 \) THEN \( \eta_2_{i+1} = \eta_2_i - \alpha_2_i \)
    These four constraints describe the degradation of the compressor efficiency during normal operation. \( z_3 \) is a help variable that prevents subtracting a negative value from the efficiency \( \eta \). The non-recoverable degradation is usually much slower and \( \alpha_2 \) is unlikely to become negative during a typical optimisation horizon of 10–20 days. Hence, a similar help variable to \( z_3 \) is not needed for \( \eta_2 \).

15. IF \( \delta_{i}=1 \) THEN \( \alpha_{i+1} = \alpha_i \)
16. IF \( \delta_{i}=1 \) THEN \( \alpha_2_{i+1} = \alpha_2_i \)
17. IF \( \delta_{i}=1 \) THEN \( \eta_{i+1} = \eta_i \)
18. IF \( \delta_{i}=1 \) THEN \( \eta_2_{i+1} = \eta_2_i \)

These four constraints describe the behaviour of the efficiency levels in the idle state. All values remain at their previous level.

19. \( z_1 = \delta_1 P_1 \)
20. \( z_2 = \delta_2 P_2 \)
21. \( z_3 = \delta_1 \alpha \)
22. \( z_4 = P_5 (\eta_z - \eta_i) \)

The constraints 19, 20 and 22 describe the costs associated with the various states. The constants \( P_1 \) and \( P_2 \) are the cost associated with chemicals, labour and lost power production of online and offline washes, respectively. \( P_5 \) describes the cost of the extra fuel needed to operate the compressor at an efficiency level below the recoverable level \( \eta_2 \).

The logical propositions above consist of IF-THEN-ELSE statements and multiplications of a boolean and a continuous variable. These types of logical constraints can easily be converted to a set of linear constraints, see for example [2]. Automatic tools for converting logical constraints to linear constraints exist, for example HYSDEL from ETH [9].

Examples of the two most common logical propositions are given below.

**Proposition 1:** Product \( z = \delta f(x) \), where \( \delta \) is boolean and \( f(x) \) continuous, is equivalent to:

\[
\begin{align*}
  z - f_{\max} \delta & \leq 0 \\
  -z + f_{\min} \delta & \leq 0 \\
  z - f_{\min} \delta - f(x) & \leq -f_{\min} \\
  -z + f_{\max} \delta + f(x) & \leq f_{\max}
\end{align*}
\]

where \( f_{\min} < f(x) < f_{\max} \).

**Proposition 2:** IF \( f(x) < 0 \) THEN \( \delta = 0 \) ELSE \( \delta = 1 \) is equivalent to:

\[
\begin{align*}
  (-f_{\min} + \kappa) \delta - f(x) & \leq -f_{\min} \\
  (-f_{\max} - \kappa) \delta + f(x) & \leq \kappa
\end{align*}
\]

where \( \kappa \) is a small positive number.

6. MODEL PREDICTIVE CONTROL

Model predictive control (MPC) can effectively be used together with a linear hybrid dynamic model. In our application, the 14 hybrid dynamic model states are duplicated for each future time step in the MPC controller, as illustrated in Figure 4. The time steps for the compressor washing application are days. Day 2 represents the unknown states for tomorrow, day 3 for the following day, etc. Day N represents the last day considered by the MPC optimiser. \( N \) is referred to as the MPC horizon. Several variables have to be predicted from day 1 to day \( N \). In the compressor washing application, these variables are \( P_1 \), \( P_2 \) and \( P_5 \) which include future fuel and power prices.

Day number 1 represents the initial state of the plant. For example, if the plant operates in normal production, \( \delta_1 = 1 \) and \( \delta_2 = \delta_3 = 0 \) for day 1. The continuous efficiency variable \( \eta \) for day 1 is set to the
current estimate from the Kalman filter. The variables corresponding to the degradation rates and the recoverable efficiency level are based on parameter estimates on historic data including a number of online and offline washes.

Given all the initial states, the 23 iterative logical constraints from section 4 relate all future states to the states for Day 1. The logical constraints will eliminate the majority of all possible state sequence combinations.

![Figure 4: Duplication of hybrid model states.](image)

The optimisation problem can be stated as follows:

\[
\text{Minimise } \sum z_1 + z_2 + z_4
\]

Subject to the 23 constraints from section 4

where the sum is taken over days 1 to N. Given the linear objective function and the fact that the 23 logical constraints can be formulated as linear constraints, the above problem can be formulated as a MILP. Since the logical constraints are iterative, it would be possible to formulate all constraints as functions of the initial states for day 1 and hence avoid the duplication of states. This is the approach taken by the Hysdel software from ETH [9]. However, because of the efficient pre-solve features of many MILP solvers, the solution times of the condensed MILP and the duplicated MILP are similar.

