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Identification and Design of the Smith Predictor-Based Process Controller with Dead Time

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Abstract. The paper describes an application of system identification techniques to obtain a model of a coal-fired boiler in a power plant and Smith predictor controller implementation to improve closed loop control performance. The first order plus dead time (FOPDT) process model of the boiler is obtained by solving nonlinear least-squares optimization problem using the Levenberg-Marquardt algorithm. The model is used in the Smith predictor controller design to compensate for the dead time. The controller is implemented in the control system of the power plant. The paper shows how to improve performance of the control loop by using a process model-based prediction controller structure. The practical aspects of implementation of the dead time in the control software are discussed. The performance of boiler control loops can be significantly improved by using the Smith predictor controller with estimated FOPDT.

Keywords: System identification, closed-loop control, Smith predictor, First Order Plus Dead Time model

Zasnova in izvedba Smithovega prediktorja za regulacijo tehnološkega procesa z mrtvim časom

V članku sta predstavljeni uporaba identifikacijskih tehnik pri razvoju modela premogovnega kotla v termoelektrarni in izvedba Smithovega prediktorja za bolj učinkovito regulacijo. Procesni model kotla prvega reda z mrtvim časom smo dobili z rešitvijo nelinearnega problema najmanjših kvadratov z uporabo algoritma Levenberg-Marquardt. Model smo uporabili pri zasnovi Smithovega prediktorja za kompenzacijo mrtvega časa. Krmilni sistem smo izvedli v nadzornem sistemu termoelektrarne. V članku smo pokazali, kako lahko izboljšamo regulacijo z uporabo prediktivne krmilniške tehnike. Opisali smo tudi praktične vidike izvedbe mrtvega časa s krmilno programsko opremo. Krmiljenje kotla je lahko bistveno izboljšano z uporabo Smithovega prediktorja in modela prvega reda z mrtvim časom.

1 INTRODUCTION

The actual trends in the power sector imposed by the globalization and competition demand the industry plants to run in the most efficient way. Keeping the process parameters at their nominal values is the main requirement for any output control problem. Many technological processes inherently have dead times that occur because of the transportation of material and energy. Processes with significant dead times are very hard to control and the corresponding loop performances are usually far from optimal. Classical proportional-integral-derivative (PID) controllers are still widely used in industry though they usually cannot provide satisfactory results when applied to control a process with a large dead time. The dead time presence in the process reduces the stability margins, which limits the controller tuning capability.

In order to achieve the desired performance of a control loop, a model based control approach should be applied. Therefore, the first step is to estimate a process model from the input and output data based on a matching criterion or a cost function. There are three main components of any identification technique: the data, the chosen structure of the model and the estimation method [1]. The estimation method calculates the process model parameters by minimizing the criterion function. The model quality depends of the quality of the data used for the identification. It is important to know that no model can be a perfect representation of the true process. It is important to build a model that is good enough for the intended purpose. The second step is to use an estimated prediction model in a model-based controller and calculate the controller parameters in order to achieve the desired performance.

The main characteristic of a coal-fired boiler is a large dead time that exists because of the finite time needed for transportation, pulverization and burning the coal and it is usually measured in minutes which depends on the boiler size. This implies that an advanced controller structure should be applied to the boiler closed-loop control.

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2 IDENTIFICATION OF THE SYSTEM DYNAMICS

A data driven system identification is a prevailing trend in process modelling, since the first-principle modelling often is either impossible or too complex to be used. Collecting the input-output data and choosing the correct sampling time considerably affect the quality and usability of the resulting model. The most important is to obtain the data covering the intended operational range to be used in everyday operation. The experiment performed to obtain the input-output data should provide all the essential process features of interest. The obtained data can be further analysed in order to estimate the order of the model and to assess whether order reduction is possible.

