## Chapter 10

## THREE NOVEL RISK MODELLING AND DECISION MAKING TECHNIQUES

## CONTENTS

**Key words:** Analytical Hierarchy Processing, artificial neural networks, cost, decision making, decision support systems, marine safety assessment, multiple criteria decision analysis, risk assessment, Taguchi concept.

***Summary***

This Chapter presents three novel safety assessment and decision making approaches. They are (1) a safety based decision support system using artificial neural network techniques, (2) a safety optimisation framework using Taguchi concepts, and (3) a multiple criteria decision approach applied to safety and cost synthesis. Such approaches provide the safety analyst with more flexibility and may be more appropriate in situations where satisfactory results cannot be obtained using other methods.

A risk estimation framework incorporating artificial neural networks (ANNs) is described with two case studies demonstrating its use. Some suggestions are made for further research and development on ANN techniques in the context of maritime safety assessment. The possibility to pool records on notation fields such as system data, function information and casualty or defect data in an agreed and standardised database structure is discussed.

A safety optimisation framework using the Taguchi concepts is described with an example demonstrating its use. The Taguchi concepts are described and discussed. Orthogonal arrays are used to study multiple parameters simultaneously with a minimum of time and resources to produce an overall picture for more detailed safety based design and operational decision making. The signal-to-noise ratio is employed to measure quality, in this case, risk level. The outcomes produced using the described framework may provide the fundamental knowledge for safety analysts to make safety based design and operation decisions.

A new safety and cost modelling approach is described and demonstrated by an example. Three typical multiple criteria decision analysis methods for safety and cost synthesis are described. Their potential for use in safety based decision making is discussed.

## 10.1 A Safety-Based Decision Support System Using Artificial Neural Network Techniques

### 10.1.1 Introduction

Artificial Neural Networks (ANNs) have been deemed successful in applications involving classification, identification, pattern recognition, time series forecasting and optimisation. ANNs are distributed information-processing systems composed of many simple computational elements interacting across weighted connections. It was inspired by the architecture of the human brain. The ability of ANNs to model a complex stochastic system could be utilised in risk prediction and decision-making research, especially in areas where multi-variate statistical analysis is carried out.

The paucity literature reported on applications of ANNs in marine and offshore safety engineering reflects that the concept of ANNs is still an extremely raw technique to this area. Published research literature providing a step by step explanation of input data identification through network architecture design and output analysis is somewhat sparse. Buxton et al. (1997) applied the techniques of ANNs to statistics of losses of bulk carriers due to fire to determine whether it is of potential value as a predictor of overall risk. More recently, some initial findings based on a feasibility study of using ANN techniques in offshore and maritime safety-based decision support system has been reported (Sii et al. (2000), Wang et al. (2001)).

Programmed computing involves utilising an algorithm and/or a set of rules for solving the problem and then correctly coding these decisions in software. However, programmed computing can only be applied in cases that can be described by known procedures or set of rules. Neuralcomputing is one of the first alternatives to programmed computing. Neuralconputing provides a new approach to information processing in which algorithm or rule development is not required. The primary information processing structure in neuralcomputing is an ANN (Hecht-Nielsen (1990)).

An ANN is depicted in Figure 10.1. The nodes of the graph are commonly called processing elements. The arcs of the graph are called connections. An adjustable value called weight is associated with each connected pair of processing elements. The weight, $w_{ji}$, represents the strength of the connection. The processing elements are organised into layers with full or random connections between successive layers. Nodes in the input layer receive input, and nodes in the output layer provide output. Nodes in the middle layers receive signals from the input nodes and pass signals to output nodes. The value entering a processing element is typically the sum of each incoming value multiplied by its respective connection weight. This is often referred to as internal activation or a summation function. The internal activation is then transformed by a non-linear function, which determines the strength of the output connection. The transformed signal will be transmitted to other nodes in the next connected layer which in turn may produce the input to one or more processing elements in subsequent layers. Because the output of the middle nodes is not directly observable, the middle layers can be thought of as hidden. Each processing element may have any number of incoming or outgoing connections but the output signal $y_j$ from node $j$ must all be the same.

ANNs build models based on historical data. The connection weights and threshold values developed by the model are then applied to a new data set. This process is analogous to fitting a regression model based on past data and then utilising the data for prediction. Both techniques require the identification and categorisation of both the input and the output. The major difference that exists is that the regression model requires specification of an exact functional model. Although the number of processing elements and layers in the ANNs

determine the complexity of the relationships that the network can capture, this is not as stringent as the development of a specific functional form.

Regression analysis and neural network modelling also require the estimation or training of the model. In both cases, it is common to validate the resulting model against data not used during estimation or training. However, in the case of regression analysis, it is usually possible to evaluate the statistical significance of the estimated parameters in terms of confidence limits, but ANNs are unable to do that.

Like regression, although the most popular firing criterion for ANNs is minimisation of the squared errors, individual values rather than their sums are estimated. ANNs are applicable in any situation where there is an unknown relationship between a set of input factors and an outcome for which a representative set of historical examples of this unknown mapping is available. The objective of building an ANN model is to find a formula or program that facilitates predicting the outcome from the input factors.

The advantages of ANNs can contribute to risk modelling, especially in situations where conventional methods could not be used with confidence to describe the relationship between the input and output variables or there is an inconsistency in input-output relationships (Sii (2001)). An inconsistency in input-output relationship here refers to situations when conventional mathematical models fail to be applied to delineate the input-output relationship due to lack of precise knowledge, or information/data with a high level of fuzziness or ambiguity, or differences (if not contradictory) of opinions about that relationship among the risk analysts. Under such circumstances ANNs may be more appropriate to be used to elicit the true input-output relationship.

Different type of neural networks, such as the Multi-Layer Perceptron (MLP), the radial basis function networks (RBF) and B-spline (Haykin (1999)) networks, etc. can be used to model a system for risk assessment. In the development of an ANN model, the success depends upon a clear understanding of the actual problem, as the selection of network inputs, number of hidden layers and number of neurons in each layer, the non-linear transfer function, and the training algorithm should be based on the features of the problem to be modelled. As ANNs learn by examples, defining and preparing the training data set is also important. The training data must sample every possibility of the problem under all possible working conditions. The data sets including the input training set and the desired output should be as orthogonal as possible, that is, the variables contained in the data sets should be independent with no correlation. Once the problem description and data for the training sets are produced, the rest of the development of the ANN will simply fall into place. ANN testing is performed with a set of test data that is different from the training data used.

### 10.1.2 A Risk Estimation Framework

A risk estimation framework incorporating ANNs is depicted in a flowchart as seen in Figure 10.2. The framework comprises the following steps (Sii (2001), Wang et al. (2001)):

Step 1: Collect Data. Collect data sets, number series or system information that have a relationship or influence to a system failure from relevant sources such as classification societies, ship owners, flag states, insurance companies and experts.

Step 2: Prepare Data: Define and prepare training input sets and decide how to handle the gathered information for presentation to the ANNs. Determine the range of data and set minimum and maximum values to these levels.

Step 3: Extract test data set: In order to be able to test the trained network, it is common to set aside some of the data for testing (cross validation). Usually, the total data set is divided into two, one for training and the other for testing.

Step 4: Train the network: Select suitable network architecture by setting the number of network inputs equal to the number of input variables and the number of network outputs equal to that of problem output. Select the number of hidden layers and the number of neurons in each hidden layer.

Step 5: Test the ANN: Apply the test data sets to the trained ANN model to test its performance.

Step 6: Evaluate the ANN model: If the estimation generated by the model lies within acceptable accuracy then, proceed to the next step. Otherwise repeat Steps 2 to 6 all over again until the estimation produced falls within the acceptable accuracy. For various applications, accuracy level requirements would be different and are judged subjectively by the user.

Step 7: Use the ANN model to carry out risk prediction: Feed new casualty data to the ANN model, to perform risk estimation.

Step 8: The risk estimation or prediction generated by the ANN model can be applied to safety based design and operation support system as a source of expert input.

The general guidance for building the framework is briefly described as follows:

1. There could be multiple inputs and multiple outputs.
2. Experience indicates that one hidden layer would be enough to deal with majority of risk modelling problems. Using more than one hidden layer will increase the computational load but may achieve faster learning or better generalisation.
3. A Signoid transfer function is usually used while other types of transfer functions may also be applicable.
4. A fast back propagation training algorithm can be used which is available in the Neural Network Toolbox in MATLAB.
5. Techniques incorporating momentum can be used to decrease back-propagation's sensitivity to small details in the error surface. This will help the ANN avoid getting stuck in shallow minima which could prevent the ANN from finding a lower error solution.
6. Adaptive learning rate helps to decrease training time and improve reliability of the back-propagation.

### 10.1.3 Two Examples

#### 10.1.3.1 Case Study 1

An ANN was developed as an aid in understanding the relationship among the different parameters or features of a generic type of vessel, such as vessel's size, age, degree of machinery redundancy, external factors, etc. Once this relationship is understood, it could be

used in predicting vessel failure. A fast back-propagation ANN in the Neural Network toolbox in MATLAB, developed by the Math works Inc., is chosen as the software package. MATLAB Neural Network uses a sigmoid function as the activation function, therefore all data must be scaled between 0 and 1.0 (Sii (2001), Wang et al. (2001)).

Configuration

The configuration of the ANN is shown in Figure 10.3. There are two nodes on the input layer corresponding to the amplitudes for the vessel's size (the dead weight (dwt)) and age of typical bulk carriers. After performing a series of experiments on the effects of number of hidden neurons on training epoch, ten nodes are selected on the hidden layer to allow for the non-linearity of the problem. The output layer has one node corresponding to the amplitude for hull failure rate. Table 10.1 outlines the major neural network characteristics.

Training the ANN

For this network, a training pair is a set of known input and output values. To train the network, an output value is computed from the known input values and the random weights. This computed output is then compared to the known output. A change in the weight is computed and propagated back through the ANN. The modified weights are then used with the known inputs to compute another output value. This process continues until the sum-squared error (sse) difference between the known output and the computed output converges to some given tolerance, arbitrarily defined to be 0.02 for this problem (sum-squared error of 0.02 is commonly used for normalised data in optimisation (Matlab (1994)).

For this initial investigation, it was decided to try and model the problem with ten training pairs. These ten training pairs to be used in training the ANN were created by interpreting (arbitrarily chosen) from LR (Lloyds Register of Shipping) defect data for bulk carriers (Buxton et al. (1997)). The set of scaled training pairs is shown in Table 10.2.

Results

The experimental results on the effects of number of hidden nodes on training epoch or training time are shown in graphical form in Figure 10.4. It is obvious that as the number of hidden nodes increase the training epochs or training time decreases to achieve the same model accuracy, and it reached the smallest number of training epochs or the shortest training time when 10 hidden nodes were used. Further increase in the number of hidden nodes will gradually increase the training epoch. Hence, in this case 10 hidden nodes were selected. This experimental findings agree well with the choosing criteria for the number of hidden neurons as suggested by (Nelson and Illingworth (1990)). According to their postulation, in most cases, except for imaging, one uses four or five hidden layer neurons to one input neuron.

Once trained, the ANN was applied to predict five different test cases. The computed outputs are shown in Table 10.3, together with the actual output from LR defect database and the comparison made between them. It can be seen from the resting results of Table 10.3 that the ANN model does not predict 100% accurately the failure rate in all the 5 test cases. The error is between 0% and 11.9%. Though the ANN was trained with limited number of training pairs, the computed outputs were considered to be quite optimistic.

### 10.1.3.2 Case Study 2

The objective of this case study is to develop an ANN model for predicting the possibility of failure or defect of a given vessel. It is based on a hypothetical vessel's design features and the ship owner's management quality.

The vessel's design features include:

- Fire-fighting capability.
- Navigation equipment level.
- Redundancy of machinery.

The ship owner management quality include:

- Quality of ship owner management.
- Quality of operation.

Configuration

An MLP network is chosen as shown in Figure 10.5. In this case, after performing several experiments on the optimal number of hidden neurons to be used for ANN training and learning; 20 hidden neurons are selected for the first hidden layer (In Figure 10.5, four nodes and two small circles with dotted lines that are not explicitly shown, are used to represent the actual 20 nodes for hidden layer). There are five nodes (neurons) on the input layer corresponding to the quality of ship owner's management, quality of operation, fire-fighting capacity, navigation equipment level and machinery redundancy. Twelve nodes (neurons) are chosen on the hidden layer to allow for the non-linearity of the problem. The output layer has one node (neuron) corresponding to the possibility of vessel failure.

The major neural network characteristics are outlined in Table 10.4.

The data used for ANN model training and learning is organised as shown in Table 10.5, which lists data that are within the following guidelines (Sii (2001), Wang et al. (2001)):

- IF either one or more of the factors from ship owner management quality or vessel's design features is classified as '*Very Low*', THEN the possibility of vessel failure is predicted to be '*Very High*';
- IF either one or more of the factors from ship owner management or vessel's design features is classified as '*Low*', THEN the possibility of vessel failure is predicted to be '*High*';
- The rest of the predicted possibilities of vessel failure will be computed according to the average scale values of the five factors listed below:

| *Level* | *Scale values* |
|---|---|
| Very High | 0.9, 1.0 |
| High | 0.7, 0.8 |
| Average | 0.4, 0.5, 0.6 |
| Low | 0.2, 0.3 |
| Very Low | 0.0, 0.1 |

In this particular case study, techniques incorporating momentum and adaptive learning rate are used to increase the speed and reliability of the back-propagation. This helps the network avoid getting stuck in shallow minima which would prevent the network from finding a lower error solution. Training time can also be decreased by the use of an adaptive learning rate which attempts to keep the learning step size as large as possible while keeping learning stable. The learning rate is made responsive to the complexity of the local error surface.

Training the ANN

It was decided to model the problem with twenty-five training sets created hypothetically, as shown in Table 10.5. After 282 epochs of training, for learning rate 0.01 (learning rate is a training parameter that controls the size of weight and bias changes during learning), it reached the pre-defined error goal 0.02.

Results

There is no clear and straightforward solution to the selection of number of hidden neurons. After performing several experiments on the optimal number of hidden neurons to be used for ANN training and learning, the experimental findings are depicted in Figure 10.6, indicating that as the number of hidden nodes increases the training epoch or training time becomes smaller or shorter. The shortest training time is reached when 12 hidden nodes were used.

The trained ANN model was applied to predict 10 different test cases. The predicted outputs were shown in Table 10.6. The predicted results were found to be good as they follow the pre-defined hypothetical criteria closely. For example, the possibility of vessel failure is predicted to be *High* IF ship owner management quality is *Low*; operation quality is *Very High*; fire-fighting capability is *Very High*; navigation equipment level is *Average*; and machinery redundancy is *Very high*.

### 13.2.4 Discussions

It has been demonstrated by the case studies that ANNs have the following characteristics:

- The capability of learning a set of non-linear patterns.
- ANNs are able to generalise and interpolate accurately within the range of the training data.
- A crucial point for a risk predicting or forecasting model, is the set of consistent, sufficiently independent variables (features) used to train and test the ANNs.
- There is no need to know the type of regression function.
- ANNs are easier to be applied, especially using the existing software packages.
- ANNs are powerful tools and a complement to statistical techniques when data are multi-variate with high degree of interdependence between factors, when the data are incomplete or “noisy”, or when many hypotheses are to be pursued and high computational rates are required. With their unique features, they can lead to a powerful decision-making, predicting and forecasting tool.

### 10.1.5 Conclusion

ANN techniques would provide new insights into assessing and predicting the risks posed by ships with different characteristics. This will permit more rational comparison between alternative ship design and operational features. It is worth noting that ANNs can be a potential tool for risk assessment.

## 10.2 Taguchi Concepts and Their Applications in Maritime Safety Assessment

### 10.2.1 Introduction

Taguchi methods of robust experimental design have traditionally been employed in manufacturing settings (Roy (1990)). Literature review indicates that there appears to be virtually no study that uses Taguchi concepts to optimise safety in any discipline of engineering applications (Sii et al. (2001)). Beyond the original intention of Taguchi to apply his methods to manufacturing settings, there are other reasons perceived why Taguchi methods have not been employed at all in safety-based decision making studies. Firstly, the safety of a system is very difficult to measure precisely or quantitatively. This induces problems in the application of Taguchi methods as they actually depend heavily on the accurate measurement of variation of 'quantified' parameters of a process. Secondly, the outcome of a safety-based decision making problem is inherently much more inconsistent in quality than its manufacturing counterpart. This is primarily due to the fact that the safety performance of a system depends largely on the behaviour of the human involvement. High variation in quality makes it difficult to make bona fide judgements about the system performance since Taguchi methods rely on only a small part of the total information pertaining to variations. Finally, safety-related problems, generally speaking, have more 'noise' factors associated with them compared with their manufacturing counterparts. Despite these attributes of a safety- related problem, by appropriately identifying a "quantitative" measure of safety, Taguchi's concepts of robust designs can be employed successfully to optimise safety-related decision making problems (Sii et al. (2001)). This may provide an alternative tool for safety analysts, designers, regulatory bodies and managers to conduct decision making with confidence in situations where other methods cannot be effectively applied.

Engineering safety involves broadly three dimensions of management, engineering and operation, underpinned by the human factors of behaviour, decision and error. The goal for marine and offshore operations can be stated as follows: 'to be competitive in meeting the client's specifications with solutions that are cost-effective at an acceptable level of safety' (Kuo (1998)).

In the context of commercial operations "competitiveness" means "level of profitability", however, in non-commercial activities "effectiveness" would be more appropriate as it has to take into account the specific objective of the activity concerned. The real challenge is that the success in achieving the goal in any project is to meet all four sets of criteria simultaneously, that is, safety, competitiveness, specification and cost-effectiveness.

The requirement of meeting any one of these sets of criteria on its own is relatively straightforward if the others do not have to be taken into consideration. Typical examples of this would be:

- To adopt the latest technology for the production process without due regard to cost.
- To achieve a very high level of safety without taking into account the need for the operation to be competitive.

In engineering terms this is often referred to as a special "multiple-level-multiple-variable optimisation" problem. 'Multiple-level' means that each of the parameters such as specification, comprises requirements, and is with varying degrees of complexity. "Multiple-variable" implies that there is more than one variable or factor involved. "Optimisation" aims to find the best solution to the problem, and in this case the most competitive solution is being sought. Existing optimisation techniques can be used to solve the problem in which the relationships within each parameter and between each other are known and expressible in mathematical terms. However, when some of the relations are qualitative, such as those relating to human factors, the solution to optimisation problems can be extremely difficult to deal with.

The performance of complex engineering systems and quality of products or processes generally depend on many factors. Taguchi separates these factors into two main groups: control factors and noise factors (Ross (1988)). Control factors are those which are set by the designers or manufacturers; noise factors are those over which the designers or manufacturers have no direct control but which vary in the environment of the system or product (Phadke (1989)).

A great deal of engineering effort is consumed in conducting experiments to obtain information needed to guide decisions related to a particular artefact. It would further complicate the situation once safety is integrated into design, especially in the initial concept design stage. This is due to the typical problems associated with a lack of reliable safety data or a high level of uncertainty in safety data. This is particularly true when dealing with the high level of novelty in design and optimisation of marine and offshore safety within both technical and economic constraints.

Taguchi's quality engineering and robust design may offer a useful method to evaluate the performance of a system when uncertainty is present and to measure the quality in the design (Sii et al. (2001)).

