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**Fielding a Multiple State Estimator Platform**

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**Abstract:**

Over the past few years the Abnormal Situation Management (ASM)[[2]](#footnote-2)™ Joint R&D Consortium, has been involved in developing a collaborative decision support technologies for improving abnormal situation management within the chemical industry. Within this collaborative decision support solution concept, applications called State Estimators (SE) provide diagnostic assessment of the current process state. State Estimators form the core of this decision support solution since they provide the first step in the decision process. During the course of the past few years, the ASM Consortium has developed a set of analysis techniques and a methodology to provide this “process state” information accurately and reliably. Following a successful laboratory demonstration of a multiple state estimator platform (MSEP), the ASM Consortium developed their first field prototype in 1998. This prototype is currently being field-tested at three refinery sites. Following early success of this platform in providing early warning, development of a beta product is underway at Honeywell Hi-Spec Solutions. This paper is intended to give a summary of our experiences with developing and deploying such a platform in ExxonMobil’s chemical plant at Baton Rouge.

# Introduction

One of the largest problem faced by operators in today’s automated world of operations is the cost of unexpected process upsets that lead to production loss, equipment damage, environmental pollution and/or death and injuries. One of the largest economic disasters in U.S. History (not due to natural causes) was a $1.6 billion at a petrochemical plant in 1989. This accident represents an extreme case in a gamut of minor to major process disruptions, which collectively has an economic impact of at least $20B annually in the petrochemical industry alone (Nimmo, 1995).

In 1992, the Abnormal Situation Management (ASM) Joint Research and Development Consortium, led by Honeywell, was formed. In addition to Honeywell, the ASM Consortium currently includes ten private industry members: BP Amoco, Brad Adams Architecture, Celanese, Chevron, Equilon, Exxon, Mobil, Nova Chemicals, Technology Training Systems and Union Carbide. In addition to the private industry members, the ASM Consortium has two university members from Ohio State and Purdue University. In 1994, the U.S. National Institute of Standards and Technology (NIST) Advanced Technology Program (ATP) awarded a 3.5-year, $16.6 million cooperative agreement to the ASM Consortium. The goal of the NIST-funded Collaborative Decision Support for Industrial program was to demonstrate the technical feasibility of collaborative decision support technologies for improving the performance of operations personnel. During this course of four years, the Consortium developed a successful research prototype for Abnormal Event Guidance and Information System called AEGIS (Bullemer, 1998). This prototype consisted of independent modules that provided process state information (state estimators), determined intervention goals (goal setter), and formulated corrective actions (planners). These independent modules exchanged messages and information in blackboard-like communication architecture.

This paper presents our experiences in fielding part of this decision support solution called Multiple State Estimator Platform (MSEP). The objective of MSEP was to provide the operations personnel accurate information about the state of the process. Such information will provide the first and possibly the most important step in assisting plant personnel in managing abnormal situations. We begin the discussion of the underlying techniques in the Multiple State Estimator Platform. Next, we present an overview of the MSEP project including metrics for evaluating success. Unlike an advanced control project, which has matured over years, this project presented some unique challenges. Next, we discuss challenges and strategies in customizing MSEP for the cold-end unit at ExxonMobil’s chemical plant at Baton Rouge. Finally, we conclude with summary of field-trial progress, present some preliminary results and future R&D plans.

# Description of the Solution

The Multiple State Estimator Platform (MSEP) realizes part of the AEGIS collaborative decision support vision (Figure 1). MSEP addresses one of the six major functional areas within the AEGIS solution—namely that of state estimation. Briefly, the State Estimator role provides a concise dynamic estimate of what is actually happening in the plant, including trend information that may be used to predict future states. The Goal Setter examines the result and proposes a prioritized agenda of high-level goals to pursue. The Planner creates a plan to achieve those goals given the current plant state. The Executor carries out the plan, ensuring that each step is executed at the right time. The Communicator manages the interface between the other Roles and the plant personnel. The Monitor examines the operation of the other Roles and regulates their activities accordingly. (See reference Bullemer 1998 for details about these functional areas)



Figure 1. AEGIS Functional Role

The role of the State Estimator is to provide a concise and a continuous estimate of what is actually happening in the plant in terms of well-defined process states. It reduces large amounts of sensor data available on the DCS every second to a relatively small number of explanatory states that are reflective of the current *situations*. These descriptive states, called diagnostic information, are an attempt to capture the necessary and sufficient information to assess the health of the process and the equipment in the plant and hence facilitate further abnormal situation mitigation decisions. The scope of the estimator encompasses the complete process area supervised by a single console operator along with major interactions with upstream and downstream process areas.

