Aspen DMC3: Robust Control Technology

A Brief Tutorial

APC Product Management and Marketing

Table of Contents

Introduction

Aspen Technology has introduced a new robust control algorithm for Aspen DMC3, available in V8.7. The intent of this document is to describe the behavior of the algorithm and to provide practical examples of its use. Some of the examples used in this document are overly simplistic by design. Our goal is to demonstrate the technology without getting distracted by technologically "interesting" problems. We invite the reader to follow our example of using simulations to see the power of the innovation.

Users can try this new algorithm in offline simulation on example controllers or on existing commissioned applications. Users can evaluate the robust feature performance by using a separate model for the plant or by using gain multipliers to simulate typical model mismatch. Those who deploy an Aspen DMC3 controller from the Aspen Process Controller Builder can use this new feature online.

Robustness vs Optimization Challenge

It is a well-known fact that a Linear Program (LP) algorithm has the ability to select the most optimal set of simultaneous constraints where a process unit will be most profitable. Most APC applications contain two to three times more controlled variables than manipulated variables, which may lead to several possible combinations of constraints. Only one of these "constraint sets" will be the most profitable. The LP algorithm enables the practitioner to preferentially find the constraint set where all controlled variables (CVs) are inside their safety and operability limits, while maximizing profitability of the process unit.

The Linear Programming approach for optimization has many advantages, but there are a few disadvantages too. If the models or the cost of feed stocks, utilities, or products are not sufficiently accurate, the LP might select an undesirable solution. Also, LP is a profit hungry optimization method that will chase very small improvements in the objective function for even large, often undesirable changes in the manipulated variables (MVs).

In any MPC formulation, a standard LP approach to optimization can make the controller performance sensitive to modeling errors. Unresolved collinearity may cause the controller to make large moves to try and achieve unrealistic benefits. In the presence of significant model mismatch, the traditional LP optimization will be constantly chasing the "corner" based on these inaccurate models. Additionally, most APC applications have some degree of unmeasured disturbances affecting the process. Although model mismatch alone can lead to less than ideal controller behavior, a combination of model mismatch and unknown disturbances will significantly degrade a controller's performance.

The LP is not flexible enough to robustly accommodate scenarios, such as unresolved collinearity, model mismatch and unmeasured disturbance. The challenge is to make a controller robust enough to handle these situations, but at the same time focus on delivering benefits. Aspen DMC3 addresses this need by providing the APC practitioner a tunable robustness factor to accommodate these undesirable, yet fairly common scenarios.

Robustness Factor (RF)

To mitigate the effects of the issues mentioned earlier—i.e. weak direction movements as a result of unresolved collinearity, model mismatch and unmeasured disturbances—Aspen DMC3 features a robustness factor which scales between 0 and 1. This factor can be used to tradeoff optimality for robustness. The robust feature detects weak direction movement (high RGA in an active constraint set) in the online model and prevents the controller from moving in that direction. The RGA threshold for rejecting a weak direction movement for an active 2x2 constraint set is depended on the robustness factor. The higher the robustness factor, the lower the threshold for 2x2 RGAs.

The robustness factor can also be helpful in the case of model uncertainty and/or in the presence of unmeasured disturbances. A controller with a robustness factor of 0 will mirror a traditional Aspen DMCplus solution where every available degree of freedom is used to push variables to appropriate constraints. For robustness factors greater than zero, Aspen DMC3 will trade-off optimality for robustness. If the RF is 0.1, then not all degrees of freedom will be used to push variables to active constraints. For example, we might observe that a 20 MV controller may have only 16 active constraints, while four variables are operating with some small distance within their limit (if the solution is feasible). In effect, the controller is now operating a little conservatively, with a small amount of profit relaxation kicking in. If we keep on increasing RF more to 0.15, we may see only three or four active constraints with the product give-away growing, as well. As mentioned before, there is an inevitable trade-off between performance and robustness. Figure 1 below depicts the robust feature for a 2x2 matrix.

