APPLICATION OF ARTIFICIAL NEURAL NETWORK IN PROCESS SAFETY ASSESSMENT

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DECLARATION

I hereby, declare that this manuscript, entitled “Application of Artificial Neural Network in Process Safety Assessment”, is the result of my own work except for quotations and citations which have been duly acknowledged. I also declare that, to the best of my knowledge and belief, it has not been previously or concurrently submitted, in whole or in part, for any other degree or diploma at Nazarbayev University or any other national or international institution.

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Abstract

Quantitative risk assessment is a crucial step in safety analysis of process systems. Advancement of modern technologies has resulted in availability of large volume of process data. This tendency urges the need of developing new risk assessment approaches. Fault tree (FT), a conventional risk analysis method, is found to be ineffective in dynamic risk analysis and data analytics due to its static nature and reliance on experts' judgment in developing stage. The use of artificial neural network (ANN) in risk assessment of process systems is not a new concept. ANN is a structured model that is built upon data samples and learning algorithms to process complex input/output data in the way that it is trained. The application of ANN can help to overcome some of the limitations of FT. The dynamic and data-driven nature, independency on prior information on events relationships, and less reliance on experts' judgement are the advantages of ANN over FT. However, there is limited work on the development of ANN-based risk assessment models using the conventional methods such as FT as an informative base. This study proposes a methodology of mapping FT into ANN to support convenient and effective application of ANN in risk assessment. The proposed method is demonstrated through its application to failure analysis of one of the causes of Tesoro Anacortes Refinery accident. The results of network's accident modelling performance have shown

that the ANN model (mapped from the FT) is an effective risk assessment technique in terms of application for estimation of the TE failure probability.

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List of Abbreviations & Symbols

ANN	Artificial Neural Network
BE	Basic Event
BT	Bow-tie
CSB	U.S. Chemical Safety Board
ET	Event Tree
ETA	Event Tree Analysis
FT	Fault Tree
FTA	Fault Tree Analysis
HTHA	High Temperature Hydrogen Attack
IE	Intermediate Event
MLP	Multi-layer perceptron
MSE	Mean squared error
P_i	Probability of event i
QRA	Quantitative risk assessment
R_{XY}	Pearson correlation coefficient of output (X) to input (Y)
RPB	Release Prevention Barrier
TE	Top Event
w_i	Synaptic weight of connection i
x_i	Input signal of neuron i

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Chapter 1 - Introduction

1.1 Past Accidents in Chemical Process Industries

Modern tendencies of sophistication and digitalization in the current process systems have resulted in increase of their performance in terms of productivity and efficiency of data utilization. Nevertheless, this progress carries a considerable risk of failure in process systems (Adedigba et al., 2017). These failures may result in catastrophic accidents with human and assets losses, such as:

- The Bhopal Disaster (1984) with immediate deaths of 3800 people caused by accidental release of around 40 tons of toxic methyl isocyanate (MIC) gas (Broughton E., 2005);
- The Arco Chemical Company plant accident (1990) resulted in 17 death from explosion of flammable gas mixture in water storage tank during maintenance operations (Ainsworth and Lepkowski, 1990);
- The BP Texas Refinery accident (2005) with 15 workers killed by ignition and explosion of flammable hydrocarbon vapor cloud released due to overflow in isomerization unit (CSB, 2007); and
- The Deepwater Horizon blowout accident in the Gulf of Mexico (2010) resulted in 11 deaths and the largest marine oil spill in human history (Adedigba et al., 2017).

The development of the Safety Engineering as a separate field of study itself and numerous recommendations to the specific processes, procedures, equipment and materials standards etc. are the results of the investigation of such accidents (Crowl and Louvar, 2011). The accident investigation process typically requires the use of special techniques or approaches to determine the causes and scenario of the accident.

1.2 Process Safety Assessment and Management

Accidents often take place as a result of abnormal events occurred in complex and nonlinear interactions between the elements of process systems including equipment, personnel, organizational structure, environmental conditions, etc. (Adedigba et al. 2016). This trend has led the chemical process industry to the incorporation of safety management in systems design, operation and control stage and to the development of effective risk assessment tools.

Process safety management (PSM) is mainly focused on the prevention and mitigation of process accidents that are presented in chemical industry mainly by fires, explosions and toxic releases. PSM usually starts from the identification of a system’s existing hazards. The hazard identification methods include checklists, surveys, hazards and operability studies (HAZOP), safety reviews, etc. (Crowl and Louvar, 2011). These approaches help to perform effective and detailed analysis of risks associated with equipment, hazardous materials and procedures.

Risk is defined as ‘a potential of loss’ that occurs due to activity of human or natural processes. Loss is mainly described by damage to human life, environment, equipment and days outage (Modarres, 2006). Risk assessment techniques are applied to selected hazards in order to identify incidents and analyze the consequences. They aim to estimate the probability and the magnitude of potential losses from an accident. After the possible accident scenarios are identified, their corresponding occurrence probabilities and consequences are predicted using risk assessment models. Those models that include consequences magnitude determination are termed as quantitative risk analysis (QRA); while the models that only deal with probability estimation are called probabilistic risk assessment (PRA) methods (Crowl and Louvar, 2011).

Safety management is applied in order to establish the correct procedures that allow prediction, minimization and control of losses occurred due to risk exposure (Modarres, 2006). The tools applicable in safety management include legal policies development, equipment and procedures standards establishment, development of operations instructions, control measures, etc. (Crowl and Louvar, 2011).

The continuing occurrence of these catastrophic accidents indicates that the development of process safety analysis approaches is unable to keep pace with the rapid technological development. This urges the need of research to advancement of safety analysis tools. Last decades have seen a number of studies on accident analysis and prediction (Adedigba et al., 2016; Ruilin and Lowndes, 2010; Zhang et al., 2018), process safety analysis (Khakzad et al., 2011; Kang et al., 2008; Diez, 2007), fault prediction and classification (Nagpal and Brar, 2014; Li et al., 2018), probabilistic risk assessment (Yang et al., 2015; Unnikrishnan et al., 2014), and etc. Risk assessment is an essential component of these approaches. The use of risk assessment methods in process safety assessment allows identifying hazards, performing accident causes and consequences analysis, and modeling the accident (Crowl and Louvar, 2011).

1.3 Risk Assessment Methods

Qualitative risk assessment approaches, such as hazard identification (HAZID) and hazard and operability (HAZOP) are used to identify potential hazards, possible accident causes, and potential solutions in process system design. Quantitative risk analysis (QRA) approaches aim to quantify the probabilities and consequences of accidents (Khakzad et al., 2013; Adedigba et al., 2017; Yang et al., 2015). The main advantage of the quantitative risk analysis is consideration of both frequency and severity in a more comprehensive mode with determination of likelihood of accident occurrence and their loss. The use of these approaches in accident scenario analysis allows evaluating the system failure risk probability and accident consequences in process systems. The results of the application of these methods include the development of such risk assessment tools as proper safety barriers, operation standards, and design solutions, etc.

Layer of protection analysis (LOPA) is a semi-quantitative method used for risk assessment. It characterizes and categorizes the consequences and evaluation of layers of protection efficiency for the identified accident scenarios. Its results are more conservative in comparison with QRA in terms of the assessment of uncertainties associated with accident modelling (Crowl and Louvar, 2011).

Accident models are the main risk assessment tools that represent theoretical structure of selected scenario. These models are used for systemization and evaluation of the accident root causes and their corresponding effects. By using accident models, the experts are able to identify the accident causes and track failure routes. Accidents models can be classified in number of ways depending on the purpose of use, which include fault tree (FT), event tree (ET), bow-tie (BT), and Bayesian network (BN) (Adedigba et al. 2016).

FT is a deductive approach which allows determining and classifying the occurrence probability of accident called top event (TE). FT is a schematic representation of accident occurrence scenarios represented by combination of components called basic events (BE) and logical gates that form a system that triggers the top event (Crowl and Louvar, 2011). FT can be easily computed using various software tools as the logical gates follow the Boolean logic rules.

Also, minimal cut sets, failure probabilities and graphical constructions can be obtained. However, several disadvantages of FT complicate the application of this method in chemical process industry. For example, the FT developer can never be certain that all failure modes have been considered as for any complicated process the fault tree will be enormous (thousands of BEs and gates). Also, no assumption of stressing of components on each other and no assumption of partial failure of component are considered in FT. Finally, structure and results of trees made by different people are different for the same process as its structure is totally based on expertise's judgment.

