ADVANCED CONTROL

OF ETHYLENE PLANTS

WHAT WORKS, WHAT DOESN'T

AND WHY

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WHAT WORKS, WHAT DOESN'T, WHY?

The complexity of ethylene plant operation makes it a good candidate for advanced process control (APC). Production starts with a battery of high temperature cracking furnaces, followed by distillation columns for separating the reactor effluent. The furnaces operate at low pressure and high temperature, whereas the reaction products are light hydrocarbons whose separation calls for high pressures and low temperatures. Thus, process and refrigeration compressors, with their many constraints, complicate plant operation. Further, the furnaces gradually foul up, lose capacity, and periodically are shut down for cleaning. That semi continuous feature prevents the plant from ever reaching steady operation.

The APC first challenge is to operate this never-at-steady-state, sensitive equipment, correctly, as the feed of the day and degree of furnace fouling dictate. Penalties for incorrect operation are premature fouling of furnaces and olefin yield reduction. Once the first challenge is met, a second challenge is to maximize the use of certain feeds while respecting plant constraints. These objectives call for the following APC functionality.

- **Cracking furnace control.**

  Control the furnace severity precisely to avoid over or under cracking. Overcracking results in accelerated fouling whereas undercracking results in a loss of production.

- **Distillation column control.**

  Maximize olefin recovery. Incorrect distillation control results in loss of ethylene and propylene yield, and in recycling olefins to the furnaces, which accelerates furnace fouling.

- **Constraint control.**

  Increase throughput of selected feeds up to equipment constraints. Constraints could be anywhere in the plant: furnace, compression, refrigeration, fractionation or hydraulic. Bottleneck locations vary with plant feed, number of furnaces in operation, weather and other causes.
  (Nudging the throughput towards constraints causes self-inflicted disturbances, on top of the semi continuous furnace disturbances.)

- **Economic optimization.**

  Maximize the overall profit of the plant. This involves not simply feed selection but trading off feed selection, reaction severity and product recovery targets against equipment constraints.

The main point of this paper is that the first two applications: cracking severity control and distillation control, require complex steady state and dynamic models with many uncertainties. Model imprecision affects how well we control the furnaces and distillation columns, and even more profoundly it affects our ability to perform the third and forth applications: run the plant near its constraints, and automatically optimize plant conditions and feed selection. Our current state of knowledge is so poor that we miss half of the incentives of throughput maximization. The remaining half still justifies the constraint control application, but that is not true for closed loop optimization. We simply do not have the kind of model precision required for closed loop optimization.

This being the case, perhaps we should concentrate on ways to improve our modeling techniques as opposed to installing closed loop optimizers.

CRACKING SEVERITY CONTROL IS THE MOST IMPORTANT APC APPLICATION

Ethylene cracker most important APC application is reaction severity control. The application manipulates furnace firing and to a lesser extent coil steam injection, to keep the extent of reaction constant without over or under cracking. The benefits of maintaining cracking severity at target are obvious:

- ⇒ Protecting against over-cracking increases the furnace run length.
- ⇒ Protecting against under-cracking increases production efficiency of the entire plant.
- ⇒ Keeping the furnace severity constant facilitates a stable operation of the fractionation train.

From the operator's point of view a good severity controller is worth its weight in gold. Without the severity control sophistication, keeping conversion high while protecting against overcracking is difficult. The operator would be forced to keep the feed steady, and even then there is no good way to cope with semi continuous furnaces. As gradual fouling proceeds, cracking severity changes even without a change of the cracking temperature.

In addition to the desire to operate the furnace correctly, our ultimate goal is to maximize throughput and optimize feedstock selection and severity. Good severity control keeps the cracking furnace under control while feed is ramped up or down. Poor severity control would render throughput maximization useless. Trade off logic between throughput and severity would fail; incorrect yield predictions would cause distillation columns to flood and products to be off purity specifications; overcracking would cause premature furnace shutdown, taking with it years' worth of APC benefits.

SEVERITY CONTROL REQUIRES BOTH A CRACKING MODEL AND TRANSFER LINE ANALYZERS

Severity is defined in several ways, depending on the nature of furnace feed. With ethane or propane feed, severity is simply the extent of conversion. With heavier feeds severity is defined as the ratio of methane to propane in the transfer line. Either way, the application must estimate furnace outlet composition. To some extent onstream analyzers can measure the transfer line compositions, yet analyzers are shared among several furnaces and that slows down the readings to once per hour, too slow for effective control. A model of the cracking process is necessary to make severity control successful.

For effective control the severity model must predict a change of composition as a function of steps in manipulated or disturbance variables: COT, coil steam, feed composition, coil flow, pressure and others. That requires a rigorous kinetic model of the reaction; not an easy task because each furnace is different in geometry, feed composition, and degree of coking, which calls for one severity controller per furnace.

Are rigorous kinetic models available? Many plants have kinetic cracking models for simple feeds: C2, C3 and sometimes C4. The composition of heavier feeds is so uncertain that our ability to validate models against production data is in question. The best models that companies have succeeded in developing for naphtha feeds are regression models with a fair degree of fidelity.