From the implementation point of view, it is always preferred to have an as simple model as possible to capture the dynamics needed to predict the output with a sufficient accuracy. Linear identification methods in combination with an a-priori knowledge of the system are usually used. Only if it is not possible to obtain a linear model that accurately describes the process dynamics, more sophisticated nonlinear methods should be applied. The experiment to collect the input-output data should be performed in absence of any external disturbance. The coal-fired boiler has a large dead time, so an accurate estimation of the dead time is essential. Using a linear identification approach to nonlinear processes that involve chemical reactions produces structural model errors in the results. This still means that the resulting prediction model can be good enough since it is much harder to obtain a good nonlinear simulation model than a prediction model.

2.1 Collecting and pre-processing the data

The experimental design consists of selecting the measured signals, collecting the input-output data with an appropriate sampling time and pre-processing the data which is a crucial step that impacts the quality of the estimated model. The data should include changes that are expected to happen in the normal operation of the plant. The sampling rate should be fast enough to capture all process dynamics. A too slow sampling rate will have a negative impact on the controller performance, so it is the best practice to choose an about ten times smaller sampling period than the process time constant which can be approximately estimated by inspecting the trend diagrams. After the input-output data is collected, the first step is to remove the initial conditions in order to properly estimate the system parameters. The data is pre-processed in order to determine the minimal order of the model that captures the process dynamics.

In this particular experimental design the input data is the total coal feeders speed and output data is the output generator power, while the steam pressure is kept constant by the turbine controller. The data is collected in the “turbine follow” mode. In the turbine follow mode the turbine controller controls the pressure whereas the load demand is given to the boiler. The changes in the input and the output values are shown in Figure 1.

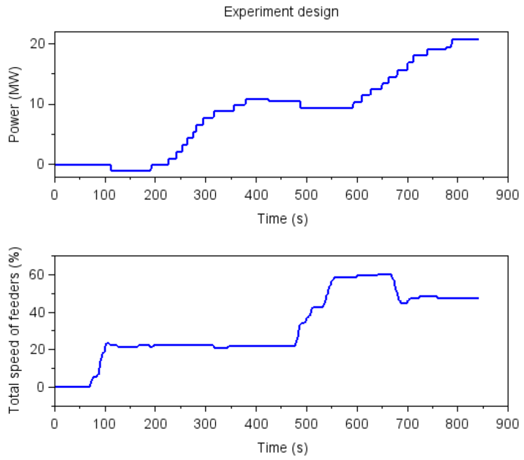

Figure 1. Input-output data.

The data is collected when the all coal feeder control loops are in the manual mode. The coal feeders speed is increased which causes the generator power to increase for about 20 MW (from 170 MW up to 190 MW).
Before estimating the model, the initial values are subtracted from the data values in order to identify the dynamics and the process gain properly.

2.2 The model structure and the estimation algorithm

The next step is to determine the structure and order of the model based on the calculation of the Singular Value Decomposition (SVD) of the data matrix [2] and examining the decrease in the singular values. The Hankel singular values indicate a measure of energy for each state in a system and are shown in Figure 2.

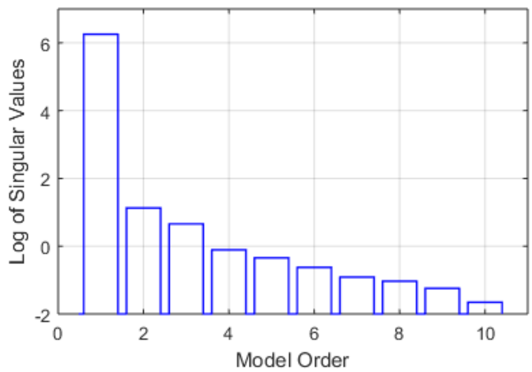

Figure 2. Hankel singular values.

As seen from Figure 2, the first state carries significantly more energy than the rest, so the process can be described with a first-order model. In Figure 1 it is evident that there is a dead time in the response of the power to change in the coal feeders speed. Therefore, the structure of the model that will be estimated is the first-order plus dead time (FOPDT).