ET is inductive technique that is aimed on determination and quantification of occurrence probability of specific post-accident consequences (Crowl and Louvar, 2011). The analysis begins with initiating event and is used to evaluate consequences prevention barriers. ETs can be easily computed using various software tools with the use of reference libraries for different types of equipment. Therefore, possible modification in process design can be done in order to improve the safety. However, ET does not provide the framework to evaluate whether the selected safeguards are sufficient. Single orientation of tree as only one initiating event is studied while independency of barriers' function is assumed in analysis which is not true in real process systems. This aspect of ET can be considered as a main disadvantage of the method as it does not provide certainty that particular consequences have taken place due to occurrence of selected failure (Rausand and Hoyland, 2004).

BT is an approach combing FT and ET. Thus, it is both inductive and deductive. This allows the experts connecting the causes of an accident to its consequences. BT represents the whole scenario of an accident where the central element is top event of fault tree and initiating event of event tree. This schematic can give a clear picture of the threat controls and consequences. It demonstrates the links between accident causes, loss events, conditional events and outcome events (Yan et al., 2016). However, the application of BT carries drawbacks of the use of both FT and ET described above.

1.4 Objectives and Aims

To overcome the limitations of conventional risk assessment methods, artificial neural network (ANN) can be applied in risk assessment of process systems. This study aims to investigate the development and application of ANN-based models for the risk assessment of process systems. The main objectives are:

- To develop the implementation and mapping algorithms to covert fault tree (FT) to ANN by using FT as an informative base;
- To study the performance ANN as a risk assessment tool; and
- To demonstrate application of the ANN-based risk assessment approach through the Tesoro Anacortes Refinery explosion accident.

1.5 Thesis Structure

The remaining part of this manuscript is organized as follows. Chapter 2 presents an overview of the main aspects of ANNs and its comparisons with other risk assessment approaches. The mapping methodology is proposed in Chapter 3. Chapter 4 presents the application of the proposed approach. The results of the application and corresponding analysis are given in Chapter 5. Finally, Chapter 6 is devoted to the conclusions and recommendations for future work.

Chapter 2 – Literature Review

2.1 Probabilistic Risk Assessment in Process Systems

Probabilistic risk assessment (PRA) is a methodology applied for translating accident initiators into risk profiles. The accident initiator is usually a failure that occurs with likelihood that can be decreased by performing preventive actions. As the failure takes place, the consequence barriers are applied in order to mitigate the losses and corresponding consequences occurrence risk profiles. Therefore, PRA can predict the main accident scenarios with some level of accuracy depending on the characteristics of selected technique (Kumamoto and Henley, 1996). However, the predictive ability of PRA approach is considered to be highest from the known methodologies (vonHerrmann and Wood, 1989).

FT is a conventional failure analysis tool of PRA, which allows determining and analyzing the occurrence probability of a system failure, i.e., TE. The strength of FT is that it provides a structured and graphical representation of failure analysis of complex systems along with the capability of failure probability quantification (Clifton A. Ericson II, 2000). This deductive method is able to analyze various occurrence scenarios of selected undesired events. The application of FT in risk assessment has the following weakness:

- FT is static in nature and it cannot perform structural adaptation to model dynamic development of process failures (Khakzad et al., 2013);
- FT cannot consider the cases of component partial failure. In the cases of partially working equipment, it is assumed that this component completely fails (Baig et al., 2013);
- The interactions and interdependency among system components are not considered in FT as all basic events are treated as independent events (Bobbio et al., 2001; Khakzad et al., 2011);
- The experts' knowledge and their assessment may be incomplete and biased. FT does not include all modes of system failure that can take place during operation (Crowl and Louvar, 2011); and
- A FT for a complex system with thousands of events and gates is challenging to handle in data analytics of process systems.

Another probabilistic risk assessment technique that combines both qualitative and quantitative study of the system is ET. It is an inductive procedure that is based on binary logic which implies that event has or has not happened or failure of system component called barrier has or has not taken place. Then, possible outcomes are considered during analysis and corresponding level of risk is possible to be estimated via use probability of failure data for barriers (Rausand and Hoyland, 2004). An ET starts from initiating event (IE) that results in activation of first barrier and basing on success or failure of it, two corresponding branches are shown. Then, the procedure repeats for following barriers depending on the system structure; therefore, probability of failure data for each barrier is required for quantitative analysis of the accident consequences. ET is useful for determination of multiple failures, probabilistic calculations, identification of system effectiveness and its weaknesses. The drawbacks list of this method includes single orientation of tree as only one initiating event is studied. Also, the barriers' function is considered to be independent on each other and thus there is possibility of missing the component failures. Additionally, binary logic that is used by this technique is not applicable for scenarios that include uncertain or partial parameters such as human error, environmental conditions etc.

Bow-tie analysis is the PRA method applied in the case of the requirement of total analysis of the accident scenario starting from the basic events of FT and ending with the consequences of the ET. The theoretical framework which is result of BT analysis consists from two parts that are represented by FT and ET where TE and initiating event coincide. Consequently, the application of this risk assessment technique carries the advantages and disadvantages of both FT and ET.

There are several other methods used in quantitative risk assessment in order to deal with the drawbacks of FT and ET. Bayesian networks (BN) have shown to be a powerful technique for analysis of systems with complex structures under uncertainty. A typical BN consists of nodes and directed arcs. The probabilistic relationships and interdependencies are shown in BN using parent and child nodes. For each child node, a conditional probability table is used to shown the relationship with its parent nodes. One of the main advantages of BN modeling is reduction of uncertainty by implementation of new data to update the event probabilities in a dynamic mode (Onisko et al., 2001). BNs are also capable of qualitatively representing the causal-effect relationship of a complex system failure or an accident.

2.2 Artificial Neural Network

Recent development of computational tools allows the creation and utilization of artificial models of biological neural networks that are graphically represented by ordered and interconnected neurons to compute the output from the input. These neurons are organized in a layered structure called multilayer perceptron (MLP). MLP is a feedforward network structure that consists from neurons of 3 types: neurons of input layer, neurons of hidden layers and neurons of output layer. The output of each neuron from the previous layer is one of the inputs to each neuron of the following layer where specific transfer function is applied to input signal of each neuron (Illias et al., 2015). The performance of an ANN model is mainly dependent on selection of input and output data sets, and network architecture (Seifeddine et al., 2012). An example of a typical ANN structure with single output is shown in Figure 2.1 (Ele and Adesola, 2013). The input signal from neurons of input layer are transferred through the weighed connections to all neurons of the hidden layer 1. The transferred signals are summed in each neuron of the hidden layer 1 with corresponding bias; then, the result is utilized in neuron activation function. The activation functions of hidden layer neurons are usually represented by bounded, continuous non-linear functions (e.g. logarithm sigmoid or hyperbolic tangent sigmoid) (Chitsazan et al., 2015). The activation function of the neurons of output layer is typically linear and is used for summing the incoming signal for output (Figure 2.1).