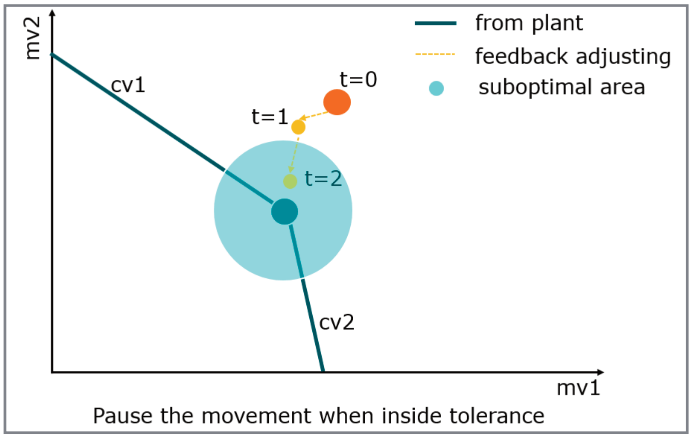
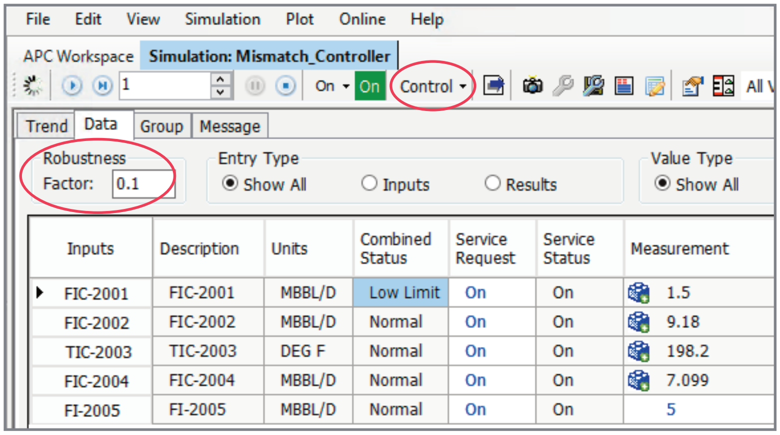


Figure 1: Robust feature for a 2x2 matrix

The suboptimal area, shaded in blue, is defined by how large the robustness factor is set. As long as the new optimal solution lies within this area, the controller will have no incentive to move. This effectively makes the controller more robust by not targeting one optimal point, but an area whose size is determined by the robustness factor.

For an online Aspen DMC3 controller, the robustness factor is accessible from the Production Control Web Server (PCWS) interface. This factor can only be used in control mode and not in Smart-Step or Calibrate mode. In simulation mode, the robustness factor is available under the data tab in Aspen Process Control Builder V8.7, as shown below in Figure 2.



Robustness Factor: 0.1

Entry Type: ● Show All ○ Inputs ○ Results

Value Type: ● Show All

Inputs	Description	Units	Combined Status	Service Request	Service Status	Measurement
▶ FIC-2001	FIC-2001	MBBL/D	Low Limit	On	On	1.5
FIC-2002	FIC-2002	MBBL/D	Normal	On	On	9.18
TIC-2003	TIC-2003	DEG F	Normal	On	On	198.2
FIC-2004	FIC-2004	MBBL/D	Normal	On	On	7.099
FI-2005	FI-2005	MBBL/D	Normal	On	On	5

Figure 2: Accessing the robustness factor from the data tab

Examples

We will demonstrate how the new robust feature can be leveraged to give a robust yet optimal response in less than ideal situations by using the following three cases.

Case 1: High RGA Case

The robust LP algorithm calculates the RGA numbers of the sub-models participating in the current active constraint set at every execution cycle. If a 2x2 sub-model with a high RGA number becomes active, indicating that the model matrix has unrepaired collinearity issues, the robust LP will not pursue moves in the weak direction for the manipulated variables, thus not allowing big moves for marginal improvements in the economic optimization. If the reduced rank LP problem has no spare degrees of freedom left, it will allow the least important (high ranked) of the CV LP targets to violate the active limits by a small amount, rather than relying on the weak direction, which typically is undesirable because it requires very large MV movements. Often these high RGA sub-models are not always accurate and the actual process might very well be perfectly collinear. If there is still enough spare degrees of freedom left after removing the weakest 2x2 directions from the LP, then the controller will move the CV a small amount inside their limits, in effect, giving up some amount of economic benefit. This relaxed LP solution is compared to every cycle with the optimal LP solution. Only if the improvement in objective function becomes too large (as determined by the robustness factor), will the new MV LP targets get implemented.

In order to demonstrate this behavior, consider a distillation tower where there is a reflux and reboiler flow available to control the top and bottom impurities (overhead and bottoms quality). This simple 2x2 system typically has two potential degrees of freedom. By changing the relative values of reflux and reboiler flow, we can affect separation, cut-point changes, or both. Of course, if the column is already running at very high separation, it may have no spare separation available, and then the column effectively has only one degree of freedom left, the cut-point.

Now, let's assume that we fitted the following model based on step test data where one MV was moved at a time. This model will be used for control. Figure 3 below shows the controller model (blue curve) and the actual process model (red curve). Notice that the determinant of the controller gain matrix is 0.02 (very close to zero) indicating that this model is getting very close to singularity (approaching perfect collinearity with RGA equal to 60). The condition number of the matrix indicates a similar fate.

Also, notice that there is a small error between the process and controller model with gains within 10% of the actual process gains. This is a very good result, as far as model identification is concerned.

