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Failure Detection on Safety Components in a Polyvinyl Chloride Batch Process

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Abstract

In this paper, a methodology of failure detection on safety components by using intelligent operational monitoring is proposed. This method is based on the fault propagation occurrence in a batch process. The batch structures are elaborated and categorized into several safety components that linked to phase level of operation. I develop failure detection in the batch process and investigate fault propagation in operational stage of safety component i.e., perform computation using neuro-fuzzy. The output of intelligent monitoring using fault propagation can be considered as performance index that represents the changes of component conditions. If a safety component works in low performance, then an initiating event will propagate and perform the hazardous outcome. Process variables (PV) are significant factor for the operating condition that affects the safety component performances. By using the performances, a reasoning mechanism for a specific phase level operation can be implemented. The new distribution of components can be estimated. After that, by implementation of the Bayesian inference method can indicate the hazards analysis in hazard identification and reliability improvement program.

Keywords: Failure detection, batch process, safety components, neuro-fuzzy

1. Introduction

Batch chemical industries have been attracting for safety engineers since they pose a number problem in behavior and operation. Comparing to the continuous plants, a batch process has unique characteristics, behavior of process changes dynamically, role of operators, and the change of process variable (ANSI/ISA-S88.01-1995, 1995). Besides using the hazardous material, a batch abnormality can be caused by the deviation of process variable and plant mal-operation. A process variable of deviation occurs during batch process and it becomes a significant factor for the safety issues in the plants. The deviations tend to influence plant operation, change the situation into abnormal state, and contribute in damaging the plants.

One of the potential accidents in the batch plants is the loss of containment (LOC). LOC of monomer has been reported as potential hazard in the batch process. Based on the newest data, LOC leads to fires and explosion, where the majority of incidents occurred during normal operation and two main causes were investigated as runaway reaction and overflow of material. LOC incidents in PVC batch process are investigated at VCM charging line that potential contributes to overflow of monomer and lead to runaway reaction (Rizal et al., 2006; Ardi et al., 2007).

2. Methodology

2.1. Literature Review

In the area of hazard identification, there are two main tasks, (i) identification of specific undesirable consequences and (ii) identification of material, system, process, and plant characteristics that can produce those consequences. A hazard identification tool that performs the possible deviations from normal operation is listed. In addition, the possible abnormal causes and the adverse consequences for these deviations are identified. The most popular methodology for hazard identification is hazard & operability studies or HAZOP (Venkatasubramanian et al., 2000).

Also, Process Hazard Analysis (PHA) is defined as the systematic identification, evaluation, and mitigation of potential hazards that could endanger the health & safety of humans and cause serious economic losses. Besides PHA and HAZOP, there are now a number technique for performing hazard identification & evaluation such as Safety Review, Checklist Analysis, Cause-Consequence Analysis, Event Tree Analysis (ETA), Fault Tree Analysis (FTA), Human Reliability Analysis, Relative Ranking, and Failure Modes & Effects Analysis (CCPS, 1992). These techniques are widely used in the chemical process industry (CPI). Some of the techniques are a laborious, time-consuming, and expensive activity. There was also who developed the computerized tool (software package: PROFAT) for conducting the probabilistic FTA that has been coded in C++ into multi-module system with several user-friendly features. PROFAT provides the estimation of initiating event; top event and minimum cut sets that lead to accident (Khan and Abbasi, 1999).

Chun and Ahn (1992) have studied the use of ETA in the area of fault propagation; they developed the model of accident progression event trees by using the fuzzy set theory. Their idea was based on the uncertainty of expert judgment in analyze the risk. The same work in ETA was shown in development of severe accident management supporting systems using quantified containment event trees (Chang et al., 1995). In managing the uncertainty and imprecision of data, ETA's model in fuzzy probability and a fuzzy event tree analysis (FETA) was introduced by Dumitrescu and Munteanu. They described a methodology to elaborate a fuzzy logic system used in safety analysis of an electric power protection system; the output was the index on general safety degree (Dumitrescu and Munteanu, 2001). There were also some researchers who introduced the systematic fuzzy event tree analysis algorithm. The algorithm was developed to evaluate the risk of a large-scale system with case study for a nuclear power plant (Huang et al., 2001). ETA is a graphical logic model that identifies and quantifies possible outcomes following an initiating event. ETA provides systematic coverage of the time sequence of event propagation (CCPS, 1989).

