CHAPTER V

PROPOSED HYBRID CONCEPTUAL ENVIRONMENTAL RISK ASSESSMENT ARCHITECTURE

5.1 Overview

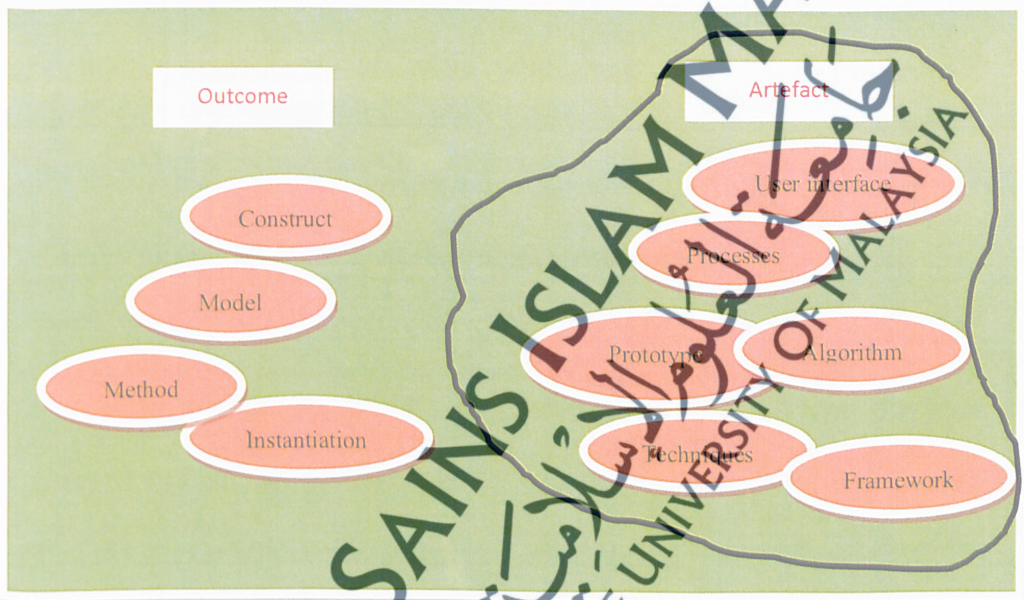
This chapter describes the proposed ERAA in detail. ERAA comprises a decision support engine, a risk assessment engine, a knowledge base and a user interface. The development of this architecture was based on the problem and solution discussed in Chapter I.

5.2 Introduction

Artefacts are considered the main outcomes of DSR projects, and they play highly essential roles in DSR that is created for a specified problem domain. These artefacts must be implemented in an appropriate domain and must be described effectively. One of the most important factors for finding an effective design solution is to search for an effective problem representation.

Solving a problem simply means representing it in such a way that the solution becomes transparent. Outcomes are classified into four types, as shown in Figure 5.1. Artefacts enable researchers to understand and address problems that are inherent in successfully implementing information systems within organisations. Artefacts can take several forms, including solution representations, design algorithms, problems, ontologies, modelling formalisms and techniques, working prototypes, frameworks, algorithms, methodologies, processes and user interfaces.

Figure 5.1: Outcomes of research design



Source: Shiratuddin, (2010)

Table 5.1 lists the DSR artefact types that have been produced in this study.

Table 5.1 : Artefacts produced in this study

Artefact Type	Description	Artefacts in This Study
Constructs	Constructs are conceptual vocabularies and symbols of a domain that are typically identified during the processing of a problem and are refined throughout the design cycle.	Null

Table 5.1 continued

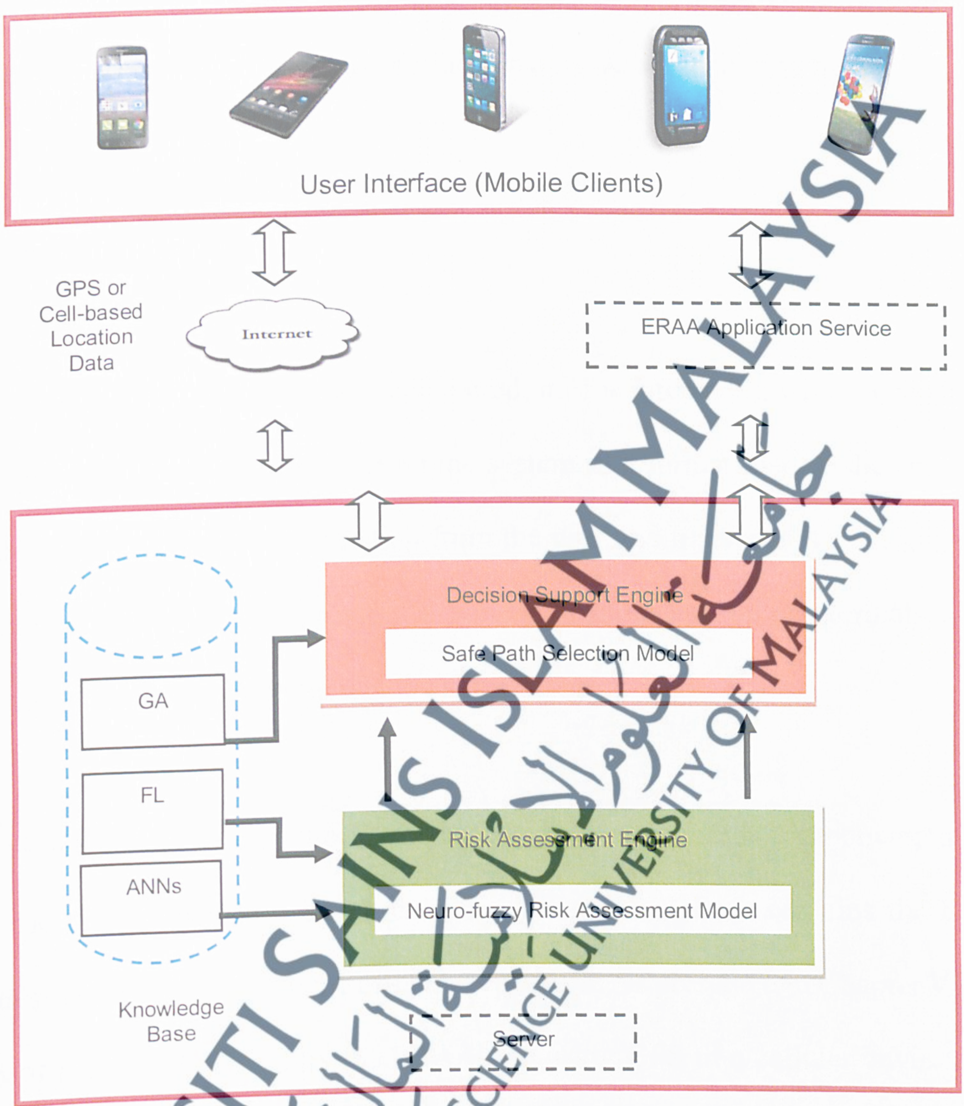
Artefact Type	Description	Artefacts in This Study
Models	Models are a set of propositions or statements that represent a general description of the activities of a system and describe the relationships among constructs	Architecture: • NFRAM model • Safe path selection model
Methods	A method is a series of steps (an algorithm or a guideline) that are used to perform a task and to build an artefact according to the constructs and models that have been previously identified.	Null
Instantiations	An instantiation is a physical implementation of an artefact in its environment.	Prototype