### 10.2.2 The Taguchi Methods and Robust Design

Driven by the need to compete on cost and performance, many quality-conscious organisations are increasingly focusing on the optimisation of product design. This reflects the realisation that quality cannot be achieved economically through inspection. Designing in quality is cheaper than trying to inspect and re-engineer it after a product hits the production floor (Gunter (1987)). Thus, new philosophy, technology and advanced statistical tools must be employed to design high quality products at low cost.

Products have characteristics that describe their performance relative to customer requirements or expectations (Ross (1988)). The quality of a product/process is measured in terms of these characteristics. Typically, the quality is also measured throughout its life-cycle. The ideal quality a customer can expect is that every product delivers the target performance each time the product is used under all intended operating conditions and throughout its intended life and that there will be no harmful side effects (Phadke (1989)). The quality of a product is measured in terms of the total loss to society due to functional variation and harmful side effects (Taguchi (1986)). The ideal quality loss is zero.

Since the late 1950s Dr Taguchi has introduced several new statistical tools and concepts of quality improvement that depend heavily on the statistical theory for design of experiments

(Gunter (1987), Phadke (1989), Wille (1990)). These methods of design optimisation developed by Taguchi are referred to as robust design (Phadke (1989)). The robust design method provides a systematic and efficient approach for finding the near optimum combination of design parameters so that the product is functional, exhibits a high level of performance, and is robust to noise factors (Bendell (1988), Phadke (1989)).

The challenge for a designer to design products with high quality is obviously driven by the need to compete on price and performance. Quality-conscious designers are increasingly aware of the need to improve products and processes (Roy (1990)). Delivering a high-quality product at low cost is an interdisciplinary problem involving engineering, economics, statistics, and management (Phadke (1989)). In the cost of a product, one must consider the operating cost, the manufacturing cost, and the cost of new product development. A high-quality product has low costs in all three categories. Robust design is a systematic method for keeping the producer's cost low while delivering a high-quality product and keeping the operating cost low. Taguchi espoused an excellent philosophy for quality control in manufacturing industries (Roy (1990)). His philosophy is founded on three very simple and fundamental concepts. These concepts are stated in (Roy (1990)) as follows:

- Quality should be designed into the product and not inspected into it.
- Quality is best achieved by minimising the deviation from the target. The product should be designed in such a way that it is immune to uncontrollable environmental factors (noise factors).
- The cost of quality should be measured as a function of deviation from the standard and the losses should be measured system-wide.

A leading indicator of quality is required by which one can evaluate the effect of changing a particular design parameter on the product's performance. This indicator is called signal-to-noise ratio. It isolates the sensitivity of the system's performance to noise factors and converts a set of observations into a simple number.

A product under investigation may exhibit a distribution which has a mean value that differs from the target value. The first step towards improving quality is to achieve a distribution as close to the target as possible. Efficiency experimentation is required to find dependable information with minimum time and resources about the design parameters (Phadke (1989)). Taguchi designs experiments using orthogonal arrays which make the design of experiments easy and consistent. The power of orthogonal arrays is their ability to evaluate several factors with a minimum number of experiments.

### 10.2.3 The Design Process

The early design phase of a product or process has the greatest impact on life cycle cost and quality (Kackar (1985), Phadke (1989), Taguchi et al. (1989)). Therefore, significant cost savings and improvements in quality can be realised by optimising product designs. The three major steps in designing a quality product are: system design, parameter design, and tolerance design (Bendell (1988), Phadke (1989), Taguchi (1986), Taguchi et al. (1989)).

System design is a process of applying scientific and engineering knowledge to produce a basic functional prototype design (Kackar (1985)). The prototype model defines the

configuration and attributes of the product undergoing analysis or development. The initial design may be functional but it may be far from optimal in terms of quality and cost.

The next step, parameter design, is an investigation conducted to identify the settings of design parameters that optimise the performance characteristic and reduce the sensitivity of engineering designs to the source of variation (noise) (Kackar (1985)). Parameter design requires some form of experimentation for the evaluation of the effect of noise factors on the performance characteristic of the product defined by a given set of values for the design parameters. This experimentation aims to select the optimum levels for the controllable design parameters using the robust design method.

Experimenting one design variable at a time or by trial and error until a first feasible design is found, is a common approach to design optimisation (Bendell (1988), Phadke (1989)). However, this approach can lead to either a very long and expensive time span for completing the design or a premature termination of the design process due to budget and schedule pressures. The result in most cases is a product design which may be far from optimal. As an example, if the designer is studying 13 design parameters at three levels, varying one factor at a time would require studying 1,594,323 experimental configuration ($3^{13}$). This is a full factorial approach where all possible combinations of parameter values are tried. Obviously, the time and cost involved in conducting such a detailed study during the advanced design is prohibitive.

In contrast, Taguchi's robust design method provides the designer with a systematic and efficient approach for conducting experimentation to determine near optimum settings of design parameters for performance and cost (Bendell (1988), Kackar (1985), Logothetis and Salmon (1988), Phadke (1989), Meisl (1990)). The robust design method uses orthogonal arrays (OA) to study the parameter space, usually containing a large number of decision variables, with a small number of experiments. Taguchi's orthogonal arrays provide a method for selecting an intelligent subset of the parameter space. Using orthogonal arrays significantly reduces the number of experimental configurations. A typical tabulation is shown in Table 10.7 (Bendell (1988), Phadke (1989), Taguchi and Konishi (1987)). In this array, the columns are mutually orthogonal, that is, for any pair of columns, all combinations of factor levels occur, and they occur at an equal number of times. There are four factors 1, 2, 3 and 4, each at three levels. This is called an $L_9$ design, where 9 indicates the nine rows, configurations or prototypes to be tested, with test characteristics defined by the row of the table. The top row of the array shows the four different levels (i.e. alternative settings). The other rows represent different combinations of control factor levels. This set-up of nine level combinations satisfies the information need just as good as a full factorial experiment in which all $3^4 = 81$ level combinations are tested.

The number of columns of an OA represents the maximum number of factors that can be studied using that array. Note that this design reduces 81 ($3^4$) configurations to 9. Some of the commonly used orthogonal arrays are shown in Table 10.8 (Bendell (1988)). As Table 10.8 shows, there are greater savings in testing for the larger arrays.

Using an $L_9$ OA means that nine experiments are carried out in search of the 81 control factors combinations which gives the near optimal mean, and also the near minimum variation away from this mean. To achieve this, the robust design method uses a statistical measure of performance called signal-to-noise (S/N) ratio (Phadke (1989)). Borrowed from electrical control theory, the S/N ratio developed by Dr Taguchi is a performance measure to choose

control levels that best cope with noise (Bendell (1988), Bryne and Taguchi (1986), Phadke (1989)). The S/N ratio takes both the mean and the variability into account. In its simplest form, the S/N ratio is the ratio of the mean (signal) to the standard deviation (noise). The S/N equation depends on the criterion for the quality characteristic to be optimised. While there are many different possible S/N ratios, three of them are considered standard and are generally applicable in following situations (ASII (1989), Bryne and Taguchi (1986), Phadke (1989)):

- Biggest-is-best quality characteristic (strength, yield).
- Smallest-is-best quality characteristic (contamination).
- Nominal-is-best quality characteristic (dimension).

Whatever the type of quality or cost characteristic, the transformations are such that the S/N ratio is always interpreted in the same way, the larger the S/N ratio the better (Bryne and Taguchi (1986)).

The third step, tolerance design, is the process of determining tolerances around the nominal settings identified in the parameter design process (Kackar (1985)). Tolerance design is required if robust design cannot produce the required performance without special components or high process accuracy (Bendell (1988)). It involves tightening of tolerances on parameters where their variability could have a large negative effect on the final system. Typically tightening tolerances leads to higher cost (Phadke (1989)).

### 10.2.4 Background of Taguchi Concepts

The fundamental principle of robust design is to improve the quality of a product by minimising the effects of the causes of variation without eliminating those causes. Efficient experimentation is necessary to find dependable information about design parameters. The information should be obtained with minimum time and resources. Estimated effects of parameters must be valid even when other parameters are changed. Employing the signal-to-noise ratio to measure quality and orthogonal arrays to study many parameters simultaneously are the keys to high quality and robust design.

Since variation in product performance is similar to quality loss, analysis of variance (ANOVA) will be carried out to interpret experimental data and factor effects. ANOVA is a statistically based decision tool for detecting differences in average performance of groups of items tested (Ross (1988), Roy (1990)).

Phadke, following Taguchi, measures the quality of a product in terms of the total loss to society due to functional variation and harmful side effects. Under ideal conditions, the loss would be zero, that is, the greater the loss, the lower the quality (Phadke (1989)). In the following, how this quality loss can be quantified, factors that influence this loss, how this quality loss can be avoided are discussed.

#### 10.2.4.1 The Taguchi Quality Loss Function

Quality is often measured in terms of the fraction of the total number of units that are defective. This is referred to as fraction defective. However, this implies that all units which are within the tolerances of the requirements are equally good. In reality, a product that is exactly on target gives the best performance. As the product's response deviates from the

target its quality becomes progressively worse. Therefore, one should not be focusing on meeting the tolerances but on meeting the target.

The quality loss is crucial in Taguchi's theory. It is based on the assumption that when a functional characteristic *y* deviates from the specified target value m, the customer and the society in general experiences an economical loss due to poorer product quality. This economic loss is expressed as the loss function *L(y).* Based on this, Taguchi defines the quality loss for not being on target by means of the quadratic quality loss function (Phadke (1989), Taguchi (1986)):

$$L(y) = k(y - m)^2 \tag{9.1}$$

where *y* is the quality characteristic of a product/process, *k* is a constant called the quality loss coefficient and *m* is the target value for *y*.

When the functional characteristic deviates from the target, the corresponding quality loss increases. Furthermore, when the performance of the product is outside the tolerance, the product is considered defective. A convenient way to determine the constant *k* is to determine first the functional limits for the value of *y*. Let $m \pm \Delta_0$ be the safety range for a vessel. Suppose the cost (loss) of losing or repairing the vessel is $A_0$ when the vessel goes beyond the safety range. By substitution into Equation (9.1), the following can be obtained:

$$k = \frac{A_0}{\Delta_0^2} \tag{9.2}$$

With the substitution of Equation (9.2) into Equation (9.1) it is able to calculate the quality loss for a given value of *y*. More on the determination of *k* can be found in (Phadke (1989)).

### 10.2.4.2 Signal-to-Noise Ratio (S/N Ratio)

Taguchi has developed a signal to noise ratio in order to provide a way of measuring the robustness of a product. In other words, he has used the signal-to-noise ratio as a predictor of quality loss after making certain simple adjustments to the system's function (Taguchi (1986), Phadke (1989)). This ratio isolates the sensitivity of the system's function to noise factors and converts a set of observations into a single number. It is used as the objective function to be maximised in robust design (Phadke (1989)).

The ratio takes into account the mean and the variance of the test results, and is as a rule of thumb always maximised. This leads to several specialised S/N ratios, depending on the nature of the comparison variable. There are three basic S/N ratios, but according to (Fowlkes and Creveling (1995)), the variety of S/N ratios is limitless. The three possible categories of quality characteristics or most widely used S/N ratios are:

- Smallest-is-better: $\eta = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right)$ e.g. seeking the minimum light weight/dead weight ratio.
- Nominal-is-best: $\eta = 10\log\left(\frac{\mu^2}{\sigma^2}\right)$ e.g. maintaining cell guide tolerances.

- Larger-is-better: $\eta = -10\log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right)$ e.g. seeking the maximum profit or the highest efficiency.

where:

$\eta$ represents the S/N ratio

$\mu$ and $\sigma^2$ are the mean value and the variance of the variables

$y_i$ is the comparison variable in experiment $i$ for a certain combination of control factor levels

$n$ is the number of experiments performed for that combination.

The conversion to the signal-to-noise ratio can be viewed as a scale transformation for convenience of better manipulation. It offers an objective way to look at two characteristics, namely, variation and mean value. Analysis using the signal-to-noise ratio has two main advantages:

- It provides a guideline to the selection of the optimum level based on least variation around the target and also on the average value closest to the target.
- It offers objective comparison of two sets of experimental data with respect to variation around the target and the deviation of the average from the target value.

For the robust design of a product, the following two steps are required:

- Maximise the signal-to-noise ratio $\eta$. During this step, the levels of the control factors to maximise $\eta$ are selected while ignoring the mean.
- Adjust the mean on target. For this step, a control factor is used to bring the mean on target without changing $\eta$.

Further information on quality loss and signal-to-noise ratios can be found in texts written in (Phadke (1989), Ross (1988), Roy (1990), Suh (1990), Taguchi (1986)). They all provide detailed discussions on how to apply statistical methods and Taguchi's approach in the selection of design parameters for satisfying functional requirements.

### 10.2.4.3 Life Cycle Quality Loss

For a ship owner, it may be of interest to study how life cycle considerations fit in the theory of Taguchi. Let $y_1, y_2, \ldots y_n$ be $n$ representative measurements of the quality characteristic $y$ taken through the life cycle of a ship, and assume that $y$ shall be as close to a specified target value $m$ as possible. Then the average quality loss $Q$ caused by this product may be expressed as:

$$Q = \frac{1}{n}\left[L(y_1) + L(y_2) + \ldots.. + L(y_n)\right] = \frac{k}{n}\left[(y_1 - m)^2 + (y_2 - m)^2 + \ldots.. + (y_n - m)^2\right]$$
$$= k\left[(\mu - m)^2 + \frac{n-1}{n}\sigma^2\right]$$

where $\mu = \frac{1}{n}\sum_{i=1}^{n} y_i \left(mean\right)$ $\sigma^2 = \frac{1}{n-1}\sum_{i=1}^{n}\left(y_i - \mu\right)^2$ *(variance)*

When $n$ is large (there are many measurements during the product life), the expression can be simplified as $Q = k\left[\left(\mu - m\right)^2 + \sigma^2\right]$. This simplified expression shows that the average quality loss depends on the following two terms:

- The deviation of quality characteristic $y$ relative to the target value $m$.
- The mean variance of $y$ relative to the observed mean value of $y$.

It is usually easy to reduce or eliminate the first term; reducing the variance of a product is generally more difficult and expensive. A systematic approach to optimise the performance is Taguchi's two step optimisation process.

### 10.2.4.4 Taguchi's Two Step Optimisation Process

Taguchi's two step optimisation process focuses on the product's performance on the target. It consists of the following two steps:

- The first step of the process is to reduce the variability of the product performance by selecting parameter values for minimum variability.
- The second step is to select and adjust parameters with strong influence on the mean and weak influence on the variability to put the performance on the target by identifying the influences of the different design parameters on the mean and variance.

### 10.2.4.5 Orthogonal Arrays

In Taguchi's theory, design parameters are set based on studies of the behaviour of the concept under different operating conditions. The parameters are set in such a way that the sensitivity of the concept performance with respect to uncontrollable factors is minimised. The sensitivity is analysed by the use of experiments, and through analysis of the information need and the use of orthogonal arrays – the core of the Taguchi's experimental design technique, the experiment efficiency is optimised. The experiments may be either analytical or physical, and the results are analysed using an appropriate comparison variable and a so-called signal-to-noise ratio.

The term orthogonal refers to the balance of the various combinations of factors so that no single factor is given more or less weight in the experiment than other factors. Orthogonality also refers to the fact that the effect of each factor can be mathematically assessed independent of the effects of the other factors (Fowlkes and Creveling (1995)). In orthogonal arrays, the columns are mutually orthogonal. Most books dealing with the Taguchi theory provide standardised orthogonal arrays. In a more advanced parameter design set-up, control factors with varying number of levels (usually 2, 3 and 4) can be performed simultaneously. It is also possible to study the interaction between the control factors in an experiment.

### 10.2.4.6 Degree of Freedom

Degree of freedom is a concept that is useful to determine how much information can be derived from an experiment in a matrix representation. The degree of freedom of a matrix experiment is one less than the combinations of levels in the experiment (i.e. number of rows in the orthogonal array): $DOFexp = \#combinations - 1$.

The degree of freedom needed to describe a factor effect (i.e. a factor's contribution to the result) is one less than the number of levels (values) tested for that factor: $DOF_f = \#levels - 1$.

The problem of solving a set of simultaneous equations for a set of unknowns is a good mathematical analogy for the experiment. The number of equations is analogous to the degree of freedom of a matrix experiment. The number of unknowns is analogous to the total degree of freedom of the factorial effects: $(Total\ DOF)_f = (\#factors)(DOF_f)$.

The *DOF* is used to select an appropriate orthogonal array for the experiment, i.e. for the testing of the parameter combinations. As a general rule, the selected standardised orthogonal array must have at least the same degree of freedom as the experiment. In addition, the number of rows must be at least one more than the $(Total\ DOF)_f$. One reason for the rationality of the Taguchi experiments is therefore that they do not produce more information than is needed.

### 10.2.4.7 Control factors

The control factors are values that can be specified freely by the designer. It is designers' responsibility to determine the best values of these parameters. Each control factor can take multiple values, called levels. Their settings or levels are selected to minimise the sensitivity of the product's response to all noise factors.

### 10.2.4.8 Noise factors

Noise factors are treated like the control factors in terms of *DOF* calculation and selection of orthogonal arrays, but might be more often represented by two-level parameters reflecting a probable operating interval. An example of this may be fuel price, where one may set an extreme high and expected price as the operating interval. The distinction between controllable and uncontrollable factors is very often an economical question, and in the extreme case with unlimited resources available, all factors may be controllable.

### 10.2.4.9 ANOVA Terms and Notations

The analysis of variance (ANOVA) computes parameters such as degree of freedom, sums of squares, mean squares, etc. and organises them in a standard tabular format. These parameters and their interrelationships are defined as shown below using the following notation:

$V$ = Mean squares (variance)

$S$ = Sum of squares

$S'$ = Pure sum of squares

$f$ = Degree of freedom

$e$ = Error (experimental)

$F$ = Variance ratio

$P$ = Percent contribution

$T$ = Total (of results)

$N$ = Number of experiments

$C.F.$ = Correction factor

$n$ = Total degrees of freedom

Variance

The variance of each factor is determined by the sum of the square of each trial sum result involving the factor, divided by the degree of freedom of the factor. Thus:

$V_A = S_A/f_A$ (for factor $A$)

$V_B = S_B/f_B$ (for factor $B$)

$V_e = S_e/f_e$ (for error terms)

Variance Ratio

The variance ratio is the variance of the factor divided by the error variance.

$F_A = V_A/V_e$

$F_B = V_B/V_e$

$F_e = V_e/V_e = 1$

Pure Sum of Squares

The pure sum of squares is:

$S'_A = S_A - f_A \text{ x } V_e$

$S'_B = S_B - f_B \text{ x } V_e$

$S'_e = S_e + (f_A + f_B) \text{ x } V_e$

Percent Contribution

The percent contribution of each factor is the ratio of the factor sum to the total, expressed in percentage.