Event propagation or accident progression can be determined as the failure of safety systems in preventing or mitigating the hazards. Therefore, the concept of fault propagation is relevant to this situation and can be adopted as a model and tool in hazard identification. Kelly and Lees (1986) introduced the term of fault propagation and it was a model that use of functional equation. The functional equations describe how an output variable is affected by the input variables and also describe the relation between an output variable of a unit, the input, and other output variables of the unit. A propagation equation may be converted directly into mini FTA. The output of their researches is the fault tree synthesis in the computerized tools and describes the process variable correlation in performing the failure. Stanley and Vaidhyanathan (1998) proposed the fault propagation that was modeled by using Causal Directed Graph (CDG) for real time fault management in large-scale system. CDG describes the propagation of failures via failure paths in the system by modeling how fault events will cause other symptom and test result events. Their model represented the cause and effect relationships or dependencies among these events. Research in computer-aided hazard identification using fault propagation was conducted using fault propagation model in a dynamic simulator environment, initiating events (component failures, human errors or materials) that propagate & perform the consequences (Suzuki et al., 1999).

2.2. Proposed Methodology

A fault propagation method is modeled as the progression of initiating events to the consequences in the specific processes. A possible reason why the propagation was taken place is the failure of safety objects in detecting, controlling, and mitigating the hazards. Safety objects failure can be classified using Boolean expression as fail or success; however, Boolean approach cannot cover a gradual transition between two extremes, i.e., safe or unsafe. To avoid this complexity, fuzzy logic idea allows the transition between safe and unsafe. It is the same situation when we estimate the performance of safety objects, it could be in the transition between success and failure. Since the measurements of the performance are done during the operation phase of safety objects, real time hazard identification can be performed.

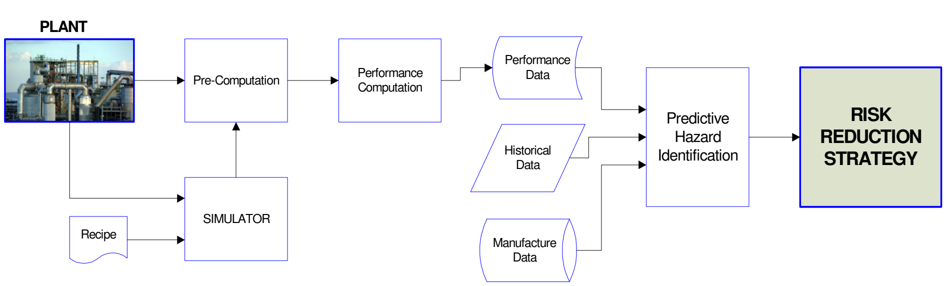
2.3. Performance based Failure Analysis Methodology

Generally, performance of safety object should be analyzed to ensure if it could handle the abnormality or not, so this method has strong correlation to the conventional method such as event tree analysis (ETA). The modified ETA is implemented according to batch process. Analysis is started with modeling the initiating event as an abnormality that affects batch process. If the safety functions cannot work in high performance in mitigating the event, then the event will propagate and produces risks. The failure of safety function leads to some possible consequences in the neighborhood area of process. The analysis for wide area of batch plant will be performed by the integration of each process action (smallest part of process model). Safety analysis and hazard identification for batch process are categorized as difficult and complex in nature. Currently, the potential risks of PVC batch process can be identified, such as:

- The use of hazardous material (VCM) that will affect storage, charging line, people, and environment.
- Reactors that represent high possible risk posed by batch chemical reaction. Undesired behavior of process can take place and contribute to high-level risk.
- Abnormality of process variables (pressure, temperature, level, etc.) during batch process. A small deviation may not cause harmful condition, however it becomes potential risk that spread along process. At this point, failure will propagate and be followed by the consequences.

The overall method can be described in Figure 1 (Ardi et al., 2008). Batch process starts with cleaning the reactor using controlled amount of de-mineralized water, surfactants and other additives. After that, a measured amount VCM is charged and charging some initiator to reactor starts polymerization and steam is added through the reactor jacket to heat inside the reactor up to about 327 K. As result of the polymerization, heat is generated and reaction will occur exothermally due to the breaking of the double bond in VCM chemical structure therefore the heat must be removed from the reactor and steam is replaced by cooling water to keep stable temperature on normal range about 333 K. Agitator in reactor maintains the contents well mixed and after 8 hours pressure will decrease and VCM has been converted.

Figure 1: The proposed methodology for risk reduction strategy



2.3.1. Safety Object for Safety Analysis

The fault propagation cannot be separated with the failure of safety functions during hazard mitigation. Safety functions reinstate process variable deviations to the normal condition. It can be valves and controllers, due to both of them are defined as inhibitor of fault propagation. A valve has abilities to stop material stream through the pipeline and to control the material flow rate during charging process. In addition, controllers those consist of sensor element & control element have capabilities to measure process variable and to control it to the normal range. However, not all of safety objects have full performance, due to aging or other factors, performance of safety objects are decreasing and a loss of function possible exists during process.

