WHITE PAPER

The Aspen DMC3™ Difference

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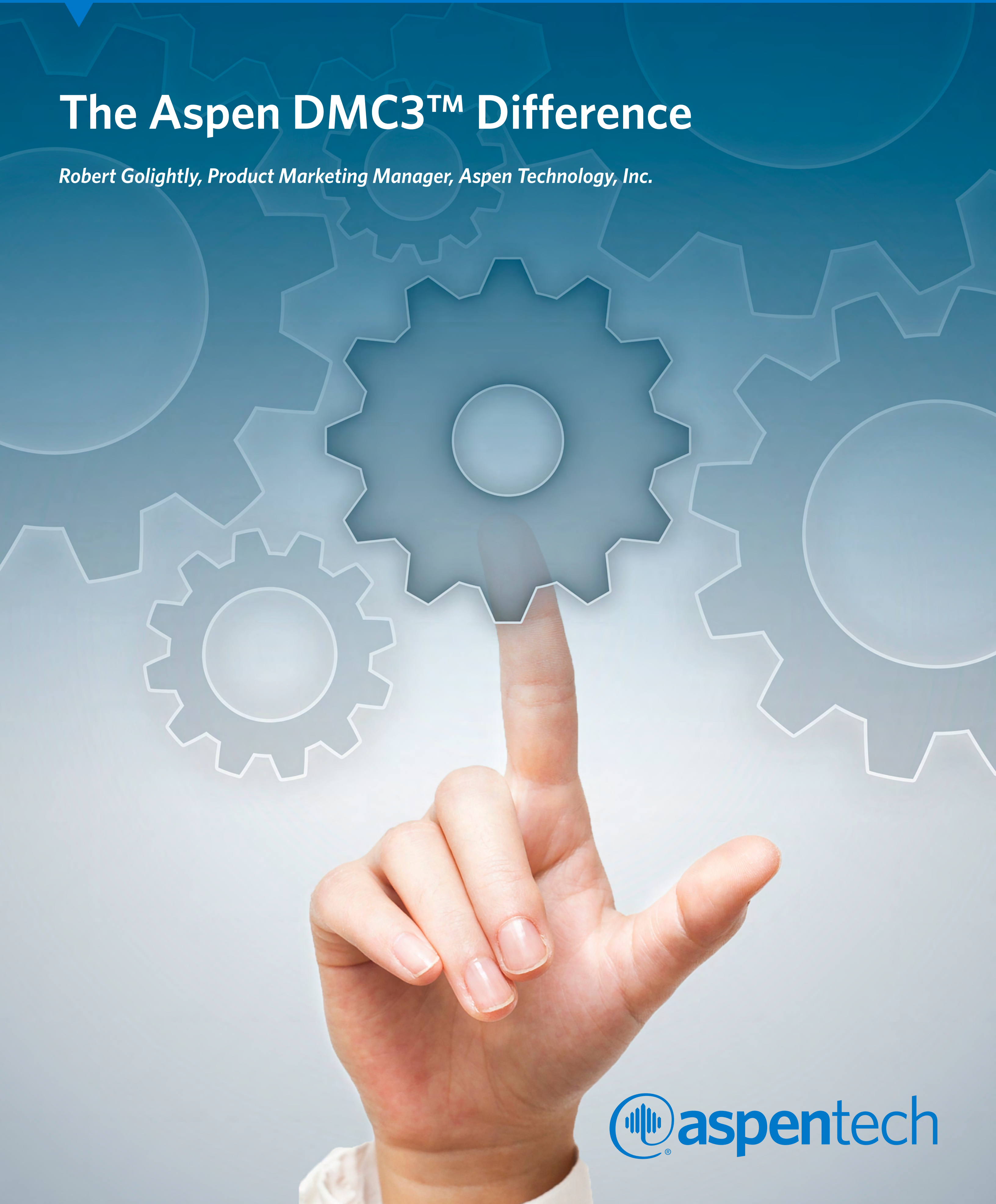

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Introduction

There is a classic dichotomy in APC: the technology delivers maximum benefits when the underlying algorithms leverage accurate models for the aggressive pursuit of profits. However, we also want the controller to gracefully handle the presence of errors or poor model conditioning. The controller algorithms have traditionally been slanted in one direction or the other; to be very aggressive in the pursuit of benefits, or be less aggressive in order to compensate for the potential for reduced accuracy in the models.

