Furnace Optimizer in a Naphtha Cracker

Hitoshi Shindo
Maruzen Petrochemical
3, Goi Minami-kaigan
Ichihara-shi, Chiba 290-8503 Japan
Hitoshi-Shindo@chemiway.co.jp

Kheng Lau and Ryuji Kaneko
Aspen Technology, Inc.
1293 Eldridge Parkway
Houston, TX 77077
Kheng.Lau@aspentech.com
Ryuji.Kaneko@aspentech.com

John S Ayala
Applied Manufacturing Technologies
3200 Wilcrest Drive
Westchase III Suite 400
Houston, TX 77042
John.Ayala@applied-mt.com

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Abstract

With changing availability and prices of feedstock as well as changing product demands, many operating olefins plants have to keep searching for the most optimum way of running their unit with several key constraints active. Rigorous real-time closed loop optimizers have been accepted by many operating olefins plants around the world as the preferred automation enabling application for optimizing the operations of the plant working in unison with advanced controllers. Depending on the plant constraints, the skill set of the engineers, the availability of technical resources and various other key factors, one has to make a decision on the economic viability of the rigorous plant wide optimizer. There have been only a few running optimizers reported where the furnaces are modeled rigorously and the rest of the process is modeled with component splitters. A furnace optimizer has been implemented recently at the world-scale naphtha cracker of Keiyo Ethylene in Japan. The optimizer has been able to move furnace severity to maximize propylene production while honoring many key plant constraints and a target ethylene production rate. The optimizer runs at a much higher frequency than a typical rigorous plant-wide optimizer. Hence, the optimizer can respond to naphtha feed composition changes much faster than a rigorous optimizer. Benefits and implementation issues will be discussed in this paper. With over capacity of ethylene, many olefins plants are trying to operate in a mode where propylene production rate is maximized. The simplified backend furnace optimizer offers a very attractive alternative in maximizing plant profitability.

Introduction

Using rigorous first principle process models to optimize the operation of olefins plants has been applied successfully at various operating plants worldwide. These optimizers play an important role in maximizing the profitability of the plants. The majority of these optimizers use SPYRO from Technip to model the cracking coil and the rest of the process is modeled using readily available rigorous models from the simulation software. These optimizers also use equation-based modeling technology. The typical size of such a process model representing a liquid cracker is well over 150 thousand equations and the number of non-zeros in the Jacobian matrix is about 2 million depending on the number of furnaces and components used in various sections of the process model. During the optimization cycle, two cases are typically solved; the first case is to tune the model to match the current operating conditions and the second case is the actual optimization case starting from the tuned process model. A model of this size took about an hour to complete the whole cycle with a very high end OpenVMS server five years ago. In the past 2 to 3 years, many optimizers were implemented with PC as the main computing platform. Also, the speed of the processor continues to improve dramatically. With a high end PC today, the optimization cycle can be completed in about 30-40 minutes depending on problem size. One main benefit of using the PC as the computing platform is the cost of the hardware. The cost of the hardware is not a significant fraction of the total cost of the optimizer anymore. However, the total cost of such an optimizer is still a significant investment.

One important task that has to be continued to achieve the economic benefit of the system is the maintenance of the optimizer post commissioning in order to maintain a high service factor. The maintenance work can take between 20 to 40 percent of a process engineer's time depending on the robustness and offline application of the model. The process engineer who was involved in the original optimization project typically performs this task. To be able to work with the optimizer effectively, several key skills are needed. These are as follows:

- Familiarity of the actual process and the control configuration (basic and advanced)
- Understanding of the process model representing the plant
- Familiarity of equation-based technology and the solver used to solve the equations
- Understanding of the modeling software
- Understanding of the online closed-loop configurations and how the optimizer interacts with the advanced controller

During commissioning of the optimizer, the project team typically strives to push the online model to the highest state of robustness possible by building many validity checks on key process tags that are brought in from the DCS or plant historian to fit the model parameters. In addition, for plants that can process various feed types, there may be a need to build initialization files so that the model can move from one feed scenario to another without any human intervention. The online model needs to be as robust as possible in order to maintain a high service factor thus delivering benefits to operating plants.