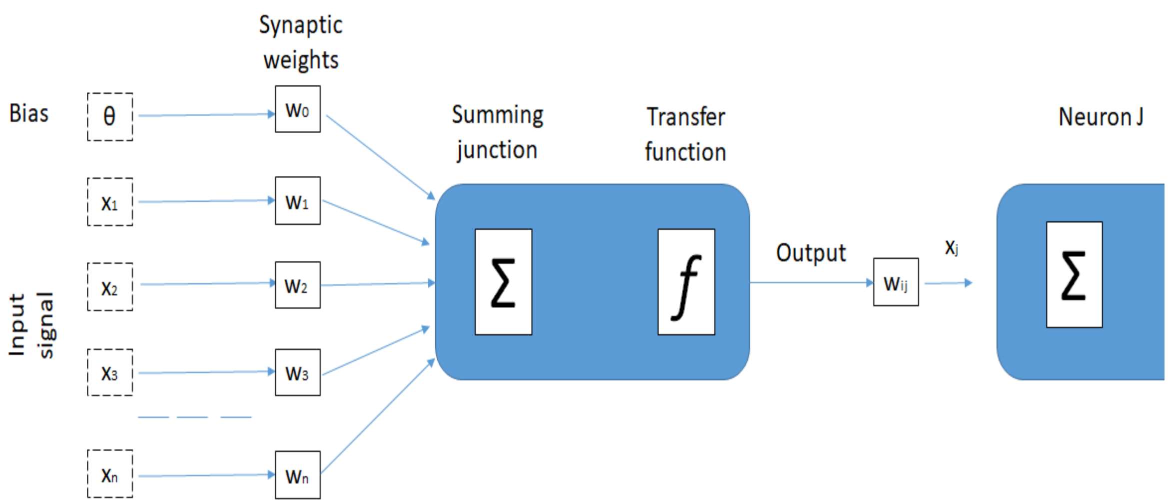

Figure 2.1 An example of a neuron in a typical structure of Artificial Neural Network (Ele and Adesola, 2013)

ANNs are used in variety of fields as the characteristics of them provide opportunity to interpolate and extrapolate expertise and analytical data; also, they are found to be useful in operation of systems with highly non-linear functional relationships. Also, ANNs carry an advantage of considering any linear and non-linear interaction between system components due to specificity of network design and training process (Zhenyuan et al., 2000). ANNs are implemented as an accident modelling method in risk assessment due to their advantages over conventional methods in terms of independence on expert's judgement, non-linearity modelling, interdependencies identification etc. Also, it was proven that in some of the implementation cases, ANNs can continuously modify network parameters to new states and train from actual site data (Gracia et al., 2005).

2.2.1 Learning Algorithm

Training and testing are two main steps after the ANN architecture has been specified (i.e., parameters and data sets specification). The MLP learning algorithms, such as backpropagation method, are used for tuning suitable weights of each neuron in order to increase accuracy of network output signal to satisfy pre-defined constrains (Lippmann, 1987). The backpropagation algorithm implies the performance of two-step iterations where the first forward step computes the results and second backward step is conducted for error calculations and weights updating. The iterations are performed until the error function reaches the pre-defined goal tolerance value (Basheer and Hajmeer, 2000). Among the list of functions used for overall error minimization such as sum squared error (SSE), mean squared error (MSE) and mean absolute deviation (MAD), the MSE performance function is the most widely used. Its expression is given by Eq. (1):

$$MSE = \frac{1}{n}\sum_{m=1}^{n}(Y_{T,m} - Y_{predicted,m})^2 \qquad (1)$$

where Y_T is the target output of the network, n is the number of samples.

Each training instance increases the network performance in terms of calculation accuracy and makes it suitable for simulation application. Finally, the mathematical representation of the prediction performance of a feedforward MLP is given by Eq. (2) and (3) (Chitsazan et al., 2015):

$$Q_{jk} = f_1(b_j + \sum_i w_{ij} i_{ik}) \qquad (2)$$

$$Q_k = b + \sum_j w_j i_i \qquad (3)$$

where Q_{jk} is the output of j^{th} neuron of the hidden layer, f_1 is neuron transfer function, b_j is the bias for neurons of hidden layer, w_{ij} and w_j are weights values of connections between the layers, i_{ik} is the value of input for the k^{th} input vector, Q_k is the *k*th predicted probability of failure, *b* is value of bias for neurons of output layer.

2.2.2 Cross validation and early stopping

The training of ANN is associated with the potential of 'overtraining' of the model. This problem occurs when the predictive power of the model is considerable for the data given in training set. However, the model simulations on data out of the training dataset show significantly less accurate results (Adedigba et al., 2017). In order to avoid 'overtraining', cross validation and early stopping techniques are used during training. The cross-validation method uses a separate validation data set. The simulations of the data from validation set called 'validation checks' are performed during the training and corresponding error of prediction is observed. In the early stopping method, training is stopped as soon as the error in the validation check is higher than it was checked last time (Chen et al., 2017). The application of these techniques helps to avoid the 'overtraining' phenomena and increase generalization capability of ANN models.

2.2.3 Network Testing and Application

The testing data set is used to evaluate the agreement between the network and target outputs. For this purpose, such indexes as regression coefficients are used (Illias et al., 2015). Failure analysis model for process systems can be developed in the form of ANN, which considers the interconnections of each specified parameter and element. It can also be further updated by performing additional training.

The application of ANNs in safety engineering is found to be effective in variety of cases where the quantitative risk assessment was required (Illias et al., 2015, Ruilin and Lawndes 2010). Consequently, ANNs are supposed to solve problems associated with subjectivity and models complexity, partial dependence and stressing effects of existing risk management techniques.

2.3 Application of ANN in Risk Assessment

Artificial Neural Networks (ANNs) are used in variety of fields; because they are able to interpolate and extrapolate expertise and analytical data (Illias et al., 2015). ANNs are capable of modeling linear and non-linear interactions between system components through the application of different linear and non-linear transfer functions in neurons along with various training algorithms. (Zhenyuan et al., 2000). Parameters of ANNs can be updated to new states of contributory factors and train from actual site data (Gracia et al., 2005). Li et al. (2018) have developed a neural network model that is capable of predicting the CO_2 leakage probability from wells using data from actual oil fields in Texas USA. It is found that their proposed method that couples FT with ANN can be used as an effective tool in prediction of coal and gas outbursts in mining industry (Ruilin and Lawndes, 2010). In these works, ANN is either used independently or in combination with other conventional approach like FT and bow-tie analysis in order to obtain system failure probabilities. ANN models are capable to learn from the newly available data to update the network's parameters and improve their performance in dynamic processes risk estimation (Li and Lian, 2007). ANNs do not require information on the relationship between input and output variables; therefore, there is minor dependence on expert's judgment on process structure and/or on complex schemes of process components interrelationships (Shahin et al., 2001). However, there are number of crucial aspects in ANN modeling that significantly influence on the network's performance including data analysis, neurons settings, and etc. (Sheela and Deepa, 2013).

The application of ANNs in risk assessment is not new. It has been widely applied to areas including fault classification (Nagpal and Brar, 2014; Ruilin and Lowndes, 2010), fault identification (Jafari et al., 2014), and accident modeling and prediction (Illias et al., 2015; Adedigba et al., 2017). Li et al. (2018) have developed neural network model that can be used for prediction of CO_2 leakage risk in oil fields in Texas USA. Ruilin and Lowndes (2010) have applied coupled ANN and FT model for the prediction of coal and gas outburst accidents. It is crucial in ANN modeling to properly set the parameters of ANN that includes hidden layer neurons number, neurons transfer function, training algorithm, etc. (Sheela and Deepa, 2013). Improper settings or use of incorrectly formed datasets can result in problems of overfitting and underfitting (problems of excess and lack of information processing capacity correspondingly).

2.4 Comparison of ANN with Conventional PRA Methods

FT and ET are developed based on experts' knowledge and understanding on possible causes and consequences of system failures. The performance of these two techniques are highly dependent on the appropriateness of experts' judgement. ANN is a data-driven model that is built and set according to the learning algorithms and training datasets (Adedigba et al., 2017). Although some of the ANN's structure elements still need to be defined by the model developer, the key parameters of the network (i.e., connection weights) are learned from data sets.

The basic events in a FT and the top events (safety barrier events) in an ET are considered independent with Boolean logic operators (i.e., either failure or success). The interactions among the events, their multiple states, and nonlinearity are ignored in both models. As ANNs are data-driven models and utilizes the numerical methods with nonlinear functions, they can 'learn' non-linear interactions between the input and output variables of the model (Adedigba et al., 2017).

In comparison with FT, ET and BT, ANNs can utilize different types of information (e.g., failure probability and operation data, process data) at the same time. Although ANN-based models can be applied to the probability assessment of system failures and their consequences; however, the ANN model structure and configurations provide no significant information about the causal-effect relationships.

BN is able to explicitly represent the dependencies of cause and effects, update probabilities, handle uncertainties, and incorporate multi-state variables. It has been found more effective than FT in risk assessment (Khakzad et al., 2011; Yang et al., 2015). Similar to ANN, BN also uses directed graphs. The structure of BN itself presents valuable information about conditional dependence between the variables; while ANN does not provide such interpretation. However, one obvious advantage of ANN over BN is that ANN can model the correlation between input variables; while BN assumes that all input variables (i.e., variable states) are independent. This explains why ANN is chosen in this study.

