Real Time Safety Verification in the Process Industry Using Fault Semantic Networks (FSN)

by

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CERTIFICATE OF APPROVAL

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ABSTRACT

In the process industry, there are uncertainties associated with each variable, which might lead to process deviations and hazards. In order to accurately quantify the risks associated with these hazard scenarios, quantitative probability should be calculated. The process dynamically changes during plant operation, which requires continuous monitoring of process risks and real time safety verification. It is challenging to both dynamically and instantaneously estimate the risks for all faults and deviations. An FSN is introduced in this thesis to systematically and continuously estimate risks for all possible fault propagation scenarios.

Intelligent reasoning algorithms are proposed using a BBN to accurately estimate risks. An FSN is used to analyze causes and consequences of different faults using automated forward and backward propagation learning techniques. Real time safety verification is applied to each fault propagation scenario. The TE process is used to illustrate the proposed real time safety verification. An FDS experimental setup is used to study real life data.

Key Words: Fault Semantic Network (FSN); Process Object Oriented Methodology (POOM); Bayesian Belief Network (BBN); Tennessee Eastman (TE) process; Fault Diagnostic System (FDS); Independent Protection Layer (IPL).

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Chapter 1: Introduction

Accidents in process industry might be the result of deviations of process variables, which are the state variables that are related to the plant equipment and physical model. The process variables for an assembly are the combined state variables of all of the components of that assembly. The proper fault propagation modelling can be achieved by linking process variables to plant physical models. From critical fault propagation scenarios accidents are developed. In order to properly model fault propagation scenarios with detailed process variable definitions, it is important to understand the accident scenarios occurred in the past.

Accidents are very common in oil and gas processing facilities. About 20 billion U.S. dollars are lost in the oil and gas industry every year (Venkatsubramanian, Regaswamy, Yin & Kavuri, 2003a) because of damage from accidents or lost revenues because of lost production from process deviation.

Figure 1.1: LNG Plant, Ras Lafan, Qatar (Hydrocarbons Technology)

Over the years, engineers and researchers have focused on improving industrial processes to increase their efficiency. These efforts led to efficient industrial processes and improved products, both quantitatively and qualitatively. This progress has advantages, which increase the complexity of industrial processes and make them more complicated. Besides the increase in process complexity, monitoring and control approaches of process industries have to be updated. Processes that were controlled manually by operators through a simple procedure now have to be controlled automatically through complex procedures. The complexity of a Liquefied Natural Gas (LNG) processing plant can be seen in Figure 1.1.

An increase in system complexity poses another potential risk of hazards because of the complex monitoring and control systems. Significant research has been done in the area of hazard identification and safety system design. Recent technologies and automation are the key players to achieve such progress. Although on the one hand, these technologies have advantages such as efficient productivity, lower cost of production, high quality of product, on the other hand, they increase the complexity of process systems. Complex systems have more chances to be subjected to faults and hazardous conditions. Any of these may result in costly and serious incidents or accidents such as explosion, plant shutdown, and injuries.

Faults in plant equipment have the potential to affect the performance of the entire process. Even minor faults might lead to a serious disruption in the whole process. Therefore, considering the fault propagations seems necessary in process industries, especially those that deal with continuous processes, where many process variables and hazardous materials such as chemical and petroleum industries, have to be dealt with,.

Recent technologies focus on controlling and monitoring processes, and modelling system dynamics, as well as predicting their behaviour and the relationships among process variables. This approach provides a means to detect abnormal events at early stages by understanding the relationship among process variables and their impact on fault propagation scenarios. These targets are achievable through an accurate fault propagation analysis, which results in a successful fault diagnosis. Given this, controlling and monitoring of process operation to implement a well-designed fault diagnosis technique is among the most important concerns in process industries.

1.1. Previous Accidents

In the United States of America (USA), 4,693 people died from industrial accidents in 2011 (OSHA, 2013), an average of 13 people per day. Approximately five people died every working day in the workplace from 1993 to 2005 in Canada (CBC, 2006). This is the situation of two of the most developed countries. As illustrated in Table 1.1, the situation in the developing world is much more extreme. Accidents and fatalities are not commonly reported to the authorities in those countries. Devastation from industrial accidents can be seen in Figure 1.2.

Figure 1.2: Fire extinguisher plant explosion in Kansas City, Missouri (Braindrips)

Ten selected previous major accidents in regard to death tolls in the process industry are summarized in Table 1.1. The accidents are categorized according to the number of death tolls.

In terms of death toll, Bopal was the worst industrial disaster in the history of mankind. On the night of December 2-3, 1984, a storage tank containing 45 tons of Methyl Isocyanate (MIC) (Grazian-Archive, 2010) exploded, releasing a plume of highly toxic gas. Approximately 4,000 people died in a few minutes (BBC, NCBI, Person, 2009). Within a few days, thousands more died.

Factors leading to the magnitude of the gas leak mainly included problems such as: storing MIC in large tanks and filling them beyond recommended levels; poor overall maintenance, leading to failure of several safety systems; and safety systems switched off to save money including the MIC tank refrigeration system, which could have mitigated the severity of the disaster.

Table 1.1: Ten major accidents occurred in the process industries

Sl.	Date	Location	Material Name	Deaths	Injuries	Source
1	December 3, 1984	Bhopal (India)	Methyl Isocyanide	More than 15,000	More than 600,000	BBC news: www.bbc.co.uk
2	February 24, 1984	Cubatao (Brazil)	Gasoline	508	-	Mannan (2004, p. 54)
3	November 19, 1984	San Juanico Ixhuatepec (Mexico)	LPG	More than 500	2500	HSE www.hse.gov.uk
4	August 04, 1993	Remeios (Columbia)	Crude Oil	430	-	Ciottone (2006, p. 788)
5	November 2, 1994	Dronka (Egypt)	Aircraft Fuel	More than 420	-	ESR www.epd.gov.hk
6	December 23, 2003	Gao Qiao (China)	Natural Gas, Hydrogen Sulphide	234	4000-9000	WHO www.who.int
7	December 19, 1982	Tacoa, Venezuela	Fuel Oil	180	500	Tacoa www.eluniversal.com
8	July 6, 1988	North Sea (UK)	Oil, Natural gas	167	-	Ciottone (2006, p. 788)
9	October 20, 1944	Cleveland (Ohaio, USA)	LNG	130	-	Foss 2012, p. 67)
10	June 20, 1991	Dhaka, Bangladesh	Amonia	104	-	Assael (2013, p. 197)

Other factors identified are: undersized safety devices; the dependence on manual operations; reduction of safety management; insufficient maintenance; and inadequate emergency action plans (BBC, NCBI, Peterson, 2009).

The second worst industrial accident happened in Bangladesh on April 24, 2013. A total of 1,127 lives perished in the accident and thousands more became disabled (BBC, CBS, CBC, Global, CTV news, 2013). Reuters (2013) reported the death toll as 1,131. Even though it was an industrial accident, it is not included in the table because the accident did not occur in the process system. The building housing the companies collapsed. The scope of this research is the process system.

1.2. Motivation

The top priorities of any plant process include implementation of a successful, productive, and safe operation. Higher efficiency at a lower cost of production and reduction of hazards are the ultimate targets. These goals are only achievable under well-controlled and well-monitored process operations. Implementing an efficient monitoring, hazard identification and fault diagnosis system makes it possible to reduce the undesired and sudden events that may result in catastrophic accidents or disasters.

In early 1980s, different techniques were introduced in order to implement fault diagnosis and hazard identification for chemical processes (Kalantarnia, 2010). These techniques included Quantitative Risk Assessment (QRA), Fault Tree Analysis (FTA), Failure Mode and Effect Analysis (FMEA), Hazard and Operability Analysis (HAZOP). Although these techniques are implemented in different industries around the world, minor and major accidents are still occurring because of their limitations, such as low accuracy of diagnosis, mainly because of lack of accuracy in fault propagation analysis and slow response time. Moreover, these techniques have to be implemented by operators whose skills and knowledge may not be adequate to monitor process plant and understand faulty conditions. Therefore, human errors are also considered as the main causes of many faults and hazard scenarios in the process industry, where more attention is required.

Accurate and quantitative fault propagation analysis is the basis of successful fault diagnosis, which is a challenging and difficult task because there are many parameters that are involved and that may affect the accuracy of diagnosis. These parameters include types of alarm equipment, their response time, quality, sufficiency of obtained process

data and the time delay in faults. Given this information, implementing an intelligent fault propagation analysis that overcomes the limitations and enhances fault diagnosis and hazard identification seems to be a necessity and concern of industries.

A predictive control and monitoring system which includes developing real-time fault propagation analysis and an automated solution for the process industry, is under development at the Energy Safety and Control Laboratory (ESCL) at the University of Ontario Institute of Technology (UOIT) in Oshawa, Canada.

1.3. Problem Definition

The current risk estimation is performed on a case-by-case basis, and not in real time. There is no solution to map safety and protection systems with fault propagation scenarios in real-time basis. There is no link between simulation and real-time plant systems, where it is difficult to predict fault propagation scenarios of new or unknown cases.

Safety verification is a key success factor for safe operation in the process industry. There are many challenges to achieve real time safety verification where fault propagation prediction and analysis is the main issue. In order to have an accurate safety verification technique, it is important to understand all possible faults and hazards in the process industry and how faults propagate. In addition, it is important to map safety protection layers to fault propagation scenarios in order to understand how protection layers will be activated in each fault propagation scenario with quantitative measures.

1.4. Objectives

The overall objective of this thesis is to develop an FSN to simulate real time and risk based accident forecasting and verify the calculated probability of risk against the reliability data. It is to enable the user with an early understanding of process deviations and link the deviations with possible accident scenarios. The final product will be a program developed across multiple platforms. In this program, a fault modelling technique will be presented to design causation-models to estimate safety measures for each operational step and process model element and validated with process conditions. **The four objectives** of this research are shown in Figure 1.4, and described as follows:

- Develop an FSN for selected case study to map quantitative risk estimation with fault propagation scenarios
- Conduct safety and protection system modelling and mapping to an FSN
- Dynamic risk estimation with real time process data and updating an FSN using a BBN
- Conduct real time safety verification of different fault propagation scenarios

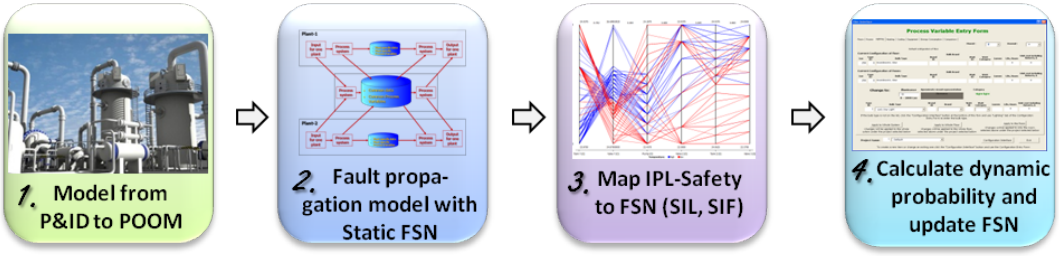


Figure 1.3: Four objectives of the research

1.5. The Innovative Contributions of This Study

The main aim of this research work is to develop a safety-related framework which would help prevent accidents. In order to demonstrate the viability of the developed system, different experimental and real world datasets are used. The main contributions of this study are summarized as follows:

- A literature review has been conducted on approximately 30 research studies to analyse the existing methodologies and to determine their shortcomings in order to bridge the gap;
- The FSN method is a new approach that can provide the dynamic safety verification that could not be implemented using the traditional techniques of FTA / ETA or other methods shown in the literature review;
- The main contribution in this work is the design of the FSN knowledge structure, and the development of an automated solution and algorithms to generate a static FSN for a given plant process using P&ID data;
- Intelligent algorithms are developed to generate a dynamic FSN based on the dynamic risk estimation for all given fault propagation scenarios;
- Programs are developed to implement these proposed algorithms for static and dynamic FSNs based on a proposed integrated framework, which is presented in this thesis;
- Initial development of two programs, FSN and ESN, has been conducted;

The concept of an FSN is first applied to a simple problem. This program will be later applied to more complex problems and the database will be enriched with complex data.

The development of the complete database and the FSN program will take at least a decade's effort to implement. In this research, the foundation for future research has been laid.

1.6. Solution Approach

- Model a case study process using POOM
- Analyze a fault propagation model using the FSN
- Process a data analysis and feature extraction from real time / process simulation data
- Model IPL with the FSN
- Estimate the dynamic risk using intelligent probabilistic methodology

The organization of rest of the thesis is as follows:

Chapter 2: In chapter 2, related literature on fault detection and semantic networks are discussed. The use of evolutionary and conventional approaches for fault diagnosis in the research literature, along with techniques for decision support and prognostics, are also discussed.

Chapter 3: In chapter 3, methodologies of this research are discussed. In this chapter from PI&D modelling to risk verification are reviewed in different steps of static and dynamic FSN. The Bayesian Belief Network (BBN) is also reviewed.

Chapter 4: In chapter 4, a case study is presented. In the case study, the Tennessee Eastman Process simulation is used to verify the implementation of the four steps of the methodology.

Chapter 5: In chapter 5, different steps of system design and implementation using FSN are discussed. System architecture, database structure, arrangements of tables, and attributes of tables are also discussed.

Chapter 6: The evaluation of the methodology, case study, and system design is summarized in this chapter. The results from the simulation are also discussed.

Chapter 7: This chapter presents conclusions, related and future works.

Summary: *In this chapter, introduction and background about the research work are described. In addition, research objectives, motivation, and organization of the thesis are presented. In the following chapter, a literature review will be analyzed in detail.*

Chapter 2: Literature Review

In this chapter, previous literary works, which are relevant to the subject matter of the dissertation research, are summarized. In most cases, these citations present formative works in the literature, or present articles that were points of controversy and led to current research paradigms and conventions. Where direct relevance to the current research exists, or where the current research directly builds upon or borrows from prior research, appropriate citations are made in the accompanying texts. Commentary on the conventions adopted in this research is presented as and when necessary, and often includes citations of existing literature extending those comments.

There is no literature published on FSN except Gabbar (2010) which was later re-written by Gabbar in 2012. But there is a significant amount of literature on semantic networks. Different literary works related to FSN are reviewed in this chapter.

2.1. P&ID Modelling

Piping and Instrumentation Diagram (P&ID) modelling of the case study was performed by the other research group in the FSN project. As P&ID modelling is an integrated part of FSN, five previous research works are reviewed.

Puttre (1993) discussed the effect of fluid flow though piping and how software can model and predict the future failure of valve opening or closing events. Piping design consists of planning the number of sections and components required to move the desired

material. The basic steps for designing and analyzing piping and components do not vary significantly even though no two piping systems are exactly the same. Puttre suggested that one of the more difficult aspects of piping analysis involves anticipating the effects of nonlinear events on the system. Nonlinear analysis of events such as water hammer and steam hammer, where interference in the flow carries shock waves through the pipes, and fast valve opening events, would be nearly impossible to perform in a timely manner using manual methods. Piping software has enabled most engineering firms to analyze nonlinear effects.

Huitt (2007) reviewed how to design and install piping and other instruments, fault and leak free. He also discussed how to prevent future possibility of fire from sparks from static charge accumulation. Furthermore, he recommended that it might be difficult to predetermine what fluid services and systems would be candidates for charge accumulation prevention and electrostatic discharge protection. The simplest and most conservative answer is to assume that all fluid services in lined pipe systems are susceptible. Therefore, it can be declared that a company's pipe specifications need to reflect a global resolution that will affect all installations.

Pohjola (2003) showed how process design can be viewed as a design project represented at the highest level of abstraction as a composite of three mutually communicating objects representing management activity, base level (design) activity, and the process. Each of the three objects, and all the sub-objects, which disaggregate or decompose to, have the same attribute list: purpose, structure, state, and performance. The generic list of attributes has important consequences. First, it unifies the representation of reality and thus makes possible and facilitates knowledge integration across disciplines. This also

makes it possible to build holistic models. Second, it solves the question of what properties should be specified for each object generated in order for the specification to be complete.

The holistic model of a process, as presented by Pohjola (2003) includes specifications of all the four attributes of a process. Under Process Purpose, the designer makes explicit the list of performance criteria. These are the criteria against which he commits himself to assess performance each time the structure and state are updated. This is how safety as an item in the list of performance criteria becomes explicitly included in the model. Being just an item in a list is not sufficient. To assess process performance against safety, the features, which have an effect on safety performance, must be found under Process Structure and State. This is possible only by including environment into the structural parts of process.

During the design project and also after the process has been built, the specifications of the attributes change, as previously discussed in the paper. This is why a model should be capable of representing a process over its lifespan. It should be possible especially in design, to prescribe the process at all the different levels of abstraction as the project advances. This feature has been taken into account by representing process as one of the three mutually communicating objects called design cycle. The same construct applies for representing control, operation, and maintenance activities during process operation.

Alha and Pohjola (1995) stated that the conceptual stage of process design is the most crucial component of the overall design process because the decisions made at this phase have a disproportionately large share of impact than later phases. A methodology for the

conceptual stage of the chemical process design has been presented in Pohjola et al. (as cited in Alha & Pohjola, 1995) and Alha and Pohjola (as cited in Alha & Pohjola, 1995). This study aims at testing the design strategy suggested in the methodology and the performance driven design strategy (Pohjola & Alha 1994). A combined method for eliciting expert knowledge from verbal data was developed for constructing a descriptive cognitive model of a design process. The method has its basis in the connectionist view of information processing and it utilizes parallel distributed computing; e.g. neural networks.

Addis (1992) observed that, apart from work conducted in the area of some expert systems, there has been little discussion of the problems of storing the knowledge used by engineering designers. It is often assumed that this comprises only the knowledge of engineering science in conjunction with a certain inner 'feel' for materials and system behaviour. Addis argued that the knowledge of how to design is different from these and merits a separate identity, with its own epistemology and philosophy. The idea of the 'design procedure' is introduced as the means by which certain engineering design knowledge and skill can be stored, communicated, learned, researched, and given its own history independent of engineering science.

2.2. Pattern Identification of Faults

Burk, Chappell, Gregory, Joslyn, and McGrath (2012) discussed pattern discovery using a semantic network analysis in their research. In their opinion cognitive information processing at higher conceptual levels requires a computational approach to knowledge

representation and analysis. Semantic network analysis bridges the gap between probabilistic pattern recognition techniques and symbolic representations by replacing cumbersome and computationally complex forms of logic-based semantic inference that is common in symbolic approaches with mathematical metrics on graph representations of labelled, directed semantic networked data. These metrics in turn support assessment of evidentiary support for the presence of patterns of interest in which entities play specified roles in complex event scenarios. The resulting system allows patterns to be specified at higher levels of conceptual abstraction, while also remaining robust to conflicting and incomplete information.

Zanoli and Astolfi (2012) presented the results concerning the detection and isolation of a break of the thrust bearing in a multi-shaft centrifugal compressor. From the inspection of historical data, there is clear evidence that, without the use of a diagnostic tool that assists the process engineer operations to recognize the true fault, it is not trivial unless its effects are not appreciable. This delayed detection/isolation may generate considerable economic loss damage and/or cause undesirable wear of the system. In the present research work, fault detection is approached by a Principal Component Analysis (PCA) model-free technique, while a Fuzzy Faults Classifier (FFC), as proposed in a previous work by Zanoli, Barboni and Astolfi (as cited in Zanoli and Astolfi, 2012), performs fault isolation.

Furthermore, Zanoli and Astolfi showed that the probabilities are the values of the membership function U in Fuzzy C Means (FCM) algorithm:

$$u_{ij} = \frac{1}{\left(\frac{d_{ij}^2}{d_{1j}^2}\right)^{\left(1/(m-1)\right)} + \ldots + \left(\frac{d_{ij}^2}{d_{kj}^2}\right)^{\left(1/(m-1)\right)}} \qquad [2.1]$$

where

u_{ij} = elements of the U matrix which denotes the membership degree of the current F_{SPE} elements from j to centroid i

F_{SPE} = faults prototype vector

k = number of centroids

m = fuzziness factor, m > 1, preferably 2

d_{ij} = Euclidean distance

According to Zanoli and Astolfi (2012), the most effective enhancements achieved are related to the modification of the membership function employed in the fuzzification module and the use of the Mahalanobis Distance as metric for the fault recognition purpose. The main benefit of this metric is the possibility of taking into account the correlation between the data and how this sensitively increases the performances of the overall system. The improvements are mainly associated with the faster response for the true fault isolation with respect to the previous FFC module. The previous module required approximately a day and a half for the true fault isolation, while with the introduction of the new metric in less than one hour from the appearance of the symptom, the fault can be correctly detected and isolated.

Ebnenasir and Cheng (2007) introduced an object analysis pattern, called the detector pattern, for modelling and analyzing failsafe fault-tolerance, where instances of the detector pattern are added to the Unified Modelling Language (UML) model of a system to create the UML model of its failsafe fault-tolerant version. The detector pattern also

provides a set of constraints for verifying the consistency of functional and fault-tolerance requirements and the fault-tolerance of the detector pattern itself. They extended the formalization framework explained by McUmber and Cheng (as cited in Ebnenasir & Cheng, 2007) to generate the formal specifications of the UML model.

Wang et al. (2003) have proposed a fault-pattern oriented methodology for semiconductor memory defect diagnostics, which greatly reduces the effort in memory product development and yield learning. The proposed notion of fault pattern combines the strengths of the conventional failure-pattern approach and the previous fault-type approach for easier isolation of real defects. They suggested that, as the fault patterns have to be customized for different products and process technologies, automation is very important. They have also developed a systematic procedure to explore the fault patterns, which includes a layout-based defect injection tool that provides very accurate results from realistic defect models. With the proposed approach, high-quality defect diagnostics can be automated.

Mendel et al. (2008) employed signal processing and pattern recognition techniques to classify faults in bearings. The envelope analysis provides the feature vector used in the subsequent classification steps. On the contrary, with the majority of the works that focus on the fault detection problem, they explored pattern recognition methods to automate the analysis of the obtained features.

2.3. Techniques of Fault Modelling

Venkatsubramanian (2003a and 2003b) classified fault diagnosis methods in three categories as follow:

- Quantitative Model-Based Methods
- Qualitative Model-Based Methods
- Process History-Based Methods

However, the disadvantages that come with these methods are their limitations in modelling nonlinear systems and having model errors due to the simplicity of approximation that considerably reduces the effectiveness of these methods.

In another study (Qian, Li, Ziang, and Wen, 2003), the researchers tried to design an expert system to implement a real-time fault diagnosis system using computer-aided techniques. When an abnormal situation arises in a process, real-time data extracted from sensors is stored in an online database and then the expert system reasons it to find causes and consequences, according to the designed knowledge base. This is similar to the work performed at Qian et al. (2003) and Nan, Khan and Iqbal. (2008), who studied other computer-aided fault diagnosis techniques. They proposed a knowledge-based fault diagnosis method that uses fuzzy-logic as an inference engine to reason, according to the extracted real-time data and knowledge base. These techniques were useful and offered practical ways to perform fault diagnosis. The performance of these fault diagnosis techniques depends on the frequency and presence of fault data, and the quality and accuracy of fault and hazard scenarios' knowledge base.

As part of the research and work completed in the area of computer-aided fault diagnosis, Gelgele and Wang (1998) have developed a software prototype called EXEDS for application of fault diagnosis in automotive engines. The software analyzes failure symptoms to diagnose faults and suggests desired maintenance actions. It consists of knowledge base and an expert system which include a list of symptoms, diagnosis modules, remedies and associated rules, respectively.

Chetouani, Mouhab, Cosmao, and Lionel (2003) have shown that, by combining the Extended Kalman Filter (EKF) for a nonlinear dynamic system with an innovation test, an efficient method for detecting faults is obtained. The detection method needs a model that describes the process behavior in the normal mode. Indeed, successful detection requires a judicious adjustment of the decision criterion, which expresses the response of the filter to breakdowns.

2.4. Probabilistic Approach in Fault Identification

Different probabilistic approaches are widely used in fault identification. The Bayesian Belief Network (BBN) is one of the promising probabilistic techniques that can offer an accurate calculation of probabilities of faults. Commonly, the BBN technique is applied to fault diagnosis of complex systems. A study performed by Guzman and Kramer (1993) compared the BBN with rule-based expert system and showed how these two methods contrast with each other. An expert system consists of a knowledge base made of heuristic rules that demonstrate successful operation in diagnosing faults. However,

this has some disadvantages and limitations. The probabilistic approaches not only overcome these drawbacks, but also construct a logical way to reason and model the underlying process in order to accurately detect faults.

Bickford and Malloy (2002) used the Bayesian approach to develop an online fault diagnosis software prototype to detect and diagnose faults in a turbine engine. The proposed software monitors and classifies the source and type of sensor, component, and engine faults. The proposed software provides a mathematical means to integrate data from multiple diagnostic instruments and algorithms in order to detect and classify faults in real time.

In another similar study, Romessis, Stamatis and Mathioudakis (2001) proposed a method for building BBNs to diagnose faults in a gas turbine. The results show that the proposed method was successful in fault diagnosis with an accuracy of 96%, which shows the high reliability of the BBN as a probabilistic method in fault detection and diagnosis. Nan et al. (2008) and Kalantarnia, Khan, and Hawboldt (2010) have discussed the development of a probabilistic framework using the BBN to analyze faults for application on hazard identification. Their approach provided new features for the accurate prediction of faults and their propagation.

Friedman, Geiger and Goldszmidt (1997) have analyzed the direct application of the Minimum Description Length (MDL) method to learning unrestricted Bayesian networks for classification tasks. They showed that, although the MDL method presents strong asymptotic guarantees, it does not necessarily optimize the classification accuracy of the learned networks. Their analysis suggests a class of scoring functions that may be better

suited to this task. These scoring functions appear to be computationally intractable. Friedman et al. (1997) therefore plan to explore effective approaches based on approximations of these scoring functions. The Bayesian theory was first introduced by Thomas Bayes (Bayes, 1763). The MDL scoring function is shown in the following paragraph, as described by Rissanen (as cited in Friedman et al. 1997).

Let $B = \{G, \theta\}$ be a Bayesian network, and let $D = \{u_1, \ldots, u_N\}$ be a training set, where each u*i* assigns a value to all the variables in U. The MDL scoring function of a network *B* given a training data set *D*, written *MDL*(B|D), is given by

$$MDL(B \mid D) = \frac{\log N}{2} \mid B \mid - LL(B \mid D) \qquad [2.2]$$

where |*B*| is the number of parameters in the network (Friedman et al., 1997).

The main contribution of the work of Friedman et al. (1997) is the experimental evaluation of the Tree-Augmented Naive Bayesian (TAN) classifiers, and the multinet classifier as described by Chow and Liu (as cited in Friedman et al. 1997), which is termed as CL hereafter. It is clear that, in some situations, it would be useful to model correlations among attributes that cannot be captured by a tree structure (or collections of tree structures). Such models will be preferable when there are enough training instances to robustly estimate higher-order conditional probabilities. Still, both TAN and CL multinets embody a good trade-off between the quality of the approximation of correlations among attributes and the computational complexity in the learning stage. The learning procedures are guaranteed to find the optimal tree structure, and, as their experimental results show, they perform well in practice against state-of-the-art

classification methods in machine learning. Therefore, Friedman et al. (1997) proposed them as worthwhile tools for the machine learning community.

Qian, Li, Jiang and Wen (2005) proposed the windowed Fourier transform for fault detection, which monitors the change of local frequencies. The algorithm is described and applied to simulated and real fringes. Its sensitivity to faults and robustness against noises are shown in Qian et al.'s (2005) study. Comparisons to the traditional Fourier transform approach as well as the correlation approach are also addressed.

2.5. Dynamic Risk Estimation

Fault is as an abnormal condition or defect at any component, equipment, or sub-system level which may lead to a failure. For example, vibration of a pump is a fault which might cause failure of the pipelines connected to the pump, which might cause a gas leak, and, consequently, fire and explosion. A schematic of propagation of a fault to an accident is shown in Figure 2.1.

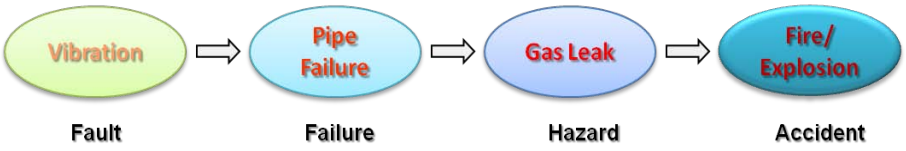


Figure 2.1: An example of propagation from a fault to an accident

Hazard may also be propagated from a process variable deviation; for example, if pressure which is higher than the set point in a vessel may cause a failure in the vessel and consequently an accident.

Kumbhakar and Tsionas (2008) analyzed the relationship between production risk and nonparametric estimation. They considered an approach in which producers maximized the expected utility of anticipated profit to solve the input allocation problem. In contrast, the risk studies in the production literature those based on built-in features such as:

i. Parametric form of the production and risk function,
ii. Parametric form of the utility function,
iii. Distributional assumptions on the error terms representing output risk.

However, Kumbhakar and Tsionas (2008) stated that the nonparametric approach avoids all these restrictive features. The production function, the risk function i.e. the output risk, and risk preference function, can be estimated non-parametrically, avoiding any functional form assumption. Furthermore, they suggested making no distributional assumption on the error term representing production risk.

Peters (2009) introduced a dynamic operational risk model which allows for significant flexibility in correlation structures introduced between risk profiles. A Bayesian framework was next established to allow inference and estimation under this model, whilst at the same time allowing incorporation of alternative data sources into the inferential procedure. A novel simulation procedure was then developed in Peters' (2009) study for the Bayesian model presented, in the case of dependence between frequency risk profiles. Simulations were performed to demonstrate the accuracy of this procedure

in multiple bivariate examples. Comparisons were made between marginal estimation and a benchmark estimation procedure. In all simulations, the estimation of the model parameters was accurate and the behaviour of the estimates of the posterior mean and standard deviation presented, which smoothed over multiple data realizations, was as expected. Initially, the influence of the biased expert observation influenced the results and as the size of the data set for actual annual loss counts grew, the estimations improved in accuracy. The result showed that the joint estimation outperformed the marginal estimation when forming predictions of future counts and that rates in year $T + 1$, given estimates based on data up to year T . A highly accurate estimation of the copula parameter, jointly with the model parameters, was demonstrated in Peters' (2009) study.

