Cranfield Univeristy

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Modelling Naturalistic Decision Making using Neural Networks

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Abstract

This thesis describes two studies conducted within a naturalistic decision making paradigm. Study One examines the choice of university for master level education. This decision is presented as a consequential choice decision task. Students, who had been offered placements at Cranfield University for the 1998/99 term, participated in this research. Factors influencing the participant's decision to attend or not to attend Cranfield were collected with a questionnaire specifically designed for this purpose. The final data set contained 267 questionnaires.

Study two describes a decision where a disruptive passenger threatens a hypothetical flight. Sixty-five professional members of flight crew participated in a series of semi-structured telephone interviews during which they described their decision-making process for dealing with this situation. This decision process is presented as a pattern-matching task.

Artificial neural networks were used to model the decision on the basis of the input variables (questionnaire items in study one and interview variables in study two) undertaken to produce an empirically verifiable model of the participants decision making process.

Cross-validation of the results showed that decision outcomes could be predicted on the basis of the models. The cross-validation results, in terms of classifications are compared with discriminant function analysis classification results, to determine if neural networks or discriminant function analysis is a more appropriate form of analysis for modelling a naturalistic decision. Both studies show that neural networks outperformed the discriminant function analysis results in terms of classification. Press's Q analyses also support this finding.

It is suggested that neural networks may be a viable way of modelling naturalistic decisions.

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I dedicate this thesis to the memory of my Nana, Molly Duggan.

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1 Introduction

The essence of this thesis is real-world, dynamic decision-making theory. Chapter One discusses generic decision-making research, focusing on a new ecological approach to real world decision-making theory termed Naturalistic Decision-Making (NDM). A brief overview of the traditional approach to decision-making research termed Classical Decision-Making (CDM) is also reviewed. The main differences between these approaches to decision-making research will be discussed. A theory of pilot judgement is introduced as it contains characteristics that relate to both CDM and NDM.

Naturalistic Decision-Making (NDM) characteristics and models are discussed in detail, a final synthesis of the models discussed in chapter one are presented to show similarities within all models. Other factors influencing decision-making are described such as individual expertise and situational awareness.

Throughout chapter one, the suggestion of viewing the NDM framework in a different way of modelling the process involved rather than proposals of hypothesising decisional outcomes will be made. Neural Networks are then presented as a means in which to accommodate this objective. Previous Neural Network (NN) and Decision-making research will also be outlined.

1.1 Real-World Decision-Making

In today's society, new technology advancements are matched by increasingly challenging risks for both the organisations who have to manage the risks and the researchers who strive to understand them (Reason, 1997; Turner and Pigeon, 1997). Decision-makers who must deal with these risks can be pilots in charge of flight decks, fire-ground commanders and those in charge of emergency control centres. Due to the increase in technological development there is an equal demand for a better understanding of decision-making in critical and hazardous situations to improve selection, training and operational performance (Flin, Salas, Strub and Martin, 1997).

Taking the case of pilots, flying a modern, highly automated civil aircraft is no longer simply a problem of skilled psychomotor performance but is one of flight management and real-time decision-making. During the course of any flight, pilots make numerous decisions, most of which are routine, well structured and quite familiar. However, pilots will also be required to solve less-routine problems. Some of these less-routine problems can be solved by references to checklists carried on the flight deck. These checklists serve as essential aids for the management of in-flight technical failures encountered. However, not all problems encountered relate to equipment malfunction, and some of the factors involved can be external to the flight deck. For example, on the 28th of March, 1977, 583 people lost their lives due to a pilot's decision to take off on a foggy runway at Tenerife without being sure that the runway was clear of traffic to take off on a foggy runway at Tenerife without being sure that the runway was clear of traffic (Stewart, 1994). Although many factors contributed to this disaster, beginning with a bomb exploding that morning in the passenger terminal at Las Palmas Airport, it was this final decision that resulted in the accident. To this day, this disaster is the worst in aviation history.

For over twenty years researchers have held the view that the majority of fatal aviation accidents are attributable to decisional rather than perceptual or action errors (Jensen and Benel, 1977). In 1991, Diehl reported that decisional errors were the cause of over 50% of accident-related human errors in military and civil aviation between 1987 to 1989. Considering this finding, it is no surprise that the aviation industry is concerned with improving the quality of decision-making in the cockpit (Orasanu, 1995). This has been attempted by including decision-making modules in Crew Resource Management (CRM) courses and automating systems in the cockpit (Wiener, 1988). However, despite these efforts poor decisions are still made.

Decision-making is no simple task; it involves situation assessment, choice amongst alternatives and assessment of risk (Orasanu, 1995, p.138). Furthermore, not all decisions call on the same cognitive processes; a pilot might use one decision process to abort a take-off and another one to determine the cause of a caution light. Decisions made on the flight deck are made all in a dynamic environment where complete information is often not available to the decision-maker and are frequently made under the influence of probabilistic factors. Furthermore, the quality of many of these outcomes can only be described in retrospect.

1.2 Classical Decision-Making (CDM) Research

Decision-making has traditionally attracted much attention. Some researchers have described decision-making using complex mathematical equations, while others have used a more deeply psychological approach. It is a broad topic that overlaps into areas such as information processing and problem solving (Lehto, 1997). This is due to the fact that people must collect, organise and combine information from various sources to make decisions. Numerous models have been developed in an attempt to build research on human decision-making. CDM research has its origins in economics (Lehto, 1997) but more recently has been researched using paradigms like operation science, psychology, sociology, management science, and cognitive engineering. Excluding cognitive engineering research, the motivation of all other fields has been (1) to develop normative prescriptions that can guide decision-makers and (2) to describe human decision-making and compare it to normative prescriptions.

Classical Decision-Making (CDM) theory first began with the development of normative models in economics and statistics. These theories specified an optimal solution to all decisions and had a heavy focus on rationality (Savage, 1954). According to CDM research, a person needs to think logically in order to make a decision. To do this a person formally describes all that is known about the problem. Following this, the probability theory. Therefore, this approach is quantitative, normative and prescriptive (Savage, 1954). CDM has focused on two areas of decision-making:

(1) Preference and choice

(2) Statistical inference.

1.2.1 CDM Research: Preference and Choice

There are four basic elements to preference and choice theories: (1) a set of potential actions to choose between, (2) a set of events within the environment, (3) a set of consequences for each combined potential action and event, (4) a set of probabilities for each combined potential action and event.

Making a decision requires an individual to make a choice between two or more options (one of which can be simply to do nothing). A given option can result in real or imagined consequences to the individual, which relates to their values and judgements and also to the environment that they are in. According to CDM, a decision-maker seeks attractive consequences and avoids unattractive consequences by applying logic and probability to the problem at hand. For example, 'should I wear a raincoat today'? Wearing or not wearing a raincoat are two actions, A_1 and A_2. The expected outcome of either action depends on whether it rains or not. Raining or not raining relates to two events, E_1 and E_2. Wearing a raincoat reduces the expected consequences of getting wet if it rains (E_1). As the probability of it raining increases (E_1) the wearing of a raincoat (A_1) would become more attractive. The cost of not wearing a raincoat (A_2) would depend on the event of it raining or not raining (E_2). When the probability of it raining decreases the likelihood of not wearing a rain coat increases.

Once the decision problem has been represented according to these basic elements, the choice is then made by applying decision rules. Decision rules are based on basic axioms (or assumptions) of rational choice. Some of the more common rules include dominance, lexicographic ordering, minimum aspiration level and satisficing, minimax cost and regret. An outline of these rules are given below:

- <u>Dominance</u>: a normative decision rule where one action is at least as good as another for all events but on at least one event it is preferred.

- <u>Lexicographic ordering</u>: Alternatives have multiple consequences. The different consequences are ordered in terms of their importance. The decision-maker sequentially compares each alternative beginning with the most important until s/he finds the best.

- <u>Minimum aspiration level or satisficing rule</u>: According to this rule the decision-maker screens all alternative actions until the best action is found.

- Minimax (cost and regret) rule: the minimax cost selects the best alternative by identifying the worst outcome first for each alternative. The alternative with the worst-case cost is then chosen to be dismissed. Minimax regret is similar but determines regret rather then cost. (Lehto, 1997).

Subjective Expected Utility (SEU) Theory and Multiattribute Utility Theory (MAUT) are probably the best known decision rules. Both theories are normative and have been used in various fields to describe how people make decisions. SEU Theory has focused mainly on decisions that have uncertain outcomes, which can be related to subjective probabilities. MAUT is similar but extended so that individuals have multiple objectives available. There is also a compensatory strategy that allows for normative trade-offs between attributes in terms of their priorities.

1.2.2 CDM Research: Statistical Inference

Statistical Inference is described as a procedure where a decision-maker uses information to test if hypotheses about the world are true. Hypotheses can represent past, present, or future states of the world or causal relationships between variables. Past and present states of the world are diagnosed, and future states are determined by prediction. Bayesian Inference and Signal Detection Theory are the best known techniques for determining if a given hypothesis is true. To determine if a hypothesis is true Bayesian Inference links the hypothesis to evidence in observed states of the world. However, people can fail to combine evidence consistently (Lehto, 1997). Another limitation is that all evidence or options need to be independent, which does not always occur in the real world.

Signal Detection Theory is a combination of the SEU theory and Bayesian Inference. Signal Detection Theory describes how an operator receives information through a device that they are using. The operator has to then determine if the information or signal received is correct or false. For example, take an operator in a control room monitoring warning signals. First the operator must determine if the machine is giving a warning signal that is true or false. There are four possible outcomes in this scenario. First, the operator can correct the false alarm. Second, the operator can recognise the signal as a true warning signal. Third, the operator can fail to recognise a false alarm to be false. Finally, fourth, the operator believes a warning signal to be false when it is in fact true. Signal detection theory is not just a theory concerned with decision-making alone. It has been applied to a wide variety of areas regarding human performance (Wickens, 1992).

1.2.3 Limitations of CDM Research

One of the main limitations of CDM research is that it was developed as a result of the research protocols used, for example research was carried out in the laboratory, participants had complete knowledge available, there was a fixed range of outcomes available etc. Carrying on from the example given previously of flight crew decision-makers it can be seen that decisions required of them would be quite different to the problem solving scenarios encountered by participants in laboratory-based research. In laboratory-based studies participants were often placed in a highly artificial situation attempting to solve a relatively simple, well structured problem with the benefit of being in possession of complete information. Often the decision required was simply the choice between several pre-determined alternatives. Resulting from the research protocols used within CDM research, it has been criticised as being a poor description of everyday Decision-making and especially of decision-making on the flight deck . Although CDM may appear to be an adequate description of human decision-making, it has been known for quite some time that this is untrue (Ellsberg, 1961). The fact that CDM theory is so precise and is based on mathematics shows the theory's limited descriptive value, as people rarely make decisions in this format (Klein G., 1997).

In fact, when one considers the various theories that have been developed within the classical decision-making field, it is rather difficult to relate any to real life decision tasks. The reason for this is not because the researchers were looking at a different concept, but more that they concentrated on only one part of the decision-making process, the 'decision event' and not the decision process (Orasanu and Connolly, 1993). In this light the individual views a fixed set of alternatives that are known and from these they weigh the consequences of choosing each to make his/her choice. The individual evaluates the options in terms of a set of goals that s/he knows quite clearly and which are stable over time. This classical research looks at the way the decision-maker pulls together the information to form their best alternative. Naturalistic Decision-Making (NDM) researchers tend to refer to the traditional decision-making research as 'event models[1]'. The main problem with the 'event model' paradigm becomes apparent when one looks at a real life decision scenario. Possible actions would be evaluated and then weighted against each other, then these ratings and weights would be projected to decide on the best course of action.

Klein (1989) has shown that decision-makers (in this case fire-fighters) do not report making decisions using this approach. According to his NDM theory, fire-fighters first define the situation and by pulling on past experience, they then choose the most plausible course of action for obtaining their goal, taking into account the restrictions of the situation. Klein's participants reported that the course of action is evaluated by projecting forward and by choosing the action that would result in the least amount of negative consequences. If there are little or no undesirable consequences then that course of action is chosen.

[1] The Event Model is a term used to describe all Classical Decision-Making Models.

Klein's research highlighted the vast difference between NDM and the decision event models. In NDM the individual assesses the situation and figures out the nature of the problem. Single options are evaluated through mental simulations of what the outcome will be (final decision), and these options are chosen if they are satisfactory (i.e. the outcome is okay) and not an optimal course of action (i.e. ideal solution). The decision event model however, suggests that individuals evaluate multiple options concurrently. Analytical methods are used for incorporating values and probabilities associated with each option for obtaining the optimal solution. As stated previously, the decision event model was developed in the laboratory, where decisions were removed from any meaningful context. In real world decision-making, the decision itself is not the end product and there is normally a wider goal to be achieved.

It has been recognised in recent years that decision-making in naturalistic environments can differ depending on the decisional context (Beach, 1993). Due to this fact, researchers have begun questioning the validity and relevance of CDM theories for decision-making in a real world environment (Cohen, 1993). The following sections of this chapter discuss theories that attempt to overcome the prescriptive quality of CDM. Naturalistic Decision-Making (NDM) attempts to describe the decisional process of expert decision makers. However, first a theory of pilot judgement will be presented, as it contains characteristics that relate to both CDM and NDM approaches to decision-making research. The theory is introduced as it has the same objective as NDM research; to describe a real-world decision-making task and it is presented here to bridge the gap between CDM and NDM.

1.3 Pilot Judgement Theory

Jensen (1995) reported that pilot judgement could not be explained in terms of the basic human decision-making theories such as utility theory[2]. Jensen suggested that there was a need for pilot judgement to be described and not prescribed, which is also the main aim of NDM research. He defined pilot judgement as the mental process used to formulate aviation decisions (Jensen, 1982) claiming that judgement in the aviation sense is not just about the outcome. Pilot judgement is not the end, 'but a process for achieving the end' (Jensen, 1995, p.5).

Before Jensen developed his theory he first set out to describe what aviation judgement is, and then if it could be taught. Dreyfus and Dreyfus (1986) suggested that aeronautical decision-making (or judgement) is basically the difference between a pilot who is competent and a pilot who is an expert. A competent pilot is one who has good technical flying skills, which have been shown through all pilot examinations taken. An expert pilot is one who has these competencies but has added judgement (Jensen, Guilke and Tigner, 1997). Pilot judgement is in a way common sense: 'sense' refers to knowledge, awareness and understanding all factors involved in making a decision. 'Common' inferring the individual's understanding of societal needs and wishes and applying these to the final decision. Another part of Jensen's theory that is similar to NDM research is

[2] Utility Theory is described as the branch of decision theory concerned with measurement and representation of preferences.

expertise (see section 1.9 for fuller discussion). Jensen, Guilke and Tigner (1997) found ten characteristics that described an expert general aviation pilot, which were as follows.

1. Pilots who possess self confidence in their skills

2. Pilots who are motivated and learn all they can about the flight domain and practise what they learn on a continuous basis.

3. Pilots who can focus attention on current tasks and change that attention if necessary.

4. Pilots who possess excellent situational awareness (SA); see section 1.10 for a discussion of SA.

5. Pilots who are aware of the flight environment, such as noise, vibration and engine changes etc.

6. Pilots who are attentive to changes, aware of possible emergencies or unusual situations and makes plans to prepare for these.

7. Pilots who have superb mental capacity for problem analysis, assessing risks and resolving problems.

8. Pilots who possess good communication skills and applies them appropriately.

9. Pilots that are aware of their own limitations and always keeps within the parameters of such.

10. Pilots that possess the ego-strength to enforce their limitations within every situation. (p.234)

Jensen et al (1997) identified three distinct problem-solving strategies, which they termed 'knee-jerk', 'two-dimensional', and 'progressive' when they developed their model of pilot expertise, see figure 1 for their model of general aviation expertise for commercial pilots. This figure depicts four main components that contribute to pilot expertise: experience, risk-management, dynamic problem solving and attentional control. Within each component there are a variety of factors that also influence the pilots experience. To name a few, these could be the recency of experience, the cost of taking a risk, the pilots motivation, or the recognition that a decision needs to be made. See Jensen 1995 for a full description.

Pilots who solved their problems in a 'knee-jerk' format were found to make immediate decisions as if they had established a predetermined course of action. They did not seek information, and spent the majority of their time trouble shooting. The participants in this study who utilised this form of decision-making stated they were looking for the 'easiest solution' or simply 'didn't want to think about the decision' itself.

Pilots who used the 'two-dimensional' approach to solving their problems seemed to only consider airports in front or behind them, without drawing any attention to the options on the left and right of them. 'Progressive' decision-makers used a stepwise approach, which Jensen et al (1997) termed 'satisficing'. Here pilots seemed to understand the situation immediately and quickly made a decision. They then attempted to seek information to confirm their decision, and sought help from Air Traffic Control (ATC) etc. They continued this behaviour until the final decision was reached. According to Jensen et al (1997) the pilots in this group appeared to possess good aeronautical knowledge and situation awareness (again see section 1.10 for definition), and seemed to be able to cope with the dynamic flight environment in a better format then the other two groups.

Jensen et al's research highlights the importance of understanding how people use their knowledge and experiences in coping with complex decisional tasks in a dynamic environment, as is discussed in section 1.3. Although the pilots in the 'progressive' group may appear to have been 'expert' decision makers, they are merely utilising the tools and information available to them in the best format possible. The strategies used by this group were relying on previous experience, whereby the 'knee-jerk' group were not able to seek and find information following their initial reaction. The progressive group could still collect information and modify their initial decision accordingly if necessary. This is similar to previous research on expertise in decision-making (Chase and Simon, 1973; Dreyfus, 1981; Anderson, 1985; Klein, Calderwood, Clinton-Cirocco, 1986; Shanteau, 1987; and Redding, Cannon, and Seamster, 1992). In general these researchers found that 'experts' could chunk together information forming meaningful patterns and therefore didn't have to remember as much as the 'novice'. This implies that their actions become almost intuitive as they could attend to the important information and ignore the less important.

Jensen et al's (1997) research has highlighted the need for aviation decision-making researchers to move on from the CDM approach and to understand that decisions made in an dynamic environment like the flight deck are different from decisions previously researched by CDM. The NDM approach to decision-making research has recognised this and has also emphasised that decisions are context dependent, therefore different decisions require different methods of coping with them. The following section (1.4) discusses NDM research in detail, and compares various models within this field.

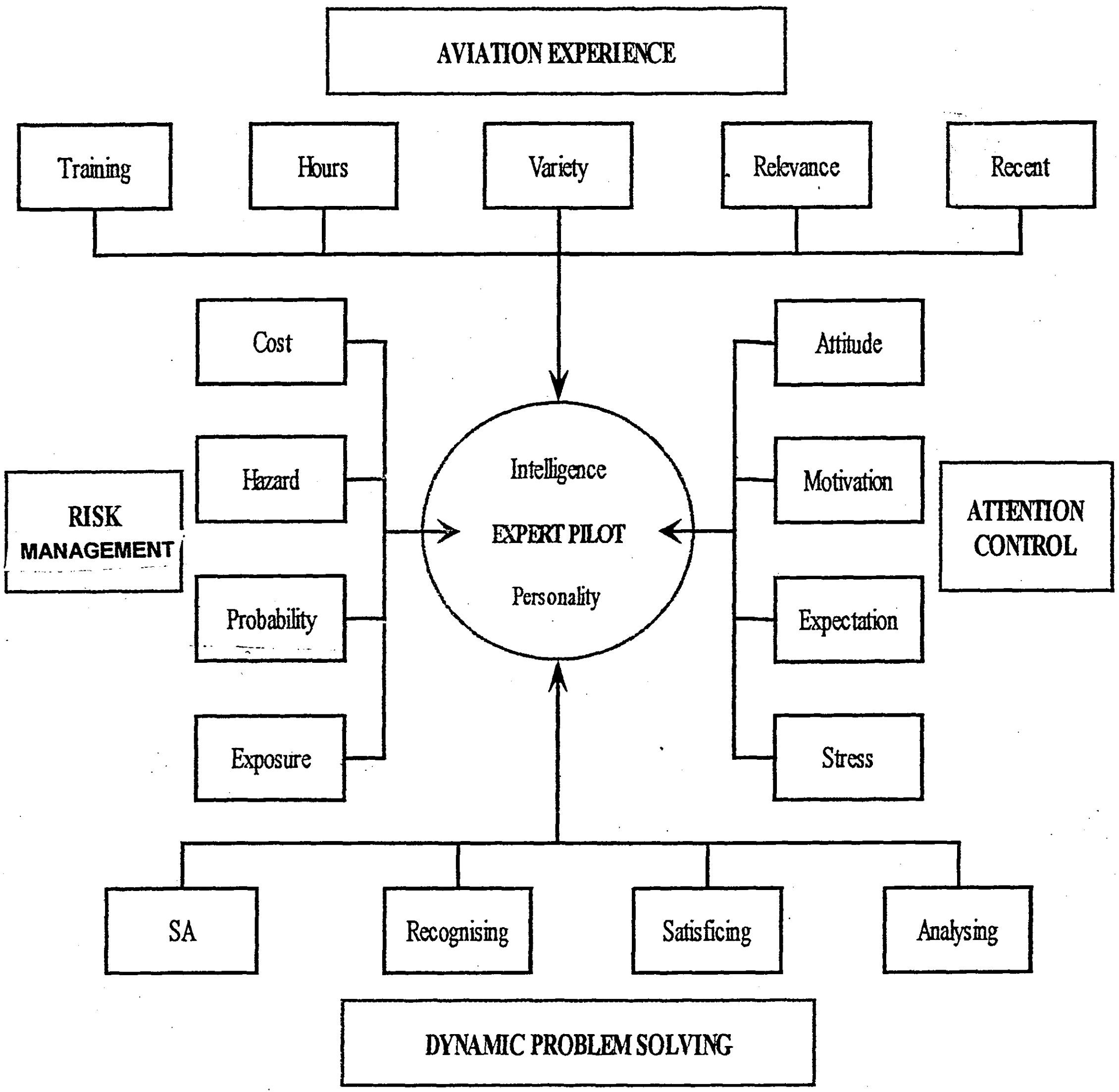

Figure One Model of General Aviation Expertise in pilots. Adapted from Jensen, Guilke and Tigner (1997).

1.4 Naturalistic Decision-Making (NDM)

In recent years a paradigm shift in decision-making research has occurred. Modern researchers are more interested in decisions that take place in the real life environment under naturalistic conditions, rather than in the laboratory. Bowers, Salas, and Pruitt (1996) took the view that research in the 1980s was limited within Classical Decision-Making (CDM) theory. CDM was seen as 'focusing on sterile, contrived decision-making situations, with results that were of little consequences to real world decision makers' (Bowers et al, 1996). During the early 90s researchers took the task of developing a theory for decision-making that encapsulated real-life situations, which previous CDM research had not yet accomplished. These researchers focused on decisions that were 'embedded in larger dynamic tasks, made by knowledgeable and experienced decision makers' (Klein, Orasanu, Calderwood and Zsambok, 1993, p.19). Brehmer (1990) also thought that decision-making should be a study of action rather than a study of choice. By this he meant that people maintain a continuous flow of behaviour aimed towards a set of goals rather then a set of 'discrete episodes involving choice dilemmas' (p.26). According to Klein and Woods (1993), NDM focused attention on how people brought their experience into the process of making decisions. Also, they broadened the focus of the decision-making process from the 'decision event to the larger processes of situational assessment' (p.405).

In 1989, Klein carried out research with fire ground commanders. This research showed that one of the basic differences between CDM and NDM was the consideration that individuals assess the nature of the situation before making a decision (situation assessment). Klein also noted that decision-makers evaluated single options sequentially through mental simulation of the outcomes before proceeding to the next stage of the decision-making process (will this option work? Yes-continue, no-reassess situation and look for another option). One of the more obvious differences that he found was that individuals chose options and actions if they were satisfactory but ***not*** necessarily optimal. By considering these three fundamental differences it is clear that NDM highlights decisions that take place in a 'real' environment. Using the previous example of a pilot to illustrate this point; the pilot may want to land in a certain airport but due to weather restrictions for instance, s/he may have to divert to an airport miles away. This would mean organising alternative transport for the passenger's and could result in the pilot and passengers not getting home for another day. Therefore the decision made would be satisfactory as it is safest option, but not the pilot's (and probably not the airline's) first choice.

The classical approach to decision-making research emphasised the concurrent evaluation of multiple options and relied on analytical methods for integrating values and probabilities associated with each option, only then would the decision-maker seek an optimal solution. Another fundamental problem with CDM research is that research took place in the laboratory away from any meaningful context. In the real environment decisions are generally placed within a broader context and the process is not complete once a decision has been made. Other differences can be portrayed on the basis of at least three factors (Bowers et al, 1996):

(1) The nature of the decision itself: what has to be done? For example, will people die if the aircraft is not landed?

(2) Associated with decision-maker and their individual differences: how much experience does the decision-maker have? How motivated is s/he?

(3) Finally the environment in which the decisions occur- factors that are not part of the decision process itself but may play a part, e.g. time of day, or the physical setting.

According to Orasanu (1993), the aviation domain is well suited to the study of NDM because:-

(1) The environment is dynamic, and problems can be ill-structured.

(2) Time pressure is often a frequent ingredient.

(3) The consequences of poor decision-making can often carry high risks. (p.475).

NDM was developed specifically to address the decision-making process of experienced decision-makers who work in stressful environments and emergency situations, such as the flight deck, firegrounds, emergency control centres etc. This theory was developed through observation of decisions made in the real-world context and the characteristics are described in the following section.

1.5 Characteristics of NDM

With a paradigm shift in decision-making research becoming apparent and the need to define this new concept of naturalistic decisions, Orasanu and Connolly (1993) identified eight factors that characterised decision-making in naturalistic settings. According to Orasanu and Connolly (1993) these eight characteristics also encapsulated areas that are frequently ignored in CDM research (p.7). These factors can complicate the decision task but it is unlikely that all will be present at any one time. Extremes of these factors would represent a 'worst case scenario' for any decision maker. In general, NDM research aims to *describe* and not *prescribe* decision-making in a real environment. This important goal of NDM research is the main area that this thesis is aiming to address.

1.5.1 Ill structured problems

In a real setting problems rarely present themselves in the complete form that the event model suggests (see section 1.2). The decision-maker has to identify the situation as one where choice is available. They will have to work hard to generate hypotheses develop options that merit appropriate responses. Complex causal links, interactions between causes and feedback loops are also present in the naturalistic setting. There can be several equally good ways of solving a problem. Decision-makers cannot rely on a single procedure for making a decision. The most important variable here is that the decision-maker must recognise that a decision is required. This is were NDM and CDM differ, the decision-maker must have situational awareness (SA) to be able to assess the nature of the problem and what to do about it (see section 1.10 for discussion on SA).

1.5.2 Uncertain dynamic environments

Problems generally occur in an environment where there is incomplete and imperfect information. The decision-maker has information about some parts of the problem but not other parts. Furthermore, this information could be ambiguous or of poor quality. The information can be presented in an incomplete and dynamic format, making the decision-maker uncertain in their decision.

1.5.3 Shifting, ill-defined, or competing goals

A decision-maker is driven by multiple goals, not all of which are clear and some may be opposed to others. These can also change over time. In NDM the problem needs to be resolved quickly, as in a dynamic environment the situation can change requiring new goals and new problems to be solved. Larger goals provide the direction, since decisions are embedded in broader tasks (Orasanu and Connolly, 1993). As discussed previously, in a naturalistic setting decision-makers are confronted with problems that are ongoing, one decision brings about another decision, etc. For example with a fire-fighter, the goals could be to save the people, put out the fire, protect other buildings from the fire, protect fire-fighters, etc. These goals need to be prioritised. For example, in this instance the first priority could be to save lives, however perhaps the commander would have to send other fire-fighters into the blazing building (therefore putting them in danger) in order to fulfil this goal. Already two goals are in conflict with one another. Through past experience and the continuing assessment of the situation the commander would come to a satisfactory solution, perhaps by saving all the people in the building, but the end result being the building is gutted.

1.5.4 Action/feedback loops

With traditional CDM research, the researchers were concerned with an event; a point in time at which the single decisive action was chosen. NDM looks at a series of events or a set of actions that are used to deal with a problem or find out more about it. This is not just gathering information until it becomes useful but rather recognising that there are multiple opportunities. In the real environment decisions are dependent and ongoing with the outcome of iterative decisions affecting subsequent decisions. If a decision-maker chooses an option and it is incorrect then they can choose another option that allows corrective action. However, feedback loops can also create problems, especially to researchers. The action chosen and the event observed may be only 'loosely coupled' to one another making it hard to attribute affect to cause.

1.5.5 Time stress

Time pressure has obvious but important implications. Firstly, time pressure will increase personal stress. Secondly, it could shift the individual's thinking, in some circumstances in the direction of using less complicated reasoning strategies (Payne, Bettmen, and Johnson, 1988). When a decision-maker is under time stress it is unlikely that a thorough evaluation of multiple options as suggested by CDM research is possible (Orasanu and Connolly, 1993). In fact Klein (1993) suggests that often only one option is analysed and then in a non-exhaustive manner.

1.5.6 High stress

High Stress can be life threatening, can affect an individual's career or the reputation of a company. Common sense, of course, would imply that not all decisions have such consequences. Classical research has mainly been carried out in the laboratory where participants have less interest in the task compared to carrying out a similar one in a real-world setting, even if there are similar decisions in the real world.

1.5.7 Multiple players

Several people may be involved in a single decision. It could even be a decision-maker delegating work to a subordinate, or it could be an entire management team working together. When there are multiple players it is rare that all will have similar goals and information, therefore the information needed to make a suitable decision may be obscured. In comparison to CDM were a decision is made according to logic (Bayesian inference, see section 1.2) it is obvious to say that when there are multiple players, making a decision in a logical format could prove difficult.

1.5.8 Organisational goals and norms

This is the final characteristic suggested by Orasanu and Connolly (1993). They reported that goals in the decision-making process may not only be personal ones. The organisation may also place procedures in the system to help the individual in his/her decision-making.

Bowers, Salas and Pruitt (1996) suggested that the above eight characteristics are central to NDM research. However, they also included some extra factors, for example (1) *Meaningful consequences*; desire to do well/consequences of an error/will to succeed/obtain certain results etc; (2) *Complexity of the decision;* which is not as explicit as the cue-criterion relations of classical research; (3) *Quantity of information to be considered;* this could relate to the complexity of the decision and the amount of knowledge an individual must harness to choose the correct option and (4) *Level of expertise;* those who use their past experience when making a decision. See table one for a summary of the factors that are central to NDM research according to Bowers et al (1996). This table presents the variable or characteristic of NDM research and indicates if it is a feature of the decision itself, a feature of the decision-maker or a feature of the external environment. The indication of each is represented as a pictorial 'tick'.

Table One Factors that are Central to NDM Research according to Bowers et al (1996).

Variable	Feature Of: Decision/ Task	Feature Of: Decision Maker	Feature Of: Environment	Comments
Uncertain, dynamic task	✓		✓	This is the single most important characteristic of NDM
Multiple event feedback loops	✓		✓	Relates to the dynamic nature of naturalistic decisions
Meaningful consequences	✓	✓		This can be related to the decision maker's motivation and/or the nature of the task
Ill-structured decision	✓			Structured decisions are not typically complex or in need of attention using 'naturalistic' methods
Multiple goals	✓		✓	These can be shifting, competing or even unclear
Time constraints	✓		✓	This is a crucial NDM characteristic as time pressure can affect decisional processes
Decision complexity	✓		✓	Complex decisions pose greater challenges for aiding and training
Multiple players			✓	Often decisions are made with multiple players, however, individual Decision-making is of interest too
Congruent organisational norms and goals		✓	✓	Decisions are more difficult if there is no congruence between the decision-maker and organisation, situations were the goals are compatible are of interest as well
Quantity of information	✓		✓	Information overload is an important characteristic in NDM research
Level of expertise		✓		This is a major goal of NDM research: to investigate decision-making by experts. There is also much to be learned by investigating processes employed by different levels of experience.

1.6 Limitations of the NDM framework

Although researchers within NDM seem to have answered questions previously ignored by the decision event model, the field is still in need of a few things (Pruitt, Cannon-Bowers, and Salas, 1997). Firstly, a theoretically-driven yet practical model of NDM needs to be developed and secondly, there is still a need for more empirical work within this important field (Flin, Salas, Strub, and Martin, 1997). Klein (1997) suggests that better methodologies of which to study NDM, both within the laboratory and in the field, could accomplish this task. Although cognitive task analysis (CTA) has helped somewhat, there is a need to go beyond CTA and develop methods of analysis that can ensure naturalistic decisions can be studied in more controlled settings. Finally, there is still a place for CDM (Pruitt et al, 1997). NDM cannot be a solution for all real world decisions. A single-minded focus on the economic view of decision-making needs to be abandoned, research from various fields such as cognitive psychology, organisational behaviour and systems theory needs to be drawn upon to accomplish a practical decision-making model (Lehto, 1997). Despite the numerous models for NDM there is still a major need for a means of analysis and validation. The next section discusses the main models of NDM research and their similarities. Section 1.12 then introduces a possible way in which to produce an empirically verifiable model of the decision-making process.

1.7 Models of NDM

The models associated with NDM emphasise that different cognitive strategies and processes are used when the decision situation is viewed as a temporally evolving one rather than as a static event; that action and perception are crucial aspects of cognition; that human resource limitations are an important factor in decision-making; and that human decision-making competence, rather than dysfunction, should be emphasised (Bowers et al, 1996). Furthermore, the focus of these models is on the 'upfront aspect of the decision event, i.e., on identification and definition of the problem rather than on the generation and evaluation of alternatives for a solution' (Mosier & Orasanu, 1995, p.474). The processes described by the models are iterative and are highly focused on situation awareness and situation assessment (see section 1.10.2 for a full discussion of these terms). Lipshitz (1993) reviewed nine models of NDM and assessed them for similarities. He found six common themes, which were (a) diversity of form; (b) situation assessment; (c) use of mental imagery; (d) context dependence; (e) dynamic processes and (f) description-based prescriptions.

The NDM models that are discussed in what follows were chosen as they all dealt with decision-making in a real world environment. Furthermore, within these models the decision-makers had to have relevant knowledge and expertise to make meaningful decisions, which is similar to Jensen's (1995) model of pilot judgement. Lipshitz (1993) grouped the nine models into two sections, the first being the process models, which described the sequence of phases in which decisions were made. This models within this category are described in section 1.7.1. The second category consisted of typological models, which classified the decisional process and are described in section 1.7.2.

1.7.1 Process Models

The process models all depict decision-making as a sequence of activities. The difference being the type of decisions and the nature of the sequences that they describe. There are five models that belong to this category (Litshitz, 1993). These are Noble's Situation Assessment (1989); Klein's Recognition Primed Decisions (1989); Pennington and Hastie's Explanation-Based Decisions (1986); Montgomery's Search for Dominance Structure (1989) and Beach and Mitchell's Image theory (1990). All five models are discussed below in detail.

1.7.1.1 Noble (1989): Situation Assessment

This model focuses on one crucial aspect of decision-making; the assessment of the situation. An accurate evaluation of the situation is very important to facilitate appropriate decision-making. Taking this view, Noble developed this theory in the hope that an insight into decisional aids would be achieved. He hoped that decisional aids would help an inexperienced or stressed decision-maker interpret the situation in a more definite manner, thus providing them with the skill to find a more effective course of action.

In Noble's theory of Situation Assessment, concrete information is combined with background or 'context' information and general knowledge (retrieved from memory). For example a doctor would use his or her experience about symptoms of diseases to discover what illness a patience was suffering from. This context knowledge forms a representation of the situation. According to Noble, a person 'matches' the current situation to a previous situation and chooses the actions that worked in the past, as these should also work in the new situation. In other words, this model is an organisation of memory where experienced decision-makers process information from previous experiences to choose their course of action. Noble referred to this process as 'reference problems'. Reference problems are activated when current problems match, therefore prompting certain actions.

The Situation Assessment model was developed when Noble (1989) carried out research on a computerised system that was to be used in operational environments. Therefore it does not simulate how people go through the stages above. Noble developed a model that would combine information of different types and from a variety of sources. This information could be 'vague, unreliable, incomplete, partially inconsistent, and deliberately misleading'. Figure two depicts Nobles theory of situation assessment. The following models are based on how people base their decisions on situation assessment.

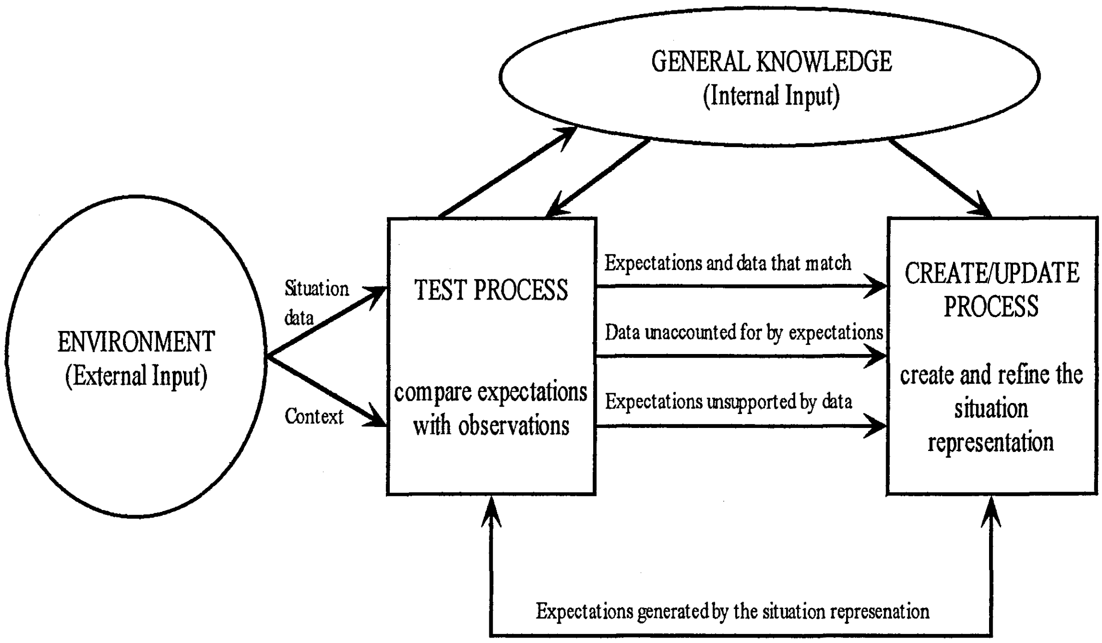

Figure Two Situation Assessment: A Schematic Representation. Adapted from Noble (1989).

1.7.1.2 Klein (1989): Recognition Primed Decisions (RPD)

This model describes how individuals make decisions under time pressure in dynamic situations, and have personal responsibility for their decisional outcomes. Klein (1989) stated that proficient decision-makers rarely compare alternatives, which is contrary to traditional research. Klein found that in typical situations, decision-makers evaluated their responses serially by anticipating what would happen if they carried out a given action. This theory accounted for later observed decision-making performance by expert decision-makers (Noble, 1993). Klein proposed that decision-makers identify and select appropriate alternatives because they appear to 'fit' a particular problem. The decision-maker does this by first assessing the situation with respect to the possibilities for various types of actions. See Figure three for Klein's theory of recognition primed decisions. Klein proposed the following three phases for recognition primed decision-making, which are presented in figure three. These are situation recognition; serial option evaluation; and mental simulation. All phases are briefly described on the following pages.

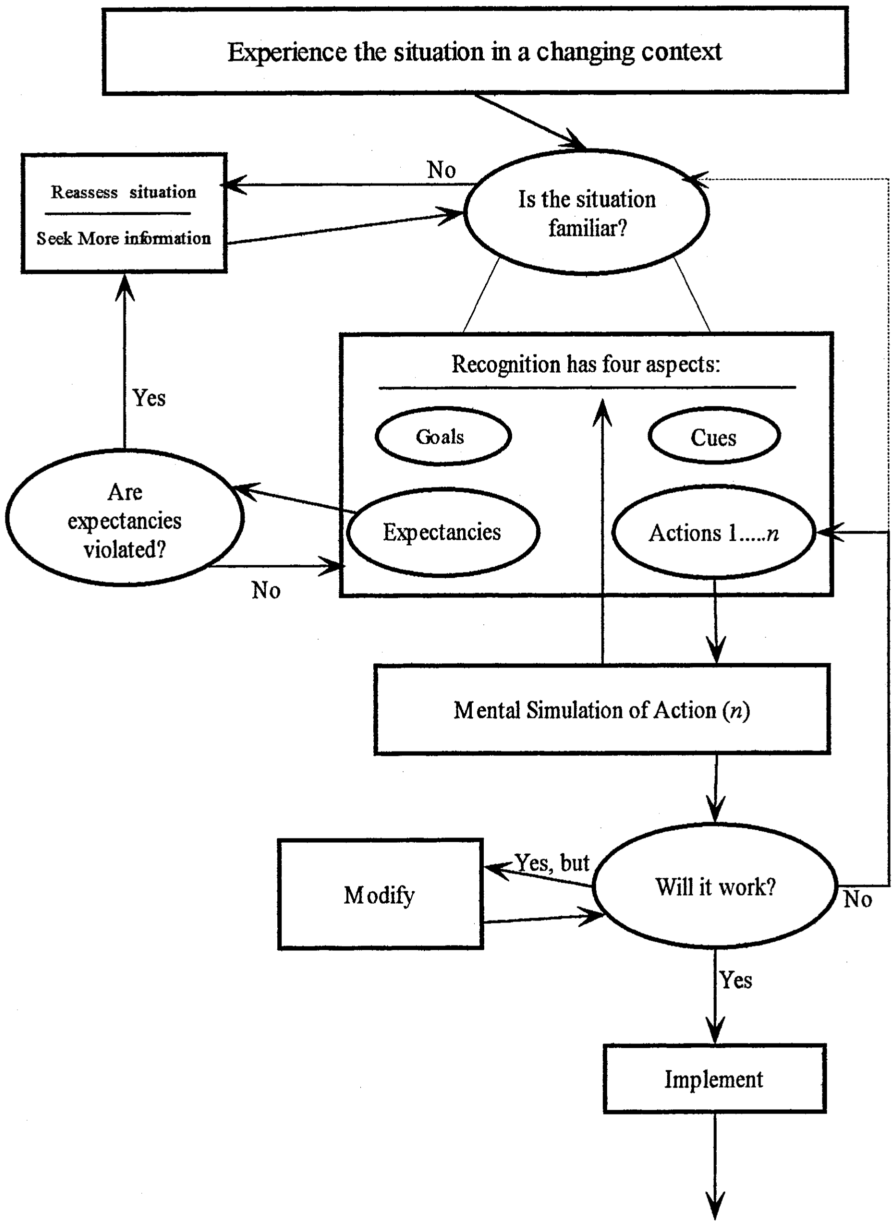

Figure Three Recognition Primed Decisions adapted from Klein (1989).

(1) <u>Situation recognition:</u>

The first stage of Klein's model is similar to Noble's Situation Assessment theory (1989; 1993). The individual recognises the situation as novel or typical. At this stage recognition is the crucial element. Typical situations lead to rehearsed actions whereas novel situations 'pose' a new challenge that cannot be dealt with using old challenges. The individual assesses the situation, and recognises the type, and also what is going to happen in the future. Based on this the individual then makes an action to achieve his or her goals.

(2) Serial Option Evaluation

The individual evaluates the actions that can be taken one at a time until a suitable one can be found. Actions are selected from an 'action queue' where they are arranged according to typicality. This is done by mental simulation.

(3) Mental Simulation

The individual evaluates the action in his/her mind, (the steps to be taken; the outcome; problems that are likely to be encountered, etc). A reassessment of the situation occurs.

