ECONOMIC OPTIMISATION OF GAS TURBINE COMPRESSOR WASHING

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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.

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 $1m and reduced CO_2 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 three options related to the compressor efficiency: A) Continue normal operation and let efficiency degrade from the current level, B) perform an online washing of the compressor and C) perform an offline washing. The online washing 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 is performed after a plant shutdown. The blades of all compressor stages are soaked with water and chemicals. Since the water and chemicals will 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. This paper addresses the scheduling problem 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 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 5 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 today until the end of the optimisation period. Section 6 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.
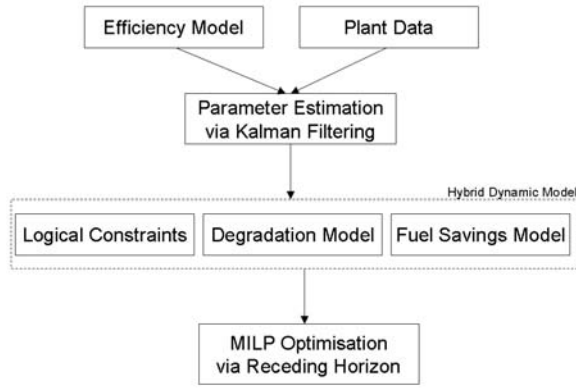

Figure 1: Overview of methods and models for economic scheduling of compressor washing.

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 [4]. The model has the following form:

$$\frac{df}{dt} = \frac{A_1}{L_c}\left(P_{ac}' - p\right)$$

$$\frac{dp}{dt} = \frac{a_{01}^2}{V_p}\left(f - k_t\sqrt{p - P_{amb}'}\right)$$

$$T_{is} = T_{amb}'\left(\frac{p}{P_{amb}'}\right)\exp\left(\frac{\kappa - 1}{\kappa}\right)$$

$$T_{ac}' = \frac{1}{\eta_{is}}\left(T_{is} - T_{amb}'\right) + T_{amb}'$$

where A_1 (cross-sectional area), L_c (length), V_p (volume) and k_t (friction flow coefficient) are constant parameters of the compressor. a_{01} and κ 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_{is} and η_{is} 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 [9]. The following variables are introduced for the standard conditions:

T_0	=	287.15 (K)
P_0	=	101325 (Pa)
κ_0	=	1.4

where T_0 is standard temperature, P_0 is standard pressure and κ_0 is the standard ratio of specific heats. The following correction procedure is suggested in [9]: First the temperature ratio θ and the pressure ratio δ are defined.

θ	=	T_{amb} / T_0
δ	=	P_{amb} / P_0

The corrected temperatures and pressures are then given by:

$$T_{amb}' = \frac{T_{amb}}{\theta} = T_0$$

$$P_{amb}' = \frac{P_{amb}}{\delta} = P_0$$

$$T_{ac}' = \frac{T_{ac}}{\theta}$$

$$P_{ac}' = \left(1 + \frac{\kappa - 1}{\kappa_0 - 1}\left[\frac{P_{ac}}{\theta}\right]^{(\kappa-1)/\kappa}\right)^{3.5}$$

κ 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 η_{is} 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:

$$\frac{dX}{dt} = F(X, U, P)$$

$$Y = H(X, U, P)$$

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 $P = (\eta_{is})$ 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] and [7] describe four different variants of the Kalman filter for continuous tracking of unknown variables, such as the isentropic efficiency, based on nonlinear ODEs. 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.
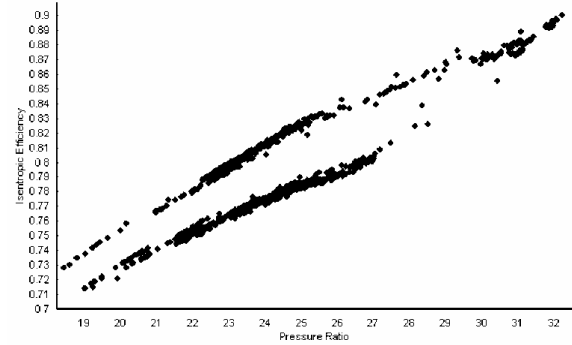

Figure 2: Two different efficiency estimates.

4. HYBRID DYNAMIC MODEL

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

δ_1 Boolean: Online washing state (0 or 1)
δ_2 Boolean: Offline washing state (0 or 1)
δ_3 Boolean: Normal operation (0 or 1)
δ_4 Boolean: Idle state (0 or 1)
δ_5 Boolean: Help state 1 (0 or 1)
δ_6 Boolean: Help state 2 (0 or 1)
η Continuous: Compressor efficiency (0 to 1)
$\eta 2$ Continuous: Recoverable efficiency (0 to 1)
α Continuous: Degradation rate of η
$\alpha 2$ Continuous: Degradation rate of η_2
z_1 Continuous: Cost of online washing
z_2 Continuous: Cost of offline washing
z_3 Continuous: Help variable for α
z_4 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 δ_5 and δ_6.

The model has a state machine of 4 main boolean states (δ_1, δ_2, δ_3, δ_4). The system will always be in 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 $\delta_5 = 0$ ELSE $\delta_5 = 1$
2. IF $\alpha_2 \leq 0$ THEN $\delta_6 = 0$ ELSE $\delta_6 = 1$

   These two constraints relate the boolean variables δ_5 and δ_6 to the continuous variables α and α_2.