And even if we could develop perfect models, the models cannot be expected to precisely predict transfer line composition because:

- ⇒ Feed composition is never fully known.
- ⇒ Calculated residence times are off due to flow (and other) measurement errors.
- ⇒ Uneven distribution of feed in the coils.
- ⇒ With varying degree of fouling it is impossible to estimate the precise temperature, nor pressure profile of each furnace coil.

Are such model imperfections fatal? Figure 1 shows how severity controllers could work in spite of model imprecision. Once an hour the transfer line analyzer comes up with actual severity measurement. Then the application reconciles the yield model against analyzer readings. We have a chance to re-calibrate the models, factoring out the uncertainties. That would permit the application to work in spite of our less than perfect models.

Reconciliation logic is key to the success of analyzer feedback. The object of such feedback is not to simply bias the model but to come up with correct model gains: Delta Yields per Delta Manipulation (of feed, steam, COT, etc). The reconciliation rules must adjust a-priori assumptions affecting model gains to ensure model fidelity.

SEVERITY MODEL RE-CALIBRATION ISSUES

Being a consultant, I had the opportunity to audit a number of APC systems, and we found that in these plants cracking model reconciliation was a secretive custom logic. We would put up with that, recognizing the need for vendors to protect their technology, if only analyzer feedback correctly re-calibrated the model gains. But what we have seen was disappointing. The logic invariably failed to adjust:

- ⇒ Feed quality assumptions: H/C ratio and molecular weight.
- ⇒ Degree of fouling, and its affect on residence time and yields.
- ⇒ Coil mal-distribution assumption (perfect distribution is usually assumed).

As a result, model gains were off by about 25%.

Can such technology perform the severity control task? How would model inaccuracy affect the APC application? As it turns out, model imprecision affects the application in three important ways:

- ⇒ It forces de-tuning of the application. IE, the controller can perform severity control with an inaccurate yield model, but only if throughput adjustments are gradual. That gives the application more time, without straying too far, until the next analyzer reading becomes available.
- ⇒ We lose the ability to compare model against analyzer, and reject the latter if the discrepancy is high. We have to accept that occasionally, due to an analyzer drift, the control actions would be completely wrong. (We can normally catch abrupt analyzer errors, but not a slow drift).
- ⇒ In the face of modeling doubts we would do well to tone down our ambition to operate just below hard constraints. Knowing that constraint targets would be exceeded, we must specify soft constrains as operating limits.

OTHER ISSUES AFFECTING CRACKING MODEL ACCURACY

Besides model inaccuracies, there are two other common problems: analyzer reliability and erroneous instrument readings.

- **Analyzer reliability**

  Analyzers are expensive to buy and maintain, and are notoriously unreliable. To cut costs one analyzer would be shared among several furnaces. That implies automatic switching of many valves, timed correctly to permit sampling and analysis of each transfer line. Any one of the valves may leak or get stuck, and the analyzer would then give misleading readings.

  Another problem of sharing analyzers is the wide range of possible compositions from all furnaces. The analyzers are GC types, and their calibration is tied to the expected composition. A wide range of composition detracts from the analyzer accuracy.

- **Erroneous instruments**

  Model failures are frequently caused by erroneous instrument readings: orifice meters, thermocouples or pressure gauges. This type of failure is common because of the number of readings required by the model: about twenty measurements around the furnace. When reading so many inputs, the likelihood of one or more of them being wrong is high, especially in a coking, high temperature environment. Once a major input is wrong, no amount of kinetic sophistication would help. Yield predictions would be completely off.

Quality APC applications subject analyzer readings as well as all model inputs to checking logic, to trap large errors such as an unexpected jump in readings, but small errors or drifts are not easy to test for. The only remedy we know for this problem is a better severity model, where model and analyzer can be checked against each other.

DISTILLATION CONTROL MAXIMIZES PRODUCT RECOVERIES

We leave now the cracking control problem and move to product separation. Ethylene crackers separate the reactor effluent via a long distillation train: fractionator, demethanizer, deethanizer, depropanizer, ethylene splitter, and propylene splitter, to name a few columns. The columns feed each other and every disturbance in plant feed or furnace slowly passes through the train. Each one of the columns can create additional disturbances coming from their cooling or heating systems. Complicates the distillation operation is the fact that the plant is never at steady state, and that the severity application cannot precisely control reactor effluent composition.

Distillation APC applications manipulate column product draw rates and reflux (or reboiler) aiming to keep olefin products at target specifications, while maximizing their recovery. The benefits of this control application are:

- ⇒ Increased recovery of ethylene and propylene.
- ⇒ Reduced olefin recycle to cracking furnaces, thus increasing run lengths.

Without advanced distillation control operators would be forced to cut down olefin recovery rates as a way to keep product purities within specification. This is not a very satisfactory solution. To minimize recycling of olefins, the operator would try to keep the plant as steady as possible, hindering our ability to vary the plant feed and maximize throughput.