$P_A = S_A \times 100/ S_T$

$P_B = S_B \times 100/ S_T$

$P_e = S_e \times 100/ S_T$

where $S_T$ is total sum of square, obtained by: $S_T = \left(Y_1^2 + Y_2^2 + ...Y_i^2\right) - \frac{\left(Y_1 + Y_2 + ... + Y_i\right)^2}{i}$

Total Variance

Total variance is:

$S_T$ = Sum of square of all trial run results – $C.F.$

where $C.F. = T^2/N$ and $T = (Y_1 + .... + Y_N)$

### 10.2.4.10 Confidence Intervals

The calculations shown in the ANOVA table are only estimates of the population parameters. These statistics are dependent upon the size of the sample being investigated. As sample size increases, the precision of the estimate would be improved. For large samples, the estimates approach the true value of the parameter. In statistics, it is therefore customary to represent the values of a statistical parameter as a range within which it is likely to fall, for a given level of confidence. This range is termed as the confidence interval (*C.I.*). If the estimate of the mean value of a set of observations is denoted by *E(m)*, then the *C.I.* values for the mean and intervals are obtained according to the following procedure:

*Upper confidence level = Mean + C.I.*

*Lower confidence level = Mean – C.I.*

$C.I. = \sqrt{\frac{FxV_e}{N_e}}$ (Roy (1990))

where:

$F$ = *F-value* from the F distribution Tables (*F*-ratio Tables) at a required confidence level and at *DOF 1* and error *DOF 8* (Roy (1990))

$V_e$ = Variance of error term (from ANOVA)

$N_e$ = Effective number of replications = {Total number of results (or number of S/N-ratios)}/{*DOF* of mean (=*1*, always) + *DOF* of all factors included in the estimate of the mean}or the total number of units in one level.

*F*-value is sometimes refereed to as *F*-ratio, used to test the significance of factor effects. It is statistically analogue to Taguchi's signal-to-noise ratio for control factor effect vs. the experimental error. The *F*-ratio uses information based on sample variances (mean squares) to define the relationship between the power of the control factor effects (a type of signal) and the power of the experimental error (a type of noise) (Fowlkes and Creveling (1995)).

### 10.2.4.11 Brainstorming

Brainstorming is an integral part of the Taguchi philosophy. Taguchi regards brainstorming as an essential step in the design of effective experiments. Through brainstorming sessions, clear statements of the problems are established, the objectives, the desired output characteristics, the methods of measurement and the appropriate experiments are designed. Taguchi does not prescribe a standard method of brainstorming as applicable to all situations. The nature and content of the brainstorming session will vary widely on the problem.

### 10.2.5 A Safety Optimisation Framework Using Taguchi Concepts

A safety optimisation framework using Taguchi concepts for maritime safety engineering applications presented in this Section has the following steps (Sii (2001), Sii et al. (2001)):

1. Define the problem.

The first step is to describe the specific maritime safety problem in detail, either in qualitative or quantitative terms. Then define the objective parameter that is to be optimised.

2. Identify factors and their interactions.

   Brainstorming technique is normally used among a panel of experts to identify all the possible factors, levels, their interactions and other pertinent information about the optimisation problem. Sometimes factor screening may be required to provide a quick and simple way of ranking factors according to their importance in the optimisation. This will reduce the number of identified factors in order to perform the optimisation more efficiently.

3. Select an appropriate orthogonal array.

   In order to select the correct standard orthogonal array, it is necessary to determine the total degrees of freedom in order to find the minimum number of level combinations to be tested. The number of factors and their interactions as identified after the screening in Step 2 will determine the total degrees of freedom according to the equation given in the nest Section.

4. Conduct experiment.

   This starts with the selection of a correct quality loss function to represent the description of loss attributed in the case. This is a purely mathematical analysis and *S/N-ratio* for each treatment is calculated according to the selected standard *S/N-ratio* expressions as described in Section 10.2.4.2. The calculated *S/N-ratios* are then normalised before proceeding to the next step.

5. Conduct analysis of variance (ANOVA) and other Taguchi-related analysis.

   This step mainly performs all the relevant operations in ANOVA. The main effects of each factor as well as interaction of factors are determined, then sum of squares for each main effect of factor is computed. The variance of each factor is calculated. The results are presented in a table.

6. Identify significant factors and their interactions.

   The contribution of each factor and their interactions are determined through division, i.e., the sum of square of each factor is divided by the total sum of squares of all the factors. Pooling is recommended when a factor is determined to be insignificant by performing a test of significance against the error term at a desired confidence level.

7. Find the optimal combination of factor levels to minimise system risk level.

   The non-linearity analysis is carried out to investigate the non-linearity of the *S/N*-ratio with respect to factor levels of each factor as well as their interactions to identify the optimal combination of factor levels. The non-linearity graphs are developed to demonstrate the outcomes of this investigation.

8. Recommend for implementation.

   Safety related recommendations pertaining to engineering design, operation and management are made based on the outcomes of the optimisation.

### 10.2.6 Application of Taguchi Concepts in Maritime Safety Studies

This example is designed for illustration purposes to demonstrate that the Taguchi method is a potential tool for maritime engineering safety studies (Sii et al. (2001)).

Background information

The ship's safety is substantially affected by many factors including ship owner management quality, crew operation quality, enhanced survey programme, degree of machinery redundancy, fire-fighting capability, navigation equipment level, corrosion control and preventive maintenance policy. In order to identify the salient factors and interactions that cause excessive variations, a trial application of Taguchi methods is performed here to optimise each factor to attain the optimal safety for the ship.

Step 1: Define the problem

Various factors such as design features, ship owner management quality, crew operation quality, etc. have different degrees of influence on ship's overall safety performance throughout its life cycle. This will further be complicated when all these factors are evaluated simultaneously to obtain the optimised solution. The prime objective of this study is to identify the factors and their associated reasons for high risks and to suggest measures that would reduce the overall risk level of the ship.

Step 2: Identify factors and their interactions

Brainstorming technique is used to gather relevant information to determine factors affecting ship's safety. The resulting list of significant factors affecting ship safety is given in Table 10.9. These factors are determined based on the information acquired. In the eight factors, seven have three levels, and one has two levels. There is a significant interaction between two factors, namely, the ship owner management quality and enhanced survey programme. The risk level values between 1 to 50 are assigned to each factor at each level by experts. The higher the risk level value, the more risky the system. These risk level values do not represent any absolute or exact degree of risk encountered by the ship and they are used only for relatively indicative purposes. To facilitate further discussion, the factors are assigned alphabet-identifiers.

Step 3: Select an appropriate orthogonal array

In order to choose an appropriate array, degrees of freedom must be computed first. Given seven factors with three-levels, one factor with two-levels, and one interaction of a two-level and a three-level factor, the number of degrees of freedom for the experiment is computed to be 7(3-1) + 1(2-1) + (3-1)(2-1) + 1 = 18. Table 10.10 shows the experimental design for an *L18* array. In all, *18* treatments must be used for the experiment with the factor levels as shown. For this study, however, three levels of risk are used in Table 10.11 representing judgements made by three experts.

The assignment of factors to columns is accomplished as follows:

- Since factor *E* is a two-level factor, it is assigned to column 1.
- As factors *E* and *D* are deemed to have significant interaction in brainstorming sessions, factor *D* is assigned to column 2.
- Other factors are thereafter assigned to columns 3 to 8 arbitrarily – factor *A* to column 3, factor *B* to column 4, and so on as clearly depicted in Table 10.11.

Interaction is not assigned to any column, since it can be computed without loss of any information or confounding.

Step 4: Conduct experiments

Three sets of experiments are conducted for each treatment as dictated by the *L18* array of Table 10.10 where the risk levels are assigned by three experts. The results are shown in Table 10.11. Then, for each treatment *S/N-ratio* is calculated using the following formula:

$$S/N\text{-}ratio \text{ for } i^{th} \text{ treatment} = -10\log_{10}\left(\frac{1}{n}\sigma^2\right) = -10\log_{10}\left(\frac{1}{n}\right)\left(Y_{i1}^2 + Y_{i2}^2 + Y_{i3}^2\right)$$

where $Y_{ij}$, $j$=1, 2 or 3 is the $j^{th}$ response of the $i^{th}$ treatment representing judgements made by three experts. These values are normalised by subtracting -27 (the average of the *S/N*-ratio) from each *S/N-ratio*. The *S/N*-ratios and their normalised values are also shown in Table 10.11.

Step 5: Conduct Analysis of Variance (ANOVA) and Step 6: Identify significant factors and their interactions

Based on the normalised *S/N-ratios* data in Table 10.11, analysis of variance is conducted. As a first step, for each level of each factor, the main effect is computed.

Example: for factor *A*, Level 1, *main effect* = 6.64 – 3.93 - 6.6 + 0.81 - 5.19 - 3.2 = -11.47

Factor *A*, Level 2, *main effect* = 10.04 + 10.4 + 0.32 + 9.29 –5.75 –6.14 = 18.16

Factor *A*, Level 3, *main effect* = -0.49 + 2.88 – 3.28 - 0.84 + 3.95 - 2.01 = 0.21

The main effects of other factors are computed likewise. For computing the effect of interaction of factors *D* and *E*, all possible combinations *(*3×2 = 6*)* of *D* and *E* are considered.

| | | | | | | |
|---|---|---|---|---|---|---|
| Level of factor *D* | 1 | 2 | 3 | 1 | 2 | 3 |
| Level of factor *E* | 1 | 1 | 1 | 2 | 2 | 2 |
| Interaction level assigned: | 1 | 2 | 3 | 4 | 5 | 6 |

Thereafter, the effect of interaction is computed as an average of each level. Sum of squares for each main effect is computed using the standard methodology.

Calculation of *D×E* column:

$D_1E_1$ = 6.64 + 10.04 - 0.49 = 16.19

$D_2E_1$ = -3.93 + 10.4 + 2.88 = 9.35

$D_3E_1$ = -6.6 +0.32 –3.28 = -9.56

$D_1E_2$ = 0.81 + 9.29 - 0.84 = 9.26

$D_2E_2$ = -5.19 – 5.75 + 3.95 = -6.99

$D_3E_2$ = -3.2 –6.14 –2.01 = -11.35

Example: For the interaction of factors *D* and *E*, the formula used is slightly different since it has six levels. Specifically,

$S_T$ = Sum of square of all trial run results – *C.F.*

where $C.F. = T^2 / N$

$T = (Y_1 + Y_2 + Y_3 + \ldots Y_i)$

$i$ = number of trials or treatments

or $S_T = \left(Y_1^2 + Y_2^2 + \ldots Y_i^2\right) - \dfrac{\left(Y_1 + Y_2 + \ldots + Y_i\right)^2}{i}$

$S_T$ for $D \times E$ = $\{16.19^2 + 9.35^2 + (-9.56)^2 + 9.26^2 + (-6.39)^2 + (-11.35)^2\} - \{16.19 + 9.35 - 9.56 + 9.26 - 6.99 - 11.35\}^2 / 6 = 703.91 - 7.94 = 696.43$

$S_T$ for $A$ = $\{(-11.47)^2 + (18.16)^2 + (0.21)^2\} - (6.9)^2 / 3 = 445.52$

The main effects are shown in Table 10.12.

Then the table for ANOVA (analysis of variance) is ready to be developed. At the outset, a significance level of 0.05 or confidence level of 95% was set as the cut-off point for pooling an effect into error. The ANOVA table is developed as follows:

- The first column is simply the factor identifier.
- The second column is taken from Table 10.12, and is the sum of squares for each factor.
- The third column is developed by simply finding the percentage of each sum of square with respect to the total sum of squares of all factors and interaction.
- The fourth column lists the degree of freedom for each factor.
- The fifth column lists the variance for each factor. The variance values are computed by dividing sum of squares by degree of freedom of each factor.
- The sixth column tries to pool in error. In an attempt to find factors that can be pooled in the error, as a first step, all factors that contributed less than 2.5% to the overall sum of squares are pooled into the error term.
- The seventh column shows the $F$-values. Each $F$-value is the variance ratio which is computed by dividing the variance of the factor by the error variance.

  $F_A = V_A / V_e$

  where:

  $F_A$ = $F$-value for factor $A$

  $V_A$ = variance for factor $A$

  $V_e$ = variance for error terms.

  In this case $V_e$ = *sum of squares for* factors *B, C and G* = 2.27 + 1.49 + 0.72 = 4.48

Since factors *B, C* and *G* contribute less than 2.5% to the overall sum of squares, they are pooled into the error term.

$F$-value *for* factor $A$ = 222.76 / 4.48 = 49.72

As shown in Table 10.13, this results in an $F$-value of 10.03 for factor $B$, 6.61 for factor $C$ and 3.16 for factor $G$, which are not significant enough to be considered as independent main effects, based on our significance confidence level of 95%. Thus, factors *C, B* and *G* are pooled into the error term. They are found insignificant and the variations arising from these constituted the error variations. These $F$-values were compared against the $F$-values provided

for 5% significance in appropriate *F* distribution tables (Roy (1990)). The effect of factors *A*, *B*, *D*, *E*, *F*, *H* and the interaction of factors of *D×E* is found significant at 99.5% confidence levels.

Non-linearity analysis

It is determined to investigate the non-linearity of these factors since most factors are at three levels. An investigation of the non-linearity of the *S/N*-ratio with respect to factor levels is carried out to identify the optimal combination of factor levels. Firstly, the average values of the main effects are computed for each factor as can be seen in Table 10.14. For factor *A*, for instance, the average value at three levels is computed as follows:

The total value of *S/N*-ratio when factor A at level 1 = -11.47 (refer to Table 10.11). Hence, the average value of *S/N*-ratio of factor *A* at level 1 = (-11.47 / 6 + 27) = 25.09, where 27 is added back which was originally subtracted in Table 10.11. Division by 6 is simply due to the fact that there are six terms containing factor *A* at level 1.

The other values for factor *A* at levels 2 and 3 are computed in a similar way. The same procedure yielded the rest of the main effects and interaction effects shown in Table 10.14. The upper and lower confidence levels of 1.99 are calculated in Step 7.

Step 7: Find the optimal combination of factor levels to minimise system risk level

Based on Tables 10.12 and 10.14, the non-linearity graphs for each of the factors (except factor E which has two levels and hence is not subject to non-linearity investigation) and interaction are developed. These are shown in Figures 10.7 to 10.15. The combination that yields the largest value of *S/N*-ratio is determined from these graphs to be as follows:

| Factor | *A* | *B* | *C* | *D* | *E* | *F* | *G* | *H* | *D×E* |
|---|---|---|---|---|---|---|---|---|---|
| Optimal level | 2 | 1 | 2 | 1 | 1 | 3 | 2 | 1 | 1 |

Thus, $A_2$, $B_1$, $C_2$, $D_1$, $E_1$, $F_3$, $G_2$ and $H_1$ provide the best combination for the lowest possible risk level for the whole system. Keeping in mind that factors *C* and *G* are not significant, the management must keep factors *A*, *B*, *D*, *E*, *F* and *H* at the optimal levels in order to reduce risk level of the ship to the maximum extent.

Confidence Intervals

Finally, to get an idea about the current variability of each factor, confidence intervals are computed. These are also shown in Table 10.14. The following procedure is used to develop the intervals (Roy (1990)):

Upper confidence level = *Mean* + *CI*

Lower confidence level = *Mean* – *CI*

$$CI = \sqrt{\frac{FxV_e}{N_e}}$$

Thus, for factors *A, B, C, D, E, F, G* and *H*,

$$CI = \sqrt{\frac{5.32x4.48}{6}} = 1.99$$

The CI for interaction *D×E*:

$$CI = \sqrt{\frac{5.32x4.48}{3}} = 2.82$$

These confidence intervals are reflected in Table 10.14.

Step 8: Recommend for implementation

As a result of the above study, the following changes are recommended in the design, operation and management system:

- Average level of preventative maintenance policy should be adopted. Factor $A_2$ is made operative.
- High degree of machinery redundancy is recommended. Factor $B_1$ is more preferable.
- Average fire-fighting capability is adequate for the system. Factor $C_2$ is selected.
- Ship owner management quality should be high. Factor $D_1$ is strongly urged.
- Enhanced survey programme should be adopted. Factor $E_1$ is strongly urged.
- Low navigation equipment is adequate. Factor $F_3$ is selected.
- Average corrosion control is recommended. Factor $G_2$ is selected.
- Competent crew operation quality is essential. Factor $H_1$ is strongly recommended.

### 10.2.7 Conclusion

This Section has introduced the Taguchi philosophy to maritime safety engineering. It provides a basic understanding and skill in utilising the Taguchi concepts and methodologies in safety related applications. A safety optimisation framework using Taguchi concepts is described and an application example is used to demonstrate how Taguchi concepts can be used to improve safety performance of a ship throughout its life-cycle via optimising its design features, operational characteristics and ship owner management quality. The results of this study show that the Taguchi methods, which have been employed for improving manufacturing processes, may provide an alternative tool for risk analysis in maritime safety engineering.

## 10.3 A Multiple Criteria Decision Making Approach

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### 10.3.1 Introduction

Safety and cost are among the most important objectives that need to be considered in the design and operational processes of a large maritime engineering system. Formal multiple criteria decision making techniques including Multiple-Attribute Utility Analysis (MAUA) may be used to generate the best compromise compromise designs. Many multiple criteria decision making techniques need to be investigated in detail for their appropriate application in a practical environment. The theme of this section is to examine several multiple criteria decision analysis methods using examples for demonstrating their application in safety and cost synthesis.

### 10.3.2 Safety and Cost Modelling

#### 10.3.2.1 Safety Modelling

Safety synthesis of an engineering system is usually conducted by aggregating safety assessments for its sub-systems, components and failure modes. A safety assessment framework may constitute a hierarchical structure with failure modes at the bottom level (Wang et al. (1996)). A failure mode could be described in several ways, for example in terms of failure likelihood, consequence severity and failure consequence probability using linguistic variables. This is a natural and sensible way for capturing ambiguity and uncertainty inherent in safety assessment.

Fuzzy sets are well suited to characterizing linguistic variables by fuzzy memberships to the defined categories for a particular situation. Failure likelihood, consequence severity and failure consequence probability could all be characterised using the same set of categories but different membership functions. In this way, the safety associated with a failure mode may also be modelled using fuzzy sets.

For example, the fuzzy safety description (*S*) associated with a failure mode can be defined as the following product of the fuzzy sets of the related failure likelihood (*L*), consequence severity (*C*) and failure consequence probability (*E*) (Wang et al. (1995, 1996)):

$$S = C \circ E \times L$$

where the symbol "$\circ$" represents the composition operation and "$\times$" the Cartesian product operation in fuzzy set theory. If seven categories are used to describe fuzzy sets, the above product could generate the safety description of the failure mode as a fuzzy set as follows:

$$S = [\mu_1/1,\ \mu_2/2,\ \mu_3/3,\ \mu_4/4,\ \mu_5/5,\ \mu_6/6,\ \mu_7/7]$$

where $\mu_i$ denotes the membership degree of the failure mode to the *i*th category.

Similar fuzzy sets could be generated for describing the safety of other failure modes, which could be aggregated using conventional fuzzy operations to generate safety descriptions for the components, the subsystems and the whole system of the assessment hierarchy. However, this process may lead to information loss.

Alternatively, safety could be more clearly expressed and communicated using linguistic variables (or assessment grades) such as "*Poor*", "*Average*", "*Good*" and "*Excellent*". Such assessment grades could be defined as distinctive safety standards on the basis of safety guidelines, regulations, laws and other situations specific to the engineering system in question. If the above four linguistic variables are used, then the safety of a failure mode could be described using the following expectation or distribution:

$$S = \{(\beta_1, Poor), (\beta_2, Average),\ (\beta_3, Good), (\beta_4, Excellent)\}$$

where $\beta_j$ denotes the degree of belief that the safety of the failure mode should be assessed to the *j*th assessment grade. A safety distribution provides a panoramic view about the safety status of a failure mode, component, subsystem or the whole system. It can be used to identify areas for improvement and to simulate action plans to improve safety. $\beta_j$ could be generated using various ways, for example by analysing historical data using statistical approaches if such data is available; otherwise expert judgements could be used to estimate $\beta_j$. If

assessment grades are initially defined as fuzzy sets, then $\beta_j$ could be generated from the fuzzy safety description using the best-fit method as described by (Wang et al. (1995)).