2.3.2. Estimating the Event Index

Deviation of process variable from its normal value is calculated using the event index, which represents the index of deviation. It can be three states of index, normal index when process variable is indicated in between allowable value. At the other hand, positive and negative index are grouped into deviation that may happen when variable higher than or lower than normal value. The event index can be calculated as follow by Equation (1):

$$Event\_Index = \frac{PV_{out} - PV_{norm}}{PV_{norm}} \times 100\% \tag{1}$$

where, PV_{out} = outlet process variable; PV_{norm} = normal value process variable.

Naturally, event index shows a level of deviation from normal range. If we classify the event index based on observation, then it can be found that there are several categories such as very high, high, normal, low and very low of index. Each of the indexes covers area of measurement in the process.

2.3.3. Estimating the Trend Index

Process variables such as pressure, temperature, flow rate and level may change dynamically. For example, may be there is no deviation (or normal condition) detected after a material is streaming through the safety objects. However, if very small positive or negative trend exist, in the future, then an abnormality will occur during process. Therefore, trend index should be indicated and can be calculated using some methods, such as regression analysis, qualitative scaling, triangular episodic, dynamic time wrapping, wavelets, and qualitative temporal shape analysis (Kivikunnas, 1999). Here, we use the simple and well-known method, i.e., a regression analysis. Data from sensing element can be collected during interval of measurement. Let PV=y_i and time=x_i, both of y_i and x_i represent the measured variable and independent variable. The sets of process variable and time can be represented as vectors:

$$X = \begin{bmatrix} x_1 \\ x_2 \\ \dots \\ \dots \\ x_n \end{bmatrix} \quad y = \begin{bmatrix} y_1 \\ y_2 \\ \dots \\ \dots \\ y_n \end{bmatrix} \tag{2}$$

After data is measured, then the model prediction can be built using as follow:

$$\bar{y} = b_0 + b_1 x \tag{3}$$

$$b_1 = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \tag{4}$$

$$b_0 = \bar{y} - b_1 \bar{x} \tag{5}$$

The coefficient of b_1 will determine trend of data from sensor element. Three categories of trend index are introduced, increasing while $b_1>0$, constant when trend $b_1=0$ and decreasing while $b_1<0$.

2.3.4. Determine the Safety Object Performance

Performance of safety objects should be monitored during batch process. Object or component reliability (or availability) depends on three main groups of parameters (Cizelj et al., 2001), as follow:

- Design and dynamic properties of the component
- Surveillance and maintenance activities, and
- Component operating conditions and operating environment

The third category reflects the two main factors, component operating condition and operating environment. Due to operating condition will contribute performance of component, and then measured process variable is formulated into event index that represents the load to the components. At the same time operating environment will affect to the component performance with tendency of process variable during batch process. Safety objects will respond the abnormalities based on their performances. An operating condition is implemented using the event index, and next operating environment is implemented using the trend index. Generally speaking, these indices represent the engineering judgment for fault propagation in the real process. However, the uncertainties of judgment cannot be used to assess condition in operating time. Therefore, a hazard is frequently predicted in design time or after operating time. This condition makes difficulties in the quantification of fault propagation during process. The hazards contribute to consequences such as explosion or gas release. To reduce the hazards, safety objects should be assessed and finding the possible consequences along the process.

The performance of safety objects is designing from 0 to 1. The ‘zero’ index represents that the safety objects fail to mitigate an initiating event and fault will propagate through equipment. The ‘one’ index depicts that the safety objects successfully mitigate an abnormality and prevent the fault propagates in the process. From ‘zero’ to ‘one’, there is a transition area, in this area, it cannot be predicted whether safety object success or failure. Perhaps, safety objects still work however they are not in good performance and fault will propagate in the process.