A typical two-product distillation control problem is shown in figure 2. Column feed, as well as each of the products, could contain several components. There are two manipulated variables: Product draw and reboiler heat duty. There may be onstream analyzers for measuring product compositions continuously, or - the laboratory may take measurements periodically. The column may have one or more tray temperature measurements. Column feed comes in from another piece of equipment, often an upstream distillation column.

The distillation control application must find a way to set reboiler heat duty and top product draw such that product compositions are steady at targets. This is a difficult control problem for a number of reasons:

⇒ Interactions between the top and bottom purities.
⇒ Slow dynamics of the columns, measurable in hours.
⇒ Nonlinear dynamic behavior, which changes with plant conditions.
⇒ Changing feed composition and flow makes distillation control a moving target.

Nowadays industry handles distillation control by multi-variable predictive control (MVPC) technology, which applies linear dynamic models for predictive control and decoupling in one algorithm, though this is only a partial solution. MVPC can deal with column constraints and analyzer feedback simultaneously, but this approach leaves out two significant issues: inferential feedforward and nonlinearity. These will be addressed in the following two sections.

SLOW ANALYZER NECESSITATES INFERENTIAL FEEDFORWARD

Distillation control that relies solely on analyzer feedback would have difficulties dealing with feed composition disturbances. A typical analyzer on a high reflux column responds in two hours to manipulation of distillate draw. The response to feed composition changes would be in the order of three hours. Such slow response makes analyzer feedback by itself ineffective. The controller would be oblivious to a feed composition disturbance for a number of hours; then it would respond by correcting the distillate draw. With the aid of a perfect dynamic model, product purities would come back to targets five hours after the disturbance had occurred. More realistically, such a disturbance might linger for over a shift. Throughout that shift, either product purities would be off specification, or olefins circulated to the furnaces.

Furthermore, most columns do not have a full set of analyzers. APC of such columns does not have a feedback option. The challenge here is to provide accurate control without relying on analyzers. If that is not possible the operator must resort to laboratory tests. IE, operation of the plant at steady state; then taking samples; then correcting column conditions; more steady state, more samples, etc. Our ability to maximize throughput would be completely lost.

How can distillation column control facilitate throughput maximization and cope with furnace start / stop disturbances? Inferential control is the only way. Inferential control models rely on column temperatures and other measurements, which quickly change in response to feed composition disturbances, thus providing information for the controller to counteract disturbances as they occur, instead of hours later.

ENGINEERING MODELS VERSUS REGRESSION MODELS

Industry has employed two kinds of inferential models: process engineering based models and regression analysis based models. While first principles engineering models are more difficult to develop, their performance in the field is superior. Our APC audits have encountered many failures of regression based inferential models, and almost no successes. We include in this assessment neural net packages, which also contain a regression analysis machine. The only models we have seen working, after the implementers had left the site are first principle models.

We would like to address this wide spread failure of regression models, because they still enjoy an undeserved degree of popularity. Their lack of success stems from several insurmountable fundamental problems.

A) Regression models require large volumes of lab data.
The vast amounts of data needed to develop a statistical correlation cannot come from high quality test run data, and the regression machine must input every-day lab data. Commonly, a small percentage of the data is directionally biased, and then there is no possibility that the resulting correlation would be reliable.

B) Much of the time units work to a fixed product quality.
Normal day-to-day operation doesn't provide enough movement in the data to give meaningful information. We all know how to conduct factorial designs for reliable regression. The common ways of developing regression based inferential models is in conflict with factorial design theory.

C) There is no replacement for chemical engineering.
Regression or not, the measurements must still be in a correct location to "have the information in them". First principle models cannot be developed based on incorrect set of instruments; a sensitivity analysis would reveal any inadequacy of the input set of measurements. But there is no such restriction on regression models. Ignoring the need for process engineering analysis replaces knowledge by luck, and cannot be very successful.

D) Regression requires independent inputs.
Regression theory requires all inputs to be independent. That is not possible with normally measured process data. For example temperature measurements on a distillation column typically all go up or down together. Correlating dependent input data puts the model validity in question.

E) Engineering models provide the means for checking instrument errors.
Given incorrect input data, the engineering model simply cannot give a reasonable result, and it would show a discrepancy between model and lab test to highlight the errors. On the other hand regression models do not discriminate between good and bad data.

Friedman (1) and Kesler - Friedman (2) detail two examples of first principle models. The former is based on process engineering shortcut methods, whereas the latter is a rigorous tray-to-tray model. Both approaches address the problem of identifying feed composition changes, and correcting column reflux and product draw to keep the product purity constant.

DYNAMIC NONLINEARITIES FORCE CONTROLLER DE-TUNING

MVPC's are sensitive to the accuracy of their dynamic models. They work well when models agree with actual plant responses. On the other hand, distillation processes are nonlinear, changing their steady state gains and dynamic behavior with operating conditions. These are not small changes. Ethylene versus propylene yields is dictated by choice of feed and severity, and the ratio of these two products may vary by a factor of two. MVPC controllers with fixed dynamic models must be de-tuned to cope with varying real dynamics. Detuning makes the controllers sluggish and the APC application can no longer move quickly and gracefully near constraints.