In order to perform this transformation a state estimator consists of two components. The first component is the process measurements and observations. Typically this consists of current and historical sensor readings from the DCS, maintenance logs, operator observations, laboratory reports etc. The second component is the process knowledge some *a priori* understanding about the process. Almost all the methods studied in literature for state estimation can be classified depending on the development, organization and update of the process knowledge component as follows: (Mylaraswamy and Venkatasubramanian 1997).

* **Model centric**. These methods rely on a mathematical model that describes various interactions and phenomenon in the process. Typically, referred to as first principle models, state estimation methods that use these kinds of knowledge tend to be expensive to develop and maintain.
* **Data centric**. These methods rely on historical data that contain representative measurements of various interactions and phenomenon in the process. Typically referred to as empirical methods, state estimation methods that use these kinds of knowledge are preferred in practical applications.



Figure 2. A state estimator provides estimate of the process state by analyzing process measurements together with process knowledge

MSEP performs state estimation using empirical methods. Techniques for analyzing empirical data in order to extract useful process knowledge has been well studied in literature. We pointed out the role of state estimator is to provide timely and accurate information of incipient process states that can lead to potential abnormal situations. It is a well-known fact in data analysis that timeliness of reporting can only be increased at the expense of too many inaccurate or false positive reports. In other words, a delicate balance has to be achieved between how small the reporting threshold is set and the number of false positive reports that can be tolerated. One way of achieving this balance is the use of hybrid strategies that utilize more than one analysis techniques (Mylaraswamy and Venkatasubramanian, 1997). Although attractive it raises a number of practical questions on selection and combination of the underlying techniques.

MSEP uses a unique state estimation strategy that allows simultaneous and independent analysis of the measurements. This strategy performs *orthogonal* analysis of the measurements, to ensure a good balance between early warning and reliability of the platform, in providing process state information. The use of orthogonal analysis and a platform design that performs this orthogonal analysis to provide early warning is the technical nugget of MSEP. In the remaining part of this section, we shall describe these techniques and provide evidence about the sufficiency of these techniques in providing reliable diagnostic information to the operations personnel.

In order, to provide the motivation behind MSEP, it is important to emphasize the precise meaning of a process state. We pointed out earlier that a state is a characterization of some underlying situation, the main intention of this abstraction is to provide the operator diagnostic information. In order to design techniques that capture process states, it is worthwhile to understand the mental model of an experienced operator. Typically, during a monitoring cycle, an experienced operator is looking at key process measurements. In particular, the operator is looking at the following three things in order to decipher the underlying process state.



Figure 3. Various ways of describing a process state

* **Temporal Analysis**: The shape of one or more measurements as they evolve over time is an important element of an operator’s monitoring cycle. These trend convey important information and hence are characteristic of the underlying process state. In other words, analyzing the temporal shape of key process trends is one way of characterizing a process state.
* **Correlation Analysis**: The relationship between two or more measurements is an important indication of the current situation. Breakdown of some of this correlation can be indicative of an incipient problem in the process. That is, monitoring the correlation between variables is one way of characterizing a process state.
* **Spatial Analysis**: The actual value of key process measurements is often indicative of potential departures from normal operating conditions. If a key process variable is far way from its normal value, it can be indicative of an developing problem. Hence monitoring the spatial distribution of key variables is an alternate way of describing a process state.