Apart from the three stages just described, Klein identified two major components in RPD; recognising the nature of the problem situation and; retrieving a response, which is evaluated for appropriateness in the situation. He found that experts and novices differed in the way that they retrieved and evaluated solutions for the problem faced. Experts tended to retrieve and evaluate the solutions in a serial fashion, whereas the novices compared a full set of options concurrently to reach their solution.

The main implication of Klein's theory is that it is descriptive. Klein does not prescribe how decisions ought to be made, but rather how people make decisions in their domain of expertise. In this, he also points to the importance of domain specific knowledge and the role it plays in effective decision-making. Klein suggests that his model of decision-making is not a universal model but is how decisions are made under stressful and time constrained conditions. This theory relates to aeronautical decision-making as pilots are experts in their own right and need to obtain relevant information in order to make effective decisions.

1.7.1.3 Pennington and Hastie (1986): Explanation-Based Decisions

This model of Decision-making was formed following research on how jurors formed verdicts. Participants on jury duty were asked to watch a condensed version of a murder trial. While watching this video the jurors were asked to think aloud. Pennington and Hastie reported a three-phase process that corresponded to the three stages of the murder trial.

(1) Processing the Evidence

During the course of any trial, jurors are presented with a lot of evidence, which will often be contradictory. For the individual juror to make sense of this evidence, Pennington and Hastie found that the juror tended to create a story that coincided with the evidence. About half of the events in the 'story' related to the evidence presented in the trial, the other half were events that had been inferred, so that the juror could make sense of the whole story by filling in the missing gaps. There may however be individual differences within the story. Pennington and Hastie suggested that there was an underlying process that they called 'episode schema'. The abstract elements of episode schemata are shown in figure four.

As can be seen from figure four, episode schemata are connected by the causal relationships between the initiating events and the physical state of the characters involved in the trial (e.g. the defendant argues with the victim in a local bar). The psychological states and goals of the characters are also examined (e.g. they both become increasingly hostile and the defendant decides to kill the victim). Then finally, the actions and consequences of those actions of the individuals involved (e.g. the defendant goes home and gets a gun, shoots the victim, who dies on his way to hospital).

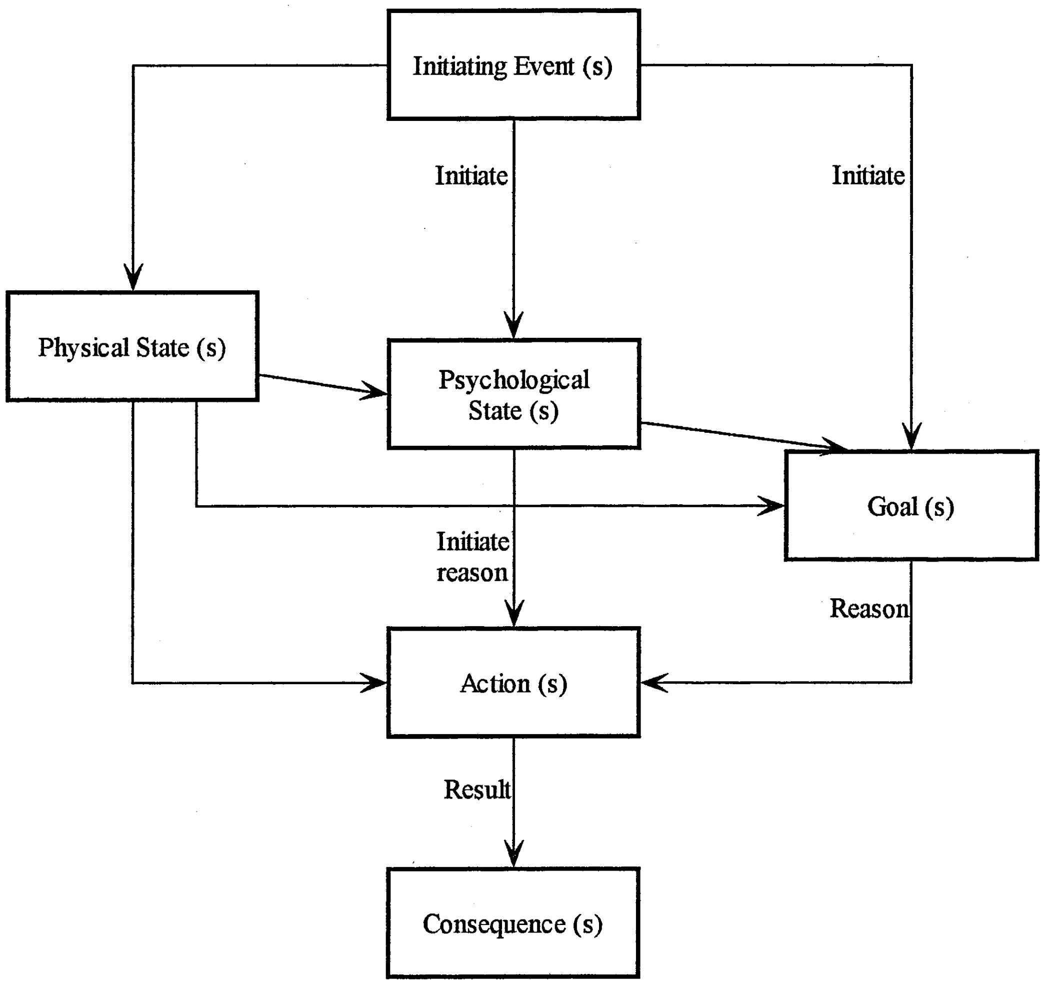

Figure Four Abstract Episode Schema adapted from 'Evidence Evaluation in Complex Decision-making' by Pennington and Hastie (1986).

(2) <u>Defining verdict alternatives</u>

The judge advises the jury on the possible verdicts that apply to the case, he then defines the attributes that need to be satisfied for each verdict. The attributes would be similar for all murder trials, and consists of: the identity, the actions, the mental state, and the circumstances of the murderer.

(3) Determining the verdict

The jury determines the final verdict by matching a verdict with the story that the individual jurors constructed from the evidence. This can be done directly by matching the verdict attributes (identity, actions, mental state, and circumstances of the murderer) and the episode schemata (characteristics, actions, mental states, initiating events, and physical states of all characters involved). If the juror believes that the defendant had an intention to kill in the individual jurors 'story', then the defendant will be found guilty of murder.

Pennington and Hastie (1993) found that jurors determined different verdicts when they had created different reconstruction's of the case. The difference between individual stories was shown to relate to differences between the attributes of the verdicts chosen by jurors. Generally this model of decision-making shows how people make decisions when a large amount of information needs to be processed and also how their individual values can affect their decisions. The story that the individual creates is an overt attempt to cope with this large amount of information, which forms a causal explanation based both on the facts presented as evidence and inferred general knowledge. However, this model is similar to CDM research as it appears to be more prescriptive than descriptive. This model would also be difficult to relate to other real life decision-making tasks. This is due to the fact that the judge presents possible verdicts and also defines the attributes that match each verdict. Attributes would also be similar for all murder trials.

The previous three decision-making models although fundamentally different all stress the importance of situation assessment, recognition and explanation in the decision-making process. The following model, another NDM theory, can be related to the 'event model' theories because it takes a look at how decisions are made when there are a set of alternatives available.

1.7.1.4 Montgomery (1989): Search for Dominance Structure

Montgomery (1989) looked at the decision-making process when there was a given set of alternatives available to the individual. This theory could be related to consumer behaviour. For example when a person is purchasing a car. It would be obvious to say that there is a certain number of vehicles that the person could contemplate before choosing the one for him or her. Montgomery suggests that in this situation the person's choice is the alternative that is the most *dominant*. An alternative can be called dominant when it is at least as attractive as its competitors on all relevant attributes, but exceeds on at least one attribute. The search for the dominant alternative is described in figure five. There are four phases that an individual goes through to determine the most dominant alternative. At each stage of each phase the decision-maker engages a different set of rules. These rules consist of adopting or rejecting an alternative or opting for one alternative over another. The four phases of dominant searching are as follows:

(1) Pre-editing

This is also known as a conjunctive decision rule. At this phase the individual determines a set of criteria that are important for his or her decision. In the case of buying a car, the individual would determine the size of the car wanted, the price s/he is willing to pay, and perhaps the style of the car required. Once s/he has decided upon these attributes s/he will be able to reject any cars that would be unsuitable, for example the car might be too small, too expensive or just the wrong colour.

(2) Finding a promising alternative

This is also known as a disjunctive decision rule. The individual chooses the alternative that appears to be most promising because of a specific criterion; e.g. the price fits within his or her budget. This phase is descriptive rather than prescriptive.

(3) Dominance Testing

The individual tests their favourite alternative to see if it matches the criterion of dominance. If the alternative is a good fit then it is selected, however, if it falls short, the individual proceeds to the next phase.

(4) Dominance structuring

At this phase the individual has already found the promising alternative is not the most dominant. The individual then attempts to make the promising alternative dominant by reinterpreting its standing compared with its competitors. Montgomery suggests several methods, which the individual can use to restructure the standing of the promising alternative with respect to the competing alternatives. These include *de-emphasising* the likelihood that a certain attribute for the promising alternative will materialise, (e.g. I really like car A but the owner seemed eager to get rid of it); *enhancing* the significance of the attributes on which it is superior by the use of vivid images is another method that Montgomery suggests. *Cancelling* can also occur, which transpires when the decision-maker calculates trade-offs between the advantages of one attribute compared to the disadvantages of another, and finally *integrating* several attributes into one single attribute (e.g. considering the monetary factor as a whole and comparing the prices of all the cars, and then considering which car would be the best value for money). According to Montgomery, decision-making is the process of simply looking for a good argument for acting in a certain way. The decision-maker chooses a promising alternative and then tests it by ensuring it is more dominant than the other alternatives.

This search for a dominant alternative has two purposes. The obvious advantage is that it is compatible with human information processing. It is easier to come to a decision when a person focuses on a limited amount of alternatives and attributes, and by stressing the differences between them. The other advantage is that when a person has a dominant alternative it can aid the person to 'persist' in its implementation. This characteristic accentuates the similarity between this model and Klein's RPD. Both models see decision-making as a quick selection of an action and then an evaluation of that action. Classical decision-making research however, involves an individual collecting all known sources of information and then evaluating those options one at a time (Beach and Micthell, 1990). In real world decision-making individuals rarely have all information available in this format.

Differences between Klein's (1989) and Montgomery's (1989) models however, are that in the RPD model, the current or projected conditions influence the selection and evaluation of alternatives (or actions), whereas in the dominance search model the alternatives are based on a set of common attributes and the selection and evaluation of these alternatives are based on their relative standing within this set. Another difference is that in the RPD model if an alternative (or action) is deemed unsatisfactory it is modified or replaced by another alternative. When the alternative is unsatisfactory in the dominance search model it can lead to the available information being reinterpreted, which Montgomery suggests can even be a distortion of reality by wishful thinking on behalf of the decision-maker himself. Rather then coming to another conclusion, Klein's (1989) model of decision-making is more appropriate for the aviation domain as situation awareness is necessary prior to taking an appropriate action. Due to time constraints and the dynamic environment of the flight deck, pilots may not have access to all available alternatives in which to make a choice, therefore Montgomerys' search for dominance structure model may not be appropriate for decision-making within the flight deck. However, this does not imply that in practice a search for dominance structure is not used by pilots. Previous research by Harris and Elwell (1991) found that pilots generated a limited amount of hypotheses when presented with a slowly developing, potentially hazardous situation, which had a non-obvious cause. The number of hypotheses generated was found to be linked with the amount of information sources interrogated. Further search by the pilot for information was biased towards confirming their initial hypothesis about the nature of the failure. In other words, in some circumstances pilots generate an initial hypothesis and rather then create other alternatives they actively seek information to confirm their original solution to a problem. Figure five depicts Montgomery's theory of the search for a dominant alternative.

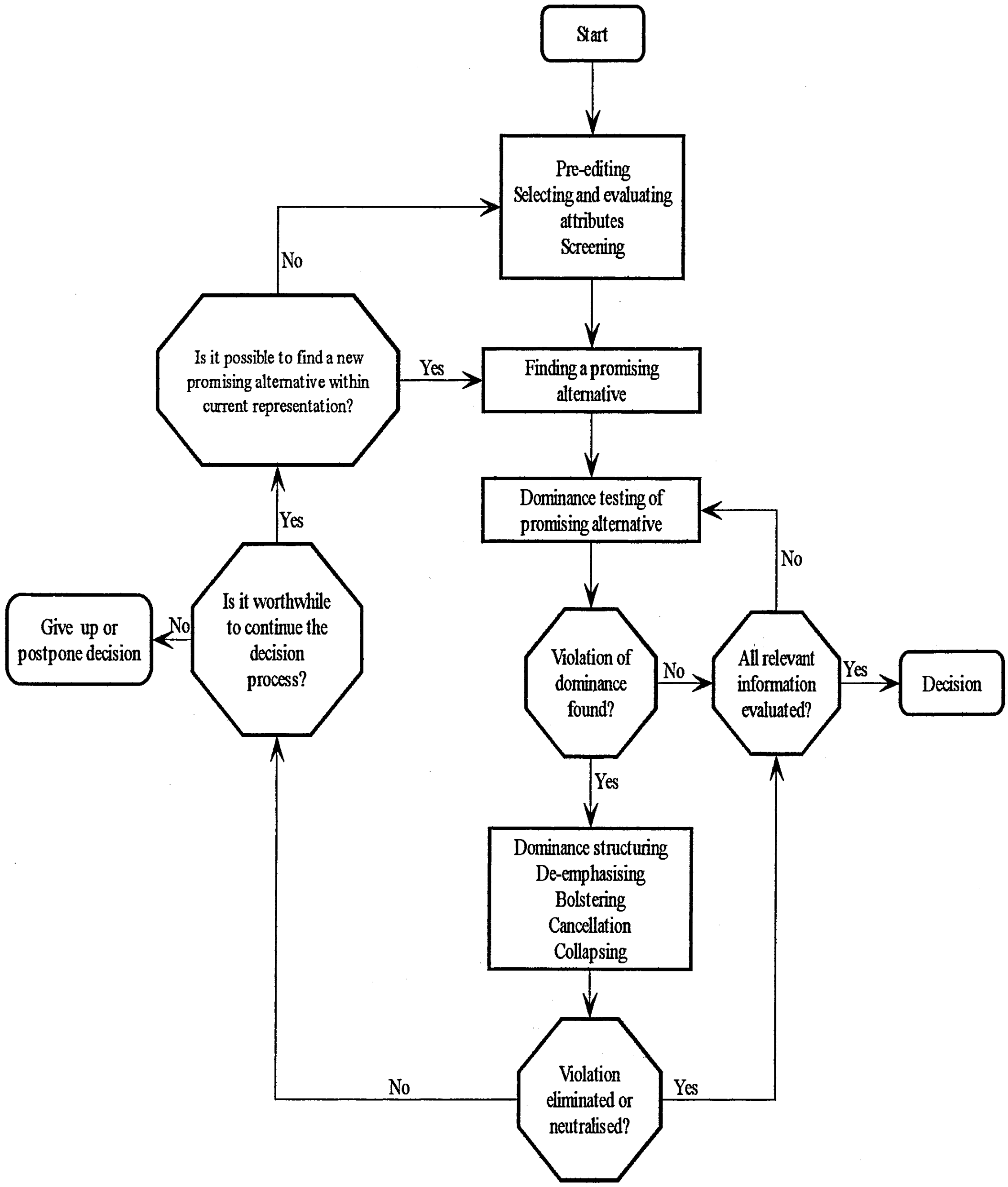

Figure Five Dominance Search Model of decision-making. Adapted from 'Process and Structure in Human Decision-Making', by H. Montgomery & O. Sevenson, 1989.

1.7.1.5 Beach and Mitchell (1990): Image Theory

This model was developed from studies of real-life decisions in widely different domains ranging from whether to commute by car or bus to work, to whether or not to accept a certain job. See figure six for a schematic representation of the Image Theory. The basic concepts of the model were as follows:

(1) Images

These were otherwise known as schemata. These cognitive structures organise the decision maker's values and knowledge and guide their decisions. There are three types of images specified by this theory. The *value image* (Why?) consists of the decision maker's conception of what is right and wrong, and also the ideals to which s/he aspires. The *trajectory image* (What?) is composed of the concrete goals that the decision-maker attempts to achieve. The *strategic image* (How?) consists of plans and tactics, which are the sequences of activities required to achieve a goal, and the forecast of the anticipated outcomes of implementing a certain plan.

(2) Adoption Decisions

As shown in figure six, adoption decisions are based on a compatibility test. A goal is chosen when it does not compete with the decision maker's three images. This can vary from decision-maker to decision-maker and also depends on the situation. Goals and plans are screened out at this stage. If more then one plan survives this screening phase, the decision-maker selects the best alternative by using a test of profitability. These tests can be intuitive, which requires little time and effort, or analytical. Analytical methods can be compensatory, when the decision-maker allows the advantages of an alternative to outweigh the disadvantages of the same alternative, or it can be noncompensatory. Beach and Micthell suggested that decisions in a realistic setting are mainly based on compatibility. They proposed that profitability tests are only used if the decision-maker cannot decide on the basis of compatibility. Also, profitability and compatibility tests are independent, in that information used in testing for compatibility is ignored when the decision-maker moves on to choose the profitability of the chosen alternatives.

Beach and Mitchell have also stated that the more complex the decision was, the more the decision-maker would use intuition (noncompensatory tests of profitability). Furthermore, decision-makers use different tests of profitability, which helps to ensure fairly good quality decisions with minimal amount of effort.

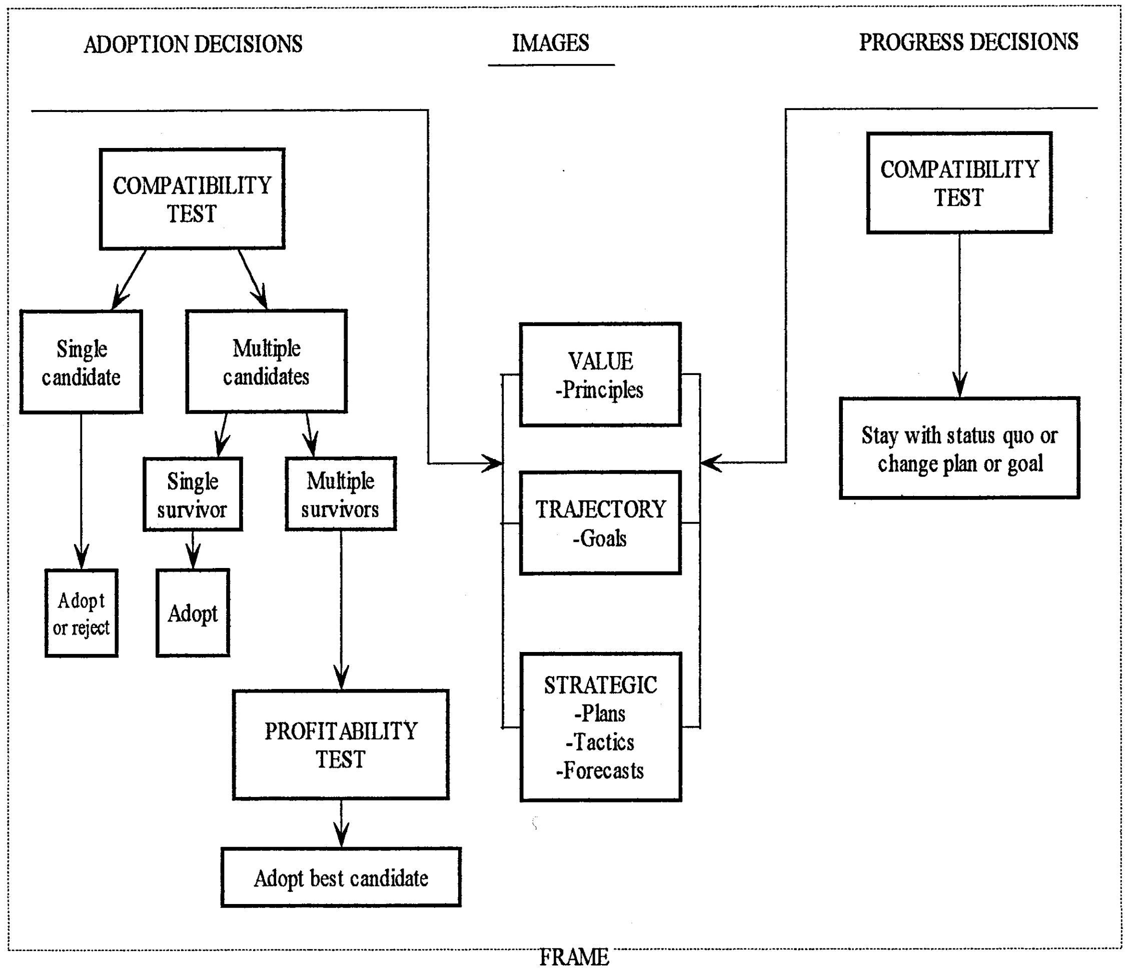

Figure Six A Schematic Representation of Image Theory adapted from Lipshitz (1993).

(3) <u>Progress Decisions</u>

There are two types of progress decisions, and both are made by a test of compatibility. The first is similar to Klein's (1989) mental simulation, and supports adoption decisions by projecting forward, (e.g., what problems is the plan likely to meet? Will it conflict with any of the decision maker's images?). If there is no perceived conflict, the plan will be added to the present images. However, if there is a conflict the plan will be revised or even replaced by another.

The other type of progress decision is used to decide if a chosen plan meets its objectives. No changes are made if the plan is adequate but if the plan does not achieve the objectives the decision-maker will either adapt the plan or adapt his or her goals to fit the plan.

(4) Frames

Frames are proposed as a subset of all the decision maker's principles, goals, and plans pertaining to any given decision. The frame defines the current state of affairs. The decision-maker has a predisposition towards this status quo, suggesting that other things being equal, people prefer existing goals and plans to possible alternatives.

Lipshitz (1993) points out the similarities between this model and the models discussed formerly. Beach and Micthell, like Pennington and Hastie suggest that decision-makers form stories based on their knowledge and values on particular decisions. Image Theory is also similar to Noble's and Klein's in that it proposes that people focus on one alternative at a time. Like Montgomery, the Image Theory is similar in that when a preferred alternative is chosen, the decision to choose that alternative is based primarily on dominance as the main criterion for the preferred choice. The main difference between Image Theory and the others discussed previously can probably be related to the type of decisions Beach and Mitchell studied, like child bearing or job selection. The principle difference lying in the value image, within Image Theory the importance of the decision-maker's values and ideals are stressed. In other words, decisions are not expressions of desired ends but rather an expression of precious values.

Beach (1990) states that real decisions never follow such an orderly fashion as presented by the Image Theory. Therefore, Lipshitz (1993), questions whether the Image theory is truly descriptive especially if the processes it presents are individual ideals rather then how decisions are actually made.

1.7.2 Typological Models

The following models are typological models of different types of decision processes (intuitive versus analytical). These prescribe the conditions under which type of model is likely to be encountered or can be properly used. Lipshitz (1993) classified four models under this category and they are Rasmussen's Cognitive Control of Decision processes (1983); Hammond's Task Characteristics and Human Cognition (1988); Connolly's Decision Cycles (1988) and Lipshiz's Decision-Making as Argument-Driven Action (1993). All four models are discussed in the following sub-sections.

1.7.2.1 Rasmussen (1983): The Cognitive Control of Decision Processes

Errors when operating complex automated systems like nuclear power plants can cost dearly, both in terms of loss of life and expensive equipment. Reason (1990) has stated that consequences of decisions may lie dormant for a long period before being triggered by other factors which can result in accidents. Therefore understanding the decisional processes involved in complex automated systems is important. Rasmussen was involved in researching this area of decision-making. By looking at actual accidents and analysing verbal protocols, Rasmussen determined three types of behaviour that he stated are controlled by qualitatively different cognitive mechanisms. The behavioural components within each of these cognitive mechanisms can be seen in figure seven. Rasmussen suggested that by following these distinctions it is possible to gain a better insight into human errors. By increasing the understanding of human errors it follows that decisional support systems can be developed which will help in the reduction of the occurrence of the said human errors. For the sake of completion all components of Rasmussen's theory will be discussed here. However, the first two components: rule-based and skill-based behaviour are not really concerned with NDM. The knowledge-based behaviour component is where NDM fits in. Rasmussen suggested that the skill-based component is unconscious behaviour where the decision-maker does not consider the outcome of the decision to be made, or indeed if a decision needs to be made at all. The rule-based component is also presented by Rasmussen as automatic behaviour and was found to be based on if, then type scenarios. Both components also represent familiar situations.

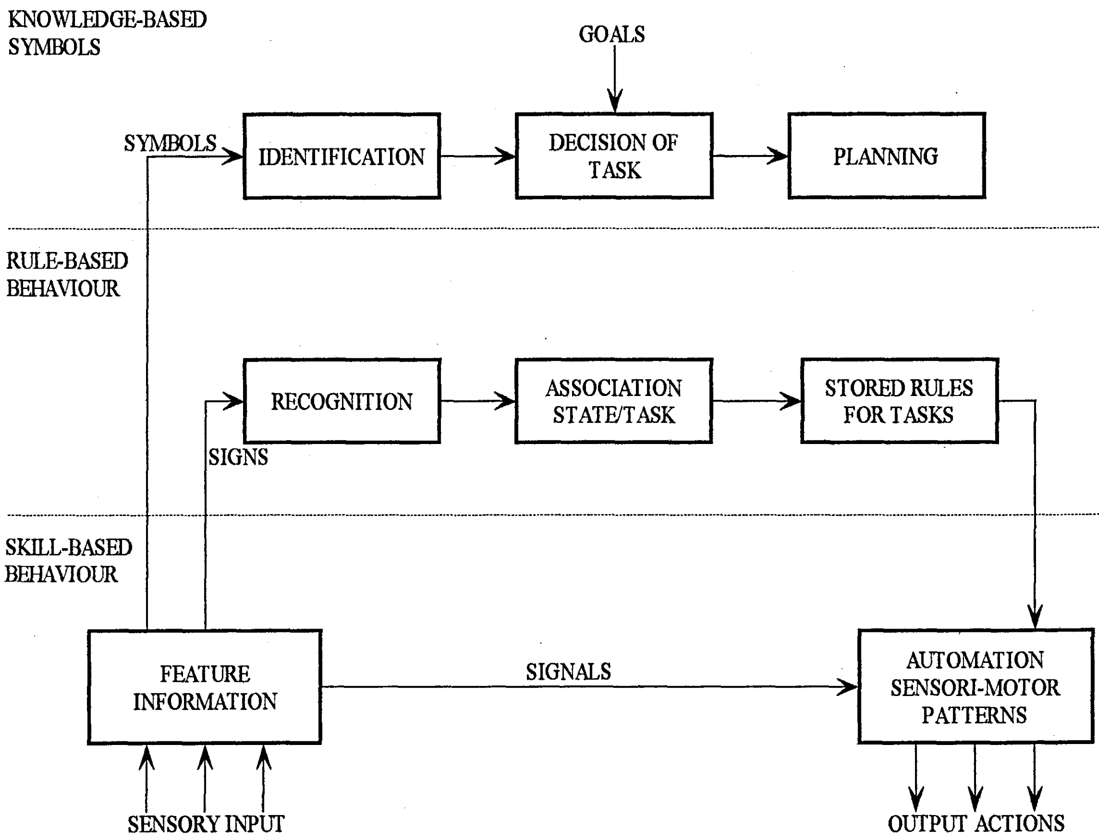

Figure Seven Schematic Model of Three Different Levels of Human Information Processing. Adapted from Rasmussen (1983).

(1) Skill-based behaviour

This type of behaviour encompasses sensorimotor performance, (e.g. driving, typing or playing music). Sensorimotor performance runs without conscious attention. Skill-based behaviours are controlled by a dynamic mental model, which includes the decision maker's movements and representation of the environment in real time, thus enabling him or her to adjust to feedback from his or her actions at any given moment. All information at this level is processed by *signals*, therefore the decision-maker implements actions without considering his or her overall goals or what the information actually means.

(2) Rule-Based Behaviour

The decision maker's rules and know-how influence this behaviour. All information at this level is processed as *signs*, 'Is this a situation that the decision-maker recognises'? Once the decision-maker recognises a situation, cue-task association takes place, which is when a rule evokes a certain behaviour which is based on past experience or training. Both rule- and skill-based behaviours are characteristics of expert decision-making, (the difference depending on whether the behaviour executed is automatic or attentive). Therefore, it depends on the individual's expertise and familiarity with the situation as to whether he operates at the skill- or rule-based level. The type of situation is also important and determines if skill- or rule- based knowledge is used.

(3) Knowledge-Based Behaviour

The previous two levels are concerned with familiar situations. The level of knowledge-based behaviour is more concerned with problems faced by individuals who must make decisions in a novel situation. To make an effective decision in a novel situation, the individual needs to have a deeper understanding of both the nature of the situation and the objectives and options available. All information at this level is processed as *symbols*. Symbols are used to construct mental models that represent causal and functional relationships in the environment. Mental models are constructed using different dimensions of *abstraction* and *decomposition*. The abstraction level expresses the fact that individuals sometimes focus on the concrete physical characteristics of the system or sometimes focus on the more abstract properties, which include the information flow within the system and its general purpose. Within the decomposition level the individual can sometimes focus on specific components or on the larger units, or even the entire system. Figure eight shows the reasoning process of an individual decision-maker who is trouble-shooting within the five levels of abstraction and five levels of decomposition.

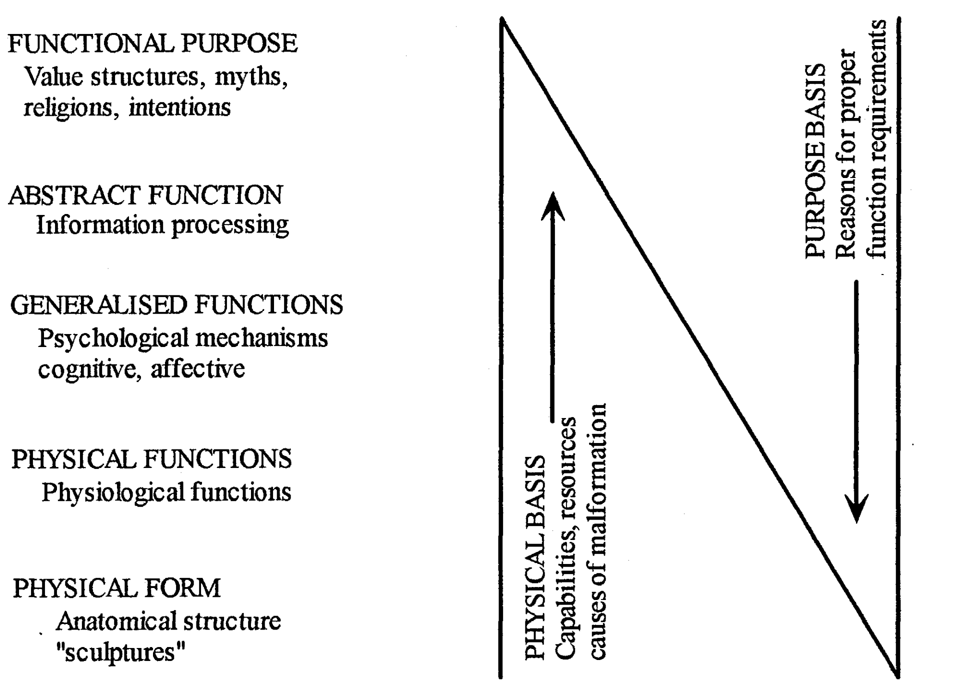

Figure Eight Levels of Modelling Human Performance adapted from J. Rasmussen (1983).

Rasmussen suggests that values and goals influence the higher levels of abstraction. This observation is familiar to the five process models discussed previously, in that, they are mostly models of knowledge-based behaviour. The exception being Noble's and Klein's assertion that individuals assess the situation in a rule-based format. The important implication of Rasmussen's model is the attention he draws to individual decision maker's almost automatic response and actions to certain familiar situations and how they operate within the realm of well rehearsed skills. The next model to be discussed is concerned with intuitive reactions and how effective these reactions are.

1.7.2.2 Hammond (1988): Task Characteristics and Human Cognition

Hammond (1988) was interested in how the processes of a decision change according to the individual dynamic decisional task and environment. He focused on the extent to which decisions are made intuitively or analytically and whether the individual assesses the situation by seeking patterns or functional relations. Hammond's model is an extension of social judgement theory (Lipshitz, 1993). Social judgement theory describes the relationships between the objective environment, the information available in that environment, and the judgments and decisions to which they lead. Figure nine, depicts the sequences taken by meteorologists in forecasting microbursts which are brief, localised windstorms. A to B is a representation of the objective data. C represents the information available in the environment. D is the forecasters perception of that data with F representing the final prediction that the forecaster arrives at.

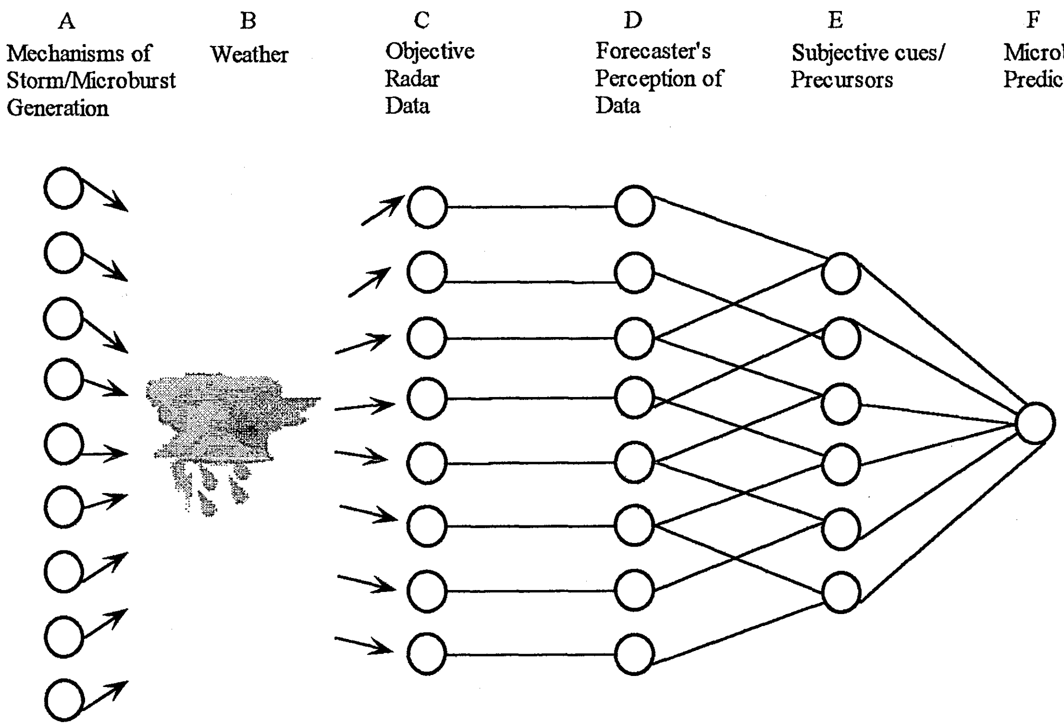

Figure Nine Sequence of Phases in Microburst Forecasting adapted from Hammond (1988).

(1) <u>Intuitive versus Analytical Decisions</u>

Cognitive processes guide decision-making, which can be located on a cognitive continuum. Hammond suggested that this cognitive continuum ranged from intuition to analysis. Several criteria determined if a cognitive process was more intuitive or less intuitive (i.e. analytical). When a snap judgment failed, decision-makers tended to become more analytical. However, when careful analysis failed, decision-makers tended to become more intuitive (i.e. began to guess). Another factor that comes into play is the nature of the task. Hammond described an *inducement principle,* which is a characteristic of decisions that produces intuitive responses. This principle explains the observation that tasks under time pressure but requiring a large amount of information to be processed tend to induce intuitive responses, however, tasks that are quantitative in nature normally induce analytical responses. Two indices, the cognitive continuum index (CCI) and the task continuum index (TCI), can be used to help locate the specific tasks and decision processes on their respective axes. When task characteristics change, individuals switch between intuitive and analytical decision-making. Due to this factor, Hammond suggested that analytical decision-making is not always the best course of action, which he called the *correspondence-accuracy principle*. This principle suggested that when the location of the cognitive process on the cognitive continuum matches the decision task on the task continuum, decision-making is more effective. Basically, this implies that changes in the characteristics of the task led to changes in the cognitive processes. The computability of both task and cognition is determined by the accuracy of the cognitive processes.

(2) Pattern versus Functional relations seeking.

In addition to inducing intuition or analytic cognition, task characteristics instigate the problem solver to seek either patterns or functional relations in the situation (for instance produce explanations for the situation by forming a story). If the situation provides highly organised information or if there is a need for the decision-maker to produce coherent explanations of events and situations, pattern seeking is induced. However, if the information is not organised in a coherent fashion or the decision-maker is required to give predictions and descriptions, functional relations are sought. Unlike analysis and intuition there is no compromise between pattern and functional relation seeking. If changes in the task occur, the individual can alternate between seeking patterns or function relations (Hammond, 1987). Hammond states that there is no need to justify the concept of pattern seeking in a decision theory as this has been recognised by researchers for quite some time (for example the Gestalt school, Hammond, 1987). Pattern matching can be induced by some of the following situations:

- Displays of information that contains a high amount of *perceptual organisation* (visual, auditory, etc.).
- Displays of information that contain a high amount of *conceptual organisation* (the presentation of a time dependent sequence of events, like a story).
- Situations that require the individual to produce coherent explanations of his or her judgement that the event has occurred, is occurring, or will occur. (Hammond, 1987, p.8).

Hammond suggests that decisions made in a naturalistic environment are a mixture of both intuition and analysis. An important implication of this model of decision-making is how it highlights the need to analyse the nature of the decision task and its description of the nature and role of intuition in dynamic decision processes (Lipshitz, 1993). Connolly (1988) took this analysis further and this theory will be discussed in the following subsection. Hammond does not really specify mechanisms, other than decision-making can be a pattern matching process, which is something that neural networks (NNs) has been proved to be particularly good at (Garson, 1998; see chapter two). In this respect, Hammond's model is very different to the other NDM models reviewed. Discussed previously was the need for NDM theories to be tested empirically. It will be argued that NNs could provide the basis for empirical testing of NDM theories, as all other models of NDM are qualitative 'best guesses' of how a decision is made (Orasanu, 1993). There is a need for quantitative work, and to do this one needs a framework. This model proposed by Hammond has all the characteristics of a Neural Network (NN). By looking at figure nine it can be shown that steps D-F is similar to how a NN performs. Steps C-D are depicting the stage of gathering information and are therefore similar to situation awareness. Steps D, E and F correspond to the components found in most NNs. NNs will be discussed in detail in Chapter Two.

1.7.2.3 Connolly (1988): Decision Cycles

Connolly (1988) also proposed that decision-making within a real environment was dynamic. Therefore one can not analyse the processes as isolated instances of choosing among alternatives. He suggested that decision-making be conceived as a cyclical interplay between situation assessment, evaluation of alternatives, and action. Connolly's model of decision-making is shown in figure ten.

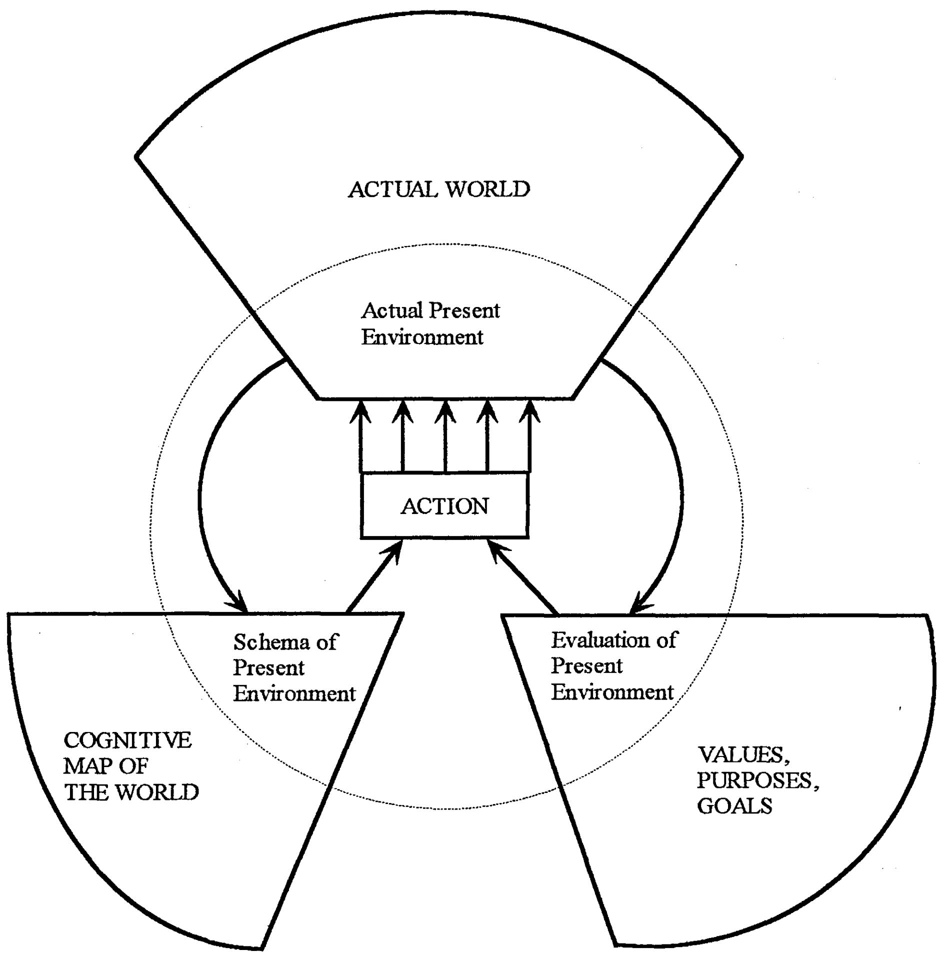

Figure Ten The Two-Cycles Model adapted from Connolly and Wagner (1988).

The Two-Cycles model consists of two cycles, or levels, and three domains. The domains consist of the actual world, the individual's subjective image of that world, and his or her values. The cycles are either the perceptual cycle or the decisional cycle. In the perceptual cycle the cognitive map is adjusted by feedback depending on the action taken. In the decisional cycle the feedback adjusts the goals. In this way Connolly's theory of decision-making is similar to Noble's (1989), Klein's (1989), Pennington and Hastie's (1989), and Rasmussen's (1983). In other words the decision-maker's cognitions guide his or her actions. Like Montgomery (1989) and Beach and Mitchell (1990), Connolly also assumes that a decision-maker's action is influenced by his or her values. In the decision cycles model both the actions and cognitions of the decision-maker are intertwined. Connolly suggests two qualitatively different decision processes in this relationship, tree-felling (action-last), and hedge-clipping (action-first). When a decision is made in a tree-felling process, the decision is sequential, the goals are well defined, and it is clear how to achieve them. When a decision is made in a hedge-clipping process, decisions are made incrementally in a series of steps. Decision-makers adjust their actions and adapt their goals as they get to understand the environment better through exploratory action. The action-first process is advantageous in that when it is difficult to know specific goals, it is better to learn as you go along, rather then invest time in thinking ahead. Here, plans are of limited value when the environment is dynamic. It is easier to adapt to feedback than to have exhaustive planning. The model has not been tested empirically, however Connolly cites research that shows that managers prefer to implement hedge-clipping rather then tree-felling when they are making decisions. The NDM theories being reviewed are all similar in some respects but are describing various decisional tasks (see section 1.8 on common themes). At present however, all theories are qualitative and therefore it is difficult to differentiate between each one. Presently the theory is 'matched' to the problem being researched which is similar to the normative approach to decision-making (Lehto, 1997). It is a lay problem that no NDM theory has been tested empirically. The main point about NDM theory is that the researchers are describing real world decisions, and real world decisions differ depending on the task. NNs are proposed in this thesis to be an analysis tool that may overcome this problem of qualitatively assessing NDM theories.