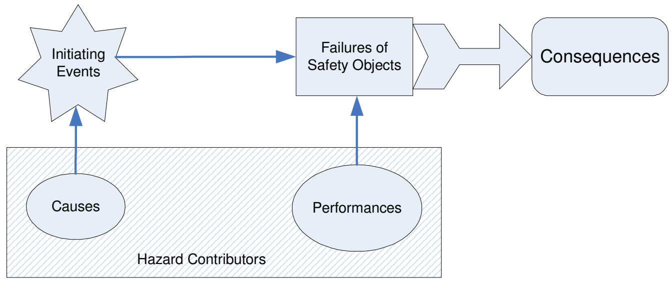
3. Fault Propagation for Performance Index Computation

Kelly and Lees (1986) introduced the fault propagation concept. They mentioned the fault propagation model and described the propagation equation that representation of the initiation of a fault at one point, its propagation through the plant and its termination at another point. Fault propagation is defined as useful method for hazard identification for complex chemical plant. In term, it is closely related to the cause-consequence relationship. In other works, Suzuki et al., (1999) introduced fault propagation approach, as relationships among initiating events, process variables, and impact event. They mentioned how failure in cooling unit can give effect abnormal reaction in the reactor and damage to property.

The fault propagation explores all of the possible hazards that may occur during the process. There are several uncertainties in fault propagation in batch process. Batch process is carried out by several processing steps and the state of behavior usually changes depend on related batch recipe. Dynamic behavior of batch process makes uncertainty in quantify of fault propagation due to process variables and parameters change frequently. Besides that, uncertainty is found in quantifying the performance of safety objects (Quelch and Cameron, 1994). It is not usually true, if safety object works, then it will prevent propagation of fault. It depends on performance of safety object. Therefore, probability approach cannot cover accurately for describing fault propagation.

Fault propagation scenario is a useful model for analyzing safety and risk, as shown in Figure 3, where the causes can trigger the initiating event. If several safety objects cannot mitigate this initiating event, it will lead to the consequences. The performance of safety objects influences to the state of safety objects that may be; success, medium or failure in mitigating the failure sequence.

Figure 2: Fault propagation model



3.1. Using Phase Level in Fault Propagation Analysis

A batch process is divided into several levels where fault propagation should be analyzed in the phase (lowest) level. In phase level, the analysis can be focused on detail process (Rizal and Suzuki, 2003). Equipments on this level are grouped for specific purpose supporting to one process task. Result of one phase level can be used for analyzing whole batch process. Each phase level has its own characteristics. For example charging process is responsible for transporting material from tank to reactor. In this process, several safety objects are employed in serial network, when initiating event is detected; safety objects are responsible to reinstate condition to normal value.

For example, during the high flow, it needs to adjust valve to appropriate position near close state. This action will stimulate flow of the material becomes lower. The flow (f) through valve can be described as follow (Bequette and Wayne, 1998):

$$f = C_v h(d)\sqrt{\frac{\Delta P}{sg}} \tag{6}$$

while ΔP (pressure drop across valve), C_V (valve coefficient) for each valve, *sg* (specific gravity of material) of VCM are obtained from component specification. However flow characteristic as function of d, h(d) for equal percentage valve type can be modeled as follow:

$$h(d) = \Omega^{d-1} \tag{7}$$

where Ω is (valve constant). For flow (f) and valve position (d) relationship can be expressed as follow:

$$f = C_v \Omega^{d-1}\sqrt{\frac{\Delta P}{sg}} \tag{8}$$

in logarithmic form, Eq. 3.8 will be

$$\log[f] = \log\left[C_V \Omega^{d-1}\sqrt{\frac{\Delta P}{sg}}\right] \tag{9}$$

Assuming $log\ \Omega = \Omega_0$, C_V, ΔP and *sg* are constant; d can be obtained as follow:

$$d = \frac{1}{\Omega_0}\log\left[\frac{F}{C_V}\sqrt{\frac{sg}{\Delta P}}\right] + 1 \tag{10}$$

The valve position *d* will vary between 0 and 1; flow through valve *F* should represent the ideal/safety value for zone 5. Information from the equation can be used to manipulate object (valve) performance index.

3.2. Knowledge Acquisition

Knowledge is formulated using two inputs from event index and trend index, also one output as object performance index. This index is implemented using natural linguistic variable that represents state classification. Event index is classified into five area X_1= {*Very Low, Low, Normal, High, Very High*}, trend index X_2= {*Decrease, Constant, Increase*} and object performance index X_3= {*Failure, Medium, Success*}. The classification can be implemented using fuzzy set representation. The use of fuzzy set to represent knowledge since one does not have enough information to assign an element to one set only. Using fuzzy, qualitative knowledge can be mathematically modeled and numerical approach can be used to estimate fault propagation along the process. The fuzzy representation is assumed to be triangular, due to have the advantage of simplicity and is commonly used in reliability analysis (Yadaf et al., 2003). Construction of fuzzy representation is generalized using linguistic variables identified by expert/operator experience in operating plant. Membership function $\mu(x)$ is arranged from 0 to 1 that represents the possibilities of event. After knowledge is elaborated into fuzzy sets information and its membership, knowledge connection phase is established using rules that restrict connection between two inputs (event index and trend index) and one output (object performance index).