There was, of course, a price to be paid for either choice. When errors are present in aggressive controllers, the optimizer can jump from solution to solution as it chases the potential profit it identified as a result of the model inaccuracies. When the choice of a less aggressive controller is made, the price equals lower benefits as the controller is essentially tuned to ignore improvements below a certain threshold.

Part of the problem is that this is also a temporal issue and not just about the initial model accuracy. We know that the changes that occur in the plant between revamps of the controller cause slowly evolving differences between the actual plant behavior and the model predictions—hence the eroding benefits of the controller.

In fact, there are several points within the APC lifecycle where these issues surface. Figure 1 depicts the facets of APC that offer opportunities to tune the behavior of the APC solution to address issues affecting benefits, operating stability, and product quality in the presence of model inaccuracies.

For the last 10 years, AspenTech has been working on a comprehensive solution for top-of-mind issues for APC practitioners. Beginning with offline collinearity repair nearly a decade ago, and now with Adaptive Process Control, LP Tuning, and Constrained Model Identification, AspenTech is again setting the standard for multivariable model predictive control and optimization with Aspen DMC3.

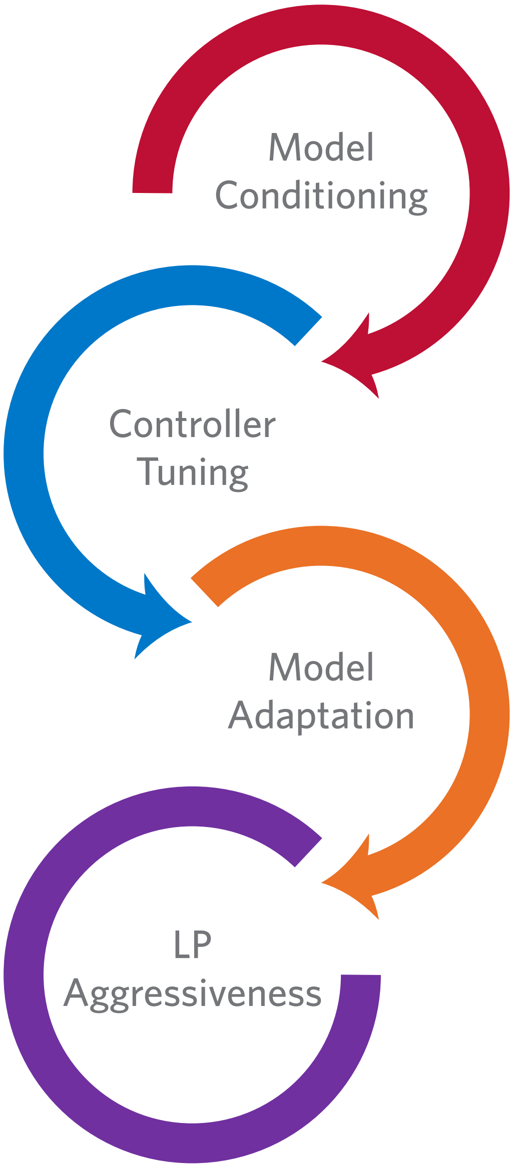
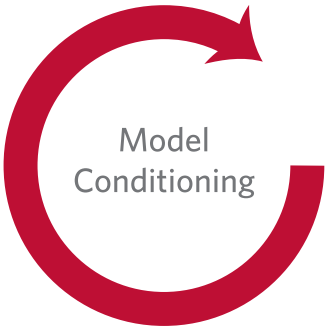