5.3 Environmental Risk Assessment Architecture

The succeeding paragraph presents the architecture of ERA and discusses major implementation challenges. The proposed architecture integrates traditional DSS, as described in Chapter II, with the improvements of FL, ANNs, GA and LBC, along with the use of smartphones for interactions between users and ERAA.

The ERAA structure comprises four components, namely, a decision support engine, a risk assessment engine, a knowledge base and a user interface. The architecture in Figure 5.2 shows the mapping between each component and the relationship between user environment and these components.

Figure 5.2: Environmental Risk Assessment Architecture



5.3.1 Knowledge Base

The knowledge base consists of the rule base and the database that are required to solve the landmine problem. The knowledge database includes the knowledge of managers and experts in the field of demining. Stored facts are information or data in a landmine field, whereas rules or heuristic rules explain reasoning procedures used to solve a landmine problem. A linguistic variable is represented in fuzzy sets that are used to facilitate the expression of rules and facts. 'IF–THEN' rules are used in this context to capture human knowledge, which are defined as a list about landmine risks.

5.3.2 User Interface

The user interface is used as an accessible medium for interacting with the system. It provides the user with information from the system in a format that he/she can easily understand; it then receives information from the user and translates it for the system. The user interface of ERAA provides a variety of input and output formats, which include maps, roads and multiple windows in a screen.

A smartphone will be used by the architecture as the user interface component, thereby making the system easy to use and understand. The smartphone contains the ERAA application service that runs on the cell phone platform, as presented in Chapter VI. The location of a user is recorded by the ERAA app using GPS in a cellular environment and the currently connected cell tower.

5.3.3 Risk Assessment Engine

This engine is the most important part of the proposed architecture where NFRAM will be built. Many engineering and science disciplines are focusing on developing mathematical models of real systems, which can be used to analyse the behaviour, simulations, design of new processes or design of controllers of systems. To build a usable model, the nature and behaviour of a system should be understood and a suitable mathematical treatment should be applied.

Many standard modelling approaches, such as white box (physical, mechanistic and first principle) modelling, black box modelling and gray box modelling, are used to understand the nature and behaviour of a system. However, these approaches have a common drawback, i.e. they cannot effectively use additional information represented by the knowledge and experience of engineers and operators, which are frequently imprecise and qualitative in nature. Human ability to manage complex tasks under uncertainty has supported the search for alternative modelling and control paradigms, which has resulted in 'intelligent' modelling and control methodologies, such as semantic networks or qualitative models, rules and natural language. ANNs are typical examples of techniques that exhibit learning and adaptation capabilities. By contrast, fuzzy modelling includes techniques that apply human knowledge and deductive processes.

A. Stages of development of Neuro-Fuzzy Risk Assessment Model

The main topic in this section is the development of NFRAM using FL and ANNs techniques. This model can be used to check the inputs and outputs of a system, to analyse system behaviour and to calculate the degree of danger that a user is facing as he/she navigates places near landmine-affected areas.

NFRAM will be developed through several stages. In the first stage, the Sugeno fuzzy method will be used to develop the primary FIS. In the second stage, a neural network will be used to fine-tune the knowledge base and MFs of a fuzzy controller whilst keeping the semantics of FIS intact by using the BP algorithm.

i. First Stage: Development of Fuzzy inference system

The identification of the indicators of landmine risk factors (linguistic variable) is the first step in designing the inference system. The relationship among these indicators was determined through interviews with experts (Deminers). Data that define the behaviour of the system were also collected.

Definition 1: Basic fuzzy linguistic variable

A linguistic variable typically carries words instead of numbers. Each variable has a defined MF, and each linguistic value is associated with a fuzzy set. FL begins with the concept of a fuzzy set. A fuzzy set is a set without a clearly defined boundary. It can contain elements with only a partial degree of membership.

A fuzzy linguistic variable is a 4-tuple (*X*, *T*, *M*, *A*), where

X is the name of a fuzzy linguistic variable [*signal strength (S), position (P), landmine intensity (LI), risk (RS)*].

T is the term set of linguistic values (fuzzy variables), i.e. poor, average, excellent.

M is the mapping rules that map every term of *T* to a fuzzy set at *A*.

A is the universe of discourse.

In fuzzy theory, fuzzy set *A* of universe *X* is defined by function $\mu A(x)$, which is called the membership function of set *A*.

$$\mu A(x) : X \rightarrow [0 \quad 1] \tag{5.1}$$

$$\mu A(x) = \begin{cases} 1, \text{if } x \text{ is totally in } A \\ 0, \text{if } x \text{ is not in } A \\ \in (0,1), \text{if } x \text{ is partially in } A \end{cases} \tag{5.2}$$

Definition 2: Extended fuzzy linguistic variable

An extended fuzzy linguistic variable is a 5-tuple $\boldsymbol{O_F} = (\boldsymbol{ca}, \boldsymbol{CF}, \boldsymbol{R}, \boldsymbol{F}, \boldsymbol{A})$, where ***ca*** is a concept on the abstract level (*signal quality*, *position*, *landmine intensity*, *risk*).