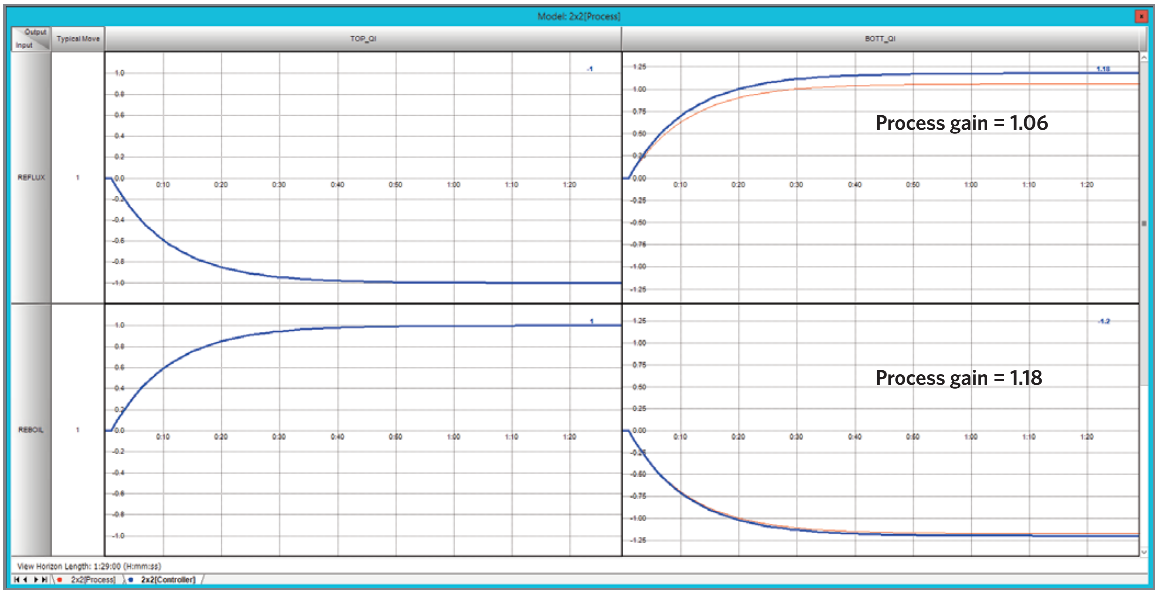


Figure 3: Controller and process model

Simulating the High RGA Case

Let's simulate this case with and without using the robustness factor. To recap, the controller model has a high RGA of 60 with a very small model error and the process model has an RGA of 10.

At first, with robustness factor of 0, the high limit of CV2 (BOTT_QI) was changed from 12 to 11. As expected, with a traditional Aspen DMCplus solution the MVs change by a considerable amount, initially because of large MV target changes. With feedback kicking in, the LP targets end up being more conservative than initially calculated (remember the process RGA is 10). That's why there's some overshoot in MVs and CVs. The controller is too aggressive because it's chasing the weak direction. This is not a dynamic tuning problem, but rather an issue due to unresolved collinearity in the model. The high limit for CV2 was then changed back to 12.