Figure 1: Facets of APC

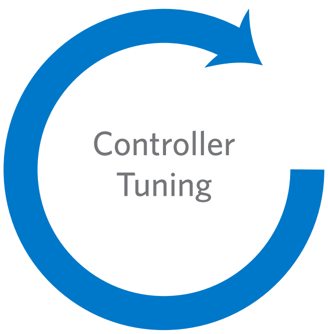


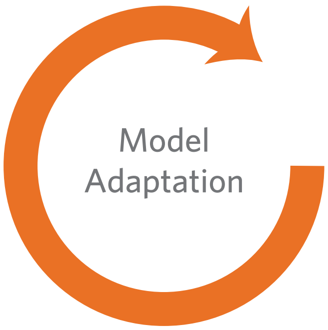
Model Conditioning

There are many reasons why a substantially inaccurate model can lead to performance issues, and this applies to all MPC formulations. In model conditioning, we are addressing aspects of the model that create ambiguity with respect to decisions made in the course of optimization. The most illustrative example is near collinearity in the models. When this condition exists, there are very small differences in the gains that an aggressively tuned optimizer will see as opportunities for profit. This type of "numerical fuzziness" can create cycling. Certain tools that have been in existence help expert practitioners fix the Relative Gain Arrays (RGAs) of the models to prevent this situation. The most recent innovations in this area surface these tools as an integrated part of the workflow and simplify the use of the tools via automation, thereby enabling non-expert practitioners to correct issues with collinearity during the offline modeling phase.

Controller Tuning

Dynamic model accuracy (curve shape) is also important as it affects the dynamic control move calculation, which can also lead to cycles if the main model curves are very inaccurate. This is usually not the dominant reason for cycling, unless MV tuning (move suppression) is very aggressive. A good control solution would need the ability to handle instability resulting from inaccuracy in the dynamic models, as well as inappropriate tuning.





Model Adaptation

AspenTech has been working steadily for the last decade to solve the model maintenance side of this issue. This technology includes the ability to alter the "personality" of the controller in terms of the aggressiveness of plant testing. The adaptive technology alters the optimization behavior of the controller to direct it to be less aggressive during testing, and in the presence of the errors, inherent in initial seed models. The Adaptive Process Control technology provides the engineer with an analog parameter to adjust the trade-off between testing aggressiveness and the capture of benefits. Previous to this technology, the choice was binary—focus on testing OR optimization, not a user-specified balance of objectives.

The adaptive technology allows the user to tune the personality of the controller to particular circumstances encountered during the testing and model construction phases. Rather than a one-size-fits-all set of binary choices, we now have the ability to fine-tune the trade-off to unique needs.

LP Tuning

To complement the Adaptive capability, we also need a way to shape the behavior of the controller when in optimizing control mode. As changes occur in the plant over time, or via transient events, we need to be able to easily modify the behavior of the controller until the issues can be addressed, or simply modify as a technical hedge tactic.

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 make the most money. Most APC applications contain two to three times more controlled variables than manipulated variables. Therefore, the controller model is referred to as "non-square," and potentially millions of constraint combinations are possible. The objective is to find the constraint set that maximizes the benefits. For most control applications, the interior point LP algorithm can select the most optimal solution within a matter of milliseconds. This is possible due to the ability of the LP to "square-up" the control problem by preferentially finding the constraint set where all controlled variables (CVs) are inside their safety and operability limits, while maximizing profitability of the process unit. If there is no feasible solution— because limits are set too conservatively or inconsistency exists in model relationship—then a ranked approach is used to decide which CVs are allowed to violate constraints.

Linear Programming has many advantages in optimization, but there are a few disadvantages too. If the model is not accurate with respect to the process variable costs, the LP might pick an unfavorable solution. It is often the case that when this occurs, operators get frustrated, complaining that the controller "is not doing the right thing."

In what follows, we'll illustrate the behavior of the Aspen DMC3 controller using its ability to adjust the LP aggressiveness to address the more common types of model inaccuracies.

Steady-State Gain Errors

The current biased prediction is used as the starting point to initialize the LP at every execution cycle. If the gain matrix is very inaccurate, then the LP might make bigger-than-required MV moves to steer the unit back toward the chosen LP targets. This leads to excessive MV movement and potential cycling between solutions. This behavior is upsetting to operators, and leads to being unprofitable.