Simulations were performed in the models for the Clayton Copula model in which the copula parameter was also unknown. Though the simulation time was increased as a factor of the number of risk cells, the results and performance were as presented for the bivariate models, making this approach suitable for practical purposes.

In probability theory and statistics, a copula is a kind of distribution function. Copulas are used to describe the dependence between random variables. They are named for their resemblance to grammatical copulas in linguistics. The bivariate copula model proposed by Clayton is called the Clayton Copula. It is one of the common bivariate copula models. It is also referred to as the Cook and Johnson Copula, originally studied by Kimeldorf and Sampson (as cited in Trivedi and Zimmer, 2005). It takes the form:

$$C(\mu_1, \mu_2; \theta) = (\mu_1^{-\theta} + \mu_2^{-\theta} - 1)^{-1/\theta} \qquad [2.3]$$

where

Domain of dependence parameter $\theta = \{\theta \mid 0 < \theta < \infty\} = (0, \infty)$

As θ approaches zero, the marginals become independent. As θ approaches infinity, the copula attains the Fréchet upper bound, but for no value does it attain the Fréchet lower bound. The Clayton Copula cannot account for negative dependence. It has been used to study correlated risks because it exhibits strong left tail dependence and relatively weak right tail dependence (Trivedi and Zimmer, 2005).

The Fréchet distribution is a special case of generalized extreme value distribution. It has the cumulative distribution function as follows:

$$\Pr(X \leq x) = e^{-x^{-\alpha}} \qquad \text{if} \quad x > 0 \qquad [2.4]$$

where Shape parameter: $\alpha > 0$ (Bosch, 2000)

It can be generalized to include a location parameter and a scale parameter with the cumulative distribution function:

$$\Pr(X \leq x) = e^{\left(\frac{m-x}{s}\right)^{-\alpha}} \qquad \text{if} \quad x > m \qquad [2.5]$$

where Location parameter: m = the minimum
Scale parameter: $s > 0$ (Bosch, 2000)

Clayton Copula is explained in Appendix C.

The main objective of Peters' (2009) study was to present a framework for the multivariate problem and to demonstrate estimation in that setting. Application of the framework to real data could be the subject of further research. In Peters' (2009) study, the estimation procedure is presented for frequencies only, but it can be extended in the same manner as presented to severities.

Simani (2003) examined the development of a comprehensive methodology for Fault Detection and Isolation (FDI) of dynamic systems by using a state estimation approach, in conjunction with residual processing schemes. The final result consists an FDI strategy based on fault diagnosis schemes to generate redundant residuals. The suggested method does not require any physical knowledge of the process under observation since, instead of exploiting complicated nonlinear models obtained by modelling techniques, linear models were obtained by means of identification schemes using Equation Error (EE) and Errors in Variables (EIV) models.

In their research Kalantarnia, Khan and Hawboldt (2009) demonstrated the use of the Bayesian theory in Quantitative Risk Assessment (QRA) and its application as a useful tool in dynamic risk assessment to prevent accidents and to enhance the overall performance of the system. This theory can also be used in event tree analysis and other techniques.

The main purpose of this research work is to initiate a safety-related framework which would help in preventing accidents. While reviewing the literature, it was found that the root causes of all accidents are the lack of a proper safety framework. There is no proper framework for safety verification. Safety Standards and Verification tools are presented in the literature. However, proper communication among them is absent. A proper framework which links the initiation of a hazard, i.e. a fault, safety measures to be adopted to prevent the propagation of a fault, and verification, is missing in the process industry. Safety verification is a key success factor which distinguishes the FSN approach from the other approaches. It is important to map safety protection layers to fault propagation scenarios. Fault tree analysis (FTA) and Event tree analysis (ETA) are

alternative options. However they require manual intervention. Only the FSN offers the opportunity to automatically map the Independent Protection Layers (IPL) in real time for online safety verification.

Summary: *In this chapter, literary works by previous researchers on P&ID modelling, pattern identification of faults, techniques of fault modelling, the probabilistic approach of fault modelling, and dynamic risk estimation were reviewed.*

In the following chapter, the steps of the methodology to formulate an FSN are presented.

Chapter 3: Methodology

In this chapter, the methodology of the research is discussed. The steps are shown in Figure 3.1. Piping and Instrumentation Diagram (P&ID) modelling to risk verification is explained in different steps of static FSN and dynamic FSN. The Bayesian Belief Network (BBN) is also described in this chapter.

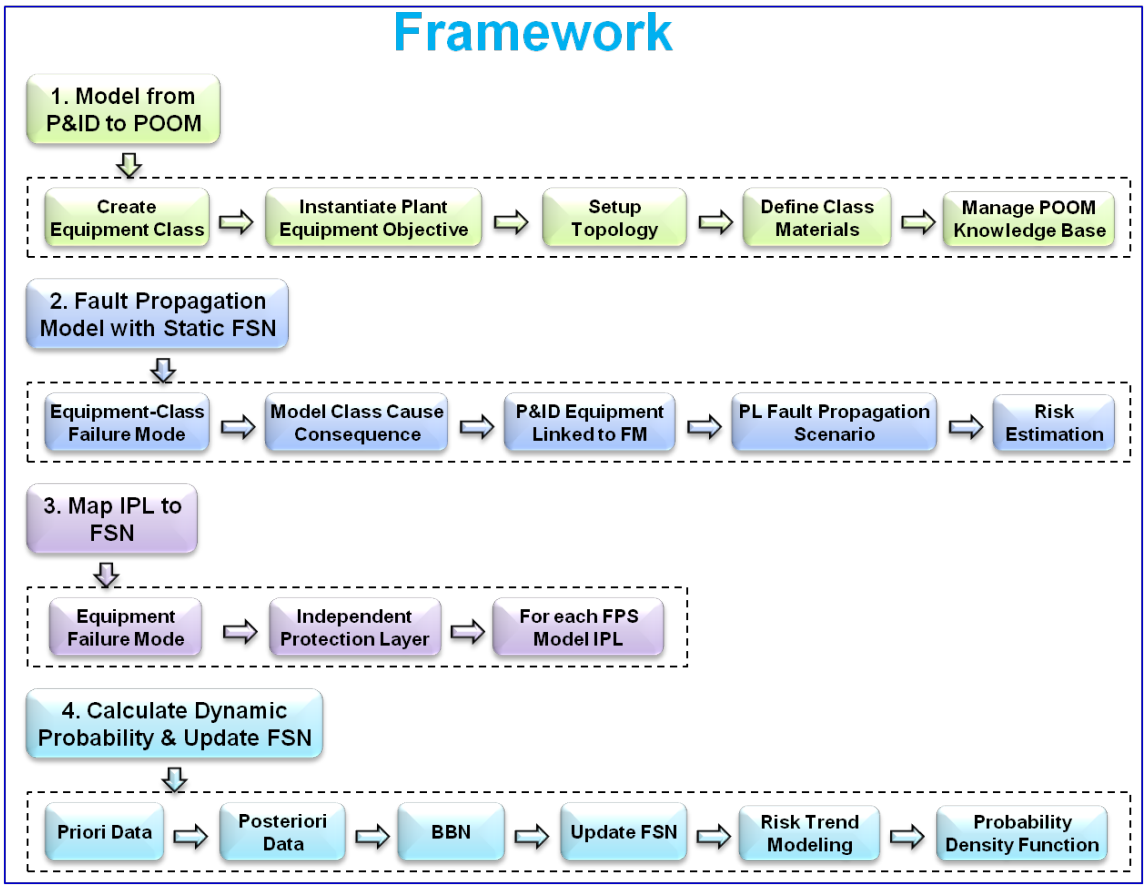


Figure 3.1: Methodology

3.1. Modelling From P&ID to Process Object Oriented Methodology

Initially, an FSN is constructed based on the ontology structure of fault models on the basis of Process Object Oriented Methodology (POOM) where Failure Mode (FM) is described using symptoms, enablers, variables, causes, consequences and repair actions, as shown in Figure 3.2. Rules are associated with each transition of the causation model within the FSN. The rules can be quantitative (probabilistic) or qualitative. A fault is an unpermitted deviation of at least one characteristic property or parameter of the system from the acceptable, usual or standard condition.

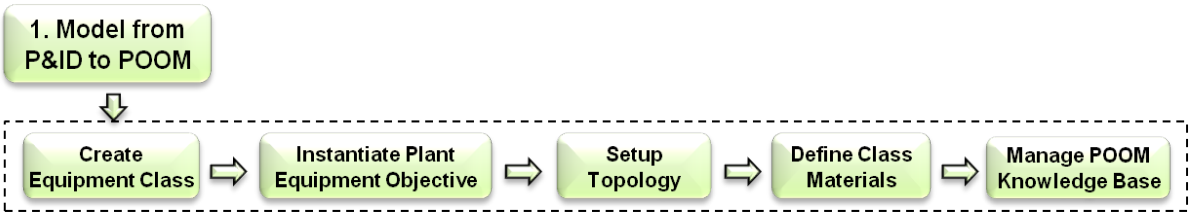


Figure 3.2: Modelling from P&ID to POOM

The POOM is an object oriented approach to construct the process model in its static, dynamic or functional paradigms. In the static paradigm, the faults are related with the structures of machines, such as pumps, valves or compressors. In the dynamic paradigm, the faults are related with the dynamic behaviour of machines, such as over-loading, saturation or overheating. In the functional paradigm, the faults are related with operation of machines, including the start-up, shutdown or wrong operation. The basic architecture of the POOM is shown in Figure 3.3. The static view describes facilities, materials and

topologies. The Dynamic view describes the behaviour required to do necessary actions and the operational view describes the purpose of each structure and set of actions to achieve the desired functions (Gabbar, 2007)

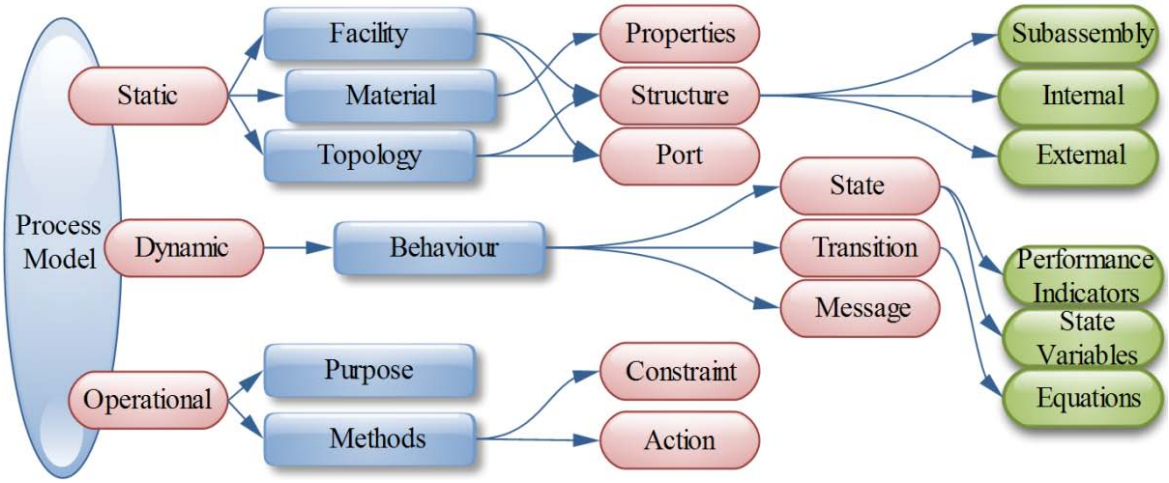


Figure 3.3: The POOM Methodology (Gabbar, 2007)

An instance of the FSN database using the POOM methodology is shown in Figure 3.4. All the tables and the fields in the database are calculated either through historical data or expert opinion.

For a particular symptom, there is a corresponding semantic network: either the fuzzy expert system (FES) or the Bayesian belief network (BBN). The symptoms also have related hypotheses with corresponding diagnoses and repairs.

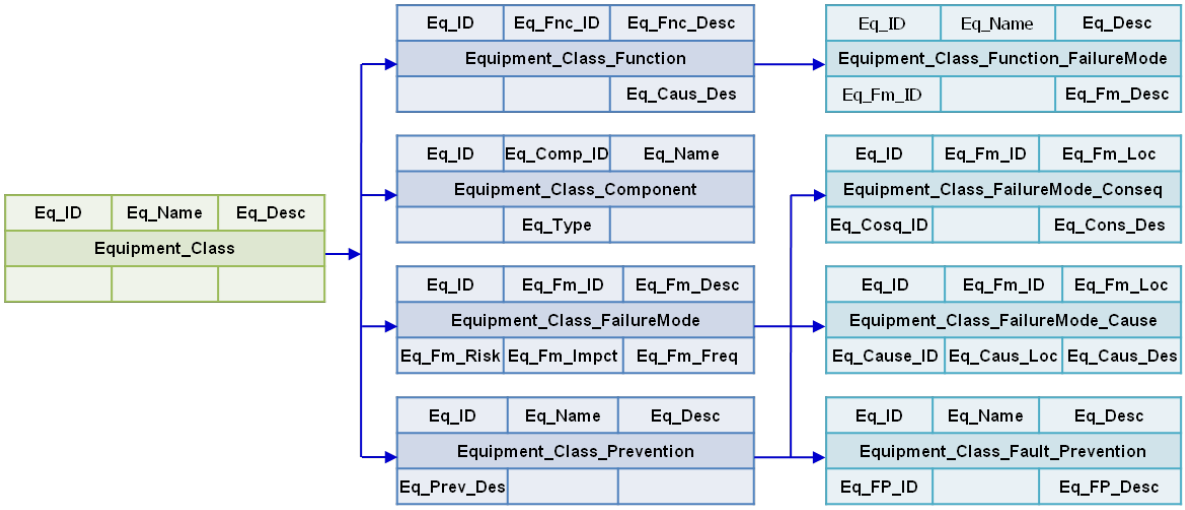


Figure 3.4: Creation of an FSN database using the POOM structure

3.1.1. Creation of the Equipment Class

Every piece of equipment has its own set of parameters, which have their own ranges of deviations that may cause some consequences. The same types of equipment have the same types of parameters and the same ranges of deviations; e.g. carbon steel pipe, inconel-600 pipe, and the 5 Mega Pascal (MPa) compressor. With the same parameters, equipment records are categorized in different classes. The classes are stored in the database. If an icon of equipment is dragged and dropped, all the parameters are saved in the database associated with the equipment and also associated with the class to which the piece of equipment belongs.

Figure 3.5: Class identification

For example, there are different types of carbon steel; i.e. mild or low; medium; high; and ultra high carbon steel. For a certain category of carbon steel there is for example, a specific density, melting point, thermal conductivity, heat capacity, and Young's Modulus. The physical and chemical properties of that material are stored as class properties.

Conversely, different pipes made of carbon steel may be of different diameters, lengths and thicknesses as seen in Figure 3.5. The specific properties of that piece of equipment are stored separately in the database.

3.1.2. Instantiation of the Plant Equipment Object

After the classes are defined, the sets of equipment are ready for drag-and-drop. When the pieces of equipment are dragged-and-dropped, they are automatically assigned a unique serial number, which contains a prefix character identifying the class category; e.g. “E” for equipment or “P” for pipe. The parameters of the specific equipment are linked in the database. For example if a pump is dragged and dropped, its class information is connected with parameters, such as cavitations, vibrations. The pump specific information, such as flow rate wattage, is stored as pump specific data. An example of instantiation of a plant equipment objective is shown in Figure 3.6.

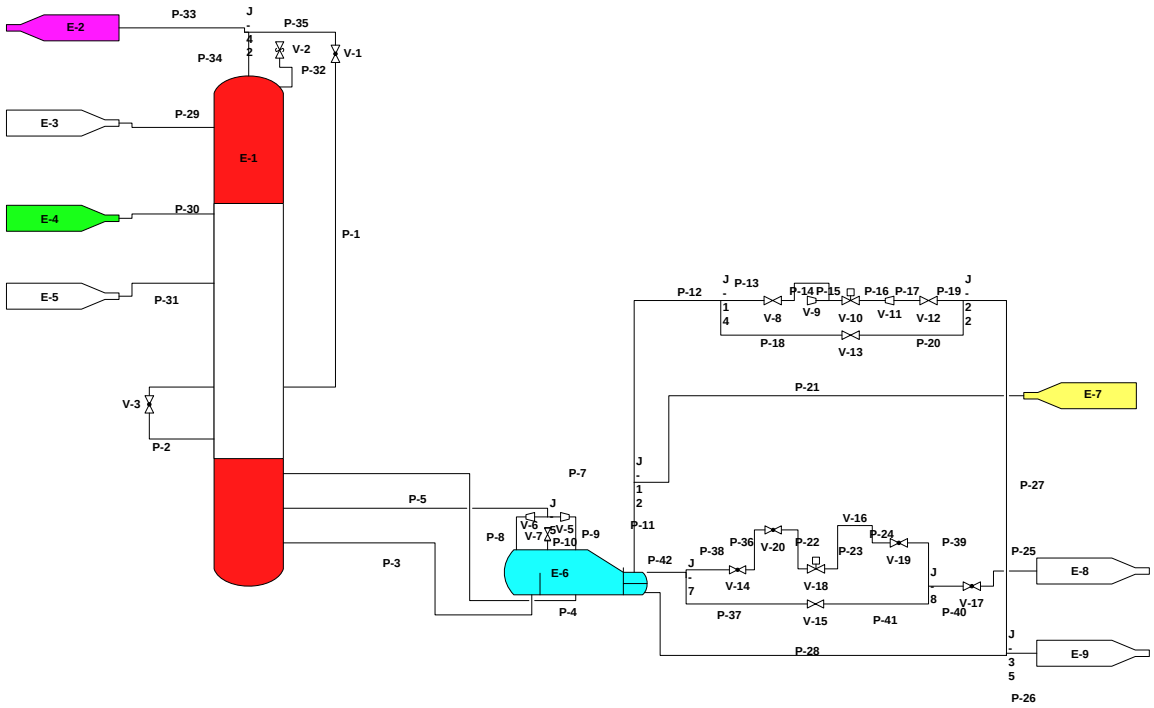


Figure 3.6: Instantiation of the Plant Equipment Object

3.1.3. Topology Setup

The pieces of equipment on the canvas are connected accordingly. As mentioned previously, every piece and class of equipment in a plant may have one or more probable faults associated with it. Each fault may have one or more associated hazards and each hazard may have one or more associated accident scenarios. The probabilities for the occurrences of faults and hazards, and the incidents of accidents as a consequence are calculated from the historical data. From the probabilities, the risk element is identified for each fault → hazard → accident propagation scenario from the root causes to the final consequences following the pathways in the topology.

3.1.4. Class Definition for Plant Materials

One of the criteria for categorization of the equipment involves defining the material of construction. Each material has its own physical and chemical properties. For example, inconel-600 has the properties shown in Table 3.1 and 3.2:

Table 3.1: Composition of Inconel-600 (Specialmetals)

Element	**Percentage (%)**
Nickel and Cobalt	72 minimum
Chromium	14.0 to 17.0
Iron	6.00 to 10.00
Carbon	0.15 maximum
Manganese	1.00 maximum
Sulfur	0.015 maximum
Silicon	0.50 maximum
Copper	0.50 maximum

Table 3.2: Physical properties of Inconel-600 (Specialmetals)

Item	**Properties**
Density	8.47 $Mg \cdot m^{-3}$
Melting Point	1354 to 1413 °C
Specific Heat (heat capacity)	444 $J \cdot kg^{-1} \cdot K^{-1}$
Electrical Resistivity	1.03 μΩ-m
Curie Temperature	−124 °C

3.1.5. Management of the POOM Knowledgebase

In the final stage of this step, the structure, all of its equipment and the connections, are stored in the POOM database. Initially, Microsoft Access is used as the database. The Open Database Connectivity (ODBC) is used to access the database from the main program. After the FSN is tested and found to be deployable, the data can be transferred to Oracle or any other robust Relational Database Management System (RDBMS).

3.2. Fault Propagation Modelling with a Static FSN

A Fault Semantic Network (FNS) is a set of terms-tokens linked by a set of predicate-tokens for the purpose of fault diagnosis. An information database based semantic network is an extension of the index set for the information database.

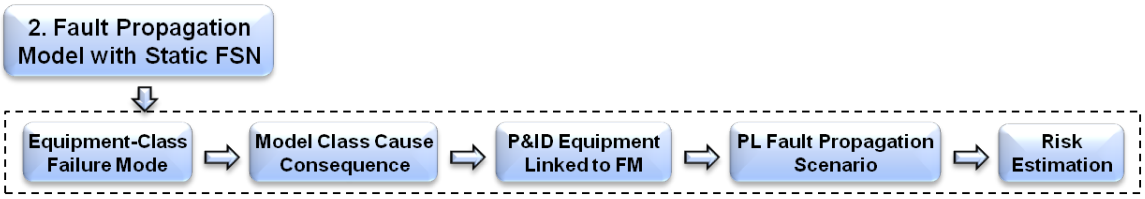


Figure 3.7: Fault propagation modelling with a static FSN

The fault propagation scenarios are generated based on the historical data. Once the accuracy of the forecasting based on the historical data and the actual consequences reaches a certain level, the system can be used for real time forecasting fault propagation scenarios based on the real time data. The fault propagation model with static FSN is shown in Figure 3.7.

3.2.1. Failure Mode Class of Plant Equipment

Any equipment may have one or more failure modes. Some failure modes are the same for each equipment class, such as leaks in pipes and tanks. Those failure modes are assigned to the class failure modes to ensure unified failure mode definitions of plant equipment, which are stored in the FSN-POOM database.

3.2.2. Modelling Class of Causes and Consequences

The link between all the causes and consequences are established with the respective class of equipment. The probability of affecting a specific piece of equipment, given that another piece of equipment has a fault is calculated and stored in the database. For

example, the probability of equipment “B” developing a fault, given that equipment “A” has a probability of failing, is P(A) which is calculated by:

$$P(B \mid A) = \frac{P(A \mid B)P(B)}{P(A)} \qquad [3.1]$$

3.2.3. Plant Equipment Linkage to Failure Mode

All pieces of equipment in the P&ID have their own equipment level failure mode and class level failure mode. Being in the unique setup of P&ID, each piece of equipment has its own unique set of failure modes. These sets of failure modes are stored in the database.

3.2.4. Plant Level Fault Propagation Scenarios

For each piece of equipment, there may be one or more probable process variable deviations, i.e. faults which may initiate fault propagation scenarios. At this stage, propagation of the faults of the individual piece of equipment is modeled in an algorithm. The algorithm that calculates the effect of fault propagation in an abnormal situation can be used to give appropriate information to plant operators.

3.2.5. Risk Estimation

After the fault propagation scenario is modeled, the risk estimation is performed for the entire plant. For risk estimation, probabilistic methods, such as the BBN is used initially on the historical data to get the static FSN. Once the estimated risk is verified with the acceptable failure rate, the algorithm is used with real time data.

3.2.6. Bayesian Belief Network (BBN)

In view of the proposed process model using the plant POOM methodology, the FSN is utilized to construct a flexible fault knowledge structure in qualitative manner. For example, failures related to leaks might be associated with rules such as:

```
IF (Structure_Material = (X or Y)) and (PV = Pressure) and (Dev <= 100/100 or
Dev >= 80/100)
        THEN
                (FM = Crack)
        ENDIF
```

These rules are initially defined in generic form, based on domain knowledge; i.e. regardless of plant specific knowledge (Gabbar, 2012).

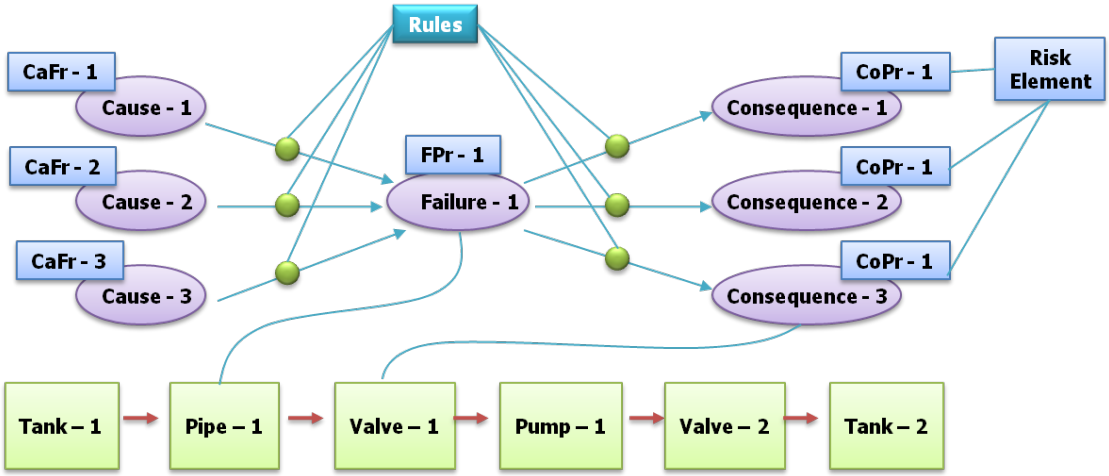


Figure 3.8: An example of an FSN (Adapted from Gabbar, 2012)

A risk element is identified for each hazard or fault propagation scenario from the root causes to the final consequences. In Figure 3.8, there are three possible risk elements associated with consequence-1: a) cause-1→failure-1→ consequence-1; b) cause-2→failure-1→ consequence-1; c) cause-3→failure-1→consequence-1.

Where

CaFr = Frequency of cause (1, 2 and 3)
FPr = Probability of failure
CoPr = Probability of that consequence to occur (1, 2 and 3) due to any cause

Total magnitude of the consequence is considered to be Colm1, which is the total impact of consequence-1. For independent events, the total risk associated with consequence-1 is shown in equation [Eq-3.2].

$$\text{Risk(Consequence-1)} = [(\text{CaFr1} + \text{CaFr2} + \text{CaFr3}) \times \text{FPr1} \times \text{CoPr1}] \times \text{Colm1} \quad [3.2]$$

Similarly, the total risk of consequence-2 and consequence-3 can be computed. In case the events are dependant, the Bayesian theorem should be used to determine the total risk based on dependencies for cause-1, cause-2 and cause-3, as shown in equation [3.3].

$$P(X \mid A) = \frac{P(A \mid X)P(X)}{P(A)} \qquad [3.3]$$

(Gabbar, 2012)

The BBN is discussed in further detail in Section 3.4.4.

3.3. Mapping Independent Protection Layers to the FSN

There are already some built-in protection layers to protect any process from failure. The parameters of the protection layers of the equipment are stored in the database and taken into consideration when calculating the risk factor. The steps of mapping the IPL to the FSN are shown in Figure 3.9.

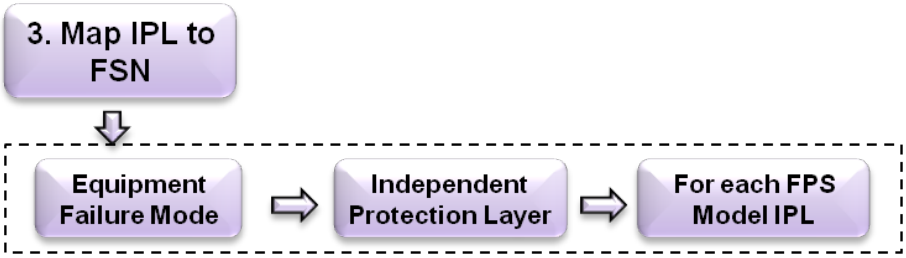


Figure 3.9: Mapping IPL to the FSN

3.3.1. Equipment Failure Mode

The failure modes of equipment are related to the process variables of the equipment. Deviation of process variables and interaction of deviated process variables may cause an unusual situation and consequently an accident. Different equipment has different failure modes.

3.3.2. Independent Protection Layer (IPL)

For every piece of equipment, there may be multiple failure modes. For each failure mode, there may already be some kind of protection layers, which are independent of each other. Hence, they are known as Independent Protection Layers (IPL). The IPL are the safeguards against process safety issues. The process industry is obligated to provide and maintain a safe working environment for the employees. Safety is provided through inherently safe design and various safeguards, such as Safety Instrumented Systems (SIS), procedures, and training. During a hazard and operability (HAZOP) study, a person or a team is responsible for assessing the process risk from various process deviations and determining the consequence of potential incidents. The person or team identifies the safeguards used to mitigate the hazardous events, which are not fully protected. Eight independent protection layers are shown in Figure 3.10.

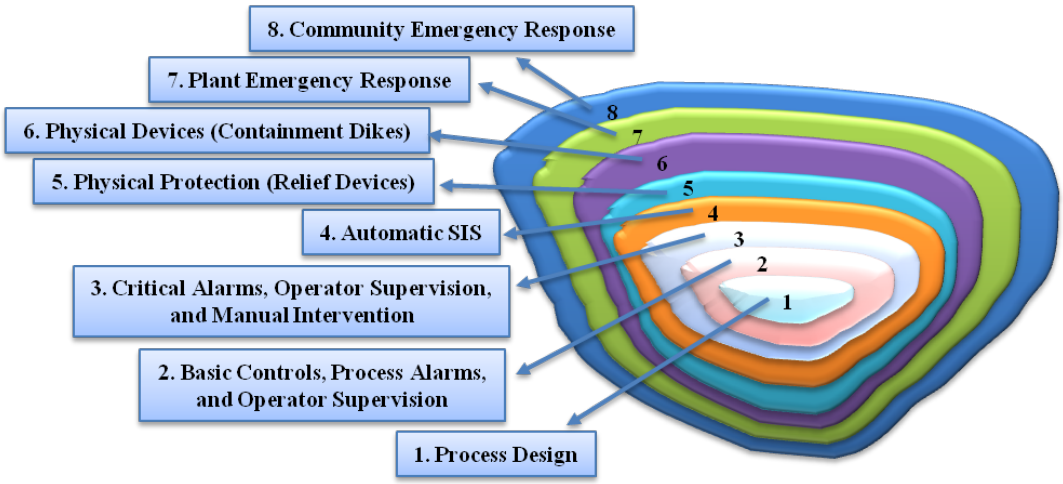


Figure 3.10: Independent Layers of Protection

In this section, the Layers of Protection Analysis (LOPA) is presented highlighting the key considerations. LOPA is a powerful analytical tool for assessing the adequacy of protection layers used to mitigate process risk. LOPA is built upon well-known process hazards analysis techniques, applying semi-quantitative measures to the evaluation of the frequency of potential incidents and the probability of failure of the protection layers (Summers, 2002).