3. IF $\delta_1 = 1$ THEN $\alpha_{i+1} = \alpha_0$
4. IF $\delta_1 = 1$ THEN $\alpha 2_{i+1} = \alpha 2_i - \varepsilon_2 \delta_6$
5. IF $\delta_1 = 1$ THEN $\eta_{i+1} = \eta_i + \gamma(\eta 2_{i+1} - \eta_i)$
6. IF $\delta_1 = 1$ THEN $\eta 2_{i+1} = \eta 2_i - \alpha 2_i$

   These four constraints describe the system after an online wash. The variable α, which describes the degradation rate of the compressor efficiency η, is reset to it's 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 γ (between 0 and 1) models the effectiveness of an online wash. Online washes usually only cleans 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 η_2.

7. IF $\delta_2 = 1$ THEN $\alpha_{i+1} = \alpha_0$
8. IF $\delta_2 = 1$ THEN $\alpha 2_{i+1} = \alpha 2_i - \varepsilon_2 \delta_6$
9. IF $\delta_2 = 1$ THEN $\eta_{i+1} = \eta 2_{i+1}$
10. IF $\delta_2 = 1$ 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 η which is restored to the maximum level given by the recoverable efficiency $\eta 2$.

11. IF $\delta_3 = 1$ THEN $\alpha_{i+1} = \alpha_i - \varepsilon \delta_5$
12. IF $\delta_3 = 1$ THEN $\alpha 2_{i+1} = \alpha 2_i - \varepsilon_2 \delta_6$
13. IF $\delta_3 = 1$ THEN $\eta_{i+1} = \eta_i - z_3$
14. IF $\delta_3 = 1$ 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 η. 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 $\delta_4 = 1$ THEN $\alpha_{i+1} = \alpha_i$
16. IF $\delta_4 = 1$ THEN $\alpha 2_{i+1} = \alpha 2_i$
17. IF $\delta_4 = 1$ THEN $\eta_{i+1} = \eta_i$
18. IF $\delta_4 = 1$ 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. $z_4 = P_5(\eta 2_i - \eta_i)$

    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 [8].

5.   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 3. 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 fuel and power prices.

Day number 1 represents the initial state of the plant. For example, if the plant operates in normal production, $\delta_3 = 1$ and $\delta_1 = \delta_2 = \delta_4 = 0$ for day 1. The continuous efficiency variable η 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.
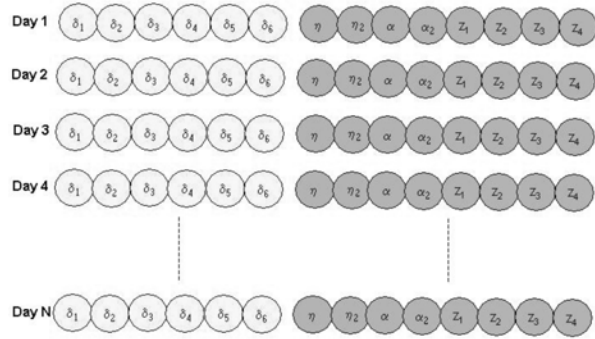

Figure 3: Duplication of hybrid model states.

The optimisation problem can be stated as follows:

Minimise Σ z1 + z2 + z4
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 [8]. 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.

6.   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 4 and Figure 5 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 6 shows the optimised compressor efficiency level.

The solid line in Figure 6 illustrates the recoverable efficiency level η2. The curve below the solid line illustrates the variable η. 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.
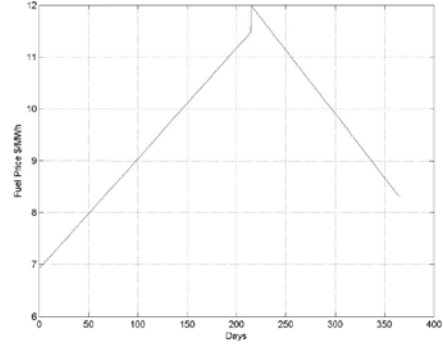

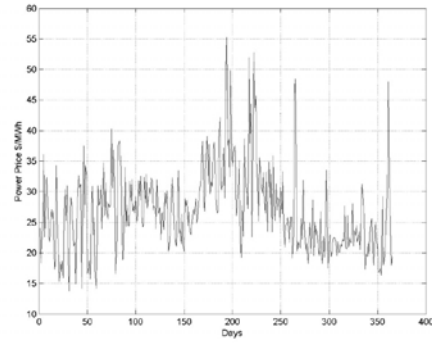**Figure 4: Forecasted fuel prices for one year ahead.**

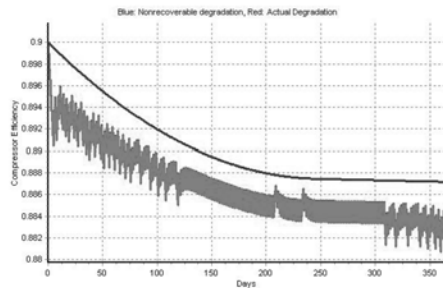**Figure 5: Forecasted power prices for one year ahead.**

Figure 6: Optimised compressor efficiency level.

It is also worth noting that during periods of high fuel costs, the MPC optimiser suggests a higher frequency of online washes than during periods of low fuel costs.

Table 1 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.

Wash Frequency	Relative Costs
MPC Optimiser	**34%**
No Washing	100%
Online Wash Every Day	49%
Online Wash Every Sunday	62%

Table 1: Relative costs associated with different washing schedules.

As can be seen from Table 1, 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 1 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.

7.   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.

8.   REFERENCES

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