

***pIDtune*TM: A GRAPHICAL PACKAGE FOR INTEGRATED SYSTEM
IDENTIFICATION AND PID CONTROLLER DESIGN**

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Abstract: This paper describes *pIDtune*TM; a MATLAB-based package that integrates system identification and PID controller design. The program addresses the PID tuning needs commonly expressed by control engineers in the process industries. The package relies on ARX estimation and control-relevant model reduction to obtain models consistent with the Internal Model Control (IMC) PID tuning rules. Furthermore, the package allows the user to simulate closed-loop behavior and provides analysis tools for assessing the benefits of choosing particular tuning parameters for setpoint tracking and load disturbances, with or without uncertainty. *Copyright © 2000 IFAC*

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1. INTRODUCTION

Despite significant progress made toward developing advanced controllers, the great majority of all control loops in the process industries today employ a PID-type algorithm. This is not surprising when one considers the characteristics that have made PID controllers popular in industry such as their structural simplicity, reliability and favorable ratio between performance and cost. But even when designing such simple structures, only a few methodologies have been developed to tune PID controllers directly from plant data. Of the ones that do, many do not perform adequately under low signal to noise ratio conditions, which are quite commonplace in industry. *pIDtune*TM overcomes these difficulties with an integrated methodology that starts with input and output plant data and ends with IMC-PID tuning parameters. These characteristics coupled with an easy-to-use graphical

user interface make *pIDtune*TM a powerful and effective tool meeting the needs commonly expressed by practicing engineers.

Two case studies will be presented in this paper. The first case study consists of a first-order with delay system subject to a nonstationary disturbance, which will be used to demonstrate *pIDtune*TM's integrated methodology. The second case study consists of industrial data from an ethylene plant quench column bottom temperature control loop (Emoto *et al.*, 1997), which will be used to demonstrate how *pIDtune*TM can be used to solve a challenging industrial problem.

2. INTEGRATED METHODOLOGY

The integrated methodology of *pIDtune*TM consists of four major steps (Rivera and Adusumilli, 1997):

- a) Preprocessing of input and output plant data
- b) High-order ARX estimation
- c) Control-relevant model reduction leading to parameters for the IMC-PID tuning rules
- d) Closed-loop simulations and analysis

These steps will be described in more detail with the aid of a data set obtained from Pseudo Random Binary Sequence (PRBS) testing of a first-order with delay system subject to a nonstationary disturbance. The first-order system with delay used here is the following:

$$P(s) = \frac{e^{-5s}}{10s + 1}; T_s = 1 \text{ min.} \quad (1)$$

This system is subjected to an autoregressive integrated output disturbance as follows:

$$H(z) = \frac{z^2}{(z - 0.91)(z - 1)}; \sigma^2 = 0.0005 \quad (2)$$

2.1 Preprocessing of well-designed input and output data plant

Any effective methodology to obtain models from plant data must begin with a well-designed input. The input must be persistently excited in the region of interest and sufficient amount of data must be collected. A well-designed input will produce plant data that contains all the important dynamic behavior of the plant under investigation. In our first case study, two cycles of a PRBS signal are used to collect data for identification. The result of this experiment is shown in Fig. 1, where the data has been loaded in *pidtune*TM.

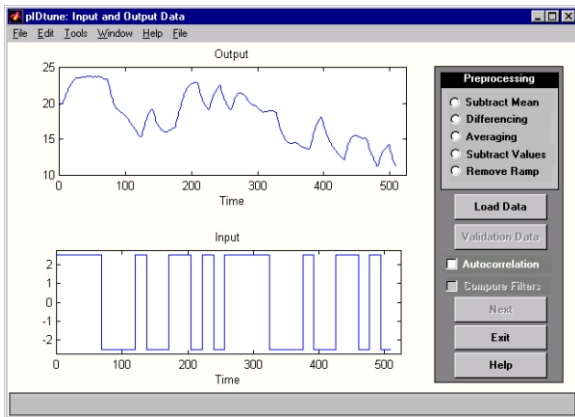


Fig. 1. Input and Output data for a first-order system with delay subject to a nonstationary disturbance after PRBS testing.