The corresponding element of *ca* is *X* in Definition 1.

CF is the set of fuzzy concepts that describes all values of *ca*. The corresponding element of *CF* is *T* in Definition 1 (poor, average, excellent).

R is the fuzzy relation among concepts in *CF*.

F is the set of membership functions at *A*.

A has same meaning as that in Definition 1.

To build a model, the input and output variables should first be defined. Then, fuzzy rules and fuzzy sets can be constructed. We partition each input variable into three fuzzy sets, which are defined using three membership functions (two trapezoidal and one triangular).

Our model has three input variables (*signal, position, landmine intensity*) to determine the degree of danger and one output (*risk of landmines*).

Most modern mobile devices available in the market have a variety of sensors that can measure orientation, position and different environmental conditions. The NFRAM model uses these sensors to obtain raw data (*signal, position*), which will be used as linguistic variables to demonstrate the fuzzy operators in a neuro-fuzzy model. The first input is a wireless network (*signal strength*) that originates from cell towers. The second input is the *position* of a user, which is provided by GPS. Lastly, the *landmine intensity* variable will be obtained from a database.

Signal Strength: GSM is a widely used mobile communication standard. It is also known as 2G, which had become considerably more popular than the first-generation analogue systems. GSM service is considered the main factor that affects the operation of the ERAA system. Checking the state of the GSM signal is crucial for the ERAA system. Falling the GSM signal level will cause the system to stop, thereby posing a threat to the life of the user. Therefore, the ERAA system is used to regularly monitor the dynamics of the strength level change of the GSM signal to avoid such risk.

Signal strength typically ranges from −113 dBm (poor) to −50 dBm (excellent).

Signal strength can be defined as Equation (5.3):

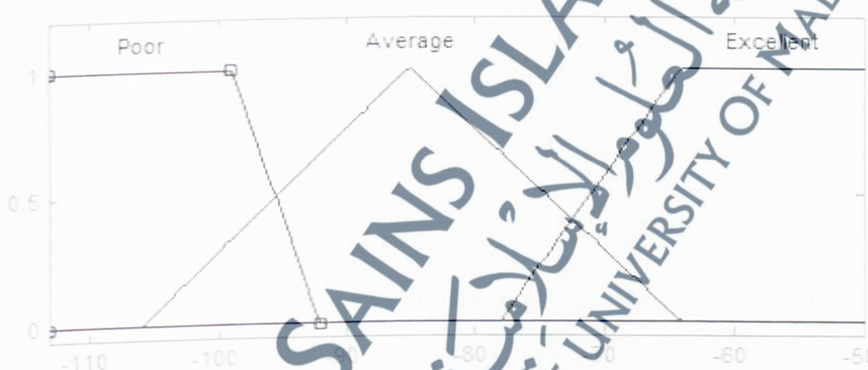
$\boldsymbol{O_{F1}}$ (signal strength) = (***ca*** = signal strength, ***CF*** = {poor, average, excellent}, ***R*** = {poor ≤ average ≤ excellent}, ***F*** = {F_{Poor} (x), $F_{Average}$ (x), $F_{Excellent}$ (x)}, ***A*** = [−50, −113]) (5.3).

The fuzzy sets of the signal strength variable are provided in Table 5.2, whereas the MFs are shown in Figure 5.3.

Table 5.2: Fuzzy sets of the input variable of signal strength

Linguistic Variable	Symbols	Interval
Poor	P	{−110, −110, −95, −92}
Average	AV	{−106, −85, −64}
Excellent	EX	{−78, −64, −50, −50}

Figure 5.3: MFs for the input variable of signal strength



Location: Obtaining the position of the end-user device is essential for the NFRAM model. GPS and positioning technologies that utilize a GSM cellular network are the most important positioning mechanisms of our tracking system. The location will be used to calculate the distance between the user and the landmine-affected areas.

Equation (5.4) will be used to measure the distance between two locations, i.e. A (LonA, LatA) and B (LonB, LatB), which have been previously obtained:

$$O_{F2} = acos[cos(latA) \times cos(latB) \times cos(lonB - lonA) + sin(latA) \times sin(latB)] \times r, \quad (5.4)$$

where O_{F2} is the distance in metre, r is the radius of the Earth in kilometre (6,371 km), *latA* is the latitude of point A, *lonA* is the longitude of point A, *latB* is the latitude of point B and *lonB* is the longitude of point B.

Location can be defined as Equation (5.5):

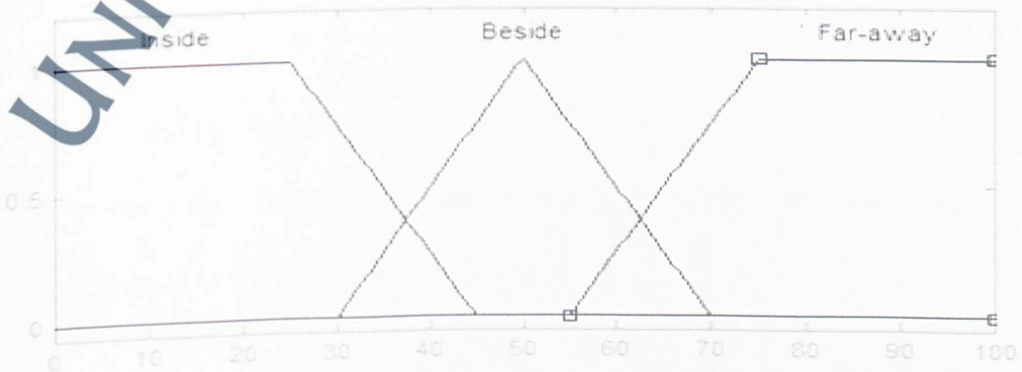
O_{F2} (location) = (*ca* = location, *CF* = {inside, beside, faraway}, *R* = {inside ≤ beside ≤ faraway}, *F* = {F_{Inside} (x), F_{Beside} (x), $F_{Faraway}$ (x)}, *A* = [0, 200]). (5.5)

The fuzzy sets of the location variable are provided in Table 5.3, whereas the MFs are shown in Figure 5.4.