The FOPDT model in a continuous domain is given with the following Laplace transfer function:

$$G_m(s) = \frac{K_p}{T_p s + 1} e^{-sT_d} \tag{1}$$

where K_p is the process gain, T_p is the process time constant and T_d is the dead time.

The input-output data are discrete values collected at a constant sampling rate. Therefore, the discrete FOPDT system model should be derived from the continuous model given in (1). Discretization of the continuous time system can be found in literature, such as [3]. The discrete model of the first-order continuous system is given with the following difference equation:

$$y(n+1) = e^{-T_S/T_P} y(n) + K_p (1 - e^{-T_S/T_P}) u(n-d) \tag{2}$$

where u(n) is the input value at time nTs, Ts is the sampling time, Tp is the process time constant, d is an integer such that the dead time value is calculated as Td = dTs.

The estimation task is to find model parameters θ that minimize the selected cost function. The cost function is defined as a squared function and the estimated model parameters can be written in the following form:

$$\theta_N = \arg\min_{\theta} \sum_{n=1}^{N} \left[y(n) - y(n|\theta) \right]^2 \tag{3}$$

where θ_N is the vector of the model parameters that minimize the selected cost function, y(n) is the actual (measured) output value and y(n|θ) is the model output value.

As seen from equation (3), estimation of the model parameters is essentially solving a nonlinear least squares problem.

To solve the nonlinear least-squares problem, the Levenberg-Marquardt (LM) algorithm is chosen [4]. The LM algorithm is a gradient-based numerical method that interpolates between the Gauss-Newton algorithm and the method of the Gradient descent. It is most accepted and widely used in practice because of its balance between the efficiency and robustness.

The LM method finds the optimal solution by iteratively finding the roots of the gradient of the cost function that make the gradient of the cost function zero (4).

$$X_{k+1} = X_k - \left[H_k(F) + \lambda I \right]^{-1} \nabla F(X_k) \tag{4}$$

where

$$\boldsymbol{H}(\boldsymbol{F}) = \begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2} & \cdots & \frac{\partial^2 f}{\partial x_1 \partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 f}{\partial x_n \partial x_1} & \cdots & \frac{\partial^2 f}{\partial x_n^2} \end{bmatrix}$$

is the Hessian of the cost function. ∇F is the gradient of the objective function and is written in the following vector form: $\left[\frac{\partial f}{\partial x_1} \frac{\partial f}{\partial x_2} \cdots \frac{\partial f}{\partial x_n} \right]^T$, λ is a step-size controlling parameter and X is the vector $[x_1\ x_2 \ldots x_n]^T$.

For this particular estimation problem, a free and open-source numerical computational package Scilab 6.0.1 and its lsqrsolve function are used. The details about the use of the lsqrsolve function are given in [5].

The estimated FOPDT model has the following parameters: *Kp* = 0.39 *Tp* = 88s *Td* = 125s and the model response is shown in Figure 3.

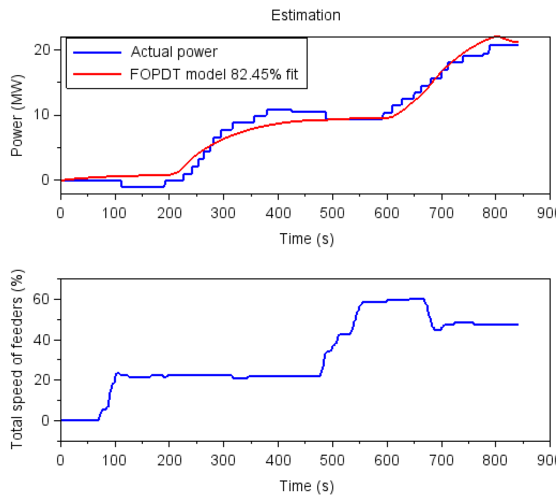

Figure 3. Estimated FOPDT model of the boiler.

