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Reliability Modelling and Safety Learning Algorithms in Complex Risk Multifunctional Systems

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RELIABILITYMODELLINGANDSAFETYLEARNINGALGORITHMSINCOMPLEXRISKMULTIFUNCTIONALSYSTEMS

Strictly as per the compliance and regulations of:

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I. Introduction

Reliability studies and assessments of process plants and production platforms are carried out during preliminary concept design and engineering phases' development to provide engineers and operator's qualitative and quantitative data to plan risk and safety targets during the life of the process or production plant [1, 2]. Qualitative studies such as Hazard and Operability (HAZOP) studies and scenario analysis are most popular in safety design [3, 4]. HAZOP studies offers simple qualitative procedure to exclusively determine initial hazards that may occur in a process production facility and selected utility systems. The practise is to use quantitative studies to determine minimum thresholds for safety and qualitative risk assessments (QRA) to plan future risk scenarios [5, 6]. Complexity in risk events occurring during operations and interrelations of multifunctional systems limits their qualification of hazards and safety categories that may exists. In the example studied, cases of accidents reported on an FPSO could be attributed to the complex interacting units and systems in petroleum production systems

The modelling methods in leaks and reliability analysis have been presented elsewhere [Abhulimen, 2007]. The risk associated with personnel on FPSO is represented in Table 1. Several techniques have been presented in literature for reliability and risk analysis (1). Among the most frequently used are quantitative risk analysis, the probabilistic safety analysis, worst-case methodology and optimal risk analysis (2). Significant advancement has been made in developing newer method for hazard and risk assessment, consequence modelling and user friendly tools. However, while foreseeing worst-case scenarios is common, little attention is paid in envisioning credible scenarios. In engineering safety analysis, intrinsically vague information may coexist with conditions of "lack of specificity" originating from evidence not strong enough to completely support a hypothesis but only with degrees of belief or credibility (Binaghi and Madella, 1999) [(3)]. Dempster-Shafer (D-S) theory of evidence (Dempster, 1968; Shafer, 1976) [(4)] based on the concept of belief function is well suited to modeling subjective credibility induced by partial evidence (Smets, 1988) [(5)]. Reliability Centred Maintenance (RCM and RCM-II) and similar techniques have been introduced recently to improve the reliability of process plants. However data analysis of typical risk and hazard components multifunctional FPSO system are complex accident paths and non-existent. Some equipment can be critical to safe operation. In engineering safety analysis, intrinsically vague information may coexist with conditions of "lack of specificity" originating from evidence not strong enough to completely support a hypothesis but only with degrees of belief or credibility (Binaghi and Madella, 1999). Dempster-Shafer (D-S) theory of evidence (Dempster, 1968; Shafer, 1976) based on the concept of belief function is well suited to modeling subjective credibility induced by partial evidence (Smets, 1988). The D-S theory enlarges the scope of traditional probability theory, describes and handles uncertainties using the concept of the degrees of belief, which can model incompleteness and ignorance explicitly. It also provides appropriate methods for computing belief functions for combination

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Global Journal of Science Frontier Research (A) Volume XX Issue III Version I Year 2020

of evidence (Pearl, 1988). Besides, the D-S theory also shows great potentials in multiple attribute decision analysis (MADA) under uncertainty, where an evidential reasoning (ER) approach for MADA under uncertainty was developed on the basis of a distributed assessment framework and the evidence combination rule of the D-S theory (Yang and Singh 1994; Yang and Sen 1994, 1997; Yang,2001; Yang and Xu, 2002a, b).The weight concept introduced here allows the possibility of representing a measure of safety Risk ratings asocial with complex interacting risk systems that has safety barriers and controls to prevent loss of containment: The weighting function for each risk classification allows us to do the following1) Determine which equipment and instruments are truly critical to reliability, as well as process

II. Learning Algorithms in Risk and Safety Modelling

Learning algorithms are useful tools to quantify future risk uncertainty from past risk events and incorporate neural network modelling of Fuzzy Belief linguistic classifications: Figure 6 is a schematic of neural network architecture:

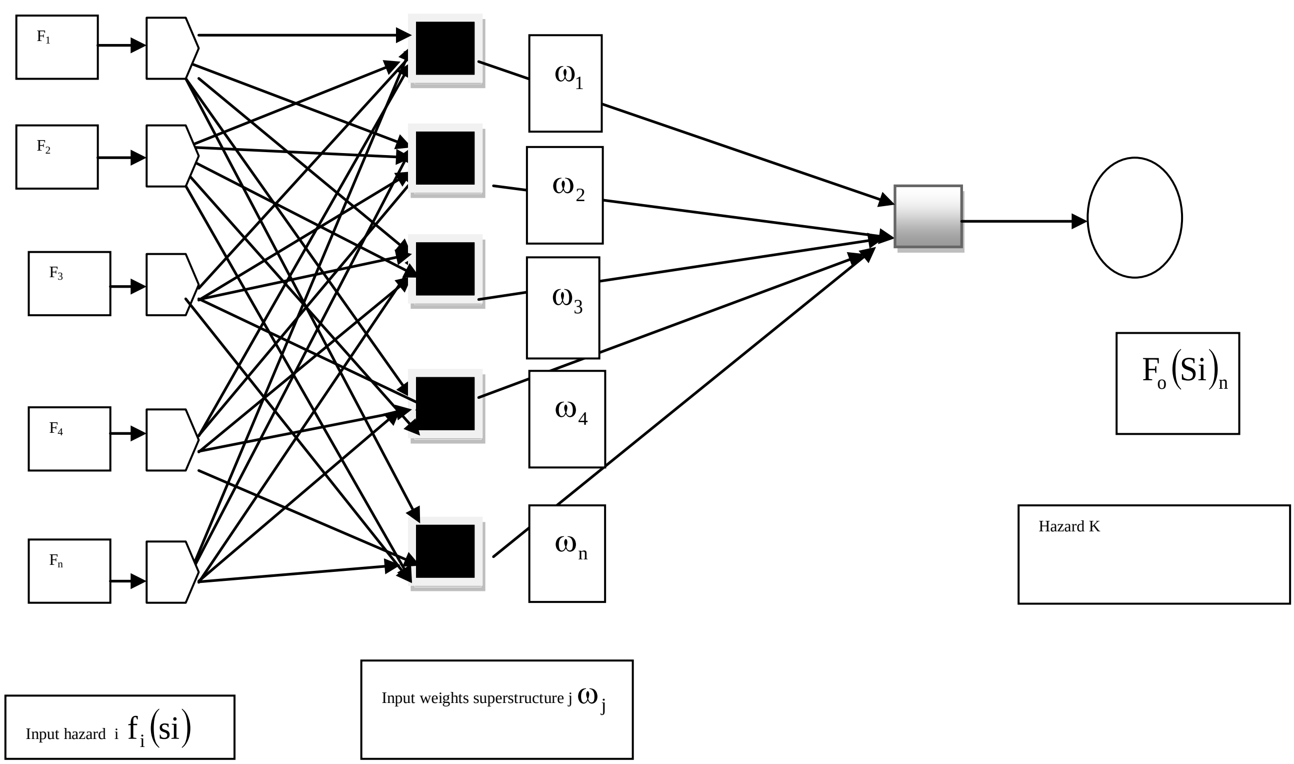


Figure 1: Neural Network Architecture

Learning algorithms incorporates neural network design in MATLAB to produce outputs comparable to the desired output and hazard measured and registered numerically. The outputs are then compared to the desired output in a process known as Feed-Forward routine. This feedback-propagating cycle is iteratively executed until the weighting Index factors converge on values or Function that minimize the Average Root Mean Square (ARMS) error within the initial training to establish hazard model trainer balck box. Once the initial training is set to the weighting factors establishing equilibrium baseline are held constant. Typical networks simulates 5000 neural network candidates to determine the optimal neural network. The actual training process involved 50 epochs cycles of back propagation training algorithm to locate the probable solution of the local minimum error. The minimized ARMS error for the training set is expressed in a nested scheme for the hazard function in eqn. 1 below;

$$\mathbf{F}(\mathbf{y}_{\mathbf{i}} = \lambda_{\mathbf{i}}) = \mathbf{f}_1(\mathbf{x}_{1\mathbf{i}}, \mathbf{x}_{2\mathbf{i}} \ldots\ldots\ldots\ldots \mathbf{x}_{\mathbf{ni}}) \qquad (1)$$

y_i represents the overall Hazard containment failure resulting from a combination of several hazard components inputs x_i of the FPSO systems. The mathematical model describing a neural network structure reflecting hazard analysis in FPSO Systems resulting in loss of containment is:

$$(\mathbf{y} = \lambda_{\mathbf{i}}) = \mathbf{a}_1\left(\mathbf{x}_{1\mathbf{i}}^{\varpi_{1i}} \bullet \mathbf{x}_{2\mathbf{i}}^{\varpi_{2i}} \bullet \ldots\ldots\ldots\ldots \bullet \mathbf{x}_{\mathbf{ni}}^{\varpi_{ni}}\right) \qquad (2)$$

$$F_1(x',w) = In(y_k = \lambda_k) = \sum_{j=1}^{M} w_{jk}\varphi_j\left(\sum_{i=1}^{N} w_{ji}x_i - \kappa_j\right) - \kappa_k \quad (3)$$

In the neural network model presented in equation3, w_{kj} is the synaptic weights from the neurons in the hidden layer j to the output neuron k and w_{ij} are the synaptic weights from the neurons in the input layer i to neurons in the hidden layer j and x_i is the i-the element of the input variable of the input vector $\tilde{\mathbf{x}}$. The weight vectors w denote the entire set of synaptic weights ordered by layer, the neurons in the layer and the synapses in a neuron. The thresholds corresponding to the hidden and the output neurons are given by κ. The activation function

$$\varphi = \frac{1}{1+\mathbf{e_i}^*} \quad (4)$$

Where: $\tilde{\mathbf{x}} = \mathbf{x} \bullet \xi$ and ξ is the pre-process scaling vector and x is the raw input data and $\tilde{\mathbf{y}} = \mathbf{y} \bullet \xi$ is the post scaling factor

The error associated with output is defined as

$$\mathbf{e_i} = (\lambda_{\mathbf{ipredicted}} - \lambda_{\mathbf{imeasured}})$$

$$\mathbf{i} = 1,2.........................\mathbf{n} \quad (5)$$

Hazard Outcomes are predicted using Neural Networks used to train the data given by:

Equation 6 can be redefined by the following equation for hazard systems

$$H_o(s_k) = \sum_{j=1}^{N} \omega_{jk} \sum_{i=1}^{N} \omega_{ji}(x_i = H_i) - \kappa_{jk} \quad (6)$$

Hazard System IN Series is given by:

$$y_i(= H_o(s_k)) = \prod_{j=1}^{N} \omega_{jk} \prod_{i=1}^{N} \omega_{ji}\left(x_i = H_i^{\omega_{ji}}\right) - \kappa_{jk} \quad (7)$$

Where the Hazards inputs $H_i^{\omega_{ji}}$ and the Hazard Outputs $H_o(s_k)$ are represented by fuzzy-belief sets described earlier. κ_{jk} represents the threshold or the error associated with each training: Equation 8 is given by the following:

$$InH_o(s_k) = \sum_{j=1}^{N} \omega_{jk} \sum_{i=1}^{N} \omega_{ji} Inf_i(Si) - \kappa_{jk} \quad (8)$$

i-input index (1-N input Hazard Synoptic Function)

j-weight index (1-N interacting Hazard Synoptic Neuron functions)

k-output index in times (1-N Hazard Output Synoptic Function).

$$\begin{bmatrix} \breve{y}_1 \\ \breve{y}_2 \\ . \\ . \\ \breve{y}_N \end{bmatrix} = \begin{bmatrix} W_{11} & W_{12} & \ldots\ldots & W_{1N} \\ W_{21} & W_{22} & \ldots\ldots & W_{2N} \\ \ldots & \ldots & \ldots & \ldots \\ \ldots & \ldots & \ldots & \ldots \\ W_{M1} & W_{M2} & \ldots\ldots & W_{MN} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \ldots \\ \ldots \\ x_N \end{bmatrix} \quad (10)$$

Where:

$$\begin{bmatrix} \breve{y}_1 \\ \breve{y}_2 \\ . \\ . \\ \breve{y}_N \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ . \\ . \\ y_N \end{bmatrix} - \bar{\lambda} \begin{bmatrix} K_1 \\ K_2 \\ \ldots \\ \ldots \\ K_N \end{bmatrix} \quad (11)$$

The Weights are given by the following Function:

$$W_{11} = [\bar{\omega}_{11}\omega_{11} + \bar{\omega}_{12}\omega_{21} + \ldots\ldots.. + \bar{\omega}_{1m}\omega_{m1}] \quad (12)$$

$$W_{MN} = [\bar{\omega}_{N1}\omega_{1N} + \bar{\omega}_{N2}\omega_{2N} + \ldots\ldots.. + \bar{\omega}_{Nm}\omega_{mN}] \quad (13)$$

$$K_N = (\kappa_{N1} + \kappa_{N2} + \ldots\ldots + \kappa_{NN}) \quad (14)$$

Equation 24 can be expressed in an Eigenvalue Equation:

$$|\vec{W} - \lambda I| = 0 \quad (15)$$

$$\begin{vmatrix} W_{11}-\lambda & 0 & 0 \\ 0 & W_{22}-\lambda\ldots.. & 0 \\ \ldots & \ldots & \ldots \\ \ldots & \ldots & \ldots \\ 0 & 0 & \ldots\ldots W_{MN}-\lambda \end{vmatrix} = 0 \quad (16)$$

$$(W_{11}-\lambda)(W_{22}-\lambda)\ldots\ldots\ldots(W_{MN}-\lambda) = 0 \quad (17)$$

Once Specific Data Sets connecting input hazards with the resulting Hazard outcomes can be predetermined, the synaptic weights constants can be determined or trained, so that any other hazard input can now be determined. Weights associated in each neural network in equation 37 are determined using Linear Network for Regression Analysis.

Using Regression Method, Equation 37 can be rearranged and solved for W:

$$\begin{bmatrix} \breve{y}_1 \\ \breve{y}_2 \\ . \\ . \\ \breve{y}_N \end{bmatrix} = \begin{bmatrix} W_{11} & W_{12} & \cdots & W_{1N} \\ W_{21} & W_{22} & \cdots & W_{2N} \\ \cdots & & & \\ \cdots & & & \\ W_{M1} & W_{M2} & \cdots & W_{MN} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \cdots \\ \cdots \\ x_N \end{bmatrix} \quad (28)$$

$$W_{MN} = \frac{\begin{vmatrix} \sum_{i=1}^{N} x_{i1} & \sum_{i=1}^{N} x_{i2} \cdots & \sum_{i=1}^{N} y_{iM} \\ \sum_{i=1}^{N} x_{i1}^2 & \sum_{i=1}^{N} x_{i1}x_{i2} \cdots & \sum_{i=1}^{N} x_{i1}y_{iM} \\ \cdots & & \\ \cdots & & \\ \sum_{i=1}^{N} x_{i1}x_{iN} & \sum_{i=1}^{N} x_{i2}x_{iN} \cdots & \sum_{i=1}^{N} x_{iN}y_{iM} \end{vmatrix}}{\begin{vmatrix} \sum_{i=1}^{N} x_{i1} & \sum_{i=1}^{N} x_{i2} \cdots & \sum_{i=1}^{N} x_{iN} \\ \sum_{i=1}^{N} x_{i1}^2 & \sum_{i=1}^{N} x_{i1}x_{i2} \cdots & \sum_{i=1}^{N} x_{i1}x_{iN} \\ \cdots & & \\ \cdots & & \\ \sum_{i=1}^{N} x_{i1}x_{iN} & \sum_{i=1}^{N} x_{i2}x_{iN} \cdots & \sum_{i=1}^{N} x_{iN}x_{iN} \end{vmatrix}} \quad (29)$$

The Average Mean Squared Error is computed as Standard Deviation measure to determine whether the weights trained give specific outputs that minimizes error associated with each predicted measurement

$$\mathbf{ARMS} = \left(\frac{1}{\mathbf{N}} \sum_{\mathbf{i=1}}^{\mathbf{N}} \mathbf{e_i}^2 \right)^{\frac{1}{2}} \quad (30)$$

Where the error being the difference between predicted and measured outputs: for example the difference between failure rates predicted by the neural network and failure rates measured for a particular Systems (e.g FPSO) resulting from combination of hazards

$$\mathbf{e_i} = \mathbf{H_{Opredicted}} - \mathbf{H_{omeasured}} \quad (31)$$

Risk and Safety Modelling. The risk and safety potential is computed using eqn. 33 and eqn.34

$$\text{Risk Potential} = \frac{\text{Risk}}{\text{Reliability of Safety Systems}} \quad (33)$$

The Risk Potential gives a measure of the True Risk inherent in a System or Sub System

$$\textit{Safety Potential} = \frac{1}{\textit{Risk Potentaial}} = \frac{\textit{Reliability of Safety Systems}}{\textit{Risk to Safety System}} \quad (34)$$

The Safety Potential gives a measure of the Safety of a given System

Maximum Risk of a System based on New Technique. The maximum risk can be evaluated from the linear programming model. The maximum risk for a system that follows series configuration is given by

$$In(1-r) = In\left(\prod_i (1-r_i)^{wi}\right) = w_1 In\, r_1 + w_2 Inr_2 + \ldots + w_n Inr_n \quad (35)$$

Subject to the constraint equation

$$0 \le r_i \le 1 \qquad \text{for } i = 1,2,\ldots..n \quad (36)$$

Equation 3 subject to eqn. 4 is our model for predicting a series system, which is solved by finding the linear programming model that multiplies the respective weights to the Natural Logarithm of the respective risk events.