After loading the input and output data one proceeds to perform a preprocessing of the data for identification. *pidtune*TM provides the user with five preprocessing types: subtracting mean, differencing, averaging, subtracting of base values, and removing of ramp. For this example, where the system has been exposed to a nonstationary disturbance, differencing is appropriate. Fig. 2 shows the data after preprocessing. By

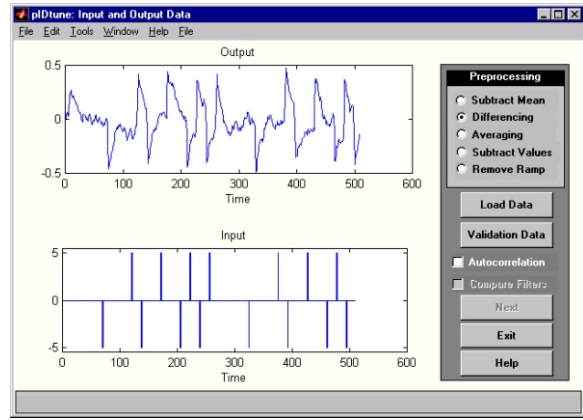


Fig. 2. Preprocessing of input and output data

comparing Figures 1 and 2, one can see that stationarity of the data has been achieved. In this case, visual inspection is sufficient to make this determination. However, in other instances this might not be the case and, therefore, *pidtune*TM allows the user to determine stationarity of the data by examining the autocorrelation.

After the preprocessing phase, *pidtune*TM requires the user to divide the data into two segments. One of the segments is used for estimating the model and the other is used for validation purposes. If the data set is long enough, which would depend on the signal to noise ratio and constraints on collection time, a crossvalidation data set will facilitate choosing the best fit during the ARX estimation phase. If the data set is short, however, one must use all of the data for estimating the model and then choose a parsimonious model order via other measures such as the Akaike Information Theoretic Criterion (AIC) or Rissanen's Minimum Description Length principle (MDL). All of these options are available in *pidtune*TM in the ARX estimation phase (see next section). In this example the data is long enough and, therefore, it is divided into two equal segments, one PRBS cycle for estimation and the other cycle for validation.

2.2 High-order ARX estimation

*pidtune*TM takes advantage of the favorable theoretical properties of ARX (AutoRegressive with eXternal input) models to overcome some of the difficulties of modeling plants under noisy conditions. ARX estimation is simple to compute, being numerically very efficient and requiring only the solution of a single linear least squares problem (Ljung, 1999). Moreover, ARX models yield a consistent, unbiased estimate provided the input signal is persistently excited and sufficient amount of data is collected. These characteristics make high-order ARX models especially suited for data with low signal to noise ratios. *pidtune*TM uses high-order ARX models in conjunction with cross-validation techniques to greatly ease the problem of model structure selection. The ARX model structure is shown in equation 3.

In *pidtune*TM, one specifies a range of orders for the A

$$y(t) = A^{-1}(z)B(z)u(t - n_k) = A^{-1}(z)e(t) \quad (3)$$

$$A(z) = I + A_1z^{-1} + A_2z^{-2} + \dots + A_{n_a}z^{-n_a}$$

$$B(z) = B_0 + B_1z^{-1} + B_2z^{-2} + \dots + B_{n_b}z^{-n_b}$$

polynomial (n_a), B polynomial (n_b) and delay (n_k). *pIDtune*TM takes this information and obtains the parameters for each of these structures based on the estimation data set. Following the specification of the model orders, a curve showing the number of parameters versus the normalized sum of squared prediction errors (loss function) based on the crossvalidation data set is presented. Fig. 3 shows this plot for our case study where the range for the A polynomial was chosen to be 1-8, the range for the B polynomial was chosen to be 1-8, and the delay range was chosen to be 1-10.