Table 5.3: Fuzzy sets of the input variable of location

Linguistic Variable	Symbols	Interval
Inside	Insi	{0, 0, 25, 45}
Beside	Besi	{30, 50, 70}
Faraway	Farw	{55, 75, 100, 100}

Figure 5.4: MFs for the input variable of location



Landmines Intensity:

Mine-affected areas differ from one region to another based on the types of landmine buried in them. The Libyan Mine Action Centre reported that some areas had an estimated 728 km^2 of land seeded with an estimated 10,000 landmines. The ranges of landmine intensity have been determined based on expert judgment (deminers).

Landmine intensity can be defined as Equation (5.6):

$\boldsymbol{O_{F2}}$ (landmine intensity) = (***ca*** = landmine intensity, ***CF*** = {low, medium, high}, ***R*** = {low ≤ medium ≤ high}, ***F*** = {F_{Low} (x), F_{Medium} (x), F_{High} (x)}, ***A*** = [0, 1000]). (5.6)

The fuzzy sets of the landmine intensity variable are provided in Table 5.4.

Table 5.4: Fuzzy sets of the input variable of landmine intensity

Linguistic Variable	Symbols	Interval
Low	L	{0, 0, 142, 400}
Medium	M	{218, 496, 800}
High	H	{597, 813, 1000, 1000}

Risk: Risk is considered the output of the fuzzy model. The ranges of the risk of landmines can be determined based on expert judgment (Deminers). That is, we can ask an expert to provide numbers between 0 and 100% to represent the safe distance between a user and landmine-affected areas.

Risk can be defined as Equation (5.7):

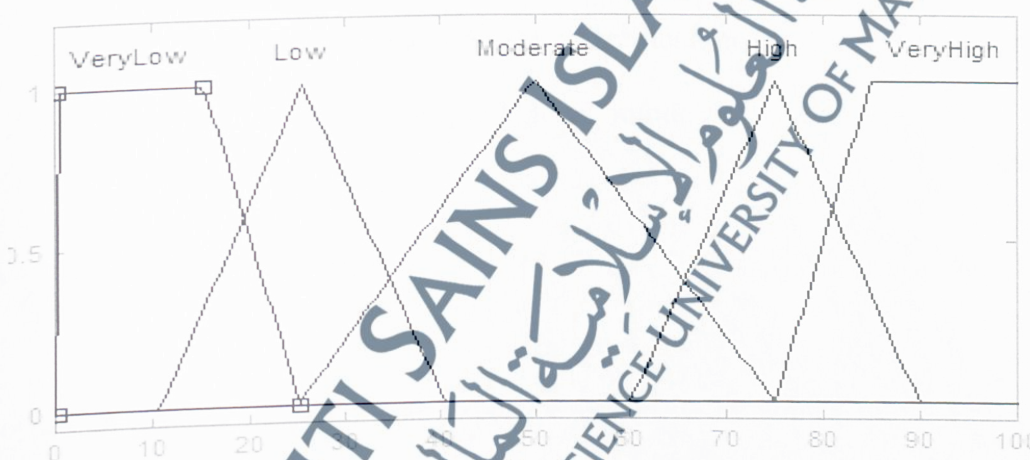
$\boldsymbol{O_{F3}}$ (risk) = (***ca*** = risk, ***CF*** = {low, medium, high}, ***R*** = {low ≤ medium ≤ high}, ***F*** = {F_{Low} (x), F_{Medium} (x), F_{High} (x)}, ***A*** = [0, 100]). (5.7)

The fuzzy sets of the risk variable are provided in Table 5.5, whereas the MFs are shown in Figure 5.5

Table 5.5: Fuzzy sets of the output variable of risk

Linguistic Variable	Symbols	Interval
Very low	VL	{0.2646, 0.2646, 15.26 ,25.26}
Low	Lo	{10.52, 25.52, 40.52}
Moderate	Mo	{25, 50, 75}
High	Hi	{60, 75, 90}
Very high	VH	{75, 85, 100, 100}

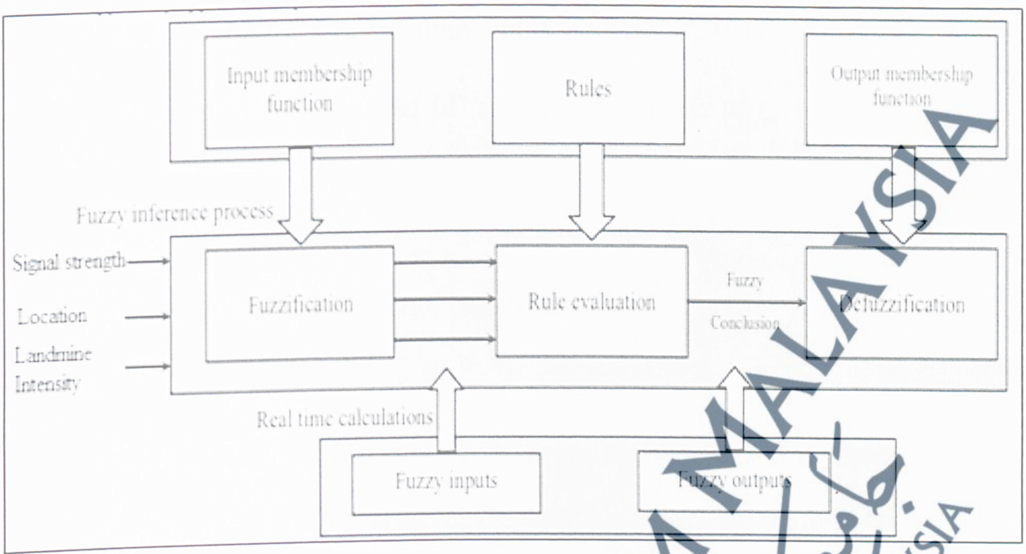
Figure 5.5: MFs for the output variable of risk



Fuzzy inference system processes:

FIS refers to the internal mechanism for producing output values for a given value through fuzzy rules. The basic structure of the fuzzy inference process for NFRAM model is shown in Figure 5.6.