1.7.2.4 Lipshitz (1993): Decision-Making as Argument-Driven Action

This model was developed from the analysis of self written reports of decision-making under uncertainty. Lipshitz suggests that there are three generic modes of decision-making. These modes include consequential choice, matching and reassessment. Consequential choice can be seen as choosing among alternatives in terms of the expected outcome; matching can occur when the individual selects an action (which is similar to Hammond's theory, 1988) on its appropriateness to the situation; and reassessment describes the mode when the individual re-evaluates the appropriateness of an action because of objections to its implementation (Lipshitz, 1993; p.129). These modes differ in terms of six basic attributes of their decisional processes. Table two, shows these characteristics and the differences between each mode.

Table Two Attributes of Consequential Choice, Matching, and Reassessment adapted from Lipshitz (1993).

Parameter/ Mode	Cons. Choice	Matching	Reassessment
Form	Comparison among alternatives Consideration of future consequences	Situation Assessment Serial rule based evaluation of action	Evaluating and satisfying objections to a certain action
Problem framing	Choosing from an available set of alternatives	Responding appropriately to a problem or situation	Countering objections to a (at least tentatively) selected action
Uncertainty	Likelihood and desirability of future outcomes	Nature of the situation and corresponding 'proper' action	Same as in consequential choice and matching
Logic	Teleological (Thinking ahead- consider the attractiveness of certain situations)	Deontological (Repeat the past learn from own or others experience)	Nonjustificational (Wishful thinking, which can also be based on past experience)
Handicaps	Limited information processing capacity: sub-optimal biases and heuristics	Ambiguous situations; Improper matching rules	Binding precommitment; Unrecognised assumptions
Therapies	Decision Analysis	Training: Expert systems	Critical inquiry (e.g. devil's advocate-reflection on action)

As can be seen on table two, the six attributes are basic characteristics of each mode. Form describes how the action is selected. Problem framing is how the decision problem is defined. Uncertainty is the resolved doubt in order to act. Logic is the underlying rationale for acting in certain ways. Handicaps refers to the barriers in making decisions and finally therapies are the methods of improvement that are in accordance to the other five attributes.

(1) Consequential choice

Individuals using consequential choice to make a decision are looking at all available options and the best consequence of these options. In other words, the decision-maker is thinking ahead and considering the attractiveness of future outcomes, (which is similar to Klein's, 1989 theory). As can be seen on Table Two, a major handicap to successful decision-making in this format is the limited capacity of human information-processing. However, therapies such as decision analysis have been developed to help cope with this problem.

(2) Matching

Situation assessment is the main factor pertaining to matching problems: *what* is this situation and what should I *do* in this situation? By asking this question, individual rules come into play that are based on personal experience, professional standards and social norms. Matching can be blocked by the individual's uncertainty of the situation and what to do when a certain situation occurs. Lipshitz described the underlying logic as *deontological,* which he described with the expression 'those who do not learn from the past are condemned to repeat it' (p.130). He suggested that when people use the matching format to make a decision they are using either their own or other's experience. Therapies that can help in this process are training and expert systems.

(3) Reassessment

When the decision-maker meets problems that need reassessment, actions are dependent on objections to uncertain present or future circumstances. The individual already has a course of action; the main handicap is the individual's acting without thinking. These actions are based on past decisions or plain wishful thinking.

Lipshitz believes that defining decisions and analysing them as a choice among alternatives is an overgeneralisation. He states that decisions are made in a variety of ways that involve at least two different modes. He suggests that decisions should be defined more as purposeful actions driven by action arguments, do 'A' because of 'R', where A is the action, and R is the reason for the action. Different action arguments relate to different decision modes. Consequential choice mode would relate to the argument "Do 'A' because it has better consequences than its alternatives", matching would relate to the argument "Do 'A' because it corresponds to the situation", and reassessment would relate to the twin argument "Do 'A' because there are no objections to its implementation or because objections can be rebutted".

All nine models reviewed above were developed by different researchers using various methods among different occupations, however all models looked at decision-making within a real and dynamic environment. It is also apparent that there are many similarities between these models. The following section outlines these and focuses on six main areas.

1.8 Common trends

The following six similarities between the models will be discussed:

(1) diversity of form
(2) situation assessment
(3) use of mental imagery
(4) context dependence
(5) dynamic processes
(6) description-based prescriptions (which, again is the problem that this thesis aims to address).

1.8.1 Diversity of Form

All nine models discussed previously suggest that decisions can be made in a variety of ways. Klein's (1989) Recognition-Primed Decision Model suggests that decisions are either based on recognition or on the individual's future projection of actions in the form of mental simulations. Pennington and Hastie's (1986) Explanation-Based Decisions model, suggest that individuals base their decisions on story construction. Montegomery's (1989) Search for Dominance Structure model outlines various methods of achieving dominance structure. Beach and Mitchell's (1990) Image Theory, identifies two types of decisions, adoption and progress, and also discusses tests of compatibility and profitability. Rasmussen's (1983) model of decision-making distinguishes between skill-, rule-, and knowledge-based decisions, whereas Hammond (1988) distinguishes between intuitive, analytical, and quasirational decisions. Connolly's (1988) Decision Cycles model suggest that decisions can be made by either 'tree felling' or 'hedge cutting'. Lipshitz' (1993) model of decision-making as argument-driven actions discusses three generic modes of decision-making, which are consequential choice, matching and reassessment.

The fact that all nine models are so diverse is an indication of the unproductiveness of attempting to understand and improve real-world decisions in terms of a single concept such as maximising expected utility (Lipshitz, 1993). It is apparent that NDM researchers cannot agree on how real decisions are made. This is probably due to the different types of decisions studied, for example Beach and Mitchell's (1990) Image Theory looked at personal problems such as whether to have children or not. In consequence their theory discussed how peoples values and ideals influence their decision process. Pennington and Hastie (1986) based their decision-making theory on jury verdicts, therefore the decision process they described included 'story making' which occurs when the jury attempts to fill in what really happened. However, despite the apparent differences in the processes discussed within each model, there are also themes that are similar. Also, although all models suggest that there are several different types of decisions or decision situations, choice and pattern matching seem to be the most common factors between models (Hammond, 1988; Lipshitz, 1993, etc).

1.8.2 Situation Assessment

All nine models discussed the importance of sizing up and constructing a mental picture of the problem situation. This is an obvious shift from the classical decision-making theories, developed during laboratory research where problems were presented as predefined entities and were presented by the researcher with complete information and limited outcomes were available. The NDM models either classify the assessment of the situation as taking place prior to the evaluation of actions, or they tie it directly to the selection of action. Noble (1989) for example, suggested that the assessment of the situation directly influenced the actions selected. Others who take this view include Rasmussen's (1983) skill-, and rule-based behaviours; Hammond's (1988) intuitive decisions; and Lipshitz's (1993) matching mode decisions. The remaining five models take the view that situation assessment is a preliminary stage to decision-making. Klein (1989) for instance saw situation assessment as the basis for mental simulation and serial selection; Pennington and Hastie (1986) reported that juries used past experience in the form of story making to reach their final verdict; both Montegomery (1989) and Beach and Mitchell (1990), took the view that situation assessment is a process of preediting the criteria for action selection. Lastly, Connolly (1988) presented situation assessment, which he called cognitive mapping, as one of his decision cycles. Therefore all nine models see situation assessment as an important part of the process in decision-making in a realistic environment.

1.8.3 Use of mental imagery

The role of weighing the costs and benefits of alternatives has always been emphasised in decisional making research, including CDM. These cognitive processes are related to creating images of the situation. Klein (1989), Rasmussen (1983) and Noble (1989) are interested in the categorisation of situations; Beach and Mitchell (1990), and Connolly (1988) looked at the use of schema; other models discussed mental modelling and story telling (Klein (1989); Pennington & Hastie (1986); Beach & Mitchell (1990); Lipshitz (1993)).

1.8.4 Context dependence

NDM researchers emphasise the importance of context when looking at the decisional process in a real world environment. Rasmussen's (1983) skill-, rule-, and knowledge-based behaviours are determined by context familiarity. The abstraction level of knowledge-based mental models is also influenced by the nature of the context (mechanical versus social systems). Hammond (1988) and Klein (1989) discuss the different contexts that invoke intuitive or analytical processes (situational or task characteristics). Connolly's (1988) two decisional processes, tree-felling and hedge-cutting, are based on the interaction between the nature of the situation, the decision-makers knowledge, and his or her values.

1.8.5 Dynamic processes

All nine models discuss decisions in a real world environment, therefore it follows that all agree on the fact that decisions are not made as isolated events. However, although some real world decisions can be dynamic, others may not be (see section 1.5 on characteristics of NDM; not all characteristics need to be present for a decision to be naturalistic). The dynamic quality of decisions can be conceptualised in two fashions. Firstly as a function of changing task requirements, individuals oscillate between intuitive and analytical decision-making (Hammond, 1988; Rasmussen, 1983; and Connolly, 1988). Secondly Noble (1989), Klein (1989), Montegomery (1989), Beach & Mitchell (1990), and Lipshitz (1993), suggest a two-phase sequence in which a fast preliminary selection is based on compatibility rules. This is then followed by a more deliberate analysis including updating, mental simulation, dominance search, profitability testing, and reassessment.

1.8.6 Description-based prescription

All the NDM models discussed attempted to *describe* the process of decision-making in a real life setting. Traditionally, classical decision-making research focused on the 'decision event' (Orasanu and Connolly, 1993). Here, the individual views a fixed set of options that are known and from these weighs the consequences of choosing each and finally makes his or her choice. Options are evaluated in terms of a set of goals that the individual knows quite clearly. This classical research looks at the way the decision-maker pulls together the information to choose their best option. Recent decision-making research however, shows that it is not possible to draw from all options in the real life environment under naturalistic conditions. This process only occurs in the laboratory (forming the best option from all possible alternatives). According to Bowers, Salas, and Pruitt (1996) these observations would imply that CDM research had little relevance to real world decision-makers. It would be fair to say that all the NDM models discussed have encapsulated real-life situations, in that the decisions researched are more focused on dynamic tasks, with individuals who are knowledgeable and experienced. The models discussed are also more focused on action aimed towards a set of goals, rather then an evaluation of multiple options and the subsequent use of analytical methods for integrating values and probabilities associated with each option in the search for an optimal solution. In conclusion, all nine models attempt to *describe* and not *prescribe* the decisional processes. Mentioned previously is the main limitation of lack of ways to analysis NDM. However, without a method of analysis predictions can not be made, which limits the utility of the approach. NNs may fill this gap in the research and are explored in chapter two as a means to analysis naturalistic decisions.

1.9 The Importance of Expertise

NDM research has highlighted the importance of understanding how people use their relevant knowledge and experiences in coping with complex decision tasks (Orasanu & Connolly, 1993, p. 11). NDM theories focused on individuals who are experienced in their field of work, and who deal with decision-making in stressful environments and emergency situations such as in the flight deck and firegrounds etc. (Flin, Salas, Strub and Martin, 1997). Within NDM, the individual can have a high level of knowledge of their problem domain. This, however, does not mean that they are expert decision-makers, rather that they are familiar with the tools and information available to them to reach their decision. Although very little research has been conducted until recently on expertise in decision-making, problem-solving researchers have been interested in this phenomena for quite some time (Chi, Glaser & Farr, 1988). Research on expertise began with deGroot's (1965/1978) study of chess masters. DeGroot compared expert chess players with less expert players in terms of their memory abilities and their depth of planning (number of moves ahead). He found that the difference between expert and novice chess players was the experts' ability to look at dozens of pieces on a chess board and determine meaningful chunks from those pieces. However, when asked to reconstruct a configuration of a random display of pieces, deGroot found that there was no difference between expert and novices. It has been suggested that the expert's ability to reconstruct meaningful chess configurations is due to the fact that they have come to see the display as chunks of familiar patterns (Chase and Simon, 1973). The master chess player can also associate a few moves with each of these patterns, so there is no need for the expert player to go through a random search-and-test process for all possible moves. The occupations chosen for expertise research are diverse (ranging from chess players to fire-ground commanders), but there is a common interest in the importance of the experts' knowledge base (Means, Salas, Crandall, & Jacobs, 1993).

Experts do not know more when it comes to decision-making than novices; it is that with experience the individual comes to know things differently. The expert forms meaningful patterns by chunking information and attends to critical information while ignoring the less important. Therefore, when a pattern or category is perceived the expert is more inclined to act in a certain predisposed way, without being necessarily aware of the process. This process is called proceduralisation of declarative knowledge (Anderson, 1985). In the first stage of acquiring expertise, the individual acquires factual knowledge about his or her domain. When a problem occurs the individual applies strategies, such as means-end analysis using available knowledge. Through experience these strategies become linked to certain actions to fit specific situations, so that actions become almost 'intuitive' (Dreyfus, 1981). The implications of this process of skill acquisition is quite plain; expertise is domain specific. It also implies that experts use their knowledge in a highly procedural format (Means, Salas, Crandall, & Jacobs, 1993). Due to the fact that an experts' knowledge is linked with his or her actions, it is difficult to separate what they know and how they use that information.

Problem-solving studies have shown that experts interpret the problem differently than novices and devise different strategies in reaching the final solution to the problem. Klein, Calderwood, Clinton-Cirocco (1986) reported that it was more characteristic of novices to explicitly consider more then one decisional option at a time while reaching a decision. Other differences include what information is used, memory for critical information, and speed and accuracy of problem solving.

Models that have emerged from NDM theory, such as Recognition-Primed Decision-Making (RPD; Klein, 1989), Image Theory (Beach & Micthell, 1990), or Situation Assessment Theory (Noble, 1989), stress the importance of the non-analytical nature of expert decision-making in naturalistic environments. Larkin, McDermot, Simon, & Simon, (1980) report that experts see underlying causes and have more complex models of the problem than novices. Shanteau (1987), also found that the difference between expert and novice decision-making was due to a difference in ability to perceive meaningful patterns. This ability to perceive meaningful patterns is directly associated with the action chosen (Means et al, 1993), and it is suggested that it is built up through experience and practice. Redding, Cannon and Seamster (1992) also found that experts are capable of developing and revising long term strategic plans. Once the situation has been defined, the expert knows what action to take because he has a far greater store of experiences to call upon (Calderwood, Crandall, & Klein, 1987).

Although expertise is important in the NDM framework, it is not just expertise that the researchers are interested in. Cannon-Bowers et al (1996) stated that there is also a lot to be learned from those who are not so expert at a given task. They claim that it is the process in which people pull together their experience and knowledge, which is of interest to NDM researchers.

1.10 Situation Awareness in Naturalistic Decision-Making

The importance of situation assessment has already been discussed throughout the previous sections. Situation assessment is the process by which the state of situation awareness (SA) is achieved (Sarter and Woods, 1991). Therefore as situation assessment has been determined as such a critical component in decision-making, it is important to discuss SA when exploring decision-making in a dynamic environment.

Due to the evolution of technology, many complex dynamic systems have been created that tax the individual's ability to act as effective, timely decision-makers when operating these systems. According to Endsley (1995a), the operator's situation awareness (SA) is a critical construct on which decision-making and performance in these dynamic systems hinge. Endsley (1995) states that SA is far more than an operator merely being aware of numerous pieces of data. The operator of a system must have advanced understanding of the situation and a projection of future system states. Operators of dynamic systems need to determine the current status and dynamics of their systems and other relevant elements in the environment in order to determine the best course of action to take at any given point in time. An individual does not simply perceive the state of the environment with their goals in mind; they must integrate the meaning of what they are perceiving. SA forms the basis for decision-making in that it 'incorporates an operator's understanding of the situation as a whole' (Endsley, 1995a, p.34). SA is not all of one's knowledge. It is only the portion pertaining to the state of the dynamic environment. Mental models of the systems, rules, procedures, and checklists etc., while important to the decision-making process, are all fairly static knowledge sources that fall outside the boundaries of SA. Researchers studying decision-making have shown that operators will classify and understand a situation before proceeding to the action selection (Klein, Calderwood, & Clinton-Cirocco, 1986; Klein, 1989; Lipshitz, 1989). Previous research has also shown that an integrated picture of the current situation can be matched onto past experience and situations in memory, which would then be mapped onto a correct action or decision. A high level of SA forms the basis for prompt decisions and immediate, appropriate and effective actions. A low level of SA has been identified as being the predominant cause of near misses and fatal accidents in both military and civil aviation. Figure eleven depicts the progression for SA and decision-making. First situation assessment must take place, here the individual determines if a decision needs to be made or not be made, this leads to the individual's awareness of that situation, a decision is made, an action is chosen and finally an outcome will result. This process is cyclical, as once the individual chooses an outcome they must reassess the situation and determine if another decision is needed.

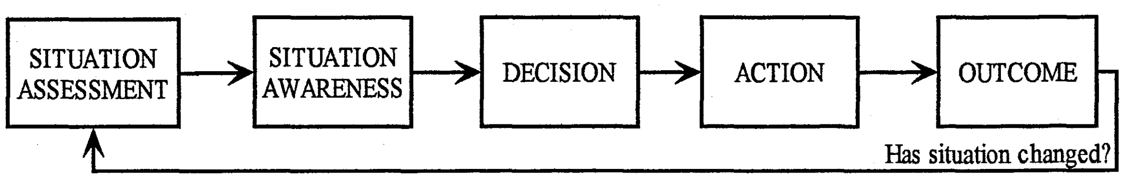

Figure 11 Progression of Situation Awareness and Decision-Making.

1.10.1 A definition of Situation Awareness

Situation awareness (SA) is more than simply perceiving information within the environment. It includes comprehending the meaning of the information in an integrated form, comparing it with operator goals and developing projected future states for the environment that are valuable for decision-making. Thus, SA is a broad construct that is applicable across a wide variety of application areas, the information being processed may be different but the underlying cognitive processes being utilised can be the same. Considering this, SA plays an important role in effective decision-making. Endsley (1995) states that SA also impacts the process of decision-making itself. There is evidence to suggest that the way a person characterises a situation determines their decisional process to solve a problem (Manktelow & Jones, 1987). It is also the decision specifics that determine the adoption of an appropriate mental model, leading to the selection of a problem-solving strategy. Bettman & Kakkar (1977) found that the presentation of a problem also influences how the person solves it. This finding has been supported in subsequent research (Herstein 1981; Tversky & Kahneman, 1981; and

Sundstrom, 1987). The given explanation is that people comprehend the situation differently by integrating information depending on how the problem is framed, thus effecting the selection of a mental model to use for solving the problem.

When individuals are given the same data they can differ in their SA. Endsley proposes that this is due to the individual's information processing mechanisms. The information processing can in turn be influenced by the individuals ability, their experience and also their training. According to Endsley's approach to SA it could be viewed as a separate construct to decision-making and performance. Even the best trained decision-makers can make mistakes if their situation awareness is incomplete or wrong. Likewise, if a person has perfect SA they could make an incorrect decision or show poor performance from an inability to carry out correct actions and therefore result in incorrect decisions.

Endsley describes a model of SA and decision-making that is descriptive and also synthesises information from a variety of areas. See figure twelve for Endsley's model of SA and decision-making. This model incorporates Klein's (1989) desire that SA should explain dynamic goal selection, attention to appropriate cues, expectancies regarding future states of the situation and the tie between SA and typical actions.

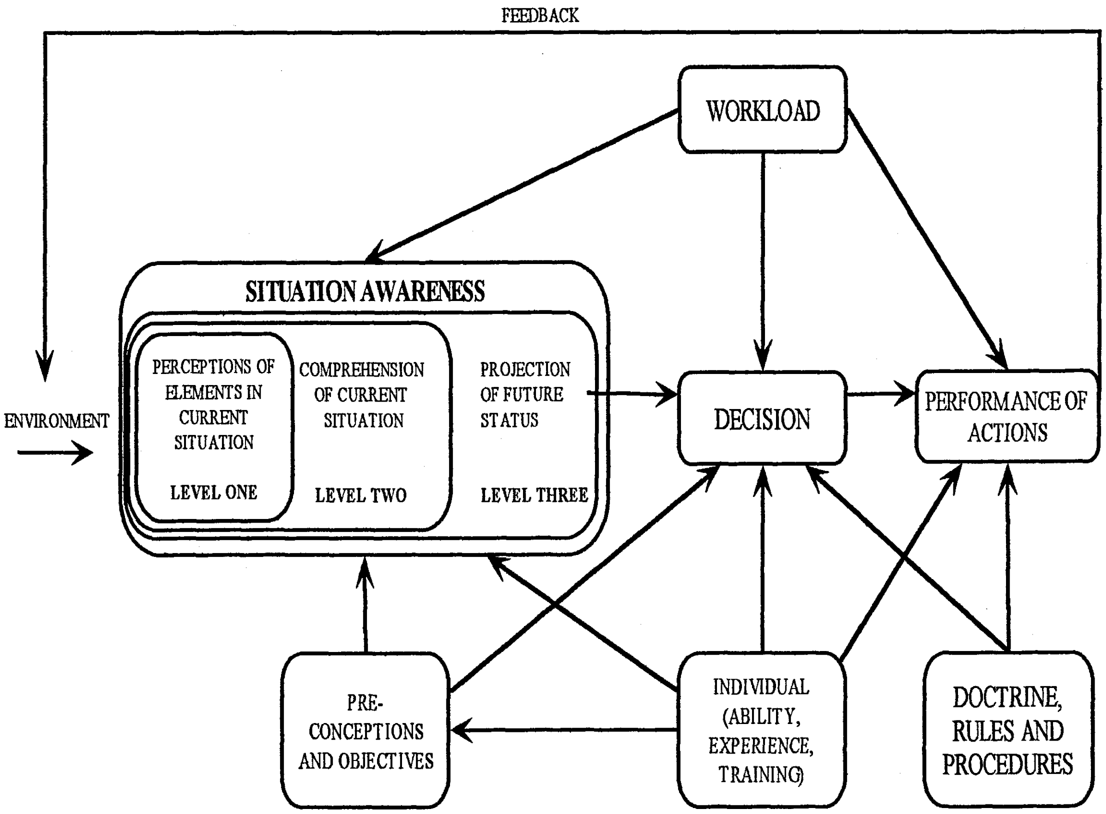

Figure Twelve Model of Situation Awareness in Dynamic Decision-Making. Adapted from Endsley (1995).

Randel and Pugh (1996) also see situation awareness as the first part of the decision-making process in a naturalistic setting involving a complex task. They looked at the differences between expert and novices in their roles and possible conflicts in rules to guide a course of action. They state that an expert's ability to perform a task arises from the interaction of several components. Factual knowledge, efficient retrieval of stored knowledge, ability to monitor motor and perceptual processes, and also the ability to efficiently allocate resources. Research has also shown that differences are not only due to the factual component but other skills (discussed previously) that can decay over time. The difference in ability to perceive meaningful patterns (Shanteau, 1987) and to associate certain action with those patterns (Means, Salas, Crandall, and Jacobs, 1993). This ability is built up over time by experience and practice. Gibson, Garland, Koonce (1994) also use the term situation awareness whereby a person is involved in a situation that requires quick decisions under stress.

1.10.2 The Difference between situation assessment and situation awareness

Situation Awareness as a state needs to be seen as separate from the process of achieving it (situation assessment). There may be different and equally valid ways of achieving the same Situation Awareness (Endsley, 1994). Endsley suggests that if researchers are concentrating on particular ways in which Situation Awareness is achieved (for example by communication, displays, or direct senses) they will become limited in the understanding of the processes and the product. Situation Awareness as a state is a product of both the individual and the environment, through the individual's knowledge and system design.

Situation assessment is the process by which the state of Situation Awareness is achieved (Sarter and Woods, 1991) and has been highlighted in a number of decision-making theories (see section 1.8.2). Lipshitz (1993) considers situation assessment important for the selection of actions and the evaluation of available alternatives. Klein's (1989) model of decision-making describes how situation assessment allows the decision-maker to understand their goals and helps the individual select important cues. Noble's (1989; 1993) model of NDM emphasises assessing the situation. Here situation assessment is described as the overall understanding of the situation including (a) interpretation of the meaning of the situation; (b) inferring the underlying causes of the situation; (c) understanding the risks and opportunities available; (d) identification of the required actions.

The main problem with the terms 'situation assessment' and 'situation awareness' is that the terms are used interchangeably. However, there is a distinction between the two terms (Prince and Salas, 1997). Adams, Tenney and Pew (1995) argue that as Situation Awareness and situation assessment affect each other they are difficult and problematic to separate. In fact Endsley's (1995) description of Situation Awareness as 'the perception of the elements in the environment within a volume of space and time, the comprehension of their meaning and projection of their status in the near future' (see

Endsley, 1995) is similar to how she explains situation assessment. Endsley states that situation assessment involves (a) perception of relevant elements including their status, dynamics and attributes; (b) understanding what is perceived; and (c) utilising this information for future projection of the elements. This explanation of situation assessment is similar to Endsley's level one situation awareness. Prince and Salas (1997) state that within the domain of NDM research, situation assessment is closely related to the problem requiring a decision. Therefore it should be seen as an ongoing process, particularly throughout a flight scenario. This is mainly due to the fact that within the flight environment there are many situations that need to be assessed and by ignoring this fact flight safety will be compromised. For the purpose of this study situation awareness is the individual's perception of the situation (does a decision need to be made?) and is an ongoing process (have I made the correct decision? what situation am I in now?). In this light SA is similar to situation assessment.

1.11 Synthesis of various models of Decision-Making in Dynamic Systems

By looking at the ten models reviewed previously (including Endsley's model of SA and decision-making) it is possible to see common trends throughout them. Most of the similarities have already been discussed, (see section 1.8). The six common trends that were outlined was diversity of form; situation assessment; use of mental imagery; context dependence; dynamic processes; and description-based prescriptions. It is obvious from Endsley's research that situation awareness is also of equal importance. The two domains of SA and decision-making are regarded as indispensable for flight (Endsley, 1995; Orasanu, 1993; Prince and Salas, 1997). For both domains situational assessment is fundamental and is a central element featured in the majority of the reviewed models presented throughout chapter one. Figure Thirteen depicts a synthesis of the reviewed models, which incorporates the common trends of the NDM theories discussed previously.

The presented model is a summary of all the common trends that have been discussed, see section 1.8. There are three common phases shown in figure 13. These are situation assessment; creation of multiple options; and implementation.

(1) <u>Situation Assessment</u>

The decision-making process begins with assessing the situation (Rasmussen, 1983; Hammond, 1988; Noble, 1989; Lipshitz, 1993; Endsley, 1995). If a decision needs to be made the individual will assess it to be either familiar or not. Individual experience will influence this stage of the decision-making process, and will also effect the individual's actions of where they will obtain other information and what kind of information they will seek. Delegation of current work will also be determined at this stage (Pennington and Hastie, 1986; Montgomery, 1989; Beach and Mitchell, 1990). If the situation is deemed to be familiar pattern matching may occur, an automatic response can take place (intuitive response) or the familiarity of the situation can help in the creation of multiple options (Hammond, 1988; Lipshitz, 1993).

(2) Multiple options

Time allowing, the next stage of the decision process is creating multiple options. Through mental simulation the individual will project the status of each option into the possible future of various outcomes. The use of mental imagery is described in terms of mental modelling or story telling (Rasmussen, 1983; Pennington and Hastie, 1986; Connolly, 1988; Klein 1989; Noble, 1989; Beach and Mitchell, 1990; lipshitz, 1993). Each option is tested individually. Options can be modified at this stage. The best available option will be chosen to bring about a satisfactory outcome. If the individual deems there is no time available for this process the best available option will be chosen directly (Hammond, 1988; Connolly, 1988; Klein, 1989)

(3) Implementation

The best available option will be implemented and the cycle continues, returning again to the individual assessing the situation.

Throughout all three phases Situation Awareness (SA) plays an important role, see section 1.10 for a full discussion on the role of SA in decision-making. SA is depicted in figure 13 as the integration of all elements within the environment to form patterns, the individual's understanding of these elements and then the future projection of these elements before implementation of the decisional outcome takes place. Once implementation occurs the situation is updated and reassessment of the situation takes place and the process begins again.

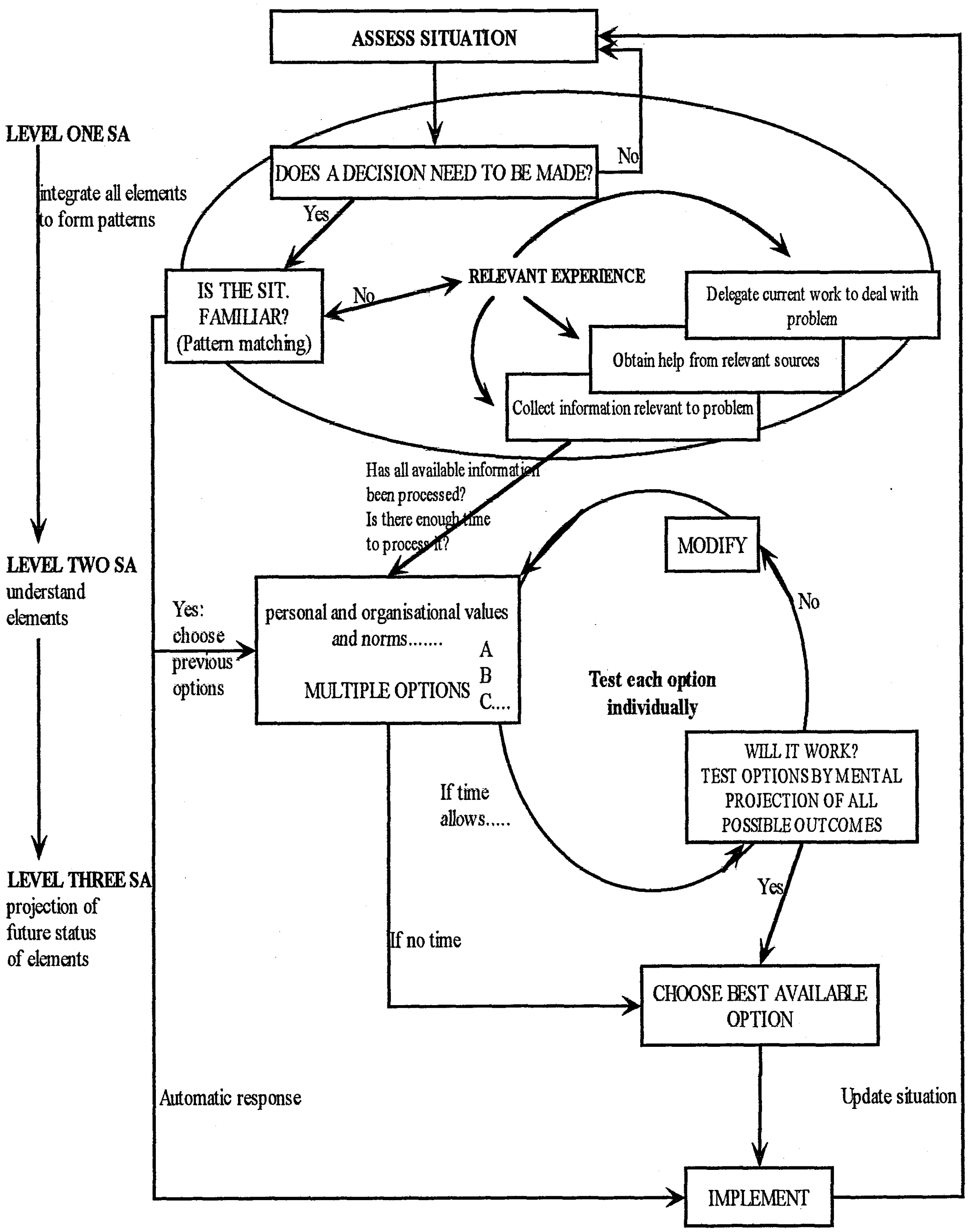

Figure 13 Syntheses of models regarding Situation Awareness and Decision-Making in a dynamic operational environment.

1.12 Chapter One Conclusions

It has been discussed that the new ecological approach to the study of decision-making is very different from the more traditional approaches, which were mainly based on experiments carried out in the laboratory. The motivation of most researchers in the decision-making field is to improve the performance of decision-makers (Klein and Woods, 1993). So far, the models of Naturalistic Decision-Making (NDM) have not made any significant changes to the training, practices or availability of tools to decision-makers (Dowell, Smith and Pidgeon, 1997). It has been suggested that as a result of this, researchers should view the NDM framework in a different way. Dowell et al (1997) propose that the improvement of natural decision-making should be viewed as an engineering process. Moray (1998) suggests that there is a definite need to move away from the traditional psychological approach of testing hypotheses and to move towards modelling the process involved itself.

The majority of NDM models have been developed qualitatively from observation and analysis of experts' decision-making processes. However, in common with most qualitative research, NDM's biggest strength is also its greatest weakness. The rich description of the decision-making process almost precludes any element of quantification or prediction. However, for NDM models to be accepted, they must be empirically testable, hence they need to be embedded within a theory. They need to offer predictions about outcomes (decisions) on the basis of context and information (Hammond, 1983). A testable model can also be replicated and the bounds of its generalisability established. The method for the quantification of parameters and their analysis in CDM allows for such things, however, NDM models do not. At present they are descriptive rather then predictive.

Conventional statistical analitical techniques, both univariate or multivariate, cannot deal with the complexities and richness of the NDM process, where many inputs may simultaneously result in many outputs. 'Conventional' statistics cannot cope with complex branching of logical conditions and cannot provide a tool to model the complex relationships between inputs and outputs, which could be taken as reflecting the decision-making process. 'Conventional' statistics can only cope with additive and/or multiplicative relationships between predictor and criterion variables (or in terms of decision-making inputs and outputs). It is also difficult to predict more than a single criterion variable and under no circumstances is logical branching allowed within an analysis. One technique for data analysis that can cope with these complexities though: neural networks.

It is a fact that the brain underlies human behaviour. Neural Networks (NNs) appear to offer some explanation about how the brain may do this. Orchard (1995) suggests that as NNs learn from experience and use that experience to formulate actions, they would therefore be a useful tool for psychological modelling. According to the naturalistic decision-making research discussed previously, an individual decision-maker collects knowledge and from previous experience combines both of these factors and decides on an action according to certain algorithms or rules. This is similar to the way that NNs selects an action or outcome (see figure fourteen for a brief description of how a NN works). Therefore, NNs presents itself as an attractive tool for analysing a naturalistic decision-making problem.

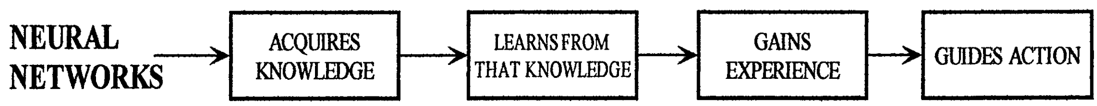

Figure 14 Brief description of how Neural Networks work.

1.12 Neural Networks and Decision-making

Decision theorists have expressed a need for a new theoretical structure for many years (Leven and Levine, 1996; Edwards, 1992). Decision-makers are not always acting to optimise a measurable utility. There is a definite need to consider the effects of context on decision-making, effects, which can often not be optimal or rational. Although the recent paradigm shift in decision-making research of observing decisions that take place in the real life environment, rather then in the laboratory has attempted to overcome this problem, there is still a need to reconsider the way decision-making is analysed.

NDM theory may have broadened the focus of the decision-making process from the decision event to the larger processes of situational assessment. However, as discussed previously NDM theory has yet to make any significant changes to the training, practices or availability of tools to decision-makers. It has been suggested that this lack of application of NDM is due to the fact that NDM is firmly based within the realm of traditional psychology, and of testing hypotheses (Dowell et al, 1997). Dowell et al suggests that if NDM theory is to progress it should be viewed as an engineering process. This thesis examines NNs as a way to model naturalistic decisions in an attempt to fill this general need to move towards modelling the process involved rather then concentrating on the experimental paradigm to test hypotheses.

Leven and Levine (1996) argue that NNs are more then just computational devices and can provide the basis for explaining multi-attributable decision-making theory. In the past there has been some conflict within decision science, between quantitative and behavioural approaches. Behavioural studies have lacked the mathematical and theoretical foundations, whereas quantitative approaches have neglected affect, habit, novelty, and other non-rational factors that are important variables in human decision-making. Leven and Levine's research showed that the neural network approach encapsulated both the quantitative and behavioural factors of decision-making.

In the past interactive algorithms have been proposed within decision theories (Geofrrion, Dyer, & Feinberg, 1972; Roy, 1976; Vanderpooten &Vincke, 1989). These algorithms suggest that the decision-maker is presented with a decision scheme of available choices. The decision-maker then defines which results are satisfactory or dissatisfactory, and may relax some criteria. The decision scheme is updated through a mathematical rule and a 'compromise' is reached. Some of these methods then went on to optimising a utility function that is linearly weighted by numerical factors measuring the importance of attributes and decision criteria. Interaction between the decision-maker and the algorithm leads to iterative changes in these weights and may ultimately converge to an optimum solution from the decision-makers point of view. According to Leven and Levine (1996) these interactions are similar to the underlying notions of backpropagation, which is the method of computing the error gradient for a supervised network (see section 2.4 for a detailed discussion).

1.13.1 Thesis Objective

The lack of empirical research within NDM research has been presented as its main limitation. Neural Network analysis will be explored as a tool for modelling NDM theory. Discriminant Function Analysis (DFA) has been shown to be an alternative to NNs (Garson, 1998), therefore a comparison between NNs and DFA will also be conducted to determine if NNs or a more 'traditional' statistical approach is appropriate for modelling NDM. Two NDM tasks are examined a consequential choice decisional task and a pattern matching decisional task. Also, although all NDM models discussed in chapter one suggest that there are several different types of decisions or decision situations, choice and pattern matching seem to be the most common factors between models (Hammond, 1988; Lipshitz, 1993, etc).

1.13.2 Structure of Thesis

An outline of the structure of this thesis is as follows:

Chapter Two:
Neural Networks are introduced and described in detail. There is a particular focus on backpropagation as this was the method used for both study one and two.

Chapter Three:
This chapter is presented as a report on study one. Study One describes research conducted within the NDM paradigm in which the decision to attend a certain university for master's level education is considered. Choice of university is presented as a consequential decisional NDM task. New literature on specific decision-making theory for university choice is presented and reviewed. An artificial neural network was used to determine if an empirically verifiable model of the participants decision-making process was possible. A comparison of DFA and NN results was also conducted.

Study one method, results and discussion/conclusions are described.

Chapter Four:
Chapter four is presented in the same format as chapter three and reports study two, which also explores a real-world decisional process in which a disruptive passenger threatens the safety of a hypothetical flight. This NDM task is presented as a pattern matching decisional task. Pilot decision-making and 'air rage' as a phenomenon is discussed. Study two method, results and conclusions are described.

Chapter Five:
This chapter is a summary of both findings from studies one and two. Some suggestions for future research are made.

2 Neural Networks (NNs)

Chapter One outlined a new ecological approach to decision-making research and proposed neural networks as a tool for analysing naturalistic decision-making problems. This chapter discusses neural networks in terms of what they are, what can be done with them, what neural networks look like and how they work. Particular focus will be on backpropagation as this will be the technique used to produce the neural networks used in studies one and two. The learning feature of a NN will also be described. This ability to learn, or 'correct itself' based on errors occurs by altering the weights of each connection between the layers of nodes and is the main feature that sets NNs apart from other multivariate techniques of analysis. The weights aligned to each connection are the network's 'best guess' as to how to make a prediction of the decisional outcomes. A comparison of neural networks to traditional multivariate forms of analysis will also be summarised, as both forms of statistical analysis (a NN and DFA) will be carried out on the same data set in studies one and two and then resulting models will be compared for statistical significance.

2.1 Definitions of Artificial Neural Networks

Neural Networks (NNs) emerged from the work carried out by Warren McCulloch and Walter Pitts who argued that brain functionality could be represented mathematically. The simple model they developed is similar to the modern models, in that, it had input, hidden and output layers (explained fully in section 2.3). NNs involve algorithms under which information is accumulated in programmed objects or nodes, which are capable of 'learning' through much iteration using simulated or real data.

Artificial Neural Networks (ANNs) were first conceptualised to enhance our understanding of the brain. The desire was to develop a system that could imitate the computations that the human brain routinely performs. Unlike conventional computations, ANNs 'learn from experience' and can solve hard computational problems rapidly (Lek and Guegan,1999). Although they were first operational in the 1950s, research into this area boomed in the 1980s due to the increase of computational power (Hair, Anderson, Tatham, & Black, 1998). ANNs are based upon a simplified model of the hypothesised manner in which the brain operates.

Perhaps the best definition of a NN is given by Keller (1998) and is as follows:

'An artificial neural network (ANNs) is an information-processing paradigm inspired by the way the densely interconnected, parallel structure of the mathematical models that emulate some of the observed properties of biological nervous systems and draw on the analogies of adaptive biological learning. The key element of the ANNs paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements that are analogous to neurons and are tied together with weighted connections that are analogous to synapses' (Keller, 1998).

This definition implies that a Neural Network is composed of a large number of neurally based simple processing elements. These elements are interconnected, yet only operate on local information.

The term 'artificial neural networks' is used interchangeable with the shorter version of Neural Network (NN), as it is customary to drop the 'A' for artificial and below, for simplicity, neural networks will be referred to as NNs.

2.2 Applications of Neural Networks

In principle, NNs can compute anything that a digital computer can do (Sarle, 1997). In practice, however, Sarle suggests that NNs are particularly useful for classification and function approximation/mapping problems which are 'tolerant of some imprecision, which have lots of training data available, but to which hard and fast rules (such as those that might be used in an expert system) cannot easily be applied'. Within the realm of social science NNs are increasingly being implemented as a source of analysis (Garson, 1998).

Researchers from different areas are now using neural networks in their research; the following is an example of some uses:

- Computer scientists exploring the properties of non-symbolic information processing and learning systems in general.
- Statisticians utilise NNs as flexible, non-linear regression and classification models.
- Engineers in many different areas use NNs, for image classification and signal processing, etc.
- Cognitive scientists use NNs to explore high-level brain function, such as thinking and consciousness, speech recognition etc.
- Neuro-psychologists use NNs to explore medium level brain function, such as memory, and motorics.
- Physicists use NNs to model phenomena in statistical mechanics and other such tasks.
- Biologists use NNs to interpret nucleotide sequences.

2.3 The Structure of a Neural Network

According to Hair et al (1998) there are four simple concepts, which describe the structure of a NN: (1) the type of model; (2) nodes; (3) system of nodes that transfer information from the input nodes to the output nodes; and (4) the learning function. These concepts are discussed in detail in the following sections.

2.3.1 Neural Network models

There are numerous kinds of NNs. Each week, new NNs are invented, some are variations of existing ones. Appendix A contains a list of the most well known methods (Keller, 1998). The main difference between these networks is the distinction between supervised and unsupervised learning (discussed in section 2.3.3). All NNs have a 'training' rule where the weights of connections are adjusted on the basis of the data. In supervised learning, the correct output data for each set of input variables is supplied to the model (in the classification set), whereas unsupervised learning involves no target values.

According to Hair et al (1998) however, there are three basic types of NN models of which the *multilayer perceptron* is the most common. A new model, which is similar to the multilayer but works differently, is the *radial basis function*. The final model, which can be used for clustering only, is the *'Kohonen'* model.