3.3. Membership Function

Membership function shows the characteristic of fuzzy set and as a translation over a universe of discourse U. This is associated with variable x, with membership degree between 0 and 1.

$$\mu(x): U = [0, 1] \qquad (11)$$

The membership function is assumed to be the degree of possibilities of variables that indicating true value of variable. This variable can have different values, for example the term of object performance index (OPI) may be:

$$OPI= \{\textit{failure, medium, success}\} \qquad (12)$$

Variable of membership function will vary from failure, medium (transitional), and success. Fuzzy representation of performance shows the uncertainty condition that may occur during process. If deviation can be mitigated, it is not usually "*success*"; it possibly gives the impacts such as fault propagation for next process. This condition may happen due to equipment in transitional condition from *medium* to *success* condition. Analysis should be done to ensure how safe the valve when mitigating deviation.

Linguistic variables can be used to construct a model for fault propagation based on manipulated variables via event and trend index. The previous researcher shows that the model of fault propagation was established using SDG (Sign Directed Graph) by explain qualitative relationship among process variable. This model effectively describes possible consequences caused by deviation. However, it is still difficult to explain the level of risk and to identify the hazard. Membership function and fuzzy system can describe fault propagation more qualitatively with indexing the process variable.

3.4. Fuzzy Inference and Indexing

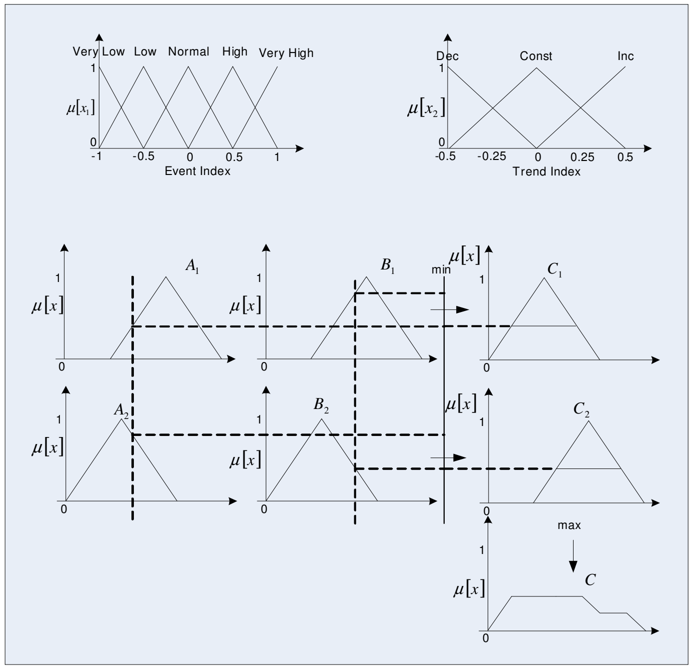
In this section, fuzzy inference algorithm is introduced to manipulate event index & trend index and to obtain the object performance. A fuzzy inference offers the connection using IF THEN rules,

$$\text{IF } \{\textit{event index}\} \text{ and } \{\textit{trend index}\} \text{ THEN } \{\textit{performance index}\} \qquad (13)$$

It can be shown that event index and trend index are premise part, while performance index is consequence part. These rules are applied due to dealing with the uncertain condition when there is not enough exact information for estimating fault propagation. The inference technique shows the appropriate technique to estimate the status of safety objects.

Fuzzy inference will combine list of rules and match input in all IF-part. The combination of the inputs will activate the rules in antecedent part and formulate fuzzy conclusion set. Figure 3 presents how fuzzy inference manipulates two inputs and converts the result to an output.

Figure 3: Construction of the consequent membership functions from two active rules for a system with two inputs and one output.



4. Neuro-Fuzzy

A neural network can model a dynamic plant by means of a nonlinear regression in the discrete time domain. The result is a network, with adjusted weights, which approximates the plant. It is a problem, though, that the knowledge is stored in an *opaque* fashion; the learning results in a (large) set of parameter values, almost impossible to interpret in words.

Conversely, a fuzzy rule base consists of readable if-then statements that are almost natural language, but it cannot learn the rules itself. The two are combined in *neuro-fuzzy system* in order to achieve readability and learning ability at the same time. The obtained rules may reveal insight into the data that generated the model, and for control purposes, they can be integrated with rules formulated by control experts (operators).