Another form of model inaccuracy, where a closed material balance does not add up to zero, is when the LP might think it can optimize in ways that violate the laws of physics i.e. by creating mass. The gain matrix does not need to be perfectly accurate, but as gain errors increase there comes a point where the LP will switch to the wrong solution.

The LP might also pick a new solution based on feedback information, allowing the controller to move in that direction. But due to the model errors, the controller will observe a process response quite different from what it predicted. A few steps later, the LP might conclude that the original constraint was better after all. This can result in a cycle where the LP flips between two or more active constraint sets.

A good robust control solution would prevent LP flipping by avoiding the use of weak process handles to deal with new CV limit excursions. The robust solution would also need to prevent giving up too much in terms of dynamic performance. It must not become so sluggish that it cannot adequately reject disturbances. In terms of optimization performance, it should not move too far away from the theoretically optimal solution.

The next few figures display some simulations of Aspen DMC3. Figure 2 shows where the controller model has a gain that is 5x too low (worst case direction).

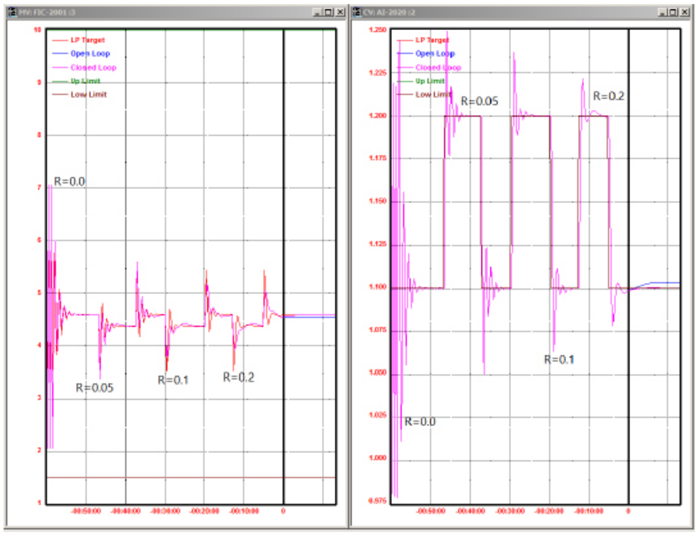


Figure 2:
Increasing the robustness factor prevents LP flipping in the presence of model mismatch

All MVs and CVs except for FC2001 and AI2020 have been turned off, making this is a simple 1x1 controller, similar to a PID single loop controller. We would typically not build applications this small, but it serves to illustrate the ability of the new algorithm to stabilize the dynamic move plan when the LP is not active since the controller is already squared up.

We intentionally started with a very large model mismatch (500% in the worst case direction), and inappropriate MV tuning (move suppression of 0.1, which is very aggressive). As can be expected, the 1x1 controller cycled poorly using the standard move plan algorithm. The new global tuning parameter called "Robustness Factor" (R) was used, a normalized number between 0 and 1. As the Robustness Factor increased, the loop became better damped (less cyclical) until acceptable performance was achieved at R=0.2. Clearly, the robust control algorithm managed to stabilize this controller in the presence of severe model mismatch. This example highlights how the robust algorithm adjusts the dynamic move plan optimization to provide improved performance.

Figure 3 below shows where we created random gain errors in the controller model varying from 0.1 (10x or 1000% too low) to 2x (200% too high).