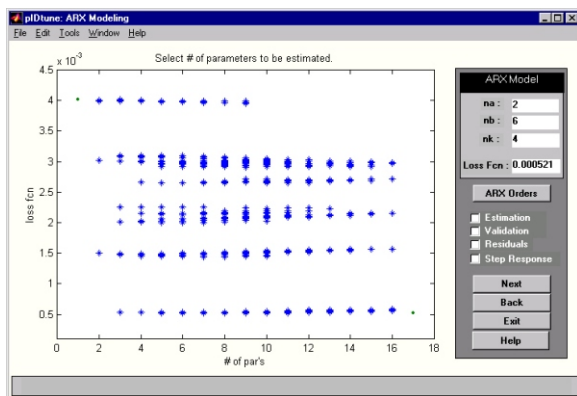


Fig. 3. ARX model estimation

From this procedure, one can obtain the model that minimizes the loss function. In this case, the loss function is at a minimum when the ARX model has the orders of $n_a = 2$, $n_b = 6$ and $n_k = 4$. Once a model structure has been chosen, *pIDtune*TM allows the user to validate the model by comparing it to the estimation data and validation data. The user can also examine the residuals to determine any underparametrization in either the plant model, the noise model, or both. Fig. 4 shows the comparison between the model and the validation data segment. Since the validation data

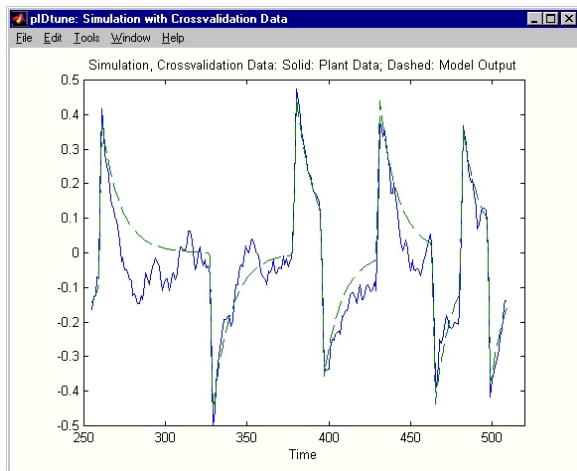


Fig. 4. Comparison between the estimated model and the validation data segment

segment was not used during model estimation, crossvalidation provides a way of establishing the predictive ability of the estimated model.

Moreover, *pIDtune*TM makes use of the MATLAB[®] command **idsimsd** to generate a nominal step response with uncertainty. The uncertainty is computed from statistics of the ARX estimation. Fig. 5 shows the step response of the estimated model and the step response of ten uncertain plants. This plot allows the user to determine if the model conforms to the proper physical restrictions of the problem (i.e. the gain has the right sign), and to determine the effect of variance.

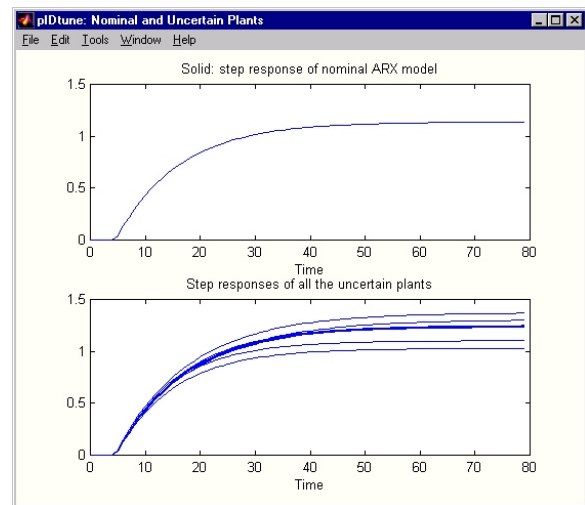


Fig. 5. Nominal step response for the estimated model (top) and uncertain plants (bottom)

2.3 Control-relevant model reduction leading to models that comply with the IMC-PID tuning rules

The control-relevant model reduction procedure in *pIDtune*TM provides the means for obtaining reduced-order models from high-order ARX models that conform to the IMC based PID tuning rules (Rivera *et al.* 1986). The low-order model retains the most important characteristics of the full-order plant which have the most impact on the closed-loop performance. PID controllers are then designed based on the IMC designed procedure applied to low-order models. These tuning rules possess the advantage that they systematically relate all the tuning parameters to the plant model. The robustness and performance of these controllers can be improved by the judicious selection of a single parameter - the IMC filter - which is closely related to the closed-loop time constant. Furthermore, the IMC filter parameter defines the performance requirements in the control-relevant model reduction procedure. Both the ideal and interactive forms of the IMC-PID tuning rules are supported. Fig. 6 shows the window where this information is specified. With this information, *pIDtune*TM performs control-relevant model reduction using the algorithm per Rivera and Morari (1987). Fig. 7 shows the reduced-order models obtained after performing this procedure compared to the high-order ARX model. Then, these low-order models are used to compute the controller parameters.

