HYDROCARBON PROCESSING®

Increase VCM output

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Using multivariate statistical techniques, this VCM operator raised productivity by more than 10% without revamping cracking furnaces

Keywords:

Polyvinyl chloride (PVC) is one of the core plastics manufactured in the Asia-Pacific region. However, environmental issues relate to this polymer's production have caused investment withdrawal from the global PVC marketplace. As the PVC market in Asia continues to expand, vinyl chloride monomer (VCM) demand is rising dramatically. Consequently, one of the greatest challenges now facing plant engineers is to raise the productivity of PVC and VCM plants.
PVC is made from VCM, which is produced by cracking EDC (1,2-dichloroethane) in a furnace tube around 500°C. The typical VCM production flow diagram is shown in Fig. 1. Recently, considerable bottlenecking and revamp efforts have been done to produce more VCM and improve plant safety. The VCM process is highly hazardous; it uses hydrochloric acid (HCl) and chlorine derivatives. When improvement ideas are suggested, it is difficult to apply them to real processes because crucial unexpected results may occur.

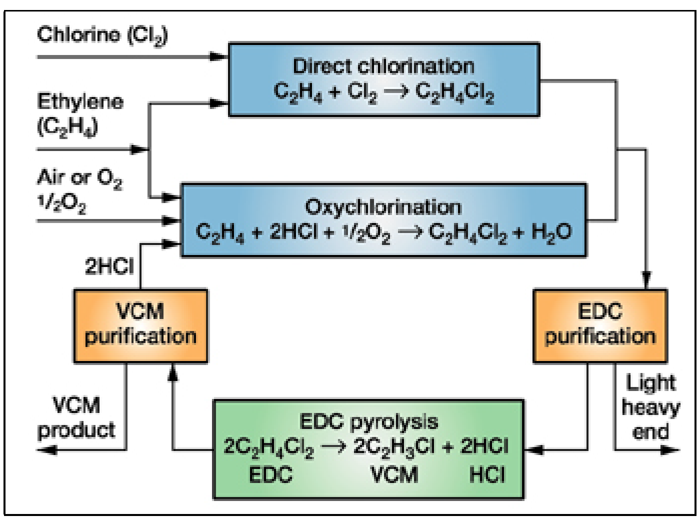

Fig. 1. VCM process flow diagram.

Optimization options. Several optimization attempts have been focused on VCM furnaces. EDC cracking furnaces (VCM furnaces) are critical equipment, which can affect the entire process, especially VCM purity. Since PVC process operation depends greatly on the VCM purity level, quality control is very important to ensure the highest quality VCM supply for PVC manufacturers. However, to increase productivity, appropriate operational changes for furnaces are inevitable. Therefore, the most important part of this project was to discover the relationship between productivity and VCM purity.

Temperature distribution along the furnace tube is strongly related to the EDC cracking rate. If the tube temperature rises, then the EDC cracking rate increases. However, temperature rise also induces more chlorine derivatives that foster carbonated-coke formation in the furnace tubes, thus reducing furnace operating time. The complicated relations among operational variables, EDC feed purity and VCM quality limits, complicates analyzing EDC cracking furnaces on productivity alone. To clarify the correlation among process variables and quality variables, we introduced multivariate statistical techniques to this project. By optimizing the analyzed correlation models, very successful results were achieved-the VCM production rate increased by more than 10% while maintaining the same VCM purity limits.

VCM furnaces. The EDC cracking process is comprised of storage tanks, furnaces, EDC vaporizers and a transfer line exchanger (TLE). Fig. 2 illustrates the basic flow diagram. The EDC feed is preheated through the preheating zone before being completely vaporized by high-pressure steam. It flows into the radiant zone and is cracked into VCM and HCl. Unreacted EDC is recycled to storage tanks after passing through a separation process. The HCl is sent to an oxychlorination reactor to produce more EDC.

The cracking furnace has many online measurement sensors for temperature, pressure and mass flowrate. The furnace-tube temperatures and EDC feed purity are major process variables. The tube length of the furnace is about 800-m long. Along the inside of the furnace and on the surface of tubes, numerous temperature sensors are located to monitor the temperature profile. Once or twice a day, feed samples are analyzed to check the EDC purity level and composition of key additives that may affect VCM yield and byproducts formation. Fig. 3 shows the schematic of the VCM furnace with its representative process variables.