However the maximum risk model for a system operating in parallel is given by eqn.38 and constraint functions is given by eqn.39 and eqn.40

$$\text{Max } \; Inr = \omega_1 Inr_1 + \omega_2 Inr_2 + \ldots\ldots + \omega rn\, Inr_n \quad (37)$$

$$0 \le r_i \le 1 \qquad \text{for } i = 1,2,\ldots..n \quad (38)$$

$$0 < \prod_i^n r_i \le 1 \quad \text{for } i = 1,2,\ldots..n \quad (39)$$

The maximum reliability of the safety systems is evaluated using eqn.8 and the constraint eqn.41 is given by eqn.42 and eqn.43

$$\text{Max } \; InR = \omega R1\, InR1 + \omega R2\, InR2 + \ldots\ldots + \omega Rn\, InRn \quad (40)$$

$$0 \le R_i \le 1 \qquad \text{for } i = 1,2,\ldots..n \quad (41)$$

$$0 < \prod_i^n R_i \le 1 \quad \text{for } i = 1,2,\ldots..n \quad (42)$$

For a parallel and series system, the maximum risk objective function is translated using the objective function eqn.44

$$r = \prod_{i=1}^{k} r_i^{\omega i} + \sum_{i=k}^{n} \omega_i r_i \quad (42)$$

Thus the above couple system by analysing the series and parallel systems separately. The linearized risk system for parallel couple.

$$\mathrm{Inr}_p = \sum_{i=1}^{k} \omega_i \mathrm{Inr}_i \tag{43}$$

Total linearized risk objective function for the series- parallel couple system

$$r_T = \sum_{i=1}^{k} \omega_i \mathrm{Inr}_i + \sum_{i=k}^{n} \omega_i r_i \tag{44}$$

This is subject to the constraint equation

$$0 \le r_i \le 1 \qquad i = L \ldots k \text{ AND } i = k, \ \ldots..n$$

$$0 \le \prod_{i=1}^{k} \omega_i r_i \le 1 \qquad i = l, \ldots k \tag{45}$$

$$0 \le \sum_{i=k}^{i=n} \omega_i r_i \le 1 \qquad I = k,..n$$

Limits of Safety

In order to find the Limits of Safety in a process system, we now apply the Lyapunov Stability Criteria that results in a matrix equation as follows given by eqn.46

$$\zeta_{i+1j} = H\,\Omega_{ij} \tag{46}$$

Where in

$$\Omega_{ij} = \begin{bmatrix} \xi_{ij} \\ \eta_{ij} \\ \gamma_{ij} \end{bmatrix} \qquad \zeta_{i+1j} = \begin{bmatrix} \xi i+1j \\ \eta i+1j \\ \gamma i+1j \end{bmatrix} \tag{47}$$

ζ_{i+1j} is Risk Matrix Vector at particular time i and position j and Ω_{ij}, is the Risk Matrix Vector at an advanced time i+1, H=J is the Jacobean or Matrix of Safety and J is the Jacobean of Safety from a stable point as follows:

$$J = \frac{\partial(F_1F_2F_3F_4F_5)}{\partial(r, R, \omega, \lambda, S)} \tag{48}$$

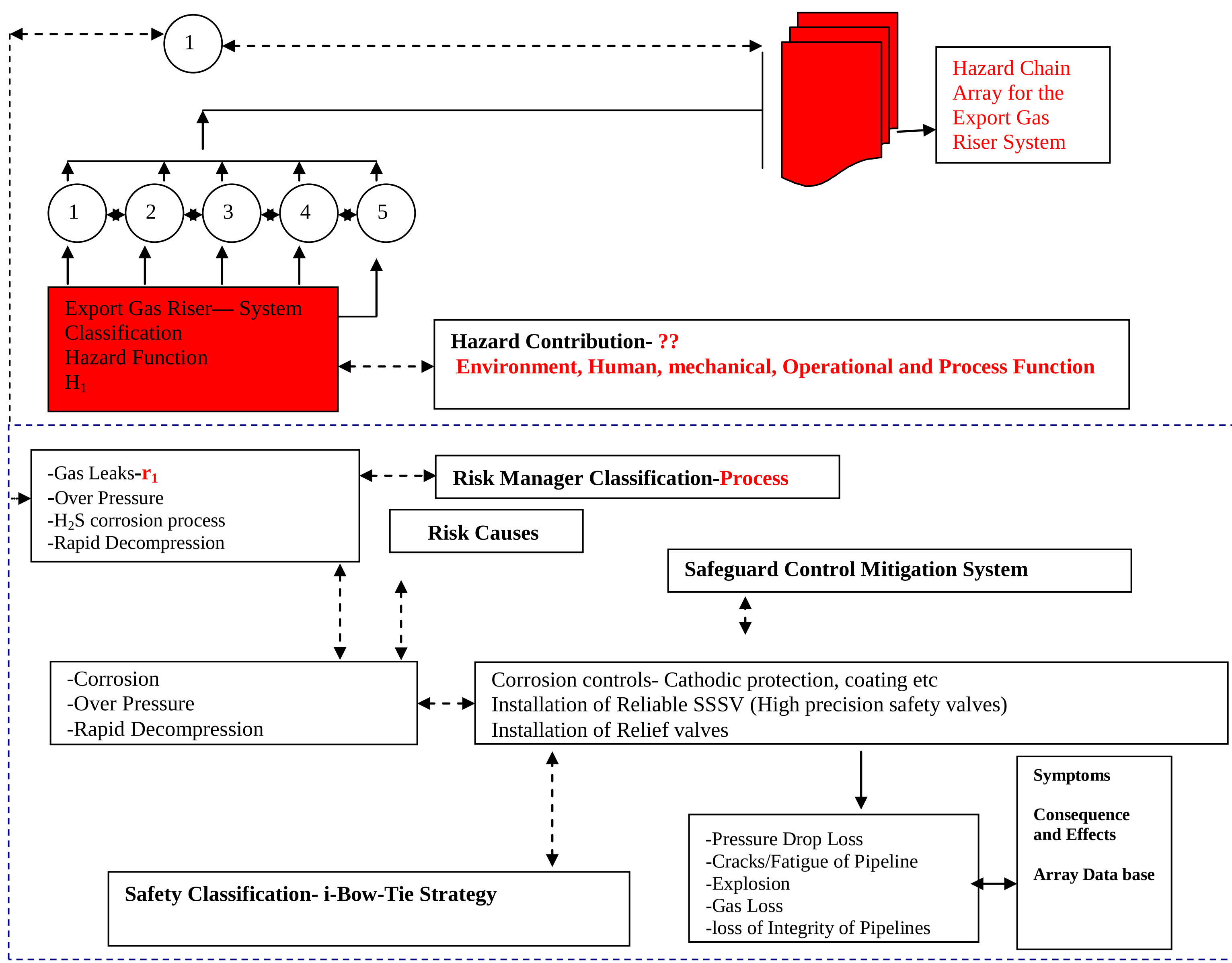
F_1 is the Function associated with risk of the Process System, F_2 is the Function associated with Reliability of the Safety System, F_3 is the Function associated with weights that each Process System carried in a given environment at a given time, F_4 is the Function associated with hazard rate of the process system, F_5 is the Function associated with Safety of the Process System.

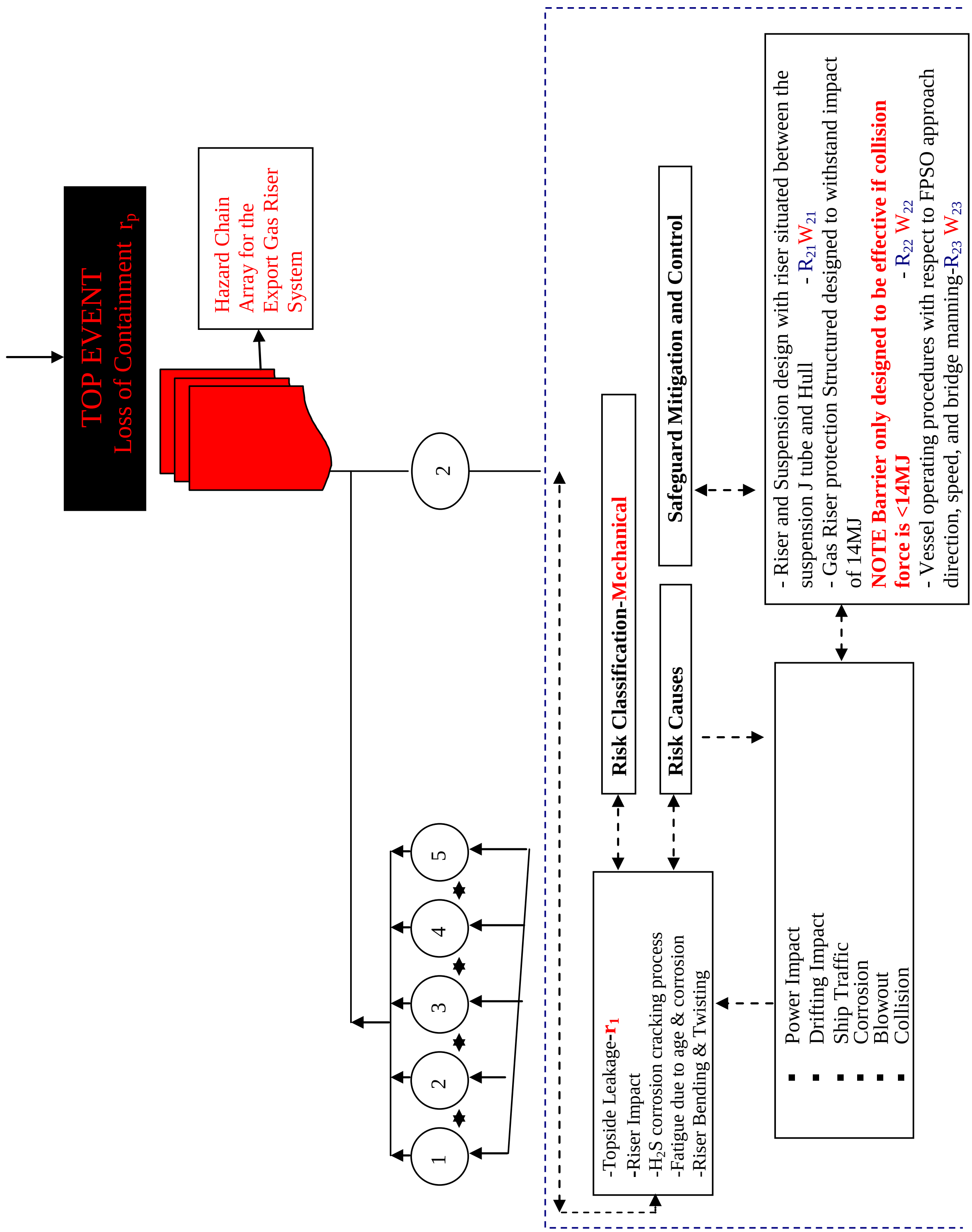
III. Functional Safety Integrity Level Performance

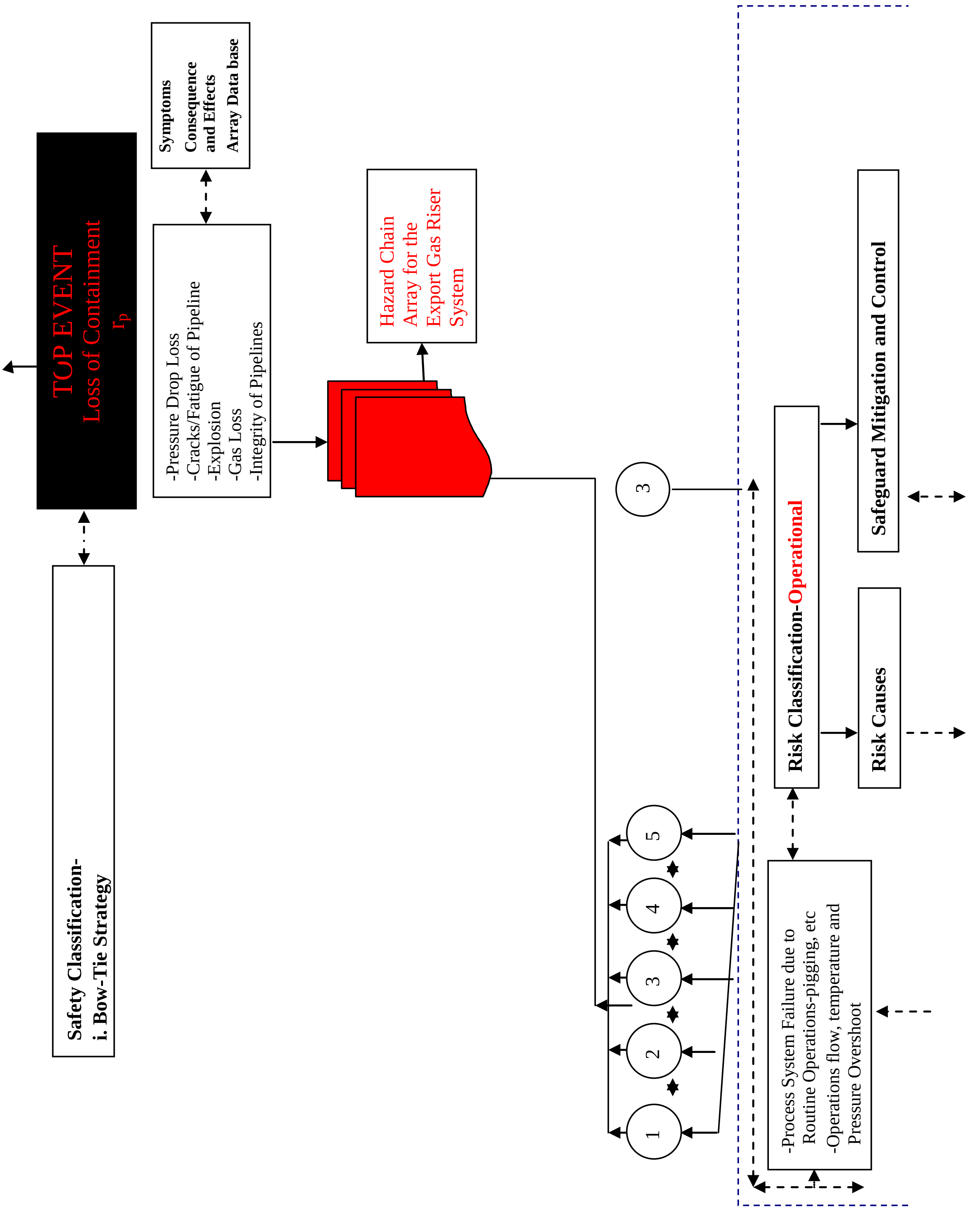
Safety Integrity Level Performance describe reliability of Safety system instrumentation in medical equipment to provide accurate input and output data, limiting the threshold of risk to data inaccuracy which may lead to loss of life. Safety Life Cycle (SLC) is an approach that addresses all necessary activities to ensure medical equipment achieve functional safety performance in relation of deployment of Leak diagnosis in conformity to IEC 61508 International Standards. This standard covers the requirements use of dedicated medical instruments and automation package solutions in relation to hazards and risk assessment methods defining requirements to SIS design and engineering as well as to testing, installation, commissioning, operation, maintenance, modification, decommissioning and documentation of medical equipment. The performance criteria involved in obtaining safety integrity levels in DSS safety functional performance are:

1. *Reliability:* Should have limited False Alarm thresholds with respect to repeated ability
2. *Sensitivity:* Should detect pinhole deviation and discrepancies in Leak diagnosis
3. *Robustness:* Should be able to adapt to changing Leak cases and environment conditions
4. *Response Time:* Should have a feedback time window to detect leaks in SIS or diagnosis within accepted thresholds should be less than 3minutes.
5. *Cost:* Should have limited damages to warrant repair or replacements is important.
6. Some important terminology, ALAARP is best common practice judgment of the balance of risk and societal benefits.