A mechanism is supposed to extract a model of the nonlinear process, depending on the current operating region. Given a model, a controller for that operating region is to be designed using, say, a pole placement design method. One approach is to build a two-layer perceptron network that models the plant, linearism it around the operating points, and adjust the model depending on the current state. The problem seems well suited for the so-called *Takagi-Sugeno* type of neuro-fuzzy model, because it is based on piecewise linearization.

Extracting rules from data is a form of modeling activity within *pattern recognition*, *Data analysis* or *data mining* also referred to as *the search for structure in data* (Bezdek and Pal, 1992). The goal is to reduce the complexity in a problem, or to reduce the amount of data associated with a problem. The field of data analysis comprises a great variety of methods; the objective of this note is to present a feasible way of combining fuzzy and neural networks.

5. Estimating the Probabilistic Function for the Safety Object

The probabilistic risk assessment (PRA) involves reliability function, industrial historical data, failure rate, and etc. However, to assess the present condition by using PRA method, it will be not accurate without recent information from the plant. Therefore, integrating the real time information (performance index) into probabilistic function should be considered by using Bayesian Inference. In the Bayesian theorem, the posterior probability function can be estimated by using the likelihood of new evidence from recent observation and prior probability density function. The Bayesian inference should be

$$\pi_1(\lambda \mid E) = \frac{L(E \mid \lambda)\pi_0(\lambda)}{\int L(E \mid \lambda)\pi_0(\lambda)d\lambda} \tag{14}$$

Let $\pi_0(\lambda)$ represent a prior probability density function for λ, prior to obtain the new evidence *E*, $L(E \mid \lambda)$ is the likelihood function. Evidence (*E*) could be expert opinions, model prediction, and fuzzy or imprecise data. $\pi_1(\lambda \mid E)$ is the posterior probability density function for λ after evidence *E* is occurred. By considering the distribution of evidence in exponential and conjugate likelihood (prior) pairs in exponential and Gamma function, the posterior distribution can be determined. Assume the exponential distribution of likelihood can be shown:

$$L(E \mid \lambda) = \lambda e^{-\lambda t_o} \tag{15}$$

and prior distribution using Gamma distribution

$$\pi_0(\lambda) = \frac{\beta^\alpha \lambda^{\alpha-1}}{\Gamma(\alpha)} e^{-\beta\lambda} \tag{16}$$

While α is shape parameter and β is scale parameter that can be defined by the mean (*M*) and standard deviation (*SD*) of λ:

$$M(\lambda) = \frac{\alpha}{\beta} \tag{17}$$

$$SD(\lambda) = \frac{\sqrt{\alpha}}{\beta} \tag{18}$$

$\Gamma(\alpha)$ is the gamma function of α. The output of de-fuzzification process is defined as an estimator in the change of the safety object reliability while an event occurs. The estimator is termed as performance index (PI), which have some restrictions:

$$\begin{aligned} &R_0 = R_1 \rightarrow \lambda_0 = \lambda_1 \Rightarrow PI = 1 \\ &R_0 > R_1 \rightarrow \lambda_0 < \lambda_1 \Rightarrow 0 < PI < 1 \\ &R_1 \approx 0 \rightarrow \lambda_1 >> \Rightarrow PI \approx 0 \end{aligned} \tag{19}$$

From equation (19), the new condition of reliability of component (R_1) depends on the generic reliability (R_0) multiply by PI.

Based on the restrictions, we obtain the new evidence (λ_1) as the ratio of generic failure rate (λ_0) to PI. Therefore, the likelihood L (E|λ) function is constructed based on the fuzzy reasoning result that incorporated the PI to λ_1. While the mean time to failure (MTTF) can be simplified as reciprocal of λ_1:

$$MTTF = \frac{1}{\lambda_1} \tag{20}$$

The MTTF should be considered as time of observation when evidence was obtained. For that reason, it can be concluded that posterior distribution after considering evidence will be different to the prior distribution. The prior distribution is generated from appropriate historical data and manufacturer data. In addition, the likelihood functions are built and updated using the result from fuzzy inference system. Based on this evidence, we predict the posterior distribution that can be used for risk assessment. During process risk assessment, the posterior distribution (the Bayesian inference output) can be more credible and actual than the value of prior distribution. The cumulative density function (CDF) and reliability of safety objects at the time (t) can be obtained by integrating the probability density function of Equation (14):

$$CDF = \int_0^t \Pi_1(\lambda \mid E) = \int_0^t \frac{L(E \mid \lambda)\pi_0(\lambda)}{\int L(E \mid \lambda)\pi_0(\lambda)d\lambda}dt \tag{21}$$

$$R = 1 - CDF = 1 - \int_0^t \frac{L(E \mid \lambda)\pi_0(\lambda)}{\int L(E \mid \lambda)\pi_0(\lambda)d\lambda}dt \tag{22}$$