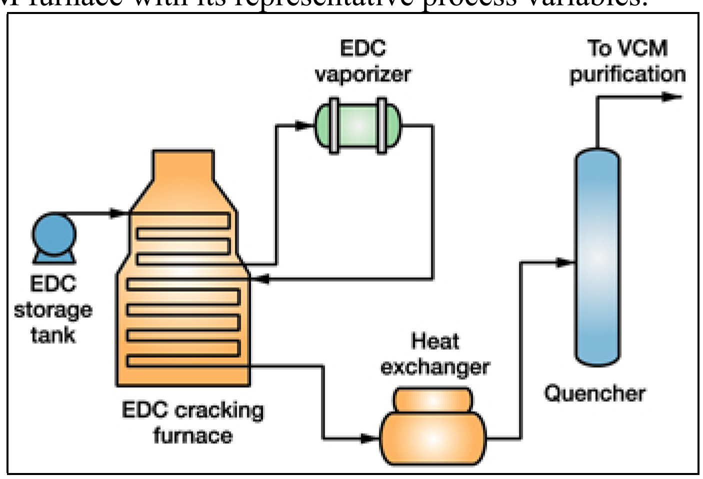

Fig. 2. Flow diagram of a VCM furnace.

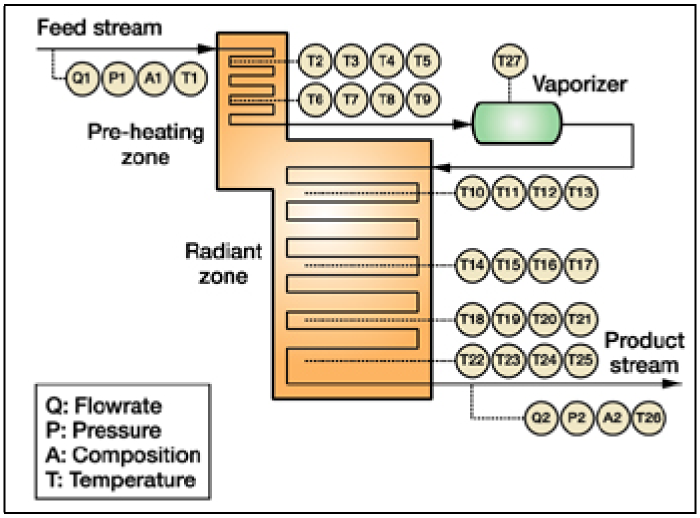

Fig. 3. A schematic diagram for VCM furnace and process variables.

Multivariate statistical process modeling. These modeling methods have been developed from least-squares regression. The multiple linear regression (MLR), principal component analysis (PCA) and principal component regression PCR) are useful tools when massive amounts of process data must be analyzed using a class analogy concept. However, MLR and PCR have some analysis problems for cases containing singular matrices, which lose vital information. Projection to latent squares (PLS) solves such problems and is the most popular multivariate statistical modeling tool. The basic concepts of PLS have been well documented.[1,2] PLS modeling can provide relations between important sets of process and response variables with little loss of information.

We applied the PLS modeling to find out the correlation between the operational conditions of VCM furnaces and final product qualities. The process variables were defined earlier. The response or target variables for the VCM furnace are VCM yield, byproduct formation and coking rate inside the tube. VCM yield can be easily estimated every minute by constantly monitoring the recycled HCl and EDC flowrates. Also, the key byproducts content in VCM production is precisely measured by sampling the product stream, followed by gas chromatography analysis. However, it is challenging to accurately estimate the coking rate and accumulation since coke grows intensively in the cracking-tube elbows, while the inside of the straight tube is nearly clean. Generally, the coke grows at a steady rate and is hardly affected by instantaneous process changes. Therefore, the coking rate is simply inferred by pressure drop changes between the inlet and outlet of the furnace tube, and is only used to monitor the status of the furnaces.

A plant information system (PIS) was installed on the LG VCM plant. It enabled users to obtain process data for any time period and provided more than three years of historical data. Several operational changes were made during this time that made PLS modeling more attractive than other equation-based models. We retrieved the VCM furnace operation data, and feed and product quality analysis data for specially selected periods. Based on the collected data, we performed PLS analysis.

PLS models can be created by several methods. One can code NIPALS algorithm with a programming language. Another way is to use a commercialized multivariate statistical packages. Once the process data is fitted into the PLS models, the results can be shown in graphical charts, making it a very useful tool.

Fig. 4 shows the overview of the PLS model for the target variables of the VCM furnace. The height of each bar in the graph indicates the fraction of the cumulative sum of squares (CSS) of response variables explained by all latent components. As the CSS fraction moves closer to 1.0, the reliability of the developed model increases. Normally, if CSS is greater than 0.5, we regard the model as an acceptable one. From Fig. 4, we can see the VCM yield and byproducts are well described by regression models.

