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THE DEVELOPMENT OF A BRIDGE NETWORK LIFECYCLE PREDICTION MODEL FOR THE IRISH NETWORK

by

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A Thesis submitted for the Degree of Doctor of Philosophy

to the University of Dublin, Trinity College

February 2013

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SUMMARY

The main aim of this thesis was the development of a bridge network condition prediction tool for the Irish network. This has been carried out with the intention of enabling the developed module to be incorporated into both new and existing BMS (Bridge Management Systems). EIRSPAN, the Irish BMS, will serve to provide the application data for the module, and since both EIRSPAN and the majority of BMS in existence worldwide, utilize a discrete condition state system to rank the structural health of their bridge stock, the research has focused on the application of Markov chain models in prediction systems - due to the ease with which the distinct condition states assigned to bridges during the visual inspection process lend themselves to the predefined states of condition needed for a Markov chain.

Different types of Markov process were investigated in the study in order to ascertain the most appropriate method for modelling and forecasting future bridge condition. In the course of the research, and following on from recommendations in the literature, it became evident that an appropriate optimisation algorithm for estimating the values of the defining variables in a Markov process was not in existence in the present systems. Consequently, Cross-Entropy, a well-known, robust algorithm previously unused in this field was investigated for its applicability and was found to be very suitable for probability estimation, due primarily to the fact that it does not tend to solutions on the bound constraints of the problem. In the process, this solver investigation involved the application of various objective functions in order to determine the most efficient optimization method and a minimization of the absolute value of predicted state distribution over time was found to be most accurate.

Ideally, future bridge prediction would be a function of past inspection data, however, at present, sufficient inspection records do not exist internationally for this to be the case. In the absence of such information, and considering also that such information can be misleading for many reasons such as (i) inspector variability, (ii) unobserved state transition sequences and (iii) irregular inspection intervals, a framework has been outlined in this thesis which enables the development of Markov transition probability matrices from analytical deterioration models for specific mechanisms.

For demonstration purposes, and since it is widely acknowledged as being a leading cause of bridge deterioration worldwide, chloride-induced corrosion has been chosen as the sample deterioration mechanism for consideration in this thesis. Hence this thesis essentially calibrates Markov transition probability matrices which describe the age-dependent process of chloride induced RC corrosion. However, this framework can easily be updated and modified to allow for the inclusion

and effect of other deterioration mechanisms such as carbonation, fatigue and freeze-thaw action etc. in the model. In the process of selecting suitable analytical models for the different degradation phases of chloride-induced corrosion, the models available in the literature were found lacking to varying degrees and hence a modified version of an earlier formula was proposed in this thesis for the time-to-first-crack phase of deterioration.

The prediction tool itself was designed with the Irish network in mind, with the idea that it could be modified to be suitable *'for all bridges in all locations'*. As a result, and in keeping with the intention of developing the tool in a state-of-the-art manner, the model was developed in an incremental, elemental level manner, with each element deteriorating according to pre-specified but adjustable parameter values. From an analysis of the EIRSPAN database, the effect of each bridge element on the overall structural rating was numerically evaluated using weighting coefficients which were derived from the data. This therefore means the methodology is sufficiently robust to allow for its adaptation to other countries and other types of bridges.

In keeping with the intention of developing a state-of-the-art system for the Irish national road network, Markov matrices were calibrated for both inland and coastal regions of Ireland with the input parameters to the analytical deterioration model of chloride-induced corrosion varied accordingly. These matrices were then applied to the relevant subsets of the Irish bridge stock to compute the expected network condition state over a period of 100 years.

Furthermore an extraction and data-cleaning procedure was also developed which enables the abstraction of data from the EIRSPAN database and which will thus ultimately allow the Markov transition matrices to be self-calibrating once sufficient inspection information becomes available. This process was then applied to the data available at present for demonstration purposes.

Finally the effect of maintenance and rehabilitation on the bridge network has been assessed with an investigation into the network effects on both the expected condition state, and the relative costs of alternative repair actions.

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CHAPTER 1 - INTRODUCTION

1 INTRODUCTION

1.1 BRIDGE MANAGEMENT SYSTEMS

As infrastructure, and bridges in particular age, environmental concerns and sustainability issues are of increased importance. Due to the current economic climate more emphasis has been placed on bridge rehabilitation than replacement. As a result of this bridge maintenance and management has become a major challenge. Many existing bridges were designed for less traffic and lighter loads than those to which they are now subjected. Combined with temporal deterioration processes related to an aging bridge stock and the general trend towards reduction in maintenance budgets, the optimal scheduling of bridge maintenance and management is of the utmost significance to the relevant authorities worldwide.

Bridge Management Systems (BMS) have been implemented in many countries worldwide to help deal with this problem in a definitive manner. These have been developed to varying extents depending on the country and system in question, but are in general quite advanced. Research is continually on-going in the area resulting in increasingly sophisticated models. Ireland however does not as yet have an optimisation routine for maintenance and repair in its BMS – EIRSPAN. Consequently this thesis outlines the initial development of such a prediction tool suitable for network-level modelling.

The developed methodology takes account of what has originated and been applied elsewhere, whilst also recognizing the shortcomings of some of these systems. Since BMS's consist primarily of both a deterioration model and a decision model, a thorough investigation and analysis of several optimisation algorithms and objective functions was undertaken in an effort to broaden the state-of the-art.

Inferences made through use of BMS should ideally be derived from real inspection data which would account for the trends and localisations present in each subset of bridge stock. Due to the fact though that most BMS only came into being in the early 1990's at the earliest, sufficient information does not exist as of yet to be utilised exclusively to calibrate these BMS. Accordingly deterioration models have been used in numerous applications in order to gain an understanding of structural degradation. However, many of those in operation in current BMS are empirically based or else are not representative of specific physical deterioration mechanisms. The developed network tool therefore has been calibrated to specifically allow for particular deterioration mechanisms, the rate of which can be altered as a function of age and environment. For application purposes chloride-induced corrosion has been chosen as the example mechanism on which to demonstrate the methodology. However, the framework can easily be modified to incorporate other

physical degradation mechanisms. Furthermore the developed network tool has been correlated on an incremental, element basis for the Irish network but could be adapted without difficulty to suit other forms of infrastructure, consisting of other sub-element types in different environments.

Essentially what has been outlined in this thesis then is a robust framework for an alternative network level management tool to those already in existence.

1.2 OBJECTIVES OF THESIS

This thesis details the development of a bridge network lifecycle management tool which could be incorporated into a BMS in an effort to rationally predict future bridge condition. This whole-life based management protocol was calibrated specifically for Irish conditions but is capable of considering bridges of all ages and exposure conditions in varying environments. It will be used to identify maintenance and repair requirements going forward, and will ultimately influence bridge management expenditure decisions on a network level, which will further improve how bridge management is carried out. In this regard three primary objectives were established at the outset of this work:

1. Initially the system methodology needs to be developed, that is the most appropriate manner of modeling future bridge condition given that the module needs to ideally be incorporated as part of a BMS.

2. The determination of how best to predict future structural condition, given that sufficient quantities of bridge inspection data are currently unavailable. Specifically this involves the integration of physically-based, analytical deterioration models into the prediction system.

3. Various additions to the developed module have been identified. These include implementing the tool on an elemental basis originally, before correlating the bridge element components and thereby obtaining a structural response and thereafter a network response. This will account for the effects of alternative environments and exposure conditions. Furthermore, the effects of alternative maintenance and repair on future network condition rating will also need to be considered.

1.3 ORGANISATION OF THESIS

This thesis is organized into eight chapters and three related appendices. Chapter 1 provides a general introduction to the problem and the objectives and scope of the current work.

Chapter 2 presents an overview and analysis of existing bridge management systems in use worldwide and the discrepancies between what has been theoretically proposed by researchers worldwide and what is actually implemented in the present systems. A framework for the proposed network prediction tool is also identified.

Chapter 3 details the development of the system methodology, specifically the most appropriate manner in which to be able to model and predict future bridge condition state in a BMS. This involves determining the most suitable optimization algorithm and objective function to be used in the optimization process.

Chapter 4 outlines the integration of mechanistic deterioration models into the developed module. Due to the absence of adequate quantities of inspection information, these have been investigated in order to make inferences regarding future bridge condition. For application of the methodology chloride-induced corrosion has been investigated in this chapter and various analytical models proposed to simulate lifetime behaviour. Lifecycle condition profiles are then obtained from these models for a sample 100 year period and Markov transition probability matrices calibrated off these for prediction purposes.

Chapter 5 presents a sensitivity analysis into the deterioration model outlined in Chapter 4 and calibrates the model from an Irish perspective with suitable parameter values. Furthermore, an analysis of the EIRSPAN database, the Irish bridge management system, has enabled the overall bridge condition rating to be expressed as a function of its minor elements. These have then been correlated accordingly. The state transition matrices are then calibrated from the lifecycle condition profiles of each bridge element.

Chapter 6 outlines the overall implementation and presents the results of the developed network prediction tool. The state transition matrices derived in Chapter 5 are applied to the relevant subsets of the Irish national bridge stock and future bridge and network condition rating built up on an incremental basis according to material, age and location. Additionally a procedure is outlined for eliciting the Markov state transition probabilities directly from the EIRSPAN database once sufficient information becomes available in the future. A framework for incorporating maintenance effects into the developed network prediction tool is also presented in this chapter. Different repair strategies and alternatives are looked at, i.e. that of repair only, rehabilitation only, or a combination of both strategies. Relative costs are also employed to act as a basis and means for comparison.

Finally a summary of the work undertaken throughout this research period is presented in Chapter 7. This is followed by a series of conclusions and recommendations for future work in the area of bridge management prediction tools.

An appendix of papers published is also included listing both journal and conference publications.

CHAPTER 2 – A REVIEW AND ANALYSIS OF CURRENT PRACTICE IN BRIDGE MANAGEMENT

2 A REVIEW AND ANALYSIS OF CURRENT PRACTICE IN BRIDGE MANAGEMENT

2.1 INTRODUCTION

As infrastructure, and bridges in particular age, and environmental concerns and sustainability issues come more and more to the fore, bridge maintenance and management has become a significant challenge. Many bridges were designed for less traffic and lighter loads than those to which they are now subjected. Combined with temporal deterioration processes associated with an aging bridge stock and the general trend towards reduction in maintenance budgets (O' Connor and Enevoldsen, 2008) the substantial problems faced by bridge management agencies worldwide become apparent. In the US for instance, the American Society for Civil Engineers (ASCE) published a report card in 2009 which stated that a $17 billion annual maintenance investment was needed to substantially improve bridge conditions but that only $10.5 billion was spent annually on both their construction and maintenance (ASCE 2009). Thus the need for efficiency in budgetary spend is paramount. The initial drive for bridge management came following the dramatic collapse of the Point Pleasant Bridge in the US in 1967, due to corrosion failure of a single eye-bar. It became evident from this that regular, intensive monitoring of bridge structures was necessary and so in 1968 The Federal Highway Act was passed. This ordered all states in the US to monitor and record the condition of their bridges according to the National Bridge Inspection Program. In 1991, the Intermodal Surface Transportation Efficiency Act (ISTEA) was passed, which stated that all states in the US must adopt a Bridge Management System (BMS) (Czepiel, 1995; Frangopol et al., 2001) Up until then, management authorities had been more concerned with the development of new structures as opposed to the upkeep of existing stock. Since then however, there has been a shift away from construction towards maintenance and rehabilitation and BMS have been adopted in many countries worldwide - e.g. Ireland, US, Japan, Switzerland, Denmark (Adey et al. 2010) to help with this objective.

''A Bridge Management System (BMS) is defined as a rational and systematic approach to organizing and carrying out all the activities related to managing a network of bridges'' (Scherer and Glagola, 1994). The guidelines accompanying the ISTEA act and the AASHTO guidelines for Bridge Management Systems both identify four distinct features of a BMS. These are (i) data archive (information from inspections), (ii) models for deterioration and cost analysis, (iii) optimisation of maintenance strategies and (iv) updating of models using new information (Czepiel, 1995). Essentially though, the three basic requirements of a BMS are (i) data storage, (ii) the prediction of the future state of structures and (iii) the prioritisation of maintenance and repair. The latter can be performed with respect to maximising or minimizing network condition state, but also, and particularly in the current economic climate, to achieving optimal network condition state

given certain budgetary constraints and considerations. In recent years, it has been of the utmost importance that limited fiscal resources are spent as economically as is inherently possible, hence much research has focused on further improving existing BMS in an effort to make them ever more efficient.

Since a primary objective of this research concentrated on the development of a bridge network condition prediction tool for the Irish network, it was necessary to first conduct a thorough literature review of the existing BMS systems in order to ascertain the current state of the art. This determines the current needs in relation to bridge management and so in this regard, the objectives for this thesis were outlined on the basis of recommendations obtained from a critical review of the literature, as well as suggestions from other practitioners.

2.2 REVIEW OF CURRENT SYSTEM BASIS

Quite a few studies have been conducted in recent years in an effort to provide owners and developers of BMS with an up-to-date view of the capabilities of the most advanced of these systems (Adey et al., 2010). This has been in an attempt to standardize and economise the relevant research areas. In short, it appears that the capabilities of these systems vary widely. In the report conducted by the 2010 IABMAS committee (Adey et al., 2010), 18 BMS from 15 different countries were considered. DISK, the Dutch system appears to be the oldest of those surveyed, with the first version dating from 1985. APTBMS in Italy dates from 2004, SGP in Spain dates from 2005 and the initial version of RPIBMS in Japan was only released in 2006. Within this though, numerous variations amongst the systems occur and not all are developed to the same standard or are in as wide usage. PONTIS for instance, the primary US system is licensed in over 40 states (Golabi and Shepard, 1997) and is the only system to be employed outside of its home country (Adey et al., 2010).

In general, the systems differ in terms of (i) how many structures are incorporated into them – RPIBMS in Japan only has 750 structures at present, while at the other end of the scale PONTIS has over 500,000, (ii) the types of structures considered, (iii) how often the structures are surveyed and what type of inspection is carried out, (iv) the condition rating system utilised – Canada and Finland only use a 4 state system while Spain has 100 states accounted for, (v) the predictive powers of the systems – whether or not they allow for future state prediction based on either empirical data or deterioration models and (vi) whether or not they allow for life-cycle management of maintenance and repair decisions. However, one note-worthy point to be made is that in all systems, regardless of the level of complexity, the success of its implementation is down to those that work with it. If for instance, the system is overly complex, it will dissuade the

respective authorities from using it. Likewise, the more elaborate the condition rating and defect scale is, the more room for inspection error there ultimately is.

Bridge Management systems themselves can be loosely categorised into two groups, (i) Markovian based and (ii) Reliability based. Both are powerful tools for whole-life optimisation of infrastructural networks and as such much research has been conducted in both fields. For the purposes of this literature review thus, the systems shall be discussed on the grounds of (i) which basis they are from, (ii) the predictive powers/modelling capabilities present and (iii) the extent to which maintenance actions can be incorporated and accounted for in the respective systems.

It must be remembered however, that a discrepancy exists at present between much of the theoretical research work which has been carried out in universities and transport laboratories worldwide, and that which is actually in practice in these BMS.

2.2.1 Markov Systems

Markovian based systems have been used extensively in the field of infrastructure management to provide forecasts of facility condition and thus enable the relevant authorities to optimize maintenance and repair decisions over time. Adey et al. (2003) and Baik et al. (2006) have shown their applicability in terms of pipe-networks. Added to this they have been used quite often in the field of pavement management (Carnahan et al. 1987; Kobayashi et al. 2010) and are used in practice as part of existing Bridge Management Systems (BMSs) such as PONTIS and BRIDGIT (Czepiel, 1995; Frangopol et al., 2001). Their popularity lies in their ability to capture the time-dependence and uncertainty of the deterioration process in addition to their computational efficiency and reliability, especially at network level.

The Markov process itself is a stochastic one and is governed by a number of restrictions. Namely that the process is discrete in time, has a finite state space and thirdly that it satisfies the 'Markov property' (Isaacson and Madsen 1976). This Markovian property states that the probability of an event occurring (i.e. moving condition state) is independent of past states, and only depends on the action applied to it and the state it is in at that point in question (Ang and Tang 1984; Cesare et al. 1992; Adey et al. 2003). Many questions have been asked regarding the applicability of this property in the literature, i.e. whether or not it is invalid to claim that the future state is independent of its past history. Many researchers just take the property to be a given (Jiang et al., 1988; Ortiz-Garcia et al., 2006; Roelfstra et al., 2004), but both Scherer and Glagola (1994) and Yang et al. (2009) conclude that frequency analysis of past condition-rating databases suggests that the property does indeed hold for over half the cases under consideration. Given access to the IQOA scoring system of the French National Road network, Orcesi and Cremona (2011) also found there

to be a relative independence from past states. Hence the use of a Markovian based protocol is deemed appropriate.

Mathematically the process is represented as:

$$P(t) = P_0 \times P^t \qquad \textbf{Equation 2.1}$$

Where $P(t)$ = Probability distribution of condition at time t, P_0 = Initial probability distribution of condition, P = transition probability matrix, the general form of which is given as:

$$\begin{matrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{matrix} \qquad \textbf{Equation 2.2}$$

Where (i) For each i, i=1:n, $\sum_{j=1}^{n} p_{ij} = 1$ and (ii) all matrix entries must be positive.

For Markovian deteriorating systems, and particularly for bridge management systems where limited condition rating scales are in operation, it is common practice to assume that the structure or element deteriorates by at most, one condition state per year (Cesare et al., 1992; Jiang et al., 1988). For instance, Figure 2.1 depicts the Markov Transition Probability Matrix as defined in Jiang et al. (1988), where $q(t) = 1\text{-}p(t)$.Note that a condition state here represents both the discrete states needed for a Markov process but also the condition ratings assigned to a bridge upon inspection – see for example Table 2.2 and Table 2.3 in the next section.

$$P = \begin{vmatrix} p(1) & q(1) & 0 & 0 & 0 & 0 & 0 \\ 0 & p(2) & q(2) & 0 & 0 & 0 & 0 \\ 0 & 0 & p(3) & q(3) & 0 & 0 & 0 \\ 0 & 0 & 0 & p(4) & q(4) & 0 & 0 \\ 0 & 0 & 0 & 0 & p(5) & q(5) & 0 \\ 0 & 0 & 0 & 0 & 0 & p(6) & q(6) \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{vmatrix}$$

Figure 2.1: Transition Matrix whereby the element is only allowed to deteriorate one state at a time and where maintenance and repair are not considered.

Here, the last state, State 7, is taken as being an 'absorbing state', since in the absence of maintenance actions, no further state change is permitted.

Many researchers take either the bridge as a whole when considering the effect of deterioration (Jiang et al., 1988), or else just consider one element such as the bridge deck (DeStefano and Grivas, 1998; Morcous, 2006; Orcesi and Cremona, 2011). Cesare et al. (1992) however developed transition matrices for the individual components of a bridge. Using these transition matrices, both the expected condition rating for an individual structure and an average condition rating for a network of structures was computed. Correlated components within a bridge were also considered taking the example of a bridge primary structure being dependant on the condition of the deck joints. If elements within a bridge were correlated, a non-stationary Markov transition matrix was used, i.e. the variables within the matrix - the p terms in Figure 2.1, are time dependant on the state of other variables. Considering the actual BMS in operation at present, both OBMS, the Ontario system and MPS, the Quebec system, employ element level Markov transition matrices and actually allow for the correlation of structural components. However, this feature is unused as the simpler models appear to be working quite well on a network level.

Markov chains can themselves be defined as both stationary and non-stationary (as utilised in Cesare et al. (1992)). Stationary means the process is stable or homogeneous in time. That is it does not change with respect to time and the probability of going from one state to another is independent of the time at which the step is being performed. For instance if the deterioration of a particular structure or group of structures is considered to be stationary, it is assumed that it will always deteriorate following the prescribed transition probabilities of one single transition matrix. In mathematical terms, the initial state vector P_0 as shown in Equation 2.1 will remain the same for all t. Conversely, non-stationary chains change with respect to time. So if the pattern of deterioration is expected to change at a certain point in time t, the deterioration process would be more accurately modelled by the use of a non-stationary chain. This implies the use of a different transition matrix before and after t. In this case the vector of probability distribution of condition at time t will become the starting vector of condition for the second chain, which will then proceed with a different transition matrix. For n groups, there are n transition probability matrices P and n initial probability distributions P_0. This is depicted in Equation 2.3.

$$P(n,t_n) = P_0(n) * P(n)^{t_n}$$

Equation 2.3

Homogenous chains are commonly used in the literature (Carnahan et al., 1987; Lounis and Madanat, 2002; Morcous, 2006; Morcous et al., 2003; Orcesi and Cremona, 2011) as well as in practice in bridge management systems such as PONTIS (Fu and Devaraj, 2011). However since non-homogeneous chains capture much more variability and allow for the incorporation of age-dependence by having a different matrix represent a different age-bracket, recent studies have looked at developing BMS using these instead. Ortiz-Garcia et al. (2006) briefly compared the efficiency of both types of process by taking a 20-year period and considering it to be comprised of

two 10-year periods, with a transition matrix devised for each period. This apparently allowed the study of stationary chains when observing the behavior between years 0 and 10, and at the same time, the study of a non-stationary chain when observing the whole analysis period. Fu and Devaraj (2011) utilized non-homogeneous chains as a means of allowing for age-dependence by grouping their structures in 20-year brackets and obtaining different transition matrices accordingly. They attempted to evaluate the effectiveness of the method by predicting the elements immediate future distribution at the network level based on one year of inspection data, i.e. 2002. This predicted distribution was compared with the measured distribution vector using the inspection data from 2004. Largely, as expected it was found that the proposed, non-homogeneous approach produced smaller errors, mainly due to the higher modeling resolution using several transition probability matrices for the entire lifespan of the element. However, in only comparing both methods over a single time-step from 2002 to 2004, it has to be concluded that a more thorough study considering the relative benefits of non-homogeneous chains is necessary. This therefore is recognized as a gap in the current literature and will be addressed as part of this thesis.

Two types of models have been used for infrastructure facility deterioration prediction: state-based models and time-based models. State-based systems predict the probability that a facility will undergo a change in condition-state at a given time, depending on certain explanatory variables such as location, age, environment and so forth. Markov processes are an example of such a state-based system. However a certain shift away from these 'state-based' models has occurred in recent years and 'time-based' hazard and survival models have become more popular (Mauch and Madanat, 2001; Mishalani and Madanat, 2002). These model the system in continuous time and it is the time between the transitions of state which is treated as the random variable and called the "holding time'' (Ng, 1996). In effect, it is possible to use one modelling approach to predict the dependent variables of another. For example, given a set of condition-state transition probabilities, one can derive the probability distribution of the time to condition-state change. Likewise, given a distribution of time-in-state, it is possible to compute time-dependent transition probabilities. As stated in both Mauch and Madanat (2001) and Mishalani & Madanat (2002) though, there are limits to the accuracy that can be achieved with time-based modelling techniques in the absence of large amounts of continuous monitoring data over a significant period of time (greater than twenty years). Specifically, Mauch and Madanat (2001) point out that a major problem exists as a result of censored data. That is to say, suppose one has a new bridge deck, and 2 years later at the next inspection (which is the recommended inspection interval in the US but can be longer elsewhere), the inspection team notice that the deck has deteriorated to a lower condition state. Here, all one can conclude is that it stayed in the initial state for less than 2 years. Similarly, if the deck drops two or more states (however negligible the chances) between consecutive inspections, one cannot tell how long it was in the middle state. Furthermore, if a bridge is in a given state at the end of the survey period, all one can say is that the time-in-current state started with the transition into the

current state and that the bridge deck was still in that same condition state when the observation period ended. Thus, the time-in-state was known up to some point, but one does not know how long the bridge remained in that same state after the termination of the data collection.

For this reason then, since many developed countries do not have enough data to make such a time-based approach economically feasible, this thesis focuses on using a state-based method as a means of estimating suitable infrastructural transition probabilities for bridge deterioration.

2.2.2 Different Methods for estimating Transition Probabilities

Traditionally Markov transition probability matrices have been populated by one of two methods – either that of expert judgement or percentage prediction. The latter is also referred to as the 'discrete cohort method' and has been equally applied to financial situations (Deng et al., 2004; Zhang et al., 2010). Many BMS in existence at present such as APTBMS (Italy) utilise this procedure for estimating the required transition probabilities. The method assumes that the raw data is available, in this case, the historic bridge condition ratings, and thus the estimate for P_{ij} is given by:

$$p_{ij} = \frac{n_{ij}}{n_i} \qquad \textbf{Equation 2.4}$$

where n_{ij} is the total number of observed transitions between states i and j per time period and n_i is the total number of bridges that started the year in condition state i. The proportions though will vary from year to year, thereby requiring an average to be determined in order to ensure accuracy in the model.

Other methods which have been investigated include ordered probit models (Madanat et al., 1995), Poisson regression (Madanat and Wan Ibrahim, 1995) and non-linear minimization (Baik et al., 2006; Butt et al., 1987; Feighan et al., 1988; Jiang et al., 1988; Morcous, 2006).

The non-linear minimization approach of 'Expected Value' was the first and by far the most common technique found in the literature for estimating matrices for bridge and pavement management systems. The method is a minimization of the sum of absolute differences in expected value between the regression curve that best fits the condition data and the conditions predicted using the Markov-chain model. For instance, as seen in Jiang et al.(1988):

$$\text{Minimize: } \sum_{t=1}^{N} |S(t) - E[\mathrm{X}(t)]| \qquad \textbf{Equation 2.5}$$

subject to:

$$\sum_{j=1}^{n} p_{ij} = 1 \quad , \; 0 \leq p_{ij} \leq 1 for \; i = 1,2,..n$$

where N = total number of transition periods; $S(t)$ = facility condition at transition period t based on a regression curve; $E[X(t)]$ = expected value of facility condition at transition period t based on Markov chains and n = the number of condition states.

An ordered probit technique was then applied by Madanat et al. (1995). This methodology was specifically developed for situations where the dependent variable is ordinal, such as condition ratings. It assumes the existence of an underlying continuous unobservable random variable and therefore allows for capturing the latent nature of infrastructure performance. The dependent variable is the difference between the condition states of the facility observed in two consecutive inspections. For every condition state, a different incremental deterioration model was developed because each drop in condition state is a realization of different mechanistic deterioration processes. Since it explicitly linked deterioration to relevant explanatory variables such as climatic region, ADT (average daily traffic), number of spans etc, the methodology was deemed more accurate than the 'Expected Value' approach outlined in Equation 2.5, which was the state-of-the-art at the time.

Similarly, Poisson regression was applied by Madanat and Wan Ibrahim (1995) as a means of obtaining the transition probabilities. Again the dependent variable is the number of drops in condition state. As a benefit of the method the authors state that contrary to linear regression, Poisson regression explicitly recognizes the discrete nature of the dependent variable, as opposed to linear regression. To validate the approach a chi-square test of statistical significance was performed on the obtained transition probabilities and the observed frequencies in a dataset from the Indiana State Bridge Inventory database.

Given however that the two methods outlined above require a great amount of data to be properly calibrated, a non-linear minimization approach is deemed to be more appropriate for the purposes of practical application. Another performance function which has been demonstrated in the literature is based on a minimisation of the expected probability distribution of condition rating at time t as computed by a Markov process versus the actual probability distribution of condition rating as defined in the database. An example of such an objective function was employed by Cesare et al. (1992), as shown in Equation 2.6. This approach also weights each term in the total error by the number of bridges of age n.

$$\min \sum_{i=1}^{x} \sum_{n=1}^{N} (f_{i,n} - P_0 T^n)_i^2 C(n) \qquad \textbf{Equation 2.6}$$

where $C(n)$ = the number of bridges of age n; P_0 = the initial state vector; $f_{i,n}$ = the relative frequency of bridges in state i at age n; T_n = transition probability matrix

A similar performance function can also be seen in Ortiz-Garcia et al. (2006) and is represented as follows:

$$\sum_{t=1}^{N} \sum_{n=0}^{n} | A(t) - A'(t) | \qquad \textbf{Equation 2.7}$$

where $A(t)$ = the probability distribution of condition rating as defined in the database and $A'(t)$ = the probability distribution of condition rating as computed by the Markov process.

Note that some researchers have performed a minimization of the absolute value of the objective function (Jiang et al., 1988; Ortiz-Garcia et al., 2006), while others have utilized a least squares method (Cesare et al., 1992). Hence, as well as ascertaining whether Equation 2.6 or Equation 2.7 is more appropriate in the context of bridge management, another objective of this thesis is to investigate whether a least squares or an absolute value minimization approach is more suitable.

As an example of how the methods in existing BMS differ to those developed or investigated by researchers, both PONTIS and the Canadian MPS system use linear algebra as opposed to any of the methods mentioned above to obtain the required transition probabilities. Firstly, a regression data set is prepared by extracting from the inspection history of an inventory all inspections of a particular element type over all bridges. Each inspection is paired with another inspection two years later on the same bridge, if such an inspection exists. Each pair then is represented by two vectors:

Conditions at the beginning of the period [X] =

$$\{x_1, x_2, \ldots, x_N\}, \sum_{i=1}^{N} x_i = 1 \qquad \textbf{Equation 2.8}$$

Conditions at the beginning of the period [Y] =

$$\{y_1, y_2, \ldots, y_N\}, \sum_{i=1}^{N} y_i = 1 \qquad \textbf{Equation 2.9}$$

Where N is the number of condition states i defined for the element, and x_i and y_i are fractions found in each condition state. These are the known values in the estimation equation. In the same notation the prediction equation for any one inspection pair is:

$$[Y] = [P][X] \qquad \textbf{Equation 2.10}$$

where [P] is the transition probability matrix. From linear algebra, the unknown transition probabilities can be estimated as follows:

Estimated transition probability matrix $[\overline{P}] = [XX]^{-1}[XY]$ **Equation 2.11**

Matrix of XX sums [XX] = $\sum_i x_j^i x_k^i$ for all combinations of j and k

Matrix of XY sums [XY] = $\sum_i x_j^i y_k^i$ for all combinations of j and k

where i is an index over all the inspection pairs in the dataset. The matrices [XX] and [XY] are both square and of the same size as the transition probability matrix. However as pointed out in both Fu and Devaraj (2011) and Thompson et al. (2010), this regression procedure does not necessarily distribute its error terms in a manner that gives rows summing evenly to 1.0. Furthermore, negative and larger than unity transition probabilities are also possible. Hence, the methods in practice could benefit from incorporating techniques such as those outlined in the research papers mentioned above.

Note that the methods reviewed above are all state-based in light of the fact that time-based methods have been deemed inappropriate for infrastructure management given the nature of the inspection data (Kallen and Van Noortwijk, 2006).

Differences also exist in the literature regarding the solvers and optimization algorithms used to estimate these transition probabilities mathematically. Given that combinatorial optimisation is by nature a complex and computationally intensive problem, generally requiring the exploration of large, multidimensional search spaces in order to obtain a solution, the accuracy of the mathematical solver is especially important and so many have been investigated heretofore. Carnahan et al. (1987) used a descent method (Fletcher and Powell, 1963), Jiang et al. (1988) used the gradient projection method, Farran and Zayed (2012) and Hegazy et al. (2004) used a Genetic Algorithm approach, and Costello et al. (2011) and Ortiz-Garcia et al. (2006) employed the use of another non-linear algorithm; the GRG2 code incorporated into the solver program in EXCEL in

their study. However the latter two both conclude that since non-linear solvers lack the guarantee of finding a global optimum, a more robust method ought to be investigated. For this reason, this has been identified as another objective of this thesis.

Concerning the BMS in operation, little information is given in the literature regarding the actual solvers employed. Many systems in fact do not have need for one as yet given that they do not estimate their transition probabilities mathematically. However, whilst the discrepancies in the PONTIS system are most likely due to the method in which the probabilities are obtained (Fu and Devaraj, 2011), more accurate, robust solvers and algorithms are also certainly needed.

2.2.3 Reliability-Based Systems

Reliability based methods of optimizing the maintenance and repair interventions of infrastructure began in the 1990's. Thoft-Christensen (1995) first proposed to apply reliability theory in bridge management systems and both Frangopol and Das (1999) and Thoft-Christensen (1999) then defined bridge reliability states and proposed a reliability-based approach to bridge management.

Reliability methods are used to take into account the uncertainty associated with deterioration, inspections and repair and by quantifying this uncertainty, decisions on repair optimization can be taken with greater confidence (Estes and Frangopol, 2001). The reliability index, β, is used as a measure of bridge safety (Ghosn and Frangopol, 1999) where the service life of a bridge is a progression of reliability states – i.e. $\beta \geq 9$ = excellent, $8 \leq \beta < 9$ = very good etc. Figure 2.2 represents such a reliability profile in the absence of maintenance actions, where the individual structure can be seen to progress through a continuous scale of reliability index with time. Note that the reliability index here is time-dependent and therefore is a function of the time period in consideration and the slope of the deterioration line, i.e. the degradation occurred. Figure 2.3 then depicts a typical whole-life bridge performance profile as affected by both essential and preventive maintenance.

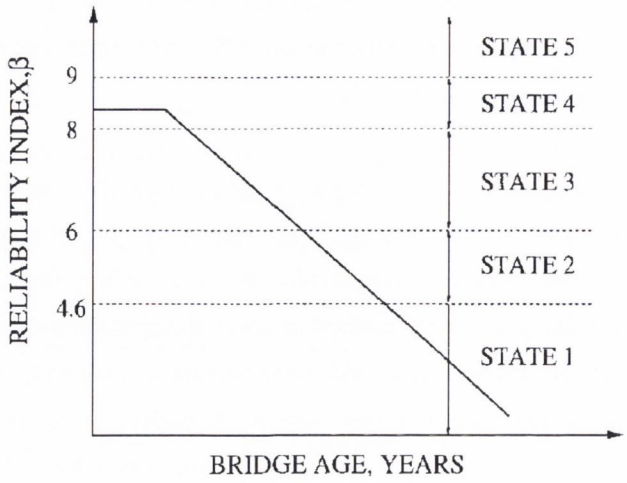


Figure 2.2: Bridge Reliability Profile without Maintenance (Frangopol et al., 2001).

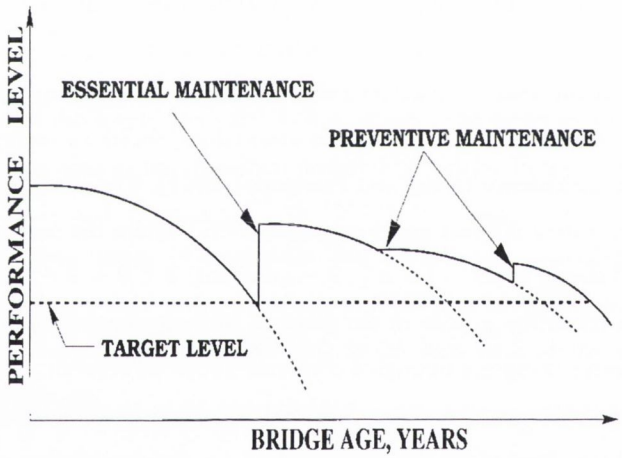


Figure 2.3: Whole-life Bridge Performance Profile as Affected by Essential and Preventive Maintenance (Frangopol et al., 2001).

However, as encompassing as a reliability-based approach is, Lounis and Madanat (2002) claim they are more appropriate for project level, as opposed to network level management due to the fact that the use of detailed mechanistic models for every structure in a network of bridges would be unmanageable in terms of both time and money.

Instead, they propose a case for formulating the bridge maintenance problem as a two-level decision, the level-1 management being based on Markovian cumulative damage models and the level-2 management based on quantitative reliability-based mechanistic deterioration models which predict the micro-response of bridge structures in terms of load-effect, resistance, cracking,

deflection etc. The level-1 management identifies the critical structures and forecasts the overall deterioration and required maintenance funds for both short and long term planning for a network or bridge component. The level-2 management then focuses in on the critical structures and attempts to evaluate their safety and serviceability levels.

Concerning the BMS in operation at present, Denmark (Lauridsen et al., 2008) have already developed guidelines for the probabilistic assessment of deteriorated bridges (DRD, 2006) and reliability based procedures, but these are supplemental to their BMS, DANBRO, which is Markovian-based. Likewise Germany is looking into incorporating a reliability-based approach into their existing systems in an effort to make them more efficient, but again this will be on an elemental, structure specific basis (Holst, 2010).

Hence, since this thesis focuses primarily on network-level management, the remainder of this thesis shall deal with Markovian based protocol.