Figure 5.6: Fuzzy inference system



A typical FIS consists of three processes: fuzzification, fuzzy rule base inferencing and defuzzification using a weighted global output.

a) Determining fuzzy rules

To design a fuzzy model, human expertise should be integrated into a set of rules, linguistic variables and fuzzy sets that will be fed to a fuzzy logic system by interviewing experts or employing them as consultants.

We have to obtain fuzzy rules in this stage. Fuzzy rules operate using a series of 'if–then' statements. Before we develop the rules, we should determine how we can solve the problem by asking experts several questions related to the previously defined fuzzy linguistic variables. We establish the following fuzzy rules that constitute the basis of FIS according to the Sugeno models based on the investigation and analysis of landmine features and the consultation with the experts.

The relations between the input parameters S^*, P^*, LI^* and the output parameter RS^* can be presented in the form of 'if–then' rules.

$$R^k : \text{if } S^* \; is \; \mu^k_{S*} \; and \; P^* \; is \; \mu^k_{P*} \; and \; LI^* \; is \; \mu^k_{LI*}, \text{then } R^* \; is \; \mu^k_{RS*}, \tag{5.8}$$

where μ^k_{S*} , μ^k_{P*} , μ^k_{LI*} and μ^k_{RS*} denote S^*, P^*, LI^* and RS^*, respectively; R^k , $K = 1,2,3,\ldots, K$ is the k_{th} rule in the rule base.

The 'if' part is called the *antecedent* or premise, whereas the 'then' is called the *consequent* or conclusion.

The mapping between the input parameters S^*, P^*, LI^* and output RS^* can be generated by FIS.

The fuzzy intersection (minimum) operation is used to connect the three parts in the premise. The implication of using the fuzzy intersection (minimum) operation is given by

$$\mu^k_R\,(x, y) = \mu^k_{S*}(x_1) \wedge \mu^k_{P*}(x_2) \wedge \mu^k_{LI*}(x_3) \wedge \mu^k_{RS*}(y), k = 1,2,\ldots,k, \tag{5.9}$$

where $x_1 \in X_1$, $x_2 \in X_2$, $x_3 \in X_3$, $X \in X_1 \times X_2 \times X_3$ and $y \in U$. X_1, X_2, X_3 and U denote the universe of S^*, P^*, LI^* and output RS^*, respectively.

Table 5.6 presents the fuzzy rules that constitute the basis of FIS.

Table 5.6: 'If–then' rules for *RS**

Rule	*If*	*Then (RS*)*
1	(S* = Av) ^ (P* = In) ^ (LI* = H)	VH
2	(S* = p) ^ (P* = In) ^ (LI* = H)	VH
3	(S* = Ex) ^ (P* = In) ^ (LI* = H)	VH
4	(S* = p) ^ (P* = Be) ^ (LI* = H)	Hi
5	(S* = Av) ^ (P* = Be) ^ (LI* = H)	Hi
6	(S* = Ex) ^ (P* = Be) ^ (LI* = H)	Hi
7	(S* = p) ^ (P* = Farw) ^ (LI* = H)	Mo
8	(S* = Av) ^ (P* = Farw) ^ (LI* = H)	Lo
9	(S* = Ex) ^ (P* = Farw) ^ (LI* = H)	Lo
10	(S* = Av) ^ (P* = Be) ^ (LI* = M)	Hi
11	(S* = p) ^ (P* = Be) ^ (LI* = M)	VH
12	(S* = Ex) ^ (P* = Be) ^ (LI* = M)	Hi
13	(S* = p) ^ (P* = Be) ^ (LI* = H)	VH
14	(S* = p) ^ (P* = Be) ^ (LI* = M)	VH
15	(S* = p) ^ (P* = In) ^ (LI* = H)	VH
16	(S* = p) ^ (P* = Be) ^ (LI* = M)	Hi
17	(S* = p) ^ (P* = Farw) ^ (LI* = M)	Lo
18	(S* = p) ^ (P* = In) ^ (LI* = H)	VH
19	(S* = p) ^ (P* = In) ^ (LI* = M)	VH
20	(S* = p) ^ (P* = In) ^ (LI* = M)	VH

For example,

R5: If the signal is average (Av), position is beside (Be) and landmine intensity is high (H), then risk is high (Hi).

R8: If the signal is average (Av), position is faraway (Farw) and landmine intensity is high (H), then risk is low (Lo).

b) Aggregation of the outputs

The truncated fuzzy MFs that represent the implication outputs of each rule can be aggregated using the fuzzy union (maximum) operation, which can be denoted by

$$\mu R\ (x, y) = \vee_{k=1}^{K} R^{k}\ (x, y), \qquad (5.10)$$

where $\mu R\ (x, y\ )$ is the output fuzzy MF after aggregation.

Given input RP^*, which represents S^*, P^* and LI^*, output RS^* is given by

$$RM^* = RP^* \circ R(x, y), \quad (5.11)$$

where symbol '$\circ$' denotes the compositional operations of fuzzy sets.

c) Defuzzification

The input of a fuzzy set (the aggregate output fuzzy set) and MFs are used to calculate a single output numerical value. Defuzzification is the conversion of the fuzzy result into a matching numerical value that can be adequately represented using FIS. The most common method used for defuzzification in the following formulais considered as

$$RS = \left(\sum_{i=1}^{q} Y_{i\mu RS*}(y_i)\right) / \left(\sum_{i=1}^{q} \mu_{RS*}(y_i)\right), i = 1, 2, \ldots q, \quad (5.12)$$

where y_i indicates the centre of the ith fuzzy term set of RS^*, and $\mu_{RS*}\ (y_i)$ indicates the MF of the ith fuzzy term set of RS^*.

ii. Second Stage: Applying a Neural Network to Develop Neuro-Fuzzy Risk Assessment Model

Once the work of the fuzzy system is completed, the next step is the application of a neural network. One of the causes of errors is the poor selection of MFs. As mentioned in the problem statement, fuzzy systems face the problem of defining MF parameters because of the lack of a systematic procedure for defining such parameters, which results in the failure of fuzzy systems to adjust to a new environment. This step can be viewed as an optimisation problem that can be solved by neural networks. Neural network learning techniques are used to tune MFs via the FIS controller whilst keeping the semantics of FIS intact.

