Early Event Detection – A Prototype Implementation

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Abstract

NOVA Chemicals Corp. and Honeywell Laboratories have been working together to evaluate the effectiveness of an Early Event Detection (EED) prototype in a typical manufacturing environment. The role of an EED application is to augment the console operators monitoring behavior and situation awareness as well as provide them with a tool to reduce or avoid process upsets. The EED application uses robust mathematical algorithms to monitor the correlations in key process measurements and estimate the state or condition of the plant unit. In this paper, we will describe the major steps of the project – including the unit selection, data selection, modeling techniques, run-time platform, and user interface – that have been executed to drive the creation of a successful online application in a petrochemical facility. Though the evaluations have not been fully completed – the early results are that the EED prototype is a very effective means to enhance the monitoring of a plant and to help avoid potential manufacturing upsets.

1. Introduction

The role of an Early Event Detection (EED) system (Mylaraswamy, Bullemer, & Emigholz, 2000) is to assist a console operator in better maintaining their situation awareness, providing early indications of potential process excursions, and therefore help the operator avoid or better manage abnormal situations. An EED application delivers multivariate monitoring of large process units and detects the preliminary patterns that forecast upcoming events that could drive the process into abnormal situations. Unlike an equipment monitoring application that is focused on specific mechanical failures, EED takes a high-level process view. EED acts as an intelligent assistant to the operations team for monitoring process functions, rather than to the maintenance team for monitoring equipment health. As an assistant, once EED has identified a potential problem, it provides diagnostic clues that orient the operator in the direction of the potential causes of the approaching problem.

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NOVA Chemicals Corp. (NOVA), as a member of the Abnormal Situation Management (ASM®) Joint Research and Development Consortium (Nimmo, 1998), is participating with Honeywell in the testing of an Early Event Detection Prototype in its Ethylene 3 facility in Joffre, Alberta. One of the major accomplishments of the ASM® Consortium over the past few years was the successful fielding of an Early Event Detection system (EED) at ExxonMobil’s Baton Rouge Chemical Plant (BRCP). The objective of the recent prototype project at NOVA is to evaluate that with the new developments and learnings from the ExxonMobil project, the new EED technology could be effectively implemented into an operating plant environment and become a valid added tool supporting Manufacturing Excellence.

NOVA has been an active member of the ASM® Consortium since 1992 and has participated in many of the ASM® research projects over that time. (Bullemer & Errington, 1998; Errington & Nimmo, 2001).

The NOVA EED project consisted of several phases as shown in Figure 1. In the initial phase, a formal systematic process was developed to select the best unit for the trial. Following the unit selection, state estimation models were built for the EED prototype using historical plant data. This offline phase used the State Estimation Tools (SETools) math package developed by the Consortium. Model validation exercises were then performed by running the model against test data sets to assess model accuracy, model performance and to fine-tune the model. After the successful evaluation of the model, a run-time execution environment was set up so that the model could be put into an online setting and interfaced with the Operations team. A specialized User Interface within the Total Plant System – along with an operator training package and an electronic annotation system to capture the user’s use of the package -- was also created as part of the Online Implementation. The project is currently in the final phase of the project (Phase 4 in Figure 1).

The overall project was executed in about 10 months. With more focused resources on the task and the technology improvements that have been made, the project team believes that a similar project could be executed in 2 – 3 calendar months.

The objective of this paper is to briefly describe each of the major project steps, some of the challenges that were encountered as well as the learnings that were captured during the project. Conclusions and the viability of the EED technology are discussed in final section of the paper.
2. Unit Selection

One goal of the project was to create a structured approach to selecting appropriate locations to apply the *EED* application. The *EED* application provides value to the manufacturing facility by supplementing the operations team in detecting events before they escalate into abnormal situations. However, these applications are not created without some significant investment in labor and capital resources. For an *EED* project to be successful, the project team must identify production units that warrant the investment and have a significant chance of being technically successful. The first key factors in this evaluation are finding the units that are experiencing:

- Events that are hard to detect,
- Events which are expensive and
- Events that can be detected by the *EED* technology.