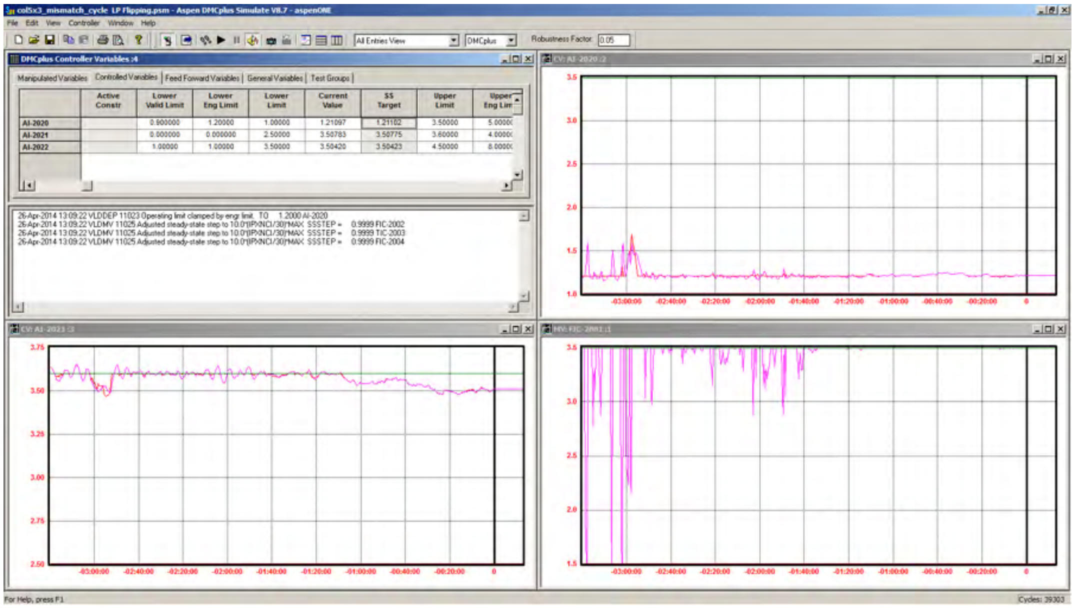


Figure 3: Cycling is cured with robust operation

The controller was started with the Robustness Factor (R) set to zero, i.e. the user is saying "no additional controller robustness is needed; I trust my model completely." Clearly, the excessive (unreasonable) model mismatch was sufficiently large in this example to cause the controller to cycle or "flip" between alternate solutions.

Errors in the gain and shape of the model curves can also contribute to controller instability, as the move plan engine will respond to bias feedback. As the R was increased to a small non-zero value (0.005), the cycle persisted and got smaller. By increasing R to 0.05 (still small, 5% of range) it cured the cycle completely.

The compromise is that AI2021 moved inside its limit instead of riding the high limit as before. The trade-off is the controller will respond slower and give up some economic benefit. Figure 4 shows a second simulation displaying a more realistic scenario where R was held constant at 0.1, and the amplitude of the random disturbances were increased by 10x.

