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INTEGRATING SYSTEM HEALTH MONITORING WITH PROCESS OPTIMIZATION USING AN ADAPTIVE PROCESS MODEL STRUCTURE

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Abstract

Modeling is an essential part of real-time optimization (RTO) implementations, where a rigorous steady-state model of the process is required. However, the process can change with time due to system degradation effects, and different models may be necessary to describe the process during its entire life time. Moreover, there is no prior evidence how the degradation evolves and when we need to change between models. We present a method for model maintenance, which identifies the model structure online while optimizing the process in an RTO fashion via Output Modifier Adaptation (MAy). The main idea is to propose several model structure candidates that can describe the plant behaviour in its entire lifetime, update its parameters online, and, then, use the modifier terms of MAy as a criterion for online selection among the available options. A case study of a degrading compressor in a subsea gas compression station illustrates the approach. The results indicate that the method chooses the best model structure with readapted parameters among the candidates and drives the process to its optimum without constraint violations.

Keywords: Model maintenance, Real-time Optimization, Modifier Adaptation.

1. Introduction

For traditional Real-time Optimization (RTO) implementations, a rigorous steady-state model of the process is required. In such models, phenomenological relations are applied to describe the process behavior. However, some effects are not so easily modeled, like hydraulic effects and reaction kinetics. Additionally, the relations that govern the plant behavior can change during the operation due to equipment degradation, for example. Typically, one tries to adapt the model parameters in order to represent these changes on the process and/or to accommodate small modeling inconsistencies. Such a strategy relies on the flexibility of the model and, depending on the magnitude of the process changes/modeling errors, the model can fail to describe the actual plant behavior. Therefore, it is interesting to allow not only the parameters but also the RTO model structure to evolve in time, whenever plant data is available.

Matias and Jäschke (2019) proposed a novel method for model maintenance, which identifies the model structure online while it optimizes the process in an RTO fashion via Output Modifier Adaptation (MAy) (Marchetti et al., 2009). The main idea is to propose several model structure candidates that can describe the plant behavior and, then, use the modifier terms of MAy as a criterion for selecting among the available options. This approach leads to a two-step approach, where, in the first, the best model structure in a pre-determined model set is chosen. Simultaneously to the model structure selection, the model parameters are updated. In the second step, the updated model is used for optimizing the process in a classical MAy framework. Note that the first step is not necessary for the Output Modifier Adaptation scheme, which guarantees convergence to the plant optimum even when the model at hand is structurally and parametrically wrong. However, keeping the model updated to the plant information is interesting for model maintenance purposes and can provide valuable insight into the process, and may be used for process condition monitoring.

In this paper, we apply the online model maintenance method to monitor the process health while optimizing it. To illustrate the proposed application, a subsea gas compression station case study is used (Verheyleweghen and Jäschke, 2017). The station boosts the pipeline pressure allowing the fluids to reach the topside facility in the desired outlet pressure. The system contains one compressor, whose bearings are prone to degradation if subjected to high mechanical stress. If the compressor stops due to failure, the complete operation also needs to stop, resulting in a high associated maintenance cost and production loss. The effects of the compressor degradation can be identified by monitoring its performance map, which is directly affected by the chosen model structure. Therefore, it is possible to include the "unhealthy" model structure in the available model set. If a degraded state is identified, actions need to be taken in order to mitigate the risks associated with the equipment exceeding design/safety limits. This adaptive model structure can be used as a prognosis tool for monitoring and predicting the process health, improving the process reliability and reducing unscheduled downtime.

2. Method description

First, we give a brief overview of modifier adaptation and, then, we introduce our method.

2.1. Modifier adaptation

Let us say that we have a steady-state model *y(u)*, where the outputs *y* can be calculated as a function of the inputs *u*. The idea behind Output Modifier Adaptation is to add zeroth (ε) and first order terms (λ) to this model:

$$y_{ad}(u) = y(u) + \varepsilon_k + (\lambda_k)^T (u - u_k) \tag{1}$$

where these terms, also known as modifiers, are computed by:

$$\varepsilon_k = y_{plant}(u_k) - y(u_k) \quad \text{and} \quad (\lambda_k)^T = \left.\frac{d\,y_{plant}}{d\,u}\right|_{u_k} - \left.\frac{d\,y}{d\,u}\right|_{u_k} \tag{2}$$