What can be done to reduce the effect of nonlinear controller behavior? There are accepted conventions for linearizing the steady state part of the distillation model via variable transformation. As an example controllers can use not the composition itself but a logarithm of composition. In the same way output transformation can factor out the effect of nonlinear valve behavior.

But these steady state transformations cannot deal with dynamic effects of changing composition. Control engineers have argued with us that in an industrial setting the dynamic variations are not substantial enough to attempt a solution to this problem. We do agree that other problems do carry higher priority and urgency, but as we name all of the problems we encounter in ethylene plant control, this is one of them.

Perhaps we have come to put up with detuning of distillation controllers as a way of life, but one should remember that control is slowed down not to cope with the average model but to cope with the worst model, and this is often too slow. Slow control forces operators to reduce olefin recovery targets and permit some recycle of olefins to the furnaces. Take for example an ethylene splitter. What should be the content of ethylene in ethane? Ideally perhaps 1%, but in practice the operator may set the target up to 3% to protect the more important ethylene product at the top of this column. How else could the operator keep the ethylene product from going off spec as yield and throughput drift, the prediction of those drifts lacks accuracy, and control actions to correct the column operation are too slow?

Recently there has been a trend of relying on larger MVPC's, combining several columns into one control problem. In our own experience this forces even more de-tuning than necessary, to cope with the least accurate model of possibly a not so important column. Some knowledgeable voices inside vendor companies do not agree with the large MVPC trend (7), but their influence so far has been minimal.

Is there a way to automatically adjust the dynamic control model of the MVPC controller and avoid de-tuning? To do that the control application must estimate gains and dynamics of the response, and change the MVPC model "on the fly". Not all MVPC software products can take model changes while at the same time continuing to manipulate the control handles, but some do. Of the two references discussed above, the Friedman method (1) permits accurate calculation of model steady state gains. Just changing the MVPC gains improves the closed loop response dramatically. The Kesler – Friedman approach (2) affords an even better solution, applying rigorous tray-to-tray dynamic simulation to estimate the complete dynamic model.

INSTRUMENT AND ANALYZER RELIABILITY ISSUES

As in the case of modeling the cracking severity, erroneous instrument readings adversely affect distillation control. Inferential calculations, which typically input dozen or more readings, may fail with any incorrect input. If we combine the number of readings required by all inferential calculations, the likelihood of one or more of them being wrong is high. The only way to deal with this issue is by additional logic for checking the input signals on two levels; first by comparing individual measurements against reasonable engineering and velocity limits; then by checking patterns of measurements.

Regarding analyzers, most MVPC's operate under the assumption that analyzer readings are more accurate than inferential calculations. They bias the inferential model to force long-term agreement between model and analyzer. That is not necessarily a correct approach. Analyzers can fail in undetectable ways such as drifting slowly. When constructing logic to check patterns of measurements, analyzer readings should be a part of the pattern.

To our knowledge only the Kesler - Friedman approach (2) compares instrument reading patterns against a rigorous tray-to-tray model. The inferential method works by comparing key instrument and analyzer readings against a rigorous model prediction with an assumed feed composition. To the extent that there is a discrepancy, the inference logic adjusts column feed composition to improve the agreement until it finds the most probable feed (and product) compositions. Outlier instrument or analyzer readings, which cannot be explained by modifying the assumed feed composition, are taken out of the inferential formulae and ignored.

We have not seen an equivalent approach anywhere in the plants we audited, and our suspicion is that pattern checking is simply not done.

THE INFLUENCE OF INACCURATE MODELS ON THROUGHPUT MAXIMIATION

Constraint control is a technique for nudging a manipulated variable, in our case usually a pre-selected feed, until bottleneck equipment is at its constraint. It is a form of optimization, except in the industry jargon “optimization” means the use of steady state simulation and economic models, running once every several hours. We deal with such form of optimization in the following section. Constraint control relies on dynamic models and it runs every two or three minutes. The controller can have more than one manipulated variable, for example several furnace feeds and/or furnace severities, with priority logic as to which one is to be manipulated first, but the logic is simple and does not automatically conform to market economics.

Feed changes influence the plant over time, from minutes on the furnaces to hours on distillation columns. To avoid overshooting constraints we employ dynamic models, describing the effect of severity and feed changes on columns and compressors. The ideal constraint controller would detect any situation leading to future violation of constraints, and take action, modifying throughput or severity to gracefully approach the constraint instead of violating it.

That necessitates first good steady state predictions: cracking yield models and inferential distillation models. Second, reasonable dynamic models to time the constraint loading and relieving actions. We have discussed the difficulties of obtaining such models. Severity models are only approximate, with model gain errors of about 25%. Distillation inferential models are problematic industry wide, and distillation dynamic models are usually empirical and not corrected for real operating conditions. Upon making a feed change to any of the furnaces we would be lucky to predict its effect on cold section constraints to ± 30% accuracy.