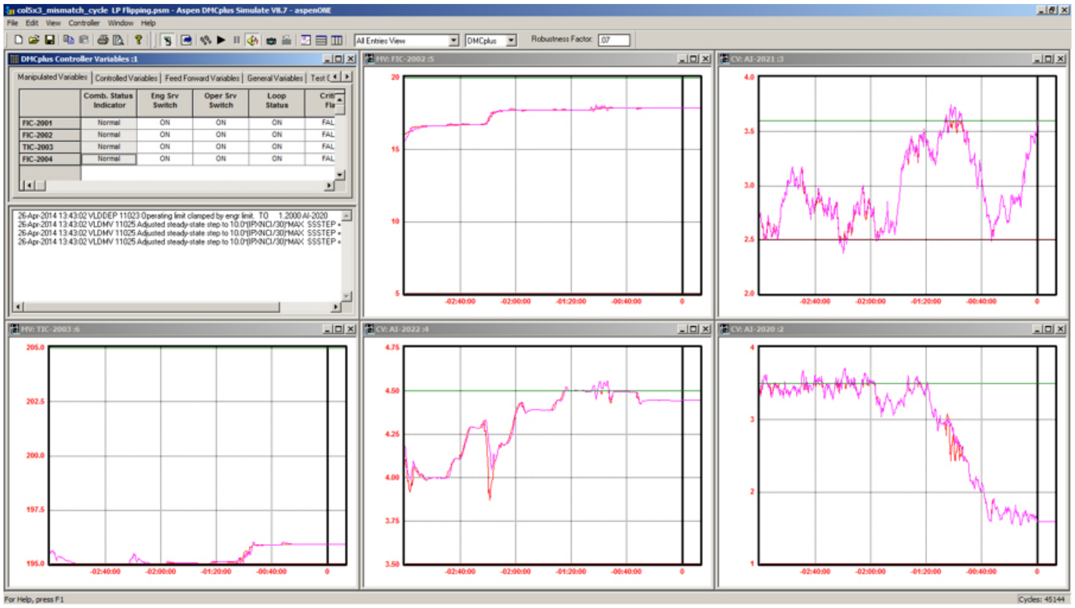


Figure 4: MV targets stay constant, changing only when there is sufficient economic reason for doing so

Notice that the red MV LP target stays constant for some period of time, changing only when there is a sufficient economic reason for doing so (too far away from the optimal LP targets), or if a disturbance drives the CV beyond limits. With less movement in the LP targets, there is of course less movement in the MVs that slow down the controller, leading to less bias updating and further stabilizing the LP targets.

The philosophy here is that if the controller moves less (or more slowly), and if the LP is somewhat less profit hungry, then there is less need for accurate models. The new robust control algorithm intentionally prevents the LP from “chasing after pennies” (a small benefit that is most likely not achievable), while keeping the LP targets as constant as possible—dictated by the economic give-up (economic relaxation), which depends on the Robustness Factor. See the figures below detailing the CV plot.

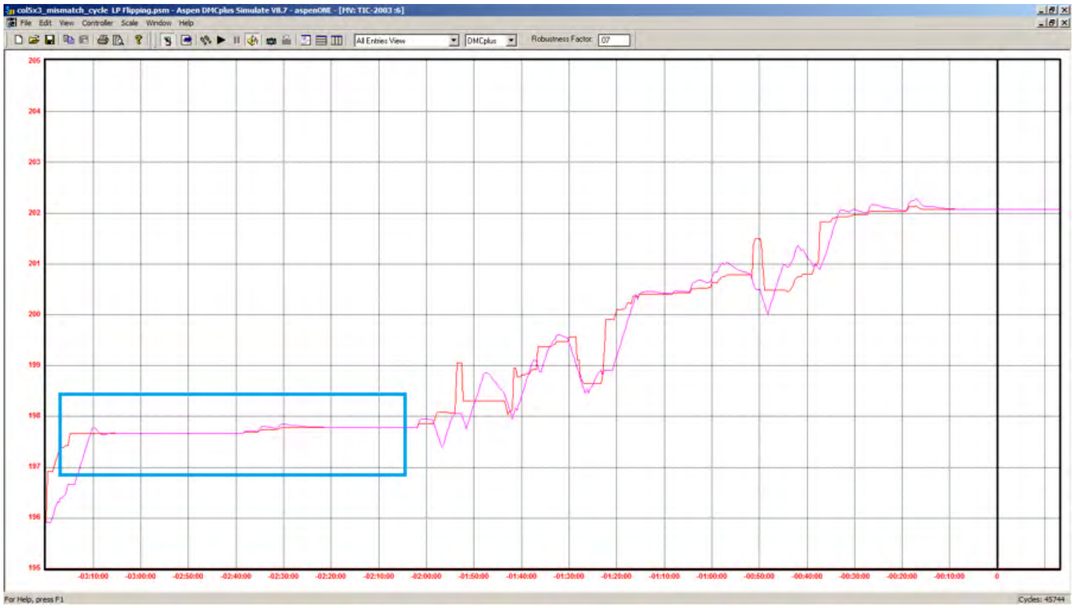


Figure 5: The MV target may be constant for long periods of time if the CV is still near the optimal solution and is not violating constraints