where, y_{plant} are the measurements, are the plant gradients (either measured or estimated) and k indicates the iteration in which these values are computed. At the k^{th} iteration, MAy uses $y_{ad}(u)$ instead of $y(u)$ to compute the optimal inputs u^*_{k+1}. By recomputing the modifiers ε and λ and readapting the $y(u)$ at every iteration, the MAy scheme reaches the plant optimum upon convergence even in the presence of plant-model mismatch, given that the model follows some adequacy condition (i.e. it is locally convex in the vicinity of the plant optimal inputs (Marchetti et al., 2009)).

In Matias and Jäschke (2019), the authors showed that the modifiers have valuable information regarding the mismatch, i.e. the relationship between a model and the plant. Hence, they can be used not only in the MAy scheme, but also for discriminating between different models. The authors introduced the total modifier as:

$$\psi_k = \|\varepsilon_k\|_F + \|\lambda_k\|_F \tag{4}$$

Where, the subscript F indicates the Frobenius norm, a matrix norm computed as the square root of the sum of the absolute squares of the matrix elements. Note that, ψ_k is an indicator of how much the model needs to be adapted to match the plant.

2.2. Online model maintenance

As discussed, our method can be divided in two basic steps, a *model selection* and an *RTO via MAy* step. The first requires an offline phase, which consists on determining several model structures candidates to describe the plant behavior. In order to determine this set of models, we divide the process model into blocks. The individual blocks represent a part of the process to be modeled, e.g. pressure drop in a pipeline. Next, we propose several candidate sub-models to describe a given block, where different set of equations constitute each sub-model. For example, different sub-model candidates for the pressure drop can include (or exclude) effects of friction, hydrostatic pressure, turbulence, etc.. Depending on the sub-models that are chosen for each block, the process model has a different shape (gradients) and prediction capacity, which can be quantified by the total modifier. Note that, even though a preliminary set of available models needs to be determined, model structures can be added whenever necessary. In the model selection online phase, in addition to identifying the model structure, we also update the model parameters because, since we are interested in model maintenance, it is necessary to have parameters that represent the true characteristics of the system. Clearly, we need to determine an appropriate parameter set for every model. Otherwise, the data-fitting problem may lead us to ill-conditioned parameter estimation problems or overfitting. Here, we chose to add a regularization penalty $R_k = (S^T V_y S)^{-1}$, where $S = dy/du\,|_{uk}$ and V_y is an estimate of the measurement noise covariance matrix, to deal with the overfitting issues.

In order to implement the method, we describe our system using a disjunctive programming strategy, where binary variables are assigned to each of the potential sub-models in the blocks. Since we use continuous variables for computing the mass and energy balances, pressures, costs, etc, the system needs to be solved by a MINLP solver. A description of the MINLP model can be seen in Matias and Jäschke (2019). A simplified diagram of the method can be seen in the figure below:

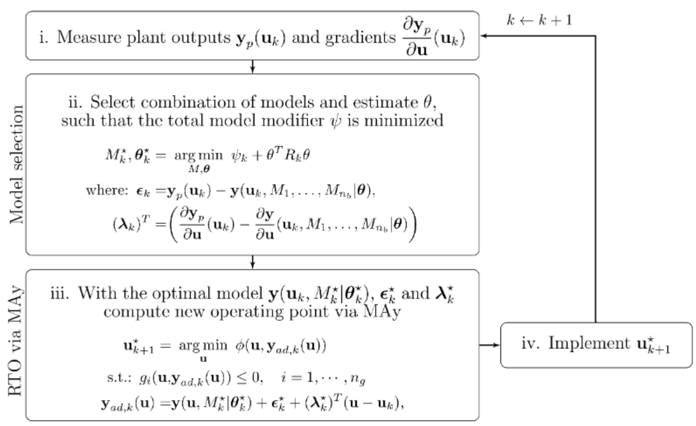


Figure 1: Simplified Diagram of the Online Model Maintenance Method

3. Case study – Subsea gas compression station

Subsea boosting technologies are important in order to counteract the natural declining production rates of oil fields, which are a result of lower reservoir pressures. By installing a compression station close to the well, it allows us to transport the production over greater distances and increase the reservoir recovery factor. There are different configurations of boosting stations. The case study deals with a single-phase compression/pumping, where the oil/gas mixture is divided and, then, a pump is used for increasing the liquid pressure and a wet gas compressor for the gas pressure. A wet-gas compressor is necessary because of the liquid carry-over due to separation inefficiency (gas-volume-fraction from 0.95 to 1). After the boosting phase, the gas and liquid are recombined and sent to the top facilities through a pipeline. A simplified flowsheet is shown in Figure 2.