The backpropagation model (see section 2.4 for description), which is a feed-forward multilayer perceptron NN is the most common form of a neural model. This is the model that will be subsequently used in studies one and two, therefore the following descriptions of what a NN is, will in general also relate to backpropagation.

2.3.2 System of Nodes (Network)

A NN consists of three basic kinds of nodes: input nodes, output nodes, and intermediate (hidden) nodes. These can be seen in figures 15 and 16. Initial data are received by the input nodes, which are then transmitted to the NN. Therefore, input nodes are similar to input variables (predictor variables). Values can also be presented to a single input node as a 'case' or matrix. The target variables (or output nodes) associated with this input node are the dependent variables. Most NNs have a third node that represents a more complex relationship then just a one-to-one relationship from input to output. This third hidden node enables each node in the NN to act independently, and also for the NN to represent non-linear relationships, which are difficult for multivariate statistics. Therefore the type of data that a NN can handle is very flexible.

2.3.2.1 Nodes

This is the most basic element in a NN. It is a self-processing unit that acts in parallel with other nodes in the NN. It simulates neurons in the human brain by accepting inputs and creating subsequent outputs. The input comes from various sources including other nodes. Figure 15 depicts a simple representation of a node and its operation. Each connection has an assigned weight. Each input value is multiplied by its assigned weight (*w*) and the summation of this value is then processed by an activation function to generate an output value, which is then sent to the next node in the system. The activation function usually takes the form of a simple function which dictates that the output of a node is of the binary form 'fire' (produce an output) or 'inhibit' (no output).

An independent node (or neuron) is of little use unless it is interconnected in a network of nodes because a NN is only as good as the combined effect of all of its components. The input nodes sends its values to the hidden nodes and then on to the output nodes. As each layer passes its values to the next layer, the values are weighted to represent *connection* strengths (Neuroshell user manual, 1990). The weight is raised to positively reinforce a connection, and lowered to inhibit a connection.

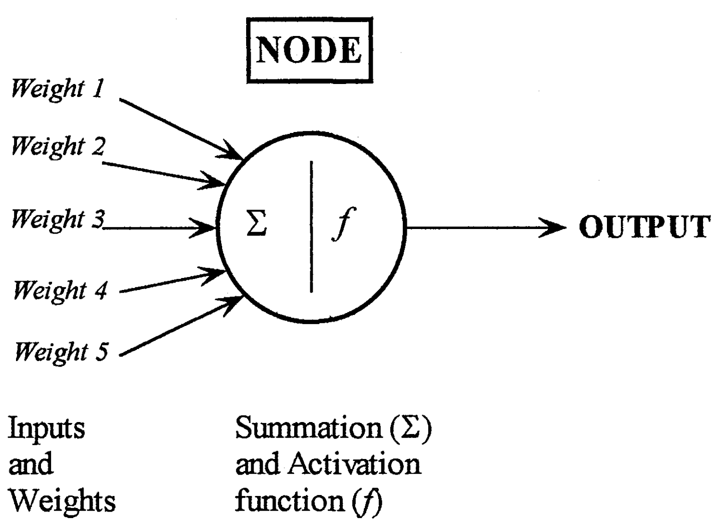

Figure 15 A node within a Neural Network.

2.3.2.2 The Hidden Layer

The hidden layer is where the major problem solving occurs. The values of the weights on the nodes of the hidden layer constitute the 'internal representations' of the network and are based on the network's experience of the training data (see section 2.3.3 on supervised learning). The hidden layer in a NN enables each input node to work independently and therefore it is here that the non-linear relationships are calculated. See figure 16, which represents a system of nodes within a NN.

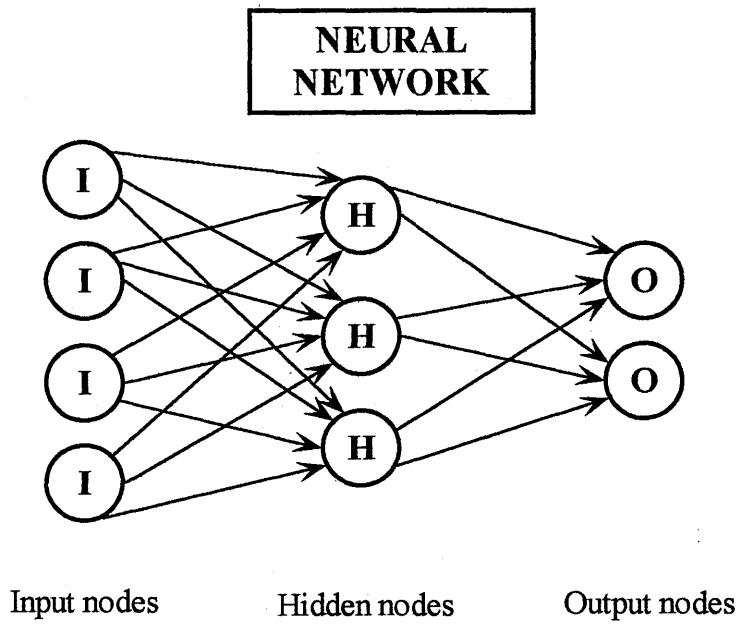

Figure 16 A representation of nodes within a Neural network.

The number of hidden nodes to be used is dependent on the specific problem. There are no fixed formula for the appropriate number of hidden nodes to be used. Too few hidden nodes result in not enough characteristics of the problem being identified in the final NN. Incorrect classification may result, or the network may not converge at all. Too many hidden nodes will increase the learning time, and the model will take longer to develop. However, sometimes increasing the number of hidden nodes will decrease learning time. There is the problem of using too many hidden nodes, in this case the network memorises the outcomes rather then learns the model. When this occurs, generalisation on new cases can be poor. In general it is suggested to err on the side of too many hidden nodes rather then not enough (Neuroshell user manual, 1990).

2.3.3 Learning within the Neural Network

Most NNs have a 'training' rule where the weights of connections are adjusted on the basis of the data. In other words, NNs learn from examples by recognising patterns and therefore display an ability for generalising beyond the training set (Sarle, 1997).

This feature of learning is what sets NNs apart from other multivariate techniques. Its ability to learn, or 'correct itself' based on errors occurs by altering the weights of each connection between the layers of nodes. The weights aligned to each connection is the network's 'best guess' as to how to make a prediction of the output nodes (Hair et al, 1998). When an input is processed through the system, it is compared to actual output data, and the connection weights are altered to get a better fit (and therefore, in theory a better model). This process is termed *'supervised'* learning. Several factors influence the operation of the network and the alignment of the connection weights (e.g. the learning rate, see section 2.4 on backpropagation).

2.3.3.1 Supervised Learning

In supervised learning, the NN recognises the patterns in the training data set. The pattern is recognised by the network when the researcher provides the desired outputs or responses for all inputs. Actual responses are compared to desired responses and the difference adapts the network accordingly. The goal is to adapt the parameters of the network so that it performs well for patterns outside the training set.

The most common NNs utilise supervised learning, such as backpropagation (see section 2.4). Other models include generalised regression NNs (GRNNS), probabilistic NNs (PNNS), and group method of data handling (GMDH) models. Please see section 2.4 on Backpropagation to gain a fuller comprehension of supervised learning.

There are four types of supervised learning: Hebbian learning; anti-Hebbian learning; error-correction learning; and competitive learning. A brief description of each follows:

(1) *Hebbian Learning*: one of the oldest forms, named after its creator, neuropsychologist D. Hebb. Here, a neuron's weight is reinforced if its input is high and the subsequent desired output is high. Therefore connections are strengthened every time they are activated.

(2) *Anti-Hebbian Learning*: subsequent researchers have added to the Hebbian rule by adding a corresponding second rule. Here, a neuron's weight is reduced whenever its input is high but the desired output is low, or vice versa.

(3) *Error-correction Learning*: also called delta rule learning. Here, the neuron's weight is reinforced in proportion to an error signal expressed as a function of the difference between the target and actual outputs, such as mean square error.

(4) *Competitive Learning* (see equation 1): this type of learning evolved from the work of Von Der Malsburg (1973) and Grossberg (1976). The neuron that gives the strongest response to a given output is reinforced. Here, only one neuron is selected to activate, the remaining output neurons remain unchanged and no learning occurs. For the winning neuron j, its connection weights are changed according to the learning rate, r:

$$\Delta w_{ji} = r(x_i - w_{ji}) \tag{1}$$

> In competitive learning only the neuron closest to the input pattern is fired implying that the change in weight w for neuron j with respect to neuron i is equal to the learning rate r. This is then multiplied by the difference between the activation level of input neuron i and the weight of neuron j from the path of neuron i.

Backpropagation will be the neural model used in studies one and two, a brief description of the process of learning in backpropagation follows. When learning takes place in backpropagation, connection weights are modified to adjust to the model. These weights are modified during learning in the direction required to produce a smaller error the next time the same pattern is presented. The amount of weight modification is proportional to how much error there is. The learning rate is the constant of proportionality. Therefore if the learning rate is set to .5, then the weight change is a function of only half of the error. The larger the learning rate, the larger the weight changes, and as a result, the faster the learning. However, when the learning rate is too large, large weights will occur, which will lock neurons into on/off positions effectively stopping learning and making the system unstable or the network can fail to converge. This can also result in a non-optimal solution for the final model. To overcome this problem, the weight change can be made a function of the previous weight change by using the momentum function. The momentum factor determines the proportion of the last weight change that is added in to the new weight change. In basic backpropagation the following occurs:

Weight change = (Learning rate)*(error)+(momentum)*(last weight change)

As with the number of hidden nodes, there is no set formula for setting these factors. Different problems require different settings, when a model fails to converge, these factors should be reduced and the network relearned.

2.3.3.2 Unsupervised Learning

Unsupervised learning involves no target values. According to Sarle (1994), in most varieties of unsupervised learning the targets are the same as the inputs. Therefore the information is compressed from the inputs and the task performed is similar to an auto-associative network (Deco and Obradovic, 1996). The most common form of unsupervised learning is 'cluster analysis' (Sarle, 1997), here we are given a set of observations with the aim of establishing the existence of classes or clusters in the data.

Unsupervised learning is not an appropriate form of analysis for naturalistic decision-making research as there is no signal to teach the network if it has a correct output or not. It is generally used for compressing information into identifiable groups based upon similarities within these groups. Therefore supervised learning will be used in both studies one and two because not only can it predict more than one single criterion, it also allows for logical branching within an analysis.

2.4 Backpropagation

The purpose of backpropagation is to decrease the overall error of the neural network until it converges. Models will converge when the system reaches some statistically desired point or accuracy. Some models never learn, which can occur when the input data does not contain specific information from which the desired output is derived, or if there is not enough input data.

Research into NNs has led to the development of various types of networks, suitable to solve different kinds of problems; auto-associative memory, generalisation, optimisation, data reduction, control and prediction tasks in various scenarios, architectures etc. (Lek and Guegan, 1999). Chronologically speaking the Perceptron (Rosenblatt, 1958), ADALINE, i.e. Adaptive linear element (Widrow and Hoff, 1960), Hopfield network (Kohonen, 1982, 1984), Boltzmann machine (Ackley, Hinton and Sejnowski, 1985), multi-layer feed-forward neural networks learned by the backpropagation algorithm (Rumelhart, Hinton, and Williams, 1986). These descriptions of the various methods can be found in various books such as Freeman and Skapura (1992), Gallant (1993), Smith (1994), Ripley (1994), Bishop (1995), Garson (1998) etc. The choice of the type of network depends on the nature of the problem to be solved. At present the two popular NNs are the backpropagation network and the kohonen network (Lek and Guegan, 1999).

The Kohonen network can be used for clustering or self-organisation mapping only. The backpropagation model is the most common form of a supervised neural model and is the model that will be subsequently used in studies one and two. The main reason it has been chosen for use in this study is its ability to 'learn' or correct itself. This ability allows the network to compare actual outcomes with predicted outcomes, if there is any difference between the values, the model will be adjusted. This is done by calculating the error in the output value and feeding it backwards through the network, changing the weights proportionally (increasing or decreasing depending on the direction of the error).

Backpropagation is the most popular algorithm for NNs. Werbos (1995) estimates that it is used in 70% of real world NN applications. It is generally applied to problems of supervised learning and pattern recognition. It generates error signals backwards from layer to layer of the network. The main benefits of backpropagation involve prediction and control (Werbos, 1995). A definition of backpropagation is as follows:

'Backpropagation is a procedure for efficiently calculating the derivatives of some output quantity of a non-linear system, with respect to all inputs and parameters of that system, through calculations proceeding backwards from outputs to inputs. It permits 'local' implementation on parallel hardware' (Werbos, 1995).

In other words backpropagation is the process whereby errors in estimating the output nodes are fed back through the network and are subsequently used as indicators for altering the weights for each node.

Backpropagation is the term used for describing the method of computing the error gradient for a feedforward network, which is an application of the chain rule of elementary calculus (Werbos, 1994). This is the most widely used method for supervised training and will be the network structure used in the subsequent studies of this thesis. The non-linear elements (neurons) are arranged in successive layers, and the information flows uni-directionally, from input layer to output layer, through the hidden layers, see figure 16. Figure 16 depicts how the nodes from one layer are connected to all nodes in the adjacent layers, but no lateral connections within any layer are possible.

The backpropagation model is relatively simple and is shown in figure 16. It assumes a multilayer network of input, hidden and output nodes. The network must be trained so it can model the process by which the inputs are mapped onto the outputs. It does this through the hidden layer, which contains a summation function and an activation rule. The activation rule has a threshold whereby the output alternates from 0 to 1 when the input threshold level is reached. Following this, the error is calculated, which is the difference between the actual and predicted outputs. This error is then used to adjust the weights in the hidden layer neurons. The change in weight is equal to the learning rate. In summary, its learning and update procedure is based on the concept that if the network gives the wrong answer, then the weights are corrected so the error is lessened, resulting in future responses of the network being more likely correct.

To cross-validate the model that is finally produced, both a training and test (holdout sample) set of data are required. Both data contain input and output information from real data. The first is used to train the network, and the second to assess the performance of the network after training. The second set of data is used as a testing phase. During the testing phase, the input patterns are fed into the network and the desired output patterns are compared with those given by the network. The agreement or disagreement of these two sets gives the overall indication of the performance of the neural network model. This process will be followed in the subsequent studies to test the performance of both neural models produced. The classification results of the neural models will also be used to compare and contrast the classification results of the discriminant function analyses results from both studies to determine which technique is appropriate for modelling a naturalistic decision.

2.5 Comparison of Neural Networks to traditional methods of multivariate statistical analysis

Compared with expert systems or equation based approaches, NNs can identify relationships that would be known (i.e. at pattern matching) and are an alternative to factor analysis and discriminant function analysis (Garson, 1998).

When NNs are the appropriate method for analysis they may be superior than conventional statistical techniques for pattern matching. Benigo (1996) reports NNs to be universal, nonparametric, and robust. When problems are unstructured, involve incomplete information, are ambiguous, and involve large sets of inputs and constraints, NNs perform better than traditional statistical procedures (Iyengar and Kashyap, 1991). Bullinaria (1995) showed that when using ambiguous data, NNs are able to realise any underlying regularity in the data and therefore increase generalisation while decreasing the problems associated with overtraining[1].

Scott Toborg and Kai Hwang (1989) described seven ways in which NN analysis differs from conventional statistical analysis. These were (1) *Massive parallelism*, which implied that NNs can utilise hundreds and thousands of neurons; (2) *High interconnectivity*, NNs involve tracking connecting paths, and these can be a large multiples of a number of neurons; (3) *Simple processing*, each neuron calculates the summing inputs and applies a threshold to determine if that particular neuron will be fired or not; (4) *Distributed representation*, outputs are not learned patterns but are connected to all the data throughout the network; (5) *Fault tolerance*, NNs continue to function even if some neurons are not fired; (6) *Collective computation*, NN problems are solved through the joint activation of all data in the system; (7) *Self organisation*, NNs can change their structure according to new data or new patterns introduced to the network.

NNs are presented as a technique for modelling the NDM process that can cope with complexities that 'conventional' statistical analytical techniques, either univariate or multivariate can not. To reiterate, conventional statistics cannot cope with complex branching of logical conditions and cannot provide a tool to model the complex relationships between inputs and outputs, which could be taken as reflecting the decision-making process. 'Conventional' statistics can only cope with additive and/or multiplicative relationships between predictor and criterion variables (or in terms of decision-making inputs and outputs). It is also difficult to predict more than a single criterion variable. NN can make multiple predictions from multiple inputs, even SEM can only may a prediction on one variable from a network of many. Logical branching is also not allowed within a 'conventional' analysis.

NNs are more tolerant of imperfect data, such as the presence of missing values or other data quality problems (noise etc). If the form of the data are unknown, non-linear or the problem is complex with highly interrelated relationships NNs will perform better then the traditional statistical method (SPSS, 1999). In NN modelling, there can never be too many input cases, which is the opposite of statistically based tests, in which the power becomes too great.

The very fact that a neural network contains a third hidden layer (see section 2.3.2.1 for discussion on hidden layers) enables each node in the NN to act independently. Therefore, the NN is able to represent non-linear relationships, which are difficult for multivariate statistics and as a result NNs can handle data that are very flexible, unlike the more traditional statistical methods. White (1981, 1989) has shown that NNs are an alternative to non-linear least squares when the training set is large.

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[1] Overtraining can result in a sample specific model.

One doctoral dissertation (Baker, 1997) compared the effectiveness of statistical and neural network models for forecasting nationally aggregated educational spending. Here, NNs were found to outperform regression models. Baker argued that educational spending was just one small component in a complex economic system and that a higher level of analysis was required through NNs, as the modelling required could not be accomplished with linear equations. Another dissertation (Li, 1997), focusing on oil's critical role in the world economy, showed that NNs are robust in modelling and forecasting complex, non-linear economic systems and provides valuable insights into market behaviour that the traditional statistical approach could not. Yet another dissertation (Zeng, 1996), compared NNs with the standard logit and probit models[2]. The results showed that NNs performed better than the logit, and were indistinguishable from the 'true' model at all noise levels.

These examples illustrate the superior functionality of neural models in forecasting, econometrics and solving a wide range of classification problems. Other researchers have found NNs to be superior to traditional statistics when modelling human behaviour (Vogh, 1997; Bengio, 1996). This shows that NNs are applicable to real data that contains noise, are non-linear, and even contains missing data. NNs are robust under these conditions, whereas, most traditional statistical methods are not. NNs are useful in prediction, classification, fault detection, time series analysis, exploratory data analysis and other problems in data mining and statistical analysis (Garson, 1998). NNs can offer solutions for cases in which a processing algorithm or analytical solutions are difficult to find; therefore NNs seem to an alternative approach to modelling a naturalistic decision-making problem.

Discussed previously in the introduction, Orasanu and Connolly (1993) suggest eight main characteristics of NDM. Problems are *ill structured*; decisions are made in *uncertain dynamic environments*; decision-makers are driven by *shifting, ill-defined, and/or competing goals*. A decision-maker may have multiple goals, which may be clearly defined, or these goals may simply be unknown. According to NDM research the individual considers a *set of events or actions* that s/he uses to deal with the problem. *Organisational goals and norms* can also be an influencing factor in the decision process, also the final decision is generally satisfactory and not the ultimate 'best' decision (due to a combination of the above factors). When faced with these characteristics, it is proposed here that NNs may perform better than traditional approaches of analysis when analysing NDM problems.

2.6 Limitations of Neural Networks

The key limitation to neural computing is the NNs inability to explain the model it has built in a useful way. It is often useful to know why the model is behaving in the way it is. While NNs get better answers, they are unable to explain how they got them. It is possible however to go through the entire matrix to explain the results that the NN produced. The statistical inference test can be shown to be significant (Hair et al, 1998)

[2] The logit and probit models are two examples of a larger class of generalised linear models.

but the problem is that the results themselves are trivial. NNs do not provide an interpretation of the relative importance of input variables and their interconnections and therefore, unlike some traditional statistical methods (e.g. discriminant function analysis) NNs can not say which variable is the most powerful in predicting the outcome as every variable's influence depends on the other variables for that case. In fact this limitation is only true on a theoretical basis, NNs are very much data driven and not theory driven. For the purposes of this thesis, this 'limitation' of NN is viewed as an advantage, as this characteristic enables NN analysis to carry out an analysis on non-linear data.

NNs may not yet be biologically or psychologically plausible. However, models that utilise backpropagation have been shown to be good at modelling some important characteristics of human memory like content addressability and generalisation from experience (Orchard, 1995). Therefore although there are problems with analysing results from NN models, they may still offer an insight into the process of modelling psychological theories and in particular naturalistic decision-making theory.

2.7 Methodological Considerations

It has already been discussed that neural networks are a particularly appropriate source of analysis when the data are fuzzy, noisy, overlapping, highly non-linear and non-continuous. It has also been shown that NNs are an alternative to various statistical methods (see section 2.5 for a full discussion). However, even though it is becoming increasingly clear that NNs have a broad applicability, it does not imply that NNs are always the optimal solution for all situations. Garson suggests that NNs are applicable to four classes of problems: mapping, prediction, control and constraint satisfaction.

1. *Mapping (classification and completion)*: When data need to be simplified for ease of analysis, it can be classified, which involves mapping a diversity of input onto a given number of outputs. Completion problems involve mapping patterns from categories. It has been suggested that in this context NNs are an alternative to factor analysis and discriminant function analysis (Garson, 1998). This class of problem is similar to pattern recognition, and is the category in which the present study of decision-making falls into.

2. *Prediction*: This involves taking estimates of continuous data. Here, NNs are an alternative to regression and other multivariate linear hypothesis statistical procedures. Backpropagation without a hidden layer is a type of linear model. However, since most NNs are implemented with a hidden layer, they are a non-linear alternative to linear regression.

3. *Control*: These problems require artificial intelligence to make decisions based on complex and fuzzy data, for example controlling a robot arm in manufacture. Here, NNs are an alternative to expert systems.

4. *Constraint Satisfaction*: These are problems that involve scheduling of complex activities, or routing of complex transportation tasks. Here, NNs are an alternative to linear programming and dynamic systems statistical procedures.

For the purpose of this thesis, naturalistic decision-making will be classified as a mapping problem. This is due to the fact that a number of input variables or information from a variety of sources is used when an individual formulates a problem and chooses a decisional outcome. Also, there will be more then one decisional outcome in both studies one and two.

As with other statistical methods, the data must be appropriate and reflect the factors involved. The data must be measured in a way that reflects the behaviour of the factors. If these data were not representative then the neural computing will not result in a good model. NN analysis does not have the ability to transform poor quality data into a successful model (Hair et al, 1998). Complex data can result in a long period of time spent training, however, the overall time to results in NNs can still be faster than other data analysis approaches (SPSS, 1999).

The process associated with constructing a NN can be time-consuming. In particular the training phase can take a long time for the network to converge depending on the network structure such as the number of input and output variables, number of hidden layers and the number of nodes in the hidden layer.

2.8 Chapter Two Conclusions

Chapter One outlined theories of decision-making that have encapsulated real-life situations in the decision-making process and highlighted the need to reconsider the way decision-making is analysed. Previous research has proposed interactive algorithms within decision theories that are similar to the underlying notions of backpropagation (Leven and Levine, 1996) see section 1.13 on Neural Networks and decision-making. Therefore NNs present themselves as an attractive form of analysis for NDM.

This chapter described NNs in detail and concluded that NNs are an appropriate form of analysis for non-linear and noisy data. The feature of learning is what sets NNs apart from other multivariate techniques. Therefore, NNs are able to represent non-linear relationships, which multivariate statistics can not and as a result NNs can handle data that are very flexible, unlike the more traditional statistical methods. NDM data was described as also being non-linear, and it was proposed that NNs would be an alternative form for modelling NDM theory. NNs are generally applied to problems of supervised learning and pattern recognition. The main benefits of backpropagation involve prediction and control (Werbos, 1995), therefore the following studies one and two will also involve mapping problems.

Garson, 1998 states that NNs are an alternative form to Discriminant Function Analysis (DFA), both forms of statistical analysis will be carried out on the same data set in studies one and two and then resulting models will be compared for statistical significance. The following chapters three and four will describe both studies in detail.

3 Study One

This chapter describes a study conducted within a naturalistic decision making paradigm where undergraduate students retrospectively describe their decisional process of which university to choose when applying for a masters level course. This decision is presented as a consequential choice decisional task. These data were collected in the format of questionnaires, specifically designed for this study. 267 questionnaires made up the final data set. A Discriminant Function Analysis (DFA) and a Neural Network (NN) analysis was used to model the decisions made on the basis of the questionnaire variables to produce a model of the participants decision-making process. Both analyses were then compared to determine which would be a viable way of modelling a consequential choice naturalistic decision.

3.1 Aim of Study One

The main limitation within NDM research has been presented as its lack of empirical research (Flin, Salas, Strub, and Martin, 1997). Neural Network (NN) analysis, which is outlined in chapter two, will be explored as a tool for modelling NDM theory. NNs were introduced (see chapter one and two) as a way to model naturalistic decisions in an attempt to fill this general need to move towards modelling the process involved rather then concentrating on the experimental paradigm to test hypotheses. Discriminant Function Analysis (DFA) has been shown to be an alternative to NNs (Garson, 1998), therefore a comparison between NNs and DFA will also be conducted to determine if NNs or a more 'traditional' statistical approach is appropriate for modelling NDM. Study one focuses on a consequential choice decisional task. The process of choosing a university for Master level education was the consequential choice decisional task selected for this purpose. Students who applied to Cranfield University for the terms of 1998/1999 were chosen for this study.

This chapter is presented as a report on study one. New literature on specific decision-making theory for university choice is presented and reviewed. Study one method and results are described. Some specific conclusions will also be outlined.

3.2 Introduction to Study One: Choice of University

The choice of postgraduate university is a complex decision and an important career choice for many young adults. For some the decision will be a painstaking process, and yet others will fall into the choice of which university to attend almost accidentally. The decision process begins with the choice of undergraduate university and course, following the completion of this course, the choice of whether to further his or her education and attend a Masters degree. A 'good' choice may mean attending a university, where the student will be successful in completing the chosen course of study and then obtaining a job in which s/he is interested in. However, the student may make a 'poor' decision, where the student finds himself or herself in a course s/he dislikes, perhaps dropping out or transferring to another course/university, which would result in expensive retraining or limited career alternatives. Hossler (1984) indicated that most students do not have a clear notion of what to expect from a university and therefore make poorly informed decisions. Incomplete information is one of the main characteristics of a naturalistic decision. The choice of university for Master level education was chosen for study one and is presented as a naturalistic decision.

3.2.1 Presenting Master Level choice of University as a Naturalistic Decision

There are many factors that could influence an individual's decision to study at Master level; motivation, current life situation, and previous experiences are but a few. But can the decision to partake in a course be considered to be a naturalistic decision? Cranfield University is just one university (although it is slightly different from others, as it is purely postgraduate). Cranfield University will be used to collect data to test if the decision to apply for a Master level degree can be modelled by NNs.

Cranfield University offers a large variety of postgraduate courses, which attract students from a wide range of backgrounds, some of who will have only recently graduated. Other applicants may have many years work experience. Cranfield also attracts students from overseas. As a result students may come to Cranfield for a variety of reasons, all of which will influence their decision to study there.

Discussed previously are the eight main characteristics of NDM (see section 1.5 for full discussion of NDM characteristics). To illustrate Master level choice of university as a NDM problem explanations in terms of hypothetical questions that could be posed by prospective students will be presented. It has been stated that these factors can complicate the decision task but it is unlikely that all will be present at any one time. Extremes of these factors would represent a 'worst case scenario' for any decision-maker. Therefore not all characteristics need to be present for this decisional task to be within the NDM paradigm.

The first characteristic that Orasanu and Connolly (1993) outlined was that problems are *ill structured*; prospective applicants will have to work hard to form causal links, for example, 'if I do an MSc I will improve my chances of gaining employment in my chosen area'. Decisions are made in *uncertain environments*; most applicants will not obtain complete information from all universities to which they could apply to: for example, they may have information on Cranfield but not on another university that may offer the same taught course. This information can also be ambiguous or of poor quality, for instance, the applicant may have heard about the course by word of mouth. According to NDM theory, a decision-maker is driven by *shifting, ill-defined, and/or competing goals*.

Therefore, a decision-maker has multiple goals; these can be clearly defined, for example, 'I want to further my education' or 'I want to increase my employment opportunities' or these goals may simply be unknown. Some may even be opposed to other goals, for example, 'I want to increase my employment opportunities because I need to clear my loans, but I need to obtain a loan to complete the desired course' etc.

Another characteristic that Orasunu and Connolly (1993) pointed out was that within NDM the individual considers a *set of events or actions* that s/he uses to deal with the problem. It is clear to see that the applicant would acknowledge that there are a number of possible universities to apply to. Furthermore, a number of events could influence the final choice of where to go to complete a course, for example, a friend of the prospective student may have attended Cranfield, or the prospectus looked nice, etc. When considering further education, an individual may have other people to bring into the final decision, a student may pose a question to themselves such as 'should I move my family with me?' or 'will my company have to employ somebody else and retrain them?' etc. Furthermore, *organisational goals and norms* can also be an influencing factor in the decision process. Perhaps a prospective student has funding from his or her company and has a limited choice of universities to attend. The choice of which university to attend is likely to be a satisfactory decision and not the ultimate 'best' decision (due to a combination of the above factors).

Obviously, there are a number of choices available to each applicant and the given examples do not provide a comprehensive picture of the decision to apply to a certain university, or whether or not to attend that university once an offer has been received. However, from the given examples and hypothetical questions, it can be shown that the decision to partake in a course can be viewed as a naturalistic decision.

Master level choice of university can also be said to be a consequential choice task, which is when an individual thinks ahead and considers the attractiveness of future outcomes. Individuals using consequential choice to make a decision are looking at all available options and the best consequence of these options. Lipshitz (1998) describes the argument that relates to consequential choice decisions as "Do 'A' because it has better consequences than its alternatives".

3.3 Models of Choice of University

Universities have been interested in student decision-making for quite some time. Just as students are concerned with making a correct decision, universities are interested in attracting students whom they believe will stay and be successful in completing their course (Smith, 1994). Universities conducted previous research on the choice of universities, but focus was placed on an administrative point of view. As a result, this research was carried out within the paradigm of normative decision-making models: mathematical formulations of how decisions 'ought' to be made through a rational weighing of alternatives (Smith, 1994). Although hypotheses involving the stages of decision-making for students where formulated, the cognitive processes underlying the decision where overlooked. According to Smith (1994), most studies of university choice were focussed on two areas, identifying student characteristics and developing normative models of student choice.

Previous research on student choice of university has mainly been based around high school or secondary level students. Little research to date has focussed on undergraduates who are contemplating entering postgraduate education. The need for postgraduate education has, in recent years, become apparent to the job market and as a result, increased numbers of students are now continuing their education. Indeed, secondary school students are now being informed about postgraduate choices before they even enter their undergraduate course. Therefore it is apparent that there is a need to understand the underlying process in student postgraduate university choice. Students contemplating postgraduate education will already posses a perception of how university life is, and therefore have a different perception of university education than high school or secondary level students. The majority of research in this field has been conducted in the United States but obviously America has a very different educational system when compared to the UK. This also implies that research on why and how students make decisions to participate in education (and in particular continuing their education) is important, especially within the British educational system.

Research on high-school students in America has found that university choice is a developmental process that begins with the possibility of going to university and then seeking admission to a particular university (Chapman, 1981; Chapman, 1984; Litten, 1981; Johnson, Stewart, & Eberly, 1991). The developmental process is considered to be a long-term one (Gilmore, Spiro & Dolich, 1981), were students begin with a broad conception of further education opportunities that are open to them. Following this the student then refines their perceptions to the final choice of a single institution.

To provide an insight into the student university choice process, models have grown from the enrolment management literature (Bateman and Spruill, 1996). Enrolment management incorporates the student's initial desire to attend university to the educational outcomes of attendance. Hossler (1984), probably one of the most influential researchers in this area suggests a model of university choice that is broken down into two sections: (1) student characteristics and (2) institutional characteristics. Figure 17 depicts the personal factors in the student university choice process according to Hossler.

3.3.1 Student Characteristics of university choice

Although the factors (see figure 17) are represented independently in this theory, Hossler (1984) points out that they all interact. According to this model the student's ability and socio-economic status are the most influential variables in the university choice process. Of the significant others, he suggests that the parents of the prospective student are the most influential factor. Students that are intending to enrol in a university degree are twice as likely to report that their parents are expecting them to attend (Tillery, 1973). Friends of the student have also been found to be influential, and are almost as influential as parents (Tillery, 1973).

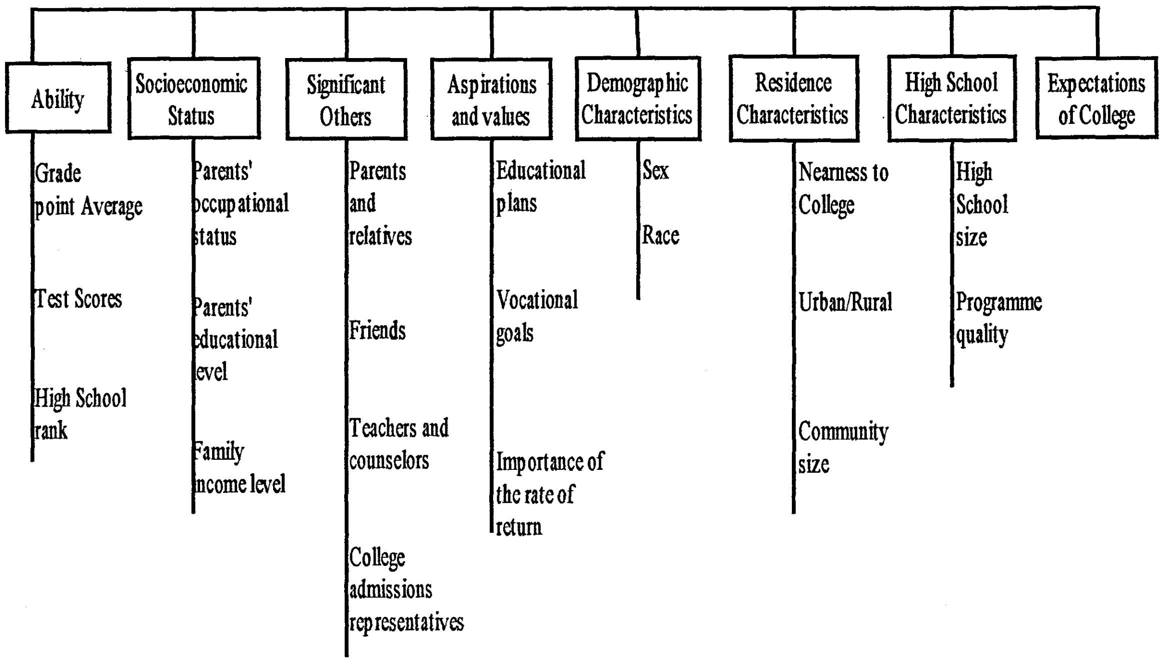

Figure 17 Personological variables in the enrolment decision. Adapted from Don Hossler (1984).

Although Hossler (1984) includes demographic details such as sex and race as determining factors of attendance to university, changes in the social climate have resulted in more women enrolling in further education. As a consequence these factors play a smaller role in predicting university attendance then they have in the past. Research by Johnson, Stewart and Eberly (1991) also found no differences attributable to race. Although proximity to a particular university is not as much of an important role as ability, socio-economic status or peers in the decisional process, Hossler (1984) suggests that when a potential student lives within a 20 mile radius then they will be more likely to attend than someone who lives beyond that radius.

The individual's perception of what university will be like greatly affects their decision to attend or not to attend. Litten, Sullivan and Brodigan (1983) suggest that there is little rationality involved in the university-choice decision of traditional-age students. This is due to the fact that they do not have a clear notion of what university life is like. Decisions may also be based on stereotypes, therefore information may be distorted or ignored to fit the individual expectation (Stern, 1965). These findings also place student university choice within the realm of NDM research, information may be incomplete and from different sources that is then combined because information can also be changed by the individual to fit a personal interpretation of what they would like university to be.

However, as discussed above, this research was focussed on high school students contemplating higher education and not undergraduates considering a postgraduate degree. It can be assumed that undergraduate students would hold a more realistic perception of university life at postgraduate level, and therefore their expectations would be more practical. Hossler (1984) also proposes that these personological variables are influential as to whether the student decides to enter into further education (i.e. should I go to university?). It would follow then that students who are already in higher education contemplating a postgraduate degree would not be influenced by these factors in quite the same way. Hossler (1984) suggests that the institutional variables shown in figure 18 determines the type of institution that the individual student will choose to attend and are therefore more relevant to study one of this thesis.

3.3.2 Institutional Characteristics of choice of university

The institutional variables consist of 'fixed' and 'fluid' characteristics. Chapman (1981) describes the fixed characteristics as the location, campus environment, programmes, and size of institution. Obviously the size and location of a university can not be easily altered and therefore they are considered fixed. Fluid characteristics include pricing strategies, programme alterations, and communication methods that are practised by individual universities. Again these variables were identified from studies carried out in America and therefore not all variables may transfer to British students; for example the price of all Master level courses in the UK is fixed. The one exception from this rule is MBA courses; here the price can differ depending on the length and location of a course. One example of programme alteration could be to increase the amount of practical experience achieved during the course.

Hossler and Gallagher (1987) proposed a three-phase model of university choice decision-making. In the first stage the student's attitudes and influences aid in their decision to attend university or not. In the second stage the students collect information and form a list of possible universities to attend. In the final stage the students narrow the list to the viable choices and make their final university choice. This is similar to Litten's (1982) model where sociological factors are dominant in the first stage while the last stages encompass econometric variables. The difference however, is the importance of the institutional policies in influencing student decision-making (Bateman and Spruill, 1996). These institutional factors are explained in Hossler's (1984) earlier model, which is discussed in detail previously. Former models have neglected to encompass the institutional variables into the decisional process, and as a result are not as developmental or interactive (Bateman and Spruill, 1996). Despite the fact that Hossler's theory provides little insight into the decision-making process, this theory is useful for identifying factors to include in the following research on choice of Master level university. Figure 18 depicts the institutional variables in the student's enrolment decision (Hossler, 1984).

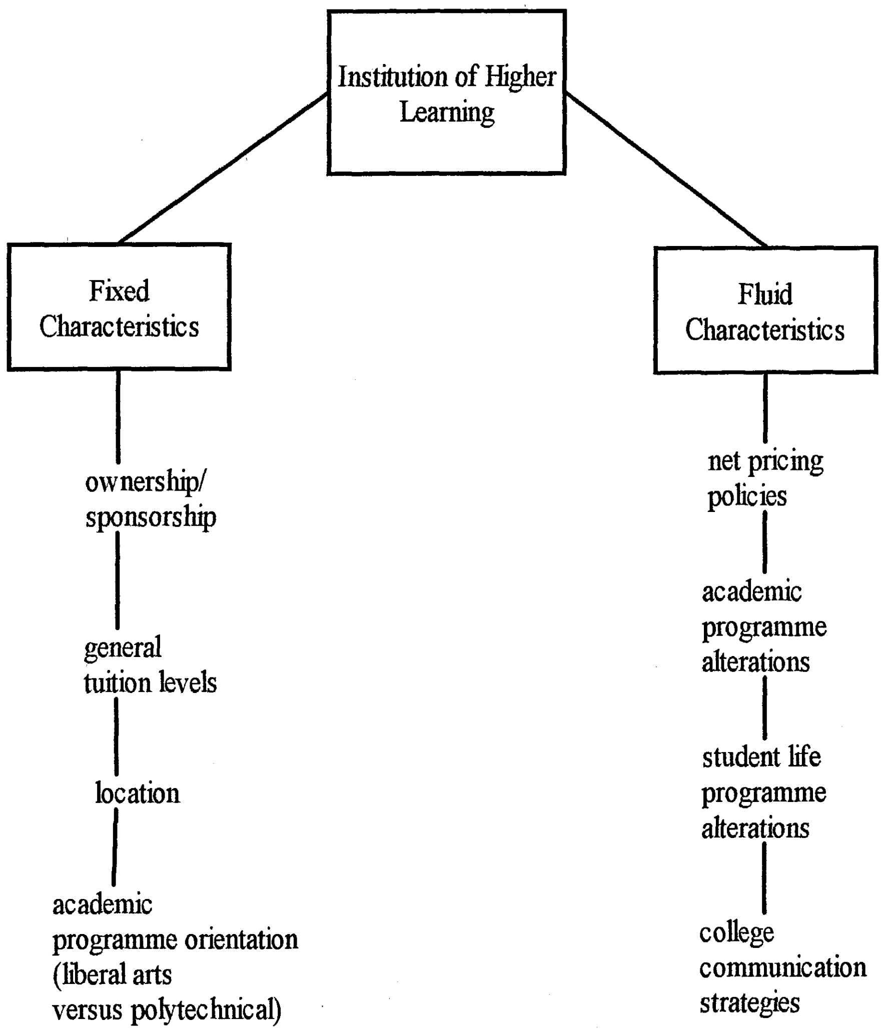

Figure 18 Institutional variables in the enrolment decision. Adapted from Don Hossler (1984)

3.3.3 Other Influences on University Choice

When looking at the concept of student university choice, it has been suggested that the researcher should view the process as consumer behaviour. Murphy (1981) utilised Webster and Wind's (1972) idea that all members of an organisation are involved in any given buying situation. The roles that Webster and Wind (1972) identified where the user (in this case the student), influencer (peers and family of the student), decider (person who makes the final choice), buyer and gatekeeper. The decider is the most crucial role to the decision of which university to attend, therefore Murphy (1981) examined the extent to which students make this final choice, i.e. does the student actually make the decision by himself or herself? The results of his study suggested that the vast majority of high school students, although influenced by peers and family, make the final decision of which university to attend on their own (81.8%). This is yet another reason for reconsidering the importance of Hossler's (1984) personological factors and their influence on the individual's choice of university.

The primary influences are generally reported to be the reputation of the university and course subject choice (Douglas and Powers, 1985). Cost and social climate also account for one of the major influences in the decision process (Johnson et al, 1991; and Martin & Dixon, 1991). Chapman (1981) has found various different influences on the student's decision of choice of university; parental and counsellor influence; location and distance from home; expectation of university life; and also the individual characteristics of the student such as socio-economic status and educational aspiration. Although it was believed that students relied heavily on parental and friends advice for which university to attend (as suggested by Hossler, 1984), studies have found that approximately three-quarters of students in the USA rely on their school counsellors as the major source of information (Johnson et al, 1991), which is contradictory to what has been found elsewhere (Murphy, 1981). In general researchers in this field agree that cost and reputation of a university are two of the biggest factors in the choice of which university to attend. However, this research was carried out on American students in America and these results may not translate to British students and how they decide on which university to attend.

Discussed previously is Hossler's (1984) model of student's decision-making, which is a multistaged process and this is the format that most researchers in enrolment management take (Jackson, 1982; Litten, 1982). These models also suggest that the students undertake the decision to attend university in a rational and orderly fashion. The process begins with the student deciding s/he will attend university, and then investigating the possibility of doing so. Following this the student begins to collect information about various universities and narrows down the possibilities to a choice list. During this stage the student decides what is important to him or her, the size of university, the courses offered etc. When the important attributes are identified, the student evaluates these according to his or her choice list and a selection of the 'best fit' takes place. This is similar to how Montgomery (1989) describes his NDM theory as a search for a dominant structure. A person would contemplate a certain number of universities before choosing the one for him or her. The final university that is chosen would be the one that is the most dominant alternative, which implies it is at least as attractive as its competitors on all relevant attributes, but exceeds on at least one.