LOPA is a semi-quantitative methodology that can be used to identify safeguards that meet the IPL criteria established by the CCPS1 (Centre for Chemical Process Safety) in 1993 (Summers, 2002). While IPLs are extrinsic safety systems, they can be active or passive, as long as the following criteria are met:

- Specificity: The IPL is capable of detecting and preventing or mitigating the consequences of specified, potentially hazardous event(s), such as a runaway reaction, loss of containment, or an explosion.

- Independence: An IPL is independent of all the other protection layers associated with the identified potentially hazardous event. Independence requires that the performance is not affected by the failure of another protection layer or by the conditions that caused another protection layer to fail. Most importantly, the protection layer is independent of the initiating cause.

- Dependability: The protection provided by the IPL reduces the identified risk by a known and specified amount.

- Auditability: The IPL is designed to permit regular periodic validation of the protective function (Summers, 2002).

3.3.3. Linking a Fault Propagation Scenario to an IPL

For each piece of equipment, there may be one or more probable process variable deviations; i.e. faults are linked with the respective fault propagation scenarios. IPLs are designed for safeguards against those process safety issues. For each Fault Propagation Scenario (FPS), a link to IPL has to be established accordingly in the POOM database.

3.4. Calculation of Dynamic Probability and Updating the FSN

So far, the work was on the static FSN. In this section, the dynamic FSN is introduced. The static FSN works with historical-real-life data, whereas the dynamic FSN works with real-time data using the BBN. The steps are shown in Figure 3.11.

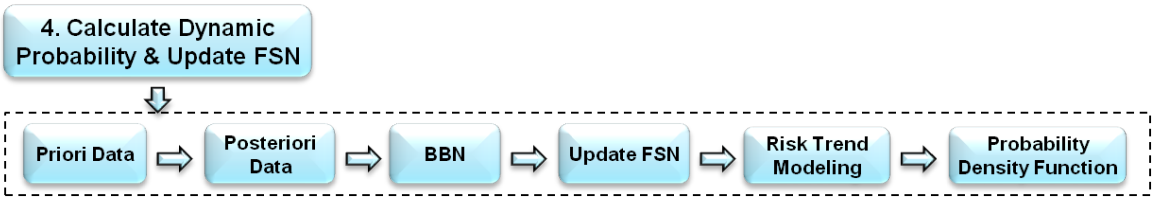


Figure 3.11: Calculating dynamic probability and updating the FSN

3.4.1. Priori Data

The static FSN was first established based on the priori data. The FSN is verified using the priori data from historical events. To verify with the historical events, there may be four types of queries, which are as follows:

1) Diagnostic
2) Predictive
3) Inter-causal and
4) Combined query

The queries are discussed in detail in section 3.4.3.

3.4.2. Posteriori Data

At this stage, real time data is used to establish the probabilistic FSN. As real life data is not available, a simulation tool is used in this paper. In the static FSN, the probabilistic approach is used to test the approach. In the historical data, the consequences are already known. The physics of fault propagation is known from the priori data which is now used to predict the consequences for posteriori data.

3.4.3. The Bayesian Belief Network

The BBN is widely used for fault diagnosis, root cause and consequence analysis. Details about some previous research in BBN for fault diagnosis are discussed in Chapter 2. The process of constructing BBN for process fault diagnosis, root cause and consequence analysis is shown in Figure 3.12. Data collected from a liquefaction process, combined with maintenance history, maintenance expert opinion and evidence collected by field operators, is used for BBN construction. The K2 algorithm (Cooper, 1992) is used for learning the BBN structure and node probabilities. After the network has learned from the training data, a junction tree algorithm (Madsen, 1999) is used to query the network. The inference process updates the network probabilities according to the evidence entered.

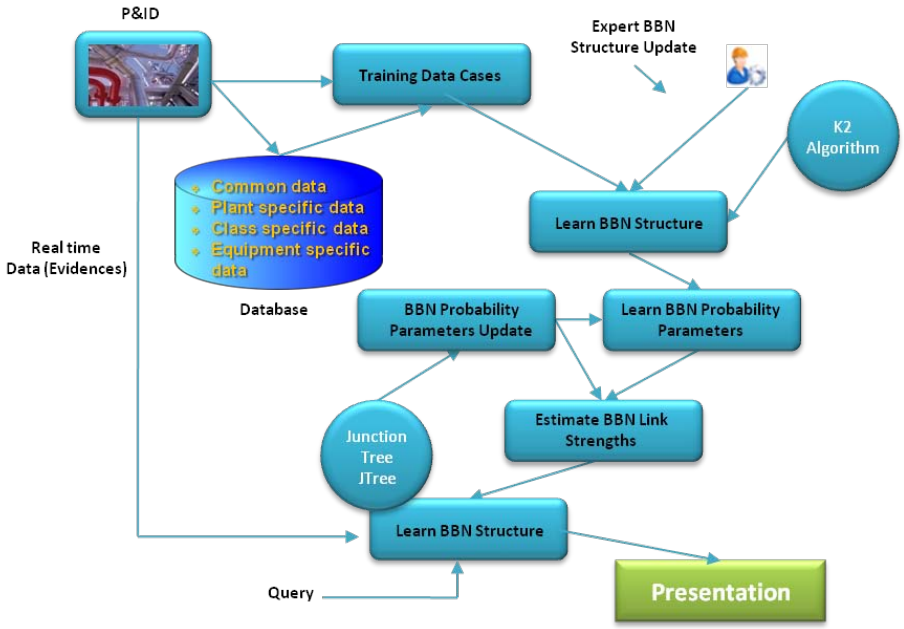


Figure 3.12: The BBN learning and inference process

The BBN has the ability to dynamically change by incorporating new data and updating its internal structure, rules and interaction strengths. In order to get the expected results, it is necessary to query the BBN in a structured way by incorporating the observations in the BBN to update the structure according to the observed nodes and to obtain an answer to the query. Different types of queries are used in the BBN. The queries are explained as follows:

- **Diagnostic Query:** This type of query can be called backtracking. Diagnostic query starts from symptoms and obtained results are the causes. Therefore, the direction of the query is opposite to the arc direction. In an example of compressor fault diagnosis, vibration test results can be considered as symptoms. The FSN can be queried to recognize the high pressure or cavitation as causes.

- **Predictive Query:** This type of query is for prediction of the consequences based on causes. Predictive query predicts faults in advance even without assuming symptoms; for instance, increasing load on a compressor can cause a particular vibration index to increase.

- **Inter-causal Query:** This type of query is used when multiple causes result in one symptom, for instance, both high pressure and vibration can result in one symptom, which may be increased temperature in the tank.

- **Combined Query:** This type of query is used when one cause results in multiple symptoms; for example rust inside a pipe can cause both high pressure in the pump and low flow.

An example of a BBN for the manufacturing process is shown in Figure 3.13. The node probabilities, as shown in the figure, are either assigned by an expert or learnt by historical data. The BBN is flexible and powerful enough to query in any direction. In the query process, we enter an evidence of an occurrence in the BBN, which returns the answer to the query and updates the probability tables.

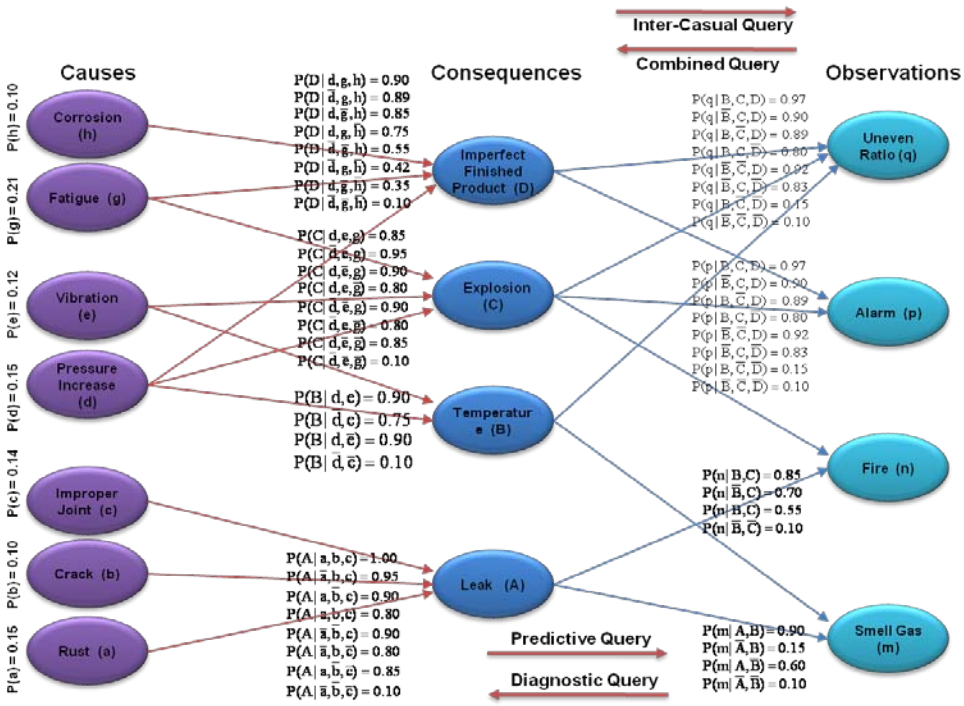


Figure 3.13: The BBN for fault diagnosis

The diagnostic query can be as follows:

What is the probability of the cause "Rust (a)" provided "Smell Gas (m)" has occurred?

Evidence: Smell Gas (m) = True

Query the BBN:

P (a | m) = 81.09% False

18.91% True

The BBN returns that there is 18.91% chance of “Rust (a)”.

The predictive query can be as follows:

What is the probability of observing “Uneven Ratio (q)” provided “Vibration (e)” has occurred?

Evidence: Vibration (e) = True

Query the BBN:

P (q | e) = 91.51% False
08.49% True

The BBN returns that there is 8.49% chance of observing “Uneven Ratio (q)” above the threshold.

The inter-causal query can be as follows:

What is the probability of observing “Fatigue (g)” and “Corrosion (h)” combined, provided “Uneven Ratio (q)” has occurred?

Evidence: Uneven Ratio (q) = True

Query the BBN:

P (g, h |q) = 76.03% False
23.97% True

The BBN returns that there is 23.97% chance of observing both “Fatigue (g)” and “Corrosion (h)” together.

The combined query can be as follows:

What is the probability of observing “Smell gas (m)” and “Fire (n)” provided “Rust (a)” has occurred?

Evidence: Rust (a) = True

Query the BBN:

P (m, n | a) = 89.01% False
10.99% True

The BBN returns that there is 10.99% chance of observing “Smell gas (m)” and “Fire (n)” above the threshold.

3.4.4. Updating the Fault Semantic Network

In a process, there may be many initial causes. Eight initial events are shown here for simplicity. These are as follows:

1) High Temperature
2) Low Temperature
3) High Pressure
4) Low Pressure
5) High Flow
6) Low Flow
7) Overflow
8) Impurities

There are several safety systems employed in a process system to prevent these initial events from happening. These may be special safety systems, or may be embedded in the form of passive safety or inherent safety systems. The vertical line after the initial events in Figure 3.14 represents the safety systems which have been installed to check the propagation of initial events. It is important to note that not every initial event leads to a fault. Some of the events eventually die out with time, while others have a potential to propagate to faults.

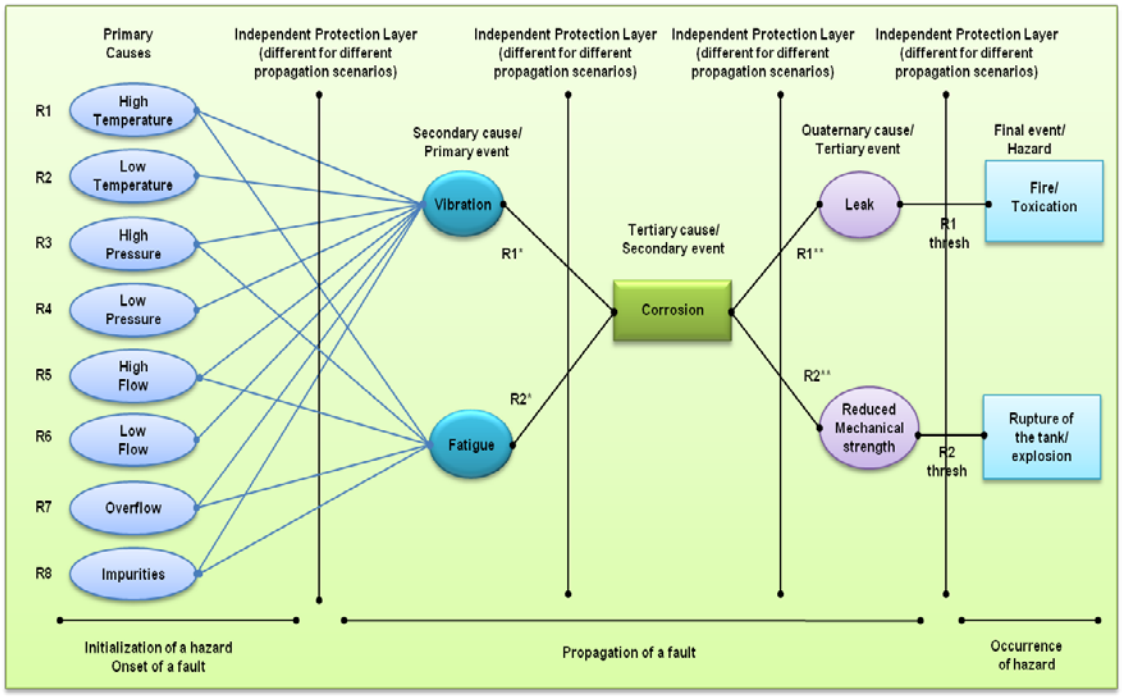


Figure 3.14: A typical fault propagation scenario in a typical process industry (Adapted from Chin, Wang, Poon and Yang, 2009)

Once an initial event has taken place, it can either be suppressed by the corresponding safety system, or could break the barrier or the IPL, and could result in a secondary cause or a primary event. Two primary events are considered for sample calculations in Chapter 6:

i. Vibration
ii. Fatigue

In Figure 3.14, high temperature, high pressure, high flow, overflow and impurities could cause vibration and fatigue. Furthermore, low temperature, low pressure and low flow cause only vibration and no fatigue. Vibrations and fatigue would cause corrosion because the initial events could not be prevented by the IPL. In other words, the primary

safety systems had failed. It can be noted that these secondary causes have a potential to give birth to tertiary events if they are not stopped by the secondary IPL.

If the secondary IPL also failed, a tertiary events may be caused, which is corrosion. Corrosion may be caused by vibrations or by continuous fatigue. It reduces the durability and performance of the tank, and hence is an undesirable event. If corrosion occurs, the probability of occurrence of a hazard rapidly increases, because if the third level IPL fails, it may lead to a leak or reduced mechanical strength. A leak can cause fire or intoxication, depending upon the contents of the tank, where as reduced mechanical strength of the tank may result in an explosion in the plant. Both of these situations are extremely undesirable.

Summary: *In this chapter, the methodology of developing the FSN in multiple steps has been presented. Even though P&ID modelling is not the subject of this research, it has been briefly discussed, because P&ID is an integral part of FSN modelling. Steps in designing the POOM database from P&ID are explained. Mapping IPL to FM is shown. The methodology of designing a static FSN is discussed. Finally, how to transform from a static FSN to a dynamic FSN is presented.*

In the next chapter, one case study on TE process is presented to verify the steps described in the methodologies.

Chapter 4: Case Study

The proposed solution is applied to the TE process to verify the steps described in the methodologies. The plant process is modeled using POOM, which includes the definitions of real time safety verification, as well as failure / fault models. This also includes systematic modelling of fault propagation scenarios, quantitatively and qualitatively, using the Fault Semantic Network (FSN) and mapping to process variables. Real time and simulation data are used to map safety protection layers; i.e. IPLs to fault propagation scenarios, with associated Probability of Failure on Demand (PFD) and risks. Risks are estimated for each fault propagation scenario and for the whole system equipment / components, and associated with FSN. Safety verification algorithm is applied to the case studies based on target risk level and anticipated dynamic system risk for each fault propagation scenario.

4.1. Piping and Instrumentation Diagram (P&ID)

The Tennessee Eastman (TE) process is a representation of a real chemical process that was introduced by Downs and Vogel in early 1990 (Downs and Vogel, 1993). It is one of the important modelling tools proposed for researchers in 1990 by the Eastman chemical company. The process modeled by the Eastman chemical company is a defined chemical process allied with the TE process. A simplified schematic view of the TE process is shown in Figure 4.1.

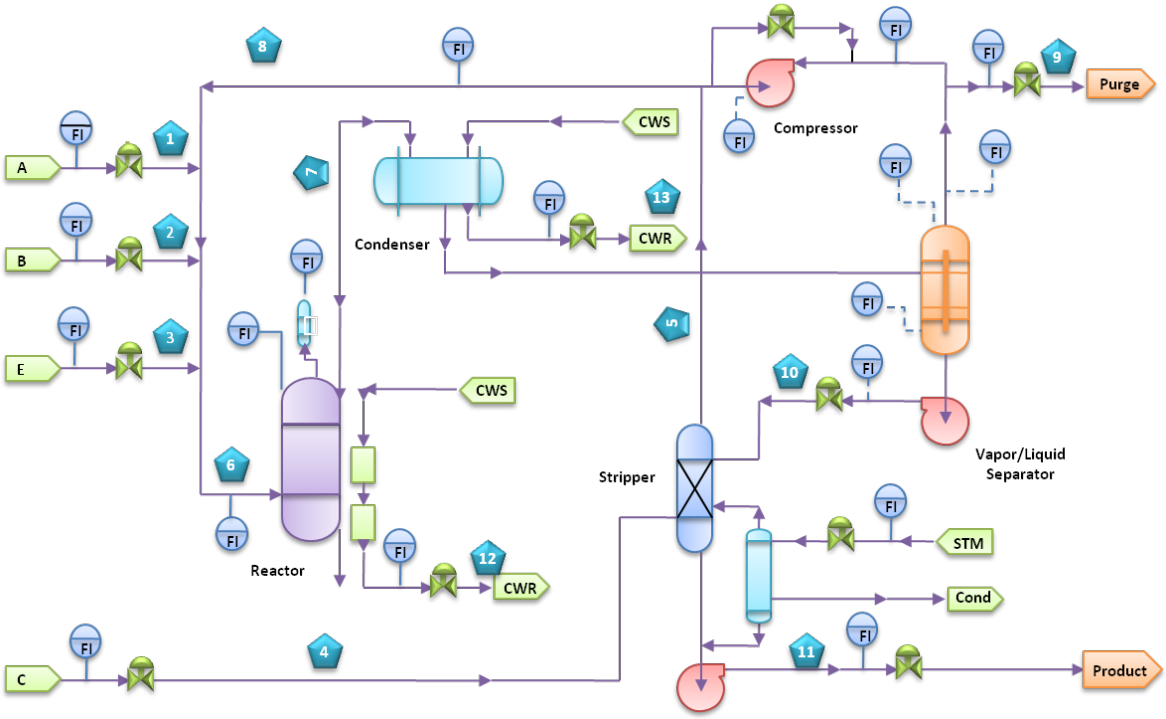


Figure 4.1: A simplified version of the TE process
(Adapted from Larsson et al., 2001)

It later became a standard process to be used by industries and researchers in different experiments with different purposes, such as a comparison of control strategies, and fault detection. Since the TE process represents a real chemical process with real faults, it is being used as a valid simulated process and published in many authors' results, based on the simulations (Larsson, Hestetun, Hovland, & Skogestad, 2001, McAvoy, 1994). A number of parameters, disturbances, complexities and control strategies implemented in the TE process made it more similar to a real process which could be reliably applied to different perspectives.

4.2. Process Modelling and Simulation

For the purpose of the case study a simulation model for the TE process is developed in MATLAB® Simulink®. In the Simulink® simulation file, parameters can be changed as per the requirements of the research. An interface was designed in LabVIEW® for inserting disturbances and visualizing the results. The front panel of the prototype was developed at the Energy Safety and Control Laboratory (ESCL), University of Ontario Institute of Technology (UOIT) (Hussain, 2013). The simulation data presented here are the output of the TE process with some parameters changed.

The process simulated here consists of five major units of operation, including a vapour-liquid separator, a compressor, two reactors, a condenser and a product stripping column. Eight components of the TE process are shown in Table 4.1 (Downs and Vogel, 1993). The nonlinearity characteristic of the process is mainly because of chemical reactions in the reactors. A schematic view of the complete TE process is shown in Figure 4.2.

The process produces two products and two by-products from four reactions as follows:

Product 1:	A(g) + C(g) + D(g)	→	G (liquid)
Product 2:	A(g) + C(g) + E(g)	→	H (liquid)
By-product 1:	A(g) + E(g)	→	F (liquid)
By-product 2:	3D	→	2F (liquid)

In the process, there are four feed streams (A, D, E, and C), one product stream, and one purge stream. Almost all of the inert B enters in the largest feed C which actually contains almost 50% of component A (Larsson et al., 2001). Table 4.1 shows the physical properties of the components.

Table 4.1: Physical Properties of the Components (Downs and Vogel, 1993)

Component	Molecular Weight ($g \cdot mol^{-1}$)	Liquid Density ($kg \cdot m^{-3}$)	Liquid Heat Capacity ($kj \cdot kg^{-1} \cdot K^{-1}$))	Vapor Heat Capacity ($kj \cdot kg^{-1} \cdot K^{-1}$)	Heat of Vaporization ($kj \cdot kg^{-1}$)
A	2.0	-	-	14.6	-
B	25.4	-	-	2.04	-
C	28.0	-	-	1.05	
D	32.0	299	7.66	1.85	202
E	46.0	365	4.17	1.87	372
F	48.0	328	4.45	2.02	372
G	62.0	612	2.55	0.712	523
H	76.0	617	2.45	0.628	486

The reactants A, D and E directly enter the reactor while the reactant C first enters the product stripper and then, through a recycle steam process, reaches the reactor. Products of the reactor exit from the upper exit of the reactor and enter the condenser for the condensation process. The condenser converts vapour to liquid and then the condenser products pass through the vapour-liquid separator. The separator has to separate the vapour from the liquid where the liquid, which is heavier, exits from below and the vapour exits from the upper exit, as it is lighter. The liquefied product from the separator transfers to the product stripper to purify, and the vapour products transfer to the compressor to the recycle reactor as feed or exits in the purge stream.

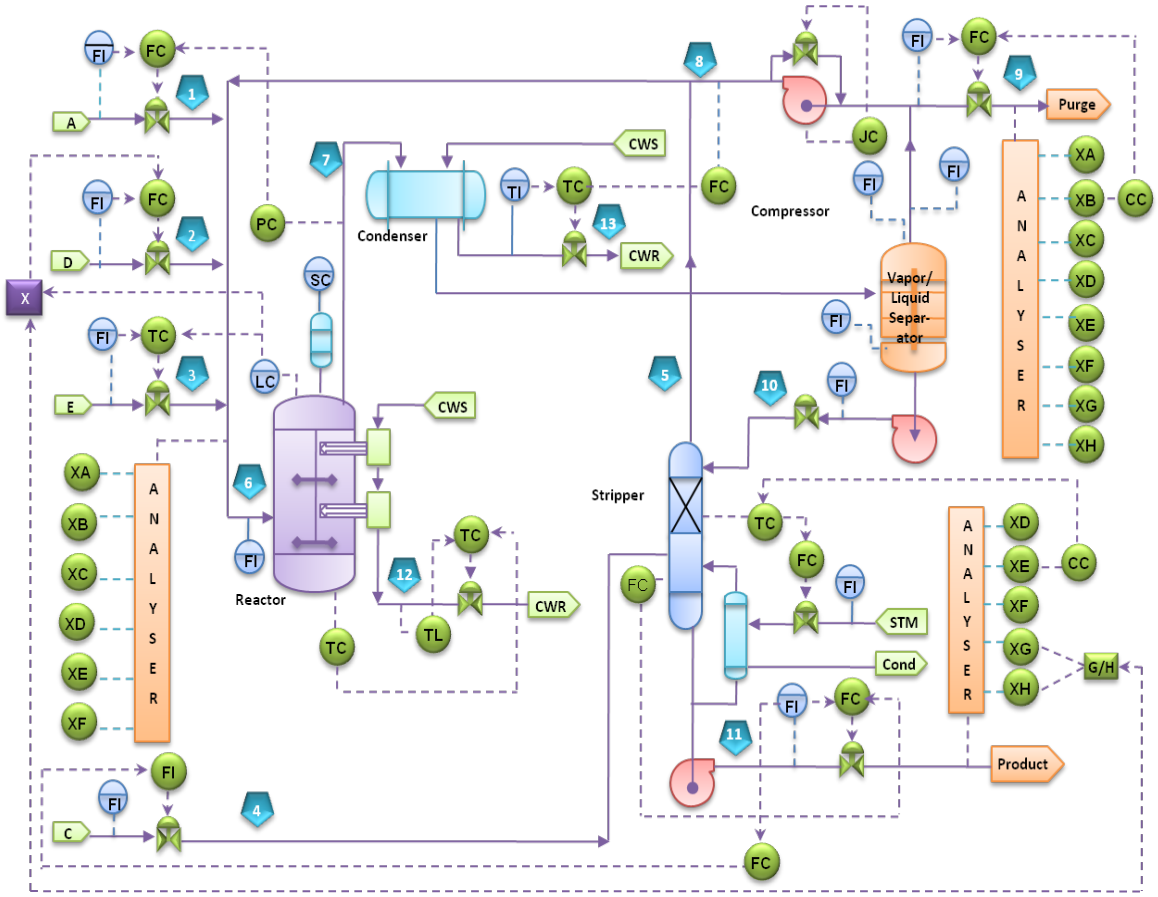


Figure 4.2: The TE Process (Adapted from Downs and Vogel, 1993)

The TE process produces two main products, G and H. All reactions are irreversible and exothermic. There are six different operating modes defined for the TE process, according to the plant production rate and the ratio between the two main products, G and H. All six operating modes are listed in Table 4.2.

Table 4.2: Operating mode of the TE Process (Downs and Vogel, 1993)

Modes	G/H Ratio	Production Rate
1	50/50	7038 $kg \cdot hr^{-1}$ G − 7038 $kg \cdot hr^{-1}$ H
2	10/90	1408 $kg \cdot hr^{-1}$ G − 12699 $kg \cdot hr^{-1}$ H
3	90/10	10000 $kg \cdot hr^{-1}$ G − 1111 $kg \cdot hr^{-1}$ H
4	50/50	Maximum Production Rate
5	10/90	Maximum Production Rate
6	90/10	Maximum Production Rate

There are 41 measured variables in the TE process, from XMEAS1 to XMEAS41. There are 12 manipulated variables, from XMV1 to XMV12. Measured variables are dependent variables; manipulated variables are considered as independent variables. The measured variables from XMEAS1 to XMEAS22 are continuous. In order to see how the manipulated variables affect the measured ones, they are changed either randomly or by steps under normal and disturbed operational conditions. The 22 measured variables, which are continuous, and 12 independent variables are shown in Table 4.3 and Table 4.4, respectively.

Table 4.3: Measured variables in the TE Process (Downs and Vogel, 1993)

Variable Name	Variable Number	Base Case Value	Units
A feed (stream 1)	XMEAS (1)	0.25052	kscmh
D feed (stream 2)	XMEAS (2)	3664.0	$kg \cdot h^{-1}$
E feed (stream 3)	XMEAS (3)	4509.3	$kg \cdot h^{-1}$
A and C feed (stream 4)	XMEAS (4)	9.3477	kscmh
Recycle flow (stream 8)	XMEAS (5)	26.902	kscmh
Reactor feed rate (stream 6)	XMEAS (6)	42.339	kscmh
Reactor pressure	XMEAS (7)	2705.0	kPa
Reactor level	XMEAS (8)	75.000	%
Reactor temperature	XMEAS (9)	120.40	^{o}C
Purge rate (stream 9)	XMEAS (10)	0.33712	kscmh
Product separator temperature	XMEAS (11)	80.109	^{o}C
Product separator level	XMEAS (12)	50.000	%
Product separator pressure	XMEAS (13)	2633.7	kPa
Product separator underflow (stream 10)	XMEAS (14)	25.160	$m^3 \cdot h^{-1}$
Stripper level	XMEAS (15)	50.000	%
Stripper pressure	XMEAS (16)	3102.2	kPa
Stripper underflow (stream 11)	XMEAS (17)	22.949	$m^3 \cdot h^{-1}$
Stripper temperature	XMEAS (18)	65.731	^{o}C
Stripper steam flow	XMEAS (19)	230.31	$kg \cdot h^{-1}$
Compressor work	XMEAS (20)	341.43	Kw
Reactor cooling water outlet temperature	XMEAS (21)	94.599	^{o}C
Separator cooling water outlet temperature	XMEAS (22)	77.297	^{o}C

Table 4.4: Variables manipulated by the TE Process (Downs and Vogel, 1993)

Variable Name	Variable Number	Base case Value (%)	Low Limit	High Limit	Units
D Feed Flow (stream 2)	XMV (1)	63.053	0	5811	$kg \cdot h^{-1}$
E Feed Flow (stream 3)	XMV (2)	53.980	0	8354	$kg \cdot h^{-1}$
A Feed Flow (stream 1)	XMV (3)	24.644	0	1.017	kscmh
A and C Feed Flow (stream 4)	XMV (4)	61.302	0	15.25	kscmh
Compressor Recycle Valve	XMV (5)	22.210	0	100	%
Purge valve (stream 9)	XMV (6)	40.064	0	100	%
Separator Pot Liquid Flow (stream 10)	XMV (7)	38.100	0	65.71	$m^3 \cdot h^{-1}$
Stripper Liquid Product Flow (stream 11)	XMV (8)	46.534	0	49.10	$m^3 \cdot h^{-1}$
Stripper Steam Valve	XMV (9)	47.446	0	100	%
Reactor Cooling Water Flow	XMV (10)	41.106	0	227.1	$m^3 \cdot h^{-1}$
Condenser Cooling Water Flow	XMV (11)	18.114	0	272.6	$m^3 \cdot h^{-1}$
Agitator Speed	XMV (12)	50.000	150	250	RPM

The list of independent variables in Table 4.4 includes some variables that are listed as thousand standard cubic metres per hour (kscmh); kilograms per hour ($kg \cdot h^{-1}$); or as cubic metres per hour ($m^3 \cdot h^{-1}$). Some variables are listed as valve positions (percentage, %). For those independent variables listed as kscmh, $kg \cdot h^{-1}$, or $m^3 \cdot h^{-1}$, the flow-rate is not a function of upstream or downstream pressure. For those independent variables listed as valve positions (%), the flow-rate is a function of pressure.

