



Faculty of Engineering

**Application of Artificial Neural Network to Predict Occupational Safety
and Health Risk in Shipyards
– a Case Study of 2 Shipyards in Sibu, Sarawak**

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Application of Artificial Neural Network to Predict Occupational Safety and Health Risk in Shipyards – a Case Study of 2 Shipyards in Sibu, Sarawak

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DECLARATION

I declare that the work in this thesis was carried out in accordance with the regulations of University Malaysia Sarawak. Except where due acknowledgements have been made, the work is that of the author alone. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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ABSTRACT

Occupational safety and health (OSH) risk management research is common in industries such as construction, chemical production, electrical and electronic production. However, to date there is a lack of research performed on the OSH risk management related to shipyard industry. OSH practitioners often make preventive decisions based on physical site audit in the shipyard and relying on individual experience. The aforementioned task is difficult to execute due to multiple influencing factors that could affect the decision-making. Therefore, this project aims to propose a risk management framework by utilising a supervised machine learning Artificial Neural Network (ANN) to predict occupational risk in an identified Malaysia shipyard. Optimization and classification with the appropriate architecture of neuron layers were trained for the risk prediction at shipyards. In this research, 10 independent input variables and 1 single layer-dependent output variable (severity of risk) were defined. 7 networks modeling were developed between 19–31 neuron nodes. Accuracy performance of the developed networks were compared by using evaluation criteria, such as correlation of coefficient (R^2), mean square error (MSE) and mean absolute percentage error (MAPE), to select the best model. The best selected ANN network no.4 achieves the highest accuracy performance of 90.22%. However, in terms of sensitivity analysis, input factors such as working hours (28.38%), and workplace factors (21.32%), have significant effects onto the OSH risk prediction. Then machine learning was intervened into the proposed framework which entails identification of hazards, risk assessment, safety decision-making, risk control, and risk prediction. With this, a dynamic risk management framework is formed and continuously improved.

Keywords: Risk prediction, OSH risk management framework, safety decision-making, machine learning, Artificial Neural Network ANN

Penilaian Ramalan Risiko Keselamatan Dan Kesihatan Pekerjaan Semasa Bekerja Di Kilang Pembuatan Kapal, Malaysia

ABSTRAK

Pengurusan risiko keselamatan dan kesihatan pekerjaan (KKP) adalah biasa dipraktikkan dalam industry pembinaan, pembuatan bahan kimia, pembuatan bahan elektronik dan sebagainya. Namun demikian, terdapat kekurangan dalam penyelidikan pengurusan risiko KKP di industry pembuatan kapal Malaysia. Didapati bahawa cara golongan pengamal KKP membuat keputusan bagi pencegahan berlakunya kemalangan KKP adalah berdasarkan kepada pemeriksaan audit secara fizikal di tempat kerja. Ia bergantung kepada pengalaman diri sendiri untuk mengenalpastikan hazard di tempat kerja. Tugas seperti ini adalah sukar kerana terdapat banyak faktor tersembunyi yang boleh menjejaskan ketepatan penilaian risiko. Oleh itu, aplikasi penggunaan teknik pembelajaran mesin rangkain nural dicadangkan dalam kerangka pengurusan risiko untuk meramalkan pendedahan risiko bekerja di kilang pembuatan kapal yang terlibat dalam kajian penyelidikan. Teknik pembelajaran mesin secara sendiri diterapkan dengan model latihan melalui sesi pengoptimuman dan klasifikasi lapisan neuron yang sesuai. Terdapat 10 pembolehubah input bebas dan 1 pembolehubah output dalam lapisan tunggal (ramalan risiko) ditakrifkan dalam penyelidikan ini. 7 rangkaian dibangunkan antara 19 – 31 nod neuron. Prestasi ketepatan ramalan juga dibandingkan antara rangkaian dengan menggunakan kriteria penilaian, seperti pekali korelasi (R^2), ralat min kuasa dua (MSE), dan min ralat peratus mutlak (MAPE). Rangkaian yang terbaik, iaitu rangkaian no.4 mencapai ketepatan ramalan 90.22%. Walau bagaimanapun, dari segi analisa sensitiviti, faktor input waktu bekerja (28.38%), dan faktor tempat kerja (21.32%), memberikan kesan yang ketara terhadap ramalan risiko. Selepas itu, rangkain ramalan akan diterapkan ke

dalam kerangka KKP iaitu, pengenaltastian hazard, penilaian risiko, keutamaan membuat keputusan terhadap risiko, kawalan risiko dan ramalan risiko. Dengan itu, kerangka pengurusan KKP secara dinamik dan berkesan dapat dirumuskan.

Kata kunci: *Ramalan risiko, kerangka pengurusan risiko, keutamaan membuat keputusan, pembelajaran mesin secara sendiri, rangkaian neural ANN*

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LIST OF ABBREVIATIONS

OSH	Occupational Safety and Health
SBSR	Shipbuilding and Ship Repair
FSA	Formal Safety Assessment
IMO	International Marine Organization
HIRARC	Hazard Identification Risk Assessment and Risk Control
RCA	Root Cause Analysis
VHA	United States Veterans Health Administration
IEE	The Institution of Electrical Engineer
PLC	Programmable Logic Controller
HAZID	Hazard Identification
HAZOP	Hazard and Operability
ETA	Event Tree Analysis
FMEA	Failure Modes and Effects Analysis
FAMECA	Failure Modes Effects and Criticality Analysis
FTA	Fault Tree Analysis
ISO/TR14121-2 2012	International Organization of Standardization for Safety of Machinery - Risk Assessment - Practical Guidance and Examples of Methods
ANSI B11 TR3	American National Standard Technical Report for Machine Tools – Risk Assessment and Risk Reduction – A Guide to Estimate, Evaluate and Reduce Risks Associated with Machine Tools
UKOOA	United Kingdom Offshore Operator Association
RIE	Risk Inventory and Evaluation
HSE	Health Safety and Environment
MLP	Multi-Layer Perceptron

MSE	Mean Square Error
MAPE	Mean Absolute Percentage Error
R	Correlation Coefficient
AP	Accuracy Performance

CHAPTER 1

INTRODUCTION

1.1 Study Background

The global shipbuilding industry has seen tremendous growth over the past several years because of the rising need for more transportation capacity, particularly in China, Japan, and Korea. In general, productivity and product quality are now significant factors in the competitiveness of the shipyard. Information technology, fabrication process flows, skilled labour, shipyard planning, and management are the main variables to improve the shipyard production chain. However, in order for the global shipbuilding industry to remain competitive, certain technology or managerial abilities are also needed. For instance, China's shipbuilding benefits from a large, skilled labour, massive capital, and a stable shipbuilding sector. The employment of qualified professionals has allowed Japan's shipbuilding industry to remain competitive, while Korean shipyards are mostly known for their expertise in managing dry docks (Bai et al., 2007). Additionally, the process of producing ships is not only dependent on technological advancement and innovation but also on a more formalised organisation of labour, the capacity of the workplace, and simulation-based design for a shipyard production process (Medeiros et al., 2000).

On the other hand, Malaysia's ship building and ship repair (SBSR) industry is a significant contributor to the nation's Gross National Income (GNI) and is expected to provide 55,500 employments by 2020 (Council et al., 2011). Consequently, SBSR is crucial to the Malaysia's business expansion. According to data, there are over 100 shipbuilding businesses registered in Malaysia, 40 of which are based in Sibu, Sarawak (Hasan, 2019). This demonstrates how Malaysia's Sarawak state dominates shipyards and shipbuilding

industries. According to the geographic analysis, most of the shipyards in Sarawak are located along the riversides instead of facing to an open sea. Literally, activities that are carried out in SBSR industry are complied under safety and health risk management. This is because most of the activity works are human capitalized.

1.2 Problem Statement

On the other hand, there is still a lot that can be done to address health and safety risks in the SBSR industry.

Othman et al. (2018) revealed that most shipyards have health safety environment management system (HSEMS) in place, some are still incomplete. This is because health safety and environment (HSE) issues were not given high attention, nearly 10% of shipyards lacked a clear HSE policy or risk management. As a result, there is a lack of OSH awareness culture and a consequent inability to properly focus on HSE management.

Besides that, many activities of fabrication works have been subcontracted. Subcontractors are fragmented into separate organizations that do not collaborate during the shipyards' fabrication process (Etherton, 2007). Therefore, commitment from the shipyard companies and the subcontractors are poor to implement OSH risk management. This has indirectly increased the workers' risk exposure at the shipyards. Without strict OSH management practiced in shipyards, a significant number of cases where workers were discovered to be suffering from lacerations, crushes, avulsions, fractures, amputations, or caught in hazardous situations and so on, have been documented (DOSHS, 2019).

Usually site audit and investigation are carried out by the OSH practitioners after the accidents happened at site to identify the significant hazards. Improvement was advised based on OSH practitioners' experience and knowledge. However, previous research has

shown that OSH practitioners have difficulties in risk analysis and making decision in the accidents (Card et al., 2012). In other words, due to varied opinions and varying degrees of expertise, it is determined that the reliability of risk analysis and the importance of making decision in risk control are inadequate.

Nevertheless, Sarkar et al. (2019) showed that risk control decision-making did not appear to be based on analytical data gathered from accidents. Data collected was not utilized to identify the contributing factor of accidents. In the other words, there is no data optimization to understand the root cause and the accidents continue to occur in the shipyard sector.

1.3 Objectives

The focus of this research project aims to accomplish the following specific goals.

1. To identify potential hazards and assess risks exposure at the shipyards case study.
2. To develop a risk management framework for shipyards case study based on the quantitative safety decision-makings.
3. To develop a model using ANN machine learning technique for occupational risk prediction at the shipyards case study.

1.4 Conceptual Framework

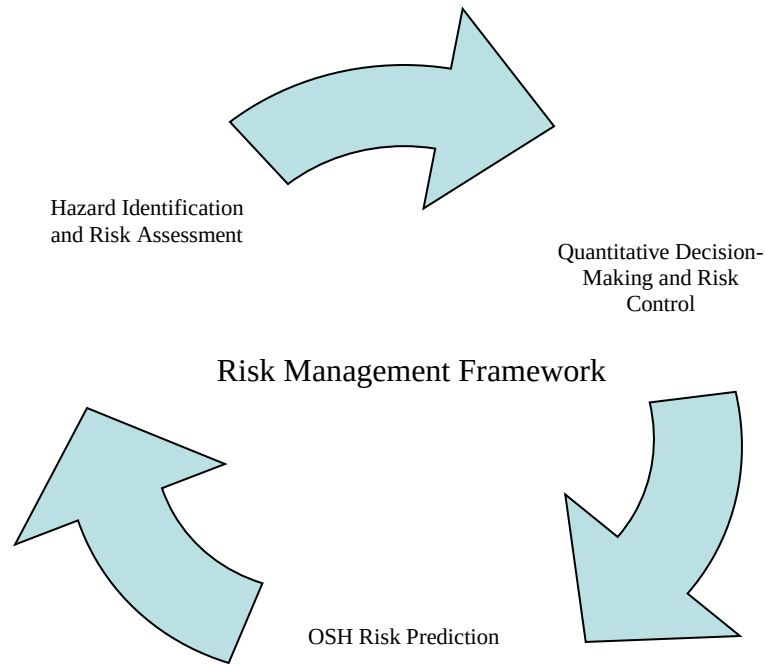


Figure 1.1: Risk Management Framework

Figure 1.1 shows the conceptual framework in this study that suits in shipyards case study. The formulated risk management framework entails potential hazards identification, risk assessment, quantitative safety decision-making, risk control, and risk prediction. It connects each other in forming a continuously improving risk management framework. This framework is used to formulate the hypothesis of this study.

1.5 Hypothesis

It is hypothesised that OSH accidents occurred in the shipyards case study can be reduced by organising a developed risk management framework that entails hazards identification, risk assessment, quantitative safety decision-making, risk control, and risk prediction.

1.6 Scope of Research and Limitation

The research is limited to shipyards whereas activities of shipbuilding and ship repairing are carried out. Under the definition of the Factory and Machinery Act 1967, shipyard is defined as an industrial factory with the combination of office building, warehouse, workshops, dry dock area, wet dock area, and wharf. These are different utilization from other commercial wharves or personal jetties, for instance, speed boat jetty, cruise wharves, bay wharves, international or local ports, and so on where shipbuilding and ship repairing activities cannot be done. In addition, SBSR operations are carried out under the direction of manpower because most fabrication works are human capitalised. Therefore, this research only discusses workplace accidents, property damaged, and development of OSH risk management framework at shipyards case study.

Following that, our scope of research limited to shipyards case study. Research identifies shipyard companies in Sibul, Sarawak for case study because majority of the shipyards are located in Sarawak.

Besides that, ethnic approval for raw data mining is given by the government agencies, Department of Occupational Safety and Health (DOSH), Social Security Organization (SOCSSO), and Department of Labour (JTK). Raw data only covers occupational safety and health at workplace which limited our study into risk exposure of workers at workplace.

1.7 Research Gap Analysis

Many researchers have done the study on OSH risk management in general industry such as construction (Al-Zwainy et al., 2012), chemical production (Xiao et al., 2011), electrical and electronic production (Rahmat et al., 2009), international port

(Celebri, 2010), and so on. Different kind of methods were applied in the typical framework that entails hazard identification, risk assessment, and risk control according to its characteristic applications, advantages, and disadvantages. However, this research applies a machine learning method into the previously described risk management framework to predict the risk exposure of workers before accidents happened.

El-Sawalhi et al. (2014) studied on the application of Machine learning in risk management. In this research, methodology of analyzing input-output paired wise of HSE factors in construction has been applied into shipyards case study. This is because HSE variables analysis in shipyards is very limited. Therefore, methodology in construction study has been adopted due to the similarity of fabrication activities in construction such as work at height, scaffold erection, hand-tools handling, working under awkward posture, and weather exposure. These similar HSE contributing factors are relevant to identify the optimization patterns from the data collected in shipyards accidents.

1.8 Chapter Summary

The objective of this research is to study the OSH risk management framework for reducing the occupational accidents in shipyards case study. The proposed concept framework entails hazard identification, risk assessment, safety decision-making, risk control, and risk prediction. Current literature relevant to hazard identification, risk assessment, safety decision-making, risk control and machine learning risk prediction are reviewed in Chapter 2.

Chapter 3 presents detail methodology of risk management framework by utilising a supervised backpropagation machine learning in Artificial Neural Network (ANN) to predict occupational risk in the identified shipyards. Optimization and classification with

the appropriate architecture of neuron layers are trained for the risk prediction at shipyards case study. 10 independent input variables and 1 single layer-dependent output variable (severity of risk) are defined. 7 network modelings are developed between 19–31 neuron nodes.

Then, the best network model is selected in term of accuracy performance and consistency analysis in Chapter 4. Results are supported with correlation of coefficient (R^2), mean square error (MSE), mean absolute percentage error (MAPE), and sensitivity analysis. Following that, Questionnaire I, II and III are distributed to the selected shipyards case study to achieve the research's objective.

Finally, the summary and conclusions from the research, along with possibilities for further work in the future, are discussed in Chapter 5.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

In this chapter, research begins with background study and literature reviews that is related to various OSH risk management framework which is consisted of hazard identification, risk assessment, safety decision-making and risk control. These frameworks are presented at different fields with respective examples and its method of advantages and disadvantages. Process of fabrication activities for shipbuilding and ship repairing are also described in this chapter for further analysis and discussion to determine the potential risk and evaluate the risk level of workers at each process of activities. Besides that, machine learning Artificial Neural Network (ANN) and its performance algorithms of prediction are also discussed in this chapter to select the best prediction model network. Subsequently, accuracy performance and sensitivity analysis of the network are further detailed to study the accountability and stability of the model network. Finally, the chapter summary is presented.

2.2 Occupational Safety and Health in Shipyards

Occupational safety and health (OSH) management framework in the shipyard industry is limited though the results of these accidents are serious.

Othman et al. (2018) has conducted a study on safety control at shipyards, with a focus on Class C and D shipyards in Peninsular Malaysia that were registered with the Malaysian Ministry of Finance. The majority of accidents that occurred at shipyards were falls from heights, fires, explosions, high-risk exposure during hot work at high elevation, and confined spaces. This made shipyard operations a well-known example of hazardous

employment. The research was done utilising a survey method in order to rank the most significant risk exposure for shipyard workers based on the analysis of the Relative Important Index (RII). The HSE management system for hot work operations at high elevation in shipbuilding projects emerged as the most crucial with an relative important index (RII) of 0.740, according to the findings (Othman et al., 2018).

Next, Celebri (2010) from Turkish, explained that the SBSR industry was classified as a heavy industrial zone. The study was conducted between the years of 2006 and 2009 on 40 shipyards in Tuzla Bay, the area of Istanbul with the highest concentration of industrial facilities. The production procedures were complex and changeable. Majority of the shipyard activities, including welding, painting, blasting, and the manufacturing of fibreglass, had an immediate impact on workers' health. The effects of each step on worker health and safety were examined. Results in the study explained that category "Fell Off" had the largest proportion in the full analysis of accident distribution data, which indicated 29% (2006) and 11% (2009) (Celebri, 2010).

In addition to the physical safety study in the shipyard industry, Lokhande (2014) proposed to evaluate and analyse the health status of employees in a shipbuilding yard in Mumbai. A random selection was made of about 100 workers at once to examine each worker's health status. The selected workers' histories of distinct health conditions, medicine misuse, usage of personal protection equipment, as well as health-related complaints were reviewed. Following then, research made several crucial discoveries. Due to irregular usage of personal protection equipment (PPEs), 50% of the paint workers had high rates of medicine misuse (69%), hypertension (20%), obesity (53%), osteoarthritis (10%), hearing loss (25%) and poor self-care (Lokhande, 2014).

Furthermore, ergonomic hazards or hand-arm vibration syndromes hazards were also common claims from the shipyard workers. A 13-year period of shipyard visits (1998–2001) was used to observe cumulative exposure to the vascular and neurological symptoms of hand-arm vibration syndrome (HAVS). According to research, sensorineural symptoms were more common in the group with the lowest lifetime vibration exposure in 2001 (52.6% vs. 20.7% in 1988), and vascular symptoms were more common in the group with the highest lifetime vibration exposure in 1988 (68.7% vs. 43.2%) (Cherniack, 2004).

2.3 Risk Management Framework

To reduce the risk exposure of workers at shipyards, Othman et al. (2018) claim that the risk management framework should have its own structure in establishing a real-time risk assessment and monitor the risk level in the way of accountability and systematically. Following that, paper reviews on risk management framework in various industries and its applications are conducted as per following:

In United State, Etherton (2007) explained that American National Standard Technical Report (ANSI B11 TR3) has been created as a technical policy and applied in risk assessment and risk reduction for machine tools. It was also adopted in International Organization of Standardization (ISO 14121) for safety of machinery practical guideline. However, the aforementioned risk assessment framework process, was better suited to new handling operations or machine tool designs (Etherton, 2007).

Furthermore, another theoretical framework was described in Web Based Decision Support System (Cebi et al., 2017). The described framework was developed to assess potential occupational risk at shipyards that performed a preventive model. It was consisted of four main phases, namely identification, analysis, respond, monitor & review. This concept was also described in Formal Safety Assessment (FSA). It was consisted of

five major steps, namely hazard identification (HAZID), risk assessment (RA), risk management option (RMO), cost-benefit assessment (CBA), and decision-making recommendation (DMR) (Paik et al., 2007). Fundamental of FSA applied in International Maritime Organization (IMO) was rational, systematic, and proactive that controlled the risk of exposure among workers. This was a goal-based standard for shipping industry.

Other than that, risk assessment was also practiced in machinery manufacturing process, which was consisted of six steps (Machmood et al., 2015). It was started with studying the mapping of the manufacturing processes. Secondly, possible failures were described via the method of Failure Mode and Effects Analysis (FMEA) or Fault Tree Analysis (FTA). Thirdly, estimation on consequences of failure that were the after-effects of potential failure. The fourth stage was the risk assessment tool that defined the frequency of potential failure. In the fifth step, the entire risk of the prospective failure was indicated by the risk level. The final approach was the risk assessment process that defined the method for mitigating the risks associated with each failure.

Additionally, the Root Cause Analysis (RCA) method was another one that had been frequently employed in deriving lessons from safety incidents and near misses. Its primary goal was to provide guidance for risk assessment (figuring out risk acceptability) and risk treatment (risk reduction). Card et al. (2012) explained that RCA has demonstrated the viability of health care risk analysis. It was implemented in the United States Veterans Health Administration (VHA). However, RCA method did not show the healthcare identification criteria, which requires a long-term exposure's consideration. Therefore, this indicated that practitioners should be patient on safety improvement risk analysis especially in the healthcare risk control recommendation and implementation (Card et al., 2012).

On the other hand, Anderson (2005) emphasized on risk assessment framework in the Institution of Electrical Engineer (IEE), which was consisted of hazard identification, risk estimation, and risk evaluation activity. These mentioned criteria were fundamental components of data collection that required development, recording, and analysis. Programmable logic controller (PLC) was implemented to evaluate the flow of chemical streams that make up an ongoing chemical reaction. Such industrial process activities were grouped as a single or limited number of interactions that presented consideration in risk assessment. From the interaction between process activities, Anderson (2005) also emphasized on failure modes and effects analysis (FMEA) to identify the consequences of multiple faults. Data was collected and analyzed in risk evaluation for relevant solutions in achieving a good quality of industrial machine (Anderson, 2005).

Table 2.1 gives a summary of comparison between different risk management framework and its applications, advantages and disadvantages that determines the management framework of the research.

Table 2.1: Comparison Summary of Different Risk Management Framework

Reference	Risk Management framework	Application	Advantages	Disadvantages
(Anderson, 2005)	Hazard identification, Risk Estimation and Risk Evaluation.	Risk assessment framework applies in the IEE Industry	A deterministic evaluation method, which is applied to determine the initial event and consequences of the identified multiple faults application in the IEE industry. Risk evaluation and risk management for relevant solutions aim to achieve in machinery safety.	Consisted of limitation in term of interaction between activities in industrial process.
(Etherton, 2007)	Identify, Estimate, Evaluate and Reduce risks.	ANSI B11 TR3 has been developed as a technical guideline, which is associated with machines tools design and operation.	Easy for understanding. Risk assessment is used in new machine tools design and new operation of handling.	Only applicable for new equipment's or tools design in term of handling.
(Paik et al., 2007)	Hazard Identification (HAZID), Risk Assessment (RA), Risk Management Option (RMO), Cost-benefit Assessment (CBA) and Decision-making Recommendations (DMR).	Formal safety evaluation from the IMO, which is a methodical and logical approach for proactive management. It has been devised for shipping industry as a goal-based future development.	Easy for understanding. Performs a proactive management that emphasizes the priority of risk reduction, budget planning and impact.	Demands a continuously high manpower monitoring.

Table 2.2: Continued

Reference	Risk Management framework	Application	Advantages	Disadvantages
(Card et al., 2012)	Risk Evaluation, and Risk Treatment .	Requires a long period of learning from previous safety incidents and near misses via root cause analysis (RCA)	Risk evaluation determines the risk acceptability and risk treatment for risk reduction.	Mainly to know the significant of risk factors, risk evaluation and risk reduction. Moreover, other criteria like risk tolerance, decision-making, or healthcare identification criteria requires a long term exposure in monitoring.
(Machmood et al., 2015)	Manufacturing Process, Failures Estimation, Consequences of Failure, Risk Assessment, Risk Level, and Risk Reduction.	Consisted of six steps of risk assessment analysis in machinery production process.	Easy for understanding. Performs a proactive management that includes the priority of risk reduction, budget planning and impact.	Demands a continuously high manpower monitoring. Risk evaluation and risk reduction in in term of healthcare identification criteria are not discussed in this method.
(Cebi et al., 2017)	Identification, Analysis, Respond, Monitor and Review.	Access potential occupational risk management at shipyards to perform a preventive model.	Easy for understanding. Aim to perform a preventive risk framework.	This model framework is not pro to judge while having few risk contributing factors.

2.4 Hazard Identification Methods

2.4.1 Hazard Identification (HAZID)

Following the literature review of general industry in risk management framework, hazard identification method has been proposed either offline or online to identify and examine any circumstances which is able to endanger the environment, human safety, or property or result in a substantial financial expenditure. From the literature review, there are some relevant methods to carry out the hazard identification, for instance, Hazard Identification (HAZID), Hazard and Operability (HAZOP), Fault Tree Analysis (FTA), Event Tree Analysis (ETA), and Failure Modes and Effect Analysis (FMEA) (Paik et al., 2007). Each of these approaches has advantages and disadvantages of its own.

Paik et al. (2007) explained that HAZID was considered as a qualitative identification method and widely used in general offshore installation works. Table 2.2 shows the examples of hazards identified during ship shaped offshore installation works:

Table 2.2: Hazards Identified at Ship Shaped Offshore Installation (Paik et al., 2007)

Subsystem	No.	Hazards
Hull and Marine	1.	Hull failure due to extreme wave load
	2.	Hull failure during loading / offloading operation
	3.	Hazardous gas leak from cargo tank
	4.	Explosion, during tank intervention
	5.	Collision with passing vessel
	6.	Collision with shuttle tanker or supply vessel
	7.	Collision with other vessels
	8.	Rapid change of wind direction
	9.	Multiple anchor failure

Table 2.2: Continued

Subsystem	No.	Hazards
Hydrocarbon systems	1.	Leak leading to fire or explosion in process facility
	2.	Leak or rupture of riser
	3.	Impacting loads due to crane operations (swing loads)
	4.	Dropped objects from retrieval of cargo pumps
	5.	Severe rolling during critical operations (e.g. crane operations)
	6.	Emergency flaring with approaching shuttle tanker or during offloading
	7.	Unintended release of riser
Auxiliary systems	1.	Failure of cargo tank explosion during normal operation
	2.	Fire or explosion in pump room
	3.	Oil spill from offloading system (e.g. hoses, valves)
	4.	Fire or explosion in engine room

2.4.2 Hazard and Operability (HAZOP)

Besides that, Hazard and Operability (HAZOP) was studied by Anderson (2005) to identify hazards in a systematic and thorough manner by taking all hazardous processes into account. This was applied in machineries handling at shipyards (Table 2.3).

Table 2.3: Type of Hazard Identified During Machine Handling at Shipyard (Anderson, 2005)

Type of Hazards	Process Activities Exposed to the Hazards
Mechanical hazards	Activities caused by, for example: shape, relative location, mass and stability (potential energy of elements) mass and velocity (kinetic energy of elements) Inadequacy of the mechanical strength, accumulation of potential energy by; elastic elements (springs), or liquids or gases under pressure; or vacuum of machine parts or work pieces);

Table 2.3: Continue

Type of Hazards	Process Activities Exposed to the Hazards
Mechanical hazards	Crushing, shearing, cutting, severing, impact, or puncturing activities
	Friction or abrasion condition
	High pressure liquids condition or gases injection activities
	Ejection of parts (of machinery or processed materials / work pieces);
	Loss of stability during lifting operation (of machinery or machine parts);
	Slip, trip and fall hazards related to workplace surroundings
Electrical hazards	Electric shock or burn due to contacting with live parts normally carrying a voltage (direct contact) or contact with parts that have become live under fault conditions (e.g. insulation failure) (indirect contact);
	Electrostatic phenomena;
	Thermal radiation or other phenomena such as ejection of molten particles, and chemical effects from short-circuits, overloads, etc.
Thermal hazards	Burns and scalds during operation when contacting with objects or materials with an temperature, flames or radiation from heat sources;
	Operation that generated by hot or cold working environment.
Hazards generated by noise	Materials and substances processed operation that carry out in hammering, contacting, sand blasting and crushing, shearing, impacting and etc.
Chemical hazards	Mostly activities involving long duration of work activities in sand blasting, painting, de-greasing, processing in solvent de-greasing and etc.
Hazards generated by vibration	Mostly activities involving long duration of work activities in crushing, shearing, impacting, cutting, hammering and etc.
Hazards generated by radiation	Mostly activities involving long duration of work activities in electrical arching, laser shooting, ionizing radiation, X-ray shooting and exposed to the electromagnetic fields.
Hazards to health	Activities that directly contacting to biology or microbiological uncertainty. Workers are advised to be concerned on the sources that affect to health in the long-term explosion such as directly handling with chemical or working under the noise generated hazards.
Ergonomic hazards	Risks resulting from disregarding ergonomic principles in machine design (mismatch between machinery and human characteristics and abilities) can caused by, for instance: unhealthy postures or excessive effort; inadequate consideration of human hand-arm or foot-leg anatomy; neglectful use of personal protective equipment; inadequate area lighting; mental overload or under-load; stress; or human error.