Chapter 3 – Methodology

The proposed method consists of the implementation process (Figure 3.1), graphical mapping algorithm (Figure 3.2) and mapping rules. The main steps and rules are described below.

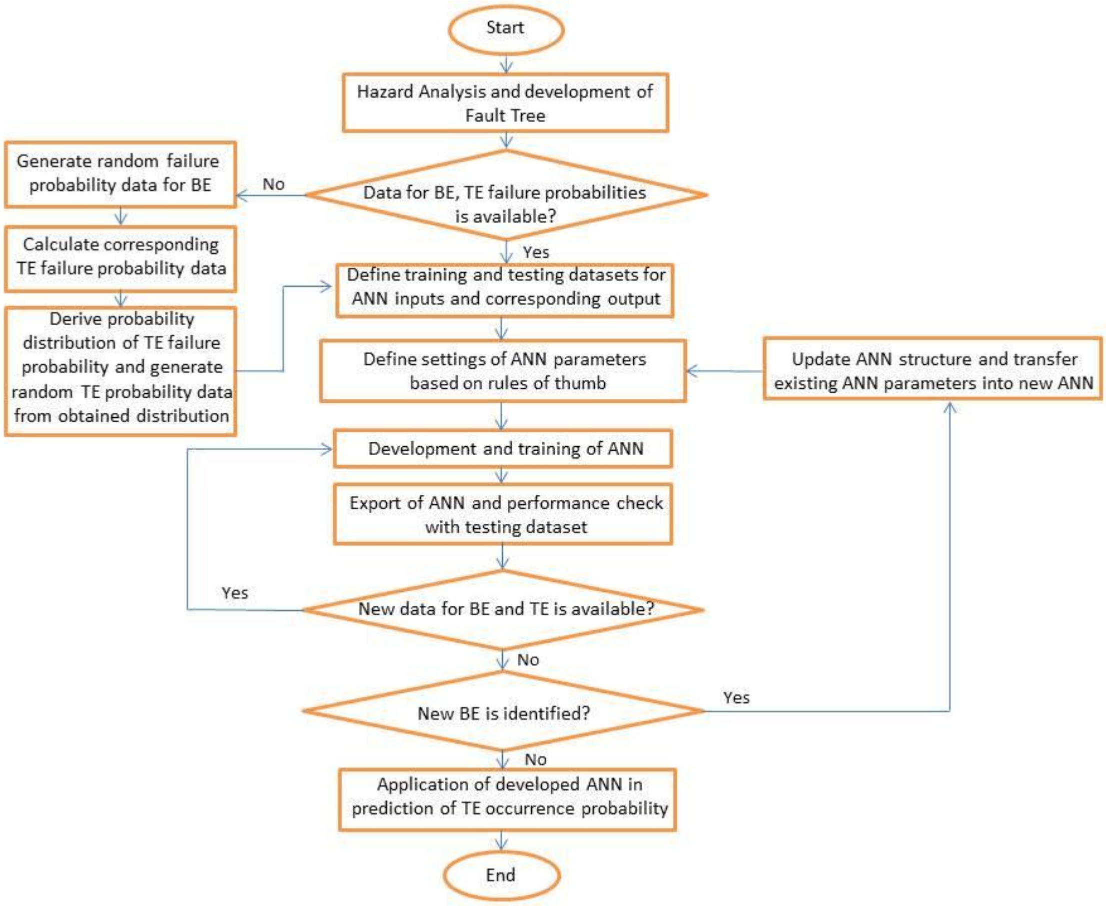

Figure 3.1 Implementation process of the proposed method

3.1 Hazard Analysis and Development of Fault Tree

Hazard analysis includes hazard identification and scenario identification. Varieties of methods can be used, which include process hazards checklists, hazard and operability (HAZOP), etc. FT is used to identify ways in which the identified hazards can cause system failures or accidents. Causes are being deductively identified and are put in a graphical form of tree as intermediate or basic events depending on their possibility to be developed further. Both IEs and BEs are connected with each other with the use of 'gates' which are Boolean logic operators 'OR' or 'AND' or others. Failure probabilities of BEs are being estimated using statistical analysis of historical failure rate data or experts' judgments. The failure probability of tree components connected using 'AND' and 'OR' gate are calculated by Eq. (4) and Eq. (5), respectively.

$$P = \prod_{i=1}^{n} P_i \tag{4}$$

$$P = \prod_{i=1}^{n} (1 - P_i) \tag{5}$$

FT is used to identify causes of a system failure. These causes (BEs) are used as input variables in the ANN to be developed. In the proposed method, the application of FT helps to identify or select input variables in ANN.

3.2 Graphical Mapping Algorithm

The elements of a FT are transformed into the components of an ANN in the step of graphical mapping. The basic events (BEs), and the TE of a FT are mapped to be the input and output neurons of an ANN, respectively. The BEs correspond to the neurons of the first layer; while the TE becomes the output of the ANN. The mathematical functions of the logic gates and intermediate events (IEs) of the FT are utilized as the synaptic weights and transfer functions in the

ANN. For example, the ‘AND’ logic gate with 2 inputs can be simulated with 2 input neurons and 1 output neuron with step transfer function of specified threshold and bias with synaptic weight. Transfer function threshold and synaptic weight values are estimated during training stage using learning algorithms. However, there is no mathematical relationship between the synaptic weights and logic gates with IEs. They are determined during the training stage through input and output data. Thus, the number of neurons in the network’s first layer is specified based on the number of the BEs; while the network output is presented by a single neuron. This step is required in order to classify and prepare the data that will be used in the following steps.

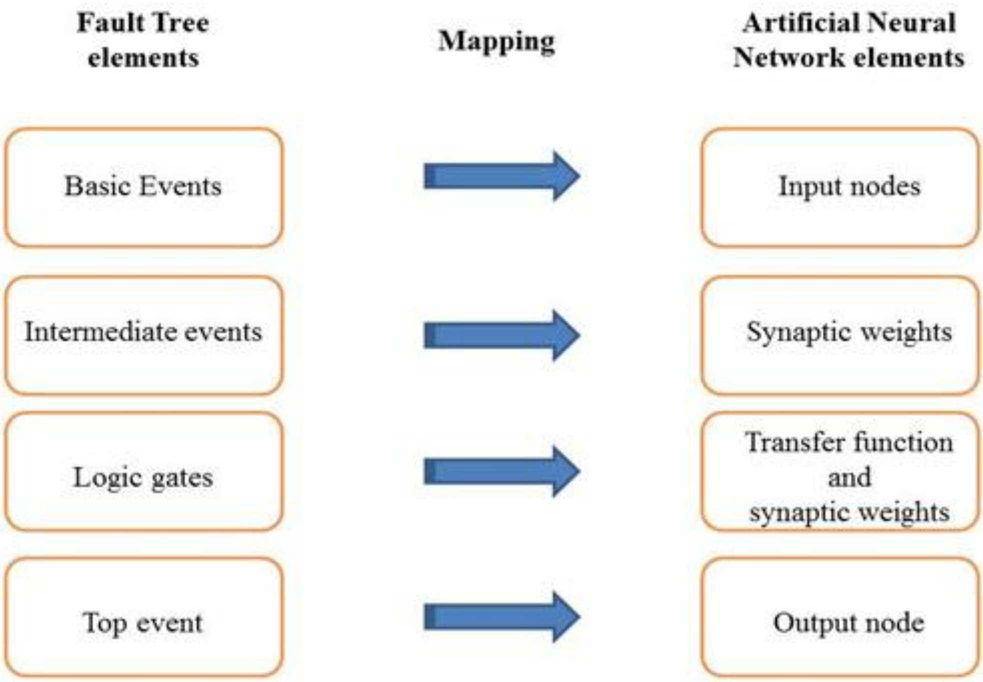

Figure 3.2 Graphical mapping algorithm from FT to ANN

3.3 Configuration of ANN Parameters

This step aims to define the ANN parameters including: a) number of hidden layers and their neurons, b) transfer function of each layer, and c) learning algorithm. The proper configuration of these parameters helps to avoid the over-fitting and under-fitting problems. Network over-fitting refers to the disability of a network to generalize the data that it is trained for. The information processing capacity of such networks is too large, so amount of data in training set is not enough to train all of the neurons in hidden layers. The under-fitting problem occurs when the model is not able to classify the data that it is trained with. There is not sufficient number of neurons in hidden layers for adequate detection of signals or specific patterns in complex data sets. There are many rule-of-thumb methods for determining an appropriate number of neurons to use in the hidden layers in order to avoid over and under-fitting. The following rules are proposed based on FT structure and rules provided in Panchal and Panchal (2017):

(1) The number of neurons in hidden layers is required to be between the number of neurons in the input layer and the number in the output layer (i.e., 1).