Global Journal of Science Frontier Research (A) Volume XX Issue III Version I Year 2020


1
1
2
3
4
5
Hazard Chain Array for the Export Gas Riser System
Export Gas Riser— System Classification Hazard Function H1
Hazard Contribution- ??
Environment, Human, mechanical, Operational and Process Function
-Gas Leaks-r1
-Over Pressure
-H2S corrosion process
-Rapid Decompression
Risk Manager Classification-Process
Risk Causes
Safeguard Control Mitigation System
-Corrosion
-Over Pressure
-Rapid Decompression
Corrosion controls- Cathodic protection, coating etc
Installation of Reliable SSSV (High precision safety valves)
Installation of Relief valves
Symptoms
Consequence and Effects
Array Data base
-Pressure Drop Loss
-Cracks/Fatigue of Pipeline
-Explosion
-Gas Loss
-loss of Integrity of Pipelines
Safety Classification- i-Bow-Tie Strategy


TOP EVENT
Loss of Containment r_p
Hazard Chain Array for the Export Gas Riser System
2
1
2
3
4
5
Risk Classification-Mechanical
Risk Causes
Safeguard Mitigation and Control
-Topside Leakage-r_1
-Riser Impact
-H_2S corrosion cracking process
-Fatigue due to age & corrosion
-Riser Bending & Twisting
Power Impact
Drifting Impact
Ship Traffic
Corrosion
Blowout
Collision
- Riser and Suspension design with riser situated between the suspension J tube and Hull - $R_{21}W_{21}$
- Gas Riser protection Structured designed to withstand impact of 14MJ
NOTE Barrier only designed to be effective if collision force is <14MJ - R_{22} W_{22}
- Vessel operating procedures with respect to FPSO approach direction, speed, and bridge manning-R_{23} W_{23}


TOP EVENT
Loss of Containment
r_p
Symptoms
Consequence
and Effects
Array Data base
-Pressure Drop Loss
-Cracks/Fatigue of Pipeline
-Explosion
-Gas Loss
-Integrity of Pipelines
Hazard Chain
Array for the
Export Gas Riser
System
Safety Classification-
i. Bow-Tie Strategy
3
1
2
3
4
5
Risk Classification-Operational
Safeguard Mitigation and Control
Risk Causes
-Process System Failure due to
Routine Operations-pigging, etc
-Operations flow, temperature and
Pressure Overshoot

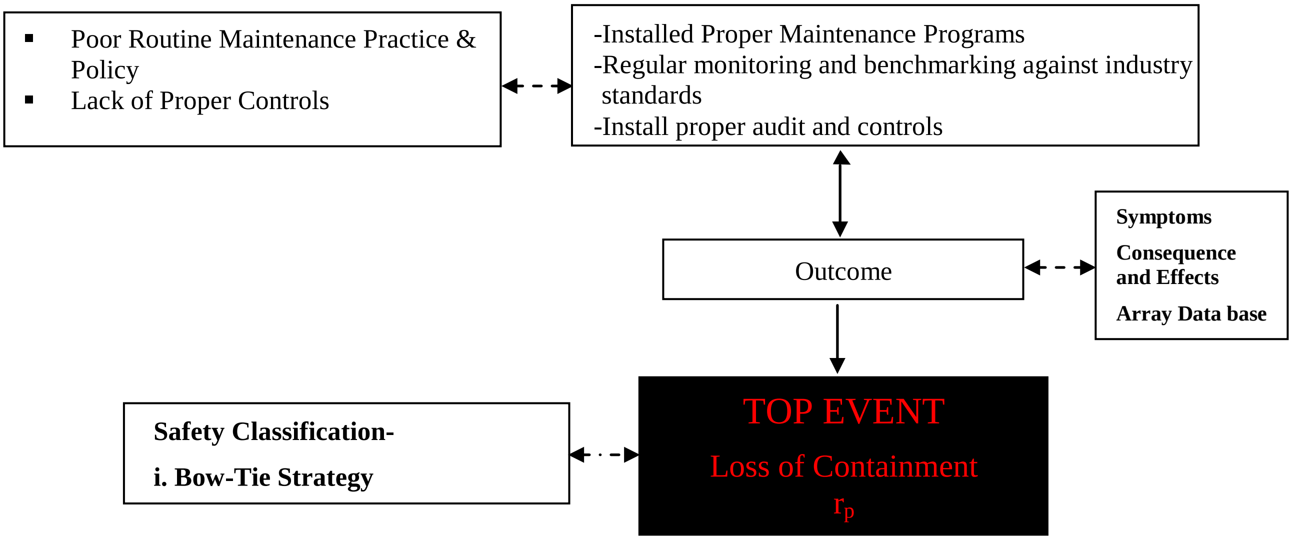
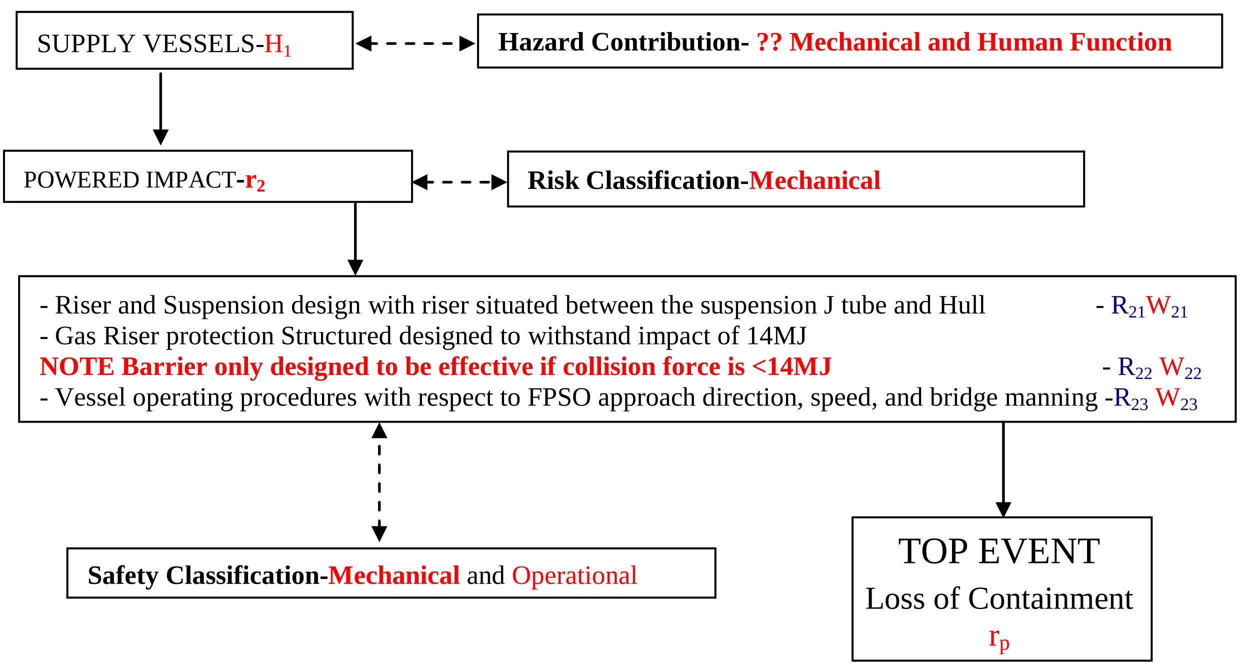


Figure 2: Safe Matrix- System

The new modifications to the Bow Tie would include a Safe Matrix System that includes a window of safety using the weighting concept. This superstructure describes the flow path- from Hazard to Top Event outcome of the process systems under a safeguard control system under the accident pathway. The application model for a typical Risk System of a typical FPSO-Export Riser is presented as Figure 3.0



The Procedure of achieving functional safety integrity levels 1) Identification of Possible Hazards and specifications of corresponding safety function 2) The following Hazard methods are normally used 1) Hazard ID, 2) Hazop 3) FMCEA (Failure Mode, Critical Effect Analysis) 4) Fault Tree 1) *Safety Function incorporating the following concepts a)* Weighting Index b) Belief Theory c) reliability d) Fuzzy Logic. Assessment of risks corresponding to safety functions and identification of the required safety integrity level 1) Probability models incorporating weights2) Mean Time before Failure (MTBF) 3) Mean Time before Repair (MTBR) 4) Markov Chain Models 5) Weibull Function 6) Weights Safety Index derived from Weibull

$$w(t) = (1 - SFR_i)\left(\frac{t}{n_i}\right)^{\beta_i - 1} \qquad (13)$$

$$\omega_{avg} = (1 - SFR_i)\left(\frac{\eta}{\beta_i}\right)\left(\frac{\left(\frac{t_{\max}}{\eta}\right)^{\beta_i} - \left(\frac{t_{\max}}{\eta}\right)^{\beta_i}}{T_{\max} - T_{\min}}\right) \quad (14)$$

$$Risk\ Potential = \frac{1 - \prod_{i=1}^{n}(1 - r_i)^{\omega_i}}{\prod_{i-1}^{n} R_{si}^{\ \omega_i}} \quad (15)$$

$$Risk\ Potential = \frac{\prod_{i=1}^{N} r_i^{\ \omega_i}}{1 - \prod_{i=1}^{n}(1 - R_{si})^{w_i}} \quad (16)$$

The exponential distribution used to describe failure

$$r_i(t) = 1 - e^{-\lambda_w t} \quad (17)$$

$$R_{st}(t) = e^{-\lambda_{wt}} \quad (18)$$

The DSS failure rate is expressed as a Homogeneous Poisson Process (HPP) with weight safety function incorporated.

$$f(n) = \frac{(w_{avg}\lambda_t)^n \exp(-w_{avg}\lambda_t)}{n!} \quad n=01, 2\ldots \quad (19)$$

Cumulative Poisson distribution is given to DSS describe failure rate:

$$f(n) = \sum_{i=0}^{n} \frac{(w_{avg}\lambda_t)^i \exp(-w_{avg}\lambda_t)}{i!} \quad (20)$$

Human reliability Models including weights define critical risk caused by human errors by different human or Leak operators

$$R_n(t) = \exp^{-\int_0^{\tau} \omega(\tau) r_e(\tau) dt} \quad (21)$$

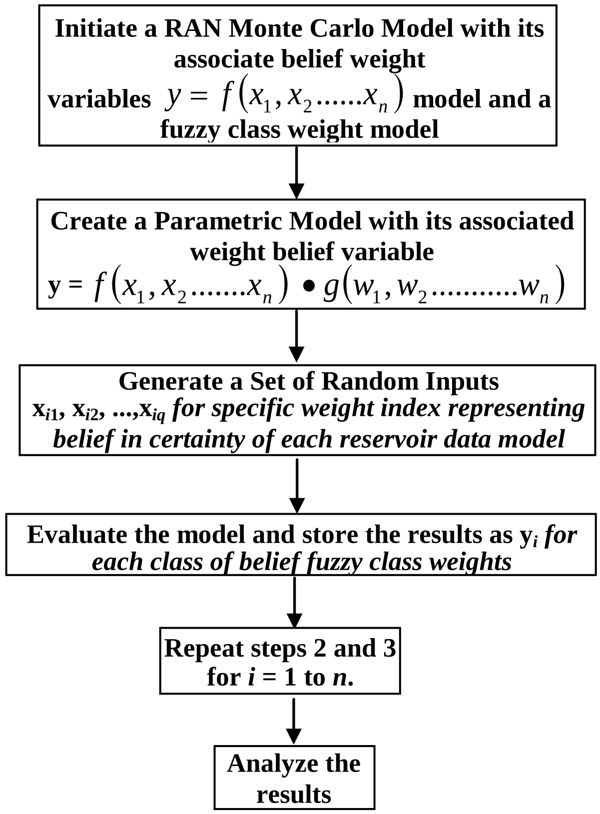
Where by:

$$w(t) = (1 - SFR_i)\left(\frac{t}{n_i}\right)^{\beta_i - 1} \quad (22)$$

Two models are considered in the risk and safety analysis1) Bow Tie Systems 2) Markov Chain Model 3) the model assumes the following A) Subjective assessments and linguistic assessments is one of the measures of safety B) Fuzzy set membership function used to define input variables C) Flexibility Safety or Jacobean Stability matrix in definition of membership D) Application of critical judgment. The probability models adopted for our case is the Bayesian Probability Framework Model. Application of Bayesian Probability Network to randomly predict Risk factors K_L is presented, which is statistically computed by listing all data in a posterior description in the Bayesian context.

$$f(F|d_1, d_2, d_3 \ldots\ldots d_n) = \frac{f(d_1|F)^{w_1}, f(d_2|F)^{w_2} \ldots\ldots f(d_n|F)^{w_n}, f(F)}{f(d_1, d_2 \ldots\ldots d_n)^W = \sum_i w_i f(d_i)} = \frac{f(F) \bullet \prod_{i=1}^{n} f(d_i / F)}{\sum_{i=1}^{n} w_i f(d_i)}$$

For the safety problem, there are two critical Risk stress factor data, the $k_{rs} = d_1$, predicted safety integrity levels, necessary condition and $k_{fs} = d_2$, predicted effect safety stress condition Sufficient Condition.