2.4.3 Fault Tree Analysis (FTA)

On the other hand, Rahmat et al. (2009) investigated the use of Fault Tree Analysis (FTA) method for hazard identification, which involved the logical synthesis of numerous basic events that led to a single critical top event. To determine all probable reasons of system failure, FTA was applied as a top-down strategy. A study on the dependability of uninterruptible power supply systems was conducted by analysing the likelihood of failures at each level (Figure 2.1). According to the study's findings, the inverter module was the most important factor in the system's failure as a whole (Table 2.4), The inverter was replaced with a bi-directional converter module in the line-interactive UPS design to address the critical system failure, and this module significantly boosted the system reliability.

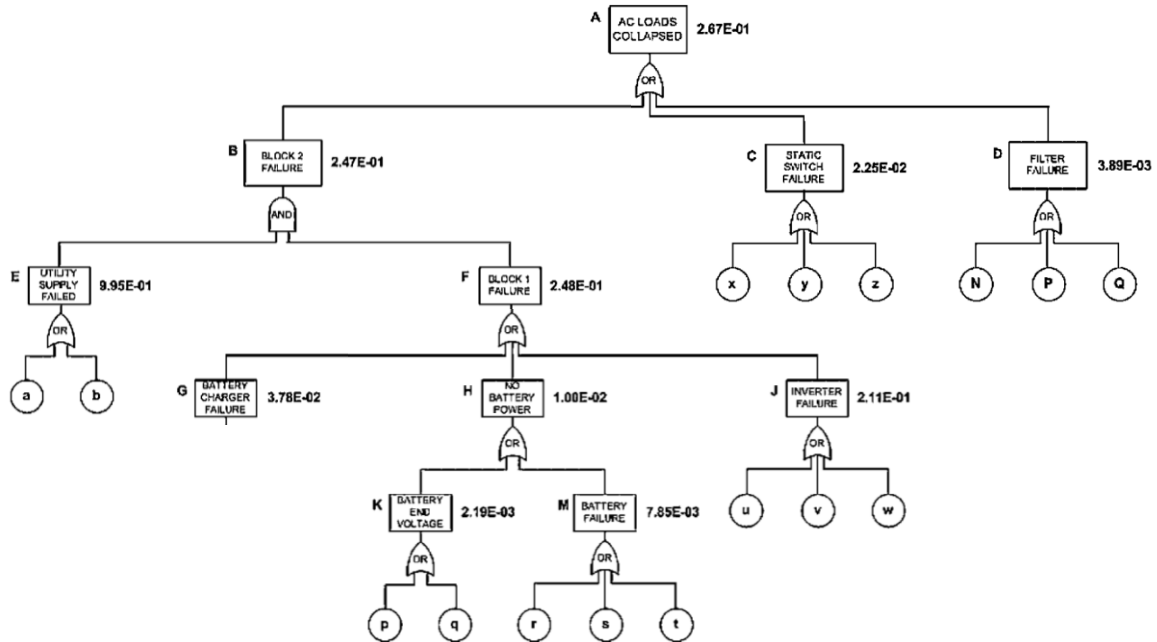


Figure 2.1: Fault Tree Analysis of UPS Failure (Rahmat et al., 2009)

Table 2.4: UPS Failure Probabilities Calculation (Rahmat et al., 2009)

Failure Probabilities Calculations	
$K = p + q - pq$	$F = G + H + J - (GH + GJ + HJ - GHJ)$
$M = r + s + t - (rs + rt + st - rst)$	$E = a + b - ab$
$H = K + M - KM$	$B = EF$
$G = l + m + n - (lm + mn - lmn)$	$C = x + y + z - (xy + xz + yz - xyz)$
$J = u + v + w - (uv + uw + vw - uvw)$	$D = N + P + Q - (NP + NQ + PQ - NPQ)$
	$A = B + C + D - (BC + BD + CD - BCD)$
Remarks:	
Capital letter A, B, C, D, E, F, G, H, J, K, M, N, P and Q represent the process of activities. Small letter a, b, p, q, r, s, t, u, v, w, x, y, and z represent the input factors.	

2.4.4 Event Tree Analysis (ETA)

Moreover, the application of event tree analysis as a logical representation of various events that followed a primary event or basic event has also been demonstrated and shown by Hong et al. (2009). This technique proved beneficial for connecting an event to other consequence model criteria, including design standard, age, historical performance, degradation, the gap between inspections, and more. At the tunnel's basic design stage, the risk was quantified using event tree analysis (ETA). According to the journal, the application involved steps to pinpoint triggering events as well as various underwater tunnelling data, including empirical analyses, design reports, case studies of real-world issues, numerical analyses model test results, and hydrological analysis results that were used as input factors for calculating the project's risk. Then, event tree analysis was constructed with three corresponding significant initiating events. Next, a quantitative risk assessment was performed on occurrence possibility and critical outcome. This is shown in Figure 2.2.

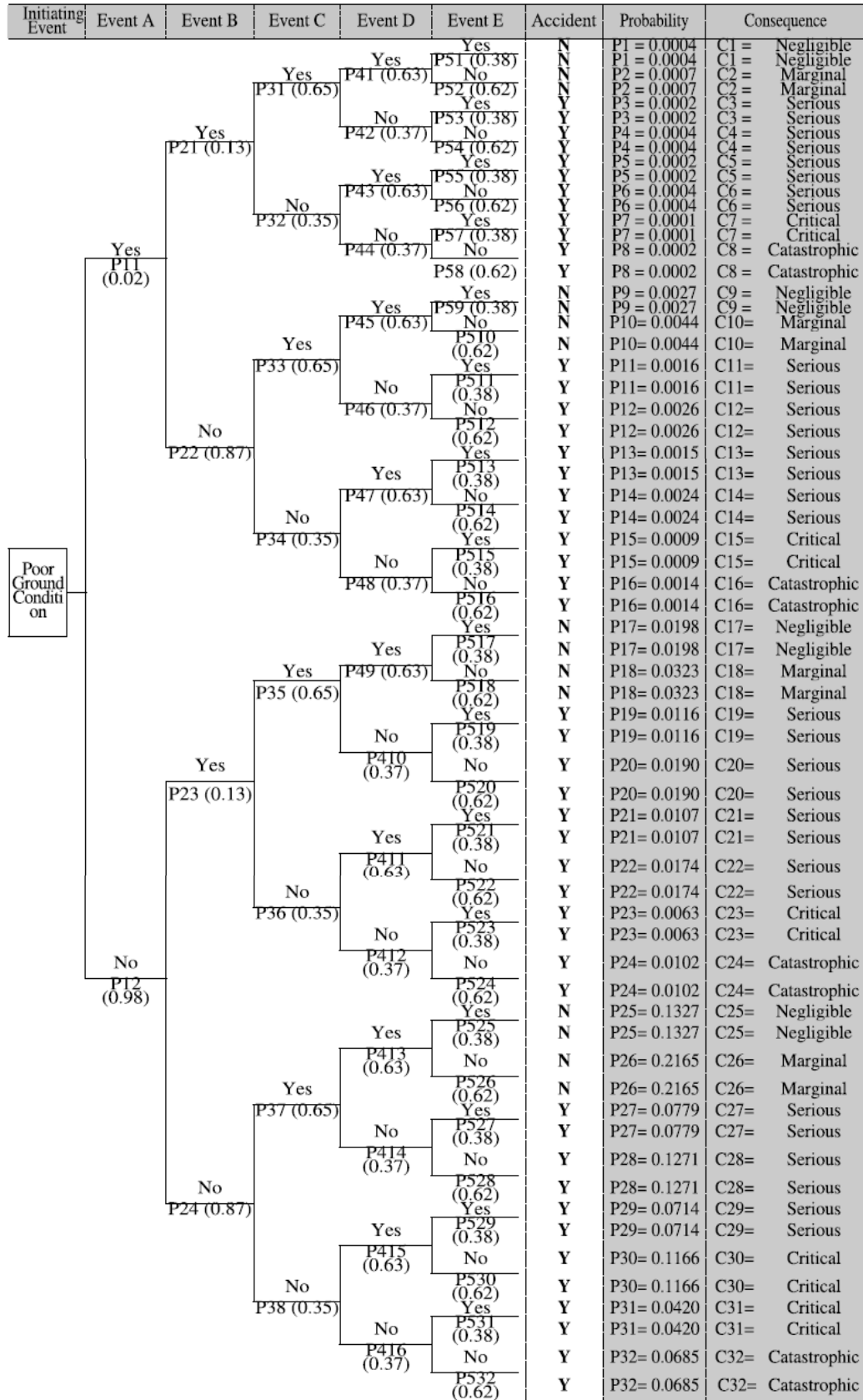


Figure 2.2: Event Tree Analysis of Tunnelling Construction (Hong et al., 2009)

2.4.5 Failure Mode Effect Analysis (FMEA)

Other than that, Failure Mode Effects Analysis (FMEA) is also a quantitative technique that has been frequently applied in engineering projects to investigate potential failure modes and eliminate prospective failures during system designs. Particularly, it provides quantitative and qualitative measures to carry out the corrective actions by focusing on main failure mode. It has been proven in many areas such as vehicles, electronics, consumer goods, manufacturing facilities, and telecommunications. A study has been performed in chemical paint industry. Xiao et al. (2011) explained the importance of risk assessment hazardous to health in chemical paint production which required a labour-intensive process. Other than that, Hu et al. (2009) also discussed the variety use of volatile and dangerous substances such as fatty acids, lead, ethers, alcohols, and colours in chemical plant. This increased the risk of factory caught in fire, workers were exposed to hazardous chemicals, and so on in the chemical production. However, Chang et al. (2009) proved that FMEA method was used to evaluate risk on a single failure. It did not solve the problem for two or more contributing factors to the failure at the same time.

Table 2.5 shows the comparative summary of different hazard identification methods with its application characteristic, advantages, and disadvantages.

Table 2.5: Comparative Summary of Different Hazard Identification Methods

Author	Type of Hazard Identification	Characteristic	Advantages	Disadvantages
(Anderson, 2005)	HAZOP	Hazard and Operability (HAZOP) is useful to identify all hazardous process in a systematic and thorough manner.	Widely used in a list of significant issues which is able to present dangers or operability issues. Widely used in a list of suggestions, activities, or modifications to improve safety or operations.	Requires time consuming to list down all the process activity.
(Paik et al., 2007)	HAZIP	Hazard Identification (HAZID) has been studied for the general offshore installation. HAZID is mostly used in the processing industry.	A thoroughly hazard identification in all categories such as physical, chemical, biological, ergonomic, and psychosocial in the process activity.	Requires time consuming to list down all the identified hazards.
(Rahmat et al., 2009)	FTA	Fault Tree Analysis (FTA) is a quantitative method that logically combines a number of minor events that contribute to a major top event. FTA is a top-down strategy to find all potential root causes of system failure.	A collection of logic diagrams which shows the relationships between different failures, mistakes, and accidents.	Quantification requires a significant calculation in combination of few risk evaluations.

Table 2.5: Continued

Author	Type of Hazard Identification	Characteristic	Advantages	Disadvantages
(Hong et al., 2009)	ETA	Event Tree Analysis (ETA) is a quantitative approach that logically represents many occurrences that happen after an initiating or fundamental event. It has been proven beneficial for connecting an event to other consequence model criteria, including design standard, age, historical performance, degradation, the gap between inspections, and more.	A set of logic diagram that illustrates the sequence of events in specific accidents. Widely used in all design phase, facility modification and operation.	Limited to one initiating event with various risk consideration.
(Xiao et al., 2011)	FMEA	Failure Mode Effects Analysis (FMEA) is another quantitative or qualitative method which is an excellent analytical tool. It has been widely used in engineering projects to investigate potential failure modes and eliminate prospective failures during system designs.	A list of equipment used in facilities. It shows the possibility method of failure as well as the consequences of those failures for the facility's equipment.	Technically, it is only able to evaluate the possibility of impact based on single failure.

2.5 Process Flow of Manufacturing at Shipyards

Then, process flow of shipbuilding in details are studied after considering hazards identification is the first step of the research framework. Hull structural unit is a diverse construction which involves different processes and assembly works as described in Figure 2.3 and Figure 2.4 (Medeiros et al., 2000). Components material are arranged into plates, painted, marked, cut and bent. Then components are assembled into blocks and ship compartments. Besides that, handouts from Sibu Shipyards Association has been referred for detailed description of the shipbuilding process (Hasan, 2019). This is clear to identify potential hazards and critical conditions at every process of manufacturing which is shown in Figure 2.5. Details process activities show in Figure 2.5.1, Figure 2.5.2, Figure 2.5.3, Figure 2.5.4 and Figure 2.5.5.

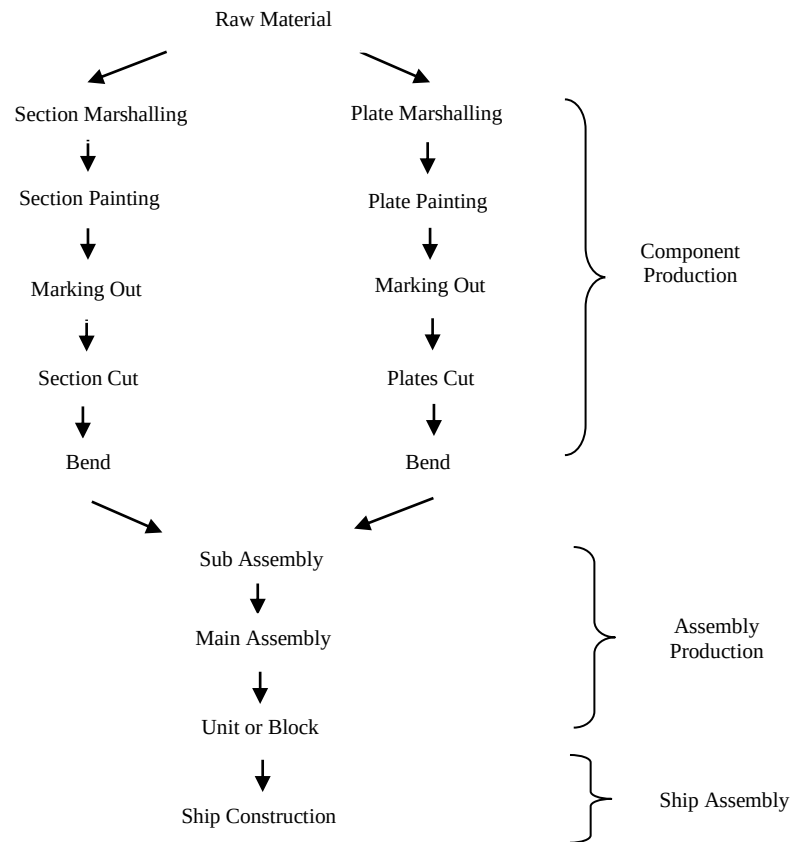


Figure 2.3: Ship Hull Fabrication Process (Medeiros et al., 2000)

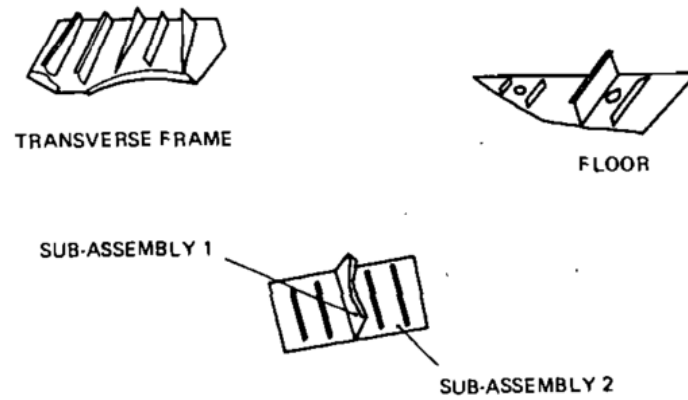


Figure 2.4: Sub-assemblies of Ship Hull Fabrication Process (Medeiros et al., 2000)

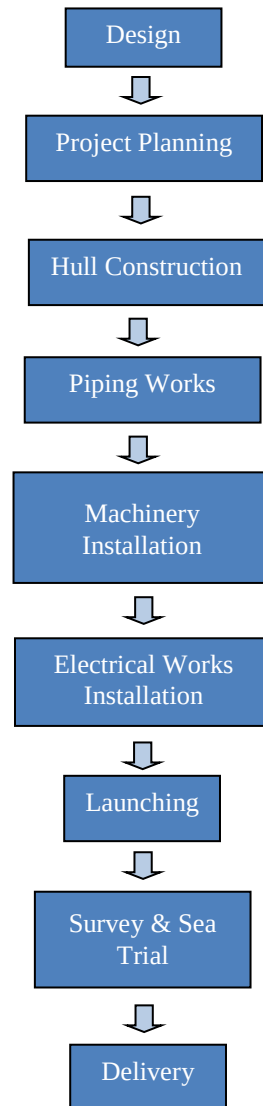


Figure 2.5: Shipbuilding Process Flow Chart (Hasan, 2019)



Figure 2.5.1: Hull Construction (Hasan, 2019)



Figure 2.5.2: Piping Works (Hasan, 2019)



Figure 2.5.3: Machinery Installation (Hasan, 2019)



Figure 2.5.4: Electrical Work Installation (Hasan, 2019)



Figure 2.5.5: Launching (Hasan, 2019)

2.6 Risk Assessment

Next, research assesses the potential of identified hazards throughout the process of activities. Risk assessment is a combination of few input parameters that make it possible to evaluate the risk at the various hazardous situations. With this, high-risk and low-risk situations can be immediately distinguished from one another (Etherton, 2007).

Shaleh et al. (2016) classified risk assessment as a quantitative tool with at least two parameters. One parameter represented the severity of harm, though some tools referred to this as a consequence (Table 2.7). The other parameter represented the probability of occurrence that harmed. Some tools used chance, frequency, or likelihood that shown in Table 2.6 instead of probability. The quantitative technique was used to calculate the frequency of a specific hazardous occurrence with respect to time. Risk assessment at each production process was calculated by using Equation 2.1:

$$R = L \times S \quad \text{Equation 2.1}$$

Where:

R is the risk;

L is the probability of risk, and;

S is consequences of risk occurrence.

Table 2.6: Indication of likelihood (L)

Likelihood (L)	Example	Rating
Most likely	The most likely result of the hazard /event being realized	5
Possible	Has a good chance of occurring and is not unusual	4
Conceivable	Might be occur a sometime in future	3
Remote	Has not been known to occur after many years	2
Inconceivable	Is practically impossible and has never occurred	1

Table 2.7: Indication of Severity (S)

Severity (L)	Example	Rating
Catastrophic	Numerous fatalities, irrecoverable property damage and productivity	5
Fatal	Approximately one single fatality major property damage if hazard is realized	4
Serious	Non-fatal injury, permanent disability	3
Minor	Disabling but not permanent injury	2
Negligible	Minor abrasions, bruises, cuts, first aid type injury	1

On the other hand, according to Samekto et al. (2020), three variables were discovered for having an impact on the likelihood of an event occurring, Namely, the maturity factor (Pm), which reflected the likelihood of risk related to the development of new technology; the complexity factor (Pc), which reflected the likelihood of risk related to the development of systems; and the dependency factor (Pd), which reflected the likelihood of risk related to dependence on facilities, contractors, and other factors. The consequence of risk occurrence was also affected by three factors, they were performance, cost, and schedule respectively (Basuki et al., 2014).

Other literature reviews proved that the risk exposure of people were included with both frequency and duration of exposure. This research was based on four-parameters categorization for probability of occurrence of harm (Ph). This is shown in Table 2.8, 2.9, 2.10, 2.11, and 2.12. The proposed risk evaluation tools model was built using the defined parameters. Then Equation 2.2 and Equation 2.3 were developed (Moatari-Kazerouni et al., 2015):

$$R = S \times Ph \quad \text{Equation 2.2}$$

Where:

R is the risk value;
S is the severity of harm, and;
Ph is probability of occurrence of harm.

$$Ph = Exf + Exd + [2 \times Pe] + A \quad \text{Equation 2.3}$$

Where:

Ph is the probability of occurrence of harm;
Exf is the frequency of exposure to the hazard;
Exd is the duration of exposure to the hazard;
Pe is the probability of occurrence of a hazardous even, and;
A is the possibility of avoidance.

Table 2.8: Severity of Harm (S)

Severity of Harm (S)	Rank
Slight injuries (bruises) requiring no first aid or injuries requiring first aid but without lost time.	1
Injuries requiring more than first aide (assistance) and with lost time or when there is irreversible harm and slight disability, but the employee is able to return to the same job.	2
Serious disability, the employee being able to return to work, but perhaps not to the same job.	3
Permanent disability, and the employee can no longer work.	4
One or more deaths	5

Table 2.9: Frequency of Exposure to the Hazard (Exf)

Frequency of Exposure to The Hazard (Exf)	Rank
Less than once per year	1
Annually	2
Monthly	3
Weekly	4
Daily to continuously, i.e. several times per hour	5

Table 2.10: Duration of Exposure to the Hazard (Exd)

Duration of Exposure to The Hazard (Exd)	Rank
< 1/20 of work time	1
1/10 of work time (45 min per 8 h shift)	2
1/5 of work time (90 min per 8 h shift)	3
Half of work time (1/2) (4 h per 8 h shift)	4
Continuously during work time	5

Table 2.11: Probability of Occurrence of a Hazardous Event (Pe)

Probability of Occurrence of a Hazardous Event (Pe)	Rank
Negligible	1
Unlikely	2
Possible	3
Likely	4
Significant	5

Table 2.12: Technical and Human Possibility of Avoiding (A)

Technical and Human Possibility of Avoiding (A)	Rank
Highly significant	1
Significant	2
Somewhat likely, with some conditions	3
Unlikely	4
Nil	5

Besides that, Anderson (2005) studied on risk analysis in industrial machines design and installation and explained that risk evaluation diagram was covered with the parameters of severity (S), avoidance (Av), probability of event reoccurrence (Pr), frequency of risk reduction (Fr). This is shown in Equation 2.4. Moreover, risk evaluation diagram was further evaluated into details that covered the parameters of severity (S), avoidance (Av), probability of event reoccurrence (Pr), frequency of risk reduction (Fr).

$$R = S \text{ Diagram } (Av + Pr + Fr) \quad \text{Equation 2.4}$$

Where:

R is the risk value;

S is the severity;

Av is the avoidance;

Pr is the probability of event reoccurrence, and;

Fr is the frequency with the life phase of risk reduction.

Project _____

Date _____

Life phase (May be one phase or multiple)

A= _____

B= _____

C= _____

This document is for: √

Preliminary risk assessment	
Intermediate risk assessment	
Follow-up risk assessment	

Risk evaluation area						
Consequences	Severity Se	Highest value of [A or B or C] from the (Fr +Pr +Av) columns in the Risk estimation area				
		3 – 4	5 – 7	8 – 10	11 – 13	14 – 15
Death, losing an Eye or limb	4					
Permanent, loss of finger or toe	3					
Reversible, needing medical attention	2					
Reversible needing first aid	1					

Darker shaded area action required

Lightly shaded area action recommended

No Shading area acceptable risk (safe)

Frequency Fr		Probability Pr		Avoidance Av	
Daily	5	Very high	5	Impossible	5
Weekly	4	Likely	4		
Monthly	3	Possible	3	Possible	3
Yearly	2	Rarely	2		
Less	1	Negligible	1	Obvious	1

In the "Risk Estimation area" find the (Fr +Pr +Av) total value for each life phase being considered, which ever the greater total is, use that value in the Risk evaluation matrix area. This example shows three life phases, more or less may be appropriate to the circumstances. An "X" in the end column = end of iteration for that identified hazard, the risk evaluation shows that de-minimus level has been reached

Figure 2.6: Risk Assessment and Risk Evaluation Checklist Diagram

However, some conflicts and questions have been raised upon the accuracy of the risk analysis method due to different standards of understanding and interpretation. Previous research revealed that numerous risk estimating systems were found to have biases in favour of high-risk or low-risk estimations. This has resulted in unsuitable risk reduction strategies or inappropriate priority of risk reduction efforts (Moatari-Kazerouni et al., 2015). Furthermore, outputs of risk estimation tools were comparative rather than perfect known. Therefore, risk estimation by using one tool cannot be compared directly with those using various tools (ISO/TR 14121-2 2012).

Table 2.13 gives a summary of comparison between different risk assessment methods at its application, advantages and disadvantages that is in line with the risk management framework.

Table 2.13: Comparative Summary of Different Risk Assessment Methods

Author	Risk Assessment Formula	Advantages	Disadvantages
(Anderson, 2005)	$R = S \text{ Diagram } (Av + Pr + Fr)$ Where: R is the risk value; S is the severity; Av is the avoidance; Pr is the probability of event reoccurrence, and; Fr is the frequency with the life phase of risk reduction.	A quantitative risk estimation tool which has converted the likelihood into the parameters of avoidance and probability of event reoccurrence.	Requires a diagram on hand for referring to the diagram on risk estimation.
(Shaleh et al., 2016)	$R = L \times S$ Where: R is the risk L is the probability of risk, and S is consequences of risk occurrence	A quantitative approach and it is simple to understand. Widely used in general industries under Malaysia guideline.	Requires a large amount of historical information for example seriousness of severity and frequency of the likelihood.

Table 2.13: Continued

Author	Risk Assessment Formula	Advantages	Disadvantages
(Moatari-Kazerouni et al., 2015)	$R = S \times Ph$ Where: R is the risk value; S is the severity of harm, and; Ph is probability of occurrence of harm. $Ph = Exf + Exd + [2 \times Pe] + A$ Ph is the probability of occurrence of harm; Exf is the frequency of exposure to the hazard; Exd is the duration of exposure to the hazard; Pe is the probability of occurrence of a hazardous even, and; A is the possibility of avoidance.	A quantitative approach and it is developed from equation $R = L \times S$ which has taken the occurrence of harm into consideration. It is similar to the other risk estimation tools. It covers different areas of OSH. It defines details in parameters.	It is a bit complicated and requires a mathematical calculation tool.

2.7 Quantitative Safety Decision-Making

Subsequently, risk level and priority of risk control are evaluated. Methods of risk level evaluation is discussed in risk matrix, risk graph, and quantified risk assessment (QRA). After that a quantitative safety decision-making is performed in risk priority number (RPN) to evaluate the priority of risk control implementation. In other words, higher risk assessment shows the more significant of safety decision-making in preference with good detection of risk control.

2.7.1 Risk Matrix

Lee (2012) explained that OSH practitioners made decisions based on the results of site audit inspection and past experience of identifying risk with comparable significant conditions, but it was a challenging process because many elements were influencing the prediction. Once the level of risk exposure was determined, measurement was necessary since risk acceptance was deemed manageable. Risk matrix method (risk level indication) showed the risk acceptance in the combination of severity of harm with the probability of occurrence that harmed. Lee (2012) also pointed out that risk matrix had been applied in general industries. This can refer to the guideline of OSH regulation in Malaysia. Risk matrix and risk level are shown in Figure 2.7 and Table 2.14 respectively.

	Severity				
Likelihood	1	2	3	4	5
1	5	10	15	20	25
2	4	8	12	16	20
3	3	6	9	12	15
4	2	4	6	8	10
5	1	2	3	4	5

High	
Medium	
Low	

Figure 2.7: Risk Matrix

Table 2.14: Risk Value that Determine the Priority Action to Effectively Manage Workplace Hazards

Risk	Description	Action
15 - 25	High	A HIGH risk requires immediate action to control as detail in the hierarchy of control. Action taken must be documented on the risk assessment form including date for completion.
5 - 12	Medium	A MEDIUM risk requires a plan approach to controlling the hazard and applies temporary measure if required. Action taken must be documented on the risk assessment form including date for completion.
1 - 4	Low	A risk identified low may be considered as acceptable and further reduction may not be necessary. However, if the risk can be resolved quickly and efficiently, control measure should be implemented and recorded.

2.7.2 Risk Graph

Nait-Said et al. (2009) studied on the method of risk graph to measure the level of safety integrity when the safety equipment is in place. An example of a risk graph shown in Figure 2.8 works from left to the right. Descriptive parameters are shown in Table 2.15. The principle of the risk graph technique had been embraced in the United Kingdom Offshore Operator Association (UKOOA) guidelines for offshore control and safety systems.