2.3 DETERIORATION MODELLING WITHIN CURRENT BMS

Although many countries now utilize BMS to help them manage their infrastructure, much variation exists between systems concerning the predictive powers and deterioration models within. In order to be able to predict future condition state, a BMS must consist of both a degradation model and a decision model, as represented in Figure 2.4.

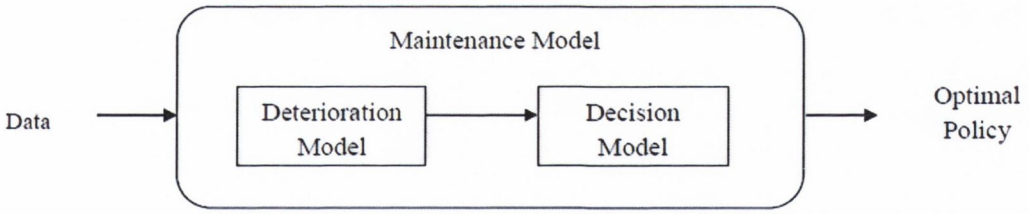


Figure 2.4: Simple representation of the two basic elements of a maintenance model.

Therefore, in order for the predictions to be as accurate as possible, the deterioration models must be quite well-developed. According to a report carried out by the 2010 IABMAS Bridge Management Committee, of the 18 systems surveyed, 9 can predict deterioration and five of these use probabilistic methods. These countries are as listed in Table 2.1.

	Country	Name	Deterioration				Improvement				Cost	
			Yes	Yes		No	Yes	Yes		No	Yes	No
				Prob.	Det.			Prob.	Det.			
1	Canada	OBMS	1	1			1	1			1	
2	Canada	QBMS	1	1			1	1			1	
3	Denmark	DANBRO				1				1	1	
4	Finland	FBMS	1								1	
5	Germany	GBMS	1								1	
6	Ireland	Eirspan				1				1		1
7	Italy	APTBMS	1	1			1	1			1	
8	Japan	RPIBMS	1									1
9	Korea	KRBMS				1				1		1
10	Latvia	Lat Brutus				1				1		1
11	Netherlands	DISK				1				1	1	
12	Poland	SMOK				1				1	1	
13	Poland	SZOK				1				1	1	
14	Spain	SGP				1				1		1
15	Sweden	BaTMan	1		1		1		1		1	
16	Switzerland	KUBA	1	1			1	1			1	
17	USA	ABMS				1				1	1	
18	USA	Pontis	1	1			1	1			1	
Total			9	5	1	9	6	5	1	9	13	5

Table 2.1: Predictive capabilities of BMS worldwide.

As can be seen, only half of the countries consider deterioration in their systems. Amongst these systems then, discrepancies exist as to how the transition probabilities are obtained. APT-BMS in Italy for instance uses the percentage prediction method from historical data described above in Equation 2.4. Rating curves can then be developed from this data and used to estimate future bridge condition. As soon as new inspection information becomes available, the transition probabilities can be updated using a Bayesian updating procedure. However, as stated in both Thompson and Johnson (2005) and Crespi et al. (2010), the development of models in this manner presents numerous problems. Firstly, it is important to remember when using actual databases that undocumented maintenance may have been performed. Secondly, variability can exist in the assessor's judgement of a defect so that even in the absence of a maintaining action, an element can be found to improve condition state between inspections. Crespi et al. (2010) state that in their experience, the results obtained from inspection data registered on the PONTIS database for the years 2002 to 2008 have been shown to be completely inappropriate for evaluating the deterioration on a medium to long term basis as they forecasted median years to failure of hundreds of years.

Clearly, if inspection information is to be used, a rigorous data-cleaning process has to ensue. Zonta et al. (2007) have also recognized this fact stating that despite the great effort spent in theoretical research developing APT-BMS, the Italian system into a state-of the-art system, proper validation of the work and calibration of the models through extensive experimental observations and data-mining is necessary. Since part of this thesis will involve working with the Irish EIRSPAN database, the data involved will have to be thoroughly checked for anomalies and so a data-cleaning and error checking process will need to be developed.

Note also that when using real data, or using real data to develop statistical models and postulate future outcomes and expected structural state, that the condition-state rating scales used in many BMS are non-equidistant (Kallen, 2007). This means that different physical damage processes may lead to the same condition state and that more importantly; the duration of time spent in each condition state is not linear or even comparable. Table 2.2 outlines the 10 bridge condition states as outlined according to the Federal Highway Administration (FHwA) in the US. It can be seen that the description of the definition and discrepancy between various condition states is not particularly clear-cut and allows for much ambiguity to arise. This non-linearity is even worse with a six state system such as EIRSPAN, the Irish system, the rating scale of which can be seen in Table 2.3. For further clarity, photographs of example condition scales are also depicted below in Figure 2.5 to Figure 2.10.

NBI Rating	State	Description
9	Excellent	
8	Very good	No problems noted.
7	Good	Some minor problems.
6	Satisfactory	Structural elements show some minor deterioration.
5	Fair	All primary structural elements are sound; may have minor section loss, deterioration, spalling or scour.
4	Poor	Advanced section loss, deterioration, spalling or scour.
3	Serious	Loss of section, deterioration, spalling or scour have seriously affected primary structural components. Local failures are possible. Fatigue cracks in steel or shear cracks in concrete may be present or scour may have removed substructure support.
2	Critical	Advanced deterioration of primary structural elements. Fatigue cracks in steel or shear cracks in concrete may be present or scour may have removed substructure support.
1	Imminent failure	Major deterioration or section loss present in critical structural components or obvious vertical or horizontal movement affecting structural stability.
0	Failed	Beyond corrective action, out of service.

Table 2.2: National US Bridge Inventory Condition Ratings as defined in FHwA (1995).

Condition State	Description
0	No or insignificant damage.
1	Minor damage but no need of repair.
2	Some damage, repair needed when convenient. Component is still functioning as originally designed. Observe the condition development.
3	Significant damage, repair needed very soon. i.e. within next financial year
4	Damage is critical and it is necessary to execute repair works at once, or to carry out a detailed inspection to determine whether any rehabilitation works are required.
5	Ultimate damage. The component has failed or is in danger of total failure, possibly affecting the safety of traffic. It is necessary to implement emergency temporary repair work immediately or rehabilitation work without delay after the introduction of load limitation measures.

Table 2.3: Condition States as defined in EIRSPAN System manual No.3 (NRA, 2008).

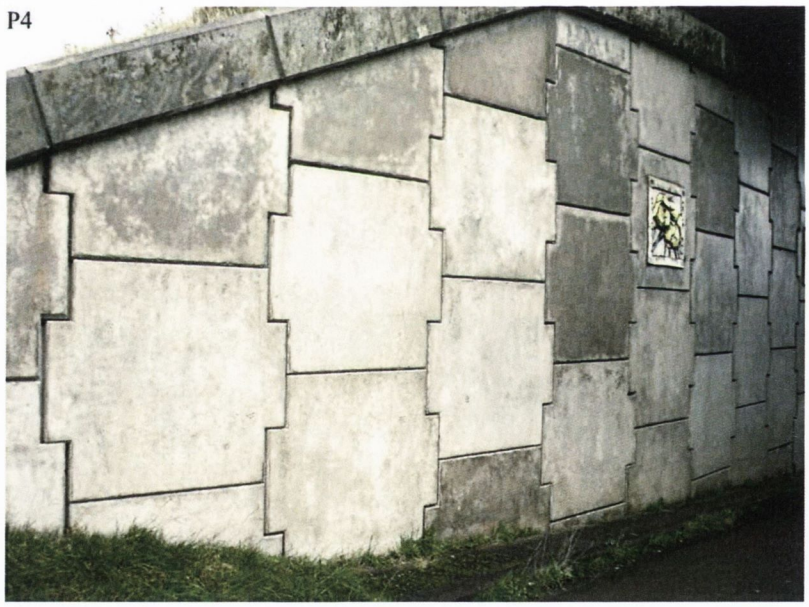


Figure 2.5: Example of Condition Rating 0 – Wingwalls.

Figure 2.6: Example of Condition Rating 1 – Bearings.

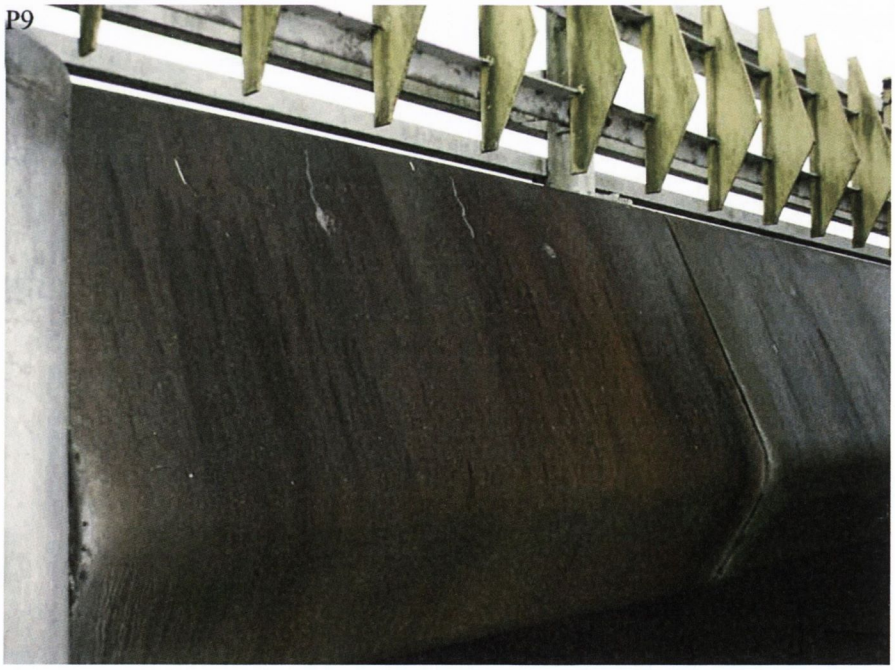


Figure 2.7: Example of Condition Rating 2 – Deck.

Figure 2.8: Example of Condition Rating 3 – Deck.

Figure 2.9: Example of Condition Rating 4 – Deck.

Figure 2.10: Example of Condition Rating 5 – Deck.

Aside from using real-time database information, other systems such as PONTIS and OBMS also have an 'expert elicitation' method whereby the transition probabilities are calculated according to expert opinion. Again though, both Thompson and Johnson (2005) and Crespi et al. (2010) maintain that expert-calibrated models should not be used since they overestimate the time to failure. Thompson and Sobanjo (2010) attempted to verify this viewpoint by comparing the average response of a panel of experts to historical transition times and found that typically, the historical transition times were 1.9 times that which the expert panelists thought.

PONTIS allows for either procedure to be used but Fu and Devaraj (2011) found that upon surveying US transportation agencies, 57% of PONTIS users employ a combination of historic data and expert elicitation for estimating the transition probabilities, with 30% using elicitation only – the rest either did not respond or have not yet reached this level of implementation.

Given that each of the common procedures outlined above are deemed to be unsuitable, it is clear that deterioration models need to be developed to help transportation officials manage their infrastructure. These models can be either statistical or physical. Statistical meaning that the data is generated by a mathematical model which does not try to emulate reality. Most commonly, this will be a probabilistic model which is fitted to inspection data by means of statistical estimation such as maximum likelihood estimation. An example of such an approach is the use of lifetime distributions fitted to lifetimes of bridges as carried out by van Noortwijk and Klatter (2004), where a Weibull type distribution was fitted to the ages of both existing and demolished bridges in the

Netherlands. Thompson and Sobanjo (2010) have also incorporated Weibull survival models into the PONTIS deterioration models in order to specifically allow for the fact that the existing Markovian models in the system have fairly rapid initial deterioration (Thompson and Johnson, 2005) which tends to make the predictions less realistic. Likewise Madanat and Wan Ibrahim (1995) employ the use of a Poisson process to categorize and predict future bridge structural condition rating. However this means that since the Markov transition probabilities are essentially estimated to fit the parameters of the model, the deterioration pattern is inherently influenced before it is observed. Instead, if a physically based model is used as the model basis, the Markov transition probabilities should model the actual expected deterioration pattern, rather than a predefined statistical one. Hence many physically based models have been implemented already in the literature. Since it is a chief cause of structural degradation worldwide, some of these will be outlined for chloride-induced deterioration of reinforced concrete in the next section.

2.3.1 Reinforced Concrete Deterioration Modelling

The vast majority of the world's bridges nowadays are constructed in either reinforced or prestressed concrete, thus chloride-induced corrosion due to either the presence of deicing salts or a saline environment is the predominant bridge deterioration mechanism. Tilly (2007) states the mechanism is responsible for more than 55% of concrete repairs across Europe and Bhide et al. (1999) report that about 173,000 bridges in the US are structurally deficient or functionally obsolete due in part to corrosion. Consequently, since it is the predominant deterioration mechanism, chloride-induced corrosion has been chosen as the example degradation model under which to model the response of a network of bridges in this thesis. It is recognized that many other deterioration mechanisms and modes of failure exist, but nevertheless the developed methodology remains the same, regardless of the failure mechanism in question. As expected, much research has been undertaken already in this field in an attempt to develop appropriate deterioration models to help infrastructure officials make informed, cost-effective decisions concerning the time to repair, rehabilitate or replace debilitated structures.

Many models, both empirical and statistical have been developed in the field of chloride-induced corrosion modelling for the purposes of predicting the time to corrosion initiation, time to first crack and the crack propagation phases (Al-Harthy and Stewart, 2006; El Maaddawy and Soudki, 2007; Mullard and Stewart, 2010). Reports have also been compiled over the last number of years concerning the various structural degradation models which should or could be applied to infrastructure management (BRIME, 2001; COST, 2011; Vesikari 2003). Many of these models however are empirically based and as stated in the COST Report, a practical problem with models such as those in the Duracrete (2000) and BRIME (2001) reports is that they call for testing of concrete, for example the model of chloride penetration calls for testing of the chloride migration

coefficient. The models outlined in these reports also require many input variables and as such are unsuitable for use on a network level prediction basis.

Roelfstra et al. (2004) were among the first to consider using physical deterioration models in the context of network level infrastructure management by modelling mathematically the process of chloride-induced corrosion. Numerical simulations were mapped to predefined condition states (as outlined in Table 2.4) within KUBA-MS, the Swiss system and the Markov transition matrices were calibrated off these simulation results. These Markov chain generated deterioration curves were then compared to those obtained from directly modeling the deterioration phenomenon and it was found that the shape of the curves significantly differed. This is claimed to be as a result of the Markov chain not considering the initiation time and thus propagating this difference onto the curves between the other condition states. However, a solitary homogeneous deterioration matrix is used over the 200 year planning period. Furthermore, the paper states that the least-squares method was used to determine the optimum fit for condition vectors at 100, 150 and 200 years, thereby implying that the overall time-period was not taken into consideration. Consequently this has been identified as another objective, i.e. ascertaining if using non-homogenous chains and minimizing over a continuous time-period improves the method described.

Transition	Condition State
CS 1	< 0.2% free Cl^-/mass of cement
CS 2	< 50μm of reinforcement radius loss
CS 3	< 10% of reinforcement section loss
CS 4	< 25% of reinforcement section loss
CS 5	>25% of reinforcement section loss

Table 2.4: Condition State Criteria Mapped to KUBA-MS Definitions (Roelfstra et al., 2004).

Crespi et al. (2010) also used physical deterioration models for the purposes of predicting the future bridge condition state of structures on the Italian highways. Carbonation-induced corrosion was the method under investigation and the results were compared to those obtained from both expert elicitation and historical databases. However, the transition matrices were not calibrated and as such the model has not been sufficiently modified to allow its incorporation into a BMS.

Concerning the BMS in use at the present time, Finland appears to be by far the most technologically advanced. Consisting of both a probabilistic Markovian network model and a deterministic model for individual projects, the main degradation models it considers are that of freeze-thaw weathering of concrete and reinforcement corrosion (Soderqvist, 1999). Like all BMS, the system initially had no data and so age-behaviour models for use in the deterioration prediction module were calibrated based on expert opinion. Like other systems such as PONTIS and

Bauwerk, the German system, these models can be updated when new bridge inspections are carried out and further information obtained – every 4 to 8 years depending on the condition state of the structure. However, the system is unique in that it has developed a reference set of approximately 120 bridges which are inspected every 6 months. This reference set has been specially selected to take account of bridges of varying structural form and age in different locations. Empirical and experimental data from these reference bridges is then used to form general deterioration models for bridge elements, and specific models for the deterioration mechanisms of reinforcement corrosion and freeze-thaw weathering. Furthermore, this reference set also serves as a quality control measure of bridge inspection techniques in effect, since not only are the bridges inspected by the experts, but also separately by the bridge engineers in the road districts. Clearly the utilization of such a reference bridge stock to directly calibrate country specific degradation models is by far the most appropriate manner of implementing deterioration models within BMS. However, in the absence of such a reference stock and given that the models outlined in the Duracrete (2000) and COST reports (2011) require too many ambiguous input variables to be suitable for network level predictions, another objective of this thesis has been the investigation of suitable analytical models for incorporation into existing BMS.

2.4 MAINTENANCE MODELLING

As stated in the introduction, the two basic requirements of a BMS are (i) the prediction of the future state of structures and (ii) the prioritisation of maintenance and repair. This naturally involves the incorporation of maintenance and rehabilitation actions on the structures in question. Like deterioration modelling, this has been incorporated and considered in both existing BMS and research work heretofore in varying degrees. Table 2.1 shows that 5 of the systems in the IABMAS 2010 report allow for improvement or maintenance to occur.

In itself, the issue of maintenance is a huge one with endless research scope. For instance, in the existing literature, it can be seen that there exists two aspects to the management of infrastructure facilities: the financial allocation of resources for MR&R (Maintenance, Rehabilitation and Repair) activities, and also the operational-level implementation, which pertains to the scheduling of activities. Commonly, three different criteria are considered when evaluating bridge network performance over time – bridge network connectivity, user satisfaction and structural reliabilities of critical bridges within the network (Liu and Frangopol, 2006). Certain studies have even investigated the significance of network configuration, and the significance which capacity losses due to construction activities affect the network capacity threshold (Medury and Madanat, 2011). Maintenance modelling has not been the focus of investigation in this thesis but nevertheless a maintenance module has been formulated in the study to show the implication of various

alternative maintenance policies. Thus, for the sake of completeness, a brief overview of the manner in which it has been incorporated into existing BMS follows.

APT BMS, the Italian system uses a Markovian based approach to statistically model the effect of an action – either repair intervention or maintenance, on the condition state of an element, the decision-making process then of which maintenance action to employ is based on the association of a priority index α to each of the potential actions. The effectiveness of each allowable action is ranked on the basis of the rate of risk reduction to cost. These costs incorporate reconstruction costs, inspection costs, maintenance costs, repair costs and failure costs. Risk then is related to the cumulative-time probability of occurrence of a structural failure. As depicted in Figure 2.11, the implementation of this overall system has required the formulation of many models for deterioration, life-cycle cost and cumulative-time reliability.

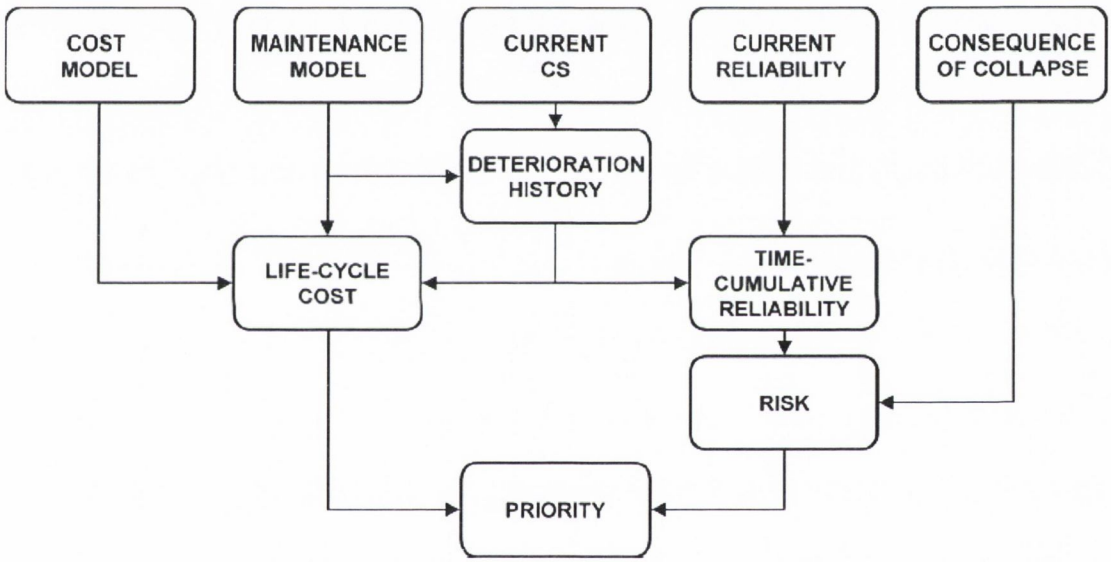


Figure 2.11: APT-BMS Prioritization System.

PONTIS and BRIDGIT, the US systems have the capability of suggesting cost-optimal strategies. From a set of alternatives that can meet the required level of performance, BRIDGIT provides a means to select the definitive optimal solution. This is achieved by an extensive model that can review the condition states of bridges, determine policies that allocate funds optimally and recommend appropriate maintenance actions. Note that the life cycle costs are calculated on the basis of a twenty year planning horizon and the expected benefits ascertained on the basis of user cost savings. A prioritization procedure can then work out the optimal minimal cost given a budget constraint. PONTIS on the other hand uses an infinite planning horizon when determining the expected life-cycle costs. The benefits are based on the potential savings which would be incurred

by delaying maintenance actions by a year. Its main objective is to reduce the costs involved hence the prioritization takes on a minimal cost approach, dictated by an acceptable level of performance.

Orcesi and Cremona (2006) set about developing a prediction model to determine trends in the French bridge stock and consequently optimize the maintenance strategies accordingly. The general prediction matrix as shown in Equation 2.2 was obtained from the IQOA database of inspection ratings (shown in Table 2.5), with the results modified to allow for deterioration only.

State	Meaning
1	Good overall state
2	Equipment failures or minor structure damage. Non urgent maintenance needed.
2e	Equipment failures or minor structure damage. Urgent maintenance needed.
3	Structure deterioration. Non urgent maintenance needed.
3u	Serious structure deterioration. Urgent maintenance needed.

Table 2.5: Definition of French IQOA states.

Various maintenance strategies were then allowed for by incorporating maintenance alternative matrices into the system. These are shown in Equation 2.12 and were chosen to emulate real-life scenarios. Certain transitions for instance have been disregarded as they do not correspond to viable rehabilitating actions.

$$S_1 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}, \; S_2 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}, S_3 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix} \qquad \textbf{Equation 2.12}$$

As an example rehabilitation strategy, S_3 above corresponds to a strategy where bridges move either from the 3rd condition state to the first, or the fifth condition state to the first. The former is equivalent to routine maintenance while the latter corresponds to a complete and total rehabilitation.

Unit costs were then applied to the various interventions as shown in Equation 2.13.

$$C = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 3 & 2 & 0 & 0 & 0 \\ 4 & 3 & 0 & 0 & 0 \\ 36 & 12 & 0 & 8 & 0 \end{bmatrix} \qquad \textbf{Equation 2.13}$$

These costs were estimated in previous studies by Orcesi (2005). The goal is to determine each year the optimal combination of the strategies to keep the bridge stock in an acceptable condition with limited resources. Every year i, a vector $X^i_j(i) = {}^t(x^i_{j1}\ x^i_{j2}\ x^i_{j2e}\ x^i_{j3}\ x^i_{j3u})$ is associated to the strategy j. This vector represents the proportion of bridges that are treated with the strategy j at year i for each of the IQOA condition ratings. The vector q at year i+1 is obtained from that at year i then using Equation 2.14.

$$q(i+1) = q(i)\sum_{j=1}^{m}\begin{bmatrix} x^i_{j1} & & 0 \\ & \ddots & \\ & & \ddots \\ 0 & & x^i_{j3u} \end{bmatrix} \qquad \textbf{Equation 2.14}$$

The fractions x^i_{jk} are the variables in the optimization process and are determined in such a way that the condition of the bridge stock remains above a minimal threshold and that the costs are as low as possible. The constraints they have set are to ensure that less than 20% of structures are in state 2e and that less than 5% are in state 3u. This corresponds to an objective function as formulated in Equation 2.15.

$$\min_{X_j(i)} \sum_{j=1}^{m} \left\langle X_j(i), C(j) \right\rangle \text{ such that: } \quad q^{threshold\,sup} \geq q(i+1) \geq q^{threshold\,inf} \qquad \textbf{Equation 2.15}$$

An annual discount rate of 5% has been taken into account. A second approach to the optimization has also been considered here in that the budget too is presented as being fixed. This is represented in Equation 2.16 where $B(i)$ is the annual budget.

$$\min_{X_j(i)} \sum_{j=1}^{m} \left\langle X_j(i), C(j) - B(i) \right\rangle \text{ such that: } \quad q^{threshold\,sup} \geq q(i+1) \geq q^{threshold\,inf} \qquad \textbf{Equation 2.16}$$

The optimization steps in this study by Orcesi and Cremona (2006) however are performed annually and so the effect of renovation frequency is not considered.

Orcesi and Cremona (2011) further expanded on the above methodology by putting in more realistic cost values as seen in Table 2.6.

Initial Score	Moving in 1 (cost/m^2)	Moving in 2 (cost/m^2)	Moving in 2e (cost/m^2)	Moving in 3 (cost/m^2)
2	85	-	-	-
2e	249	249 x 0.9	-	-
3	335	335 x 0.9	335 x 0.8	-
3u	2265	433	433 x 0.8	433 x 0.7

Table 2.6: Maintenance Cost per m^2.

These were based on a previous study by the French Roads Directorate (Odent and Berthellemy, 2002). Further quality indicators were also included in this study. However, the optimization process was still performed year by year on the basis that the budget of the Ministry of Transport is annually based.

Hegazy et al. (2004) also consider three different repair options, i.e. that of light repair, medium repair and extensive (full replacement) repair. These costs are also unit costs and are expressed as a percentage of total replacement cost at 28.5%, 65% and 100% respectively. A minimization is then performed whereby the total life-cycle cost over the planning period is minimized while maintaining acceptable bridge conditions. The effects of alternative repairs or imperfect repairs are not considered.

Lounis and Vanier (1998) utilize a compromise programming approach attempting to satisfy several conflicting objectives – (i) minimization of MR&R (Maintenance , Rehabilitation and Replacement) costs; (ii) minimization of bridge closures; (iii) maximization of network reliability or condition rating; (iv) minimization of user cost; and (v) maintenance of bridges with high traffic volumes or ADT (Average Daily Traffic). Four possible MR&R strategies are considered – (i) d_1, do nothing; (ii) d_2, minor repair with a unit cost of \$100/m^2; (iii) d_3, major repair with a unit cost of \$250/m^2; and (iv) d_4, replacement with unit cost of \$400/m^2. Using stationary Markov chains the future bridge condition is computed then assuming that maintenance decisions d_2, d_3 and d_4 for appropriate condition state transitions.

Yokota et al. (2006) present a much more basic approach to maintenance management and modeling. A Markov approach is adopted, however, they simply have one variable to represent the entire degradation process, i.e. as in Equation 2.2, $P_{ij} = P_{ii} \ \forall \ i$. After a repair has been carried out then, the degradation rate is simply taken to be 50% of that which it originally was, i.e. the transition probability P_{ii} is simply halved. The first repair is arbitrarily carried out after 18 years of service. Concerning the repair costs then, the total cost is calculated by multiplying the number of members repaired by the average cost of a typical structural member. However, no such costs are stated in the paper.

The LIFECON Report (Vesikari, 2003) also employed a Markov approach, yet repair actions were too just performed at pre-ordained times – i.e. after every 15 years in the study. Percentage repair effectiveness is not studied. The rate of degradation however can be changed accordingly, to take into account the material and structural properties of the repaired structure. It must be noted though that this degradation model is purely statistical in that it has no physical or mechanical basis unlike those discussed in Section 2.3.1.

Cesare et al. (1992) had previously studied the effects of different percentage repair, i.e. whether or not to repair 10% or 20% of the structures once they reach a certain condition state. Furthermore, uncertainties as to the quality of the workmanship were incorporated in that different percentages were deemed to have moved to the second-best state as opposed to the best state. Interestingly they found that the lower percentage of repair actually was the most beneficial in maintaining the same average future condition rating for the network under investigation.

An in-depth investigation of various maintenance strategies and alternatives was not the focus of this thesis. However, on the basis of the above, brief literature review, a framework for incorporating maintenance effects has been identified. Like Lounis and Vanier (1998), different repair strategies and alternatives will be looked into, i.e. that of repair only, rehabilitation only, or a combination of the two. Like Orcesi et al. (2006), only relative costs will be employed. Unfortunately, these are subjective, implemented purely to demonstrate the importance and effect of alternative, potential maintenance strategies. The development of more accurate costing models which would incorporate such things as user delay costs and penalty costs for reduced service is something which needs to be looked into in further work. As in Cesare et al. (1992) though, a sensitivity analysis considering the effect of various percentage repair and percentage repair effectiveness will be looked into.

2.5 OBJECTIVES BASED ON LITERATURE RIVIEW OF EXISTING SYSTEMS

In summary, based on the findings of the above literature review of bridge management techniques and systems as well as the primary objectives listed in Section 1.2, the sub-objectives of this thesis have been identified as:

1. To develop the system methodology, particularly the most appropriate manner of modelling future bridge condition, given the fact that the module needs to ideally be incorporated as part of a BMS. This involves determining whether or not homogeneous or non-

homogeneous chains should be used as well as ascertaining the most appropriate optimization procedure.

2. To implement a more robust solver for use in transition probability estimation, given that many of those in use at the present time are unsuitable.
3. To determine how best to calibrate suitable transition matrices in the absence of sufficient quantities of inspection data, specifically, the incorporation of physically-based, analytical models into prediction systems.
4. To investigate the phenomenon of chloride-induced corrosion of reinforced concrete and particularly the most suitable analytical models for use in predicting future condition state in a cracking-limit state, service life model.
5. To 'calibrate' in effect such systems for use with regard to the Irish Bridge network, i.e. conduct a literature review and sensitivity analysis of the most appropriate parameter values.
6. To develop the system on an elemental basis, i.e. to build up the overall bridge condition rating as a function of its minor elements and to consider the overall condition rating then as dependant on the correlations between these elements. In this respect, the system will be most robust and adaptable for other kinds of structures in alternative locations.
7. To consider the effects of maintenance and repair on equilibrium network condition rating, taking into account different maintenance policies, imperfect repairs and alternative costs.
8. To develop a data-cleaning procedure which could be used to elicit suitable transition probabilities from infrastructure inspection databases as soon as sufficient information becomes available.

CHAPTER 3 – SYSTEM DEVELOPMENT

3 SYSTEM DEVELOPMENT

3.1 INTRODUCTION

This chapter focuses on the development of the system methodology, i.e. specifically the most appropriate manner in which to model and predict future bridge deterioration in order to be able to incorporate the module into a BMS. In particular and as previously outlined in Chapter 2, this has been broken down into a number of steps.

1. In keeping with existing network management tools, a Markovian basis has been decided upon. However as described in 2.2.1, while existing systems such as PONTIS and BRIDGIT (Czepiel, 1995; Frangopol et al., 2001) use homogeneous or stationary Markov chains, a review of the literature has suggested that non-homogeneous chains, i.e. non-stationary chains that are dependent on time may be more appropriate.

2. The most appropriate manner of calibrating the Markovian transition matrices needs to be established. A non-linear minimization approach is by far the most common technique found in the literature but various objective functions need to be researched in order to determine the optimum.

3. Different solvers need to be investigated and implemented. As stated in the review of current practice in Chapter 2, many of the methods and algorithms in use at the present time are unsuitable for probability estimation, due to the fact that some have a tendency to converge to the bound constraints of the problems – inherently undesirable when the variables to be optimized constitute a series of probabilities. Consequently, a more robust solver needs to be identified.

In the absence of sufficient quantities of real data, a normally distributed random database was generated for the purposes of these investigations. The use of the normal distribution here can be supported by various studies which have been performed in the field such as those by Ortiz-Garcia et al. (2006) and Li at al. (1997). In an effort to simulate a non-linearly deteriorating network, as would be expected with real-life deterioration mechanisms, the mean bridge condition at each year t increases annually, by a random amount with the variance also set to increase annually – in order to model the increased variability which accrues with age. Initially the mean condition rating was set at 1.15 with the initial variance at 0.2. The database is developed to consider a sample of 2000 bridges over $t = 25$ years, so as to be able to study the effects of the various objective functions and algorithms on a network of bridges, as opposed to a single bridge, over a reasonable time-period –

taken to be 25 years here. This also allows for the effects of variability in reaching an equilibrium position to be incorporated. All simulations were carried out using MatLab r2010a.

Essentially, the first few sections introduce each of these aforementioned objectives in turn, i.e. both homogeneous and non-homogeneous chains are discussed, different objective functions for Markov chain calibration are illustrated, and the available solvers and algorithms available to implement the method are introduced. The results and analysis are then presented following on from this. Note that the results of the investigations form the basis of a paper by Reale and O'Connor (2012a), which has been published in the ASCE Journal of Transportation Engineering.

3.2 SELECTION OF MODEL BASIS

The selection of the model basis essentially involves ascertaining which type of Markov process should be implemented and which objective function should be used to estimate the parameters of the chosen model.

3.2.1 Homogeneous Chains v Non-Homogeneous Chains

As stated, Markov chains can themselves be defined as either homogeneous or non-homogeneous. Homogeneous means the process is stable or stationary in time. That is it does not change with respect to time and the probability of going from one state to another is independent of the time at which the step is being performed. In mathematical terms, the initial state vector P_0 as shown in Equation 2.1 will remain the same for all t.

Non-homogeneous chains change with respect to time. This implies the use of a different transition matrix before and after t. In this case the vector of probability distribution of condition at time t will become the starting vector of condition for the second chain, which will then proceed with a different transition matrix. This is illustrated in Equation 2.3 where for n groups, there are n transition probability matrices P and n initial probability distributions: P_0.

Since this study involves 25 years of data, the effects of both stationary and non-stationary chains can be studied. The algorithms and objective functions are tested using a stationary chain over the 25 year period as well as using 5 non-stationary chains of 5 years duration each. Note that the 5 year duration period was chosen for efficiency but also it was deemed a reasonable period in which to allow for a variation in condition between groups of bridges – were the time period chosen of lesser duration, there is a chance that the system would have not started behaving overly non-linearly and so the homogeneous chains might actually be able to capture sufficient variability to disguise the benefits of the non-homogeneous chains. Figure 3.1 thus depicts the variables which

need to be estimated - one transition matrix of 5 transition probabilities/variables in the stationary case, and $n = 5$ matrices or 25 variables in the non-stationary case.

$$P(n) = \begin{vmatrix} P_{00} & 1-P_{00} & 0 & 0 & 0 & 0 \\ 0 & P_{11} & 1-P_{11} & 0 & 0 & 0 \\ 0 & 0 & P_{22} & 1-P_{22} & 0 & 0 \\ 0 & 0 & 0 & P_{33} & 1-P_{33} & 0 \\ 0 & 0 & 0 & 0 & P_{44} & 1-P_{44} \\ 0 & 0 & 0 & 0 & 0 & 1 \end{vmatrix}$$

Figure 3.1: Markov Chain Matrix where $n = 1$ for the Stationary case and $n = 5$ for the non-stationary case.

3.2.2 Objective Function Analysis.

As outlined in Section 2.2.2 many methods abound in both practice and literature as to how best to obtain the desired Markovian transition probabilities. For the purposes of bridge management, despite the fact that techniques such as ordered probit models (Madanat et al., 1995) and Poisson regression have been applied (Madanat and Wan Ibrahim, 1995), a non-linear minimization approach has proved to be the most popular, due in part to its ease of implementation. Differences arise however as to how the objective function is formulated, i.e. is it the difference in expected condition rating which is to be minimized as in Equation 2.5, or is it the difference in condition rating distribution which should be expressed as the target function – Equation 2.7. Baik et al. (2006), Butt et al. (1987), Feighan et al. (1988), Jiang et al. (1988) and Morcous (2006) have all implemented the problem as though it is solely the expected condition rating which should be included in the optimization function. Cesare et al. (1992) and Ortiz-Garcia et al. (2006) however focused on minimizing the difference in condition rating distribution. Furthermore, when adopting a minimization of expected condition rating, it is generally a regression equation of condition rating data which provides the estimate of future condition. This regression equation can take different forms, hence in this study the degree of polynomial in question will be varied in order to achieve the best fit and ascertain the effect of using varying degrees of polynomial on the overall optimisation process.