Although these models consider the influences on student's choice of university, they do not consider the complex nature of the task or the student's ability and motivation to process fully the information required, for this kind of decision-making (Smith, 1994). In a complex decisional task, individuals tend not to process all of the available information at a given time, and therefore only a limited amount of information is used (Hogarth, 1980). According to Smith (1994) there are several points that individuals experience with this difficulty of processing information:

1. Individuals do not conduct exhaustive searches; information is attended to selectively.

2. Some pieces of information are ignored.

3. Individuals have a limited capacity to retrieve and process information that has been gathered.

Considering the above factors, it is hard to imagine that students make their university decision in such a logical, pre-planned format, as the previously described models of university choice would suggest. Smith (1994) states that people rarely make such informed and carefully planned decisions as suggested by the normative models on university choice. Post graduate choice differs from the choice to first attend a university in that, students will already have a perception of what university life is like. The fact that they may have already moved away from their parental home may imply that their parent's influence is not as strong or that moving further away will not play as an important role in their decision. At that stage in their academic career students will have a clearer notion of what they would like to study, or on which area they would like to expand their knowledge. This fact alone may be the important variable in their decision of which university to attend and not the influence of peers, or where their friends would like to attend. Are they looking for a stable course or something challenging? As already discussed, researchers have found that the personological factors only play a role in determining *if* the individual will actually attend university and not *which* university (Hossler, 1984). Students applying for a postgraduate degree will already have experience in applying for courses. In today's economic climate the need for a postgraduate degree is becoming more and more apparent, perhaps the very need for this education to obtain a desired position is the most influential variable to undertake or not to undertake a Masters degree.

3.3.4 Previous Research from Department of Psychology on Master level choice of attending Cranfield University

The Registry at Cranfield University commissioned this group project research. Therefore the registries role and the role of available information to prospective students was also investigated, as well as the individual's decision-making process (Lane, 1995). How students heard about Cranfield, and what influenced their decision to apply were important elements of this research. It was found that the subject specialisation and the reputation of the course and university where the most influential factors in the decision to apply. Examining the information received, the students found that the course information influenced their decision-making process the most. The students who received an offer but did not accept indicated that funding played a major role in non-attendance (51.4% of students not attending made this statement). A better course offer was reported by only 13.5% of the non-attending students. Unfortunately only basic descriptive statistical procedures were used in this study and it is therefore difficult to make many conclusions from the research (Lane, 1995).

3.3.5 Master level university choice; a 'consequential choice' decision

Both Hammond (1988) and Lipshitz (1993) regard consequential choice as an important component in their theories. Lipshitz described individuals using consequential choice to make a decision when they looked at all available alternatives and the best consequence of these alternatives. In other words, the decision-maker is thinking ahead and considering the attractiveness of future outcomes, (which is similar to Klein's, 1989 theory, see also the proposed synthesis of all nine NDM models reviewed, figure 13). Here choice of Master level university is presented as a consequential choice decision. First, a student will attempt to collect information about as many universities as possible, either by asking people who are in their desired area, friends, career counselors, etc. The student will try to see the possible outcomes of attending various universities, for example, s/he may pose the question 'if I attend A, I will be close to my family, however if I attend B I might have better job prospects'. To re-iterate, the choice of where to attend university can have a big impact on a student's life. A good choice can imply choosing the 'right' university for that individual resulting in completing the degree and improving career prospects. The alternative to this could be the individual dropping out, or having to undergo expensive retraining. Neural Networks will be explored as an analytical tool for modelling master level university choice as a consequential choice NDM decision. The method and results of this study are described in the following sections.

3.4 Method

3.4.1 Overview of Study One

A decision-making process of Master level choice of university was selected to establish if consequential choice naturalistic decision could be modelled through the use of neural networks. A questionnaire was developed to determine the factors and influences involved in a student's decision to attend or not to attend a certain university at Masters level. A Discriminant Function Analysis and Neural Network Analysis was carried out and results were compared to ascertain which analysis would be a more appropriate technique for modelling consequential choice NDM data.

3.4.2 Pilot Questionnaire Development

Cranfield University attracts applicants from overseas as well as the UK therefore; a self-completion questionnaire was selected as the most appropriate technique for this study. A self-completion questionnaire was also deemed the most appropriate way to collect data from the applicants who had applied to Cranfield, but subsequently rejected the offer of a place (due to employment or attendance to another university etc.). This approach is rare as many admissions personnel has previously neglected to collect information on students who applied, but did not attend, to determine whether they eventually went to university (Hossler, 1984).

However, in order to ascertain both the negative and positive outcomes of the decision-making process it was deemed necessary to obtain information from applicants who had received an offer from Cranfield but had subsequently declined. Due to the difficulty of gaining information from applicants who had refused their offer, previous research from the Human Factors Technology Group at Cranfield on this area was used to develop the questionnaire (MSc Group Project, 1995). The questionnaire devised by this project (see appendix B) was examined to help formulate questions for the semi-formal interview. To supplement the group project questionnaire, an answer sheet devised by the registry was also incorporated. This answer sheet can be seen in appendix C. These data consisted of a form that was sent out to applicants when they had received an offer of placement, and requested them to return it if they accepted or refused the said offer. These forms were a primary source of data as a result of not being able to interview people who did not take up their offer of a place at Cranfield.

From examining these data from previous work and from the Registries survey answers it was determined that two basic questions would constitute the semi-structured interview. These questions are as follows:

1. What factors did you consider before applying to take a Master level degree?

2. Did any of these factors come into your decision to attend Cranfield when choosing a university to apply to study at Master level?

Age and sex were also recorded and any other comments that the students had to make.

Informal semi-structured interviews were conducted face to face with 27 current Master level students from various taught courses (including MBA), eight females and 19 males. The majority of the sample (over 50%) were aged between 20-25 years. During this interview, subjects were asked what factors had influenced their choice of universities when applying for a Master's degree course. Following this, the subjects were then asked what factors had they considered when they received an offer to attend Cranfield University. Due to the qualitative nature of the interview, tape-recording was used to facilitate interview flow and avoid selective recording of the data. The agreement to record of the participants to record the interview was elicited before the interview commenced. These transcripts were then subsequently transcribed.

Statements from the transcripts were elicited. Two researchers triangulated this list of items to determine which statements should form the basis of the pilot questionnaire. Thirty-one items were chosen as a result of the triangulation (see appendix D for pilot questionnaire). The statements chosen needed to reflect influential factors of the student's decision process of attending a certain university (in this case Cranfield). All items needed to have the quality of saying something about the proposed course/place of study. For example the statement 'I had nothing better to do' was not included in the questionnaire, as it was felt that this statement was of a general nature and for inclusion in the questionnaire needed to be more specific towards the choice of university. Both personologial and institutional factors were included in the questionnaire according to the theory discussed previously (see Hossler, 1984).

An extra section including demographic details was also included and a section describing the outcome of the students decision (attend Cranfield/ attend other university/ obtain employment). The pilot questionnaire was tested on ten Cranfield Masters students and was subsequently modified to ensure ease of completion. The questionnaire took approximately 15-20 minutes to complete.

3.4.3 Final Questionnaire

The pilot questionnaire had a likert-type scale that went from one (negative influence) to five (positive influence). Following the pilot study this was changed so that the final questionnaire consisted of a scale that went from one (negative influence), with three meaning no influence, to five (positive influence). The final questionnaire also had an extra option meaning 'not relevant' to the individual completing the questionnaire. It was also decided that the questionnaire statements should be more generic and not be sectioned as to whether the student attended Cranfield or not. Both cover letter and final questionnaire can be seen in appendix E. There were eight sections in the final questionnaire, which largely related to all Master level courses, not just to the taught courses at Cranfield University. The eight sections in the final questionnaire were as follows:

Future employment benefits- this section contained five items that related to the individual's perception of the university's contact with industry and perception of the departments' employment record. It also related to the student's perception of an improved career, and need for qualifications.

Individual course attributes- this section consisted of five items relating to the course subject matter; how interesting it seemed; the reputation of the course and the experience that would be gained from attending it.

Location- this short section of two items determined if the student would be influenced by the location of the university.

Financial Considerations- this section was concerned with the availability of funding; cost and length of course; relocation costs; and the need to pay off previously obtained loans.

Availability of Knowledge about University- as discussed at the beginning of chapter 3, knowledge about the university can have a large impact on an individual's decision to study there. This section contained five items that related to the quality of the advertisement and prospectus, the web site, reputation of the university and what the people in the department were like.

Cranfield University Characteristics- this section was included to determine if characteristics of Cranfield could have been the negative influence on why people didn't accept their offer of a placement. There were nine items in this section and related to the link with aviation; the fact that Cranfield is entirely postgraduate; has a large male population; has a good family environment; the standard of accommodation etc.

Personal Reasons- five items composed this section and related to the individuals desire to do a Master level course; the students being unable to obtain employment; and even if the student desired to be nearer friends and family (as discussed previously friends and family can have a large impact on an individual's decision to enter education).

A space was left available for questionnaire participants to write any further factors that could have affected their decision to study or not to study at Master level. The final questionnaire also contained a demographic section. Five questions were asked in the demographic section to reveal details on:

1. The age of the participant
2. The sex of the participant
3. The marital status of the participant
4. If the participant has any children
5. Place of residence of participant

An ultimate criterion variable was also present in the final questionnaire. This variable determined the participant's final decisional choice. There were three options, of which all were equally valid outcomes for this study. This study was not just concentrating on the choice of attending Cranfield University or not, but on the various factors that come into the decisional process when deciding whether to attend university at masters level. The criterion variables determined if the participant had attended a postgraduate course, if they had attended Cranfield University or another university, and if they obtained employment instead of attending a postgraduate course. Therefore the three outcomes were - attending Cranfield University, attending another university, or obtaining employment.

3.4.4 Sampling and questionnaire distribution

The final questionnaire was then sent to 640 students currently studying at Master level on Cranfield campus (internal) and 340 applicants who had received an offer but had subsequently declined (external). The Registry printed the name and address labels of all prospective students that had received an offer but had declined the placement, to ensure confidentiality. Responders were supplied with a freepost envelope in which to return the questionnaire once completed.

The 'external' questionnaires were sent out before Christmas so students would receive them during the holidays in case they had moved to attend university elsewhere. The 'internal' questionnaires were placed in the student's pigeonholes during the Christmas break. Internal and external questionnaires were printed on different coloured paper so when they returned the outcome of their decision would be clear (Cranfield = blue, not Cranfield = green). Analysis of the data took place in the end of January 1999.

3.5 Results

3.5.1 Participants and Treatment of Data Set

There was an overall response rate of 33.1% (n=324). From this, 222 questionnaires were from current Masters students and 102 were from individuals who had declined their offer to attend Cranfield. Of the total data set, 75% were male, 44.1% were aged between 20-25, 71.6% were single, 83.6% had no children, and over half the subjects were resident in the UK (55.6%). For a fuller description of demographic details please see appendix F.

Following an examination of the data set, it was decided to remove any cases with missing data, as Discriminant Function Analysis (DFA) automatically removes them when computing but the neural network programme being used does not. This was done to enable a direct comparison between the two analyses. There was no particular pattern to report on the missing data sets. Two hundred and sixty nine fully completed cases remained in the analysis. All three outcomes of attending Cranfield, not attending Cranfield, or obtaining employment were represented in the remaining data set. The frequencies of each outcome are shown in table 3.

Table 3 Overall frequency of possible outcomes in remaining data set (n = 269). Outcomes are (1) Obtain Employment; (2) Attend Masters at Cranfield; (3) Attend Masters at another University.

POSSIBLE OUTCOMES	FREQUENCY	PERCENT
Obtain Employment	32	11.9
Attend Masters at Cranfield	186	69.1
Attend Masters at another University	51	19.0
TOTAL	269	100.0

The data file was 'cleaned' and spilt into two groups. Group One was the analysis data set, which was used to construct the model and Group Two was the holdout sample for model validation. The first group contained 179 cases, the second group 90 cases, the second set of data was approximately one third of the total cases as recommended by Garson (1998) for cross validation in neural networks and DFA. The cases were removed randomly from the total data set, but ensured approximately 30% of each decisional outcome was present.

The number of independent variables was reduced from 36 to 32 as four were removed from the analysis. These variables were as follows: 'Cranfield University is the only university connected to my home university', 'Cranfield is the only university that offered me a place', 'I couldn't obtain employment' and finally 'there was no need to attend an interview'. It was decided to remove these variables from the analysis, as they were more 'fact' than opinions and therefore wouldn't affect the decision-making process. Demographic details were not used in the final analysis also for this reason. For example, if a person has a child but has already decided to apply to attend a course, their family will already have come into their decision. Furthermore it was concluded that this variable would show up in other variables in the questionnaire like, 'Good family environment' etc. Also, although historically the sex and race of potential students has been related to the likelihood of university attendance, these factors have diminished in importance in recent years (Hossler, 1984). As discussed previously, personological data generally affects the student's decision to first attend university but not to continue in education or re-attend university. Bateman and Spruill, (1996) also found that the institutional factors played a more important role in determining which university a student chose to attend. It was therefore decided that these institutional factors would be concentrated on for the analysis in study one.

3.6 Discriminant Function Analysis

Discriminant Function Analysis (DFA) is the usual form of analysis used for the prediction and explanation of the relationships between predictor and criterion variables (for example the affect of availability of funding on the final decision to attend or not to attend Cranfield). A DFA is the appropriate form of analysis when the dependent variable is categorical (outcome: Cranfield, not Cranfield, other university) and the independent variables are metric (for example, likert scales). In this case a three group DFA was appropriate, as there were three 'outcomes'. Discrimination is achieved by setting the variate weights for each variable relative to the within group variance. This is similar to the way that neural networks work, the difference being that NNs work in a nonlinear manner. The other difference between DFA and NNs are that NNs learn from experience and recognise existing data patterns, especially when the structure of the model is unknown prior to analysis.

A three group DFA was carried out on the analysis data set to determine the equation (derivation set) and the holdout sample set was used for cross-validation. The DFA was used to examine if the questionnaire variables could discriminate between the three outcomes. DFA predicts membership on a basis of a weighted linear combination of predictor variables. The DFA's coefficient matrix was rotated. The results of the DFA can be seen on the following pages. Table 4 depicts the mean scores for each questionnaire item broken down by outcome. Table 5 shows the Wilks' lambda, univariate F-ratios and the standardised canonical discriminant function coefficients for each questionnaire item. The items in the questionnaire were scored so that a high number meant a positive influence on the individual's choice, and a low number represented a negative influence on the individual's choice of university.

Table 4 Mean Ratings for each questionnaire item broken down by outcome. Group Standard Deviations are depicted in parentheses.

QUESTIONNAIRE ITEM	JOB	CRANFIELD	OTHER UNI.
Contact with Industry	4.36 (0.73)	4.25 (0.80)	4.49 (0.92)
Needed qualification to fit experience	4.41 (1.18)	4.13 (1.18)	4.23 (1.21)
Improve chance of gaining employment	4.64 (0.66)	4.50 (0.70)	4.60 (0.65)
Disliked job and needed career change	4.41 (1.50)	4.39 (1.56)	4.00 (1.99)
Good employment record from department	3.64 (0.90)	4.25 (1.18)	4.40 (1.17)
Course offered practical experience	4.05 (0.95)	4.07 (1.01)	3.83 (1.12)
Course seemed interesting	4.41 (0.51)	4.43 (0.70)	4.49 (0.95)
Quality of course	4.41 (0.51)	4.31 (1.00)	4.43 (0.85)
Accredited by professional body	3.91 (0.87)	4.15 (1.10)	4.29 (0.83)
Quality of information received	4.09 (0.68)	3.87 (0.91)	4.11 (0.90)
University surroundings	3.32 (1.32)	2.98 (1.57)	3.83 (1.54)
University in UK	4.41 (1.22)	4.10 (1.19)	3.91 (1.38)
Availability of grants	3.18 (1.53)	3.88 (1.54)	3.54 (1.79)
Cost of relocation	3.23 (1.51)	3.56 (1.66)	3.49 (1.62)
Length of course	3.82 (1.05)	4.07 (1.03)	3.94 (1.33)
Cost of course	3.00 (1.66)	3.40 (1.54)	3.17 (1.74)
Need to pay of undergraduate loans	3.73 (1.67)	4.61 (1.64)	4.26 (1.84)
Quality of advertising	3.82 (0.91)	3.59 (1.11)	3.86 (1.00)
Reputation of University	4.59 (0.59)	4.46 (0.82)	4.51 (0.74)
People in my department	4.14 (1.04)	4.10 (1.32)	3.77 (0.97)
Presentation of prospectus	4.09 (0.81)	3.89 (0.75)	3.89 (0.74)
Web site	3.73 (1.08)	3.85 (1.22)	3.81 (1.21)
Strong link to aviation	4.82 (1.22)	4.46 (1.40)	4.43 (1.44)
Being entirely postgraduates	3.77 (0.75)	3.96 (1.27)	4.00 (1.18)
Large male population	3.73 (1.70)	2.96 (1.78)	3.13 (1.78)
Standard of accommodation	3.91 (1.38)	3.50 (1.53)	3.29 (1.53)
Good family environment	4.32 (1.36)	4.21 (1.62)	3.86 (1.85)
I thought I would do more due to the isolation	4.45 (1.22)	3.85 (1.46)	3.69 (1.84)
I always wanted to do a Masters	4.36 (1.00)	4.13 (1.16)	4.40 (1.14)
I always wanted to do a PhD	4.73 (1.35)	4.33 (1.73)	3.94 (1.97)
I wanted to be near family and friends	4.18 (1.99)	4.09 (1.78)	3.37 (2.12)
I wanted to gain work experience before completing a Masters	4.45 (1.57)	4.57 (1.64)	4.11 (1.75)

Table 5 Wilks' Lambda, Univariate F-ratios with (2,176) degrees of freedom and Standardised Canonical Discriminant Function Coefficients for each variable.

VARIABLES	Wilks' Lambda	F-ratio	Significance	DFA function 1	DFA function 2
Contact with Industry	0.987	1.146	0.320	0.077	0.211
Needed qualification to fit experience	0.994	0.542	0.582	0.177	0.254
Improve chance of gaining employment	0.994	0.561	0.571	0.344	0.166
Disliked job and needed career change	0.991	0.789	0.456	0.232	-0.087
Good employment record from department	0.964	3.306	0.039	-0.733	0.000
Course offered practical experience	0.992	0.735	0.481	0.109	-0.106
Course seemed interesting	0.999	0.089	0.914	-0.273	0.093
Quality of course	0.997	0.273	0.761	0.156	0.047
Accredited by professional body	0.990	0.916	0.402	-0.321	-0.132
Quality of information received	0.984	1.397	0.250	-0.024	0.340
University surroundings	0.953	4.297	0.015	-0.161	0.668
University in UK	0.988	1.091	0.338	-0.015	-0.293
Availability of grants	0.977	2.080	0.128	-0.189	-0.441
Cost of relocation	0.996	0.384	0.682	0.071	0.185
Length of course	0.993	0.605	0.547	-0.170	-0.107
Cost of course	0.992	0.748	0.475	0.014	-0.162
Need to pay off undergraduate loans	0.969	2.828	0.062	-0.517	-0.170
Quality of advertising	0.998	1.088	0.339	-0.002	0.302
Reputation of University	0.997	0.292	0.747	0.138	0.067
People in my department	0.988	1.042	0.355	0.106	-0.189
Presentation of prospectus	0.986	1.262	0.286	0.370	-0.207
Web site	0.997	0.235	0.791	-0.175	-0.091
Strong link to aviation	0.979	1.848	0.161	0.378	-0.386
Being entirely postgraduates	0.983	1.528	0.220	-0.492	0.251
Large male population	0.977	2.069	0.129	0.252	0.224
Standard of accommodation	0.987	1.151	0.319	0.049	-0.052
Good family environment	0.991	0.766	0.467	-0.014	-0.125
I thought I would do more due to the isolation	0.979	1.871	0.157	0.417	-0.055
I always wanted to do a Masters	0.989	0.983	0.376	0.090	0.275
I always wanted to do a PhD	0.984	1.421	0.244	0.214	0.007
I wanted to be near family and friends	0.976	2.170	0.117	0.228	-0.077
I wanted to gain work experience before completing a Masters	0.988	1.056	0.350	-0.054	-0.162

Table 6 Canonical Discriminant Function Analysis Summary Statistics for analysis set.

Function	Eigenvalue	Percentage of Variance	Canonical Correlation	Correlation Squared
1	.365	55	.516	.267
2	.299	45	.480	.230

Table 7 Canonical Discriminant Function Analysis Summary Statistics for analysis set.

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1 through 2	.564	91.903	64	.013
2	.770	41.957	31	.091

Table 8 Group Centriods for Canonical Discriminant Function.

OUTCOMES	Function 1	Function 2
Obtain Employment	1.531	0.282
Attend Cranfield	- 0.128	- 0.348
Attend Other University	- 0.516	1.034

Tables 4-8 contain the overall summary of the discriminant function analysis. The first function accounts for 55% of the overall variance accounted for. Function One maximally discriminates between obtaining employment and attending another University. Function Two maximally discriminates between attending Cranfield and attending another University. Four variables influenced Function One. Their discriminant function coefficients can be seen in table 9.

Table 9 Rotated Standardised canonical Discriminant Function Coefficients: four most influential variables in Function One (cut off criterion > 0.4)

Variable	Function Coefficient
Good employment record from department	-0.733
Need to pay off undergraduate loans	-0.517
Being entirely postgraduate	-0.492
I thought I would do more work due to the isolation	0.417

The first three variables were the most influential to the participants' decision to attend another University. The last variable in the above table influenced the participants' decision to obtain employment. Two variables (coefficients shown in table below) influenced Function Two. These results are similar to the results found by the MSc group project in 1995, they reported that location and availability of funding where important factors in the decisional process of students when they were deciding to attend or not to attend Cranfield (Lane, 1995).

Table 10 Rotated Standardised canonical Discriminant Function Coefficients: two most influential variables in function Two.

Variable	Function Coefficient
University surroundings	0.668
Availability of grants	-0.441

Table 11 depicts the classification for both the analysis sample, which was used to compute the discriminant function, and the holdout sample, which is the validation set.

Table 11 Classification Matrix for Three-Group Discriminant Function Analysis for Analysis and holdout Samples

A: CLASSIFICATION RESULTS: ANALYSIS SAMPLE

Actual Outcome	Predicted Group Membership		
	Job	**Cranfield University**	**Other University**
Job (total=22)	9 (40.9%)	12 (54.5%)	1 (4.5%)
Cranfield University (total=122)	1 (0.8%)	113 (92.6%)	8 (6.6%)
Other University (total=35)	2 (5.7%)	20 (57.1%)	13 (37.1%)

B: CLASSIFICATION RESULTS: HOLDOUT SAMPLE

Actual Outcome	Predicted Group Membership		
	Job	**Cranfield University**	**Other University**
Job (total=10)	0 (0%)	8 (80%)	2 (20%)
Cranfield University (total=64)	5 (7.8%)	52 (81.3%)	7 (10.9%)
Other University (total=14)	2 (12.5%)	12 (75%)	2 (12.5%)

Analysis sample: percent of 'grouped' cases correctly classified: 75.4%
Holdout sample: percent of 'grouped' cases correctly classified: 60%

The analysis sample correctly classified 75.4% of the overall cases. However, more importantly, the holdout sample correctly classified 60% of cases on the basis of the three outcomes: Job, Cranfield, and other University. The DFA (in the holdout sample) showed a high degree of success in predicting the outcome of attending Cranfield, which can be seen in the previous table (81.3% success). However, the classification matrix showed little ability in distinguishing the other two outcomes from the data set, which also can be seen in table 11. The holdout sample classification matrix failed to correctly classify any of the cases on the basis of obtaining employment, and only 12.5% of the cases on the basis of attending another university. Therefore although the overall success rate seems quite high (60%), it is clear to say that the overall success rate on the basis of all three outcomes was rather poor.

3.7 Neural Network Architecture

Neuroshell 1 was used for the analysis of the data. Neuroshell 1 is a neural network, which attempts to 'classify patterns according to other patterns it has learned and to give the most reasonable answer based upon the variety of learned patterns'. It was designed to follow biological neural functioning and differs significantly from all other conventional computer software. It utilises the backpropagation technique and it is particularly applicable to many kinds of problems that rule based expert systems can be applied (see chapter two for discussion on backpropagation).

The analog version of Neuroshell 1 was used as is recommended that this option is used when there is a range of values as there is in this case (all variable items in the questionnaire could be rated from 1-5, with an extra option of not relevant, therefore there was a range of values from 1-6). It is also best to use the analog version of Neuroshell 1 when there is a clear near neighbour relationship between the values. Previous research has shown that the backpropagation paradigm yields higher generalisation levels then other supervised learning techniques (Shastri, Rabelo, Onjeyekwe, and Vila, 1998). Shastri et al (1998) found that the backpropagation technique learns adequate internal representations using deterministic units to provide a mapping from the inputs to the outputs.

3.7.1 Data preparation

NNs are like any other statistical methods, in that bad input data will give you bad output data. Some researchers claim that NNs can be used for almost all types of data, however, Hair et al (1998) suggest that the data set be treated in the same manner as with other multivariate statistic analysis. NNs are more tolerant of imperfect data, such as the presence of missing values or other data quality problems (noise etc). If the form of the data is unknown, non-linear or the problem is complex with highly interrelated relationships NNs will perform better then the traditional statistical method (SPSS, 1999). In general poor quality data will result in a poor quality model. If the problem has calculable parameters such that answers can be computed, then traditional statistical procedures are more appropriate (Garson, 1998). Also, just like with other statistical procedures, input variables, which are invariant for the range of the dependent variable, should be removed from the NN as they lack explanatory power. Outliers should be examined, or set to a limit as they can have a large impact on the final model. Categorical variables also need to be converted to dummy variables as in multiple regression. Therefore the data needs to be examined just as thoroughly as with any other statistical procedure.

3.7.2 Sample Size and Distribution of Data Set

When the data sets are created for estimating the NN, it needs to be split into two. The first data set is the calibration sample, or otherwise known as the training set, which estimates the weights. The second set of data is the validation set, which assesses the predictive ability of the model (Hair et al, 1998). For cross-validation of this type the sample is split into training and validation sets, as a rule of thumb on an 80:20 ratio (Garson, 1998). The sample size used to formulate the model can have as much impact on the results as with any multivariate technique. If the sample size is less then the number of estimated weights a model can be perfectly fitted. However, as the number of cases approaches the number of weights, overfitting occurs and the model becomes too sample specific, losing generalisability. The number of weights in a NN adds up quickly, (for example see figure 16 in Chapter Two). If, for example there are 12 weights between the input layer and hidden layer, and six weights between the hidden layer and the output nodes, a total of 18 weights. Therefore, the number of weights is related to the number of layers and the number of nodes. Adding one more input node would add three more weights, whereas adding another hidden layer would add nine more weights. The model requires just one more case then the number of weights.

3.7.3 Cross validation

Cross validation is a form of split-sample model validation. The sample is split into training and validation sets; Garson (1998) suggests a rule of thumb on an 80:20 ratio. Neuroshell (manual, 1990) suggests that with a sample number of 300 a rough number of 50 (around 16% of total sample size) should be removed randomly to act as the validation set. Spilt sample validation eliminates tautological findings arising from a high number of hidden nodes overfitting the training data set. For simple comparison the sample was spilt into a 75:25 ratio, as was done with the DFA, where this is also the recommended ratio for cross-validation (Hair et al, 1997).

3.7.4 Neural Network Analysis for Study One

The same data were used for the neural network analysis as the DFA. Group one (n = 179) was the learning set and group two (n = 90) was the cross validation set. All cases converged with total and minimum error = 0.012726. Table 12 depicts the network factors used in the analysis. For a full description of each network factor see chapter two.

Group one was used as the learning set. The training process utilising backpropagation can be a difficult problem. An appropriate architecture needs to be found (number of hidden units and layers etc.). Several approaches were used in this analysis to find the appropriate numbers of hidden layers; the learning parameters were changed regularly to speed up convergence and to avoid overtraining effects. This process of altering the various factors (shown in table 12) is the normal approach taken when performing a neural network analysis. The only way to determine the various network factors is to complete training on a number of various occasions, and to alter the parameters each time until a maximum convergence has taken place and the best results from the network are obtained.

Table 12 Network Factors for final Study one Neural Network

Network Factors	**Value**
Output Threshold (0-1.0)	0.4000
Learning Threshold (0-3)	0.0001
Hidden Nodes	37
Learning Rate	0.1000
Momentum	0.0000
Presentation (0=rotate, 1=random)	1

Due to the obvious complexity of the network being discussed only a small sample of it is shown in the following figure 19. As can be seen each input or variable is connected to each hidden node, which in turn is connected to the output, or final outcome. For further information regarding the weights for each connection see appendix G.

Outcome bias and the weights for each hidden node connection to outcome can be seen in appendix H. Actual and predicted outputs of the cross validation set can be seen in appendix I.

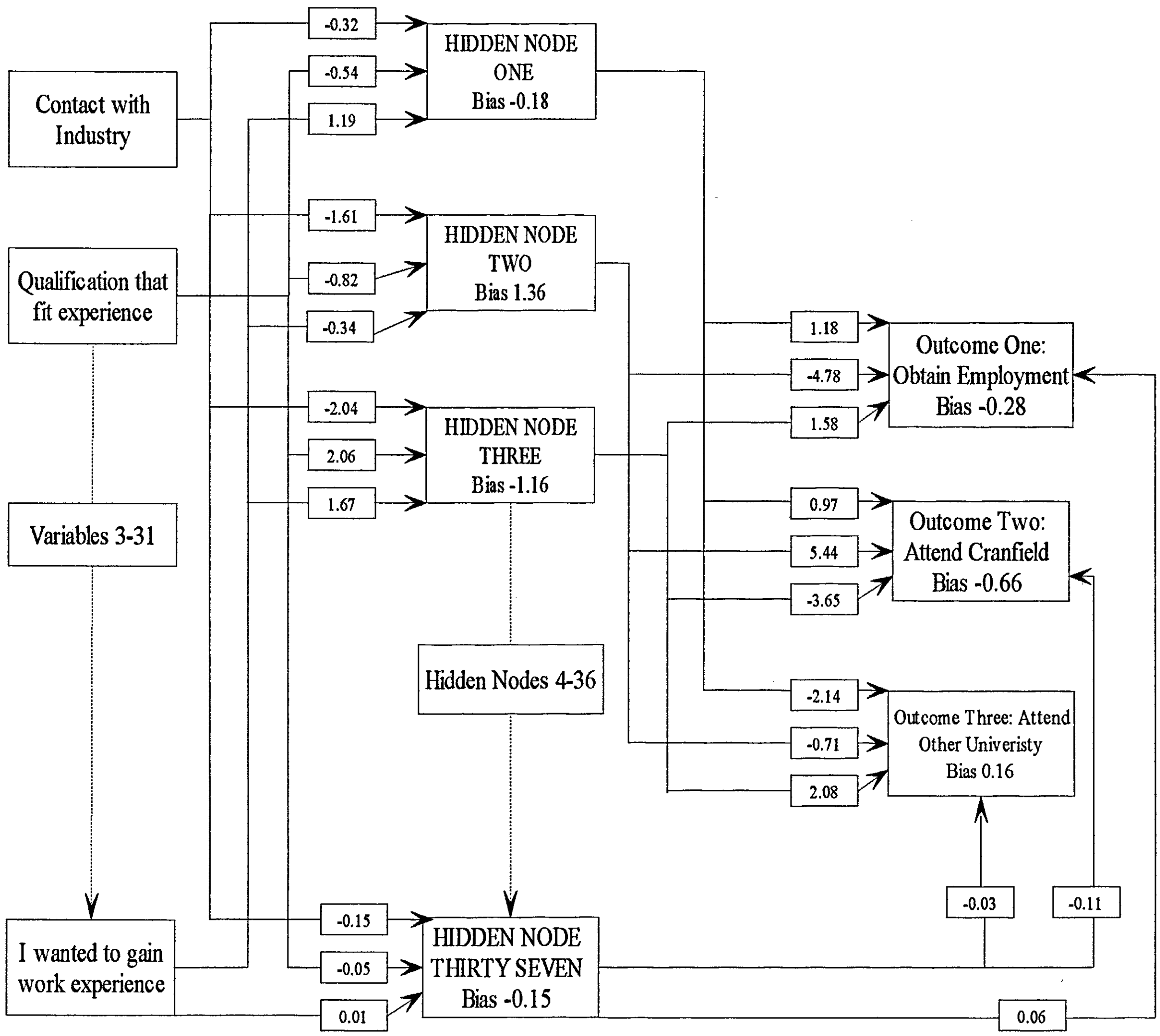

Figure 19 Part of Master Level University Choice Neural Network

To analyse the veracity of the predictions made by the NN model a classification matrix was produced. The predictions made for each output node (or decision) in the cross-validation data set were categorised as 'hits' (correct predictions of participants decision) or 'misses' (the NN predicted that the participant would chose a certain decision but in fact the NN predicted incorrectly). The results of this classification can be seen in table 13.

Table 13 Neural Network prediction of student decision-making to attend a Masters course or obtain employment (n=90)

Actual Outcome	**Predicted Group Membership**		
	Job	**Cranfield University**	**Other University**
Job (total = 10)	3 (30%)	5 (50%)	2 (20%)
Cranfield University (total = 64)	3 (0.05%)	52 (81.3%)	9 (0.14%)
Other University (total = 16)	0 (0.0%)	10 (62.5%)	6 (37.5%)

Holdout sample: percent of 'grouped' cases correctly classified: 68%

Overall, 68% of cases were correctly classified on the basis of the three outcomes: Job, Cranfield, and other University. The Neural Network showed the same degree of success in predicting the outcome of attending Cranfield as the DFA (holdout sample), which can be seen in the above table (81.3% success). However, the neural network showed more ability in successfully classifying the other two outcomes from the data set; 30% of cases (compared to 0% for DFA) were correctly classified for obtaining employment, and 37.5% of cases (compared to 12.5% for DFA) were correctly classified for attending a Masters degree at another University.

Following the comparison of both the DFA and NN classification matrixes, it was necessary to carry out further investigations to determine if the results from both analyses were significantly predicting outcomes or if the models produced where resulting from chance. A Press's Q Analysis was therefore used to resolve this issue.

3.8 Press's Q analysis

This is a statistical test for discriminatory power of a classification matrix when compared to a chance model. It is a simple model that compares the number of correctly classified variables with the total sample size and the number of groups. The calculated value is then compared with a critical value for one degree of freedom in chi squared distribution at the desired confidence level. If the number exceeds the critical value then the classification matrix can be deemed statistically better than chance.

PRESS's Q =

$$\frac{[N-(nK)]^2}{N-(K-1)} \tag{2}$$

Where

N = total sample size
n = number of observations correctly classified
K = number of groups

The results of the Press's Q Analyses can be seen in table fourteen. It can be seen from the table fourteen that both classification matrixes exceed at the statistically significant level the classification accuracy expected by chance. Both matrixes exceed this at the 99.9% confidence level. It can also be seen from these results that the NN has performed better than the DFA.

Table 14 PRESS's Q analysis for both Discriminant Function Analysis and Neural Network

	PRESS's Q	Accuracy Better than Chance?
DFA	58.91	✓
NN	98.28	✓

Chi square at one degree freedom, at the .001 confidence level =10.83

3.9 Discussion

Eight variables were identified as the main determinants of an individual student's decision to attend or not to attend a certain university. These were as follows, 'future employment benefits', 'individual course attributes', 'location', 'financial considerations', 'availability of knowledge about university', 'Cranfield University characteristics' and 'personal reasons'. These factors are discussed in detail in section 3.4.3. The questionnaire developed incorporated both 'personological' and 'institutional' characteristics that has been found in other theories (Tillery, 1973; Litten et al, 1983; Hossler, 1984; Hossler and Gallagher, 1987; MSc Group Project; 1995). This questionnaire was developed to determine the influences on students' choice to attend or not to attend Cranfield University in particular. The enrolment management research that is discussed in section 3.3 was mainly carried out in the United States. In today's economic climate the need for a postgraduate degree is becoming more apparent, therefore students equate masters education with obtaining a desired career. This increase in further education within the UK implies that more research needs to be carried out within this important field. Of the research reviewed within this chapter not only was it carried out in America but it also concentrated on the choice of undergraduate university and course. Therefore although some of the determinants of an individual students decision to attend or not to attend a certain university for a Masters level course were similar to the American studies, more research needs to be carried out within the UK with the main interest being undergraduate students entering postgraduate courses.

The discriminant function analysis (DFA) that was carried out on the questionnaire was not particularly successful in discriminating between the three outcomes (attend Cranfield; attend another university; obtain employment). It was successful in predicting group membership for attending Cranfield University, but not for the other two outcomes. This could be due to the fact that the majority of the sample came from students studying at Cranfield (see results section). The Press's Q analysis also found that the DFA was classifying cases significantly and not just due to chance.

Two functions were derived through the DFA, function two was non-significant, although it did account for 23% of the total sample variance. Function Two discriminated mainly on the basis of university surroundings (i.e. location) and availability of grants. These findings support previous research, for example the MSc Group project (Lane, 1995) carried out by the Psychology Department at Cranfield, found that of the factors influencing applicants who chose not to attend, lack of funding was the most influential. This research also found that location was another important dimension in the students' decision to attend or not to attend (Lane, 1995). Obviously little can be done about the location of any university, however, added amenities may help to influence a student's desire to attend a particular university. This function maximally discriminated between attending Cranfield and attending another university. Chapman (1981) also states that location is one of the important influences on a student's decision to attend a particular university. Hossler (1984) reported that students who live within a 20-mile radius of a university would be more likely to attend that university then somebody who lives beyond that radius. Availability of grants has also been found to be one of the most important factors in the choice of university (Chapman, 1981; Johnson et al, 1991; Martin & Dixon, 1991 etc.). However, this variable (termed 'cost' in the enrolment literature) was identified from studies carried out in America and relates to the different costs of similar courses in different universities. Therefore it does not really transfer to British universities; for example the price of all MSc courses in the UK is fixed. The one exception from this rule is MBA courses; here the price can differ depending on the length and location of a course.

DFA function One accounted for 27% of the variance and maximally discriminated between obtaining employment and attending another university. This function discriminated mainly on the basis of 'good employment record from department', 'need to pay off undergraduate loan', 'being entirely postgraduate' and 'I thought I would do more work due to the isolation'. The last two factors are specific to Cranfield University, with the latter relating to location, which is discussed previously. It is obvious to conclude that the desire to pay off undergraduate loans would influence a person to obtain employment rather then attend another course and risk getting further in debt (which can relate to lack of funding, also discussed previously). As no research has been carried out in the past on postgraduate student's decision of which university to attend, it is difficult to relate these findings with previous work in the field. However, it is possible to say that 'good employment record from department' could relate to the student's perception of a given universities reputation. This has been found in previous research to be an influential factor in a student's decision to attend a given university (Douglas & Powers, 1985).

By examining the classification matrix for the DFA and the Neural Network for predicting student decision-making on the basis of the three outcomes: Job; Cranfield; or other University, it can be seen that the neural network performed slightly better. Overall, the neural network correctly classified 68% of the cases, whereas the DFA only predicted 60% of the cases. The Neural Network showed the same degree of success in predicting the outcome of attending Cranfield (81.3% success) as the DFA, which can be seen in the tables eleven and fourteen. However, as can be seen in table three, the sample size of the students who attended Cranfield was larger then the other two groups. It is logical then why both analyses performed better in predicting this outcome of attending Cranfield University.

The neural network showed more ability in correctly predicting the other two outcomes from the data set, 30% of cases (compared to 0% for DFA) were correctly classified for obtaining employment, and 37.5% of cases (compared to 12.5% for DFA) were correctly classified for attending a Masters at another University. The NN analysis may have been superior in this case as they are better able to analyse nonlinearly, and also consider all parameters in connection with one another. In NN analysis there are many ways to achieve one outcome. The DFA is also using both functions to perform the classification, even though only function one was significant.

The press's Q analysis showed that both classification matrixes exceeded at a statistically significant level to be showing results that were not due to chance. Both matrices exceeded this at the 99.9% confidence level. The NN analysis performed slightly better when one considers the press's Q results (DFA= 58.91; NN= 98.28).

The main limitation of NNs is the inability to interpret why the model is predicting these outcomes. It is possible to go through the entire matrix, as is discussed in chapter two, to see why the NN is achieving certain results and models. However, it is not yet possible to say which variable is the most powerful in predicting the outcome as every variable is included in the computation of the NN model. Each variable's influence depends on the other variables for a given case. Therefore, NNs should only be interpreted as a whole as it is meaningless to interpret any single part of an entire NN model.

However, by comparing the results in study one of both analyses it can be said that the NN performed marginally better then the DFA for predicting student's outcome in choice of university (by 8%). Nevertheless, with DFA the functions that resulted in the prediction of certain outcomes can actually be shown, this is not possible with NN analysis. Although this is the case, Neural Networks have performed better in predicting group allocation then the Discriminant Function analysis, not only in overall performance and prediction, but with distinguishing between all three outcomes.

Master level choice of university was presented as a naturalistic decision, which was a consequential choice task (see 3.2.1). According to Lipshitz (1993) a consequential choice task is when there is a choice among alternatives in terms of an expected outcome (e.g. obtaining a degree). Consideration of future consequences takes place and there is a choice from an available set of alternatives (e.g. x amount of universities). Montgomery (1989) describes a theory of NDM were the attributes are also based on a set of common attributes and the selection and evaluation of these alternatives are based on their relative standing within this set. Stern (1965) also reported that students based their decisions of which university to attend on stereotypes, he found that students sometimes distorted information to fit their expectations, which supports this view of Master level choice of university as a consequential choice task. The neural network analysis performed better then the discriminant function analysis as an analysis tool for modelling a consequential task.

In Study One the neural model performed commendably in predicting the decisions made in a consequential decisional task of choosing a university to study at Masters level. The common theme throughout all NDM models (see chapter one for a discussion of various models) is the decision situation of which choice and pattern matching are the most prevalent. Therefore, study two will now examine NNs as a tool for modelling a pattern matching decisional task.

3.10 Study One Conclusions

- The developed questionnaire incorporated both personological and institutional data, which related to the theories in this field of student's choice of university.

- Two functions were disclosed through the Discriminant Function Analysis, function one accounted for 27% of the variance explained and function two accounted for 23%.

- The Neural Network Analysis performed marginally better then the Discriminant Function Analysis in predicting the three outcomes from the questionnaire. The NN correctly classified 68% of the cases, whereas the DFA only predicted 60% of the cases.

- The Neural Network Analysis appeared to have performed slightly better then the Discriminant Function Analysis when the press's Q analysis was carried out (DFA= 58.91; NN= 98.28).

- The Neural Network Analysis appears to have performed marginally better then the Discriminant Function Analysis for predicting student's decision-making of choice of university for Master's study.

4 Study Two

This chapter describes a study conducted within the NDM paradigm in which a disruptive passenger threatens the safety of a hypothetical flight. This decisional process is presented as a pattern matching NDM task. Sixty-five professional members of flight crew participated in a series of semi-structured interviews during which they described their decision-making process for dealing with a hypothetical situation. A DFA and NN analysis was used to model the decisions made on the basis of the interview variables. Both analyses are compared to determine which is a more viable tool for modelling a pattern-matching naturalistic decisional task.