Furnace Optimizer

The concept of a furnace optimizer is not new. There have been a few such optimizers implemented around the world. Most of them were employed in gas crackers. The reported results were good and the furnace optimizer definitely delivered economic benefits to the plant. The furnace optimizer essentially only optimizes the furnace severity/conversion due to the rigor of the modeling approach taken. For the furnaces, SPYRO is used to represent the cracking coil. For the rest of the plant, only simple flow splitters, component splitters and mixers are used in the process model. Hence, the model only performs material balance for the plant sections after the furnaces. In addition to the material balance, key constraints of the process that are not captured by the process model have to be represented in the optimizer. The linear gain model from the advanced controller (DMCPlus) is typically used to capture such constraints. Since simplification is needed in implementing furnace optimizer, there can be several variations of the furnace optimizer. That is, the rigor of the model after the furnaces can vary from one optimizer to the other depending on the key active constraints.

Keiyo's olefins plant is furnace limited during decoking and back end limited with all furnaces in operation. This plant is the largest and one of the most modern olefins plants in Japan. The primary feedstock is naphtha. The naphtha composition changes regularly. Hence, there is a strong need for the automation of setting furnace severity while running the backend of the process as close to the process constraints as possible. With the demand of ethylene and propylene changing so rapidly, the plant quite often runs in maximizing propylene mode while maintaining a certain desired ethylene production rate. However, the plant can be backend limited if all of the furnaces are online. Keiyo decided that significant benefits could be captured by implementing a furnace optimizer.

For the furnace optimizer implemented at Keiyo Ethylene's olefins plant, SPYRO was used to model the cracking coil. The rest of the process was represented using simple component and flow splitters, mixers and linear gain models from DMCPlus. As one of the key initiatives in improving the plant profitability, DMCPlus and Feed Maximizer technology from Aspen Technology were implemented providing the backbone for implementing the furnace optimizer. DMCPlus is a multi-variable controller software package and Feed Maximizer is the composite linear program that combines all of the key DMCPlus controllers to maximize the feed to the furnace while honoring all of the key constraints in the backend of the process. More information about these technologies can be found in several papers published in the literature. For the furnace control, SPYRO was also used to predict furnace severity. For the naphtha feed, there is an online analyzer providing a carbon number based PINA composition of the feed. This is obviously very important; otherwise, there is no point in using SPYRO to predict furnace severity since the feed composition affects the furnace cracking prediction directly. The principle of garbage-in-garbage-out still applies. Although furnace effluent analyzers are present, they are not used to update the model in a closed loop fashion. The overall structure of the system is shown in Figure 1. A+ Optimizer is the equation-based environment within the standard AspenPlus modeling tool. This is the modeling tool that was used to implement the furnace optimizer. The optimizer is a layer on top of the advanced controller.

Implementation Details

While the controller was being implemented, the process model needed to implement the furnace optimizer was developed. It is very important that both of the SPYRO models (control and optimization) use the same furnace tuning parameters. Since the problem size of the furnace optimizer was very small compared to a typical full-scale rigorous optimizer, the optimization cycle could be completed in less than 5 minutes using a Pentium 3 processor running at 1GHz with 1GB of memory. The furnace optimizer has about 15 thousand equations. Averaged values of process tags for all of the furnace related process measurements were used. For the backend of the plant, the steady state predictions from DMCPlus linear program were used as measurements as shown in Figure 1. Since the furnace optimizer was configured to wait for only 30 minutes after implementation of new targets, it was not possible to see the changes in the backend of the process if the actual process measurements coming from the backend of the plant were used. Also, using the DMCplus steady state predictions allowed the typical steady state check which starts the optimization cycle to be tuned very loosely. The optimizer was able to send more than 40 solutions a day to the controller. During the commissioning of the furnace optimizer, findings indicated that it was imperative to include feed forward effects to the backend process variables for changes in furnace severity in the controller; otherwise, the feed maximizer would cut too much feed and put the feed back again later. Also, since the furnace optimizer ran at a much higher frequency compared to a rigorous optimizer, if there was any inconsistency between the controller and the optimizer, the problem would manifest itself quickly when the optimizer was switched on. This was particularly true as the plant was approaching the critical constraints.