Table 2.15: Quantitative Description of Parameters (Nait-Said et al., 2009)

Risk Parameter	Descriptions	Quantitative Description
Consequence (C)	Minor Injury	No deaths per event
	Marginal: One death or permanent injury	$[10^{-2}, 10^{-1}]$ probable death per event.
	Critical: Several deaths	$[10^{-1}, 1]$ probable death per event.
	Catastrophic: Many deaths	>1 probable death per event.
Exposure (F)	Rare	$< 10\%$ of the time
	Frequent	$> 10\%$ of the time
Avoidance (P)	Possible	90% possibility of avoidance hazard.
	Not likely	$<90\%$ possibility of avoidance hazard.
Demand Rate (W)	Very low	< 1 in 30 years $\sim < 0.03$ per year
	Low	1 in (3, 30) years $\sim [0.03, 0.3]$ per year
	Relatively high	1 in [0.3, 3] years $\sim [0.3, 3]$ per year

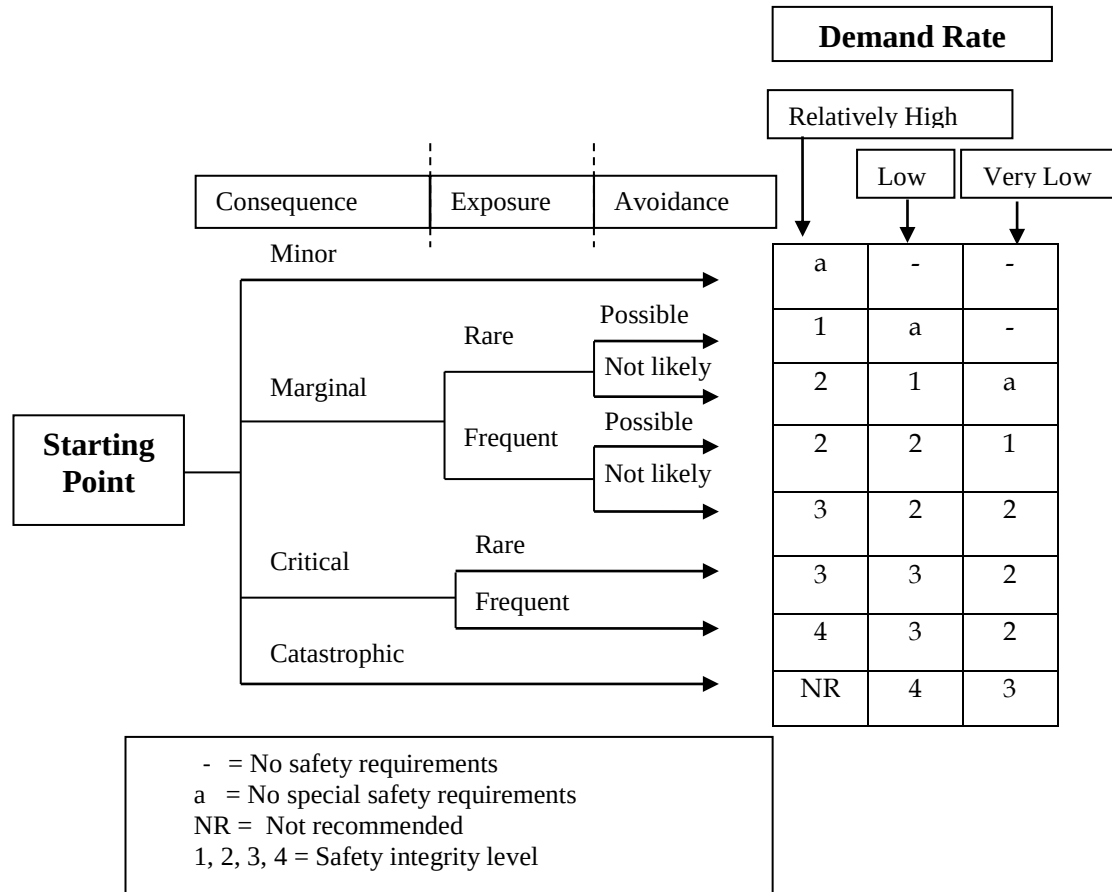


Figure 2.8: Risk Graph with Quantitative Description of Parameters (Nait-Said et al., 2009)

2.7.3 Quantified Risk Assessment (QRA)

Moreover, Buyong et al. (2019) evaluated quantified risk assessment (QRA) as quantitative method that showed in mathematical calculation. This is to show the likelihood of a certain outcome occurring during a specific duration of time. The risk was often described as the annual frequency of the death of the individual. Therefore, QRA allowed the estimated risk to be compared with criteria that can be traced back to the number of annual death or accidents statistics. Small number was used to express risk such as 1.54×10^{-4} , that is able to provide a high-precision imprint. The advantage of QRA was that a high precision number of risks can be indicated the achievement in health and safety. From there, a comparison can be done on the effectiveness of decision-making in risk

management within a duration of time. In the highly safe demand industry, Centre for Marine and Petroleum Technology (CMPT) suggested QRA guideline to be applied at offshore platforms in UK and Norway (Buyong et al., 2019).

2.7.4 Risk Priority Number (RPN)

Furthermore, Chang et al. (2009) explained the application of risk priority number (RPN) methods on safety decision-making. The three-factor parameters mentioned in RPN origin from FMEA and it was evaluated as severity (S), occurrence (L), and detection (D) as shown in Equation 2.5.

$$RPN = S \times L \times D \quad \text{Equation 2.5}$$

RPN method had been widely used in engineering-based risk analysis. All parameters were examined and assigned with RPN value. An excellent detection (D) of current practiced risk control shows the lowest in RPN. However, an undetectable risk control shows the highest in RPN. This explains that current practiced risk control is not practicable and has the priority to be improved. In other words, corrective action is implemented by considering the highest RPN value down to the least. The intention of the corrective action is to eliminate or minimise the critical failure mode.

Table 2.16: Indication of Detection (D)

Detection (D)	Example	Rating
Catastrophic	Undetectable	5
Fatal	Poor	4
Serious	Moderate	3
Minor	Good	2
Negligible	Excellent	1

Table 2.17 shows the summary of comparison of risk priority methods at their application, advantages, and disadvantages.

Table 2.17: Comparative Summary of Different Risk Priority Methods

Author	Risk Priority Method	Application	Advantages	Disadvantages
(Nait-Said et al., 2009)	Risk Graph	Risk Graph is used to identify the safety integrity level for safety instrumented functions. The tree structure of the risk graph is working from the left to the right.	Encourage thorough discussion of the hazards and risks. Provide risk prioritisation.	A quantitative and qualitative method which is a bit complex and it requires skill graph reader to identify the risk level.
(Chang et al., 2009)	Risk Priority Number	Three-factors of Risk Priority Number (RPN) in FMEA stands for severity (S), occurrence (L) and detection (D). $RPN = S \times L \times D$ RPN method is widely used in engineering analysis. Once all items have been examined and assigned with a RPN value, an appropriate corrective action is implemented by considering the highest RPN value down to the least.	A quantitative and qualitative method which shows the priority of risk reduction and it is easy to understand. The intention of the corrective action is to eliminate or minimise the critical failure mode, which displays the highest severity, most frequent occurrence, and lowest detection ranking.	RPN results are subjective due to personal perception of rating in severity, occurrence, and detection.

Table 2.17: Continued

Author	Risk Priority Method	Application	Advantages	Disadvantages
(Lees, 2012)	Risk Matric	Risk Matrix is a multidimensional table of risk level indication which allows the combination of any class of harm's severity with any class of probability of occurrence that harm. It can be referred to the guideline of the OSH regulation in Malaysia	A qualitative method and easy to understand and most used in general industries. Risk assessment for supporting to the risk evaluation	The lack of depth is an issue because should the tool be used as the only method of risk evaluation; the intricacies of the hazard could be oversimplified.
(Buyong et al., 2019)	Quantified Risk Assessment	A quantitative approach that uses calculation to determine the likelihood of a particular result occurring over time, as precisely as possible given the data at hand. In general, risk is often expressed as the annual frequency of the death of an individual, for example: 1.54×10^{-4} .	High precision number of risks to indicate the achieved goal in health and safety. Comparison can be done on the effectiveness of decision-makings in risk management which is carried out within a period of time.	In general, the value only indicates the frequency of the death of an individual.

2.8 Risk Control

Subsequently, from the quantitative safety decision, risk control is implemented to prevent and reduce either a single element risk or multiple elements risk. Card et al. (2012) showed that risk controls in general were categorized according to the hierarchy chart shown in Figure 2.9. The hierarchy chart entails elimination, substitution, engineering control, administrative control and personal protective equipment, is referred to the National Institute for Occupational Safety and Health (NIOSH) risk control version.

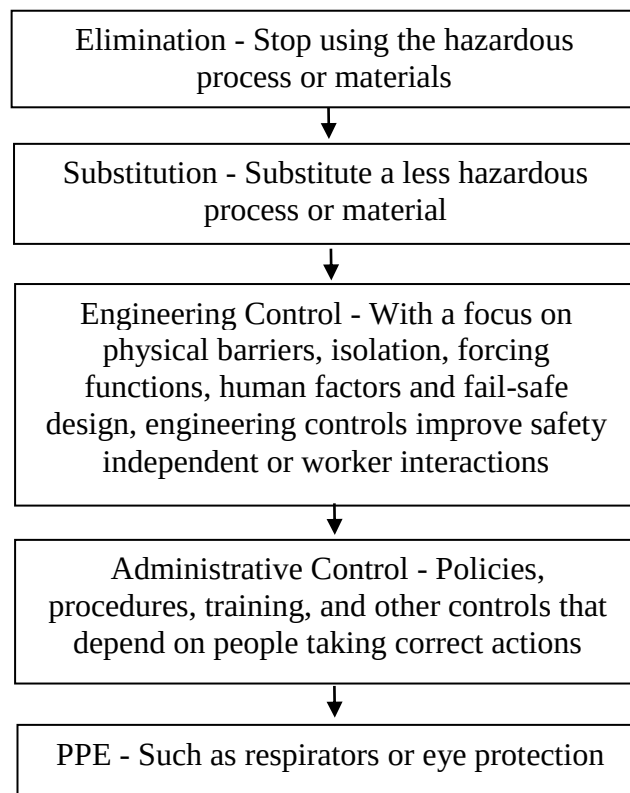


Figure 2.9: Hierarchy of Risk Control

Etherton (2007) justified that the implementation of risk control at the earlier stage can contribute a significant beneficial, especially when the risk level was high (for example, design stage rather beneficial than the operational stage). This is because risk-reduction strategies can be implemented at a cheaper cost. Other than that, Etherton (2007) also suggested that parameters of “probability of occurrence” of a hazardous event and “possibility of avoidance” should be taken into consideration to reduce the risk. This is shown in ANSI B11 TR3, namely “The risk reduction process is completed when protective measures with the hazard control hierarchy are applied and tolerable risk has been achieved for the identified task/hazard combinations and the machines as a whole” (Etherton, 2007).

However, on the physical hazards risk control-wise, Celebi (2010) emphasized that workers working at height were exposed directly to the hazards. Accidents involving fall from height can be prevented by wearing protective equipment and establishing legal regulations control at the source of the risk. Papazoglou et al. (2007) also suggested risk reducing measurements to provide the least expensive solution satisfied in the risk acceptable criteria. This is shown in Table 2.18 and Table 2.19.

Table 2.18: Description of Risk Reducing Measures Providing the Least Expensive Solution Satisfying the Risk Criteria

In List	Short Description for Risk Measures
3	Safety Training
8	Company protocol on unacceptable behaviour
11	Visual inspection of the condition of materials
35	Information about objects subject to voltage
41	Physical partitioning-off of machine
47	Check all the tools, equipment and securing systems prior to using machine or vehicle
52	Fit blind spot mirrors
53	Correct environment for patients /customers
63	Periodic maintenance and inspection
64	Personal protective equipment
65	Practical training
69	Guardrails
70	Clean and tidy working space
71	Stable surface
72	Anti-slip feet
73	Work shoes
74	Cordon-off working area
75	Procedures using ladders
76	Ladders of the correct type and the right length
78	Suitability of additional structures and when erecting scaffolding.
80	Fixed ladder
81	Carry out RIE (Risk Inventory and Evaluation) on working condition
82	Cordoning and sign for danger area
83	Introduce a system of recorded competencies, task and authorities for each employee
84	Toolbox meeting

Table 2.19: Description of Risk Reducing Measures Providing the Largest Possible Risk Reduction at a Given Budget

In List	Short Description for Risk Measures
3	Safety training
7	Safety cage for ladder
8	Company protocol in unacceptable behaviour
21	Secure objects that can fall
35	Information about objects subject to voltage
41	Physical partitioning-off of machine
51	Training on risk due to inattentiveness
63	Periodic maintenance and inspection
69	Guardrails
70	Clean and tidy workplace
71	Stable surface
76	Ladders of the correct type and the right lengths
78	Suitability of additional structure used when erecting scaffolding
79	Self-defence course
81	Carry out RIE (Risk Inventory and Evaluation) on working condition
82	Cordoning and signs for danger area
83	Introduce a system of recorded competencies, tasks and authorities for each employee
84	Toolbox meeting

On the other hand, Lokhande (2014) studied on occupational health risk control in the chemical paint industry. Findings showed that 50% of the paint workers do not consistently wear personal protective equipment (PPE). Health education exposure to occupational hazards and lifestyle diseases were suggested to be introduced to the workers. Other than that, proper PPEs application and regular health examination were also suggested to be a necessity in further reinforcement (Lokhande, 2014).

Moreover, research also concerns with fabrication process activities that use tools handling such as cutter, grinder, breaker, and so on where proper risk control should be taken in place. For workers that have long-term vibration exposure, they end up having HAVS syndrome which is known as an occupational health disease. A study has been conducted on vibration exposure. Cherniack et al. (2004) discussed that sensor neural symptoms were more common in the group with the lowest lifetime vibration exposure in 2001 (52.6% vs. 20.7% in 1988) while vascular symptoms were more common in the group with the highest lifetime vibration exposure in 1988 (68.7% vs. 43.2%). According to the survey, former groups' risk exposure can be reduced by rotating jobs, weakening conventional trade unions, and using less specialised vibratory equipment (Cherniack et al., 2004).

Nevertheless, human errors also play an important role in injuries sustained at the human-system interface. Braithwaite et al. (2015) identified a range of simple phenotypes, namely repetition of an action, reversing the order of action, omission of actions, late actions, early actions, replacement of one action by another, insertion of an additional action from elsewhere in the task, and intrusion of an additional action unrelated to the task. These deviations of behaviours have become the target for evaluation in some accidents that involved in human errors.

As far as practical in risk prevention and risk control, it is advised not to go into the administrative control and PPE approach without really understanding the most appropriate method of risk control. Card et al. (2012) pointed out that elimination or design controls had a 1.6 times higher likelihood of explicitly reporting success, contrary to the use of administrative controls. However, 80% of the risk control recommendations made in the 28

study reports were implemented with administrative controls. It should be improved by having a good aim on the hierarchy of risk control (Card et al., 2012).

2.9 Machine Learning Artificial Neural Network

From the risk management framework developed, research reviews that judgment of decision-making can be changed when there are numerous of cognitive biases. Dehghani et al. (2022) reviewed that biases would lead to uncertainty of decision-making. Therefore, a study of predictive models has been done to optimize the contribution of the various causal factors towards an accident to happen (Sarkar et al., 2019). With the causes known, outcomes of accidents can be predicted.

Generally, predictive model for workplace accidents is based on statistical learning or machine learning (ML). Supervised machine learning Artificial Neural Networks (ANN) has been extensively utilised as intelligent techniques that can be developed for a particular application, such as pattern recognition, function approximation, or data classification through an optimization (Mohamed et al., 2017). The architecture of ANN are consisted of several neurons. Kumruoglu et al. (2021) explained that these architectures of the interconnection of neurons were popularly known as Multi-Layer Perceptron (MLP) which can be developed for risk prediction. Ceribasi et al. (2017) reviewed that ANN risk prediction algorithm emphasized on Back-Propagation Neural Network learning (BPNN). All weights in the network were initialised to small random values at the start of the learning phase. The algorithm employed a learning set of input-output pairs that were produced through the offline analysis of historical data. However, Zeynalian et al. (2016) explained that with a large amount of historical data, ANN supervised technique was not able to produce a good result with the unclear data and filled with the noisy system. Therefore, data mining and data cleansing has been carried out in the shipyards industry to

get accurate input-output paired data. Gokler et al. (2022) discussed that the weights in the network were adjusted using the pair wise data to reduce the Mean Square Error (MSE), which varied the actual and desired values across all output neurons and learning patterns. After finding MSE, the weights adjustment in Back-Propagation approach is applied for the usage of ANN modeling architecture.

2.10 Artificial Neural Network Application, Architecture and Algorithm

ANN machine learning has been proven in various fields, such as die cast's shrinkage prediction in engineering (Kumruoglu et al., 2021), analysis of stream flow trend and rain flow trend under environmental prospects (Ceribasi et al., 2017), construction's capital forecasting (Zeynalian et al., 2016), and it yielded very useful results (Sarkar et al., 2019) (Baykal et al., 2023). However, to the authors' knowledge, literature review showed that occupational accident risk analysis had only demonstrated the use of ANN in terms of their predictive and explanatory capacities, with limited details on the data optimization to find out the root cause of workplace accidents (Matías et al., 2008) (Martin et al., 2009) (Erzin et al., 2019) (Niazka et al., 2021). Hence, ANN technique in various types of algorithm architecture is developed to perform a good risk prediction model.

In medical line, a study has been done on ANN model application of heart disease risk prediction. Yazdani et al. (2015) explained in details that Levenberg-Marquardt (trainlm) backpropagation algorithm was carried out with training, validation, and testing from a data set of 297 samples. The experiment was repeated for different training algorithms such as scaled Conjugate Gradient backpropagation (trainscg), BFGS Quasi-Newton backpropagation (trainbfg), and Resilient backpropagation (trainrp). Data pre-processing was done by eliminating 6 samples with missing values and 13 data set descriptions of inputs were turned into encodings as an input to the ANN model. The

output indicated the risk prediction of heart disease. With the architecture of input neurons, a number of hidden neurons layers and output neurons were consisted of 13-30-1. 297 data were extracted to 80-10-10 for training-validation-testing. Based on the empirical findings, the architecture with the hidden layer's hyperbolic tangent sigmoid activation function (tansig), and the output layer's log-sigmoid activation function (logsig) trained data, achieved accuracy performance 100%, sensitivity 100%, precision 100%, and specification 100%. This facilitated doctors to forecast the likelihood of heart disease (Yazdani et al., 2015).

On the other hand, Nassiri et al. (2014) reviewed accident prediction methods in traffic management. Evaluation was implemented by developing two types of the model, namely count regression and machine learning, to predict the number of crashes and severity of the crashes. Negative Binomial Regression (NBR) and Zero Inflated Negative Binomial Regression (ZINBR) models were the most common types of count regression to model accident frequency. On the other hand, Support Vector Machine (SVM) and Back-Propagation Neural Network (BPNN) were the most well-known supervised machine learning paradigms. The models' ability to forecast outcomes was assessed by computing error values. Study was done on data of 185 roadway accidents segments that happened in the city of Mashhad, Iran, in the year 2007, to develop accident prediction models. 70% of the roadway segments' observations (i.e. 130 roadway segments) were utilized to calibrate the training. The remaining 30% of roadway segments' observations (i.e. 55 roadway segments) were employed to compare the prediction capability of the testing models and compute error values. The hyperbolic tangent function was used as the activation function, which had a greater range than other common functions. The numbers of epochs, the learning rate, and the momentum for the training process are set to 1000, 1, and 0.7, The

BPNN model was trained with 17neurons hidden layers to achieve in performance of accuracy 97.02%, MSE 39.98%, MAE 2.98%, RMSE 6.32% while 18neurons hidden layers to achieve in performance of accuracy 95.85%, MSE 31.43%, MAE 4.15%, RMSE 5.61% (Nassiri et al., 2014). Comparison findings demonstrated that the BPNN model was the most successful model for forecasting the number of accidents, due to its low prediction and fitting error values. However, discussion revealed that, ANN technique had a black box structure without an analytical foundation. It required a time-consuming computational effort to minimize the over-fitting issues especially when the sample size was small.

Besides that, ANN is also applied in construction project cost estimation which was covered in a previous research. El-Sawalhi et al. (2014) developed an ANN model for the prediction of the overall structural cost of building projects in the Gaza Strips, by using historical data from 169 completed projects. The data were randomly divided into three groups. Namely, 69% for training, 16% for performance validation, and 15% for a completely independent evaluation of network generalisation. Eleven input factors parameter namely; type of project, area of a typical floor, number of floors, type of foundation, type of slab, number of elevators, type of external finishing, type of air-conditioning, type of tilling, type of electricity, and type of sanitary. Finally, specifying the desired parameter (output) which was the total cost of the project. Multilayer Perceptron (MLP) included one input layer with 11 input neurons and one hidden layer with (22 hidden neurons) and finally one output layer with one output neuron, total cost was used to carry in the architecture with Tanh transfer function, and Momentum learning rate which belonged to backpropagation algorithm. By reviewing this research, the result of ANN in cost estimation performance was summarized as accuracy performance, AP 94%; mean

absolute percentage error, MAPE 6%; mean square error, MSE \$ USD 33,757; and correlation coefficient, R 0.995 (El-Sawalhi et al., 2014) .

Moreover, paper reviews that estimation of the productivity in the management of construction projects has also been applied with the ANN method. This is because the quality of construction management is depending on the accurate estimation of the construction productivity. Al-Zwainy et al. (2012) developed an ANN model network by utilising the historical data from 150 data projects, 60% of which were used for training, 25% for performance validation, and the remaining 15% for computation. This network was used to estimate the labour productivity of marble finishing works for floors. Data from residential, commercial, and educational projects in various regions of Iraq were used in the study to train the model and assess its effectiveness. A hyperbolic tangent sigmoid function was employed as the transfer function. Ten influencing factors, including age, experience, the number of assist labour, the height of the floor, the size of the marble tiles, security conditions, the health status of the work team, the weather, the site condition, and the availability of construction materials were used by the ANN model to forecast productivity. The productivity of marble finishing work for floors was then predicted using a model. With a coefficient of correlation (R) of 89.55%, an average accuracy percentage (AP) of 90.9%, and a mean absolute percentage error (MAPE) of 9.1%, it was discovered that ANN can estimate productivity for finishing activities with a very high degree of accuracy. Hence, backpropagation neural network (PBNN) model has proven very successful in modeling nonlinear relationships (Al-Zwainy et al., 2012).

In the paper review for risk forecasting, artificial intelligence based modeling has been employed in cash flow forecasting ranging from mathematical, statistical, and simulation techniques. Odeyinka et al. (2002) reviewed and modelled the difference

between the expected and actual cost flow due to inherent risks in construction. Data was obtained through a questionnaire survey and empirical data collection. The effect of risk factors on cost flow forecast was then examined by gathering information on expected and actual cost flow from finished construction projects to ascertain their variation. The cost flow risk assessment model was developed utilising the neural network and the backpropagation method. The developed model was tested on 20 brand-new projects with satisfactory predictions of variations between the forecast and actual cost flow at 30%, 50%, 70%, and 100% completion stages. A cost flow risk assessment model was developed using 40 of the 50 data sets collected from the questionnaire survey. The remaining 10 data sets and the additional 10 data sets obtained from a construction business were used for the model's testing and validation. Neural network's inputs were associated with the 11 identified major risk variables through the questionnaire scores. Number of input data and output data also demonstrated that 11 input neurons and 4 output neurons were a good network architecture to start with. After a number of trials and errors, the network was found to be stabilized with 12 hidden nodes with a sigmoid transfer function. Thus, the result obtained was respectively error square, $R^2 = 0.626$ (30%), $R^2 = 0.748$ (50%), $R^2 = 0.653$ (70%) and $R^2 = 0.767$ (100%) with actual cost flow at 30, 50, 70 and 100% completion stages. And the relative Mean Absolute Deviation measured for the 20 new projects varies from Project No. 8 (0.067) to Project No. 7 (1.158). This showed that Project No. 7 had the least error prediction and was the nearest to the actual risk prediction cash flow (Odeyinka et al., 2002).

Besides that, there is another research done on comparison between ANN, Support Vector Machines (SVM), and Decision Tree (C5) in the prediction of risk factors for diabetes cases. Barakat et al. (2004) developed a prediction model based on 500

nondiabetic and 268 diabetic data. Inputs risk factors were consisted of pregnancy, 2-hour OGTT plasma glucose, diastolic blood pressure, triceps skinfold thickness, 2-hour serum insulin, body mass index (BMI), diabetic pedigree function, and age with a binary output class (tested positive or negative for diabetes). Architecture 8-1-1 Quasi-Newton was developed and trained in ANN, SVM and C5 model according. Performance result showed that ANN training accuracy performance 83% and precision 82%; SVM training accuracy performance 83% and precision 87%; and C5 training accuracy performance 87% and precision 88% (Barakat et al., 2004). The research showed that the result of training accuracy in ANN and SVM were very much consistent and suggested that C5 be carried out based on the training data generated by ANN and SVM classifier to show the significant risk factors that contributed to the diabetes diagnosis.

In brief, Table 2.20 shows a summary of the comparison between different ANN architectures and algorithms at their application and performance for reference.

Table 2.20: Comparative Summary of Different ANN Architectures and Algorithms

Author	Type of Model	ANN Architecture	Research Objective	Performance Measurement	Application
(Barakat et al., 2004)	Multi-Layer Perceptron	• Quasi Newton algorithm • Single layer • 8-1-1	Prediction of risk factor for diabetes cases	And ANN training AP 83% and precision 82%. SVM training AP 83% and precision 87%. C5 training AP 87% and precision 88%.	Comparison is done between SVM, ANN and Decision Tree (C5). Decision Tree (C5) is carried out on the training data generated by ANN and SVM classifier to show the significant risk factors that contributed to the diabetes diagnosis.
(Al-Zwainy et al., 2012)	Multi-Layer Perceptron	• Feedforward Back Propagation Algorithm • 60% training, 25% validation, 15% testing • Single Layer • Transfer function hyperbolic tangent sigmoid • 10-1-1	Estimation of the labor productivity construction projects	AP = 90.9% MAPE = 9.1% R = 89.55% $R^2 = 80.19\%$	The backpropagation neural network (BPNN) model is proven in modeling nonlinear relationships. Therefore, ANNs can be used instead of statistical programs to show the nonlinear function for any problem.

Table 2.20: Continued

Author	Type of Model	ANN Architecture	Research Objective	Performance Measurement	Application
(Nassiri et al., 2014)	Multi-Layer Perceptron	• Feedforward Back Propagation Algorithm • Single Layer • 70% training. 30% testing. • Transfer function hyperbolic tangent is used as the activation function • Numbers of epochs, learning rate and the momentum of the training process are set to 1000, 1 and 0.7, • Comparison data set with 17 neurons layer and 18 neurons layer. • Comparison of prediction was done between NBR, ZINBR, SVM and BPNN	Roadway accident number of crash and prediction severity of crash.	ANN 17 neurons hidden layer AP 97.02%, MSE 39.98%, MAE 2.98%, RMSE 6.32% ANN 18 neurons hidden layer AP 95.85%, MSE 31.43%, MAE 4.15%, RMSE 5.61%	BPNN model has the best prediction but does not have the best fitting among the trained models between NBR, ZINBR, and SVM. Disadvantage of ANN method is that these models has a black box form without an analytical basis, and it requires time consuming computational effort to minimize over-fitting issue especially when the sample size is small.

Table 2.20: Continued

Author	Type of Model	ANN Architecture	Research Objective	Performance Measurement	Application
(El-Sawalhi et al., 2014)	Multi-Layer Perceptron	• Feedforward Back Propagation Algorithm • 69% training, 16% validation, 15% testing • Single Layer • Transfer Function tanh • 11-22-1	Total Cost Estimation in Construction Project	AP = 94% MAPE = 6% MSE = \$ USD 33757 R = 0.995	Questionnaire survey is used to identify the most effective parameters on building projects cost at the early stages of project.
(Yazdani et al., 2015)	Multi-Layer Perceptron	• Feedforward Back Propagation Algorithm • Single Layer • 80% training, 10% validation, 10% testing. • Different training function algorithms like trainscg, trainrp, trainlm, and trainbfg were carried out. • 13-30-1	Risk Prediction of Heart Disease	AP 100% Sensitivity 100%, Precision 100% Specification 100%	Comparison is done with different training algorithms and transfer algorithms. It is concluded that target accuracy of 100% can be obtained using trainlm algorithm with the architecture of 13-30-1.

2.11 Chapter Summary

By summarizing the literature review, research suggests risk management framework that entails hazard identification, risk assessment, safety decision-making, risk control and risk prediction. It is easier for understanding and generally been accepted in the shipyards case study.

ANN Machine learning is integrated with the typical risk management framework for forming a continuously improving risk management framework. Research focuses on analysing ANN modeling with various algorithms and architectures, such as the quantity of input neurons, quantity of hidden layers, quantity of output neurons, quantity of training functions, quantity of transferring functions, and so forth, at various applications and characteristics.

A comparison of various network modeling in ANN machine learning has been analyzed in term of relationship in nonlinear data (correlative of coefficient), accuracy of performance (AP), and the least minimum error (mean square error and mean absolute percentage error). Next, the best ANN network modeling is selected for risk prediction of workers at shipyards. From the risk prediction, the shipyard companies are suggested to carry out the appropriate risk control for improvement accordingly.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Ethic Statement

Ethics approval is given by few government bodies related with occupational safety and health database centralization, which are the Department of Occupational Safety and Health (DOSH), Social Security Organization (SOCSO), and Department of Labour (JTK). This is shown in Apendix 5.