There are other ways to describe safety. The simplest approach would be to use a scale for scoring the safety of a failure mode. While this may be easy for safety aggregation to produce an average indicator about system safety, it could not capture uncertainty inherent in safety assessment and thereby the credibility of such assessment may become questionable. Unfortunately, several well known multiple criteria decision analysis methods, which could be used for safety synthesis, can only be implemented using certain types of scores. This will be discussed in detail in the next section.

### 10.3.2.2 Cost Modelling

Safety is closely related to cost. Although safety must have paramount importance over cost in most situations, there are cases where safety standards are already achieved and cost effectiveness needs to be given more attention. In such cases, cost should be analysed in conjunction with safety. Costs can be modelled using the methods discussed in Section 10.3.2.1. Costs related to safety improvement are usually affected by a number of factors (Wang et al. (1996)), including

a. Costs for the provision of redundancies of critical components, the provision of protection systems and alarm systems to reduce or eliminate the probabilities of occurrence of undesirable events, and the use of more reliable components.

b. Costs of labour incurred in redesign of the system.

c. Benefits resulting from the likelihood reduction of undesirable events and the improvement of system efficiency as a result of the improvement of system safety.

Ideally, costs could be estimated using precise numerical figures so that conventional methods could be applied to analyse costs together with safety. However, this is often not achievable due to the high uncertainty in estimation of safety related costs. Fuzzy sets provide an alternative way to model costs. For example, costs could be described using linguistic variables such as "*Very low*", "*Low*", "*Moderately low*", "*Average*", "*Moderately high*", "*High*" and "*Very high*". If the seven categories are used to describe fuzzy sets, a fuzzy cost description can be represented as $C = [\gamma_1/1,\ \gamma_2/2,\ \gamma_3/3,\ \gamma_4/4,\ \gamma_5/5,\ \gamma_6/6,\ \gamma_7/7]$ where $\gamma_i$ is the membership degree of the cost to the *i*th category.

Alternatively, costs could be clearly described using expectations or distributions to indicate to what degrees costs are preferred, for example using linguistic variables (or assessment grades) such as "*Slightly preferred*", "*Moderately preferred*", "*Preferred*" and "*Greatly preferred*". Such an assessment grade could be defined as a clear cost threshold that an organisation determines for a specific situation. If the above four linguistic variables are used, then the cost of a design option could be described using the following expectation or distribution

$$C = \{(\beta_1, \textit{Slightly preferred}), (\beta_2, \textit{Moderately preferred}),$$
$$(\beta_3,\ \textit{preferred}), (\beta_4, \textit{Greatly preferred})\}$$

where $\beta_j$ denotes the degree of belief that the cost of the design option should be assessed to the *j*th assessment grade. A cost distribution provides a range of possible financial

consequences with different probabilities, which may be incurred in order to develop and adopt the design option. As discussed before, $\beta_j$ could be generated using various ways, either statistically or subjectively.

### 10.3.3.3 Safety and Cost Modelling – an Example

In safety modelling, the safety associated with a failure mode of a component may be judged by multiple designers. A diagram for synthesis of the safety for a failure mode is shown in Figure 10.16. Suppose there are *e* designers, each of whom is given a relative weight in the design selection process. The designers' judgements can be aggregated to generate assessments on the safety of failure modes, which can in turn be aggregated to produce assessments for component safety. Assessments for component safety can eventually be aggregated to generate an assessment for system safety using various methods such as those to be investigated in the next section.

In cost modelling, the cost incurred for each design option can also be judged by *e* designers. These judgements can be aggregated to generate an assessment for a design option using various methods such as those to be investigated in the next section. A diagram for synthesis of costs incurred for design options by multiple designers is shown in Figure 10.17.

In this section, safety and cost modelling is discussed for an engineering system in order to demonstrate the multiple criteria decision analysis methods in the next section. Consider a hydraulic hoist transmission system of a marine crane (Wang et al. (1995, 1996)), which is used to control the crane motions such as hoisting down loads as required by the operator. It consists of five subsystems: the hydraulic oil tank, the auxiliary system, the control system, the protection system and the hydraulic servo transmission system. Suppose there are four options for selection by four designers. The safety modelling and cost modelling of the four design options are described as follows using expectations or distributions. To simplify discussion and without loss of generality, the same set of evaluation grades are used to model both safety and cost, that is "*Slightly preferred*", "*Moderately preferred*", "*Preferred*" and "*Greatly preferred*". More detailed discussions about safety and cost modelling can be found in (Wang et al. (1996)).

**Option 1**: No failure mode is eliminated in the design review process.

For this first design option, suppose the safety assessments provided by the four designers are the same and are represented as the following expectation:

$$
\begin{aligned}
S_1^1 = S_1^2 = S_1^3 = S_1^4 \\
= \{&(0.122425,\ \textit{Slightly preferred}),\\
&(0.180205,\ \textit{Modertaely preferred}),\\
&(0.463370,\ \textit{Preferred}),\\
&(0.233999,\ \textit{Greatly preferred})\}
\end{aligned}
$$

For this option, there is no additional cost for eliminating failure modes. Suppose the four designers judge the cost incurred for this option as follows:

$$
\begin{aligned}
C_1^1 = C_1^2 = C_1^3 = C_1^4 \\
&= \{(0,\ \textit{Slightly preferred}), \\
&\quad (0,\ \textit{Modertaely preferred}), \\
&\quad (0,\ \textit{Preferred}), \\
&\quad (1,\ \textit{Greatly preferred})\}
\end{aligned}
$$

**Option 2**: Eliminate "hoist up limit failure" and "hoist down limit failure" associated with the protection system.

For this second design option, suppose the safety assessments provided by the four designers are represented as follows:

$$
\begin{aligned}
S_2^1 = S_2^2 = S_2^3 = S_2^4 \\
&= \{(0.102676,\ \textit{Slightly preferred}), \\
&\quad (0.156934,\ \textit{Modertaely preferred}), \\
&\quad (0.38486,\ \textit{Preferred}), \\
&\quad (0.355531,\ \textit{Greatly preferred})\}
\end{aligned}
$$

Suppose the four designers have different opinions about the costs incurred to eliminate the failure modes and their individual assessments are given as follows:

$$
\begin{aligned}
C_2^1 = \{&(0.054309,\ \textit{Slightly preferred}), \\
&(0.066442,\ \textit{Modertaely preferred}), \\
&(0.821848,\ \textit{Preferred}), \\
&(0.057400,\ \textit{Greatly preferred})\}
\end{aligned}
$$

$$
\begin{aligned}
C_2^2 = \{&(0.102638,\ \textit{Slightly preferred}), \\
&(0.134831,\ \textit{Modertaely preferred}), \\
&(0.657202,\ \textit{Preferred}), \\
&(0.105330,\ \textit{Greatly preferred})\}
\end{aligned}
$$

$$
\begin{aligned}
C_2^3 = \{&(0,\ \textit{Slightly preferred}), \\
&(0,\ \textit{Modertaely preferred}), \\
&(1,\ \textit{Preferred}), \\
&(0,\ \textit{Greatly preferred})\}
\end{aligned}
$$

$$
\begin{aligned}
C_2^4 = \{&(0.067060,\ \textit{Slightly preferred}), \\
&(0.083011,\ \textit{Modertaely preferred}), \\
&(0.777240,\ \textit{Preferred}), \\
&(0.072689,\ \textit{Greatly preferred})\}
\end{aligned}
$$

**Option 3**: Eliminate the failure modes involving "major leak" and "no output from the package motor" associated with the hydraulic servo transmission system.

For the third design option, suppose the safety assessments provided by the four designers are represented as follows:

$$
\begin{aligned}
S_3^1 = S_3^2 = S_3^3 = S_3^4 \\
= \{&(0.022722,\ \textit{Slightly preferred}),\\
&(0.033659,\ \textit{Modertaely preferred}),\\
&(0.073367,\ \textit{Preferred}),\\
&(0.870253,\ \textit{Greatly preferred})\}
\end{aligned}
$$

Suppose the four designers' individual cost assessments are given as follows:

$$
\begin{aligned}
C_3^1 = \{&(0.067604,\ \textit{Slightly preferred}),\\
&(0.084062,\ \textit{Modertaely preferred}),\\
&(0.777037,\ \textit{Preferred}),\\
&(0.071297,\ \textit{Greatly preferred})\}
\end{aligned}
$$

$$
\begin{aligned}
C_3^2 = \{&(0.102638,\ \textit{Slightly preferred}),\\
&(0.134831,\ \textit{Modertaely preferred}),\\
&(0.657202,\ \textit{Preferred}),\\
&(0.105330,\ \textit{Greatly preferred})\}
\end{aligned}
$$

$$
\begin{aligned}
C_3^3 = \{&(0.067060,\ \textit{Slightly preferred}),\\
&(0.083011,\ \textit{Modertaely preferred}),\\
&(0.777240,\ \textit{Preferred}),\\
&(0.072689,\ \textit{Greatly preferred})\}
\end{aligned}
$$

$$
\begin{aligned}
C_3^4 = \{&(0.067060,\ \textit{Slightly preferred}),\\
&(0.083011,\ \textit{Modertaely preferred}),\\
&(0.777240,\ \textit{Preferred}),\\
&(0.072689,\ \textit{Greatly preferred})\}
\end{aligned}
$$

**Option 4**: Eliminate the two failure modes associated with the protection system in design option 2 and the two failure modes associated with the hydraulic servo transmission system in design option 3.

For the fourth design option, the safety assessments provided by the four designers are given by:

$$
\begin{aligned}
S_4^1 = S_4^2 = S_4^3 = S_4^4 \\
= \{&(0.013049,\ \textit{Slightly preferred}),\\
&(0.019045,\ \textit{Modertaely preferred}),\\
&(0.035897,\ \textit{Preferred}),\\
&(0.932027,\ \textit{Greatly preferred})\}
\end{aligned}
$$

The four designers' individual cost assessments are given as follows:

$$
\begin{aligned}
C_4^1 = \{&(0.059846,\ \textit{Slightly preferred}),\\
&(0.822751,\ \textit{Modertaely preferred}),\\
&(0.062553,\ \textit{Preferred}),\\
&(0.054850,\ \textit{Greatly preferred})\}
\end{aligned}
$$

$$
\begin{aligned}
C_4^2 = \{&(0.028571,\ \textit{Slightly preferred}),\\
&(0.912923,\ \textit{Modertaely preferred}),\\
&(0.031480,\ \textit{Preferred}),\\
&(0.027027,\ \textit{Greatly preferred})\}
\end{aligned}
$$

$$
\begin{aligned}
C_4^3 = \{&(0.057708,\ \textit{Slightly preferred}),\\
&(0.826250,\ \textit{Modertaely preferred}),\\
&(0.062819,\ \textit{Preferred}),\\
&(0.053223,\ \textit{Greatly preferred})\}
\end{aligned}
$$

$$
\begin{aligned}
C_4^4 = \{&(0,\ \textit{Slightly preferred}),\\
&(1,\ \textit{Modertaely preferred}),\\
&(0,\ \textit{Preferred}),\\
&(0,\ \textit{Greatly preferred})\}
\end{aligned}
$$

### 10.3.3 Safety and Cost Synthesis Using Typical Multiple Criteria Decision Analysis (MCDA) Methods

Once safety and cost are assessed for a design option, there is a need to combine the assessments to provide an overall assessment for the option and eventually rank it against others. Several methods could be used in such a synthesis process. In this section, three methods are discussed and compared in dealing with the example presented in Section 10.3.2, including the additive utility function approach, the analytical hierarchy process (AHP) approach and the evidential reasoning approach. The assessment hierarchy for the example is shown in Figure 10.18.

Let $\omega_S$ and $\omega_C$ denote the relative weights of safety and cost, and $\omega_1$, $\omega_2$, $\omega_3$, $\omega_4$ the relative weights of the opinions of designers 1, 2, 3 and 4, respectively. For demonstration purpose, suppose safety is twice as important as cost and the opinions of designers 2 and 3 are twice as important as those given by designers 1 and 4 (i.e. $\omega_S = 2\omega_C$ and $\omega_2 = \omega_3 = 2\omega_1 = 2\omega_4$). Suppose the relative weights of the same group of criteria are normalised so that they are

added to one. Then, we have $\omega_S$ = 0.6667, $\omega_C$ = 0.3333; and $\omega_2 = \omega_3$ = 0.3333, $\omega_1 = \omega_4$ = 0.1667. It should be noted that a range of weights could be assigned to test the robustness of the assessments generated.

### 10.3.3.1 Additive Utility Function Approach

Before this method can be applied, each assessment of a design option on either safety or cost given by a designer must be quantified using for example a score. Since an assessment in the example is represented as an expectation using the four evaluation grades, we need to quantify the grades first for example by using a scale or estimating the utilities of the grades (Winston (1994)). Suppose the utilities of the four evaluation grades are given as follows (Wang et al. (1996)):

$$u(\textit{Slightly preferred}) = 0.217$$

$$u(\textit{Moderately preferred}) = 0.478$$

$$u(\textit{preferred}) = 0.739$$

$$u(\textit{Greatly preferred}) = 1$$

Then the scores of the four options on both safety and cost for each designer can be calculated as the following weighted average scores of the expectations with the degrees of belief used as weights:

***Option 1***

$u_1$(*safety*/*designer* 1) = $u_1$(*safety*/*designer* 2)

= $u_1$(*safety*/*designer* 3) = $u_1$(*safety*/*designer* 4)

$= 0.122425 \times 0.217 + 0.180205 \times 0.478 + 0.46337 \times 0.739 + 0.233999 \times 1$

= 0.6891

$u_1$(*cost*/*designer* 1) = $u_1$(*cost*/*designer* 2) =

$u_1$(*cost*/*designer* 3) = $u_1$(*cost*/*designer* 4)

$= 0 \times 0.217 + 0 \times 0.478 + 0 \times 0.739 + 1 \times 1 = 1$

***Option 2***

$u_2$(*safety*/*designer* 1) = $u_2$(*safety*/*designer* 2)

= $u_2$(*safety*/*designer* 3) = $u_2$(*safety*/*designer* 4)

$= 0.102676 \times 0.217 + 0.156934 \times 0.478 + 0.38486 \times 0.739 + 0.355531 \times 1$

= 0.7372

$u_2$(*cost*/*designer* 1)

$= 0.054309 \times 0.217 + 0.066442 \times 0.478 + 0.821848 \times 0.739 + 0.0574 \times 1$

= 0.7083

$u_2$(*cost*/*designer* 2) = 0.6777

$u_2$(*cost*/*designer* 3) = 0.7390

$u_2$(*cost*/*designer* 4) = 0.7013

***Option 3***

$u_3$(*safety*/*designer* 1) = $u_3$(*safety*/*designer* 2)

= $u_3$(*safety*/*designer* 3) = $u_3$(*safety*/*designer* 4)

$= 0.022722 \times 0.217 + 0.033659 \times 0.478 + 0.073367 \times 0.739 + 0.870253 \times 1$

= 0.9455

$u_3$(*cost*/*designer* 1)

$= 0.067604 \times 0.217 + 0.084062 \times 0.478 + 0.777037 \times 0.739 + 0.071297 \times 1$

= 0.7004

$u_3$(*cost*/*designer* 2) = 0.6777

$u_3$(*cost*/*designer* 3) = 0.7013

$u_3$(*cost*/*designer* 4) = 0.7013

***Option 4***

$u_4$(*safety*/*designer* 1) = $u_4$(*safety*/*designer* 2)

= $u_4$(*safety*/*designer* 3) = $u_4$(*safety*/*designer* 4)

$= 0.013049 \times 0.217 + 0.019045 \times 0.478 + 0.035897 \times 0.739 + 0.932027 \times 1$

= 0.9705

$u_4$(*cost*/*designer* 1)

$= 0.059846 \times 0.217 + 0.822751 \times 0.478 + 0.062553 \times 0.739 + 0.05485 \times 1$

= 0.5073

$u_3$(*cost*/*designer* 2) = 0.4929

$u_3$(*cost*/*designer* 3) = 0.5071

$u_3$(*cost*/*designer* 4) = 0.4780

***Assessment of Design Options***

The above scores show the average assessments of the four design options on both safety and cost provided by the four designers. Note that the four designers provided the same average assessment for each design option on safety. The additive utility function approach operates on average scores, as summarised in a decision matrix shown in Table 10.15.

One way to synthesize the assessments is to generate an overall weight for the cost provided by every designer. For example, the overall weight for the cost provided by designer 1 can be calculated as $0.3333 \times 0.1667 = 0.0556$. The overall weight multiplied by a score results in a weighted score. For example, the weighted score for the safety of design option 1 is given by $0.6667 \times 0.6891 = 0.4594$ and that for the cost of design option 1 provided by designer 1 is given by $0.3333 \times 0.1667 \times 1 = 0.0556$. All the other weighted scores are shown in Table 10.16.

In the additive utility (value in this case) function approach, the weighted scores on the safety and cost attributes are added up for an option, resulting in an overall score for the option. For example, the overall score for option 1 is given by:

$$u(\text{option 1}) = 0.4594 + 0.0556 + 0.1111 + 0.1111 + 0.0556 = 0.7928.$$

Similarly, the overall scores of the other three options are given by

$$u(\text{option 2}) = 0.7273,\ u(\text{option 3}) = 0.8615,\ u(\text{option 4}) = 0.8129.$$

The ranking of the four design options is then given on the basis of the magnitude of their overall scores as follows:

$$\text{option 3} \succ \text{option 4} \succ \text{option 1} \succ \text{option 2}$$

The additive utility (value) function approach provides a simple process for criteria aggregation. To use the method properly, however, one should be aware of its limits and drawbacks. Despite the loss of the original features and diversity of the distributed assessments given in Section 10.3.2.3, this approach assumes preference independence, a linear utility function for each criterion, and direct and proportional compensation among criteria. These assumptions are not always acceptable. For example, a linear utility function implies that the decision maker is neutral to risk. In many decision situations, however, decision makers are often averse to risk. This is particularly the case when safety is assessed. Preference independence means that tradeoffs between two criteria are independent of other criteria. While this is not easy to test, it is not appropriate to assume that this is always satisfied.

### 10.3.3.2 AHP

AHP is another method that can be used to deal with MCDA problems. AHP is based on the eigenvector method that is usually applied to estimating relative weights of criteria by means of pairwise comparisons. The basic theory on AHP has been described in Chapter 9. In this Chapter, some extra descriptions and discussions of this method are given in order to solve the above design selection problem.

Since it is already assumed that safety is twice as important as cost in selection of design options, a pairwise comparison matrix can be constructed as in Table 10.17, where the element "2" in the second row of the last column means that safety is twice as important as cost.

In AHP, the normalised right eigenvector of the pairwise comparison matrix with respect to its largest eigenvalue is employed as the weights of safety and cost. Suppose $A$ represents the pairwise comparison matrix, or

$$A = \begin{bmatrix} 1 & 2 \\ 1/2 & 1 \end{bmatrix}$$

$W$ a weight vector or $W = [\omega_s \quad \omega_c]^{\mathrm{T}}$, and $\lambda_{\max}$ the maximum eigenvalue of the matrix $A$. Then, $W$ is calculated using the following equation:

$$AW = W\lambda_{\max}$$

There are software packages that can be used to solve the above vector equation to find $W$ (Saaty (1988)). An approximate solution procedure can be found in (Sen and Yang (1998)), as summarised below.

Step 1: Provide an initially normalised vector $W^0 = [1 \ 0 \ \cdots \ 0]^T$ and let $t = 0$.