Additionally, while some researchers have adopted a least-squares minimization approach (Bastidas-Arteaga and Schoefs, 2012; Cesare et al., 1992), others have used an absolute value method (Jiang et al., 1988; Ortiz-Garcia et al., 2006). An absolute value approach lends more weight to the tails of the distribution than that obtained using a least-squares approach. This ensures that the variables under estimation are not under as much influence to outliers in the data, i.e. they are not chosen purely to fit the tails of the distribution. This should mean that the results are more

exact, yet nevertheless both methods shall be compared in this chapter in order to ascertain the most appropriate one for the given problem.

3.3 SOLVER IDENTIFICATION

Morcous and Lounis (2006) state that the development of a practical and effective bridge maintenance management system depends primarily on the existence of a reliable performance prediction model and an effective optimization algorithm. Since combinatorial optimization is by nature a complex and computationally intensive problem, generally requiring the exploration of large, multidimensional search spaces in order to obtain a solution and since as outlined above, there are only 5 variables to be obtained to characterize the process in the stationary case, and 25 in the non-stationary case, it is the accuracy of the mathematical solver which is especially important. Many non-linear procedures have been investigated heretofore - Carnahan et al. (1987) used a descent method (Fletcher and Powell, 1963), Jiang et al. (1988) used the gradient projection method and Costello et al. (2011) and Ortiz-Garcia et al. (2006) employed the use of another non-linear algorithm; the GRG2 code incorporated into the solver program in EXCEL in their study. However, the latter two both concluded that since non-linear solvers lack the guarantee of finding a global optimum, a more robust method ought to be investigated.

In the search for such a successful suitable algorithm for the development of the model, many solvers were investigated. Initially the work focused on employing the GRG2 EXCEL code, before then moving on to the pre-programmed MatLab solvers Fmincon and GlobalSearch. The results of these algorithms under the various objective functions and Markov chains shall be presented in the following section for completeness, yet they were all found lacking for the purposes of transition probability estimation to some degree. To this end it was clear that like Costello et al. (2011) and Ortiz-Garcia et al. (2006), a more powerful algorithm was necessary.

Dynamic methods such as Neural Networks (Mohamed et al., 1995; Razaqpur et al., 1996) and Genetic Algorithms (Farran and Zayed, 2012; Hegazy et al., 2004; Morcous and Lounis, 2005; Orcesi and Cremona, 2008) had previously been applied, but a review of the literature found that a technique known as Cross Entropy had yet to be implemented. Since it requires fewer input parameters than either of the above techniques (thereby leaving less room for input error) and since it has been successfully applied to a variety of difficult problems including buffer allocation, queueing models, neural computation and so forth since its introduction (Chen and Trivedi, 2005; Harris et al., 2010), it is investigated here as an appropriate means of obtaining the transition probability variables.

3.3.1 Solver Description

In order to fully compare and contrast the efficiency of the various solvers, two Matlab solvers were chosen as a basis for comparison. These were Fmincon and GlobalSearch, whose procedures are described briefly below.

Fmincon

The Fmincon Active Set Algorithm is a Matlab solver suitable for constrained non-linear optimization. It finds a vector x that is a local minimum to a scalar function $f(x)$ subject to constraints on the allowable x:

$Min_x f(x)$ **Equation 3.1**

Such that depending on the problem to be evaluated one or more of the following holds:

$$c(x) \leq 0, ceq(x) = 0, A.x \leq beq, l \leq x \leq u$$

The Active Set Algorithm of Fmincon works by finding a solution of the KKT (Karush-Kuhn-Tucker) equations. These KKT equations are necessary conditions for optimality of a constrained optimisation problem.

GlobalSearch

GlobalSearch, a global Matlab solver only available from R2010 onwards, is a solver suitable for global optimisation in particular. The scatter search algorithm is used to generate a set of trial points as potential start points. (For more information on the scatter search algorithm, see Ugray et al. (2007)). It runs Fmincon from this start point. If this run converges, GlobalSearch records the start point and end point for an initial estimate on the radius of a basin of attraction. It then evaluates the score function of this set of trial points, takes the point with the best score and runs Fmincon from this point. The score function is the sum of the objective function value at a point and a multiple of the sum of the constraint violations. So a feasible point then has a score equal to its objective function value. The multiple for constraint violations is initially 1000 and GlobalSearch updates this multiple during the run. Note that since it also employs the use of both distance and merit filters to sort the start points, it is an extremely efficient procedure.

3.3.2 Sensitivity of Solvers to Algorithm Variables

The first solver investigated was the GRG2 code in the EXCEL program. Following that, the two Matlab solvers were employed. Described above, a sensitivity analysis of these algorithms was performed to consider:

(i) Importance and effect of initial guesses

(ii) Convergence to same solution regardless of run number, i.e. repeatability

Note that for the purposes of ascertaining which algorithm is most suitable in the current context of probability estimation, the objective function of Equation 2.5 shall be utilized here with the complete set of results to follow in Section 3.4. For clarity, this is depicted again here:

$$\sum_{t=1}^{N} |S(t) - E[X(t)]|$$

Non-homogeneous chains of five year duration will be used over the simulated 25 year period to compare and contrast these algorithms and a polynomial of the fourth degree will be utilized. The effect of varying the degree of the polynomial will however be investigated later in this chapter. These polynomials have been ascertained from a best-fit line through the simulated database and the fourth degree polynomial is described by:

$$S = -3.612t^4 + 0.002t^3 - 0.034t^2 + 0.271t - 0.121 \qquad \textbf{Equation 3.2}$$

As stated, the first solver investigated was the EXCEL solver. For the sake of completeness some initial results shall be shown below in Table 3.1 and Table 3.2. It can be seen that the algorithm is highly dependent on the initial seed, and that while it does converge to the same solution each time, it appears to converge to solutions on the bound constraints, i.e. the search space is limited to between 0.0 and 1.0 for probability estimation. The first five year period only is tabulated but this was sufficient to realize the inappropriateness of the algorithm for the case in question due primarily to the lengthy implementation time, as well as its dependency on initial guesses. This dependency is highly undesirable since by definition, at the outset the solution is not known, hence the guesses are arbitrary and should have negligible effect on the final objective function value.

Initial Seed	P_{00}	P_{11}	P_{22}	P_{33}	P_{44}	Obj Func Value
[0.5,0.5,0.5,0.5,0.5]	0.887	0.903	0.696	0.617	0.535	0.178
[0.6,0.6,0.6,0.6,0.6]	0.863	0.94	1.0	0.795	0.64	0.105
[0.7,0.7,0.6,0.7,0.7]	0.860	0.958	0.804	0.758	0.739	0.108
[0.8,0.8,0.8,0.8,0.8]	0.861	0.944	1.0	0.83	0.802	0.104

Table 3.1: Sensitivity of Excel GRG2 algorithm to initial guesses for the first 5-year period.

Run No.	P_{00}	P_{11}	P_{22}	P_{33}	P_{44}	Obj Func Value
1	0.861	0.944	1.0	0.83	0.802	0.104
2	0.861	0.944	1.0	0.83	0.802	0.104
3	0.861	0.944	1.0	0.83	0.802	0.104

Table 3.2: Repeatability of Xcel GRG2 algorithm under initial seed of [0.8,0.8,0.8,0.8,0.8].

The next algorithm examined was the Fmincon solver in Matlab with the dependency on initial guesses and repeatability listed in Table 3.3 and Table 3.4 below.

Initial Seed	P_{00}	P_{11}	P_{22}	P_{33}	P_{44}	Obj Func Value
[0.5,0.5,0.5,0.5,0.5]	0.862	0.942	1.0	0.987	0.54	0.104
[0.6,0.6,0.6,0.6,0.6]	0.853	0.9636	1.0	0.907	0.2	0.106
[0.7,0.7,0.7,0.7,0.7]	0.86	0.947	1.0	0.901	0.716	0.104
[0.8,0.8,0.8,0.8,0.8]	0.86	0.96	0.817	0.836	0.802	0.108

Table 3.3: Sensitivity of Fmincon algorithm to initial guesses.

Run No.	P_{00}	P_{11}	P_{22}	P_{33}	P_{44}	Obj Func Value
1	0.86	0.96	0.817	0.836	0.802	0.108
2	0.86	0.96	0.817	0.836	0.802	0.108
3	0.86	0.96	0.817	0.836	0.802	0.108

Table 3.4: Repeatability of Fmincon algorithm under initial seed of [0.8,0.8,0.8,0.8,0.8].

As can be seen, the algorithm is still rather dependent on the initial seed, though it is repeatable, i.e. it does converge to the same solution each time if the initial seed is unvaried. However, the problem lies with the fact that it tends to converge to solutions on the bound constraints of the problem, i.e. probabilities of 0.0 and 1.0 in this context. Naturally, given the fact that the transition probabilities obtained are multiplied by initial state vectors P_0, as in Equation 2.1, this convergence to a boundary value is highly undesirable since the error is propagated out and leads to the probability distribution of state being unchanged over the period in question, as illustrated in Table 3.5.

Year	State 0	State 1	State 2	State 3	State 4	State 5
P(4)	0.528	0.423	0.049	0	0	0
P(5)	0.445	0.472	0.0734	0	0	0
P(6)	0.445	0.458	0.042	0.045	0	0
P(7)	0.445	0.444	0.03	0.063	0.008	0
P(8)	0.445	0.431	0.025	0.069	0.015	0.004
P(9)	0.445	0.418	0.022	0.072	0.02	0.017
P(10)	0.445	0.4063	0.021	0.072	0.02	0.023
P(10)	0.447	0.376	0.05	0.069	0.031	0.028

Table 3.5: Probability Distribution of Condition States under Fmincon when $P_{00} = 1.0$

In a continuation of the search for a suitable solver, as outlined as an objective at the outset of this chapter, the possibility of using Globalsearch was then explored. As mentioned in Section 3.3.1, this works by repeatedly calling Fmincon from a set of startpoints, so essentially it should converge to a solution or final objective function value at least equal to that of Fmincon. Comparing Table

3.3 and Table 3.6, it can be seen that GlobalSearch does indeed return lower values of objective function than Fmincon. However, like Fmincon, it tends to converge to solutions on the bound constraints of the problem – see Table 3.6. Furthermore, it is highly dependent on the initial algorithm seed, but while Fmincon gives the same end result for the same initial seed, Globalsearch does not. Table 3.7 illustrates that quite different transition probabilities can be obtained which naturally gives rise to quite different distributions of condition state. For the context of bridge management, budget allocation and maintenance and repair protocol, it is evident that the predicted future distribution of state is highly important, hence it must be as accurate as possible and not be subject to repeatability problems whereby if the program is rerun, the solution obtained changes. These changing probability distributions can be seen below in Table 3.8.

Initial Seed	P_{00}	P_{11}	P_{22}	P_{33}	P_{44}	Obj Func Value
[0.5,0.5,0.5,0.5,0.5]	0.862	0.942	1	0.507	0.0026	0.1038
[0.6,0.6,0.6,0.6,0.6]	0.862	0.942	1	0.261	0.67	0.1038
[0.7,0.7,0.7,0.7,0.7]	0.925	0	1	0.49	0.239	0.0937
[0.8,0.8,0.8,0.8,0.8]	0.925	0	1	0.073	0.653	0.0937

Table 3.6: Sensitivity of Globalsearch algorithm to initial guesses

Run No.	P_{00}	P_{11}	P_{22}	P_{33}	P_{44}	Obj Func Value
1	0.925	0	1	0.073	0.653	0.0937
2	0.862	0.942	1	0.121	0.696	0.1038
3	0.925	0	1	0.187	0.215	0.0937

Table 3.7: Repeatability of Globalsearch algorithm under initial seed of [0.8,0.8,0.8,0.8,0.8].

Run No.	0	1	2	3	4	5
1	0.648	0.053	0.299	0	0	0
2	0.455	0.472	0.073	0	0	0
3	0.648	0.053	0.299	0	0	0

Table 3.8: Sensitivity of condition state distribution after 5 years under GlobalSearch algorithm due to lack of repeatability.

Figure 3.2 and Figure 3.3 also represent this in graphical form. The first, Figure 3.2, graphs the probability of being in each state, each year, for the first five years under two different runs of the algorithm. The two lines are differentiated by the markers used, circles and dashes respectively. It can be seen that the probability of being in states 3, 4 and 5 remain zero for both runs, and that consequently those six lines (two for each state) all run along the x-axis. However, the probabilities of being in states 0, 1 or 2 vary greatly between the algorithm runs. As stated this lack of convergence is highly undesirable. Figure 3.3 then illustrates the widely varying probability

distributions of condition state which are obtained from these two different runs. As a direct result of this inconsistency then, Globalsearch is deemed to be an inappropriate algorithm for the purposes of bridge transition probability determination where there are few defining variables in question.

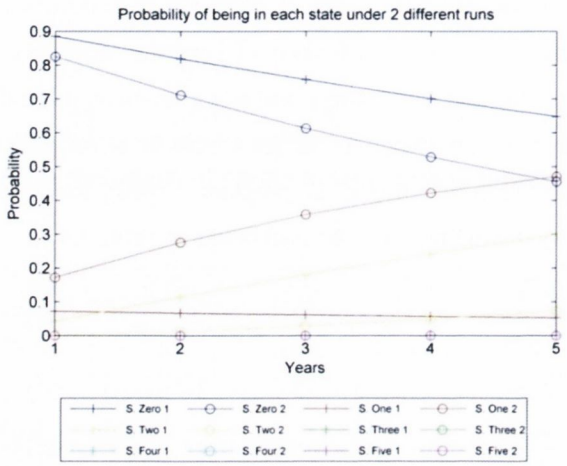


Figure 3.2: Probability of being in each state for the first five years under 2 different runs of the GlobalSearch algorithm.

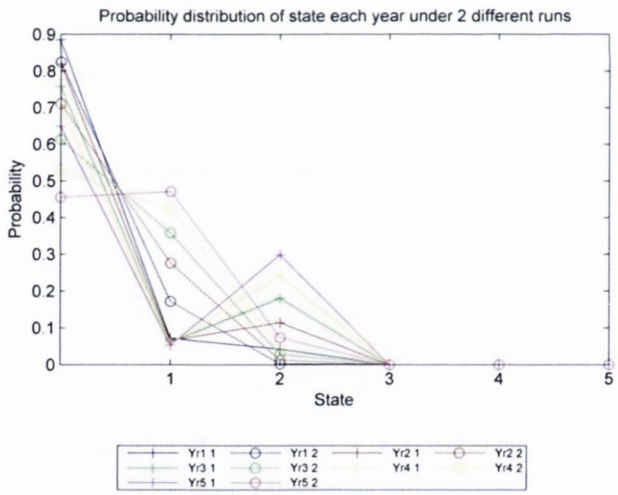


Figure 3.3: Probability distribution of condition state over years 1 to 5 for 2 different runs of Globalsearch.

It is clear then from the above analysis that the solvers mentioned heretofore are inappropriate for the purposes of bridge deterioration transition probability estimation. All algorithms appear to be susceptible to the value given to the initial seed – Table 3.1, Table 3.3, Table 3.6, but this is recognized as being a common optimization problem. It is instead the fact that all three tend to converge to solutions on the bound constraints of the problem, namely 0.0 and 1.0 that is the

problem as it gives rise to inconsistent distributions of state as illustrated in Table 3.5. Consequently, taking this into account, it is clear that a new solver needed to be implemented and so Cross Entropy, an iterative algorithm pioneered by Reuven Rubinstein in 1997 which had the noted advantage of being quite robust under different starting conditions (Botev and Kroese, 2004) was chosen.

3.3.3 Investigation of Cross Entropy as an Appropriate Algorithm

Cross Entropy itself is a relatively new method which has its origins in an adaptive importance sampling technique pioneered by Reuven Rubinstein in 1997 (Rubinstein, 1997) for the simulation of rare events. In 1999, it was realized that the same adaptive importance sampling method could be used to solve combinatorial optimization problems by viewing the set of solutions to the optimization problem as a rare event. The process itself is of an iterative nature and comprises two distinct and separate phases:

(1) Generation of a sample of random data (e.g. in this case bridge transition probabilities) using a specified random mechanism.

(2) Updating the parameters of this random mechanism in order to generate an improved sample for use in the next iteration.

More formally, as adapted from De Boer et al. (2005), the procedure is outlined as follows:

Consider a finite set of states, X, which for instance may contain all possible values for bridge transition probabilities. Let S then be a real-valued function on X which describes some measurable output, such as bridge condition state. There must then be an array of optimal variables which optimize S, i.e.:

$$S(\phi^*) = \max S(\phi), \phi \in X \qquad \textbf{Equation 3.3}$$

This is an equation of a general optimisation problem. When ϕ contains more than one variable, it becomes a combinatorial optimisation problem. In order to obtain an estimation of $\phi*$, a set of N_x independent and identically distributed (iid) random samples of ϕ are generated from the probability distribution characterized by the set of parameters, v (e.g. mean and standard deviation):

$$x_1, x_2, \ldots . x_N \sim f(\phi \mid v) \qquad \textbf{Equation 3.4}$$

where $f(\phi \mid v)$ is some probability distribution (e.g. Gaussian, Lognormal etc). Generally the distribution is assumed to be Gaussian and thus v contains the means and variances of the

distribution. Because at the beginning very little is known about the variables to be optimized, arbitrary mean values with quite large variances are chosen to reflect this lack of knowledge. For each randomly generated X the performance or objective function $S(\phi)$ is evaluated. From this then, the sample (1-p) quantile is determined, i.e. if $p = 0.95$, then the top 5 percent are taken. An updated estimate, of the probability distribution parameters is then obtained by taking the mean and variance of this sample quantile. v itself is generally updated by means of smoothing the present generation with the previous generation, as shown in Equation 3.5:

$$v_t = \alpha v_t^* + (\alpha - 1)v_{t-1}^* \qquad \textbf{Equation 3.5}$$

The reason for this smoothed updating is twofold:

(a) to smooth out the values of v_t.
(b) to reduce the probability that some component of v_t will be 0.0 or 1.0 at the first few iterations.

Reason (b) is particularly important when v_t is a vector or matrix of probabilities. This is because for $0 < \alpha < 1$, v_t is always greater than 0, while for $\alpha = 1$, one might find that $v_t = 0$ or $v_t = 1$ for some indices. As a result the algorithm would converge to a wrong solution (Kroese et al., 2006; Rubinstein and Kroese, 2008).

The process is repeated until a stopping criterion is reached, such as sufficient convergence of estimates or a pre-specified number of iterations. Figure 3.4 outlines the general form of the Cross Entropy algorithm, while the algorithm as used for this study will be outlined in the following section.

Injection of Variance

When using the CE method to solve practical optimization problems with many constraints and many local optima, it is sometimes necessary to 'inject' variance into the problem in order to prevent the sampling distribution from shrinking too quickly, and thus reaching a sub-optimal solution. This is mentioned numerous times in the available literature (Botev and Kroese, 2004; Rubinstein and Kroese, 2008; Taimre, 2009).

This is implemented as follows. Formally, let S_t^* denote the best performance found at iteration and σ_t^* denote the largest standard deviation at iteration t. If σ_t^* is sufficiently small, and $|S_t^* - S_{t-1}^*|$ is also small, then add $A = b|S_t^* - S_{t-1}^*|$ to each standard deviation, for some fixed b. If A is found to be very small, a constant value can just be added in order to avoid injections that are too small (Kroese et al., 2006). This injection of variance technique was also employed by Szita

and Lörincz (2006) in the form of adding noise to their solutions after successive iterations of variables had converged satisfactorily.

Initialisation

Define v_0 - a relatively arbitrary array set to initially describe the potential values of φ.

- Generate N_x iid samples from $f(\varphi|v)$

Optimisation

While count < F and $\max(S(\varphi_t)) \geq tol$(predefined)

For j = 1,2,....N_x

- Compute $S(\phi_1), S(\phi_2)$ etc and obtain the (1-p) quantile
- Estimate v^* from the mean and variance of this top performing quantile
- Inject variance if $\left|S_t^* - S_{t-1}^*\right| < \text{tol}$
- Update v_t
- count = count + 1

End

- Sort Solutions in order to find optimum

Figure 3.4: Pseudocode of General Cross Entropy Algorithm.

3.3.4 Implementation of Cross Entropy Algorithm

The Cross Entropy algorithm as implemented in this study is much as illustrated in Figure 3.4. The algorithm variables are essentially:

(i) v_0 - the relatively arbitrary array set to initially describe the potential values of φ.

(ii) F - the number of runs of the algorithm, i.e. the sample size

(iii) N_x - the number of estimations for v_0 each iteration

(iv) p - the fraction of top performing guesses re-evaluated each iteration

(v) tol - predefined tolerance or stopping criterion

(vi) S – the objective function value

The algorithm is self-tuning with the exception of the parameters listed above. The first parameter, v_0 was generated N_x times each iteration using the *randn* function in Matlab with a predefined mean and variance. This mean was arbitrarily set to vary between 0.7 and 0.8 as it was felt this would reasonably represent the expected probability of staying in the same state from one time period to another. The variance was taken to be 0.15 each time.

N_x was taken to be 100 and F was taken to be 1000 as these were felt to give a reasonable space in which to expect an accurate estimate to be obtained. The percentage of top-performing guesses each time, p, was taken to be 0.05 – the literature suggests values between 0.01 and 0.1 (De Boer et al., 2005).

After the initial guesses have been defined, a counter is then implemented in the code with the intention of counting the number of runs which converge on each algorithm run. This counter basically increments whenever a run yields an objective function value less than a pre-specified tolerance - taken here to be 0.1. Alternatively, the stopping criteria can be taken to be a particular number of runs of the algorithm. On each run, the objective function is then computed

Having computed the objective function, if X, its value is less than the tolerance the *countconverged* counter is updated. The objective function values are then sorted in ascending order using the *sort* function in Matlab for the N_x estimations at each iteration. An index I was denoted to reference these initial guesses so as to be able to easily cross-reference memory cells. The top-performing percentage of these guesses is taken forward and the parameter vector v, which contains the means and variances of each guess is updated according to the mean and variance of these superior guesses. As stated in Section 3.3.2 and as shown in Equation 3.5, each iteration is smoothed with the previous iteration also in an effort to prevent the solutions converging to the bound constraints of the problem. Furthermore, if the algorithm has converged sufficiently, an injection of variance of 0.2 per guess is implemented in order to stop the sampling distribution from shrinking too quickly. Having updated these parameters, the overall *count* counter is incremented. The best performing objective function from this run of the algorithm is then computed and the value stored. This process continues until as stated the algorithm converges sufficiently or the number of algorithm runs exceeds the allowable. A matrix is then declared which stores the best X, objective function value each run of code. This matrix is sorted subsequently and another index II declared, which again allows for cross-referencing to occur. Note that this index II contains only the best guess from the N_x guesses each run and is then ordered to give the best overall run.

Note also that the stopping criterion used is based on both the discrepancy between the value of the objective function and 0 being less than a pre-specified tolerance as well as the number of iterations of the algorithm. Empirically though, it was found that the number of iterations of the algorithm was the defining factor.

The smoothing process outlined above usually employs a constant smoothing parameter α (De Boer et al., 2005; Kroese et al., 2006; Ridder, 2005) which has empirically been found to give best results when between 0.4 and 0.9 (De Boer et al., 2005). Consequently, it is generally taken to be

an arbitrary value between these bounds. Kroese et al. (2006) and Rubinstein and Kroese (2008) do mention a dynamic smoothing parameter β:

$$\beta_t = \beta - \beta\left(1 - \frac{1}{t}\right)^q \qquad \textbf{Equation 3.6}$$

Botev and Kroese (2004) also mention this as a means of stopping the algorithm converging too quickly to a degenerate solution. This value is iteration dependant and β and q are parameters which are to be estimated. Kroese et al. (2006) state that q is typically an integer between 5 and 10, and β is generally between 0.8 and 0.99. Hu and Hu (2009) use another dynamic parameter which is iteration dependant:

$$\alpha_k = 2/(k+100)^{0.501} \qquad \textbf{Equation 3.7}$$

However, while both of these have been found to outperform constant smoothing parameters in certain cases (Kroese et al., 2006), it tends to be used instead of injection and not as well as, i.e. purely to prevent sub-optimal convergence. Furthermore, since parameters are still estimated in the case of Equation 3.6 and Equation 3.7 is completely iteration dependant on k, the value of α is still not being optimized as such. It is proposed then here to include α as a variable within the optimization in order to ascertain whether or not its inclusion increases the efficiency of the solution for each particular problem under investigation. Unlike in Kroese et al. (2006), the smoothing parameter α will be used to update both the mean and the variance, and will be used in conjunction with the injection of variance technique. This idea corresponds to considering a subclass of the class of probability measures $Q(\rho,\alpha)$ as mentioned also in Ridder (2005). Likewise Botev and Kroese (2004) also suggested that it might be worth considering the ''optimal'' choice of the internal Cross Entropy parameters.

This inclusion of α as a variable in the optimization process itself is expected to add to the accuracy of the established Cross Entropy method and will be compared to both the Matlab solvers described in Section 3.3.1 and the generalized, original Cross Entropy algorithm in the next section. Note that all of this analysis of various solvers was in an effort to carry out the initial objective of finding a solver suitable for transition probability investigation given that many of those in use at the present time are unsuitable.

3.3.5 Sensitivity Analysis of Cross-Entropy Algorithm

Principally the main advantage Cross Entropy has over the other algorithms previously mentioned is that it does not tend to converge to solutions on the bound constraints of the problem as shown in

Table 3.9 and Table 3.10. This importance has been already illustrated in Table 3.5 where it can be seen what happens when such probabilities are reached. It is recognized that the actual final objective function value is slightly higher than those obtained under Globalsearch for example, but this is not the primary aim of the optimization. Rather, it is the obtaining of appropriate, realistic probabilities which will not give rise to inconsistent distributions of state, unlike their mathematically optimal counterparts. To reiterate, since the main purpose of BMS is to predict future distributions of the condition state of a network of bridge structures in order to schedule maintenance and plan for budgetary requirements, inaccurate distributions of state are highly undesirable since they will give rise to inaccurate budget requirements. Furthermore, as demonstrated in the following section, this slightly lower objective function value does not adversely influence the predicted distribution of future condition rating distribution. Note that this attainment of realistic probabilities is in accordance with objective number 2 as outlined in Section 2.5. That is, many of the solvers implemented in BMS at the present time give probability values of less than or equal to 0.0 and greater than or equal to 1.0, which means that either some 'expert judgement' or additional constraints need to be employed to obtain reasonable solutions (Fu and Devaraj, 2011; Jiang and Sinha, 1989). Since Cross Entropy does not tend to such solutions, it is deemed to be a more appropriate solver and thus has been encapsulated into this bridge management module.

Note that the above analysis has purely been conducted in order to illustrate the advantages and disadvantages of the various algorithms for the module 'engine'. The most appropriate manner of ascertaining the transitions probabilities shall be investigated and discussed in both the following section and later chapters.

Initial Seed	P_{00}	P_{11}	P_{22}	P_{33}	P_{44}	Obj Func Value
[0.5,0.5,0.5,0.5,0.5]	0.861	0.945	0.976	0.584	0.513	0.1048
[0.6,0.6,0.6,0.6,0.6]	0.861	0.933	0.998	0.653	0.72	0.1054
[0.7,0.7,0.7,0.7,0.7]	0.865	0.916	0.998	0.823	0.364	0.1055
[0.8,0.8,0.8,0.8,0.8]	0.862	0.942	0.988	0.768	0.661	0.1044

Table 3.9: Sensitivity of Cross-Entropy algorithm to initial guesses for the first 5-year period.

Run No.	P_{00}	P_{11}	P_{22}	P_{33}	P_{44}	Obj Func Value
1	0.862	0.942	0.988	0.768	0.661	0.1044
2	0.862	0.942	0.972	0.132	0.926	0.1055
3	0.86	0.947	0.987	0.561	0.374	0.1051

Table 3.10: Repeatability of Cross-Entropy algorithm under initial seed of [0.8,0.8,0.8,0.8,0.8].

3.4 RESULTS AND DISCUSSION

The results themselves are essentially three-fold. Firstly, the expected condition rating spread of distribution will be examined using both homogeneous and non-homogeneous chains. Secondly, the objective functions themselves as described in Section 3.2.2 will be investigated, and lastly the results of including the CE smoothing parameter alpha in the optimization will be presented. Furthermore, although it has been shown above that Cross Entropy is the most appropriate algorithm in the current context, the two Matlab solvers shall continue to be included for comparative purposes – i.e. to show the robustness of the Cross Entropy Solver in reaching a solution from the same basin of attraction as the two other standard alternatives.

Note that for all graphs and results presented hereafter, objective function 1 refers to Equation 2.5, objective function 2 refers to Equation 2.7 and groups 1 to 5 respectively correspond to $n = 1$ *to* 5 for the 25 years of simulated data as in Figure 3.1. This group segmentation was chosen to allow for the study of non-stationary Markovian chains and the effects they have on the optimization process.

3.4.1 Homogeneous Chains v Non-Homogeneous Chains

The 'goodness of fit' of expected condition rating spread of distribution under both performance functions and both types of Markov process are presented with the aid of histograms in Figure 3.5 to Figure 3.8 below. In all figures and examples, the topmost histogram depicts the simulated condition rating spread at year 15 according to the generated database. The second corresponds to the expected condition rating spread at year 15 utilizing the GlobalSearch procedure, the third to the spread of condition rating under the Fmincon algorithm and lastly, the fourth histogram depicts the spread of condition rating as predicted under the Cross Entropy algorithm. Year 15 was arbitrarily chosen for depiction purposes but the summed objective function value over the entire 25-year simulation period is listed in the relevant tables also so as to obtain an overall picture of the prediction values, regardless of the chosen year of depiction. Note that this final summed objective function value cannot be compared between methods, since the minimization function is different, i.e. Table 3.11 can be compared to Table 3.13 but not to Table 3.12 or Table 3.14 since one is minimizing expected condition rating – one value, in one while the other is minimizing expected condition state distribution, or six values. Therefore it is expected that regardless of accuracy, the numerical value of the minimization routine will be greater for objective function 2, that of minimizing the expected distribution. The results as obtained using the less computationally intensive homogeneous chains are presented first, with the non-homogeneous chains presented after.

Homogeneous Chains

- **Objective Function 1**

It can be seen in Figure 3.5 that while the three algorithms give similar results (the exact numbers in each condition state as predicted by the three solvers can be seen in Table 3.11), the condition rating spread of these results is significantly different from the actual condition rating histogram. At year 15 there is a 19.5% discrepancy between the average condition rating given by the solvers and the actual average stock condition rating, therefore it can be concluded that for homogeneous chains at least, far too much accuracy is lost in the model under Objective Function 1. This suggests that widely used as it may be, the performance function is unsuitable for this particular application to bridge transition probability estimation. Too many numerical combinations of probabilities in differing states give rise to the same specific solution. This problem however is not just confined to the realm of transition probabilities and bridge management systems but to any field which has a dependent variable as a function of multiple other variables. The problem is referred to as equifinality and has been noted in fields such as hydrology (Beven, 2006) as well as organization science (Gresov and Drazin, 1997). A chi-squared analysis as illustrated in Equation 3.8 has been conducted therefore purely to test the hypothesis of all three algorithms converging to the same basin of attraction and thereby lend further weight to the suggestion that the solution is as mathematically optimal as possible. Hence, the focus is on the validity of the solvers as opposed to the validity of the method used. With 5 degrees of freedom, even for an extremely low level of significance of 0.001, the figures are clearly, as expected, far greater than the test statistic of 20.51 (Devore, 2004). However, it is the lack of convergence to an even slightly reasonable answer for condition states 0, 4 and 5 which is throwing the chi-square statistic off particularly, as the effect of having no observed states significantly amplifies the deviation when squared. Objective function 2 will now be investigated in an attempt to quantify whether or not it is a better minimization procedure in this context.

$$\chi^2 = \sum_{i=1}^{k} \frac{(N_i - np_i)^2}{np_i}$$ **Equation 3.8**

Where n is the observed sample and np is the expected for i is equal to the number of variables.

	Numbers in States at year 15							Chi-Squared Value
	0	**1**	**2**	**3**	**4**	**5**	**Avg. Rat**	
Act.	0	277	1575	148	0	0	1.935	-
FM	598	612	326	170	90	204	1.577	406938
GS	600	611	323	171	93	202	1.576	409067
CE	607	616	315	160	87	215	1.575	421852

Table 3.11: Numbers in respective condition states at year 15 under Objective Function 1 using Stationary Chains.

Where FM = Fmincon, GS = GlobalSearch and CE = Cross Entropy

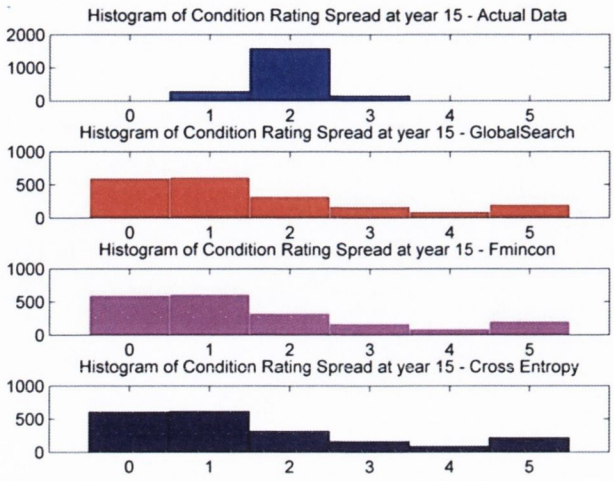


Figure 3.5: Condition rating spread at year 15 under objective function 1 using homogeneous chains.

- **Objective Function 2**

As seen in Figure 3.6, Objective Function 2 immediately appears to be much more suitable as a performance function for obtaining appropriate transition probabilities. The shape of the histograms as obtained using the three algorithms is now approximately the same as that derived from the actual condition ratings in the database itself. However, closer inspection reveals that there is a discrepancy in the scale of the pictorial representations. This is evident from the tabulated values in Table 3.12 as while the error in average condition rating is much less (~4%), the predicted number of bridges in each state still differs significantly from the actual number – i.e. although the actual number of structures for example in state number 2 is 1575, all three algorithms give this number to be approximately 900. Again, the chi-squared analysis thus was merely conducted to test the hypothesis of all three coming from the same basin of attraction. The results of this chi-squared analysis are also included in Table 3.12 and it can be seen that while even for the same extremely low level of significance as the previous example, none of the three algorithms remotely converge to a solution which would allow one to accept the null hypothesis of their being an accurate solution. However, they do all give a relatively similar value, thereby implying they come from the same parent solution. This again proves the robustness of the Cross-Entropy method.

Consequently, although Objective Function 2 itself performs better than the more common Objective Function 1, homogeneous Markovian chains as a whole appear unsuitable for transition probability estimation for a network of bridges over a considerable period of time. Hence, non-homogeneous chains will now be implemented in order to ascertain if they provide a more accurate solution.

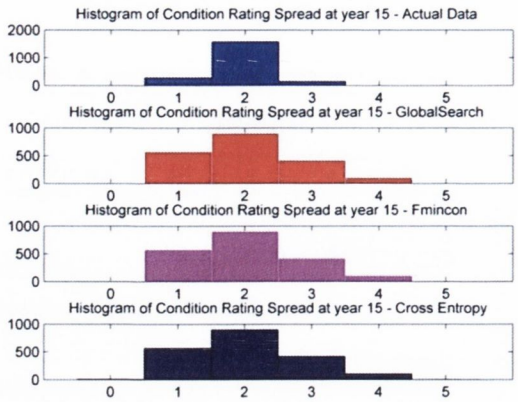


Figure 3.6: Condition rating spread at year 15 under Objective Function 2 using homogeneous chains.

	Numbers in States at year 15							Chi-Squared Value
	0	**1**	**2**	**3**	**4**	**5**	**Avg. Rat**	
Act.	0	277	1575	148	0	0	1.935	-
FM	8	572	901	415	103	1	2.018	11495
GS	8	572	901	415	103	1	2.018	11495
CE	8	570	899	418	103	2	2.022	11510

Table 3.12: Numbers in respective condition states at year 15 under Objective Function 2 using homogeneous chains.