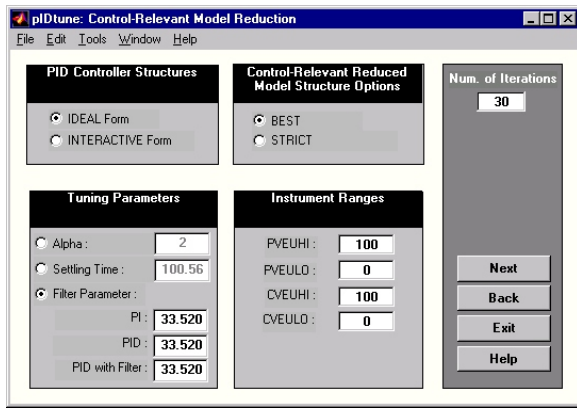


Fig. 6. Control-relevant model reduction window

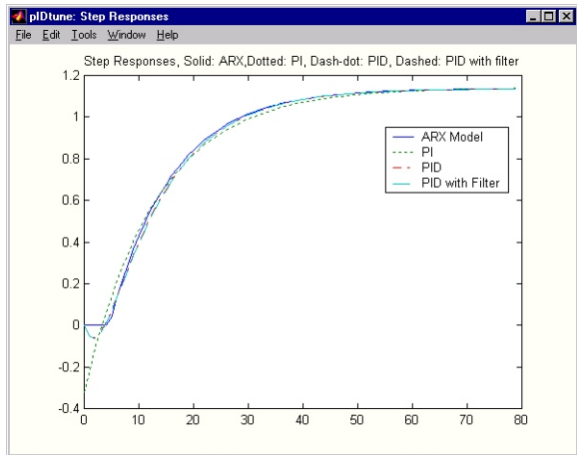


Fig. 7. Control-Relevant reduced models complying with the IMC-PID tuning rules compared to the ARX model.

In turn, the controller parameters are scaled according to the instrument ranges supplied in the previous phase to guaranteed compatibility with the Honeywell TDC3000 distributed control system. Fig. 8 shows the results obtained for our case study after the control-

relevant model reduction procedure and the computation of the controller parameters using the IMC-PID tuning rules.

2.4 PID Control Parameters and Closed-loop simulations.

Having obtained the tuning parameters, one can use them for simulation. *pIDtune*TM allows for open-loop and closed-loop simulations in continuous time and closed-loop performance analysis in the frequency domain. *pIDtune*TM provides the ability to produce simulations under setpoint changes and input and output disturbance changes with or without uncertainty. Fig. 9 shows the closed-loop behavior for the PI, PID and PID with filter controllers for the first-order with delay system case study. Moreover, *pIDtune*TM allows the user to simulate the responses for the TDC3000 “bumpless” forms such as Equation A, B and C.

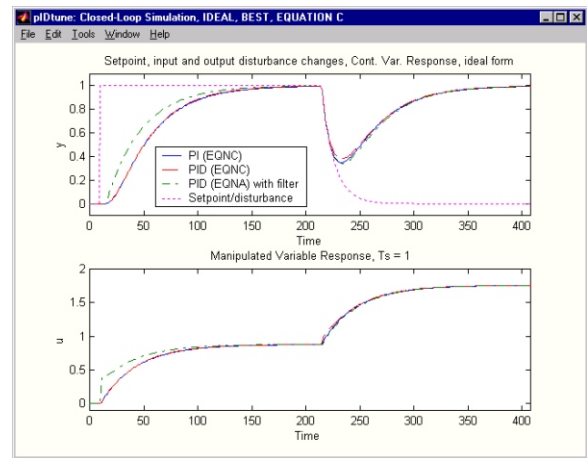


Fig. 9. Closed-loop simulation for PI, PID and PID with filter controllers under setpoint, and load disturbance changes