To determine the quality of the estimated model, a comparison is made between the actual output values and simulated model output y_s. The most objective measure is to use the validation data that are not used to estimate the model and to calculate the measure of the fit in the following way:

$$fit = 100\left(1 - \sqrt{\frac{\sum [y(n) - y_s(n)]^2}{\sum [y(n) - \bar{y}]^2}} \right)(\%) \tag{5}$$

where y(n) are the actual output values, $y_s(n)$ are simulated model output values and $\bar{y}$ is the mean value of the output.

The fit defined in (5) determines the percentage of how much of the output variation is correctly reproduced by the model.

A similar test is repeated by decreasing of the unit power and the estimation is performed once again. The result is shown in Figure 4 with added initial values to the data, i.e. the data taken from the process:

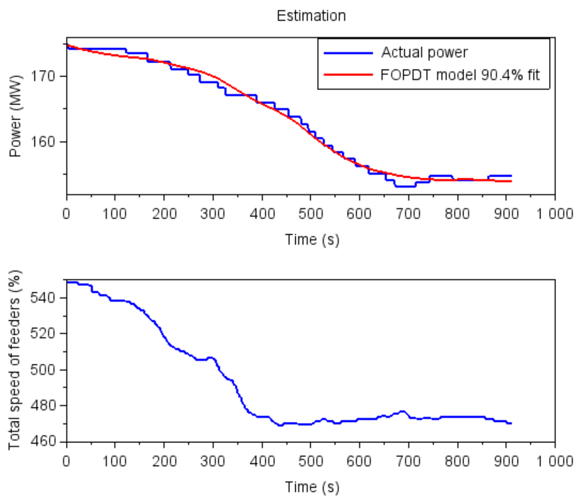

Figure 4. Repeated FOPDT model estimation.

The parameters of the estimated FOPDT model in case of decreased power are: *Kp* = 0.25, *T* = 110s, *Td* = 116s, but the fit is better and is about 90%.

In both experiments, the dead time is very accurately estimated and it is about 120s as shown in the plots. The differences between the estimated values of the process gain and time constants in the two experimental designs can be caused by nonlinearities and unforeseen disturbances such as the change in coal calorific value. However, these differences do not negatively affect the controller design. An ideal experimental design in real operating conditions is not possible because there are always different kinds of the disturbance present. The following parameters of the FOPDT model are used in the controller design: *Kp* = 0.3, *Tp* = 100s, *Td* = 120s.

3 PREDICTIVE CONTROLLER DESIGN

After the FOPDT model of the boiler is estimated and validated with the data that cover the intended use of the model, a predictive controller is designed to improve the control loop performance compared to the classical PID controller.

3.1 *The structure of the Smith predictor*

The Smith predictor is a predictive controller design to compensate the dead time and to improve control loop performance. The structure of the Smith predictor is given in Figure 5.

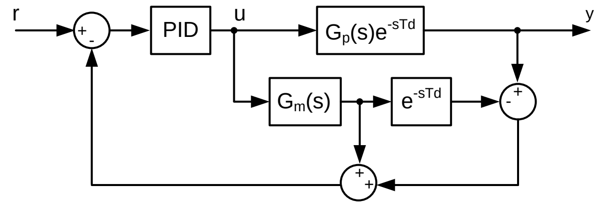

Figure 5. The structure of the Smith predictor.

In order to understand how the Smith predictor can improve closed-loop performance, the overall transfer function should be found. For the structure shown in Figure 5, the overall transfer function is given with (6).

$$\frac{Y(s)}{R(s)} = \frac{G_{PID}G_p e^{-sT_d}}{1 + G_{PID}G_m + G_{PID}G_p e^{-sT_d} - G_{PID}G_m e^{-sT_d}} \quad (6)$$

If $G_m = G_p$, then the overall transfer function is (7):

$$\frac{Y(s)}{R(s)} = \frac{G_{PID}G_p e^{-sT_d}}{1 + G_{PID}G_p} \quad (7)$$

From equation (7) it is clear that the Smith predictor structure eliminates the dead time in the closed-loop transients, i.e. characteristic equation of the closed loop system contains no dead time. The Smith predictor can be therefore used together with the classical PID controller.