Step 2: Calculate a new eigenvector as follows:

$$W^{t+1} = AW^t$$

Step 3: Calculate the maximum eigenvalue by:

$$\lambda_{\max} = \sum_{i=1}^{n} w^{t+1}$$

Step 4: Normalise and update the eigenvector as follows:

$$\overline{w}^{t+1} = \frac{w^{t+1}}{\lambda_{\max}}, \text{ and let } w^{t+1} = \overline{w}^{t+1} \text{ for all } i=1, \ldots, n$$

Step 5: Calculate the error between the old and new eigenvectors and then check if

$$\left| w^{t+1} - w^t \right| \le \delta \text{ for all } i=1, \ldots, n$$

where $\delta$ is a small non-negative real number (say $\delta = 1.0 \times 10^{-6}$). If the condition is satisfied, go to step 6. Otherwise, let $t=t+1$ and go to Step 2.

Step 6: Calculate the consistency index ($CI$) as follows:

$$CI = \frac{\lambda_{\max} - n}{n-1}$$

If $CI \le 0.1$, the pairwise comparisons provided in the matrix $A$ are satisfactorily consistent. Otherwise, the comparisons need to be revised.

Applying the above procedure to solve the eigenvector equation ($n$ = 2) leads to the following results:

$$W = [\omega_s \ \omega_c] = [0.6667 \ \ 0.3333]$$

In the above pairwise comparison matrix, the weights between safety and cost are already made clear. Generally, if pairwise comparisons are provided for three or more criteria, they may not be completely consistent and as such it is not straightforward to obtain relative weights of criteria from the comparisons. The AHP method and several other methods can be used to generate weights using pairwise comparisons. For example, suppose the pairwise comparison matrix is provided for the importance of the opinions of the four designers, as shown in Table 10.18

A pairwise comparison matrix $A = (a_{ij})_{n \times n}$ is completely consistent if $a_{ij} = a_{ik} a_{kj}$ for all $i, j, k = 1, \ldots, n$ where $n$ is the dimension of the matrix. It is easy to show that the comparison matrix

of Table 10.18 is completely consistent. Using the above procedure, the normalised eigenvector of the matrix is given by

$$W = [\omega_1 \quad \omega_2 \quad \omega_3 \quad \omega_4] = [0.1667 \quad 0.3333 \quad 0.3333 \quad 0.1667]$$

To use AHP for ranking design options, one also needs to compare them in a pairwise fashion with respect to each criterion. This may not be an easy task in general. Given the assessment data as in Table 10.15, however, a pairwise comparison matrix can be constructed for each criterion (Huang and Yoon (1981)). With respect to safety, for example, the four design options can be compared as in Table 10.19.

A number in Table 10.19 denotes the extent to which one option is more attractive than another. For example, the number "1.4085" in the second column of the last row means that option 4 is 1.4085 times as attractive as option 1 in terms of safety. It can be seen from Table 10.19 that the differences between the four design options are quite small and this would make it difficult to provide direct pairwise comparisons between the options without reference to the assessment data shown in Table 10.15.

In AHP, the scores of the four design options in terms of safety are generated, using the above solution procedure, as the eigenvector of the pairwise comparison matrix with respect to its largest eigenvalue, as shown in Table 10.20.

In a similar way, the pairwise comparison matrices of the cost criteria for the four designers can be generated, as shown in Tables 10.21 to 10.24.

The scores of the four design options in terms of cost for the four designers can also be generated by identifying the eigenvectors of the matrices in Tables 10.21 to 10.24 with respect to their respective largest eigenvalues, as shown in Table 10.25.

In AHP, different ways are suggested to aggregate the scores generated from the pairwise comparisons (Saaty (1988)). One way is to use the simple weighting approach for aggregation from one criteria level to another (Huang and Yoon (1981)). Firstly, aggregate the cost scores of the four designers by multiplying each score with the relevant weight and then adding up the weighted scores for each option, which leads to an aggregated cost score for each option, as shown in Table 10.26. Finally, the safety score and the cost score for an option are multiplied by their weights and then added up to generate an overall score for the option, as shown in Table 10.27.

Based on the overall scores of Table 10.27, the ranking of the four design options are given as follows:

**Deleted:** 28

$$\text{option } 3 \succ \text{ option } 1 \succ \text{ option } 4 \succ \text{ option } 2$$

This ranking is different from that generated using the additive utility function approach in that the positions of option 1 and option 4 are swapped. In fact, the AHP method does not significantly differentiate the two options, as the difference between the overall scores of the two options is very small. AHP is usually applied to generating relative weights. However, the use of AHP to assess design options may lead to problems like rank reversal (Belton (1986), Islei and Lockett (1988), Stewart (1992), Barzilai (1997)), that is, the introduction of new options for assessment may cause the unexpected and irrational change of the ranking of the current options.

### 10.3.3.3 The Evidential Reasoning Approach

The evidential reasoning (ER) approach can be used to deal with multiple criteria decision analysis problems of both a quantitative and qualitative nature with uncertainty (Yang and Singh (1994), Yang and Sen (1994), Yang (2001)). It can process several types of information within an ER framework. The ER framework is different from most conventional MCDA modelling frameworks in that it employs a belief structure to represent an assessment as a distribution. In Section 10.3.2.3, four evaluation grades were defined as follows:

$$\begin{aligned} H &= \{H_1,\ H_2,\ H_3,\ H_4\} \\ &= \{\textit{Slightly preferred},\ \ \textit{Modertaely preferred},\ \textit{Preferred},\ \textit{Greatly preferred}\} \end{aligned}$$

Using the four evaluation grades, the assessment of an attribute $A_1$ on option $O_1$, denoted by $S(A_1(O_1))$, can be represented using the following belief structure:

$$S(A_1(O_1)) = \{(H_1, \beta_{1,1}), (H_2, \beta_{2,1}), (H_3, \beta_{3,1}), (H_4, \beta_{4,1})\}$$ -- (Please note changes have been made to this equation)

where $1 \geq \beta_{n,1} \geq 0$ ($n$ = 1, …, 4) denotes the degree of belief that the attribute $A_1$ is assessed to the evaluation grade $H_n$. $S(A_1(O_1))$ reads that the attribute $A_1$ is assessed to the grade $H_n$ to a degree of $\beta_{n,1} \times 100\%$ ($n$ = 1, …, 4) for option $O_1$.

There must not be $\sum_{n=1}^{4} \beta_{n,1} > 1$. $S(A_1(O_1))$ can be considered to be a complete distributed assessment if $\sum_{n=1}^{4} \beta_{n,1} = 1$ and an incomplete assessment if $\sum_{n=1}^{4} \beta_{n,1} < 1$. In the ER framework, both complete and incomplete assessments can be accommodated (Yang (2001)).

In the ER framework, a MCDA problem with $M$ attributes $A_i$ ($i$ = 1, …, $M$), $K$ options $O_j$ ($j$ = 1, …, $K$) and $N$ evaluation grades $H_n$ ($n$ = 1, …, $N$) for each attribute is represented using an extended decision matrix with $S(A_i(O_j))$ as its element at the $i$th row and $j$th column where $S(A_i(O_j))$ is given as follows:

$$S(A_i(O_j)) = \{(H_n, \beta_{n,i}(O_j)),\ \ n = 1, \cdots, N\} \quad i = 1, \ldots, M, \quad j = 1, \ldots, K$$

It should be noted that an attribute can have its own set of evaluation grades that may be different from those of other attributes (Yang (2000)).

Instead of aggregating average scores, the ER approach employs an evidential reasoning algorithm developed on the basis of the evidence combination rule of the Dempster-Shafer theory to aggregate belief degrees (Yang and Singh (1994), Yang and Sen (1994), Yang (2001)). Thus, the ER approach is different from traditional MCDA approaches, most of which aggregate average scores.

**Deleted:** scaling grades are not necessary for aggregating attributes in

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Suppose $\omega_i$ is the relative weight of the attribute $A_i$ and is normalised so that $1 \geq \omega_i \geq 0$ and $\sum_{i=1}^{L} \omega_i = 1$ where $L$ is the total number of attributes in the same group for aggregation. To simplify the discussion, only the combination of complete assessments is examined. The description of the recursive ER algorithm capable of aggregating both complete and incomplete assessments is detailed in (Yang and Sen (1994), Yang (2001)). Without loss of

generality and for illustration purpose, the ER algorithm is presented below for combining two assessments only.

Suppose the second assessment $S(A_2(O_1))$ is given by

$$S(A_2(O_1)) = \{(H_1, \beta_{1,2}), (H_2, \beta_{2,2}), (H_3, \beta_{3,2}), (H_4, \beta_{4,2})\}$$

The problem is to aggregate the two assessments $S(A_1(O_1))$ and $S(A_2(O_1))$ to generate a combined assessment $S(A_1(O_1)) \oplus S(A_2(O_1))$. Suppose $S(A_1(O_1))$ and $S(A_2(O_1))$ are both complete. Let

$$m_{n,1} = \omega_1 \beta_{n,1} \ (n = 1, \ldots, 4) \text{ and } m_{H,1} = 1 - \omega_1 \sum_{n=1}^{4} \beta_{n,1} = 1 - \omega_1$$

$$m_{n,2} = \omega_2 \beta_{n,2} \ (n = 1, \ldots, 4) \text{ and } m_{H,2} = 1 - \omega_2 \sum_{n=1}^{4} \beta_{n,2} = 1 - \omega_2$$

where each $m_{n,j}$ ($j$ = 1, 2) is referred to as basic probability mass and each $m_{H,j}$ is the remaining belief unassigned to $H_j$ ($j$ = 1, 2, 3, 4).

The ER algorithm is used to aggregate the basic probability masses to generate combined probability masses, denoted by $m_n$ ($n$=1, …, 4) and $m_H$ using the following equations:

$$m_n = k(m_{n,1} m_{n,2} + m_{H,1} m_{n,2} + m_{n,1} m_{H,2}), \qquad (n = 1, \ldots, 4)$$

$$m_H = k(m_{H,1} m_{H,2})$$

where

$$k = \left( 1 - \sum_{t=1}^{4} \sum_{\substack{n=1 \\ n \neq t}}^{4} m_{t,1} m_{n,2} \right)^{-1}$$

The combined probability masses can then be aggregated with the third assessment in the same fashion. The process is repeated until all assessments are aggregated. The final combined probability masses are independent of the order in which individual assessments are aggregated. The combined degrees of belief $\beta_n$ ($n$ = 1, …, 4) are generated by:

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If there are only two assessments, t

$$\beta_n = \frac{m_n}{1 - m_H} \quad (n = 1, \ldots, 4)$$

The combined assessment for the option $O_1$ can then be represented as follows:

$$S(O_1) = \{(H_1, \beta_1), (H_2, \beta_2), (H_3, \beta_3), (H_4, \beta_4)\}$$

An average score for $O_1$, denoted by $u(O_1)$, can also be provided as the weighted average of the scores (utilities) of the evaluation grades with the belief degrees as weights, or

$$u(O_1) = \sum_{i=1}^{4} u(H_i) \beta_i$$

where $u(H_i)$ is the utility of the *i*th evaluation grade $H_i$. For $i$ = 1, for example, we have $u(H_1) = u(Slightly\ preferred) = 0.217$.

An intelligent decision system (IDS[1]) has been developed on the basis of the ER approach (Yang and Xu (2000)). The IDS software is designed to transform the lengthy and tedious model building and result analysis process into an easy window-based click and design activity. The rest of this sub-section is devoted to demonstrating the solution process of the above safety and cost-based design selection problem using the IDS software.

The main window of IDS for solving the design selection problem is shown in Figure 10.19, which has a menu bar, a tool bar and a model display window. The hierarchy of the assessment criteria can be readily constructed using the modelling menu or the related short cuts on the tool bar. IDS also provides an assistant model builder for building large-scale models that may have hundreds of criteria and options.

In the model display window, each criterion object is coloured in blue and has three boxes for displaying the criterion name, its weight and average score. For example, the criterion "1. Safety" has a weight of "0.6667" and its average score for "Design option 1" is "0.6956". Each alternative object is coloured in yellow and also has three boxes for displaying the alternative name, its ranking and overall average score. For example, "Design option 1" is ranked the third and has an overall average score of "0.776495". Apart from an average score, IDS is capable of generating a distributed assessment for each option on any criterion. Figure 10.20 shows the overall distributed assessment of "Design option 1". In Figure 10.20, the degrees of belief to the evaluation grades clearly show the merits and drawbacks of the design option.

In IDS, a number of dialog windows are designed to support model building, data input, result analysis, reporting and sensitivity analysis. For example, Figure 10.20 is generated using an IDS dialog window for reporting results graphically. Figure 10.21 shows an IDS dialog window for data input for "Design option 1" on a cost criterion for "2.1 Designer 1". All data can be entered using similar dialog windows, whether they are precise numbers, random numbers with probabilities, or subjective assessments. Figure 10.22 shows the visual cross comparison of the four design options on both safety and cost generated using the IDS visual comparison dialog window.

In IDS, AHP and other methods are used for generating relative weights of criteria and the evidential reasoning approach is used to aggregate criteria from the bottom level of criteria to the top level criterion "Design selection". The overall assessment for each option can be characterised as shown for option 1 in Figure 10.20. In IDS, dialog window are designed to support visually scaling the evaluation grades or estimating the utilities of the grades. For example, Figure 10.23 shows a utility curve for the four evaluation grades. The curve can be changed onscreen to suit the requirements of individual designers. For the given utility curve, the average scores for the four design options are generated as shown in Table 10.28.

Based on the overall scores of Table 10.28, the ranking of the four design options are given as follows:

$$\text{option } 3 \succ \text{ option } 4 \succ \text{ option } 1 \succ \text{ option } 2$$

The above ranking is the same as that generated using the additive utility function approach. Apart from the average scores and the related ranking for the design options, however, the ER

[1] A free demo version of IDS can be obtained from Dr J B Yang via email: jian-bo.yang@umist.ac.uk

approach can provide much richer information for analysis. The distributed assessment at any attribute provides a panoramic view on each design option so that the benefits and risks involved in selecting an option are made clear to the designers.

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### 10.3.4 Discussion of the Results

When designing a large maritime engineering product, especially at the initial design stages, there are usually several design options. It should be noted that such options are produced at the top level where only non-numerical data may be available. The information available for making decisions on which option to select at this stage may be incomplete. As a design proceeds to a more detailed stage, the selection of design options at lower levels is required and again a similar process for selecting a particular design option may be required. It should be noted that the decision making process at all levels needs to deal with multiple objectives and may involve uncertain or incomplete information. The MCDA methods described may prove useful to select the best design option by taking into account safety and other design objectives in a rational manner.

As the best design option is chosen, the design can further proceed. More and more information becomes available for more detailed safety analysis. Decision making may need to be carried out at the next level. At this stage, it may be the case that only part of the information is complete for quantitative safety estimate. This may also be true for modelling of other design objectives. In such cases, MCDA techniques may be required to combine safety estimate with other design objectives to arrive at the best designs within both technical and economic constraints.

As the design further proceeds, it reaches a stage where there is enough information for carrying out design optimisation based on quantitative safety assessment. At this stage, safety may be assessed using various safety assessment techniques in terms of likelihood of occurrence and magnitude of consequences. A mathematical model can be formulated and then again MCDA techniques can be used to process the model in order to optimise the design.

It is also worth mentioning that the MCDM techniques described can also be used make decisions in maritime operations.

### 10.3.5 Conclusion

There is a great potential for MCDA methods to be applied in the design selection and optimisation processes. Appropriate application of MCDA tools can facilitate decision making in maritime engineering design and operations to improve efficiency.

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**Table 10.1 Artificial Neural Networks Characteristics**

| | |
|---|---|
| Number of layers | 2 |
| Number of input units | 2 |
| Number of output units | 1 |
| Learning rule | Back-propagation |
| Transfer function | Sigmoid: tan-sigmoid for hidden layer, purelin for output layer |
| Number of neurons (layer 1) | 10 |
| Number of neurons (layer 2) | 1 |

**Table 10.2 Training Pair Data from LR Defect Data for Bulk Carriers not Lost**

| | Training | Pairs | Output |
|---|---|---|---|
| Ship | dwt | Age | Hull Incidents Per Year |
| S1 | 72,000 | 16 | 1.25 |
| S2 | 81,000 | 22 | 1.14 |
| S3 | 26,500 | 12 | 1.58 |
| S4 | 35,000 | 14 | 0.36 |
| S5 | 26,500 | 11 | 1.91 |
| S6 | 31,500 | 19 | 0.53 |
| S7 | 20,000 | 13 | 0.92 |
| S8 | 25,000 | 7 | 0.86 |
| S9 | 25,000 | 18 | 0.50 |
| S10 | 27,000 | 18 | 0.83 |

**Table 10.3 Comparison of Predicted Results with Actual Data on Hull Incidents per year**

| Test Case | Ann Prediction [Failure Per Year] | Actual From LR Defect Data [failure per year] | Different |
|---|---|---|---|
| T1 | 1.04 | 1.18 | 11.9% |
| T2 | 1.53 | 1.33 | 15% |
| T3 | 1.95 | 1.64 | 19% |
| T4 | 0.93 | 0.85 | 9.4% |
| T5 | 0.61 | 0.61 | 0% |

**Table 10.4 ANN Characteristics**

| | |
|---|---|
| Number of layers | 2 |
| Number of input units | 5 |
| Number of output units | 1 |
| Learning rule | Fast back-propagation |
| Transfer function | Sigmoid: tan-sigmoig for hidden layer, purelin for output layer |
| Number of neurons (layer 1) | 12 |
| Number of neurons (layer 2) | 1 |

**Table 10.5 Hypothetical Input Data for Risk Prediction ANN**

| Ship Owner Management Quality | Operation Quality | Fire-Fighting Capability | Navigation Equipment Level | Machinery Redundancy | Possibility of Vessel Failure |
|---|---|---|---|---|---|
| Very low | Very high | Very high | Very high | Very high | Very high |
| Very high | Very low | Very high | Very high | Very high | Very high |
| Very high | Very high | Very low | Very high | Very high | Very high |
| Very high | Very high | Very high | Very low | Very high | Very high |
| Very high | Very high | Very high | Very high | Very low | Very high |
| Very high | Very high | Very high | Very high | Very high | Very low |
| High | High | High | High | High | Low |
| Average | Average | Average | Average | Average | Average |
| Very low | Very low | Very low | Very low | Very low | Very high |
| Very low | Low | Average | High | Very high | Very high |
| Low | Very low | Very high | Average | High | Very high |
| Average | High | Very low | Very high | Low | Very high |
| Very high | Low | High | Very low | Average | Very high |
| High | Very high | Low | Low | Very low | Very high |
| High | Very high | Low | Average | Low | High |
| Low | Average | Very high | Low | High | High |
| Average | Low | Low | Very high | Very high | High |
| Very high | High | Average | High | Low | High |
| Low | Average | High | Low | Average | High |
| Low | High | Low | Very high | Low | High |
| High | Low | Very high | Low | Low | High |
| Low | Low | High | Low | Low | Very high |
| Low | High | Low | Low | Low | Very high |
| Low | Low | Low | Low | Very high | Very high |
| Low | Low | Low | Low | Low | Very high |