To create the structured selection methodology the project team elected to use a Six Sigma analysis tool called Quality Function Deployment (QFD). Typically a QFD analysis is used to differentiate between two or more competing products and in this situation it was modified to differentiate between competing units.

A QFD analysis starts with a cause-effect analysis that decomposes the various factors that contribute to the project’s success. The factors are broken down until the analyst reaches a factor or design element that can be quantified. These design elements are then used to generate a QFD table as illustrated in Figure 2.
### Figure 2: Layout of a Typical QFD table

From the cause-effect analysis – a hierarchy was created to drive down to the design elements. A simplified example is shown in Figure 3.

- **A method to quantify the element**
- **How does this unit fare for this element?**
- **Importance of this element**
- **Overall ranking for each unit?**

### Figure 3: Cause Effect Breakdown
Looking at the “Events are Expensive” branch of Figure 3 shows an example of what the hierarchy describes. If an event has a high cost or happens very frequently then the overall cost of that event will add up quickly. Similarly a unit that is already at a production limit or bottlenecked in some way can likely ill afford an event to occur and would have a high cost of each event. Today’s plants are often tightly integrated with other units; upsets in one propagate with negative repercussions throughout the plant – potentially driving the total cost of an event upwards.

Following the cause-effect analysis, each final element is quantified and ranked in terms of importance in the QFD, which completes the definition of the element.

NOVA’s Joffre production facility offered the project team several application opportunities for the unit selection process. At Joffre, there are 3 ethylene plants, 2 polyethylene units, a hydrogen offgas unit as well as an offsites utility process. From these plants, five potential candidate units were compared.

From the QFD analysis the Ethylene-Ethane (C2) Splitter in Ethylene 3 was selected as the best candidate unit. The C2 Splitter is the final separation column where the overhead stream from the tower is the product ethylene that is fed into a pipeline for distribution to NOVA’s customers. The bottoms stream is unconverted ethane that is recycled back to the cracking furnaces. A simplified process diagram is shown in Figure 4 that shows these 2 major streams.

Quality control of the product ethylene stream is the ultimate function of the C2 Splitter and any major disturbance in this tower can represent significant cost impacts. The tower is also difficult for the Operating Technicians to monitor and
control due to a long process time constants and its tight heat integration as it employs a heat-pump compressor that supplies both the overheads cooling and bottoms heat supply. Due to its complexity and high-energy use, the tower has also recently had a new multi-variable controller application added to it.

### 3. Model Development and Validation

**EED Technology**

The *EED* technology that was developed by the ASM Consortium and used in this project has four basic parts as shown in Figure 6. The first element is the data processing component that lets the user view and select “normal” data from which to build the model. The second element that is applied to the data is an Exponentially Weighted Moving Average (EWMA) filter to remove long-term trends. The third piece creates the actual model using Principal Component Analysis (PCA) techniques. Finally a fuzzy logic block is used as a tuning parameter to adjust the sensitivity of the results and to avoid chattering.

![Figure 6: EED Technology Elements](image)

The initial *EED* tool was constructed in Matlab using the ASM Consortium’s SETools package. Data was extracted from the plant historian using Microsoft Excel.

**What is Normal Data?**

In order to detect abnormalities in the C2 Splitter operation the *EED* team had to find process data that represented “normal” splitter operation. This “normal” data would then be used to develop a C2 Splitter model. By comparing the model to actual process data, we can determine if the process is behaving normally. This is shown mathematically in the unexplained error or Q statistic generated by the PCA model. Finding “normal” data is therefore one of the key components to a successful project.
The first effort at finding “normal” data was to sift through two years of process data looking for process conditions where key process variables such as feed composition, feed rate, purity specs, etc. were at low levels, medium levels and high levels and the C2 Splitter unit was working very well. This data search gave us approximately 60 one-day data sets of 1-minute data. These data set were not 60 contiguous days but were scattered throughout the entire two-year period. After performing a standard Principal Component Analysis it was found that the variance in a concatenated 60-day data set did not represent normal plant variation, as it was much too large due to the discontinuities in the concatenation of the multiple data sets. In contrast, modeling with a single day’s worth of data unfortunately did not contain enough plant variation to create an effective PCA model.