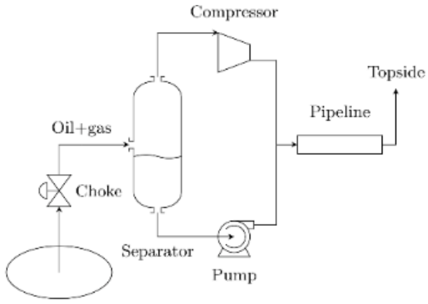
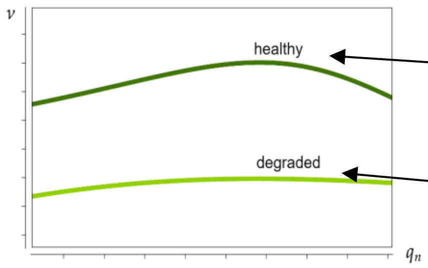


Figure 2: Subsea Gas Compression Station (Verheyleweghen and Jäschke, 2017).

There are two steady-state degrees of freedom, which are the choke opening [%] and normalized compressor flowrate [%]. The system has 8 measured variables that are: choke outlet pressure, reservoir volumetric flow, compressor inlet volumetric flowrate, compressor outlet temperature and pressure, compressor power, inlet pump volumetric flowrate, and pump power. For a complete description of the system model, please refer to Verheyleweghen and Jäschke (2017).

Regarding system reliability, we assume that the main degrading component is the compressor. Since it is a rotation equipment, it is likely to suffer damage because its complexity and moving parts. In order to illustrate the compressor wear damage, we assume that the compressor efficient map changes with time. This change is represented by one "healthy state" and one "degraded state". The equations for representing the different efficiency maps are:



$$\nu_{healthy} = \frac{\theta_1^H q_N^2 - 2.4 q_N + \theta_2^H}{q_N^2 - 4 q_N + \theta_3^H}$$

$$\nu_{degraded} = \theta_1^D + \frac{0.7 q_N^2}{\theta_2^D + q_N^2 \left(1 + q_N^2 / \theta_3^D\right)}$$

Figure 3: Compressor efficiency (ν) map as a function of compressor normalized flowrate (q_N). To choose the estimable parameter set θ^H and θ^D, a sensitivity analysis was performed. The true values of the parameters are: $\theta^H = [0.6, 2.7, 4.3]$ and $\theta^D = [0.4, 5, 2]$.

4. Simulation setup and results

We simulate the system for 150 steady-state cycles/MAy iterations (each last a month), in which the compressor changes from healthy → intermediary → degraded. We assume that the it stays for 30 iterations at the healthy state, then it starts to degrade linearly between iterations 31 and 120 (i.e. $v_{plant} = (1 - d)v_{healthy} + d\ v_{degraded}$, where $d = (k - 30)/(120 - 30)$ and k is the iteration number). Finally, we consider the compressor at the degraded state from iteration 121 to the simulation end. In order to track the changes in the plant, we use the online model maintenance method of Figure 1.

To assess how the method works, we fix the system feed (reservoir temperature, pressure and flowrate) and add white noise with a standard deviation of 0.1% of the current value to the measurements. Also, we use plant experiments with central finite differences for estimating plant gradients. The objective function, which should be maximized, is the ratio between compressor flowrate and power ($J = Q_{compressor}/P_{compressor}$), where we optimize the efficiency indirectly increasing the transported volume per energy unit. There is also an operating constraint, the compressor outlet pressure should remain above 100 bar. We show the method performance in this scenario for tracking the true plant optimum (Figure 4/left), tracking the model structure (Figure 4/right), and estimating the model parameters (Figure 5).