**Table 10.6 Predicted Results by the ANN Model**

| Ship Owner Management Quality | Operation Quality | Fire-Fighting Capacity | Navigation Equipment Level | Machinery Redundancy | Possibility of Vessel Failure |
|---|---|---|---|---|---|
| Low | Very high | Very high | Average | Very high | High |
| Very high | High | Average | Low | Very low | Very high |
| Low to very low | High | Average | Low | Very high | Very high |
| High | Very low | High | Average | High to very High | Very high |
| High | High | Very low | High | Average | Very high |
| High | Average | High | High | Very high | Low |
| Average | High | Average | Average to high | Average | Average |
| Low to very low | Very high | Very high | Average | High | High to very high |
| Low | Low | Low | Low | Average | Very high |
| High | Average to low | Very high | Very high | Very high | High to very high |

**Table 10.7 A Typical Standardised L9 Orthogonal Array for up to Four Tree Level Control Factors**

| Combination | Control factor #1 | Control factor #2 | Control factor #3 | Control factor #4 |
|---|---|---|---|---|
| 1 | 1 | 1 | 1 | 1 |
| 2 | 1 | 2 | 2 | 2 |
| 3 | 1 | 3 | 3 | 3 |
| 4 | 2 | 1 | 2 | 3 |
| 5 | 2 | 2 | 3 | 1 |
| 6 | 2 | 3 | 1 | 2 |
| 7 | 3 | 1 | 3 | 2 |
| 8 | 3 | 2 | 1 | 3 |
| 9 | 3 | 3 | 2 | 1 |

**Table 10.8 Some Commonly Used Orthogonal Arrays**

| Orthogonal array | Number of factors | Number of levels per factor | Number of trial required by orthogonal array | Number of trials in a traditional full factorial experiment |
|---|---|---|---|---|
| $L_4$ ($2^3$) | 3 | 2 | 4 | 8 |
| $L_8$ ($2^7$) | 7 | 2 | 8 | 128 |
| $L_9$ ($3^4$) | 4 | 3 | 9 | 81 |
| $L_{12}$ ($2^{11}$) | 11 | 2 | 12 | 2048 |
| $L_{16}$ ($2^{15}$) | 15 | 2 | 16 | 32768 |
| $L_{16}$ ($4^5$) | 5 | 4 | 16 | 1024 |
| $L_{18}$ ($2^1$)x ($3^7$) | 1 | 2 | 18 | 4374 |
| | 7 | 3 | | |

## Table 10.9 List of Factors Affecting Ship Safety

| Factor Identifier | Factor | Level 1 | Level 2 | Level 3 |
|---|---|---|---|---|
| *A* | Preventative maintenance policy | Adequate | Average | Sketchy (identify the malfunction parts) |
| *B* | Degree of machinery redundancy | 75% High | 50% Average | 25% Low |
| *C* | Fire-fighting capability | High | Average | Low |
| *D* | Ship owner management quality | Good | Moderate | Poor (inadequate procedures) |
| *E* | Enhanced survey programme | Yes (adequate) | No | Nil |
| *F* | Navigation equipment level | High | Average | Low |
| *G* | Corrosion control | Good | Average | Poor |
| *H* | Crew operation quality | Competence (well-trained) | Average | Poor (inadequate knowledge) |

## Table 10.10 *L18* of Taguchi Experimental Design

| Treatment | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 2 | 1 | 1 | 2 | 2 | 2 | 2 | 2 | 2 |
| 3 | 1 | 1 | 3 | 3 | 3 | 3 | 3 | 3 |
| 4 | 1 | 2 | 1 | 1 | 2 | 2 | 3 | 3 |
| 5 | 1 | 2 | 2 | 2 | 3 | 3 | 1 | 1 |
| 6 | 1 | 2 | 3 | 3 | 1 | 1 | 2 | 2 |
| 7 | 1 | 3 | 1 | 2 | 1 | 3 | 2 | 3 |
| 8 | 1 | 3 | 2 | 3 | 2 | 1 | 3 | 1 |
| 9 | 1 | 3 | 3 | 1 | 1 | 2 | 3 | 2 |
| 10 | 2 | 1 | 1 | 3 | 3 | 2 | 2 | 1 |
| 11 | 2 | 1 | 2 | 1 | 1 | 3 | 3 | 2 |
| 12 | 2 | 1 | 3 | 2 | 2 | 1 | 1 | 3 |
| 13 | 2 | 1 | 1 | 2 | 3 | 1 | 1 | 2 |
| 14 | 2 | 2 | 2 | 3 | 1 | 2 | 1 | 3 |
| 15 | 2 | 2 | 3 | 1 | 2 | 3 | 2 | 1 |
| 16 | 2 | 3 | 1 | 3 | 2 | 3 | 1 | 2 |
| 17 | 2 | 3 | 2 | 1 | 3 | 1 | 2 | 3 |
| 18 | 2 | 3 | 3 | 2 | 1 | 2 | 3 | 1 |

## Table 10.11 Ship Safety in Terms of Risk Levels Under Various Treatments

| Trial Number | Factor Identifier | | | | | | | | Risk Level | | | S/N-Ratio | Normalised S/N-Ratio |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Trial No. | *E* | *D* | *A* | *B* | *C* | *F* | *G* | *H* | | | | | -(-27) is added to each S/N-Ratio |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 6 | 13 | 11 | -20.36 | 6.46 |
| 2 | 1 | 1 | 2 | 2 | 2 | 2 | 2 | 2 | 6 | 8 | 7 | -16.96 | 10.04 |
| 3 | 1 | 1 | 3 | 3 | 3 | 3 | 3 | 3 | 24 | 25 | 22 | -27.49 | -0.49 |
| 4 | 1 | 2 | 1 | 1 | 2 | 2 | 3 | 3 | 25 | 28 | 25 | -30.93 | -3.93 |
| 5 | 1 | 2 | 2 | 2 | 3 | 3 | 1 | 1 | 7 | 6 | 7 | -16.60 | 10.40 |
| 6 | 1 | 2 | 3 | 3 | 1 | 1 | 2 | 2 | 17 | 14 | 17 | -24.12 | 2.88 |
| 7 | 1 | 3 | 1 | 2 | 1 | 3 | 2 | 3 | 46 | 47 | 50 | -33.60 | -6.60 |
| 8 | 1 | 3 | 2 | 3 | 2 | 1 | 3 | 1 | 22 | 17 | 25 | -26.68 | 0.32 |
| 9 | 1 | 3 | 3 | 1 | 3 | 2 | 1 | 2 | 33 | 33 | 32 | -30.28 | -3.28 |
| 10 | 2 | 1 | 1 | 3 | 3 | 2 | 2 | 1 | 21 | 22 | 18 | -26.19 | 0.81 |
| 11 | 2 | 1 | 2 | 1 | 1 | 3 | 3 | 2 | 8 | 8 | 7 | -17.71 | 9.29 |
| 12 | 2 | 1 | 3 | 2 | 2 | 1 | 1 | 3 | 25 | 24 | 25 | -27.84 | -0.84 |
| 13 | 2 | 2 | 1 | 2 | 3 | 1 | 3 | 2 | 42 | 42 | 38 | -32.19 | -5.19 |
| 14 | 2 | 2 | 2 | 3 | 1 | 2 | 1 | 3 | 42 | 47 | 41 | -32.75 | -5.75 |
| 15 | 2 | 2 | 3 | 1 | 2 | 3 | 2 | 1 | 11 | 17 | 14 | -23.05 | 3.95 |
| 16 | 2 | 3 | 1 | 3 | 2 | 3 | 1 | 2 | 33 | 33 | 31 | -30.20 | -3.20 |
| 17 | 2 | 3 | 2 | 1 | 3 | 1 | 2 | 3 | 47 | 47 | 42 | -33.14 | -6.14 |
| 18 | 2 | 3 | 3 | 2 | 1 | 2 | 3 | 1 | 25 | 33 | 26 | -29.01 | -2.01 |

## Table 10.12 Main and Interaction Effects

| Level | *A* | *B* | *C* | *D* | *E* | *F* | *G* | *H* | *D×E* |
|---|---|---|---|---|---|---|---|---|---|
| 1 | -11.47 | 6.53 | 4.45 | 25.45 | 15.98 | -2.33 | 3.97 | 20.11 | 16.19 |
| 2 | 18.16 | 5.8 | 6.34 | 2.36 | -9.08 | -4.12 | 4.94 | 10.54 | 9.35 |
| 3 | 0.21 | -5.43 | -3.89 | -20.9 | | 13.35 | -2.01 | -23.75 | -9.56 |
| 4 | | | | | | | | | 9.26 |
| 5 | | | | | | | | | -6.99 |
| 6 | | | | | | | | | -11.35 |
| Total | 6.9 | 6.9 | 6.9 | 6.9 | 6.9 | 6.9 | 6.9 | 6.9 | 6.9 |
| Sum of Square | 445.52 | 89.90 | 59.26 | 1074.2 | 314 | 184.76 | 28.33 | 1063.7 | 696.43 |

## Table 10.13 The Final ANOVA Table After Pooling Insignificant Factors

| Source/ Factors | Sum of squares | Sum of square (%) | Degree of freedom | Variance | Pooled in error | F-Value | Minimum confidence |
|---|---|---|---|---|---|---|---|
| A | 445.52 | 11.26 | 2 | 222.76 | | 49.72 | >99.5 |
| B | 89.90 | 2.27 | 2 | 44.95 | Pooled | 10.03 | >99.5 |
| C | 52.26 | 1.49 | 2 | 29.63 | Pooled | 6.61 | >99.5 |
| D | 1074.2 | 27.15 | 2 | 537.1 | | 119.9 | >99.5 |
| E | 314 | 7.94 | 1 | 314 | | 70.1 | >99.5 |
| F | 184.76 | 4.67 | 2 | 92.38 | | 20.62 | >99.5 |
| G | 28.33 | 0.72 | 2 | 14.17 | Pooled | 3.16 | >99.5 |
| H | 1063.7 | 26.89 | 2 | 531.85 | | 118.72 | >99.5 |
| D×E | 696.43 | 18.06 | 2 | 348.22 | | 77.73 | >99.5 |
| Sum | 3956.1 | | | | | | |

## Table 10.14 Confidence Interval and Optimal Setting Of Factors

| Level | A | B | C | D | E | F | G | H | D×E |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 25.09 | 28.09 | 27.74 | 31.24 | 29.66 | 27.39 | 27.66 | 30.35 | 32.40 |
| 2 | 30.03 | 27.97 | 28.06 | 27.39 | 25.49 | 26.31 | 27.82 | 28.71 | 30.12 |
| 3 | 27.04 | 26.10 | 26.35 | 23.52 | | 29.23 | 26.70 | 23.04 | 23.81 |
| 4 | | | | | | | | | 30.09 |
| 5 | | | | | | | | | 24.67 |
| 6 | | | | | | | | | 23.22 |
| Upper confidence level | +1.99 | +1.99 | +1.99 | +1.99 | +1.99 | +1.99 | +1.99 | +1.99 | +2.82 |
| Lower confidence level | -1.99 | -1.99 | -1.99 | -1.99 | -1.99 | -1.99 | -1.99 | -1.99 | -2.82 |
| Optimal Level | 2 | 1 | 2 | 1 | 1 | 3 | 2 | 1 | 1 |

**Table 10.15 Decision Matrix for Design Selection**

| Attribute | | Alternative design | | | |
|---|---|---|---|---|---|
| | | Option 1 | Option 2 | Option 3 | Option 4 |
| Safety (0.6667) | | 0.6891 | 0.7372 | 0.9455 | 0.9705 |
| Cost (0.3333) | Designer 1 (0.1667) | 1 | 0.7083 | 0.7004 | 0.5073 |
| | Designer 2 (0.3333) | 1 | 0.6777 | 0.6777 | 0.4929 |
| | Designer 3 (0.3333) | 1 | 0.7390 | 0.7013 | 0.5071 |
| | Designer 4 (0.1667) | 1 | 0.7013 | 0.7013 | 0.4780 |

**Table 10.16 Weighted Decision Matrix for Design Selection**

| | Option 1 | Option 2 | Option 3 | Option 4 |
|---|---|---|---|---|
| Safety | 0.4594 | 0.4915 | 0.6304 | 0.6470 |
| Cost by Designer 1 | 0.0556 | 0.0394 | 0.0389 | 0.0282 |
| Cost by Designer 2 | 0.1111 | 0.0753 | 0.0753 | 0.0548 |
| Cost by Designer 3 | 0.1111 | 0.0821 | 0.0779 | 0.0563 |
| Cost by Designer 4 | 0.0556 | 0.0390 | 0.0390 | 0.0266 |

**Table 10.17 Pairwise Comparison 1**

| | Safety | Cost |
|---|---|---|
| Safety | 1 | 2 |
| Cost | ½ | 1 |

**Table 10.18 Pairwise Comparisons between Designers**

| | Designer 1 | Designer 2 | Designer 3 | Designer 4 |
|---|---|---|---|---|
| Designer 1 | 1 | ½ | ½ | 1 |
| Designer 2 | 2 | 1 | 1 | 2 |
| Designer 3 | 2 | 1 | 1 | 2 |
| Designer 4 | 1 | ½ | ½ | 1 |

**Table 10.19 Pairwise Comparisons of Designs on Safety**

| | Option 1 | Option 2 | Option 3 | Option 4 |
|---|---|---|---|---|
| Option 1 | 1 | 0.9348 | 0.7288 | 0.7100 |
| Option 2 | 1.0697 | 1 | 0.7797 | 0.7596 |
| Option 3 | 1.3721 | 1.2826 | 1 | 0.9742 |
| Option 4 | 1.4085 | 1.3165 | 1.0264 | 1 |

**Table 10.20 Scores of Design Options on Safety**

| | Option 1 | Option 2 | Option 3 | Option 4 |
|---|---|---|---|---|
| Safety | 0.2062 | 0.2206 | 0.2829 | 0.2904 |

**Table 10.21 Pairwise Comparisons of Designs on Cost by Designer 1**

| | Option 1 | Option 2 | Option 3 | Option 4 |
|---|---|---|---|---|
| Option 1 | 1 | 1.4118 | 1.4278 | 1.9712 |
| Option 2 | 0.7083 | 1 | 1.0113 | 1.3962 |
| Option 3 | 0.7004 | 0.9888 | 1 | 1.3806 |
| Option 4 | 0.5073 | 0.7162 | 0.7243 | 1 |

**Table 10.22 Pairwise Comparisons of Designs on Cost by Designer 2**

| | Option 1 | Option 2 | Option 3 | Option 4 |
|---|---|---|---|---|
| Option 1 | 1 | 1.4756 | 1.4756 | 2.0288 |
| Option 2 | 0.6777 | 1 | 1 | 1.3749 |
| Option 3 | 0.6777 | 1 | 1 | 1.3749 |
| Option 4 | 0.4929 | 0.7273 | 0.7273 | 1 |

**Table 10.23 Pairwise Comparisons of Designs on Cost by Designer 3**

| | Option 1 | Option 2 | Option 3 | Option 4 |
|---|---|---|---|---|
| Option 1 | 1 | 1.3532 | 1.4259 | 1.9720 |
| Option 2 | 0.7390 | 1 | 1.0538 | 1.4573 |
| Option 3 | 0.7013 | 0.9489 | 1 | 1.3830 |
| Option 4 | 0.5071 | 0.6862 | 0.7231 | 1 |

**Table 10.24 Pairwise Comparisons of Designs on Cost by Designer 4**

| | Option 1 | Option 2 | Option 3 | Option 4 |
|---|---|---|---|---|
| Option 1 | 1 | 1.4259 | 1.4259 | 2.0921 |
| Option 2 | 0.7013 | 1 | 1 | 1.4672 |
| Option 3 | 0.7013 | 1 | 1 | 1.4672 |
| Option 4 | 0.4780 | 0.6816 | 0.6816 | 1 |

**Table 10.25 Scores of Options on Safety and Cost**

| | | Option 1 | Option 2 | Option 3 | Option 4 |
|---|---|---|---|---|---|
| Safety (0.6667) | | 0.2062 | 0.2206 | 0.2829 | 0.2904 |
| Cost (0.3333) | Designer 1 (0.1667) | 0.3429 | 0.2429 | 0.2402 | 0.1740 |
| | Designer 2 (0.3333) | 0.3511 | 0.2379 | 0.2379 | 0.1731 |
| | Designer 3 (0.3333) | 0.3393 | 0.2507 | 0.2379 | 0.1720 |
| | Designer 4 (0.1667) | 0.3471 | 0.2435 | 0.2435 | 0.1659 |

**Table 10.26 Aggregated Assessment of Options on Safety and Cost**

| | Option 1 | Option 2 | Option 3 | Option 4 |
|---|---|---|---|---|
| Safety (0.6667) | 0.2062 | 0.2206 | 0.2829 | 0.2904 |
| Cost (0.3333) | 0.3451 | 0.2439 | 0.2392 | 0.1717 |

**Table 10.27 Overall Assessment of Options on Safety and Cost (AHP Generated Results))**

| | Option 1 | Option 2 | Option 3 | Option 4 |
|---|---|---|---|---|
| Safety & cost | 0.2525 | 0.2284 | 0.2683 | 0.2508 |

**Table 10.28 Overall Assessment of Options on Safety and Cost (ER Generated Results)**

| | Option 1 | Option 2 | Option 3 | Option 4 |
|---|---|---|---|---|
| Safety & cost | 0.7765 | 0.7407 | 0.9085 | 0.8818 |