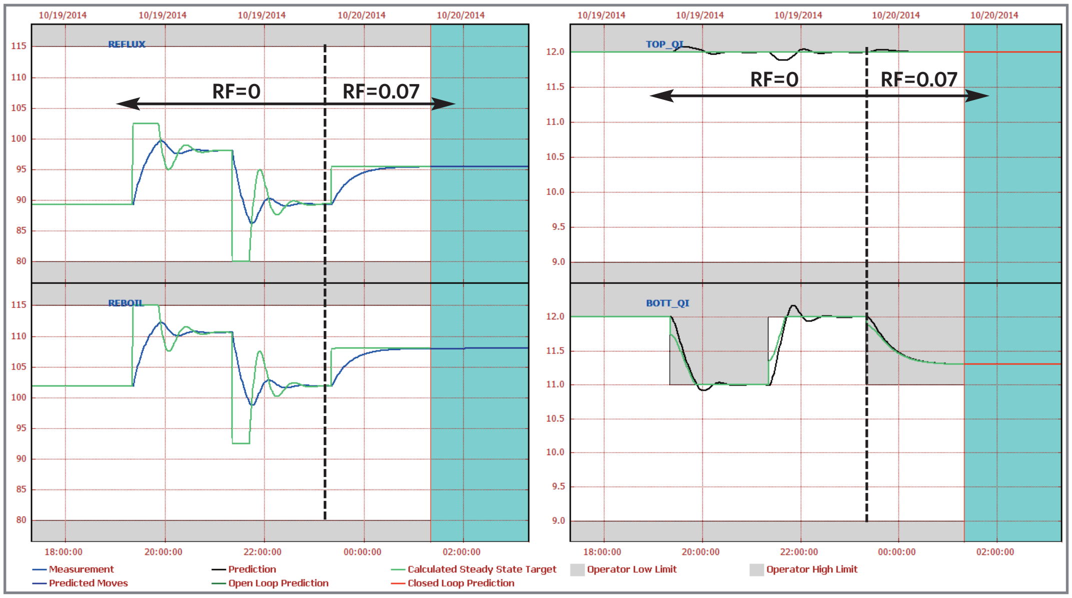


Figure 4: High RGA simulation results using robustness factor

With the robustness factor set to 0.07, change the CV2's high limit from 12 to 11. For the same limit change, but with robustness factor of 0.07, the manipulated variables moves are less aggressive, the MV targets are stable, and the controller does not try to pursue the new limit since it detected movement in the weak direction. This prevents the controller from making significant moves in the manipulated variables for small improvements in the constraint violation. The messages tab (not shown here) will also mention "weak move direction detected for MVs and CVs with an RGA of 60."

Clearly, by using the robustness factor, the LP solution stabilizes even in the presence of unrepaired collinearity. The controller gets more conservative by giving up on some of the economic benefits in exchange for higher stability.

Case 2: Model Mismatch

In this example, we will see how the robust feature available in Aspen DMC3 significantly improves controller performance even in the presence of severe model mismatch. The plant model (5x3) used for this demo is shown below in Figure 5. This controller has four manipulated variables and one feed-forward (FI-2005) with three CVs.

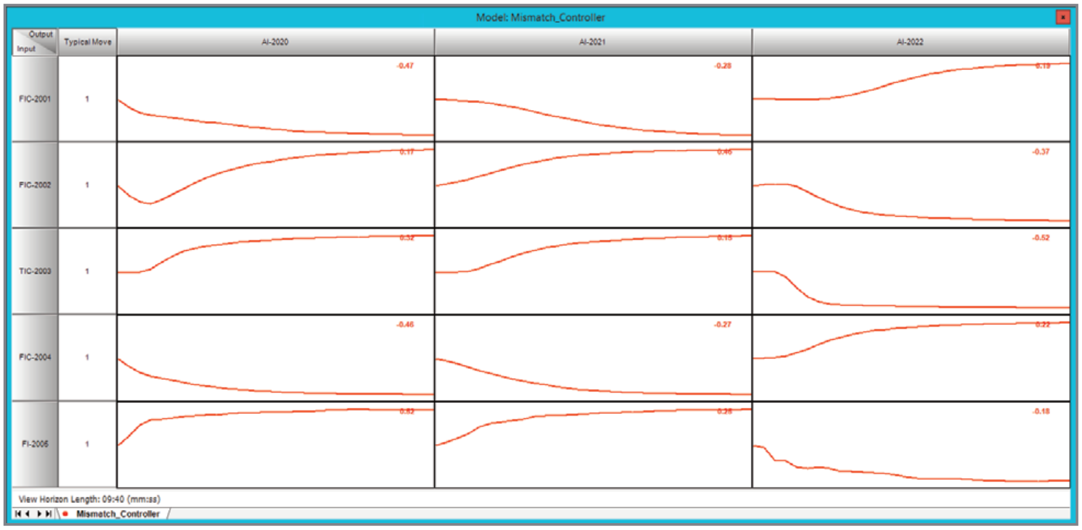
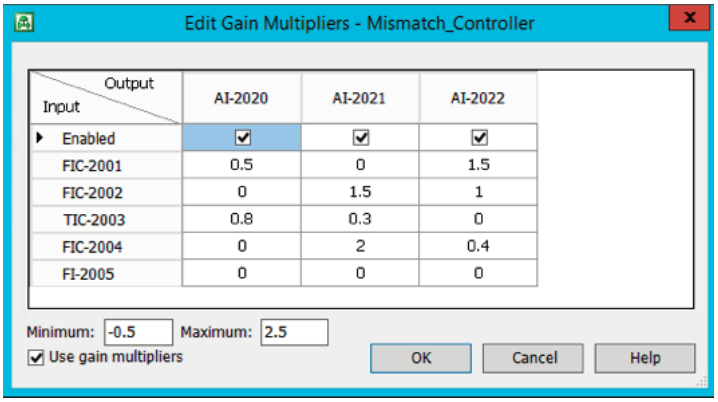


Figure 5: Plant model

To test the robust feature, model mismatch is introduced by using gain multipliers in the controller, as shown below in Figure 6. The gain multipliers are randomly introduced and varied from 0 to 2 (up to 200% error). Although we would never commission a controller with such severe model mismatch, the purpose of this demo is to highlight the controller's performance even in the presence of significant model mismatch.