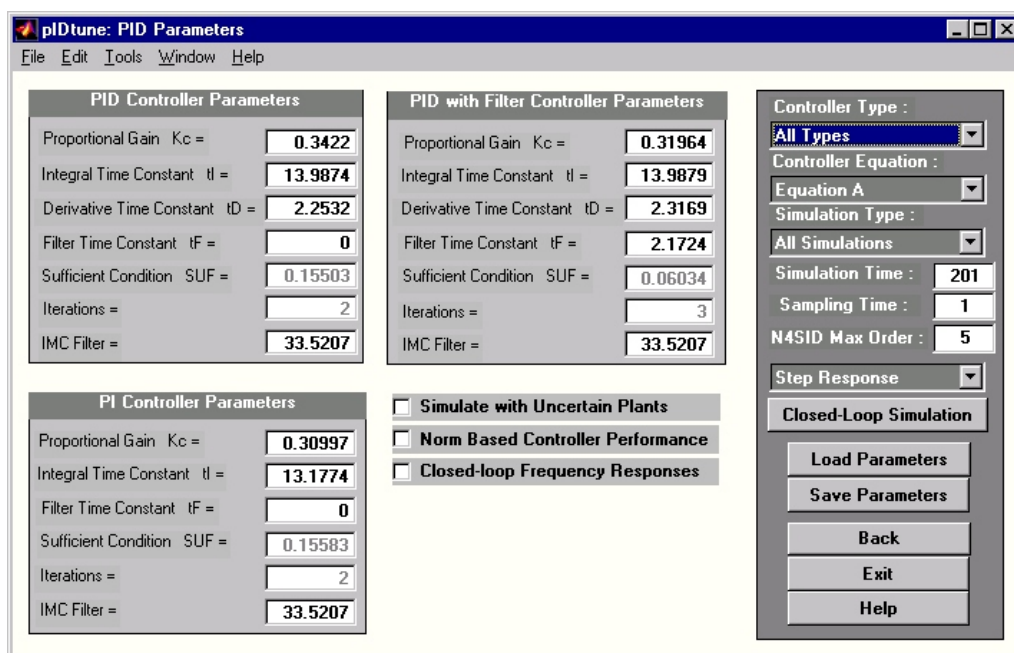


Fig. 8. PID controller parameters and closed-loop simulation window

3. QUENCH COLUMN BOTTOM TEMPERATURE LOOP - CASE STUDY

*pIDtune*TM's integrated methodology makes it a powerful and appropriate tool for solving a large variety of industrial problems. In this section, the problem per Emoto *et al.* (1997) from Mitsubishi Chemical Corporation will be studied. The system consists of an ethylene plant quench column bottom temperature control loop. The data collected for this system after an open-loop pulse test is shown in Fig. 10.

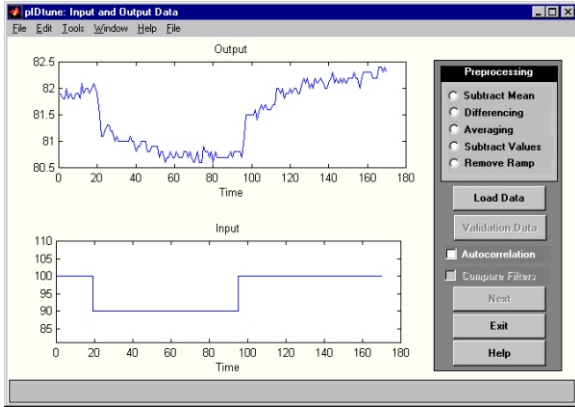


Fig. 10. Identification data for an ethylene plant quench column bottom temperature control loop

Since this a deterministic pulse test, one subtracts the base values from the original data. Moreover, because the data set is short, the whole data set is chosen for estimation. As mentioned in section 2.1, in these cases where no validation data set is available, it is not appropriate to choose the best fit obtained from the ARX estimation phase. Alternative measures such as the AIC and MDL are used for these cases. Proceeding to the ARX modeling phase, one chooses the range for the A and B polynomial orders and the range for the delay. In this case, the range for the A polynomial order was chosen to be 1-8, the range for the B polynomial order was chosen to be 1-8, and the range for the delay was chosen to be 1-10. With these ranges and using the AIC choice, the following ARX model orders are obtained: $n_a = 6$, $n_b = 5$, $n_k = 1$. Fig. 11 shows the step response for the nominal model and uncertainty