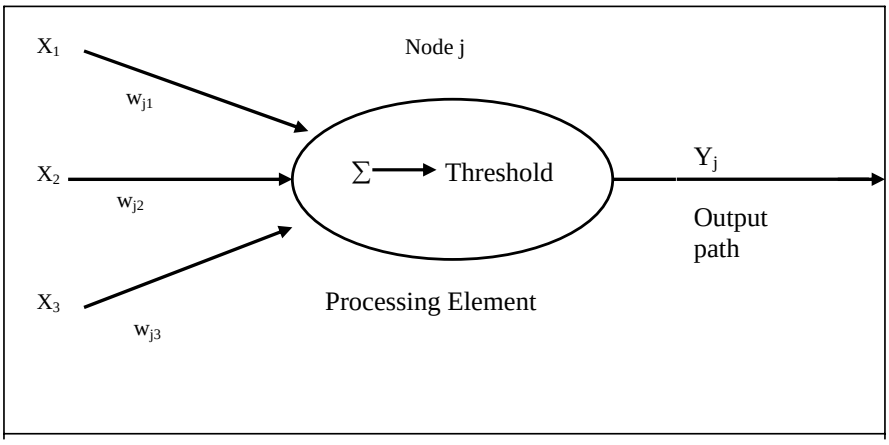


**Figure 10.1 An ANN**

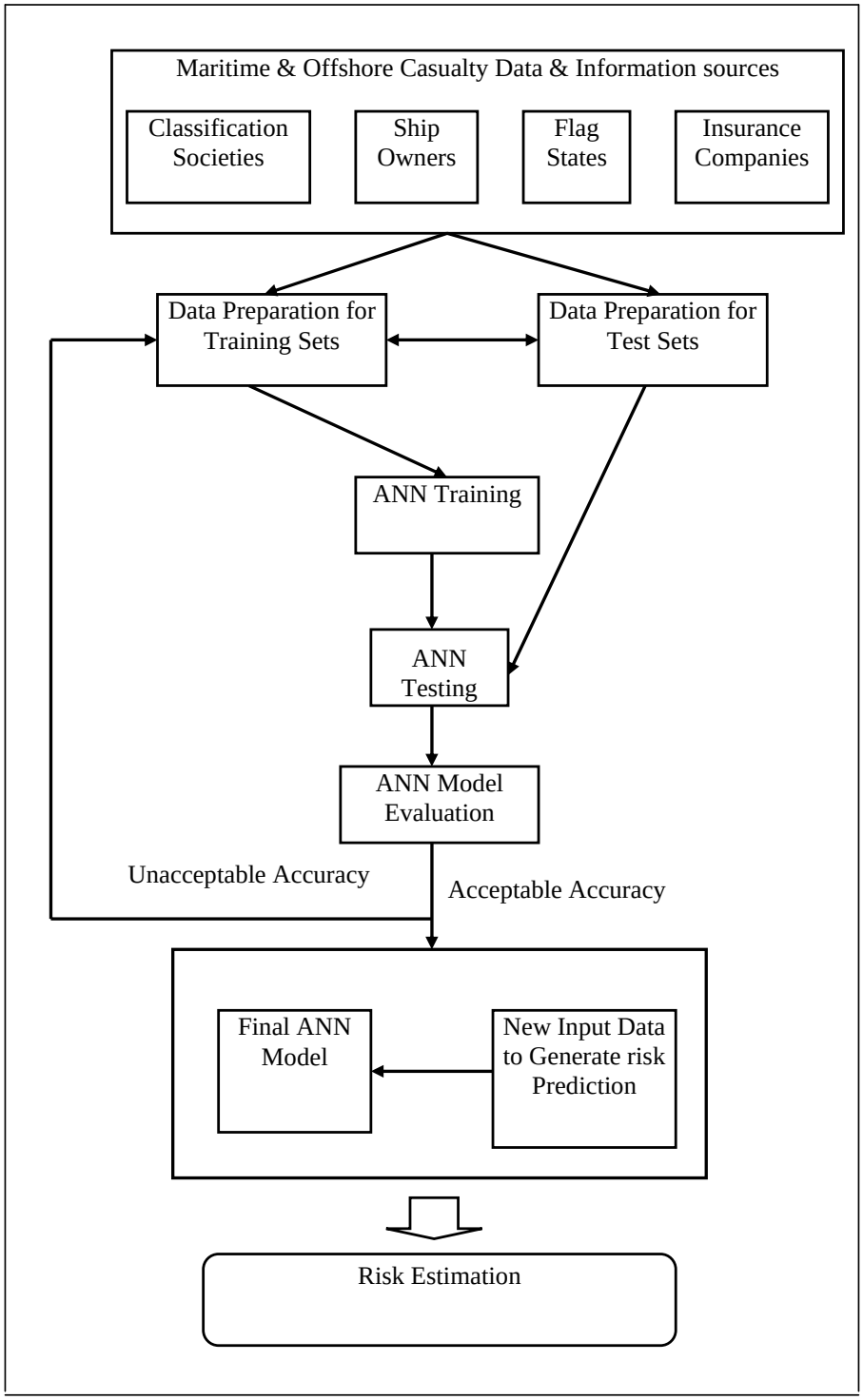


**Figure 10.2 The risk estimation framework incorporating ANN**

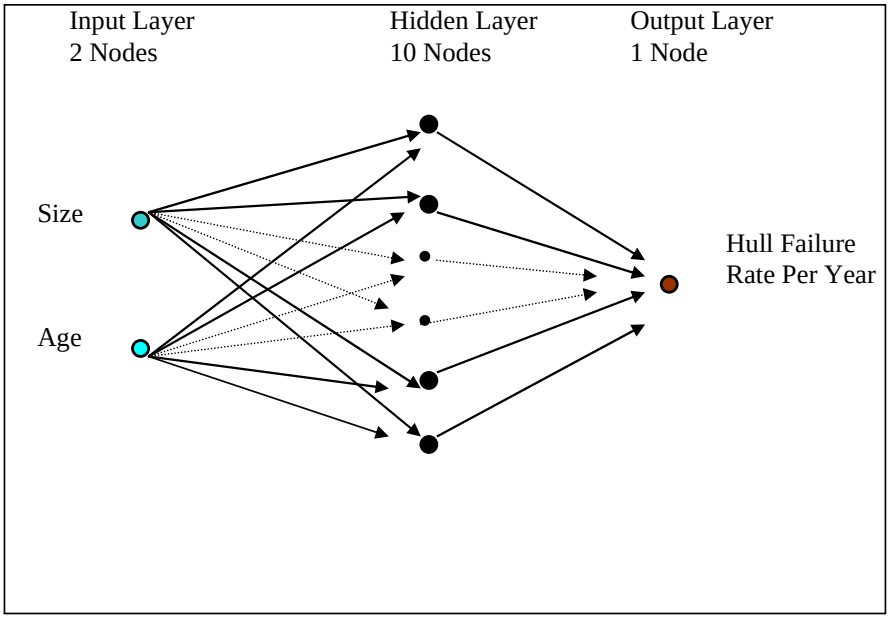


**Figure 10.3 An ANN for bulk carrier hull failure prediction**

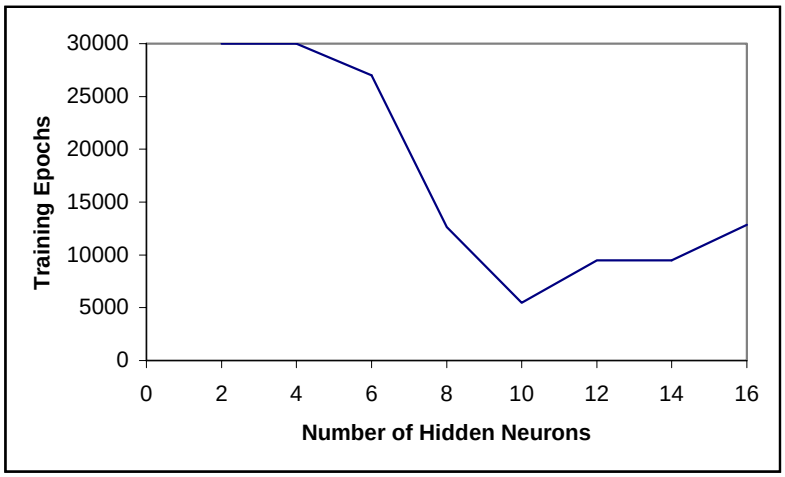


**Figure 10.4 Effect of number of hidden neurons on training epoch for back-propagation learning algorithm**

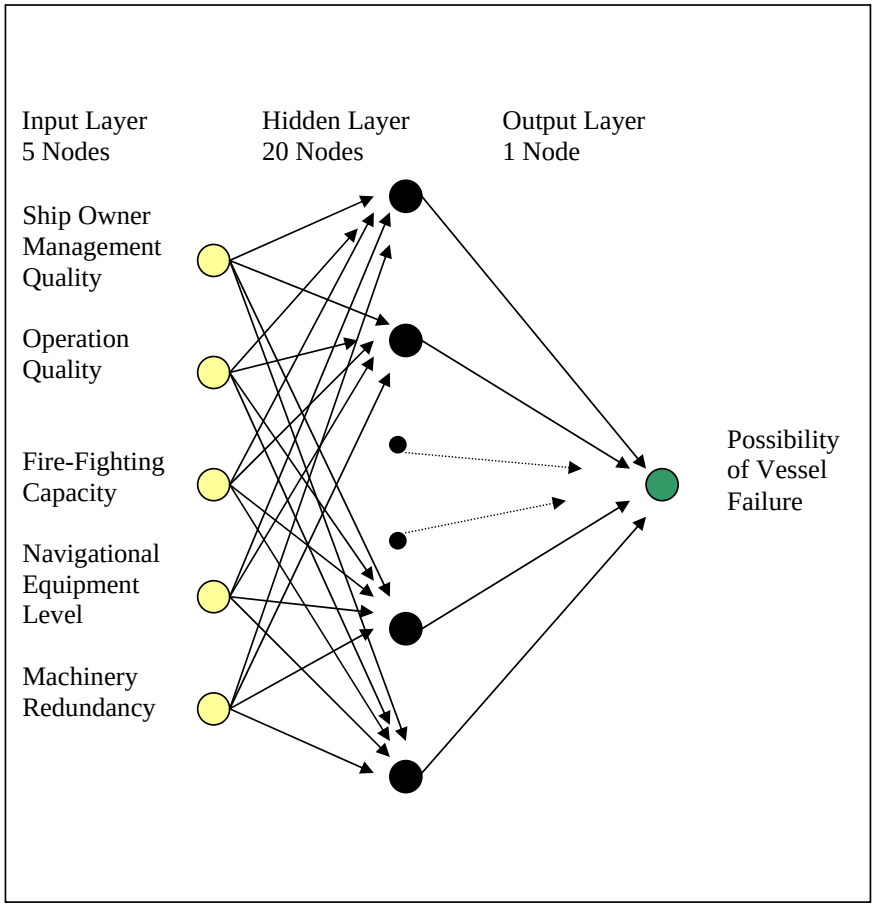


**Figure 10.5 An ANN For vessel failure possibility prediction**

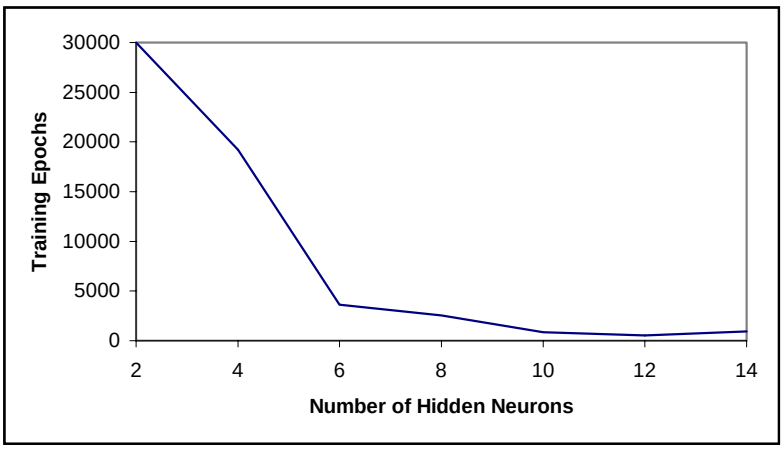


**Figure 10.6 Effect of number of hidden neurons on training epochs for back-propagation learning algorithm with momentum and adaptive learning rate techniques**