Edit Gain Multipliers - Mismatch_Controller

Input \ Output	AI-2020	AI-2021	AI-2022
Enabled	☑	☑	☑
FIC-2001	0.5	0	1.5
FIC-2002	0	1.5	1
TIC-2003	0.8	0.3	0
FIC-2004	0	2	0.4
FI-2005	0	0	0

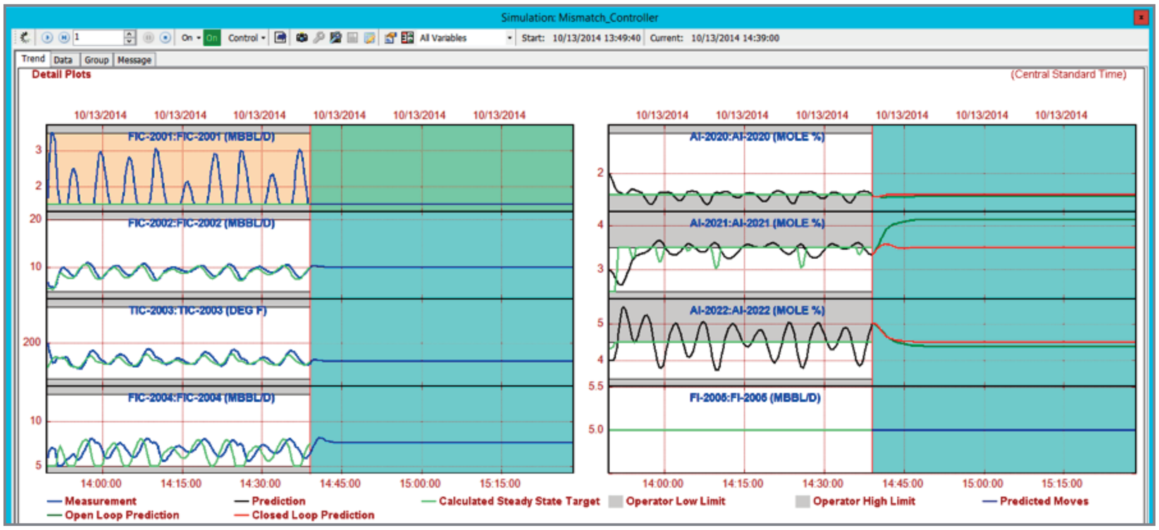
Minimum: -0.5 Maximum: 2.5

☑ Use gain multipliers

Figure 6: Controller gain multipliers

Simulating the Model Mismatch Case

Next, simulate the controller with the robustness factor set to 0 (traditional Aspen DMCPlus solution). The results of the simulation are shown below in Figure 7.



Start: 10/13/2014 13:49:40 Current: 10/13/2014 14:39:00

Figure 7: Model mismatch simulation with robustness factor set to 0

It comes as no surprise that the controller performance is very poor. The model errors caused the MV LP targets to change direction to try and keep the CVs at their optimal targets (limits). With severe gain errors, there is cycling which results in poor control of CVs, especially AI-2022 in this case.

The results of this simulation with a robustness factor set at 0.1 are shown below in Figure 8.

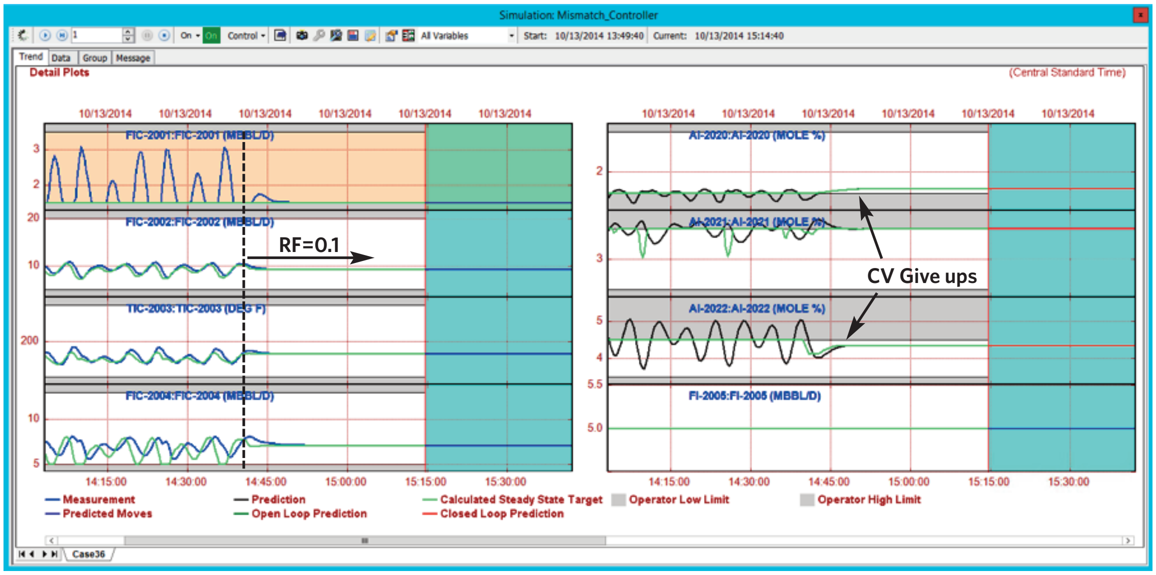


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Figure 8: Model mismatch simulation with robustness factor set to 0.1