4.1 Aim and of Study Two

Study One focused on a consequential choice decisional task of choosing a certain university for studying at masters level. The results of study one determined that NNs were better than DFA for modelling a consequential choice naturalistic decision. Cross validation of the results showed that decision outcomes could be very accurately predicted on the basis of the model produced. The two most common decisional tasks are consequential choice and pattern-matching, as discussed in detail in Chapter One. Study One focused on Consequential Choice, therefore study two will focus on a pattern-matching decisional task. The decisional process of pilots' responses to a disruptive passenger incident was chosen for this task- the rationale behind this choice is discussed in detail in section throughout this chapter, specifically in 4.2.2, 4.2.3 and 4.3.2. Study Two will also focus on a comparison between NNs and DFA to determine if NNs or a more 'traditional' statistical approach is appropriate for modelling a pattern matching naturalistic decision. This chapter is presented as a report on study two. Study two method and results are described. Some specific conclusions will also be outlined.

4.2 Introduction to study two: Pilot Judgement

Naturalistic Decision-making (NDM) was developed as the need for understanding decision-making in critical hazardous situations increased. Experienced decision-makers in these critical hazardous situations were those who were in charge of flight decks, firegrounds, emergency control rooms and warfare operations (Flin, Salas, Strub and Martin, 1997). Individuals, who perform decision-making under stressful and high-risk situations such as in the flight deck, do so as part of their job. In general their accomplishments are rarely noticed until a disaster occurs and the potential limitations of their decision-making under conditions like time and high personal stress are revealed (Flin et al, 1997). In fact no matter how safe an aircraft is designed to be, human factors account for two-thirds of airline accidents (Bor, 1997).

The development of the flight data recorder (black box) led to the realisation that pilot error was the major factor in aviation accidents (Jensen, 1995). Human error was the cause of 80% of accidents in general aviation and 70% in airline operations. Figure 20 depicts the causes of airline accidents as percentages of the total, and it can easily be seen just how high the amount was a result of human factors (also termed pilot error). Despite extensive research and technological advances, aircraft accidents still happen, and it is now suggested that humans (i.e. the aircraft pilot and crew) are the weak link in the safety chain (Feggetter, 1985). However, reporting that the accident was due to pilot error does not resolve the problem. In fact, in many cases the pilot was flying to the best of his/her ability and it does not (at least should not) imply that the pilot was negligent in any way (Jensen, 1995).

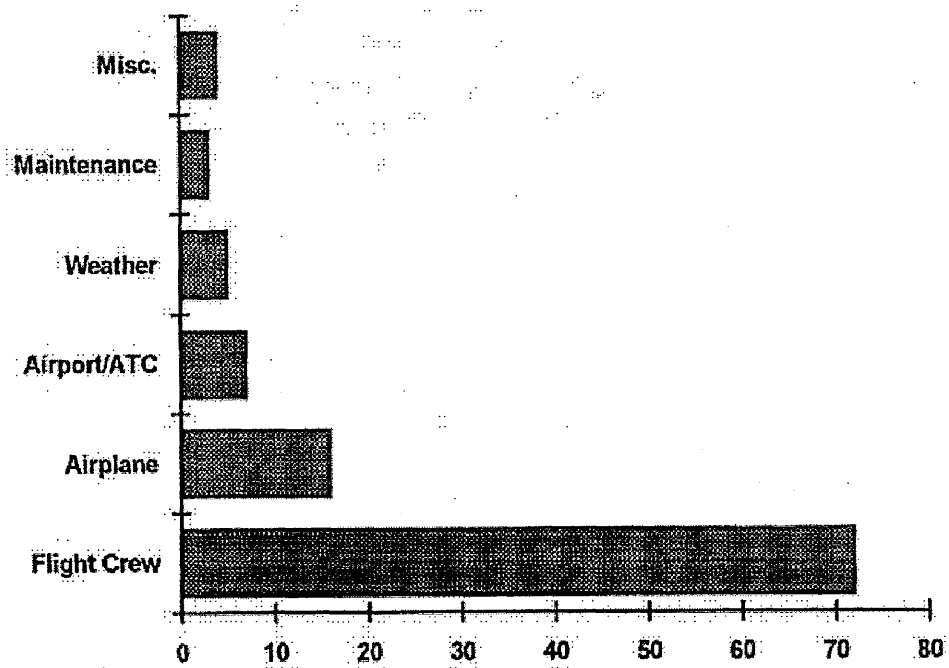

Figure 20 Total percentages of the causes of airline accidents. Taken from Jensen (1995), *Pilot Judgement and Crew Resource Management, p. 8.*

In general, the outcome of a decision may be correct, but the pilot may make numerous errors along the way. During any routine flight, the pilot compares actual outcome with the desired or intended outcome (Roscoe, 1980). If the actual outcome departs from the intended outcome then the pilot notices it and makes a decision and attempts to bring the two outcomes (desired and actual) closer together. According to Jensen (1995) straight and level flying is in fact a defined series of error correction movements. He suggests that correcting errors is what flying is all about. This statement supports NDM theory, as the pilot's awareness of the situation and continuous effort's to rectify deviations from what the actual situation should be (the so called 'loop' of making a decision, assessing the situation, making another decision etc.). Therefore, when pilot decision-making is viewed like this it can be seen as a 'pattern matching' decision. The pilot recognises the problem and calling on experience (either his or another's) examines the same options or actions that match the particular problem in an attempt to rectify the current situation. Research to support this statement has shown that pilots engage in a certain amount of 'trial and error' control behaviour to gain perceptual information about the visual scene (Owen, Warren, Jensen, Mangold, and Hettinger, 1981).

The fact that 'pilot error' accounts for such a large percentage of human factors related accidents and incidents is not a recent phenomenon. Considering that the FAA's Advisory Circular in 1991 reported that decision related accidents accounted for 52% of all fatal general aviation pilot error accidents (FAA, 1991), it is not surprising that there is a need for more research in this important field.

4.2.1 Decision-making in Aviation

Aeronautical Decision-making (ADM) is defined by the FAA (1991) as 'a systematic approach to the mental process used by aircraft pilots to consistently determine the best course of action in response to a given set of circumstances' (p. 3).

Seamster, Redding and Kaempf (1997) state that decision-making, judgement and problem solving are all important components of flying. They suggest that what separates first officers and captains is the fact that captains have to make the decisions. When training for making aeronautical decisions, pilots are taught to understand the situation, generate all possible courses of action, evaluate these courses of actions based on some criteria, select the course of action that is deemed the most valuable according to these criteria, implement this course of action and finally evaluate the success of the outcome. In itself not a bad strategy, but only possible under a limited set of circumstances. On the flight deck for instance, rarely does a pilot have the time to implement his/her decision in this format, and more often then not s/he does not have all information readily available (even if s/he has the time to retrieve it). Yet, pilots make successful, rapid, frequent decisions everyday. Is s/he remembering similar decisions made in the past and simply implementing those past actions? This is exactly what Seamster et al (1997) suggests pilots do. Pilots do not generate a set of multiple options and then compare and contrast the merits of each against each other. Instead pilots 'collect' past situations and when they reoccur s/he matches 'which patterns in the environment provide relevant cues and obtain feedback about what does and does not work in each situation' (Seamster et al, 1997).

According to the FAA (1991) the recognition of the situation is the 'key' to successful decision-making. The FAA claim that the recognition that a decision needs to be made is the acknowledgement that something has changed or an expected change did not occur. Not noticing a change can lead to an error. Recognising that a situation has not occurred means the pilot would implement an action to modify it. Therefore situation awareness is fundamental to 'good' pilot decision-making. As discussed in chapter one, this is also the main component of naturalistic decisions (see section 1.10).

4.2.2 Presenting pilot judgement as a naturalistic decision

In aviation there are stresses present that are normally not present in other fields where decision-making occurs. The decision problems are normally ill defined and the information is probabilistic. If the pilot recognises the problem there can be enough time available but decisions can also be made under time pressure, and the pilot has social and psychological forces working on him (Jensen, Guilke, and Tigner, 1997). Fear of losing one's license can be a major stress factor, or being reprimanded by the organisation is another. Fear of losing one's life can also be a factor in the equation.

As discussed in chapter one, Orasanu (1995) states that the following three features are the reasons why the aviation domain is well suited to a naturalistic approach to decision-making:

(1) the environment is dynamic, and problems can be ill-structured,

(2) time pressure is often a frequent ingredient,

(3) the consequences of poor decision-making can often carry high risks. (p.475)

Neural network applications are not new to the field of aviation. However, most of these attempts have been in the area of pilot decisional aids or associated with high demand situations like missile evasion (Hong, 1988; Krile, Rothstein, McAulay, & Juang, 1989; Endres, 1991).

Study One showed that for choice of university at Master level, neural networks performed better then the traditional form of analysis for decision-making. Master level university choice was presented as a 'consequential choice' decision, whereas when one looks at Jensen's (1995) model of pilot judgement (discussed in chapter one) it can be seen that aeronautical decision-making is often a 'pattern matching' decision. Therefore it was proposed that the following study should examine a potential 'pattern matching' decision. It has been identified that NNs are particularly good at pattern matching (see chapter two for a full discussion). A neural network is a tool that attempts to classify patterns according to other patterns it has 'learned' and results in the most reasonable answer based upon the variety of learned patterns (Neuroshell manual, 1990).

4.2.3 Pilot Judgement; a 'pattern matching' decision

It has been established that the problem with NDM models is the lack of empirical evidence to support the models derived, or even to choose between the models that have been developed. Although the discussed NDM models in chapter one are describing various decisions, one common theme appears to be consequential choice and pattern matching components of decisions. Master level choice of university was presented as a consequential choice decision task. Here, pilot judgement is presented as a pattern matching decision. Pattern matching decisions occur in the flight deck all of the time as situation assessment is the main factor pertaining to matching problems, for example a decision-maker might pose the question, *what* is this situation and what should I *do* in this situation? Individual rules such as personal experience, professional standards and social norms influence the assessment of the situation. Matching can be blocked by the individual's uncertainty of the situation and what to do when a certain situation occurs. Lipshitz (1993) suggested that when people use the matching format to make a decision they are using either their own or other's experience. Most pilots discuss with others the situations they were in and how they dealt with it (David, 1998), also most pilots will read incident reports regularly. The whole point of simulator training is to present to the pilot certain situations, so if they occur in real life, the pilot will have some experience of how to deal with them. NNs have been shown to be particularly good at pattern matching problems, and therefore it is assumed that they will be successful in modelling a naturalistic decision-making problem of pilot judgement.

The main aim of this thesis was to examine the possibility of utilising NNs to model a naturalistic decision. Study One showed that NNs were successful in classifying a consequential choice decision, study two examines NNs as a modelling tool for a pattern-matching decision. It is proposed that NNs should perform better on a pattern matching task then a consequential choice task as they are known to be good at modelling pattern-matching problems (Garson, 1998).

4.3 Method

4.3.1 Overview of Study Two

The aim of this study was to examine the underlying influences involved in pilot judgement and develop a model of those influences utilising Neural Networks (NN). Although the final decision of each of the participants was considered important and useful, the influences and way they collected and formulated information was of primary interest. An air rage scenario was used to collect data, which was carried out over the telephone. A Discriminant Function Analysis and Neural Network Analysis was carried out and results were compared to ascertain which analysis would be a more appropriate technique for modelling a pattern matching task in NDM.

4.3.2 Scenario Design and Development

An unstructured problem scenario with indirect, incomplete and inferential information was developed. The scenario developed had to be suitable for administration to flight crew using a semi-structured telephone interview in order to gain a reasonable sample size with diverse experience from a geographically widely dispersed population and within a moderate time frame. It also had to have no prescribed 'correct' solution. The scenario could also not involve a well-defined course of action prescribed by such flight deck items as the checklists in the quick reference handbook. Due to these criteria, interviewees would be required to make a decision based only upon their assessment of the situation.

Following much discussion with various experts and pilots in the area, it was decided that a technical difficulty arising in the cockpit would be mainly covered by standard operational procedures (SOPs). Therefore a scenario based around a technical failure would not tap into the individual pilots decisional processes. On occasions pilots may divert from the SOPs, depending on the specific problem that they are facing, however developing a problem of this nature would be difficult and the chance of differences arising in the study due to operational differences would be high.

A scenario was developed that required the pilots to make a decision based on their past experience and knowledge rather then one that required a well defined solution contained in the SOPs. The scenario chosen was an 'air rage' scenario. This was selected for several reasons. Firstly, while many airlines promote guidelines and give advice to their pilots about prospective courses of action to take when there is an unruly passenger in the aircabin, there are currently no standard protocols to follow in such circumstances. Secondly, the interviewee would require no instrument readings or air traffic control instructions. The information the interviewee would receive over the telephone from the interviewer would be similar in content and mode of communication as that they would receive from the cabin crew in an actual incident.

The interview scenario was developed with the aid of two senior training captains from a major international airline both of whom has experienced in-flight incidents involving a disruptive passenger and also a senior member of cabin crew. The scenario and interview protocol was subject to several iterations using a further flight crew before commencing the study proper.

4.3.2.1 Advantages of the telephone interview technique

Telephone interviews share many advantages of face-to-face interviews (Robson, 1993). There is a high response rate, interviewers can correct misunderstandings, probes can be used, etc. Although there may be difficulty establishing rapport, this disadvantage is outweighed by less evidence of interviewer effects and a lower tendency towards socially desirable responses (Bradburn and Sudman, 1979). The other advantage of using a telephone interview technique for a sample of pilots is also that they are geographically dispersed and therefore are more assessable over the telephone. There is also the added advantage of having no missing data. It was also felt that an air rage incident would be easier to explain then a technical difficulty when using this form of media.

4.3.2.2 The role a pilot takes in handling a disruptive passenger

When faced with a disruptive passenger incident the Captain of the aircraft has various choices. S/he can elect to attempt to diffuse the situation; s/he can have the passenger physically restrained and/or s/he can make an immediate diversion to the nearest suitable airfield if s/he believes that there is any danger to passengers, crew or the aircraft itself. In the latter case, the costs incurred may be recovered from the passenger/s responsible.

To maintain good order and discipline onboard the aircraft it may be necessary to either restrain or disembark disruptive passengers. The only procedure that is described for pilots in the incidence of an air rage is how to restrain a disruptive passenger. If restraint is to be used the following issues should be considered (British Airways SOPs, 1999):

The Captain before making the decision to restrain a passenger should consider the following:

1. Have all verbal measures of placating the passenger been exhausted?

2. Is the passenger's conduct prejudicial to the safety of other passengers, crew or the aircraft?

3. Does the urgency of the situation demand immediate restraint or is it possible to divert the aircraft to an aerodrome where security or police authorities can take the necessary action, and thus avoid the use of a restraint device?

4. Will the act of attempting to place a restraint device on the passenger further aggravate the person and provoke violent resistance or cause and increase the safety hazard?

Overall, the pilot is entitled to take any measures to protect the aircraft and passengers on board that aircraft. S/he must review the situation and consider if police authorities should be contacted, if the aircraft can and should be diverted, and if the passenger needs to be restrained (and if other passengers should be asked to help).

4.3.2.3 Disruptive Passenger Behaviour

'Air rage', or disruptive passenger behaviour, has been receiving a great deal of media attention of late due to claims that it is an increasing phenomenon. UK airlines have begun to log all new cases of air rage incidents due to this growing concern that passenger anger and violence is increasing. The Civil Aviation Authority (CAA) who is responsible for policing safety in the sky, has called for all UK passenger airlines to supply it with details of all air rage cases. This follows a number of high-profile incidents, such as the instance where a man stabbed an airhostess in the face with a broken vodka bottle (Bor, 1999). For a list of other reported incidents see Appendix J. The CAA hopes to build up a database of incidents, assess the extent of air rage and identify possible solutions. In the past, only details of incidents, which endangered flights, were logged. The CAA now says it wants to build up a "wider picture". Last year British Airways carried 41 million passengers, of which they reported 266 incidents of disruptive behaviour on board their aircraft over a twelve month period ending March 1998 (Jack, 1998). The CAA UK Flight Safety Committee presumes that thousands of other incidents where passengers have ignored directions, become intoxicated and subsequently violent towards other passengers or air stewards, have not been reported. Incidents have been reported of passengers attempting to break into the flight deck, some being successful. One disruptive passenger even managed to grab the pilot away from the control. This is obviously a potentially dangerous situation. The UK Flight Safety committee believes that the true number of incidents on UK airliners is more in the region of 6000 a year (Roy Humphreyson, World in Action). Pilots are becoming so aware of the problem that recently a SABRE airline pilot wouldn't let any passengers on board a flight as delays had resulted in a fight before departure and he couldn't distinguish the troublemakers from the other passengers. For safety reasons he assumed it would be a better course of action to refuse entry to all passengers and delay the flight even further.

The CAA is interested in what is causing the increase in violent incidents involving passengers on aeroplanes. Until recently it was pure speculation as to what triggered disruptive passenger behaviour. On-air violence often builds up before passengers even board the aeroplane. Alcohol, stress, anxiety and on-board smoking bans are among the known causes. Air transport companies are attempting to limit these stress triggers and are attempting to cut down on the number of delayed flights, etc.

The accessibility of flying is increasing, especially as it becomes cheaper. People see the travelling experience as more of a cumbersome procedure rather then the exciting luxury of the past. The general public do not consider safety when they are contemplating which airline to fly (Duggan, 1996). This leads to an incorrect public perception of cabin crew being there to serve and pamper the passengers (Bor, 1999). The checking in procedure can be very stressful and it is estimated that 30% of the population suffer from severe flight anxiety. For some passengers, coping strategies are not adequate enough for dealing with the experience and demands of flying as air travel becomes more stressful (Lucas, 1987; McIntosh, Power and Reed, 1996; Rayman, 1997).

This is a world wide problem and is not only present on UK flights. Only recently (July 1999) a passenger aboard a Japanese Airline entered the cockpit and stabbed the pilot, who subsequently died. American Airlines reported a 200% increase between 1994 and 1995 (Hicks and Morrison, 1997). In 1998 United Airlines reported 450 incidents (Longmuir, 1998). Cabin crew interactions appear to be the biggest cause of air rage, disruptive behaviour can occur as a response to request on behalf of the air steward - for instance asking to put a seat in an upright position (Bor, 1999). Resulting from these incidents, all cabin crew now receive training on how to deal with potentially disruptive passengers including body language and interpersonal skills, telling an agitated person off will only increase their agitation.

In response, the Air Navigation Order (1995) was revised. This can be seen in Appendix K. This has recently been further amended. From September 1st 1999 it has been an offence to intentionally interfere with the duties of cabin crew, punishable by up to two years in prison (British Airways News, 1999). Any disorderly and threatening behaviour will also carry the same maximum penalty or an unlimited fine. Endangering an aircraft will carry a five-year sentence. It is now believed that these measures will ensure that no disruptive passenger will escape punishment and that they will provide a strong deterrent for possible offenders. Other measures are taking place, such as British Airways who have recently introduced a 'yellow card' system. The card warns disruptive passengers that they face arrest on landing if they do not stop their behaviour. They will also be told that if the aircraft needs to divert as a result of their behaviour, they will be charged with the diversion costs. BA have found that the yellow card system has successfully defused 90% of incidents when used, however violent incidents are up by 22% (British Airways News, 1999). It has been suggested that information of this nature should be printed on all the safety cards aboard the aircraft, warning passengers of the penalties they will receive should they become violent. These are now the sort of decisions pilots have to make, which is why an air rage scenario is an appropriate data collection tool for study two.

4.3.3 Sample Distribution

All pilots interviewed were volunteers. Some pilots had been requested to volunteer for this particular study and others had volunteered for a departmental pilot panel and had sent in their telephone numbers, therefore no random dialling was used. All interviewees were in possession of a full UK Airline Transport Pilot's License and were flying heavy passenger-carrying, commercial transport aircraft at the time of the study. In total, sixty-five participants were interviewed.

4.3.4 Telephone Scenario

A brief over view of the telephone scenario can be seen in Figure 21. It was designed with a group of pilots and experts in the area. Although Figure 21 appears to be a flowchart it depicts an hypothesised version of certain options an interviewee could take rather then a set of predetermined decisions. After much consideration Figure 21 was created as a type of prompting tool for interview flow. It depicts many potential sources of information that the interviewee could request. Obviously the interview was not restricted to this flowchart. Figure 21 began as a list of possible sources of information and was reviewed by a number of highly qualified pilots. Following much reconsideration between various pilots and researchers the 'flowchart' type of scenario was created. Not only did it act as a prompt for the interview but also ensured that when interviewees asked certain questions (e.g. is the disruptive passenger travelling alone?) the interviewees would receive an identical answer each time (e.g. he is travelling in a group).

All interviewees were presented with the following information. They were told that they were flight crew on a four-hour flight from airport A to airport B. The aircraft was flying over a country in mainland, Western Europe. Prior to take-off there had been a minor technical problem with the aircraft that had delayed departure. Many passengers were unhappy about this delay and several had been drinking. On this particular flight there was an all-female cabin crew compliment. The 'air rage' incident commenced about halfway through the flight. At the time of the incident there was a diversionary airport available (airport C), approximately 30 minutes flying time away.

Other information that the interviewee could request was as follows, facilities at airport C for passenger handling were rudimentary, however, due to poor weather in the vicinity, it was the only airport with a suitably equipped runway of adequate length available. The disruptive passenger was a moderately large man, travelling as part of a group of passengers. He was deemed to have become abusive toward the cabin crew after having (apparently) consumed a large amount of alcohol. He was not on medication.

The general requirements of the scenario were that it had to have characteristics of a naturalistic decision. A scene was set that revealed some of the story but had restricted information. In a real environment problems are rarely presented in a complete form that classical decision-making research suggests (Orasanu & Connolly, 1993). Interviewees first had to assess the situation. All ten models discussed in chapter one stressed the importance of sizing up and constructing a mental picture of the problem situation. The scenario also had to be a problem that could be matched onto a personal mental model, either relating to personal experience or from others experience. This was necessary to test NNs as a tool for modelling a pattern matching decisional task. Some elements of the scenario had to have incomplete information, for example, if the interviewee was to ask if the passenger was a nervous flyer the response would be 'I don't know'. Other characteristics of NDM that came into play were organisational goals in terms of if the interviewee wished to divert the aeroplane. Problems with stress due to time restriction in flying is quite unusual, there should be adequate time to make a decision (Jensen et al, 1997). Therefore an element of restricted time was also included in the scenario (half hour to alternate airport)- however, this also implied an hour for the final decision to be made as there was also a half hour following the alternate airport. Multiple players were present in terms of the cabin crew and first officer (this scenario involved a two man flight deck). Feedback loops were also present, in that if the interviewee mentioned that s/he would either talk to the disruptive passenger personally or through the purser in order to actively calm the passenger down, then the passenger would calm down, so the situation could be reassessed. All options were still present in this case, for example when the passenger was calmed perhaps one pilot would decide to continue whereas another might decide to restrain this passenger, etc. The scenario was designed so the interviewees had to actively seek information to gain a mental model of the situation and then seek to resolve it.

Four outcomes were proposed. These can also be seen in Figure 21. These outcomes were as follows: (1) calm disruptive passenger down and continue to destination; (2) restrain the disruptive passenger and continue to destination; (3) divert to alternate but without restraining passenger; and finally (4) restrain disruptive passenger and divert to alternate airport. To restrict the scenario, pilots were told that due to bad weather only one airport was available for an alternate. At the time of the incident the aircraft was one and a half-hours from Airport A, 30 minutes from alternate C, and two and a half-hours from destination B.

The telephone interview took between 5 and 15 minutes to complete. All participants were given a brief summary of the scenario (delayed departure, unhappy passengers, an hour and half into flight head purser comes to pilot and says that they have a problem: which is a disruptive passenger) and the scene was set. Following this the interviewee was told s/he could ask any questions they liked. Participants were prompted on occasion, for example 'would you contact your company?' however, depending on their answer (yes/no) they would then be asked 'why?' rather than given options of why (for instance for this example it could be to inform them, to ask them for options, to organise police etc.). This scenario was designed to see how pilots collected information, and which information they actively sought. It was deemed that too much prompting would bias the resulting data. Although the final decision of each of the participants was important and useful, the processes and the way they collected and formulated information was of primary interest.

4.3.5 Procedure

The interviewee was contacted prior to the telephone interview to establish if they were willing to participate in the study. If they indicated that they were willing to do so, they were telephoned on a later occasion at a mutually agreed time.

The interviewer gave a brief overview of the purposes of the study before commencing the interview. All interviews were recorded to facilitate interview flow and avoid selective recording of the data. The agreement of the interviewee to record the interview was also elicited at this time. The interview started with a request for some simple demographic details. The age, sex, current position (Captain/ First Officer), number of years flown, approximate total hours flown, type of aircraft regularly flown and the initial training (Civil/Military) of each participant was recorded. This was carried out to describe the sample.

The interviewee was given the initial scenario information described in section 4.3.4. They were asked what actions they would take to assess the situation and what decisions they would make about actions to control the situation. To obtain the information described in the latter part of the scenario participants had to specifically request it. If they asked a question that required information not contained within the scenario, the interviewer, who was essentially playing the part of the Purser reporting the incident to the flight deck, replied that she did not know. The 'flow diagram' depicted in figure 21 was available at all times to the interviewer to maintain consistency in the responses. At the end of the interview, the interviewee was asked if they had any questions and thanked for their time.

All interview transcripts were then subsequently transcribed. All possible sources of information or hypothesised actions on behalf of the interviewee were coded and entered into the database. In other words if it was mentioned it was included in the analysis. The categories were coded on a present (mentioned)/ absent (not mentioned) bases.

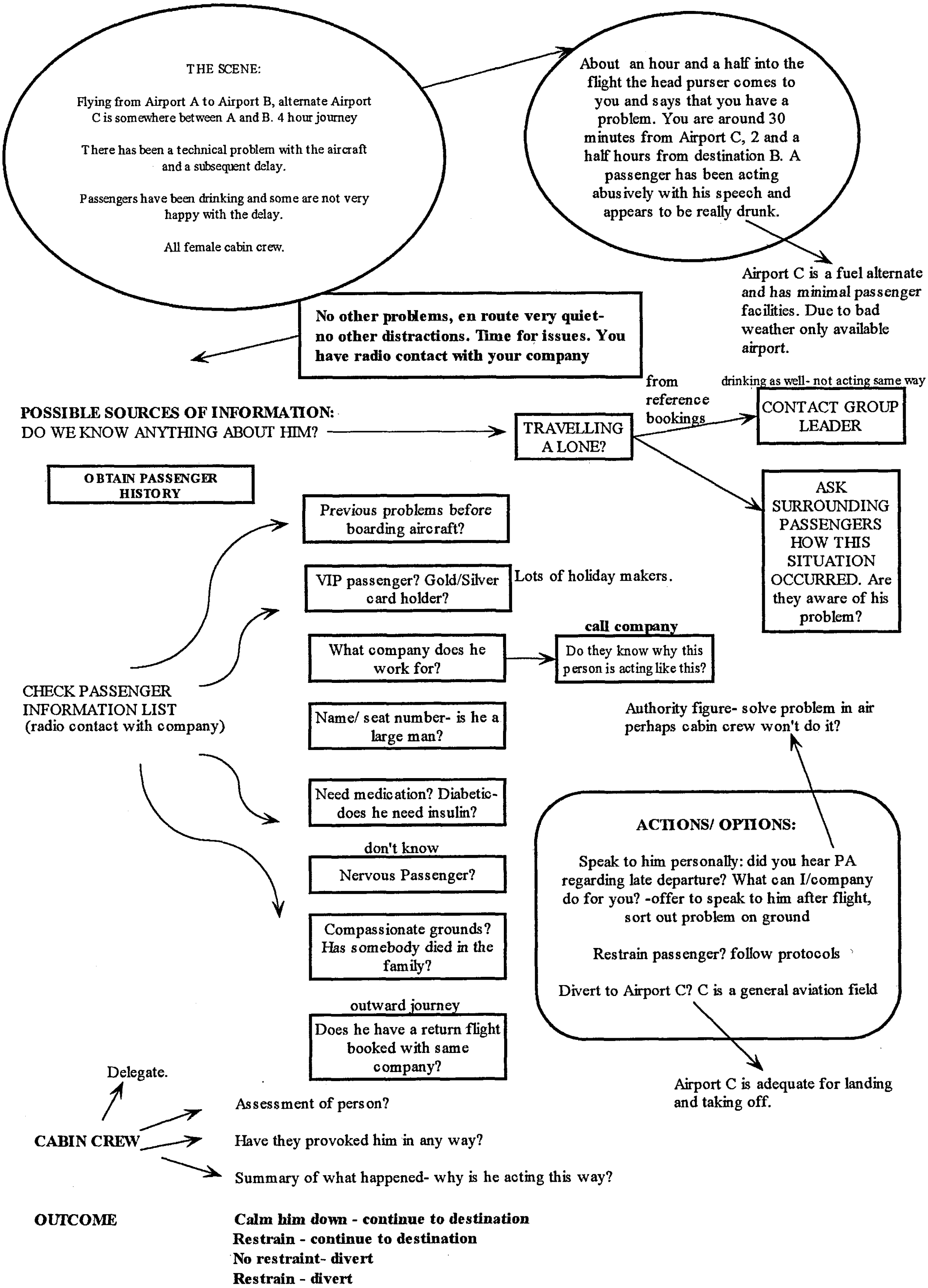

Figure 21 Pilot Scenario for study two.

4.4 Results

4.4.1 Participants and Treatment of Data Set

Overall 65 pilots were interviewed. 61 interviewees were male and four were female. Twenty were First Officers and 45 were Captains. All interviewees were in possession of a full UK Airline Transport Pilots License at the time of the study. Mean flying experience (in years) was 20.3 (with a standard deviation of 11.3 years); mean flight experience (in hours) was 9,027.7 hours (standard deviation of 6,069.1). See appendix L for more demographics details.

The data file was cleaned and spilt into two groups. Group one was the analysis set, which was used to construct the model. Group two was the holdout sample for model validation. The first group contained 44 cases, with the second group containing approximately one third of the total sample size (n=21) as is recommended by Garson (1998) for cross validation in neural networks and DFA. There was no missing data, and all four outcomes were represented in the data set. The frequencies of each outcome for the analysis set are shown in table 15. Table 16 shows the overall frequency of possible outcomes in the holdout sample.

Overall there were 26 variables in the data set. These variables can be seen on table 17. Demographic details were only used to describe the sample set.

Table 15 Overall frequency of possible outcomes in remaining data set ($n = 44$).

POSSIBLE OUTCOMES	FREQUENCY	PERCENT
Calm passenger down and continue to destination	24	54.5
Restrain passenger and continue to destination	7	15.9
Restrain passenger and divert to Airport C	3	6.8
Divert to Airport C, no restraint	10	22.7
TOTAL	44	100

Table 16 Overall frequency of possible outcomes in holdout sample ($n = 21$).

POSSIBLE OUTCOMES	FREQUENCY	PERCENT
Calm passenger down and continue to destination	9	43
Restrain passenger and continue to destination	5	24
Restrain passenger and divert to Airport C	2	9
Divert to Airport C, no restraint	5	24
TOTAL	21	100

4.4.2 Discriminant Function Analysis (DFA)

A discriminant function analysis was carried out on the data set, as in study one. A four group DFA was carried out on the analysis set and the holdout sample was utilised for cross-validation. The DFA was used to examine if the interview variables could discriminate between the four outcomes.

The variables were coded in a yes/no format (mentioned/not mentioned) so were coded 1/0. The results of the DFA can be seen on the following pages. Table 17 depicts the mean ratings for each interview variable broken down by outcome. Table 18 shows the Wilks' lambda, univariate F-ratios and the standardised canonical discriminant function coefficients for each interview variable.

Table 17 Mean Ratings for each item broken down by outcome (one to four).

Variable item	Calm, continue	Restrain, continue	Restrain, divert	Divert, no restraint
Is he travelling alone?	0.42	0.57	0.00	0.00
Send a pilot down.	0.38	0.00	0.67	0.30
Do not send a pilot down	0.63	0.86	0.00	0.60
Get friends to help	0.38	0.57	0.00	0.00
Obtain help from other passengers	0.71	0.71	0.33	0.40
PIL: helpful off duty passengers?	0.29	0.29	0.00	0.30
Move seats: person or other passengers	0.13	0.00	0.00	0.00
Prepare for next stage in case he continues to get out of hand	0.33	0.14	0.00	0.40
Story and assessment from cabin crew	0.79	0.43	0.67	0.90
Deny person any more alcohol	0.38	0.00	0.00	0.00
Summary of what happened from person	0.0417	0.00	0.00	0.10
Contact company to inform them	0.54	0.57	0.67	0.40
What facilities are available at C? Ask if it is practical and for other options	0.29	0.29	0.33	0.30
Contact company/ATC to organise police	0.46	0.14	0.67	0.20
Previous problem before boarding?	0.21	0.00	0.00	0.00
Speak to person or group leader in flight deck	0.0417	0.00	0.00	0.10
Have a look from a distance	0.0417	0.14	0.00	0.10
Is he a large man?	0.0833	0.00	0.00	0.20
Is he on medication?	0.21	0.00	0.00	0.10
Collect information: address etc.	0.0417	0.29	0.00	0.10
Seat belt sign	0.0417	0.00	0.00	0.10
Cabin crew are trained, get them to recruit ABP and monitor etc (delegate)	0.58	0.43	0.00	0.30
Does he have a return flight?	0.13	0.00	0.00	0.00
Which country are we dealing with?	0.13	0.00	0.00	0.10
Make PA to back up purser and inform passengers	0.21	0.14	0.00	0.20
Have a talk and issue warning to person	0.96	0.43	0.33	0.30

Table 18 Wilks' Lambda, Univariate F-ratios with (3,40) degrees of freedom and Standardised Canonical Discriminant Function Coefficients for each variable.

VARIABLES	Wilks' Lambda	F-ratio	Sig.	DFA fn 1	DFA fn 2	DFA fn 3
Is he travelling alone?	0.791	3.529	0.023	-1.255	1.577	-2.013
Send a pilot down	0.879	1.833	0.157	-0.247	1.442	0.688
Do not send a pilot down	0.851	2.326	0.089	-0.296	0.731	1.435
Get friends to help	0.801	3.306	0.030	1.688	-2.445	1.715
Obtain help from other passengers	0.906	1.380	0.263	0.580	-0.596	-0.129
PIL: helpful off duty passengers	0.972	0.378	0.770	-0.504	0.311	0.154
Move person or other passengers	0.939	0.866	0.467	-0.150	-0.083	0.435
Prepare for next stage in case he continues to get out of hand	0.938	0.883	0.458	-0.117	-0.209	0.466
Story and assessment from cabin crew	0.877	1.862	0.152	0.107	0.709	0.047
Deny person any more alcohol	0.786	3.636	0.021	0.626	-0.127	0.063
Summary of what happened from person	0.973	0.364	0.779	-0.602	0.386	-0.102
Contact company to inform them	0.978	0.295	0.828	0.193	-0.795	-0.485
What facilities are available at C? Is it practical, look for other options	0.999	0.008	0.999	-0.243	0.333	-0.135
Contact company/ATC to organise police	0.892	1.614	0.201	0.353	0.343	-0.819
Previous problem before boarding?	0.893	1.595	0.206	0.210	0.794	0.224
Speak to person or group leader in flight deck	0.973	0.364	0.779	0.003	0.185	-0.248
Have a look from a distance	0.971	0.393	0.759	0.614	-0.626	0.127
Is he a large man?	0.944	0.788	0.507	-0.775	-0.179	0.157
Is he on medication?	0.938	0.888	0.456	0.876	-0.423	0.349
Collect information: address etc.	0.904	1.418	0.252	-0.255	-0.199	0.223
Seat belt sign	0.973	0.364	0.779	0.472	-0.541	0.782
Cabin crew are trained, get them to recruit ABP and monitor (delegate)	0.884	1.743	0.174	0.597	-0.434	0.95
Does he have a return flight?	0.939	0.866	0.467	-0.462	0.476	-1.084
Which country are we dealing with?	0.969	0.421	0.739	-0.682	0.438	0.182
Make PA to back up purser and inform passengers	0.980	0.270	0.847	-0.524	0.259	0.650
Have a talk and issue warning to passenger.	0.570	10.065	0.000	0.947	0.129	0.361

The following tables 19-21 contain the overall summary of the discriminant function analysis. The first function accounts for 50% of the overall variance accounted for. Function two accounts for 34% of the overall variance accounted for. However, no functions were found to be significant. Table 21 depicts the group centriods, which shows Function one was maximally discriminating between outcome one and four, calm the passenger down and continue or divert the aircraft and not restraining the disruptive passenger.

Table 19 Canonical Discriminant Function Analysis Summary Statistics for analysis set.

Function	Eigenvalue	Percentage of Variance	Canonical Correlation	Correlation Squared
1	2.716	50.4	0.855	0.731
2	1.808	33.6	0.802	0.643
3	0.862	16.0	0.680	0.462

Table 20 Canonical Discriminant Function Analysis Summary Statistics for analysis set.

Test of Function(s)	Wilks' Lambda	Chi-square	Df	Sig.
1 through 3	0.051	83.067	78	0.326
2 through 3	0.191	46.311	50	0.622
3	0.537	17.402	24	0.831

Table 21 Group Centriods for Canonical Discriminant Function

OUTCOMES	Function 1	Function 2	Function 3
Calm down, continue	1.314	0.418	0.148
Restrain, continue	-0.453	-2.922	-0.083
Restrain, divert	-1.181	0.874	-3.146
Divert, no restraint	-2.482	0.780	0.648

The following table 22 depicts the classification for both the analysis sample and the holdout sample.

Table 22 Classification Matrices for Four-Group Discriminant Function Analysis for Analysis and Holdout Samples.

A: CLASSIFICATION RESULTS: ANALYSIS SAMPLE

Actual Outcome	**Predicted Group Membership**			
	Calm, continue	**Restrain, continue**	**Restrain, divert**	**Divert, No restraint**
Calm, continue (total = 24)	24 (100%)	0 (0%)	0 (0%)	0 (0%)
Restrain, continue (total = 7)	0 (0%)	7 (100%)	0 (0%)	0 (0%)
Restrain, divert (total = 3)	0 (0%)	0 (0%)	3 (100%)	0 (0%)
Divert, No restraint (total = 10)	1 (10%)	0 (0%)	0 (0%)	9 (90%)

B: CLASSIFICATION RESULTS: HOLDOUT SAMPLE

Actual Outcome	**Predicted Group Membership**			
	Calm, continue	**Restrain, continue**	**Restrain, divert**	**Divert, No restraint**
Calm, continue (total = 9)	4 (44.4%)	2 (22.2%)	2 (22.2%)	1 (11.1%)
Restrain, continue (total = 5)	4 (80%)	0 (0%)	0 (0%)	1 (20%)
Restrain, divert (total = 2)	0 (0%)	1 (50%)	0 (0%)	1 (50%)
Divert, No restraint (total = 5)	3 (60%)	0 (0%)	1 (20%)	1 (20%)

Analysis sample: percent of 'grouped' cases correctly classified: 97.93%
Holdout sample: percent of 'grouped' cases correctly classified: 23.81%

The analysis sample correctly classified 97.93% of the overall cases. However, more importantly, the holdout sample correctly classified only 23.81% of the cases on the basis of the four outcomes: calm passenger down, continue to destination; restrain passenger and continue to destination; restrain passenger and divert; and finally divert to alternate airport, do not restrain passenger. The DFA showed a high degree of success in predicting the first outcome (calm, continue), which can be seen in the previous table (80% success). However, the classification matrix showed little ability in distinguishing the other three outcomes from the data set, which can also be seen in table 22. In fact the holdout sample classification matrix failed to correctly classify any cases in outcome two (restrain, continue) and outcome three (restrain, divert). It also only classified 20% of the cases for outcome four (divert, no restraint). Therefore, although the classification matrix for the analysis set was highly successful, the DFA appeared to be sample specific. This could be due to overfitting which will be discussed later.

4.4.3 Neural Network Analysis

Neuroshell 1 was also used for the analysis of the data (see section 3.7 for a full discussion of this tool). Neuroshell 1 is based on the multilayer perceptron and utilises the backpropagation method for controlling the learning rate and assessing the convergence of the NN model. See chapter two for a full discussion on backpropagation. The binary version of Neuroshell 1 was used for the analysis of the air rage scenario. The binary version of Neuroshell 1 is specifically designed for the analysis of binary, categorical data. This version was chosen because the data were collected in terms of items either mentioned or not mentioned during the interview. Therefore the data were in a yes/no format, or in other words on/off characteristics for the purposes of constructing a NN.

The same data were used for the neural network analysis as the DFA. Group one (n=44) was the learning set and group two (n=21) was the cross validation set. All cases converged with the total and minimum error of 0.0356. Table 23 depicts the network factors used in the analysis. For a full description of how each node works within a network see chapter two, figure 15.

As in study one, various approaches were used in this analysis to find the appropriate numbers of hidden layers. The learning parameters were changed regularly to speed up convergence and to help avoid overtraining effects. As discussed previously this process of altering factors to complete training is the normal approach taken when performing a neural network analysis. Network factors are determined by letting the network converge on a number of occasions to obtain the best possible results.

Table 23 Network Factors for final Neural Network

Network Factors	**Value**
Output Threshold (0-1.0)	0.5000
Learning Threshold (0-3)	0.0001
Hidden Nodes	5
Learning Rate	0.1000
Momentum	0.0000
Presentation (0=rotate, 1=random)	1

A small sample of the neural network model for pilots' responses to a disruptive passenger scenario can be seen in figure 21. This is shown to help the reader visualise how the inputs are connected to each hidden node, which are in turn connected to each outcome. The complexity of the network means it is very difficult to display the whole network diagrammatically, therefore for more information regarding weights and biases please see appendixes M-P. Outcome bias and weights for each node connection to each hidden node can be seen in appendix M. See Appendix N for the weights for each connection from each interview variable to each hidden node. See Appendix O for Neural Network Weights and Hidden Node Biases. Actual and predicted outputs of cross validation set can be seen in appendix P.

The figures in these appendixes correspond to the weigths on the paths from the input nodes to the hidden nodes. As the input nodes were of a binary format, coded '1' for mentioned the variable and '0' for not doing so, the weight also represents the path's contribution to making a hidden node fire (or not). A large positive weight will encourage a hidden node to fire: a large negative weight will inhibit the node. The biases, calculated by Neuroshell 1, represents the threshold above which hidden node will fire. The hidden nodes also produce a binary output. The output from each hidden node is also binary, implying that the weights are essentially the contribution to making an output node fire.