A neuro-fuzzy system is actually a neural network that is functionally equivalent to FIS. To develop a neuro-fuzzy system, we will use the FIS that was developed in the previous stage and then add a neural network. In general, a neuro-fuzzy system consists of input and output layers and three hidden layers, which are used to represent MFs and fuzzy rules, as shown in Figure 5.7.

Firstly, the MFs that represent the linguistic terms of the linguistic inference rules are determined. This system uses three inputs (*signal strength, position, landmine intensity*), where the linear relation among these inputs can be presented as Equation (5.13):

$$if\ (x\ is\ A_1)\ AND\ (y\ is\ B_1)\ AND\ (z\ is\ C_1),\ then\ (f_1 = p_1x + q_1x + s_1x + r_1); \tag{5.13}$$

where, x, y and z are the numerical inputs, whereas A, B and C are the numerical variables that will be identified by the MFs. Moreover, p, q, s and r are the parameters that determine the relation between input and output.

Layer 1 is the input layer with the risk factors of mine-contaminated areas (*signal strength, position, landmine intensity*). The factor *landmine intensity* was determined by experts (Deminers), and the data have already been saved into a database. By contrast, *signal strength* and *position* are obtained from the sensor of a smartphone. This layer aims to transmit external crisp signals (risk factors) directly to the next layer.

The output of the first layer is calculated by Equation (5.14):

$$\begin{cases} o_i = \mu_{A_1}(x) \ ; \ \ i=1,2 \ ; \\ o_i = \mu_{B_1}(y) \ ; \ \ i=3,4 \ ; \ , \\ o_i = \mu_{C_1}(y) \ ; \ \ i=5,6 \ ; \end{cases} \tag{5.14}$$

where $\mu_{A_1(x)}$, $\mu_{B_1(y)}$ and $\mu_{c_1(y)}$ are the MFs for the fuzzy sets of A, B and C, respectively.

Layer 2 is the input membership or fuzzification layer. Every node in this layer is a fixed neuron that represents fuzzy sets used in the antecedents of fuzzy rules. A crisp input is received by a fuzzification neuron, which determines the degree to which this input belongs to the fuzzy set of the neuron. Nine neurons are assigned to Layer 2.

The outputs of *w* can be calculated by Equation (5.15):

$$O_i = w_i = \mu_{A_1(x)} \cdot \mu_{B_1(x)} \cdot \mu_{C_1(x)};\ i = 1,2\ . \tag{5.15}$$

Layer 3 is the fuzzy rule layer. Each neuron in this layer is a rule node that represents one fuzzy rule. We have set fuzzy rules in the first stage according to the investigation and analysis of landmine features and expert consultation.

In this layer, the outputs of the previous layer can be divided into all the outputs of that rule equation, i.e. Equation (5.16):

$$O_i = \overline{w_i} = \frac{w_i}{\sum_1 w_i}. \tag{5.16}$$

Layer 4 has the same inputs as the first layer. The neurons in this layer represent fuzzy sets used in the consequent fuzzy rules. This layer receives inputs from the corresponding fuzzy rule neurons and combines them with the algebraic sum. The involvement of each rule for calculating the model output is computed by Equation (5.17):

$$O_i = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + q_i z + r_i) ; i = 1,2 . \tag{5.17}$$

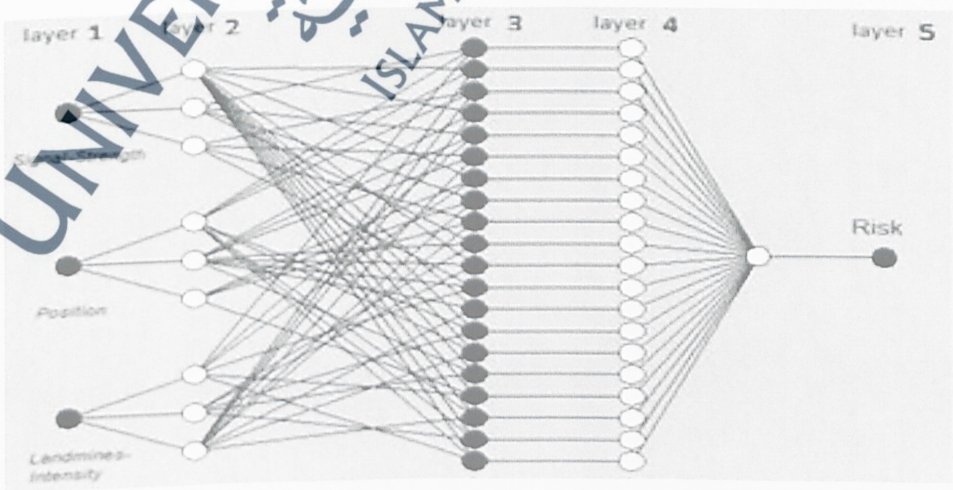
Layer 5 is the fuzzy aggregation layer. The risk level of the input parameters inside this layer is calculated via normalised aggregation with the outputs of the consequent layer result. The outputs of this layer can be calculated by Equation (5.18):

$$f(x,y) = \frac{w_1 f1(x,y) + w_2 f2(x,y)}{w_1 (x,y) + w_2 (x,y)} = \frac{w_1 f1 + w_2 f2}{w_1 + w_2} , \tag{5.18}$$

$$O_i = f(x,y) = \frac{\sum_i w_1 f1}{\sum_i w_1}.$$

In this state, the network learns the rules based on the supervised learning rules. Finally, the best values for a parameter are obtained by training each value of *a, b, c, p, q, r* changes.