Rearranging incorporating with thresholds associated with internal and external synaptic weights of Neural Network System:

$$\begin{bmatrix} y_1 \\ y_2 \\ \cdots \\ \cdots \\ y_N \end{bmatrix} = \begin{bmatrix} W_{11}\ W_{12} .... W_{1N} \\ W_{21}\ W_{22} .... W_{2N} \\ .... \\ .... \\ W_{N1}\ W_{N2} .... W_{NN} \end{bmatrix} \begin{bmatrix} X_1(x_1 - k_1) \\ X_2(x_2 - k_2) \\ .... \\ .... \\ X_N(x_N - k_N) \end{bmatrix} - \begin{bmatrix} K_1 \\ K_2 \\ ..... \\ ..... \\ K_N \end{bmatrix} \tag{24}$$

$$W_{11} = \left[\tilde{\omega}_{11}\omega_{11} + \tilde{\omega}_{12}\omega_{21} + ... + \tilde{\omega}_{1N}\omega_{N_1}\right] \tag{25}$$

$$W_{12} = \left[\tilde{\omega}_{11}\omega_{12} + \tilde{\omega}_{12}\omega_{22} + ... + \tilde{\omega}_{1N}\omega_{N_2}\right] \tag{26}$$

$$W_{1N} = \left[\tilde{\omega}_{11}\omega_{1N} + \tilde{\omega}_{12}\omega_{2N} + ... + \tilde{\omega}_{1N}\omega_{NN}\right] \tag{27}$$

Similarly for 2

$$W_{21} = \left[\tilde{\omega}_{21}\omega_{11} + \tilde{\omega}_{22}\omega_{21} + ... + \tilde{\omega}_{2N}\omega_{N_1}\right] \tag{28}$$

$$W_{22} = \left[\tilde{\omega}_{21}\omega_{12} + \tilde{\omega}_{22}\omega_{22} + ... + \tilde{\omega}_{2N}\omega_{N_2}\right] \tag{29}$$

$$W_{2N} = \left[\tilde{\omega}_{21}\omega_{1N} + \tilde{\omega}_{22}\omega_{2N} + ... + \tilde{\omega}_{2N}\omega_{NN}\right] \tag{30}$$

Similarly for N

$$W_{N1} = \left[\tilde{\omega}_{N1}\omega_{11} + \tilde{\omega}_{N2}\omega_{21} + ... + \tilde{\omega}_{NN}\omega_{N_1}\right] \tag{31}$$

$$W_{N2} = \left[\tilde{\omega}_{N1}\omega_{12} + \tilde{\omega}_{N2}\omega_{22} + ... + \tilde{\omega}_{NN}\omega_{N_2}\right] \tag{32}$$

$$W_{NN} = \left[\tilde{\omega}_{N1}\omega_{1N} + \tilde{\omega}_{N2}\omega_{2N} + ... + \tilde{\omega}_{NN}\omega_{NN}\right] \tag{33}$$

$$K_1 = k_{11} + k_{12} + ... + k_{1N} \tag{34}$$

$$K_2 = k_{21} + k_{22} + ... + k_{2N} \tag{35}$$

$$K_N = k_{N1} + k_{N2} + ... + k_{NN} \tag{36}$$

A linear Network for Regression Analysis can be used to determine the weights. The Average Mean Square error is used to train the Network.

$$ARMS = \left(\frac{1}{N}\sum_{i=1}^{N} e_i^{\,2}\right) \tag{37}$$

Where:

$$e_i = H_{opredicted} - H_{oobserved} \tag{38}$$

The error function can be deduced from the Gaussian Function: The Gaussian Function (also referred to as beel-shaped or bell curve) is of the following form

$$G(x) = Ae^{-\frac{x^2}{2\sigma^2}} \tag{39}$$

Where σ is referred to as the spread of standard deviation and A is the constant. The function can be a normalized so that the integral from minus infinity to plus infinity equals one yeilding the normalized Guassian

$$G(x)=\frac{1}{\sqrt{2\pi\sigma}}e^{-\frac{x^2}{2\sigma^2}} \quad (40)$$

By using the following definite integral

$$\int_0^{\infty} e^{-ax^2}dx=\frac{1}{2}\sqrt{\frac{\pi}{a}} \quad (41)$$

The Gaussian function goes to zero at plus and minus infinity while all the derivatives of any order evaluated at x=0 are zero

The error function equals twice the integral of a normalized Gaussian function between 0 and x

$$erfx=\frac{2}{\sqrt{\pi}}\int_0^{\infty} e^{-u^2}du \quad (42)$$

The relation between the normalizd Gaussian distribution and error function equals:

$$\int_{-x}^{x} G(x)dx = Erf\left(\frac{x}{\sigma\sqrt{2}}\right) \quad (43)$$

A series approximation for small value of x of this function is given by:

$$erfx=\frac{2}{\sqrt{\pi}}\left(x-\frac{x^3}{3.1!}+\frac{x^5}{5.2!}+\frac{x^7}{7.3!}+......\right) \quad (44)$$

While an approximation for large value of x ocan be obtained

$$erfx=\frac{2}{\sqrt{\pi}}\left(x-\frac{x^3}{3.1!}+\frac{x^5}{5.2!}+\frac{x^7}{7.3!}+......\right) \quad (45)$$

$$erfx=1-\frac{e^{-x^2}}{\sqrt{\pi}x}\left(1-\frac{1}{2x^2}+\frac{1.3}{(2x^2)^2}+\frac{1.3.5}{(2x^2)^3}+.....\right) \quad (47)$$

The complementary error function equals one minus the error function yielding

$$erfcx=1-erfx=\frac{2}{\sqrt{\pi}}\int_x^{\infty} e^{-u^2}du \quad (48)$$

Defining the Limits of functional Safety:The vector field F(x) of the whole phase portrait for all individual safety functions f(x) at the designated nodes is described by the matrix. In difference form, the concept has evolved in the Safety Functional model as presented:

$$\Phi_{1i+1}=F_1(\Phi_{1i},\Phi_{2i}.....\Phi_{ni}) \quad (49)$$

$$\Phi_{2i+1}=F_2(\Phi_{1i},\Phi_{2i}.....\Phi_{ni}) \quad (50)$$

$$\Phi_{Ni+1}=F_1(\Phi_{1i},\Phi_{2i}.....\Phi_{ni}) \quad (51)$$

The Liapunov Stability Criterion is used as basis for evolving functional safety incorproating risks involved in uniform and systematic configuration of all technology process, methods and dedicated medical safety instrument systems (SIS) equipment to core sector specific standards IEC61508, deployed in accessing Leak diagnosis and treatment performance as provided in equation below.

$$\begin{bmatrix}\xi_{1k+1}\\ \xi_{2k+1}\\ ....\\ \xi_{nk+1}\end{bmatrix}=j\begin{bmatrix}\xi_{1k}\\ \xi_{2k}\\ ....\\ \xi_{nk}\end{bmatrix} = \quad (52)$$

Where:

$$J=\begin{bmatrix}\left(\frac{\partial F_1}{\partial\Phi_1}\right) & \left(\frac{\partial F_1}{\partial\Phi_2}\right) & \cdots & \left(\frac{\partial F_1}{\partial\Phi_N}\right)\\ \left(\frac{\partial F_2}{\partial\Phi_1}\right) & \left(\frac{\partial F_2}{\partial\Phi_2}\right) & \cdots & \left(\frac{\partial F_2}{\partial\Phi_N}\right)\\ \cdots & \cdots & \cdots & \cdots\\ \left(\frac{\partial F_N}{\partial\Phi_1}\right) & \left(\frac{\partial F_N}{\partial\Phi_2}\right) & \cdots & \left(\frac{\partial F_N}{\partial\Phi_N}\right)\end{bmatrix} \quad (53)$$

IV. DSS Performance using Liapunov Stability Function Criteria

The concept of stability and instability of Decision Support systems (Lyapunov equilibrium stability criteria) was applied to a transient flow Leak Detection system; to evolve a model for DSS functional safety defect in SIS. The two dimensional invertible maps in time and space domain for the DSS Leak system is τ→z, t, and are presented for DSS Leak Systems Data, DSS Electronic Systems Data, DSS Blood Flow System Data, in equations (54), (55) and (56), respectively.

$$DSS-CSD(J,K+1)=F1[CSD(J,K),ESD(J,K),BFSD(J,K)] \quad (54)$$

$$DSS-ESD(J,K+1)=F2[CSD(J,K),ESD(J,K),BFSD(J,K)] \quad (55)$$

$$DSS-BFSD(J,K+1)=F3[CSD(J,K),ESD(J,K),BFSD(J,K)] \quad (56)$$

Where, $CSD(J,K), ESD(J,K), BFSD(J,K)$ are the DSS Leak System Output Data, DSS Electronic Systems Output Data and DSS Blow Flow System Output Data in j patient node and k time domain, respectively? For DSS Functional Safety (DSS-FS) to be accurate, DSS-FS is defined as the domain of stability where, CSD, ESD and BSFD are consistently steady, that is not change in output for each patient measurement not related to fluctuation, that is for the same input, the output must be repeatable therefore

$$CSD(J,K+1) = CSD_E(J,K) \quad (71) \quad ESD(J,K+1) = ESD_E(J,K) \quad (57)$$

$$BFSD(J,K+1) = BSFD_E(J,K) \quad (58)$$

54 to 58 in matrix form is given by 74

$$\zeta_{jk+1} = H\Omega_{jk} \quad (59)$$

Where:

$$\Omega_{jk} = \begin{bmatrix} \xi_{jk} \\ \eta_{jk} \\ \gamma_{jk} \end{bmatrix} \zeta_{jk+1} = \begin{bmatrix} \xi_{jk+1} \\ \eta_{jk+1} \\ \gamma_{jk+1} \end{bmatrix} \quad (60)$$

$$H = \begin{bmatrix} A\ B\ C \\ D\ E\ F \\ G\ H\ I \end{bmatrix} = \begin{bmatrix} \left(\frac{\partial F_1}{\partial CSD}\right)_{jK} & \left(\frac{\partial F_1}{\partial ESD}\right)_{jK} & \left(\frac{\partial F_2}{\partial BFSD}\right)_{jK} \\ \left(\frac{\partial F_2}{\partial CSD}\right)_{jK} & \left(\frac{\partial F_1}{\partial ESD}\right)_{jK} & \left(\frac{\partial F_2}{\partial BFSD}\right)_{jK} \\ \left(\frac{\partial F_3}{\partial CSD}\right)_{jK} & \left(\frac{\partial F_3}{\partial ESD}\right)_{jK} & \left(\frac{\partial F_3}{\partial BFSD}\right)_{jK} \end{bmatrix} \quad (61)$$

J is the Jacobean differential given by the formula: For a DSS functional safety to be repeatable $J = 1$

$$J = \frac{\partial[F_1 F_2 F_3]}{\partial[CFD, ESD, BSFD]} \quad (62)$$

$|H-\lambda I|\Omega_i = 0$ is the characteristic equation of the matrix of equation (62) from where the eigenvalues or the roots can easily be evaluated. In this way, the problem is decoupled into three dimensional maps and the stability question is answered once the eigenvalues (λ_{1k},λ_{2k},λ_{3k}) for each iteration are known. If the Jacobeans are real and symmetric such that one would expect real eigenvalues, the system is asymptotically stable if $-1<\lambda_{1k}, \lambda_{2k}, \lambda_{3k}<1$, but unstable if $\lambda_{1k}, \lambda_{2k}, \lambda_{3k} > 1$ in absolute terms. If one of the eigenvalues λ_{1k}or λ_{2k} or λ_{3k} has modules equal to1 in absolute value, then the critical point is established for stability. A leak in a pipeline causing instability is observed when the simulation results in at least one of the roots $\lambda_{1k}, \lambda_{2k}, \lambda_{3k}<-1$. Similarly a surge causing instability is observed when at least one of the roots $\lambda_{1k}, \lambda_{2k}, \lambda_{3k}>1$. The absolute value of 1 is the critical bifurcating state. If $\lambda_{1k}, \lambda_{2k}, \lambda_{3k}$ is such that, the Jacobean are complex conjugates, (i.e. $\lambda_{1k}, \lambda_{2k}, \lambda_{3k} = \alpha + i\beta$), the stability criterion for three dimensional maps can be solved. The system is stable (for complex conjugates) if all eigenvalues are inside the unit circle, whereas the system is asymptotically unstable, if at least one of the eigenvalues is outside the circle.

The stability boundary is the unit circle itself. If the eigenvalues are real, there are only two points where they can cross the stability boundary at 1 and –1. This concept is similar to saying that the stability condition exists once the Jacobean is equal to 1 in absolute terms. In order to describe the unstable phase portrait, a bifurcation model to assign a relative magnitude to the disturbed phase is proposed, as the standard deviation from the critical point, which gives a robust measure of the width of distribution. These are indicated below in equations (41) to (43) for the eigenvalues.

$$SD(\lambda_{1ij}) = \sqrt{\sum_{i=0}^{n} \frac{(|\lambda_{1ij}|-1)^2}{(n-1)}} \quad (63)$$

$$SD(\lambda_{2ij}) = \sqrt{\sum_{i=0}^{n} \frac{(|\lambda_{2ij}|-1)^2}{(n-1)}} \quad (64)$$

$$SD(\lambda_{3ij}) = \sqrt{\sum_{i=0}^{n} \frac{(|\lambda_{3ij}|-1)^2}{(n-1)}} \quad (65)$$

The standard deviation model evaluates the width of deviation of a typical flow vector point at time i = 0…n. Once a leak is suspected at a time envelope, a relative magnitude of the disturbance can be ascertained. A standard deviation close to zero indicates a small leak, and vice versa. $|\lambda_{1ij}|, |\lambda_{2ij}|, |\lambda_{3ij}|$ are the absolute eigenvalues of velocity, mass and pressure, at a particular time and pipeline node point. Hence, using the standard deviation model, it is possible to classify the leak being considered. This model is useful for assigning a value to a disturbance after the eigenvalue criterion for a leak or surge has been ascertained.

Very Likely

Fuzzy Class 1

WeibullSigmond Function	Safety Index=0	Safety Index=0.1	Safety Index=0.5	Safety Index=0.8	Safety Index=0.9
0	Safety Integrity Levels (Weighted) on the Risk Function				
0.1	1.02745	0.9247	0.5137	0.2055	0.1027
0.2	0.791344	0.7122	0.3957	0.1583	0.0791
0.4	0.938869	0.8450	0.4694	0.1878	0.0939
0.6	1.485194	1.3367	0.7426	0.2970	0.1485
0.8	2.643102588	2.3788	1.3216	0.5286	0.2643
1	5.01734	4.5156	2.5087	1.0035	0.5017
1.2	9.921146	8.9290	4.9606	1.9842	0.9921
1.4	20.1783	18.1605	10.0892	4.0357	2.0178
1.6	41.895	37.7055	20.9475	8.3790	4.1895
1.8	88.36478	79.5283	44.1824	17.6730	8.8365
2	188.7084	169.8376	94.3542	37.7417	18.8708

Fuzzy Class 2

Weibull Sigmoid Constant	Safety Index=0	Safety Index=0.1	Safety Index=0.5	Safety Index =0.8	Safety Index=0.9
0	Safety Integrity Levels (Weighted) on the Risk Function				
0.1	0.82422	0.741798	0.41211	0.164844	0.082422
0.2	0.50925	0.458325	0.254625	0.10185	0.050925
0.4	0.388808	0.349928	0.194404	0.077762	0.038881
0.6	0.395803	0.356223	0.197902	0.079161	0.03958
0.8	0.453289425	0.407960482	0.226644712	0.090657885	0.045328942
1	0.553733	0.49836	0.276867	0.110747	0.055373
1.2	0.704619	0.634157	0.352309	0.140924	0.070462
1.4	0.922237	0.830013	0.461118	0.184447	0.092224
1.6	1.232212	1.108991	0.616106	0.246442	0.123221
1.8	1.672506	1.505256	0.836253	0.334501	0.167251
2	2.298504	2.068653	1.149252	0.459701	0.22985

Unlikely

Fuzzy Class 3

Weibull Sigmond Function	Safety Index=0	Safety Index=0.1	Safety Index=0.5	Safety Index=0.8	Safety Index=0.9
	Safety Integrity Levels(Weighted) on the Risk Function				
0.1	0.514808	0.463327	0.257404	0.102962	0.051481
0.2	0.198671	0.178804	0.099336	0.039734	0.019867
0.4	0.059176	0.053258	0.029588	0.011835	0.005918
0.6	0.023501	0.021151	0.011751	0.0047	0.00235
0.8	0.0105007	0.009450063	0.005250035	0.002100014	0.001050007
1	0.005004	0.004504	0.002502	0.001001	0.0005
1.2	0.002484	0.002236	0.001242	0.000497	0.000248
1.4	0.001268	0.001142	0.000634	0.0000254	0.000127
1.6	0.000661	0.000595	0.000331	0.000132	6.61E-05
1.8	0.00035	0.000315	0.000175	7.00E-05	3.50E-05
2	0.000188	0.000169	9.39E-05	3.75E-05	1.88E-05

a) Leak Finder Development Platforms

The Leak Finder development platforms is presented in eq.1

Table 1.0: Leak finder Development Platforms

#	Requirement	Description	How To Test	Test Result Ok?
1	Development Platform	Lab VIEW Graphical Development Platform	Verify that the system runs on LabVIEW platform	
2	Operating System Platform	Window 2000/NT/XP	Verify that the VI runs properly on the OS.	