There are 20 disturbances in the TE process simulation with different probabilities of occurrences, from IDV1 to IDV20. The disturbances are chosen in a way to cover all the operational aspects of the TE process. A brief description of all the disturbances is mentioned in Table 4.5.

Table 4.5: Disturbances in the TE Process (Downs and Vogel, 1993)

Process Variable	Variable Number	Type
A/C feed ratio, B composition constant (stream 4)	IDV (1)	Step
B composition, A/C ratio constant (stream 4)	IDV (2)	Step
D feed temperature (stream 2)	IDV (3)	Step
Reactor cooling water inlet temperature	IDV (4)	Step
Condenser cooling water inlet temperature	IDV (5)	Step
A feed loss (stream 1)	IDV (6)	Step
C header pressure loss-reduced availability (stream 4)	IDV (7)	Step
A, B, C feed composition (stream 4)	IDV (8)	Random variation
D feed temperature (stream 2)	IDV (9)	Random variation
C feed temperature (stream 4)	IDV (10)	Random variation
Reactor cooling water inlet temperature	IDV (11)	Random variation
Condenser cooling water inlet temperature	IDV (12)	Random variation
Reaction kinetics	IDV (13)	Slow drift
Reactor cooling water valve	IDV (14)	Sticking
Condenser cooling water valve	IDV (15)	Sticking
Unknown	IDV (16)	Unknown
Unknown	IDV (17)	Unknown
Unknown	IDV (18)	Unknown
Unknown	IDV (19)	Unknown
Unknown	IDV (20)	Unknown

Description of the disturbances:

- Disturbance-1: This is caused by an increase of component C in stream 4, the component A decreases and the component B is constant. Disturbance-1 causes an imbalance in the reactor feed and as a result, reactor pressure increases.

- Disturbance-2: This is same as Disturbance-1 with the same A/C feed ratio. However, in Disturbance-2, there is an increase in component B in feed C.

- Disturbance-3: The temperature of feed D increases, causing an increase in temperature and pressure of the reactor.

- Disturbance-4: As with Disturbance-3, this is a step change increase in the reactor cooling water temperature that in turn causes an increase in the reactor inlet temperature.
- Disturbance-5: As with Disturbance-3, this is a step change increase in the condenser cooling water inlet temperature.
- Disturbance-6: This is because of loss of feed A which causes an imbalance of chemical composition in the reactor feed. As a result, the plant shuts down.
- Disturbance-7: This disturbance is because of loss of C head pressure. A decrease in reactor pressure is the effect.
- Disturbance-8: This happens when there is a random variation on compositions in the reactor feed stream which causes imbalance in the components inside the reactor.
- Disturbance-9: This disturbance is because of random variation of temperature in feed D.
- Disturbance-10: As with Disturbance 9, this is because of random variation of temperature in feed C.
- Disturbance-11: This is because of random variation of reactor cooling water inlet temperature that causes temperature variation in the reactor.
- Disturbance-12: Rapid fluctuation in the condenser cooling water inlet temperature results in a decrease in condenser output temperature.
- Disturbance-13: This is due to imbalances in reactor kinetics. A slower than normal operation may affect the reaction products.
- Disturbance-14: Stickiness in the reactor cooling water valve is the cause of Disturbance-14. Fluctuation in flow rate, pressure and temperature are the consequences of the sticky valve.

- Disturbance-15: Stickiness in the condenser cooling water valve is the cause of Disturbance-15. Fluctuation in flow rate, pressure and temperature are the consequences of sticky valves.

- Disturbance-16: Even though there is no detailed explanation of Disturbace-16 to Disturbance-20 in Downs and Vogel (1993), other references, such as Sukumaran (2003) showed that it is because of a slow drift in temperature of the utility stream.

- Disturbance-17: According to Sukumaran (2003), it is a sinusoidal variation of the utility stream's temperature. As a result, it is expected to have sinusoidal variation in other process variables, such as reactor pressure and temperature.

- Disturbance-18: This is probably due to extra noises during the process of sampling measurement values.

- Disturbance-19: The probable existance of noise in the stripper is the cause of Disturbance-19. Fluctuation in production rate is expected as a consequence.

- Disturbance-20: This is a blockage in the condenser tube which consequently causes fluctuation in the temperture of cooling water (Sukumaran, 2003).

4.3. Fault Simulation of the TE Process

In this section FSN, is implemented using LabVIEW® as the front-end graphical user interface. MATLAB® is used to implement the BBN, and the Simulink® for the TE process simulation. The interface can be seen in Figure 4.3. In this simulation, two disturbances are created by clicking the "Step 1: Create Disturbances" tab. After clicking the tab, another window opens, as shown in Figure 4.4(a).

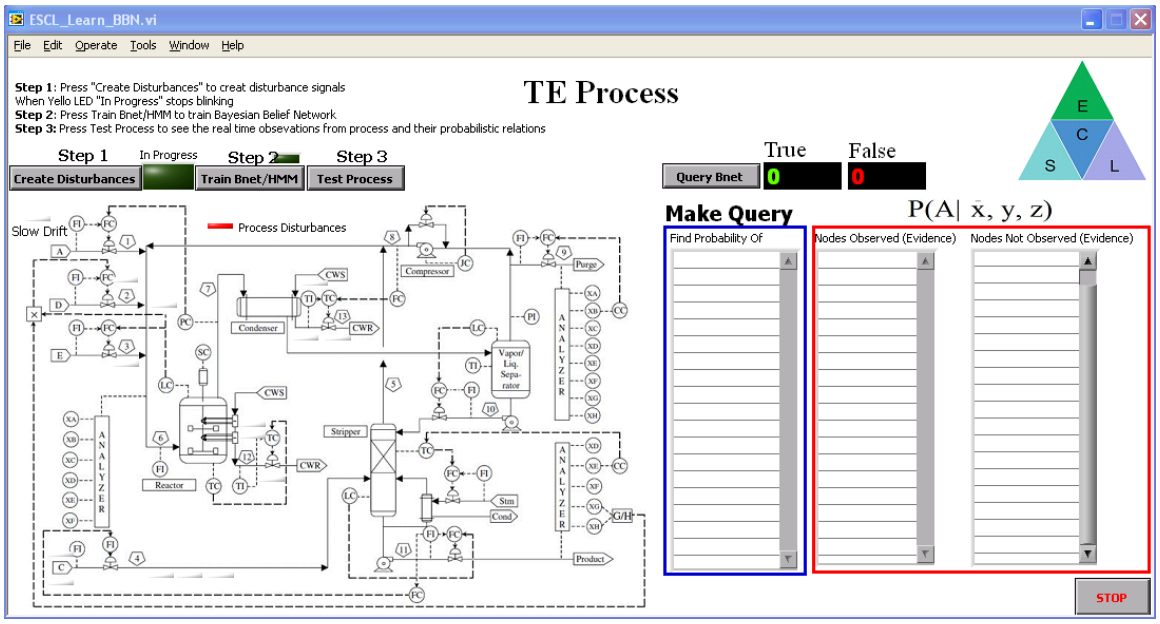
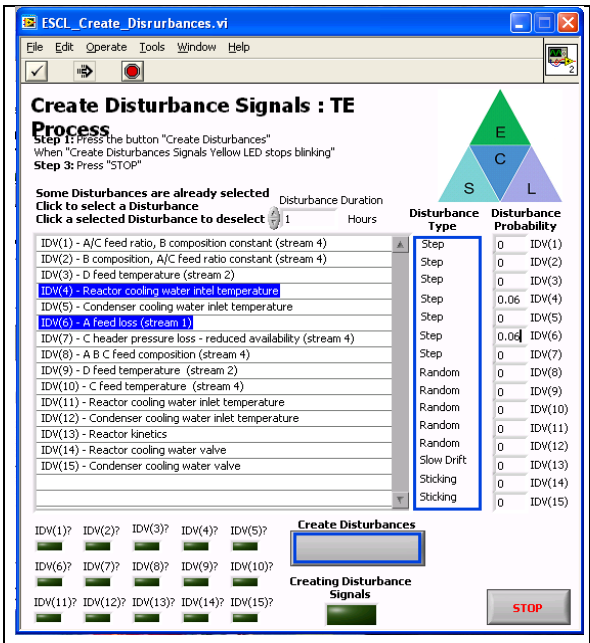


Figure 4.3: The TE Process interface in LabVIEW®

The disturbances selection is shown in Figure 4.4(a). Any combination of disturbances can be selected from Disturbance-1 to Disturbance-15. The disturbance affecting the variables can be seen in Figure 4.4(b). The two nodes on top of the spider web like structure are the two disturbances. The rest of the nodes are the affected variables. The probabilities of the disturbances entered were as follows:

Reactor cooling water inlet temperature:	IDV4 = 0.06
"A" feed loss steam 1:	IDV6 = 0.06



a) Two disturbances were inserted, IDV(4) and IDV(6)

b) Relationship between the variable with disturbances and the affected variables

Figure 4.4: Insertion of disturbances and the relationships between disturbances and the affected variables

After the disturbances are created, the LabVIEW® program automatically calls the TE process simulation engine to simulate the process for a few seconds (representing 72 hours in the simulation), incorporating the disturbances. The TE process simulation engine simulates the process and displays the results. The MATLAB® engine is called by clicking the "Step 2: Train Bnet/HMM" tab to train the BBN on the simulated data. The BBN training engine uses the K2 algorithm, as described by Coopers (1992), and learns the structure of the BBN along with the corresponding probabilities. The results are displayed as a graph with participating nodes and the arcs connecting the nodes. In this particular case, the nodes are IDV4 and IDV6, and from XMEAS1 to XMEAS22. After the BBN is fully trained, the query engine of the FSN follows. The query engine uses the

junction tree algorithm to make structured queries. The query interface is shown in Figure 4.5. The probability of IDV6 present, when the impact on XMEAS10 was observed, is 0.1253, as shown in the figure.

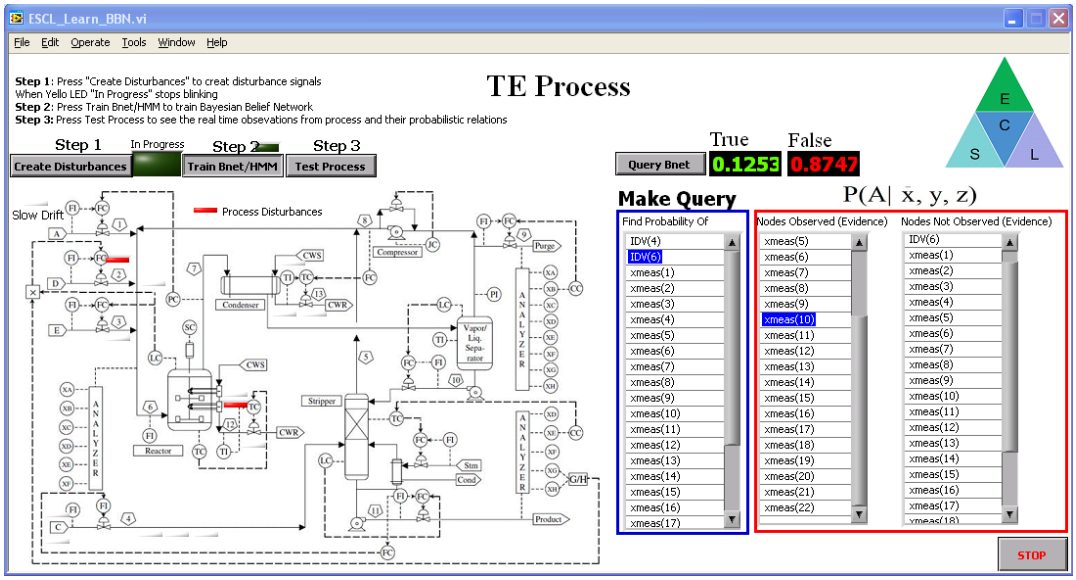


Figure 4.5: The result of a diagnostic query

The effect of the disturbance IDV6 is shown in Figure 4.6. The IDV6 is a step change in the A feed loss. The effect of this disturbance is propagated in the measured variables from XMEAS1 to XMEAS22.

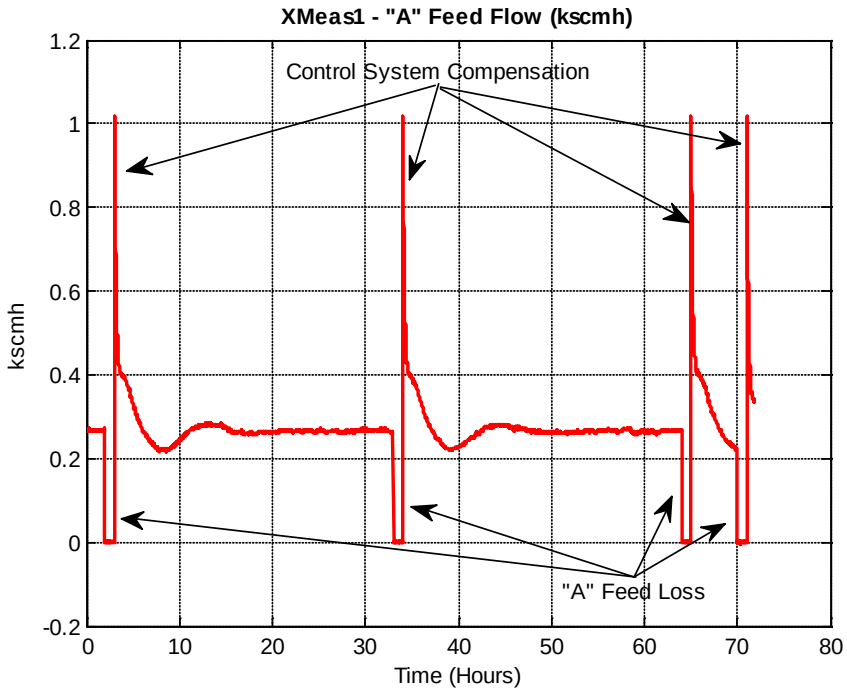


Figure 4.6: Measured variable-1 A feed flow

The effect of A feed loss (XMEAS1) on the reactor pressure (XMEAS7) is shown in Figure 4.7. As listed in Table 4.3, the nominal flow value of XMEAS1 is 0.25052 thousand standard cubic meters per hour (kscmh) but the loss occurs at time steps of 3rd, 34th, 65th and 70th hours for one hour as seen in Figure 4.7. After the feed is restored at the time step of the following hours, the control system peaks the A feed flow at 1 kscmh to compensate the loss, and slowly decreases the flow to reach the nominal value of 0.25052 kscmh. Because of this abrupt peak in the A feed flow to the reactor, the reactor pressure also exhibits a peak and abruptly changes from 2785 kPa to 2828 kPa, as shown in Figure 4.7.

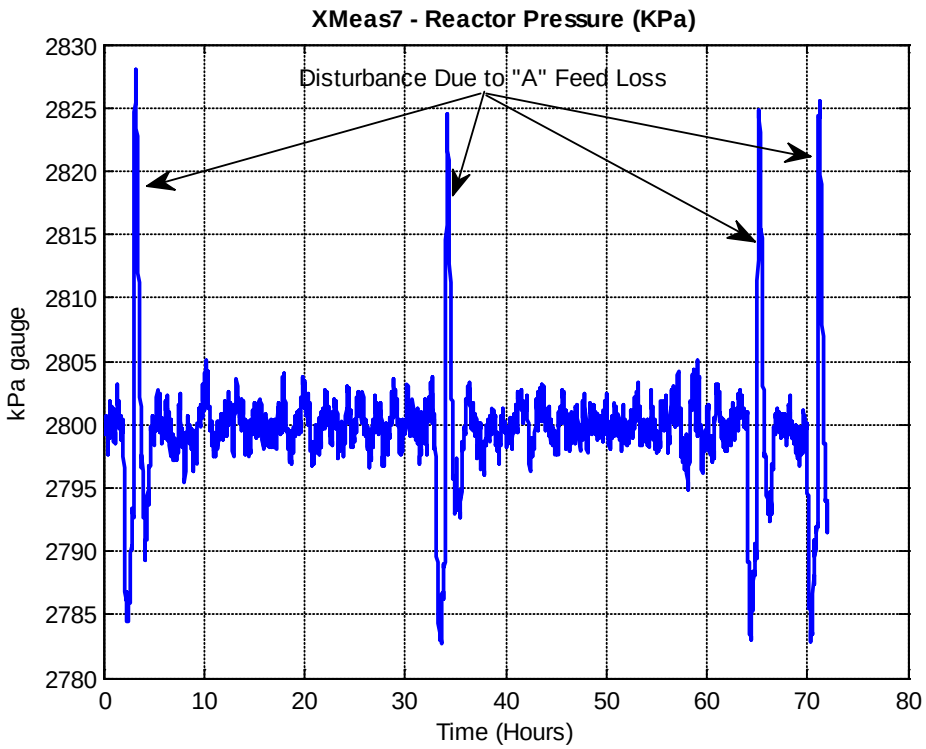


Figure 4.7: Measured variable-7 Reactor Pressure

The IDV4 is a step increase in the reactor cooling water inlet flow that eventually disturbs the reactor temperature. When the cooling water flow is increased through the reactor, there is not enough time for the cooling to take place and, as a result, the reactor temperature increases. The disturbance IDV4 as a step increase in the cooling water flow rate is shown in Figure 4.8.

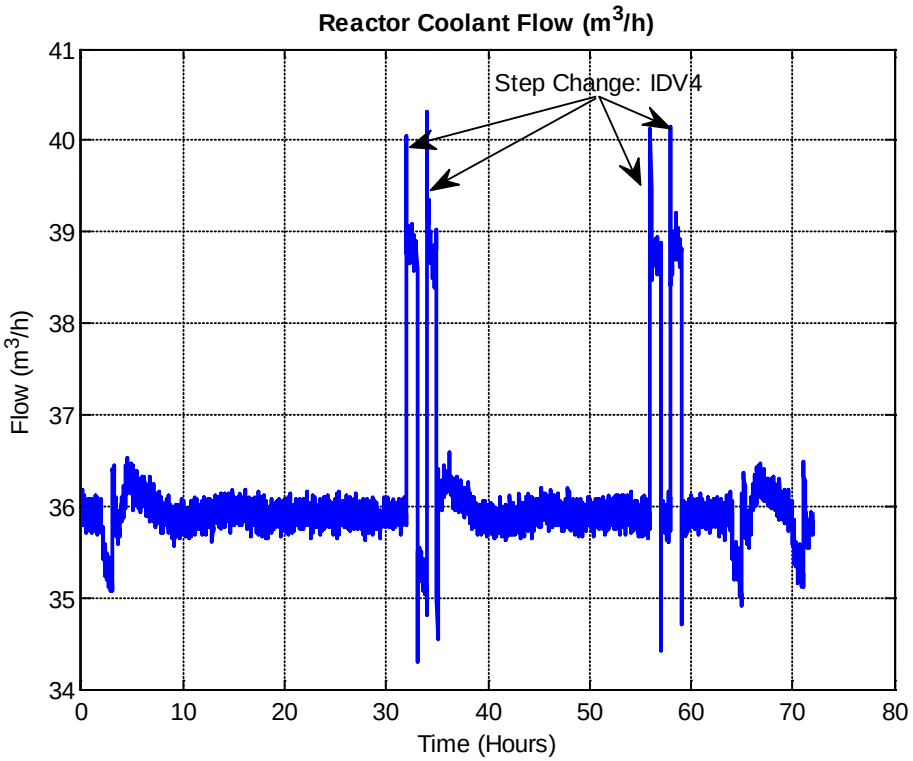


Figure 4.8: Reactor coolant flow

Table 4.6: Probability of dependency

P (XMEAS | IDV4, IDV6)	IDV4 (%)	IDV6 (%)
XMEAS7	0.047	98.80
XMEAS8	0.74	91.90
XMEAS9	99.50	82.60
XMEAS20	17.70	96.19
XMEAS21	99.90	71.75

Some probabilities of dependency among IDV4 (step increase in the reactor cooling water inlet flow), IDV6 ("A" feed loss), and XMEAS7 (reactor pressure), XMEAS8 (reactor level), XMEAS9 (reactor temperature), XMEAS20 (compressor work), and

XMEAS21 (reactor cooling water outlet temperature) are listed in Table 4.6, while it can be seen that IDV6 (A feed loss) affects the XMEAS7 (reactor pressure) by 98.8% as shown in Figure 4.6, while IDV4 (step increase in the reactor cooling water inlet flow) does not have any effect on XMEAS7 (reactor pressure).

Similarly, IDV6 ("A" feed loss) affects the XMEAS8 (reactor level) by 91.9% while IDV4 (step increase in the reactor cooling water inlet flow) does not have any effect on XMEAS8 (reactor level). IDV4 (step increase in the reactor cooling water inlet flow) has a strong effect (99.5%) on XMEAS9 (reactor temperature). IDV6 (A feed loss) affects the XMEAS9 (reactor temperature) by 82.6% as loss in A feed can result in temperature change in the reactor. In the case of IDV6 (A feed loss), no or less liquid is delivered to the compressor and as a result the compressor works more, XMEAS20 (compressor work).

A transient change in the reactor temperature is shown in Figure 4.9. There is also a small effect on the reactor temperature due to IDV6 - A feed loss, as shown.

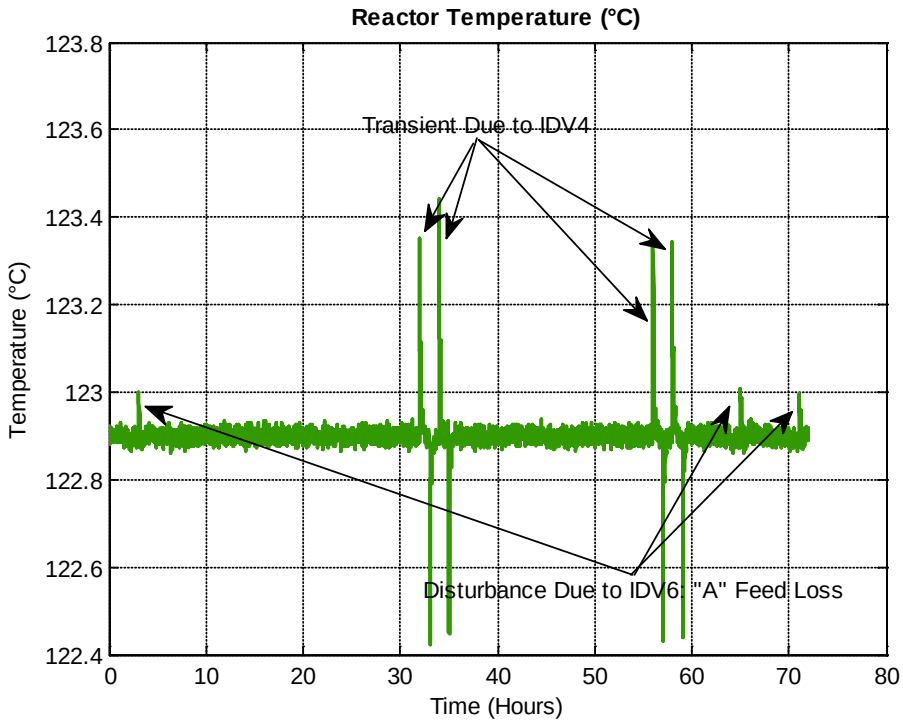


Figure 4.9: Reactor temperature

4.4. Real Time FSN Simulation

An implementation of the FSN to monitor the data emanating from the TE process in real time is shown in Figure 4.10. At any given time, the FSN detects the disturbance, plots the dependency lines, and calculates the relative probabilities by querying the BBN. The probabilities of top events are also calculated with associated risks and safety barriers are introduced as Risk Reduction Factors (RRF). Neither A feed loss nor the Level Control Valve (LCV) respond when given a command to open, as shown in Figure 4.10. In both cases, the liquid delivered to the reactor decreases and the top events can be “No Level” or “Low Level”. If there are safety barriers in place with RRF to detect and mitigate the

causes, the FSN calculates the probabilities of the top events (TE) and the probabilities of the final risks.

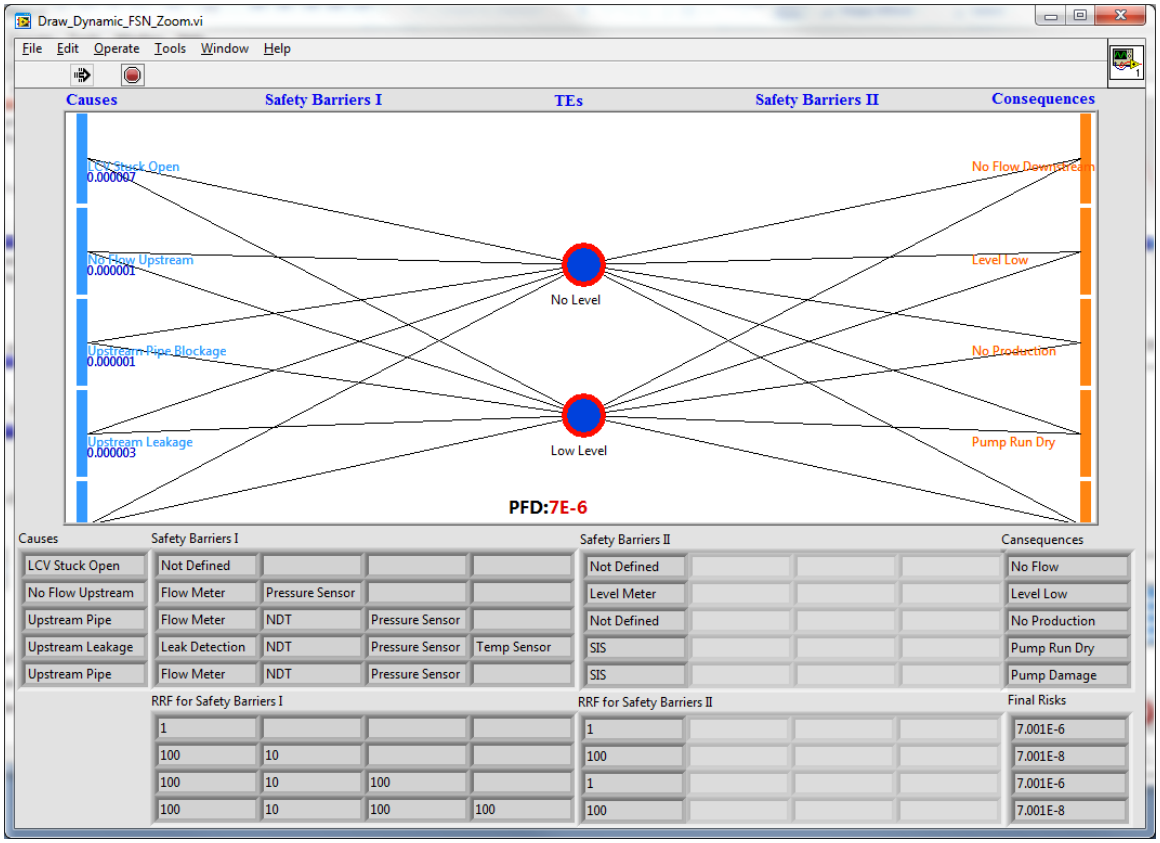


Figure 4.10: Relationships between causes and consequences in the LabView simulation

The parameters of the MATLAB® Simulink® simulation file are shown in Figure 4.11. The parameters have to be updated to fit individual research needs. The output product ratio, i.e. G/H, is shown in Table 4.2. In the Simulink® file, the G/H can be set to any ratio. Random numbers can be fed-in for all 20 disturbances. However, our team decided to use LabVIEW® to insert specific numbers for specific selected disturbances.

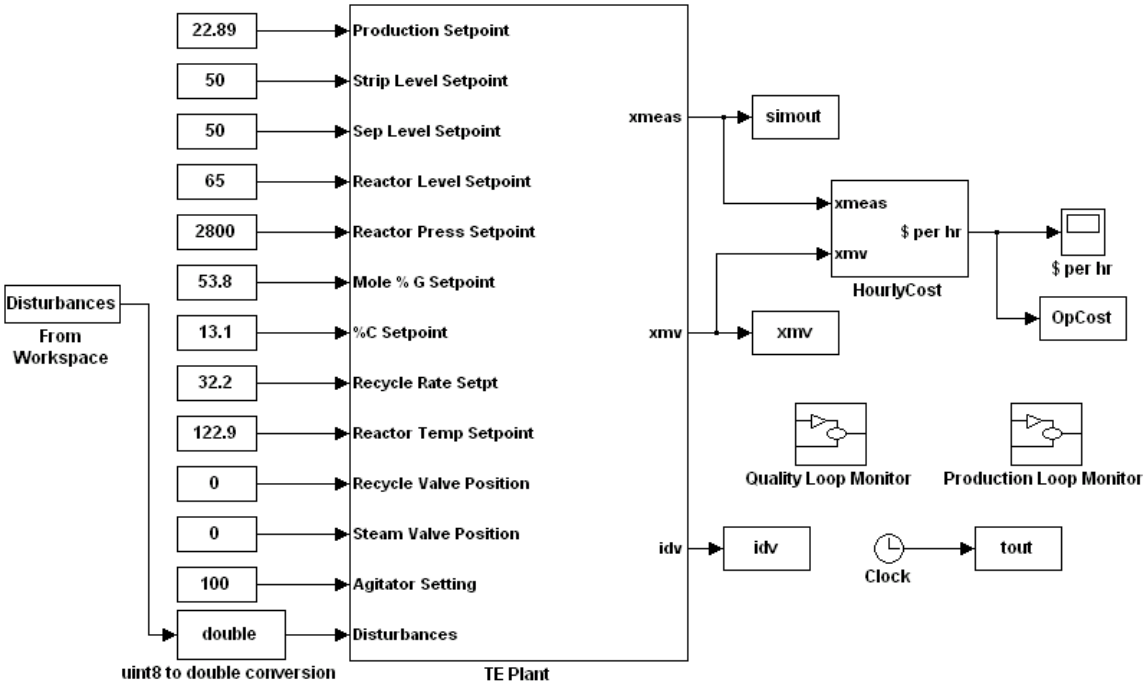


Figure 4.11: The parameters in the MATLAB® Simulink® simulation model

The variables that can be updated in the MATLAB® Simulink® file are:

1) Production setpoint
2) Strip Level setpoint
3) Step level setpoint
4) Reactor level setpoint
5) Reactor pressure setpoint
6) Mole percentage (%) of G setpoint
7) Percentage (%) of C setpoint
8) Recycle rate setpoint
9) Reactor temperature setpoint
10) Recycle valve position
11) Steam valve position
12) Agitator setting
13) Disturbances

Summary: *In this chapter, the TE process, which is a well defined simulation, is presented as a case study. A MATLAB® Simulink® file was created for the simulation purpose. LabVIEW® was used to interact with the MATLAB® Simulink® file. An analysis has been performed on simulation data to construct the static FSN. Using real time data, the dynamic FSN was updated and simulated.*

In the next chapter, system design and implementation of the FSN are discussed. The software and database design are explained.