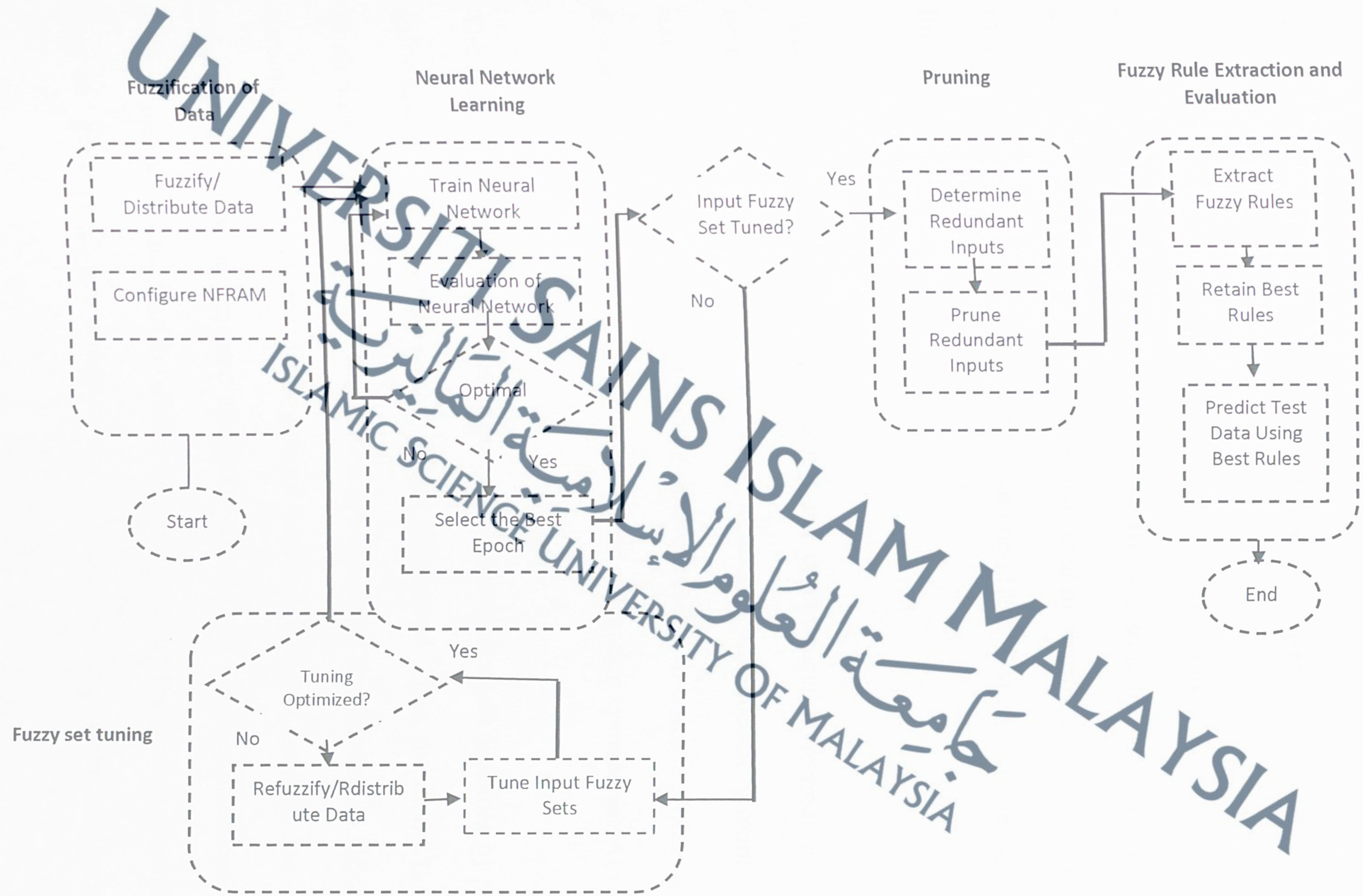
Figure 5.7: Architecture of the 20-rule



iii. Third Stage: Training Neuro-Fuzzy Risk Assessment Model

The first step in training a neuro-fuzzy assessment model is collecting the dataset that defines the behaviour of the system through consultation with experts (Deminers). The BP algorithm is used to generate the adjustments of the input and output MFs, thereby further reducing the rules that tend to take control away from the desired path. The mechanism of the BP algorithm is represented in the calculation of the system output and compared with the desired output of the training sample. Then, the error (difference) is propagated backwards through the network from the output layer to the input layer. This algorithm is based on the philosophy of rewarding the rules. Figure 5.8 shows the steps applied to landmine risk assessment using a neuro-fuzzy technique.

Figure 5.8 : *Architecture of the learning stage of Neuro-Fuzzy Risk Assessment Model*



5.3.4 Decision Support Engine

A. Developing the Safe Path Selection Model Based on GA

Good decision-making is crucial for saving lives and reducing loss in a dynamic and dangerous environment such as a landmine-affected area. In such environment, users are typically susceptible to risk if they wander near mine-affected areas. Therefore, new methods that will help people pass landmine-affected areas without accidents are imperative.

With the rapid advances in positioning and communication technologies, guiding objects that are moving from one place to another has become possible by using navigation systems. Although planning different routes to a destination is a common feature of navigation systems, only a few human navigation systems use AI tools.

The role of DSS is to assist decision makers in making strategic decisions by presenting information and interpretations for various alternatives. Thus, the model that will be implemented aims to aid a user in choosing a safe route that he/she can follow to pass through landmine-affected areas without accidents. In this context, the safe path selection model is implemented using GA. This model provides directions from the current location of the user to outside the mined area by updating the location of the user and generating a new direction once the previous one has been completed.