Non-Homogeneous Chains

- **Objective Function 1**

Although Figure 3.5 and Table 3.11 have suggested that objective function 1, i.e. that of minimizing the discrepancy in expected condition rating is unsuitable for the purposes of predicting future structural condition rating since it seems far too inaccurate, non-homogenous chains will be implemented now with this objective function for completeness sake, in order to ascertain if they improve the method. Table 3.13 and Figure 3.7 respectively depict the condition rating spread of the structural stock then at year 15 under Objective Function 1 using non-homogeneous Markovian chains. As can be seen, the obtained solutions are still highly incorrect, possibly even more so than Figure 3.5 according to the figures and chi-squared statistic in Table 3.11 and Table 3.13, since neither the shapes of the histograms nor the numbers in each particular state concur with that expected. This again validates the suggestion that the performance function itself is unsuitable for the purposes of bridge transition probability estimation, possibly because of there being two sources of dataloss – the first when deriving the regression equation from the database and the

second when comparing the regression equation against the Markovian expected condition rating. Interestingly though, while all algorithms fail to find an accurate, viable solution, Cross-Entropy does appear to give the most 'acccurate' solution, again reiterating its validity. Note the non-homogeneous chains are thought to be more inaccurate here than the homogeneous chains, simply because the objective function is so unsuitable, i.e. having more variables is actually just adding to the increased inaccuracy.

	Numbers in States at year 15								Chi-Squared Value
	0	1	2	3	4	5	Avg. Rat	∑ Obj. Func.	
Act.	0	277	1575	148	0	0	1.935	-	-
FM	889	428	289	131	84	179	1.315	0.2386	818488
GS	980	199	415	115	201	90	1.314	0.2647	1007245
CE	780	640	123	197	139	121	1.319	0.2386	642116

Table 3.13: Numbers in respective condition states at year 15 under Objective Function 1 using non-homogeneous chains.

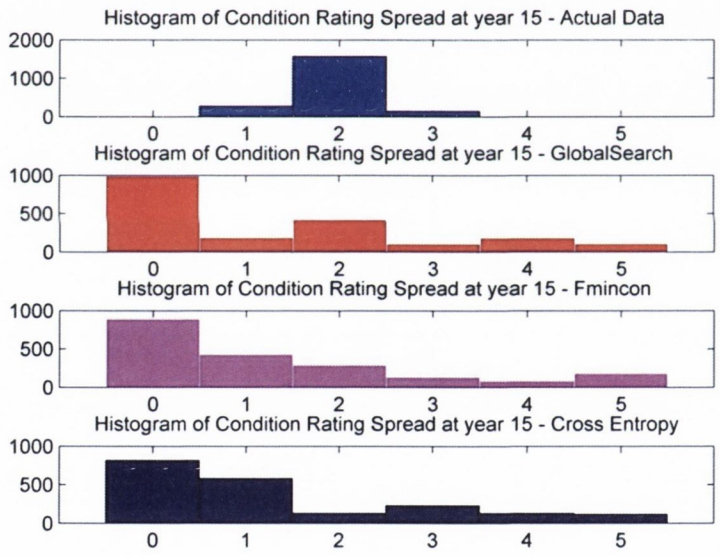


Figure 3.7: Condition rating spread at year 15 under Objective Function 1 using non-homogeneous chains.

- **Objective Function 2**

Figure 3.8 and Table 3.14 represent the condition rating spread of the structural stock at year 15 using non-homogeneous Markovian chains under Objective Function 2. As can be seen, not only do the shapes of all four histograms now correlate, the numbers in each state under the different algorithms also concur with one another quite well, and much better with the actual distribution.

This implies that although non-stationary chains are often disregarded as being too computationally intensive - in this study for instance, with $n = 5$ groups, there are now 25 or 5 times as many, variables to estimate, the program runtime does increase significantly from 808 seconds to 3917 seconds on a 2.8GHz, 6GB RAM machine, the improved accuracy in results obtained illustrate that such a computational effort is more than merited. The chi-squared statistic while still remaining above the test value of 20.51, is now much improved and again, Cross Entropy gives a much more accurate solution as signified by it having the lowest chi-squared value. Hence, not only is it the most appropriate solver in terms of obtaining realistic, feasible solutions within the probability domain as discussed earlier, it is at least as good, if not better, mathematically than other commonly used algorithms.

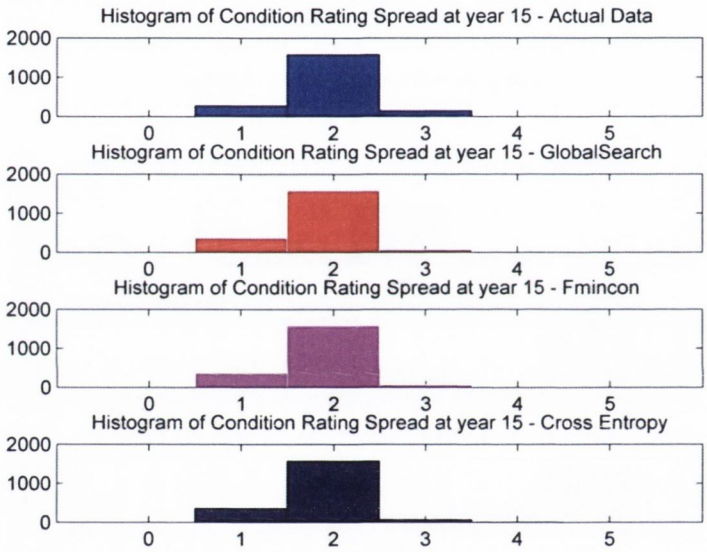


Figure 3.8: Condition rating spread at year 15 under Objective Function 2 using non-homogeneous chains.

	Numbers in States at year 15								Chi-Squared Value
	0	**1**	**2**	**3**	**4**	**5**	**Avg. Rat**	**∑ Obj. Func.**	
Act.	0	277	1575	148	0	0	1.935	-	-
FM	0	363	1574	63	0	0	1.85	2.558	75.5
GS	0	363	1574	63	0	0	1.85	2.555	75.5
CE	0	357	1565	75	2	1	1.856	2.563	60.1

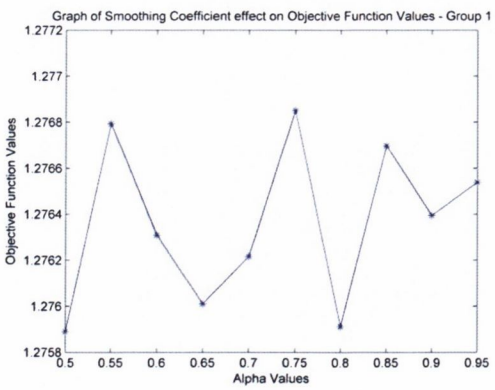
Table 3.14: Numbers in respective condition states at year 15 under Objective Function 2 using non-homogeneous chains.

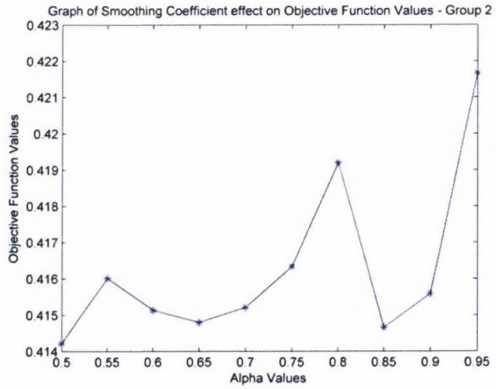
Regarding the choice of objective function, Figure 3.5 to Figure 3.8 together imply that the second objective function as shown in Equation 2.7 is a much more suitable method to employ in this

context of transition probability estimation – possibly because there is only one source of error in the formulation of the function, i.e. between the expected Markovian distribution of condition state and the actual distribution of condition state. From Table 3.14 it is noted that there is still a drift in predicted expected condition state as the deviation from the mean increases. However whilst no formulation may give 'perfect' results, it is clear that it is much more suitable for use as an optimization minimization function than objective function 1, that of minimizing the difference in expected state. Furthermore if only the expected condition at time t is available, the decision maker cannot deduce the state distribution, which is naturally of the utmost importance for maintenance planning. Hence, objective function 2 in conjunction with non-homogeneous Markov chains shall be encapsulated into the developed module.

3.4.2 Development of Cross Entropy

Finally, as mentioned in Section 3.3.4, instead of using a constant smoothing parameter for use in the CE method as is de rigeur, the parameter α was included as a variable in the optimization process itself. Ten values of alpha, linearly spaced from 0.5 to 0.95 were utilized. These results were then sorted and thus the best value of α for each particular problem was selected. This range was chosen as it was felt to be representative of values which are often chosen (De Boer et al., 2005). This ensures even more accurate results are obtained as the final answer the algorithm converges to becomes closer to the global minimum. Figure 3.9 illustrates the effect which variation in α has on the value of the objective function under objective function 2 for each group. As can be seen, the value of the performance function varies for each value and in fact each run of the program, hence there is clearly no 'correct' value and so its addition to the optimization process is worth the significantly increased computational effort (increases linearly with number of values of alpha, i.e. 10 times as long since 10 values are chosen) since it leads to increased accuracy and increased performance of the algorithm as a whole.





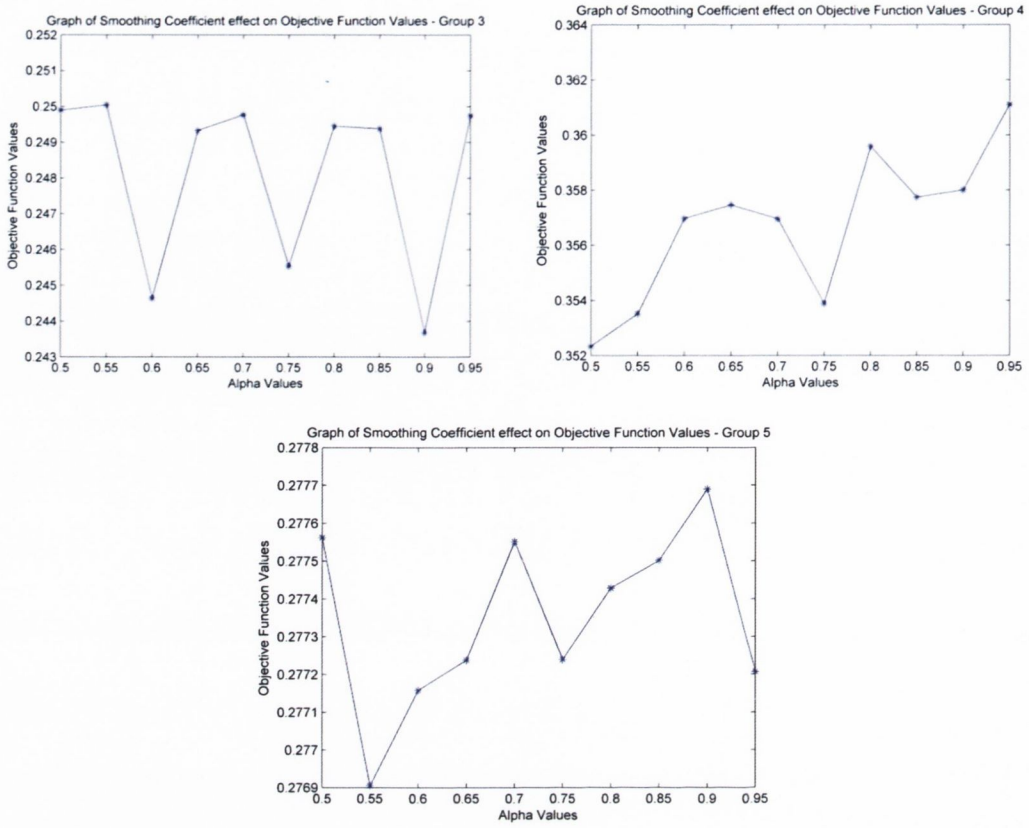


Figure 3.9: Objective Function 2 final values for groups 1 to 5 under a varying smoothing parameter.

Note that the version of the CE code developed and tested in this chapter has included α as a variable as a result of this increased accuracy. To further illustrate the benefit of including α in the optimization process, a fifth histogram added to the diagram in Figure 3.10. This additional graph corresponds to a CE algorithm where the smoothing parameter is a constant of 0.7. Note this value was chosen in accordance with the recommendations in De Boer et al. (2005). Table 3.15 lists the number of bridges in each state as represented by these histograms and it is evident from the discrepancy between the distribution of condition state as predicted under both CE algorithms, and the calculated chi-squared values that the inclusion of α is a beneficial addition.

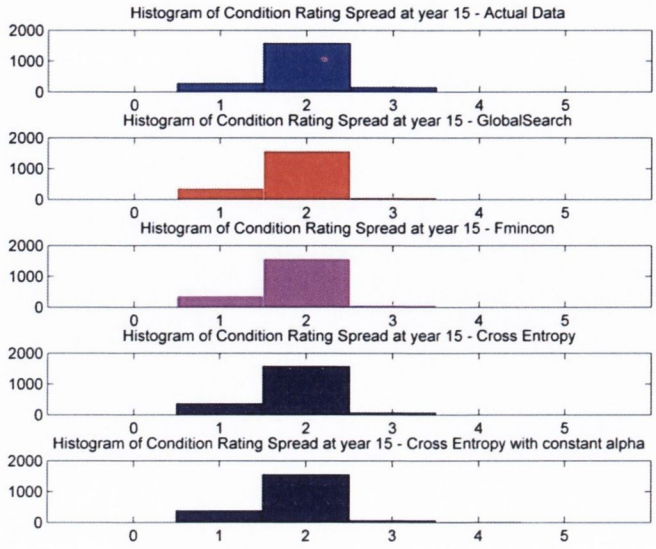


Figure 3.10: Condition rating spread at year 15 under objective function 2 using non-homogeneous chains and both Cross Entropy algorithms.

	Numbers in States at year 15							Chi-Squared Value
	0	1	2	3	4	5	Avg. Rat	
Act.	0	277	1575	148	0	0	1.935	-
FM	0	363	1574	63	0	0	1.85	75.5
GS	0	363	1574	63	0	0	1.85	75.5
CE Varying α	0	357	1565	75	2	1	1.856	60.1
CE Constant α	0	380	1556	62	1	1	1.843	88.5

Table 3.15: Numbers in respective condition states at year 15 under objective function 2 using non-homogeneous chains and both Cross Entropy algorithms.

3.5 FURTHER OBJECTIVE FUNCTION INVESTIGATION

In ascertaining the most appropriate form of Markov Chain, both objective functions implemented in this chapter were in the form shown in Equations 2.5 and 2.7 respectively, that is to say it was the absolute value of the minimization which was utilized. However, as mentioned in Section 3.2.2, the squared value of these functions is often employed so in accordance with Objective 2 as listed in Section 2.5, a thorough comparison of the different methods will be illustrated below. It is clear from Section 3.4.1 above that the second objective function, i.e. that of minimizing the discrepancy in expected future distribution, as opposed to expected future state is much more appropriate. However, it needs to be determined whether or not the squared value of the function should be used in the optimization as opposed to the absolute value illustrated in Figures 3.5 to 3.8. Additionally,

although it appears quite apparent that Objective Function 1 is inappropriate, as an aside it was investigated whether or not shifting the condition rating scale from 0 to 5 to 1 to 6 might improve the results. Note that this was done as it was felt that perhaps it was the zero of the rating scale which was affecting the optimization, since naturally the results are most susceptible to undue weight being given to the higher rating bounds such as 4 and 5, when the least condition rating has no effect mathematically. Likewise, for completeness sake, the effect of varying the degree of the polynomial was also investigated.

3.5.1 Absolute Value v Squared Value of Objective Functions

Since the purpose here is to ascertain whether or not the absolute value or the squared value should be used in the formulation of the optimization objective function, only non-homogeneous chains shall be used. Likewise, only the results for the more appropriate method, i.e. objective function 2 will be presented.

Figure 3.11 and Table 3.16 below illustrate numerically that all 3 algorithms give similar results. Also it is noted that the final objective function value over the 25 year period is less using the absolute value method than using the least squares method – this absolute value is listed in Table 3.14. This is as expected mathematically since the absolute value method is falling to e^{-1} as opposed to e^{-2}, and so there is a much wider confidence interval. Consequently the absolute value method is preferred as it has more weight on the tails of its distribution than the squared value method, thereby meaning the probabilities obtained are more likely to be chosen based on their best fit ability to the entire distribution as opposed to the tails alone.

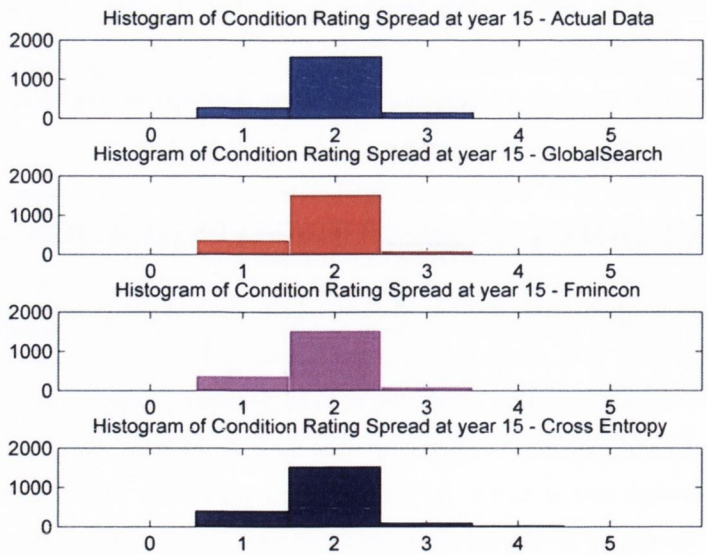


Figure 3.11: Condition rating spread at year 15 under the minimized square value of Objective Function 2 using non-homogeneous chains.

	Numbers in States at year 15							
	0	**1**	**2**	**3**	**4**	**5**	**Avg. Rat**	**∑ Obj. Func.**
Act.	0	277	1575	148	0	0	1.935	-
FM	0	376	1531	93	0	0	1.858	2.665
GS	0	376	1532	92	0	0	1.858	2.663
CE	0	398	1539	95	11	0	1.9125	2.673

Table 3.16: Numbers in respective condition states at year 15 under the minimized square value of Objective Function 2 using non-homogeneous chains.

3.5.2 Additional Examination of Expected Value Method

From the above investigations, it is evident that objective function 2, i.e. that of minimizing the discrepancy in expected condition state distribution, appears to be more suitable a procedure than objective function 1, that of minimizing the expected condition state value. This is as expected since as stated by Kallen (2007), the non-equidistant condition rating scale makes the mathematically computed average expected rating obsolete. However, for thoroughness, the effect of using different degrees of polynomial on objective function 1, i.e. that of Equation 2.5 will be investigated below. Furthermore, since the rating scale as used in EIRSPAN, the Irish system which will be utilized in this study, has a condition rating system ranging from 0 to 5 as outlined in Table 2.3, it was felt that maybe the 0 was affecting the outcome. Hence the rating scale was shifted so to speak from 0 to 5 to 1 to 6 to see if the overall result became any better.

- **Effect of Different Polynomials on Objective Function 1**

Year	Data	Poly. Fit (4)	Abs. Error	E(X) Computed	Data-E(X)
1	0.150	0.118	0.032	0.181	0.030
2	0.357	0.301	0.056	0.305	0.053
3	0.396	0.439	0.043	0.418	0.021
4	0.502	0.542	0.040	0.521	0.020
5	0.544	0.618	0.074	0.618	0.074
6	0.608	0.677	0.068	0.674	0.065
7	0.697	0.725	0.028	0.725	0.029
8	0.804	0.770	0.034	0.774	0.030
9	0.920	0.816	0.104	0.819	0.101
10	0.947	0.869	0.078	0.862	0.085
11	0.997	0.934	0.063	0.932	0.065
12	1.020	1.011	0.008	1.015	0.005
13	1.086	1.105	0.019	1.113	0.027
14	1.178	1.217	0.039	1.218	0.040
15	1.390	1.347	0.043	1.324	0.066
16	1.451	1.494	0.043	1.493	0.042
17	1.670	1.657	0.018	1.667	0.009
18	1.790	1.835	0.041	1.846	0.052

19	1.908	2.024	0.116	2.028	0.119
20	1.974	2.221	0.247	2.209	0.235
21	2.467	2.421	0.045	2.426	0.041
22	2.857	2.618	0.239	2.627	0.229
23	2.984	2.806	0.178	2.812	0.173
24	3.008	2.977	0.030	2.980	0.02
25	2.953	3.124	0.172	3.134	0.181
			∑ 1.864		∑1.822

Table 3.17: Table showing fit of fourth Degree polynomial for use in Equation 2.5 or Objective Function 1.

Year	Data	Poly. Fit (4)	Abs. Error	E(X) Computed	Data-E(X)
1	0.150	0.250	0.099	0.172	0.021
2	0.357	0.323	0.034	0.284	0.074
3	0.396	0.394	0.002	0.380	0.016
4	0.501	0.464	0.037	0.464	0.037
5	0.544	0.533	0.011	0.536	0.008
6	0.609	0.603	0.006	0.603	0.006
7	0.697	0.673	0.023	0.673	0.024
8	0.804	0.747	0.057	0.747	0.057
9	0.920	0.823	0.097	0.824	0.097
10	0.947	0.903	0.044	0.904	0.044
11	0.997	0.989	0.007	0.988	0.009
12	1.020	1.081	0.061	1.081	0.061
13	1.086	1.180	0.093	1.181	0.0952
14	1.178	1.287	0.108	1.287	0.108
15	1.390	1.402	0.012	1.395	0.005
16	1.451	1.528	0.077	1.535	0.084
17	1.676	1.664	0.012	1.678	0.002
18	1.794	1.812	0.018	1.825	0.031
19	1.908	1.973	0.065	1.973	0.065
20	1.974	2.147	0.173	2.121	0.147
21	2.467	2.336	0.131	2.347	0.120
22	2.857	2.540	0.317	2.570	0.287
23	2.984	2.761	0.223	2.789	0.196
24	3.008	2.999	0.008	2.999	0.008
25	2.953	3.256	0.303	3.201	0.248
			∑ 2.022		∑ 1.851

Table 3.18: Table showing fit of third degree polynomial for use in Equation 2.5 or Objective Function1.

Year	Data	Poly. Fit (4)	Abs. Error	E(X) Computed	Abs(Data-E(X))
1	0.150	0.345	0.195	0.165	0.015
2	0.357	0.371	0.013	0.272	0.085
3	0.396	0.405	0.008	0.365	0.031
4	0.501	0.446	0.055	0.446	0.055
5	0.544	0.496	0.048	0.517	0.027
6	0.609	0.554	0.055	0.558	0.050
7	0.697	0.619	0.077	0.619	0.078
8	0.804	0.693	0.111	0.693	0.111
9	0.920	0.774	0.146	0.775	0.145
10	0.947	0.864	0.084	0.864	0.084
11	0.997	0.961	0.035	0.965	0.032
12	1.021	1.067	0.046	1.073	0.053
13	1.086	1.180	0.094	1.186	0.099
14	1.178	1.301	0.123	1.301	0.123
15	1.390	1.430	0.040	1.419	0.029
16	1.451	1.568	0.117	1.568	0.117
17	1.676	1.713	0.037	1.720	0.044
18	1.794	1.866	0.071	1.873	0.079
19	1.908	2.027	0.119	2.027	0.119
20	1.974	2.196	0.222	2.179	0.206
21	2.467	2.373	0.094	2.380	0.087
22	2.8572	2.558	0.299	2.576	0.281
23	2.984	2.751	0.234	2.767	0.217
24	3.008	2.952	0.056	2.952	0.056
25	2.953	3.161	0.208	3.128	0.176
			∑ 2.589		∑ 2.398

Table 3.19: Table showing fit of second degree polynomial for use in Equation 2.5 or Objective Function 1.

From Table 3.17 to Table 3.19 above then, it is clear that a polynomial of the fourth degree provides the most accurate fit to the data, as the sum of the objective function over the twenty-five year period is lowest for this value, i.e. 1.822 as opposed to 1.851 or 2.398. Hence, as the calculations and investigations in Sections 3.4.1 and 3.5.1 pertain to objective Function 1 with a polynomial of the fourth degree, it is clear that changing the order of polynomial will only serve to make the function less accurate. Therefore it is evidently entirely inappropriate despite its widespread use.

- **Effect of Scale Shift**

Lastly, since the condition rating scale employed by EIRSPAN ranges from 0 to 5, this was shifted to 1 to 6, in order to see if the zero was affecting the computation values under objective function 1 – since objective function 2 deals with minimizing the probability distribution, the name or rank given to each rating has no bearing on the final computed value. Figure 3.12 and Table 3.20 below

illustrate the predicted future distribution spread accordingly and it can clearly be seen that the modification bears no improvement to the objective function itself, there is no improvement in accuracy of expected future condition state distribution when compared to Table 3.13. Consequently, as a result of the above investigations, it can be concluded without doubt that Objective Function 2 is by far the more appropriate method regardless.

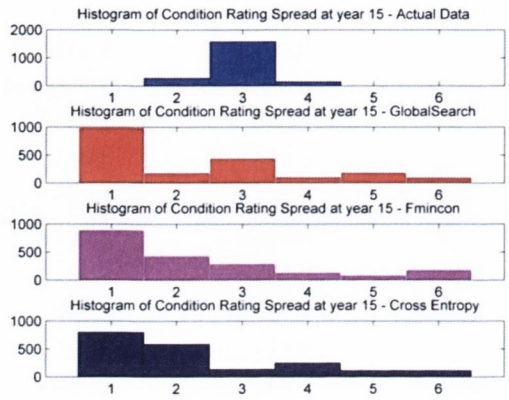


Figure 3.12: Condition rating spread at year 15 under the 'shifted scale' of Objective Function 1 with non-homogeneous chains.

	Numbers in States at year 15							
	1	**2**	**3**	**4**	**5**	**6**	**Avg. Rat**	**∑ Obj. Func.**
Act.	0	277	1575	148	0	0	2.936	-
FM	889	428	289	131	84	179	2.315	0.2591
GS	987	181	437	107	186	102	2.315	0.2558
CE	800	586	137	249	114	114	2.317	0.2510

Table 3.20: Numbers in respective condition states at year 15 under the 'shifted scale' of Objective Function 1 with non-homogeneous chains.

3.6 CONCLUSIONS

This chapter has outlined the system development or methodology behind the bridge management module developed in this thesis. The main aims were as stated at the beginning of this chapter and in Section 2.5:

1. To develop the system methodology, particularly the most appropriate manner of modelling future bridge condition, given the fact that the module needs to ideally be incorporated as part of a BMS. This involves determining whether or not homogeneous or non-homogeneous chains should be used as well as ascertaining the most appropriate optimization procedure.

2. To implement a more robust solver for use in transition probability estimation, given that many of those in use at the present time are unsuitable.

From the analysis carried out in this chapter it is clear that these stated objectives have been fulfilled. Firstly, non-homogeneous chains have been shown to more than merit the added complexity which they bring to the model. Secondly, a minimization of the absolute discrepancy in predicted distribution of condition state as opposed to a minimization of the expected value of condition state has proved to be far more accurate.

Regarding the solver then, it has been found that the distributions of expected condition state over time obtained using cross-entropy tend to concur with those obtained using other methods, thereby indicating the method is certainly an appropriate substitute. However, closer investigation shows that the procedure is actually far more robust than established methods in certain aspects, specifically the fact that it does not tend to converge to probabilities of zero and one, thus making it especially suitable for use in this particular application.

Furthermore, by including alpha, the smoothing parameter as a variable in the optimization process, it was found the accuracy and efficiency of the CE algorithm itself increased, therefore suggesting it to be a beneficial modification to the traditional algorithm.

Finally, it is recognized that using the above recommended method, i.e. non-homogeneous chains and a modified Cross Entropy algorithm leads to a much greater computation time than other possible combinations. Speed generally is of the essence in problem solving and in fact Patidar et al. (2011) claim that the best methods and algorithms are those consistent with the least computational time. However, in the context of transition probability estimation, it is more important that the solution obtained is as accurate as is inherently possible, hence not as much emphasis is placed on computational-time.

This chapter has carried out the above analysis using a randomly generated database of condition ratings generated in Matlab. Hence, the following chapter will look at the application of more accurate data, i.e. the simulation of data deteriorating according to pre-specified degradation mechanisms which could be used in the absence of sufficient quantities of bridge inspection information.

CHAPTER 4 – INTEGRATION OF DETERIORATION MODELS

4 INTEGRATION OF DETERIORATION MODELS

4.1 INTRODUCTION

The preceding chapter has outlined the development of the system methodology, i.e. the basis behind the operation of the module. Both an algorithm and appropriate objective function have been selected. In order to discern these premises, a random, normally generated database was utilized. These simulated results were sufficient for identification purposes, but in order to obtain realistic, useful outputs and results in the context of an actual BMS, the inputs or information must be as correct as possible.

Ideally, given enough inspection data, the prediction modules of Bridge Management Systems would be calibrated directly from the raw data obtained from inspections. As outlined in Chapter 2 however, the majority of systems do not yet contain sufficient information to populate the deterioration modules in such a fashion. In the interim the future bridge condition needs to be estimated using predictive models. Naturally, the predictive powers of these systems then are only as good as the underlying models describing the physical deterioration processes themselves.

Section 2.3 outlined the state of the art with regard to deterioration modelling and the predictive powers of current BMS. Both statistical and physical models have been developed - statistical meaning that the data is generated by a mathematical model which does not try to emulate a real-life degradation mechanism. Most commonly, this will be a probabilistic model which is fitted to inspection data by means of statistical estimation such as maximum likelihood estimation. An example of such an approach is the use of lifetime distributions fitted to lifetimes of bridges as carried out by van Noortwijk and Klatter (2004), where a Weibull type distribution was fitted to the ages of both existing and demolished bridges in the Netherlands. Thompson and Sobanjo (2010) have also incorporated Weibull survival models into the PONTIS deterioration models in order to specifically allow for the fact that the existing Markovian models in the system have fairly rapid initial deterioration (Thompson and Johnson, 2005) which tends to make the predictions less realistic. Likewise Madanat and Wan Ibrahim (1995) employ the use of a Poisson process to categorize and predict future bridge structural condition rating. However, this means that since the Markov transition probabilities are essentially estimated to fit the parameters and data in existence, the deterioration pattern is inherently influenced before it is observed. Instead, if a physically based model is used as the model basis, the Markov transition probabilities should model the actual expected deterioration pattern, rather than a predefined statistical one. Consequently models which attempt to describe the deterioration process from a physical point of view have also been developed. The Finnish system outlined in Chapter 2 appears to be the most technologically advanced of the systems in use at the present time, but the models employed in the system are

specific to Finland only. Consequently this thesis deals with the incorporation of a physical deterioration model, suitable for use within the Irish 6-state Bridge Management System.

Apart from masonry arch, reinforced-concrete structures are by far the most popular bridge type on the national roads of Ireland – see Figure 4.1. For this reason then, the developed physical model was chosen to represent this subsection of the Irish bridge stock in order to have as much real-time information as possible to draw from.

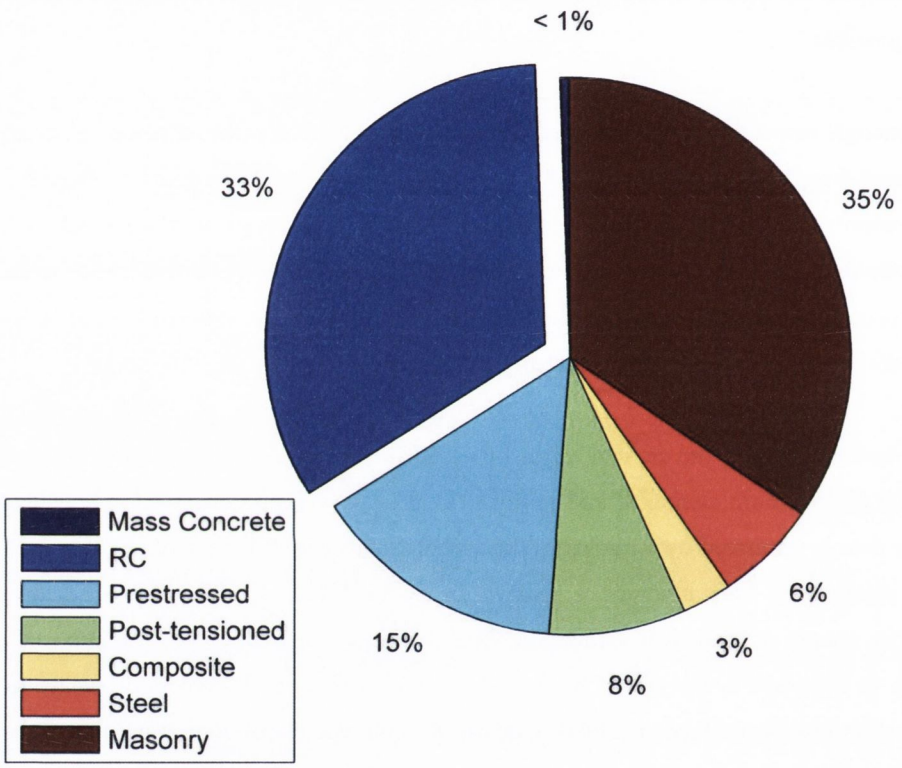


Figure 4.1. Pie-chart showing percentage of different bridge superstructure materials on Irish national road network.

Reinforced-concrete bridges deteriorate due to a number of different mechanisms acting in tandem but for application purposes, the physical mechanism chosen to demonstrate the developed methodology is based on that of chloride-induced corrosion on the grounds that it is responsible for more than 55% of concrete repairs across Europe (Tilly, 2007). By far the most prolific RC deterioration mechanism - it was estimated by Tosi in 2009 that the annual cost of corrosion effects on bridges in the United States alone was $8.3 billion (Tosi, 2009), much research has been conducted in the past in an effort to comprehend better its effect on a structure's lifecycle. Existing models represent structural degradation both in terms of mass loss of steel (Vidal et al., 2004) and in terms of propagated crack-width (Mullard and Stewart, 2011). However, given the fact that the

model in this instance needs to be incorporated into a BMS, a cracking-limit state model was deemed to be most appropriate to the visual nature of bridge inspections and therefore the quality of inspection data. Note that these crack widths correspond to:

1. Reduced cross-section due to corrosion of bar

2. Reduced bond between reinforcement and concrete due to presence of corrosion products

3. Change in material properties (strength, modulus) due to corrosion process

Specifically then, the aims of this chapter are to fulfill objectives 3 and 4 as stated in Section 2.5, i.e.

1. To determine how best to calibrate suitable transition matrices in the absence of sufficient quantities of inspection data, specifically, the incorporation of physically-based, analytical models into prediction systems.

2. To investigate the phenomenon of chloride-induced corrosion of reinforced concrete and particularly the most suitable analytical models for use in predicting future condition state in a cracking-limit state, service life model.

Note that, the developed model is for framework purposes only. In order to simulate total structural degradation with time, carbonation and other forms of attack should also be modelled as appropriate and the overall deterioration combined and aggregated.

4.2 CHLORIDE-INDUCED CORROSION

The main indicator of the presence of chloride-induced corrosion is cracking of the concrete cover – see for instance Figure 4.2. Usually excessive cracking occurs before the corrosion has any significant effect on the overall structural capacity of the member (Chernin and Val, 2011). However, once cracks have developed, they can lead to spalling and rapid structural degeneration and consequently much work has been undertaken in recent years in an effort to predict the time to initiation of these cracks with sufficient accuracy.

Figure 4.2: Hairline cracking of concrete abutment due to RC abutment (NRA, 2008).

The mechanism of chloride-induced corrosion is generally accepted to be electrochemical in nature (Bazant, 1979a; Liu and Weyers, 1998). The alkaline environment of concrete results in the formation of a passive film of iron oxides at the steel-concrete interface which protects the steel from corrosion. Chloride ions can destroy this passive film and once the layer breaks down, corrosion is initiated. Due to the presence of both moisture and oxygen, a range of expansive, corrosive products (i.e. rust) are then formed. These expansive products give rise to tensile stresses on the concrete surrounding the reinforcing bar, which leads to cracking and spalling of the cover layer (Bazant, 1979a; El Maaddawy and Soudki, 2007; Liu and Weyers, 1998).