Chapter 5: System Design & Implementation

A Semantic network (SN) is a network structure that represents relations between concepts. The earliest attempt was made by Collins and Quillian (1969) when they introduced a semantic network in a tree structure (directed or undirected graph) that consists of nodes and arcs where the nodes represent concepts and connections showed relations between nodes. A tree-structured of the SN is shown in Figure 5.1.

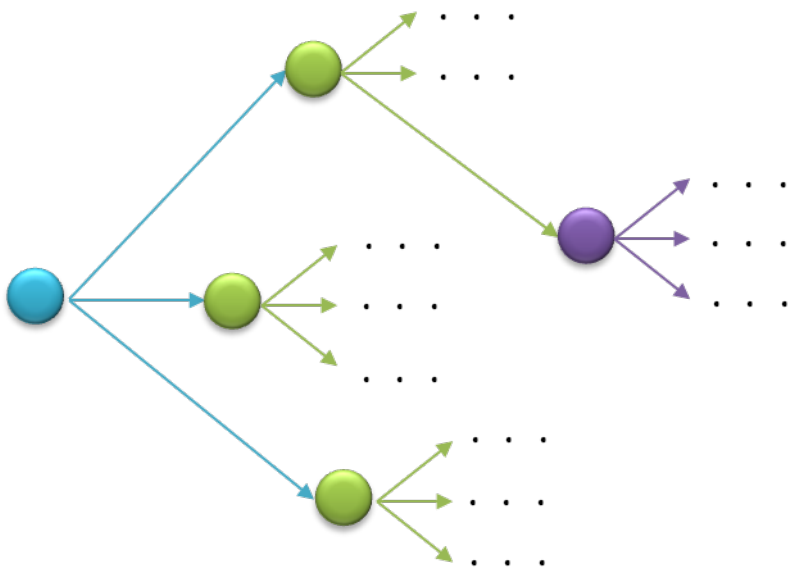


Figure 5.1: Tree structure of a Semantic Network

An SN models systems in order to represent different concepts such as, statistical, taxonomic and industrial, and specifies relations between them. Specifying relations between concepts is possible by implementing a special set of procedures that performs reasoning between them.

An SN could attain success and gain more attention in different industries because of its wide applications such as fault recognition and root cause analysis. A Fault Semantic Network (FSN) can identify the causes and consequences, as well as any events in-between, and is also applicable to a variety of industrial processes. Thus, it is an example of a promising application of an SN.

The structure of the proposed FSN follows the design explained by Gabbar (2012). The proposed FSN is developed in two layers: static (offline) and dynamic (online). A static FSN includes failure, fault, hazard and accidents as structured and linked in the form of causation models, which are associated with process equipment, as individual and between adjacent process equipment. A dynamic FSN is constructed using dynamic real time or simulated process data from operation, maintenance, safety and control (Gabbar, 2012).

The structure of an SN is somewhat similar to a tree in that they have common terminologies. The *root node* is the node which does not have any parent and the node that has no child is called the *leaf*. Any other node in between is called an *intermediate node*. Hence, in a semantic network the root node represents the root cause and the leaf represents the consequence. *Pressure* and *vapor inside* of a process vessel can be considered as root causes.

5.1. Proposed System Architecture

There may be a deviation in one level which may propagate to the next level; i.e. class level, equipment level, plant level. A reverse model, i.e. how plant level deviations affect class level or class level deviations affect equipment level, is shown in Figure 5.2.

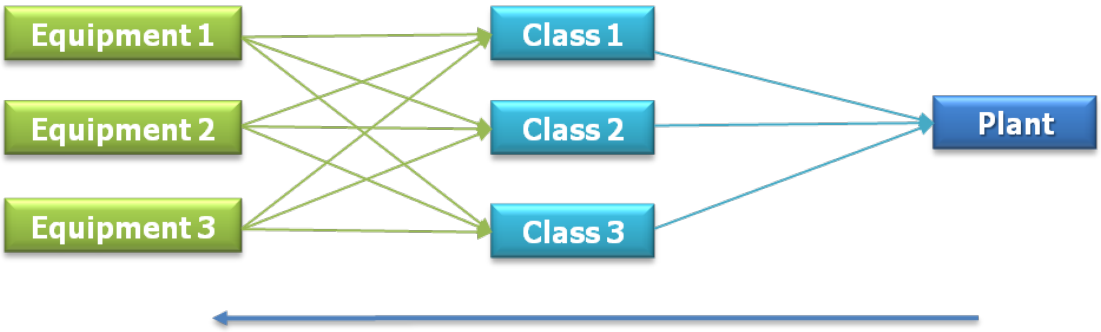


Figure 5.2: Class level and equipment level deviations

Equipment level deviation affects class level and plant level, while class level deviation affects plant level and equipment level and plant level deviation affects equipment level and class level

The system architecture is carefully selected to capture qualitative / quantitative fault, failure, hazard, and accident data as shown in Figure 5.3. Real time data is captured from a Digital Computer System (DCS) and analyzed using code written in MATLAB®-Simulink®. Cape-Mode is developed within Microsoft Visio to capture and structure process design models for Process Block Diagrams (PBD), Process Flow Diagram (PFD), and Piping and Instrumentation Diagram (P&ID), based on ISA-S95 / 88. A Fault

Diagnostic System (FDS) is developed to construct fault models using qualitative-quantitative and deterministic-probabilistic techniques. A Fault simulator engine is developed within MATLAB®-Simulink®, where fault propagation, equipment reliability, and material degradation are calculated and used to construct and maintain fault / failure propagation models. A Computational Fluid Dynamics (CFD) tool is used to evaluate the granular level of process and equipment condition data such as temperature and pressure profile within a process vessel, or corrosion profile in pipeline a body (Gabbar, 2012).

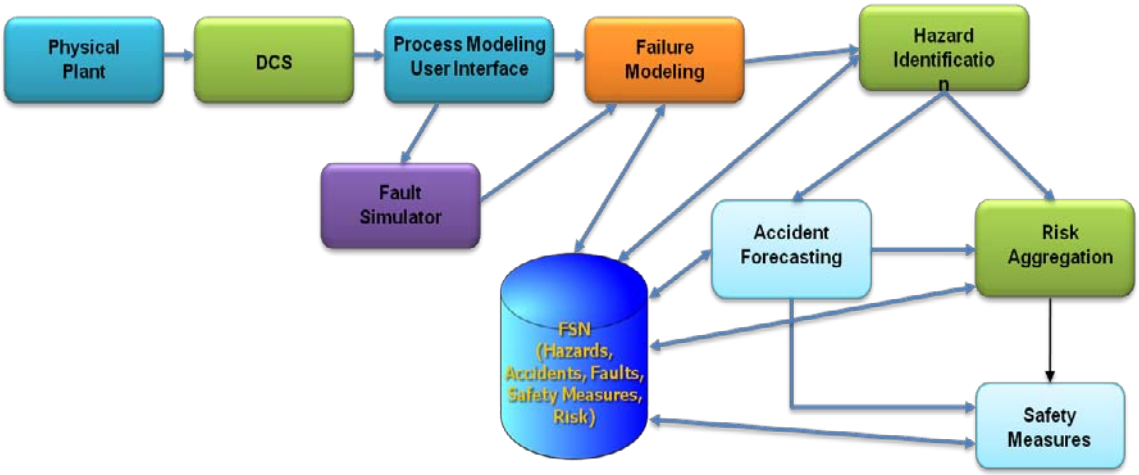
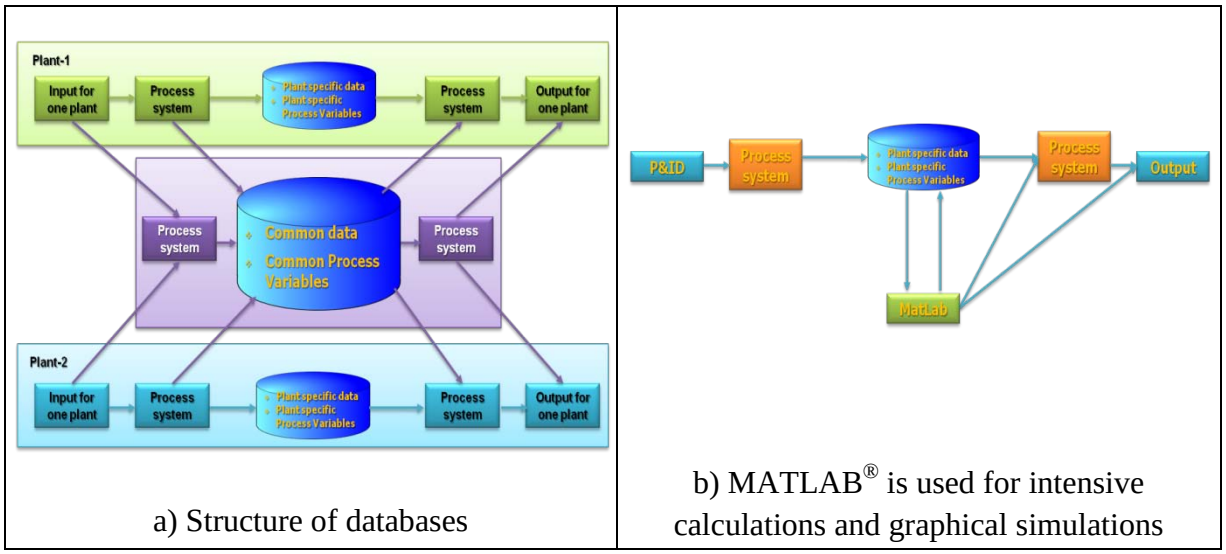


Figure 5.3: Proposed system architecture for failure, fault, hazard and accident data acquisition

The data related to faults, failures, hazards and accidents are stored in databases. Any database management program such as Oracle or Microsoft SQL Server can be used for this purpose. Common data which relates to all plants are stored in a common database. The data for specific plants are stored in a database specific to that plant. The structure is shown in Figure 5.4(a). Use of an appropriate level of detail in the computer program primarily depends on the nature of the desired outputs and the applications under study.

Based on the requirements and availability of the program, Microsoft Visio has been selected to be the main program as it has the capability of drawing diagrams as well as interacting with databases through ODBC. The basic descriptive constructs provided by the program for developing the thermal models will be created within the constraints of the program. Given the correct input parameters that cover different aspects of the plant, parent-class, daughter-class and equipment-class, and other related parameters surrounding the plant, Visio along with its supporting programs, is able to internally convert them to a mathematical form suitable for numerical solutions. Initially, Microsoft Access is used as database management system. Later on data will be ported to Oracle. Other software such as MATLAB® and C++ are being used as and when required for simulation, along with Visio as shown in Figure 5.4.b).



a) Structure of databases

b) MATLAB® is used for intensive calculations and graphical simulations

Figure 5.4: Relationships between different databases, between databases and programs and between different programs

In the final step of this stage, the program reads the P&ID from the canvas and uses the information from the database, analyzes them according to the algorithm developed in the static FSN development stage. The FSN is then updated at the dynamic stage, and presents the output in an understandable manner. The output can be the result of a predictive, diagnostic, inter-causal or a combined query.

5.2. The TE Process / Fault / Hazard / Accident Data Acquisition

For data acquisition purposes, in a processing plant the equipment is assigned to different predefined groups. These groups are equipment classes. The classes are defined based on the function of the equipment belonging to that class. Some classes can be regrouped in parent classes. Classes are related to specific functions, components and process variables, as shown in Figure 5.5. Each piece of equipment is assigned an equipment identification code (Eq_ID) and each class is assigned a class identification code (Clss_ID).

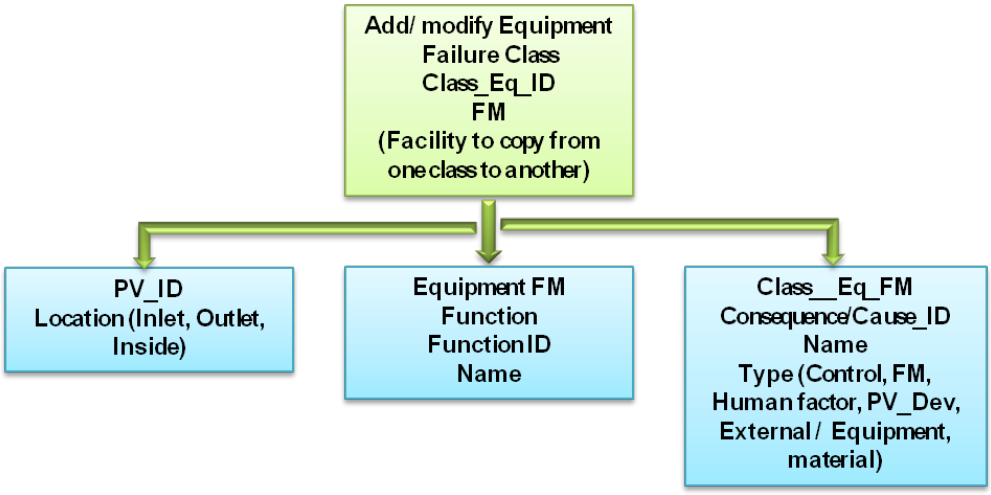


Figure 5.5: Proposed data acquisition model
(Adapted from Gabbar, 2012)

For implementation of the FSN, a database was selected. Initially Microsft Access was used. In future, the database will grow. As Access is not capable of handling large scale data, in a later stage large scale database such as Oracle can be used. To access the database from Visio, Open Data-Base Connectivity (ODBC) is used. Therefore, without changing the program, the database in the background can easily be changed.

The tables are created in the database. Moreover, relationships between the tables are established. For example in the equipment table there are attributes such as Eq_ID, Eq_Name, and Eq_Desc. In the equipment-failure-mode table, there are attributes such as Eq_ID, FM_ID, and Eq_FM_Desc. Between the equipment-failure-mode table and the equipment table there is a relationship defined by Eq_ID. Similarly, in the failure-mode table there are attributes such as FM_ID, FM_Desc, and FM_Loc. Between the

equipment-failure-mode table and the failure-mode table, there is a relationship defined by FM_ID. An example is shown in Figure 5.6.

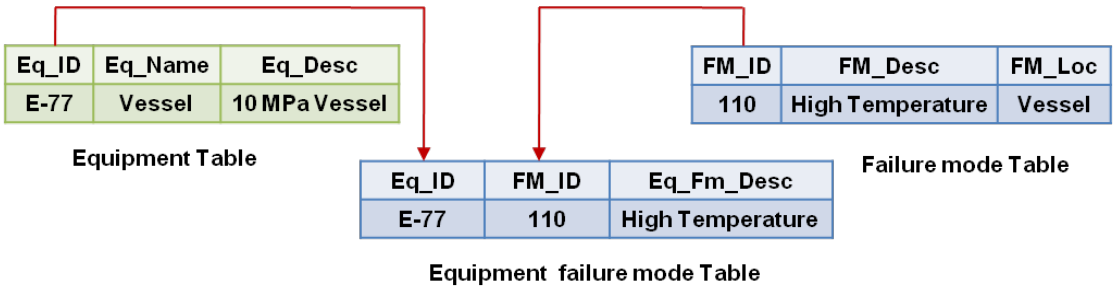


Figure 5.6: An example of relationships between tables

For front end programming, Microsoft Visio is used for convenience. In Visio, equipment can be dragged and dropped from the equipment database. The equipment can be connected using connector tools.

The concept was used in two different fields: one is P&ID of the process industry and the other is the energy industry, i.e. the Energy Semantic Network (ESN).

5.3. Implementation of the FSN

Using user interface, different parameters of the equipment can be changed or updated as and when necessary. Material of construction is linked with the equipment and pipes. All the causes and consequences are linked with the equipment and pipes. The equipment class parameter modification screen in the user interface is shown in Figure 5.7.

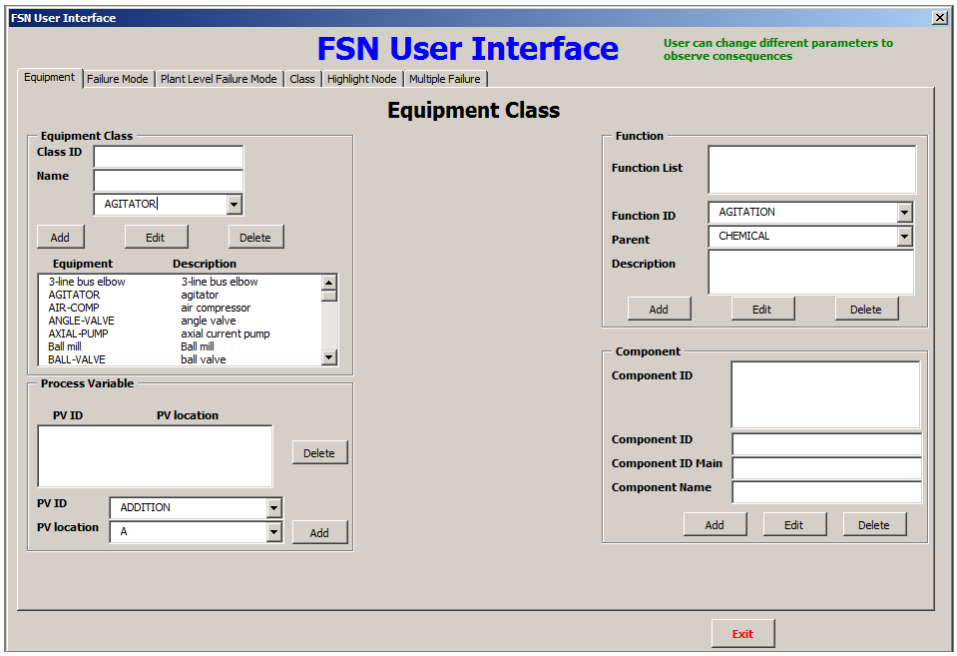


Figure 5.7: User interface can be used to change parameters

The link between the equipment can be changed, or parameters of the nodes can be updated from the user interface as and when necessary. The consequences, generated by the background program and listed on the user interface, are shown in Figure 5.8. The sample background programs are shown in Appendix G.

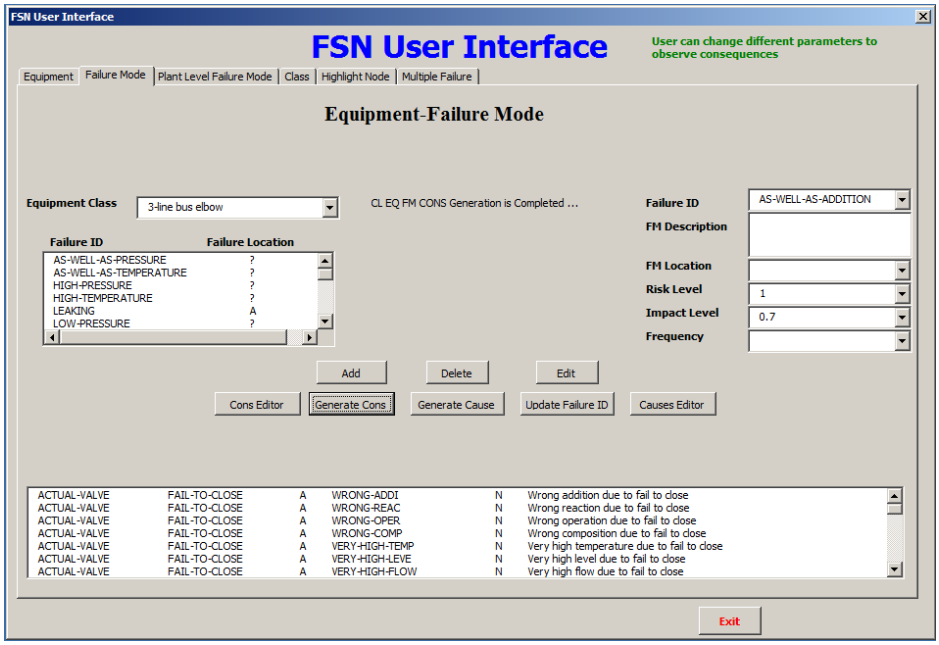


Figure 5.8: User interface can be used to generate consequences

Summary: *In this chapter, the implementation process of the system design of the FSN is presented. The software and database selection procedure, and the advantages and disadvantages associated with the software, are explained. Designing of the FSN in node and tree concepts are presented. There are root nodes and leaf nodes. Roots are the causes and leaves are the consequences. The creation of the database, tables in the database and attributes of the tables are discussed. The front-end, i.e. the user interface to manipulate the variables and to observe the effects on KPI, is presented.*

In the next chapter, application and other implications of FSN are explained.

Chapter 6: Evaluation and Results

In the case study chapter, propagation scenarios of faults were simulated. The relationships between deviations and hazards and, ultimately, accidents were mostly established based on historical data. Many of the relationships were established based on scientific facts and engineering calculations.

Initially, the FSN was constructed based on the ontology structure of fault models on the basis of POOM, where failure mode was described using symptoms, enablers, process variables, causes, and consequences. Implementing the FSN for a process with many process variables is not easy, especially in the real world. There are steps that should be undertaken by engineers and researchers to let them create a dynamic modelling of a process as a Semantic Network (SN) that contains all the possible faults and relationships between variables. In the FSN, the strength of the relationship between variables can be assigned both qualitatively and quantitatively through different reasoning approaches such as the probabilistic approach and mathematical formulation.

In a process, there may be many variables that affect the operation. In order to implement complete analysis of the process, it is necessary to consider all variables. In the FSN, the number of process variables affects the accuracy of analysis. The analysis can be conducted by using just a manipulated and a measured variable. However, it will be incomplete. In summary, the more process variables selected, the greater the accuracy obtained.

6.1. The Static FSN of the TE Process

The FSN was introduced in the TE process as a valuable tool with considerable abilities. Nodes correspond to different process variables/faults/causes/consequences and directed arcs are links between them that describe the dependencies and any node associated with its risk value. Therefore, it is possible to calculate risks of occurring failures or accidents. Links between causes, events, and consequences were implemented in the TE process simulation using the BBN algorithm, three examples of which are shown in Figures 6.1, 6.2 and 6.3.

In Figure 6.1, the event, “Insufficient Pressure”, was inserted. The probable causes identified by the BBN are:

a) Instrumentation error
b) Broken impeller
c) Bent pipes
d) Incorrect impeller
e) Incorrect impeller diameter
f) Cavitation
g) Rotating backwards
h) Rotational speed too low
i) Insufficient Net Positive Suction Head (NPSH) available

The probable consequences identified by the BBN are:

a) Seal leakage
b) Fire
c) Toxic release
d) Human injury

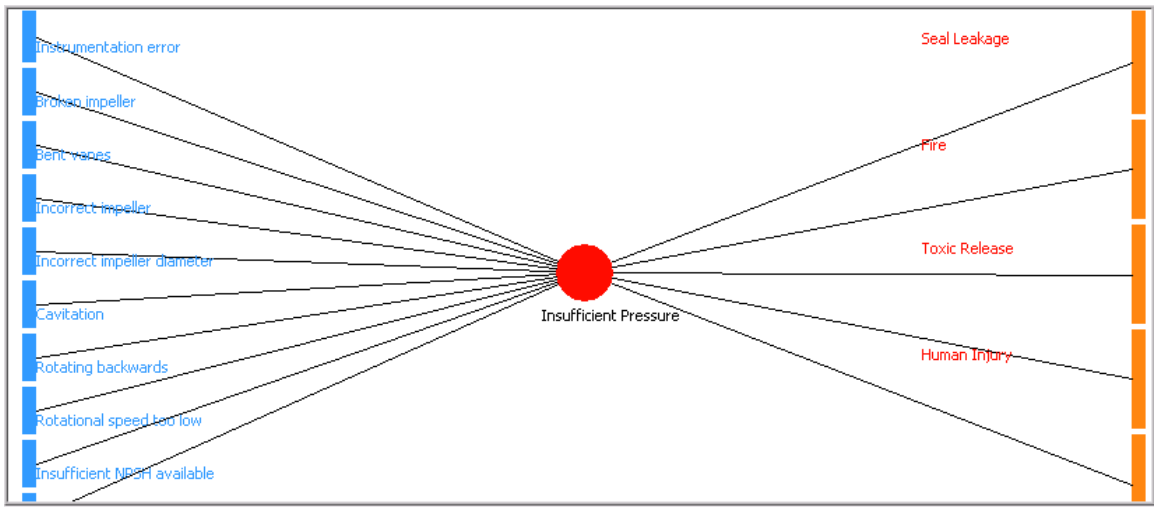


Figure 6.1: Causes and consequences of the event Insufficient Pressure

In Figure 6.2, the event, "No Liquid Delivered", was inserted. The probable causes identified by the BBN are:

a) Pump not primed
b) Liquid returned backward
c) Suction valve shut
d) Suction piping blocked
e) Discharge piping blocked
f) Insufficient NPSH available
g) Motor failure
h) Impeller jammed by foreign boddy
i) Impeller seized
j) Supply tank / vessel empty
k) No liquid supply in pipe
l) Motor wrongly wired
m) Specific gravity higher than specified
n) Viscosity higher than specified
o) Volute shattered
p) Broken drive coupling

q) Broken drive shaft

r) Bearing in housing seized

The probable consequences identified by the BBN are:

s) Production lost

t) Property Damage

u) Excessive maintenance

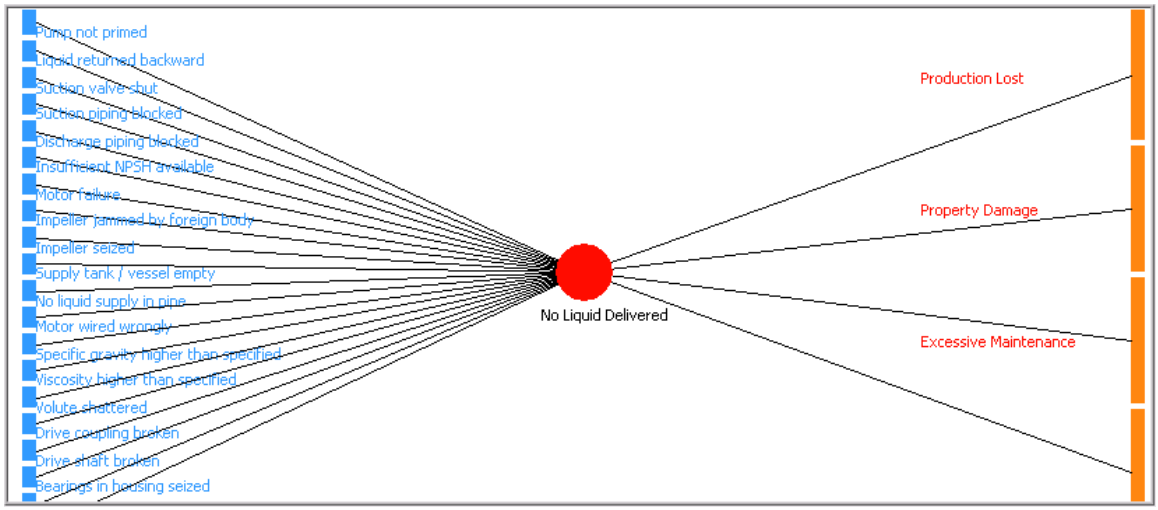


Figure 6.2: Causes and consequences of the event No Liquid Delivered

In Figure 6.3, the event, “Pump Leakage”, was inserted. The probable causes identified by the BBN are:

a) Mechanical seal passes

b) Stuffing box packing excessively worn (for packed gland)

c) Stuffing box bore damaged

d) Pump shaft surface damaged

e) Packing incorrectly installed

f) Flange leaks (flange not sealing)

g) Incorrectly assembled

h) Volute cracked

i) Volute corroded

j) Volute eroded

The probable consequences identified by the BBN are:

a) Seal leakage

b) Fire

c) Production loss

d) Human injury

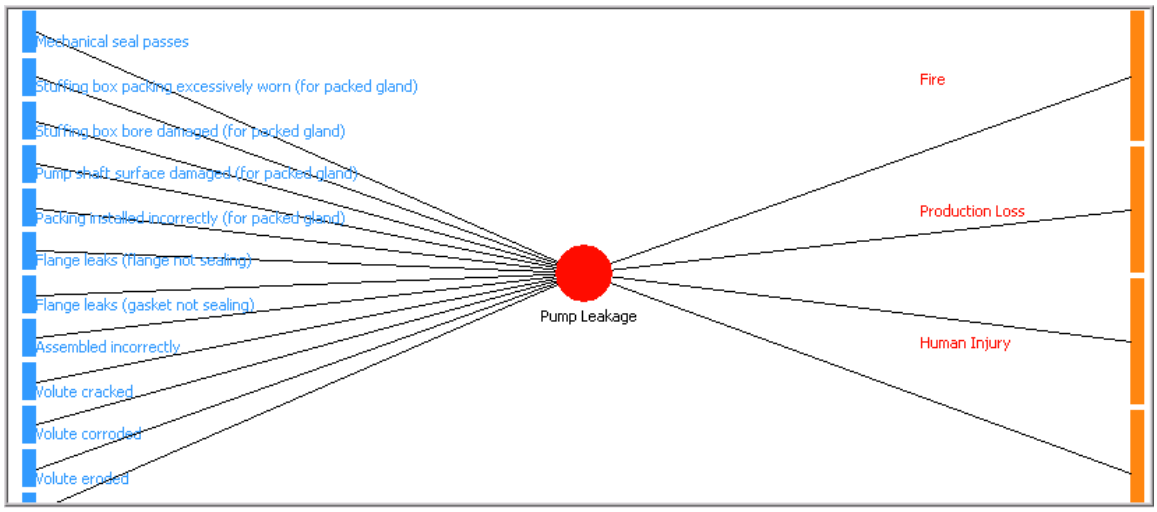


Figure 6.3: Causes and consequences of the event Pump Leakage

In the TE process the events are manually inserted; the causes and consequences related to the events are dynamically determined by the BBN. The algorithm of the BBN was established using historical-real-life data, in the learning stage. In the dynamic FSN, the BBN algorithm is updated by the system without any human intervention after certain intervals from the real-life data which makes the system faster than the other proposed

systems. As there is minimal human intervention, the probability of human error is also less.