From the raw material data collected, 2 shipyards are chosen for the case study due to majority of shipyards are concentrated in Sibu, Sarawak. Though the 2 selected shipyards show frequent reporting in government agencies, such as SOCSO, JTK, and DOSH, it does not imply that accidents occurred frequently in these shipyards. The more cases at workplace are reported, the more alert on rules and regulations compliance by the shipyard companies. Reported cases include dangerous occurrences at the workplace which involved near-missed accidents or property damages, non-permanent disability, permanent disability and fatality. However, most of the reported cases are non-permanent disability, which only requires less than four days of sick leave.

3.2 Research Methodology

3.2.1 Developing Risk Management Framework

Occupational accidents at the 2 selected shipyards company can be improved and prevented by developing a practicable and effective risk management framework. Research methodology flow chart starts with the derivation of risk management structure shown in Figure 3.1. It emphasizes on hazard identification (Paik et al., 2007), risk assessment

(Shaleh et al., 2016), safety decision-making (Chang et al., 2009), and risk control (Card et al., 2012). Each of the process is important to achieve the objective of the research.

Hazard identification and risk assessment are carried out onto the 2 selected shipyards case study. Paik et al. (2007) described that the potential hazards are identified according to the fabrication process. These potential hazards include physical hazards, chemical hazards, biological hazards, ergonomic hazards, physiological hazards and so on. Self risk-assessments in term of ($R = L \times S$) whereas likelihood (L) and severity (S) are filled up by the shipyards company. Results from the risk assessment ($R = L \times S$) of each fabrication process are shown in risk level matrix number. Shaleh et al. (2016) explained that risk level matrix number 1-14 shows a low risk level can it can be proceeded to safety decision making. However, risk level matrix number 15-25 shows a high risk level and it should be improved.

Following that, (Chang et al., 2009) described the safety decision-making in term of risk level matrix of each fabrication process based on the current risk control practice. It is derived into Risk Priority Number ($RPN = L \times S \times D$) by considering the detection of to current control practice. Since likelihood (L) and severity (S) has been determined in the previous stage, the consideration in this process focus on the effectiveness of the current practice risk control detection. This is to determine the priority level of risk assessment in each fabrication process. RPN 1-30 shows a good detection of current risk control practice. However, Card et al. (2012) explained that RPN 31-100 shows a low detection of risk control and it should be improved.

Next, OSH risk prediction is carried out by using the best ANN network model developed. Risk prediction result 1-2 shows a low risk of workers working at shipyards. Workers exposed in the low risk exposure are mostly having a severity either minor or

non-permanent injuries within four days. From the low risk prediction result, shipyards case study companies can maintain the current risk control at workplace. However, risk prediction result 3-5 shows a high risk of workers working at shipyards. Workers are having a higher risk exposed which end up either permanent injuries, or fatality, or multi fatalities. From the high risk prediction result, it is defined that current risk control practise has a low detection and should be reviewed for elimination, substitution, engineering control, administration and PPE subsequently.

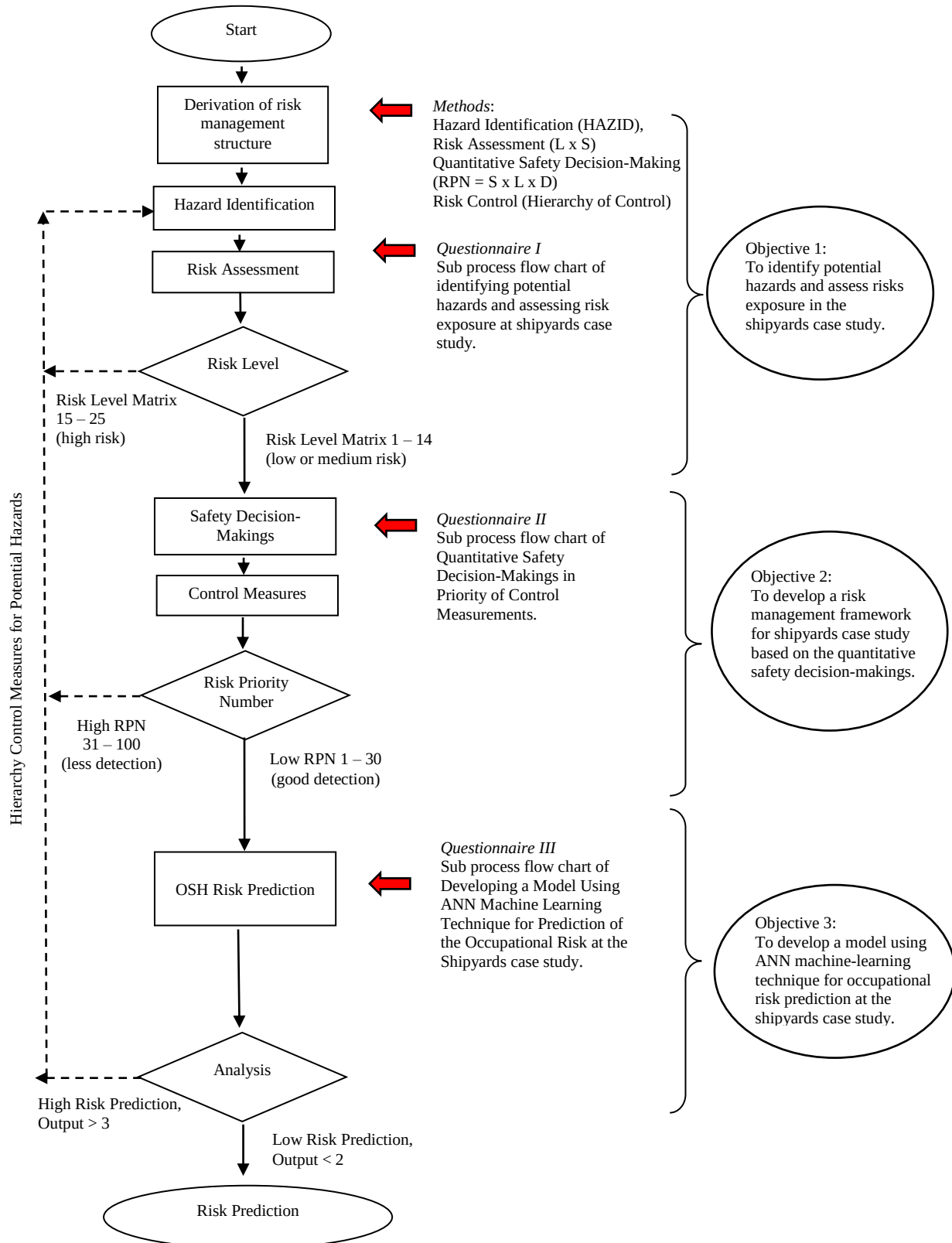


Figure 3.1: Process Flow Chart of Research Methodology

3.2.2 Hazard Identification and Risk Assessment

Figure 3.2 shows the process flow of hazard identification and risk assessment at the shipyards case study. Site visit and face-to-face discussion are carried out at the identified shipyards to promote good engagement at the workplace. Besides that, site visit also helps to reduce the amount of questions that remain unanswered and provide shipyard management the opportunity to ask. In addition, researcher can share the result of research to increase the awareness of self-risk assessment. Questionnaire I shown in Appendix 2 is distributed to the management for data collection. Potential hazards identification is done by the shipyards management based on the fabrication process and repairing activities. Next, risk assessment is done according to the process work and activities.

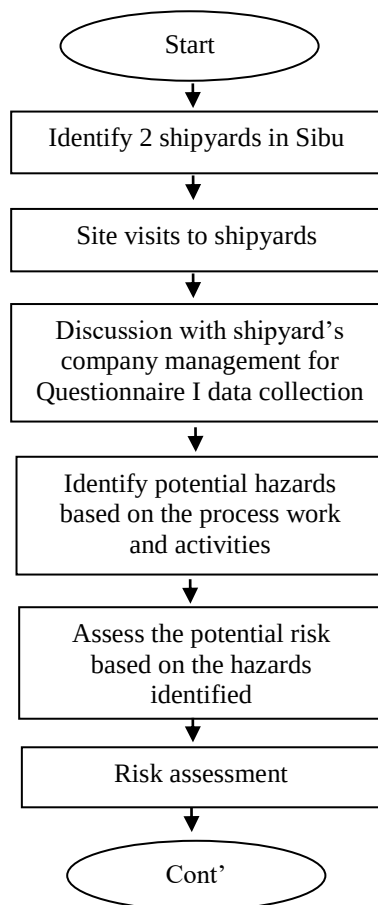


Figure 3.2: Sub-Process Flow Chart of Potential Hazards Identification and Risk Assessment at Shipyards Case Study

3.2.3 Safety Decision-Making and Risk Control

Following that, Questionnaire II shown in Appendix 3 is distributed to the management to set a priority of safety decision-making, mainly on reviewing the severity (S), likelihood (L), and detection (D) of the current practice risk control. From there, a risk priority number (RPN) is evaluated. RPN shows the priority of decision-making in terms of effectiveness of current risk controls detection (D) (Saleh et al., 2016). Control measurements are improved in the hierarchy form of elimination, substitution, engineering control, administrative control and PPE. All improved control measurements are recorded, and photos are taken as an evidence. After that, the effectiveness of eliminating potential hazards and lowering the risk exposure to the workers are discussed with the management. This is shown in Figure 3.3.

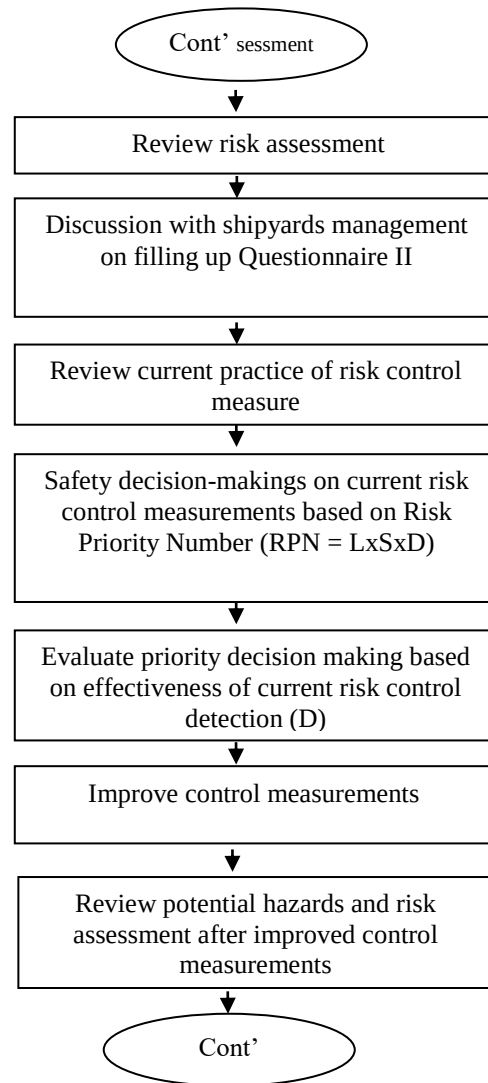


Figure 3.3: Sub Process Flow Chart of Quantitative Safety Decision-Makings in Priority of Risk Control Measurements

3.2.4 Data Mining and Data Pre-processing

Figure 3.4 shows the process flow of developing the OSH risk prediction in shipyards industry using the ANN machine learning technique. Data mining 813 cases in Malaysia are collected from few government bodies, which are the Department of Occupational Safety and Health (DOSH), Social Security Organization (SOCISO), and Department of Labour (JTK). This is shown in Appendix 6.

The size of the data collection is then reduced by data pre-processing in order to create homogeneous subgroups from a complex data set. This is to raise prediction accuracy and improve the quality of the data set. A complex data set would lead to serious queries (Hariharakrishnan et al, 2017) (Noori et al., 2010). Relevant network modelings are developed referring to the good modeling criteria. From there, optimization is carried out based on the correlation of coefficient comparison. Best network modeling is then determined with accuracy performance and sensitivity analysis to indicate the reliability of the best selected network model. After determining the best ANN network, Questionnaire III, which is shown in Appendix 4, is distributed to the selected workers, subcontractors, and visitors who accessed the designated shipyard workplace for OSH risk prediction. Risk prediction is then to be analysed.

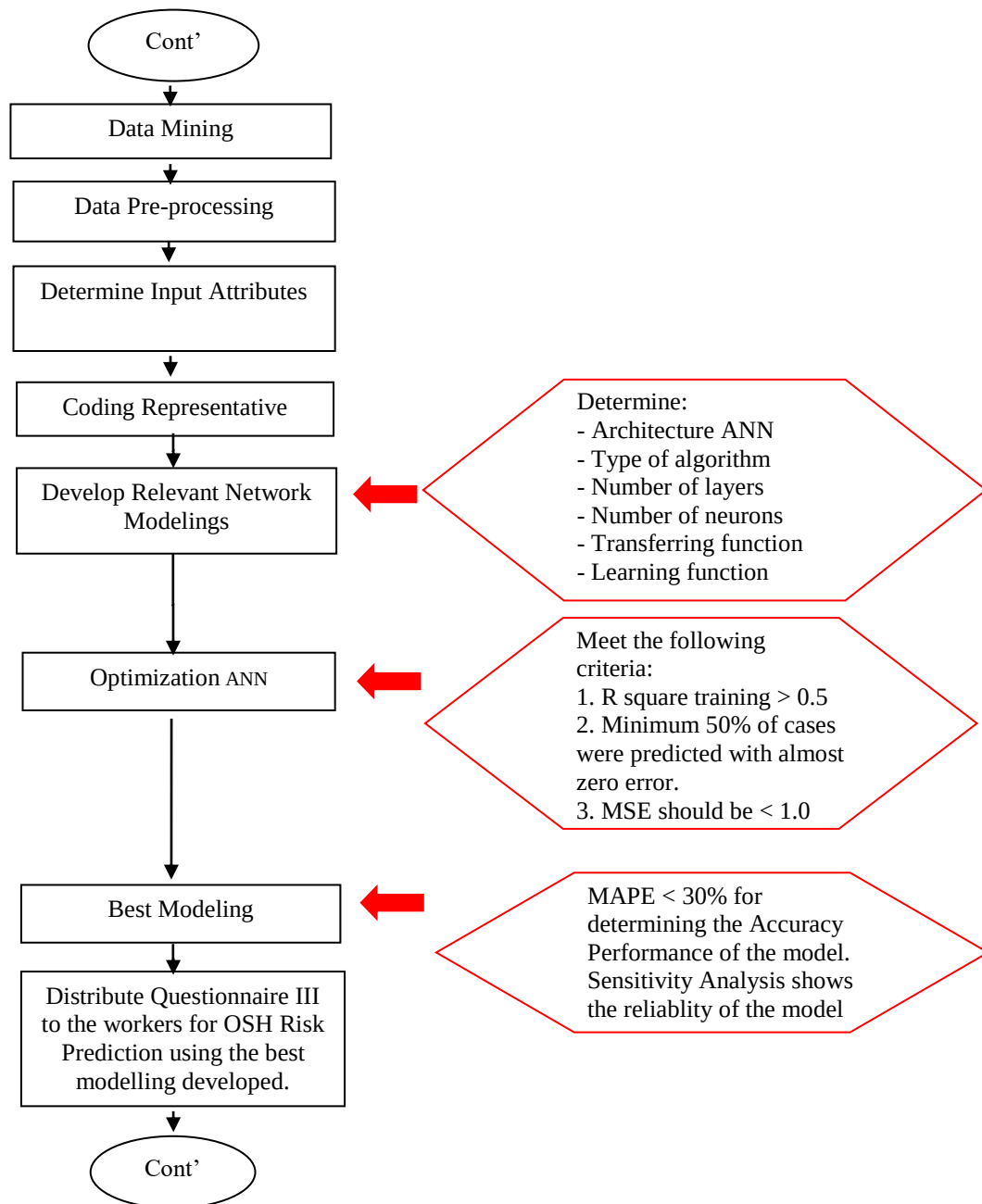


Figure 3.4: Sub Process Flow Chart of Developing a Model Using ANN Machine Learning Technique for OSH Risk Prediction at the Shipyards Case Study

3.2.5 Data Input Attributes and Data Encodings

Literature reviewed that applying machine learning method risk prediction in shipyards is quite new and there is very little research on analyzing the HSE factors in shipyards. However, risk prediction by analyzing input-output paired wise of HSE factors has been applied in construction. Research reviewed the similarity of activities between construction and shipyards operation, such as working at height, scaffold erection, hand tools handling, working under awkward posture, weather exposure, and so on. These similar HSE contributing factors were suitable to be analyzed to identify optimization patterns from the data collected in shipyards accidents.

In construction risk prediction, Ayhan et al. (2019) categorized the general attributes in textual terms from the data collection, and grouped them under 5 main attributes. They are consisted of gender, age, occupation, workplace factors, and activities conducted. These main attributes data are then analyzed in terms of input-output related wise. However, in our research, the input factor is enlarged while maintaining a smaller size of quality. Victim's nationality, working hours, education level, years of employment, and working zone, are also been considered. Finally, 46 attributes under 10 categories are available to describe incident cases and they are turned into coding for the computational progress shown in Table 3.1 and Figure 3.5.

Table 3.1: Encoding Data for the Input and Output Attributes

Attributes	Description	Encoding Data	Descriptive Statistical Data	Data Type
Gender	Gender of workers Binary data	Male: 1 Female: 2	Median: 1 Min: 1 Max: 2	Binary
Age	Age in years	<16 years: 1 16–18 years: 2 >18 years: 3	Median: 3 Min: 1 Max: 3	Categorical
Working hours	Working hours of the workers	8 hours or overtime working days: 1 Non-working hours: 2	Median: 1 Min: 1 Max: 2	Binary
Years of employment	Working experience at the shipyard company	<3 years: 1 3–5 years: 2 6–8 years: 3 9–10 years: 4 >10 years: 5	Median: 2 Min: 1 Max: 5	Categorical
Occupation	Position held in the shipyard company	General worker: 1 Operator: 2 Technician: 3 Contractor: 4 Visitor: 5	Median: 1 Min: 1 Max: 5	Categorical
Nationality	Nationality of workers	Malaysian workers: 1 Foreign workers: 2	Median: 2 Min: 1 Max: 2	Binary

Table 3.1: Continued

Attributes	Description	Encoding Data	Descriptive Statistical Data	Data Type
Education level	Educational level indicates the understanding of communication, self-risk assessment, and rational mindset for not conducting any miss-communication or unsafe act	Primary School: 1 Secondary School: 2 Certificate / Diploma: 3 Degree and above: 4 Non-educational background: 5	Median: 1 Min: 1 Max: 4	Categorical
Workplace factor	The working environment that leads to the incident.	Physical hazard: 1 Chemical hazard: 2 Biological hazard: 3 Ergonomic hazard: 4 Psychosocial hazard: 5 Environment hazard: 6	Median: 1 Min: 1 Max: 5	Categorical
Working zone	Working zone at shipyards	Dry dockyard: 1 Wet dockyard: 2 Machinery workshop: 3 Inside building/others: 4	Median: 1 Min: 1 Max: 4	Categorical

Table 3.1: Continued

Attributes	Description	Encoding Data	Descriptive Statistical Data	Data Type
Activities involved	Nature of work /duties	Welding/hot works: 1 Working at height: 2 Lifting & mobilization works: 3 Equipment installation works: 4 Use of hand tools/equipment: 5 Electrical installation works: 6 Sandblasting and painting works: 7 Repair/maintenance works: 8 Working in confined space: 9 Sea launching works: 10 Site supervision/visiting: 11 Other activities: 12	Median: 5 Min: 1 Max: 12	Categorical
Severity of accident	OSH risk prediction	Negligible injury: 1 Non-permanent injury: 2 Permanent disability: 3 Fatality: 4 Catastrophic: 5	Min: 1 Max: 5	Categorical

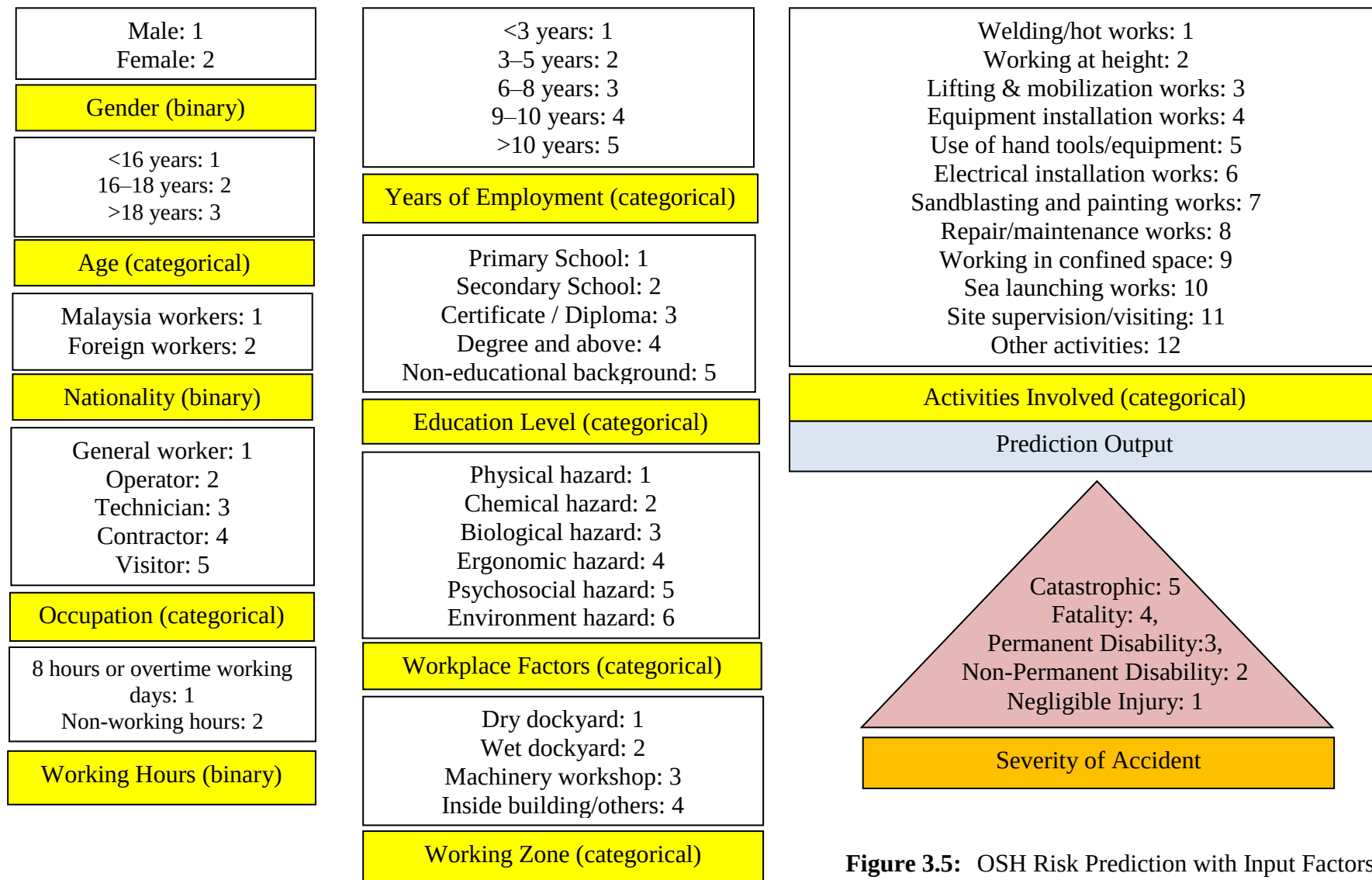


Figure 3.5: OSH Risk Prediction with Input Factors (attributes distributed in Questionnaire III)

3.2.6 ANN Data Set Modeling and Optimization

Search in the literature has shown limited study of ANN modeling in OSH risk prediction at shipyards. However, research reviews Health, Safety and Environment (HSE) input-output paired data modeling in construction has a high degree of prediction accuracy (Waziri et al., 2017) (Azadeh et al., 2011) (Patel et al., 2015). This can be applied in risk prediction modeling in the shipyards industry.

Encoding data is keyed into MatLab 2017 to developed network modelings. Ayhan et al. (2019) explained that the relevant number of hidden layers' neurons cannot exceed 2.5 times of the input size factor. Oversize can cause instability of the network. Wang et al. (2002) showed a good model development by multiplying all the neurons nodes (10x25x1). Input factors are referring to the 10 input factors identified in the research, which are gender, age, working hours, years of employment, education level, occupation, nationality, workplace factors, working zone, and activities conducted. Data base requires a least of 250 cases. And relevant neuron nodes stand for 19, 21, 23, 25, 27, 29 and 31 (Alshihri et al., 2009). The relevant ANN modeling architecture used for risk prediction is shown in Figure 3.6.

Besides that, Waziri et al. (2017) pointed out that in general modeling, data was extracted 70% for training, 15% for validation, and 15% for testing. While Patel et al. (2015) showed that data modeling can be extracted into 75% for training, 10% for validation, and 15% for testing. Moreover, Ayhan et al. (2019) studied on creating 13 models and it were trained with extraction 80% for training, and 20% for testing. The common practice between all these researchers shows that the number of training sets must be greater than the number of network inputs (an independent variable) to learn the complicated interactions between inputs and outputs. Supervised learning modeling with

Back-Propagation Neural Network (BPNN) is trained for output risk prediction. Training would stop once the error in the testing set increased. ANN models are built with different network architectures. They are varied in terms of the number of nodes, activation function, and the number of network layers. (Khamis et al., 2014).

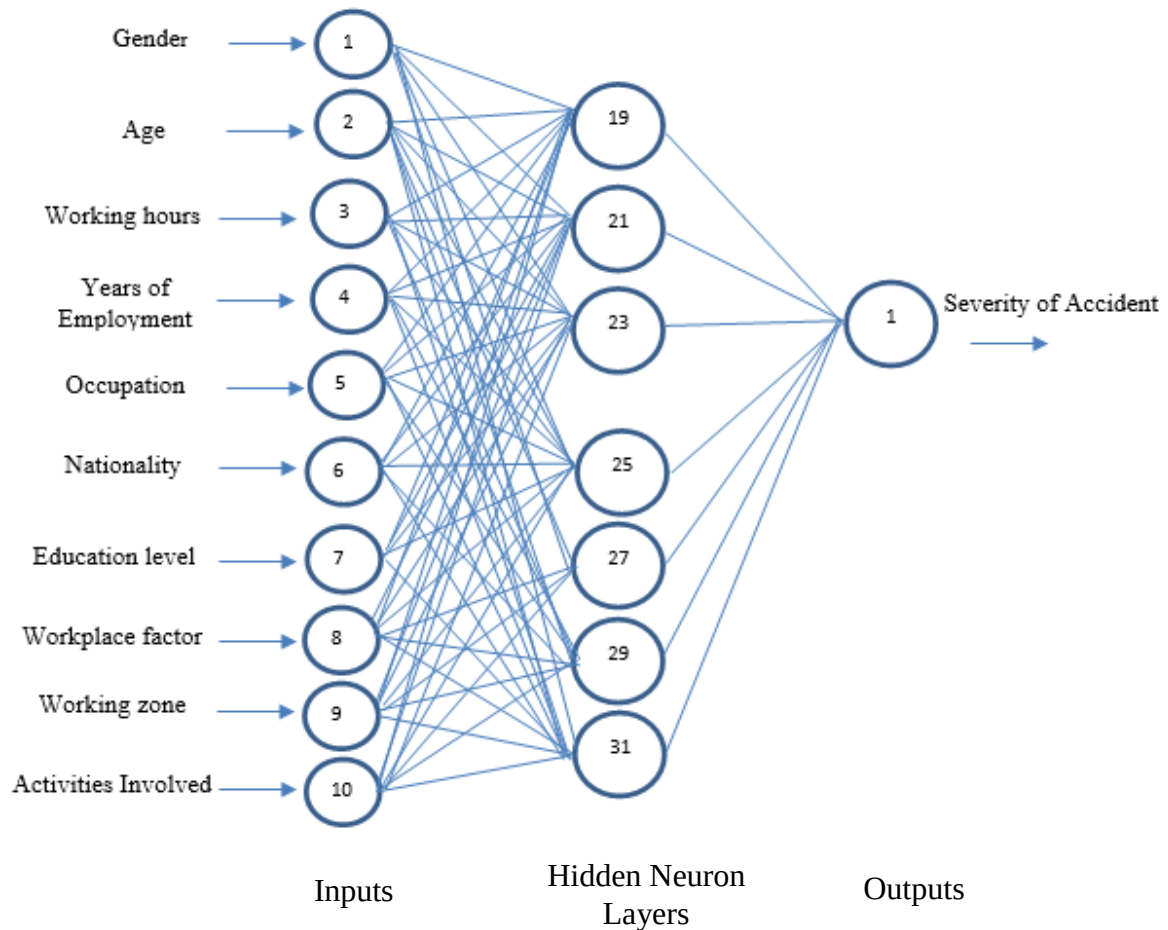


Figure 3.6: Relevant Modeling Architecture for OSH Risk Prediction

3.2.7 Selecting the Best ANN Modeling

Next, the developed ANN models are tested, and they are used to compare with each other to full fill with the following requirements and criteria:

- (1) Correlated Coefficient, (R) that is computed in Equation 3.1 and Error Square (R^2) should be higher than 0.5;

- (2) Minimum 50% of cases are predicted with almost zero errors, and;
- (3) The Mean Square Error (MSE) is calculated by using Equation 3.2 should be smaller than 1.0.