$$J = \begin{bmatrix} \frac{\partial F_{1j}}{\partial r_{ij}} & \frac{\partial F_{1j}}{\partial R_{ij}} & \frac{\partial F_{1j}}{\partial \omega_{ij}} & \frac{\partial F_{1j}}{\partial \lambda_{ij}} & \frac{\partial F_{1j}}{\partial S_{ij}} \\ \frac{\partial F_{2j}}{\partial r_{ij}} & \frac{\partial F_{2j}}{\partial R_{ij}} & \frac{\partial F_{2j}}{\partial \omega_{ij}} & \frac{\partial F_{2j}}{\partial \lambda_{ij}} & \frac{\partial F_{2j}}{\partial S_{ij}} \\ \frac{\partial F_{3j}}{\partial r_{ij}} & \frac{\partial F_{3j}}{\partial R_{ij}} & \frac{\partial F_{3j}}{\partial \omega_{ij}} & \frac{\partial F_{3j}}{\partial \lambda_{ij}} & \frac{\partial F_{3j}}{\partial S_{ij}} \\ \frac{\partial F_{4j}}{\partial r_{ij}} & \frac{\partial F_{4j}}{\partial R_{ij}} & \frac{\partial F_{4j}}{\partial \omega_{ij}} & \frac{\partial F_{4j}}{\partial \lambda_{ij}} & \frac{\partial F_{4j}}{\partial S_{ij}} \\ \frac{\partial F_{5j}}{\partial r_{ij}} & \frac{\partial F_{5j}}{\partial R_{ij}} & \frac{\partial F_{5j}}{\partial \omega_{ij}} & \frac{\partial F_{5j}}{\partial \lambda_{ij}} & \frac{\partial F_{5j}}{\partial S_{ij}} \end{bmatrix} \quad (49)$$

i= time element j= component under consideration working as a network to other components

J is the safety matrix function which is tells operators the Limits of Safety, such that If J =1 in absolute terms the Safety status is stable or good, if J < -1, the safety status is unstable and a Fault may exist in the System and an Unsafe position results, if J > 1, the safety function becomes over stable, which indicates the systems functioning above normal or over design for safety. These criteria can be an important tool for Safety operators to mark the limit of design or operation. Any factor that tends to push safety function above or below absolute 1 should be minimized. This technique for determining safety is not available in previous method for safety analysis

V. Results and Discussions

Table 3 shows the hazard register and the weights for safety. Based on models disclosed in previous section a weights were simulated in a risk management software system developed for purpose. The software simulator is design in visual basic macro scripts of an Excel sheet programme modules and the weights simulated in Excel sheet produce the weights values for different risk/hazard scenarios and events likely to occur. The weights values represents the safety function of the FPSO system subject the maximum hazards risk test analysis of 95% and minimum reliability test of 5% for both process and occupational hazards. These values expressed extreme scenarios and design is computed based on extreme scenarios in the hazard register. The Hazard register contains all possible hazards that is possible in FPSO system. The weights on occupational accidents is 0.36, offloading events 0.24, Hull failure due to extreme wave load is 0.24, Passing vessel collision with FPSO or shuttle tanker 0.959682, Strong collision by supply vessel with FPSO or shuttle tanker 0.206752, Hydrocarbon associated risk (process, turret and riser systems) is 0.454357, Hydrocarbon and Topsides systems accidents is 0.268701, , Leak that may lead to fire or explosion in process plant is 0.272354, Helicopter crash Leak from turret systems that may cause fire or explosion in turret is 0.204447, Leak or rupture of riser is 0.123299, Auxiliary systems accidents, 0.698367, Engine room fire or explosion is 0.566394, Fire or explosion in pump room is 0.718306, Helicopter crash 0.891995, Human and Organisational Factors (HOF) is 0.160624, People is 0.688105, Management systems is 0.71663, Collision risk represents a significant contribution for two of the FPSOs (all potential collision) is 0.005607, *Uncontrolled Release of Hazardous Materials is* 0.769407, Blowouts is 0.142786, Turret and Cargo Tank Release is 0.949124. This cases show the weight values that assumes a value of 1 represent the best case for safety under the scenarios of the risk and reliability of design and weight values that assume close to zero represent the work case for safety. In the few examples selected collision risks represents the worst case of safety with a value of 0.005607 followed by human and organisational factors (HOF) which is 0.160624. The best case for safety are the Turret and Cargo Tank release with a value of 0.949124, followed by Helicopter crash of 0.891995, followed uncontrolled release of hazardous materials 0.769407, followed by Fire or explosion in the pump room of value 0.718306, management system which are typical for most Exploration and production companies that have very strong integrated vertical management systems with a value of 0.71663. The results enable us not only to qualify the hazard register for the worst cases and best cases of safety for all components the FPSO system but allows a risk expert to quantify the amount allotted in each case for design, remedial or repair actions.

Table 3: Hazard Register And Weights of Safety

SN	Hazard Register	
	FPSO	
	Fuzzy Class: General	
	Fuzzy Class: Weighted	
	Two Class of Safety	
	Occupational Related Hazards Risk (95%)	
	Process Related Hazards Reliability (5%)	
	Occupational Related Hazards Risk (95%)	
	Process Related Hazards Reliability (5%)	
1	Occupational Related Hazards	Weights of Safety
2	Process fires and explosions	0.58
3	Riser and pipeline releases	0.30
4	Ship collisions	0.26
5	Fires and explosions in accommodation spaces	0.14
6	Fires and explosions in machinery spaces	0.81
7	Fires and explosions in cargo and ballast tanks	0.06
8	Structural failure	0.54
9	Helicopter accidents	0.37
10	Occupational accidents	0.36
11	Offloading Events	0.24
12	Dropped objects	0.51
13	Position loss	0.48
14	Ballasting failures	0.92
	Fuzzy Class: General	
	Fuzzy Class: Weighted	
	Two Class of Safety	
	Occupational Related Hazards Risk (95%)	
	Occupational Related Hazards Reliability (5%)	
	Process Related Hazards risk (95%)	
	Process Related Hazards Reliability (5%)	
15	Marine and hull related accidents, structural impacts	Weights
16	Hull failure due to extreme wave load	0.245383
17	Hull failure or marine accident due to ballast failure	0.296617
	or failure during loading/offloading Operations	0.160162
18	Leak from cargo tank caused by fatigue	0.137528
19	Accident during tank intervention	0.785583
20	Passing vessel collision with FPSO or shuttle tanker	0.959682
21	Strong collision by supply vessel with FPSO or shuttle tanker	0.206752
22	Other vessels or floating structures operating on the field	0.704976
	colliding with FPSO or shuttle tanker	0.081861
23	Collision during offloading	0.130822
24	Rapid change of wind direction	0.583432
25	Multiple anchor failure	0.09615
	Fuzzy Class: General	
	Fuzzy Class: Weighted	
	Two Class of Safety	
	Occupational Related Hazards Risk (95%)	
	Occupational Related Hazards Reliability(5%)	
	Occupational Related Hazards Risk (95%)	
	Occupational Related Hazards Reliability (5%)	

26	Hydrocarbon and Topsides systems accidents	0.268701
27	Leak that may lead to fire or explosion in process plant	0.272354
28	Leak from turret systems that may cause fire or explosion in turret	0.204447
29	Leak or rupture of riser	0.123299
30	Impacting loads due to crane operations (swinging loads) on a moving vessel	0.456445
31	Dropped object from retrieval of cargo pumps	0.96504
32	Severe rolling during critical operations, such as crane operations	0.160463
	(considered as included)	0.401012
33	other scenarios, therefore not addressed separately)	0.92856
34	“Topside” fire threatening cargo tank resulting from gas leaks	0.191856
35	Emergency flaring with approaching shuttle tanker or during off-loading	0.494471
36	Unintended release of gas or oil from riser	0.862935
37	Gas and oil release from other sources	0.585676
38	Auxiliary systems accidents	0.698367
39	Failure of cargo tank explosion prevention function during normal operation	0.460309
40	Fire or explosion in pump room	0.718306
41	Spill from off-loading system.	0.366799
42	Engine room fire or explosion	0.566394
43	Helicopter crash	0.891995
44	Human and Organisational Factors (HOF)	0.160624
45	People	0.688105
46	Equipment (e.g. hardware)	0.344732
47	Management systems	0.775929
48	Culture and environment	0.58924
49	Management systems Failure	0.694851
50	Procedures	0.973734
51	Communication	0.408983
52	Training	0.505835
53	Management of change	0.71663
54	Risk assessment Policy and Procedures	0.991488
55	Hydrocarbon associated risk (process, turret and riser systems)	0.454357
	is the highest contribution for all FPSOs considered.	0.694676
57	Collision risk represents a significant contribution for two of the FPSOs (all potential collision)	0.005607
58	Scenarios are included, but shuttle tanker impact is the dominating contribution.	0.527423
59	Occupational accidents and accidents during helicopter transport were only included for one	0.25107
60	All the cases.	0.261401
61	Uncontrolled Release of Hazardous Materials	0.769407
62	Blowouts	0.142786
63	Turret and Cargo Tank Release	0.949124
64	Release of Non-Process Materials	0.901016
65	Topside Process Release	0.769164
66	Bunkering Operations	0.800986
67	Natural Adverse Occurrences Hazards	0.430831
68	Earthquakes	0.519753
69	Subsidence	0.846755
70	Severe Storm	0.033608
71	Tornadoes	0.900927
72	Physical Impacts Hazards	0.419685
73	Vessel Collisions	0.562891
74	Drilling Jackup Collision	0.356217
75	Fixed Wing Aircraft	0.806782

76	Missile	0.66652
77	Submarine Collisions	0.198745
78	Helicopter Collisions	0.402451
79	Dropped Objects	0.531651
80	**Structural Failures**	0.054705
81	FPSO Structural Failure	0.064833
82	Crane Structural Failure	0.300675
83	Process Vent Stack Failure	0.342143
84	**Fires Hazards within Enclosed Areas**	0.489227
85	Indirect Events	0.314163
86	Communications Failure	0.055235
87	Process Control Failure	0.206388
88	Operations or Maintenance Error	0.607366
89	Power Supply Failure	0.183286
90	Construction Error	0.465601
91	**Other Hazards**	0.893934
92	Diving Hazards:	0.843267
93	Process Analysis	0.757956
94	Occupational Hazards	0.555226
95	Environmental Hazards	0.03813
96	Offloading Operations	0.113766
97	FPSO Mooring System Failure	0.147519
98	Marine Operations	0.532911
99	Stability and Water Tightness	0.511993
100	Sea Keeping	0.418401
101	Structural Failure	0.921399
102	Personnel Transfer	0.600707
103	**TR Impairment**	0.770934
104	process/deck piping pool fire	0.391826
105	non-field vessel collision	0.629452
106	mooring line failure	0.905579
107	offloading vessel collision	0.992711
108	cargo tank fire/explosion	0.342772
109	others	0.237412
110	**Electrical Failure /Blackout**	0.102311
111	Power Management Systems	0.918463
112	Blackout	0.828628
113	1.Load Demands	0.865375
114	2.Generator Trips	0.605228
115	**Subsea Flowlines and Risers Failure**	0.803487
116	**Gas Lift/Export Flowline and Riser Systems**	0.864006
117	**Process Risks Causes**	0.49596
118	**Gas Leaks**	0.888224
119	a. Over Pressure	0.249184
120	b. Corrosion	0.648887
121	c. Blowout	0.402292
122	**2. Over Pressure**	0.651338
123	a. Rapid Valve Closure	0.342516
124	b. Pump Over Pressure	0.476087
125	**3. H2SCracking**	0.955437
126	a. Presence of H2S conditions	0.811973
127	**4. Rapid Decompression**	0.800665
128	**Mechanical Risks**	0.563077

129	1. Fatigue	0.846947
130	a. Age	0.832021
131	b. Pipeline Wear	0.252996
132	2. Riser Movement	0.916733
133	a. Water Current	0.750846
134	b. Movement of FPSOs	0.381637
135	Operational Risks	0.767096
136	1. Safety Valves Failure	0.92734
137	2. Operational Maintenance Negligence	0.617795
138	Human Risks	0.461933
139	In experience Operators	0.675503
140	Operational Negligence	0.790135
141	Design Oversight	0.402744
142	Lack of Training	0.493624
143	Poor Work Ethics	0.039122
144	Management Oversight	0.138692
145	Process Risks	0.757267
146	1. Wax Formation	0.421924
147	a. Operating Conditions at or below pour Temperature	0.069952
148	2. Hydrate Formation	0.445984
149	a. Operating Below Cloud Temperature	0.577469
150	3. Surges	0.074496
151	a. Over pressure	0.328886
152	4. Scaling	0.432894
153	a Presence of Barium Sulphate	0.320005
154	b. Corrosion materials	0.508234
155	5. H2S Corrosion	0.219939
156	a. H2S present	0.114418
157	b. Corrosion Environment	0.653914
158	6. CO2 Corrosion	0.989972
159	a. CO2 Present	0.605648
160	b. Corrosion Environment	0.561565
161	Mechanical Risks	0.522539
162	1. Dynamic Loading of FPSOs	0.948076
163	a. Movement of FPSOs	0.047636
164	b. Water or Ocean Currents	0.698753
166	2. Stress Corrosion Cracking , SCC	0.557259
167	a. H2S present	0.031665
169	3. Bending Load at Interfaces	0.474349
170	a. Operating Conditions	0.180089
171	b. Movement of FPSOs	0.099551
173	4. Leaks	0.572271
174	a. Over Pressure	0.6867
175	b. BlowOut	0.383203
176	c. Corrosion	0.916813
178	5. Operational Risks	0.819863
179	a. Pigging Operations	0.159734
180	b. Depressurization and Blow Out	0.585767
181		0.616658
182	Human Risks	0.377874

183	In experience Operators	0.783507
184	Operational Negligence	0.033003
185	Design Oversight	0.45068
186	Lack of Training	0.475881
187	Poor Work Ethics	0.283339
188	Management Oversight	0.252755
189	Turret Design Failure	0.943661
190	The passive nature of the turret design minimizes	0.46419
191	the station-keeping risk but increases the fire and explosion	0.302457
192	risks as the wind direction tends to align with the dec	0.290569
193	1.Damage to equipment caused by dropped objects	0.117465
194	2.Fishing gear impacts	0.86409
195	3.Leaks in the flexible piping because of aging riser	0.799673
196	4.Latent defects in design or manufacturing.	0.67855
197	Process Fires and Explosions.	0.051717
198	Note that because of the	0.252564
199	passive turret design, the wind tends to align with the deck, and a	0.201168
200	gas leak would reach the turbine intakes 77% of the time.	0.778077
		0.542618
	Fuzzy Class: General	
	Fuzzy Class: Weighted	
	Two Class of Safety	
	Occupational Related Hazards Reliability (95%)	
	Occupational Related Hazards Reliability(5%)	
	Occupational Related Hazards Reliability (95%)	
	Occupational Related Hazards Reliability (5%)	
203	Human Personnel Resourse Hazards	0.785607
204	OIM	0.511124
205	Production Supervisor	0.865187
206	Maintenance Coordinator	0.180422
207	Shift Supervisor	0.8816
208	Production Operators Staff (oil, gas, utilities)	0.148113
209	Instrument Engineer	0.498624
210	Instrument Technician	0.060353
211	Electrical Staff	0.850599
212	Mechanical Engineer	0.803781
213	Mechanical Technician	0.119317
214	Subsea Staff	0.181005
215	Berthing Master (Also Tanker Safety Supervisor)	0.995288
216	Marine Supply	0.796298
217	Offloading Support Staff	0.583852
218	Telecoms Engineer	0.111915
219	Medics/Admin	0.093324
220	Core Offshore Crew	0.668866
221	Crane Operator	0.612093
222	Facility Management (including Catering)	0.356764
223	Core Offshore Services Crew	0.838698
224	Specialist Operations Staff (including Loading)	0.034068
225	Intergated Service Contractor Staff	0.091184
226	Revenue Engineering	0.287148
227	Commisioning Allowance	0.000236
228	Total Services and Suport	0.562159

230	Campaign Offshore Crew	0.073438
231	Government Reps	0.785982
232	Human Hazards	0.138105
233	Human errors are of Seven Types	0.144795
234	1. Design Errors	0.229739
235	2. Operators Error	0.294726
236	3. Fabrication Error	0.171199
237	4. Maintenance Error	0.818781
238	5. Inspection Error	0.32683
240	6. Contributory Error	0.893129
241	7. Handling Error	0.615725
242	1. Poor Training or Skill	0.171947
243	2. Poorly documented or Lack of Documented and Updated Operational Procedures	0.213275
244	3. Environmental Factors and Occupational Safety	0.733409
244	4. Poor Incentives by Management	0.661781
244	5. Negligence and Organizational Attitudes	0.543797

a) Safety Factors Design

The plot of failure rate and reliability rate as revealed in Figure 7 and Figure 8 respectively show a parabolic curve with a peak maximum at five years. The measure of failure rate determined as number of failures per year of personnel for the FPSO predicted a peak of 2 fatalities within 5 years which is good performance and tapers down due to improve performance. Whereas the predicted reliability FPSO degrades over a period of time reaching all time high of 2.7% poor performance. The poor performance of reliability may be due to over design of some facilities. Figure 9 and Figure 10 are the predicted safety and risk potential which is the net risk and safety factors put in place based on all possible scenario of Table 3.0, we have a net average risk potential to FPSO increasing slowly in a parabolic fashion reaching a threshold after 15 years and peaking at a maximum. The risk potential is the measure of risk over the reliability of the safety systems. Since the studied FPSO risers, hull and production facilities have been overdesign against risk by putting in place the safety measures, the relative risk profile is low and therefore risk potential is a good measure to determine the measure of risk. A cursory look at the safety potential shows a continual degrade of safety measures of time. The complicated interrelated threats all work to undermine facility and therefore recommended repair operations is recommended. The plots presented in Figure 7, Figure 8, Figure 9 and Figure 10 are based on the simulated table based on Monte Carlos simulation of the hazard data supplied by operators assuming occupational related hazard risks of 95%, process related hazards reliability of 5%, and their measures of safety simulated by the deterministic model and learning algorithm disclosed in our work.