3.2 *Controller parameters tuning*

There are many PID controller tuning rules such as Ziegler-Nichols (Z-N), Internal Model Control (IMC), Integral of the Time Absolute value of the Error (ITAE) etc., depending on which performance indicator is chosen as the minimization criterion. In this particular case, because of the nature of the process, only a proportional-integral (PI) controller is used and it is desired that the controller performance is optimized for better disturbance rejection.

The PI controller parameters are chosen to minimize the ITAE criterion for step disturbance rejection given by equation (8):

$$I_{ITAE} = \int_0^\infty t\left|y_s(t) - y(t)\right|dt \quad (8)$$

The following transfer function of the PI controller is assumed:

$$G_{PI}(s) = K_c + \frac{K_c}{T_i s} \quad (9)$$

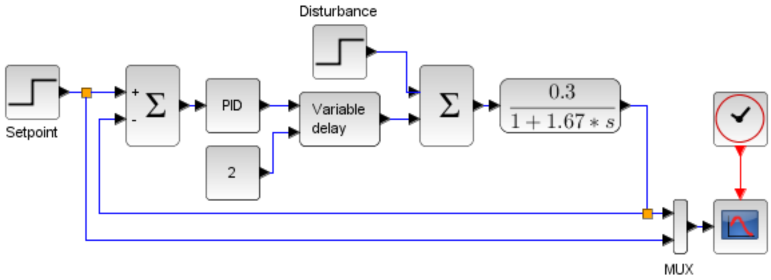

Figure 6. Scilab/Xcos FOPDT model.

The PI controller parameters can be calculated from the ITAE-1 tuning rules for the FOPDT model [6]:

$$KK_c = 0.859\left(T_d / T_p\right)^{-0.977}$$
$$T_p / T_i = 0.674\left(T_d / T_p\right)^{-0.68} \tag{10}$$

where *Kc* is the controller gain and *Ti* is the integral time constant.

The PI controller parameters values calculated from (10) are: *Kc* = 2.4 and *Ti* = 168s.

In order to analyze how the Smith predictor control scheme improves performance of the control loop, the Scilab/Xcos FOPDT model is set up. The Xcos model is shown in Figure 6. All the time constants are shown in minutes.

The step response and disturbance rejection for the PI controller parameters *Kc* = 2.4 and *Ti* = 2.8 min. are shown in Figure 7.

As shown in Figure 7, the control performances of the tuned PI controller are relatively conservative and it takes a significant time for the output to reach the step input.

By adding the Smith predictor, much better control performances are to be expected.

The Scilab/Xcos FOPDT model with the Smith predictor is shown in Figure 8.

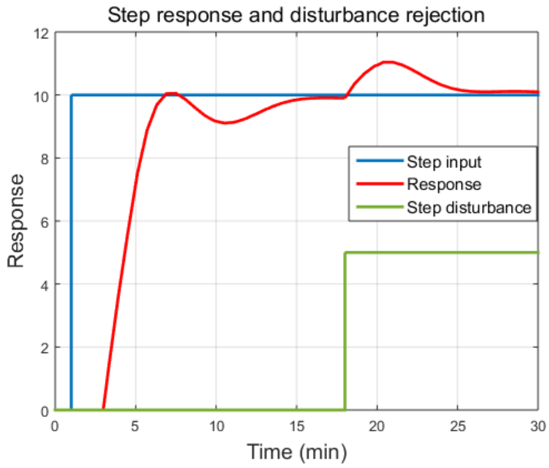

Figure 7. Step response and disturbance rejection.