The best network modeling requirement and criteria are referred to the journals (Ayhan et al., 2019) (Waziri et al., 2017) (Vakili et al., 2015). This is to indicate the optimised correlation of coefficient (R) between the input data that contributes to the output risk prediction.

Following that, the correlation of coefficient (R) data calculated is analysed to observe the risk accuracy performance criteria in term of mean square error (MSE) and mean average percentage error (MAPE) respectively. MAPE values of each target are computed by using Equation 3.3 and the most suitable MAPE is less than 30% (Ayhan et al., 2019) (Azadeh et al., 2011). A severity scale of 1 to 5 risk prediction was assigned to represent the output encoding. Lastly, the best modelling to determine risk prediction is shown in Figure 3.5.

$$\text{Correlated Coefficient (R)} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad \text{Equation 3.1}$$

Where x_i represents the input variables, $\bar{x}$ represents the mean input; and y_i represents the actual target and $\bar{y}$ represents the mean target.

$$\text{Mean Square Error (MSE)} = \frac{1}{n} \sum_{i=1}^n (ti' - ti)^2 \quad \text{Equation 3.2}$$

$$\text{Mean Average Percentage Error (M}_a\text{)} = \frac{1}{n} \sum_{i=1}^n \frac{|ti' - ti|}{ti} \quad \text{Equation 3.3}$$

Where ti represents the actual target, where ti' stands for the predicted one, while M_a symbolizes the incident target demonstrated in Figure 3.5.

3.2.8 OSH Risk Prediction in the Proposed Risk Management Framework

Next, result of risk prediction based on the data collected in Questionnaire III is reviewed. Low-risk prediction is estimated to end up with non-permanent injuries ($s < 2$). Shipyard companies have no issue continue practicing with current risk control measurements. However, the high-risk prediction would end up with permanent injuries, fatality, or catastrophic injuries, ($s > 3$). In this case, a process flow is diverted back to risk assessment. From the risk assessment (SxL), the severity (S) of risk prediction is estimated. Since the severity is predicted with high accuracy, the management is required to review the quantitative decision-making (SxLxD) and to improve risk control measurements according to the hierarchy of risk control. This is to lower the likelihood (L) of the accidents from happening, and to improve the detection and effectiveness (D) of a risk control measurement. To improve the risk control, potential hazards should be either eliminated, substituted, or reduced in the way of the engineering control method. This requires some discussions with the company's HSE team. From there, a revised safe operating procedures is required to be done, and recorded.

In the other words, literature reviewed that other traditional risk management framework consisted of hazard identification, risk assessment, and risk control. However, this research proposes a dynamic, and continuously improving risk management framework which entails potential hazards identification, risk assessment, quantitative safety decision-making, risk control, and risk prediction. Research emphasizes on the quantitative safety decision-making that is standardising a benchmark of priority risk control, and risk mitigation. Besides that, research also intervenes a high accuracy performance of supervised ANN machine learning into the proposed risk management framework in order to predict the risk exposure. This is to manage the risk exposure of

workers earlier before any occupational accident happened. By connecting each criteria, the proposed concept can perform a dynamic, and continuously improving risk management framework, which is shown in Figure 3.7.

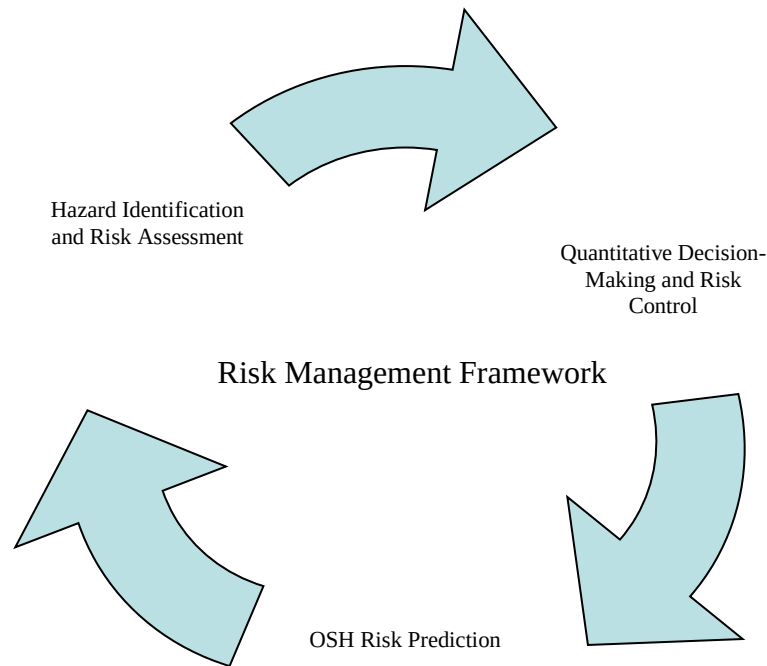


Figure 3.7: Develop a Dynamic Risk Management Framework at Shipyards Case Study

3.3 Sensitivity

ANNs are effective in prediction. However, they are criticized as black-box form due to their inability to explain the outcomes. Sensitivity analysis is carried out in this study to assess the impact of each input parameter on the output variable after the best ANN modeling network is selected. According to the relative importance of each input element, Gevrey et al. (2003) suggested performing the sensitivity analysis by using the perturbed output and weights algorithms. Both algorithms can classify the input variables' contribution to the output. However, the outcomes seen when employing both methods are not necessarily the same. In this case, an opinion from an ecologist is helpful.

While performing the perturbed output's algorithm, network's weights are disabled, maintain with unchanged. When the network's inputs are perturbed, the corresponding change is reported as a percentage deviation in the output (Fish et al., 2003) (Fish et al., 2004) (Principe et al., 2000). The first input, which is either binary or categorical, is adjusted between its median value and the upper and lower value limits (plus or minus), while the other inputs are fixed at their respective medians. The absolute percentage change over and below the median of that output variable is calculated as the network output and recorded. This procedure is performed for each input variable (Delen et al., 2006).

3.4 Chapter Summary

Research methodology is to achieve the objectives, which is to identify potential hazards and assess the potential risks, analyze with quantitative safety decision-making, and priority of risk control to be carried out. Research also develops a model using ANN machine learning technique to predict OSH risk prediction in the shipyards case study.

Therefore, in summary:

- Relevant ANN networks modeling are developed with different algorithms, architectures, number of input neurons, number of hidden layer neurons, and output neurons. They are compared among each other to determine the best modeling of risk prediction.
- Accuracy performance, such as correlation coefficient (R) of the input-output attributes relevant, means square error (MSE), mean absolute percentage error (MAPE) are carried out to justify the accuracy of output OSH risk prediction.
- Sensitivity analysis is carried out to identify the deviation degree between the independent (input) variables that contribute to the dependent (output) variable.

ANN machine learning risk prediction has been integrated into the typical risk management framework for creating a dynamic OSH risk management at the shipyards case study by eliminating the potential hazards, and reducing the risk exposure to the workers.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Overview

Occupation Safety and Health risk management framework is helpful in reducing the accidents happened at shipyards case study. A case study on the formulated risk management framework has been carried out at Berjaya Dockyard Sdn Bhd, and Tuong Aik Shipyard Sdn Bhd via Questionnaire I, II & III. In this chapter, research discusses on the summary of results from questionnaire collected.

Potential hazards identification and risk assessment based on the shipyards fabrication process are determined to meet the objective 1.

Quantitative safety decision-making is analysed to evaluate the priority of control measurements according to the detection on current practiced risk control. This is to achieve objective 2.

Relevant ANN risk prediction network models are developed in term of accuracy performance and consistency performance. Calculation on neurons nodes, hidden layers, correlated of coefficient (R^2), mean square error (MSE), and mean absolute percentage error (MAPE) are compared, and discussed for selecting the best risk modeling. Besides that, sensitivity analysis has also been discussed in term of consistency, and reliability performance. After that, the best selected risk prediction network model is integrated to formulate a dynamic risk management framework for shipyards case study, which stands for hazard identification, risk assessment, risk control, and risk prediction. This is to achieve the objective 3.

A case study on the formulated risk management framework has been carried out at Berjaya Dockyard Sdn Bhd, and Tuong Aik Shipyard Sdn Bhd via questionnaire I, II & III.

Numerical results, and analysis are presented in the following section.

4.2 Develop Relevant Network Models

Relevant network modelings are developed by considering the number of hidden layers which do not exceed 2.5 times of the input size. Input factors are referring to the 10 input factors identified. Alshiri et al. (2009) discussed the number of neuron nodes is examined by two nodes increasing or reducing from the optimum nodes $[\pm(2.5 \times 10)]$. So, relevant neuron nodes stand for 19, 21, 23, 25, 27, 29 and 31. Oversize can cause instability of the network. Network weights of each input factors were reinitialized while training was carried out. Patel et al. (2015) explained that training was on until the hidden layers and neuron nodes achieved the optimum observation based on training error, and testing error. Network weights were finalised at the optimum observation. Training error, and testing error started to increase while regression square (R^2) dropped.

4.3 Neuron Nodes and Hidden Layers Effects on Neural Network Performance

Figure 4.1, and Figure 4.2 demonstrate training errors and testing errors varied between 19 and 31 neuron nodes, with a single hidden layer (7 networks). Network 4 shows the highest value 0.91 (R), in term of correlation of coefficient from the training data. This is justified that 70% of the total cases (210 cases) were extracted for training, and the result indicates the minimum training error performance, 0.086 (1–training R), compared with other networks. Furthermore, 15% of the cases (45 cases) were used for testing, and network 4 shows the lowest testing error performance, 0.38, compared with

other networks. Therefore, 25 neuron nodes with a single layer was considered optimal with the least error found.

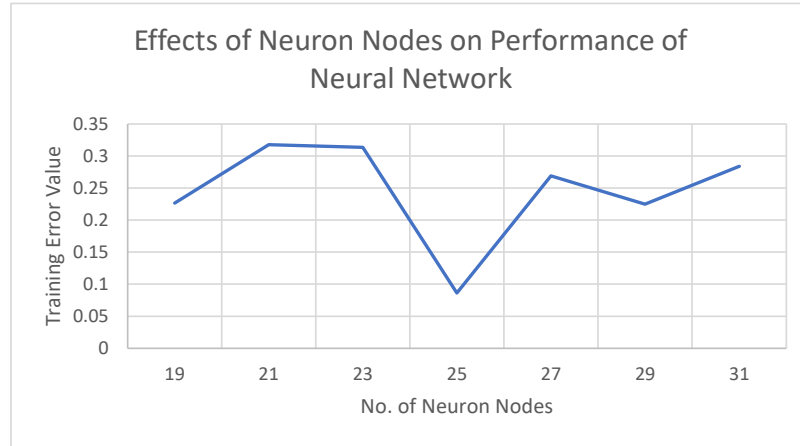


Figure 4.1: Effects of Neuron Nodes onto Training Error

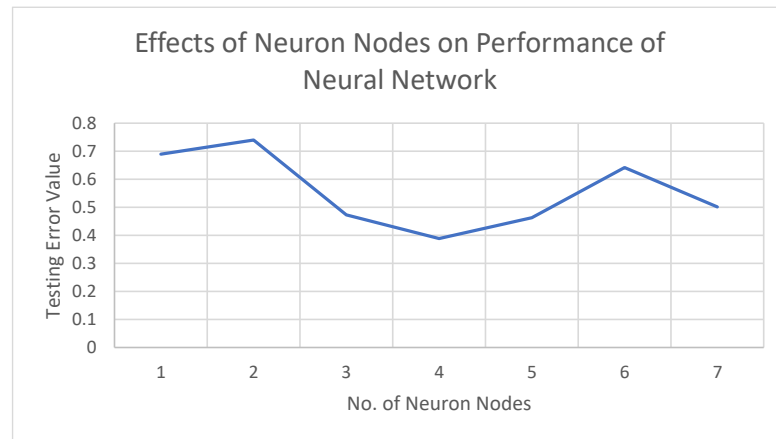


Figure 4.2: Effects of Neuron Nodes onto Testing Error

4.4 Accuracy Performance Analysis

To select the best neural network, this study evaluates the performance of the ANN model in terms of accuracy performance (AP), and sensitivity analysis. From the seven networks developed (neuron node starts from 19 to 31), The least error calculated network in the AP is selected as the best ANN modeling among different algorithms, architectures, number of neurons, types of training, and transfer functions (Abhishek et al., 2012).

Table 4.1 presents a comparison of the seven networks trained using the given criteria. Regression analysis for network 4 can be conducted to determine the relationship between the input–output paired wise, as presented in Figure 4.3. The result of linear regression is illustrated graphically in the training data with $R = 0.91$. $R^2 = 0.83$ (> 0.5), has shown the highest correlation of coefficients, compared with other networks. The training phase explained that network 4 demonstrates a strong linear association between the actual input factors and the predicted risk. Furthermore, network 4 shows an MSE of 0.13 for training (< 1.0), indicated that network 4 has the least MSE compared with other networks. Subsequently, a minimum of 50% of cases are predicted for network 4, which has the least errors, 0.14. This has also met the requirement criteria for having almost-zero errors. In the other words, network 4 has the optimum architecture, and algorithm. Therefore, network 4 has been selected as the best network modeling. Furthermore, network 4, with the MAPE output in accidents, has shown an AP of 9.77%, which is less than 30%. It is also expressed in another form of AP, which is defined as $(100 - \text{MAPE})\%$ (Willmott et al., 2005). In the other words, network 4 has achieved an AP of 90.22%. This explained that network 4 has a high prediction accuracy. Table 4.2 summarizes the ANN modeling for OSH risk prediction.

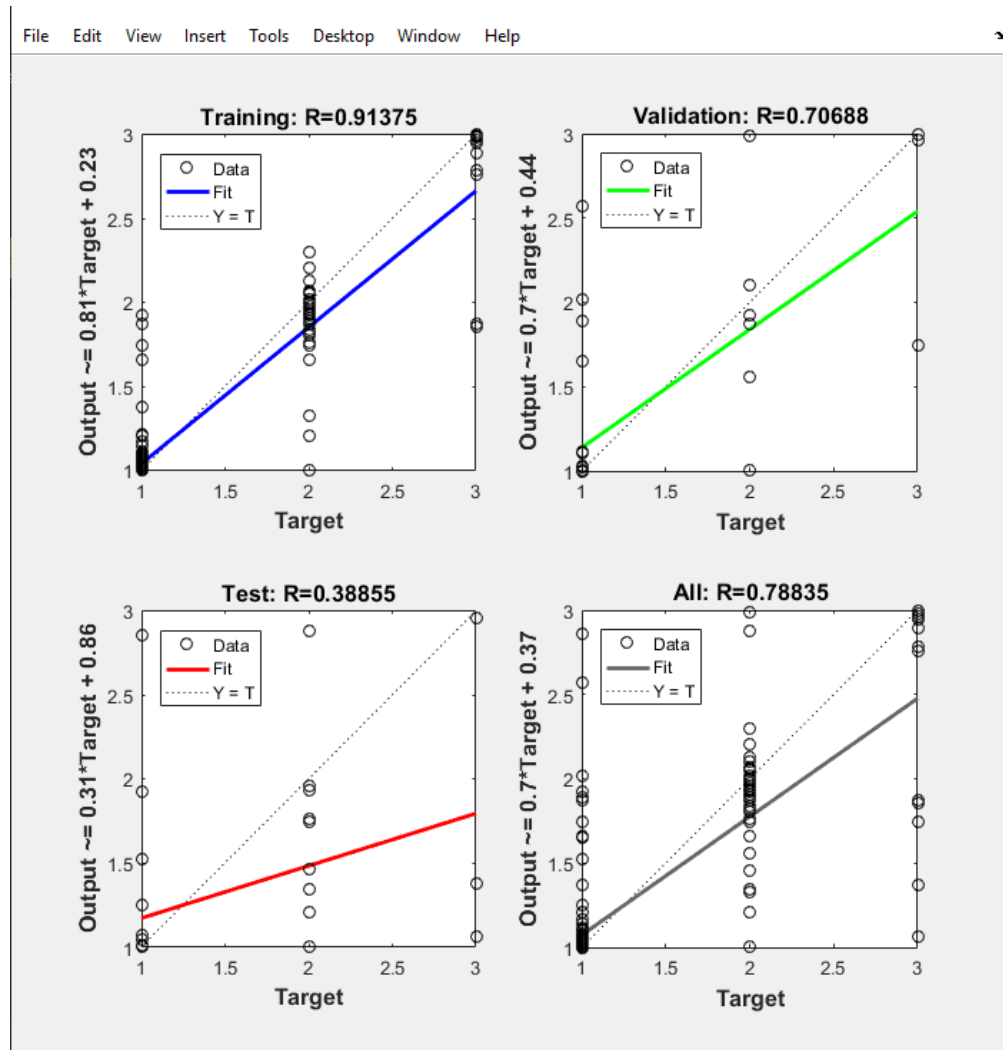


Figure 4.3: Result of Training, Validation and Testing for Network Modeling No.4

Table 4.1: Result of ANN Modeling for OSH Risk Prediction

ID	Number of Neurons Used In the Training	Average 50% Sample Prediction Value Error	Error Square Training R^2 (>0.5)	Best Mean Square Error (MSE) (<1)	Mean Average Percentage Error (MAPE)	Correlated of Coefficient (R)
Network1	19	0.27	0.59	0.16	18.24	0.77
Network2	21	0.25	0.46	0.18	18.56	0.68
Network3	23	0.29	0.47	0.26	17.97	0.68
Network4	25	0.14	0.83	0.13	9.77	0.91
Network5	27	0.27	0.53	0.19	19.95	0.73
Network6	29	0.26	0.60	0.15	18.95	0.77
Network7	31	0.37	0.51	0.21	25.81	0.71

Table 4.2: Summary of ANN Modeling for OSH Risk Prediction

Description	ANN for Model 4
MAPE	9.77%
AP%	90.22%
R	91.37%
R ²	0.83

After determining the accuracy performance, research continues to verify the AP in term of testing performance. 15% (45 cases) was randomly obtained from the actual and predicted data from network 4. From the variation between the actual and predicted data severities, any error exceeds 9.77%, has indicated that the prediction performance was poor. Other than that, the prediction performances were good. Figure 4.4 presents the comparison of randomly picked data, demonstrating that the value of the prediction is almost the same as the actual severity. The randomly picked data for testing performance indicates a linear regression relationship between the actual data and predicted data, as presented in Figure 4.5. Hence, the prediction result indicates a good estimation with a testing prediction performance of 90.22%.

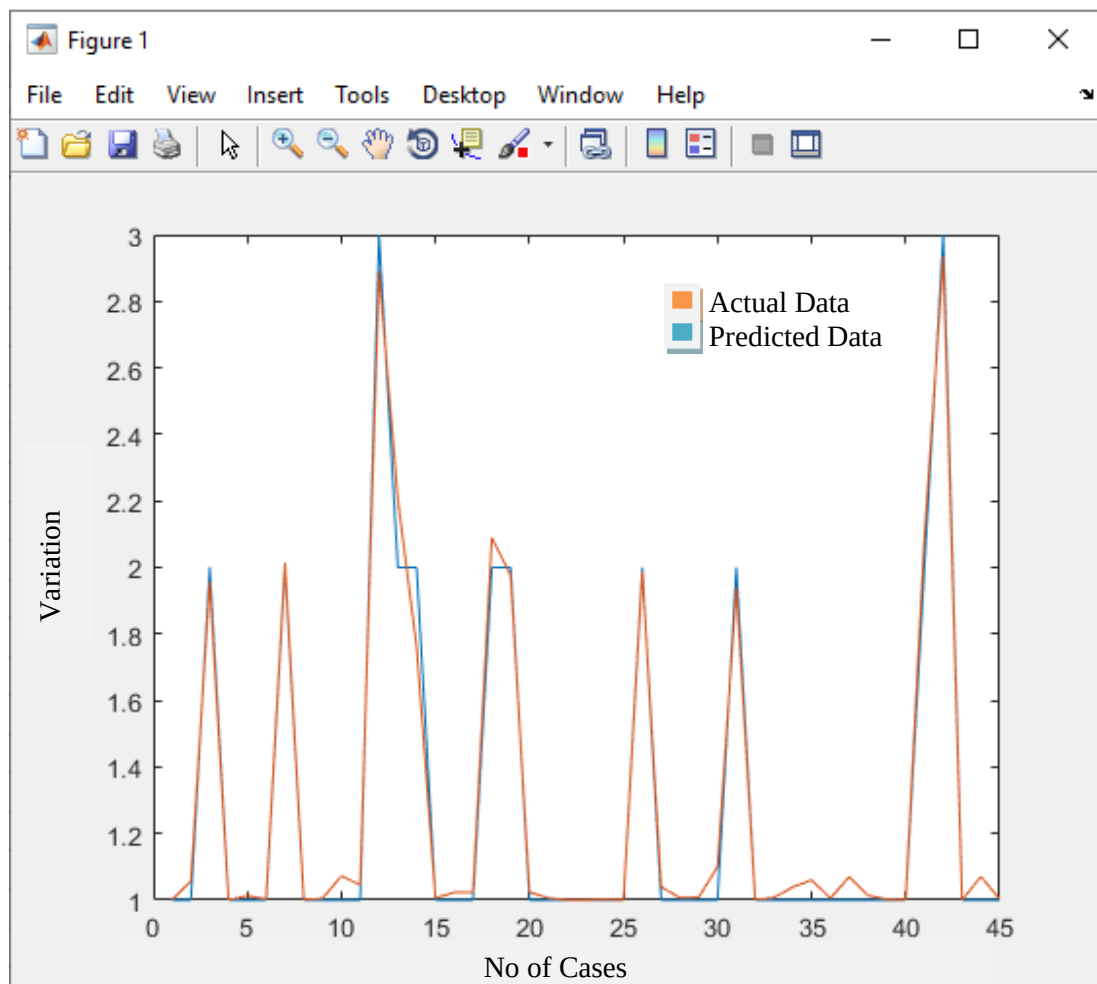


Figure 4.4: Comparison of Actual and Predicted Data (45 cases of Validation Test)

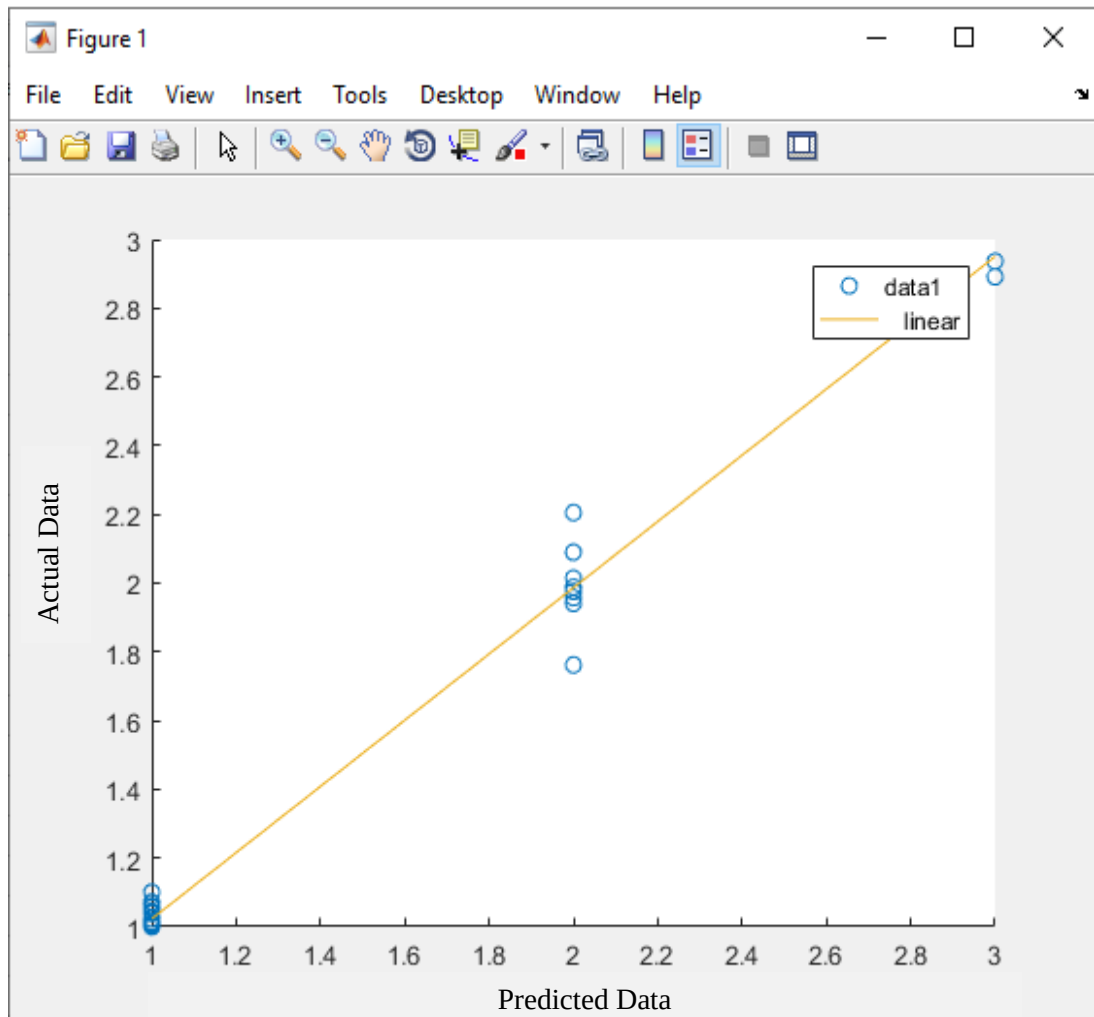


Figure 4.5: Linear Regression Analysis Between Actual and Predicted Data (45 cases of Validation Test)

4.5 Sensitivity Analysis

Other than that, sensitivity analysis has been carried out to find out the network consistency performance. The most significant contributors among the input variables at their median value, minimum limits, and maximum limits has been determined, as shown in Table 4.3. This is done in order to determine the essential elements affecting the percentage of perturbed output risk exposure. Following that, Table 4.4 displays the output variables. However, Table 4.5 summarises output volatility in terms of the relative weight of each input element. Then, research presents an overview of the relative significance of each input component in Figure 4.6, from most significant to least significant.

Table 4.3: Variation of Input (Sensitivity) that Affects Variation of Output

Output	Gender	Age	Working Hours	Years Employment	Occupation	Nationality	Output Educational Level	Output Workplace Factor	Working Zone	Activities Involved
Input Variables Sensitivity	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03
Minimum	2.03	1.58	2.03	2.47	2.03	2.01	2.03	2.03	2.03	1.58
Median	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03
Maximum	1.91	2.03	1.12	2.23	2.47	2.03	2.06	1.34	1.76	1.53

Table 4.4: Summary of Output Variables Due to Input Variables

Item	Gender	Age	Working Hours	Years Employment	Occupation	Nationality	Educational Level	Workplace Factor	Working Zone	Activities Involved
Output Variables Due to Input Variables	2.03	1.58	2.03	2.47	2.03	2.01	2.03	2.03	2.03	1.58
	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03
	1.91	2.03	1.12	2.23	2.47	2.03	2.06	1.34	1.76	1.53

Table 4.5: Output Variance in Percentage

Items	Gender	Age	Working Hours	Years Employment	Occupation	Nationality	Educational Level	Workplace Factor	Working Zone	Activities Involved
Output Variance	4.85E-05	0.44	4.85E-05	0.43	4.85E-05	0.01	4.85E-05	4.85E-05	4.85E-05	0.44
	0	0	0	0	0	0	0	0	0	0
	0.11	4.85E-05	0.91	0.19	0.44	4.85E-05	0.03	0.68	0.26	0.49
Range	0.11	0.44	0.91	0.24	0.44	0.01	0.031	0.68	0.26	0.04
Output Variance in Percentage (%)	3.66	13.94	28.38	7.55	13.73	0.54	0.98	21.32	8.31	1.54
Rank	7	3	1	6	4	10	9	2	5	8

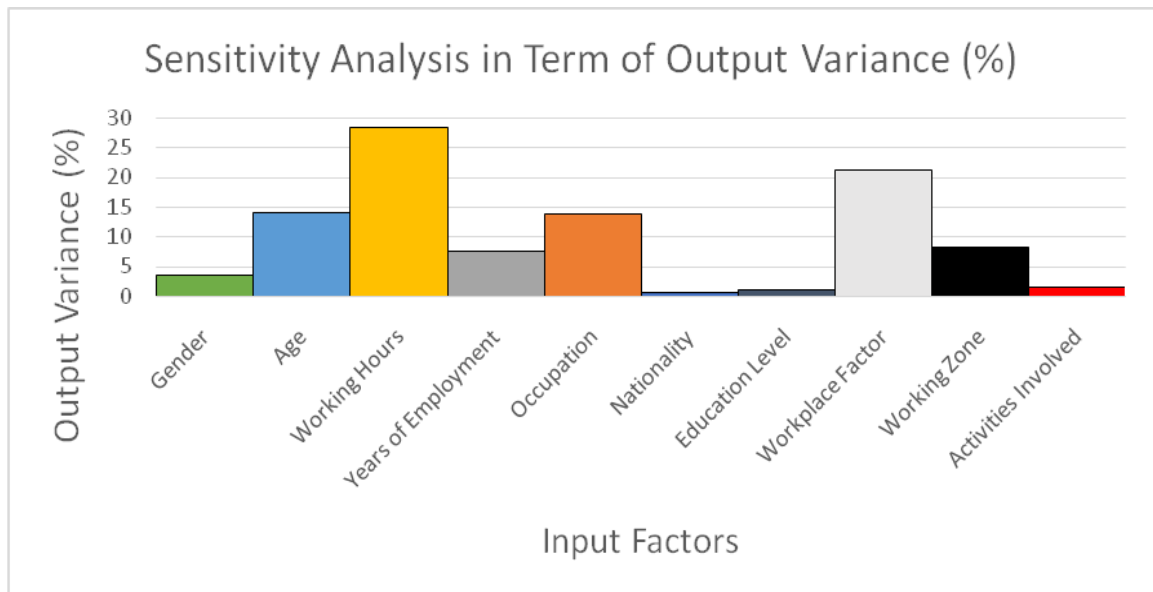


Figure 4.6: Sensitivity Analysis in Term of Output Variance in Percentage (Delen et al., 2006)

According to the sensitivity analysis result shown in Figure 4.6, the variables nationality (0.54%), education (0.98%), activity involved (1.54%), and gender (3.66%) are the least significant predictors of increased levels of injury. This explains that nationality, education level, activity involved, and gender criteria, do not contribute to the risk exposure among the workers. However, the finding should prompt a detailed investigation into the influencing factors of risk exposure in shipyards. Likewise, Abdelwahab et al. (2001) explained that while males were more likely to be engaged in fatal accidents and females were more likely to sustain more severe injuries.