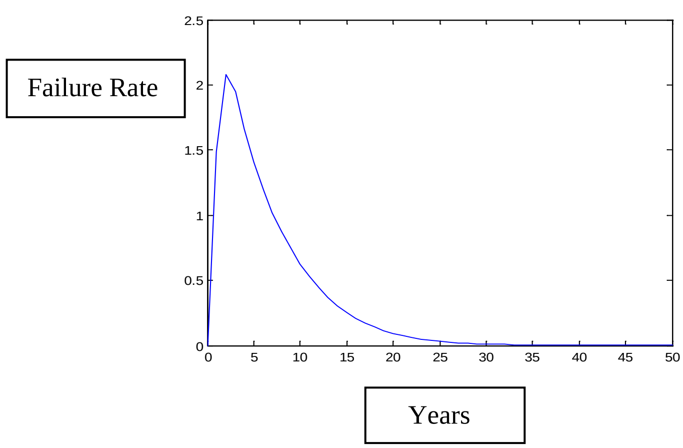


Figure 3: Plot of Reliability rate with time of Riser System

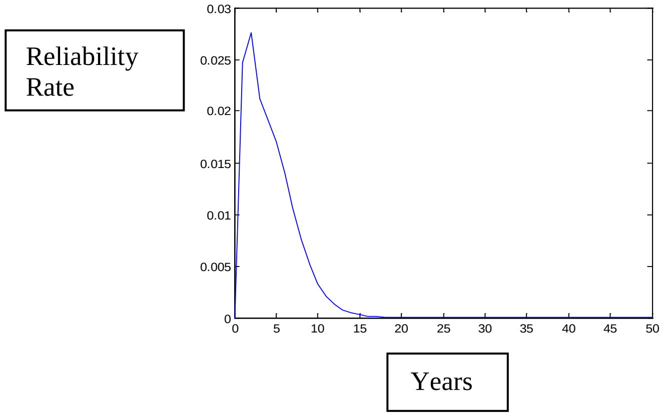


Figure 4: Plot of Reliability Rate with time of FPSO Riser System

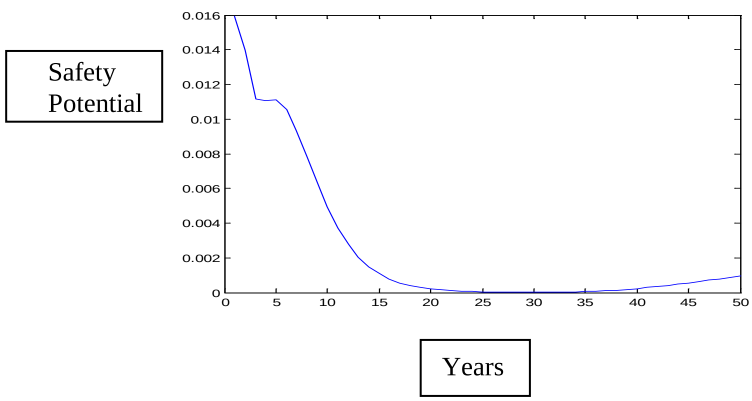


Figure 5: Plot of Safety Potential with time of FPSO Riser System

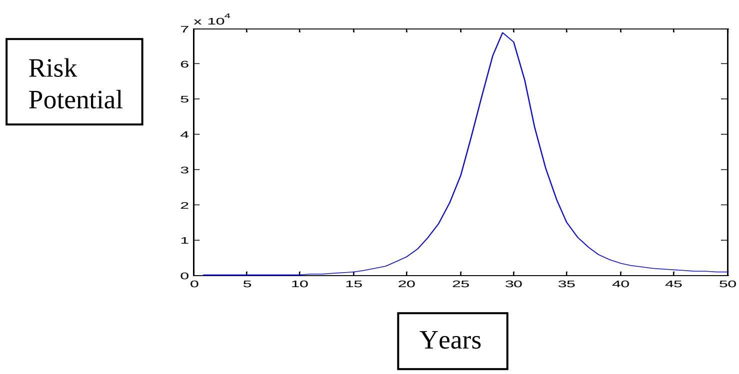


Figure 6: Plot of Risk Potential with time of FPSO Riser System

b) Weighted Hazard Rate and the Belief Function

This section discusses plots of weighted hazard rated and belief function. Thus Figure 11 shows the weighted hazard rate with the hazard shape function. The hazard shape function describes the nature of risk. A hazard shape function of 1 is a constant hazard rate, below 1, is a decreasing hazard rate and above is the increasing hazard rate. The weighted hazard rate shows increasing hazard rate is significant. By the term weighted hazard rate implies a safety measures have been incorporated and takes into consideration change in hazard behaviour. A safety fraction of 0 shows a hazard rate at its minimum and decreases as safety fraction increases. The belief function describes the level of confidence an operator views the reliability of such systems. A reliability of 90% at fuzzy class 1, very likely to occur, a linguistic term shows a belief function that is parabolic with time.

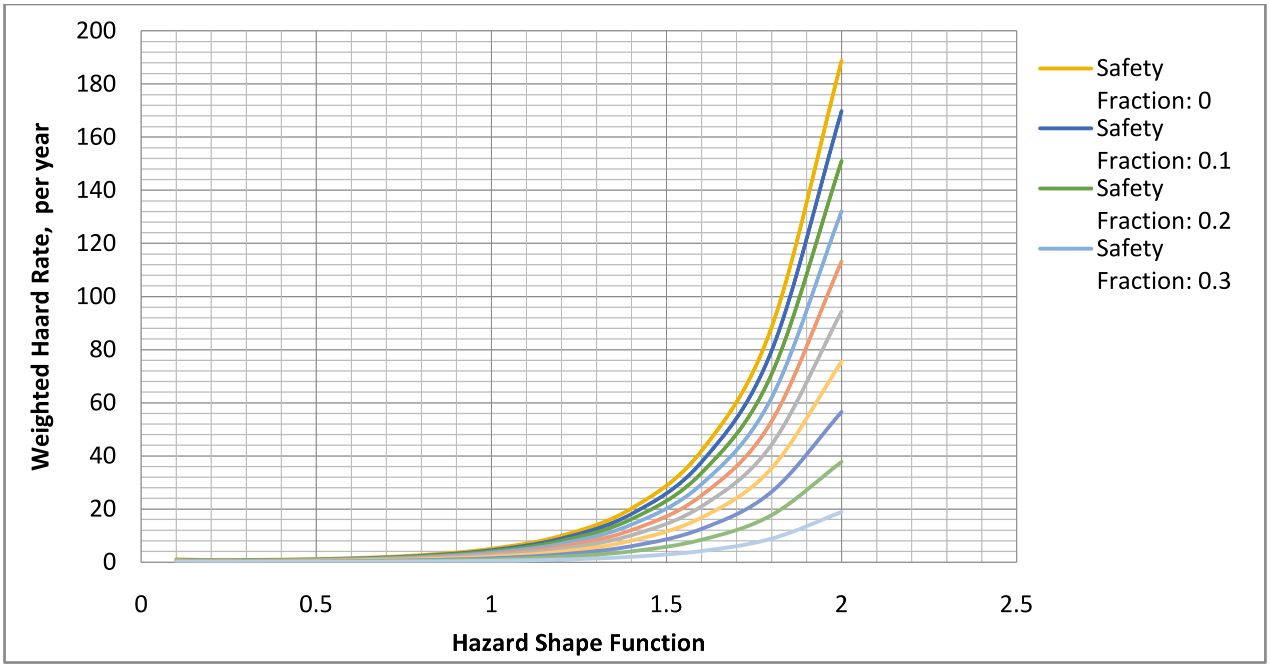


Figure 7: Weight Hazard Rate with Hazard Function for Fuzzy Class 1

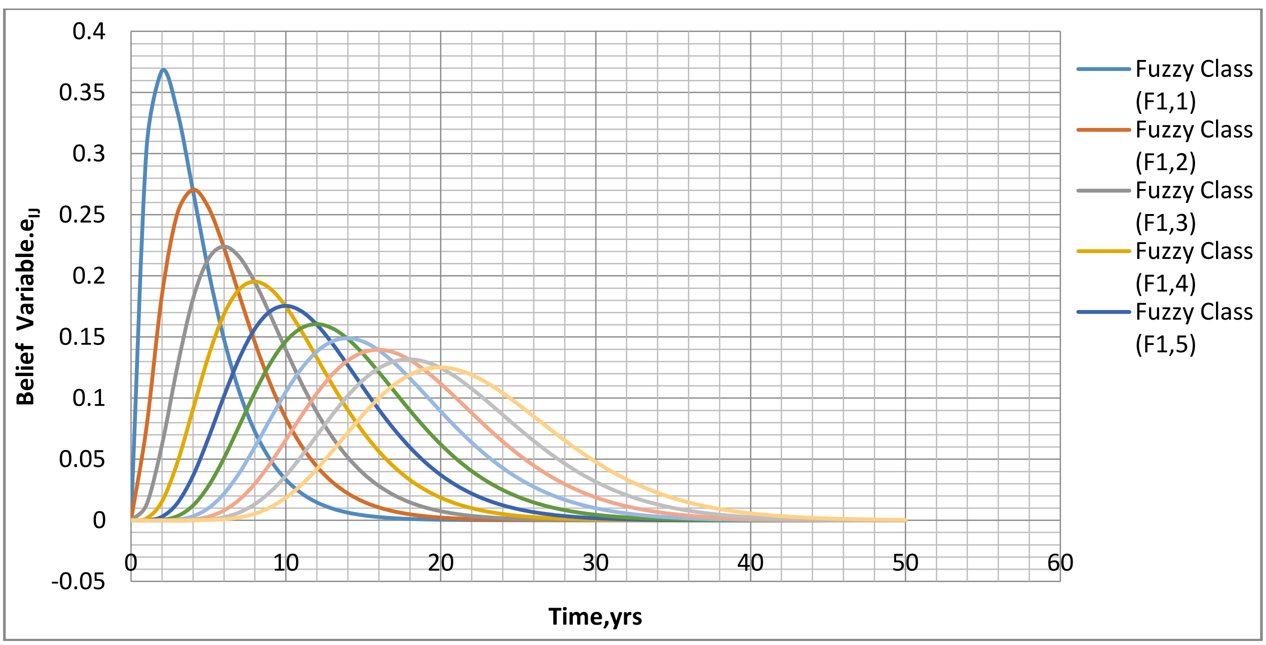


Figure 8: Plot of Belief Variable e_{ij} with Time (yrs) for Fuzzy Class 1 for 90% Safety Level Protection for different fuzzy failures F1(1,-10)

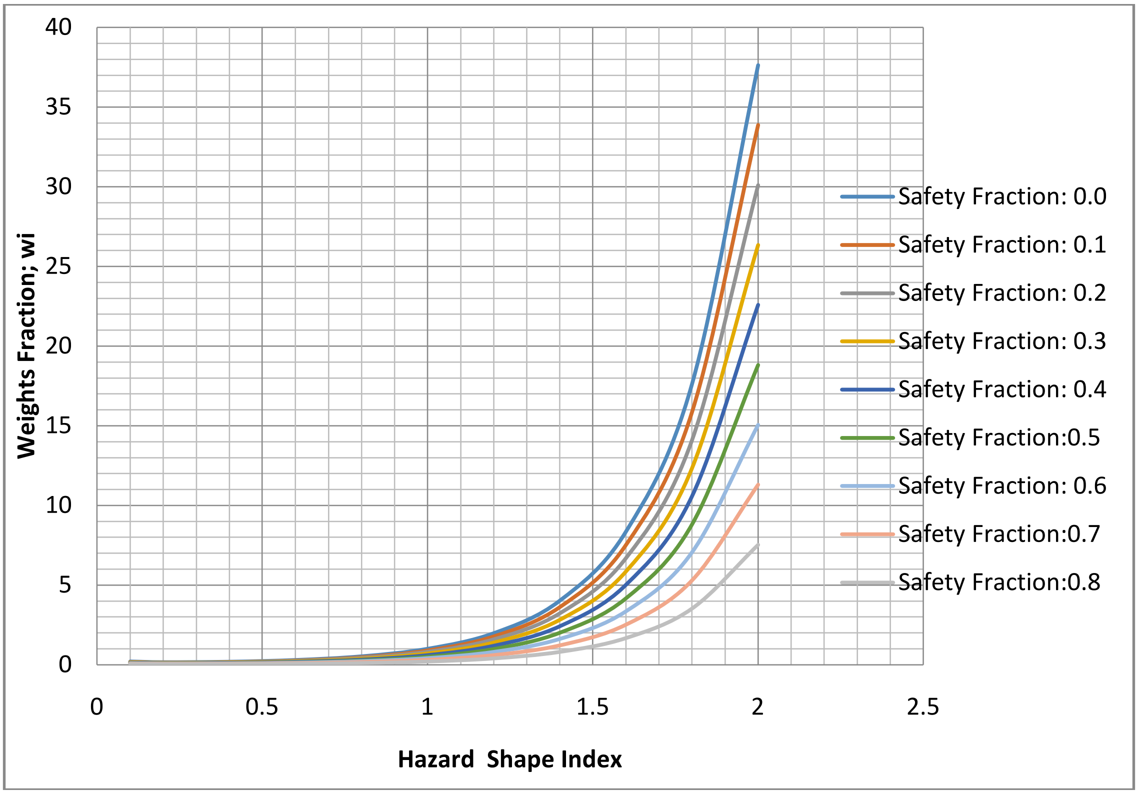


Figure 9: Weight Index Variation with Hazard Shape Index for Different Class of Safety Fraction for Fuzzy Class 1