(2) The number of hidden neurons should be 2/3 of the number of neurons in the input layer, plus the number of neurons in the output layer (i.e., 1).

(3) The number of neurons in the first hidden layer should be equivalent to the number of IEs directly linked to BEs in FT if the above-two rules are satisfied.

(4) The number of neurons in the second hidden layer should be equivalent to the number of IEs directly linked to TE in FT. If the second rule is not satisfied, the number of neurons in the first hidden layer should be: the maximum allowed total number of hidden neurons minus the number of IEs directly linked to the TE.

The above-rules are tested and validated in Chapter 5.

The number of hidden layers is determined according to the model requirement. In absence of hidden layers, the model is only able to represent linear functions or dependencies. The network with one hidden layer can usually simulate any function that represents a mapping of data from one specified set to another. The ANN with two hidden layers is capable of approximation of given boundary of arbitrary accuracy using linear and non-linear transfer functions. It is able to approximate any smooth mapping to any accuracy. The ANN with three and more hidden layers is rarely implemented due to high network complexity and long total training time without sufficient increase of efficiency (Heaton, 2017; Karsoliya, 2012). Therefore, two hidden layers are chosen in this proposed mapping method.

3.4 Network Training

The ANN training process is the crucial part in ANN creation because ANN is data driven model. The training is performed via providing the data on the input and the corresponding output variables of studied process. The backpropagation training algorithm is applied to the networks elements in order to adjust the connection weights. The passages of the signals from the inputs to the outputs and backwards during training are observed and corresponding errors in prediction are used for adjustment of the weights (Adedigba et al., 2017). Therefore, the accuracy and objectivity of the training data is important for the whole training process of the ANNs.

Mapping FT into ANN requires the use of non-linear log-sigmoid transfer function for neurons in hidden layers and linear transfer function for output layer. The use of log-sigmoid transfer functions in hidden layers enables learning nonlinear relationships between input and output vectors in the training of ANNs. The linear transfer function of output neuron is used for function fitting purposes (The MathWorks, 2018). Therefore, the network processes the input from each node according to the specified parameters settings. Learning algorithm is required for training purposes. The suggested technique is Levenberg–Marquardt backpropagation algorithm that is widely used in the literature (Lippman, 1987). This algorithm processes the input data in a network in forward direction and then the output is compared with given data. The difference in values is processes in backward direction for updating each connection's weight and neurons biases in order to minimize the error. The Levenberg-Marquardt algorithm applies the Jacobian in the iterative calculations which requires the use of mean or sum of squared errors as a performance indicator. The mathematical expression of the Levenberg-Maqardt optimization is given by Eq (6) (Hagan and Menhaj, 1994):

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \tag{6}$$

Where J^T is the transpose Jacobian of the performance function with respect to weights and bias variables X, $J^T e$ is the matrix of all errors, I is the identity matrix and μ is the scalar value that is being adapted during training with each iteration in order to reduce the value of performance function to a specified value.

The abovementioned process is repeated by the network during training stage to continuously improve the performance. One of the several conditions occurrence leads to the stop of the training process (The MathWorks, 2018):

- Limit of iterations number is reached;
- The maximum training time is exceeded;
- Target value of the performance function is reached;
- Adaptive value μ exceeds maximum magnitude; and
- Increase of performance function values for specified number of times in a row on a validation dataset.

When the actual data for the BEs is not sufficiently available, Monte-Carlo simulation technique is proposed to generate the data for network training in this study. In this step, failure probability data of BEs can be generated based on their failure probability distributions whose types and parameters are determined by experts. The TE failure probabilities are calculated based on the generated BEs failure probabilities. The probability distribution can be derived from the calculated TE failure probabilities. The obtained probability distribution is used to generate random TE failure probability data applicable for training.

3.5 Network Testing

This step aims to check the performance of the developed ANN with testing data set. The main parameter used for determination of successful mapping is the regression coefficient. The testing process consists of computation using the testing dataset in the network and comparison of the results with the actual output data. This step is crucial in the mapping process as these results can indicate the needs for additional data, changes in the network's structure, and whether the mapping is proper or not.

Chapter 4 – Case Study

4.1 Description of the Andeavor Anacortes Refinery Explosion

The Andeavor Anacortes Refinery (Tesoro Anacortes Refinery prior to 2017) is located on March Point, Washington state in the U.S.A. The disaster took place on April 2, 2010 due to rupture of heat exchanger and ignition of the released flammable hydrogen and naphtha from the process unit. The rupture occurred on E-6600E heat exchanger in Catalytic Reformer/ Naphtha Hydrotreater unit ("the NHT unit") during heat exchangers bank startup procedure. The consequent explosion and fire resulted in seven fatalities, assets and reputation losses of the company. This accident resulted in the largest human loss at United States petroleum refineries since the BP Texas City disaster in March 2005 (U.S. Chemical Safety and Hazard Investigation Board, 2014).

4.2 Application of the Proposed Method

The proposed approach was applied to map the fault tree of release prevention barrier developed by Adedigba et al. (2016) for the Tesoro Anacortes Refinery accident. The analysis was performed based on the data and information from the accident investigation report presented by U.S. Chemical Safety and Hazard Investigation Board (2014). The fault tree of the release prevention barrier, one of the safety barriers used to prevent the fire and explosion in the refinery, is presented in Figure 4.1. 21 basic events were used in the analysis and presented in Table 4.1.

Table 4.1 Basic events description and failure probability data (Adopted from Adedigba et al. (2016))

BEs	Event description	Mean probability
1	High temperature hydrogen attack (HTHA)	0.025
2	Difficulty with valve operation during start up	0.015
3	No report on leaks from heat exchanger during start up	0.050
4	Hydrogen induced cold cracking	0.001
5	Inexperience	0.010
6	No permition on job carrying	0.010
7	Failure of external supervision	0.083
8	Incorrect procedure	0.005
9	Poor construction material for NHT heat exchanger	0.010
10	High mechanical stress	0.010
11	Insufficient instrumentation to measure process conditions	0.001
12	Long delay in inspection schedule	0.050
13	Inadequate methods for detecting HTHA	0.090
14	Inadequate training of the inspectors to detect HTHA easily	0.025
15	Failure of HTHA inspection of heat exchanger	0.055
16	Failure of detection of leaks from heat exchanger flanges	0.050
17	Failure of minor release detection	0.050
18	Wrong maintenance procedure (Nelson curve methodology)	0.005
19	Delay maintenance operations	0.050
20	HTHA degradation monitoring performed but failed to detect	0.066
21	HTHA degradation monitoring specified but not performed	0.050

The top event in the fault tree is the failure of release prevention barrier (RPB). The failure probability of top event according to the collected data is found to be 0.0842 with the use of developed FT and by computing the data for BEs.