Another interesting finding shows that risk prediction has affected by input variables such as years of employment (7.55), working zone (8.31), occupation (13.73), and age (13.94). Dissanayake et al. (2002) obtained similar results when they used a linear regression model to study age, location, and personal factors that affected the degree of injury. The research explained that location (working zone) with is more likely to result in

severe injuries, as shown by the positive coefficient. While elder workers involved in accidents, they were less likely to have severe injuries. In other words, young workers have a higher probability of experiencing severe injuries. However, age and years of employment are not the determining criteria that distinguished between a fatality and an incapacitating injury.

Finally, the sensitivity analysis result indicates that workplace factors (21.32), and working hours (28.38) appear to be with the severity of the injuries. Card et al. (2012) explained that workplace factors were crucial in leading towards more OSH accidents. Furthermore, Theofilatos et al. (2012) explained that the working hours positively correlated with the severity of the accidents. This indicates that accidents that occurred at night are more severe than those that occurred during the day time. It is predicted that less accident occurred during non-working hours as less manpower are involved.

4.6 Questionnaire I, II and III

Following that, a case study has been carried out at Berjaya Dockyard Sdn Bhd, and Tuong Aik Shipyard Sdn Bhd by distributing questionnaire I, II, and III. These questionnaires apply with the risk management framework which entails hazard identification, risk assessment, safety decision-making, risk control, and risk prediction. Results are shown in the following section:

4.7 Hazard Identification, Risk Assessment (Questionnaire I), Safety Decision-Making and Risk Control (Questionnaire II) at Berjaya Dockyard Sdn Bhd

Results from questionnaire I, and II have shown that the management from Berjaya Dockyard is aware with the hazards surrounding at shipyard. Risk level, and safety decision-making (risk priority number) are equally low at shipyard designated areas. This shows that the current practiced risk control has a good detection to reduce the likelihood

of risk exposure. Positive observation is shown in Table 4.6. During the site visit, it is noticed that Berjaya Dockyard Sdn Bhd has constructed a concrete graving dry dock with 150m length x 50m breath x 9.0m depth. Ship repair works are mainly taken at the designated modern dry dock, provided with modern facilities and safety equipment such as high working platform, guarded working platform, gantry crane (100 tonne lifting capacity), crawler crane (80 tonne lifting capacity), high voltage electric substation, distribution board, and so on. Dockyard, and wet dock are well maintained and removed from hazardous factors. Chemical exposure such as sand blasting, welding, painting, explosive materials are controlled in term of engineering, and workers are provided with personal protective equipment.

Table 4.6: Hazard Identified, Risk Level, Safety Decision-Making (Risk Priority Number) and Observation at Berjaya Dockyard Sdn Bhd

Activities	Hazard Identified – filled up by the shipyard company	Risk Level (x/25) – filled up by the shipyard company	Safety Decision-Making (x/100) – filled up by the shipyard company	Shipyard Condition
Welding / Hot works	Physical hazards, chemical hazards, and ergonomic hazards	6	18	
Working at height	Physical hazards	2	16	
Lifting and mobilization works	Physical hazards, and ergonomic hazards	6	18	
Equipment Installation works	Physical hazards, and ergonomic hazards	6	18	

Table 4.6: Continued

Activities	Hazard Identified – filled up by the shipyard company	Risk Level (x/25) – filled up by the shipyard company	Safety Decision- Making (x/100) – filled up by the shipyard company	Shipyard Condition
Use of hand tools / Equipment	Physical hazards, chemical hazards, and ergonomic hazards	2	12	
Electrical installation / Electrical maintenance works	Physical hazards	4	16	

Table 4.6: Continued

Activities	Hazard Identified – filled up by the shipyard company	Risk Level (x/25) – filled up by the shipyard company	Safety Decision-Making (x/100) – filled up by the shipyard company	Shipyard Condition
Sand blasting and painting works	Physical hazards, chemical hazards, and ergonomic hazards	6	18	
Repair / Maintenance works	Physical hazards, chemical hazards, and ergonomic hazards	4	16	
Working at confined space	Physical hazards, and chemical hazards	5	20	
Sea launching works	Physical hazards	4	16	
Site supervision / Visiting	Physical hazards	4	16	

4.8 Hazard Identification, Risk Assessment (Questionnaire I), Safety Decision-Making and Risk Control (Questionnaire II) at Tuong Aik Shipyard Sdn Bhd

On the other hand, results from questionnaire I, and II explain that management at Tuong Aik Shipyard Sdn Bhd has taken hazards identified for granted, and underestimated the risk exposure of workers at shipyard. Risk level, and safety decision-making (risk priority number) identified from the management were generally low. However, this is different during the site visit. There are physical hazards, chemical hazards, biological hazards, ergonomic hazards, and negative observations at shipyard. This is shown at Table 4.7. During the site visit, vessels are dragged, and pulled onto the dry dock with crawler crane, and heavy duty winching machine. There is a lack of proper management at dry dock, it is noticed that the raw material such as steel plate, and equipment are separated at dry dock. Many fabrication, and repair works are contracted out, and there is a lack of management, and supervision onto the subcontractors. Subcontractors are found not wearing protective equipment, and not following the proper advice from the management. Some of the electrical cables are found not properly connected to the distribution board. Hazardous chemicals, and explosive material are not stored at designated area.

Table 4.7: Hazard Identified, Risk Level, Safety Decision-Making (Risk Priority Number) and Observation at Tuong Aik Shipyard Sdn Bhd

Activities	Hazard Identified – filled up by the shipyard company	Risk Level (x/25) – filled up by the shipyard company	Safety Decision- Making (x/100) – filled up by the shipyard company	Shipyard Condition
Welding / Hot works	Physical hazards, chemical hazards, and ergonomic hazards	12	56	
Working at height	Physical hazards	10	41	
Lifting and mobilization works	Physical hazards, and ergonomic hazards	14	62	
Equipment Installation works	Physical hazards, and ergonomic hazards	6	38	

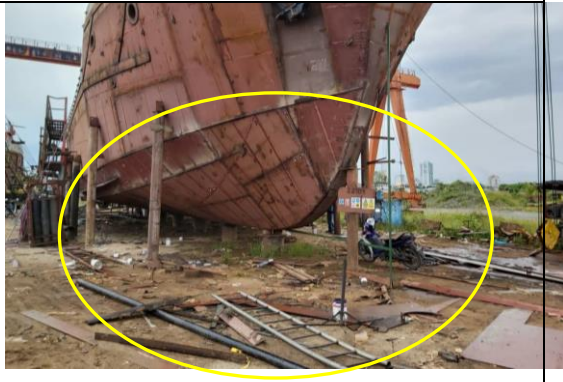
Table 4.7: Continued

Activities	Hazard Identified – filled up by the shipyard company	Risk Level (x/25) – filled up by the shipyard company	Safety Decision- Making (x/100) – filled up by the shipyard company	Shipyard Condition
Use of hand tools / Equipment	Physical hazards, chemical hazards, and ergonomic hazards	2	22	
Electrical installation / Electrical maintenance works	Physical hazards	8	28	

Table 4.7: Continued

Activities	Hazard Identified – filled up by the shipyard company	Risk Level (x/25) – filled up by the shipyard company	Safety Decision- Making (x/100) – filled up by the shipyard company	Shipyard Condition
Sand blasting and painting works	Physical hazards, chemical hazards, and ergonomic hazards	12	66	
Repair / Maintenance works	Physical hazards, chemical hazards, and ergonomic hazards	8	46	

Table 4.7: Continued

Activities	Hazard Identified – filled up by the shipyard company	Risk Level (x/25) – filled up by the shipyard company	Safety Decision- Making (x/100) – filled up by the shipyard company	Shipyard Condition
Working at confined space	Physical hazards, and chemical hazards	16	68	
Sea launching works	Physical hazards	10	52	
Site supervision / Visiting	Physical hazards	6	26	

4.9 Risk Prediction (Questionnaire III) at Berjaya Dockyard Sdn Bhd

Subsequently, Questionnaire III is distributed to the subcontractors, and workers at Berjaya Dockyard Sdn Bhd. Twenty are selected for risk prediction. It is observed in Table 4.8 that worker's risk prediction is generally low which is below level 2 severity (minor injuries). Only two person of workers are predicted with BD1, severity level 2.32 (non-permanent injuries), and BD5, severity level 2.46 (non-permanent injuries). By considering the risk prediction network model with accuracy performance 90.22%, it is proven that risk exposure is generally low at Berjaya Dockyard Sdn Bhd with currently risk control practiced.

Table 4.8: Risk Prediction at Berjaya Dockyard Sdn Bhd by Workers via Questionnaire III

Worker	Gender	Age	Nationality	Years of Employment	Occupation	Working Hours	Education Level	Type of Hazard	Working Zone	Involved Activities	Risk Prediction
BD1	1	3	1	1	1	1	2	1	1	8	2.32
BD 2	1	3	2	3	3	1	2	1	1	1	1.15
BD 3	1	3	1	1	1	1	2	1	2	7	1.27
BD4	1	3	1	1	1	1	2	4	4	4	1.00
BD 5	1	3	1	2	1	1	2	1	1	7	2.46
BD 6	1	3	2	1	1	1	2	1	1	9	1.95
BD 7	1	3	1	3	3	1	4	1	1	11	1.04
BD 8	1	3	2	3	3	1	4	1	4	11	1.00
BD 9	1	3	2	2	1	1	2	1	1	1	1.06
BD10	1	3	2	2	3	1	2	4	2	3	1.04
BD11	1	3	2	2	3	1	3	6	1	4	1.08
BD12	1	3	2	1	3	1	3	5	1	2	1.06
BD13	1	3	1	1	3	1	3	5	1	3	1.13
BD14	1	3	2	2	3	1	3	4	2	1	1.01
BD15	1	3	1	1	3	1	3	2	2	10	1.05
BD16	1	3	2	1	2	1	2	1	3	5	1.02
BD17	1	3	1	1	3	1	2	1	1	6	1.25
BD18	1	3	2	1	1	1	2	6	1	1	1.03
BD19	1	3	1	2	3	1	2	4	2	6	1.08
BD20	1	3	1	3	2	1	2	1	3	8	1.05

4.10 Risk Prediction (Questionnaire III) at Tuong Aik Shipyard Sdn Bhd

However, twenty pieces of Questionnaire III risk prediction are collected from the subcontractors, and workers at Tuong Aik Sdn Bhd, which is shown in Table 4.9. It is observed that risk prediction was high reaching level 3 of severity (permanent injuries). Fourteen of workers are predicted with severity level 3, permanent injuries (ranging from 2.61 to 2.99). Four persons are predicted with severity level 2, non-permanent injuries (ranging from 1.64 to 2.08). Only one person is predicted with severity level 1, minor injury (1.27). High severity risk prediction reveals the actual situation at site which is a lack of safety management, and supervision at shipyard compounds. Many hazardous factors are found at the site.

Table 4.9: Risk Prediction at Tuong Aik Shipyard Sdn Bhd by Workers via Questionnaire III

Worker	Gender	Age	Nationality	Years of Employment	Occupation	Working Hours	Education Level	Type of Hazard	Working Zone	Involved Activities	Risk Prediction
TA1	2	3	1	2	3	1	2	4	3	12	2.95
TA2	1	3	1	5	4	1	2	1	1	6	2.97
TA3	1	3	1	5	4	1	1	1	1	5	2.97
TA4	2	3	1	4	3	1	4	4	4	12	1.64
TA5	1	3	1	5	3	1	4	4	1	11	1.95
TA6	1	3	2	1	1	1	2	1	1	10	2.08
TA7	1	3	2	2	1	1	2	1	1	5	1.27
TA8	1	3	1	5	2	1	2	1	3	1	2.61
TA9	1	3	1	2	4	1	1	1	1	1	2.87
TA10	1	3	1	5	2	1	2	1	1	1	2.98
TA11	1	3	1	5	2	1	2	1	1	7	2.87
TA12	1	3	1	5	2	1	2	4	1	5	2.87
TA13	1	3	1	5	3	1	3	1	1	10	2.76
TA14	1	3	1	5	4	1	2	1	1	3	2.99
TA15	1	3	1	5	4	1	1	1	1	3	2.98
TA16	1	3	1	3	2	1	2	1	1	1	2.82
TA17	1	3	1	3	2	1	2	1	1	1	2.82
TA18	1	3	1	2	2	1	2	1	1	5	2.02
TA19	1	3	1	5	2	1	1	1	1	7	2.86
TA20	1	3	1	5	2	1	1	1	1	7	2.86

4.11 Revised Hazard Identification, Risk Assessment, Safety Decision-Making, Risk Control and Risk Prediction

Following that, flow chart discussed in the methodology is referred. It is suggested that management from Tuong Aik Shipyard Sdn Bhd to study the particular high risk prediction workers' background, and nature of work. Those high risk workers are mainly subcontractors, and workers working at the shipyard compound areas including dry dock, wet dock, wharf, and so on. Their routine works are mainly maintenance, equipment handling, heavy lifting, working at height, and hot work activities.

Referring to the risk assessment formula (likelihood x severity), a low risk assessment is considered by reducing the likelihood of accident. In order to reduce the likelihood, the reviewed risk control should be performed. This is done by identifying details of the physical hazards, chemical hazards, biological hazards, and ergonomic hazards happened at shipyards (high RPN). From there, a reviewed risk control such as elimination, substitution, and engineering control are the priority to be considered. Some improvements have been carried out, such as building a working at high platform, ladder platform, dockyard raw material relocation, electrical safety, and so on.

Then, the same 20 selected subcontractors, and workers are conducted for a revised risk prediction, and it is shown in Table 4.10.

Table 4.10: Revised Risk Prediction at Tuong Aik Shipyard Sdn Bhd by Workers via Questionnaire III

Worker	Gender	Age	Nationality	Years of Employment	Occupation	Working Hours	Education Level	Type of Hazard	Working Zone	Involved Activities	Risk Prediction
TA1	2	3	1	2	3	1	2	4	3	12	2.96
TA2	1	3	1	5	4	1	2	1	1	6	2.64
TA3	1	3	1	5	4	1	1	1	1	5	2.69
TA4	2	3	1	4	3	1	4	4	4	12	2.81
TA5	1	3	1	5	3	1	4	4	1	11	2.55
TA6	1	3	2	1	1	1	2	1	1	10	1.01
TA7	1	3	2	2	1	1	2	1	1	5	1.06
TA8	1	3	1	5	2	1	2	1	3	1	2.95
TA9	1	3	1	2	4	1	1	1	1	1	1.81
TA10	1	3	1	5	2	1	2	1	1	1	1.09
TA11	1	3	1	5	2	1	2	1	1	7	1.93
TA12	1	3	1	5	2	1	2	4	1	5	1.04
TA13	1	3	1	5	3	1	3	1	1	10	2.89
TA14	1	3	1	5	4	1	2	1	1	3	2.99
TA15	1	3	1	5	4	1	1	1	1	3	2.92
TA16	1	3	1	3	2	1	2	1	1	1	1.05
TA17	1	3	1	3	2	1	2	1	1	1	1.51
TA18	1	3	1	2	2	1	2	1	1	5	1.21
TA19	1	3	1	5	2	1	1	1	1	7	2.49
TA20	1	3	1	5	2	1	1	1	1	7	2.98

4.12 Comparison

The revised risk prediction result is compared with the previous risk prediction at Tuong Aik Shipyard Sdn Bhd. It is found out there is a slightly reduction of risk prediction among the previous selected subcontractors, and workers. Six of the workers are predicted with severity level 1, minor injury (ranging from 1.01 to 1.21). Four workers are predicted with severity level 2, non-permanent injury (ranging from 1.51 to 2.49). Total ten workers ($10/20 = 50\%$) with minor injury and non-permanent injury, have achieved 15% validation test and 15% test performance. And the other ten workers are predicted with severity level 3, permanent injury (ranging from 2.55 to 2.99). This revised prediction (permanent injury) has been reduced from 70% to 50%. However, there are workers still remained with high risk prediction severity (permanent injury) even after some improvements has been done. This shows that there is still having a room for a better improvement. Table 4.11, and Figure 4.7 are referred with. The risk management framework that practiced in this case study entails hazard identification, risk assessment, risk control, and risk prediction. Improvements that have been done in shipyard compound areas are shown at Table 4.12.

Table 4.11: Comparison Between Risk Prediction Before and After Improvement

Worker	Risk Prediction	Risk Prediction after Improvement
TA1	2.95	2.96
TA2	2.97	2.64
TA3	2.97	2.69
TA4	1.64	2.81
TA5	1.95	2.55
TA6	2.08	1.01
TA7	1.27	1.06
TA8	2.61	2.95
TA9	2.87	1.81
TA10	2.98	1.09
TA11	2.87	1.93
TA12	2.87	1.04
TA13	2.76	2.89
TA14	2.99	2.99
TA15	2.98	2.92
TA16	2.82	1.05
TA17	2.82	1.51
TA18	2.02	1.21
TA19	2.86	2.49
TA20	2.86	2.98

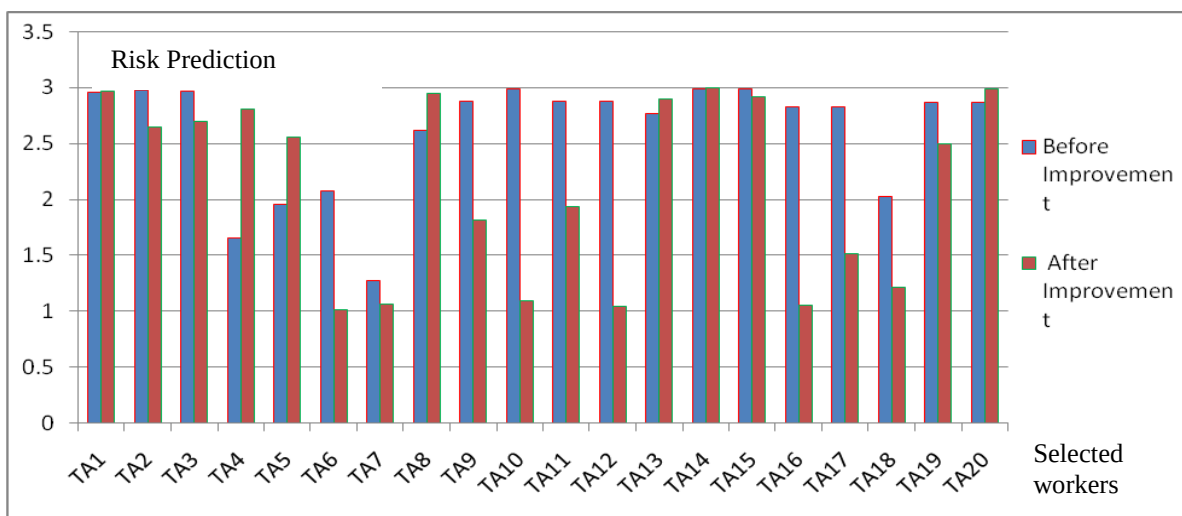
**Figure 4.7:** Comparison Between Risk Prediction Before and After Improvement

Table 4.12: Comparison Shipyard Condition Before and After Improvement

Activities	Shipyard Condition Before Improvement	Shipyard Condition After Improvement	Control Measurements
Welding / Hot works			House keeping has been done and unwanted materials are eliminated. A stable working platform and ladder with handle in term of engineering control are provided.
Working at height			
Lifting and mobilization works			House keeping is done. Accessibility of the transferring path way is cleared from any obstacles. Crawler crane and overhead travelling crane are used for lifting big size and heavy materials. Workers are provided with PPE.
Equipment Installation works			

Table 4.12: Continued

Activities	Shipyard Condition Before Improvement	Shipyard Condition After Improvement	Control Measurements
Use of hand tools / Equipment			Hand tools / equipments are kept and stored properly. House keeping has been done.
Electrical installation / Electrical maintenance works			Wires are inspected and proper connection has been done with distribution board.

Table 4.12: Continued

Activities	Shipyard Condition Before Improvement	Shipyard Condition After Improvement	Control Measurements
Sand blasting and painting works			Hand guarding and platform isolation has been done. Workers are provided with appropriate PPE.
Repair / Maintenance works			Hazardous chemical such as flammable and explosive materials are kept and stored properly. Only use when it is required.

Table 4.12: Continued

Activities	Shipyard Condition Before Improvement	Shipyard Condition After Improvement	Control Measurements
Working at confined space			Administrative improvement has been done. Workers are provided with appropriate PPE.
Sea launching works			House keeping has been done. Accessibility of the slipway is cleared from any obstacles. Airbags are used for ship launching.
Site supervision / Visiting			

4.13 Chapter Summary

In this chapter, the formulated risk management framework which entails hazard identification, risk assessment, risk control, and risk prediction, is experimented with case study at shipyards. The experiment shows that the proposed approach is able to predict the risk exposure of workers. This has been proven as a dynamic, and continuously improving risk management framework in the shipyards case study.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

In this study, the effectiveness of risk management framework on reducing the accidents at shipyards case study, is investigated. It stands for potential hazards identification, risk assessment, quantitative safety decision-making, risk control, and risk prediction. ANN machine learning is adopted to optimize the 10 input parameters (gender, age, working hours, years of employment, education level, occupation, nationality, workplace factors, working zone, and activities conducted) onto output parameter (risk prediction). Additionally, simulation utilizing Matlab is performed to calculate the risk prediction for the workers in shipyards case study. Conclusion from the results and discussion are drawn as follows:

Hazard identification and risk assessment have been proven to examine the awareness of shipyard management to identify potential hazards that affect to the fabrication process in the shipyard. Following that, risk exposure is assessed to identify the risk level of each fabrication process via Questionnaire I (Objective 1). It shows that welding, lifting materials, sand blasting and working at confined space, have the common physical hazards. This also indicates a medium or high risk level at these fabrication process.

Next, quantitative safety decision-making and risk control have carried out to standardize the priority to make decision on risk control, and risk prevention. In this stage, it applies and strengthens the knowledge and experience of the management to improve and prevent the occupational accidents from happening. The detection of risk control is

considered in the sequence of safety decision-making in term of risk priority number (RPN). RPN is applied to improve the decision-making for a clearer option, and method to prevent the accident from happening. This goes on elimination, substitution, engineering control, administration, and personal protective equipment engagement in sequence (Objective 2).

Following that, ANN with supervised learning Back-Propagation Neural Network (BPNN) is trained for output risk prediction. ANN modeling has been proven to examine several variables, and their interrelationships between independent and dependent variables for risk prediction. It has been proven as a successful linear modeling relationship. In the network architecture, 10 independent input variables, and 1 single layer-dependent output variable (severity of risk prediction) were defined. Then 7 network modelings were developed between 19–31 neuron nodes. The accuracy performance of the developed networks was compared using evaluation criteria to select the best model. To be more specific, the best ANN model selected has a high AP of 90.22% in predicting OSH risk exposure in the shipyard industry. This falls within the MAPE performance requirement, which is less than 30%. However, in terms of sensitivity analysis, input factors such as working hours (28.38%), and workplace factors (21.32%), have significant effects on the output OSH risk prediction. Alternatively, educational level (0.98%), and nationality (0.54%), are the least influencing factors (Objective 3).

From there, it is observed that application of a high accuracy risk prediction has improved the current typical risk management framework. Case study has done a comparison between Berjaya Dockyard Sdn Bhd, and Tuong Aik Shipyard Sdn Bhd. It is proven that risk prediction model developed in this research has identified that Tuong Aik Shipyard Sdn Bhd has a higher risk level at work place. The identified areas, and

workplace factors have been improved to prevent accidents from happening. Therefore, the formulated risk management framework that stands for potential hazards identification, risk assessment, quantitative safety decision-making, risk control, risk prediction has been proven to be a continuously improving risk management framework that suits to shipyards case study (Hypothesis).

5.2 Recommendation

From the literatures study, there is a room of improvement to increase the accuracy performance of risk prediction. Sensitivity analysis has identified that independent variables such as working hours, and workplace factors, have significant effects onto the output risk prediction. Therefore, research suggests a clearer, and detailed information defined in the aspect of working hours, and workplace factors for the next study.

Other than that, in the normal working situation, workers are multitasked at most of the time. In the other words, workers are flexible to move around in the shipyard. They were assigned with various tasks in their routine works are exposed to multi hazards. Therefore, research suggests that workers' risk prediction in the shipyard can be applied with a multi criteria optimization genetic algorithm by taking into account of workers' various tasks, activities, and the associated hazards (Papazoglou et al., 2017).

REFERENCES

- Abdelwahab, H. T., and Abdel-Aty, M. A. (2001). Development of artificial neural network models to predict driver injury severity in traffic accidents at signalized intersections. *Transp. Res. Rec.* 1746(1), 6-13.
- Abhishek, K., Kumar, A., Ranjan, R., & Kumar, S. (2012). A rainfall prediction model using artificial neural network. *IEEE Control and System Graduate Research Colloquium*, 82-87.
- Alshihri, M. M., Azmy, A. M., & El-Bisy, M. S. (2009). Neural networks for predicting compressive strength of structural light weight concrete. *Construction and Building Materials*, 23(6), 2214-2219.
- Al-Zwainy, F. M. S., Rasheed, H. A., & Ibraheem, H. F. (2012). Development of the construction productivity Estimation model using artificial neural network for finishing works for floors with marble. *ARPJN Journal of Engineering and Applied Sciences*, 7(6), 714-722.
- Anderson, W. E. (2005). Risk analysis methodology applied to industrial machine development. *IEEE transactions on industry applications*, 41(1), 180-187.
- Ayhan, B. U., & Tokdemir, O. B. (2019). Safety assessment in megaprojects using artificial intelligence. *Safety science*, 118, 273-287.
- Azadeh, A., Rouzbahman, M., Saberi, M., & Fam, I. M. (2011). An adaptive neural network algorithm for assessment and improvement of job satisfaction with respect to HSE and ergonomics program: the case of a gas refinery. *Journal of Loss Prevention in the Process Industries*, 24(4), 361-370.