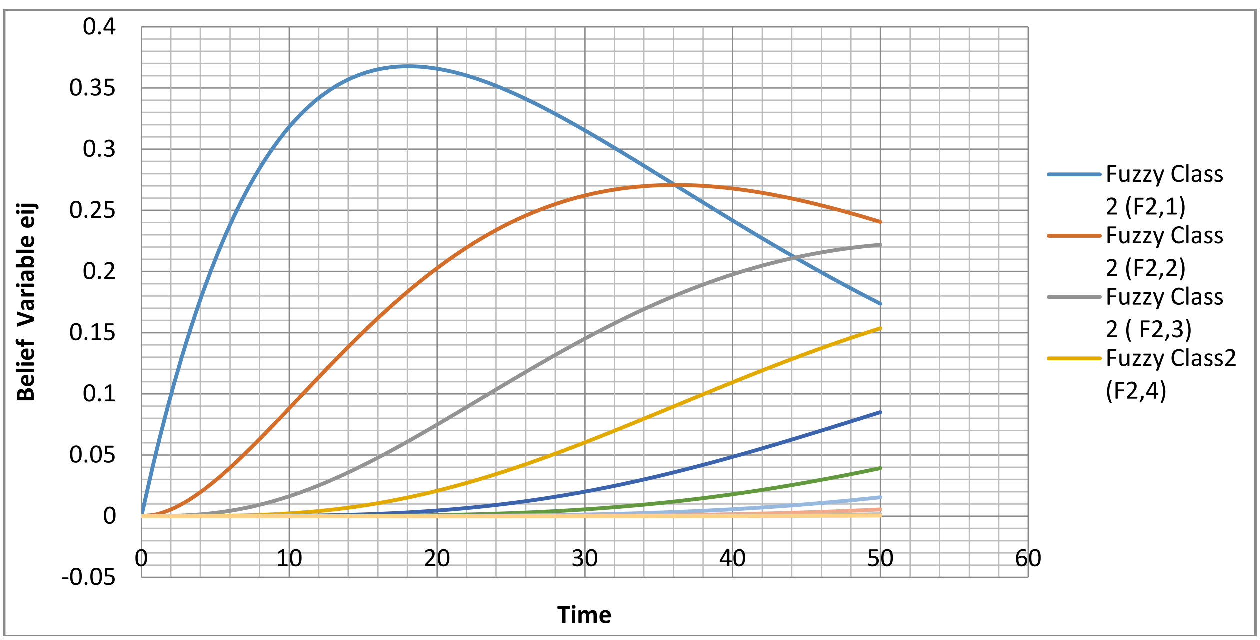


Figure 10: Plot of Belief Variable e_{ij} with Time for 90% Safety Protection for Fuzzy Class 2 for Fuzzy Failures 1-10

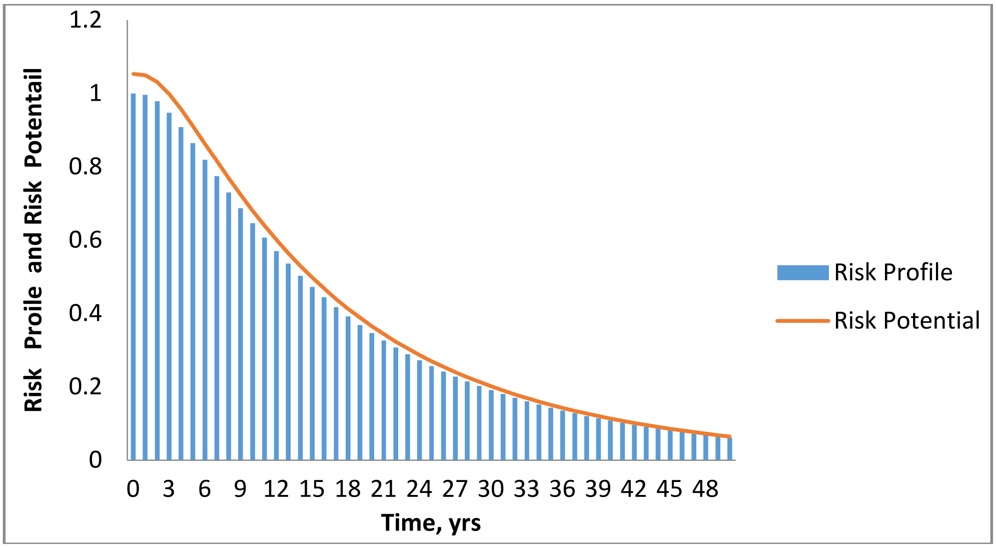


Figure 11: Plot of Risk Profile and Risk Potential for 0.95 Safety Reliability

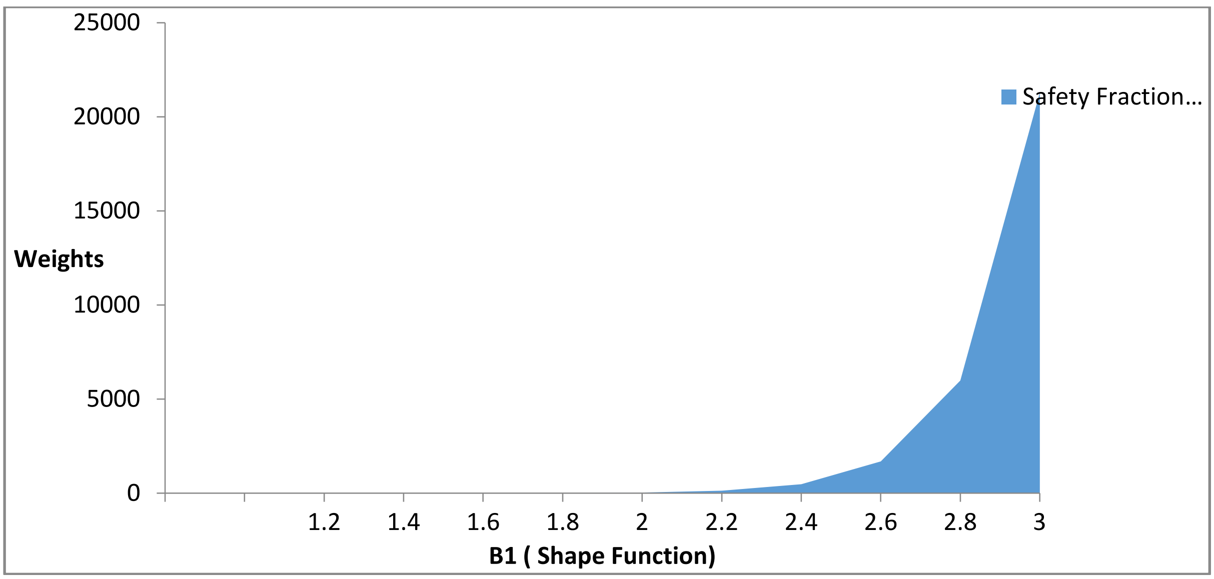


Figure 12: Weights Function against Hazard Shape Function B1 for Safety Fraction of 0.9

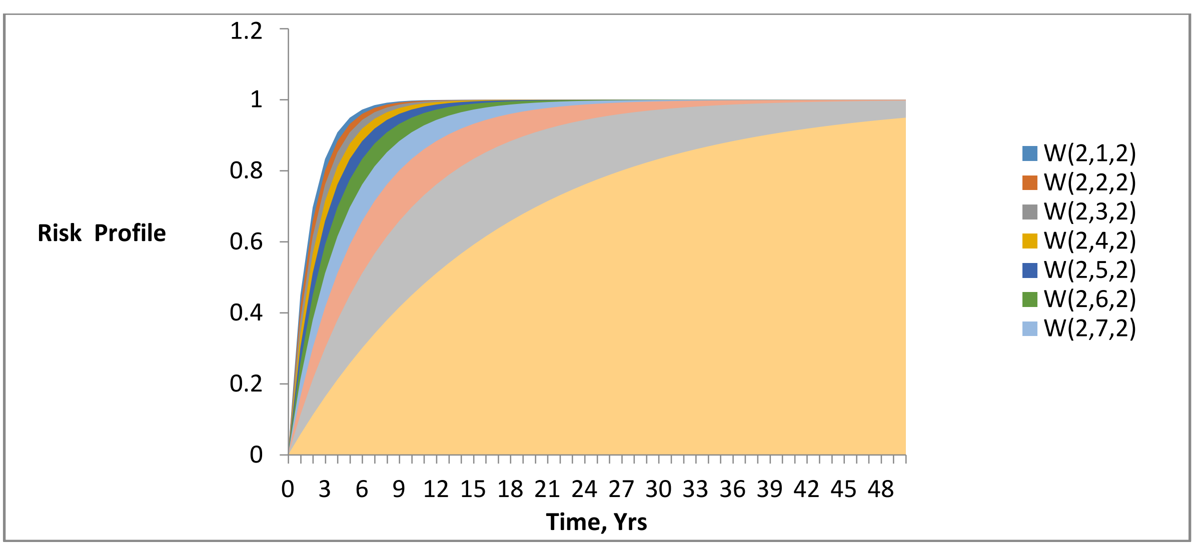


Figure 13: Risk Profile with Time for B (1.8) , Fuzzy Class 2 and Weight Function (B1, SRFi) : SFRi (0,0.1, 0.2......0.9)

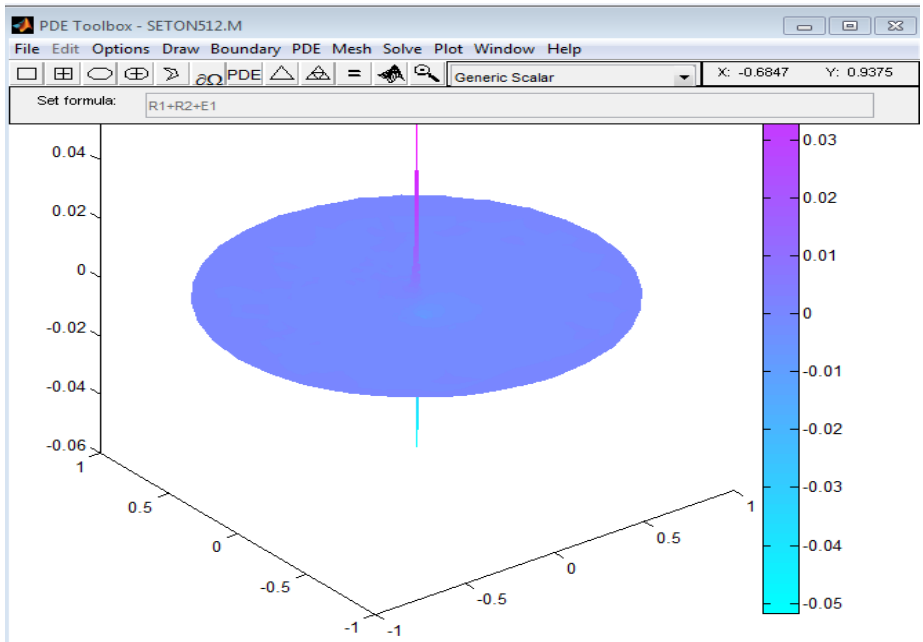


Figure 14: PDE tool box displaying a plot of the initial boundary conditions

The MAT file derived from the PDE tool is feed into the neural networks tool box as a source of raw data in other for the fitting networks, Perceptions and predictive control networks to be trained. In this work, it was saved as data.mat

For the curve fitting networks

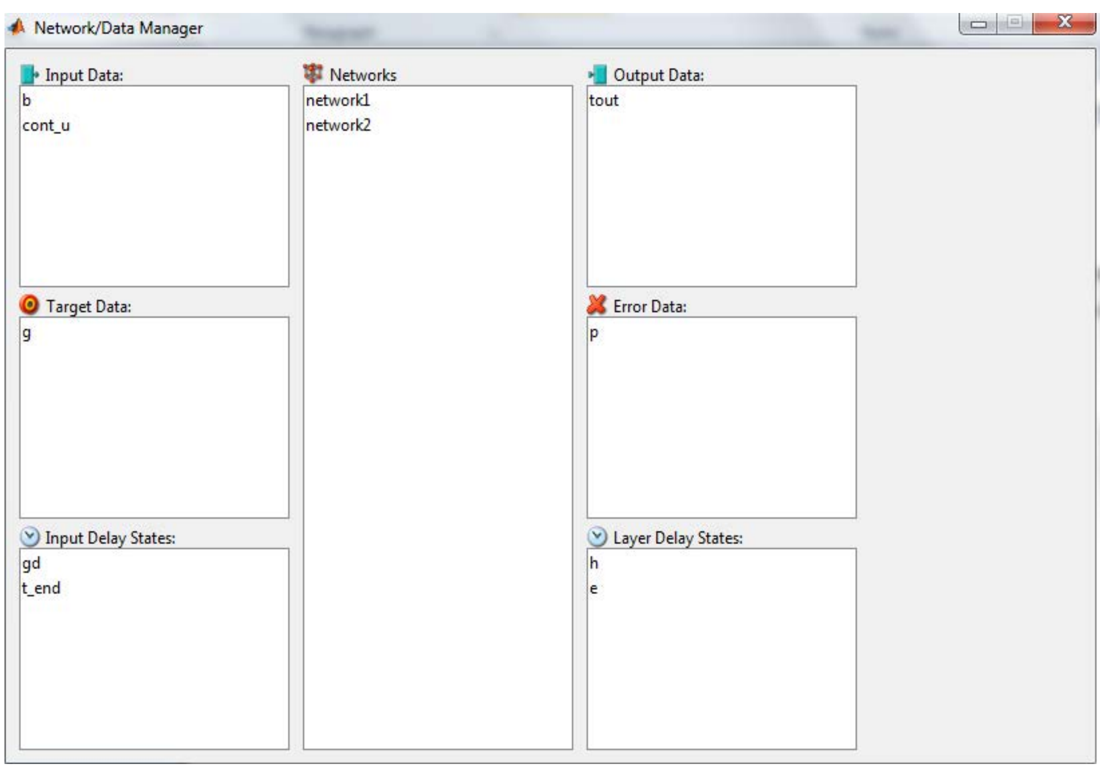


Figure 15: MATLAB neural networks data manager

Here is the neural networks data manager showing the functions and data imported from the model in the PDE tool. All variables represented by letters in the network/data manager signify various vectors and matrices derived from the risk that have been further simplified with learning algorithms.

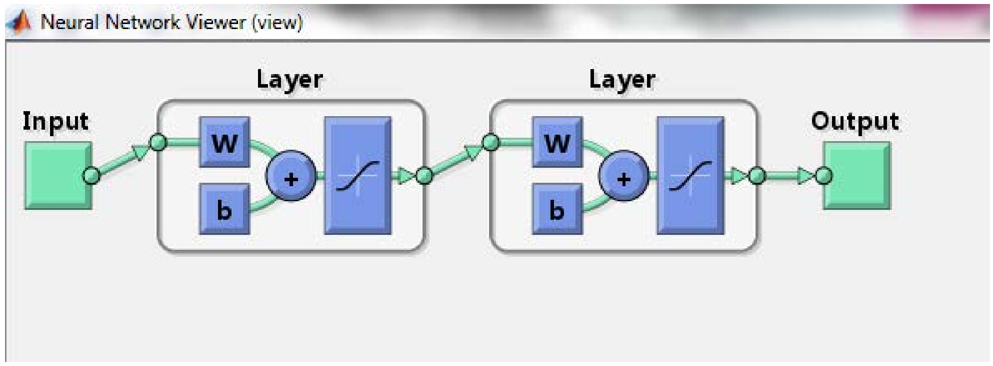


Figure 16: MATLAB neural network viewer

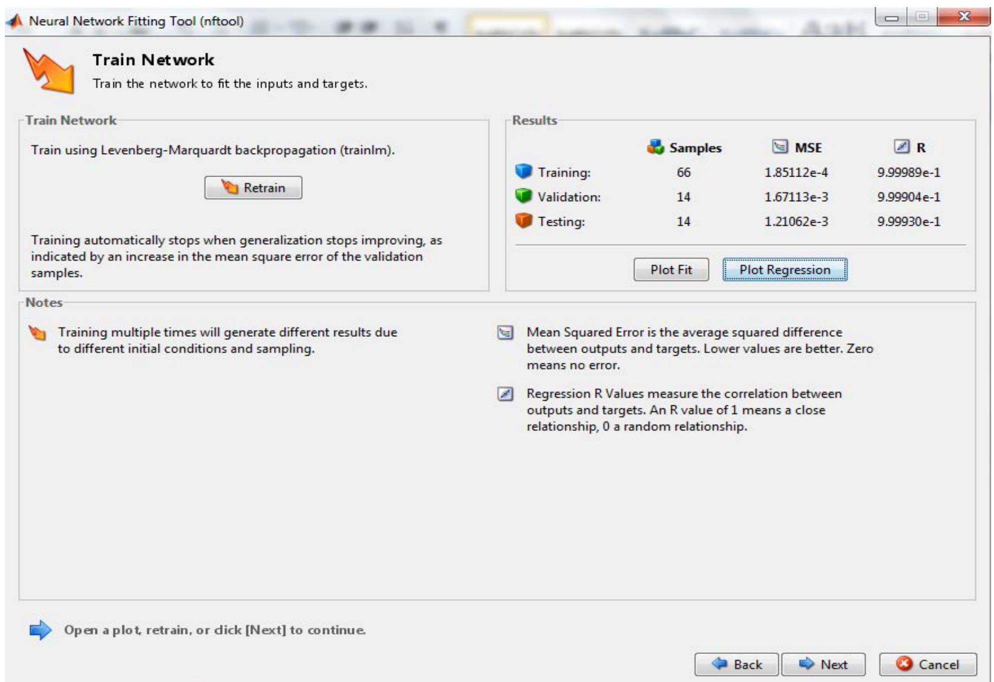


Figure 17: MATLAB neural network fitting tool

The network is to be trained using levenberg-Marquardt back propagation. Levenberg-Marquardt is the best training algorithm adopted for .complex problems and the application of multiple networks in solving problems like Risk system in oil and gas riser systems