The correlation between two variables can be still being intact, but their temporal behavior may be unacceptable. Sustained oscillation is a good example of this case. The temporal shape of the key variables can be acceptable, but the numerical values can be close to trip limits. The numerical value of a measurement may be acceptable, but have an unacceptable trend. These arguments suggest that the above three analyses provide *distinct* characterization of a process state. Therefore, these three analysis are necessary to describe a process state adequately. Further, these three analyses are also sufficient to capture departures in a process state that may lead to abnormal situations. That is, any departure can be completely explained in terms deviations either in the spatial, temporal and correlation distributions of the measurements.



Figure 4. MSEP uses an orthogonal set of descriptors for analyzing a process state

The description of a process state in terms of these orthogonal coordinates is the technical nugget of MSEP. These three orthogonal descriptors are the necessary and sufficient descriptors of a process state. Using such a description, we can attain a good balance between generating too many false positives and reliability in generating diagnostic reports. Using this orthogonal analysis, MSEP overcomes a major bottleneck in deployment of such diagnostic applications. The remaining part of this section describes briefly the actual techniques used to perform these orthogonal analysis. Since this paper is not intented to be a tutorial on these techniques, we simply point to some key references that describe these techniques in detail.

1. Qualitative Trend Analysis (QTA) uses a syntactic language to capture the temporal description of a process state. The qualitative nature of this analysis makes it robust to constantly changing process gains. For details on this technqiue see references [Rengaswamy and Venkatasubramanian, Vedam and Venkatasubramanian]
2. Multivariate Statistical Analysis (MVS) using principal component analysis (PCA) to provide the correlation description of a process state. A moving average update scheme that removes the mean makes this technique robust to changing operating conditions. For details on this technique see references: [Jackson]
3. Adaptive Resonance Theory (ART-II) uses *n*-dimensional clusters to capture the spatial description of a process state. The built-in adaptation scheme allows these clusters to grow and shrink to reflect changing operating conditions. For details on this technique see references: [Davis]

To summarize this section, MSEP uses three orthogonal descriptors for describing process state. These are: temporal, correlation and spatial descriptors. The current version of MSEP uses QTA, MVS and ART-II techniques to perform this orthogonal analysis. The results from these analysis are then combined using a simple “AND” conjunction to provide reliable and complete diagnostic state information.

# The MSEP Project

This section provides a description of the MSEP project that was implemented at ExxonMobil’s Baton Rouge Chemical Plant. Unlike an advanced control project, MSEP is possibly the first attempt in building a large-scale practical decision support system. In particular, this section describes the following aspects of this project.

1. Process area selection
2. Success criterion
3. Project implementation

Similar to any large-scale project, the above steps are iterative and get successively refined as one moves further into the project.

## Process Area Selection

The following criterion was used in selecting a process area for demonstrating the utility of MSEP.

1. Cost and importance to the plant. Process areas that have chronic ASM related issues are prime candidates. Selecting such process areas makes it easy to justify the cost or implementing an MSEP project.
2. The availability of *rich* historical data. With the advent of cheap historians, most plants store vast amount of history. We pointed out earlier that MSEP uses empirical analysis methods to characterize a process state. This warrants the need of good *annotated* data. Annotations are defined as additional information stored along with the data. This information can be stored electronically or in operator logs.
3. Process instrumentation. A poorly instrumented process area may not provide enough measurements to capture the spectrum of process states that can lead to abnormal situations. For example, if you are dealing with separation columns, select the ones that in which quality measurements, tray temperature measurements are available.

Apart from these criterion, the interest and the enthusiasm of the plant personnel in supporting and participating in the project is important. For example, a bottleneck process area may justify the cost of implementing a MSEP project, but may lack plant personnel who can support this project.

## Success Criterion

This section describes a set of metrics that was used for evaluating the success of MSEP in providing online real-time diagnostic information. Apart from the stability and the maintainability of the platform, the success was based primarily on the usefulness of the information. In order to measure the usefulness quantitatively, we developed the following performance metrics. In order to provide the basis behind the development of this metrics, it is important to understand the concept of an *event*. An event is something that happens in a process that leads to either the control system or the operator to act. Based on the type and the severity of the action, various events in a process can be classified as listed in Table 1.