The next section presents the design and realisation of the safe path selection model in areas with risk of landmines. GA, GPS and Google Maps will be adopted in this model.

i. **Google Maps:** Google Maps are free sources that have been developed and designed by Google LLC. To use and adopt Google Maps in our model, we should get the API key that will allow us to monitor our application in Google Maps. Google Maps will be used to show the safety of a road that was generated by GA.

ii. **GPS technology***:* Many navigation and tracking approaches are becoming increasingly popular with the emergence and spread of mobile devices. Such approaches can be used to locate the position of a user. A mobile system already has location information, which will be used to determine the position of a user in real time. In our model, we need to pinpoint the position of the user in real time (latitude and longitude) to determine the starting point that will be used later by GA.

iii. **GA:** Several algorithms are used to solve shortest path problems. The most famous of these problems is the travelling salesman problem, which aims to find the shortest route that connects m given cities. This algorithm is used to encode a path in a graph into a chromosome.

a. Encoding

We have to define a number of nodes that can produce an optimal itinerary. These nodes (latitude and longitude) must be determined by experts (deminers) using special devices and then saved into a database. In our case, the sequence number will be used as the path-coding identity, which can be expressed as a matrix.

b. Initialisation of parent population

We will assign a numerical name for each node. The chromosome will be used to represent a route through the nodes. By contrast, we use appropriate genetic operators to create new routes. Safe path representation can be presented mathematically via a complete graph $G = (V, E)$, where V is a set of nodes = {1, 2, …, n}, whereas E is a set of its links (edges), with each edge $e_i \epsilon E$.

C_{ij} is a cost associated with each link (i,j), which can be specified by the cost matrix $C = [C_{i,j}]$.

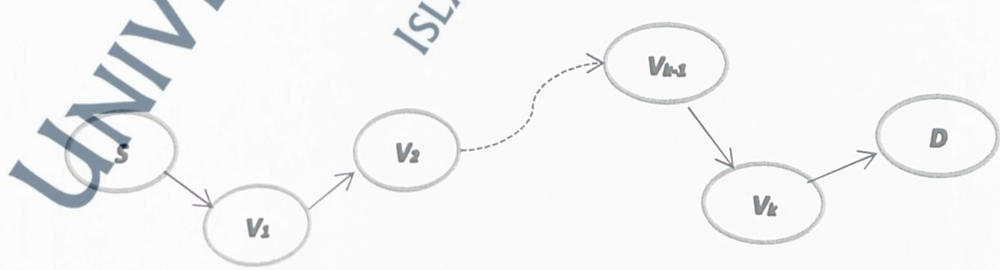
The starting and ending nodes are denoted by S and D, respectively.

I_{ij} is the link connection indicator between each link, which can be defined as follows:

$$I_{ij} = \begin{cases} 1, & \text{if edge (i,j) is included in the path} \\ 0, & Otherwise. \end{cases}$$

Figure 5.9 presents an example of a chromosome (safe path representation) encoding from node to node.

Figure 5.9: Example of safe path representation



Locus	*1*	*2*	*3*		*l−2*	*l−1*	*l*
Chromosome	*S*	V_1	V_2	…	V_{k-1}	V_k	*D*

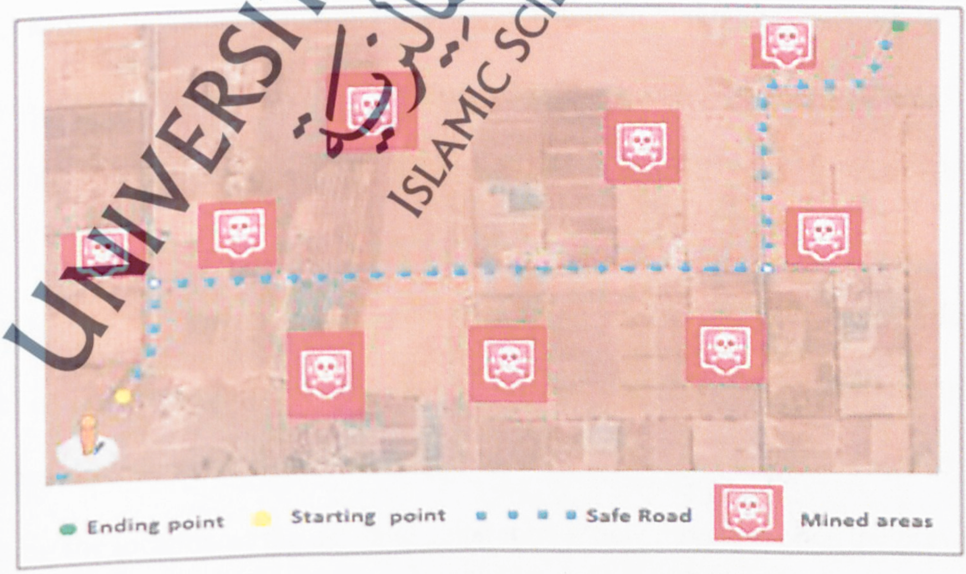
c. Fitness function

This step aims to evaluate the goodness of each chromosome by using a fitness function. P_n is set of individual adaptation values in the initial population $f(P_n)$. In our model, a set of training data is used to calculate the fitness of each chromosome based on the following function (Zhou et al., 2012):

$$f(P_n) = \sum_{i=1}^{N}[d_i + w_c c_i - w_s c_s]. \tag{5.21}$$

Figure 5.10 presents an example of the safe route using Google Maps, which can be followed by a user to avoid mine-affected areas. Each blue circle represents nodes that have been identified by experts (Deminers). The yellow node represents the starting point, whereas the green node represents the ending point.

Figure 5.10: Representation of a safe route



5.4 Summary

The integration of AI techniques can provide numerous improvements in tracking environmental risks and in helping decision makers during different phases of decision-making. Several improvements were made to enhance the performance of previous frameworks on ERA. In this context, a new conceptual architecture was constructed and its function was designed. The architecture was developed to remove the restriction of integration among AI techniques and to support the essential characteristics of ERA systems, such as responsiveness, security requirements, short session activities and variability of user interfaces.

The architecture comprises four major components: a decision support engine, a risk assessment engine, a knowledge base and user interface. NFRAM and the safe path selection model are among the most important components of the architecture.

NFRAM was developed through three stages using FL and neural network techniques. FL was used in the first stage to develop the primary FIS. In the second stage, the BP algorithm was used to train the network. The last stage involved training the model.

The safe path selection model was presented based on GA, GPS and Google Maps. This model can be used to help people avoid mine-affected areas by using a smartphone. It provides directions from the current location of a user to outside the mined area by updating the location of the user and generating a new direction once the previous one has been completed.