Besides being consistent in process active constraint prediction, the behavior of the optimizer must be consistent with the feed maximizer as well when increasing or decreasing coil outlet temperatures. The coil outlet temperature effects of different furnaces were balanced in the optimizer just like the feed maximizer. That is, coil outlet temperatures were increased or decreased in groups. Also, the optimizer was configured to cut feed as well when key constraints were violated because the feed maximizer would do the same thing. Feed rates to furnaces were also balanced the same way the feed maximizer managed the furnace feed rates.

Results and Discussions

The furnace optimizer delivered the nonlinear trade-off between severity and yield while honoring the key constraints in the process. The feed maximizer alone could not deliver the nonlinear trade-off benefit since it was solving the linear problem. In addition, the combination of the furnace optimizer and the feed maximizer allowed more constraints to be pushed simultaneously. The feed maximizer alone can only adjust feed rates. The severity adjustments provided by the furnace optimizer allowed more benefits to be achieved. Also, since the furnace optimizer ran at a higher frequency than a typical rigorous plant wide optimizer, it was able to respond to feed composition changes quickly. If the optimizer was switched off, one would see that the operators were much more conservative in setting the furnace severity while pushing the plant constraints during naphtha tank swap.

The furnace optimizer required much less engineering effort in configuring the process model than a typical rigorous plant wide optimizer. Also, the process model can be upgraded to a full-scale rigorous optimizer as the need arises on a step-by-step approach. This makes it possible to balance the implementation cost and the potential benefit. The offline benefit of the furnace optimizer is clearly limited compared to the one delivered by a rigorous optimizer. Findings also indicated that the furnace optimizer requires much less maintenance since most of the process models are splitters and mixers. The overall process model obviously has less complexity due to simplification of the separation sections of the process. Very few convergence problems were encountered during the commissioning of the optimizer.

Since the furnace optimizer used the controller gain model in predicting backend constraints and the steady state prediction of backend process variables were used in the furnace optimizer model as measurements, it was very critical that the controller gain model was accurate. For instance, if the steady state prediction were cycling, the move calculated by the optimizer would cycle as well. As mentioned earlier, the furnace optimizer ran at a higher frequency than a rigorous plant-wide optimizer. These cycling problems would have shown up quickly if they did exist during commissioning. Due to the tight integration between the furnace optimizer and the controller, experience shows that it is critical that both the advanced control team and the optimization team to be at the site at the same time during commissioning.

Figure 2, 3, 4 and 5 have about 3 days of operating data at Keiyo ethylene plant. All figures cover the same period of plant operations. During that period, the furnace optimizer was switched on. The furnace severity used in the figures is the effluent propylene to ethylene (P/E) ratio. In light of confidentiality, plant naphtha feed rate, ethylene production rate and P/E ratio were scaled using typical nominal value. The plant had 10 furnaces running initially and one furnace was brought down for decoke at the end of operating data shown. There were two feed naphtha composition swaps in the data as shown in Figure 4 where naphtha specific gravity increased twice. Figure 2 shows the severity adjustment made by the furnace optimizer when the plant was approaching the DC5 feed constraint. When there was no room in the DC5 area, the furnace optimizer reduced the P/E ratio to maximize ethylene production. As indicated in Figure 2, the high limit of the DC5 feed was raised. The furnace optimizer immediately took advantage of the extra capacity by increasing P/E ratio to maximize propylene production and hence pushing more gasoline feed to DC5 column. Figure 3 shows the charge gas compressor (CGC) power as the furnace severity was adjusted by the optimizer. Looking at both Figure 2 and Figure 3, it was clear that the optimizer moved the plant to approach both the DC5 feed constraint and the charge gas compressor constraint. Ethylene production is shown in Figure 4. When the plant was approaching the DC5 feed constraint, the furnace optimizer increased ethylene production by reducing P/E ratio while maintaining the plant at or close to the DC5 feed high limit. Plant total naphtha feed is shown in Figure 5. Working with the CLP, the total feed naphtha was maximized while the backend constraints (DC5 feed and CGC power) were active. Also shown in Figure 5 is the total charge prediction from the furnace optimizer and the actual total charge. The optimizer prediction agreed with the actual charge quite well. This illustrates that the optimizer's prediction on backend constraints was very good and the prediction was consistent with the control (DMCPlus). The prediction of two major backend constraints was shown in Figure 2 and Figure 3. DMCPlus' steady state prediction and the optimizer prediction were very close to each other. This is a key factor in the success of the furnace optimizer guiding the plant successfully to its constraints. During the period of 10-furnace operation, the plant was either very close to or at both the DC5 feed constraint and the charge gas compressor power constraint. When a furnace was brought down for decoke, the plant was furnace limited. Then, the furnace optimizer increased the P/E ratio to increase the yield of propylene.