Table 1 . Categorization of event types from an operations point of view

|  |  |  |
| --- | --- | --- |
| **Event Type** | **Description** | **Examples** |
| ACTION | These events require action from the operations team.  | 1. Instrument requires calibration
2. Loss of condenser
 |
| MONITOR | These events require that the operations team monitors the current situation, as it could escalate to something that may require an ACTION | 1. Re commissioning of an upstream furnace that provides part of the feed
2. Change in user demands that draws products from the unit and are beyond normal spec and could affect controllability of the unit
 |
| IGNORE | These events are routine day-to-day operations that occur in the plant. These are typically planned events and/or the control system is designed to handle it adequately. Under conditions that the event cannot be handled by the control system, the event can escalate to MONTIOR | 1. Feed quality changes
2. User demands that are within specs
3. CW temp increase in hot summer days
 |
| NOISE | These event essentially correspond to process noise |  |

Each of these events will change either the temporal, correlation or spatial distribution of one or more measurements. Therefore, for each of these events, MSEP can potentially generate a diagnostic report or a notification. Useful of the information was measured in terms of the following two criterion:

1. Timely detection. In order to provide useful information, MSEP should be able to provide diagnostic report before it is *too late*. This qualitative metric was quantified by comparing the time at which MSEP provided the first diagnostic report that would have given the right clue to an operator to take appropriate corrective action. This time was compared with the time when the first DCS alarm would have triggered a similar preventive action.
2. Number of misleading notifications. Table 1 shows that not all events are interesting from an operations point of view. In order to quantify the success of MSEP, we put bounds on the number of notifications MSEP would generate corresponding to each of the above listed events. Ideally one would want to
* Eliminate all notifications that correspond to NOISE events.
* Suppress all notifications that correspond to IGNORE events by successfully identifying and classifying them
* Notify all MONITOR and ACTION events

In other words, if we can

* set the thresholds high enough to eliminate notifications due to noise, and
* successfully *learn* commonly occurring operational events and hence suppress them using appropriate filters

then

* the only notifications that MSEP will generate are due to events that require either monitoring and/or action

In order to meet this success criterion, we employed a bootstrapping approach to implement this project.

## Project Implementation

MSEP relies on a set of empirical data analysis techniques that provide orthogonal description of process states. In order to build or train these techniques requires annotated data. Although most operating plants maintain an operator log, the information contained in such logs is rarely complete. We adopted a bootstrapping approach to incrementally build these techniques. Such an incremental approach also allowed use to monitor progress periodically. This staged approach was one of the many strategies we adopted to minimize risk associated with implementing this innovative concept.

The MSEP project was divided into four major phases [Emigholz, K.E., 1999].

1. **Project definition**. process selection, establishing success criterion, etc.
2. **Data Annotation**. A baseline model was built using *normal* data. The assumption of normality in this data set was based on the lack of any significant *event* reported by the operations. That is, we selected data segments that did not contain any MONITOR or ACTION events defined in Table 1. This baseline model serves as an *origin* for our orthogonal descriptor system (Figure 4). Notifications that are generated as a result of deviation from this origin are annotated by a process engineer. In the Baton Rouge project, this translated to 25—30% of the site engineer’s time. During this time, for every notification generated by MSEP, the site engineer would:
3. Gather additional information either by talking with operators and/or by looking at operator logs. The intent of this activity was to understand the underlying event.
4. Classify the event that generated this notification into one of the categories listed in Table 1.
5. Group two or more notifications that may have been generated from the same underlying event.
6. Provide a verbal and a process-related explanation of the underlying event and link it with the appropriate notifications.

The objective of this phase is to cover almost all commonly occurring operational events. For example in the Baton Rouge project, which consisted of a separation column, common operational events we were looking for were:

1. Feed rate swings
2. Feed quality swings
3. Cooling water swings
4. Upstream/downstream pressure swings

The decreasing number of new operational events was used as guideline to determine the length of this phase.