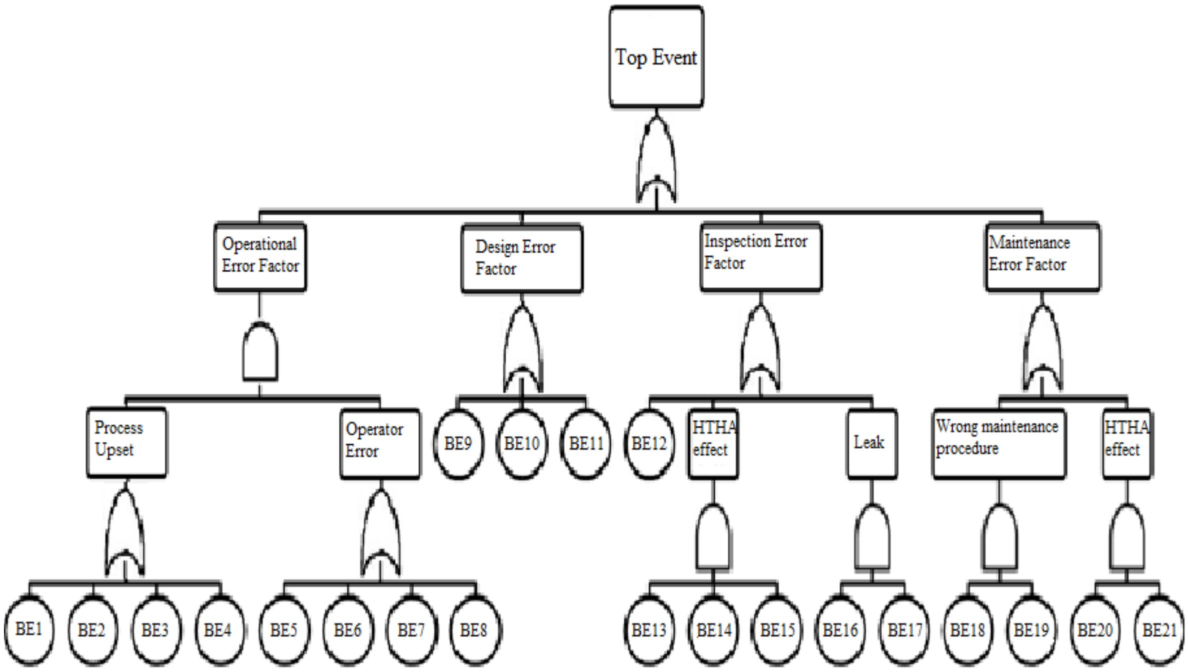

Figure 4.1 Fault tree of release prevention barrier for heat exchanger in NHT unit

4.2.1 Data Acquisition

Equipment failure data needs to be collected at this stage. Due to the unavailability of actual site data, for illustrative purpose, a set of 500 random failure probabilities were generated for each one of the 21 BEs. Normal distributions (with means given by Table 4.1 and assumed 15% standard deviations) were adopted for the generation of failure probabilities. The probabilities of TE were generated based on the generated probabilities of BEs. Table 4.2 presents the data samples that were used for ANN training and testing in the case study. The division between testing and training sets was done using the principle of consistency and representativeness in order to avoid possible contradictions in simulations.

Table 4.2 Failure probability data for FT of release prevention barrier

	BE1	BE2	BE3	BE4	BE5	…	BE21	TE
1	0.0260	0.0152	0.0462	0.0010	0.0098	…	0.0571	0.0896
2	0.0259	0.0155	0.0536	0.0010	0.0094	…	0.0550	0.0961
3	0.0257	0.0136	0.0711	0.0011	0.0125	…	0.0520	0.0893
4	0.0219	0.0161	0.0563	0.0011	0.0096	…	0.0588	0.0787
5	0.0231	0.0141	0.0567	0.0009	0.0111	…	0.0662	0.0927
…	…	…	…	…	…	…	…	…
499	0.0254	0.0123	0.0533	0.0010	0.0112	…	0.0560	0.0930
500	0.0268	0.0151	0.0462	0.0011	0.0090	…	0.0435	0.0902

4.2.2 ANN Development

The ANN was developed based on the fault tree presented in Figure 4.1 according to the graphical mapping (Figure 3.2) algorithm, implementation process (Figure 3.1), and corresponding mapping rules. 450 of the samples were used as training data and 50 samples were dedicated for testing of the ANN. All 21 basic events were treated as input variables of the network; while the top event is used as the output of the model. The feedforward backpropagation type ANN with 2 hidden layers and 1 output layers was defined following the rules of thumb. The training function was set to be Levenberg-Marquardt backpropagation (trainlm) and performance function was set to MSE. Transfer functions of neurons in hidden neurons were logsig and linear for output layer. The validation checks were used to ensure the ability of network to generalize the input data. The training stopped when subset error rate increased for more than 10 epoch iterations in a row. The data generation, fault tree computations and the creation of ANN models were computed using the neural network toolbox in Matlab R2014b.

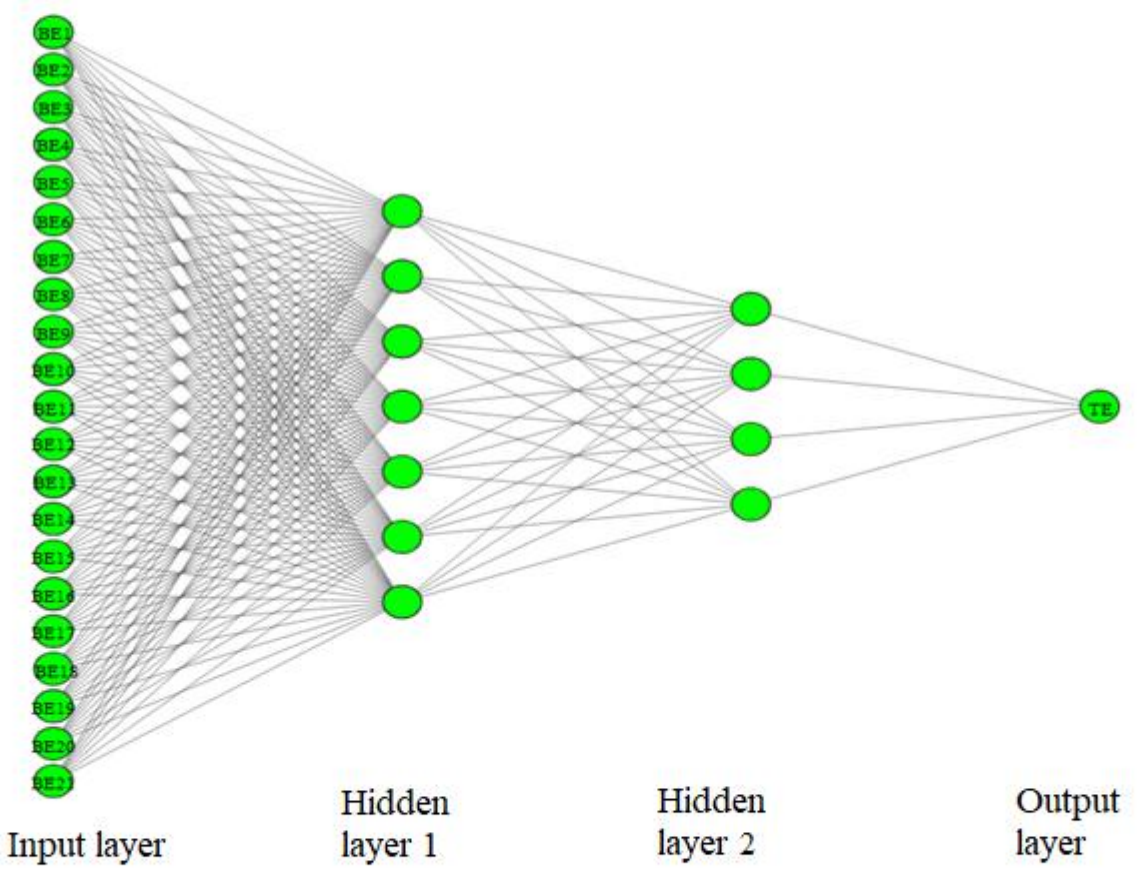

Figure 4.2 Developed ANN schematics

4.2.3. Mapping Performance Check

The developed ANN (Figure 4.2) was tested in order to simulate the FT with different input data and predict the failure probability of the top event. 50 cases of different BEs and corresponding TE failure probabilities were used for ANN testing. The results obtained from the ANN and FT models were compared and presented in Figure 4.3, which shows good matches. The mean, maximum and MSE of the differences between the results of these two models were also calculated for mapping performance check: (a) mean difference is 0.41%, (b) maximum difference is 1.11%, and (c) MSE is 5.38E-06.