Once a PLS model is made, the correlations among process and response variables provide good information, which clarify their complicated relations (Fig. 5). From the loading vector plot, byproduct formation is closely related with the EDC feed purity (v1 ~ v15), and the EDC cracking rate is related to the radiant zone temperatures (v43 ~ v78). Also, each response variable can be expressed by the relative heights of regression coefficients that are shown in Fig. 6. Those regression coefficients become the model parameters of VCM yield and byproduct 1 and 2 formation level, and are used to predict the changes in those variables. With the model parameters defined, we can now optimize the process.

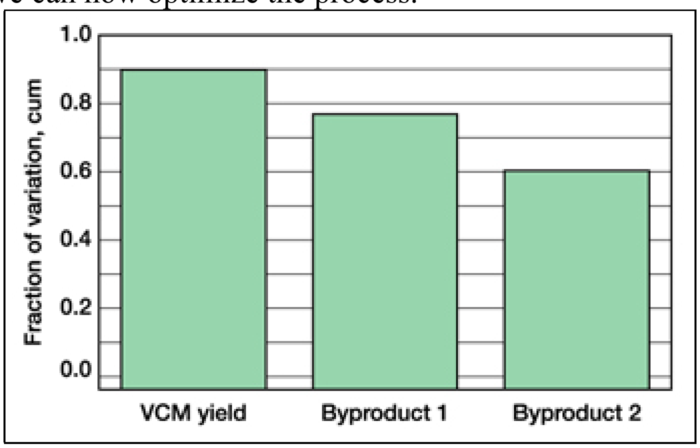

Fig. 4. Cumulative sums of square response variables explained by all latent components.

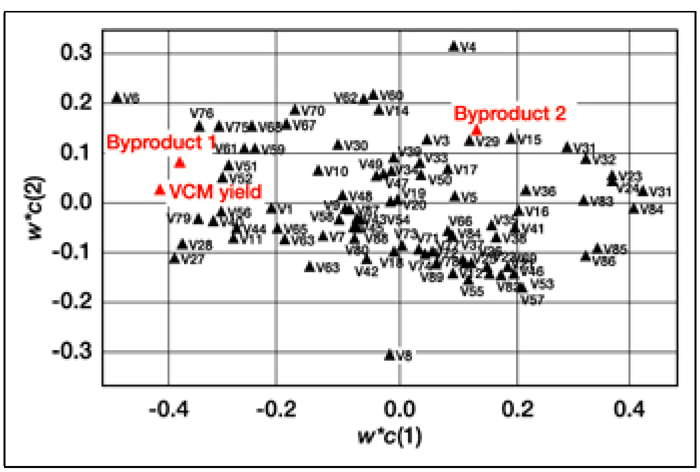

Fig. 5. PLS weights of response and process variables for first two components.

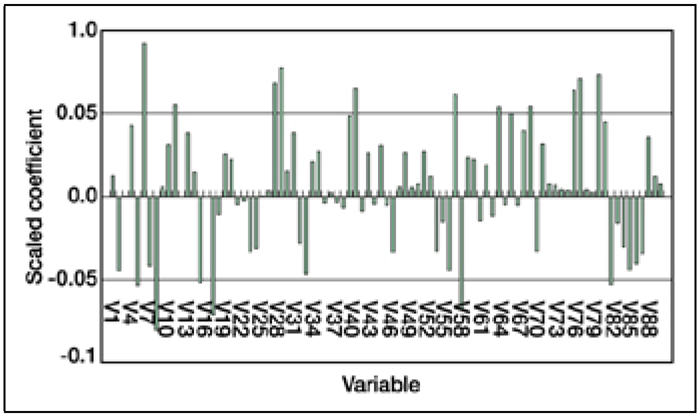

Fig. 6. Model coefficients for VCM yield.

Optimization. The optimization objective is to increase yield without creating unstable operating conditions and violating the VCM quality limits. Therefore, the regression model for VCM yield is used as the cost function for the optimization routine and the others-byproduct level and allowable hardware operating range, etc.-as constraint boundaries. The critical byproduct 1 and 2 are modeled by the regression procedure and their evaluation models are easily formulated as inequality constraint forms.
Coke formulation in the cracking tube is also an important constraint since it is the main cause for reduced furnace operation time and decreased cracking rate. However, the coking rate grows steadily in normal operation and then it suddenly soars. This is most likely due to faulty startup or high impurity levels in the EDC feed. Therefore, the coking rate as a constraint hardly affects optimization. The simplified final optimization problem is as follows:

$$\underset{x}{Max}\ f(x) = \sum_{i=1}^{M} a_i x_i + \sum_{j=1}^{K} b_j x_j^2 \ : \ \textbf{VCM yield}$$

$$S.T.$$

$$g_1(x) = \sum_{i=1}^{M} c_i x_i + \sum_{j=1}^{K} d_j x_j^2 \le \textbf{Byproduct 1 limit}$$

$$g_2(x) = \sum_{i=1}^{M} e_i x_i + \sum_{j=1}^{K} h_j x_j^2 \le \textbf{Byproduct 2 limit}$$

$$x_{i,low} \le x_i \le x_{i,high} : \textbf{Process variables boundary}$$

Since both the cost function and inequality constraints include nonlinear terms, successive quadratic program (SQP) is applied to obtain the optimized solution.
Field Application. From the optimization procedure, we devised an action plan to increase VCM yield by more than 5%, compared to normal operating condition. The key process variables to be controlled were radiant zone temperatures and EDC feed purity.
A VCM plant normally has two EDC cracking furnaces. To validate the above results, we changed the operating conditions for one single furnace to the optimized conditions. The VCM yield improved by 4%, and it was confirmed that the byproducts fraction in the product and

pressure drop through the cracking tube had not changed much over a week's operation. Since these results were very satisfactory, the optimized operating conditions were applied to the second furnace for an extended test.

Fig. 7 shows the trend of VCM yield over 40 days. The VCM yield increased up to 7% while satisfying the other constraints. Also additional energy savings were realized in steam and burner oil consumption from the new operating conditions. The total energy consumption for VCM production fell slowly as the VCM yield increased (Fig. 8). Although these modeling and optimization techniques were undertaken very easily with multivariate statistical techniques, the results made a great contribution to VCM production.

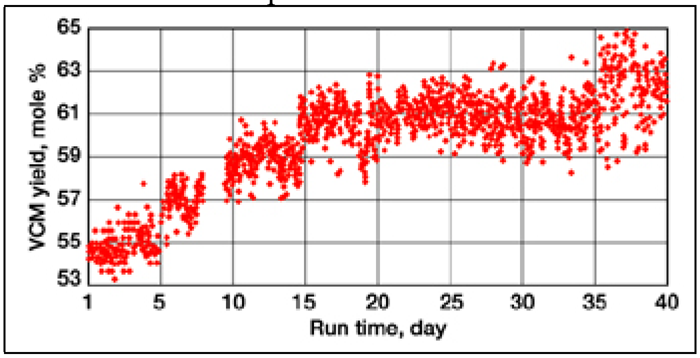

Fig. 7. VCM yield profile.

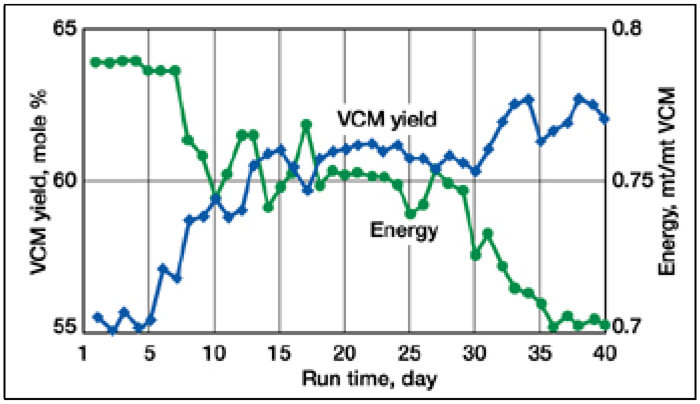

Fig. 8. Total energy consumption with corresponding VCM yield.

Multivariate statistical techniques were applied to analyze EDC cracking furnaces that are inherently complicated with numerous process variables and critical VCM quality limitations. PLS, as a simple modeling tool, is very efficient and intuitive in relating target variables with process variables. By using this technique, we determined the important correlations and optimized the EDC cracking furnaces to increase VCM yield without violating its allowable quality limitations. The models we developed proved to be quite appropriate to predict VCM yield and expected by-products level for various operating conditions.

The optimization of the EDC cracking furnaces resulted in a VCM productivity increase by 11%, which translated to $5 millions in net profit, and reduced energy consumption by $500,000. The net profit would be doubled to $10 million after application of these results to LG's second VCM plant. This result is very valuable because we were able to increase VCM productivity without needing any hardware revamping or additional investment. Previously, the VCM supply to the

LG PVC plant was below its capacity. These new conditions make it possible to supply enough VCM to the LG PVC plant and its subsidiary plant.

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