6.2. The Mapping of the IPL to the FSN

The mapping of the IPL was performed in six steps, as described in Summers (2002):

1) All reference documentation, including hazard analysis documentation, pressure relief valve design and inspection reports, and protection layer design documents are recorded.

2) The process deviations and hazard scenario under consideration are documented. Specifically, high pressure anywhere in the system is focused on, as high pressure may result in equipment rupture.

3) All of the initiating causes for the process deviation are identified and the frequency of each initiating cause was determined. All initiating causes of the hazard scenario, such as loss of flow control, loss of pressure control, and loss of temperature control were listed.

4) The consequences of the hazard scenarios are determined. The evaluation included an examination of safety and environmental and economic losses.

5) The IPLs that can completely mitigate all listed initiating causes are listed. It may be noted that the IPL must be completely independent from the initiating cause; e.g., if a process control loop is the initiating cause, an alarm generated by the process control transmitter cannot be used for risk reduction.

6) Specific implementable recommendations are recorded. They are listed in such a way that the best option can be selected from an implementation ease and cost standpoint.

An example of the mapping of IPL in the TE process is shown in Figure 6.4. For the cause “LCV Stuck Open”, Safety Barriers I and II are not defined. For the cause “No Flow Upstream”, Safety Barrier I is the Flow Meter and Safety Barrier II is the Level Meter.

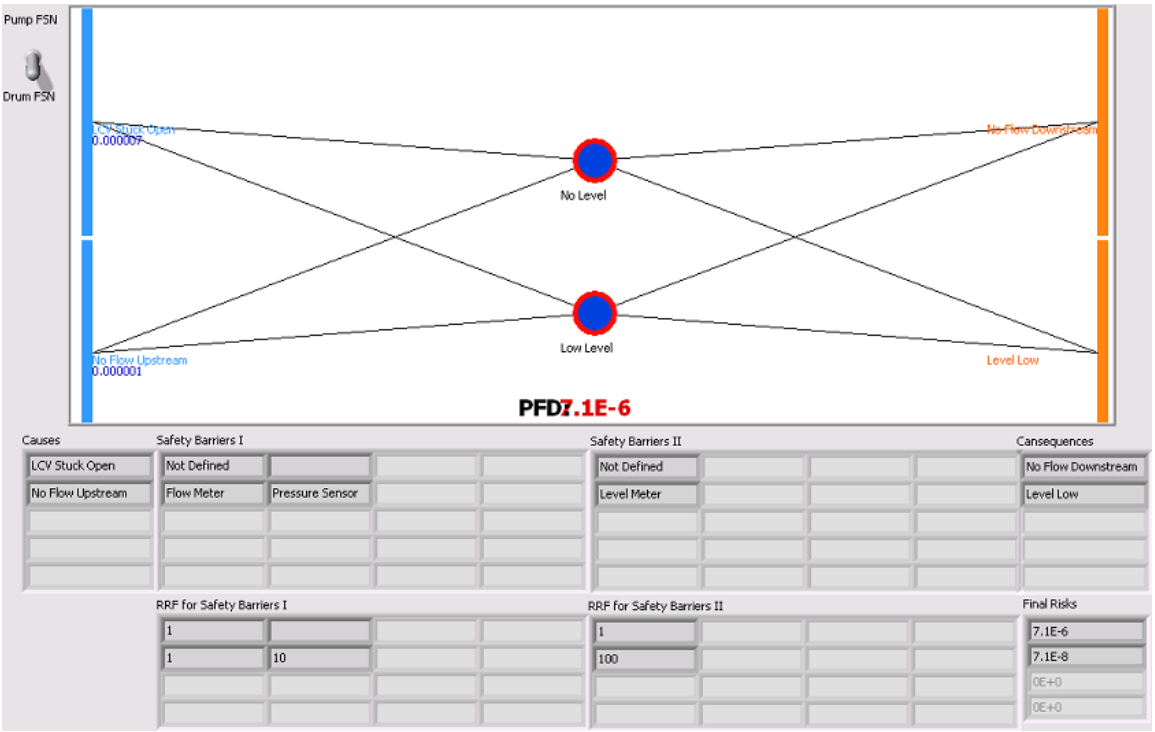


Figure 6.4: Mapping of IPLs in the TE process

6.3. The Dynamic FSN and Safety Verification of the TE Process

An example of safety verification, along with the safety verification in the TE process is presented in this section. A fault propagation scenario of a particular initial event, for example high temperature is show in Figure 6.5.

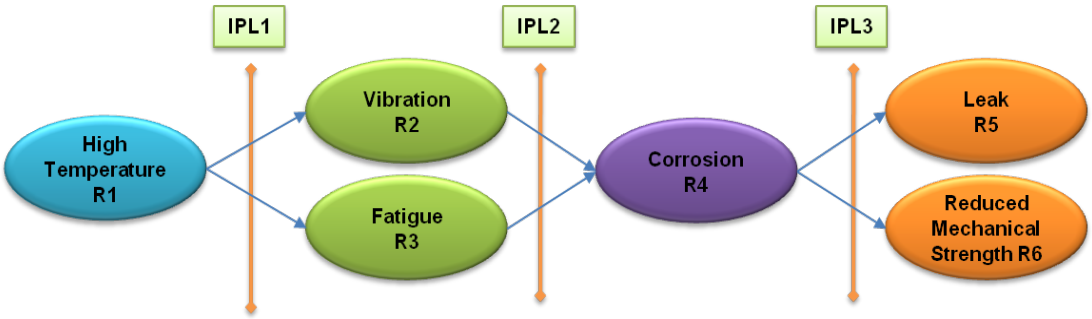


Figure 6.5: Fault propagation scenario of high temperature

The first step of safety verification is control limits estimation. For this purpose, the data in Table 6.1 is used. The Exponentially Weighted Moving Average (EWMA) technique is used for estimating the control limits of the tank (Pillay and Wang, 2003, p. 149-177). Only two control limits are estimated: Upper Control Limit (UCL); and Lower Control Limit (LCL).

Table 6.1: Historical tank temperature data (Wiersma, 1999)

Day	Specific Gravity	Level (inches)	Temp (Celsius)
1	1.51	80	30
2	1.53	38	35
3	1.27	293	33
4	1.31	325	29
5	1.43	75	37
6	1.48	229	27
7	1.44	53	48
8	1.38	262	35
9	1.4	310	30
10	1.45	70	30
11	1.46	52	27
12	1.22	271	23
13	1.2	241	32
14	1.26	72	19
15	1.1	33	17
16	1.05	259	19
17	1.02	191	21
18	1.06	78	20
19	1.36	78	34
20	1.32	41	39
21	1.45	46	34
22	1.4	104	57
23	1.18	55	31
24	1.41	85	45
25	1.45	253	51

The UCL and LCL to be calculated are defined with the help of the following expressions:

Upper control limit: $UCL = EWMA_0 + k \cdot s^2_{ewma}$ [6.1]

Lower control limit: $LCL = EWMA_0 - k \cdot s^2_{ewma}$ [6.2]

$$s^2_{ewma} = \frac{\lambda}{2-\lambda} \cdot \sigma^2 \qquad [6.3]$$

where:

σ = standard deviation of the data

s^2_{ewma} = estimated variance

λ = a constant, such that $0.2 \leq \lambda \leq 0.3$

$EWMA_0$ = mean of historical data

k = a factor

values:

$\sigma = 10.19$

$EWMA_0 = 32.12$

$\lambda = 0.21$

$k = 0.85$

calculation:

$$s^2_{ewma} = \frac{0.21}{2 - 0.21} \times 10.19^2 = 12.18$$

$UCL = 32.12 + 0.85 \times 12.18 = 42.47$

$LCL = 32.12 - 0.85 \times 12.18 = 21.77$

The values of the dataset, the UCL and the LCL are plotted on a EWMA graph in Figure 6.6. The data points that lie outside the specified zone of operation can be seen in the figure. Whenever the temperature crosses either the UCL or the LCL, there is a possibility of an initial event taking place. A few out-of-zone points do not cause problems, but when they successively remain out, as depicted by the last five data points as seen in the figure, it is an indication of a potential problem which, if not addressed, could result in a hazard.

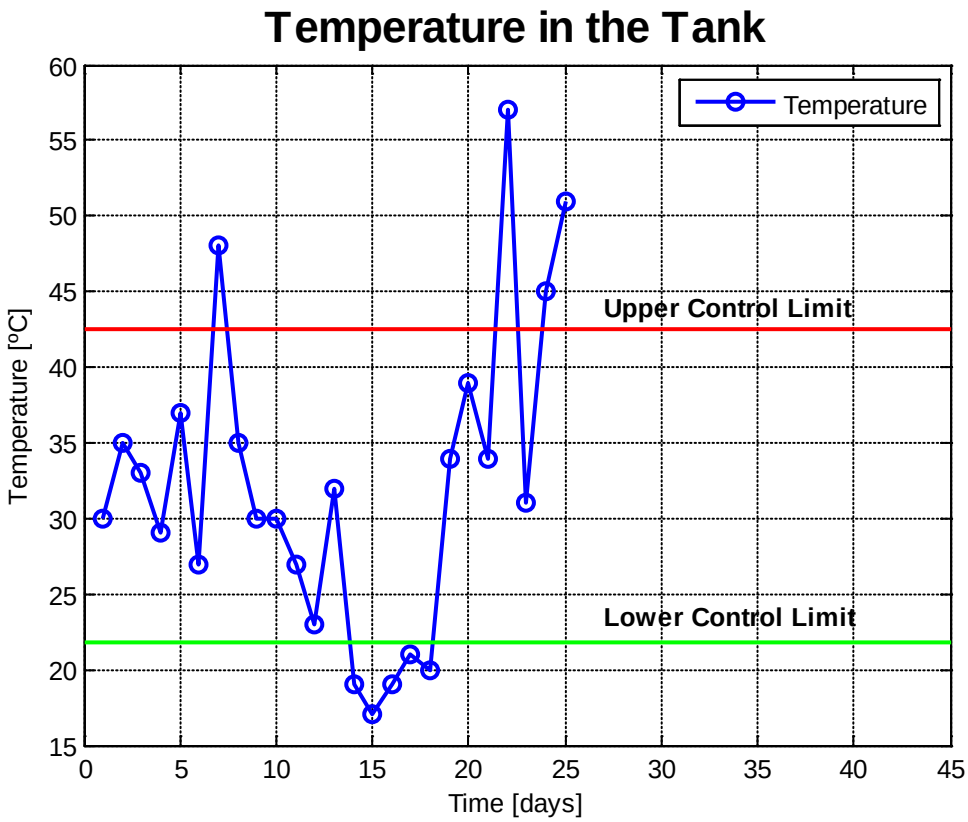


Figure 6.6: An EWMA plot for the data set with the UCL and the LCL

6.3.1. Hazard Identification

Once the process exceeds the control limits, any possible hazard should be evaluated. Hazard identification means checking for all the hazardous conditions and events associated with the machine. Hazard identification includes predicting the hazards that may occur in a process. These hazards can be mechanical, electrical, thermal, chemical or environmental in nature. Failure mode and effect analysis is a comprehensive technique which is commonly used in fault scenarios, resulting in multiple failure modes. It is a method that examines potential failures in products or processes, and has been used in many quality management systems (Chin, Wang, Poon and Yang, 2009). This risk

analysis tool assumes that a failure mode occurs in a system or component through some failure mechanism. The effect of this failure is then evaluated. A risk ranking is produced in order to prioritise attention for each of the failure modes identified (Pillay and Wang, 2003, p. 149-177).

The risk analysis tool has become increasingly important in new product development, manufacturing or engineering applications. Risk assessment in Failure Mode and Effect Analysis (FMEA) is generally carried out by using Risk Priority Numbers (RPNs), which can be determined by evaluating three factors: occurrence (OCC), severity (SEV) and detection (DET) (Zhang and Chu, 2011).

The major hazards identified are leak, fire and explosion, which can cause widespread injuries and consequences to the workers and surrounding environment.

Based upon the values of the three parameters used in FMEA, risk priority numbers are determined. The values of occurrence (OCC), severity (SEV) and detection (DET) are determined on a scale of 10 based upon the category in which a particular process lies. These categories are shown in Table 6.2. The higher the value of RPN, the higher the likelihood of hazard occurrence. In Figure 6.6, most of the data points lie between the UCL and LCL. Few of the data points are either over the UCL or under the LCL. This indicates a slight possibility of a hazard occurrence.

Table 6.2: Determination of Severity, Occurrence and Detection (Zhang and Chu, 2011)

Scale	Severity	Occurrence	Detection
1	Will not notice	1 in 1000000	100%
2	Probable slight annoyance	1 in 20000	99%
3	Slight annoyance	1 in 5000	95%
4	Dissatisfaction	1 in 2000	90%
5	Uncomfortable	1 in 500	85%
6	Slight compliant	1 in 100	80%
7	High dissatisfaction	1 in 50	70%
8	Very high dissatisfaction	1 in 20	60%
9	Endangered with warning	1 in 10	50%
10	Endangered without warning	1 in 2	Less than

6.3.2. Risk Estimation and Evaluation

Risk estimation is an essential part of risk analysis in a process, because the categorisation and allocation of safety requirements is based on this (Hietikko, Malm and Alanen, 2011). Once the hazards are identified, the next step is the quantification of risk. This risk evaluation is carried out using the Proportional Risk Assessment Technique (PRAT), which covers risk estimation and evaluation, and forms the third and key step in the safety verification framework.

For better understanding, an example is presented in this section using the data in Table 6.1 from Blanchard (1999). This data is failure rate data for various equipment and parts of the process.

Table 6.3: Failure Rate (Blanchard, 1999)

Symbol	Meaning	Magnitude
R1	Risk associated with high Temperature	9.00
R2	Risk associated with Vibrations	2.50
R3	Risk associated with Blockage	1.20
R4	Risk associated with Corrosion	0.85
R5	Risk associated with Leak	0.055
R6	Risk associated with Reduced Mechanical Strength	0.085
PFD1	Probability of Failure on Demand of IPL-1	0.003
PFD2	Probability of Failure on Demand of IPL-2	0.0025
PFD3	Probability of Failure on Demand of IPL-3	0.0035

The risk can be quantified as:

Risk: R = (Probability of failure) × (Magnitude of its consequence)

The magnitude of failure is calculated based on the historical data of accidents and the occurring consequences per event. This can be considered as a constant in the static FSN, while in the dynamic FSN it is continually recalculated based on real time data. The risk associated with any event is a function of failure rate and directly proportional to it.

Risk Associated = f (failure rate)

The fault propagation scenario shown in Figure 6.5 can be broken into four individual fault propagation scenarios for simplicity of calculation. Once broken down into individual fault propagation scenarios, they are evaluated and then combined to calculate the overall risk of the entire process. The individual fault propagation scenarios are shown in the following sections. The following formula is used to calculate the risk:

Risk associated (Path - i) = (Risk associated, event-1)
× (Probability of failure on demand of safety measure-1)
× (Risk associated, event-2)
× (Probability of failure on demand of safety measure-2)
.
.
× (Risk associated, event-n)
× (Probability of failure on demand of safety measure – n)
× (Risk associated with Final event)

or

Risk associated (Path - i) = (R1) × (PFD1) × (R2) × PFD2) × ..... × (Rn) × (PFDn) × (Rf) [6.4]

- **Risk for Fault Propagation Path-1**

The first fault propagation scenario is shown in Figure 6.7. The risk associated with fault propagation path-1 is calculated as follows:

Risk associated (Path - 1) = (R1) × (PFD1) × (R2) × (PFD2) × (R4) × (PFD3) × (R5)
= 9 × 0.003 × 2.5 × 0.0025 × 0.85 × 0.0035 × 0.055
Or Risk associated (Path - 1) = $\mathbf{2.76 \times 10^{-8}}$

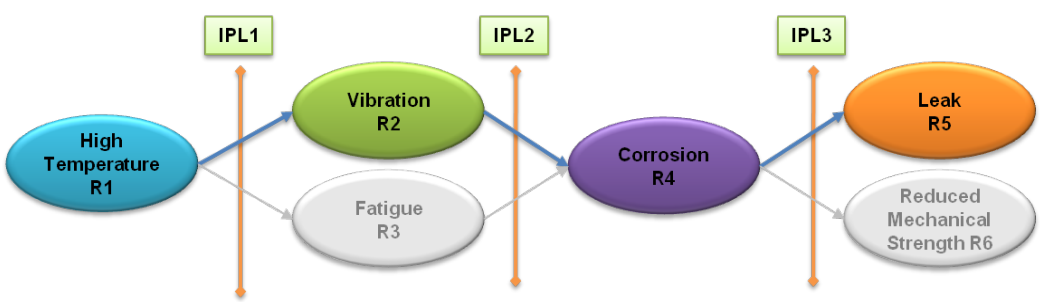


Figure 6.7: Risk associated with Path-1

- **Risk for Fault Propagation Path-2**

The second fault propagation scenario is shown in Figure 6.8. The risk associated with fault propagation path-2 is calculated as follows:

Risk associated (Path - 2) = (R1) × (PFD1) × (R2) × (PFD2) × (R4) × (PFD3) × (R6)

= 9 × 0.003 × 2.5 × 0.0025 × 0.85 × 0.0035 × 0.085

Or Risk associated (Path - 2) = $\mathbf{4.27 \times 10^{-8}}$

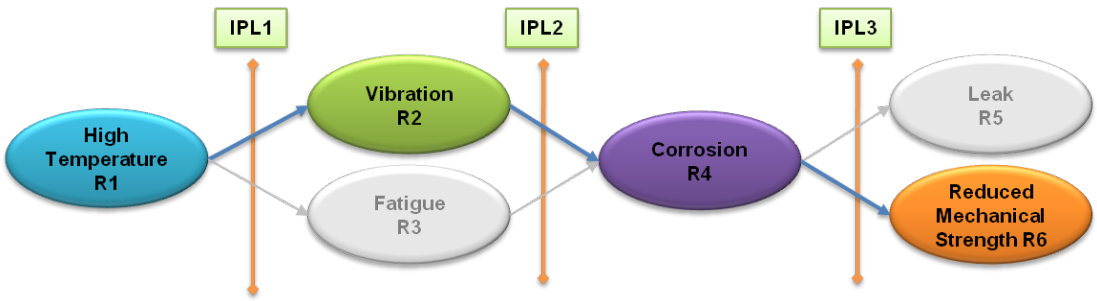


Figure 6.8: Fault Propagation Scenario, Path-2

- **Risk for Fault Propagation Path-3**

The third fault propagation scenario is shown in Figure 6.9. The risk associated with fault propagation path-3 is calculated as follows:

Risk associated (Path - 3) = (R1) × (PFD1) × (R3) × (PFD2) × (R4) × (PFD3) × (R5)

= 9 × 0.003 × 1.2 × 0.0025 × 0.85 × 0.0035 × 0.055

Or Risk associated (Path - 3) = $\mathbf{1.33 \times 10^{-8}}$

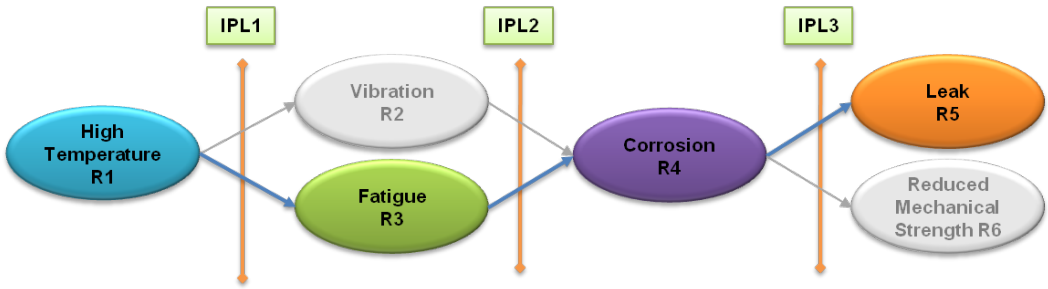


Figure 6.9: Risk associated with Path-3

- **Risk for Fault Propagation Path-4**

The fourth fault propagation scenario is shown in Figure 6.10. The risk associated with fault propagation path-4 is calculated as follows:

Risk associated (Path - 4) = (R1) × (PFD1) × (R3) × (PFD2) × (R4) × (PFD3) × (R6)

= 9 × 0.003 × 1.2 × 0.0025 × 0.85 × 0.0035 × 0.085

Or Risk associated (Path - 4) = $\mathbf{2.05 \times 10^{-8}}$

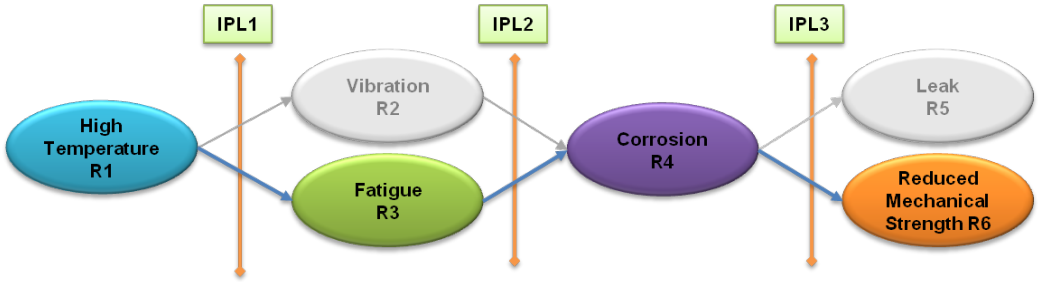


Figure 6.10: Individual Fault Propagation Scenario for Path-4

- **Total Risk Associated**

The total risk associated with the process that an onset of a fault will lead to a hazard, i.e. fire or explosion, is the sum of the total risk associated with all the pathways. The calculation is as follows:

Total Risk Associated (TRA) = (Risk associated (Path-1))
+ (Risk associated (Path-2))
+ (Risk associated (Path-3))
+ (Risk associated (Path-4))

$$= 2.76 \times 10^{-8} + 4.27 \times 10^{-8} + 1.33 \times 10^{-8} + 2.05 \times 10^{-8}$$

Or Total Risk Associated (TRA) = $\mathbf{1.04 \times 10^{-7}}$

6.3.3. Safety Verification

If the total risk associated is less than the threshold risk, i.e. the maximum level of acceptable risk, the process is considered to be safe. Otherwise, it is not safe. This value of the threshold risk is calculated from the process historical data and other equipment data. It is calculated on the basis of the following formula:

Threshold Risk (TR) = (Frequency of failure) × (Magnitude of failure)

Considering the risk as a function of failure rate, the threshold risk is calculated. The typical value of failure rate can be taken as 5.00×10^{-6} per year (Blanchard, 1999). Thus, if the TRA is more than this value, the process is unsafe.

This value is the risk level of a single event scenario. In this case, high temperature comprises all the possible fault propagation scenarios which the event could take to be converted into a hazard. The safety verification is shown in Figure 6.11 and the calculation is shown as follows:

The values:

Threshold Risk (TR) $= 5.00 \times 10^{-6}$

Total Risk Associated (TRA) $= 1.04 \times 10^{-7}$

Verification:

$$\mathbf{1.04 \times 10^{-7} < 5.00 \times 10^{-6}}$$

TRA < TR

Conclusion:

The process is safe

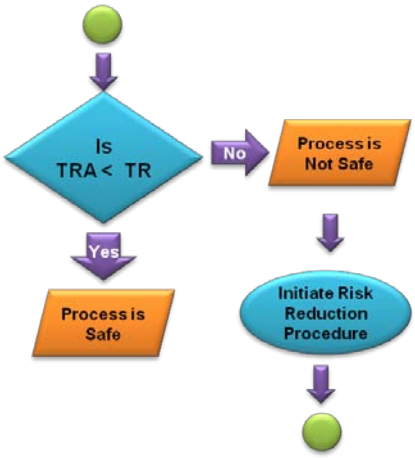


Figure 6.11: Safety Verification Results

For one or more causes in the TE process simulation, safety verification is performed automatically and the final risk is shown. Two random causes, upstream leakage and upstream pipe blockage, are applied by LabVIEW® as shown in Figure 6.12. The final risk, i.e. TRA, for the causes, calculated by the BBN, is 1.0×10^{-11}. It is significantly lower than the TR.

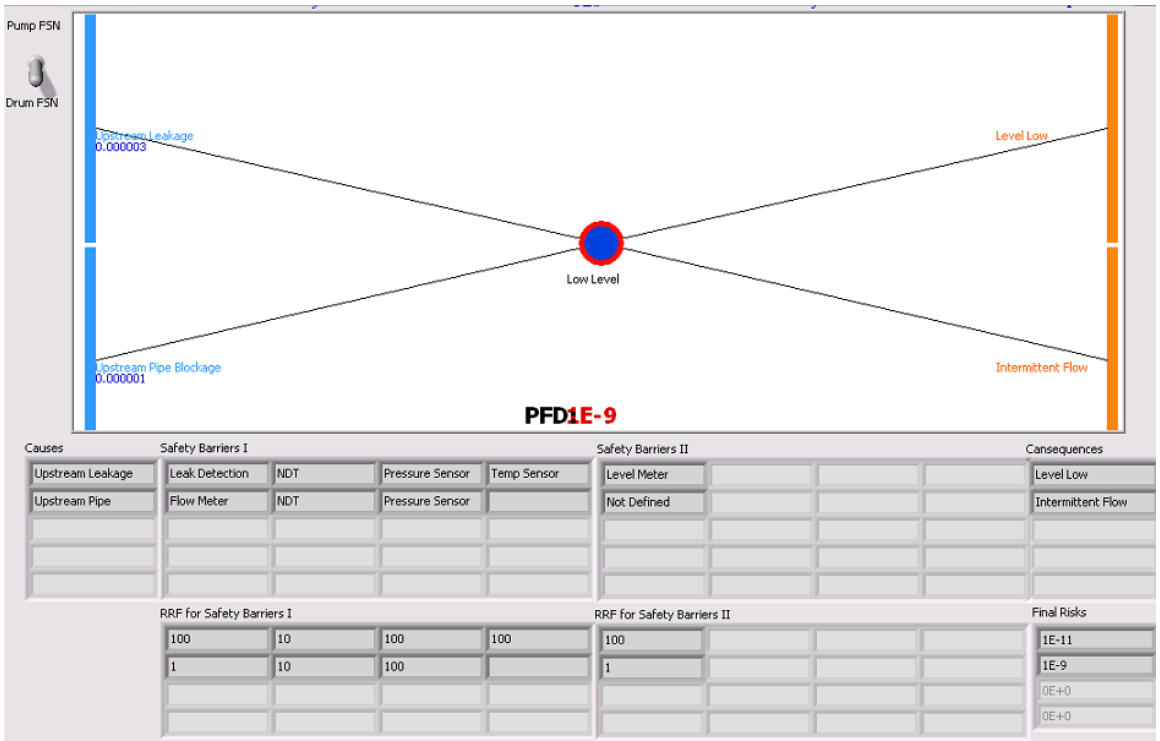


Figure 6.12: Safety verification for upstream pipe blockage

After the risk is calculated and compared with the predefined threshold risk, the links are established in the POOM database based on the accumulated information. The database is continually updated in every predefined interval with all of the updated information.

6.3.4. Risk Reduction

In the example and the simulation result above, the processes are safe. There is no immediate need of any risk reduction procedure. If the TRA were greater than the TR, immediate risk reduction would have become necessary. However, some methods which

will help in reduction of risk are listed below and the steps are shown in Figure 6.13. The following actions are taken to reduce the risk associated with any process:

- Eliminate or reduce exposure to the hazard as far as practical.
- Reduce the probability and severity.
- Use safeguards and safety devices.
- Determine that the performance and functional characteristics of the safety measures are suitable for the machine and its use.