7. BENEFIT ANALYSIS

In this section we briefly present the economic benefits that can be expected from the optimised compressor washing schedule compared to a fixed schedule. Figure 5 and Figure 6 show forecasted fuel and power prices in US$/MWh. These prices are used at daily intervals for the future days 1 to N by the MPC optimiser. Figure 7 shows the optimised compressor efficiency level.

The solid line in Figure 7 illustrates the recoverable efficiency level $\eta_2$. The curve below the solid line illustrates the variable $\eta$. The discrete jumps in the efficiency level are caused by online washes. During this one year prediction, the plant has a continuous 100% power production and no planned shutdowns. Hence, no offline washes are chosen due to the excessive costs associated with plant shutdowns and lost power production.
Figure 5: Forecasted fuel prices for one year ahead.

Figure 6: Forecasted power prices for one year ahead.

Figure 7: Optimised compressor efficiency level.
Table I shows the economic results of the MPC optimised compressor washing schedule compared to fixed schedules. If no washing is performed, the efficiency level deteriorates and the cost of 100% refers to the cost of extra fuel to maintain power production at 100%. When performing online washes every day, the cost of 49% mainly refers to chemicals and labour. When performing washes every Sunday, the costs are a combination of extra fuel costs and chemical and labour costs associated with the washing operation.

As can be seen from Table I, the MPC optimised schedule is clearly better than any of the fixed schedules. Because of high volatility of fuel and power prices, no fixed washing schedule is expected to be close to MPC optimised schedules. The economic benefit figures in Table I were forecasted for a 300MW power plant that runs at 100% power production level for one year. The benefits are expected to be somewhat lower for plants that have regular shutdowns, for example on weekends. On such days, offline washes are obvious maintenance operations that can be performed at very low additional cost. However, during periods of high fuel prices, it can still be of significant economic benefit to perform online washes between fixed offline washing schedules.

Compared to simpler washing strategies, the optimisation approach presented in this paper provides several benefits. For example, instead of scheduling washes immediately before expected increases in gas prices, the MPC approach takes several other factors into account, such as power prices and costs of the scheduling operations. In addition, the MPC handles multiple price events inside the MPC horizon. For example, if there is a significant expected increase in gas prices followed by a significant decrease a few days later, it is not easy to determine manually what the optimal scheduling sequence would be. Scheduling based on fixed degradation rates will also perform worse than the MPC approach, as degradation depends heavily on varying daily and seasonal conditions, such as ambient temperatures and pollutants in the air. By updating the efficiency levels based on plant measurements, the accuracy of the models is significantly improved. Without accurate efficiency models, the MPC approach will only yield sub-optimal washing schedules. Figure 7 illustrates the benefits of the MPC approach. When fuel is relatively cheap (days 0 to 100), washing schedules are performed infrequently and mainly determined by the amount of real-time degradation. When fuel is expensive (days 200 to 250) the scheduling is performed more frequently. Finally, when power prices are high (day 360), the compressor efficiency is allowed to drop lower than normal (0.7% below the non-recoverable level, vs. 0.3% under normal conditions).

8. CONCLUSIONS

In this paper a new approach to scheduling of online and offline compressor washing has been presented. The new method is based on a Model Predictive Control (MPC) optimisation that takes expected future fuel and power prices into account. The MPC optimiser is built on a hybrid dynamic systems model that describes the natural degradation of compressor efficiency and the discrete jumps in efficiency after washing operations. The hybrid dynamic model contains discrete states for the operational mode of the compressor and continuous states for the efficiency levels. The parameters of the efficiency model are estimated from thermodynamic models and the extended Kalman filter based on historic plant data. The proposed scheduling approach clearly shows the achievable economical benefits compared to the traditional way of scheduling, especially for plants that are in continuous operation.
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ABOUT THE AUTHORS

Geir Hovland received the MSc degree from the Norwegian University of Science and Technology, 1993, and the PhD degree from the Australian National University, 1997. From 1997 to 2003 he worked as a research scientist at ABB Corporate Research in Oslo (Norway), Västerås (Sweden) and Baden (Switzerland). Since January 2004 he has been at the University of Queensland, Australia as a senior lecturer in the areas of mechatronics, automation and control systems.

Marc Antoine received the MSc degree in mechanical engineering from the University of Brussels, Belgium, in 1982. He joined Virginia Polytechnic Institute, Blacksburg, as research assistant in the Department of Aerospace and Ocean Engineering. In 1985, he joined the Brown Boveri control systems division, Baden, Switzerland. Currently product manager at ABB Power Technology Systems, Baden, where he is responsible for plant monitoring and optimization systems.