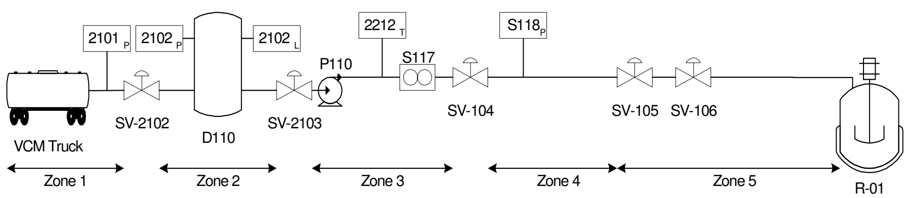
If we substitute the Equation (3.15) and (3.16) to the Equation (3.22), we can obtain the new reliability (R) as the function of likelihood and prior distribution:

$$R = 1 - \int_0^t \frac{\lambda e^{-\lambda t_o} \dfrac{\beta^\alpha \lambda^{\alpha-1}}{\Gamma(\alpha)} e^{-\beta\lambda}}{\int \lambda e^{-\lambda t_o} \dfrac{\beta^\alpha \lambda^{\alpha-1}}{\Gamma(\alpha)} e^{-\beta\lambda} d\lambda}dt \tag{23}$$

6. Case Study: Hazard in VCM (Vinyl Chloride Monomer) Charging Line

VCM is identified as colorless gas with empirical formula C_2H_3Cl. VCM is also known as carcinogen and explosive gas. VCM charging line can be drawn in Figure 4 (Rizal et al., 2006).

Figure 4: Overview of VCM charging line



VCM gas is loaded from tank truck into the vessel (loading process), after that gas is stored in vessel for a temporary time. Gas in vessel is charged to reactor through VCM charging line. There are five zones from VCM tank truck to the vessel. Several safety objects will prevent from hazardous condition. When there is a problem in pump P-110 (zone 3), pump failure causes high output, therefore material stream flow will escalate and several problems may arise. The assessment method for VCM charging line can be seeing in Table 1.

Table 1: The assessment method for VCM charging line

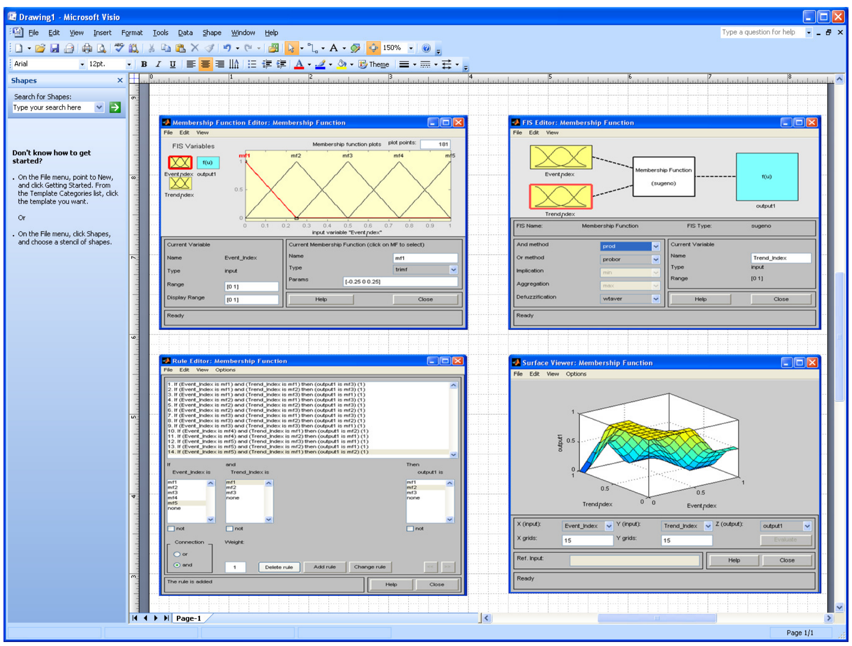
Steps	Description
1. Determine the initiating event	• Line pressure = 6 – 8 kg/cm^2 • Flow material from pumping system = 70 m^3/s
2. Determine the safety objects	• Informative safety objects: S117; S118 • Non-informative safety objects: SV-104; SV-105; SV-106
3. Develop the pre-computation	The control valve ◊ valve position indicator (from 0 to 1).
4. Perform computation using neuro-fuzzy (the simulation as shown in Fig. 3.8)	Adaptive Neuro-Fuzzy Inference System (ANFIS). Initiating event, high flow about 90 m^3/s
5. Develop prediction of hazard identification (PHI):	Performance index
5.1. Identify the parameters for the prior distribution	Historical data.
5.2. Integrate the performance index	Data of failure rate (mean, standard deviation) ◊ using OREDA (Offshore Reliability Data).