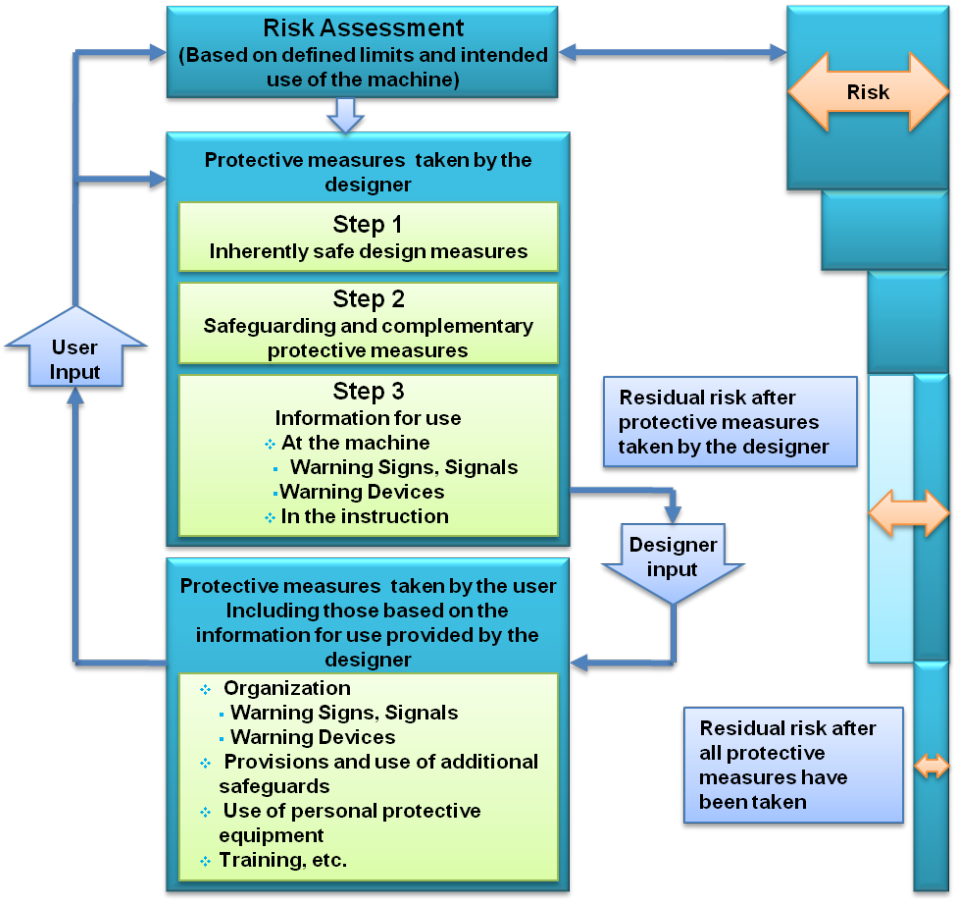


Figure 6.13: Risk Reduction Process (Redrawn based on Omron, 2010)

Chapter 7: Conclusion and Future Work

In any processing facility failure and accident as a consequence of fault or process variable deviation are a major concern. It is a challenge to keep the risks in processing plants at an acceptable level.

In the case study chapter, propagation of faults were simulated as well as tested in a real life situation. The relationship between deviations and hazards, and ultimately accidents, are mostly established based on historical data. Many of the relationships were established based on scientific facts and engineering calculations. This effort is to lay a foundation for accident prediction and prevention in processing facilities.

In this project, the design of an automated fault semantic network has been investigated. The investigation was carried out by examining various process deviations and examining the propagation of faults to accident scenarios. In the investigation, process variable interaction analysis is used to develop a simulation-based fault propagation analysis. The investigation has adopted two approaches that consist of a simulation of a chemical process, along with identifying relationships among process variables, quantitatively and qualitatively, for the purpose of finding causes and consequences, and tracing faults associated with them.

In this research, real life data was used from an experimental setup of the FDS. LabView and MATLAB® Simulink were used to simulate the selected chemical process plant for

the purpose of extracting process data. Microsoft Visio and Visual Basic are used to implement the FSN.

The FSN is introduced as a great tool with considerable abilities. In the FSN, nodes correspond to different faults/causes/consequences, and directed arcs are links between the nodes which describe the dependencies.

Initially, the FSN is constructed based on the ontology structure of fault models on the basis of POOM where failure mode is described using symptoms, enablers, process variables, causes, and consequences. Implementing the FSN for a process with many process variables is not an easy job, especially when someone is asked to do it in the real world. There are steps that should be undertaken by engineers and researchers to let them create a dynamic modelling of a process as a semantic network that contains all the possible faults and possible relationships between variables. In the FSN, the strength of the relationship between variables can be assigned both qualitatively and quantitatively through different reasoning approaches such as a probabilistic approach and mathematical formulation.

In a process, there may be many variables that affect the operation. In order to implement a complete analysis of the process, it is necessary to consider all variables. In the FSN, the number of process variables affects the accuracy of analysis. The analysis can be performed by just using a manipulated and a measured variable. However, it will be incomplete. In summary, the more process variables selected, the greater the accuracy obtained.

It is a difficult task to analyze some mechanisms, such as corrosion and aging, which are affected by many parameters. To implement corrosion and aging related hazard scenarios in the FSN, thickness and oxidation sensors have to be installed according to standards. Extracted data from the sensor has to be analyzed to uncover the inter-relation pattern among wall thickness and other flow parameters such as pressure, temperature and flow rate.

7.1. Potential Applications

During the development of the proposed method, an effort has been made to maintain the generality as much as possible. As a consequence of this effort, the proposed method is envisioned to solve a wide range of problems. Application of this study is not limited to LNG or chemical processing plants; however, the FSN would solve a variety of problems in different industrial processing plants and mechanical systems. Some of these applications are already started and implemented in the ESCL at UOIT as presented in this chapter and in Appendix D.

7.1.1. Risk Calculation

In the FSN, nodes correspond to different process variables/faults/causes/consequences and directed arcs are links between the nodes that describe the dependencies and any node associated with its risk value. Therefore, it is possible to calculate risks of any occurring failure or accident.

7.1.2. Safety Performance Indicator

Considerable work was done during the study for developing an indicator that shows safety performance index, which gives the possibility to include the Safety Performance Index (SPI) in the FSN, so it can dynamically show the effectiveness of a safety system in a plant as the SPI consists of two main phases that analyze the effectiveness of the safety system.

- Predictive actions analysis is the first phase that analyzes in installed safety system in a plant. It includes a database that consists of all possible safety barriers (best practice) for each equipment, its associated failure modes and risk reduction factor. It shows how effectively the safety system can reduce probability of occurrence of an undesired event.

- Proactive actions analysis is the second phase of the SPI that analyzes consequences of an undesired event from an occupational safety point of view.

7.1.3. Applications in Automated Hazard Identification

Analysis of industrial data sets is an important issue in the industries, especially when seen from the point of view of safety issues. Identifying hazards and predicting incidents and accidents ensures the processes operate under safe conditions and prevents any deficiencies or mal-operation. Detecting inter-relation pattern between variables quantitatively, followed by an accurate fault propagation analysis in an intelligent way, would be a major step in reaching the aim of Automated Hazard Identification. The FSN

is a great technique to model a system and processes as a semantic network. Once the inter-relation pattern is uncovered and the FSN built, the basic needs of hazard identification implementation will be met as the FSN allows finding the cause, which is a manipulated variable; the root cause, which is the disturbances and consequence, which is the measured variable and failure modes. Such information helps operators to act effectively in any faulty and/or critical situation.

7.2. Future Work

Application of the FSN in fault propagation analysis and hazard identification in a chemical process is demonstrated through FDS analysis and TE process simulation. To further demonstrate its application, the ESCL at UOIT plans to perform the FSN on LNG, hydrogen production process plant through the simulation.

Application of the FSN in fault propagation analysis is demonstrated in this study. As described in a previous chapter, FSN is the main module of automated hazard identification. Given that implementing automated hazard identification in chemical processes is the work that the ESCL considered as future work, as some parts of the work are discussed in Hossaini and Gabbar (2011). Fault identification of the sensor, used for fault identification of the mechanical components, would be investigated in future studies.

7.2.1. Application of Automated hazard Identification in Hydrogen Production Processing Plant CU-Cl Cycle

Implementing automated hazard identification in a hydrogen production process plant built at the Clean Energy Research Laboratory (CERL) at UOIT is another goal of the ESCL as discussed in the work of Hossaini and Gabbar (2011). The schematic view of the cycle is shown in Figure 7.1.

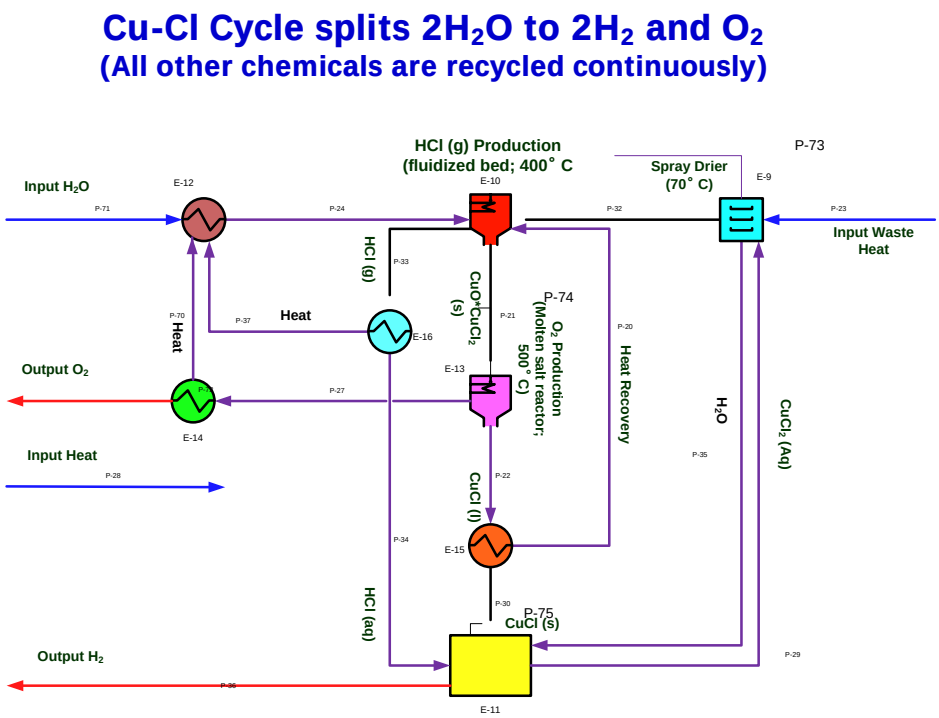


Figure 7.1: Hydrogen Production process Cu-Cl Cycle

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Appendices

A. List of Abbreviations

2PP	2 Part Predicate
ANOVA	ANalysis of VArinace
BBC	British Broadcasting Corporation
BBN	Bayesian Belief Network
CBC	Canadian Broadcasting Corporation
CBS	Columbia Broadcasting System
CCPS	Center for Chemical Process Safety
CFD	Computational Fluid Dynamics
DCS	Digital Computer System
DET	Detection
DPCA	Dynamic Principle Component Analysis
EE	Equation Error
EIV	Errors in Variables
EKF	Extended Kalman Filter
EPA	Environmental Protection Agency
ERS	Emergency Response Systems
ESS	Emergency Shutdown Systems
ETA	Event Tree Analysis
EUC	Equipment Under Control
EWMA	Exponentially Weighted Moving Average
FCM	Fuzzy C Means
FDI	Fault detection and identification
FDI	Fault Detection and Isolation
FDS	Fault diagnostic system
FES	Fuzzy Expert System

FFC	Fuzzy Faults Classifier
FIS	Fuzzy Inference System
FMEA	Failure Mode and Effect Analysis
FTA	Fault Tree Analysis
HAZOP	Hazard and Operability Analysis
HIR	Hazard Isolation Rate
HMR	Hazard Mitigation Rate
HRR	Hazard Resistance Rate
HSE	British Health and Safety Executive
IEC	International Electro-technical Commission
ISA	Instrumentation, Systems and Automation
ISS	Inherent Safety Systems
LCL	Lower Control Limit
LCV	Level Control Valve
LNG	Liquefied Natural Gas
LOPA	Layers of Protection Analysis
LPG	Liquefied Petroleum Gas
MDL	Minimum Description Length
MPa	Mega Pascal
NCBI	National Center for Biotechnology Information
NMPC	Nonlinear Model Predictive Control
NPSH	Net Positive Suction Head
OCC	Occurrence
ODBC	Open Database Connectivity
OSHA	Operational Safety and Health Administration
P&ID	Piping and Instrumentation Diagram
PBD	Process Block Diagrams
PCA	Principal Component Analysis
PFD	Probability of Failure on Demand
PFD	Process Flow Diagram
POOM	Process Object Oriented Modelling

PRAT	Proportional Risk Assessment Technique
PSM	Process Safety Management
PVC	Poly Vinyl Chloride
QRA	Quantitative Risk Assessment
RDBMS	Relational Database Management System
RPN	Risk Priority Number
RRF	Risk Reduction Factor
SEV	Severity
SIL	Safety Integrity Level
SIS	Safety Instrumented Systems
SLC	Safety Life Cycle
SOC	Safe Operating Conditions
SPC	Statistical Process Control
SPI	Safety Performance Index
SRS	Safety Related Systems
TR	Threshold Risk
TRA	Total Risk Associated
UCL	Upper Control Limit
UML	Unified Modelling Language
UOC	Unsafe Operating Conditions
USA	United States of America

B. Nomenclature

1. States and Signals

Disturbance: An unknown and uncontrolled input acting on a system.

Error: A deviation between a measured or computed value of an output variable which is true or theoretically correct.

Failure: A permanent interruption of a system's ability to perform a required function under specified operating conditions.

Fault: An unpermitted deviation of at least one characteristic property or parameter of the system from the acceptable, usual or standard condition.

Malfunction: An intermittent irregularity in the fulfillment of a system's desired function.

Residual: A fault indicator, based on a deviation between measurements and model-equation based computations.

Symptom: A change of an observable quantity from normal behavior.

2. Functions

Fault detection: Determination of faults present in a system and the time of detection.

Fault isolation: Determination of the kind, location and time of detection of a fault. Follows fault detection.

Fault identification: Determination of the size and time-variant behavior of a fault. Follows fault isolation.

Fault diagnosis: Determination of the kind, size, location and time of detection of a fault. Follows fault detection. Includes fault detection and identification.

Monitoring: A continuous real-time task of determining the conditions of a physical system, by recording information, recognizing and indicating anomalies in the behaviour.

Supervision: Monitoring a physical operation and taking appropriate actions to maintain the operation in the case of fault.

3. Models

Quantitative model: Use of static and dynamic relations among system variables and parameters in order to describe a system's behavior in quantitative mathematical terms.

Qualitative model: Use of static and dynamic relations among system variables in order to describe a system's behavior in qualitative terms such as causalities and if-then rules.

Diagnostic model: A set of static or dynamic relations which link specific input variables, the symptoms, to specific output variables, the faults.

Analytical redundancy: Use of more (not necessarily identical) ways to determine a variable, where one way uses a mathematical process model in analytical form.

4. System properties

Reliability: Ability of a system to perform a required function under stated conditions, within a given scope, during a given period of time.

Safety: Ability of a system not to cause danger to persons, equipment or the environment.

Availability: Probability that a system or equipment will operate satisfactorily and effectively at any point of time.

5. Time dependency of faults

Abrupt fault: Fault modeled as a stepwise function. Represents bias in the monitored signal.

Incipient fault: Fault modeled by using ramp signals. Represents drift of the monitored signal.

Intermittent fault: Combination of impulses with different amplitudes.

6. Fault typology

Additive fault: Influences a variable by an addition of the fault itself. They may represent, for example, offsets of sensors.

Multiplicative fault: Represented by the product of a variable with the fault itself. They can appear as parameter changes within a process.

C. Glossary

Clayton Copula: In probability theories and statistics, a copula is a kind of distribution function. Copulas are used to describe the dependence between random variables. They are named for their resemblance to grammatical copulas in linguistics. The bivariate copula model proposed by Clayton is known as Clayton Copula. It is one of the common bivariate copula models. It is also referred to as the Cook and Johnson Copula, originally studied by Kimeldorf and Sampson (Trivedi and Zimmer, 2005). It takes the form:

$$C(\mu_1, \mu_2; \theta) = (\mu_1^{-\theta} + \mu_2^{-\theta} - 1)^{-1/\theta} \qquad [D.1]$$

where

Domain of dependence parameter $\theta = \{\theta \mid 0 < \theta < \infty\} = (0, \infty)$

As θ approaches zero, the marginals become independent. As θ approaches infinity, the copula attains the Fréchet upper bound, but for no value does it attain the Fréchet lower bound. The Clayton Copula cannot account for negative dependence. It has been used to

study correlated risks because it exhibits strong left tail dependence and relatively weak right tail dependence (Trivedi and Zimmer, 2005).

Fault Semantic Network (FNS): A set of term-tokens linked by a set of predicate-tokens for the purpose of fault diagnosis.

K2 algorithm pseudo code:

```
Procedure K2
{Input: A set of n nodes, an ordering on the nodes, an upper bound u on the
        number of parents a node may have, and a database D containing m cases.}
{Output: For each node, a printout of the parents of the node.}
for i: := 1 to n do
        π_i := 0;
        P_old := g(, π_i); {This function is computed using equation (12).}
        OKToProceed := true
        while OKToProceed and |π_i| < u do
                let z be the node in Pred(x_i) − π_i that maximizes g(i, π_i U {z});
                P_new := g(i, π_i U {z});
                if P_new > P_old then
                        P_old := P_new;
                        π_i := π_i U {z}
                else OKToProceed := false;
        end {while};
writefNode:', xh 'Parents of this node:', TT,)
end {for};
end {K2};
```

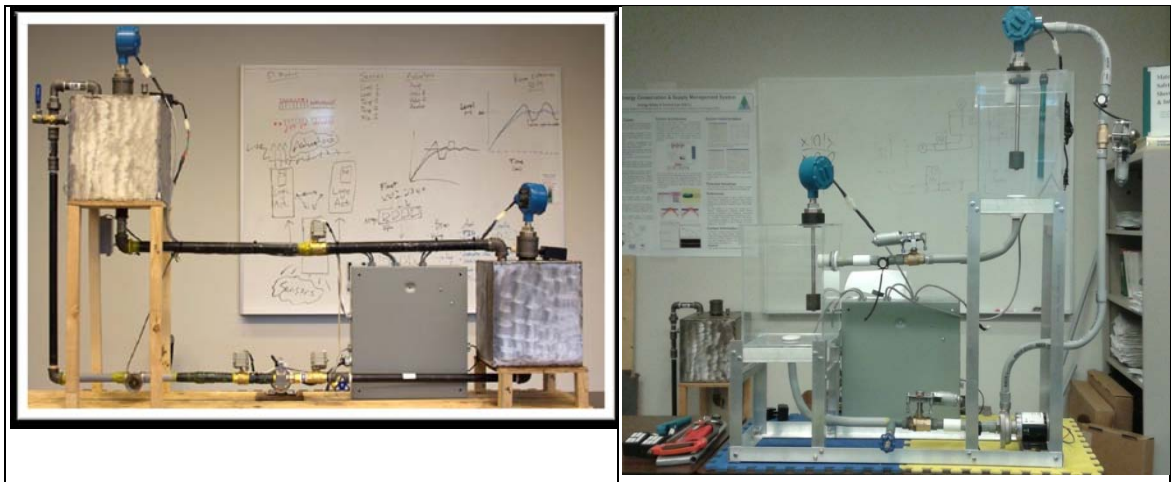
Project Object Oriented Methodology (POOM): An object oriented approach to construct a process model in its static, dynamic or functional paradigms. In a static paradigm, the faults are related with structures of machines such as pumps, valves or compressors. In a dynamic paradigm, the faults are related with the dynamic behaviour of machines such as over-loading, saturation or overheating. In a functional paradigm, the

faults are related with the operation of machines such as start-up, shutdown or wrong operation.

Semantic Network (SN): A set of term-tokens linked by a set of predicate-tokens.

D. Fault Diagnostic System

An experimental setup was assembled in the Energy, Safety and Control Laboratory (ESCL), at the University of Ontario Institute of Technology (UOIT), Oshawa, Canada, by a research team, which was assigned to set up a P&ID and obtain the real life data. In this section, analysis is performed on the acquired data. Photographs of the P&ID is shown in Figure D.1.



a) Initial setup of FDS.	b) Upgraded setup.

Figure D.1: An experimental setup of an FDS in the ESCL

The purpose of this setup is to observe relationships between the process variables and hazards. In the initial setup, carbon steel pipes and carbon steel tanks were used. In the

upgraded setup, poly-carbon tanks and poly vinyl chloride (PVC) pipes are used. Flow meters, vibration sensors, surface temperature sensors and infrared temperature sensors are used for input signals. For controlling the flow of liquid in different directions, signals are fed from the computer. Computer programs are developed to send output signals and to record the input signals. The location of the sensors and the control signal feeds are shown in Figure D.2.

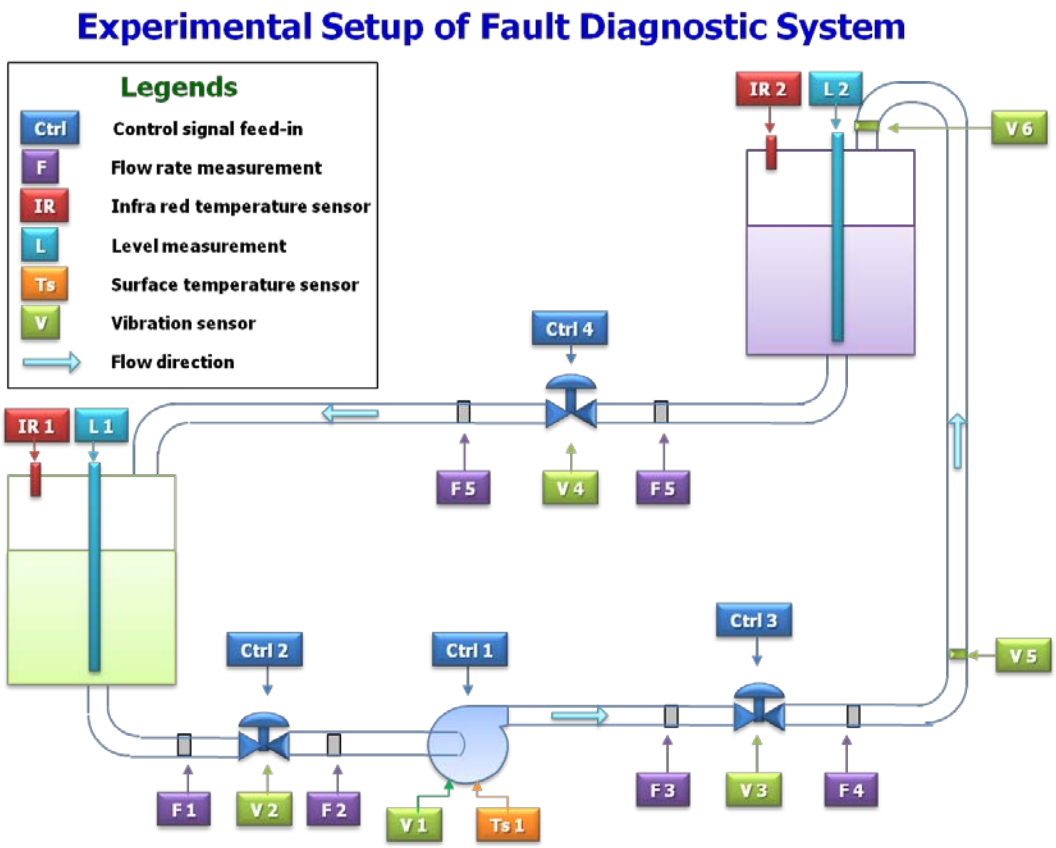
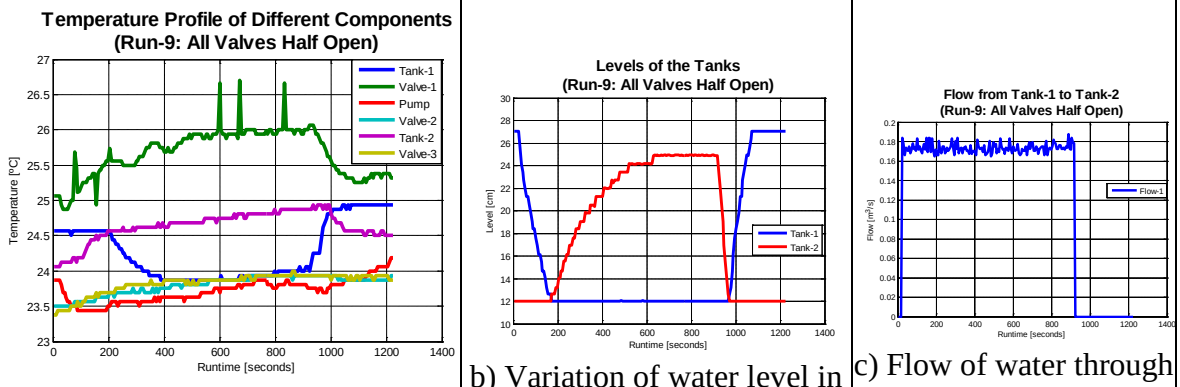


Figure D.2: Location of the sensors and other equipment of the experimental setup in the ESCL

Data was collected from the initial experimental setup. Multiple sets of data were collected by changing different process variables. Data was captured at six second

intervals. The first set of data was not used for analysis, as it was not recorded properly. Change of temperature, pressure and vibration were recorded with the change of different parameters. The data is plotted using MATLAB® and analyzed with Microsoft Excel and Orange, a statistical analyzing software.

In Figure D.3 data set 8 is plotted. In this experiment, all three valves were half opened. The flow from tank-1 to tank-2 was much higher because the pump was exerting more pressure from tank-1 to tank-2 than the gravitational pressure from tank-2 to tank-1.



a) Temperature increase of different components over time

b) Variation of water level in tank-1 and tank-2 over time

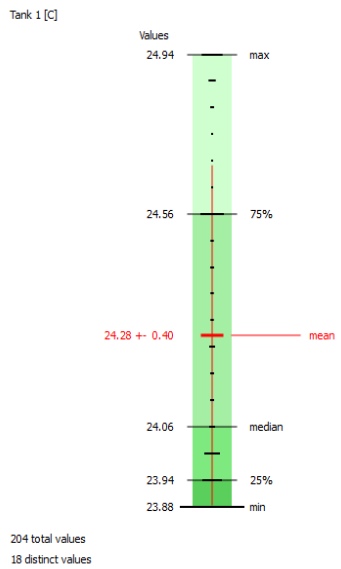
c) Flow of water through flow rate measurement F-4

Figure D.3: Temperature change of different components and variation of level & flow of water

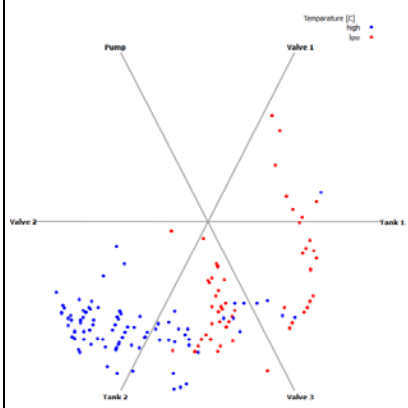
D.1. Statistical Visualization

In this section, descriptive statistics are used to visualize the data. Orange was used to plot the data. In Figure D.4, the mean and median temperature, the co-relation between

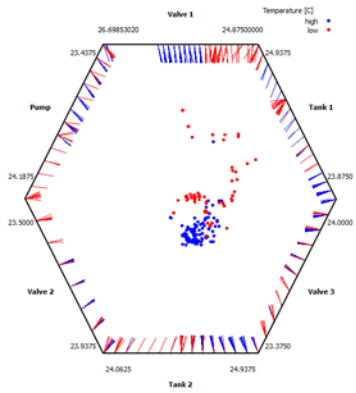
the temperature profiles, and the level of temperatures of the different components are visualized.



a) Maximum, minimum, mean and median of temperature.



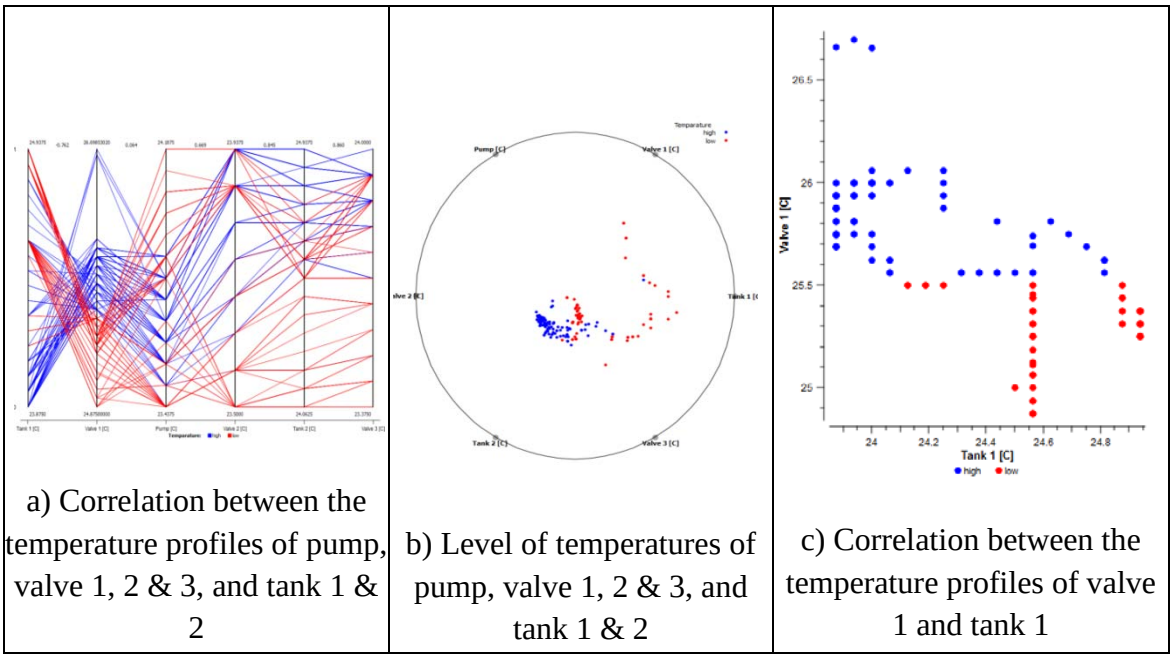
b) Co-relation between the temperature profiles of pump, valve 1, 2 & 3, and tank 1 & 2.



c) Level of temperatures of pump, valve 1, 2 & 3, and tank 1 & 2.

Figure D.4: Temperature profile of different components during the experiment

In Figure D.5, the co-relation between the temperature profiles and level of temperatures of the different components are visualized. In Figure D.5.a) the relationship of temperature of one component with another is shown by the connecting lines. In Figure D.5.b), the clusters of temperatures are shown. In Figure D.5.c), components with a higher temperature and those with a lower temperature are grouped together, along with their trends.



a) Correlation between the temperature profiles of pump, valve 1, 2 & 3, and tank 1 & 2	b) Level of temperatures of pump, valve 1, 2 & 3, and tank 1 & 2	c) Correlation between the temperature profiles of valve 1 and tank 1

Figure D.5: Relationships between the temperatures of different components

D.2. Regression Analysis of the Data from FDS

In this analysis, prediction of one event, based on one or more events, has been shown. Linear regression in Microsoft Excel has been used to analyze the data. Prediction of temperature changes in tank-1 was taken as a test case. From the acquired data, the temperature of tank-1 has been predicted using the pump temperature and tank-2 temperature. Temperature prediction can also be attained based on all of the variables. The summary of the regression is shown in Tables D.1, D.2, and D.3.