- Azuaje, F. (2016). Review of Data Mining: Practical Machine Learning Tools and Techniques by Witten and Frank. *BioMedical Engineering OnLine*, 5, 51.
- Bai, X. P., Nie, W., & Liu, C. M. (2007). A comparison of Chinese, Japanese, and Korean shipyard production technology. *Journal of Marine Science and Application*, 6(2), 25-29.
- Barakat, N., & Diederich, J. (2004). Learning-based rule-extraction from support vector machines.
- Basuki, M., Manfaat, D., Nugroho, S., & Dinariyana, A. A. B. (2014). Probabilistic risk assessment of the shipyard industry using the Bayesian method. *International Journal of technology*, 5(1), 88-97.
- Baykal, T., Ergezer, F., Eriskin, E., & Terzi, S. (2023). Accident Severity Prediction in Big Data Using Auto-Machine Learning. *Scientia Iranica*.
- Braithwaite, J., Wears, R. L., & Hollnagel, E. (2015). Resilient health care: turning patient safety on its head. *International Journal for Quality in Health Care*, 27(5), 418-420.
- Buyong, R., Ahmad, M. Z., & Atan, Z. (2019). Comparison and Effective Approaches for Quantitative Risk Assessment (QRA) Oil & Gas Offshore Installation. *Open International Journal of Informatics*, 7(Special Issue 1), 191-198.
- Card, A. J., Ward, J., & Clarkson, P. J. (2012). Successful risk assessment may not always lead to successful risk control: a systematic literature review of risk control after root cause analysis. *Journal of Healthcare risk management*, 31(3), 6-12.
- Cebi, S., Akyuz, E., & Sahin, Y. (2017). Developing Web Based Decision Support System For Evaluation Occupational Risk At Shipyard. *Brodogradnja*, 68(1), 17–30.
- Çelebi, U. (2010). The Risk of Occupational Safety and Health in Shipbuilding Industry in Turkey.

- Ceribasi, G. (2017). Application of trend analysis and artificial neural networks methods: The case of Sakarya River. *Scientia Iranica*, 24(3), 993-999.
- Chang, J. I., & Liang, C.-L. (2009). Performance evaluation of process safety management systems of paint manufacturing facilities. *Journal of Loss Prevention in the Process Industries*, 22(4), 398–402.
- Cherniack, M., Morse, T. F., Brammer, A. J., Lundstrom, R., Meyer, J. D., Nilsson, T., & Bruneau, H. (2004). Vibration exposure and disease in a shipyard: A 13-year revisit. *American journal of industrial medicine*, 45(6), 500-512.
- Council, M. A. (2011). Malaysian Industry-Government Group for High Technology (MIGHT). *Online Database, Government of Malaysia*, available at: <http://steer.might.org.my/aironline/index2>.
- Dehghani, F., Eslamloueyan, R., and Sarshar, M. (2022). A hybrid model for simulation of lithium-ion batteries using artificial neural networks and computational fluid dynamics, *Scientia Iranica*.
- Delen, D., Sharda, R., & Bessonov, M. (2006). Identifying significant predictors of injury severity in traffic accidents using a series of artificial neural networks. *Accident Analysis & Prevention*, 38(3), 434-444.
- Department of Occupational Safety and Health, Occupational Accident Statistic. (2019). *Sector/State*, available at <https://www.dosh.gov.my/index.php/statistic-v/occupational-accident-statistics-v/occupational-accident-statistic-2019>
- Dissanayake, S., and Lu, J. J. “Factors influential in making an injury severity difference to older drivers involved in fixed object–passenger car crashes”, *Acc. Anal. Prev.* 34(5), 609-618.

- El-Sawalhi, N. I., & Shehatto, O. (2014). A neural network model for building construction projects cost estimating. *Journal of Construction Engineering and Project Management*, 4(4), 9-16.
- Erzin, Y., and Tuskan, Y. (2019). The use of neural networks for predicting the factor of safety of soil against liquefaction, *Scientia Iranica*. 26(5), 2615-2623.
- Etherton, J. R. (2007). Industrial machine systems risk assessment: A critical review of concepts and methods. *Risk Analysis: An International Journal*, 27(1), 71-82.
- Fish, K. E., and Blodgett, J. G. (2003). A visual method for determining variable importance in an artificial neural network model: an empirical benchmark study, *J. Target. Meas. Anal. Mark.* 11(3), 244-254.
- Fish, Kelly E., and Richard S. Segall. (2004). A visual analysis of learning rule effects and variable importance for neural networks in data mining operations, *Kybernetes* .
- Gevrey, M., Dimopoulos, I., and Lek, S. (2003). Review and comparison of methods to study the contribution of variables in artificial neural network models, *Ecol Modell*160(3), 249-264.
- Gokler, S. H., and Semra B. (2022). Determining optimal machine part replacement time using a hybrid ANN-GA model. *Scientia Iranica*, 29(2), 721-782.
- Hariharakrishnan, J., Mohanavalli, S., & Kumar, K. S. (2017, January). Survey of pre-processing techniques for mining big data. In *2017 International Conference on Computer, Communication and Signal Processing (ICCCSP)*. 1-5.
- Hasan, Nor Halim (Nov 2019). Generic HIRARC Sektor Pembuatan Kapal, Bengkel Membangunkan Generic HIRARC bagi Sektor Pembuatan Kapal di Sibu Sarawak. *Jabatan Keselamatan Dan Kesihatan Pekerjaan Sarawak*. 5-6.

- Hong, E.-S., Lee, I.-M., Shin, H.-S., Nam, S.-W., & Kong, J.-S. (2009). Quantitative risk evaluation based on event tree analysis technique: Application to the design of shield TBM. *Tunnelling and Underground Space Technology*, 24(3), 269–277.
- Hu, A. H., Hsu, C.-W., Kuo, T.-C., & Wu, W.-C. (2009). Risk evaluation of green components to hazardous substance using FMEA and FAHP. *Expert Systems with Applications*, 36(3), 7142–7147.
- Khamis, A., & Abdullah, S. N. S. B. (2014). Forecasting wheat price using backpropagation and NARX neural network. *The International Journal of Engineering and Science*, 3(11), 19-26.
- Kumruoglu, L. C. (2021). Prediction of shrinkage ratio of ZA-27 die casting alloy using artificial neural network, computer-aided simulation, and comparison with experimental studies, *Scientia Iranica*.
- Lees, F. (2012). Lees' Loss prevention in the process industries: Hazard identification, assessment and control. *Butterworth-Heinemann*.
- Lokhande, V. R. (2014). Health profile of workers in a ship building and repair industry. *Indian Journal of Occupational and Environmental Medicine*, 18(2), 89.
- Machmood, K., & Shevtshenko, E. (2015). Analysis of machine production processes by risk assessment approach. *Journal of Machine Engineering*, 15.
- Martin, J. E., Rivas, T., Matías, J. M., Taboada, J., & Argüelles, A. (2009). A Bayesian network analysis of workplace accidents caused by falls from a height. *Safety Science*, 47(2), 206-214.
- Matías, J. M., Rivas, T., Martín, J. E., & Taboada, J. (2008). A machine learning methodology for the analysis of workplace accidents. *International Journal of Computer Mathematics*, 85(3-4), 559-578.

- Medeiros, D. J., Traband, M., Tribble, A., Lepro, R., Fast, K., & Williams, D. (2000, December). Simulation based design for a shipyard manufacturing process. In *2000 Winter Simulation Conference Proceedings (Cat. No. 00CH37165)* 2, 1411-1414.
- Moatari-Kazerouni, A., Chinniah, Y., & Agard, B. (2015). A proposed occupational health and safety risk estimation tool for manufacturing systems. *International journal of production research*, 53(15), 4459-4475.
- Mohamed, A. E. (2017). Comparative study of four supervised machine learning techniques for classification. *International Journal of Applied*, 7(2).
- Murat, Y. S., & Ceylan, H. (2006). Use of artificial neural networks for transport energy demand modeling. *Energy policy*, 34(17), 3165-3172.
- Nait-Said, R., Zidani, F., & Ouzraoui, N. (2009). Modified risk graph method using fuzzy rule-based approach. *Journal of Hazardous Materials*, 164(2-3), 651–658.
- Nassiri, H., & Mohamadian Amiri, A. (2014). Prediction of roadway accident frequencies: Count regressions versus machine learning models. *Scientia Iranica*, 21(2), 263-275.
- Niazkar, Majid, Nasser T., and Seied H. A. (2021). Bridge backwater estimation: A comparison between artificial intelligence models and explicit equations, *Scientia Iranica*. 28(2), 573-585.
- Noori, R., Karbassi, A., & Sabahi, M. S. (2010). Evaluation of PCA and Gamma test techniques on ANN operation for weekly solid waste prediction. *Journal of Environmental Management*, 91(3), 767-771.
- Odeyinka, H., Lowe, J., & Kaka, A. (2002, September). A construction cost flow risk assessment model. In *The 18th Annual ARCOM Conference*, 3-12.

- Othman, I., Mohamad, H., Sapari, N., Shafiq, N., Ibrahim, F., & Kamil, S. (2018). HSE Management System At High Elevation In Shipbuilding Project. *International Journal of Engineering Technologies and Management Research*, 5(11), 117-127.
- Paik, J. K., & Thayamballi, A. K. (2007). Ship-shaped offshore installations: design, building, and operation. *Cambridge University Press*.
- Papazoglou, I. A., Aneziris, O. N., Bellamy, L. J., Ale, B. J., & Oh, J. (2017). Multi-hazard multi-person quantitative occupational risk model and risk management. *Reliability Engineering & System Safety*, 167, 310-326.
- Patel, D. A., & Jha, K. N. (2015). Neural network model for the prediction of safe work behavior in construction projects. *Journal of Construction Engineering and Management*, 141(1), 04014066.
- Principe, J. C., Xu, D., Fisher, J., & Haykin, S. (2000). Information theoretic learning. *Unsupervised adaptive filtering*, 1, 265-319.
- Rahmat, M. K., & Jovanovic, S. (2009). Reliability modeling of uninterruptible power supply systems using fault tree analysis method. *European Transactions on Electrical Power*, 19(2), 258–273.
- Samekto, A. A., & Kristiyanti, M. (2020). Development of Risk Management Model in Maritime Industry. *Calitatea*, 21(178), 122-127.
- Sarkar, S., Vinay, S., Raj, R., Maiti, J., & Mitra, P. (2019). Application of optimized machine learning techniques for prediction of occupational accidents. *Computers & Operations Research*, 106, 210-224.
- Shaleh, M. K., & Leman, A. M. (2016). Systematic Approach for Hazard Identification, Risk Assessment and Risk Control (HIRARC) in Workplace. *DOSH Guidelines*.

- Shirode, R., & Ramdasi, D. (2018, April). Exhaled Breath Analysis for Renal Diseases Using Artificial Neural Network Classifier. In *2018 International Conference on Communication and Signal Processing (ICCSP)*, 0989-0993.
- Theofilatos, A., Graham, D., and Yannis, G. (2012). Factors affecting accident severity inside and outside urban areas in Greece, *Traffic Inj. Prev.* 13(5), 458-467.
- Vakili, M., Sabbagh-Yazdi, S. R., Kalhor, K., & Khosrojerdi, S. (2015). Using artificial neural networks for prediction of global solar radiation in Tehran considering particulate matter air pollution. *Energy procedia*, 74, 1205-1212.
- Wang, L., & Buchanan, T. S. (2002). Prediction of joint moments using a neural network model of muscle activations from EMG signals. *IEEE transactions on neural systems and rehabilitation engineering*, 10(1), 30-37.
- Waziri, B. S., Bala, K., & Bustani, S. A. (2017). Artificial neural networks in construction engineering and management. *International Journal of Architecture, Engineering and Construction*, 6(1), 50-60.
- Willmott, C. J., & Matsuura, K. (2005). Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. *Climate research*, 30(1), 79-82.
- Xiao, N., Huang, H.-Z., Li, Y., He, L., & Jin, T. (2011). Multiple failure modes analysis and weighted risk priority number evaluation in FMEA. *Engineering Failure Analysis*, 18(4), 1162–1170.
- Yazdani, A., & Ramakrishnan, K. (2015, December). Performance evaluation of artificial neural network models for the prediction of the risk of heart disease. In *International Conference for Innovation in Biomedical Engineering and Life Sciences*, 179-182.

Zeynalian, Mehran, and Iman K. D. (2016). Choice of optimum combination of construction machinery using modified advanced programmatic risk analysis and management model, *Scientia Iranica*. 25(3), 1015-1024.

APPENDICES

Appendix 1 – Application of Matlab and Process Function in ANN

Detailed steps and process in Figure 3.1 is recorded for a better understanding of developing ANN risk prediction modeling:

Step 1: Raw data mining from various government agencies is done to get the accidents cases happened in SBSR industry. Data pre-processing is carried out to filter the occupational accidents happened at industrial shipyards. Some of the data collection are insufficient.

Step 2: Input variables (S), output variables (P) from the data collected, are determined and put into coding representatives.

Step 3: Data coding are keyed into Matlab 2017.

Step 4: Data is extracted into 70% training, 15% variation and 15% testing.

Step 5: Relationship between input variables and output are trained by using ANN Back-Propagation Neural Network (Murat et al., 2006):

- Architecture, and determination by the type of algorithm, number of layers, number of neurons, transferring function, learning function, and other training parameters are selected in developing relevant ANN network modelings (Shirode et al., 2018).
- Relevant ANN neural networks with layer neuron nodes 19, 21, 23, 25, 17, 29 and 31 are developed.
- 70% of data are trained.
- Correlation of coefficient (R^2) of training data is determined (> 0.5). The highest R^2 shows the significant relationship of input-output paired.
- Minimum 50% of trained data is determined with almost zero error.
- Mean Square Error (MSE) is determined (< 1.0). Otherwise, data collection and input variables should be reviewed. The lowest MSE shows the least error of the trained data.
- Accuracy performance is compared among those relevant ANN network modelings in R^2 and MSE.

- The best ANN network No.4 with 25 neuron nodes is selected for ANN risk prediction at shipyards case study.
- Mean Absolute Percentage Error (MAPE) from the best ANN network No.4 is determined ($<30\%$). This determines the accuracy performance of the risk prediction model.
- Consistency performance in term of sensitivity analysis is also be carried out by determining the percentage of perturbed input variables onto the output risk prediction.
- ANN network modeling No.4 is integrated in risk management framework.

Step 6: Shipyards case study are identified for the implementation of risk management framework which includes hazard identification, risk assessment, quantitative safety decision-making and risk prediction.

Step 7: Questionnaire I is distributed for hazard identification and risk assessment based on fabrication process.

Step 8: Questionnaire II is distributed for priority of quantitative safety decision-making. The effectiveness of current practised risk control shows a good detection in risk control.

Step 9: Questionnaire III is distributed for risk prediction to the 20 selected workers.

Step 10: Risk prediction was evaluated.

Step 11: Improved control measurement to be done if the risk prediction is high (> 3.0). Control measurement is done in elimination, substitution, engineering control, administrative, and PPE subsequently.

Step 12: Site visit is carried out to analyse the effectiveness of risk management framework for reducing accidents happened case shipyards accordingly.

Step 13: Revised of risk prediction after improvement is done to achieve a risk prediction (< 2.0).

Step 14: Comparison of shipyard condition before and after improvement is done for recording purpose.

Appendix 2 – Questionnaire I, Hazard Identification and Risk Assessment at Shipyards Case Study

Hazard Identification and Risk Assessment - HIRARC (*Pengenalpastian Hazard, Penaksiran Risiko, Kawalan Risiko*)

COMPANY		PREPARED & UPDATED BY	
PROCESS/ LOCATION			
APPROVED BY			
DATE		REVISION DATE	

Hazard Identification				Risk Assessment		Current Prevention Control		Risk Level	Safety Decision-Making	
No.	Task Description	Hazard (s)	Which Can Cause / Effect	Severity	S	Prevention Control	L	RL	D	RPN

NOTE:

L = Likelihood (*kemungkinanberlakurisiko*) PPD – *PeralatanPerlindunganDiri*
S = Severity (*keterukanrisiko*) RL = Risk Level (*nilairisiko*)

RPN = Risk Priority Number (*penilaianrisiko*) D = Dectection (*Keberkesanan*)
PIC = Person In Charge PL = Priority Level
RPN= S x L x D

REFERENCE:

Indication of Severity (S)

Severity (L)	Example	Rating
Catastrophic	Numerous fatalities, irrecoverable property damage and productivity	5
Fatal	Approximately one single fatality major property damage if hazard is realized	4
Serious	Non-fatal injury, permanent disability	3
Minor	Disabling but not permanent injury	2
Negligible	Minor abrasions, bruises, cuts, first aid type injury	1

Indication of likelihood (L)

Likelihood (L)	Example	Rating
Most likely	The most likely result of the hazard /event being realized	5
Possible	Has a good chance of occurring and is not unusual	4
Conceivable	Might be occur a sometime in future	3
Remote	Has not been known to occur after many years	2
Inconceivable	Is practically impossible and has never occurred	1

Indication of Detection (D)

Detection (D)	Example	Rating
Catastrophic	Undetectable	5
Fatal	Poor	4
Serious	Moderate	3
Minor	Good	2
Negligible	Excellent	1

Likelihood (L)	Severity (S)				
	1	2	3	4	5
5	5	10	15	20	25
4	4	8	12	16	20
3	3	6	9	12	15
2	2	4	6	8	10
1	1	2	3	4	5

Table C

High ■
Medium ■
Low ■

RISK	DESCRIPTION	ACTION
15 - 25	HIGH	A HIGH risk requires immediate action to control the hazard as detailed in the hierarchy of control. Actions taken must be documented on the risk assessment form including date for completion.
5 - 12	MEDIUM	A MEDIUM risk requires a planned approach to controlling the hazard and applies temporary measure if required. Actions taken must be documented on the risk assessment form including date for completion.
1 - 4	LOW	A risk identified as LOW may be considered as acceptable and further reduction may not be necessary. However, if the risk can be resolved quickly and efficiently, control measures should be implemented and recorded.

Appendix 2 – Example 1 Welding and Cutting

Hazard Identification and Risk Assessment - HIRARC (Pengenalpastian Hazard, Penaksiran Risiko, Kawalan Risiko)

COMPANY	Berjaya Dockyard (Sibu) Sdn Bhd	PREPARED & UPDATED BY	Eric Tang (HSE Officer)
PROCESS/ LOCATION	Welding & Cutting		
APPROVED BY	Jonathan Ling (General Manager)		
DATE		REVISION DATE	

Hazard Identification				Risk Assessment		Current Prevention Control		Risk Level	Safety Decision Making	
No.	Task Description	Hazard (s)	Which Can Cause / Effect	Severity	S	Prevention Control	L	RL	D	RPN
1	Akses tempat kerja dan persediaan tempat kerja	1. Terjatuh dari tempat tinggi	Kecederaan anggota badan atau kematian	Fatality	4	- Gunakan abah-abah keselamatan (<i>safety harness</i>) untuk ketinggian 2.0 m dan ke atas - Pelantar kerja yang sesuai	1	4(L)	4	16
		2. Ruangan sempit	Kecederaan anggota badan	Body injury	2	- Pengemasan tempat kerja - Rancang aktiviti/ langkah kerja	2	4(L)	3	12
		3. Permukaan lantai yang licin & kabel yang tak tersusun	Bahaya tergelincir/ tersungkur/ terjatuh yang boleh menyebabkan kecederaan anggota badan	Seriously body injury/ Fatality	4	- Pengemasan tempat kerja - Pencahayaannya yang mencukupi	1	4(L)	4	16
		4. Objek tajam	Kecederaan anggota badan	Body injury	2	- Gunakan PPD yang sesuai - Pengemasan tempat kerja	2	4(L)	3	12

Appendix 2 – Example 1 continued

Hazard Identification and Risk Assessment - HIRARC
(*Pengenalpastian Hazard, Penaksiran Risiko, Kawalan Risiko*)

COMPANY	Berjaya Dockyard (Sibu) Sdn Bhd	PREPARED & UPDATED BY	Eric Tang (HSE Officer)
PROCESS/ LOCATION	Welding & Cutting		
APPROVED BY	Jonathan Ling (General Manager)		
DATE		REVISION DATE	

Hazard Identification				Risk Assessment		Current Prevention Control		Risk Level	Safety Decision Making	
No.	Task Description	Hazard (s)	Which Can Cause / Effect	Severity	S	Prevention Control	L	RL	D	RPN
2	Melakukan kerja kimpalan dan pemotongan	1. Percikan api & Kebocoran gas	Kejadian kebakaran atau letupan yang boleh merosakan harta benda syarikat, kecederaan dan kematian	Damage property / Serious body injury / Fatality	4	- Periksa keadaan peralatan sebelum mulakan kerja - Periksa keadaan dan sambungan kabel dan hos - Gunakan <i>flashback arrestor</i>	1	4(L)	4	16
		2. Ruangan sempit	Kecederaan anggota badan	Ergonomics	2	- Tahu laluan selamat - Pencahayaan dan pengudaraan yang mencukupi	3	6(M)	3	18
		3. Kerosakan kabel welding	Renjatan elektrik yang membolehkan kematian	Fatality	4	- Gunakan peralatan piawai - Periksa sambungan kabel - Elakkan kabel dari permukaan basah - Gunakan PPD yang sesuai	1	4(L)	4	16
		4. Terkena objek/ permukaan panas	Kecederaan anggota badan	Body injury	2	Gunakan sarung tangan yang sesuai untuk memindahkan objek panas	2	4(L)	4	16

Appendix 2 – Example 1 continued

Hazard Identification and Risk Assessment - HIRARC
(*Pengenalpastian Hazard, Penaksiran Risiko, Kawalan Risiko*)

COMPANY	Berjaya Dockyard (Sibu) Sdn Bhd	PREPARED & UPDATED BY	Eric Tang (HSE Officer)
PROCESS/ LOCATION	Welding & Cutting		
APPROVED BY	Jonathan Ling (General Manager)		
DATE		REVISION DATE	

Hazard Identification				Risk Assessment		Current Prevention Control		Risk Level	Safety Decision Making	
No.	Task Description	Hazard (s)	Which Can Cause / Effect	Severity	S	Prevention Control	L	RL	D	RPN
3	Pengemasan tempat kerja	1. Terjatuh dari tempat tinggi	Kecederaan anggota badan atau kematian	Fatality	4	- Gunakan abah-abah keselamatan (<i>safety harness</i>) untuk ketinggian 2.0 m dan ke atas - Pelantar kerja yang sesuai	1	4(L)	4	16
		2. Ruangan sempit	Kecederaan anggota badan	Ergonomics	2	- Tahu laluan selamat - Pencahayaan dan pengudaraan yang mencukupi	3	6(M)	3	18
		3. Objek tajam	Kecederaan anggota badan	Body injury	2	- Gunakan PPD yang sesuai - Amalkan sistem kerja berteman (<i>Buddy System</i>)	2	4(L)	3	12

NOTE:

L = Likelihood (*kemungkinan berlaku risiko*)
S = Severity (*keterukan risiko*)

PPD – Peralatan Perlindungan Diri
RL = Risk Level (*nilai risiko*)

RPN = Risk Priority Number (*penilaian risiko*)
PIC = Person In Charge
RPN= S x L x D
D = Detection (*Keberkesanan*)
PL = Priority Level

Appendix 2 – Example 2 Working at Height

Hazard Identification and Risk Assessment - HIRARC (*Pengenalpastian Hazard, Penaksiran Risiko, Kawalan Risiko*)

COMPANY	Berjaya Dockyard (Sibu) Sdn Bhd	PREPARED & UPDATED BY	Eric Tang (HSE Officer)
PROCESS/ LOCATION	Yard Area Working at Height		
APPROVED BY	Jonathan Ling (General Manager)		
DATE		REVISION DATE	

Hazard Identification				Risk Assessment		Current Prevention Control		Risk Level	Safety Decision Making	
No.	Task Description	Hazard (s)	Which Can Cause / Effect	Severity	S	Prevention Control	L	RL	D	RPN
1	Akses tempat kerja dan persediaan tempat kerja	1. Terjatuh dari tempat tinggi	Kecederaan anggota badan atau kematian	Fatality	4	- Gunakan abah-abah keselamatan (<i>safety harness</i>) untuk ketinggian 2.0 m dan ke atas - Pelantar kerja yang sesuai	1	4(L)	4	16
		2. Papan perancah yang licin	Bahaya tergelincir/ tersungkur/ terjatuh dan menyebabkan kecederaan anggota badan atau kematian	Seriously body injury/ Fatality	4	- Pengemasan tempat kerja - Gunakan abah-abah keselamatan (<i>safety harness</i>) untuk ketinggian 2.0 m dan ke atas	1	4(L)	4	16
		3. Terkena objek tajam	Kecederaan anggota badan	Body injury	2	- Gunakan PPD yang sesuai - Pengemasan tempat kerja	2	4(L)	3	12

Appendix 2 – Example 2 Continued

Hazard Identification and Risk Assessment - HIRARC (*Pengenalpastian Hazard, Penaksiran Risiko, Kawalan Risiko*)

COMPANY	Berjaya Dockyard (Sibu) Sdn Bhd	PREPARED & UPDATED BY	Eric Tang (HSE Officer)
PROCESS/ LOCATION	Yard Area Working at Height		
APPROVED BY	Jonathan Ling (General Manager)		
DATE		REVISION DATE	

Hazard Identification				Risk Assessment		Current Prevention Control		Risk Level	Safety Decision Making	
No.	Task Description	Hazard (s)	Which Can Cause / Effect	Severity	S	Prevention Control	L	RL	D	RPN
2	Melakukan kerja di tempat tinggi	1. Terjatuh dari tempat tinggi	Kecederaan anggota badan atau kematian	Fatality	4	- Gunakan abah-abah keselamatan (<i>safety harness</i>) untuk ketinggian 2.0 m dan ke atas - Pelantar kerja yang sesuai	1	4(L)	4	16
		2. Objek terjatuh	Kecederaan anggota badan	Body injury	2	- Gunakan topi keselamatan - Simpan peralatan kerja dalam bekas - Ikatan yang betul dan selamat - Kawalan kawasan kerja	1	2(L)	4	8
3	Pengemasan tempat kerja	1. Terjatuh dari tempat tinggi	Kecederaan anggota badan atau kematian	Fatality	4	Gunakan abah-abah keselamatan (<i>safety harness</i>) untuk ketinggian >2.0 m	1	4(L)	4	16
		2. Terkena objek tajam	Kecederaan anggota badan	Body injury	2	- Gunakan PPD yang sesuai - Amalkan sistem kerja berteman (<i>Buddy System</i>)	2	4(L)	3	12

NOTE:

L = Likelihood (*kemungkinan berlaku risiko*)
S = Severity (*keterukan risiko*)

PPD – Peralatan Perlindungan Diri
RL = Risk Level (*nilai risiko*)

RPN = Risk Priority Number (*penilaian risiko*)
PIC = Person In Charge
RPN= S x L x D
D = Detection (*Keberkesanan*)
PL = Priority Level

Appendix 2 – Example 3 Lifting

Hazard Identification and Risk Assessment - HIRARC (*Pengenalpastian Hazard, Penaksiran Risiko, Kawalan Risiko*)

COMPANY	Berjaya Dockyard (Sibu) Sdn Bhd	PREPARED & UPDATED BY	Eric Tang (HSE Officer)
PROCESS/ LOCATION	Lifting		
APPROVED BY	Jonathan Ling (General Manager)		
DATE		REVISION DATE	

Hazard Identification				Risk Assessment		Current Prevention Control		Risk Level	Safety Decision Making	
No.	Task Description	Hazard (s)	Which Can Cause / Effect	Severity	S	Prevention Control	L	RL	D	RPN
1	Worksite preparation	1. Confine space	Body injury	Fatality	4	- Work area housekeeping. - Activities planning and lifting steps - Identify communication means. - Know the safe route - Apply PTW.	1	4(L)	4	16
		2. Uneven ground	Trip and fall	Serious bodily injury	3	Work area housekeeping.	2	6(M)	3	18
		3. Steel pieces	Stunt by sharp object	Cut or prick injury	2	- Used suitable PPE. - Work area housekeeping.	2	4(L)	3	12
2	Installing lifting equipment to the load	1. Heavy tools	The hand is stuck between two objects that can cause hand injuries	Pressed or rolled injury	3	- Keep hands away from moving objects. - Amalkan sistem kerja berteman	2	6(M)	3	18
3	Pra-angkat muatan	1. Defect tools	Lifting equipment failure and load being dropped / dropped	Fatality	4	- Use equipment with appropriate load limits - Check the condition of the equipment before use.	1	4(L)	4	16

Appendix 2 – Example 3 Continued

Hazard Identification and Risk Assessment - HIRARC (*Pengenalpastian Hazard, Penaksiran Risiko, Kawalan Risiko*)

COMPANY	Berjaya Dockyard (Sibu) Sdn Bhd	PREPARED & UPDATED BY	Eric Tang (HSE Officer)
PROCESS/ LOCATION	Lifting		
APPROVED BY	Jonathan Ling (General Manager)		
DATE		REVISION DATE	

Hazard Identification				Risk Assessment		Current Prevention Control		Risk Level	Safety Decision Making	
No.	Task Description	Hazard (s)	Which Can Cause / Effect	Severity	S	Prevention Control	L	RL	D	RPN
3	Pra-angkat muatan	2. Heavy load	Load slip and fall	Fatality	4	• Verification of eye lug integrity from the Quality Control (QA) Department. • Proper and secure bonding. • Be at a safe distance from the load. • Control of lifting activity areas. • Crane operators and supervisors need to check re -tie and safety latch is used before starting the force (effective 10 Oct 2016).	1	4(L)	4	16
			Crane overturn	Fatality	4	• Competent crane operator. • Communication between signaller and crane operator. • Identify soil structure. • Appropriate boom position. • The gravity point of the load is appropriate.	1	4(L)	4	16
			Crane wire broken	Fatality	4	• Be at a safe distance from the load. • Control of lifting activity areas. • Routine checking	1	4(L)	4	16

Appendix 2 – Example 3 Continued

Hazard Identification and Risk Assessment - HIRARC (*Pengenalpastian Hazard, Penaksiran Risiko, Kawalan Risiko*)

COMPANY	Berjaya Dockyard (Sibu) Sdn Bhd	PREPARED & UPDATED BY	Eric Tang (HSE Officer)
PROCESS/ LOCATION	Lifting		
APPROVED BY	Jonathan Ling (General Manager)		
DATE		REVISION DATE	

Hazard Identification				Risk Assessment		Current Prevention Control		Risk Level	Safety Decision Making	
No.	Task Description	Hazard (s)	Which Can Cause / Effect	Severity	S	Prevention Control	L	RL	D	RPN
3	Pra-angkat muatan	3.Unskilled signalers	The load being lifted hits other property which allows damage	Fatality	4	- Toolbox talk. - Proper lifting signal training. - Plan lifting activities/ steps. - Use taglines. - Make sure the storage space is safe. - Signals are given by trained people. - Control of lifting activity areas.	1	4(L)	4	16
			The load hit the limbs of the worker allowing injury	Fatality	4	- Use taglines. - Practice buddy system. - Be at a safe distance from the load.	1	4(L)	4	16
4	Remove the shackle from the eye lug	1. Heavy load	Hands stuck between two objects	Pressed or rolled injury	3	- Keep hands away from moving objects. - Practice buddy system	2	6(M)	3	18

NOTE:

L = Likelihood (*kemungkinan berlaku risiko*)
S = Severity (*keterukan risiko*)

PPD – Peralatan Perlindungan Diri
RL = Risk Level (*nilai risiko*)

RPN = Risk Priority Number (*penilaian risiko*) D = Detection (*Keberkesanan*)
PIC = Person In Charge PL = Priority Level
RPN= S x L x D

Appendix 3 – Questionnaire II, Priority of Quantitative Safety Decision-Making and Risk Control Measurement

Priority of Quantitative Safety Decision-Making and Risk Control Measurement

COMPANY		PREPARED UPDATED BY	&	
PROCESS/ LOCATION				
APPROVED BY				
DATE		REVISION DATE		

Safety Decision-Making		Risk Control Measurement	Reference Document	Picture Description Before Improvement	Picture Description After Improvement
D	RPN - (PL)				

NOTE:

RPN = Risk Priority Number (*penilaianrisiko*)

PL = Priority Level

D = Detection (*Keberkesanan*)

RPN= S x L x D

Appendix 3 – Example 1 Lifting

Priority of Quantitative Safety Decision Making and Risk Control Measurement

COMPANY	Berjaya Dockyard (Sibu) Sdn Bhd	PREPARED & UPDATED BY	Eric Tang (HSE Officer)
PROCESS/ LOCATION	Lifting		
APPROVED BY	Jonathan Ling (General Manager)		
DATE		REVISION DATE	

Safety Decision Making		Risk Control Measurement	Reference Document	Picture Description Before Improvement	Picture Description After Improvement
D	RPN - (PL)				
3	18	Work area housekeeping.			
3	18	- Keep hands away from moving objects. - Buddy System			

Appendix 3 – Example 1 Continued

Priority of Quantitative Safety Decision Making and Risk Control Measurement

COMPANY	Berjaya Dockyard (Sibu) Sdn Bhd	PREPARED & UPDATED BY	Eric Tang (HSE Officer)
PROCESS/ LOCATION	Lifting		
APPROVED BY	Jonathan Ling (General Manager)		
DATE		REVISION DATE	

Safety Decision Making		Risk Control Measurement	Reference Document	Picture Description Before Improvement	Picture Description After Improvement
D	RPN - (PL)				
4	16	• Verification of eye lug integrity from the Quality Control (QA) Department. • Proper and secure bonding. • Be at a safe distance from the load. • Control of lifting activity areas.			