Conclusions

The furnace optimizer was implemented successfully at a naphtha cracker. There is an upgrade path for the optimizer as the need arises to include more rigor in the backend of the process. The payback of the implementation cost for the optimizer is very good even in today's investment requirements demanded by many manufacturing companies. For olefins plants that have many feed changes and are operating against back end constraints strongly affected by cracking severity, the furnace optimizer is an attractive option to consider. The furnace optimizer was able to capture more than 80 percent of the potential benefits of applying rigorous online optimization associated with severity adjustment. These benefits were captured with a significantly lower implementation cost and maintenance requirement. The furnace optimizer was not able to capture energy conservation benefits due to the simplified models employed for the recovery section of the ethylene plant.

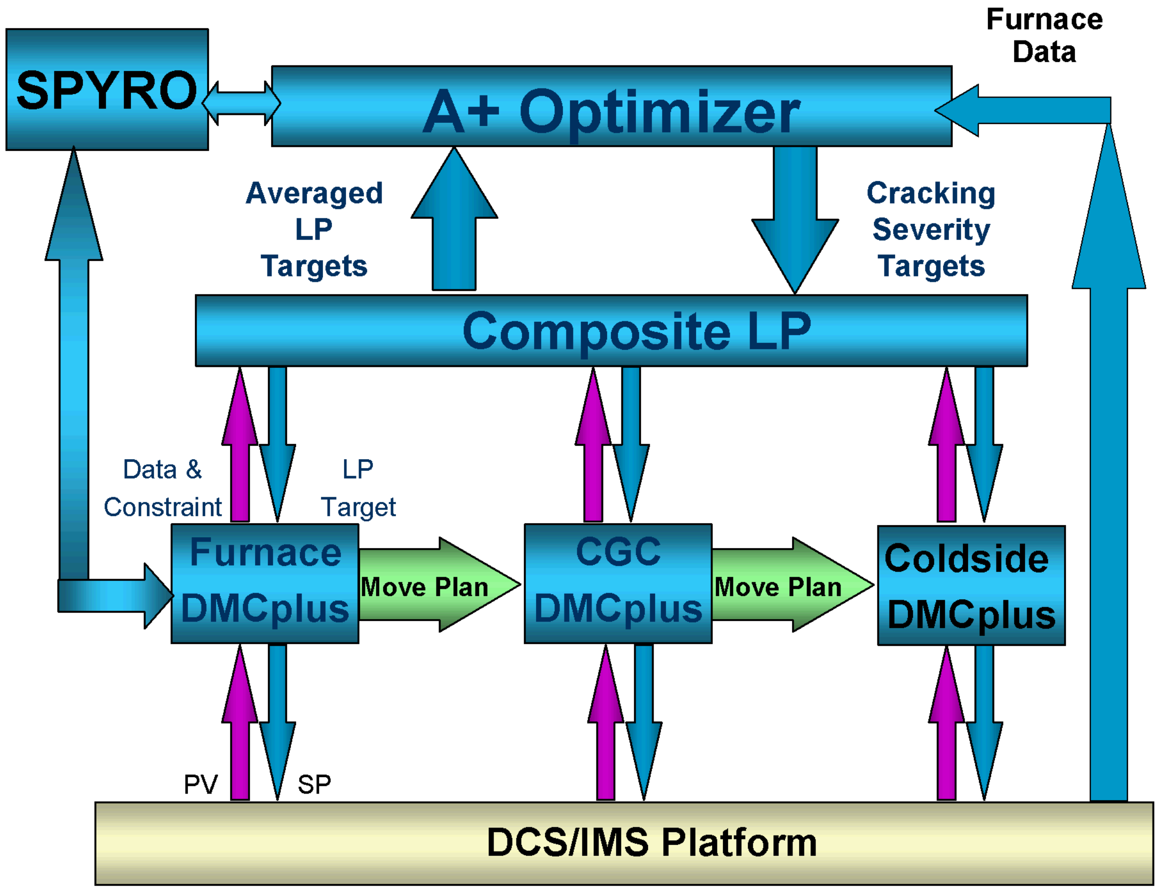

Figure 1 Overall Structure of Furnace Optimizer

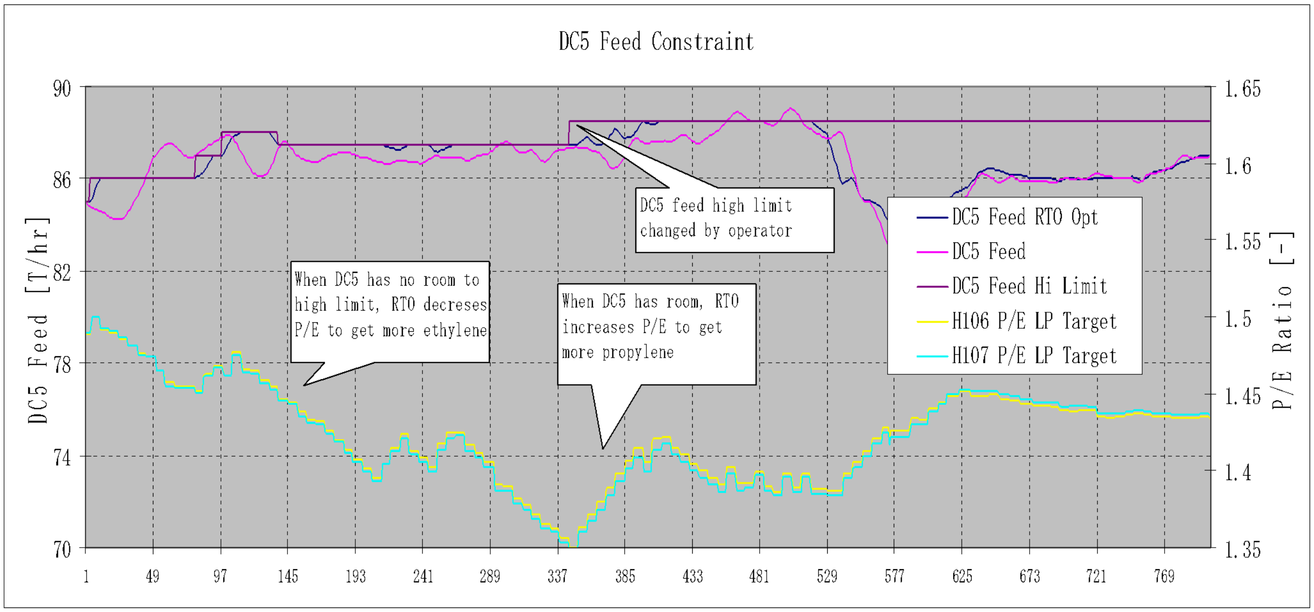

Figure 2 DC5 feed constraint and furnace severity