Table D.1: Regression Summary

Regression Statistics	
Multiple R	0.6512
R Square	0.4240
Adjusted R Square	0.4183
Standard Error	0.3070
Observations	204

Table D.2: Analysis of Variance

	df	SS	MS	F	Significance F
Regression	2	13.946	6.973	73.988	8.32E-25
Residual	201	18.944	0.094		
Total	203	32.890			

In the Analysis of Variance (ANOVA), Table D.2, the attribute "Significance" is the goodness of fit. For this regression the value of Significance is 8.32×10^{-25}, i.e. close to zero, that means the regression is almost a perfect fit (Gupta, 2000). The Adjusted R Square in Table D.1 is also a measurement of the goodness of fit, which is 41.83%. The higher it is, the better it is. The Sum of Squares (SS) are the deviation of the data. Total SS (TSS) is the total of all sums of squares. Smaller the TSS, the better the result (Gupta, 2000).

In Figure D.6, the probability of a certain level of temperature in tank-1 is shown. For example, the probability of the temperature is 24.75 °C in tank-1 is more than 84%.

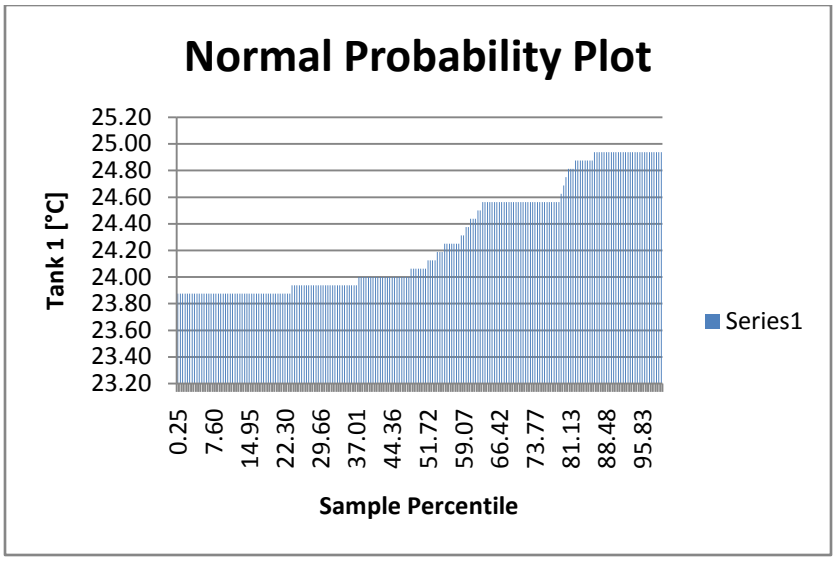


Figure D.6: Normal probability plot

The coefficients column in Table D.3 is needed to determine the trend line for all the independent variables. The dependent variable is the temperature of tank-1 (Tt1). The intercept is 28.049.

Table D.3: The intercept and coefficients of linear regression

	Coefficients	**Standard Error**	**t Stat**	**P-value**	**Lower 95.0%**	**Upper 95.0%**
Intercept	28.049	3.552	7.896	0.000	21.045	35.054
Pump [°C]	1.059	0.133	7.948	0.000	0.796	1.322
Tank 2 [°C]	-1.173	0.107	-10.955	0.000	-1.384	-0.962

The line for tank-1 temperature vs. pump-1 temperature and tank-2 temperature is:

$$Tt1 = \beta_0 + \beta_1 Pt + \beta_2 Tt2$$

where β_0 = intercept
β_1 = first coefficient
β_2 = second coefficient

The equation of the line is: $Tt1 = 28.049 + 1.059 \cdot Pt - 1.173 \cdot Tt2$ [D.2]

Test case:

when

Pump temperature $Pt = 23.625$ °C

Tank-2 temperature $Tt2 = 24.125$ °C

The predicted temperature of tank-1:

$Tt1 = 28.049 + 1.059 \cdot (23.625) - 1.173 \cdot (24.125)$ [°C]

$= 24.769$ °C

The actual temperature is 24.563

The difference is 0.206 °C; i.e. 0.81% is acceptable in regard to this FDS system.

In Figure D.7, the predicted temperature of tank-1, based on the temperature of tank-2, is shown in maroon colour. The actual temperature of tank-1 is shown in blue colour. For example if the temperature of tank-2 is 24.5 °C then the actual temperature of tank-1 is about 24.90 °C and the predicted temperature is about 24.60 °C.

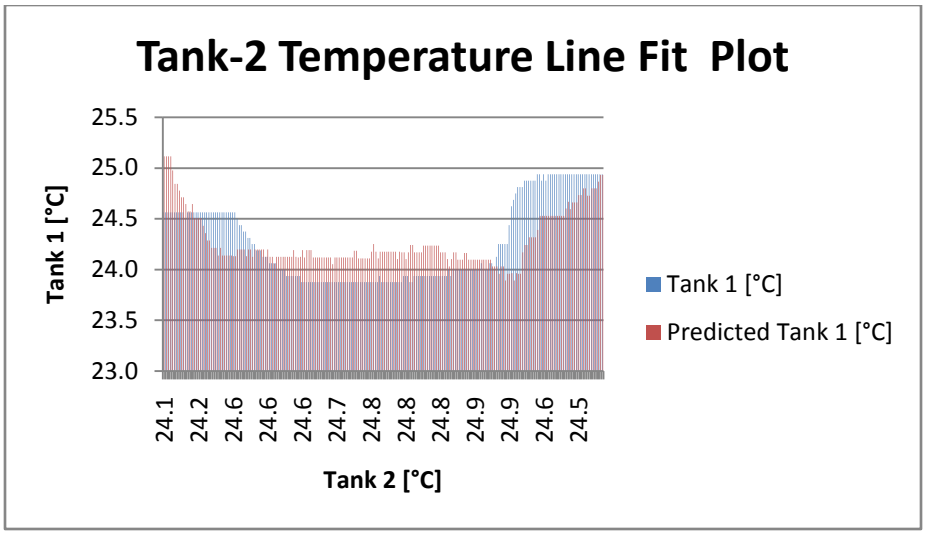
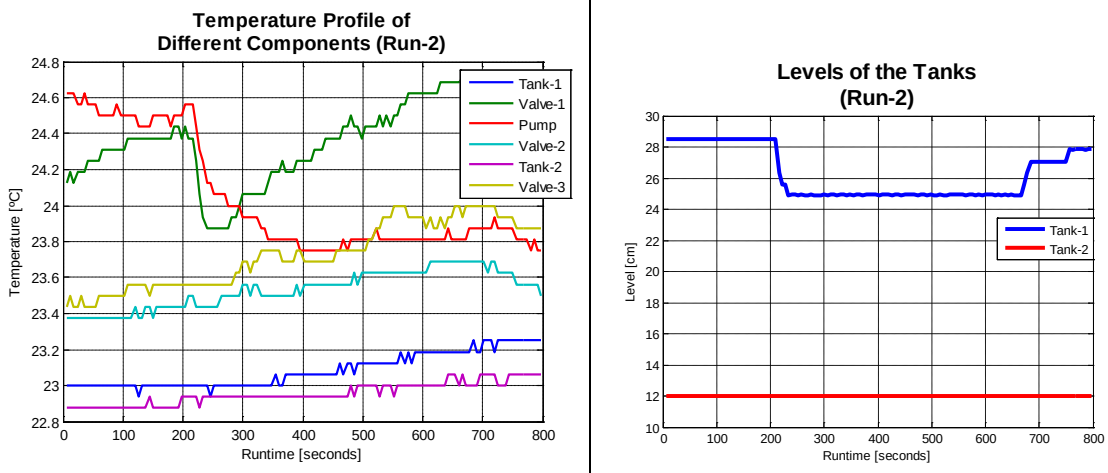


Figure D.7: Temperature of tank-1, predicted based on temperature of tank-2

E. Additional Plots of the FDS Data

Multiple sets of data were recorded, changing different parameters. Data was captured at six second intervals. The change of temperature, pressure and vibration were recorded, with the change of different parameters. A total eight sets of data were recorded from nine experimental runs. Data from the first run was discarded. In Figure E.1, data set-1 is plotted. In the plots it can be observed that the level of tank-2 has not changed, but the level of tank-1 first decreased and then increased. This is because valve-1 (Ctrl-2) was closed. As a consequence, the temperature of valve-1 increased.

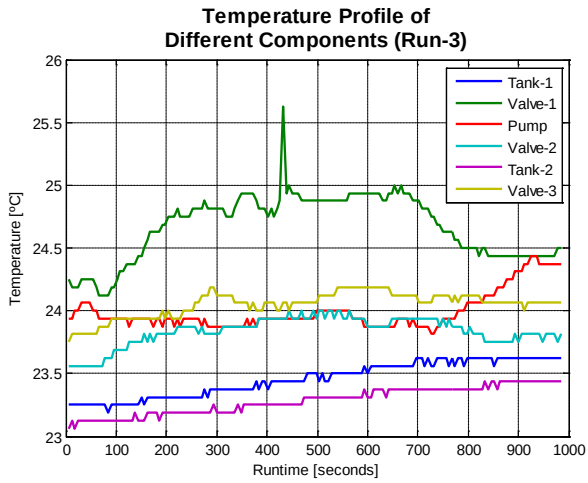


a) Temperature increase of different components over time when valve-1 is closed

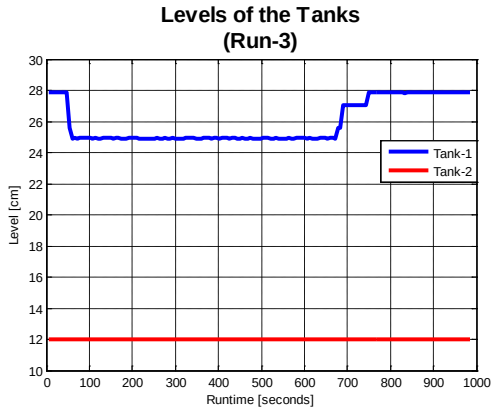
b) Variation of water level in tank-1 and tank-2 to over time

Figure E.1: Temperature profile of different components and water levels in the tanks, data set-1

In Figure E.2, data set-2 is plotted. In this run, valve-2 (Ctrl-3) was closed. The level of tank-2 did not change. The level of tank-1 decreased, stayed low for some time, then rose again. The temperature of valve-1 spiked at about 430 seconds into the experiment, then decreased again.



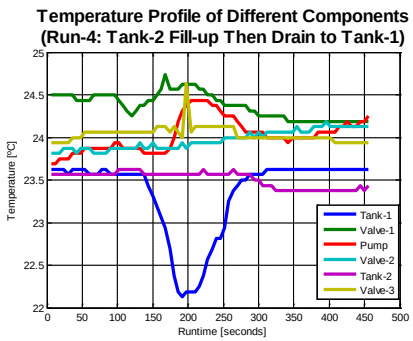
a) Temperature increase of different components over time



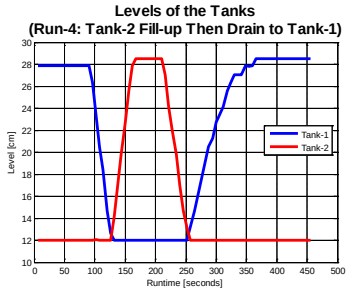
b) Variation of water level in tank-1 and tank-2 to over time

Figure E.2: Variation of water level in the tanks and temperature profile of components, data set-2

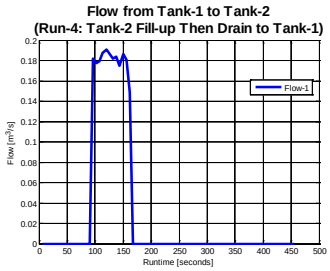
In Figure E.3, data set-3 is plotted. In this experiment, valve-3 (Ctrl-4) was closed when the pump (Ctrl-1) was running. When the pump stopped, the valve was opened, and as a result tank-2 was filled first, emptying tank-1 and then drained to tank-1 emptying tank-2. The temperature of tank-1 decreased.



a) Temperature increase of different components over time



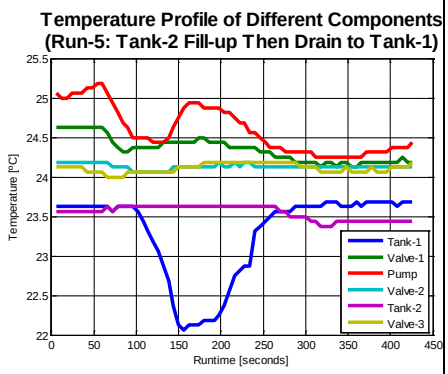
b) Variation of water level in tank-1 and tank-2 over time



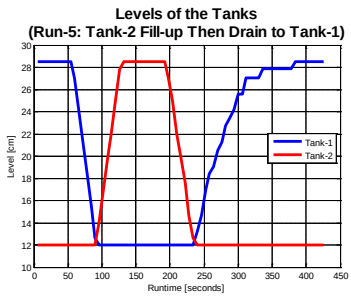
c) Flow of water through flow rate measurement F-4

Figure E.3: Temperature change of different components and variation of level & flow of water, data set-3

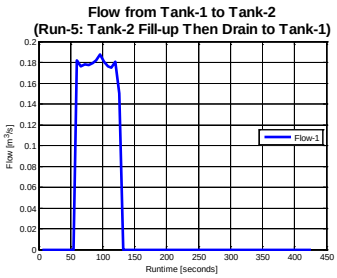
In Figure E.4, data set-4 is plotted. This experiment is a repeat of the previous experiment. In this experiment, valve-3 (Ctrl-4) was closed when the pump (Ctrl-1) was running. When the pump stopped, the valve was opened, and as a result tank-2 was filled first, emptying tank-1 and then drained to tank-1, emptying tank-2. The temperature of tank-1 decreased. The temperature of other components showed slightly different trends.



a) Temperature increase of different components over time



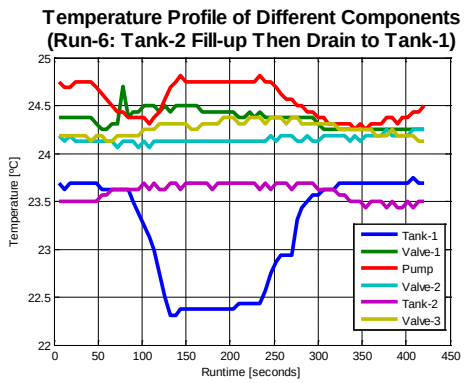
b) Variation of water level in tank-1 and tank-2 over time



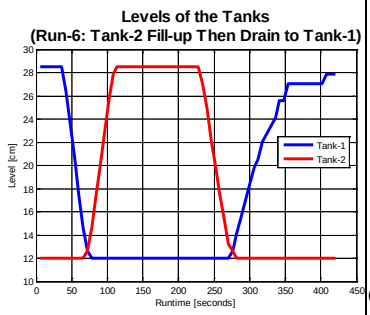
c) Flow of water through flow rate measurement F-4

Figure E.4: Temperature change of different components and variation of level & flow of water, data set-4

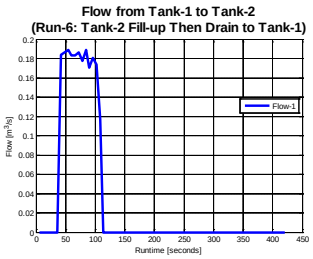
In Figure E.5, the data set-5 is plotted. This experiment is a repeat of the previous experiment. In this experiment, valve-3 (Ctrl-4) was closed when the pump (Ctrl-1) was running. When the pump stopped, the valve was opened, and as a result tank-2 was filled first, emptying tank-1 and then drained to tank-1, emptying tank-2. The temperature of tank-1 decreased. The temperature of the other components showed slightly different trends.



a) Temperature increase of different components over time



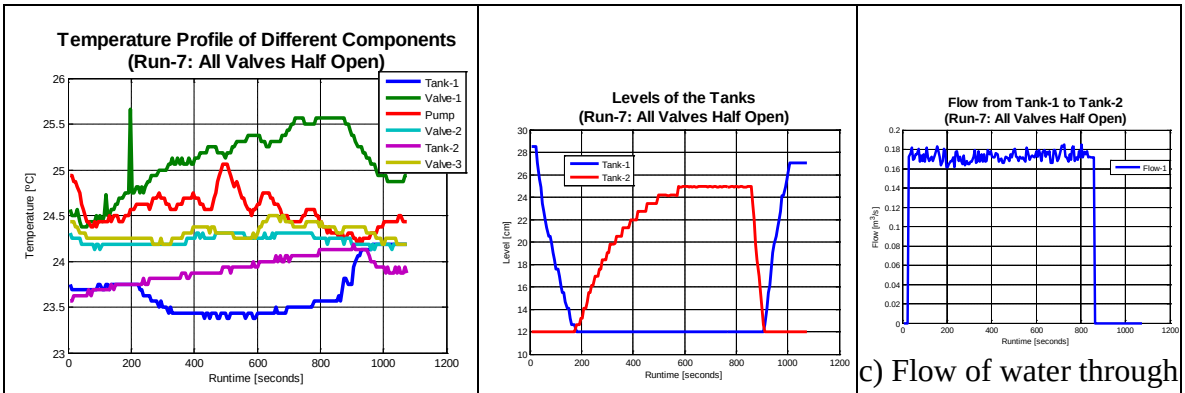
b) Variation of water level in tank-1 and tank-2 over time



c) Flow of water through flow rate measurement F-4

Figure E.5: Temperature change of different components and variation of level & flow of water, data set-5

In Figure E.6, data set-6 is plotted. In this experiment, all three valves were half-opened. The flow from tank-1 to tank-2 was much higher because the pump was exerting much more pressure from tank-1 to tank-2 than the gravitational pressure from tank-2 to tank-1.



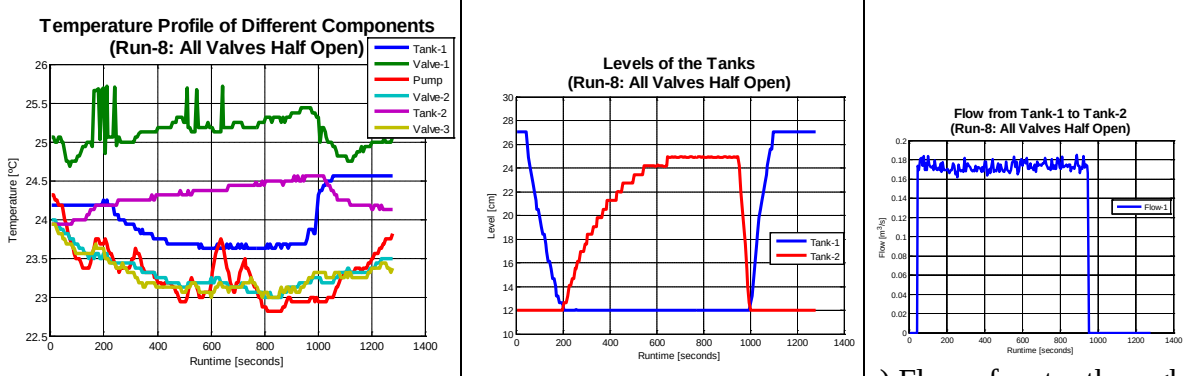
a) Temperature increase of different components over time

b) Variation of water level in tank-1 and tank-2 over time

c) Flow of water through flow rate measurement F-4

Figure E.6: Temperature change of different components and variation of level & flow of water, data set-6

In Figure E.7, data set-7 is plotted. This is a repeat of the previous experiment. In this experiment, all three valves were half-opened. The flow from tank-1 to tank-2 was much higher because the pump was exerting more pressure from tank-1 to tank-2 than the gravitational pressure from tank-2 to tank-1.



a) Temperature increase of different components over time

b) Variation of water level in tank-1 and tank-2 over time

c) Flow of water through flow rate measurement F-4

Figure E.7: Temperature variation of different components and change of level & flow of water, data set-7

F. Sample MATLAB® Program

```
%-----------------------------------------------------
% FDS data ploting
% March 13, 2013
% Created by Manir U. Isham
% -------- Declaration of the basic environment-----------
clf
format              % Sets format of numerical output to default mode
clear               % Clears the variables from memory
clc                 % Clears the screen
format compact      % Sets the format of numerical output to compact
mode

% Declaration of the variables ----------------------------------------
-----

load FDS_Bst_Sht_9.txt;
c1 = FDS_Bst_Sht_9(:,1);
c2 = FDS_Bst_Sht_9(:,2);
c3 = FDS_Bst_Sht_9(:,3);
c4 = FDS_Bst_Sht_9(:,4);
c5 = FDS_Bst_Sht_9(:,5);
c6 = FDS_Bst_Sht_9(:,6);
c7 = FDS_Bst_Sht_9(:,7);
c8 = FDS_Bst_Sht_9(:,8);
c9 = FDS_Bst_Sht_9(:,9);
c10 = FDS_Bst_Sht_9(:,10);
c11 = FDS_Bst_Sht_9(:,11);

figure(1)
plot(c1, c2, c1, c4, c1, c5, c1, c6, c1, c8, c1, c11, 'linewidth', 3)
title({'Temperature Profile of Different Components',...
    '(Run-9: All Valves Half Open)'},...
    'Fontsize', 16, 'FontWeight', 'bold'); grid
xlabel('Runtime [seconds]')
ylabel('Temperature [ºC]')

legend('Tank-1', 'Valve-1', 'Pump', 'Valve-2', 'Tank-2', 'Valve-3')

figure(2)
plot(c1, c3,'b-', c1, c9, 'r-', 'linewidth', 3)
ylim([10 30])

title({'Levels of the Tanks',...
    '(Run-9: All Valves Half Open)'},...
    'Fontsize', 16, 'FontWeight', 'bold'); grid
xlabel('Runtime [seconds]')
ylabel('Level [cm]')

legend('Tank-1', 'Tank-2')

figure(3)
plot(c1, c7,'b-', 'linewidth', 3)
```

```
title({'Flow from Tank-1 to Tank-2',...
    '(Run-9: All Valves Half Open)'},...
    'Fontsize', 16, 'FontWeight', 'bold'); grid
xlabel('Runtime [seconds]')
ylabel('Flow [m^3/s]')

legend('Flow-1')
```

G. Sample FSN Macro

```
Private Sub UserForm_Initialize()

   Dim connstr As Variant
   Dim counter As Integer

   connstr = connection()
   Set connecDB = New ADOdb.connection
   connecDB.Open connstr

counter = 0

   """""""""Inserts the eq-cl-id and cq-cl-name into the list box

   Set tbleq = New ADOdb.Recordset
   tbleq.Open "[cl-eq]", connstr, adOpenDynamic, adLockOptimistic, adCmdTable
   List_eq_class.Clear
   If tbleq.BOF And tbleq.EOF Then Exit Sub
      With tbleq
         'FirstRec = .Bookmark
      Do Until .EOF
         List_eq_class.AddItem
         List_eq_class.Column(0, counter) = ![eq-cl-id]
         List_eq_class.Column(1, counter) = ![eq-cl-name]
         counter = counter + 1
         .MoveNext
      Loop
      End With

   Set tbleq = Nothing

   Dim strSQl As String
   Dim temptbl As ADOdb.Recordset
   Set temptbl = New ADOdb.Recordset
```

```
''''''''''''Inserts func-id-mn into the parent combo box

strSQl = "Select DISTINCT [func-id-mn] FROM [cl-func]"
    temptbl.Open strSQl, connstr, , , adCmdText
    cmb_parent.Clear
    Do Until temptbl.EOF
        cmb_parent.AddItem temptbl("func-id-mn")
        temptbl.MoveNext
    Loop
    Set temptbl = Nothing

    '''''''''''' Inserts func-id into the func combo box

    Set tblfunc = New ADOdb.Recordset
    tblfunc.Open "[cl-func]", connstr, adOpenDynamic, adLockOptimistic, adCmdTable
    tblfunc.MoveFirst
    Do Until tblfunc.EOF
        cmb_funid.AddItem tblfunc![func-id]
        tblfunc.MoveNext
    Loop
    Set tblfunc = Nothing

    '''''''''''' Inserts all the pv-id values into the pv value combo box
    Set tblpv = New ADOdb.Recordset
    tblpv.Open "[cl-pv]", connstr, adOpenDynamic, adLockOptimistic, adCmdTable

    tblpv.MoveFirst

    Do Until tblpv.EOF
        cmb_pvid.AddItem tblpv![pv-id]
        tblpv.MoveNext
    Loop
    Set tblpv = Nothing

    '''''''''' Inserts all the values into the pv loc combo box

    Set temptbl = New ADOdb.Recordset
    strSQl = "Select [fm-loc] FROM [cl-fm-loc]"
    temptbl.Open strSQl, connstr, , , adCmdText
    cmb_pvloc.Clear
    Do Until temptbl.EOF
        cmb_pvloc.AddItem temptbl("fm-loc")
        temptbl.MoveNext
    Loop
    Set temptbl = Nothing
```

```
        '''''''''''''inserts the eq-cl-mn values into the combo box from cl-eq

        Set temptbl = New ADOdb.Recordset
        strSQl = "Select DISTINCT [eq-cl-mn] FROM [cl-eq]"
        temptbl.Open strSQl, connstr, , , adCmdText
        cmb_eqclmn.Clear
        Do Until temptbl.EOF
            cmb_eqclmn.AddItem temptbl("eq-cl-mn")
            temptbl.MoveNext
        Loop
        Set temptbl = Nothing

End Sub
```

H. Sample ESN Macro

```
Private Sub UserForm_Initialize()

    Dim StrSql As String
    Call Prjct_Lst
    Call Flr_Lst
    Call Flr_Dflt_Val_Lst
    Ltng_Page_Initialize
    Call Ltng_Nw_Blb_Typ_Lst
    Call PV_Clss_Lst

    ' --------------- String for Opening any Table ----------------------
    Dim connstr As Variant
    connstr = DB_Path.DB_Path()
    Set connecDB = New ADODB.connection
    connecDB.Open connstr
    ' ---------------------------------------------------------------

    MultiPage1.Value = 0
    MultiPage2.Value = 0
    'TabControl.SelectedIndex = 2
    Set tmptbl = New ADODB.Recordset
    StrSql = "SELECT [Lx] FROM [ESN_Tbl_Room] where [Prjct_ID]= 1"
    tmptbl.Open StrSql, connstr, , , adCmdText
    If Not tmptbl.BOF And Not tmptbl.EOF Then
        If Not IsNull(tmptbl("Lx")) Then
            Ltng_Lx = tmptbl("Lx")
```

```
        Else
            Ltng_Lx = 250
        End If
    Else
        Ltng_Lx = 250
    End If
    tmptbl.Close
    Set tmptbl = Nothing
    connecDB.Close
    Set connstr = Nothing

End Sub

Private Sub Prjct_Lst()

                    ' Inserts all the Project name values into the Prjct_Nm and Sl value
combo box

    Dim counter As Single

    ' --------------- String for Opening any Table ----------------------
    Dim connstr As Variant
    connstr = DB_Path.DB_Path()
    Set connecDB = New ADODB.connection
    connecDB.Open connstr
    ' ------------------------------------------------------------

    counter = 0

    Set Tbl_Pid = New ADODB.Recordset
    Tbl_Pid.Open "[ESN_Tbl_Prjct]", connstr, adOpenDynamic, adLockOptimistic,
adCmdTable

    If Not Tbl_Pid.BOF And Not Tbl_Pid.EOF Then
        Do Until Tbl_Pid.EOF
            Frm_Prjct_Nm.AddItem Tbl_Pid![Prjct_Nm]

            If counter = 1 Then
                'Frm_Prjct_Id.Caption = Tbl_Pid("Prjct_Id")
            End If

            counter = counter + 1
            Tbl_Pid.MoveNext
        Loop

        Frm_Prjct_Nm.ListIndex = 1
```

```
    End If

    'counter = 0
    Tbl_Pid.Close
    Set Tbl_Pid = Nothing
    connecDB.Close
    Set connstr = Nothing

End Sub


' ================ Floor Page =========================

Private Sub Flr_Lst()

    ' --------------- String for Opening any Table ----------------------

    Dim connstr As Variant
    connstr = DB_Path.DB_Path()
    Set connecDB = New ADODB.connection
    connecDB.Open connstr
    ' ---------------------------------------------------------------
    Flr_Flr.Clear
    Rm_Flr.Clear
    Ltng_Flr.Clear
    Htng_Flr.Clear
    Colng_Flr.Clear
    Eqpmnt_Flr.Clear
    Enrgy_Flr_Flr.Clear
    Enrgy_Rm_Flr.Clear

    Set temptbl = New ADODB.Recordset
    StrSql = "Select DISTINCT [eq-lev] FROM [fclty-eq]"
    temptbl.Open StrSql, connstr, , , adCmdText
    If Not temptbl.BOF And Not temptbl.EOF Then
        Do Until temptbl.EOF
            Flr_Flr.AddItem temptbl("eq-lev")
            Rm_Flr.AddItem temptbl("eq-lev")
            Ltng_Flr.AddItem temptbl("eq-lev")
            Htng_Flr.AddItem temptbl("eq-lev")
            Colng_Flr.AddItem temptbl("eq-lev")
            Eqpmnt_Flr.AddItem temptbl("eq-lev")
            Enrgy_Flr_Flr.AddItem temptbl("eq-lev")
            Enrgy_Rm_Flr.AddItem temptbl("eq-lev")
            temptbl.MoveNext
```

```
        Loop
    End If
    Flr_Flr.ListIndex = 0
    Rm_Flr.ListIndex = 0
    Ltng_Flr.ListIndex = 0
    Htng_Flr.ListIndex = 0
    Colng_Flr.ListIndex = 0
    Eqpmnt_Flr.ListIndex = 0
    Enrgy_Flr_Flr.ListIndex = 0
    Enrgy_Rm_Flr.ListIndex = 0

    temptbl.Close
    Set temptbl = Nothing
    connecDB.Close
    Set connstr = Nothing

End Sub
```