Notice that the oscillations have stopped and the MV and CV targets are stable. The controller is also "well-behaved". With there being no change in the model, tuning, etc., how is this possible? As always, to achieve this kind of performance in the presence of significant model mismatch there are some give-ups. If you notice carefully, the CV targets (AI-2020 and AI-2022) are close to their limits but not quiet at the limits. The robustness factor allows the controller to not always "chase" the optimal steady-state solution, which in this case lies at the three CV limits and FIC2001 MV limit (using up all degrees of freedom). In turn, a robustness factor of 0.1 gives the controller some room to accommodate modeling errors and thereby make it more robust.

Although the modeling errors in this example are exaggerated and not really representative of a real controller, it's fairly common to have varying degrees of modeling errors in every controller. There are many reasons for modeling errors; feed composition changes, non-linearity, catalyst degradation, and poor PID performance to name a few. Although we strive for perfect models to improve controller performance and benefits, in most cases good models come with a cost (suboptimal process conditions during additional testing, engineering time, etc.). The user should weigh-in the cost and benefits of generating and maintaining very good models vs commissioning a robust controller to handle less than perfect models.

Case 3: Unmeasured Disturbances

This example will focus on demonstrating the benefits of using the robust feature in the presence of unmeasured disturbances entering the process. Similar to the model used in Case 2, the plant model used in this example is a 5x3 matrix. An unmeasured disturbance is simulated by using zero gains for the CV's associated with the feed forward FI-2005 in the controller model. A comparison of the plant model (red curves) and that used in the controller (blue curves) is shown below in Figure 9. Notice that the plant model has non-zero gains for the feed forward FI-2005, whereas the controller has zero gains. The controller is effectively "blind" to any changes in FI-2005.

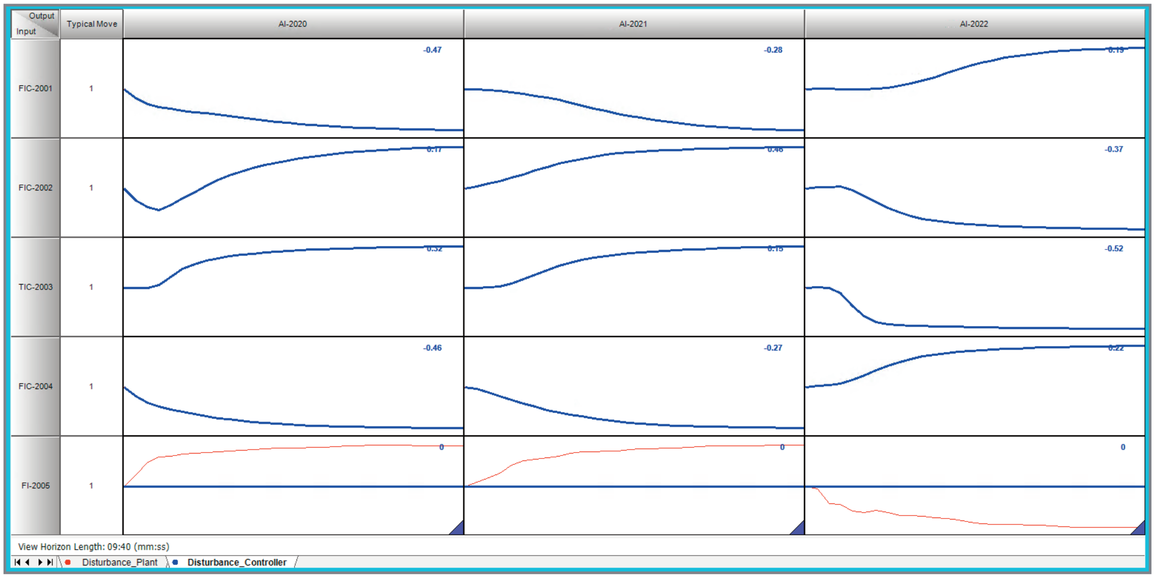

Figure 9: Comparison of the plant and controller model

Simulating the Disturbance Case

We simulated the controller first with the robustness factor set to zero. The feed forward FI-2005 signal is randomly varied. The results of this simulation with RF = 0 are shown below in Figure 10.