A data compromise was then made. During the development of a MVC controller eleven days of continuous plant testing was performed. During this test, column reflux, reboil and feed enthalpy conditions were varied significantly within the acceptable control range and hence, served as ideal training data for the normal PCA model. Two additional data sets were also used as “normal”: one contained a significant feedrate change and the other contained a compositional change coming from a furnace conversion change. An exponential filter was used so that slow moving trends in the data would be filtered out. A total of about 15 days of data was used in this model development.

As the data sets were not contiguous but 3 separate data sets, standard PCA techniques did not handle the discontinuities well from a variance point of view. The actual “normal” process variance is over estimated at the boundaries. A special method (patent pending) was developed to allow for incremental training of the PCA model using non-contiguous data. A 10 Principal Component model, which serves as the basis for the general excursion detection, was developed from these three data sets. This model explained about 70% of the variance in the data set.

As the general excursion detection model was developed more rapidly than anticipated by the EED team, the project team set about looking at C2 Splitter data that contained two specific known events. The first event was the level excursion in vaporizer seal pot. This level normally sits at 100% but periodically it will drop rapidly as the vessel is quite small. At 80% level, an alarm is configured to ring in. Serious operation problems will occur if the vessel completely empties. The second event occurs when variations in the ethane (C2H6) content of the tower overhead become significantly larger than normal variations (e.g., 4 times). The benefits of catching this event early would be tighter spec quality without exceeding the spec, with associated energy savings driving the economic benefits.

New training data sets were found for each of the known events and in these 2 cases by creating Principal Component models for the time just prior (1 hour or so) to the actual event - a repeatable event precursor pattern was identified. The plot shown below in Figure 7 illustrates that by using the precursor pattern; an early event...
A notification could often be generated over 1 hour before the event would occur. By generating additional PC models on data that contained known events, the project team was able to augment the general excursion detection model to provide event identification for known, problem events.

**Figure 7: Precursor Event**

Tuning of the fuzzy logic portions of the aggregated *EED* application was performed to adjust the sensitivity of the detection algorithm. To verify the *EED* application performance, the model was tested on 40 days of continuous data. Our known event was considered detected if (1) the data was determined to be not normal by evaluating the Q statistic and (2) it exhibited the proper precursor pattern. Over the 40-day test data, our success ratio for detecting this specific known event was approximately 75%. Additionally, the general excursion detection functionality detected approximately two other non-normal events per day. While these events may have been known by the Operations team, the general PC model was only trained to detect deviations from normal process performance.
MVC Changes

Significant changes were made to the C2 Splitter unit’s MVC controller about 2 months after the EED model was created. As a team, we were interested in to what extent changes to the controller would affect the performance of the EED system. The major changes to the C2 Splitter operation as a result of MVC changes were: (1) the bottoms level of the splitter was now used as surge capacity and (2) by monitoring and controlling the $\Delta T$ across the ethane recycle vapourizer, the level in vapourizer seal pot could be controlled better. As a result of these changes in operations, the performance of the EED system changed significantly. Because PCA performance is a function of normal process variation, changes in the bottoms splitter control for surge control dramatically increased the process’ standard deviation. This caused the overall Q-statistic calculation to indicate non-normal process performance most of the time. This result required that the project team perform some remodeling to achieve the previous performance results.

Before remodeling, new data sets had to be added to the original training set. Two new data sets were added – one in which the MVC was performing normally and one the MVC was performing exceptionally well (about 12 days of data). Remodeling was performed with 10 Principal Components, resulting in the final model that described about 70% of the normal data set variation. The Principal Component models for event identification were also remodeled. However, the ethane recycle vapourizer level event had essentially disappeared because its severity had been greatly reduced as a result of the MVC modifications. The increased $\text{C}_2\text{H}_6$ variation event still remained, although its precursor changed. In fact the event could now be classified into increased variance caused by a furnace coming back online and one for as of yet an unknown reason. New Principal Components were made for these events and the combination of new models is currently running online at NOVA.

4. Online Implementation

Many pieces had to come together to create the online application. The first piece was to export the model created in SETools and encapsulate it into a runtime executable program using Honeywell’s WrapperBuilder. This executable was then installed within the ProfitSuite environment that has an OPC interface to read and write information to the TPN Server that is part of Ethylene 3’s Total Plant System (TPS). Figure 9 is an illustration of the system components.