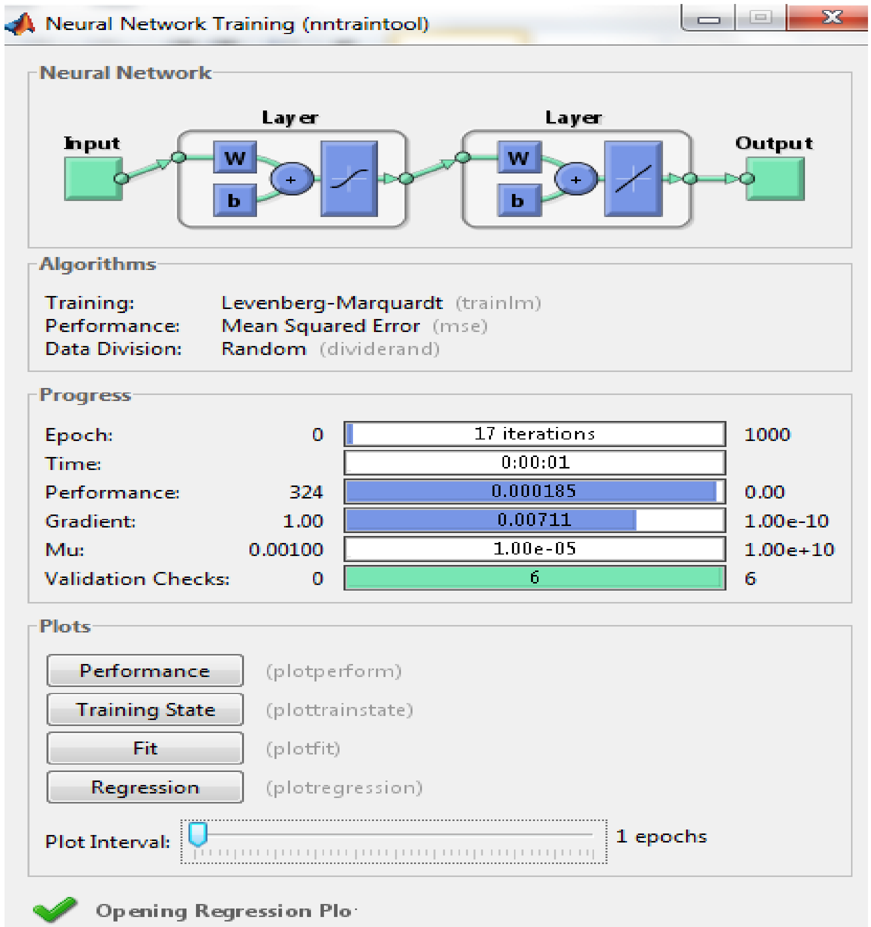


Figure 18: MATLAB neural network training tool

The general graphic user interface (GUI) for the neural network in training showing the training procedures and a link for the outcomes of the training like the performance, training state, fit, regression Here is the performance plot for the performance.

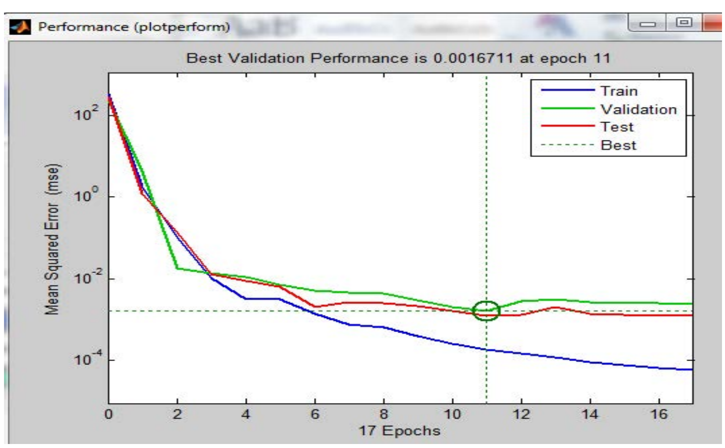


Figure 19: performance plot

This is for 11 iterations known as epochs

This training stopped when the validation error increased for six iterations, which occurred at iteration 23. If you click Performance in the training window, a plot of the training errors, validation errors, and test errors appears, as shown in the following figure. In this example, the result is reasonable because of the following considerations: The final mean-square error is small. The test set error and the validations set error have similar characteristics. No significant over fitting has occurred by iteration 17 (where the best validation performance occurs).

Global Journal of Science Frontier Research (A) Volume XX Issue III Version I Year 2020

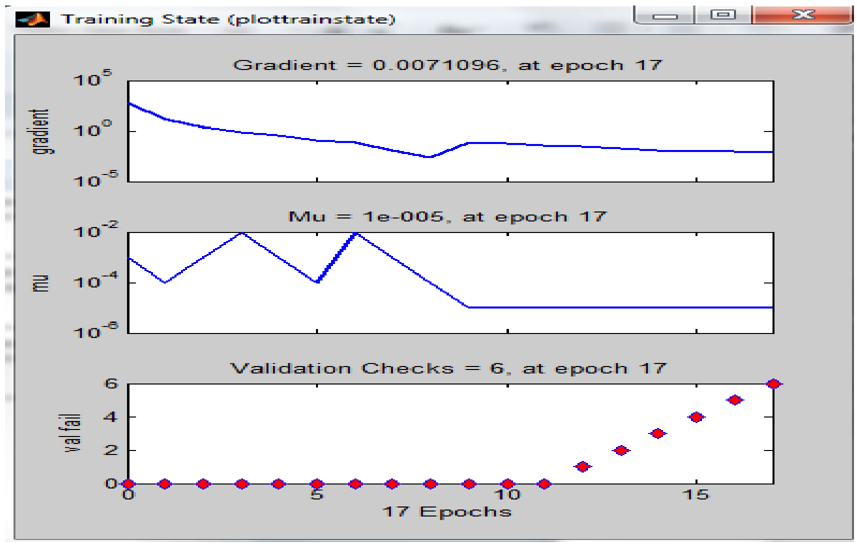


Figure 20: Training state

This is the training state. These plots are characteristic to a group of distributions of vectors fed from the model to be used in predictive control and decision support. Any deviation from this plot will be recorded and seen as anomaly during Risk system.

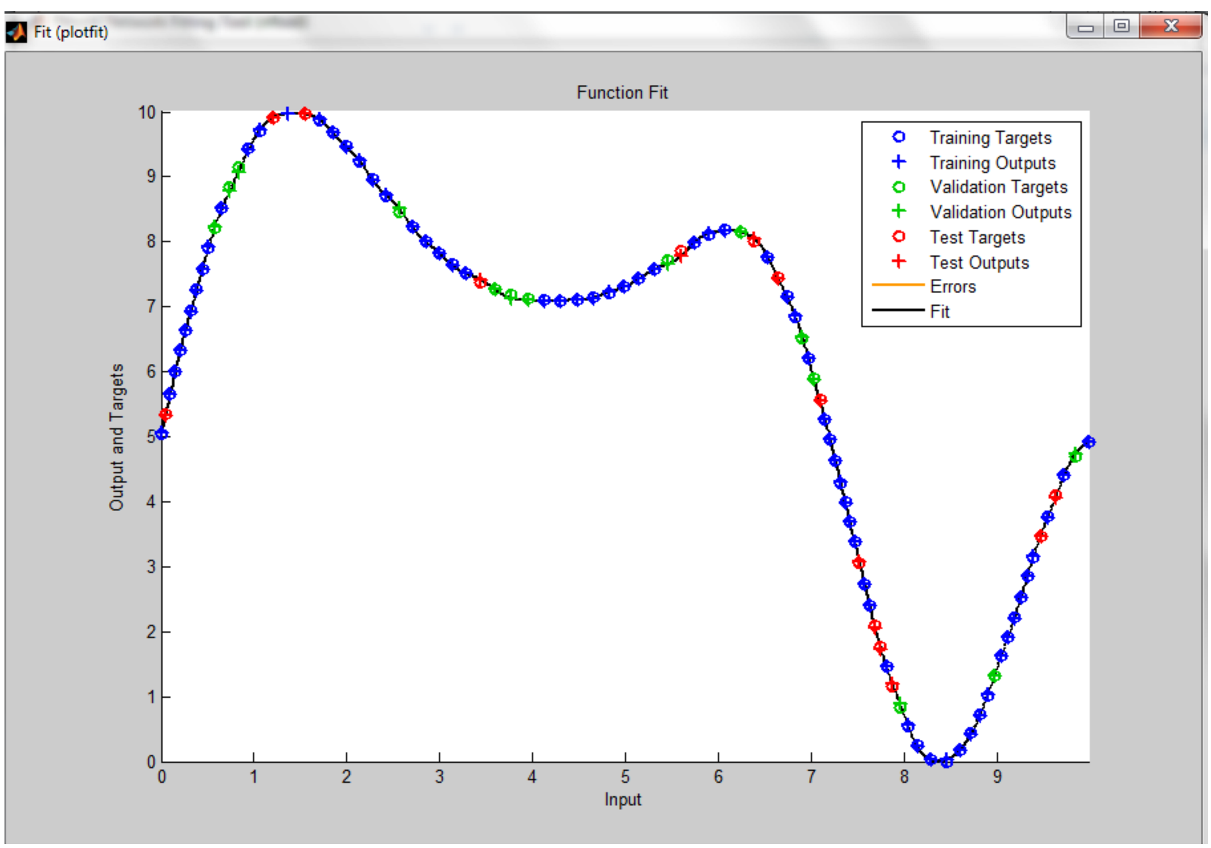


Figure 21: Neural Network Fit

This is a plot fit between the input functions (the pressure distribution data of the field during Risk system production) and the output data which is the Risk systeming factor C_f and the targets which is the true value the dimensionless pressure used in the IMPES PDE model. The training targets are shown by the blue circles while training inputs are the blue +, validation targets and Output d is green respectively while test details are red, Errors appear orange the fit is black.

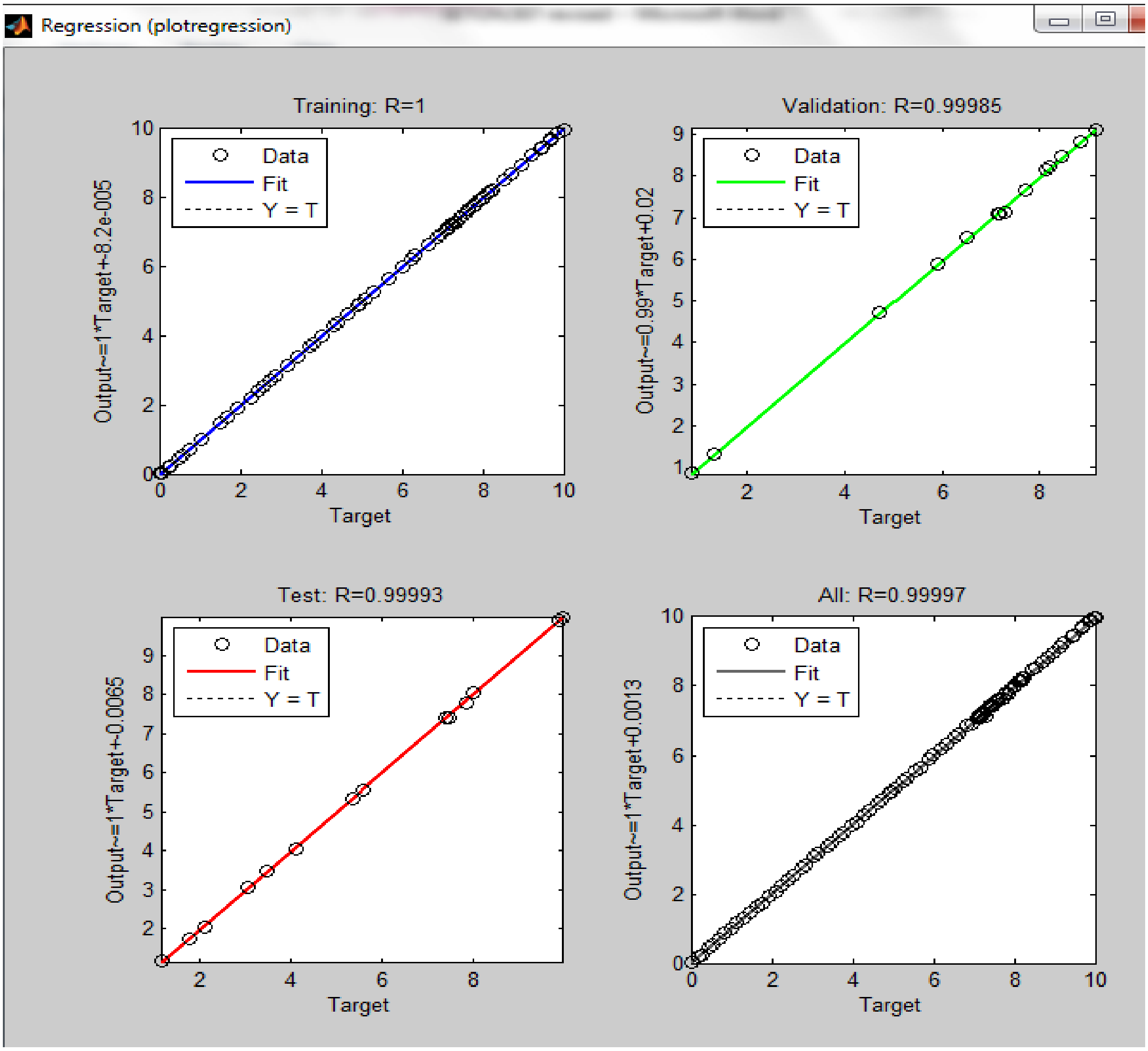


Figure 22: Regression plot

Here is the regression analysis for the network trained. An interpretation of these reports can be used for the decision support system. Further production process management can be conducted to a point where each Risk systeming rate and Risk systeming factor will be identified separately by a Regression pattern of two characteristic to it. This can help in predicting future rate of Risk system. And in the decision making process of a production team. All the output from the neural networks can be used to design a hardware system that has been programmed to generate these output when fed with data from the production system, this system generates output, stores them in its memory and compares them with the previous output generated as production continues. A transition from a point of minimal Risk systeming to a critical Risk systeming can be noticed by this system. The system would trigger an alarm or other forms of communications (probably red light) to inform the Production Personnel.

VI. Conclusion and Recommendation

The Learning algorithms provides a method of resolving risk modelling of complex production systems. The production platforms, storage and riser/flowline systems was considered for distribution of risk factor at different times and along the. Data is obtained from the production system and fed into the neural networks the difference in patterns signifies a difference in the condition of the production system. This project involves a series of projects starting from Risk system production modelling, to Risk system management technologies, Risk system transportation modelling and simulations etc. it is recommended that the background of Risk systeming problems be taught in Petroleum Production Engineering courses. The knowledge of various tools for this kind of simulation should be introduced to the engineering curricular.

Global Journal of Science Frontier Research (A) Volume XX Issue III Version I Year 2020