A conceptual model for service life prediction of corroded RC structures was first developed by Tuutti (1979). As shown in Figure 4.3, it consists of both an initiation phase, T_i and a propagation phase, T_{cr}. The first phase, T_i, represents the time required for the chloride ions to diffuse to the steel-concrete interface, and the surface chloride concentration to exceed a limiting value, thereby initiating corrosion. The second phase, the propagation period, T_{cr}, represents the time after corrosion initiation, as crack generation occurs.

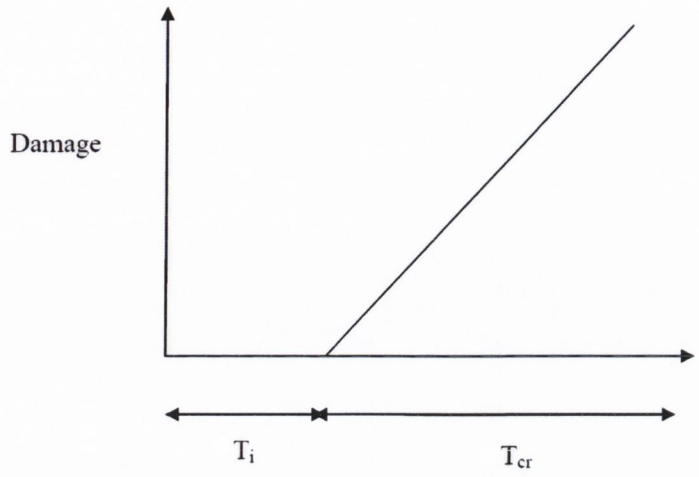


Figure 4.3: Two-stage chloride-induced corrosion process.

Further research carried out by Weyers (1998) suggested that in fact, not all of the corrosion products contribute immediately to the expansive pressure on the concrete. Instead, some were considered to fill the voids and pores around the reinforcing bar. This porous zone results in dividing the propagation period into two distinct and separate phases. The first, commonly referred to as T_{1st} is the time to the appearance of first crack - generally taken to be a hairline crack of approximately 0.05mm (Mullard and Stewart, 2009; So et al., 2009; Vu et al., 2005), and represents the period of free expansion until the rust products reach the concrete and thus initiate cracking. This is depicted diagrammatically in Figure 4.4. The second part of the propagation phase, T_{sp} is then referred to as the time to severe cracking. Note that the duration of T_{1st} and T_{sp} in Figure 4.4 combined is equivalent to T_{cr} in Figure 4.3.

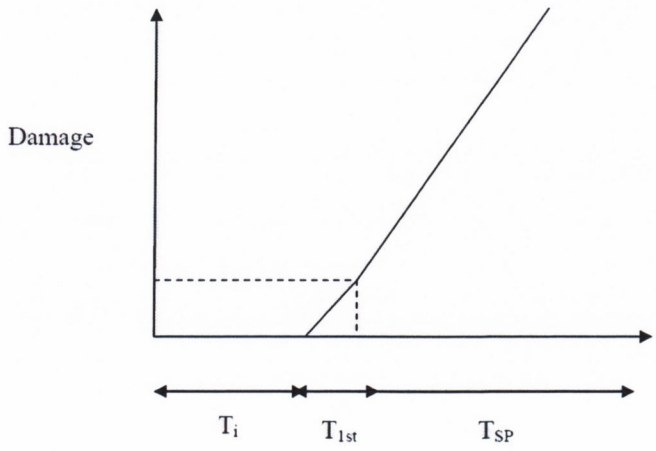


Figure 4.4: Three-stage chloride-induced corrosion process.

Although many empirical models abound in the literature (Alonso et al., 1998; Andrade et al., 1993; Morinaga, 1990) for estimating the duration of each deterioration phase, an analytical approach was deemed to best represent the three phases of deterioration shown above in Figure 4.4. The models themselves will be highlighted in the next section, with the defining model parameters for alternative environments and situations investigated in the following chapter. The overall integration of such a methodology into a BMS and the most appropriate manner of calibrating the Markovian transition matrices from the outlined mechanism will also be included in that chapter.

4.3 ANALYTICAL MODELS IMPLEMENTED

A rigorous literature review revealed the existence of many models and methods available to estimate the duration of each deterioration phase (Al-Harthy and Stewart, 2006; Markeset and Murdal, 2008; So et al., 2009; Stewart et al., 2011a). However, given the end purpose of integrating the model into a bridge condition prediction module the three analytical models outlined below were selected as being most appropriate for use. As mentioned above, these predict future condition state in a cracking limit state service life structural model suitable for incorporating into a visually-based bridge assessment procedure. Monte Carlo simulation about defined means and variances of the parameters involved was used to construct a database of 2000 bridges over a 100-year period, suitable for simulating an overall network life-cycle effect. Note that in particular, a great deal of information is given about the most fitting model to use for modelling the T_{1st}, time-to-first-crack phase. This aside came about as a result of the confusion which arose from a multitude of different models postulating to give the most accurate results for this phase of deterioration. The complete results and background to this problem can be found in Reale and O'Connor (2012b). Note that for implementation purposes all analysis below was carried out under the Eurocode specifications for the tensile strength and the effective Young's Modulus of C50 concrete (CEN, 2004). Again this is purely for demonstration purposes though and the inputs to all models can be easily varied to allow for structures built under different specifications. Again, this further demonstrates the robustness of the developed methodology.

4.3.1 Time to Initiation, T_i

The corrosion initiation phase T_i is generally the longest of the three phases since it represents the time taken for the chlorides to diffuse from the concrete surface, down to the reinforcement and initiate corrosion. The duration of this phase is estimated, as is common practice, using Fick's 2nd Law with Crank's error solution (So et al., 2009; Suo and Stewart, 2009). This is represented as follows:

$$C(x,t) = C_i + (C_s - C_i)\left[1 - erf\left(\frac{x}{2\sqrt{D_{app}t}}\right)\right] \qquad \textbf{Equation 4.1}$$

where $C(x,t)$ = Chloride content at depth of reinforcement x, at time t, C_s = Surface chloride concentration, C_i = Initial chloride concentration - taken as being zero for new structures, D_{app} = Apparent diffusion coefficient and t = time.

When this equation is reformulated with t as an unknown, x as a known variable equal to the cover depth, C inputted as C_{cr}, the critical chloride concentration, i.e. the chloride concentration necessary to initiate corrosion, the predicted t becomes the time to initiation of corrosion. This is shown in Equation 4.2.

$$T_i = \frac{C^2}{4D_{app}} erf^{-1}\left[\frac{C_{cr} - C_s}{C_i - C_s}\right]^2 \qquad \textbf{Equation 4.2}$$

If the mean cover depth, C has been specified, and the initial chloride concentration at year $t = 0$ is taken to be zero, three input variables are left to be defined - D_{app}, C_{cr} and C_s. D_{app} depends on the material parameters of the concrete in question. For instance it is influenced by such things as cement type, water-cement ratio, the addition of admixed or ingressed chlorides, compaction, relative humidity, temperature and time etc. Time-dependency is not considered in this model however, as like in the LIFECON report (Lay and Schießl, 2003) a decrease of the coefficient in time is neglected on the safe side. Similarly, since Ireland is a small island with relatively negligible temperature and climate gradient, the variability effects of relative humidity and temperature are not modelled. Instead parameters appropriate and applicable to Irish conditions shall be used as discussed and reiterated in the following chapter. The parameter is quoted in terms of both mm^2/yr and m^2/s. For application purposes a D_{app} of 1×10^{-12} m^2/s is considered here. This corresponds to a standard value for OPC concrete (Vu and Stewart, 2000). The coefficient of variance is taken to be 0.2 and a normal distribution is also utilised as in Vu and Stewart (2000) also. Note that should future development consider the inclusion of time-dependent and temperature-dependent parameters necessary, the framework developed easily allows for their inclusion via substitution of the models chosen here in this thesis.

Regarding C_{cr}, there is much debate concerning the exact value of this parameter. Angst, Elsener et al. (2009) conducted a comprehensive study of experimental testing and site measurements and found that on the basis of the literature it was not possible to select a reliable range of chloride threshold values. As expected then, a variety of values have been documented in the literature. Researchers such as Bastidas-Arteaga et al. (2009) and So et al. (2009) used a mean C_{cr} value of 0.0375% by weight of concrete in probability based deterioration models. A similar value was adopted by Stewart in some of his earlier work (Stewart and Rosowsky, 1998; Vu and Stewart, 2000). However, in more recent papers by Stewart a higher value of 0.1% by weight of concrete has been utilized (Suo and Stewart, 2009). The chosen C_{cr} value evidently has a great bearing on the time to corrosion initiation with a higher value resulting in a longer time to corrosion initiation

since the percentage chlorides required to initiate corrosion has now increased. For application purposes a mid-range value of .057% by weight of concrete or 0.4% by weight of cement is utilised.

The C_s value, the surface chloride concentration can also be quoted in terms of percentage weight of both concrete and cement. However, since this thesis deals with the development of a model for use in a practical bridge management system, it was deemed best to utilise a value quoted in kg/m^3 and so a mean value of 5 kg/m^3, with a coefficient of variance of 0.25 (Stewart et al., 2011b) is used here for illustration purposes. This was lognormally distributed as suggested in papers (Morcous et al., 2010; Stewart et al., 2011b). Note that a sensitivity analysis of the literature quoted parameter values will be performed in the following chapter. In particular, values as appropriate for Irish conditions will be selected.

4.3.2 Time to First Crack

Generally, the time to repair/replacement of reinforced concrete structures due to chloride-induced corrosion is determined by cracking of the concrete cover, since this is the first indication of damage. Hence, many researchers have focused on the development of calculation methods for this time-to-first-crack. As stated, difficulties were encountered in the search for a reliable, consistent analytic model for predicting future condition state in a cracking limit state, service life structural model. These complications are outlined below by means of examining and comparing three well known mathematical models. The problems with them are illustrated and a required modification, arising from an earlier trigonometrical derivation error, is also presented and directly paralleled with the original versions. This consequently results in compliance with previous experimental results and thus is ultimately proposed as a means of predicting time to crack initiation when the use of more advanced, computationally intensive FE models is inappropriate, i.e. in a deterioration module suitable for use in a BMS, as is the case here.

Modelling Approach

In the literature, it can be seen that two approaches to analytic crack-modeling can be found; that of the thick-walled uniform cylinder approach (TWUC) whereby the concrete is modeled as a single layer which becomes perfectly plastic when in tension and the second approach, that of the thick-walled double cylinder approach (TWDC) which considers the concrete cylinder as having two parts: a cracked inner cylinder and an un-cracked outer one. This is depicted in Figure 4.5.

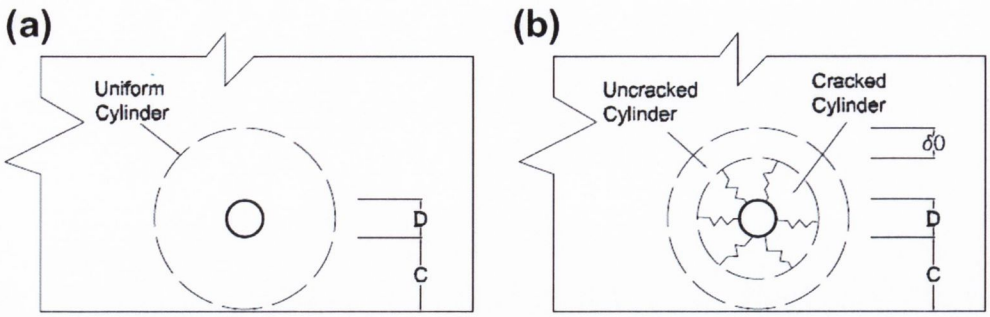


Figure 4.5. Analytical models of corrosion-induced cover cracking (a) thick-walled uniform cylinder model (TWUC) ; (b) thick-walled double cylinder model (TWDC).

Unfortunately, neither model can be properly validated against results of tests/field observations of RC elements subjected to either natural or accelerated corrosion. This is because an essential parameter of these models is the amount of corrosion products penetrating into the concrete pores instead of contributing directly to pressure between the rebar and the concrete. This amount has never been measured experimentally and although Val and Chernin (2011) have attempted to evaluate the amount of corrosion products, the uncertainty in the amount of corrosion products prevents proper comparison of either the TWUC or TWDC model with real-time results. At the same time, it is important to be able to compare the models and provide recommendations as to their applicability. Chernin and Val (2011) have examined both models in detail, particularly the theoretical shortcomings with the assumptions inherent in either model. Both models were validated against a nonlinear finite element model and various situations investigated. In conclusion, they state that all aspects considered, an improvement of analytical models based on a thick-walled cylinder in terms of the description of the non-linear behaviour of concrete may not prove beneficial compared with simple TWUC models. Consequently, TWUC models were focused on solely in an effort to obtain at least realistic numerical values, suitable for prediction purposes. The following sections therefore outline three well-known TWUC models, highlighting the shortcomings and anomalies associated with the models themselves and the literature which refers to them.

Existing TWUC Models

For clarity, this section describes the three well-known analytic models investigated during the course of this research. Their development is charted as the latter two models have their basis in the first. The shortcomings of these various models will then be discussed after.

- **Bazant Model**

Based on plane-strain linear elasticity theory, Bazant (1979b) developed the first analytical model which attempted to calculate the time to corrosion induced crack initiation – T_{1st} as in Figure 4.4. The model is based on a number of assumptions:

(i) The concrete surrounding a corroding reinforcing bar is considered to be a homogeneous linear elastic material, and

(ii) Steady-state corrosion is assumed.

The expansion caused by a larger volume of corrosion products compared to that of the corroded steel is modeled by a uniform increase in the diameter of the cylindrical hole around the reinforcing bar, ΔD. Consequently, a bar having original diameter D, will increase its diameter to $D+\Delta D$.

If M_r denotes the total mass of rust per unit length of one bar, and steady-state corrosion begins at T_i, the time to initiation of corrosion, then

$$M_r = s\, j_r T_{1st} \qquad \textbf{Equation 4.2}$$

where s = spacing of bars, j_r = rate of rust production per unit area of plane, and T_{1st} = duration of steady-state corrosion. Note also that in Bazant's model, the mass of steel that was consumed to produce M_r is $M_{st} = 0.523\ M_r$, where 0.523 is the molecular weight of Fe divided by the molecular weight of $Fe(OH)_3$. It was assumed that only $FeOH_3$ contributed to the volume expansion and so the corrosion product $Fe(OH)_2$ was neglected.

Expressing the increase in volume per unit length of bar by means of M_r and ΔD then, Bazant obtained:

$$\frac{M_r}{\rho_r} - \frac{M_{st}}{\rho_{st}} = [(D + \Delta D)^2 - D^2]\frac{\pi}{4} \qquad \textbf{Equation 4.3}$$

where ρ_r, ρ_{st} are the mass densities of $Fe(OH)_3$ and steel respectively, and were taken as: ρ_{st} = 7.85g/cm^3 and $\rho_r = \rho_{st}/4$. Substituting for M_r and M_{st}, Bazant obtains:

$$(D + \Delta D)^2 = D^2 + \frac{2sj_r t_{cor}}{\rho_{cor}} \qquad \textbf{Equation 4.4}$$

Where $\rho_{cor} = \left[\left(\frac{1}{\rho_r}\right) - \left(\frac{0.583}{\rho_{st}}\right)\right]^{-1} \frac{\pi}{2} \approx 3.6$ g/cm^2. Assuming that $\Delta D^2 \ll D$, the equation can be simplified to:

$$T_{1st} = \rho_{cor} \frac{D\Delta D}{sj_r} \qquad \textbf{Equation 4.5}$$

Since it is assumed that concrete is a homogeneous, linear elastic material, the pressure p_r at the surface of the bar is the pressure that is needed to expand a cylindrical hole of diameter D by ΔD. This p_r is larger than for a hole in a thick-wall cylinder of external diameter $D+2C$ (where C is cover) and smaller than the pressure for a hole in an infinite medium. Using the well-known formula for bar-hole flexibility (Timoshenko and Goodier, 1982):

$$\Delta D = \delta_{pp} p_r \qquad \textbf{Equation 4.6}$$

and Lame's stress solutions (Timoshenko and Goodier, 1982) of:

$$\delta_{pp} = (1 + \nu)\frac{D}{E_{ef}} \qquad \textbf{Equation 4.7}$$

and $$\delta_{pp} = \left[1 + \nu + \frac{D^2}{2C(C+D)}\right]\frac{D}{E_{ef}} \qquad \textbf{Equation 4.8}$$

the solution is obtained by averaging both solutions. Note that Equation 4.7 refers to the lower bound solution for a thick-walled cylinder. Equation 4.8 refers to the upper bound solution for infinite space.

The effect of multiple bars on ΔD is considered by assuming that the expansion of one bar (normal to the concrete surface), caused by applying pressure p_r at the surface of both adjacent bars would be approximately $2p_r D^3/s^2 E_{ef}$. Adding this to the previous bounds:

$$\delta_{pp} \approx \frac{1}{2}(\delta_{pp}^0 + \delta_{pp}^1) \qquad \textbf{Equation 4.9}$$

with

$$\delta_{pp}^{0} = \frac{D}{E_{ef}}(1+v) + \frac{2D^3}{s^2 E_{ef}}$$ **Equation 4.10**

$$\delta_{pp}^{1} = \frac{D}{E_{ef}}\left[1 + v + \frac{D^2}{2C(C+D)}\right] + \frac{2D^3}{s^2 E_{ef}}$$ **Equation 4.11**

If the spacing s of the bars is large, (greater than $6D$), Bazant assumes that the failure mode consists of planar cracks at an incline of 45°, emanating at opposite sides of the bar. If at failure the average tensile stress on the crack surfaces equals the tensile strength of concrete f_t', equilibrium requires that:

$$P = \frac{2Cf_t'}{D}$$ **Equation 4.12**

Since $\Delta D = \delta_{pp} p_r$,

$$\Delta D = 2f_t' \frac{C}{D} \delta_{pp}$$ **Equation 4.13**

For determination of j_r, the rate of rust production, Bazant proposed a complex physical model, depending on a large number of parameters including anodic and cathodic areas which were not verified experimentally. No appropriate values for this parameter as such were outlined in the paper. However, if a value is assumed - perhaps through a sensitivity analysis of the variance of the parameter, since ρ_{cor}, D, s and ΔD are known, the time to first crack can be calculated using Equation 4.5.

- **Liu and Weyers Model**

Another commonly used model, the Liu and Weyers model (1998) came about as a result of accelerated corrosion testing carried out over a 5-year period on 44 RC slabs by incorporating high dosages of chlorides into the admixes. Each slab size was 1180x1180x216 mm with five 16mm or 19mm reinforcing bars. Only 10 slabs developed cracks within 2 to 5 years. The Bazant model was adapted to model the process based on these results by considering (i) the rate of corrosion/rust production to decrease with time and (ii) the introduction of the concept of a 'porous zone', d_0, around the steel/concrete interface. Therefore the amount of corrosion products needed to initiate cracking consists of: (i) the amount of corrosion products needed to fill this porous zone during free expansion and (ii) the amount of additional products required to generate the critical tensile stresses in order to induce cracking.

If d_s is taken to be the thickness of the corrosion products needed to generate tensile stresses, W_{crit}, the critical amount of corrosion products that generate these stresses is given by:

$$W_{crit} = \rho_{rust}\left(\pi(d_s + d_0)D + \frac{W_{st}}{\rho_{st}}\right) \qquad \textbf{Equation 4.14}$$

Like Bazant (1979b), concrete was considered to be a homogeneous elastic material. However, in order to increase the estimated time to crack initiation compared to that yielded by Bazant's model in an effort to make the experimental results more in line with those calculated, the relationship between the expansion ΔD and pressure P was solely based on the solution for a thick-walled cylinder, as expressed in Equation 4.7. If, as shown in Figure 4.5, $a = ((D + 2d_0))/2$ is taken to be the inner radius, and $b = X + ((D + 2d_0))/2$ as the outer radius, with C denoting the cover depth, the pressure P at the concrete/rust interface can be expressed as:

$$P = \frac{2E_{ef}d_s}{(D + 2d_0)\left(\frac{b^2 + a^2}{b^2 - a^2} + v_c\right)} \qquad \textbf{Equation 4.15}$$

Where v_c is Poisson's Ratio of concrete, E_{ef} is the effective elastic modulus of the concrete and equal to $E_c/((1 + \varphi_{cr}))$, E_c is the elastic modulus of the concrete and φ_{cr} is the creep coefficient.

As in Bazant (1979b) ,the minimum stress required to cause cracking of the concrete cover is equated to the tensile strength of the concrete (as in Equation 4.12), except that now the diameter term D has been replaced by $D+2d_0$ to reflect the inclusion of this new 'porous zone'.

$$P = \frac{2Cf_t'}{D + 2d_0} \qquad \textbf{Equation 4.16}$$

Equating Equations 4.15 and 4.16, d_s can be expressed as

$$d_s = \frac{Cf_t'}{E_{ef}}\left(\frac{a^2 + b^2}{b^2 - a^2} + v_c\right) \qquad \textbf{Equation 4.17}$$

Therefore, the critical amount of corrosion products needed to induce cover cracking can be estimated by substituting Equation 4.17 into Equation 4.14.

In order to further increase the estimated time to crack initiation, the rate of rust production, k_p, was assumed to be not constant as Bazant had stated, but rather to be inversely proportional to the amount of corrosion products, and hence to decrease with time. In kg^2/m^2year it is given as:

$$k_p = \frac{0.098}{1.08}\left(\frac{1}{\alpha}\right)\pi d i_{corr} \qquad \textbf{Equation 4.18}$$

The time to crack initiation is then expressed as being:

$$T_{1st} = \frac{W_{crit}^2}{2k_p} \qquad \textbf{Equation 4.19}$$

For application purposes, $f_t^{'}$, the tensile strength is given as being 3.3 MPa, the elastic modulus of concrete E_c = 27GPa, creep coefficient φ_{cr} =2.0, Poisson's ratio, v_c = 0.18, density of rust ρ_{rust} = 3600 kg/m^3, d_0, the thickness of the porous zone is taken to be 12.5μm, and α, a factor which depends on the composition of the corrosion products, is varied between 0.523 (for $Fe(OH)_2$) and 0.622 for $Fe(OH)_2$. Unlike Bazant, $Fe(OH)_2$ was considered as adding to the expansion effect here.

- **El Maaddawy Model**

El Maaddawy and Soudki (2007) further developed the Liu and Weyer's model in that they noted that the use of the assumption of a decrease in the rate of rust production with time led to underestimation of the mass loss of steel observed in tests and therefore an overestimation in the time to first crack. Therefore it was suggested to essentially merge both approaches outlined above and continue to use the thick-walled uniform cylinder option with Bazant's hypothesis about the constant rate of rust production. This rate of rust production was estimated using Faraday's Law. Liu and Weyer's (1998) assumption of the existence of a 'porous zone' was also incorporated into their model. Consequently the time to first crack, in days is given by:

$$T_{1st} = \left[\frac{7.117.5(D + 2\delta_0)(1 + v + \psi)}{i_{corr}E_{ef}}\right]\left[\frac{2Cf_{ct}}{D} + \frac{2\delta_0 E_{ef}}{(D + 2\delta_0)(1 + v + \psi)}\right] \qquad \textbf{Equation 4.20}$$

where i_{corr} is the corrosion rate in μA/cm^2, v is Poisson's ratio, ψ is a parameter dependant on cover depth and reinforcing bar diameter.

For application purposes, d_0 is suggested as being in the range of 10-20 μm, φ_{cr} is taken to be 2.35 as per the CSA standard (Canadian Standards Association, 1994) and v, Poisson's ratio is given to be 0.18. Two empirical formulae for the tensile strength of the concrete and the modulus of elasticity of concrete are given, Equation 4.21 and Equation 4.22 respectively, the former proposed by Carasquillo et al. (1981) and the latter as recommended by the CSA standard (Canadian Standards Association, 1994).

$$f_{ct} = 0.94\sqrt{f_c'} \text{ MPa} \qquad \textbf{Equation 4.21}$$

$$E_c = 4500\sqrt{f_c'} \text{ MPa} \qquad \textbf{Equation 4.22}$$

where f_c' is the compressive strength of the concrete.

In summary, a brief synopsis of these three models has been given in order to contextualize and chart the progression of chloride-induced corrosion modeling as documented in the literature. Unfortunately, all models appear to have been developed based on highly limited data, thereby leading to variability on a general scale – see for instance Table 4.1 as excerpted from Liang et al. (2002). This is due in part no doubt to the fact that the corrosion process itself takes a considerable time to initiate and so sufficient quantities of field data do not exist. However, an extensive review of the published work also found numerous other problems to exist as discussed in the following section.

Bazant Method	Liu and Weyers
6.94	8.90
6.51	2.66
6.29	12.34
6.51	2.83
6.51	2.79
7.16	3.66
6.51	4.45
7.16	0.74
6.51	4.89
6.51	0.87

Table 4.1: Comparison of values obtained for T_{ist} (in years) under different methods with the same input parameters for 10 different locations on a bridge deck.

Critique of existing models

Although many studies have been carried out to date concerning the comparison and analysis of existing models of time-to-first-crack (Al-Harthy and Stewart, 2006; Chernin and Val, 2008; Chernin and Val, 2011; Liang et al., 2002; Markeset and Murdal, 2008), a conclusive decision on which particular model to use appears not to have been reached. The biggest reason for this is as stated in the COIN report (Markeset and Murdal, 2008) that the existing models do not sufficiently explain the actual underlying physical processes and so naturally cannot be expected to provide accurate, reliable results. As stated previously, sufficient data does not exist. This purpose of this section however deals with the three models described in the preceding section, and specifically the

problems encountered from a researcher's perspective in the context of unreliable, inaccurate cross-references to model parameters as well as model shortcomings.

- **Difficulty in obtaining j_r value**

The j_r value in Equation 4.2 proved especially difficult to obtain. Liang et al. (2002) quote a value of 1.5 x 10^{-15} g/m^{2}s which they claim to come from Bazant (1979b). However, examination of the original Bazant paper reveals no such reference exists. Instead rather, all other parameters being equal, a sample calculation with j_r = 1 x 10^{-9} g/m^{2}s gives a T_{1st} for the given values of 2131 years. Another sample calculation, with the same input parameters except j_r = 1 x 10^{-11} g/m^{2}s, gives a T_{1st} for the given values of 212,000 years. Under the same reasoning, and considering the fact that the other input parameters are similar to those quoted in the literature, a j_r of 1 x 10^{-15} g/m^{2}s would give a T_{cr} of 2,120,000,000 years. Following this logic, it would seem that a value of j_r in the region of 10^{-7} g/m^{2}s would be more appropriate. Furthermore, Chernin and Val (2011) claim that the model used initially to determine this parameter is too subjective and has not been verified experimentally. Hence they use Faraday's Law with a known corrosion current density to evaluate the time to cover cracking. This, whilst it may be more exact, is not in keeping with Bazant's original method; hence it can hardly be used in a direct comparison of Bazant's method with other methods, since it is a modification of the original method.

- **Discrepancy in quoted α parameter**

Concerning α, a parameter which depends on the composition of the corrosion products being considered, Bazant (1979b) only considers the corrosion products containing $Fe(OH)_3$ as contributing to the expansion pressures, whereas Liu and Weyers (1998) consider an upper and lower bound for the values, pertaining to either solely $Fe(OH)_3$ or $Fe(OH)_2$ ions. The El Maaddawy model then considers the upper bound value relating to $Fe(OH)_2$ ions only. Whilst variations in this parameter are logical, since the chemical composition of the products formed will indeed vary, for comparison purposes, it makes sense that the models should all use the same input reference value for the parameter.

Such a rigorous investigation of the background to the model used is not always conducted however and consequently this leads to extreme variation in results obtained. This is illustrated later in the section.

- **Discrepancy in results based on utilization of empirical formulas for E and f_t'.**

Another problem which has been noted is that if the empirical formulae for concrete tensile strength and concrete modulus of elasticity are both expressed as a function of the square root of

the concrete compressive strength as in Equations 4.21 and 4.22, as recommended by El Maaddawy under the Canadian Standards, the effect of concrete tensile strength cancels out in both the El Maaddawy and the Liu and Weyers models. This effect was also noted by Vu et al. (2005) when they remarked that the formulae as recommended by the Australian standards were of a similar nature. For clarity, the values according to the empirical formulae of Equations 4.21 and 4.22 are shown in Table 4.2, with the corresponding Eurocode (CEN, 2004) in brackets.

Concrete Class	E_c	E_{eff}	f_t'
f_c 30	24.65 **(32.8)** GPa	8.21 **(10.93)** GPa	5.15 **(2.9)** MPa
f_c 50	31.82 **(37.28)** GPa	10.61 **(12.43)** GPa	6.65 **(4.1)** MPa
f_c 90	42.69 **(43.63)** GPa	14.23 **(14.54)** GPa	8.92 **(5)** MPa

Table 4.2: CSA values for *E* and f_t' as per Equations 20 and 21, Eurocode values in brackets.

For illustration purposes, the time-to-first-crack has been computed using El Maadawy's model. This can be seen in Table 4.3. It is evident that the increase in concrete strength under the CSA, empirical formulae, has no bearing on the predicted time to first crack. Considering that the change in concrete strength should have an effect on the predicted time, it is clear that empirical formulae are unsuitable for use. For this reason the Eurocode (CEN, 2004) recommendations for these values appear more appropriate.

Code	El Maaddawy	Percentage Diff between Eurocode & El Maaddawy
CSA, Eurocode, C30	1.98 (1.12)	43%
CSA, Eurocode, C50	1.98 (1.27)	36%
CSA, Eurocode, C90	1.98 (1.31)	34%

Table 4.3: Predicted T_{1st} (years) under both CSA and Eurocode recommendations for f_t' and *E*.

- **Value of d_0 to be used**

In particular, the idea of whether or not a porous zone exits and if so, how thick it should be taken to be has been the subject of much discussion and investigation in recent years. Both the Liu and Weyers model (1998) and the El Maaddawy model (2007) account for it as a means of slowing down the time to the development of the first crack. Liu and Weyers suggest using a value of 12.5 μm and El Maaddawy et al. consider two values, 10 μm and 20 μm. However, according to Mehta and Monteiro (2006), it can range from 10 to 50 μm. It is understood that this parameter is naturally difficult to validly assess, yet nevertheless the chosen value has a considerable impact on the predicted times to crack initiation, as demonstrated in subsequent sections.

Further research by Chernin et al. (2010) has demonstrated though that the assumption that corrosion products diffuse into the surrounding concrete only until they fully fill the 'porous' zone leads to physically meaningless results. In their investigation it was found that in many cases the calculated values of the porous zone thickness were greater than 20 μm. However, they also noted that the thickness of this porous zone appeared to increase with an increase in the compressive strength of concrete. From a physical point of view this makes no sense, as an increase in compressive strength usually results in a decrease in the water-cement ratio and hence the porosity of the concrete. In order to account for this they state that the assumption that the corrosion products diffuse into the surrounding concrete only until they fill a finite thickness zone is incorrect. Instead, they propose that while a thin, high-porosity zone does exist at the steel-concrete interface, corrosion products diffuse into the surrounding concrete constantly over time and not only until they fully fill this zone. Consequently, it is the amount of corrosion products penetrating into the concrete that is of importance and not merely the thickness of this zone.

In their subsequent paper, Chernin and Val (2011) present a comparison of the times to first crack as obtained from accelerated corrosion tests versus the results as predicted using both the Bazant model and the El Maaddawy model with two porous zones of 10 μm and 20 μm considered. They conclude that while none of the models are sufficiently accurate, the El Maaddawy model with the larger porous zone yields the best results and that perhaps utilizing a larger porous zone, whilst it might not make physical sense might prove beneficial for the sake of obtaining more realistic prediction times. For completeness Figure 4.6 as taken from Chernin and Val (2011) reproduces these results. Note that the points marked with a circle refer to results obtained if the Bazant formula described above is utilized, while the triangle marks refer to the results obtained under the El Maaddawy formula with two different porous zone thicknesses.

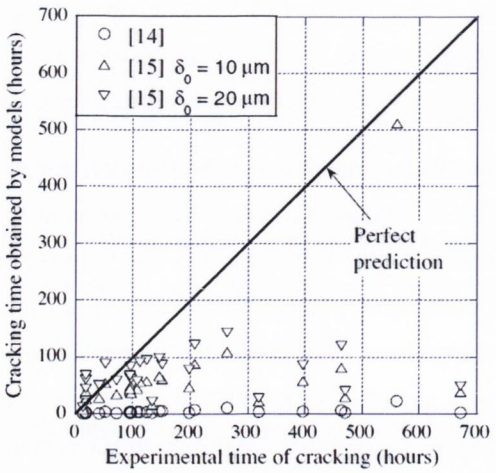


Figure 4.6: Comparison between times to first crack as calculated by analytical models and observed in accelerated tests as taken from Chernin and Val (2011).

- **Effect of Multiple Bars**

Finally, with the exception of the original Bazant model, the other models discussed above only allow for the effect of one reinforcing bar on the surrounding concrete. Mullard and Stewart (2010) conducted an experimental programme to investigate the rate of crack propagation in slabs containing multiple bars and found that the cracks over the external edge bars were observed to have a higher propagation rate than that for internal bars. Hence, the degree of confinement of the reinforcing bar (including such aspects as the bar-spacing and the volume of concrete surrounding the bar) clearly has an effect on crack propagation. Generally, it was found that the rate for external bars was found to be between 20% and 45% higher than those measured for the internal bars under the same conditions. This is as expected, since middle bars are more confined by the surrounding concrete in comparison with the corner bars.

Investigation of T_{1st} obtained

Table 4.4 below lists parameter values used for comparison purposes of the three formulae. These are for the most part standard parameters; however in a sensitivity analysis of the formulae, α, the ratio of molecular mass of rust to molecular mass of steel and d_0, the thickness of the 'porous' zone will be varied in order to show the bearing they have on the overall predicted time. Furthermore the effect of using empirical formulae for f_t' and E_c will be shown and finally the times to first crack obtained using all three methods will be presented in both tabulated and graphic format.

Parameter	Value	Literature Reference
D	16 mm	-
$icorr$	1 μA	(Al-Harthy and Stewart 2006)
C	50 mm	-
Φ_{cr}	2.0	(Bazant 1979b; Liu and Weyers 1998)
ρ_{st}	7850 kg	(Bazant 1979b; El Maaddawy and Soudki 2007)
ρ_{rust}	3600 kg	(Liu and Weyers 1998)
α	0.622	(El Maaddawy and Soudki 2007)
s	100 mm	(Bazant 1979b)
v	0.18	(Bazant 1979b; Liu and Weyers 1998; El Maaddawy and Soudki 2007; Chernin and Val 2011)
d_0	Varies in study	-
f_t'	Varies in study	-
E_c	Varies in study	-

Table 4.4: Values used for comparison of time-to-first crack formulae.

Importance of choosing appropriate α parameter value in Liu & Weyers model

It is noted that a review of the literature has shown that while the Bazant method takes $Fe(OH)_3$ ions only into consideration and therefore takes the value of α, the ratio of molecular mass of rust

to molecular mass of steel, to be 0.523, El Maaddawy's formula (2007) takes α to be 0.622, as if it is taking into account $Fe(OH)_2$ ions only. The Liu and Weyers model (1998) makes no such recommendation as to which value in particular to use since the value inherently depends on the actual composition of the rust products in every individual case. Hence, the ratio can be varied in the Liu and Weyers model and the effect of choosing different values for α on T_{1st} is shown below in Figure 4.7.

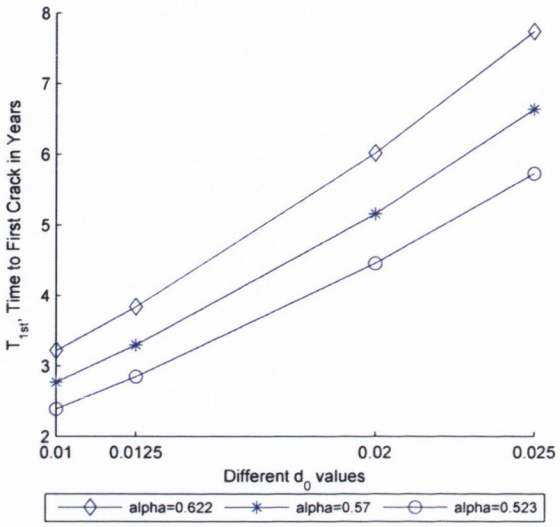


Figure 4.7: Influence of α parameter on predicted crack-initiation times using Liu and Weyers model.