Since the Smith predictor control scheme compensates the dead time, the PI controller can now be tuned again with some optimization routine using the current parameters as the initial values. The controller gains can now be much higher in compared to the controller without the Smith predictor. When tuning the PI parameters, there should be a good balance between the performance and robustness. There should be enough of the gain and phase margin to allow for the modelling errors or variations in the system dynamics. The response of the system with the Smith predictor control scheme and with the PI controller parameters *Kc* = 11.6 and *Ti* =1.4 min is represented in Figure 9.

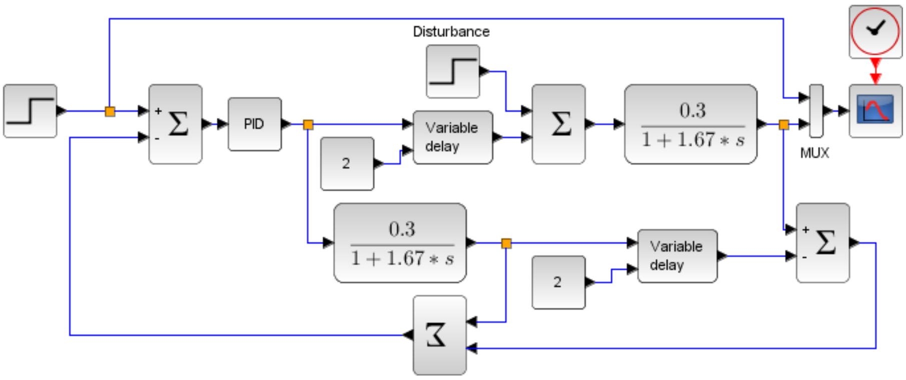

Figure 8. Sclab/Xcos FOPDT model with the Smith predictor.

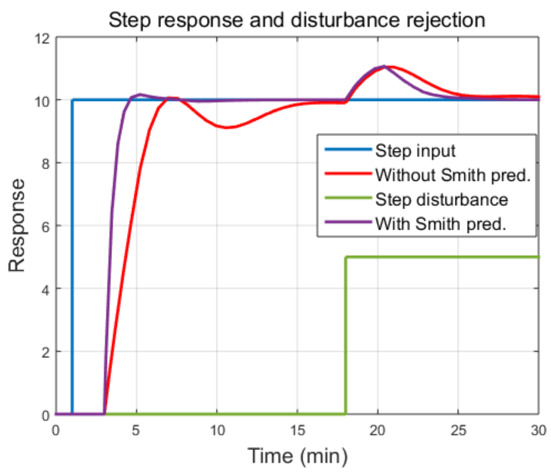

Figure 9. Performance with the Smith predictor.

As seen from Figure 9, the control performances are much better with the Smith predictor, because this structure allows higher PI controller gains while effectively removing the dead-time transients in the closed loop transfer function of the whole control system.

3.3 Practical controller implementation

After the controller structure is simulated and verified with the simulation software, the final step is to implement the Smith predictor controller in an actual Distributed Control System (DCS) that runs the process. The Smith control structure is implemented at the Tuzla Thermal Power Plant, Bosnia and Herzegovina on its 200 MW unit 5. DCS installed on unit 5 is Siemens SPPA-T2000 (Teleperm XP) and the Smith controller is implemented in this control system. The problem often encountered in a practical implementation of the Smith predictor is simulation of the dead time in the control software. Many Programmable Logic Controllers (PLCs) have dead time as a standard function block in their standard library. If this is not the case, then the dead time can be approximated using the Padé approximation. Even though, SPPA-T2000 has the dead time function block in its software library and the dead time is implemented using the first order Padé approximation, which is suitable for an application in PLC/DCS control software.