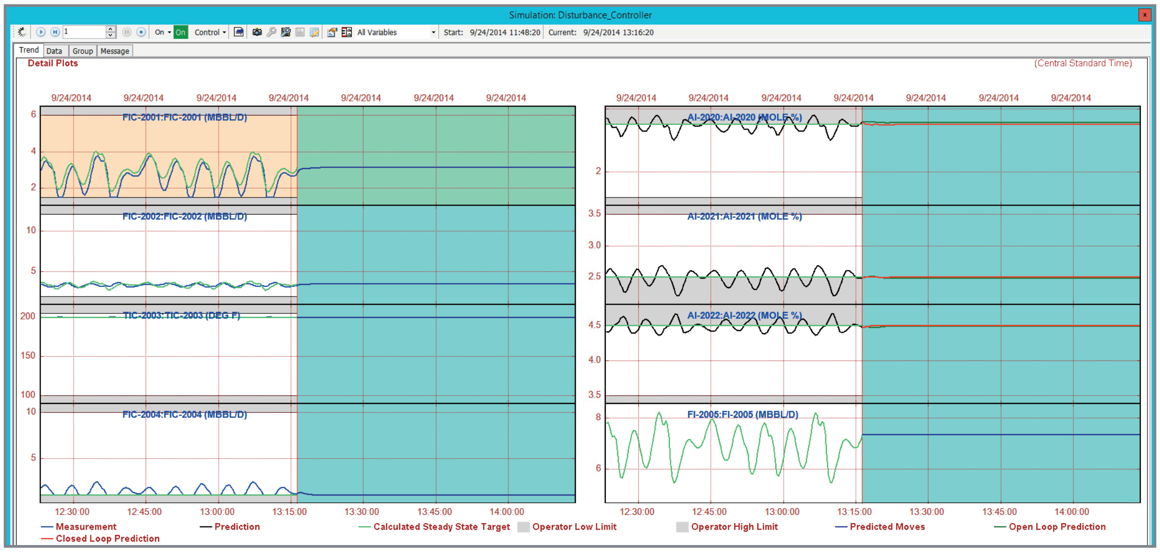

Figure 10: Unmeasured disturbance simulation results with robustness factor set to 0

As expected with a traditional Aspen DMCplus solution, the MVs are constantly reacting to the unmeasured disturbance from FI-2005 (shown in bottom right). In a real controller, unmeasured disturbances of this magnitude will be dealt with by identifying and including it in the models, thereby improving predictions. The idea is to demonstrate how the robust feature can help with some inevitable unmeasured disturbances, such as upsets in upstream process, rapid ambient changes, etc.

Let's use the robust feature in Aspen DMC3 to see how the controller performance can be improved in the presence of unmeasured disturbances. The Figure below shows the controller response when the robustness factor is set at 0.05.

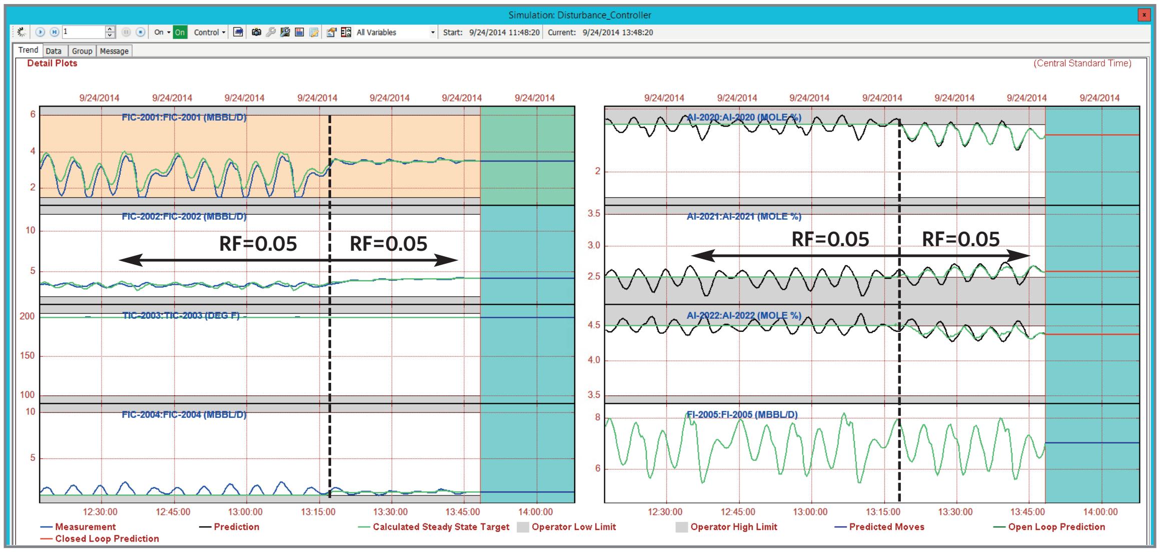

Figure 11: Unmeasured disturbance simulation results with robustness factor set to 0.05

Note that after the RF was changed to 0.05, the MVs have stopped cycling. The MV targets are not moving, yet the CV targets (in green) are changing and remaining close to the limits. This is by design. If the CVs move too far away from optimality/limits (which is tunable), the robust feature will calculate a new MV LP target and drive the process closer to optimality again. You can also see that we are averaging a little higher on MVs, especially FIC-2001. This is where some give-up in benefits exist. Although the CVs and MVs targets are not at their optimal values, the controller response is much more acceptable.