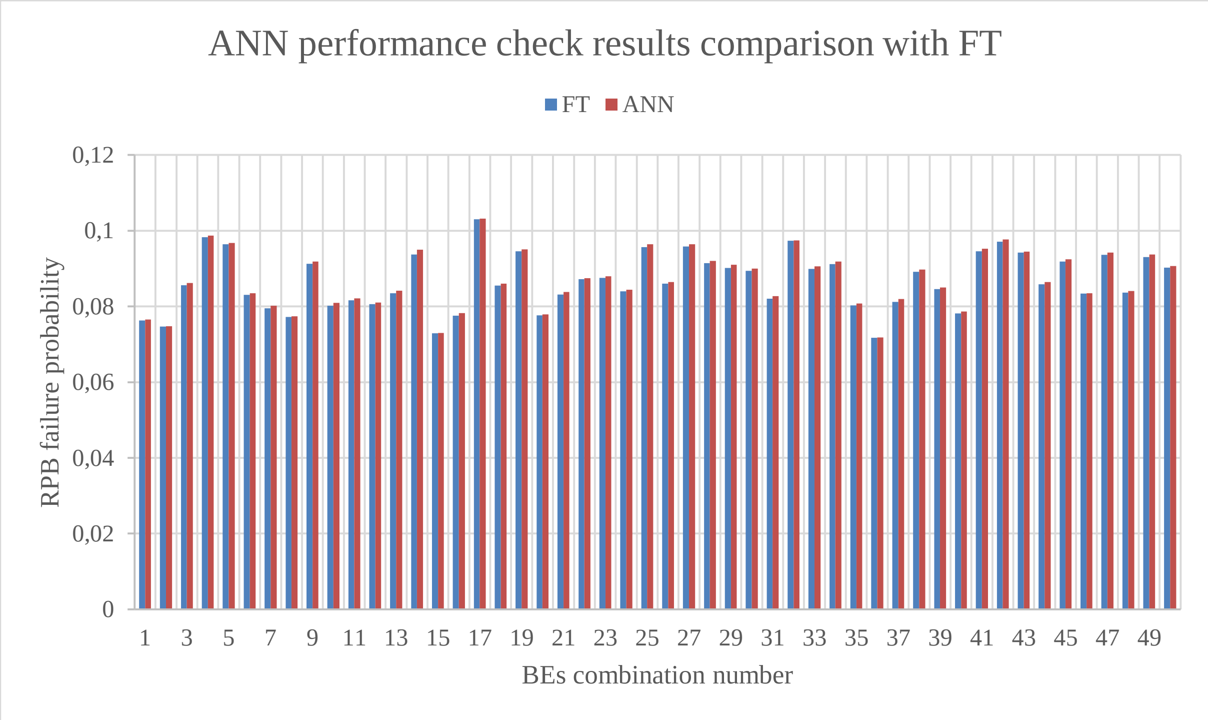

Figure 4.3 Plot of RPB failure probability results for testing data set from FT and those obtained from ANN

Chapter 5 – Results and Discussion

5.1 The Development of ANN with FT as the Base

ANN models are trained using informative dataset by adjusting its internal parameters (synaptic weights and biases) in order to "memorize" the mathematical relationship between input and output variables. It is true that the ANN model can be developed without the use of FT as the base by providing necessary datasets for BEs and TE. However, identification of proper inputs of ANN models may be challenging in risk analysis of complex systems. It is more beneficial to use FTA to support ANN model development as it implies causal effect relationships that are useful for selection of inputs and outputs of ANN models.

5.2 The Effect of Availability of New Data

Given new data, the established ANN model can be updated to re-assess the system failure probability. A set of 50 new samples of BE and TE failure probabilities was generated as newly available data. The training of the developed ANN was performed using new data in order to update the network's weights of connections and biases. It has shown performance improvement as the mean and maximum differences decreased to 0.35% and 1.03%, respectively. The results show that the availability of new data can improve the accuracy of ANN-based mode for failure analysis.

5.3 The Effect of FT Structure Change

The change of FT structure (e.g., addition of new BEs) was considered to study its influence on the ANN mapping process and its performance. Assuming that the presence of 20 BEs in the previous study was taken; all of the mapping steps were performed following the same algorithm as described above. The ANN consisted of 20 inputs, 7 first hidden layers, 4 second hidden layers and 1 output neuron was created with the TE failure probability prediction performance characteristics of 0.45% for mean and 1.56% for maximum difference. The training dataset consisted of the same 450 failure probability samples excluding the samples of 21^{st} basic event.

The addition of new 21^{st} BE was assumed with a new dataset for 50 failure probabilities of the 21^{st} BE and TE. The parameters of the present ANN (i.e., connection weights and biases) were used as initial estimates for those of the new ANN during the model setting step. The parameters for connections weights and bias for 21^{st} input neuron were set to default values. The mean and maximum differences of ANN with initial estimates for its parameters transferred from the existing ANN model are 0.13% and 0.70%, respectively. In the case of training of the same ANN without the parameter transfer, the mean and maximum difference is 0.41% and 1.11%, respectively. This indicates that it is more beneficial to transfer the parameters of the existing ANN to the new model corresponding to the change of FT.

5.4 Sensitivity Analysis of Outputs to Input Variables

Sensitivity analysis has been performed to determine the critical contributory input variables on the model output. We adopted the profile approach proposed by Shojaeefard et al. (2013). This analysis investigated the change of RPB failure probability with respect to the input variation. Each input variable (BE failure probability) was divided into 20 equal intervals between its minimum and maximum values. All input variables except one were set 20 times at their minimum, first quartile, median, third quartile, and maximum values sequentially. For each scale point, 5 output results were obtained. The sum of them was divided by 5 to find the mean value. The same process was repeated for all input variables. A contribution curve was obtained for each input variable. The comparisons of output profiles of all input variables were conducted. The magnitude of the output change along the scale is the main criterion for choosing the most important variable. For example, the comparison between the contribution of BE1 and BE2 is shown in Figure 5.1. The change of output along the scale of the variable of BE1 is greater than that of BE2. This can be explained by stronger influence of HTHA on RPB failure than “the difficulty with valve operation during start up”. Therefore, the BE1 is considered as more contributory to the TE in comparison with BE2. The same procedure was repeated for all 21 BEs in order to rank them according to their level of contribution to the TE.

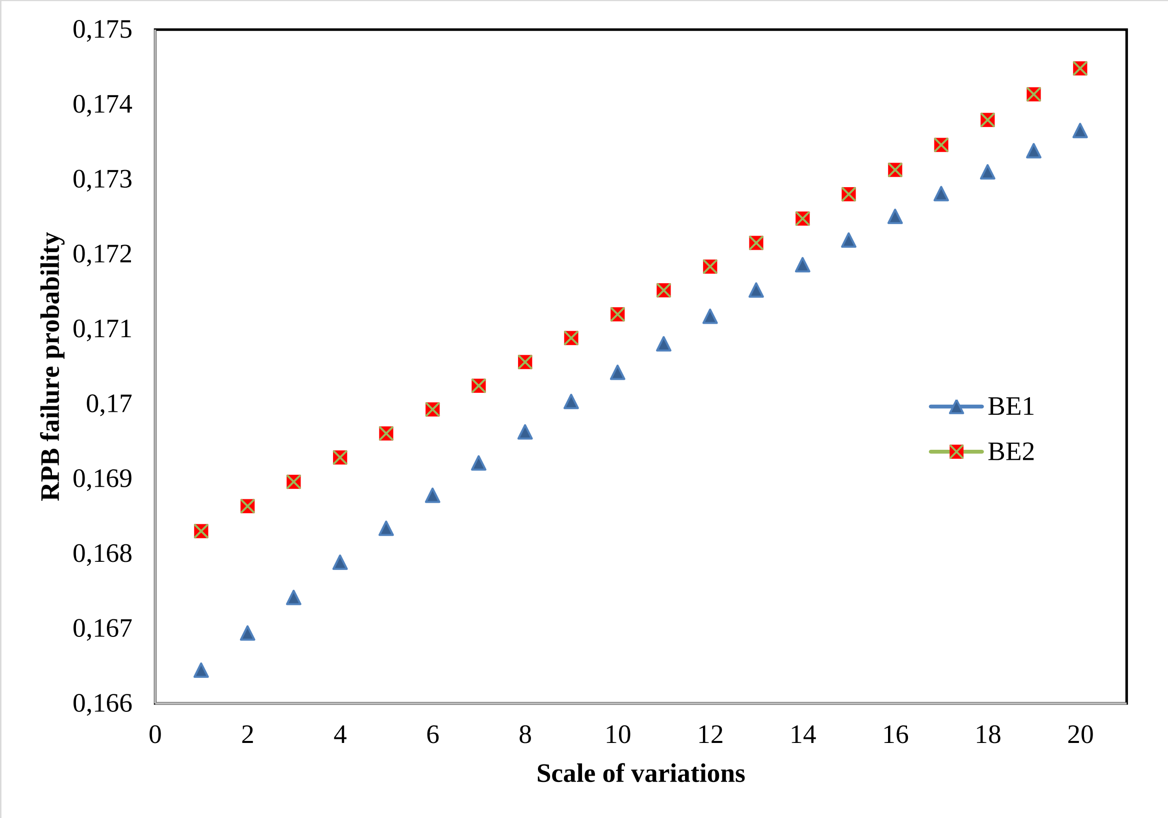

Figure 5.1 Contribution profiles of BE1 and BE2 used in the ANN model for RPB, by the profile algorithm with a scale of 20

The results of sensitivity analysis of contribution of all of the 21 BEs in RPB failure are reported in Table 5.1.