1. **Developing State Estimators**. For each of the event identified in the data annotation process, an application specialist maps the distinguishing features it in terms of the three orthogonal descriptors. This mapping helps in training the appropriate techniques (QTA, PCA and ART-II) to recognize and hence classify these events. This phase involves embedding the knowledge acquired in the data annotation phase in various analysis techniques. This development is done with active participation from the application specialist and the site engineer. In the Baton Rouge project, this translated to 25—50% of the site engineer’s time and a full time application specialist. In the Baton Rouge project, this phase was completed offline and offsite.
2. **Platform Installation and Maintenance**. At the end of the previous phase, it is assumed that state estimators within MSEP have learnt most commonly occurring operational events and hence can suppress them. The thresholds have been set appropriately to eliminate or minimize notifications due to noise events. The platform is installed at the site to provide online diagnostic support to the operations personnel. Occasional tuning is necessary to accommodate new operational events and slow drifts in the process. We anticipate this phase may use 0—20% of the site engineer’s time.

# Results and Conclusions

The MSEP project is being tested on a cold-end ethylene unit at ExxonMobil’s Baton Rouge Chemical Plant. We have completed three out of the four phases in the project. Over the last two years, we conducted three performance evaluations of MSEP. The evaluation strategy consisted of an evaluation period of about 2 weeks, during which, the site engineer actively annotated notifications generated from MSEP, the main emphasis was on classifying the notifications based on Table 1

Due to the extreme proprietary nature of the results, we cannot present complete results in this paper. However, we do present some highlights and limitations of MSEP in this paper. Some of the highlights of MSEP were:

* Detected over a dozen events ranging from minor to significant upsets in the process
* Successfully detected several events with a minimum early detection of 20 minutes. In one case, this early detection was quantifiable in terms of large operational downtime.
* There was one incident where both the correlation and temporal analysis was necessary to pinpoint a failing control valve.

We provide the performance data in terms of normalized numbers. We define a dimensionless number that captures the usefulness of MSEP notifications in providing the operator early warning without distracting him/her with too many false positives or redundant information. 

where:

Nk,op: Number of notifications that were correctly classified as known OPERATIONAL events

NM: Number of notifications that were classified as MONITOR events

NA: Number of notifications that were classified as ACTION events

NTot: Total number of notifications generated by MSEP during the evaluation period

NN: Number of notifications that were classified as NOISE events

Figure 5 shows the progress we have made in increasing the usefulness of MSEP notifications over the last two years. Currently, this number stands at 81%. Ideally one would want this number to close to 100%.

Figure 5. Progress of MSEP at the Baton Rouge trial site

Note the denominator in the above expression includes notifications not only due to noise events but also redundant notifications that essentially describe the same operational event. An important activity during the data annotation process was to *aggregate* notifications that were generated from the same event. This gap in the usefulness factor indicates the inability of the current techniques in adequately capturing the causal cascades of an operational event. Although we have made substantial progress in reducing the number of redundant notifications, there is room for improvement. The redundancy ratio is defined as:



Figure 6. Progress of MSEP at the Baton Rouge trial site

We pointed out earlier, that we cannot present detailed evaluation results given the proprietary nature of the results. The intent of the results presented in the preceding paragraphs was to provide reasonable evidence with respect to the progress we have made in fielding a Multiple State Estimator Platform.

To summarize this paper,

1. Multiple State Estimator Platform (MSEP) is the first realization of a large scale realization of the ASM Consortium’s vision of an Abnormal Event Guidance and Information System.
2. MSEP consists of several state estimator modules that reduces large amounts of sensor data available on the DCS every second to a relatively small number of explanatory states that are reflective of the current *situations*. These descriptive states are an attempt to capture the necessary and sufficient information to assess the health of the process and the equipment in the plant and hence facilitate further abnormal situation mitigation decisions.
3. MSEP uses three orthogonal descriptors to adequately capture and analyze process states. These three distinct ways of describing a given process state increases the reliability of the detection system by reducing false positive notifications.
4. The field trial of MSEP provided valuable guidelines for developing and executing similar decision support projects.
5. The performance metrics developed during the MSEP trial can be used as a reference for establishing similar projects.

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