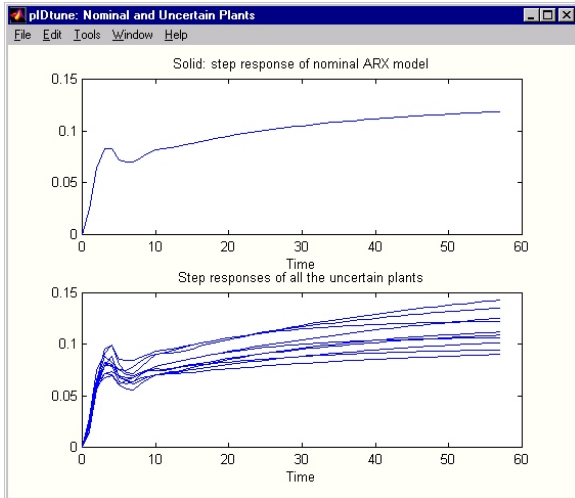


Fig. 11. Nominal step response for the ARX(6,5,1) model and uncertainty plants

plants. This result closely matches that obtained in Emoto *et al.* (1997).

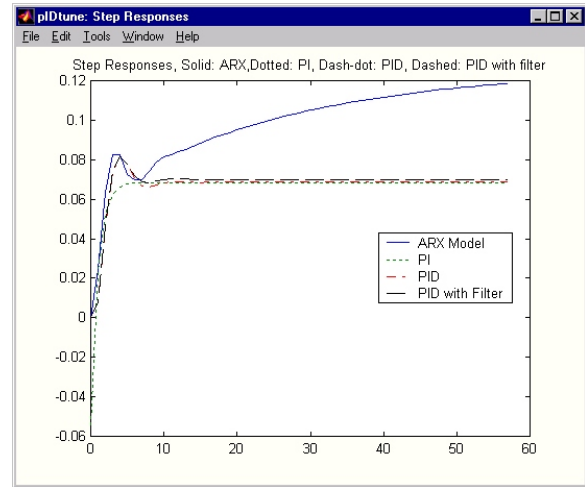


Fig. 12. Control-Relevant model reduction of ARX(6,5,1) with an IMC filter of 1.5

After the system identification phase, one proceeds to the PID controller design phase. For this case study, the key decision is to perform a control-relevant model reduction, so as to capture the desired dynamics of the system. This decision has to be made based on an *a priori* knowledge of the system or a particular design objective. In this case, the goal is to avoid sluggish servo and regulatory performance, which leads to the conclusion that one has to capture the fast dynamics of the process (high frequency region). In *pIDtune*TM this is accomplished by a judicious selection of the IMC filter parameter. A low value for the IMC filter results in an emphasis of the high-frequency dynamics of the system. Choosing an IMC filter value of 1.5 for this system resulted in reduced-order models that describe well the initial time dynamics of this process as can be seen in Fig. 12. For comparison with the Emoto *et al.* (1997) results, the closed-loop simulation for the PID controller using the Equation C bumpless form is shown in Fig. 13.