Table 5.1 BEs contribution ranking according to sensitivity analysis

Rank of contribution	BE number	Event description
1	12	Long delay in inspection schedule
2	9	Poor construction material for NHT heat exchanger
3	10	High mechanical stress
4	11	Insufficient instrumentation to measure process conditions
5	7	Failure of external supervision
6	3	No report on leaks from heat exchanger during start up
7	20	HTHA degradation monitoring performed but failed to detect
8	1	High temperature hydrogen attack (HTHA)
9	4	Hydrogen induced cold cracking
10	2	Difficulty with valve operation during start up
11	13	Inadequate methods for detecting HTHA
12	15	Failure of HTHA inspection of heat exchanger
13	16	Failure of detection of leaks from heat exchanger flanges
14	17	Failure of minor release detection
15	6	No permition on job carrying
16	8	Incorrect procedure
17	19	Delay maintenance operations
18	21	HTHA degradation monitoring specified but not performed
19	5	Inexperience
20	18	Wrong maintenance procedure (Nelson curve methodology)
21	14	Inadequate training of the inspectors to detect HTHA easily

5.5 Correlation Analysis of Input Variables

Correlation between input variables is a key consideration in ANN. A large number of available variables, correlations between them and absence of predictive power of some of them can result in problems such as long-time requirement and redundancy of data for network training. Selection of input variables based on correlation analysis can improve the performance of ANN during training stage and its post-development application (May et al., 2011).

Inputs ranking based on the Pearson correlation is suggested for input variable selection, where variables are graded by their correlation coefficients. The analysis is based on application of Eq.(7) to output (Y) and each available input variable (X) for determination of Pearson correlation coefficient (R) which value lies in the range from -1 to +1. The deviation of coefficient from 0 is the main criterion of correlation presence and choice of input variable for modelling.

$$R_{XY} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{7}$$

In the current ANN model, correlation analysis of input variables is not included due to random nature of the generated data. The future development of the proposed methodology should consider actual process system variables (e.g., temperature, pressure, flowrate) and their correlations in system failure analysis.

5.6 Interdependency Analysis between BEs/Inputs

In this section, the ability of the ANN model of handling interdependent variables is studied. Firstly, all 21 BEs were ranked based on their level of contribution to the occurrence of TE using the data from Table 4.1. The following steps were performed and the results are given in Table 5.2:

(1) The failure probability value of each BE was divided on the estimated RPB failure probability of 0.0842 and multiplied by 100%.

(2) The BEs contribution values were found by normalizing the result obtained for each BE in the first step.

(3) The ranking of BEs was achieved based on the normalized contribution factors in the second step.

Table 5.2 BEs ranking basing on the contribution factor

Rank #	Contribution factor	BE #	Assigned failure probability
1	0.12658	BE13	0.09
2	0.11674	BE7	0.083
3	0.09283	BE20	0.066
4	0.07736	BE15	0.055
5	0.07032	BE3	0.05
6	0.07032	BE12	0.05
7	0.07032	BE16	0.05
8	0.07032	BE17	0.05
9	0.07032	BE19	0.05
10	0.07032	BE21	0.05
11	0.03516	BE1	0.025
12	0.03516	BE14	0.025
13	0.0211	BE2	0.015
14	0.01406	BE5	0.01
15	0.01406	BE6	0.01
16	0.01406	BE9	0.01
17	0.01406	BE10	0.01
18	0.00703	BE8	0.005
19	0.00703	BE18	0.005
20	0.00141	BE4	0.001
21	0.00141	BE11	0.001

Secondly, we assumed that the BE and TE data given in Table 4.2 are actual site data and the FT model was built without the least contributory event (BE11 – “Insufficient instrumentation to measure process conditions”). The ANN model of the same architecture with 20 inputs was trained using 400 samples for the corresponding 20 BEs and the TE given in actual data set (Table 4.2, in which TE data is generated based on all 21 BEs). The model performance of FT and ANN was checked by using 50 samples for 20 BE and comparing obtained results with actual data for TE. The predictive power was estimated by calculating the difference between the predicted TE value and its actual value.

The results of simulations have shown better predictive performance of ANN with mean error value of 0.43% in comparison with 1.05% mean error of FT. The result indicates that the interdependencies among input variables can be considered by the ANN model; otherwise, the ANN model should have produced similar results with those of the FT model. However, it is worth noting that the performance of ANN model in handing the interdependency among inputs is highly linked to the amount and quality of data available for training. This was found by training the same ANN model with 20 inputs by using only 50 samples. The results of simulations of obtained ANN model have shown larger errors in predictions with mean value of 3.69%.

5.7 Performance Analysis of ANNs with Different Architectures

The performance analysis of ANNs with different number of neurons in hidden layers was performed in order to test the rules proposed in Section 3.3. The training of each case with different combination of number of neurons in the hidden layers was performed using the same data set generated for 21 BEs and TE. Table 5.3 gives a summary of the mean and maximum differences between the outputs of the ANN model and the testing data.

Table 5.3 Testing results of accident ANN models with different architectures

Training data set volume	**Number of neurons in hidden layer 1**	18	14	10	7	7	7
	Number of neurons in hidden layer 2	9	7	5	6	4	2
50	Mean diff. [%]	21.35	23.23	4.89	22.41	23.62	20.12
50	Maximum diff. [%]	92.31	96.79	26.53	92.4	92.68	91.31
250	Mean diff. [%]	3.68	4.22	1.93	2.01	1.74	1.91
250	Maximum diff. [%]	18.43	21.06	7.64	8.21	6.04	7.12
450	Mean diff. [%]	1.91	2.12	2.11	0.96	0.77	1.00
450	Maximum diff. [%]	7.36	10.13	16.62	4.93	3.07	3.67

The obtained results shown in Table 5.3 show that the ANN model with 7 and 4 neurons in the first and second hidden layers produces better results. This partially validates the rule-of-thumb proposed in Section 3.3. The results also confirm that the both appropriate ANN architecture and training data set volume would greatly influence on the model performance. It is worth nothing that the ANN model with another architecture could be built with better results of predictive performance if the training data set would be of larger size and better quality.

Chapter 6 – Conclusions

6.1 Summary of Research Findings

This thesis attempts to propose a methodology of mapping FT into ANN to support the development of ANN-based risk assessment model using FT as an informative basis. The association of ANN's architecture and configuration with the FT structure has been investigated. This study shows that FT is effective to help identifying proper input and output variables for the ANN model. The results also indicate that the ANN model could perform better if the numbers of neurons in its hidden layers were defined according to the numbers of intermediate events directly linked to the BEs and TE in the FT, from which the ANN was mapped. The availability of new data for training helps to improve the performance of the ANN model. The newly available data/information may lead to changes in the FT. This may result in the addition of new inputs in the developed ANN. This study shows that better mapping performance can be achieved by adopting the parameters of the developed network in the new network. The ANN model mapped from FT has demonstrated its strength and effectiveness as a risk assessment tool.

6.2 Future work

Future work will be devoted to improving the method by including process variables (e.g. temperature, pressure, flowrate, concentration) that can be monitored and recorded online and real-time in the ANN model. In this way, we can utilize the large amount of process data for training and testing of the ANN model for system failure analysis. However, there is a need of investigation on the pre-processing of the data as the magnitude of ANN inputs of different scale can negatively affect on the ANN performance. The possible ways of avoiding of such cases is detection and removal of data samples “out” of the studied range and normalization of the input data. Additionally, the study of the use of different architectures, transfer function and training algorithms will be considered. Work in this direction is under progress.

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