What are the consequences of inaccurate models? Being in danger of overshooting the constraints, we must protect plant equipment in two ways:

- ⇒ De-tuning the application, allowing only gradual throughput adjustments. That slows down the speed of approaching constraints, and gives the model more chance to correct itself by feedback, and reduce the inaccuracy from 30 to about 10%. The model is still incorrect and overshooting would occur, but not by much.
- ⇒ Slowing down feed manipulation affects the applications ability to quickly cut down feed to relieve constraints. We accept that the relieving action would operate slowly and in the mean time constraints would be violated. If the plant were at steady state we could, to some extent, overlook the slow response and inferential model inaccuracy, but in ethylene plants, operators cope with slow response and inaccurate feed forward by setting conservative constraint targets.

An operator can operate the never-constant olefin plant at possibly 90% of ultimate throughput, whereas a perfect constraint control application could perhaps hold the plant at 96% of ultimate throughput. We estimate that a perfect application could only reach 96% because of the unsteady nature of the plant and because instruments and analyzer would continue to occasionally fail. In financial terms, that incentive of 6% throughput increase is very large, giving the plant more capacity with minimal investment. However the 30% prediction errors precludes us from taking advantage of the full potential of the application. The de-tuned application, working to meet a reduced set of constraints, could reach only about 93% of the ultimate plant capacity. Half the benefits are lost because of model imprecision.

While the increase of 3% capacity handsomely justifies a throughput maximization application, we would do well to try to improve severity and distillation modeling to approach the potential value of 6%.

MORE ON THE ETHYLENE PRODUCTION OPTIMIZATION PROBLEM

Ethylene plants typically receive several feeds. Certain feeds are economically more attractive because they produce a more desirable product pattern. The feed allocation economy calls for consuming first all the inflexible feeds, then the most economical feeds, and then “swing” feeds. One or more swing feeds are to be maximized, subject to furnace or separation constraints. These constraints can be traded off however. Altering severity, selectivity or feed selection can modify furnace or downstream equipment loads. Choice of feed or severity also affects furnace fouling and run length, which is of course an important factor in determining the average plant throughput. Further, in the separation section, reducing reflux and accepting lower recoveries of certain products can relieve distillation or compressor constraints.

On paper – optimization of the ethylene plant in closed loop is attractive, but in practice solving the feed allocation problem in closed loop has not been very successful. Having witnessed a number of failures in this field I published a paper (3), discussing the problems and what it takes to make optimization work. While modeling problems reduce our ability to maximize feed against constraints, the incentives are not completely wiped out. But in the case of closed loop optimization, the technology is simply not here yet. In response to my paper, other authors (4, 5 and 6) have begun to address the difficulties of applying real time optimizers. Following are three of the main reasons for failing to achieve the promised financial benefits.

- **Modeling difficulties**

  Optimization of feed allocation and production requires a detailed simulation of the entire plant, including all furnaces, heat exchangers, distillation columns, compressors, certain pumps, etc. This simulation, in addition to predicting very accurately the result of any process change, must automatically adapt to the equipment configuration and economics of the day. We have discussed how difficult it is to construct a cracking model to cope with unknowns such as feed composition, precise coil temperature profile and mal-distribution of feed among the coils. Plant wide optimization is much more difficult because the simulation is much larger than one furnace, and accuracy requirements are more stringent. Cracking severity controllers would achieve excellent results with prediction inaccuracy of 10%, but optimization routines, which rely on first and second derivatives, would be misled into giving the wrong result. The accuracy required for mathematical optimization is in the order of ±2%, which does not seem feasible.

- **Furnace run length prediction**

  We single out the furnace run length prediction because it is not needed for severity control, and was not addressed in our discussion of cracking model difficulties. One of the most difficult values to predict and verify is furnace fouling rate. Also, one of the most important optimization parameters is furnace fouling rate. It is important because throughput increases may, through distillation constraints, cause an increase of olefins in furnace feed, and shortening of furnace run length. If that shortening is insignificant, throughput increases are justified, but if run length shortening is substantial, the throughput increase becomes very temporary, and in fact on average it would be a throughput reduction. In the author's opinion we do not have enough precision in our models to distinguish between these two cases and are in danger of implementing a counterproductive application.

- **Steady state models in a dynamic environment**

  Before optimization takes place any model must be reconciled against current plant measurements. The reconciliation process involves changing certain a-priori assumptions to re-calibrate the model on-line. Reconciliation is a very basic requirement, because optimization cannot begin before model and instruments are in agreement, or at least the reason for disagreement is known.

  Present day optimization models are based on steady state simulation whereas the measurement data is dynamic. Tests are employed to check for steady state conditions, but as we discussed, ethylene plants are never at steady state. We can only test for "approximate" steady state and there is a danger of again misleading the optimizer. The only way to obtain a set of steady state measurements is via dynamic models for predicting the ultimate steady state value of measurements, but even then, our ability to come up with dynamic models of the required accuracy is questionable.

Can we ignore the three issues above and still go ahead with an optimization program? Judging by the number of persons who claim to have succeeded in this task – yes. Judging by the theoretical difficulties expressed in this paper – no. One can always solve a mathematical set-up and come up with a set of numbers, but proving that those numbers actually improve the plant economics is another matter.