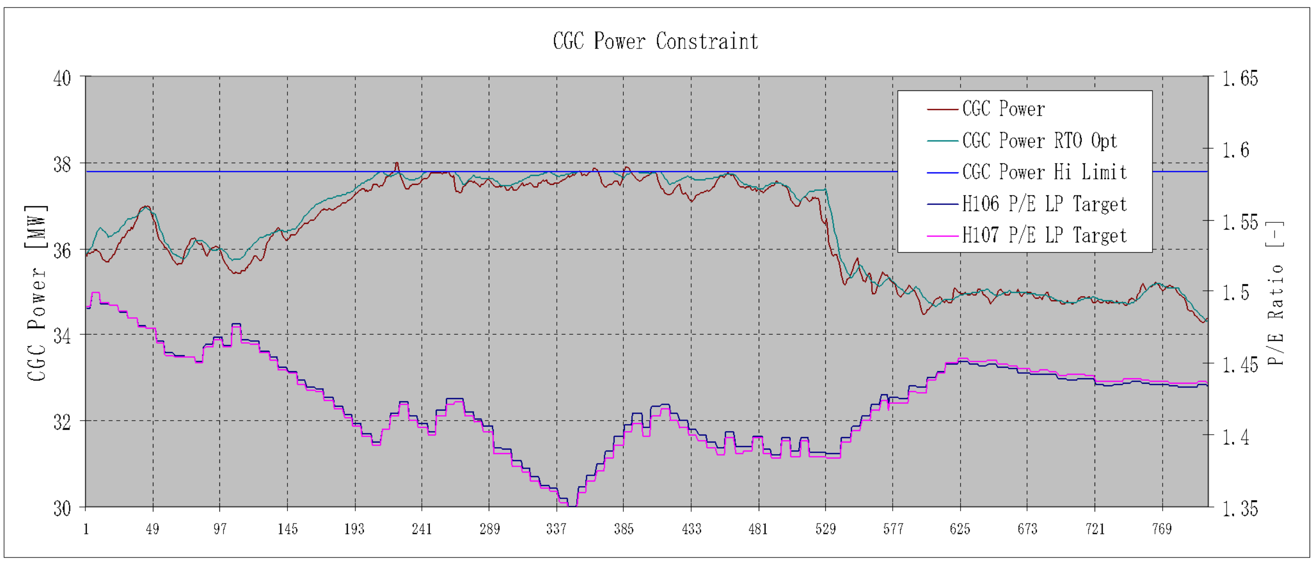

Figure 3 CGC power constraint and furnace severity

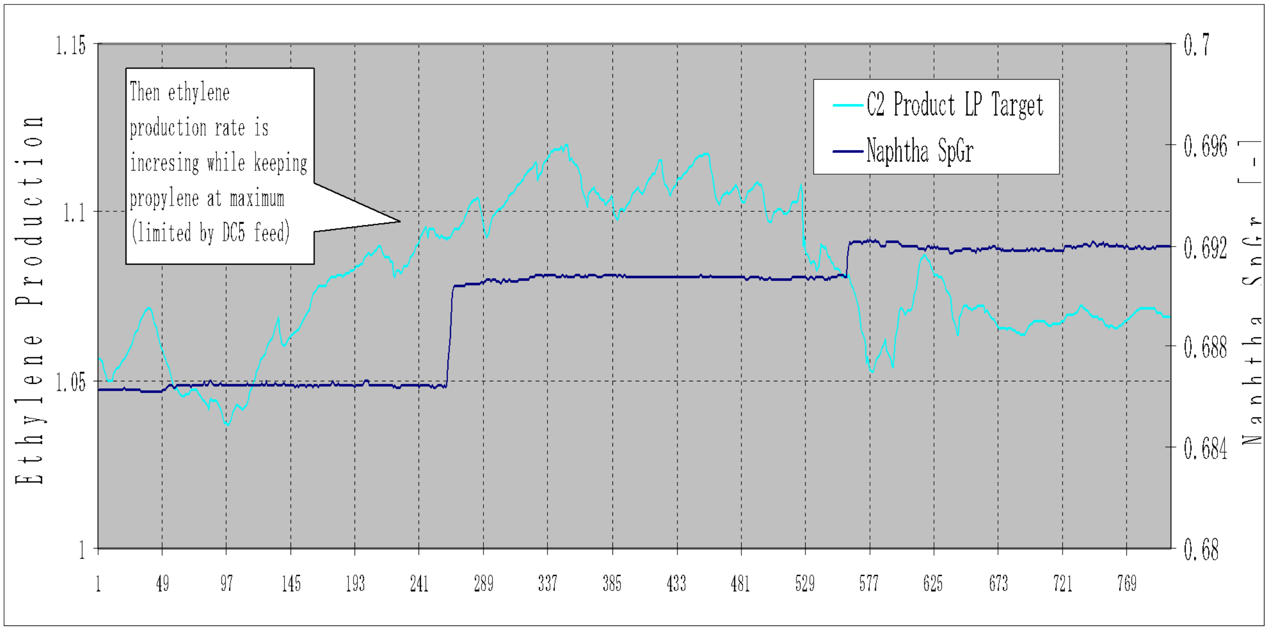

Figure 4 Plant ethylene production and feed naphtha specific gravity

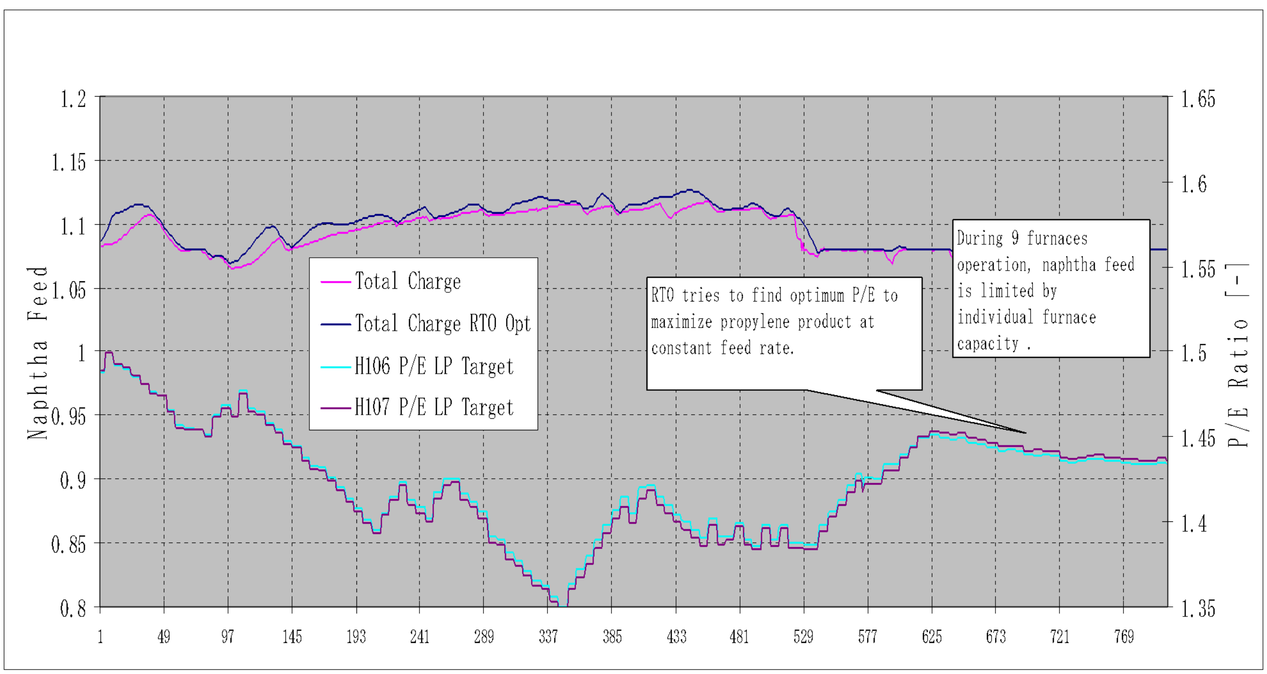

Figure 5 Total plant naphtha feed rate and furnace severity

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