Table 1: The assessment method for VCM charging line - continued

5.3. Estimate the posterior distribution using Bayesian inference	Results: flow sensor λ_{F0} = 3.26 x 10^{-6}/h; SD=2.1 x 10^{-6} /h, control valve λ_{V0} = 3.11 x 10^{-5}/h; SD = 1.89 x 10^{-5}/h and pressure sensor λ_{P0} = 1.14 x 10^{-6} /h; SD = 1.61 x 10^{-6}/h. Using Eq.3.31 and Eq.3.32, we can get the α and β, the results for each safety objects, α_F = 2.409; β_F = 7.39 x 10^5 h, α_V = 2.702; β_V = 8.7 x 10^4 h, α_P = 0.501; β_P = 4.40 x 105 h.

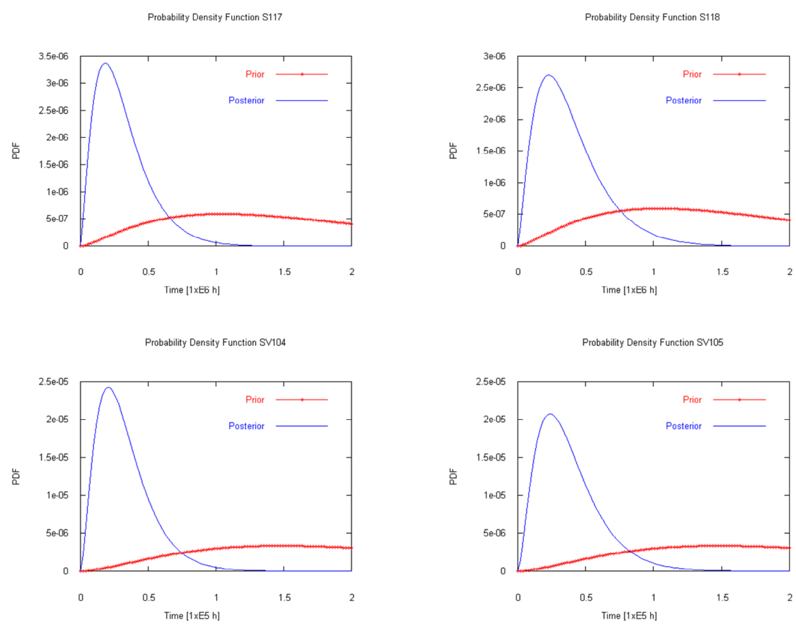
Perform computation using neuro-fuzzy with the simulation can be shown in Figure 5. The simulation results consist of the membership function, rule base that consists of "if-then" rules, fuzzification-defuzzification, and surface viewer. The analysis using this computation will combine the trend and event index and perform the performance index of sensor system.

Figure 5: Perform computations using neuro-fuzzy by the simulation



The results from Step 5.2, the changes in failure rate have an effect on probability density function (PDF), as shown in Figure 6. The figures show that evidence in likelihood function has great influence on posterior (new) distribution and the data from performance index represents strong evidence. The posterior distribution for failure rate is large different form the prior distribution. PHI can be estimated as a new hazard function of posterior distribution, so it can be assumed that failures will increase during process operation.

Figure 6: Probability density functions for safety objects in VCM charging line



7. Summary

Failure detection using performance index (PI) can be implemented in a real time process. A fault propagation assessment is implemented to estimate the likelihood function of safety objects. This method shows the ability to compute the index during process. The indices are treated as the monitoring results that can changes the new condition of safety objects. With the indices and prior distribution function, a new (posterior) distribution function of safety object can be recognized. These indices was produced by neuro-fuzzy inference system and employed in the Bayesian inference. It can be seen that the performance index influences the reliability/hazard and gives the significant impact to posterior distribution of safety objects.

Fault propagation method can be used for real time safety analysis of batch chemical plant and give recommendation to the plant management level to take appropriate action in preventing consequences during process monitoring. The results of simulations give the impressions to use this method for further analysis in hazard identification and reliability improvement program in batch chemical process.

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