It can be seen from Figure 4.7 that the larger value of α, that of 0.622 gives the largest time to first crack and that each value gives an increase in T_{1st} of approximately 16% on the lower value. In the context of the overall process of chloride-induced corrosion then, this means that an increased value of alpha increases the longevity of the structure by pronging the deterioration process.

It must be noted however, that in a comparison of 'like with like', the same value for α should be taken in all models under consideration, hence if comparing the Liu and Weyers model with that of El Maaddawy and Soudki (2007), the value of 0.622 should be used. For this reason, in the comparison of all formulae from here onwards, α shall be taken to be 0.622.

Overall comparison of T_{1st} obtained under different methods

If the Bazant method as outlined in the original paper and as described earlier is strictly adhered to, the variables in Table 4.4, together with an α value of 0.523 combine to give the predicted times to first crack as listed in Table 4.5. Since no recommendation is given in the paper for j_r, the rate of rust production, as mentioned earlier in the section, Faraday's Law as utilised by Chernin and Val

(2011) will be implemented instead. It is noted that increasing the value of the porous zone thickness does not increase the time-to-first-crack since the model is independent of such a parameter. All other methods are as have been presented, with values for E and f_t' those quoted for C30 concrete as per Eurocode specifications (CEN, 2004).

It is noted that Bazant's original method accounts for the effect of multiple reinforcing bars by including s, the bar spacing as a variable in the model. In his paper he gives a recommendation of a standard value of 100 mm for this. However as can be seen from Table 4.5, this has the effect of decreasing the time-to-first-crack ten-fold. It is recognized, that as mentioned previously, crack propagation rates are lower for confined bars than external bars, therefore when multiple bars are taken into account, it is expected that that the time-to-first-crack will decrease, but a factor of 10 is considered excessive. Hence since this part of Bazant's model is deemed to be inappropriate and since both the Liu and Weyers and the El Maaddawy models only take one bar into account, in a further comparison of 'like with like', Bazant's method shall be employed without accounting for the effect of adjacent bars. This technique was also used by Chernin and Val (2011) in their investigation of corrosion-induced time-to-first-crack models. Further to this Figure 4.8 now represents the most accurate comparison possible between all three models using the same parameter values.

Model	d_0 **= 10μm**	d_0 **= 12.5μm**	d_0 **= 20μm**	d_0 **= 25μm**
Bazant	2.34 ***(0.23)***	2.34 ***(0.23)***	2.34 ***(0.23)***	2.34 ***(0.23)***
L & W	3.22	3.84	6.02	7.74
El Maaddawy	1.07	1.16	1.46	1.65

Table 4.5: Comparison of T_{1st} (years) obtained under different models using Bazant's original model, with Bazant's model if only 1 bar is accounted for in brackets.

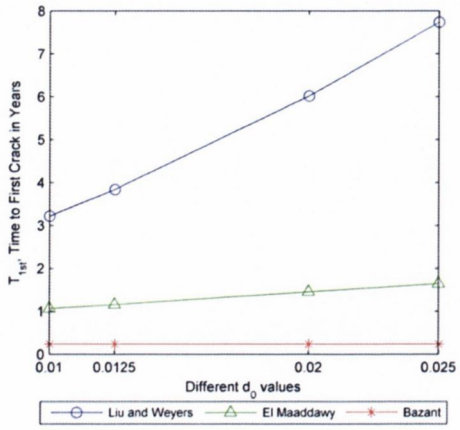


Figure 4.8: Comparison of different models on time-to-first-crack including influence of d_0.

Influence of d_0

As discussed, the thickness of the 'porous' zone is an oft disputed parameter and so as Table 4.5 and Figure 4.8 depict, it has been varied in this study in order to show the bearing it has on the overall predicted time. It can be seen that increasing the value of this parameter results in an increase in time-to-first crack, in accordance with what would be expected.

Proposed Modifications to Existing Models

The results as presented heretofore are based on the original analytic models as outlined respectively in Bazant (1979a; 1979b), Liu and Weyers (1998) and El Maaddawy (2007). However, a review of the literature demonstrates that Liang et al. (2002) proposed a modification to the original Bazant method. This was based on the fact that Bazant had made a slight trigonometrical error in his calculations and subsequent derivation of his formula. Figure 4.9 below is as reproduced from Liang et al. (2002) and presents a diagrammatic representation of crack formation.

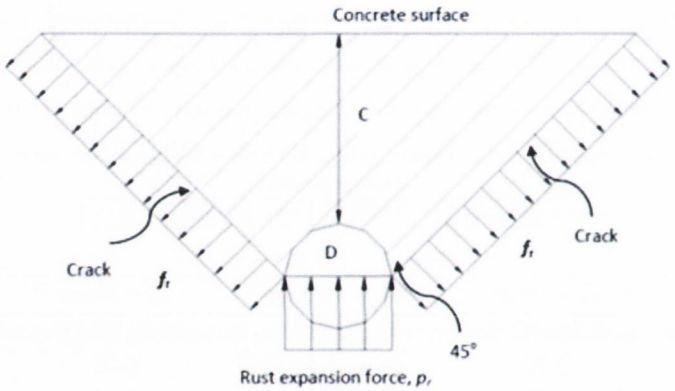


Figure 4.9: Radial crack process due to chloride-induced corrosion (Liang et al. 2002)

Bazant stated that if, at failure, the average tensile stress on the crack surface equals the tensile strength of the concrete, f_t', equilibrium requires that:

$$P_r D = 2f_t'(C)\sqrt{2}Cos45^o = P_r D = 2f_t'(C) \qquad \textbf{Equation 4.23}$$

However, as noted by Liang et al. (2002) and as can be seen from Figure 4.9, the length of crack surface due to f_t' is actually $(C + D/2)/\sin 45^\circ = (C + D/2)\sqrt{2}$, as opposed to C /sin 45°. Bazant had originally not allowed for the reinforcing bar in his calculations. Therefore

$$P_r D = 2f_t'(C + D/2)\sqrt{2}Cos45^o = P_r D = 2f_t'(C + D/2) \qquad \textbf{Equation 4.24}$$

Hence,

$$P_r = f_t'\left(2\left(\frac{C}{D}\right)+1\right) \qquad \textbf{Equation 4.25}$$

Thus the critical value of ΔD that produces inclined cracks emanating from a single bar is

$$\Delta D = P_r\delta_{pp} = f_t'[2\left(\frac{C}{D}\right)+1]\delta_{pp} \qquad \textbf{Equation 4.26}$$

This is then substituted into Equation 4.5 to calculate the time to first crack.

Upon examination of both Liu and Weyers Model (1998) and the El Maaddawy model (2007), it was realised that since both were derived in a similar fashion to Bazant's model (1979a), the same modification essentially, i.e. correction of the length of the crack surface, should be applied to both models.

Consequently, both formulas were reviewed in this study and the modified formulas thus outlined below. A discussion on the influence this modification has on T_{lst} follows.

Modified Liu and Weyers Model

Instead of $P(D+2d_0) = 2Cf_t'$, resulting in $P = (2Cf_t')/(D+2d_0)$ as outlined in Equation 4.16, accounting for Bazant's error, $P(D+2d_0) = 2(C+D/2)f_t'$. This results in

$$P = \left(\frac{2C+D}{D+2d_0}\right)f_t' \qquad \textbf{Equation 4.27}$$

Consequently d_s, the thickness of the corrosion products may be expressed as

$$d_s = \frac{(2C+D)f_t'}{2E_{ef}}\left(\frac{a^2+b^2}{b^2-a^2}+v_c\right) \qquad \textbf{Equation 4.28}$$

as opposed to $d_s = \frac{Cf_t'}{E_{ef}}\left(\frac{a^2+b^2}{b^2-a^2}+v_c\right)$, as in Equation 4.17.

Modified El Maaddawy Model

Likewise El Maaddawy's model when $P = (2Cf_t')/D$ is replaced by $P = ((2C+D/2)f_t')/D$ results in the modified model equation of

$$T_{1st} = \left[\frac{7.117.5(D + 2\delta_0)(1 + v + \psi)}{i_{corr}E_{ef}}\right]\left[\frac{(2C+D)f_{ct}}{D} + \frac{2\delta_0 E_{ef}}{(D + 2\delta_0)(1 + v + \psi)}\right] \quad \textbf{Equation 4.29}$$

Investigation of T_{1st} obtained with modified method

For clarity, all three methods and their 'modified' versions shall be presented below in terms of T_{1st} obtained. Table 4.6 represents an updated picture of Table 4.5, i.e. the modified versions of the original models are now included. Likewise, Figure 4.10 depicts an updated Figure 4.8.

Model	d_0 = 10μm	d_0 = 12.5μm	d_0 = 20μm	d_0 = 25μm
Bazant	0.23 ***(0.3)***	0.23 ***(0.3)***	0.23 ***(0.3)***	0.23***(0.3)***
L & W	3.22 ***(3.92)***	3.84 ***(4.59)***	6.02 ***(6.94)***	7.74 ***(8.78)***
El Maaddawy	1.07 ***(1.17)***	1.16 ***(1.28)***	1.46 ***(1.57)***	1.65 ***(1.76)***

Table 4.6: Comparison of T_{1st} (years) obtained under different analytical models, with modified versions in brackets.

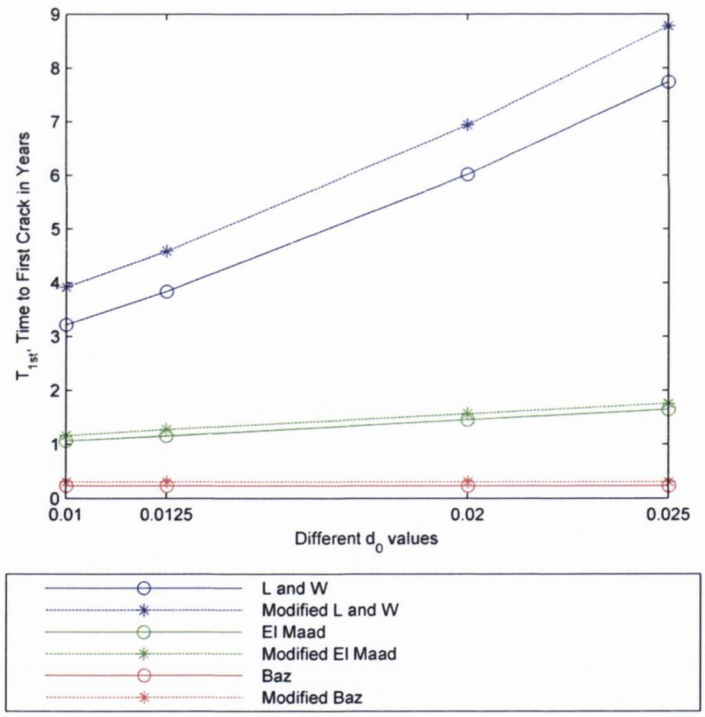


Figure 4.10: Comparison of all different models on time-to-first-crack including influence of d_0.

Final Analysis of T_{1st} models

As is evident from Figure 4.10, the Liu and Weyers model consistently gives the largest values for T_{1st}. According to El Maaddawy and Soudki (2007) though, the Liu and Weyers model is incorrect

since it underestimates the rate of steel loss caused by corrosion which in turn overestimates the time-to-first-crack. Since the modified Liu and Weyers method as outlined in this paper is only further increasing this T_{1st}, and since Chernin and Val (2010) also claim the Liu and Weyers model to be incorrect since it proposed an incorrect formula for a model parameter which violated Faraday's law of electrolysis, the model shall be deemed inappropriate.

Furthermore, if the Bazant method is utilized allowing for the stresses emanating from a single bar only, it appears to significantly underestimate the time to the appearance of first crack according to Chernin and Val (2011).

For this reason the El Maaddawy model seems to be the most suitable original model under investigation in this section. It is noted that in El Maaddawy's original paper, the results obtained using his original, unmodified formulas were deemed for the most part to be in agreement with observed test values (Alonso et al., 1998; Andrade et al., 1993; Cabrera and Ghoddoussi, 1992; El Maaddawy et al., 2005; Mangat and Elgarf, 1999).

As shown in Table 4.7, the observed values that did not concur were 9-11% higher than the calculated values, and for tests of a much greater duration – 208 hours, 264 hours and 2643 hours respectively according to tests carried out by Alonso et al. (1998), i.e the models underestimated the time to the appearance of first crack. Note that this variation in predicted time occurs as a result of a variation in d_0. Chernin and Val (2011) depict this graphically, illustrating that El Maaddawy's model with a porous zone thickness of 20 μm closely correlates the observed times when the T_{1st} is less than 150 hours. However this agreement sharply drops off as the T_{1st} increases. These results have been reproduced in Figure 4.6 above.

To overcome this, Chernin and Val suggest that the thickness of the porous zone may be larger than was previously estimated. Hence a porous zone of 25μm was investigated in this research. This increase from 20μm to 25 μm results in an increase in T_{1st} of ~13% and from Table 4.7, it can be seen that the predicted result for the 208 hour test is now in line with that expected. However, for the two tests of a longer duration, i.e. 264 hours and 2643 hours respectively, the observed result is still 4% higher than the model predicted results.

Reference	Observed Time (h)	Predicted Time (h) - El Maaddawy	Remarks on observed time	Predicted Time (h) – Increased d_0	Remarks on observed time
Andrade et al. (1993)	96	84-119	Within Limit	84-136	Within Limit
Mangat and Elgarf (1999)	14.4	12-16	Within Limit	12-18	Within Limit
Cabrera and Ghoddoussi (1992)	108	96-110	Within Limit	96-117	Within Limit
Alonso et al. (1998)	113	89-123	Within Limit	89-140	Within Limit
	208	156-191	9% Higher [a]	156-208	Within Limit
	264	203-237	11% Higher [a]	203-254	4% Higher [a]
	2643	2028-2372	11% Higher [a]	2028-2544	4% Higher [a]
El Maaddawy et al. (2005)	95	78-101	Within Limit	78-113	Within Limit

[a] compared with upper predicted limit.

Table 4.7: Comparison between predicted and experimental results under El Maaddawy's original model and El Maaddawy's model with increased d_0.

On the other hand, if one is to use the modified version of El Maaddawy's formula, which has been developed in the course of this research and outlined above, with the increased upper bound for d_0, the observed results for these longer duration tests now also fall within the limits of the calculated results. These results can be seen in Table 4.8. The observed value for the test carried out by Andrade et al. (1993) is now 8% lower than the predicted value, but this could be a function of the particular parameters of that test. Else the modified model may simply be inappropriate for tests of a shorter duration and further research should be conducted.

For completeness, the predicted times using both the modified version by itself and the modified version with increased porous zone thickness are given below in Table 4.8. If one compares Table 4.7 and Table 4.8, it can be seen that both changes to the previously used method, i.e. that of increasing the porous zone thickness and that of using the modified formula with the original bounds, result in a similar increase in T_{1st}, i.e. sufficient to ensure that the predicted result for the 208 hour duration test is now in line with the observed result. Hence if it is felt that this increased porous zone thickness is unrealistic, the modified version by itself gives similar results.

Reference	Observed Time (h)	Predicted Time (h) – Modified El Maddawy	Remarks on observed time	Modified El Maaddawy with increased d0 as upper bound	Remarks on observed time
Andrade et al. (1993)	96	104-139	8% Lower [b]	104-156	8% Lower [b]
Mangat and Elgarf (1999)	14.4	13.8-18	Within Limit	13.8-20	Within Limit
Cabrera and Ghoddoussi (1992)	108	103-117	Within Limit	103-124	Within Limit
Alonso et al. (1998)	113	110-145	Within Limit	110-162	Within Limit
	208	176-210	Within Limit	176-227	Within Limit
	264	222-256	3% Higher [a]	222-274	Within Limit
	2643	2221-2565	3% Higher [a]	2221-2737	Within Limit
El Maaddawy et al. (2005)	95	92-115	Within Limit	92-126	Within Limit

[a] compared with upper predicted limit.
[b] compared with lower predicted limit.

Table 4.8: Comparison between experimental results and modified model predicted results.

Recommendation of T_{1st} model to use

A review, analysis and necessary modification of three well-known time-to-first-crack models has been outlined above. The work arose throughout the course of the research due to a lack of adequate implementation information in the currently available literature. It is noted that all models presently available do not correctly represent the actual degradation process and numerous issues concerning their validity abound. In particular, there are too many unexplained structures which present abnormal levels of chloride concentrations and yet are completely uncorroded (Melchers and Li, 2009). This suggests that the mechanism of chloride-induced corrosion is not sufficiently explained by the present models. There are too many anomalies. Therefore the recommendation given is for the purposes of prediction of future state only, i.e. to provide suitable estimations for use in a BMS. It does not purport to represent the physical mechanism.

In conclusion, the Modified El Maaddawy model, together with an increased porous zone thickness and Eurocode specifications for E and $f_t^{'}$ is suggested as being the most appropriate model currently available for predicting the duration of the time-to-first-crack phase in a structure subject to chloride-induced corrosion. Further research is needed however to investigate the effect of adjacent bars on the rate of crack propagation. Likewise, longer duration testing is recommended to improve and validate the current models. Nevertheless the developed model has been encapsulated into the developed chloride-induced corrosion deterioration prediction module in accordance with Objective number 4 as listed in Section 2.5. Analytical models have thus been selected for the first

two phases of chloride-induced corrosion as shown in Figure 4.4, hence a model will now be presented for the final phase, that of severe cracking.

4.3.3 Time to Severe Cracking

The third and final deterioration phase, corresponding to T_{sp} in Figure 4.4, is referred to as the time to severe cracking. The model used is based on work by Mullard and Stewart (2010) and works on the principle that it estimates the time to a specific crack width, up to a limiting value of 1.0 mm. This is quite conducive for the purposes of developing a state-based deterioration system for use in a BMS, since the state limits or bounds can be defined in terms of crack width which can be visually assessed. The equation is represented as:

$$T_{sp} = T_{1st} + k_R \frac{w_{\lim} 0.05}{k_c r_{crack}} \frac{0.0114}{i_{corr}} \qquad \textbf{Equation 4.30}$$

where T_{sp} = the time to severe cracking, T_{1st} = time to first crack from Equation 4.29, k_R = the rate of loading correction factor if applied, k_c is a confinement factor which represents an increase in crack propagation due to the lack of concrete confinement around external reinforcing bars – taken to be 1.0 if the reinforcing bar is in an internal location, r_c is defined as the rate of crack propagation or the slope of crack width versus time between the time of first crack T_{1st} and time of severe cracking T_{sp} in Figure 4.4. Since w_{lim} is the limiting crack width, specific to each condition states up to a limiting value of 1.0 mm, this rate is given in terms of mm/hr. A normalized parameter is defined thus as

$$\psi_{cp} = \frac{C}{Df_t'} \qquad \textbf{Equation 4.31}$$

where C is concrete cover in mm, D is reinforcing bar diameter in mm and f_t' is the concrete tensile strength in MPa. A line of best fit from the experimental data then produced an estimate for r_c of :

$$r_c = 0.0008e^{-1.7\psi_{cp}} \qquad \textbf{Equation 4.32}$$

Note that for the purposes of defining state bounds for the system under development, the limiting values for w_{lim} are outlined in the following section.

4.4 MODEL IMPLEMENTATION

In order to combine the three analytical models outlined in the above sections into a standalone deterioration module suitable for use in a condition-state BMS, a condition rating vector Q needs to be applied. This is necessary in order to be able to directly correlate damage due to chloride-induced corrosion to a discrete Markov state. For application purposes the rating system is listed in Table 4.9. A six state system has been selected in order to correspond to the six state system employed in the EIRSPAN database - described in Table 2.3.

Condition State	Degradation State
0	$t <= T_i$, Initiation has yet to begin
1	$T_i < t < T_{1st}$, Initiation has begun, before time to first crack
2	$w \leq 0.2$ mm
3	$0.2\text{mm} < w \leq 0.5\text{mm}$
4	$0.5\text{mm} < w \leq 1\text{mm}$
5	$w > 1\text{mm}$

Table 4.9: Markov condition states as applied to chloride-induced corrosion in model

Hence while the time t is less than T_i, the time to initiation, in the generated database, the structure is considered to be in a state 0. When sufficient time has passed for T_i to be exceeded but T_{1st}, the first visible crack has not yet been observed, the structure is in state 1.

Thereafter, the condition states have been expressed as a function of the crack-width. The limiting value is up to 1.0 mm since that is what the model was developed up until, the relationship does not hold after such a value. Note that while, these values may seem low, in effect it does not matter as these crack-widths do not represent observed crack-widths. Rather, they are used solely to define appropriate state-limit bounds for the generated database in order to generate suitable or at least, realistic in time, life-cycle curves. For illustration purposes, the models described above have been implemented and typical life-cycle curves of expected condition state against time are shown below in Figure 4.15. The values used for this simulation are listed in Table 4.10.

It is worthwhile noting also that since this developed model relies on many stochastic inputs, it enables the overall deterioration model to be built up in an incremental fashion, with different parameter values for different bridge elements or bridges in different environments. This is in accordance with objectives number 5 and 6 as listed in Section 2.5 and will be further developed in Chapter 5.

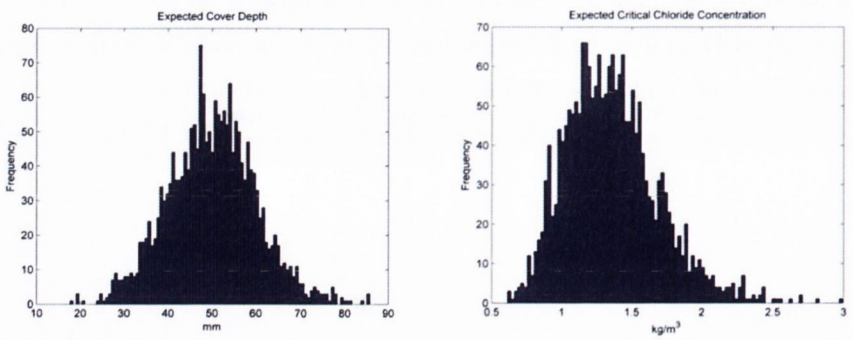
Parameter	Units	Mean	COV	Dist.	Lit. Ref
C_o	kg/m^3	0	-	-	(Vu and Stewart, 2000)
C_s	kg/m^3	5	0.25	LN	-
C_{cr}	kg/m^3	1.36	0.25	LN	(Bastidas-Arteaga and Schoefs, 2012)
D_{app}	m^2/s	1.27 x 10^{-12}	0.25	N	(Lounis and Daigle, 2012)
C	mm	50	0.2	N	(Sudret, 2008)
D	mm	16	-	-	-
δ_0	mm	0.025	-	-	(Reale and O' Connor, 2012)
v		0.18	-	-	(Bazant, 1979b; Chernin and Val, 2011)
I_{corr}	μA/cm^2	1	-	-	(Al-Harthy and Stewart, 2006)
f_c	kN/mm^2	35.65	0.1	N	(CEN, 2004)
f_t	N/mm^2	3.5	0.1	N	(CEN, 2004)
φ_{cr}		2	-	-	(Bazant, 1979b; Liu and Weyers, 1998)

Table 4.10: Chloride-induced corrosion model parameters.

4.5 PROBLEMS ENCOUNTERED WHILE MODELLING

In theory, straightforward Monte Carlo simulation carried out using Matlab should provide appropriate times to initiation, times to first crack and times to severe cracking. However, taking T_i, the time to initiation as an example, it can be seen below that careful analysis and modifications are needed to ensure relevant results.

In calculating the T_i, time to initiation of corrosion, it can be seen from Equation 4.2 that there are 4 variables which need to be predefined, i.e. C, the cover depth, C_r, the critical chloride concentration, C_s, the surface chloride concentration and D_{app}, the apparent diffusion coefficient. Individually, these generated distributions appear reasonable – as shown in Figure 4.11.



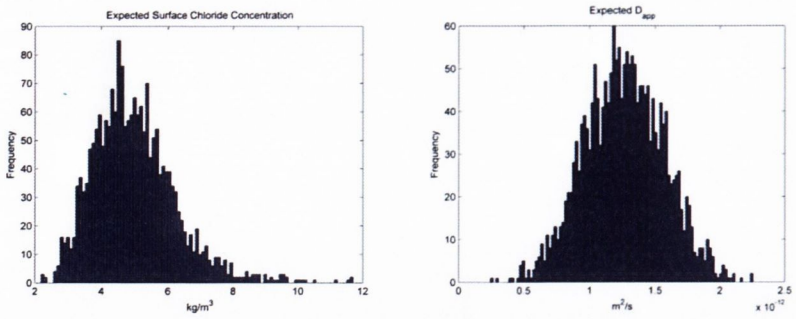


Figure 4.11: Generated distributions of input parameters C, C_{cr}, C_s *and* D_{app} respectively to Equation 4.2 for calculating the T_i.

Combining all of these in a Monte-Carlo simulation analysis, results in a mean time to initiation of 37.6 years with a range of 2.05 to 1847 years. This is illustrated in Figure 4.12.

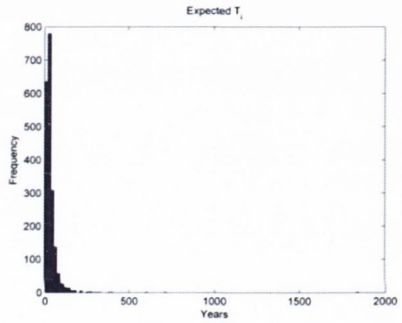


Figure 4.12: Distribution of T_i, Expected Time to Initiation.

However, if instead a C_s value of 2.95, with a COV of 0.7 is lognormally distributed as suggested in Stewart et al. (2011b), and combined with the other parameters for Fick's Law as listed in Table 4.10, it can be seen in Figure 4.13 that a nonsensical mean time to initiation of 14219 years now results. Compared to Figure 4.12, there is now an even larger tail with extreme values. Upon investigation it was found that this was as a result of a number of outliers. For example, of the 2000 generated values, 360 of them were greater than 500 years and a further 285 are greater than 800 years. The inlaid graph then represents the distribution of the time to initiation obtained if values are truncated at 500 years, arbitrarily. This gives a mean time to initiation of 93.6 years. The truncation point is debatable, but nevertheless, it is evident that a need for one exists if such a high coefficient of variation is used for C_s with the defined C_{cr} value as the concentration gradient is adversely affected – too many values now fall below the chloride threshold required to initiate corrosion.

Truncating the parameters naturally gives rise to more appropriate values of corrosion initiation time, but the process must be looked into, in order to ascertain what exactly is causing these values,

i.e. which parameter is giving rise to it. Consequently, a sensitivity analysis of Fick's law will be implemented in the following chapter.

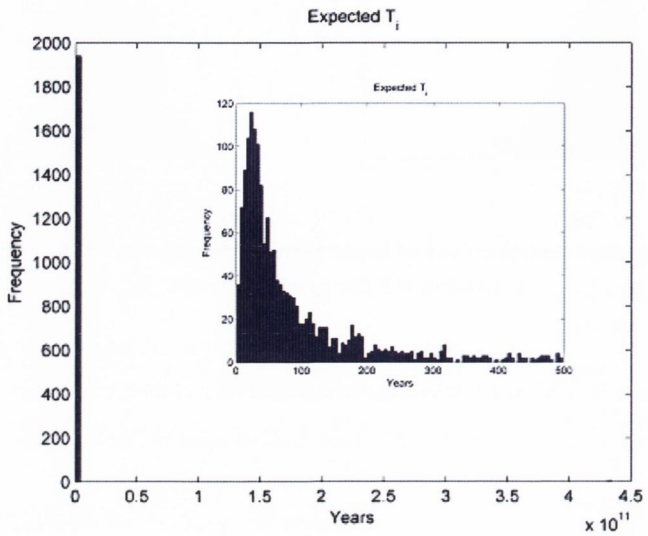


Figure 4.13: Distribution of T_i, Expected Time to Initiation before and after truncation.

Such calculations were carried out for all three phases and the results aggregated to simulate a distribution of expected bridge condition. For completeness, repeatability of results was also considered and Figure 4.14 shows that the model converges to approximately the same mean value each run when multiple runs are overlaid on the same graph. Note that this figure corresponds to a truncation value of 250 years, nevertheless, regardless of the truncation year chosen, the result remains the same, i.e. the process is repeatable.

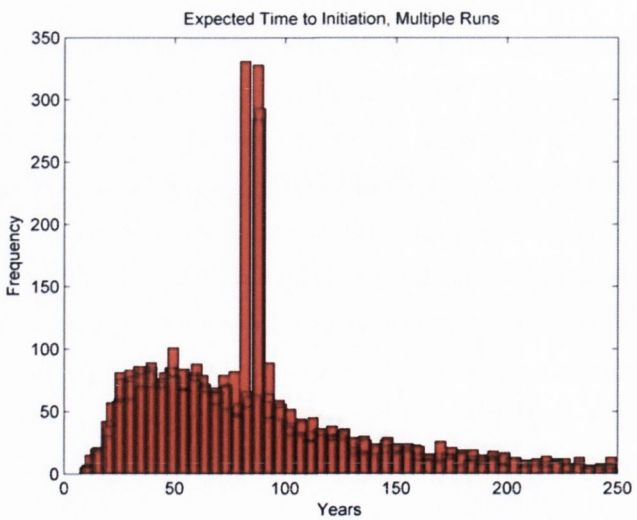


Figure 4.14: Repeatability of Model

4.5.1 Lifecycle Curves

Figure 4.15 below then shows average lifecycle curves, based on average network condition rating at each year, *t*. As outlined in Bond et al. (2006) two potential specifications for elements in primary exposure class XD3 and secondary exposure class XF2 have been selected. These are (i) C45 concrete (cube strength) with a w/c ratio of 0.45 and 60mm cover and (ii) C50 concrete with a w/c ratio of 0.40 and 55mm cover.

It can be seen that these two different combinations of concrete classification deteriorate in approximately the same manner with time, therefore indicating that they are appropriate substitutes and that the selection of either method is acceptable.

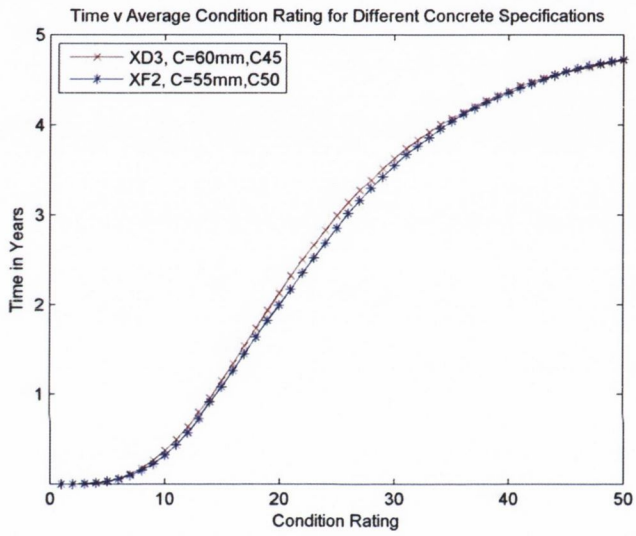


Figure 4.15: Variation in assigned condition rating with time for different concrete specifications for the same exposure conditions.

For completeness then, 40 mm, 50 mm and 60 mm cover will now be used with the C45 concrete described above in order to show the effect of alternative concrete cover depths on expected bridge lifetime. This is illustrated in Figure 4.16. As expected, it can be seen that the average time taken to reach a limiting condition state value of five decreases with a corresponding decrease in concrete cover.

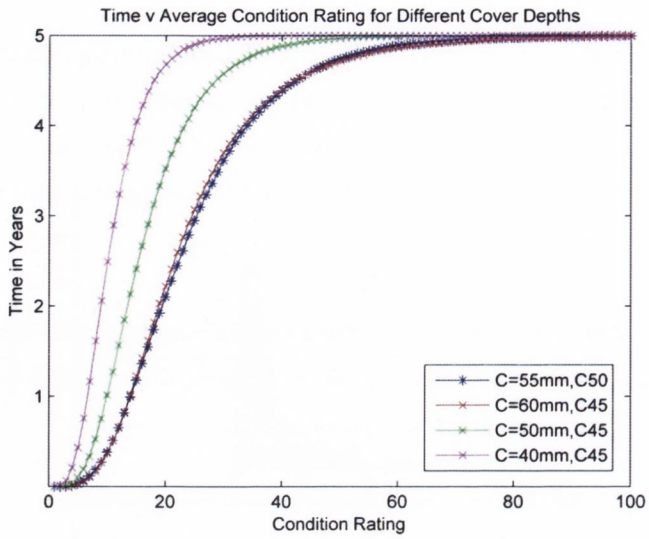


Figure 4.16: Variation in assigned condition rating with time for different cover depths.

These curves are then used to calibrate the Markov transition matrices used to describe the deterioration process and thus help predict future structural condition state as expressed in Equation 2.1. This calibration process will be described in the following chapter, but it is evident that different matrices will be used to describe the alternate lifecycle paths illustrated by the different lifecycle curves in Figures 4.15 and 4.16.

Note that as mentioned in Section 2.3, this approach is quite similar to that found in (Roelfstra et al., 2004) whereby a relationship was established to convert the results from physically based corrosion deterioration models to a visual appearance of the concrete surface in terms of condition states. However, the T_{1st}, time to first crack phase as detailed in Section 4.3.2 was not accounted for. Furthermore, only homogeneous Markov chains were used and as shown in Chapter 3, non-homogeneous Markov chains are necessary for reliable predictions.

4.6 CONCLUSION

This chapter has outlined the development of the physical deterioration model for use in the prediction module. Specifically, the two objectives listed at the outset and in Section 2.5 relating to this have been satisfied, i.e.

1. The determination of how best to calibrate suitable transition matrices in the absence of sufficient quantities of inspection data, particularly the inclusion of physically-based, analytical models into prediction systems.

2. To investigate the phenomenon of chloride-induced corrosion of reinforced concrete and particularly the most suitable analytical models for use in predicting future condition state in a cracking-limit state, service life model.

In particular, whilst completing the latter objective above, it was found that the existing models for predicting the T_{1st}, time-to-first-crack phase of chloride-induced corrosion were unsuitable for use and had many anomalies, hence an aside to the work involved the thorough investigation of these irregularities, which has been documented in this chapter.

The following chapter will deal with a sensitivity analysis for the proposed model to test its robustness, as well as the actual model implementation and calibration.

CHAPTER 5 – DETERIORATION MODEL IMPLEMENTATION AND CALIBRATION

5 DETERIORATION MODEL IMPLEMENTATION AND CALIBRATION

5.1 INTRODUCTION

Chapter 4 has outlined the methodology behind the selected deterioration mechanisms and models, i.e. chloride-induced corrosion of Reinforced Concrete and its respective phases. However, the example given for the purposes of illustration just involved the use of sample variables and parameters. As can be seen from Figure 4.13, it is extremely important that the values and coefficients of variation given to these variables are reasonable, else nonsensical values arise. Hence the purpose of this chapter is to investigate different parameter values and conduct a sensitivity analysis of these, thereby clarifying their respective impact on the overall expected lifetime duration.

Following on from this the Markov transition matrices outlined in Chapter 3 will be calibrated on an elemental basis here, based on the deterioration model described in Chapter 4. EIRSPAN, the Irish BMS, uses fourteen elemental ratings for each bridge structure, namely, thirteen different primary components such as the deck, piers, wing-walls, parapets, abutments etc., and then a final global structural condition rating which has been based on these individual ratings. Appropriate parameters will be selected for each of these elements in order to model their specific deterioration. Furthermore, in keeping with the objective of developing a robust system capable of considering bridges of all ages in all environments, these matrices will be calibrated for both inland and coastal regions.

Lastly the most appropriate manner of ascertaining the Markov transition matrices themselves from the developed models will be determined. In accordance with Section 2.5, the objectives thus are as listed below:

1. To 'calibrate' in effect such systems for the Irish Bridge network, i.e. conduct a literature review and sensitivity analysis of the most appropriate parameter values.

2. To develop the system on an elemental basis, i.e. to build up the overall bridge condition rating as a function of its minor elements and to consider the overall condition rating then as dependant on the correlations between these elements. In this respect, the system will be most robust and adaptable for other kinds of structures in alternative locations.

5.2 SENSITIVITY ANALYSIS OF DETERIORATION MODEL

In an attempt to illustrate and signify the importance of choosing appropriate parameter values when modeling and implementing the deterioration model described in Chapter 4, Fick's law for modeling the T_i, time to initiation phase of chloride-induced corrosion has been chosen as an example due to its widespread use (Lounis and Daigle, 2012; Morcous et al., 2010; Vu and Stewart, 2000). For clarity, this equation has been represented in Equation 4.2.