NOTE:

RPN = Risk Priority Number (*penilaian risiko*)

PL = Priority Level

D = Detection (*Keberkesanan*)

RPN= S x L x D

Appendix 3 – Example 2 Block Lifting

Risk Reduction – Quantitative Safety Decision Making and Risk Control Measurement

COMPANY	Berjaya Dockyard (Sibu) Sdn Bhd	PREPARED UPDATED BY	& Eric Tang (HSE Officer)
PROCESS/ LOCATION	Block Lifting		
APPROVED BY	Jonathan Ling (General Manager)		
DATE		REVISION DATE	

Safety Decision Making		Risk Control Measurement	Reference Document	Picture Description Before Improvement	Picture Description After Improvement
D	RPN - (PL)				
3	18	• Use suitable PPE • Housekeeping • Apply PTW			
3	18	• Jauhkan tangan dari objek bergerak • Practice buddy system			

Appendix 3 – Example 2 Continued

Risk Reduction – Quantitative Safety Decision Making and Risk Control Measurement

COMPANY	Berjaya Dockyard (Sibu) Sdn Bhd	PREPARED UPDATED BY & Eric Tang (HSE Officer)	
PROCESS/ LOCATION	Block Lifting		
APPROVED BY	Jonathan Ling (General Manager)		
DATE		REVISION DATE	

Safety Decision Making		Risk Control Measurement	Reference Document	Picture Description Before Improvement	Picture Description After Improvement
D	RPN - (PL)				
4	16	- Periksa sijil peralatan - Gunakan peralatan dengan had muatan (SWL/ WLL) yang sesuai - Periksa keadaan peralatan sebelum digunakan - Penyelenggaraan berkala kren/ peralatan			
4	16	- Ikatan yang betul dan selamat - Gunakan tagline - Komunikasi antara pemberi isyarat dan operator kren - Berada pada jarak yang selamat dari blok - Kawalan kawasan aktiviti mengangkat			

NOTE:

RPN = Risk Priority Number (*penilaian risiko*)

PL = Priority Level

D = Detection (*Keberkesanan*)

RPN= S x L x D

Appendix 4 – Questionnaire III, Data Collection for Risk Prediction

Information about Workers

Information about worker 基本信息	Company 公司:
	Worker's name 员工姓名:
	Gender 性别: 1. Male 男 2. Female 女
	Age 年龄: 1. <16 years 2. 16-18 years 3. >18 years
	Nationality 国际: 1. Malaysian workers 马来西亚国籍 2. Foreign workers 非我国国籍
	How many years of employment in this shipyard company 请问您在这家这家船厂公司工作了多少年: 1. <3 years 2. 3-5 years 3. 5-8 years 4. 8-10years 5.>10 years
	What is your occupation in this shipyard company 请问您在这家造船厂工作的职业是什么: 1. General worker 普通工人 2. Operator 操作员 3. Technician/ Administrator 技工/行政人员 4. Contractor 承包商/自由业者 5. Visitor 外来检查官/客户监督员
	What is your working hours to perform your work most of the time 请问您的工作时间在于: 1. 8 hours or over time working days 8 小时或超越时间的工作日 2. Non-working hours / Anytime upon request by management 非工作时间/假日/管理层要求的任何时间

	What is your educational level to perform your work 请问您从事工作的教育水平是: 1. Primary School 小学程度 2. Secondary School 中学程度 3. Certificate / Diploma 拥有文凭 4. Degree and above 学士学位以上 5. Non educational background 没有教育背景
Workplace factor (Categorical data)	Do you exposed to the following the hazard? 请问您是否有接触危害? 1. Physical hazard 物质性的危害 2. Chemical hazard 化学性的危害 3. Biological hazard 生物学性的危害 4. Ergonomic hazard 搬运/操作姿势不正确 5. Psychosocial hazard 心理焦虑 6. Environment hazard 环境/周围对自身的危害
Working Zone (Categorical data)	Which part of the working zone that you are involved in 请问您参与的工作区: 1. Dry dockyard 干船坞 2. Wet dockyard 靠岸的船坞 3. Machinery workshop / warehouse 机械操作间/储存仓库 4. Inside building / others 室内/其他建筑物内
Activities Involved (Categorical data)	Which activities that your nature of work that covers 请问您的工作性质涵盖哪些活动? 1. Welding/hot works 焊接/切割/打磨等工作 2. Working at height 高空作业 3. Lifting & Mobilization works 起重和重工业移动等操作 4. Equipment installation works 设备安装等操作 5. Use of Hand-tools / Equipment 使用手动工具等设备 6. Electrical installation / Electrical maintenance works 电源安装/电源维修等操作 7. Sand blasting and painting works 打磨喷砂和喷漆等操作 8. Repair / maintenance works 维修/保养等操作 9. Working at confined space 在密室空间工作 10. Sea launching works 船子下水启动操作 11. Site supervision / visiting 检擦/监督/参观等 12. Other's activities 其他操作
Risk Prediction (Categorical data)	Risk prediction of your work 工作风险预测:

Appendix 4 – Example 1

Information about Workers	
Information about worker 基本信息	Company 公司: B&I / BDPK
	Worker's name 员工姓名: SYED DANIAL FAZREE BIN NAWAN SHOKRAN
	Gender 性别: ☒ 1. Male 男 ☐ 2. Female 女
	Age 年龄: ☐ 1. <16 years ☐ 2. 16-18 years ☒ 3. >18 years
	Nationality 国际: ☒ 1. Malaysian workers 马来西亚国籍 ☐ 2. Foreign workers 非我国国籍
	How many years of employment in this shipyard company 请问您在这家这家船厂公司工作了多少年: ☒ 1. <3 years ☐ 2. 3-5 years ☐ 3. 5-8 years ☐ 4. 8-10years ☐ 5. >10 years
	What is your occupation in this shipyard company 请问您在这家造船厂工作的职业是什么: ☐ 1. General worker 普通工人 ☐ 2. Operator 操作员 ☐ 3. Technician / Administrator 技工/行政人员 ☒ 4. Contractor 承包商/自由业者 ☐ 5. Visitor 外来检查官/客户监督员
What is your working hours to perform your work most of the time 请问您的工作时间在于: ☒ 1. 8 hours or over time working days 8 小时或超越时间的工作日 ☐ 2. Non-working hours / Anytime upon request by management 非工作时间/假日/管理层要求的任何时间	

Appendix 4 – Example 1 Continued

	What is your educational level to perform your work 请问您从事工作的教育水平是: 1. Primary School 小学程度 2. Secondary School 中学程度 ☒ 3. Certificate / Diploma 拥有文凭 4. Degree and above 学士学位以上 5. Non educational background 没有教育背景
Workplace factor (Categorical data)	Do you exposed to the following the hazard? 请问您是否有接触危害? ☒ 1. Physical hazard 物质性的危害 2. Chemical hazard 化学性的危害 3. Biological hazard 生物学性的危害 ☒ 4. Ergonomic hazard 搬运/操作姿势不正确 5. Psychosocial hazard 心理焦虑 6. Environment hazard 环境/周围对自身的危害
Working Zone (Categorical data)	Which part of the working zone that you are involved in 请问您参与的工作区: 1. Dry dock 干船坞 2. Wet dock 靠岸的船坞 3. Machinery workshop / warehouse 机械操作间/储存仓库 ☒ 4. Inside building / others 室内/其他建筑物内
Activities Involved (Categorical data)	Which activities that your nature of work that covers 请问您的工作性质涵盖哪些活动? ☒ 1. Welding/hot works 焊接/切割/打磨等工作 ☒ 2. Working at height 高空作业 3. Lifting & Mobilization works 起重和重工业移动等操作 4. Equipment installation works 设备安装等操作 ☒ 5. Use of Hand-tools / Equipment 使用手动工具等设备 ☒ 6. Electrical installation / Electrical maintenance works 电源安装/电源维修等操作 7. Sand blasting and painting works 打磨喷砂和喷漆等操作 8. Repair / maintenance works 维修/保养等操作 9. Working at confined space 在密室空间工作 10. Sea launching works 船子下水启动操作 11. Site supervision / visiting 检擦/监督/参观等 12. Other's activities 其他操作
Risk Prediction (Categorical data)	Risk prediction of your work 工作风险预测: <i>Risk is controlled</i>

Appendix 4 – Example 2

Information about Workers

Information about worker 基本信息	Company 公司: E&F / BDEWC
	Worker's name 员工姓名: HARON BIN NARAWI
	Gender 性别: ① Male 男 2. Female 女
	Age 年龄: 1. <16 years 2. 16-18 years ③ >18 years
	Nationality 国际: ① Malaysian workers 马来西亚国籍 2. Foreign workers 非我国国籍
	How many years of employment in this shipyard company 请问您在这家这家船厂公司工作了多少年: 1. <3 years 2. 3-5 years ③ 5-8 years 4. 8-10years 5. >10 years
	What is your occupation in this shipyard company 请问您在这家造船厂工作的职业是什么: 1. General worker 普通工人 2. Operator 操作员 3. Technician / Administrator 技工/行政人员 ④ Contractor 承包商/自由业者 5. Visitor 外来检查官/客户监督员
	What is your working hours to perform your work most of the time 请问您的工作时间在于: ① 8 hours or over time working days 8 小时或超越时间的工作日 2. Non-working hours / Anytime upon request by management 非工作时间/假日/管理层要求的任何时间

Appendix 4 – Example 2 Continued

	What is your educational level to perform your work 请问您从事工作的教育水平是: 1. Primary School 小学程度 2. Secondary School 中学程度 ③ Certificate / Diploma 拥有文凭 4. Degree and above 学士学位以上 5. Non educational background 没有教育背景
Workplace factor (Categorical data)	Do you exposed to the following the hazard? 请问您是否有接触危害? ① Physical hazard 物质性的危害 2. Chemical hazard 化学性的危害 3. Biological hazard 生物学性的危害 ④ Ergonomic hazard 搬运/操作姿势不正确 5. Psychosocial hazard 心理焦虑 6. Environment hazard 环境/周围对自身的危害
Working Zone (Categorical data)	Which part of the working zone that you are involved in 请问您参与的工作区: 1. Dry dock 干船坞 2. Wet dock 靠岸的船坞 3. Machinery workshop / warehouse 机械操作间/储存仓库 ④ Inside building / <u>others</u> 室内/其他建筑物内
Activities Involved (Categorical data)	Which activities that your nature of work that covers 请问您的工作性质涵盖哪些活动? ① Welding/hot works 焊接/切割/打磨等工作 ② Working at height 高空作业 ③ Lifting & Mobilization works 起重和重工业移动等操作 4. Equipment installation works 设备安装等操作 ⑤ Use of Hand-tools / Equipment 使用手动工具等设备 6. Electrical installation / Electrical maintenance works 电源安装/电源维修等操作 7. Sand blasting and painting works 打磨喷砂和喷漆等操作 8. Repair / maintenance works 维修/保养等操作 9. Working at confined space 在密室空间工作 10. Sea launching works 船子下水启动操作 11. Site supervision / visiting 检擦/监督/参观等 12. Other's activities 其他操作
Risk Prediction (Categorical data)	Risk prediction of your work 工作风险预测: <i>Risk UNDER CONTROL</i>

Appendix 4 – Example 3

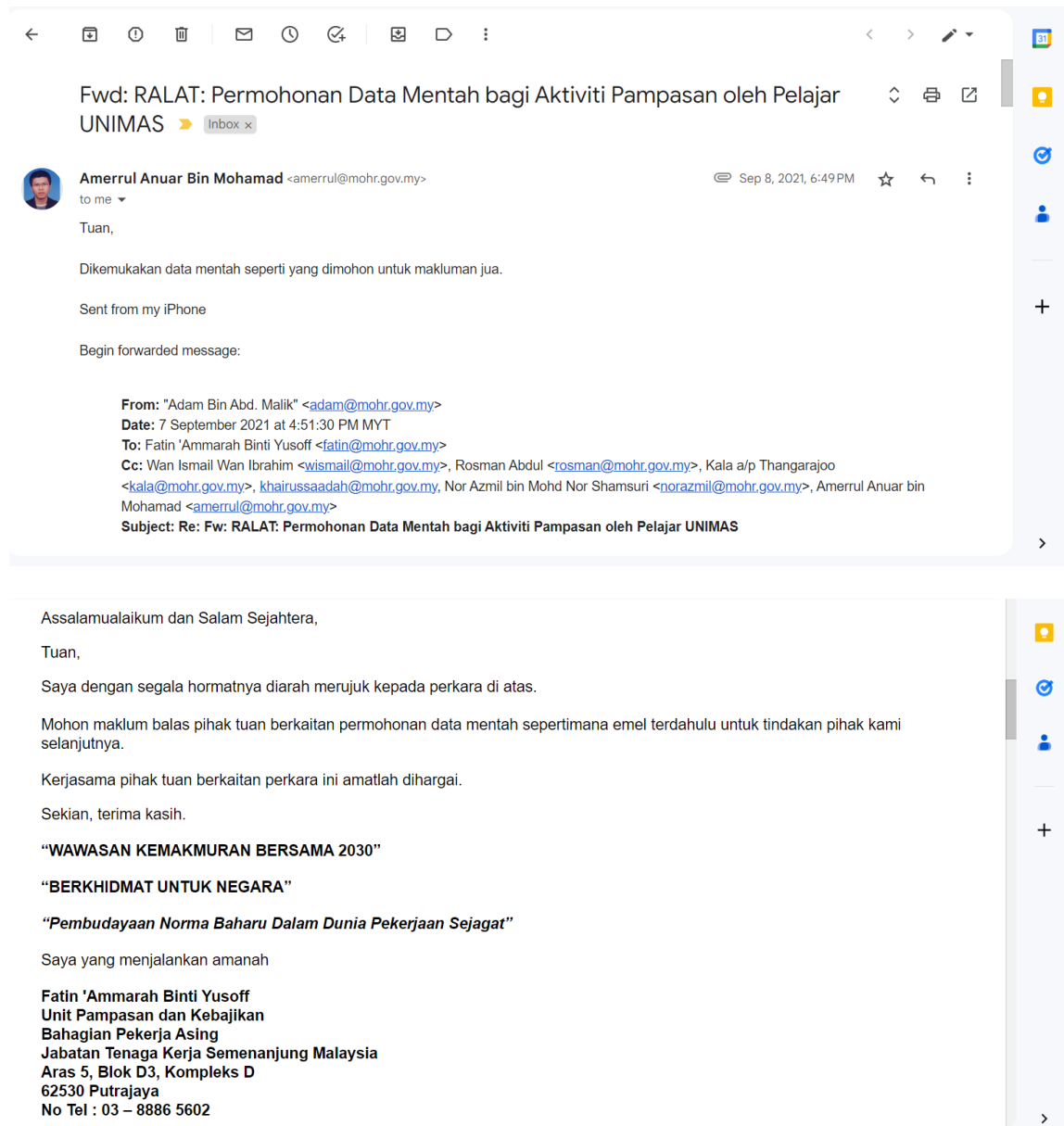
Information about Workers

Information about worker 基本信息	Company 公司: EAT / BDEWC Worker's name 员工姓名: ROSLI SIKIRUN Gender 性别: ① Male 男 2. Female 女 Age 年龄: 1. <16 years 2. 16-18 years ③ >18 years Nationality 国际: ① Malaysian workers 马来西亚国籍 2. Foreign workers 非我国国籍 How many years of employment in this shipyard company 请问您在这家这家船厂公司工作了多少年: 1. <3 years 2. 3-5 years ③ 5-8 years 4. 8-10years 5. >10 years
	What is your occupation in this shipyard company 请问您在这家造船厂工作的职业是什么: 1. General worker 普通工人 2. Operator 操作员 3. Technician / Administrator 技工/行政人员 ④ Contractor 承包商/自由业者 5. Visitor 外来检查官/客户监督员 What is your working hours to perform your work most of the time 请问您的工作时间在于: ① 8 hours or over time working days 8 小时或超越时间的工作日 2. Non-working hours / Anytime upon request by management 非工作时间/假日/管理层要求的任何时间

Appendix 4 – Example 3 Continued

	What is your educational level to perform your work 请问您从事工作的教育水平是: 1. Primary School 小学程度 ☒ 2. Secondary School 中学程度 3. Certificate / Diploma 拥有文凭 4. Degree and above 学士学位以上 5. Non educational background 没有教育背景
Workplace factor (Categorical data)	Do you exposed to the following the hazard? 请问您是否有接触危害? ☒ 1. Physical hazard 物质性的危害 2. Chemical hazard 化学性的危害 3. Biological hazard 生物学性的危害 ☒ 4. Ergonomic hazard 搬运/操作姿势不正确 5. Psychosocial hazard 心理焦虑 6. Environment hazard 环境/周围对自身的危害
Working Zone (Categorical data)	Which part of the working zone that you are involved in 请问您参与的工作区: 1. Dry dock 干船坞 2. Wet dock 靠岸的船坞 3. Machinery workshop / warehouse 机械操作间/储存仓库 ☒ 4. Inside building (others) 室内/其他建筑物内
Activities Involved (Categorical data)	Which activities that your nature of work that covers 请问您的工作性质涵盖哪些活动? ☒ 1. Welding/hot works 焊接/切割/打磨等工作 2. Working at height 高空作业 3. Lifting & Mobilization works 起重和重工业移动等操作 4. Equipment installation works 设备安装等操作 ☒ 5. Use of Hand-tools / Equipment 使用手动工具等设备 6. Electrical installation / Electrical maintenance works 电源安装/电源维修等操作 7. Sand blasting and painting works 打磨喷砂和喷漆等操作 8. Repair / maintenance works 维修/保养等操作 9. Working at confined space 在密室空间工作 10. Sea launching works 船子下水启动操作 11. Site supervision / visiting 检擦/监督/参观等 12. Other's activities 其他操作
Risk Prediction (Categorical data)	Risk prediction of your work 工作风险预测: <i>RISK UNDER CONTROL</i>

Appendix 5 – Ethic Approval



----- Original message -----

From: Calvin Chin <calvincychih@gmail.com>

Date: Wed, 4 Aug 2021, 12:50

To: grismail@mohr.gov.my

Cc: David Chua Sing Ngie <csndavid@unimas.my>

Subject: Sincere Application On Data Mining In Years For Research OSH Risk Prediction At Malaysian Shipyard Industry

Tuan Pengarah Tn Wan Ismail Bin Wan Ibrahim,
Pengarah Pekerja Asing
Jabatan Tenaga Kerja Semenanjung Malaysia (JTKSM),
Aras 5, Block D3, Kompleks D,
Pusat Pentadbiran Kerajaan Persekutuan,
62530 Putrajaya
Malaysia

A very good day dear Sir,

Sincerely refer to our tele-conversation before on an application of data mining for a research.

For your kind information, the research on OSH Risk Prediction At Malaysia Shipyards Industry is to be carried out in year 2020/2022 at UNIMAS under my supervisor Ir Dr David Chua Sing Ngie.

For your department kind information, the objective of this research is to identify potential hazards in shipyards industry, to assess the potential risks identified based on quantitative safety decision making and to develop a model using ANN soft computing machine learning technique for the prediction of occupational risk as part of the quantitative safety decision makings. We hope that this research would help the shipyards industry for reducing OSH accidents happened at shipyards. Therefore, by using the machine learning Artificial Neural Network method for OSH Risk Prediction, research starts with carrying out a data mining in years (data are advised more than 1000cases) and screening down data into specific parameters according to the previous literature reviews to analyzed the paired wised input-output parameters. Based on previous literature reviews, these input parameters includes Gender, Age, Nationality, Occupation, Working Hours, Educational Level, Experience Level, Activities conducted during accidents, Time of Accidents, Working Zone, Workplace Factors, PPE Provided, Training Provided, Company Commitment in safety and health management, Type of Injuries, Parts of Body Injuries, Medical Leaves, Cost of Safety Failure and etc (agent of accidents, factors of incidents, description of accidents and etc). Besides that, we also sincerely hope that data collection would include shipyard companies, shipbuilding companies, ship maintenance, repair and overhaul companies and so on within Malaysia. We hereby attach the list of Shipyard Companies, Shipbuilding Companies and list of Shipyards carrying out Maintenances, Repairs and Overhauls (MRO) in Malaysia year 2020 for your reference if it would help in data mining.

We hope that your department would look into our application and we hope to hear from you soon.

Thank you very much.

Warm Regards,
Calvin Chin Yen Chih
No Matrics : 20020336
0168161996

CC : Ir Dr David Chua Sing Ngie
Supervisor
Department of Mechanical and Manufacturing Engineering
Faculty of Engineering,
University Malaysia Sarawak

Appendix 6 – Example of Raw Data Set

Nama Majikan	Year	Age	Jantina	Sektor	Waktu Kemalangan	Sebab	Jenis	Bahagian	Agen	Tarikh	Faedah
FORWARD MARINE ENTERPRISE SDN BHD	1975	24	Lelaki	Shipbuilding and repairing	Bekerja	Caught betw a stationary obj and a moving obj	Other wounds	Leg (lower leg)	Spinning, weaving and other textile machines	17/03/20 18	HUS
FULL WAVE SHIPPING SDN BHD	1984	49	Lelaki	Supporting services to water transport	Bekerja	Other types of accident, not classified	Other and unspecified injuries	Multiple locations, unspecified	Other traffic and working surfaces	14/02/20 18	HUS
FULL WAVE SHIPPING SDN BHD	1987	25	Lelaki	Supporting services to water transport	Bekerja	Other types of accident, not classified	Other wounds	Ankle	Other traffic and working surfaces	10/03/20 18	HUS
INTERCARGO SDN BHD	1988	59	Lelaki	Supporting services to water transport	Bekerja	Over-exertion in handling or throwing objects	Other wounds	Hand (except fingers alone)	Other agencies, not elsewhere classified	20/11/20 17	HUS
JASA ASALJAYA SDN BHD.	1970	66	Lelaki	Shipbuilding and repairing	Bekerja	Other types of accident, not classified	Other and unspecified injuries	Fingers	Other traffic and working surfaces	22/01/20 18	HUS
JINCORP (BINTULU) SDN BHD	1960	33	Perempu an	Manufacturing industries, n.e.c.	Bekerja	Over-exertion in handling or throwing objects	Other wounds	Unspecified location of injury	Other agencies, not elsewhere classified	05/03/20 18	HUS
KAIBOUK SHIPYARD (M) SDN BHD	1967	23	Lelaki	Shipbuilding and repairing	Bekerja	Other types of accident, not classified	Other and unspecified injuries	Leg (lower leg)	Other traffic and working surfaces	27/12/20 17	HUS
NGIE LEE DOCKYARD SDN BHD	1965	30	Lelaki	Shipbuilding and repairing	Bekerja	Other types of accident, not classified	Concussion s and other internal injuries	Eye	Other equipment, not elsewhere classified	22/02/20 18	HUS

Appendix 6 – Continued

Nama Majikan	Year	Age	Jantina	Sektor	Waktu Kemalangan	Sebab	Jenis	Bahagian	Agen	Tarikh	Faedah
RAJANG MAJU MARINE INDUSTRIES SDN BHD	1959	28	Lelaki	Shipbuilding and repairing	Bekerja	Over-exertion in handling or throwing objects	Superficial injuries	Hand (except fingers alone)	Other traffic and working surfaces	30/01/20 18	HUS
SARAWAK SLIPWAYS SDN BHD	1996	40	Lelaki	Shipbuilding and repairing	Bekerja	Accidents not classified for lack of data	Other and unspecified injuries	Unspecified location of injury	Agencies not classified for lack of data	23/02/20 18	HUS
SARAWAK SLIPWAYS SDN BHD	1978	48	Lelaki	Shipbuilding and repairing	Bekerja	Accidents not classified for lack of data	Other and unspecified injuries	Fingers	Agencies not classified for lack of data	10/01/20 18	HUS
SEALINK SHIPYARD SDN BHD	1971	24	Lelaki	Shipbuilding and repairing	Urusan rasmi	Accidents not classified for lack of data	Other and unspecified injuries	Unspecified location of injury	Motor vehicles, not elsewhere classified	19/02/20 18	HUS
SEALINK SHIPYARD SDN BHD	1965	42	Lelaki	Shipbuilding and repairing	Bekerja	Accidents not classified for lack of data	Other and unspecified injuries	Unspecified location of injury	Agencies not classified for lack of data	09/01/20 18	HUS
SHIN YANG SHIPPING SDN BHD	1977	57	Perempu an	Supporting services to water transport	Bekerja	Falls of persons on the same level	Other wounds	Other multiple locations	Others - outdoor	19/01/20 18	HUS
SHING LIANG SHIPPING SDN BHD	1969	23	Lelaki	Supporting services to water transport	Bekerja	Accidents not classified for lack of data	Other and unspecified injuries	Fingers	Agencies not classified for lack of data	04/03/20 18	HUS
SUNG FATT SHIPYARD SDN BHD.	1960	24	Lelaki	Shipbuilding and repairing	Bekerja	Other types of accident, not classified	Other and unspecified injuries	Multiple locations, unspecified	Other traffic and working surfaces	01/02/20 18	HUS