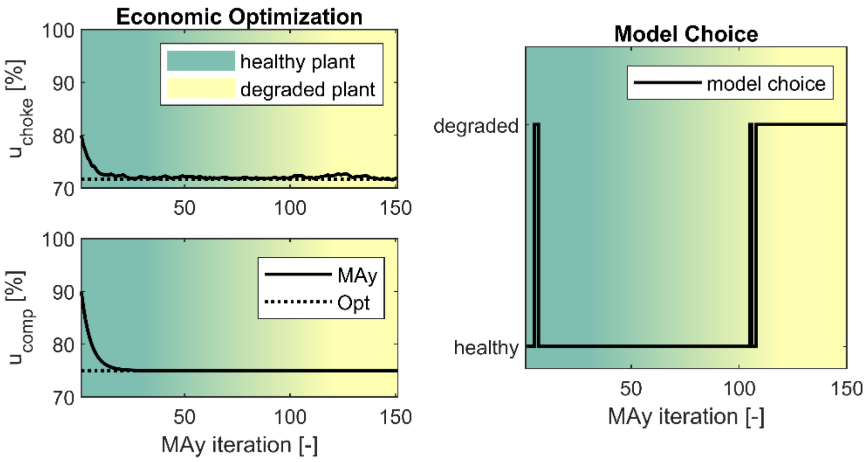


Figure 4: Tracking the true "plant" optimum (left) and the compressor degradation (right).

Figure 4 (left) shows that the method can find the actual process optimum starting from a suboptimal point. However, due to the nature of the optimization problem, a simple active constraint tracking can be used here to achieve the minimum choke opening and compressor flowrate that guarantee compressor outlet pressure at 100 bar. The main advantage of applying the method is presented in Figure 4 (right), where we track the degradation of the compressor. The healthy plant is indicated by the green region and the degraded plant by the yellow one. In the intermediary region, we use a color pattern to show that the system is changing and there is no correct model. Nevertheless, in the beginning of the intermediary region, the healthy model is a better representation of the plant, while the degraded model is better near the end of the intermediary region.

Despite an incorrect model choice in the beginning of the simulation, as a result of poor gradient estimation, we track the best model structure in the healthy and degraded plant region. However, the most important result is that, even with no correct model in the intermediary region, we can track that something is affecting the system and it is likely that the compressor is changing to a degraded state. Regarding the parameters, we show in Figure 5 that we can reliably estimate the healthy model parameters when we are in the green region, where this model represents what is happening in the "plant". On the other hand, the parameters $\theta^D{}_2$ and $\theta^D{}_3$ of the degraded model are more difficult to identify due to the low gain in relation to the estimation objective function (i.e. the values of the parameters can change substantially without affecting the estimation objective function, leading to larger deviations from the true values), which was concluded after a sensitivity analysis of the parameter estimation that is not shown here for the sake of brevity.

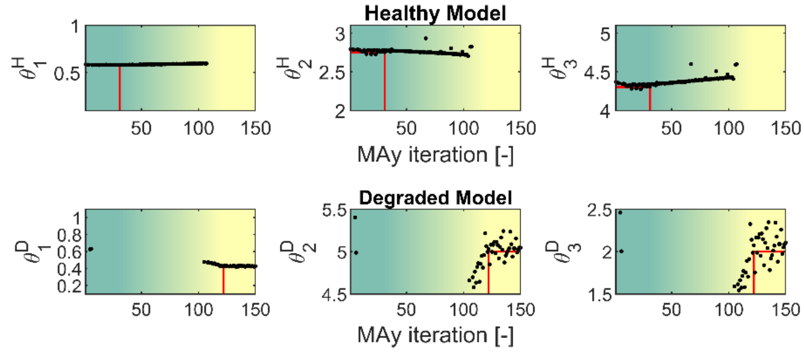


Figure 5: Estimated parameters. The red dashed line shows the true value of the parameters, while the black dots represent their estimated values (the compressor equations are shown in Figure 3).

5. Conclusions

We have proposed an extension of the method developed by Matias and Jäschke (2019), not only identifying the model structure, but also estimating its parameters. The method is applied to a subsea gas compression station to track the degradation of the system compressor. Two compressor "states" (healthy and degraded) are included in the available model set. The method finds the model that best fits the plant information online and updates its parameters while driving the system to its true optimum. The case study shows promising results and a motivation to extend the application to more complicated systems and to include dynamic aspects to the proposed method.

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