This sensitivity analysis is essentially three-fold. Firstly, the parameters involved will be varied according to the wide range of values quoted in the literature. Secondly, the values will be varied according to the specific values considered in the example in order to test the variation within chosen parameter distributions. Lastly, the types of distributions involved will be varied in order to demonstrate the difference in values obtained between the oft utilised lognormal and normal distributions.

Regarding the first part of this sensitivity analysis, a review of the currently available literature shows that many values have been quoted for the parameters in question. As mentioned in Section 4.5, the parameters which are most disputed are C_s and C_r, the surface chloride and critical chloride concentration respectively.

Naturally some of the variation arises due to environmental considerations, material composition and differing regulations regarding concrete mix and the level of chlorides allowed etc. However, it can be seen that while some researchers advocate normally generated distributions, others consider lognormally distributed parameters to be more appropriate. Table 5.1 below lists some of the cited means, coefficients of variance and stochastic distributions for the Fick's Law variables in an effort to demonstrate the range in quoted values. Note that this list is not exhaustive, it merely serves to highlight the discrepancy in quoted parameters and the difficulties which could arise if care is not exercised in their implementation.

It is clear from this table that large variances exist in the literature quoted values. For the most part, the larger values for C_s arise either due to marine action (BRIME, 2001; Stewart et al., 2011) or due to extremely severe weather conditions such as those experienced in Canada and Northern America (Lounis and Daigle, 2012; Morcous et al., 2010). The smaller values refer to either atmospheric deterioration (Stewart et al., 2011), or corrosion due to normal de-icing salt application (BRIME, 2001).

Parameter	Units	Mean	COV	Dist.	Lit. Ref
C_s	kg/m^3	3.05	0.74	N	(Stewart and Suo, 2009);
	kg/m^3	8	0.25	N	(Lay and Schießl, 2003)
	kg/m^3	4.57	0.4	LN	(Morcous et al., 2010)
	kg/m^3	6	0.25	-	(Lounis and Daigle, 2012)
	kg/m^3	5.78	0.25	N	(Li et al., 2004)
	kg/m^3	7.35	0.7	LN	(Stewart et al., 2011)
		2.95	0.7		
		1.15	0.5		(BRIME, 2001)
		9.6	-	-	
		2.4	-	-	
C_{cr}	kg/m^3	2.4	0.2	N	(Mullard and Stewart,
	kg/m^3	0.48	0.5	N	2009)
	kg/m^3	1.35	0.1	LN	(Lay and Schießl, 2003; Stewart and Suo, 2009) (Morcous et al., 2010)
	kg/m^3	0.7	0.2	-	
	kg/m^3	1.7	0.2	N	(Lounis and Daigle 2012)
	kg/m^3	3.35	0.375	N	(Li et al., 2004)
	kg/m^3	4.8	-	-	(Stewart, Wang et al. 2011)
		1.44	-	-	(BRIME, 2001)
	kg/m^3	0.9	0.19	Uniform (0.6-1.2)	(Vu and Stewart, 2000)
D_{app}	m^2/s	1.27 e^{-12}	0.25	N	(Lounis and Daigle, 2012)
		1 e^{-12}	0.2	LN	(Vu and Stewart, 2000)
		1.62 $^{e-12}$	0.31	LN	(Morcous et al., 2010)

Table 5.1: Stochastically defined literature quoted parameters.

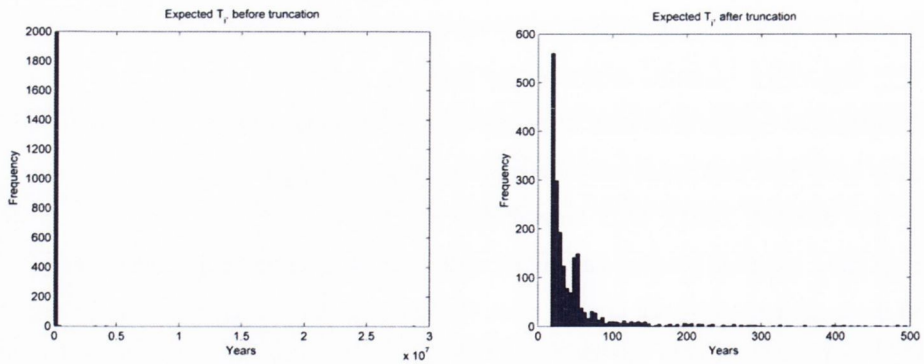
Likewise for C_{cr}, significant variation exists in the literature. The exact value for the chloride threshold, C_{cr}, required to initiate corrosion is unclear and is best judged on the risk of corrosion. Numerous studies have been conducted but no conclusive figure has been decided upon (Angst et al., 2009; Lay and Schießl, 2003). It is known that it is dependent on factors such as the chloride/hydroxyl ratio, chloride binding capability of the cement, use of replacement materials, admixtures and the condition of the reinforcing steel. Generally, it is taken as falling in the region of between 0.2% and 0.4% chloride per weight of cement (0.68 kg/m^3 to 1.36 kg/m^3), though values as high as 1% have been found in structures where corrosion has not initiated while corrosion has been evident in structures with values as low as 0.1% (Alonso et al., 2000; Glass and Buenfeld, 1997). Values such as 2.4 kg/m^3 and 4.8 kg/m^3 however, such as those in Mullard and Stewart (2009) and BRIME (2001), seem overly high and caution is advised in using them.

Concerning the apparent diffusion coefficient D_{app}, a mean value in the region of 1 x10^{-12} m^2/s is a standard value for OPC and the values quoted in the literature as derived from chloride profiles of examined bridges appear to vary around this (Lounis and Daigle, 2012; Morcous et al., 2010).

A sensitivity analysis which considers the range of these values will thus follow.

5.2.1 Sensitivity Analysis of Range of Literature Values

In order to consider the impact each variable specifically has on the overall predicted time to initiation of corrosion, each variable will be varied in turn according to a defined range while the other three will be held constant at their defined mean value as listed in Table 4.10. This defined range for each variable will consist of a uniformly distributed set of values which will lie between the highest and lowest value for each variable as listed in Table 5.1. Figure 5.1 thus lists the distribution of time to initiation of corrosion if a uniformly distributed range of values between 1.15 kg/m^3 and 7.35 kg/m^3 is considered for C_s. It can be seen that truncation of values surely needs to be implemented as outliers are evidently throwing the scale off. For instance, the values illustrated in Figure 5.1 (i) yield a mean time to corrosion initiation of 19887 years, with a range of 17.8 to 17656000 years. After truncating it at 500 years though as seen in Figure 5.1 (ii), a mean time to initiation of 50.78 years is obtained, with a range of 17.8 to 498.3 years. Truncating at 800 years then gives a mean time to initiation of 69.96 years. Upon investigation of these values it is found that the highest C_s value of 7.35 kg/m^3 gives the shortest time to initiation, as expected. However, a much lower C_s value of 1.356 gives 2383900 years, while a value of 1.5143 gives 1906.3 years. This is as a result of the approximations to the error function in Fick's Law where C_s values near to the C_{cr} value give unreasonable times to initiation as initiation will never occur. Furthermore, if the C_s value is less than the C_{cr} value, corrosion will never initiate. For this reason then truncation of values beyond a certain point is considered necessary.



(i) (ii)

Figure 5.1: Distribution of expected T_i, C_s alone varied.

D_{app}, the apparent diffusion coefficient was the next variable to be considered. Figure 5.2 illustrates the distribution as obtained when a range of 1 x10^{-12} to 1.628 x10^{-12} is considered. The mean time to initiation is now 29.15 years, within a range of 20.3 to 32.8 years. Hence truncation is not necessary since no values beyond 500 years are predicted.

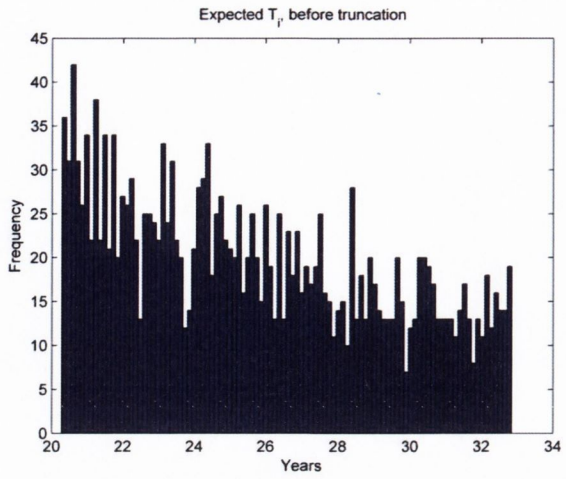


Figure 5.2: Distribution of expected T_i, D_{app} alone varied.

Concerning C, the cover depth, the parameter values were varied between 30 and 100 mm in accordance with industry expected standards. This results in a predicted range of T_i between 9.34 and 103.5 years, with a mean time of 48.25 years. Hence there is again no need for truncation. This range of T_i is illustrated in Figure 5.3.

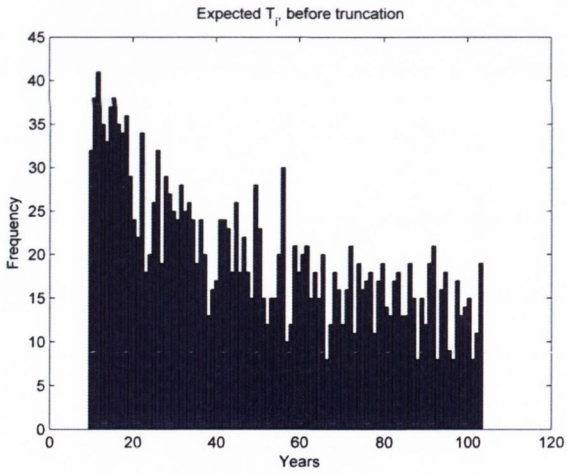


Figure 5.3: Distribution of expected T_i, C alone varied.

Lastly C_{cr}, the critical chloride concentration was varied between 0.48 kg/m^3 and 3.35 kg/m^3 as the extremes listed in Table 5.1. The mean time to initiation is now 54.49 years within a range of 11.3 to 172 years. This is illustrated in Figure 5.4.

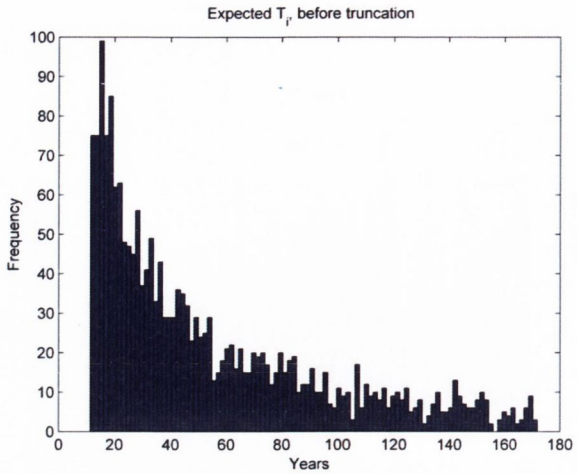


Figure 5.4: Distribution of expected T_i, C_{cr} alone varied.

Figure 5.5 now depicts the relative importance of the values of these parameters to Fick's Law. Note that the first set of columns pertain to C_s, the surface chloride value at the untruncated, truncated at 800 years and truncated at 500 years respectively. The second set refers to the effects of D_{app}, the third to the effects of X and the fourth to C_{cr}. The inlay chart then illustrates the relative effects of each parameter when the untruncated C_s value is removed as it distorts the scale and makes it difficult to see the impact of other variables. The two first bars represent the relative impact of C_s after truncating at 800 and 500 years respectively.

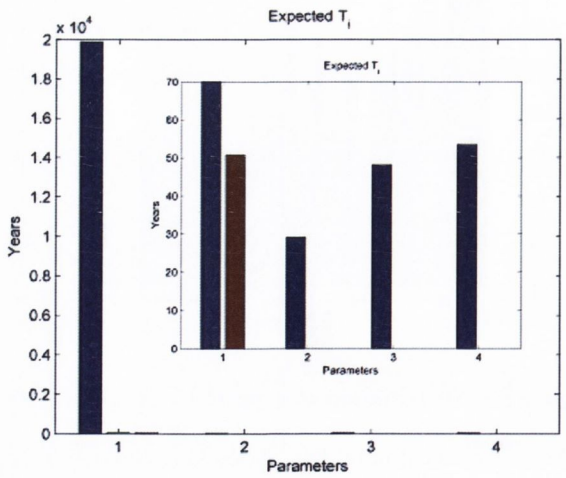


Figure 5.5: Relative importance of parameters to Fick's Law.

For further clarity, the histograms of Figure 5.1 to Figure 5.5 are illustrated together in Figure 5.6. Evidently C_s, the surface chloride value has by far the most impact on the predicted time to initiation. Hence as stated earlier, care must be taken when selecting a parameter range and distribution.

The next part of the sensitivity analysis considers the effects of variation within the model, i.e. having ascertained certain parameter values and distributions as in Table 4.10, this next analysis will look at the range of values obtainable within the predefined distributions, both when each variable at a time is individually varied by an extra 10%, varying all other parameters too, and also when all other parameters are kept constant at their predefined mean values and one parameter at a time is varied as defined.

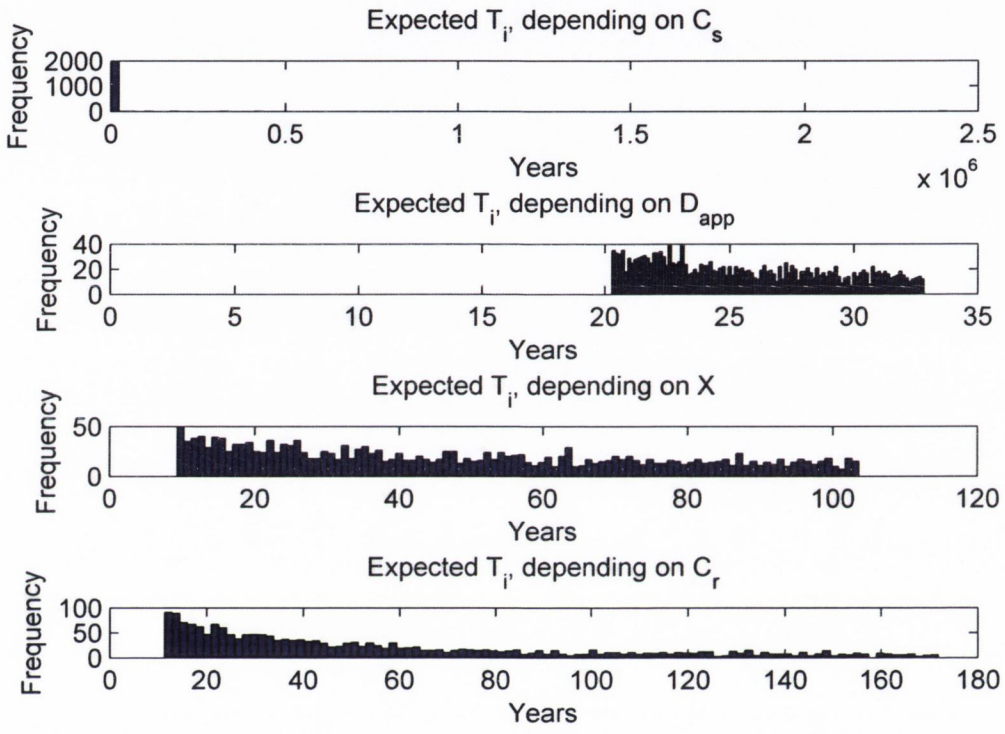


Figure 5.6: Distribution of expected T_i, looking at the effect of each parameter separately.

5.2.2 Sensitivity Analysis of Model to Variation within Defined Parameters.

The sensitivity analysis of the model to variation within the defined parameters is itself two-fold. Firstly, the parameters as defined in Table 4.10 will be individually assessed for their impact on the overall computed time to initiation of corrosion by running the model numerous times, each time varying only one parameter – i.e. either the mean or standard deviation of the defined parameter by 10% each time. This will give an overall gauge as to how the value of each parameter impacts upon the expected result. Secondly then, the parameters as defined in Table 4.10 will be analysed for variation within the generated 2000 values.

Impact of varying Defined Parameters upon Expected Time to Initiation

Initially all parameters were varied according to the values listed in Table 4.10 and the time to initiation of corrosion obtained. This resulted in a mean result of 35.7 years, with quite a large range of values from 1.7 to 998.2 years as can be seen in Figure 5.7 below. Note that this value is different to that illustrated in Figure 4.12 due to the large range in the computed times to initiation and the effect one extreme outlier has on the mean value as previously discussed in Section 4.5.

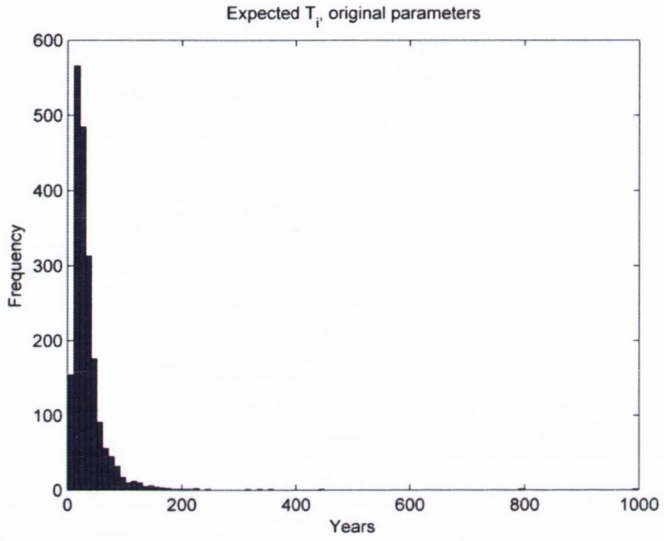


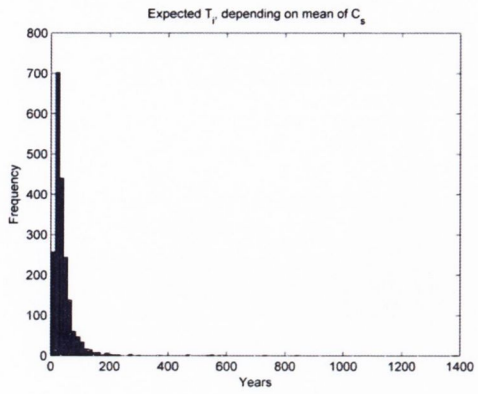
Figure 5.7: Distribution of expected T_i, varying all parameters.

Following on from this, all parameters were varied one at a time by adding 10% to the previously defined value in order to assess the sensitivity of each individual parameter. For clarity the initial input values are reiterated in Table 5.2 and their modified values are also listed.

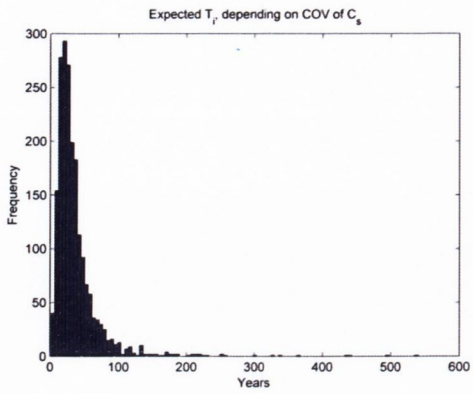
	μ	COV	μ + 10%	COV + 10%
C_s	5 kg/m^3	0.25	5.5 kg/m^3	0.275
D_{app}	1.27 x 10^{-12} m^2/s	0.25	1.39^{-12} m^2/s	0.275
C	50 mm	0.2	55 mm	0.22
C_{cr}	1.36 kg/m^3	0.2	1.496 kg/m^3	0.22

Table 5.2: Stochastically defined parameters for Sensitivity Analysis.

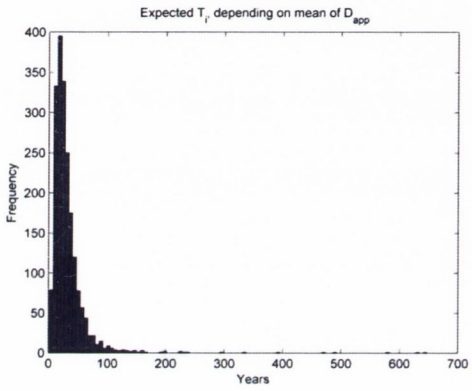
The times to initiation thus for the eight runs whereby one parameter at a time is increased by 10% are as illustrated in Figure 5.8 below. For completeness the mean values are also listed in Table 5.3.



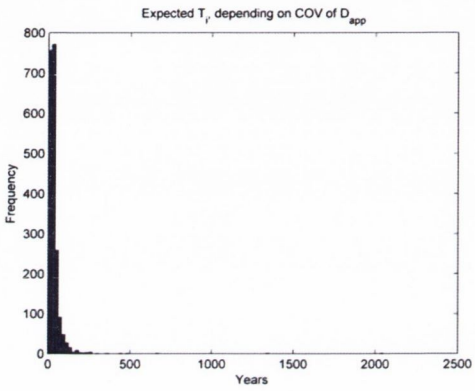
(i)



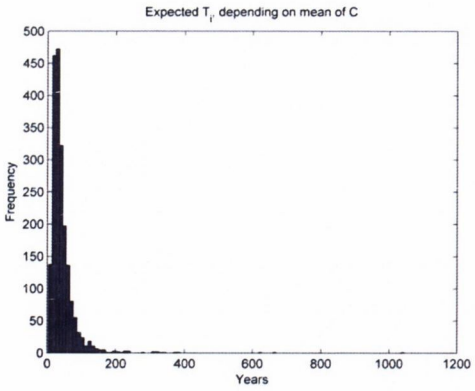
(ii)



(iii)



(iv)



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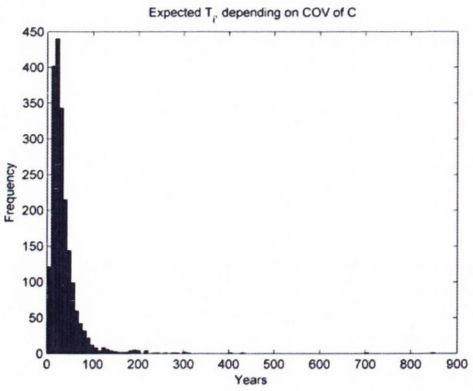

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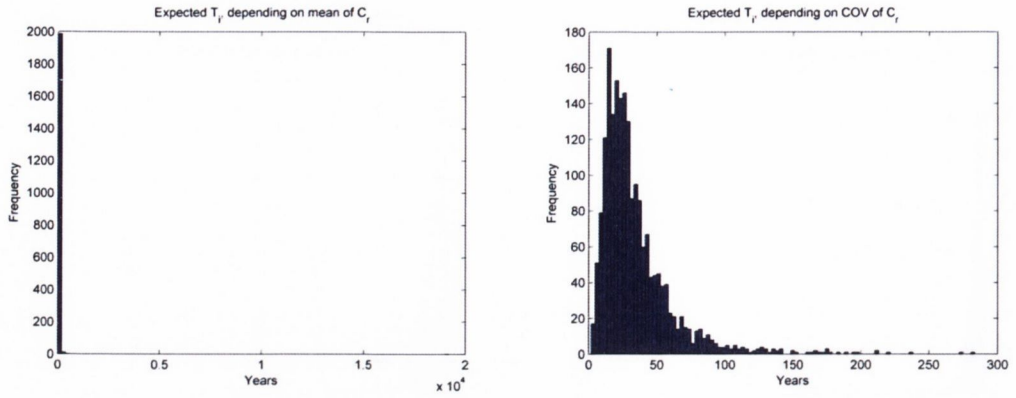

(vii) **(viii)**

Figure 5.8: Distribution of expected T_i, varying (i) the C_s mean, (ii) the COV of C_s, (iii) the D_{app} mean, (iv) the COV of D_{app}, (v) the C mean, (vi) the COV of C, (vii) the C_{cr} mean and (viii) the COV of C_{cr}.

	μ T_i (years)	*Standard Deviation (years)*	*μ T_i (years)*	*Standard Deviation (years)*
Original	35.7	40.9	35.4	33.8
μC_s + 10%	42.4 *(3)*	58.2	49.5 *(1)*	184.9
$COVC_s$ + 10%	37.3 *(5)*	38.2	35.6 *(5)*	35.5
μD_{app} + 10%	32.6 *(8)*	38.0	33.0 *(8)*	42.0
$COVD_{app}$ + 10%	37.5 *(4)*	65.0	36.7 *(4)*	37.9
μC + 10%	42.7 *(2)*	45.9	43.4 *(2)*	44.0
$COVC$+ 10%	36.5 *(6)*	41.6	35.5 *(6)*	33.6
μC_{cr} + 10%	49.7 *(1)*	430.0	42.3 *(3)*	125.7
$COVC_{cr}$ + 10%	34.8 *(7)*	28.6	35.3 *(7)*	33.3

Table 5.3: Mean times to initiation for Sensitivity Analysis.

As can be seen from Table 5.3 above, the mean of the surface chloride content, C_s, and the mean of the critical chloride concentration, C_{cr}, have a large impact on the computed time to initiation – the actual effect is ranked in italics. This is in agreement with the findings from section 5.2.1 above. The cover depth, C, also has a considerable effect on the computed time, again as expected and previously shown in Figure 4.16.

For completeness, the defined parameters will now be investigated for the inherent variation within the generated distributions.

Impact of individual Defined Parameters upon Expected Time to Initiation

The first parameter to be varied is C_s, the surface chloride content. As listed in Table 4.10, the value chosen for this study is 5 kg/m^3 with a COV of 0.25, in keeping with similar values suggested in Morcous (2010) and Lounis and Daigle (2012). Essentially, a distribution of 2000 values is generated for this parameter and the time to initiation computed for each one. All other parameters are kept constant at their mean values as defined in Table 4.10. Figure 5.9 depicts the obtained distribution of T_i which arises as a consequence. The mean time to initiation is computed as being 29.1 years, within a range of 13.57 to 299 years. Unlike in section 5.2.1, where the C_s value was varied within the literature quoted range thereby producing some extreme values which made truncation necessary, the sample distribution here does not tend to such values, hence truncation of values is not necessary. A significant range of predicted times to initiation does exist however, thereby reiterating the significance of choosing an appropriate C_s parameter value.

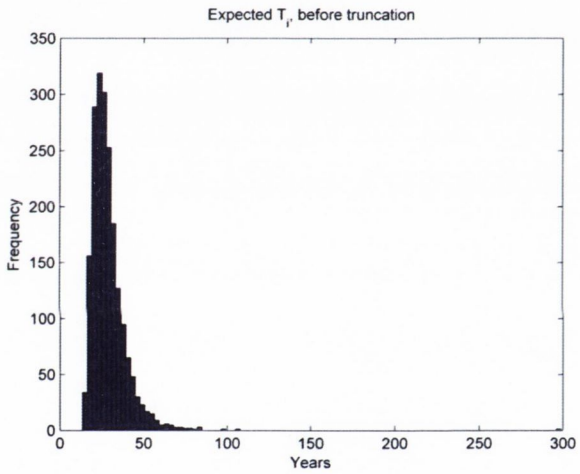

Figure 5.9: Expected T_i, looking at the variation in the defined C_s input distribution.

Looking at the apparent diffusion coefficient, D_{app} next, a value of 1.27 x10 $^{-12}$ m^2/s with a COV of 0.25 was used as the defining input parameter, whilst again the other 3 parameters were kept constant at their mean values. This results in a mean time to initiation of 28.34 years, and again no truncation of values is necessary since the range lies between 14.8 and 222 years. This is illustrated in Figure 5.10.

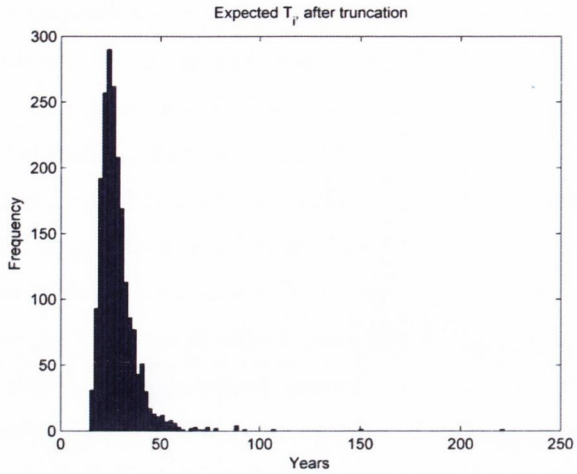

Figure 5.10: Expected T_i, looking at the variation in the defined D_{app} input distribution.

Varying C, the cover depth within the defined range also results in a mean time to initiation of 26.67 years. This is a quite a similar value to those obtained for C_s and D_{app}, though the range of values here is much less – 1.98 years to 67.8 years. This distribution of predicted time to initiation is shown in Figure 5.11. Note that this distribution of generated times appears more normal than lognormal as expected, since the cover depth was generated as a normal variable.

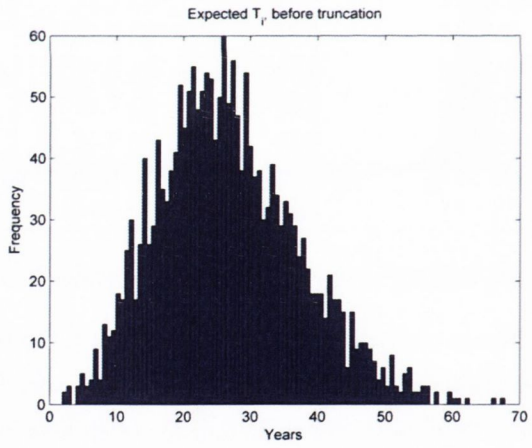

Figure 5.11: Expected T_i, looking at the variation in the defined C input distribution.

Finally, varying C_{cr}, the critical chloride concentration within its predefined range results in a mean time to initiation of 26.6 years, within a range of 12.8 to 101.3 years. A barchart showing the susceptibility of the parameters in Fick's law to variation in the predefined distributions is now depicted in Figure 5.12. As can be seen, the variation in C_s, gives rise to the largest T_i, thereby reiterating the importance this parameter has on the predicted time. Note that no truncation of values was necessary when considering the variation within the defined parameters, as the parameter values chosen and their corresponding coefficients of variance did not give rise to such

values. Stewart et al. (2011) also mention the use of truncation in their paper as a manner of avoiding nonsensical solutions. However, they make no mention of truncating the surface chloride content, rather instead the chloride threshold content, C_{cr} at 0.35 kg/m^3. As shown earlier though, it is the surface chloride values which appear to be responsible for the biggest range in solutions and the most ludicrous values. Hence, particularly when the generated results are for use in a deterioration prediction module for a BMS as is the case here, care must be taken when analyzing and implementing the generated results.

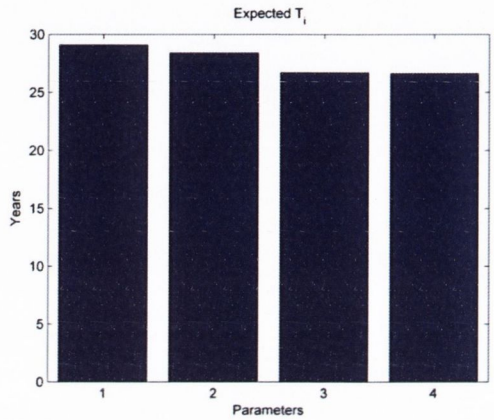

Figure 5.12: Expected mean time to initiation of corrosion when variation within the defined model parameters is considered.

5.2.3 Sensitivity Analysis of Model to Chosen Parameter Distribution Types.

Thirdly, the last part of this sensitivity analysis concerns the type of distribution used when defining the model input parameters. It is noted from Table 5.1 that both normal and lognormal distributions appear to be used interchangeably. The lognormal distribution has of course the advantage of not producing negative output, hence if the normal distribution is used, a caveat must be introduced into the code to ensure negative, nonsensical values are not generated. In particular, Fick's 2nd law with Crank's error solution as in Equation 4.2 will generate NaN's (not a number i.e. error) if it receives inputs greater than an absolute value of 1, hence this must be avoided. Again, if the chosen parameter distribution has a tendency to this, another caveat must be added into the code to avoid this.

In this thesis, if such a computed value arose, the value was overwritten and replaced with a mean value of all the preceding generated values. Naturally, one is slightly skewing the results by this overwriting process, but by the least possible amount it is felt as this mean is constantly shifting as more and more values are generated in a random fashion. The parameters chosen for analysis in Sections 5.2.1 and 5.2.2 involve a combination of both normal and lognormally distributed

variables but for extreme purposes Figure 5.13 depicts histograms for both untruncated and truncated at 500 years distributions on generated time to initiation depending on whether or not all normal, or all lognormal distributions are used. It is clear however from the figure that normal distributions can tend to give unsuitable results since negative values can be obtained.

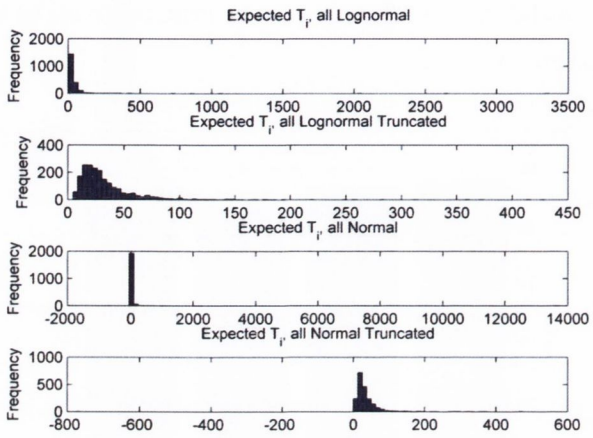

Figure 5.13: Comparison of expected T_i when either all lognormal or all normal variables are used for both truncated and untruncated cases.

Hence, the analysis above has illustrated the importance of choosing appropriate parameter and distribution values as there is potential for unrealistic values to occur which can have a profound impact on the results. As expected also, it is the surface chloride content C_s, and the critical chloride content C_{cr} which has the most effect on the computed time to initiation.

The analysis so far has focused on the analytical model for the first phase of deterioration for illustration purposes. Looking at the models however for the time to first crack phase T_{1st}, and time to severe cracking phase, T_{sp} as represented in Equations 4.29 and 4.30 respectively, it can be seen that there are only two parameters which can reasonably be expected to vary noticeably – i_{corr}, the corrosion rate and C, the cover depth. The other parameters which define this part of the deterioration can be considered to be relatively constant, given that they represent industry defined and regulated materials such as steel and concrete, i.e., E_{ef}, the effective strength of the concrete, $f_t^{'}$, the tensile strength of concrete, v, Poisson's ratio and D, the reinforcing bar diameter. Nevertheless since manufacturing standards are expected to vary somewhat, the Eurocode values for $f_t^{'}$, and $f_c^{'}$, and consequently E_{ef} will be normally distributed about their means as listed in Table 4.9 with a COV of 0.1. Note that realistically however, the value for the coefficient of variation of $f_t^{'}$ is expected to be higher than that for $f_c^{'}$.

The parameters as implemented thus far have been purely for illustration purposes. In keeping with the objective of developing an adaptable model suitable for *'bridges of all ages in all environments'* though, this next section now describes the parameters chosen as was deemed appropriate for Irish conditions and the purposes of this thesis. Note though that these estimates are just that, estimates and it is recommended that further work be carried out in this area through both experimental and theoretical means. This was also a suggestion of the LIFECON report (Lay and Schießl, 2003).

5.3 DEVELOPMENT OF MODEL FOR IRISH NETWORK

In keeping with the stated aim of developing the module on an elemental basis, a separate deterioration model will be calibrated for each element. The overall bridge condition rating will then be built up as a function of its minor elements. This dependency will be obtained through an analysis of the bridge inspections and observations recorded in the EIRSPAN database.

Furthermore, since the system needs to be applicable for the entire Irish network and since Ireland is a small island heavily influenced by the sea with approximately 5576 km of coastline in the republic - the area under the jurisdiction of the NRA (Neff, 1998), the model will be calibrated for both marine conditions and inland conditions due to the application of deicing salts. Note that this corresponds to the recommendation in Orcesi and Cremona (2010) to develop Markov transition matrices on a geographical basis whereby the effects of the environment on condition rating can be considered in order to give more accurate results.