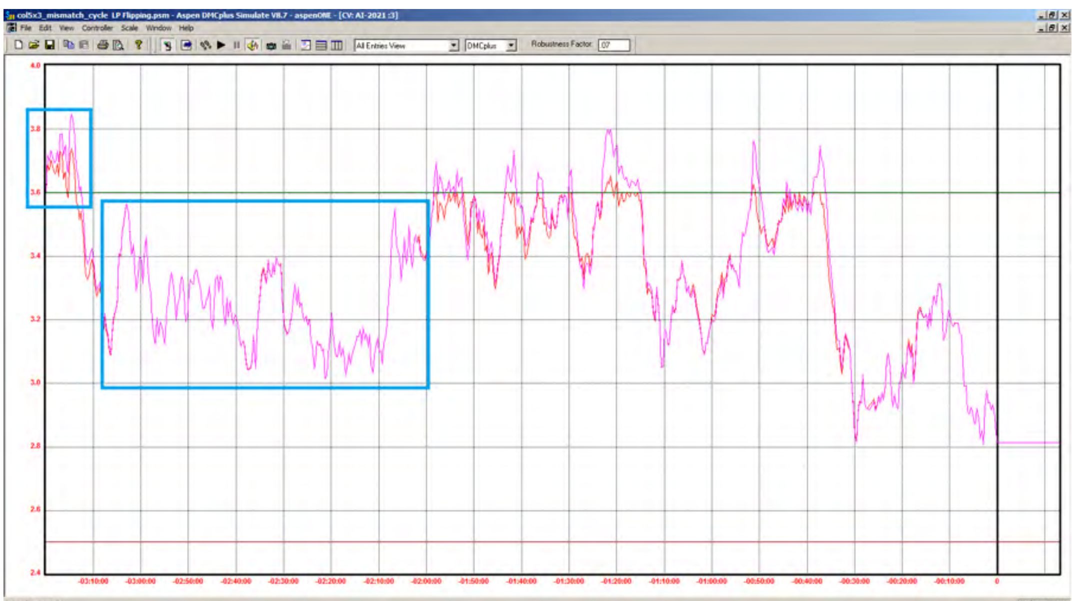


Figure 6: The CV LP steady-state target is underneath the actual CV value, while the MV target is held constant

Notice that the CV LP target is occasionally set equal to the current CV value. This indicates that the MV LP targets are being held constant during this time period, and that the algorithm has concluded that it is OK for the CV to move around by this amount. Once the CVs move too far away, the LP will make an MV LP target change, pick new CV targets, and try to drive the process closer to optimality.

Also, the controller internally calculates the RGA numbers of the sub-models participating in the current active constraint set. If sub-models with high RGA numbers become active, indicating that the model matrix has unrepaired collinearity issues, the LP will drop these degrees of freedom by preventing movement in the weak process direction. If the reduced rank LP problem has no spare degrees of freedom left, it will allow some of the CV LP targets to violate the active limits by a small amount, rather than rely on the weak directions of the process to try and drive inside the limits, which typically does not work well because it requires very large MV movement.

Often these high RGA sub-models are not accurate anyway and the actual process might very well be perfectly collinear. The user is encouraged to set the CV Validity Limits, such that the controller will turn off if the CV exceeds these limits. 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 every minute with the optimal LP solution, and only if the delta cost function (delta J) becomes too large (as determined by the Robustness Factor) will new MV LP targets be picked.

Clearly, as we increase the Robustness Factor, the controller slows down (move suppression values will go up internally), and the LP solution will stabilize nicely even in the presence of an unrepaired model matrix. The controller will also become more conservative, giving up some of the economic benefits in exchange for higher stability.

Conclusion

Aspen DMC3 provides the control engineer with a set of modes and analog parameters that modify the behavior of the controller based on the lifecycle needs. Adaptive Process Control provides a complete range of economic trade-offs for managing step testing and model construction. The LP tuning feature of Aspen DMC3 provides the same ability to shape the personality of the controller when in optimizing control mode. By adjusting the LP tuning factor, the controller aggressiveness can be set by the engineer to mitigate the risk of poor model conditioning.

Engineers now have the ability to configure a controller personality to address specific issues. Binary choices are replaced with analog choices, giving fine control over the technical and economic trade-offs involved in APC. Aspen DMC3 gives users the ability to shape the economics of APC solutions to meet business objectives. Users can now modify the behavior of the controller to fit the needs of any phase of the lifecycle.

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