What then is a practical way to optimize the production? In our opinion it is best to simplify the problem by pre-selecting trade-offs. Determine optimal severities, olefin recovery targets and swing feeds. Then apply constraint control techniques to maximize the swing feeds against constraints. The plant scheduler, after consultation with engineers, maintenance supervisor, operations supervisor, and possibly a simulation program, would make the trade-off decisions.

What have we gained by moving the optimizer from the closed loop environment into the off-line environment of the scheduler?

- ⇒ Money, about $3,000,000 for not setting up such a complex application.
- ⇒ Manpower, two engineers who would be dedicated to keep the models and economics updated.
- ⇒ Scheduler control of decisions that are not simply mathematical but also depend on equipment conditions, maintenance schedule, furnace cleaning schedule, etc.

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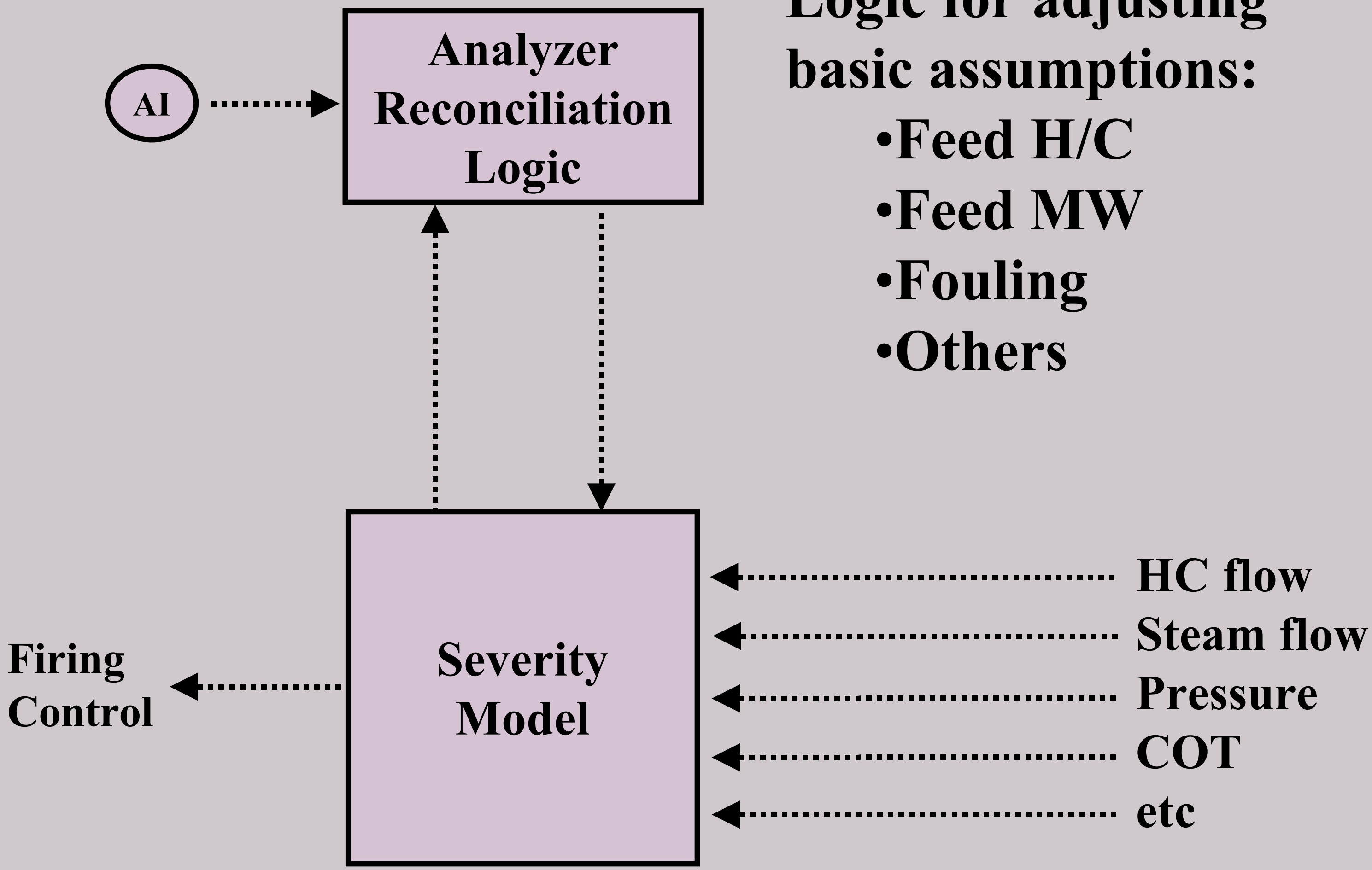
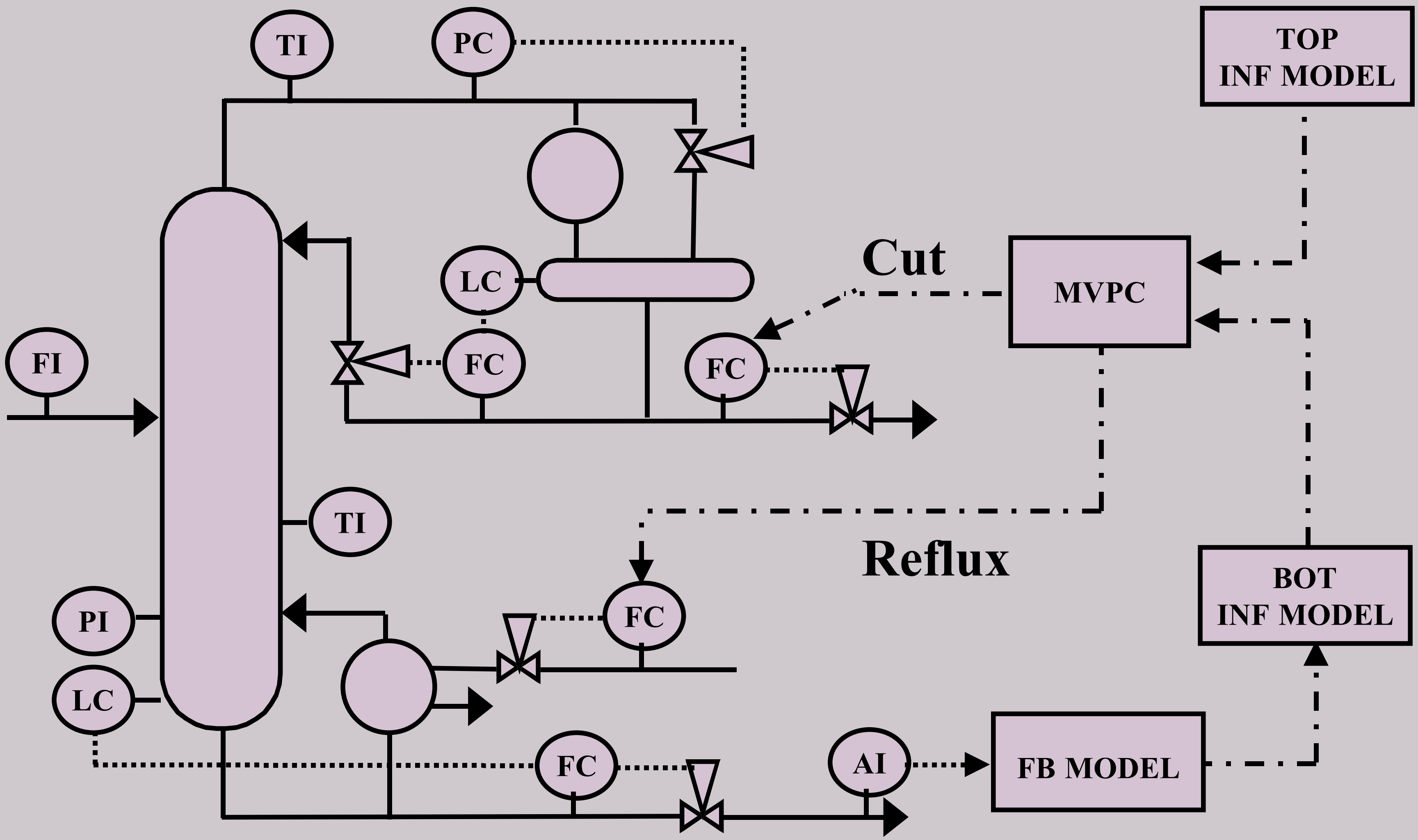
Fig. 1. Severity control with analyzer feedback