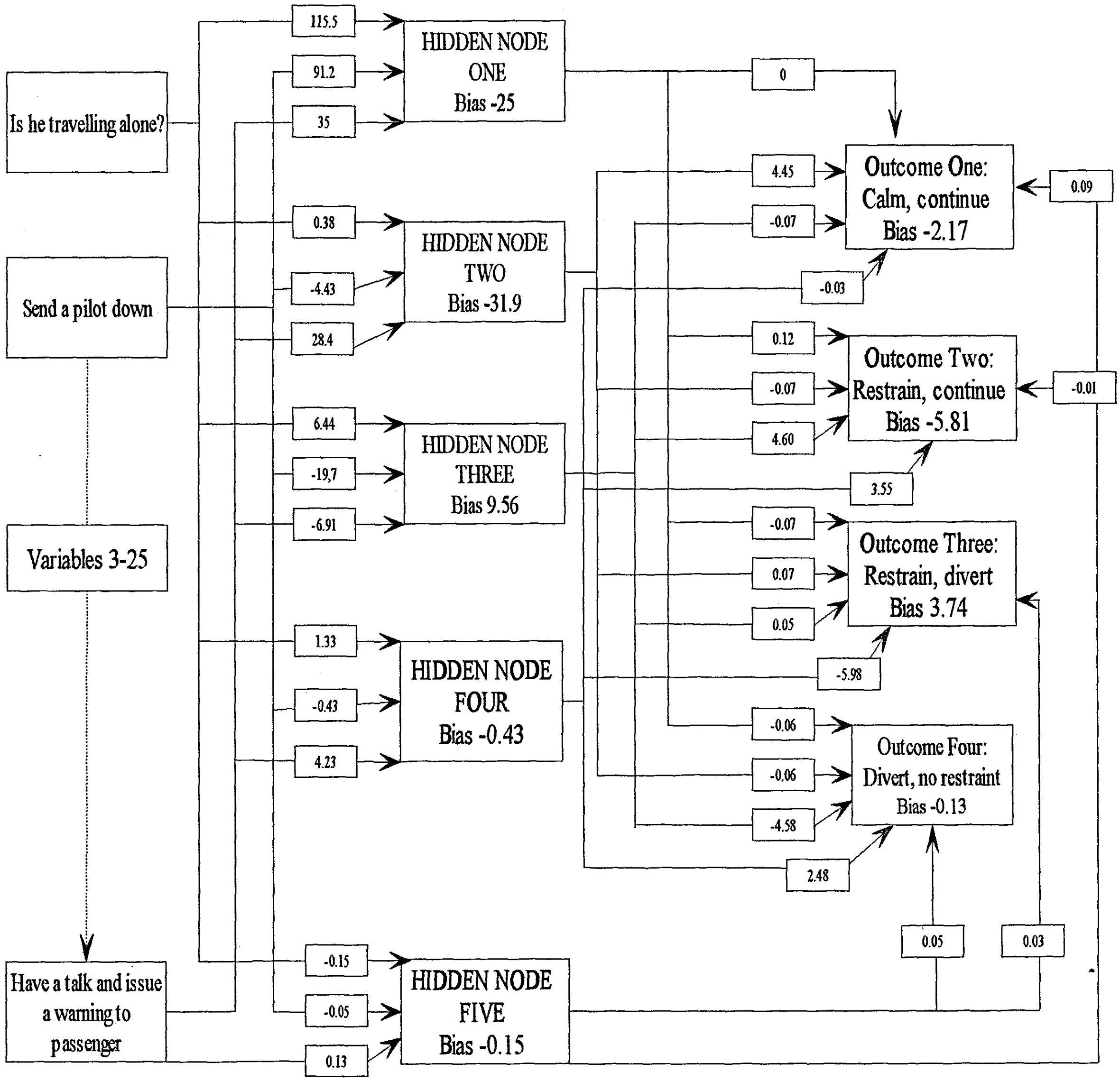

Figure 22 Small sample of neural network for study two: air rage scenario.

To analyse the veracity of the predictions made by the NN model a classification matrix was produced. The predictions made for each output node (or decision) in the cross-validation data set were categorised as 'hits' (correct predictions of participant's decision) or 'misses' (the NN predicted that the participant would chose a certain decision but in fact the NN predicted incorrectly). The results of this classification can be seen in table 24.

Table 24 Classification matrix for neural network prediction of pilot decision-making for air rage scenario (n=21).

Actual Outcome	**Predicted Group Membership**			
	Calm, continue	**Restrain, continue**	**Restrain, divert**	**Divert, No restraint**
Calm, continue (total = 9)	5 (55.55%)	0 (0%)	0 (0%)	4 (44.44%)
Restrain, continue (total = 5)	0 (0%)	4 (80%)	0 (0%)	1 (20%)
Restrain, divert (total = 2)	0 (0%)	1 (50%)	0 (0%)	1 (50%)
Divert, No restraint (total = 5)	3 (60%)	0 (0%)	0 (0%)	2 (40%)

Percent of 'grouped' cases correctly classified: 52.38%

Overall, 52.38% of cases were correctly classified on the basis of four outcomes: Calm, continue; Restrain, continue; Restrain, divert; Divert, no restraint. The Neural Network analysis was better in predicting the four outcomes than the DFA, which can be seen in the previous table (NN=52.83% in comparison with DFA=23.81%).

4.4.4 Press's Q analysis

To determine if the classification results were due to chance a Press's Q analysis was carried out (see section 3.8 for full discussion, see also equation 2). See table 25 for Press's Q analysis results for both DFA and NN analysis.

Table 25 PRESS's Q analysis for both holdout samples for Discriminant Function Analysis and Neural Network Analysis.

	PRESS's Q	Accuracy Better than Chance?
DFA	0.055	X
NN	29.39	✓

Chi square at one degree freedom, at the .001 confidence level =10.83, at the .01 confidence level=6.63

It can be seen from table 25 that the DFA classification matrix did not exceed at the statistically significant level that the classification accuracy was no better then that expected by chance. However, the NN classification matrix predictions are significantly better than chance and exceeded this at the 99.9% confidence level. It is logical to conclude therefore that the NN classification has performed better then the DFA.

4.5 Study two discussion

Twenty-six variables were produced as a result of the interviews. These variables can be seen in table 17. The variables were very similar to the proposed model (see figure 21) which was used to direct the interview. However, some variables were present in the final analysis, which were not considered at the design stage. For example putting the seat belt light on, and denying the disruptive passenger more alcohol.

The discriminant function analysis (DFA) that was carried out on the interview variables was not very successful in discriminating between the four outcomes. The four outcomes were: (1) calm disruptive passenger down and continue to destination; (2) restrain the disruptive passenger and continue to destination; (3) divert to alternate but without restraining passenger; and finally (4) restrain disruptive passenger and divert to alternate airport. The analysis sample correctly classified 97.93% of the overall cases. However the holdout sample correctly classified only 23.81% of the cases on the basis of the four outcomes. It was successful in predicting group membership for the first outcome: calm passenger down and continue to destination, but not for the other three outcomes. This could have been due to overfitting. However, the sample size did not affect the NN analysis, highlighting that NNs can cope with noisy data very well.

It has been discussed that the experience of an individual is an important factor when making naturalistic decisions (Orasanu and Connolly, 1993; Flin, Salas, Strub & Martin, 1997; etc.). Study Two examined an air rage scenario, which involved participation from pilots with a large range of experience, some pilots had 2 years flying experience whereas others had 52 years. However, all pilots had a commercial pilot license and therefore had to have a certain amount of experience to partake in this study. Further work on the differences between methods employed to seek a solution to this problem between pilots with a couple of years experience and pilots with a lot of years experience would be interesting. This comparison of methods employed would test DeGroot's (1978) prediction that experts can examine dozens of pieces of information and determine chunks of familiar patterns. Others have found this to be true (Means, Salas, Crandall & Jacobs, 1993). Individuals with more experience have a tendency to attend to the critical information while ignoring the less critical. However, the main aim of study two was to determine if NNs were a better means to analysis a pattern matching decisional task. Therefore the differences between various years of experience was not examined.

The air rage scenario was designed as a pattern matching exercise. Therefore situation assessment and awareness were important factors in this scenario. Researchers studying decision-making have shown that operators will classify and understand a situation before proceeding to the action selection (Klein, Calderwood, & Clinton-Cirocco, 1986; Klein, 1989; Lipshitz, 1989). Rasmussen (1983), Noble (1989) and Hammond (1988) also found that the assessment of the situation directly influenced the subsequent selection of an action. Previous research has also shown that an integrated picture of the current situation can be matched onto past experience and situations in memory, which would then be mapped onto a correct action or decision. The majority of participants in this study reported that either something similar had happened to them or to a colleague in the recent past. This highlighted the importance of awareness of problems of this nature, but also that pilots do rely on personal or others experience to formulate decisions. This finding would support Rasmussen's (1983) inducement principle of an automatic response for actions to familiar situations. Hammond's (1988) intuitive response is similar, when tasks require a decision that was under time pressure but required information the responding decision tended to be intuitive. Lipshitz (1993) also found that individuals making decisions appeared to do action 'A' because it responded to a similar situation they had encountered in the past. For this task of pattern matching the pilot needed to match the current situation to a previous one and implement the actions that worked in the past. Noble (1993) suggests that concrete information in situations similar to the air rage scenario, is combined with background knowledge that is retrieved from memory. This context knowledge then forms a representation of the situation. These findings relate to Jensen's (1995) theory of pilot judgement.

The Press's Q Analysis showed that the DFA did not classify to a result better than chance. None of the functions were significant.

The Neural Network (NN) analysis performed better then the DFA. By looking at the matrix for the NN and DFA for predicting which outcome a pilot would decide upon it can be seen that the NN matrix correctly classified 52.38% of the cases whereas the DFA matrix only correctly classified 23.82%. The NN showed a higher degree of success in predicting outcomes two, restrain and continue (80% compared to DFA=0%) and outcome four, divert, no restraint (40% compared to DFA=20%). Both analyses failed to successfully classify outcome three, however as can be seen in table 16 this outcome had a small frequency (only 9% of total holdout group). The Press's Q analysis showed that the NN classification matrix exceeded at a significant level to be showing results that were not just due to chance at the 99.9% confidence level.

It has been established in chapter two that neural networks are particularly good at problems where patterns are matched. This air rage scenario is a pattern matching exercise (recognise situation, implement actions that matched a previous situation). Therefore it is suggested that the NN analysis performed better then the DFA due to this fact. Pattern matching as a decisional task modelled by NNs is discussed in the final discussion and is compared with the consequential choice task researched in study one. The NN also performed better then the DFA because the NN analysis could cope with more complex interactions and non-linear combinations of variables that the DFA can not cope with.

4.6 Study Two Conclusions

- Although three functions were disclosed through the DFA, none were significant.

- The NN analysis performed better than the DFA at modelling a pattern matching decisional task. The NN correctly classified 52.38% of the cases, whereas the DFA only predicted 23.82% of the cases.

- The NN results were shown to be significantly better then chance at the 99.9% confidence level.

5 Discussion of thesis objective and findings

No previous study has examined the use of Neural Networks (NNs) for modelling a naturalistic decision-making process. A brief description of each study will be outlined below, however the focus of this chapter will be on the combination of results from both studies and will assess the utility of artificial NNs for the modelling of NDM. Some suggestions for further research will be made throughout the chapter.

To re-iterate, classical decision-making (CDM) research was presented as a normative and prescriptive means to studying decision-making (Savage, 1954; Lehto, 1997) and was discussed in chapter one. According to CDM research, an individual will view a fixed set of options that are known and from these weighs the consequences of choosing each alternative to make his/her decision choice. The individual evaluates the options in terms of a set of goals that s/he knows quite clearly, which are stable over time. It has been stated that the CDM approach to decision-making is difficult to relate to real life decisional tasks (Klein, 1989; Orasanu and Connolly, 1993; etc.). Klein (1989) has shown that people do not make decisions in the normative format. During the early 90s decisional researchers began looking at a new way to study decision-making. Naturalistic decision-making (NDM) research focused on decisions in a real life environment and attempted to describe the processes used by individuals rather then prescribe them (Brehmer, 1990; Klein and Woods, 1993; Bowers, Salas and Pruitt, 1996). One of the most obvious differences between CDM and NDM is that according to NDM individuals chose options and actions if they were satisfactory and not optimal. Although NDM research has made a lot of developments in the realm of decision-making research, such as their approach to describe and not prescribe decisions, there is still a need for more empirical work within this important field (Flin, Salas, Strub, and Martin, 1997). The method for quantification of parameters and their analysis in CDM allows for such things, however, NDM models do not. This thesis suggested viewing the NDM framework in a different way of modelling the process involved rather than hypothesising decisional outcomes. NNs were presented as a means in which to do this.

NNs were presented as a technique for modelling the NDM process as NNs can cope with complexities that 'conventional' statistical analytical techniques, either univariate or multivariate can not. 'Conventional' statistics cannot cope with complex branching of logical conditions and cannot provide a tool to model the complex relationships between inputs and outputs, which could be taken as reflecting the decision-making process. 'Conventional' statistics can only cope with additive and/or multiplicative relationships between predictor and criterion variables (or in terms of decision-making inputs and outputs). It is also difficult to predict more than a single criterion variable. Logical branching is also not allowed within a 'conventional' analysis. The primary objective of this thesis was to establish if naturalistic decision-making could be modelled using neural networks. In so doing an empirical model of NDM should be accomplished. Discriminant Function Analysis (DFA) has been shown to be an alternative to NNs (Garson, 1998), therefore a comparison between NNs and DFA was also conducted to determine if NNs or a more 'traditional' statistical approach is appropriate for modelling NDM. Two NDM tasks were examined, a consequential choice decisional task and a pattern matching decisional task.

Study One characterised MSc choice of university as a naturalistic decision and this decision was utilised to establish if a naturalistic consequential choice decision could be further analysed with the help of neural networks. Students who applied to Cranfield University for the terms of 1998/1999 were chosen for this study. A questionnaire was developed to determine the factors and influences involved in a student's decision to attend or not to attend a certain university. A Discriminant Function Analysis (DFA) and Neural Network (NN) Analysis was carried out and results were compared to ascertain which analysis would be a more successful technique for analysing this naturalistic decision.

Study Two characterised pilot judgement as a naturalistic, pattern matching decision and examined the processes involved in pilot judgement and aimed at developing a model of the considerations underlying pilot decision-making utilising Neural Networks. The sample consisted of a group of volunteer commercial pilots. An air rage scenario was used to collect data, which was carried out over the telephone. A DFA and NN analysis was again carried out and results were compared to ascertain which analysis was most successful for modelling NDM.

A certain degree of artificiality was introduced into both studies through the subsequent analysis and coding of the data collected in the questionnaire for study one and the interview for study two. The coding was necessary for the preparation of data for analysis using the NN shell, however, as far as possible; it has been attempted to maintain this analysis within the NDM tradition.

Master level choice of university was described as a 'consequential choice' decision (Lipshitz, 1993) see 3.2.1 for a full discussion. The air rage scenario was described as a 'pattern matching' decision (Hammond, 1988) see section 4.2.3. Both studies showed that neural networks were better than a discriminant function analysis at classifying on the basis of decisional outcomes. Study One: MSc choice of university showed both analyses to classify at a high rate (DFA=60%, NN=68%). A Press's Q analysis revealed both to be classifying cases significantly better than chance. Although the NN analysis only performed slightly better then the DFA, the NN classified all three outcomes better then the DFA (outcome one, attend Cranfield University resulted in the same classification; outcome two, attend another university NN=30%; DFA=0%; outcome three, obtain employment NN=37.5%; DFA=12.5%).

Study two showed the DFA was not very successful in classifying on the basis of the four outcomes for the pilot scenario (see 4.3.2 for description of outcomes), in fact the DFA only classified 23.81% of the cases correctly. None of the DFA functions were significant and Press's Q analysis revealed the DFA classification matrix to be producing a result that was not significantly better than chance. In comparison, the NN analysis predicted 52.38% of the cases correctly. Press's Q analysis also showed the NN classification to be significantly better then chance. This problem of a disruptive passenger was seen as a pattern matching problem and could explain such a good result as NNs are known to cope with pattern matching and mapping problems very well (Garson, 1998).

A NDM decision is dynamic and can evolve over time, also each individual will make decisions according to his or her values and training; therefore it follows that data from a NDM study could be noisy. The strong results from both NN analyses showed that they are good at coping with noisy data (which could also explain the poor result from the DFA analysis carried out in study two). This supports previous findings that NNs are robust and are better at coping with imperfect data and other data quality problems when compared to traditional linear analyses (Iyengar and Kashyap, 1991; Bullinaria, 1995; Benigo, 1996; Garson, 1998, SPSS, 1999).

Although both studies showed the NN analyses to classify better then both discriminant function analyses, there is still the limitation of NNs inability to interpret why the model was predicting better results. With DFA the researcher can easily see which functions are discriminating between certain variables, which can not be done with NNs. The main limitation of NNs is the inability to interpret why the model is predicting these outcomes. It is possible to go through the entire matrix, as is discussed in chapter two, to see why the NN is achieving certain results and models. However, it is not yet possible to say which variable is the most powerful in predicting the outcome, as every variable is included in the computation of the NN model. Each variable's influence depends on the other variables for a given case. Therefore, NNs should only be interpreted as a whole for its efficacy in predicting outcomes rather than interpreting the contribution of individual variables. It is meaningless to interpret any single part of an entire NN model as variables can only be evaluated in the context of the other variables and their stated relationships. The value in a NN lies in the model as a whole, not its individual components or specific relationships within it. In this case it would be wrong to suggest that one input variable is more important than another in determining the final course of action chosen. It is essential that only the overall results should be interpreted and not the individual paths between nodes. The NN is as good as the combined effect of its components.

Some insight may be gained about the manner in which a given input variable affects a subsequent decision by studying the weights to and from the relevant hidden nodes. However, it again needs to be emphasised that variables can only be evaluated in the context of the other variables and their stated relationships. The following description merely describes the manner in which a variable operates with a NN.

Take study two as an illustration; see figure 22 for a small sample of the NN representing the decision process for the air rage scenario. Consider the weights to the hidden nodes from the input variable 'is he travelling alone?' if this information was requested from the participant then the input node took a value of unity. This value is then multiplied by the various weights to each of the hidden nodes. Its effect begins to spread throughout the NN. The sums of all the weights from each input variable are computed at each hidden node. If the sum of the input functions to the hidden node exceeds a critical value, the node 'fires' and an output from the hidden node is made. For simplicity, only the larger weights in this illustration will be considered. From the node associated with the pilot asking if the passenger is travelling alone, it can be seen that this input variable will help to activate hidden node one. This node will also suppress (inhibit from firing) hidden node 5 (see appendix N for the weights for each connection from the interview variable to each hidden node for study two). From Appendix M (outcome biases and weights for each node connection to outcome) the influence of hidden node 1 (for example) can be established on the outcome (decision) variables. Taking just the larger weights associated with this node to illustrate further this principle, this element will 'fire' the output variable that suggests the pilot will restrain the disruptive passenger and continue. It will also inhibit the firing of the output node suggesting that the pilot will call for the passenger to be restrained and then divert to the alternative airport.

While the above example gives some insight to into how the inputs, hidden nodes and outputs in the NN operates it is essential that only the overall results should be interpreted, and not individual paths between nodes. The greatest problem faced by the researcher lies in the interpretation and evaluation of NN models. The efficacy of a model can only be evaluated in its ability to predict accurate outcomes. In the case of both studies the evaluation of the accuracy with which each output (decision) variable was predicted was evaluated in terms of the holdout sample correctly classified the decision taken or did not correctly classify the decision taken.

The adequacies of the input variables to the NN are also hard to assess. A poor input variable that may have little or no contribution toward the prediction of the NN outputs and can adversely affect the whole of the network. However, in the instance of including a poor input node into a NN model, it is likely that either the model will fail to converge or the predictions made by the model will be inaccurate upon cross validation. Unfortunately there is no other way to identify poor input variables other then by trial and error. The high classification rate in the cross-validation data set for study one would suggest that the input variables as a whole were good predictors of the decisions a student would make when choosing a university in which to study at masters level. The slightly lower classification rate for study two, however was still showing results that were significantly better than chance and would also indicate that the input variables as a set were predictors of the decisions a pilot will make when dealing with a disruptive passenger.

This thesis aimed at providing an empirical means of modelling naturalistic decision-making problems. To attempt this a comparison of a traditional linear method of analysis with a non-linear method of analysis was carried out. The fact that NNs performed better than the DFA for two NDM problems might be explained by the following.

As discussed in chapter one and throughout this thesis, people do not make decisions in the logical format that the 'event model' suggested (Ellsberg, 1961; Klein, 1989; Cohen, 1993; Orasanu and Connolly, 1993; Jensen, 1995). Therefore to analyse individual's decisions in a linear format appears unrealistic. Nevertheless, the results of

CDM experiments could be quantified and subject to statistical analysis. For decisional aids and operator control design classical decision-making has its place (Pruitt, Cannon-Bowers, and Salas, 1997). In fact Klein suggests that his model of decision-making is not a universal model but is how decisions are made under stressful and time constrained conditions. CDM has also helped in our overall understanding of human decision-making (even if just to help us realise that humans don't always make decisions in this way). In this light NNs as a non-linear method of analysis seem to be a way forward towards a better understanding of human decision-making.

NDM cannot be a solution for all real world decisions. A single-minded focus on the economic view of decision-making needs to be abandoned, research from various fields such as cognitive psychology, organisational behaviour and systems theory needs to be drawn upon to accomplish a practical decision-making model (Lehto, 1997). A combination of CDM and NDM theories may accomplish this.

The main issues in a NN such as the two produced in this thesis are basically concerned with the content and criterion validity of the models produced. The criterion (predictive) validity is relatively easy to establish through the use of the classification approach described previously. The greatest challenge lies in assessing the content validity of the NN models. The question of content validity applies to both the input variables and the decisional outputs of the NN models. Kerlinger (1973) suggests the researcher should ask themselves the question 'is the substance or content of this measure representative of the universe of content of the property being measured?' (p.458). In the case of the NN modeller it is essential to establish if the input and output nodes are an exhaustive set of all the pieces of information that the decision-maker would interrogate and a reasonably representative set of the universe of possible or likely subsequent actions. It should be noted that at any one point in time a human being actually has an almost infinite number of possible behaviours open to them. As a result of this, it is not possible to define the entire universe of behaviours on the output side of the model. Content validity can never be totally established. It can only be reasonably assured by employing appropriate data gathering and analytical methodologies. In the case of both studies it has been attempted to ensure content validity by employing a reasonable sample of master's level students (study one) and qualified pilots with a range of experience (study two) and by employing a data gathering technique commensurate with the NDM paradigm.

Previous research has shown that good aeronautical decision-making can not be achieved by following a checklist procedure (see David, 1993 for a full discussion). David found that the concepts of NDM research were more useful for a basis of training aeronautical decision-making then the normative approaches of CDM. He suggests that the way forward for aviation training is decision-making modules in the classroom, simulator and also in the flight deck. He simplified Orasanu's (1993) model of NDM as a basis for discussing a broad range of circumstances influencing good/poor aeronautical decision-making. The training implications resulting from this thesis would be if NNs can provide a means in which to model NDM scenarios, then a framework could be provided for training purposes. Also, models of less frequent scenarios could be used as a decisional aid for pilots on the flight deck. By increasing the understanding of human errors it follows that decisional support systems can be developed which will help in the reduction of the occurrence of human errors. This would support Noble's (1989) desire that decisional aids would help an inexperienced or stressed decision-maker interpret the situation in a more definite manner, thus providing them with the skill to find a more effective course of action. This could be achieved by combining information of different types and from a variety of sources. This requires further investigation.

This thesis recognised the need for quantitative work within NDM as all other models of NDM are qualitative 'best guesses' of how a decision is made (Orasanu, 1993). The main problem with NDM is the way the models have been developed in a qualitative nature. There is not a lot of empirical evidence to support the models that have been developed, or even to help in the choice between different theories. However, to attempt a quantitative analysis one still needs a framework. Hammond (1988) proposed model of NDM has all the characteristics of a NN. Firstly Hammond suggests that the processes of a decision can change according to the individual dynamic decisional task and environment. This is a common theme throughout many of the NDM theories (Beach, 1993). Hammond's theory is also based on the social judgement theory were there is a direct relationship between the objective environment, the information that is available in that environment and the judgement to which they lead. By looking at figure nine it can be shown that steps D-F is similar to how a Neural Network (NN) performs and corresponds to the components found in most NNs (D: individual perception of the data → E: subjective cues and precursors → F: final prediction). Steps C-D are depicting the stage of gathering information and are therefore similar to situation awareness (C: objective data found in environment → D: individual perception of that data). Situation awareness has been shown to be important when making decisions in a real environment (Rasmussen, 1983; Noble, 1989; Klein, 1989; Pennington and Hastie, 1986; Connolly, 1988; Montegomery, 1989; Beach and Mitchell, 1990; Sarter and Woods, 1991; and Lipshitz, 1993). All of the NDM models discussed in chapter one stressed the importance of sizing up and constructing a mental picture of the problem situation. The NDM models either classifies the assessment of the situation as taking place prior to the evaluation of actions, or they tie it directly to the selection of action. It is therefore suggested that Hammond's theory of NDM is a good starting point for analysing NDM tasks objectively, especially when using NNs. This is due to the fact that this theory is a general description of individual's decisions in various environments and also that this theory is similar to how NNs work.

The experience of an individual is an important factor when making naturalistic decisions, see chapter one (Orasanu and Connolly, 1993; Flin, Salas, Strub & Martin, 1997; etc.). Study One involved an MSc choice of university task. Undergraduate students contemplating entering a postgraduate course are assumed to already possess a perception of what college life is like, and will already have gone through a similar experience of choosing where to go for undergraduate education. Study Two examined an air rage scenario, which involved participation from pilots with a large range of experience, some pilots had 2 years flying experience whereas others had 52 years. However, all pilots had a commercial pilot license and therefore had to have a certain amount of experience to partake in this study. Further work on the differences between methods employed to seek a solution to this problem between pilots with a couple of years experience and pilots with a lot of years experience would be interesting and could also have implications for the field of situation awareness. This comparison of methods employed would test DeGroot's (1978) prediction that experts can examine dozens of pieces of information and determine chunks of familiar patterns. Others have found this to be true (Means, Salas, Crandall & Jacobs, 1993). Individuals with more experience have a tendency to attend to the critical information while ignoring the less critical. However, the main aim of this thesis was to determine if NNs were a better means to analyse two NDM tasks: a consequential choice decisional task and a pattern matching decisional task. Cannon-Bowers et al (1996) also stated that NDM research was not just interested in expertise, therefore for the purpose of this thesis, the differences between various years of experience was not examined.

In study one a questionnaire was developed to determine the influences on students' choice to attend or not to attend Cranfield University in particular. The enrolment management research that is discussed in section 3.3 was mainly carried out in the United States. In today's economic climate the need for a postgraduate degree is becoming more apparent therefore students equate masters education with obtaining a desired career. This increase in further education within the UK would imply that more research should be carried out within this important field. Of the research reviewed within chapter three not only was it carried out in America but it also concentrated on the choice of undergraduate college and course. Therefore although some of the determinants of an individual student's decision to attend or not to attend a certain university for a masters course were similar to the American studies, more research needs to be carried out within the UK with the main interest being undergraduate students entering postgraduate courses.

This study examined two decision scenarios, more research needs to be done on more NDM scenarios for cross-validation, and different types of decisions too before more conclusions can be reached about empirical methods for the study of NDM. Larger data samples would also be suggested for further work.

NN models are useful in prediction, classification, fault detection, time series analysis, diagnosis, optimisation, system identification and control, exploratory data analysis and many other problems (Garson, 1998). This study has shown NNs to be good at modelling two decisional tasks, however they can be used to offer solutions for cases in which analytical solutions are hard to find, hidden or non-existent (Garson, 1998). NN modelling is a vastly evolving area. At present research is attempting to combine neural methods with other modelling tools such as genetic algorithms, fuzzy logic, expert systems, decision tress, etc. More sophisticated architects of NNs are available on the market each week. The availability of NNs in social scientists statistical packages like SAS and SPSS will ensure a steady diffusion of modelling techniques into this field. Although the limitation of NNs that restricts any conclusions of how and why people make decisions is still a problem. Perhaps in the future development of neural models, more tools will be available that will have the benefits of DFA (i.e. to be able to figure out 'why did s/he do that?'), yet will still remain non-linear. The prospect of Genetic Algorithms and NNs combining may achieve this goal.

Both studies however have shortcomings. Study One's data collection involved a questionnaire specifically designed to capture the participants decisional process when deciding on which university to chose when studying at master's level after their decision had been made. Questionnaires were sent to individuals and they were put under no time pressure to complete, sections were also available for participants to detail any information that was not already factored into the overall questionnaire.

Study two also, was not conducted within the context of either a flight deck or a real 'air rage' incident. Context, time pressure and multiple actors are important aspects of decision making, as recognised by many NDM theorists (e.g. Klein, 1989; Orasanu, 1993; Orasanu and Connelly, 1993). While the study presented the information to the interviewee in a manner similar to the way it would be presented in a real incident, some other aspects of the situation were different. For example, the interviewee did not have the opportunity to discuss options with other colleagues on the flight deck and the time-scale for the interview did not reflect the time-scale of an actual incident. All the sources of information and the decision subsequently made were proffered in a short period of time. The opportunities for collecting information, implementing a decision and monitoring the situation as would be done in a real-life situation were limited. However, the methodology employed was not at all that different to that employed in many other NDM studies, which have utilised retrospective introspection about the manner in which a decision was reached and were necessary given the methodology employed.

It is suggested that future investigation employs verbal protocol, and requests the participants to think aloud while working on given problems. This would be especially useful for studying flight deck decisions, and the use of a simulator or mock cockpit could overcome much of the issues outlined above relating to study two.

Both studies do however suggest that the use of an artificial neural network may be a way of empirically modelling NDM. NNs have been used with success in similar applications in the past. This thesis has shown that NNs are useful for modelling two categories of NDM tasks, 'consequential choice' and 'pattern matching'. Consequential choice mode would relate to the argument "Do 'A' because it has better consequences than its alternatives", matching would relate to the argument "Do 'A' because it corresponds to the situation". The next stage would be to test NNs for modelling a reassessment NDM task, Lipshitz (1993). Reassessment would relate to the twin argument "Do 'A' because there are no objections to its implementation or because objections can be rebutted".

Despite the need for considerably more work to evaluate the utility of using NNs to model naturalistic decisions, the present work has demonstrated that multiple decisional outcomes can be accurately predicted from a model based upon multiple sources of input information. In both studies the NN models performed commendably in predicting the decisions made in a real-world setting.

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Appendix A

List of the most well known Neural Network methods (Keller, 1998).

UNSUPERVISED LEARNING (i.e. without a "teacher"):

1). Feedback Nets:

a). Additive Grossberg (AG)
b). Shunting Grossberg (SG)
c). Binary Adaptive Resonance Theory (ART1)
d). Analog Adaptive Resonance Theory (ART2, ART2a)
e). Discrete Hopfield (DH)
f). Continuous Hopfield (CH)
g). Discrete Bidirectional Associative Memory (BAM)
h). Temporal Associative Memory (TAM)
i). Adaptive Bidirectional Associative Memory (ABAM)
j). Kohonen Self-organizing Map/Topology-preserving map (SOM/TPM)
k). Competitive learning

2). Feedforward-only Nets:

a). Learning Matrix (LM)
b). Driver-Reinforcement Learning (DR)
c). Linear Associative Memory (LAM)
d). Optimal Linear Associative Memory (OLAM)
e). Sparse Distributed Associative Memory (SDM)
f). Fuzzy Associative Memory (FAM)
g). Counterprogation (CPN)

2. SUPERVISED LEARNING (i.e. with a "teacher"):

1). Feedback Nets:

a). Brain-State-in-a-Box (BSB)
b). Fuzzy Cognitive Map (FCM)
c). Boltzmann Machine (BM)
d). Mean Field Annealing (MFT)
e). Recurrent Cascade Correlation (RCC)
f). Backpropagation through time (BPTT)
g). Real-time recurrent learning (RTRL)
h). Recurrent Extended Kalman Filter (EKF)

2). Feedforward-only Nets:

a). Perceptron
b). Adaline, Madaline
c). Backpropagation (BP)
d). Cauchy Machine (CM)
e). Adaptive Heuristic Critic (AHC)
f). Time Delay Neural Network (TDNN)
g). Associative Reward Penalty (ARP)
h). Avalanche Matched Filter (AMF)
i). Backpercolation (Perc)
j). Artmap
k). Adaptive Logic Network (ALN)
l). Cascade Correlation (CasCor)
m). Extended Kalman Filter(EKF)
n). Learning Vector Quantization (LVQ)
o). Probabilistic Neural Network (PNN)
p). General Regression Neural Network (GRNN)

Appendix B

The Cranfield Experience Questionnaire, MSc Group Project (1995)

THE CRANFIELD EXPERIENCE QUESTIONNAIRE

For boxed questions please place a tick in the appropriate box(es).

When using the 'other' option please also specify your response.

GENERAL INFORMATION

1. Sex: F ☐ M ☐
2. Age in years: ________
3. Where are you normally resident? UK ☐ EC ☐ Overseas ☐
4. What best describes your current marital status?

   Single ☐ Married/Co-habiting ☐

   Other ☐ Please specify ______________
5. Do you have any children (aged 0 - 18) living or staying with you regularly?

   Yes ☐ No ☐
6. Where are you currently living? Campus ☐ Cranfield Village ☐

   Surrounding villages ☐ Bedford ☐ Milton Keynes ☐

   Other ☐ please specify ______________
7. In what year did you commence your studies at Cranfield? __________
8. What is the title of your current course? __________
9. How long is your current course? __________
10. Do you have a first degree? Yes ☐ No ☐

- If yes how many years have elapsed since your first degree? __________

11. In what subject was your first degree? __________
12. What was your first degree classification? 1st ☐ 2.1 ☐ 2.2 ☐

    3rd ☐ Pass ☐

    Other ☐ Please specify __________

APPLYING TO CRANFIELD

13. How did you first hear about the course for which you applied at Cranfield University?

Word of mouth ☐ Journal/Newspaper advertisement ☐ Please specify________________

University/Careers notice board ☐

Other ☐ - Please specify ______________________

14. When did you apply to Cranfield? Month________ Year__________

15. Who did you first contact at Cranfield? Department ☐ Registry ☐

Other ☐ Please specify ______________________

16. How did you first contact Cranfield? Letter ☐ Phone ☐ Fax ☐

Other ☐ Please specify ______________________

17. Prior to making your application what information did you receive from Cranfield?

(Please tick the appropriate boxes)

TYPE OF INFORMATION	SOURCE OF INFORMATION		
	Department	Registry	Don't know
Postgraduate Prospectus			
Cranfield Campus Map			
Course Information Pack			
Accommodation Information			
Guide to Cranfield campus handbook			
'Welcome to Cranfield' handbook			

Other ☐ Please specify ______________________

- Can you remember the information? Yes / No

18. After making your application what information did you receive from Cranfield?

(Please tick the appropriate boxes)

TYPE OF INFORMATION	SOURCE OF INFORMATION		
	Department	Registry	Don't know
Postgraduate Prospectus			
Cranfield Campus Map			
Course Information Pack			
Accommodation Information			
Guide to Cranfield campus handbook			
'Welcome to Cranfield' handbook			

Other ☐ Please specify ____________________

- Can you remember the information? Yes / No

19. Upon accepting your application what information did you receive from Cranfield?

(Please tick the appropriate boxes)

TYPE OF INFORMATION	SOURCE OF INFORMATION		
	Department	Registry	Don't know
Postgraduate Prospectus			
Cranfield Campus Map			
Course Information Pack			
Accommodation Information			
Guide to Cranfield campus handbook			
'Welcome to Cranfield' handbook			

Other ☐ Please specify ____________________

- Can you remember the information? Yes / No

20. Of all the information that you received how much did you read?

None (0%)	
Little (25%)	
Some (50%)	
Most (75%)	
All (100%)	

21. For what reasons did you decide to apply to Cranfield?

Course reputation ☐ Specialised subject ☐

Course funding was available ☐ Locality ☐ Aircraft aspect ☐

Other ☐ Please specify ____________

22. Did you apply to do a similar course elsewhere?

No ☐ Yes ☐ If yes please specify where ____________

23. Were you accepted anywhere else?

No ☐ Yes ☐ If yes please specify where ____________

24. How much contact did you have with the University after being offered a place?

None	
Very little	
Some	
Quite a lot	
A lot	

- Who did you contact at Cranfield after being offered a place? Department ☐ Registry ☐

  Other ☐ Please specify ____________

- How was this contact made? Letter ☐ Phone ☐ Fax ☐

  Other ☐ Please specify ____________

- How did you feel about making contact with your referent, if applicable

Could contact them freely	
Could contact them if need arose	
Did not know who to contact or if initiation of contact was acceptable	
Did not feel comfortable making contact	
Felt contact made was unpleasant or unwanted	

- Who contacted you from Cranfield after you were offered a place? Department ☐

  Registry ☐ Other ☐ Please specify ____________________

- How was this contact made? Letter ☐ Phone ☐ Fax ☐

  Other ☐ Please specify ____________________

25. Which of the following influenced your decision to come to Cranfield?

Only offer	
Course reputation	
Specialised subject	
Finance/Funding	
Locality	
Aeroplanes	

- Other ☐ Please specify ____________________

ARRIVING AT CRANFIELD

26. On first impressions, once you started studying how did Cranfield compare to your expectations, from **an academic perspective?**

A lot better than expected	
Better than expected	
About the same as you expected	
Worse than you expected	
A lot worse than you expected	

27. On first impressions, how did Cranfield compare to your expectations from **a social point of view?**

A lot better than expected	
Better than expected	
About the same as you expected	
Worse than you expected	
A lot worse than you expected	

28. Did you come to Cranfield for an interview or visit the campus before you started studying?

No ☐ Yes ☐

29. How do you feel about Cranfield now?

Highly satisfied	
Satisfied	
Neither satisfied or dissatisfied	
Dissatisfied	
Highly dissatisfied	

30. Was there a single piece of information that particularly influenced your choice to attend Cranfield ? Yes ☐ No ☐

If so , what was it ? ______________________________

____

31. What information would you have liked to receive about Cranfield prior to coming, that you did not receive? ______________________________

____

32. What was the single piece of information that you received that you found most useful? ______________________________

____

33. Who did you find your most useful contact? ______________________________

____

34. Is there anything you would like to add that you think is important. Please do so in the space provided: ______________________________

____

____

THANK YOU FOR YOUR TIME AND CO-OPERATION

Appendix C

Registry Decision Form

Cranfield UNIVERSITY

Post-graduate Admissions
The Registry
Cranfield University
Bedford MK43 0AL
United Kingdom

DECISION FORM

Reference No ______ (Please insert)

1. Decision

(Please delete as appropriate)

I accept / decline the offer of a place at Cranfield in the School / College of

______

Signed ______ Date ______

Name (Please print) ______

Reasons for declining the offer (If applicable)

Please place 1 in the box which best describes your primary reason for declining our offer and tick (✓) any other boxes where there were secondary reasons

Unable to obtain financial support from:
- company sponsorship 10 ☐
- scholarship 11 ☐
- grant 12 ☐
- personal loan 13 ☐

Unable to obtain part time employment to supplement income during my studies 20 ☐

Cost of course too high:
- tuition fee 30 ☐
- living costs 31 ☐

More suitable course elsewhere:
- in UK 40 ☐
- outside UK 41 ☐

Please give details ______

Offered employment 50 ☐
Location of Cranfield 60 ☐
Personal reasons 70 ☐
Other reason 80 ☐

Please give details ______

2. Accommodation (Full time courses only)

(Please delete as appropriate)

I enclose an application form for accommodation in Lanchester Hall / Mitchell Hall / House / Flat / Self Catering

or I do not enclose an accommodation form

3. Correspondence

Please insert your address in the space below if it is different to the one / those you have already provided. We will be writing to September / October starters again in July.

(Please print)

______

Please return this form to the address shown above not later than one month after the date on the letter accompanying this form.

Thank You

Appendix D

Pilot Questionnaire for MSc Choice of University

Section One: *Factors that influenced your decision when choosing Universities to apply for a masters course- please indicate the effect each factor had on your decision by ticking the appropriate box.*

	No Influence				Strong influence
Future Employment Benefits:	1	2	3	4	5
Universities contact with industry	❑	❑	❑	❑	❑
Needed qualification that fit my practical knowledge	❑	❑	❑	❑	❑
Improve chances of gaining employment	❑	❑	❑	❑	❑
Reputation of University	❑	❑	❑	❑	❑
I disliked my job and needed a career change	❑	❑	❑	❑	❑
Individual Course Attributes:	1	2	3	4	5
Course offered hands-on practical experience	❑	❑	❑	❑	❑
Course subject matter seemed interesting	❑	❑	❑	❑	❑
Quality of individual course (as rated by journals or people spoken to)	❑	❑	❑	❑	❑
Accredited to professional body/society	❑	❑	❑	❑	❑
Location:	1	2	3	4	5
Close to home	❑	❑	❑	❑	❑
Not close to home	❑	❑	❑	❑	❑
City	❑	❑	❑	❑	❑
Countryside	❑	❑	❑	❑	❑
In UK	❑	❑	❑	❑	❑
Financial Considerations:	1	2	3	4	5
Sponsorship available	❑	❑	❑	❑	❑
Length of course	❑	❑	❑	❑	❑
Cost of course	❑	❑	❑	❑	❑
	1	2	3	4	5
I liked the presentation of the prospectus	❑	❑	❑	❑	❑

Other factors that influenced your decision when applying to Universities for a masters course ______________________________

____

____

____

If you declined an offer to attend Cranfield please ignore section two and complete section three. Thank you.

Section Two: *Factors that influenced your decision to attend Cranfield once you had received an offer. Please indicate the effect each factor had on your decision to attend Cranfield.*

	No Influence				Strong influence
Future Employment Benefits:	1	2	3	4	5
Link with industry	❑	❑	❑	❑	❑
Link to aviation	❑	❑	❑	❑	❑
Affiliation to professional body	❑	❑	❑	❑	❑
Good employment record from individual department	❑	❑	❑	❑	❑
The company I want to work for employs Cranfield Graduates	❑	❑	❑	❑	❑
Location:	1	2	3	4	5
Thought I would do more work due to the isolation	❑	❑	❑	❑	❑
I didn't want to be in the city	❑	❑	❑	❑	❑
Airfield	❑	❑	❑	❑	❑
Good family environment	❑	❑	❑	❑	❑
Knowledge about University:	1	2	3	4	5
Advertised in New Scientist/paper	❑	❑	❑	❑	❑
Reputation	❑	❑	❑	❑	❑
No undergraduates	❑	❑	❑	❑	❑
Liked the people in my department	❑	❑	❑	❑	❑
Personal reasons:	1	2	3	4	5
I always wanted to do a master's course	❑	❑	❑	❑	❑
I wanted to do a PhD eventually and figured it would be easier to follow on from a masters	❑	❑	❑	❑	❑
Cranfield was the only University that offered me a course	❑	❑	❑	❑	❑
Cranfield is the only University connected to my Home University	❑	❑	❑	❑	❑
I didn't get a job	❑	❑	❑	❑	❑
I had nothing better to do	❑	❑	❑	❑	❑
Financial Considerations:	1	2	3	4	5
Received sponsorship	❑	❑	❑	❑	❑
Length of course	❑	❑	❑	❑	❑
Cost of course	❑	❑	❑	❑	❑
No need to attend an interview so I didn't have extra cost in flying until course started	❑	❑	❑	❑	❑

Thank you for your time and co-operation, it is greatly appreciated.

<u>Section Three:</u> *Factors that influenced your decision to refuse the offer to attend Cranfield. Please indicate the effect each factor had on your decision not to come to Cranfield.*

	No Influence 1	2	3	4	Strong influence 5
I was unable to obtain financial support	☐	☐	☐	☐	☐
I found a more suitable course elsewhere	☐	☐	☐	☐	☐
The cost of the course	☐	☐	☐	☐	☐
The length of the course	☐	☐	☐	☐	☐
I was unable to obtain part-time employment to supplement income during studies	☐	☐	☐	☐	☐
I was offered full-time employment	☐	☐	☐	☐	☐
The accommodation was too expensive	☐	☐	☐	☐	☐
Location of Cranfield	☐	☐	☐	☐	☐
Personal reasons	☐	☐	☐	☐	☐
Link with aircraft	☐	☐	☐	☐	☐
Lack of information	☐	☐	☐	☐	☐
Quality of information was poor	☐	☐	☐	☐	☐
Accommodation was unsuitable	☐	☐	☐	☐	☐
The course was unsuitable	☐	☐	☐	☐	☐
I disliked the university	☐	☐	☐	☐	☐

Other factors that influenced your decision to not study at Cranfield____________

____

____

____

____

____

____

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____

Thank you for your time and co-operation. It is much appreciated.

DEMOGRAPHIC DETAILS

Please tick the appropriate boxes:

AGE — 20-25 ❑ / 26-30 ❑ / 31-35 ❑ / 36-40 ❑ / 41 and over ❑

SEX — Male ❑ Female ❑

MARITAL STATUS — Single ❑ / Married ❑ / Cohabiting ❑ / Separated ❑

Do you have any children (under 18 years) living or staying with you regularly?