This system architecture allowed the model to be developed with the rich mathematical tool set of SETools and Matlab while utilizing an already field proven run-time engine with a standard OPC interface. Two advantages of this configuration are that an EED solution can be used on a variety of control systems and it is also capable of supporting multiple state estimators simultaneously.
The second piece that had to come together was the online User Interface (UI) that was to be used by the Operations team. The EED generates diagnostic clues aimed at orienting the Operating Technician to potential upcoming events. The success of any EED solution in reducing the impact of an abnormal event depends on how well the EED’s outputs are presented to the operations team.

In order to present the EED outputs to the operators the project team chose to enhance the E3 UI with the addition of 2 new ActiveX controls. The E3 UI is a GUS-based GPB solution modeled after the ASM Consortium’s AEGIS prototype that was developed for the NIST program (Bullemer & Errington, 1998). The E3 UI uses a layered structure that attempts to maintain the overall plant awareness of the operating technicians while simultaneously giving them greater access to critical, detailed information.

For the EED project the Level 1 – Area Status View and Level 2 – Unit Summary displays were modified with the addition of a Polar Star display object (Woods, Wise, & Hanes, 1981), while new Level 3 and 4 displays were created to show the detailed EED information. Operator attention is directed to the EED detailed information displays when the polar stars on the Level 1 or 2 displays change to present a readily identifiable “off-normal” shape. An illustration of an overall workstation layout is shown in Figure 10.
Figure 10: Workstation Layout

An example of the detailed information level for the Level 3 display is shown in Figure 11. Key elements of this display include the Polar Star plot, the dual trend information plus the “Worst Actors” list of key contributors to the event detection. The Polar Star is configured so that under normal conditions the shape is symmetrical and close to the middle circle. The spokes represent the overall Q Statistic from the model plus the scaled values of the individual Principal Component Statistics. The Worst Actor list is dynamically updated by the EED model to show the tags that are currently having the largest deviation from their expected or modeled values. These are the tags that should be examined first by the operators. The Dual Trend display at the right hand side – shows a time series plot of the Q Statistic, the Principal Components’ statistic plus the point values for the 4 worst actor tags. This display allows the operator to look for changes in the key tags identified by the model.

Included in the display is an Event Diagnostic message window that will display specific EED information if a known event has been identified such as the ethane recycle vapourizer level problem.
Selection by the operator of one of the principle components in the Summary Statistic section of the Level 3 EED display will invoke a detailed Level 4 Group display showing the major contributors to that particular principle component along with their current values, model’s predicted values and a bar graph. This is shown in Figure 12.
Once the online interface had been built, the third piece that had to come together involved modifications to the electronic logbook so that the operating technicians could annotate the EED output information when it was received. Annotation information included elements such as EED_Useful, EED_Redundant and EED_Not_Useful. As this annotation information goes into service over the next month – the project team hopes to be able to quantify the model’s performance and benefits to the plant’s operation. The project team does not envision the need for continuous operator annotations after the quantification period has concluded.

5. Summary and Conclusions

Early Event Detection systems will continue to increase with our increasing plant complexities, heat integration, fewer resources, and the continuous push for manufacturing excellence. The ASM Consortium has taken a major step forward in the development and testing of EED technologies that can now be proven to be available and effectively deployed in our plants today.

The C2 Splitter EED Prototype project has demonstrated many valuable components of the EED technology including a unit selection process, modeling tools capable of iterative improvement, a run-time environment that can support multiple state estimators and operate with most common control systems and a User Interface approach which can present the EED output information to the end users in an effective manner. With the prototype – potential events are identified 40 – 60 minutes before they will likely occur and giving the plant operators a clear path of investigation so that the corrective actions can be taken to avoid the event.
Though still too early to fully quantify the benefits of this application to Ethylene 3, the project team is proceeding to look at ways to provide additional diagnostic information once an event has been detected. The modeling package is also being extended to include additional temporal model components to improve the resolution of the events that have a strong time series component.

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**References**