Logic for adjusting basic assumptions:

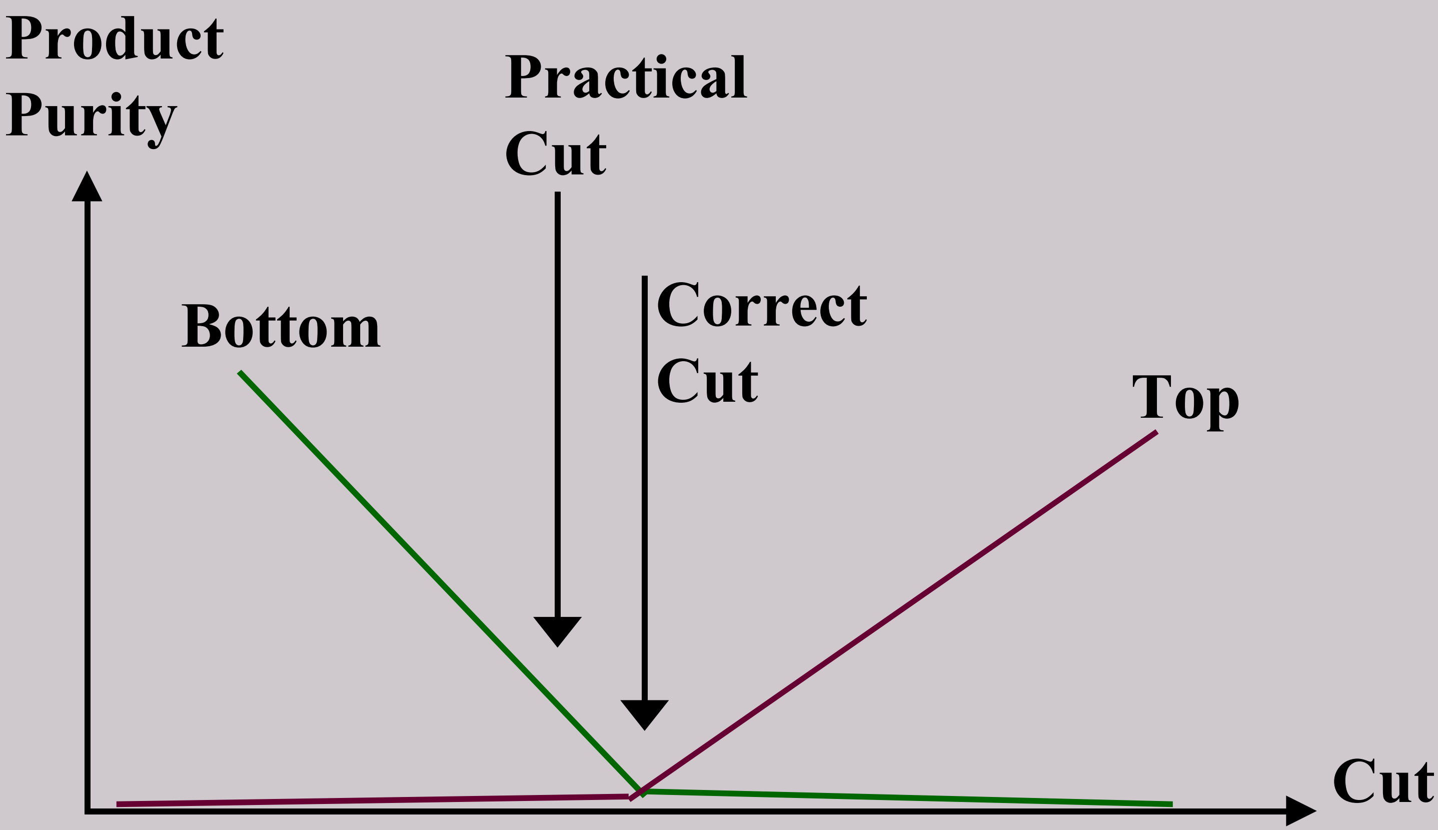
- Feed H/C
- Feed MW
- Fouling
- Others

Fig. 2. Distillation control example

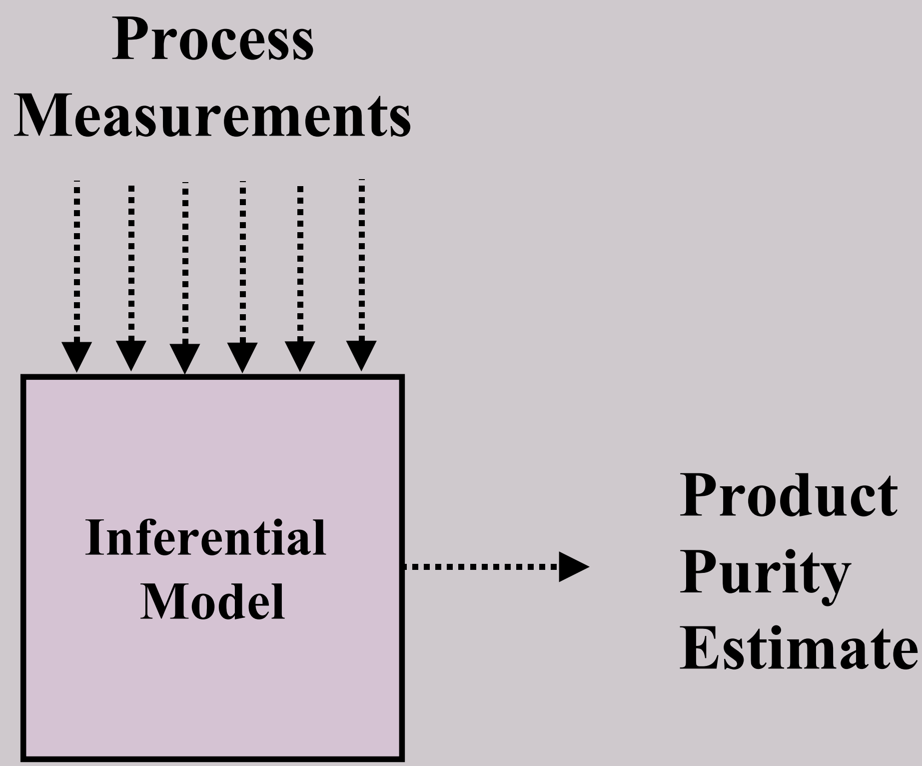


PetroControl

Distillation control problem
Loss of Olefin Product



What is an inferential model?



Response to feed Composition change