The first order Padé approximation is given by equation (11) and can be easy implemented in the control software with one differentiator and one first-order filter.

$$e^{-sT_d} \approx \frac{-T_d s + 2}{T_d s + 2} \tag{11}$$

A practical implementation is relatively simple. A differentiator with time constants $T_d/2$ is connected to the minus port of the summation block. The first-order filter with same time constant $T_d/2$ is connected to the plus port of the summation block as shown in Figure 10.

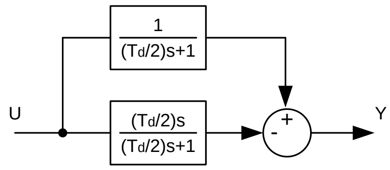

Figure 10. A first-order Padé approximation

The overall transfer function of the structure shown in Figure 10 is the following:

$$\frac{Y(s)}{U(s)} = \frac{(-T_d/2)s + 1}{(T_d/2)s + 1} = \frac{-T_d s + 2}{T_d s + 2} \tag{12}$$

This approximation is a very rough and it is a non-minimal phase system. Therefore, a considerable worsening of the control loop performance is to be expected, because introducing a non-minimal phase element in the system is likely to cause stability issues. That is why when tuning a controller a considerable emphasis must be placed on its robustness.

The control loop performance with the first-order Padé approximation of the dead time for the same controller parameters: *Kc* = 11.6 and *Ti* =1.4 min is given in Figure 11.

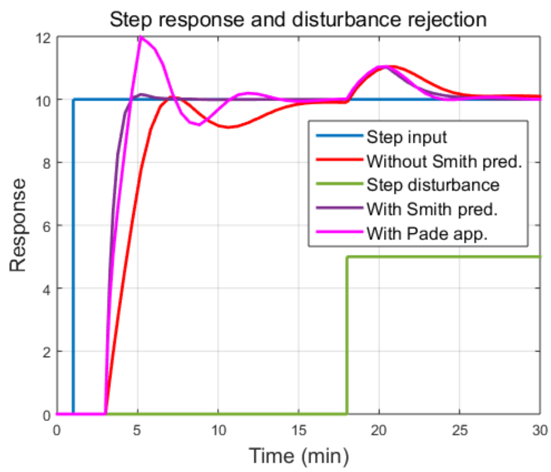

Figure 11. Controller performance with the first-order Padé.

As expected, the controller performance decreases when the dead time is simulated with the first-order Padé approximation. The controller response to a step input change is now significantly worse and it has an overshoot of about 20%. However, the step disturbance rejection performance is not affected. In this particular process, in normal operating conditions, the set point usually never changes in steps but as a ramp with the gradient in MW/min defined by the operator. In this particular application, the disturbance rejection capability is much more important than the response to a step input change. If there is a doubt about the loop stability, it is recommended to decrease the initial controller gains and then gradually increase them by observing the process behaviour. The Smith predictor controller has been successfully implemented at Tuzla Thermal Power Plant on its 200 MW unit 5

4 CONCLUSION

The presence of the transport delay or dead time makes the process very hard to control. As the dead time increases, the stability margins decrease. This means that the classical PID controller must be tuned very conservatively which affects the control loop performance. If the dead time is large, more advanced control algorithms should be implemented in order to improve the control loop performance. The paper shows how implementation of the Smith predictor significantly improves the process control performance. In order to successfully implement the Smith predictor, a reasonably good process model must be obtained. Most technological processes can be described by the first-order plus dead-time (FOPDT) models. The system identification procedure is performed in order to estimate the FOPD model of a boiler response to change in the coal feeders speed. The input-output data collected from the experimental design to be used for the system identification should cover the range expected to occur during a normal plant operation.
When model is obtained and validated it can be used in the predictor control algorithm.

The Smith predictor enables higher controller gains to be used in order to produce a faster and more accurate response and better disturbance rejection. If the actual programming software contains no dead-time function blocks, alternatives such as the Padé approximation of the dead time can be used. The first-order Padé approximation reduces the control performance but it still preserves a good disturbance rejection capability.

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