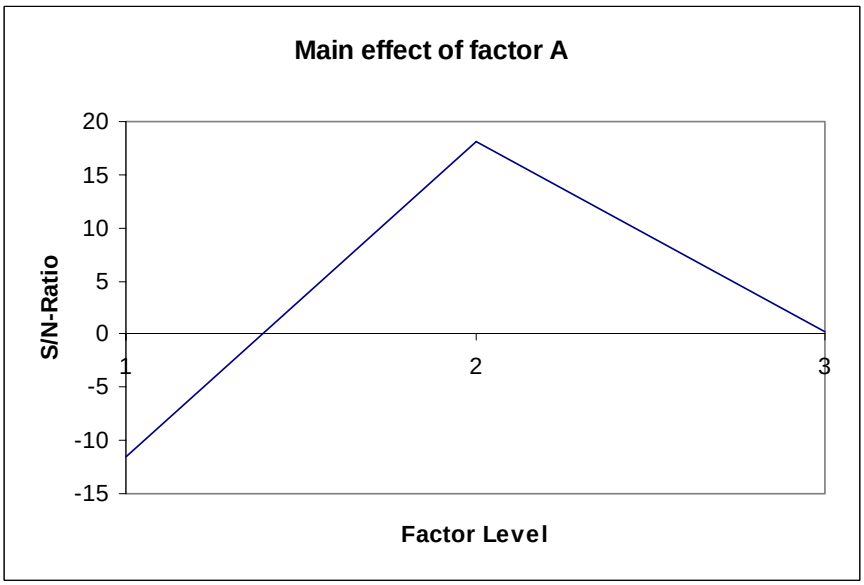


**Figure 10.7 The non-linearity graph for factor A**

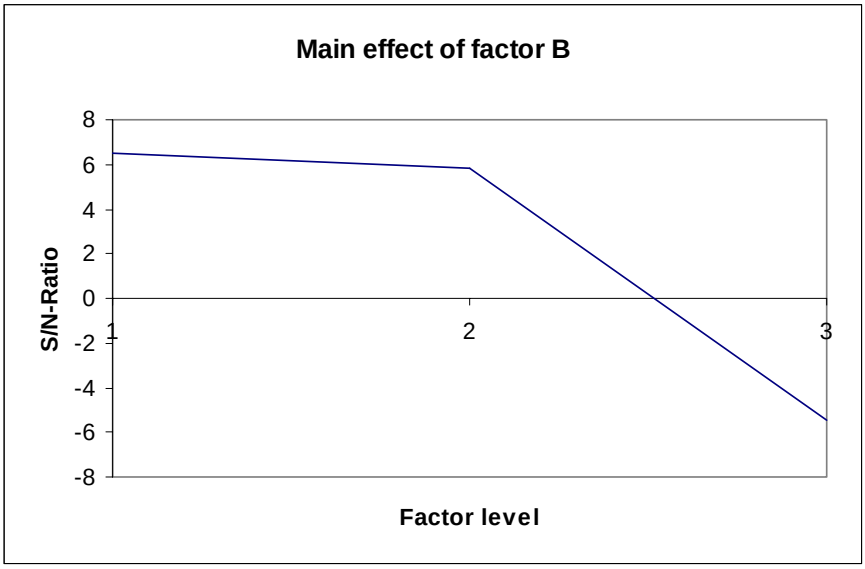


**Figure 10.8 The non-linearity graph for factor B**

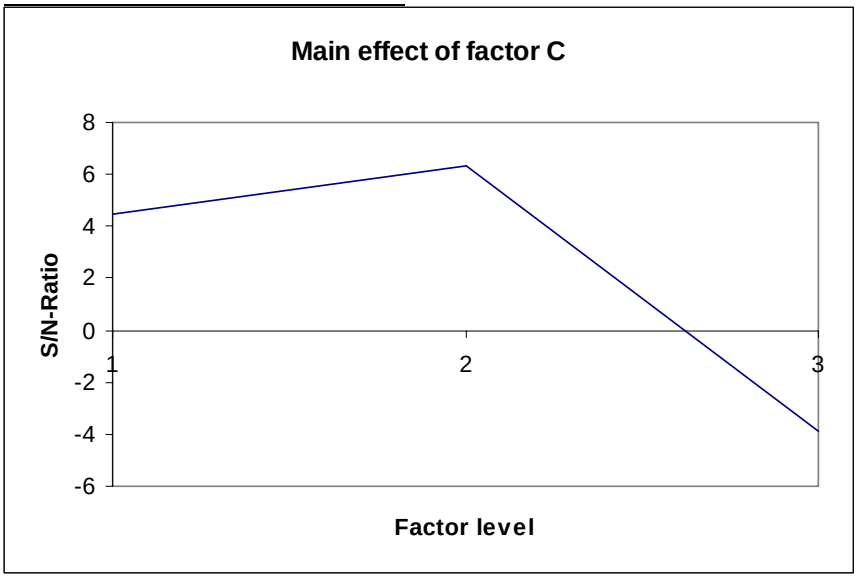


**Figure 10.9 The non-linearity graph for factor C**

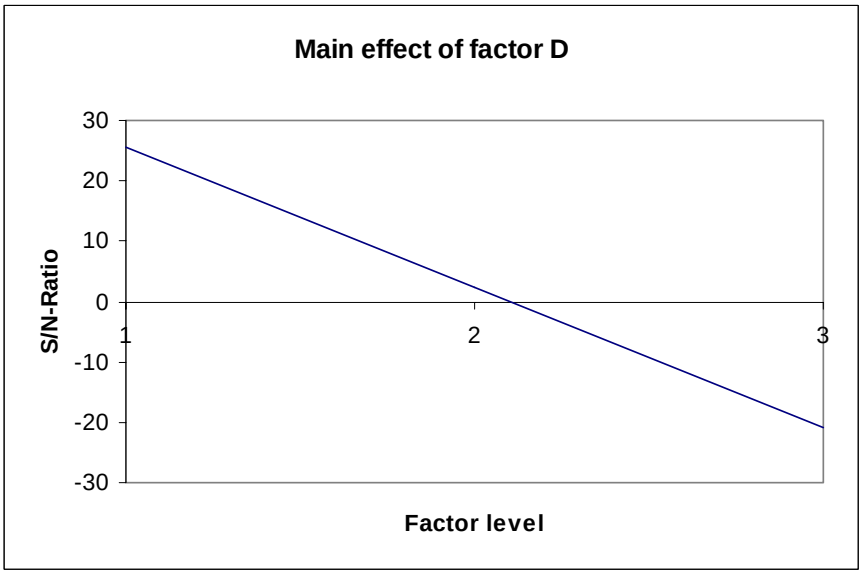


**Figure 10.10 The non-linearity graph for Factor D**

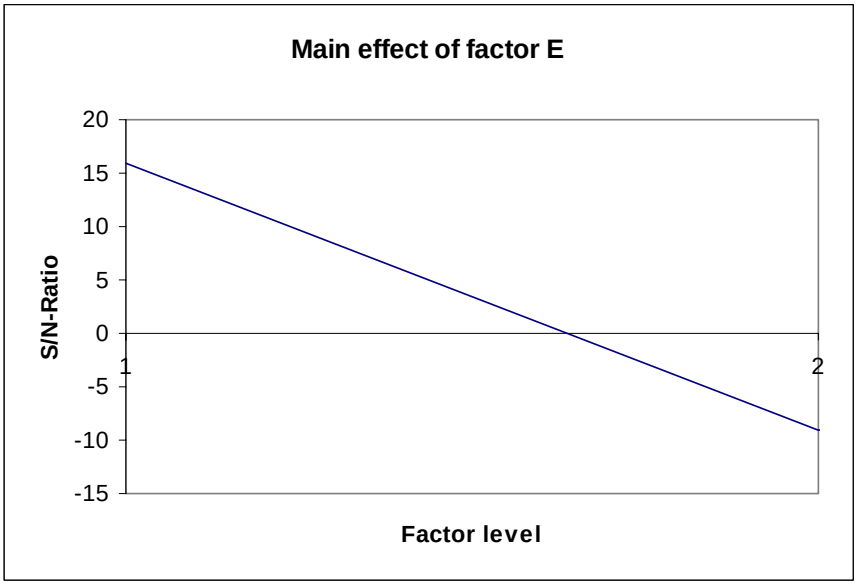


**Figure 10.11 The non-linearity graph for factor E**

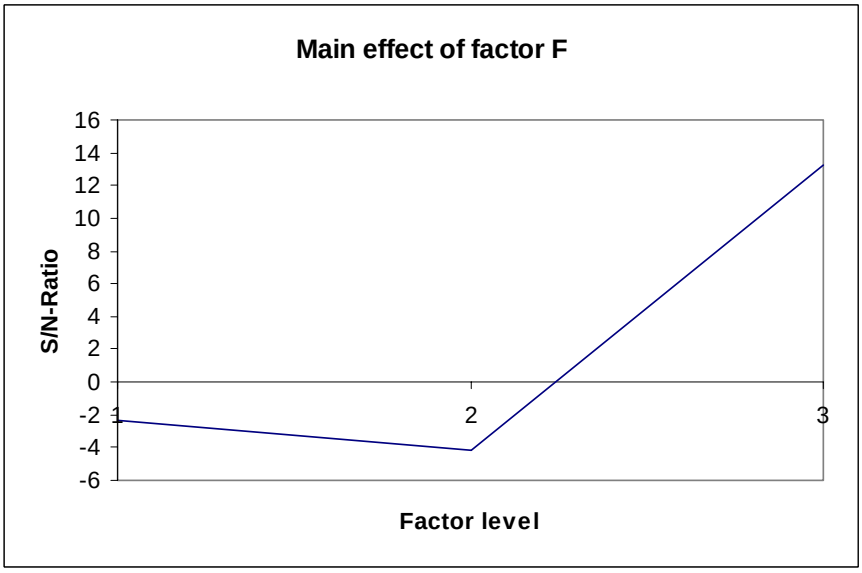


**Figure 10.12 The non-linearity graph for factor F**

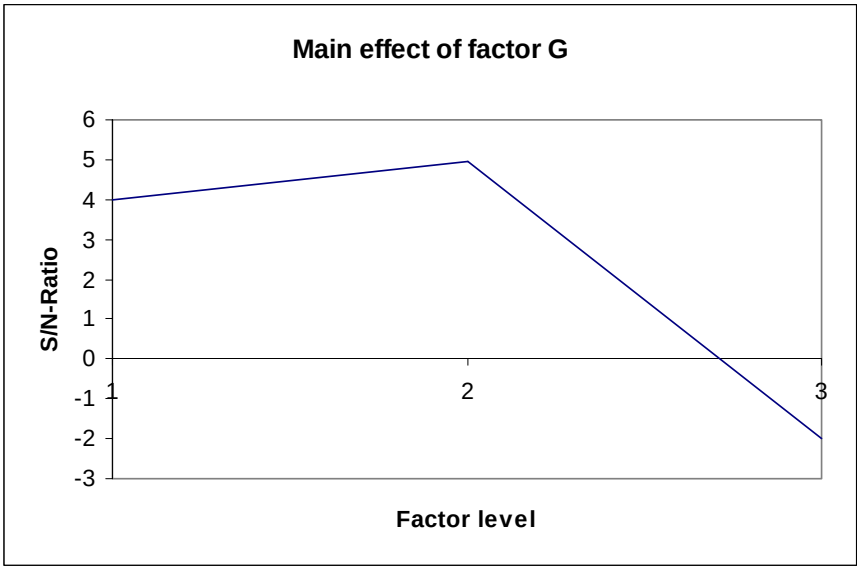


**Figure 10.13 The non-linearity graph for factor G**

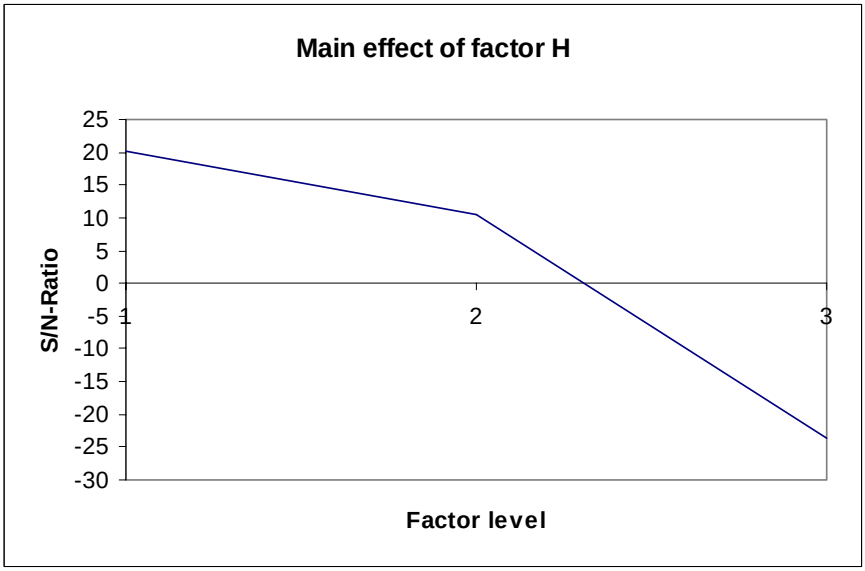


**Figure 10.14 The non-linearity graph for factor H**

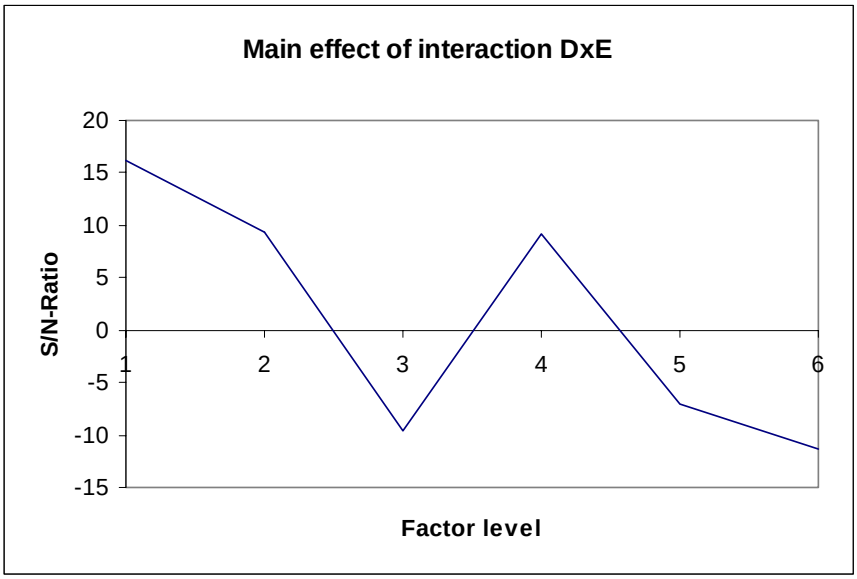


**Figure 10.15 The non-linearity graph for factor D×E**

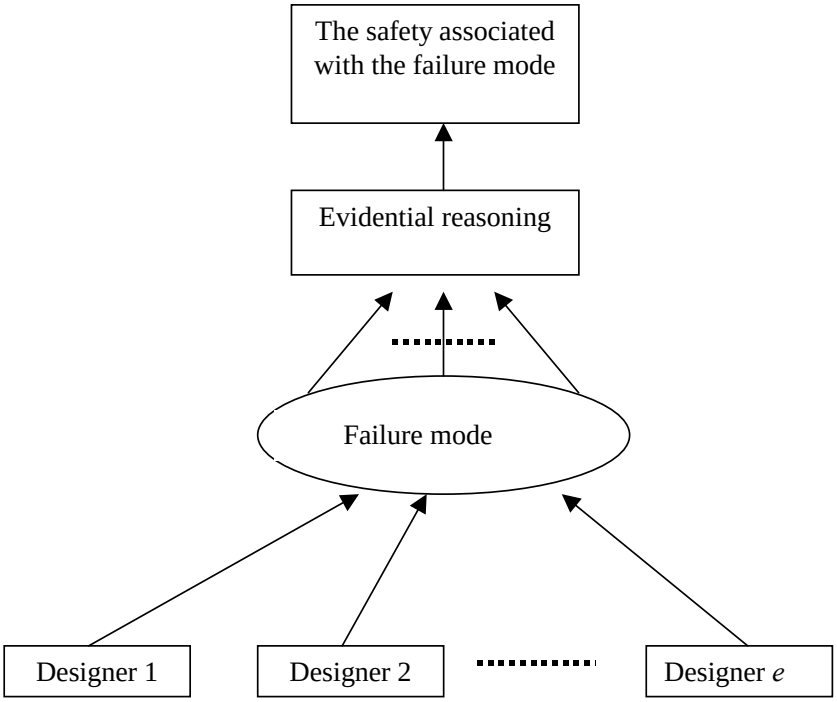


**Figure 10.16 A diagram for synthesising the safety associated with a failure mode**

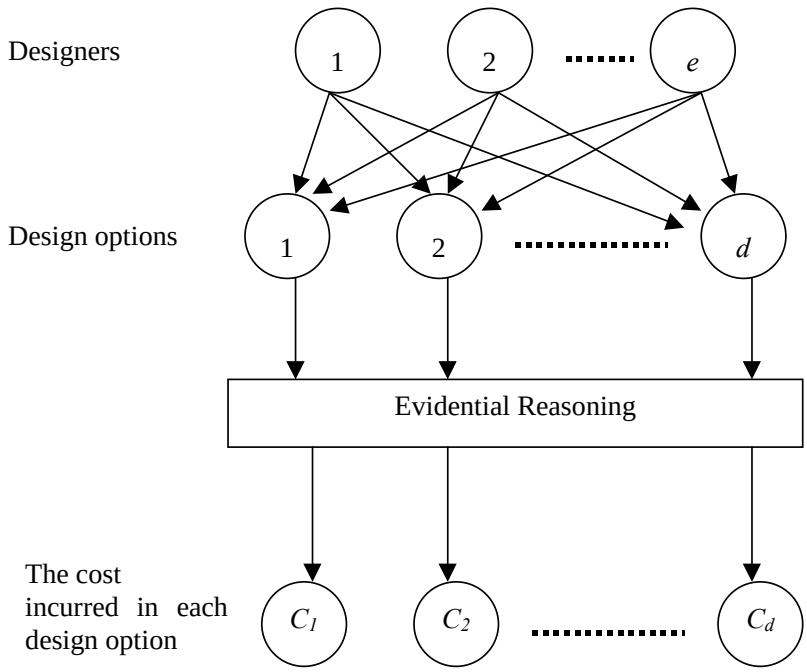


**Figure 10.17 A hierarchical diagram of cost modelling**

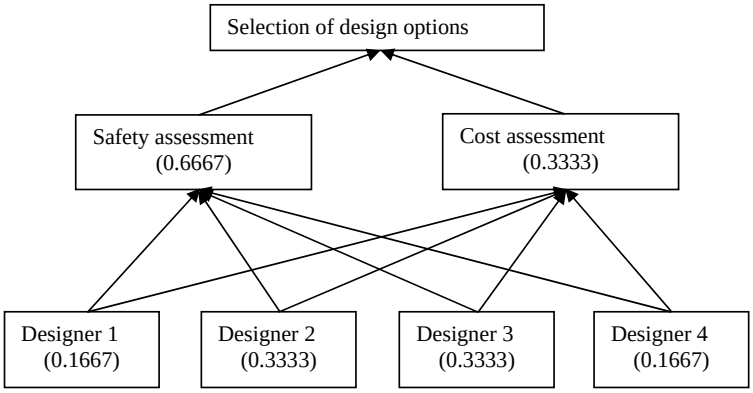


**Figure 10.18 Safety and cost assessment hierarchy**

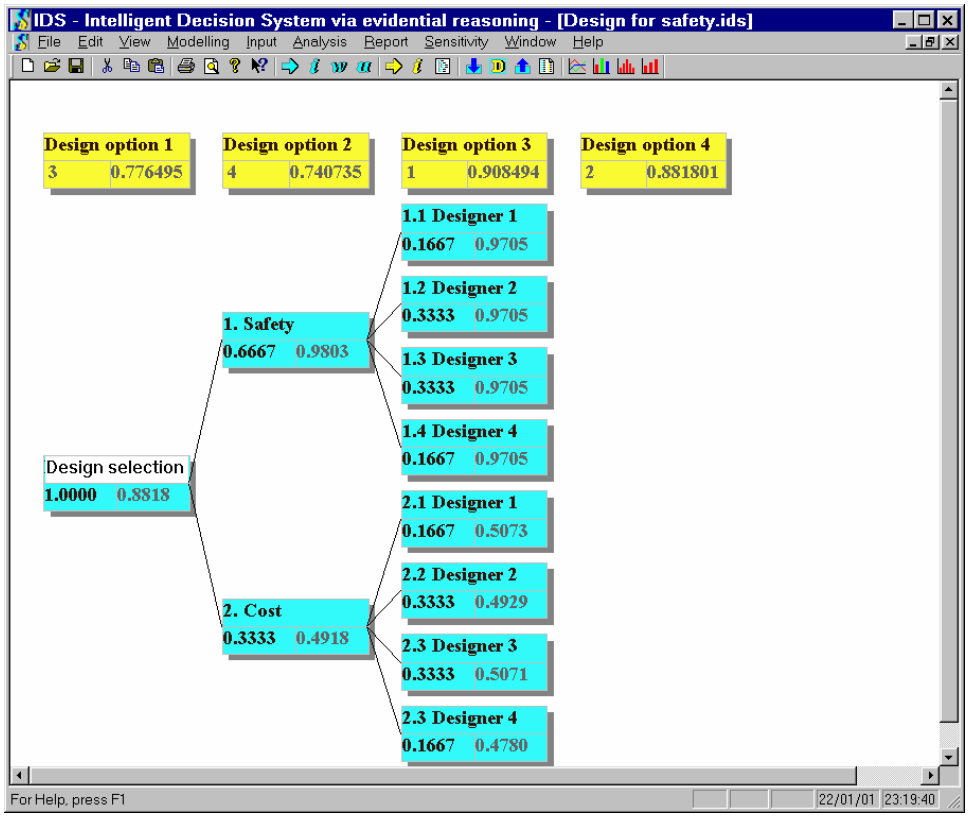


**Figure 10.19 IDS Main Window for Safety & Cost Based Design Selection**

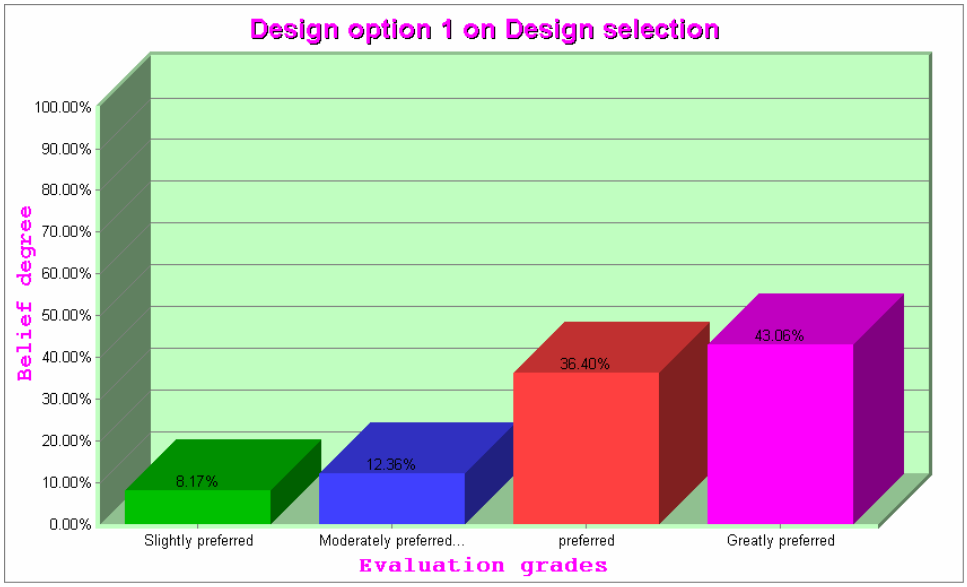


**Figure 10.20 The overall distributed assessment of design option 1 generated by IDS**

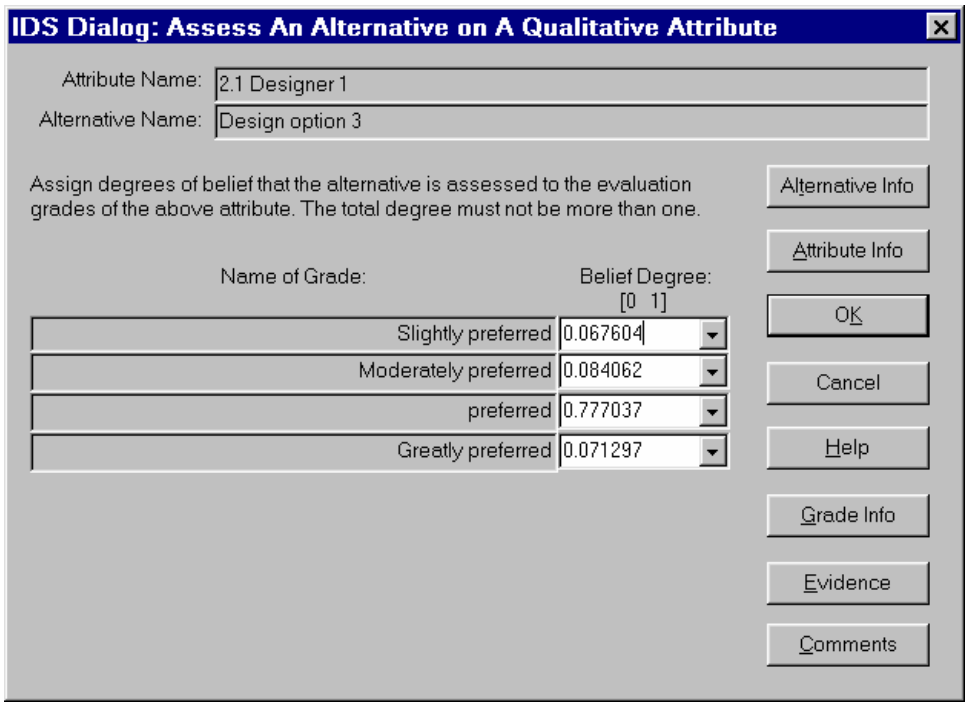


**Figure 10.21 IDS Data input dialog window**

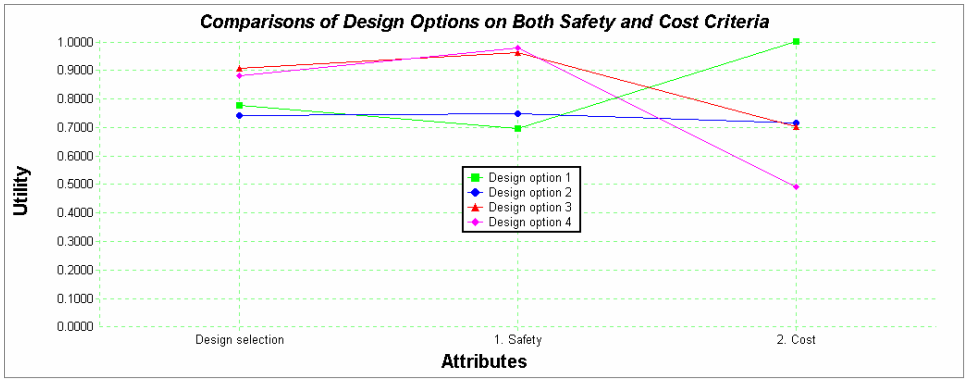


**Figure 10.22 Comparison of design options on both safety and cost generated by IDS**

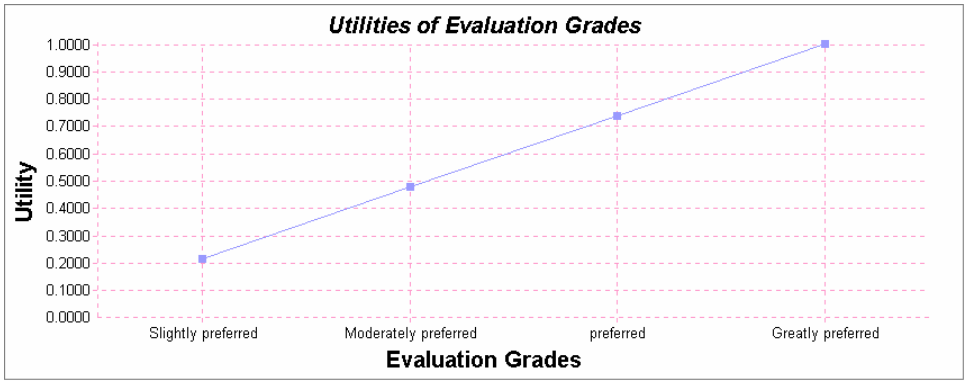


**Figure 10.23 Utility curve of evaluation grades generated by IDS**