With a stable controller, even in the presence of severe unmeasured disturbances, one could even consider opening up the limits. With that in mind, let's see what we can achieve with this setup. We raised AI-2020's high limit from 3.5 to 3.7, AI-2021s low limit is lowered from 2.5 to 2.35, and AI-2022's high limit is raised from 4.5 to 4.6. The results of this simulation are shown below in Figure 12.

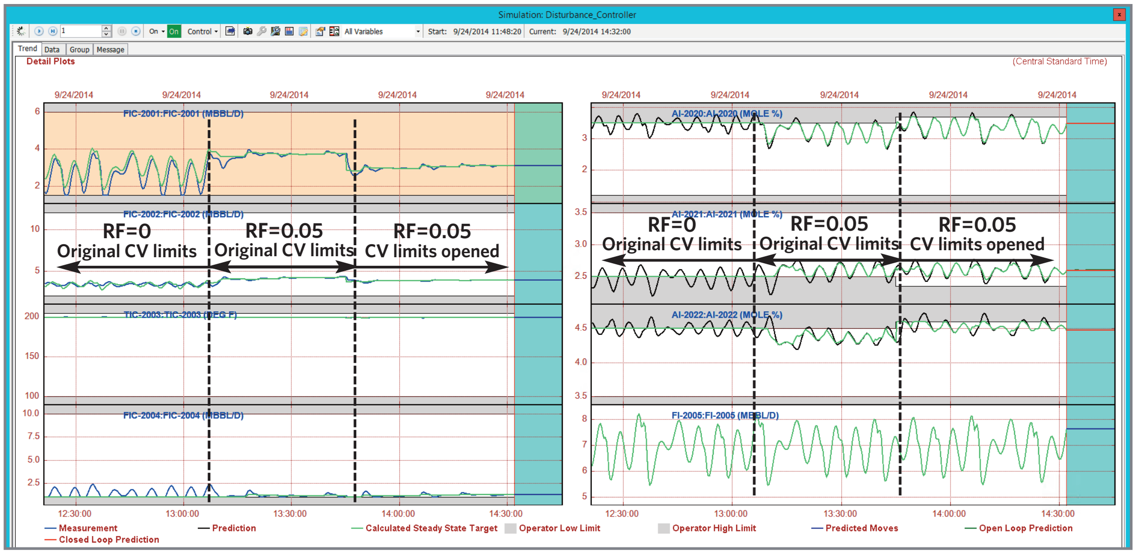

Figure 12: Unmeasured disturbance simulation with robustness factor set to 0.05 and CV limits opened

With the CV limits open and the robustness factor set at 0.05, we notice that the MVs moved closer to the original average optimal solution and remained stable (easier to see this in FIC2001). Also, observe that now we are averaging approximately similar CV process values (including overshoots) when compared to the case with an RF of zero and original limits. In essence, the controller is generating similar benefits but is much more stable than before—even in the presence of unmeasured disturbances.

Summary

Poor controller performance due to unforeseen collinearity, model degradation, and unmeasured disturbances generally force operators to run CV and MV limits a little more conservatively, in turn reducing benefits of the APC applications. Worst case scenario, loops or even the whole controller are turned off. In cases of model degradation, the benefits can be improved by carefully re-testing the unit. There are benefit giveaways associated with the testing phase, because of suboptimal process conditions required for generating data. It also requires APC engineers to spend some time and effort using either Smart-Step or Calibrate mode to generate the necessary data to re-test the unit and then redo the model identification and model conditioning work. This requires some degree of skills, experience, and consumes valuable APC engineering hours. In addition, there are many unforeseen situations that were not experienced during commissioning, like different operating points (non-linearity issues), unexpected disturbances, different active constraint sets, etc. All these factors contribute towards the reduced benefits of APC applications.

This is where we can leverage the robust feature available in Aspen DMC3, which has the benefit of ensuring stable, yet profitable controller performance in less than ideal, but fairly common scenarios. In effect, the robust functionality contributes to a useful reduction in maintenance cost and helps extend revamp periods for controllers. It frees up APC engineers to build new controllers or revamp existing ones that have higher overall benefits. It also provides a “safety net” for unforeseen situations mentioned earlier. The robust feature effectively provides complimentary ways for maintaining our Aspen DMC3 controllers.

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