Yes ❑ No ❑

PLACE OF RESIDENCE — UK ❑ / EU ❑ / Other ❑

OUTCOME OF YOUR DECISION:

Are you currently attending/ or did you attend a postgraduate course?

Yes ❑ No ❑

If you answered yes, what is/was the course title?

____

Which University did you attend?

Cranfield ❑ **Other** ❑ **Please specify**____________________

Are you currently employed? Yes ❑ No ❑

Thank you for your time and co-operation. It is much appreciated.

Appendix E

Postgraduate Choice Decisional Scale, including cover letter and demographics.

POSTGRADUATE CHOICE DECISIONAL SCALE

Please indicate the influence that EACH following factor had on your decision to attend or not to attend a postgraduate course. 1 indicates a strong negative influence, 3 indicates no influence on your decision either way, and 5 indicates a strong positive influence.

	NEGATIVE		*NONE*		*POSITIVE*	*Not Relevant*
Future Employment Benefits:	*1*	*2*	*3*	*4*	*5*	*NR*
University's contact with industry	❑	❑	❑	❑	❑	❑
Needed qualification that fit my experience	❑	❑	❑	❑	❑	❑
Improve chances of gaining employment	❑	❑	❑	❑	❑	❑
I disliked my job and needed a career change	❑	❑	❑	❑	❑	❑
Good employment record from individual department	❑	❑	❑	❑	❑	❑

Individual Course Attributes:	*1*	*2*	*3*	*4*	*5*	*NR*
Course offered hands-on practical experience	❑	❑	❑	❑	❑	❑
Course subject matter seemed interesting	❑	❑	❑	❑	❑	❑
Quality of individual course (as rated by journals or people spoken to)	❑	❑	❑	❑	❑	❑
Accredited by professional body/society	❑	❑	❑	❑	❑	❑
Quality of information received describing program of study	❑	❑	❑	❑	❑	❑

Location:	*1*	*2*	*3*	*4*	*5*	*NR*
University surroundings (city/countryside)	❑	❑	❑	❑	❑	❑
University was in the UK	❑	❑	❑	❑	❑	❑

Financial Considerations:	*1*	*2*	*3*	*4*	*5*	*NR*
Availability of sponsorship/grants	❑	❑	❑	❑	❑	❑
Cost of relocation	❑	❑	❑	❑	❑	❑
Length of course	❑	❑	❑	❑	❑	❑
Cost of course	❑	❑	❑	❑	❑	❑
The need to pay off my Undergraduate loans	❑	❑	❑	❑	❑	❑

Continued on following page

Availability of Knowledge about University:	1 NEGATIVE	2	3 NONE	4	5 POSITIVE	NR Not Relevant
Quality of advertising	❑	❑	❑	❑	❑	❑
Reputation of University	❑	❑	❑	❑	❑	❑
People in my department	❑	❑	❑	❑	❑	❑
Presentation of the prospectus	❑	❑	❑	❑	❑	❑
Web site	❑	❑	❑	❑	❑	❑

Cranfield University Characteristics:	1	2	3	4	5	NR
Strong link with aviation	❑	❑	❑	❑	❑	❑
Being entirely postgraduates	❑	❑	❑	❑	❑	❑
Large male population	❑	❑	❑	❑	❑	❑
Cranfield was the only University that offered me a course	❑	❑	❑	❑	❑	❑
Standard of accommodation	❑	❑	❑	❑	❑	❑
Good family environment	❑	❑	❑	❑	❑	❑
There was no need to attend an interview so I didn't have extra travelling costs until the course started	❑	❑	❑	❑	❑	❑
I thought I would do more work due to the isolation	❑	❑	❑	❑	❑	❑
Cranfield is the only University connected to my undergraduate University	❑	❑	❑	❑	❑	❑

Personal reasons:	1	2	3	4	5	NR
I always wanted to do a Master's course	❑	❑	❑	❑	❑	❑
I wanted to do a PhD eventually and figured it would be easier to follow on from a Master's	❑	❑	❑	❑	❑	❑
I was unable to obtain employment	❑	❑	❑	❑	❑	❑
I wanted to be near family/friends	❑	❑	❑	❑	❑	❑
I wanted to gain work experience before completing a post-graduate course	❑	❑	❑	❑	❑	❑

Other factors that influenced your decision to study *or not to* study at Master's level:

____

____

____

Continued on following page

<u>DEMOGRAPHIC DETAILS:</u> *Please tick the appropriate boxes*

AGE	**20-25**	❑
	26-30	❑
	31-35	❑
	36-40	❑
	41 and over	❑
SEX	**Male ❑ Female**	❑
MARITAL STATUS	**Single**	❑
	Married	❑
	Cohabiting	❑
	Separated	❑

Do you have any children (under 18 years)
living or staying with you regularly? **Yes ❑ No ❑**

PLACE OF RESIDENCE	**UK**	❑
	EU	❑
	Other	❑

OUTCOME OF YOUR DECISION:

Are you currently attending/ or did you attend a postgraduate course?
Yes ❑ No ❑

If you answered yes, what is/was the course title?

____

Which University did you attend?

Cranfield ❑ Other ❑ Please specify______________________

Are you currently in full-time employment?
Yes ❑ No ❑

Did you obtain employment instead of attending a postgraduate course?

Yes ❑ No ❑

Thank you for your time and co-operation. It is much appreciated.

Human Factors Group

Fax +44 (0) 1234 750192
Tel + 44 (0) 1234 750111 x 5199
Internet e-mail: S.J.D.Duggan@cranfield.ac.uk

03 December 1998

To whom it may concern,

My name is Sarah Duggan, and I am undertaking a Ph.D. studying applied decision making at the Human Factors Group, College of Aeronautics, Cranfield University. The aim of this letter is to ask for your participation with some of my research. I am writing to people who applied to attend Cranfield University and subsequently received an offer. The enclosed questionnaire is concerned with the factors that influenced your decision to accept or reject an offer of a course at Cranfield University. It also investigates the influences of why you decided to attend a postgraduate course in the first place.

I would be grateful if you would be willing to participate in my research. The questionnaire is an exploratory study to investigate a simple decision making process. If you would like to volunteer please complete the enclosed questionnaire. It should take no longer then 10 minutes to complete. When completed, please return the questionnaire in the **free post** envelope that is provided (NO STAMP REQUIRED).

Participation in this independent study is voluntary. Please be assured that all replies will be used for this project only and all information obtained will be held in complete confidence. I do hope that you will be able to take part in this interesting and important project.

If you have any queries regarding this research or need further information, do not hesitate to contact me at the above address. I look forward to hearing from you soon.

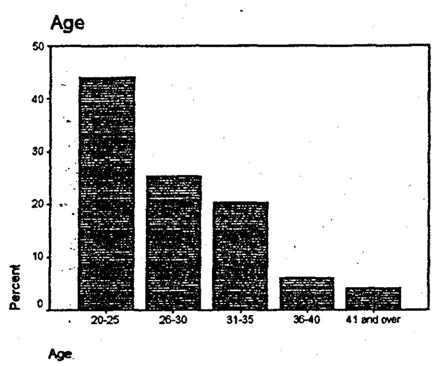
Thank you for your time and co-operation,

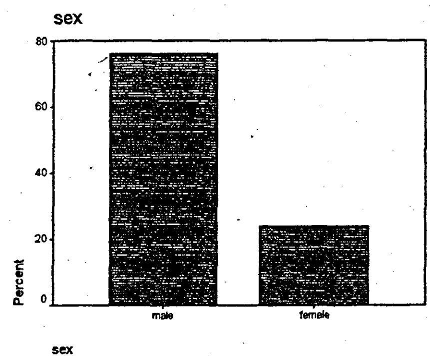
Yours sincerely,

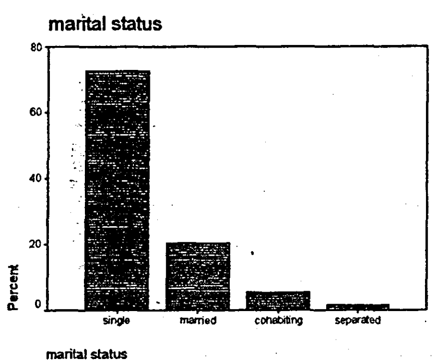
Sarah Duggan, Ph.D. Student.

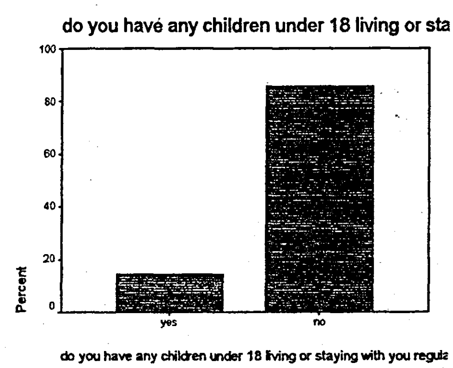
Appendix F

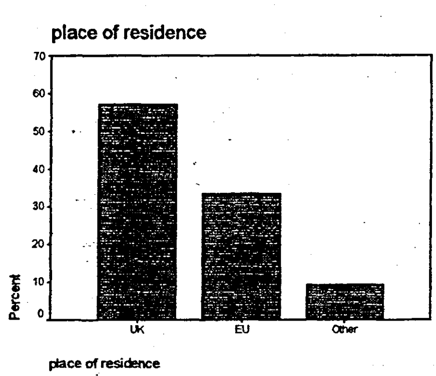
Demographic details of prospective students for study one.

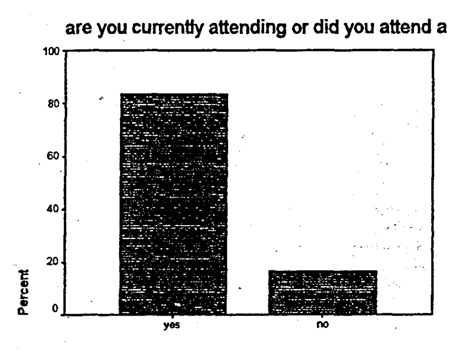

Age
Percent
20-25
26-30
31-35
36-40
41 and over
Age

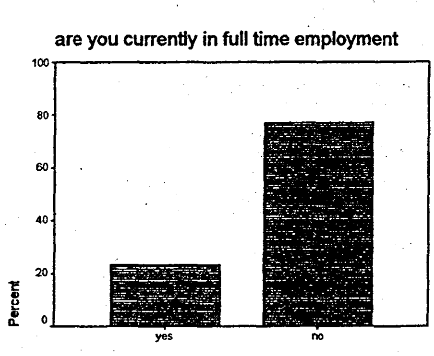

sex
Percent
male
female
sex

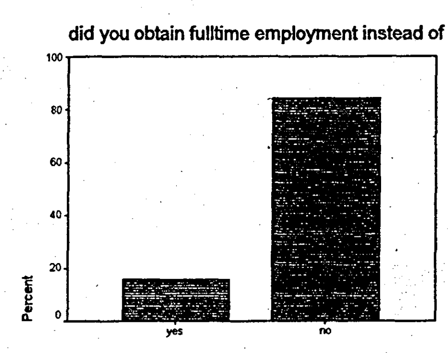

marital status
Percent
single
married
cohabiting
separated
marital status


do you have any children under 18 living or sta
Percent
yes
no
do you have any children under 18 living or staying with you regula


place of residence
Percent
UK
EU
Other
place of residence


are you currently attending or did you attend a
Percent
yes
no
are you currently attending or did you attend a postgraduate cours


are you currently in full time employment
Percent
yes
no
are you currently in full time employment


did you obtain fulltime employment instead of a
Percent
yes
no
did you obtain fulltime employment instead of attending a postgrad

Appendix G

Hidden Node Weights to Outputs for study one.

HIDDEN NODES	JOB	CRANFIELD	OTHER UNI.
BIAS	-0.28	-0.66	0.16
1	1.18	0.97	-2.14
2	-4.78	5.44	-0.71
3	1.59	-3.65	2.08
4	2.97	-2.81	-0.17
5	0.13	-1.25	0.68
6	-0.31	-0.29	0.51
7	0.64	-1.38	0.59
8	1.65	2.46	-4.12
9	2.44	-2.16	-0.22
10	-0.38	0.11	-0.48
11	2.25	-5.42	3.20
12	-0.46	6.38	-5.93
13	-0.18	-0.47	0.54
14	0.97	-1.43	0.41
15	-1.32	-2.04	3.42
16	-2.83	4.20	-1.38
17	4.26	4.67	-8.92
18	-4.69	3.27	1.41
19	0.73	-3.81	3.09
20	1.87	2.49	-4.36
21	0.34	-1.00	0.82
22	-3.23	1.14	2.07
23	0.26	-0.24	-0.04
24	0.25	-0.50	-0.07
25	0.37	0.19	-0.23
26	0.05	-0.01	-0.28
27	1.23	-6.46	5.23
28	-4.27	2.72	1.52
29	2.07	-2.22	0.27
30	1.74	-3.02	1.26
31	0.60	0.06	-0.44
32	1.80	1.74	-3.56
33	-0.28	-4.14	4.46
34	-0.70	-0.05	0.65
35	0.06	-0.01	-0.08
36	-5.41	4.59	0.86
37	0.06	-0.11	-0.03

Appendix H

Neural Network Weights and Hidden Node Biases for study one: Master level choice of University.

Neural Network Weights and Hidden Node Biases for study one: MSc choice of University.

INPUT	VARIABLE NAME
1	Contact with Industry
2	Needed qualification to fit experience
3	Improve chance of gaining employment
4	Disliked job and needed career change
5	Good employment record from department
6	Course offered practical experience
7	Course seemed interesting
8	Quality of course
9	Accredited by professional body
10	Quality of information received
11	University surroundings
12	University in UK
13	Availability of grants
14	Cost of relocation
15	Length of course
16	Cost of course
17	Need to pay off undergraduate loans
18	Quality of advertising
19	Reputation of University
20	People in my department
21	Presentation of prospectus
22	Web site
23	Strong link to aviation
24	Being entirely postgraduates
25	Large male population
26	Standard of accommodation
27	Good family environment
28	I thought I would do more due to the isolation
29	I always wanted to do a Masters
30	I always wanted to do a PhD
31	I wanted to be near family and friends
32	I wanted to gain work experience before completing a Masters

Input	HN1	HN2	HN3	HN4	HN5	HN6	HN7	HN8	HN9	HN 10	HN 11	HN 12	HN 13	HN 14	HN 15	HN 16	HN 17	HN 18
Bias	-0.18	1.36	-1.61	-0.74	0.07	0.20	0.11	1.11	0.20	0.84	0.42	2.22	0.14	0.23	-0.95	-0.09	-0.76	-0.02
1	-0.32	-1.61	-2.04	2.15	-0.16	0.07	0.32	-1.40	0.06	0.25	1.62	1.22	0.24	-0.24	-0.35	-0.70	-0.44	-0.16
2	-0.54	-0.82	2.06	2.29	0.28	0.27	-0.06	-0.02	-0.56	0.03	-1.16	3.23	0.60	0.36	1.43	1.67	-0.16	-0.04
3	-0.86	0.29	0.11	0.97	0.49	-0.00	0.45	0.16	0.47	0.06	1.36	2.45	-0.05	0.27	1.12	-1.55	1.26	-1.85
4	0.30	-1.47	1.12	-0.63	0.18	0.28	0.16	-0.64	-1.01	0.24	-0.41	2.85	-0.19	0.16	0.61	0.13	4.32	2.05
5	-0.61	4.47	0.87	-1.02	0.37	0.33	0.26	-3.04	-0.28	0.24	-1.23	-0.01	0.30	0.00	0.47	0.27	-0.48	2.42
6	1.20	2.99	-0.37	1.29	0.46	0.02	0.23	2.18	0.17	0.57	1.30	-1.48	0.48	0.91	0.23	1.55	2.79	0.79
7	-0.90	1.65	-0.11	-0.90	0.07	0.19	0.59	-1.63	-0.66	-0.03	-1.16	-3.04	0.02	0.17	-1.74	0.56	1.48	0.13
8	-0.83	-1.11	-1.53	0.12	0.52	-0.00	-0.05	-1.60	0.82	-0.25	0.90	-2.13	0.46	0.11	0.22	-1.79	-1.01	-2.25
9	-0.41	4.63	0.85	-0.31	0.46	0.57	-0.31	-2.59	-0.08	0.58	-0.38	0.97	0.31	0.02	1.66	0.43	-0.92	-1.55
10	-0.19	-0.68	0.57	-0.09	0.23	0.39	0.22	0.86	0.29	0.11	1.71	2.28	-0.02	0.20	1.82	-0.01	-6.42	-1.55
11	-0.16	1.24	-1.85	-4.10	-0.29	0.25	-0.30	2.17	0.76	-0.10	0.46	-8.34	-0.01	-0.21	-1.00	-3.40	0.54	0.02
12	0.33	1.71	-0.25	0.50	-0.07	0.52	-0.12	2.02	0.96	0.89	1.08	0.00	0.48	-0.39	0.79	-0.48	1.92	2.85
13	0.98	-1.88	-2.01	-3.92	0.04	0.28	0.74	0.57	1.85	0.73	0.64	-0.32	0.23	0.21	-0.84	-2.31	4.31	4.41
14	-0.12	0.02	0.12	0.68	0.44	0.02	0.12	1.37	-0.29	0.15	0.66	-3.49	0.23	0.26	-0.24	-1.19	1.57	1.47
15	0.43	0.24	0.17	-0.81	0.32	0.02	0.38	0.14	-0.60	-0.01	-0.29	-7.30	0.24	0.11	0.12	1.23	4.98	2.45
16	0.11	-0.11	1.71	-1.21	0.00	-0.24	0.15	4.52	0.09	0.15	-1.31	-1.85	0.12	0.61	-0.98	-1.28	3.91	4.29
17	0.52	0.52	1.33	0.34	0.14	-0.05	-0.14	0.77	-0.01	0.26	-0.06	-2.30	0.36	0.74	-1.70	-1.13	0.79	1.43
18	-0.47	1.32	0.30	-1.98	0.40	0.44	-0.30	-0.06	0.15	-0.32	1.37	-4.33	0.25	-0.15	0.40	-1.10	0.13	0.34
19	-0.32	3.31	-0.21	-0.24	0.22	0.15	-0.02	0.25	-0.11	-0.09	2.25	1.01	0.19	0.27	0.05	-0.48	1.07	-4.40
20	-1.28	-2.53	-1.23	1.66	0.31	0.24	-0.01	-1.46	0.03	0.26	-.60	3.65	0.51	0.33	-0.74	-1.28	0.19	2.24
21	0.53	-1.64	-1.23	0.94	0.06	-0.03	0.05	1.20	-0.69	0.53	2.14	1.00	0.06	-0.35	0.20	-0.16	0.62	0.09
22	0.37	1.69	-1.49	-1.43	0.29	-0.13	-0.33	1.82	0.29	0.49	2.43	-0.91	-0.06	-0.03	-1.30	0.33	-0.31	-2.03
23	1.31	-0.09	0.58	0.61	-0.05	0.59	0.16	-2.42	-0.12	0.33	2.72	5.26	0.55	-0.70	2.10	1.68	4.78	-1.64
24	-0.26	1.75	-0.62	-0.18	0.02	-0.14	0.86	2.15	1.14	-0.01	-3.93	3.38	0.40	-0.13	-0.91	0.38	-6.87	-2.71
25	0.39	-2.23	-0.61	0.95	-0.16	-0.03	0.30	1.45	1.02	-0.25	-2.49	2.37	-0.12	0.10	-1.14	0.60	-5.27	-2.90
26	1.18	0.16	1.22	0.32	-0.08	-0.22	-0.50	1.28	-0.09	0.13	-2.14	0.26	0.08	0.14	-0.67	0.07	-2.89	2.27
27	1.00	-0.45	0.26	1.72	0.25	0.47	-0.25	0.41	-0.47	0.61	-1.32	3.34	-0.07	-0.17	0.39	2.03	0.41	0.13
28	0.00	-3.06	-0.39	1.65	-0.30	0.15	0.31	-0.02	0.27	0.13	-1.37	2.82	-0.09	-0.83	-0.56	-0.45	-0.71	2.33
29	-0.39	-3.14	0.72	1.78	0.26	0.21	-0.03	-0.95	-0.54	-0.13	1.61	-0.25	0.41	0.00	0.55	-0.07	-3.25	0.30
30	0.64	0.13	2.74	0.96	-0.09	-0.03	-0.60	-0.10	-1.28	0.38	-2.57	0.87	0.31	0.70	1.73	0.83	0.56	0.45
31	0.24	-0.49	-0.26	-1.07	0.42	0.19	-0.19	1.49	-0.79	0.09	3.57	-0.39	0.06	0.30	0.71	-0.80	2.94	-0.86
32	1.19	-0.34	1.67	-3.35	0.77	0.13	0.84	-1.06	1.73	-0.07	-2.13	3.13	0.08	0.83	1.12	0.12	2.68	1.00

Input	HN 19	HN 20	HN 21	HN 22	HN 23	HN 24	HN 25	HN 26	HN 27	HN 28	HN 29	HN 30	HN 31	HN 32	HN 33	HN 34	HN 35	HN 36	HN 37
1	-1.39	-0.08	-0.05	0.63	-0.29	0.04	-0.05	0.33	1.56	0.28	-0.57	0.50	0.22	-0.78	-1.21	0.51	-0.08	1.67	-0.15
2	-0.88	1.91	-0.00	2.02	0.02	0.27	0.27	0.42	0.53	-1.10	-0.21	-0.98	0.45	0.05	0.38	0.31	0.03	-1.15	-0.05
3	0.60	-0.33	0.54	-1.18	0.10	0.29	0.00	0.10	-0.42	0.75	0.29	0.61	0.60	-0.10	0.26	-0.53	-0.01	-3.40	-0.14
4	0.74	2.82	0.47	-1.20	0.33	0.04	0.64	0.35	1.68	-0.79	0.04	0.71	0.71	-0.62	1.08	-0.28	0.28	-0.47	-0.04
5	-0.44	2.07	-0.20	-0.76	0.00	0.06	-0.01	-0.04	0.24	1.43	-0.19	0.27	0.33	2.42	2.73	0.49	0.25	5.22	-0.08
6	0.38	-0.37	0.06	-0.10	0.21	0.46	0.02	0.59	0.37	-0.41	0.23	0.01	0.27	0.17	0.12	-0.21	0.12	0.03	0.01
7	-0.59	-2.05	0.61	-0.44	0.50	-0.16	-0.13	0.17	-0.94	0.08	0.71	0.95	0.00	1.64	-0.30	0.03	0.29	0.19	-0.09
8	-0.43	-0.73	0.13	0.76	0.11	0.38	0.13	-0.03	-0.26	-1.10	0.31	0.61	0.55	0.31	-1.09	-0.02	0.03	-0.98	0.06
9	0.16	0.65	0.47	1.89	0.17	0.42	0.39	0.46	2.90	-0.12	0.00	0.22	0.22	1.87	-1.74	0.70	0.46	2.41	0.13
10	-0.86	-1.25	-0.03	0.76	-0.08	0.03	-0.16	-0.05	-1.66	0.87	0.42	-0.47	-0.02	1.59	1.53	-0.05	0.41	0.52	-0.07
11	-2.59	-1.16	0.04	-1.01	0.20	-0.43	-0.04	-0.26	4.90	-1.67	0.12	-0.90	-0.26	-1.07	-1.88	-0.21	0.19	1.17	-0.02
12	-2.20	1.61	-0.24	0.97	0.44	0.24	0.37	0.46	1.87	-1.95	-0.39	-0.88	0.45	-1.31	-0.51	0.02	0.48	1.71	-0.12
13	-1.09	0.77	0.04	0.98	0.38	0.25	0.59	0.43	3.42	1.54	0.75	0.46	0.33	0.44	0.57	0.64	0.15	2.17	0.06
14	2.32	-1.73	0.50	0.71	0.15	-0.06	-0.16	-0.13	-4.75	-1.59	0.64	1.23	-0.09	-0.37	0.31	0.12	0.06	-1.25	0.02
15	2.49	0.16	0.05	0.07	0.52	0.15	0.52	0.35	-0.19	2.50	0.06	0.67	-0.06	-0.48	0.05	0.12	0.47	-0.23	-0.14
16	-0.56	1.07	0.03	1.62	0.23	0.48	0.15	0.20	0.14	0.61	0.09	-1.12	0.29	-0.27	1.04	0.39	0.14	-0.13	-0.10
17	1.93	-0.13	0.01	2.37	0.54	0.25	0.30	0.14	-4.86	2.05	1.68	0.88	-0.02	-1.15	0.41	0.52	0.48	5.00	0.09
18	1.41	0.95	0.35	0.49	-0.15	0.31	-0.04	-0.04	-0.84	1.56	1.01	0.67	-0.07	0.35	-0.43	0.23	-0.16	-1.90	0.06
19	0.17	-0.69	0.23	-0.90	0.02	0.30	0.24	0.29	-1.51	-0.91	0.23	0.11	0.07	-0.11	-0.32	-0.09	0.28	-1.44	0.08
20	1.45	-1.27	0.55	-0.39	0.17	0.24	0.25	0.25	-2.05	0.56	0.37	0.09	0.40	0.35	-1.04	0.48	0.05	0.35	0.10
21	-0.99	-0.69	0.46	0.66	0.37	0.42	0.45	0.51	1.81	-1.33	0.35	0.40	0.22	-1.08	1.20	0.06	0.17	-1.76	0.14
22	-2.88	-0.60	-0.09	0.06	0.13	0.59	0.35	0.12	0.19	0.00	-0.32	-0.59	0.34	0.44	2.78	-0.01	0.36	-1.35	-0.08
23	0.38	-0.60	0.01	0.17	0.20	0.21	0.40	0.10	-0.74	-2.10	-1.79	-0.72	0.63	-1.66	-1.43	0.25	0.63	-2.24	-0.02
24	1.43	0.33	0.80	1.65	0.23	-0.09	-0,14	0.27	-0.02	2.65	1.49	2.74	-0.09	1.31	2.95	0.21	-0.07	1.04	0.14
25	-0.20	0.09	-0.10	0.83	0.04	0.05	0.42	0.24	2.74	-2.65	0.07	-0.44	0.20	-2.11	-3.15	0.12	0.22	-0.29	0.10
26	2.51	-0.10	0.21	-1.00	0.12	0.28	0.54	0.29	-1.86	-2.10	0.25	1.10	0.21	-1.46	1.11	-0.39	0.24	-1.20	0.13
27	1.53	-2.45	0.16	-0.93	0.50	0.14	0.30	0.58	-1.35	0.25	0.26	-0.45	0.16	1.54	0.16	-0.13	-0.01	2.47	0.09
28	-0.08	1.55	0.00	-0.41	0.29	0.18	0.29	0.31	-0.65	-0.71	-0.15	0.81	0.93	-2.02	-1.25	-0.01	0.52	-0.05	-0.01
29	-1.20	-0.03	0.33	0.29	0.23	-0.04	-0.24	-0.30	-0.25	1.25	-0.19	-0.93	0.25	0.24	-2.24	0.40	0.25	0.61	0.03
30	1.13	1.05	0.31	-1.40	0.32	0.45	0.60	0.43	-0.84	-2.11	0.51	-0.85	0.50	-1.88	-0.54	0.18	0.29	-2.00	0.05
31	-2.70	1.42	0.20	-1.44	0.31	0.41	0.15	0.12	2.30	3.11	-0.11	-0.64	0.33	-0.47	1.35	0.32	0.41	0.32	0.03
32	0.77	0.06	0.10	-0.27	0.11	0.42	0.12	-0.12	-1.69	1.99	1.20	0.52	0.16	1.50	2.29	-0.11	0.27	-1.39	0.01

Appendix I

Actual and Predicted outputs of cross validation set for study one.

Actual and Predicted outputs of cross validation set, **NN**= Neural Network, **J**= Obtained Employment, **C**= Came to Cranfield University, **O**= Went to Other University.

Case Number	Actual Value	Predicted Value	NN Value	Correct prediction?
1	2	1	J =0.8	✘
2	2	2	C=1.0	✔
3	2	2	C=1.0	✔
4	2	2	C=0.7	✔
5	2	2	C=1.0	✔
6	2	2	C=0.4	✔
7	2	2	C=1.0	✔
8	2	2	C=1.0	✔
9	2	2	C=1.0	✔
10	2	2	C=1.0	✔
11	2	2	C=1.0	✔
12	2	2	C=1.0	✔
13	2	1	J =1.0	✘
14	2	2	C=0.9	✔
15	2	2	C=0.7	✔
16	2	3	O=0.9	✘
17	2	2	C=0.9	✔
18	2	2	C=1.0	✔
19	2	2	C=0.6	✔
20	2	2	C=0.9	✔
21	2	2	C=1.0	✔
22	2	2	C=1.0	✔
23	2	2	C=1.0	✔
24	2	3	O=1.0	✘
25	2	2	C=1.0	✔
26	2	2	C=0.3	✔
27	2	3	O=0.5	✘
28	2	2	C=1.0	✔
29	2	3	O=0.8	✘
30	2	2	C=0.8	✔
31	2	2	C=1.0	✔
32	2	2	C=1.0	✔
33	2	2	C=0.7	✔
34	2	2	C=0.8	✔
35	2	2	C=0.8	✔
36	2	3	O=1.0	✘
37	2	2	C=0.5	✔
38	2	3	O=1.0	✘
39	2	2	C=1.0	✔
40	2	2	C=0.5	✔
41	2	1	J=1.0	✘
42	2	2	C=0.5	✔
43	2	2	C=0.5	✔
44	2	3	O=1.0	✘
45	2	2	C=0.7	✔
46	2	2	C=0.7	✔
47	2	2	C=0.8	✔

Case Number	Actual Value	Predicted Value	NN Value	Correct prediction?
48	2	2	C=1.0	✔
49	2	2	C=1.0	✔
50	2	2	C=1.0	✔
51	1	2	C=0.8	✖
52	1	2	C=1.0	✖
53	3	3	O=1.0	✔
54	1	2	C=1.0	✖
55	3	2	C=0.9	✖
56	3	3	0=0.3	✔
57	3	2	C=0.9	✖
58	1	2	C=1.0	✖
59	3	3	O=0.7	✔
60	3	3	O=0.7	✔
61	3	2	C=1.0	✖
62	3	2	C=1.0	✖
63	1	3	O=0.8	✖
64	3	3	O=0.8	✔
65	1	3	O=0.5	✖
66	1	2	C=0.7	✖
67	3	3	O=0.5	✔
68	1	1	J =1.0	✔
69	3	2	C=1.0	✖
70	3	2	C=1.0	✖
71	1	1	J =0.5	✔
72	3	2	c-0.5	✖
73	3	2	C=1.0	✖
74	3	2	C=1.0	✖
75	2	3	O=0.7	✖
76	2	2	C=1.0	✔
77	2	2	C=0.5	✔
78	2	2	C=1.0	✔
79	2	2	C=1.0	✔
80	2	2	C=1.0	✔
81	2	2	C=1.0	✔
82	2	2	C=0.9	✔
83	2	2	C=1.0	✔
84	2	2	C=1.0	✔
85	1	1	J =0.9	✔
86	3	2	C=0.9	✖
87	2	3	O =1.0	✖
88	2	2	C=1.0	✔
89	2	2	C=1.0	✔
90	2	2	C=1.0	✔
TOTAL				61

Appendix J

Recent examples of air rage incidents

1. An intoxicated first class passenger was denied further alcohol so he pulled down his trousers and pants and defecated on the cabin floor and food trolley.

2. A young gentleman bit his father's nose off and proceeded to head putt his mother.

3. A stewardess was pushed and threatened: 'I'll kill you if you don't get me home on time'.

4. A male steward grabbed the arm of a passenger who was threatening a hostess, so the passenger turned on him.

5. A disruptive passenger tried to get into the flight deck but the door was locked. He still managed to break a panel in the door.

6. Recently two passengers were arrested and 15 were deported after a mini riot broke out on a plane coming from London.

7. A male passenger under the influence of LSD wanted to bless the passengers and flight crew; it took four people to restrain him.

8. A passenger tried to throw a flight assistant off the aircraft.

9. A passenger hit a steward after being asked to remove his headset while the aircraft was taxiing (he was sent into the next row of seats).

10. A passenger hit a steward when he was told there was no more chicken dinners left.

11. A flight attendant received second degree burns from coffee, after a pair of passengers were refused an upgrade to first class.

12. Four passengers were arrested after a couple smoked in a non smoking section on a flight to Las Vegas, and another couple refused to let an airhostess put a painting into the overhead cabin.

13. After consuming three double whiskeys and a valium tablet a man became increasingly violent towards an air hostess.

14. A BA jet was forced to land in Tenerife after a passenger, who drunk, attempted to force his way into the pilot's cabin during a flight from Rio de Janeiro to London.

Etc. From various newspaper articles, World in Action television programme, Bor (1999), and Potell et al (1983).

Appendix K

The Air Navigation Order 1995

Criminal offences such as assault, theft or criminal damages are all serious felonies on board an aircraft. However, the air navigation order includes four other offences that can be committed by passengers:

Article 55

A person shall not recklessly or negligently act in a manner likely to endanger an aircraft, or any person therein.

Article 57(1)

A person shall not enter any aircraft when drunk, or be drunk in any aircraft.

Article 58(2)

A person shall not smoke in any compartment of an aircraft registered in the UK at a time when smoking is prohibited in that compartment by a notice to that effect exhibited by or on behalf of the commander of the aircraft. (Can only be committed on an UK registered aircraft).

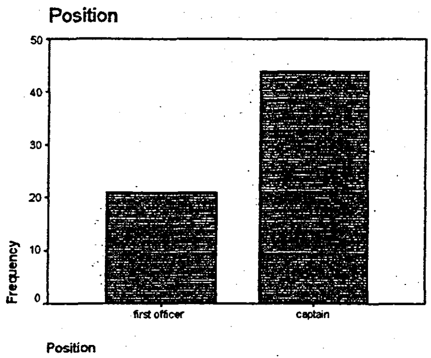
Article 59

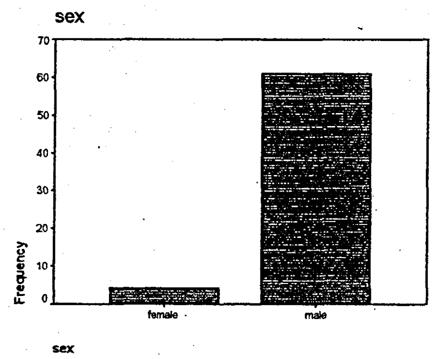
Every person in an aircraft registered in the UK shall obey all lawful commands which the commander of that aircraft may give for the purpose of securing the safety of the aircraft and of the persons or property carried therein, or the safety, efficiency or regularity of air navigation. (Can only be committed on an UK registered aircraft).

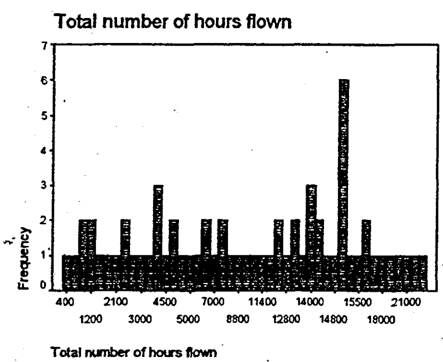
From '*A protocol for dealing with disruptive passengers and crime in the air*' Sussex Police, Gatwick Division.

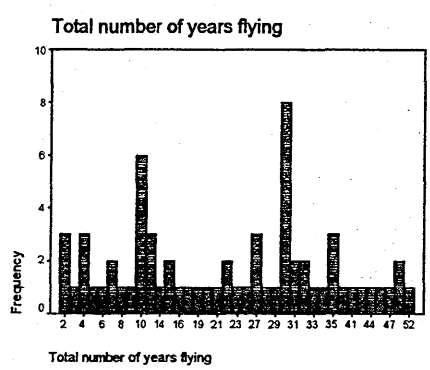
Appendix L

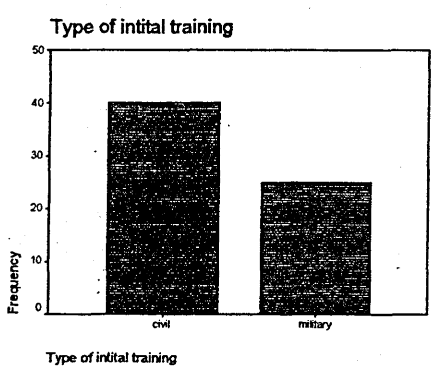
Demographic Details for Study Two: Air Rage Scenario


Position
Frequency
first officer
captain
Position


sex
Frequency
female
male
sex


Total number of hours flown
Frequency
400 1200 2100 3000 4500 5000 7000 8800 11400 12800 14000 14800 15500 18000 21000
Total number of hours flown


Total number of years flying
Frequency
2 4 6 8 10 14 16 19 21 23 27 29 31 33 35 41 44 47 52
Total number of years flying


Type of intital training
Frequency
civil
military
Type of intital training

Appendix M

Outcome bias and weights for each node connection to outcome for study two: air rage scenario.

Outcome bias and weights for each node connection to outcome for study two: air rage scenario.

HIDDEN NODES	Calm, continue	Restrain, continue	Restrain, divert	Divert, no restraint
BIAS	-2.17	-5.81	3.74	-0.13
1	0	0.12	-0.07	-0.06
2	4.45	-0.07	0.07	-4.47
3	-0.07	4.60	0.05	-4.58
4	-0.03	3.55	-5.98	2.48
5	0.09	-0.01	0.03	0.05

Appendix N

Weights for each connection from interview variable to each hidden node for study two: air rage scenario.

Weights for each connection from interview variable to each hidden node for study two: air rage scenario.

Variable Name	Hidden Node 1	Hidden Node 2	Hidden Node3	Hidden Node 4	Hidden Node 5
Is he travelling alone?	115.5	0.38	6.44	1.33	-0.15
Send a pilot down	91.2	-4.43	-19.7	-0.43	-0.05
Do not send a pilot down	10.6	-12.7	-20.0	3.17	-0.14
Get friends to help	49.8	0.17	6.64	1.31	-0.04
Obtain help from other passengers	28.1	31.0	3.38	3.12	-0.08
Helpful off duty passengers	116.8	-2.53	-1.60	1.17	0.01
Move seats	-87.8	8.06	-3.96	0.54	-0.09
Prepare	16.3	-4.02	-4.05	4.48	0.06
Story and assessment from cabin crew	16.7	4.64	-9.13	-0.55	0.13
Deny Alcohol	12.7	36.3	-2.45	0.77	-0.07
Summary from person	-39.2	-3.54	0.23	0.67	-0.02
Contact Company	-79.5	7.02	15.2	0.90	-0.12
What facilities at C? Other options?	-37.0	-8.70	-1.29	1.58	0.06
Organise Police	-36.5	-3.00	2.25	-5.24	0.02
Previous problem before landing?	73.9	24.4	-6.26	0.36	-0.14
Speak to person/group leader in flight deck	-14.6	0.57	0.13	0.25	-0.10
Have a look from a distance	96.1	17.0	-0.22	0.45	0.09
Large man?	-54.1	-27.9	-1.01	0.42	0.06
Medication?	59.4	33.5	-2.97	0.65	0.08
Collect Information	-66.4	-23.1	-2.98	1.26	0.10
Seat belt sign	112.3	-7.40	-0.02	0.41	0.14
Delegate	47.4	7.21	6.26	1.63	-0.08
Return Flight?	-81.3	5.62	-0.66	0.12	-0.02
Country?	2.99	-19.4	-15.7	-0.05	0.14
PA	127.2	-18.0	-6.31	2.22	0.10
Warning	35.0	28.4	-6.91	4.23	0.13

Appendix O

Neural Network Weights and Hidden Node Biases for study two: Air rage scenario.

Variables for Study Two

INPUT	VARIABLE
1	Is he travelling alone?
2	Send a pilot down
3	Do not send a pilot down
4	Get friends to help
5	Obtain help from other passengers
6	PIL: helpful off duty passengers
7	Move person or other passengers
8	Prepare for next stage in case he continues to get out of hand
9	Story and assessment from cabin crew
10	Deny person any more alcohol
11	Summary of what happened from person
12	Contact company to inform them
13	What facilities are available at airport C?
14	Contact company/ATC to organise police
15	Previous problem before boarding?
16	Speak to person or group leader in flight deck
17	Have a look from distance
18	Is he a large man?
19	Is he on medication?
20	Collect information: address etc.
21	Seat belt sign
22	Cabin crew are trained, get them to recruit ABP and monitor (delegate)
23	Does he have a return flight?
24	Which country are we dealing with?
25	Make a PA to back up purser and inform passengers
26	Have a talk and issue a warning to passenger

Neural Network Weights and Hidden Node Biases for study two: Air rage scenario.

Input	Hidden Node 1	Hidden Node 2	Hidden Node 3	Hidden Node 4	Hidden Node 5
Bias	-25.0	-31.9	9.56	-0.43	-0.15
1	115.5	0.38	6.44	1.33	-0.15
2	91.2	-4.43	-19.7	-0.43	-0.05
3	10.6	-12.7	-20.0	3.17	-0.14
4	49.8	0.17	6.64	1.31	-0.04
5	28.1	31.0	3.38	3.12	-0.08
6	116.8	-2.53	-1.60	1.17	0.01
7	-87.8	8.06	-3.96	0.54	-0.09
8	16.3	-4.02	-4.05	4.48	0.06
9	16.7	4.64	-9.13	-0.55	0.13
10	12.7	36.3	-2.45	0.77	-0.07
11	-39.2	-3.54	0.23	0.67	-0.02
12	-79.5	7.02	15.2	0.90	-0.12
13	-37.0	-8.70	-1.29	1.58	0.06
14	-36.5	-3.00	2.25	-5.24	0.02
15	73.9	24.4	-6.26	0.36	-0.14
16	-14.6	0.57	0.13	0.25	-0.10
17	96.1	17.0	-0.22	0.45	0.09
18	-54.1	-27.9	-1.01	0.42	0.06
19	59.4	33.5	-2.97	0.65	0.08
20	-66.4	-23.1	-2.98	1.26	0.10
21	112.3	-7.40	-0.02	0.41	0.14
22	47.4	7.21	6.36	1.63	-0.08
23	-81.3	5.62	-0.66	0.12	-0.02
24	2.99	-19.4	-15.7	-0.05	0.14
25	127.2	-18.0	-6.31	2.22	0.10
26	35.0	28.4	-6.91	4.23	0.13

Appendix P

Actual and Predicted outputs of cross validation set, NN analysis for study two: air rage scenario.

Actual and Predicted outputs of cross validation set, **NN**= Neural Network, **O1**=Outcome 1, **O2**= Outcome 2, **O3**= Outcome 3, **O4**= Outcome 4.

Case Number	Actual Value	Predicted Value	NN Value	Correct prediction?
1	1	1	O1= 0.91	✓
2	2	2	O2= 0.91	✓
3	1	4	O4= 0.91	✗
4	2	2	O2= 0.91	✓
5	4	1	O1= 0.91	✗
6	4	1	O1= 0.91	✗
7	2	2	O2= 0.92	✓
8	1	4	O4= 0.84	✗
9	2	2	O2= 0.92	✓
10	1	1	O1= 0.90	✓
11	3	4	O4= 0.80	✗
12	4	1	O1= 0.91	✗
13	1	1	O1= 0.90	✓
14	1	1	O1= 0.91	✓
15	2	4	O4= 0.91	✗
16	1	1	O1= 0.90	✓
17	4	4	O4= 0.91	✓
18	3	2	O2= 0.92	✗
19	4	4	O4= 0.91	✓
20	1	4	O4= 0.91	✗
21	1	4	O4= 0.91	✗
TOTAL				11