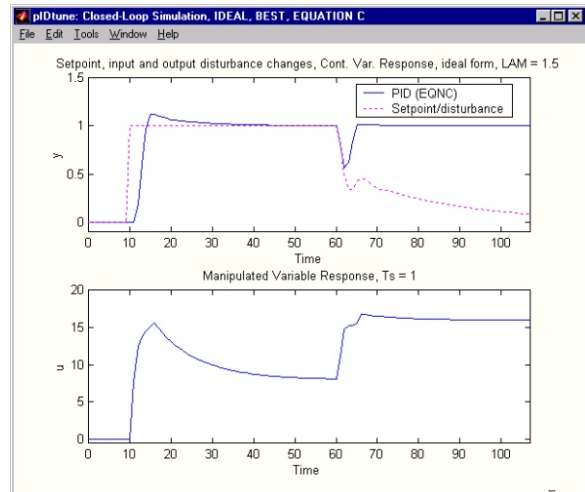
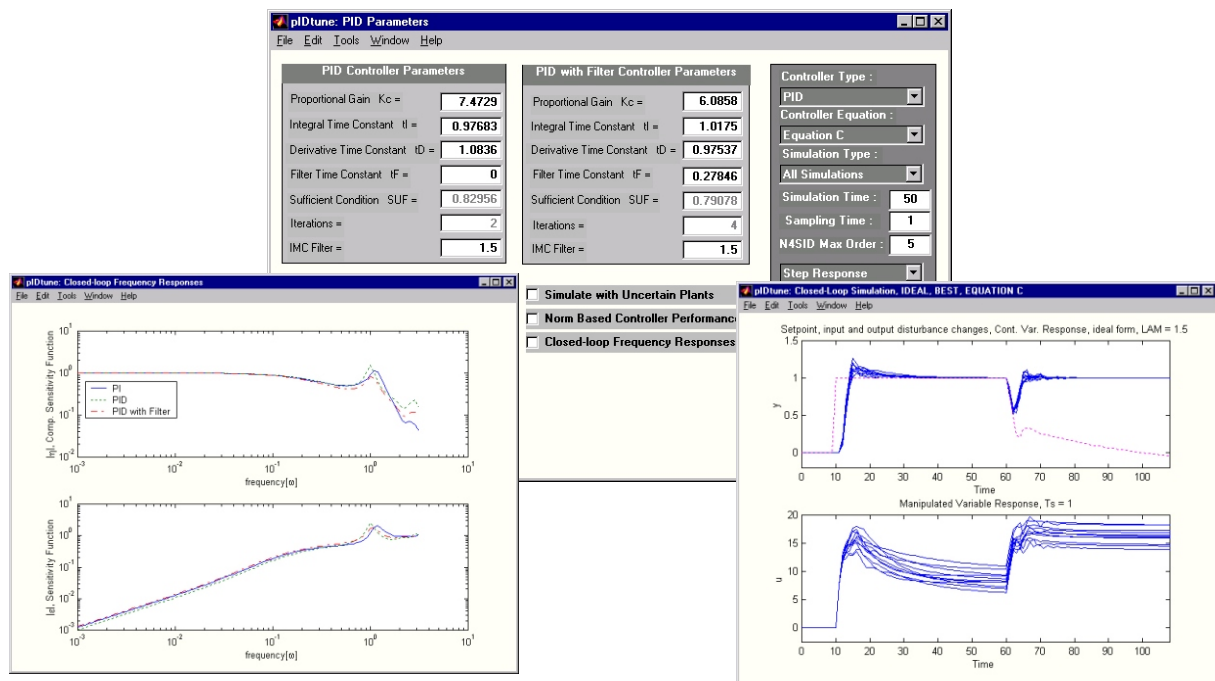


Fig. 13. Closed-loop simulation for a PID controller (Equation C form), setpoint tracking and disturbance rejection



Performance Calculations

Setpoint Tracking:

IAE-PID control = 4.4561

ISE-PID control = 2.8987

Disturbance Rejection:

IAE-PID control = 1.3051

ISE-PID control = 0.39352

Fig. 14. Control parameters for PID and PID with filter (Top), Sensitivity and complementary sensitivity functions for PI, PID and PID with filter controllers in the frequency domain (Left), closed-loop responses for the PID controller using the bumpless Equation C form with uncertainty (Right) and Performance Calculations (Bottom)

Furthermore, using *pidTune*TM, one can also look at the sensitivity and complementary sensitivity functions for the controllers in the frequency domain, examine norm-based performance criteria and simulate closed-loop behavior with or without uncertainty. Fig. 14 shows a collection of these various measures resulting from the analysis of the Emoto *et al.* (1997) case study. In particular, note the closed-loop behavior for the PID controller under uncertainty conditions. There is much variability in the manipulated variable (*u*) as a result of uncertainty in the model. However, the controlled variable (*y*) shows much less variance due to the robustness of the designed controller.

4. SUMMARY AND CONCLUSIONS

In this paper, *pidTune*TM has been introduced as a software package that integrates system identification and PID controller design. *pidTune*TM's methodology starts with well-designed input and output plant data and ends with IMC-PID tuning parameters. Finally, it was demonstrated how this methodology performs under low signal to noise conditions and its effectiveness in an industrial case study.

*pidTune*TM requires Matlab with Simulink and the Signal Processing, Control System and System Identification toolboxes. For more information on *pidTune*TM please visit www.pidtune.com.

5. REFERENCES

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