5.3.1 Element-Level Deterioration Model

Like the majority of BMS in existence (Adey et al., 2010), EIRSPAN records condition ratings on an elemental basis. Unlike PONTIS in the US, which has 151 standardized structural elements (Thompson and Sobanjo, 2010), EIRSPAN only has 13 - i.e. bridge deck, bridge beams, abutments, wing walls, piers, bearings, parapets, bridge surface, expansion joints, footways, embankments, riverbed (if applicable) and 'other elements'. Of these, it can be seen that some have more of an influence on structural capacity and overall bridge condition rating than others – for instance the condition of the bridge deck clearly has more of an impact on the overall rating than the condition of the parapets. Likewise, the considered deterioration mechanism, i.e. that of chloride-induced corrosion will not be applicable to all elements as other deterioration mechanisms will be at force.
From examining the database, it can be seen that five elements can be singled out as having a notable bearing on the overall structural rating. They are:

1. Bridge Deck
2. Bridge Beam
3. Abutment

4. Wing Walls
5. Piers

Of the 1576 RC bridges listed in the database, a condition rating is recorded for 1531 of them. Of these then, as can be seen in Figure 5.14, 614 are in State Zero, 609 are in State One, 272 are in State Two, 32 are in State 3, 4 are in State 4 and none are in State Five. Table 5.4 to Table 5.8 below list the number of elements in each particular condition state when the overall structural state is equal to State Zero, State One, State Two, State Three or State Four. No bridges are currently in State Five according to the database hence no inferences regarding elemental correlations will be derived for this state.

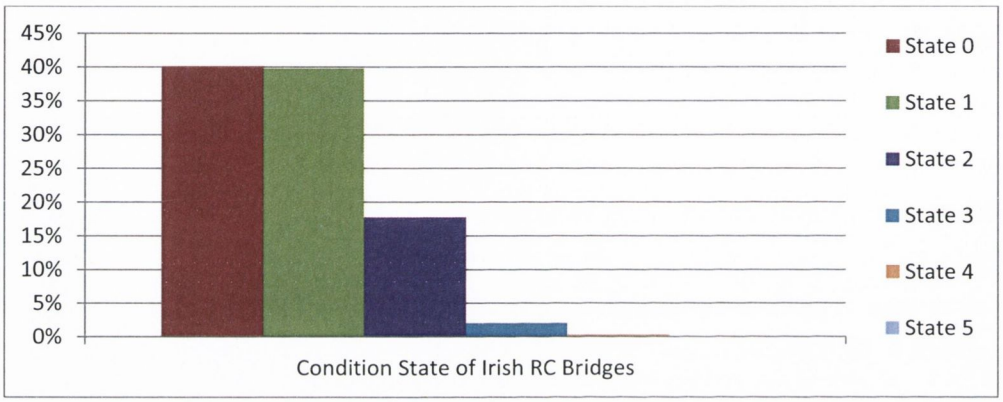

Figure 5.14: Spread of condition rating amongst concrete bridges in EIRSPAN database.

State	Wing	Abutment	Pier	Deck	Beam
0	*490*	*472*	*217*	*486*	*164*
1	58	12	1	12	1
2	10	1	1	0	1
3	0	0	0	0	0
4	0	0	0	0	0
5	0	0	0	0	0
NaN	56	129	395	116	448

Table 5.4: Elemental spread of condition state ratings when overall structure is in State Zero.

State	Wing	Abutment	Pier	Deck	Beam
0	255	181	110	223	88
1	*260*	*349*	*115*	*316*	*50*
2	32	4	3	10	0
3	2	0	0	0	0
4	1	0	0	0	1
5	0	0	0	0	0
NaN	59	75	381	60	470

Table 5.5: Elemental spread of condition state ratings when overall structure is in State One.

State	Wing	Abutment	Pier	Deck	Beam
0	90	57	36	43	17
1	119	122	51	70	23
2	*38*	*70*	*27*	*138*	*27*
3	2	2	0	1	0
4	0	0	0	0	0
5	0	0	0	0	0
NaN	23	21	158	20	205

Table 5.6: Elemental spread of condition state ratings when overall structure is in State Two.

State	Wing	Abutment	Pier	Deck	Beam
0	11	6	6	7	2
1	12	12	8	7	2
2	6	7	4	4	1
3	*1*	*6*	*4*	*13*	*9*
4	0	0	0	0	0
5	0	0	0	0	0
NaN	2	1	10	1	18

Table 5.7: Elemental spread of condition state ratings when overall structure is in State Three.

State	Wing	Abutment	Pier	Deck	Beam
0	1	0	0	1	0
1	1	2	1	1	0
2	0	2	0	0	0
3	0	0	0	0	0
4	*1*	*0*	*1*	*2*	*0*
5	0	0	0	0	0
NaN	0	0	0	0	4

Table 5.8: Elemental spread of condition state ratings when overall structure is in State Four.

The tables above list the number of elements with each condition rating whilst under an overall umbrella structural rating. This analysis has been conducted in an attempt to ascertain the contribution of each individual element to the overall rating. From inspecting the above tables briefly, it can be seen that the bridge deck appears immediately to have to most influence and very rarely is a structure assigned a better overall condition rating than the elemental level deck condition rating. This is in keeping with that expected since bridge decks are the most stressed elements in highway bridges (Lounis et al., 2001).

Table 5.9 below now lists the percentages of each component as to how they appear to contribute to the overall rating from examining the tables above. Note that while for instance, only 4 structures have an overall structural rating of 4, and that there is no overlap or doubling up of ratings (i.e. 2 of these ratings can be assumed to be as a result of the bridge deck having a rating of

4, while the other 2 are attributed to the wing-walls and pier being in poor condition), for condition ratings zero and one especially, significant overlap occurs. Consequently, the percentage ratings have been normalized in these cases.

State	Wing (%)	Abutment (%)	Pier (%)	Deck (%)	Beam (%)
0	26.8	25.8	11.8	26.6	9
1	24	32	10.5	29	4.5
2	12.7	23.3	9	46	9
3	3	18	12	39.5	27.5
4	25	0	25	50	0

Table 5.9: Individual contribution of each element to each overall structural condition state.

For the purposes of combining this information into a generalized equation that can be used to predict the overall future structural state as a function of elemental level deterioration models, a weighting system has been developed whereby each element of n elements is signified by C_i and the weighting coefficient to each element is signified as α_i. These combine to give the expected structural rating at time t as $S(t)$. This is represented in Equation 5.1.

$$S(t) = \sum_{i=1}^{n} \alpha_i . C_i \qquad where \qquad \sum_{i=1}^{n} \alpha_i = 1.0 \qquad \textbf{Equation 5.1}$$

In order to obtain these weighting coefficients, each element has been ranked as to how it affects each overall structural rating. This is shown in Table 5.10. Clearly, the bridge deck is by far the most important element to the overall structural rating – twice as significant as the wing-walls, almost twice as significant as the abutments and two and a half times as significant as the bridge pier and bridge beam. Having ranked the elements, they are then given an average ranking over all condition states by dividing this overall ranking by five. This is then normalized to give the weighting coefficients in Table 5.11.

State	Wing (%)	Abutment (%)	Pier (%)	Deck (%)	Beam (%)
0	1	3	4	2	5
1	3	1	4	2	5
2	3	2	4	1	4
3	5	3	4	1	2
4	2	3	2	1	3
	∑14	∑12	∑18	∑7	∑19

Table 5.10: Ranked contribution of each element to overall structural rating.

	Wing	Abutment	Pier	Deck	Beam
All elements present	0.176	0.204	0.137	0.35	0.13
No Beam	0.203	0.237	0.157	0.403	-
No Pier	0.204	0.238	-	0.406	0.151
No Beam or Pier	0.240	0.281	-	0.478	-

Table 5.11: Elemental Weighting Coefficients.

These coefficients are then employed in Equation 5.1 to obtain the overall structural rating as a dependent function of its elements. Hence a method has been derived whereby overall structural condition rating can be expressed as a function of its sub-elements, as was an objective of this thesis stated in Section 2.5. As an example, the case where all bridge elements are present is illustrated in Equation 5.2. These equations will be used in Chapter 6 to combine the predicted state of each individual bridge component into an overall expected future condition state for the structures and network as a whole.

$$S(t) = 0.176W + 0.204A + 0.137P + 0.35D + 0.13B \qquad \textbf{Equation 5.2}$$

5.3.2 Parameter values as suited to Irish conditions

As stated previously, the model has to account for bridges in varying environments. Hence Markov transition matrices have been calibrated for both inland and coastal regions for the five bridge components detailed above. The preceding chapter has outlined the details of the implementation of the model along with the equations to be used. The parameters as implemented there though were purely for illustration purposes using values quoted in the literature. In order to calibrate the system and derive matrices for Irish conditions Table 5.12 and Table 5.13 below list the input parameters for the three mathematical models for the deterioration phases of T_i, T_{1st} and T_{sp} respectively for each of the 5 identified bridge elements for both exposure conditions, i.e. marine exposure and deicing salts. A 100-year design life has been selected for implementation purposes. For marine conditions then – i.e. tidal, splash and spray zones, this results in an exposure class of XS3 in accordance with the Eurocode (CEN, 2004). Consequently C50 concrete (cube strength) has been selected and together this results in a recommended concrete cover depth of 50 mm with a w/c ratio of 0.40. A COV of 0.2 has been used as in Sudret (2008).

Regarding the values quoted in Table 5.12, a figure of 7.35 kg/m^3 has been chosen for the surface chloride content in a tidal region according to Stewart et al. (2011). A coefficient of variance of 0.7 is listed in that paper but it has been decided ultimately to use a lower coefficient of 0.25 for the purposes of this model, to lessen the probability of unreasonable values for the time to initiation phase as illustrated in Section 5.2. This coefficient of variance is the same as that quoted by Lounis and Daigle (2012) for a similar analysis. Furthermore Bastideas-Arteaga and Schoefs (2012) also utilise a lower COV of 0.2 in their work on the deterioration of a bridge in a marine environment, hence this lower COV value is considered justified. As discussed earlier in Section 5.2, the exact value for the chloride threshold, C_r, required to initiate corrosion is unclear and is best judged on the risk of corrosion. Numerous studies have been conducted but no conclusive figure has been decided upon (Angst et al., 2009; Lay and Schießl, 2003). Hence, for the purposes of the model developed here, it has been taken to be 1.36 kg/m^3, an often quoted value in the literature (Bastidas-Arteaga and Schoefs, 2012; Morcous et al., 2010). Concerning the apparent diffusion coefficient

D_{app}, a mean value in the region of 1 e^{-12} m^2/s is a standard value for OPC, the material of choice of Irish bridges. Lounis and Daigle (2012) utilise a value of 1.268 e^{-12} which pertains to OPC concrete with a 0.40 w/c ratio, a typical ratio in Ireland, hence 1.268 e^{-12} is used as the D_{app} value with a COV of 0.25.

The i_{corr}, corrosion current rates then are taken from the Duracrete (2000) report on durability design and redesign of concrete structures. The abutment, deck and pier were considered to be in the tidal zone, hence they are deemed to belong to exposure class C15 as stated in the report and thus have a corresponding mean i_{corr} of 6.035 $\mu A/cm^2$, with a standard deviation of 3.448 $\mu A/cm^2$. The wing and beam then on the other hand were considered to be in exposure class C13, i.e. exposed to airborne seawater. Consequently, they have a lower mean i_{corr} of 2.586 $\mu A/cm^2$, with a standard deviation of 1.724 $\mu A/cm^2$.

Parameter		Wing	Abutment	Pier	Deck	Beam
C_s	μ	7.35	7.35	7.35	7.35	7.35
kg/m^3	COV	0.25	0.25	0.25	0.25	0.25
LN	Ref.	(Stewart et al., 2011)	Stewart, Wang et al. 2011)	Stewart, Wang et al. 2011)	Stewart, Wang et al. 2011)	Stewart, Wang et al. 2011)
C_{cr}	μ	1.36	1.36	1.36	1.36	1.36
kg/m^3	COV	0.25	0.25	0.25	0.25	0.25
LN	Ref.	(Bastidas-Arteaga and Schoefs, 2012)	(Bastidas-Arteaga and Schoefs, 2012)	(Bastidas-Arteaga and Schoefs, 2012)	(Bastidas-Arteaga and Schoefs, 2012)	(Bastidas-Arteaga and Schoefs, 2012)
D_{app}	μ	1.268 e^{-12}	1.268 e^{-12}	1.268 e^{-12}	1.268 e^{-12}	1.268 e^{-12}
m^2/s	COV	0.25	0.25	0.25	0.25	0.25
N	Ref.	(Lounis and Daigle, 2012)	(Lounis and Daigle, 2012)	(Lounis and Daigle, 2012)	(Lounis and Daigle, 2012)	(Lounis and Daigle, 2012)
C	μ	50	50	50	50	50
mm	COV	0.2	0.2	0.2	0.2	0.2
N	Ref.	(Sudret, 2008)	(Sudret, 2008)	(Sudret, 2008)	(Sudret, 2008)	(Sudret, 2008)
i_{corr}	μ	2.586	6.035	6.035	6.035	2.586
$\mu A/cm^2$	COV	0.67	0.57	0.57	0.57	0.67
LN	Ref.	(Duracrete, 2000)	(Duracrete, 2000)	(Duracrete, 2000)	(Duracrete, 2000)	(Duracrete, 2000)
E_{cm}	μ	35.22	35.22	35.22	35.22	35.22
kN/mm^2	COV	0.1	0.1	0.1	0.1	0.1
N	Ref.	(CEN, 2004)	(CEN, 2004)	(CEN, 2004)	(CEN, 2004)	(CEN, 2004)
f_t	μ	3.5	3.5	3.5	3.5	3.5
N/mm^2	COV	0.1	0.1	0.1	0.1	0.1
N	Ref.	(CEN, 2004)	(CEN, 2004)	(CEN, 2004)	(CEN, 2004)	(CEN, 2004)

Table 5.12: Input parameters for elemental deterioration model due to corrosion caused by chlorides in seawater.

Table 5.13 considers the case of deicing salts applied to the road surface. Again a 50 year design life has been considered. In accordance with Eurocode 2 (CEN, 2004), the bridge deck and beam were deemed to be in exposure class XD3, i.e. exposed to cyclic wetting and drying periods, with XF4 as a secondary exposure class, i.e. subject to moderate freeze-thaw attack. Hence grade C50 concrete, with a w/c ratio of 0.40 is used with 55 mm cover (Bond et al. 2006). The bridge pier, wing and abutments are deemed to be in XD1, as they are subject to airborne deicing agents. Hence C50 concrete (cube strength) with a w/c ratio of 0.45 is used with 35mm cover (Bond et al., 2006). The C_{cr}, the critical chloride content, has remained the same. However the C_s, surface chloride content has now lowered to reflect the application of salts as opposed to marine exposure. Likewise, the elements are now deemed to be in exposure class C12 according to the Duracrete report (2000), i.e. elements subject to cyclic wetting and drying. This corresponds to a corrosion current, i_{corr} of 2.586 μA/cm^2 with a standard deviation of 1.724 μA/cm^2. The D_{app}, apparent diffusion coefficient has also changed slightly to 1.62 e^{-12} in respect of measurements taken from the Dickson Bridge in Canada due to the application of deicing salts (Morcous et al., 2010). However, in order to avoid negative times to initiation, a lognormal as opposed to a normal distribution has been utilized. Table 5.14 shows the mean times to T_i, T_{1st} and T_{sp} respectively for each element under varying environmental conditions. Note that the T_{sp} referred to in the table is the time to condition state 4 for comparison sake.

Parameter		Wing	Abutment	Pier	Deck	Beam
C_s kg/m^3 LN	μ	2.95	2.95	2.95	5	5
	COV	0.25	0.25	0.25	0.25	0.25
	Ref.	-	(Stewart et al., 2011)	(Stewart et al., 2011)	-	-
C_r kg/m^3 L N	μ	1.36	1.36	1.36	1.36	1.36
	COV	0.25	0.25	0.25	0.25	0.25
	Ref.	(Bastidas-Arteaga and Schoefs, 2012)	(Bastidas-Arteaga and Schoefs, 2012)	(Bastidas-Arteaga and Schoefs, 2012)	(Bastidas-Arteaga and Schoefs, 2012)	(Bastidas-Arteaga and Schoefs, 2012)
D_{app} m^2/s LN	μ	1.62 e^{-12}	1.62 e^{-12}	1.62 e^{-12}	1.62 e^{-12}	1.62 e^{-12}
	COV	0.31	0.31	0.31	0.31	0.31
	Ref.	(Morcous et al., 2010)	(Morcous et al., 2010)	(Morcous et al., 2010)	(Morcous et al., 2010)	(Morcous et al., 2010)
C mm LN	μ	35	35	35	55	55
	COV	0.2	0.2	0.2	0.2	0.2
	Ref.	-	-	-	-	-
i_{corr} μA/cm^2 LN	μ	2.586	2.586	2.586	2.586	2.586
	COV	0.67	0.67	0.67	0.67	0.67
	Ref.	(Duracrete, 2000)	(Duracrete, 2000)	(Duracrete, 2000)	(Duracrete, 2000)	(Duracrete, 2000)
E_{cm}	μ	35.22	35.22	35.22	35.22	35.22

kN/mm^2	COV	0.1	0.1	0.1	0.1	0.1
N	Ref.	(CEN, 2004)	(CEN, 2004)	(CEN, 2004)	(CEN, 2004)	(CEN, 2004)
f_t	μ	3.5	3.5	3.5	3.5	3.5
N/mm^2	COV	0.1	0.1	0.1	0.1	0.1
N	Ref.	(CEN, 2004)	(CEN, 2004)	(CEN, 2004)	(CEN, 2004)	(CEN, 2004)

Table 5.13: Input parameters for elemental deterioration model due to corrosion caused by chlorides from deicing salts.

Environment	Wing	Abutment	Pier	Deck	Beam
T_i *Marine*	32.6	32.6	32.6	32.6	32.6
T_i *Deicing Salts*	38.3	38.3	38.3	40.9	40.9
T_{1st} *Marine*	1.0	0.41	0.41	0.41	1.0
T_{1st} *Deicing Salts*	0.89	0.89	0.89	1.05	1.05
T_{sp} *Marine*	9.43	4.21	4.21	4.21	9.4
T_{sp} *Deicing Salts*	5.76	5.76	5.76	11.2	11.2

Table 5.14: Average phase times in years for each element under both environments.

5.4 CALIBRATION OF MARKOV TRANSITION MATRICES

A primary aim of this thesis was to develop a network prediction tool which would be capable of considering bridges of all ages and all conditions. The main goal therefore is to maintain groups of bridges rather than to evaluate the soundness or predict the deterioration of individual bridges. As outlined above, the model has been developed to represent structural degradation due to chloride-induced corrosion of reinforced concrete. As part of a framework, the model parameters have been listed for both marine and inland instances, but naturally the bridge stock could be further broken down with regard to concrete cover, expected corrosion rate etc. Section 4.5.1 shows average lifecycle curves which have been rendered based on the chloride-induced deterioration model. However these curves represent average condition rating every year, hence the true variation in condition state is not accurately captured – as discussed previously the condition rating scale inherently skews the average result when represented in expected condition state format. As outlined in Chapter 3 then, the average condition state will not be used to calibrate the Markov transition matrices from. Instead, the entire generated database of 2000 bridges over a 100 year lifetime will be used, with the minimization function as in Equation 2.7, i.e. a minimization in expected condition rating distribution as opposed to condition state rating. Non-homogeneous chains are also to be used, as stated in Chapter 3. However, the time-period per matrix and the actual manner of calibration, i.e. whether or not a matrix should be used to describe a state or a time period needs to be ascertained.

Two approaches have been identified; calibration based solely on time, the time-based brackets being dependant on structure age, or a second approach dependant on state. This state-based approach attempts to obtain a matrix to describe each state, so for a 6 state condition state system as in EIRSPAN, there would be 6 matrices to be calibrated, one each for each condition state. In order to implement this, the mean times for each state were used as the calibration periods. So for the case of a bridge deck in a marine environment, transition matrix 1 minimizes the discrepancy in Markov computed expected condition state distribution to analytical model probability distribution for years 1 to 32 (see Table 5.15). Transition matrix 2 then models the time to first crack phase, so in this case here using the parameters outlined, it would only minimize the discrepancy over one year. Transition matrices 3, 4, 5 and 6 are calibrated accordingly. Essentially then this is a study into using Markov deterioration models for bridge management, a study into how applying them in different manners affects the end result.

For evaluation purposes, an example of each method is given below with the total error for each method clarified in order to enable a direct comparison to be made. The element which has been chosen for illustration purposes is that of a bridge beam, in a marine environment with model parameters as stated in Table 5.12.

5.4.1 Time-Based Matrices

This Time-Based method is dependent purely on structure age or the lifecycle point in time at which a structure is at. Since a 100 year lifecycle has been modelled in order to represent a return period of 100 years for bridges as is customary, it was decided to utilise ten different transition matrices to each represent ten year blocks of deterioration. This was deemed sufficient since increasing the number of matrices beyond this adds greatly to the computation time as stated in Chapter 3.

5.4.2 State-Based Matrices

Another method involves calibrating the matrices according to what state they are expected to be in. This was investigated as it was thought that this might capture the variation better perhaps since each matrix now would describe the particular rate or pattern of deterioration associated with each condition state. Essentially it still incorporates age-dependence in one sense however though as structures which are expected to be in an initiation phase, i.e. for the first 32 years, they are set to follow transition matrix 1 as they are expected to still be initiating. The expected and modelled state duration times are as outlined in Table 5.15. It can be seen that for state 1, even though the expected duration time was only 1 year, 2 years was allowed for in order to capture some model variability. For state 5 then, since no upper bound has been declared - it pertains to cracks of greater than 1 mm, the discrepancy between actual and predicted condition state distribution was minimized over an arbitrary period of 15 years, as it was felt that minimizing it over the entire, remaining 55 year lifespan would lead to inaccuracy.

State	Expected Duration (Years)	Modelled Duration (Years)
0	32	32 - years 1:32
1	0.4	2 - years 33:34
2	1.58	2 – years 35:36
3	3.5	4 – years 37:40
4	5.25	5 –years 41:45
5		15 allowed – years 46:60

Table 5.15: Expected state duration times and allowed computation minimization times.

For comparison purposes, both methods were investigated with future condition state for each plotted on the same graph. The total error each year is summed too for both methods so as to ascertain the more appropriate method.

5.4.3 Comparison of Methods

From Figure 5.15 and Figure 5.16 below it is evident that the Time-Based method is far more appropriate for calibrating the Markov transition matrices. Table 5.16 shows the total error over the 100 years is approximately six times less than the State-Based approach. Naturally, some of this discrepancy and error is due to the fact that some states have extremely short duration times as a direct consequence of the state definitions and chosen parameters. However, it is felt regardless that a generic system comprising of a matrix for every ten year period is more suitable as it allows for and incorporates much more variability in deterioration pattern.

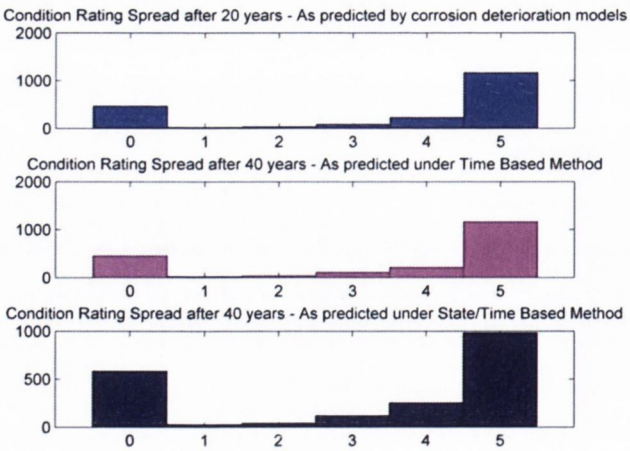

Figure 5.15: Histograms showing comparison of distribution spread between (a) actual generated database, (b) that computed under the 'Time-Based' method or (c) the 'State-Based' method.

	0	1	2	3	4	5	∑ Error
Actual	467	19	34	87	226	1167	-
'Time' Method	453	23	38	109	213	1164	2.05
'State' Method	583	26	40	117	253	981	11.71

Table 5.16: Number of elements in each condition state after 40 years.

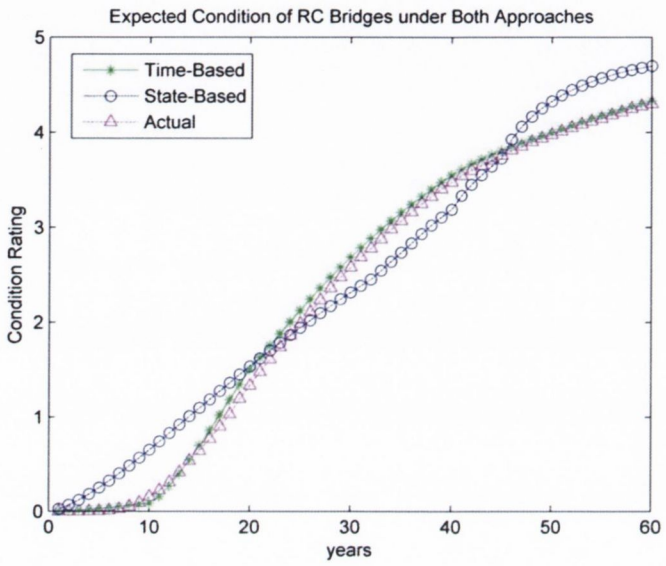

Figure 5.16: Expected average condition rating over 60-year simulated lifetime under both approaches vs. generated database.

5.5 TRANSITION MATRICES FOR MODEL

Based on the recommendations and findings of Chapters 3, 4 and 5, the Markov Transition Matrices have been calculated using a non-linear minimization of expected condition state distribution over time, using non-homogeneous chains. They have been derived to represent the process of chloride-induced corrosion of reinforced-concrete, and have been calibrated for both inland and marine conditions, suitable for application to an Irish bridge network. Furthermore, the EIRSPAN bridge management system database has been queried and it has been ascertained that five bridge elements in particular have a notable impact on a structure's overall condition state rating. Accordingly, these are the wing-walls, the abutments, the piers, the deck and the beams. Matrices have been calibrated therefore for each of these five elements on an individual basis, for both environments specified, the idea being that the model is now capable of being modified on an elemental level, whilst also taking into account the interdependence of bridge elements on one another. For completeness, the matrices are represented below in Table 5.12 to Table 5.20.

Time Period	P_{00}	P_{11}	P_{22}	P_{33}	P_{44}
Years 1:10	0.99	0.56	0.27	0.47	0.47
Years 11:20	0.96	0.06	0.16	0.53	0.62
Years 21:30	0.95	0.05	0.35	0.64	0.77
Years 31:40	0.94	0.02	0.32	0.68	0.80
Years 41:50	0.96	0.29	0.48	0.68	0.84
Years 51:60	0.96	0.14	0.46	0.75	0.82
Years 61:70	0.97	0.04	0.36	0.73	0.85
Years 71:80	0.97	0.16	0.30	0.63	0.82
Years 81:90	0.97	0.001	0.001	0.67	0.84
Years 91:100	0.99	0.55	0.43	0.32	0.74

Table 5.12: Time-Dependent Transition Matrices for a Bridge Wing/Beam in a Marine Environment.

Time Period	P_{00}	P_{11}	P_{22}	P_{33}	P_{44}
Years 1:10	0.99	0.001	0.02	0.2	0.34
Years 11:20	0.94	0.001	0.001	0.001	0.13
Years 21:30	0.94	0.001	0.001	0.1	0.47
Years 31:40	0.95	0.001	0.001	0.18	0.59
Years 41:50	0.95	0.001	0.001	0.27	0.60
Years 51:60	0.95	0.001	0.001	0.001	0.54
Years 61:70	0.96	0.001	0.001	0.205	0.56
Years 71:80	0.98	0.001	0.06	0.39	0.46
Years 81:90	0.97	0.005	0.001	0.18	0.47
Years 91:100	0.99	0.03	0.21	0.68	0.76

Table 5.13: Time-Dependent Transition Matrices for a Bridge Abutment/Pier/Deck in a Marine Environment.

Time Period	P_{00}	P_{11}	P_{22}	P_{33}	P_{44}
Years 1:10	0.98	0.35	0.18	0.5	0.36
Years 11:20	0.96	0.001	0.001	0.26	0.53
Years 21:30	0.98	0.16	0.17	0.51	0.70
Years 31:40	0.97	0.03	0.29	0.46	0.67
Years 41:50	0.93	0.001	0.001	0.001	0.48
Years 51:60	0.99	0.74	0.60	0.63	0.76
Years 61:70	0.97	0.001	0.001	0.41	0.62
Years 71:80	0.99	0.45	0.03	0.47	0.76
Years 81:90	0.98	0.001	0.001	0.08	0.47
Years 91:100	0.99	0.84	0.68	0.87	0.94

Table 5.14: Time-Dependent Transition Matrices for a Bridge Wing/Abutment/Pier in an Inland Environment.

Time Period	P_{00}	P_{11}	P_{22}	P_{33}	P_{44}
Years 1:10	0.99	0.58	0.38	0.57	0.58
Years 11:20	0.97	0.01	0.25	0.53	0.61
Years 21:30	0.97	0.04	0.43	0.69	0.80
Years 31:40	0.96	0.20	0.45	0.71	0.82
Years 41:50	0.96	0.001	0.28	0.73	0.83
Years 51:60	0.98	0.19	0.58	0.78	0.86
Years 61:70	0.97	0.10	0.39	0.76	0.88
Years 71:80	0.98	0.21	0.48	0.74	0.84
Years 81:90	0.99	0.25	0.28	0.66	0.80
Years 91:100	0.99	0.21	0.57	0.68	0.82

Table 5.20: Time-Dependent Transition Matrices for a Bridge Deck/Beam in an Inland Environment.

It can be seen that in all four matrices P_{00}, that is the probability of being in condition state zero and remaining in condition state zero, is extremely high for all age-groups. This can be explained by the fact that in the example presented in this thesis state zero has been defined according to Table 4.9 as being the time before corrosion initiation is expected to occur. According to Table 5.14 then, the mean time to corrosion initiation is 32.6 years for elements in a marine environment, and either 38.3 or 40.9 years for elements subject to corrosion from the application of deicing salts. As shown in Section 5.2 though, the computed T_i can have a range of up to 300 years. Given therefore that the expected state duration is so high – particularly with respect to the other state duration times, it is reasonable at all stages in the lifecycle of an element or structure to expect that if it is in state zero at the outset, it will remain there.

Concerning P_{11} and P_{22}, it is evident from Tables 5.17 to 5.20 above that the probabilities of remaining in either state after one year is extremely low. Again though, this can be explained by the fact that according to Table 5.14 and Table 5.15, for the parameter values considered here, the expected duration of time in states 1 and 2 is extremely short – less than one year in the case of state one and less than 2 years in the case of state two. Furthermore it can be seen that the values are especially low in Table 5.18, i.e. for the case of a bridge abutment/pier/deck in a marine environment. This is in line with that expected, given that from Table 5.14 it can be seen that the time to first crack, i.e. that the duration of time spent in state 1 according to the definition of state 1 for this example, is only 0.41 years for this group, compared with 1.0 years for the other groups.

Finally, concerning P_{33} and P_{44}, they are again lower for Table 5.18 and 5.19 than for the other two tables. Again this is as expected since the state duration time of state 4 – T_{sp} in Table 5.14 is much lower for these groups than the other two. Consequently, it is expected that the structures will deteriorate and move to the next condition state.

Finally, it must be remembered that the probabilities listed here in Tables 5.15 to 5.18 are dependent on both the state definitions outlined in Table 4.9, and the inputs to the deterioration model as listed in Table 5.12 and 5.13. If any of these definitions or parameter values change, the probabilities themselves will change also.

5.6 CONCLUSION

This chapter has investigated the effect of different parameter values on the chloride-induced corrosion deterioration model developed in the last chapter. A sensitivity analysis has been carried out which has found that as expected, the surface chloride content C_s, and the critical chloride content C_{cr} had the most effect on the computed time to initiation. In particular, it was noted that care must be exercised when choosing stochastic parameters for distributions of these parameters as there is potential for unrealistic values to occur which can have a profound impact on the results. As also expected, the cover depth, C, was also found to have a considerable impact on the computed time to initiation, with increasing cover resulting in an increased time to corrosion initiation. Consequently representative parameter values for the Irish bridge network and therefore the model developed in this thesis have been determined.

An elemental weighting system which considers the impact of each bridge element on the overall structural rating has also been determined. In short therefore the two objectives as listed at the outset of this chapter and in Section 2.5 have been accomplished, i.e.

1. To 'calibrate' in effect such systems for use with regard to the Irish Bridge network, i.e. conduct a literature review and sensitivity analysis of the most appropriate parameter values.

2. To develop the system on an elemental basis, i.e. to build up the overall bridge condition rating as a function of its minor elements and to consider the overall condition rating then as dependant on the correlations between these elements. In this respect, the system will be most robust and adaptable for other kinds of structures in alternative locations.

CHAPTER 6 – EIRSPAN AND OVERALL MODEL IMPLEMENTATION

6 EIRSPAN AND OVERALL MODEL IMPLEMENTATION

6.1 INTRODUCTION

The overall aim of this thesis was to develop a network-level prediction model, the term network level in this context representing a collection of bridges, with the application data being those on the Irish national road grid. This model is to *'be suitable for bridges of all ages in all environments'*, and to incorporate bridge element interdependence. The preceding chapters have outlined the most appropriate method of modeling future bridge deterioration in general given that it needs to be defined so as to enable the model to be incorporated into a discrete condition state BMS.

Specifically, as has been previously discussed in Chapters 3 and 4, a non-homogeneous Markovian approach has been decided upon and chloride-induced corrosion selected as the framework mechanism for demonstration purposes. Chapter 5 has identified a methodology to deal with the correlation of bridge elements in predicting overall bridge condition state and an equation has been developed from the EIRSPAN database to represent this reliance and interdependence. Markov transition matrices for the bridge elements have thus been calibrated as a result of this analysis. In an effort to fulfill the criteria that the model must be applicable to structures in all environments, these elemental matrices have also been calibrated for both inland and coastal regions of Ireland. These have all been listed in Section 5.5.

However, the matrices represent only one part of the Markov prediction model. As seen in Equation 2.1 and again below for clarity, the initial state vectors p_0, i.e. the proportion of structures in a given condition state, need to be ascertained also:

$$P(t) = P_0 \times P^t$$

Like the matrices these need to be determined for all elements and environments in the Irish case.

Ultimately then, using the equation developed in Chapter 5 for bridge element interdependence, together with the calibrated transition matrices and initial state vectors, this chapter pieces together in its entirety the developed prediction model, presenting the overall expected network condition for a 100 year period. As an aside, and for completeness, this expected model network condition rating will also be compared to the expected network condition rating if one were to use the procedure of percentage prediction as described in Section 2.1.2, and thereby obtain transition probabilities directly from the database itself, foregoing the use of analytical deterioration models.

Furthermore, as stated in Section 2.5, the effect of maintenance and repair on equilibrium network condition rating, taking into account different maintenance policies, imperfect repairs and alternative costs, was also to be considered. To do this a framework for incorporating maintenance effects has also been developed in this chapter whereby different repair strategies and options will be looked into, i.e. that of repair only, rehabilitation only, or a combination of the two.

Specifically, corresponding to objectives 6, 7 and 8 in Section 2.5 the objectives of this chapter thus are:

1. To present the results of the developed prediction model which has been built up to take account of structures of all ages in varying environments.

2. To consider the effects of maintenance and repair on equilibrium network condition rating, taking into account different maintenance policies, imperfect repairs and alternative costs.

3. To develop a data-cleaning procedure which could be used to elicit suitable transition probabilities from infrastructure inspection databases as soon as sufficient information becomes available.

In order to apply the developed methodology then to the Irish network and obtain real-time information, a data-cleaning or extraction and handling process needs to be identified. This will be discussed in the following section.

6.2 DATA EXTRACTION PROCESS

EIRSPAN, the Irish BMS, comprises an extremely thorough database, thus all of the required information such as year of construction, material, GPS coordinates etc. should be obtainable from it. Firstly, on a site by site basis, information fields exist as to the primary and secondary material of the structures, the year of construction and the GPS coordinates of each bridge. Secondly, the 13 different elemental ratings have all been recorded along with the overall rating for each bridge for each inspection date. Using the SHAZAM report wizard then, inbuilt relational tables can be used to extract the necessary information fields. An example of these tables and fields can be seen in Figure 6.1.

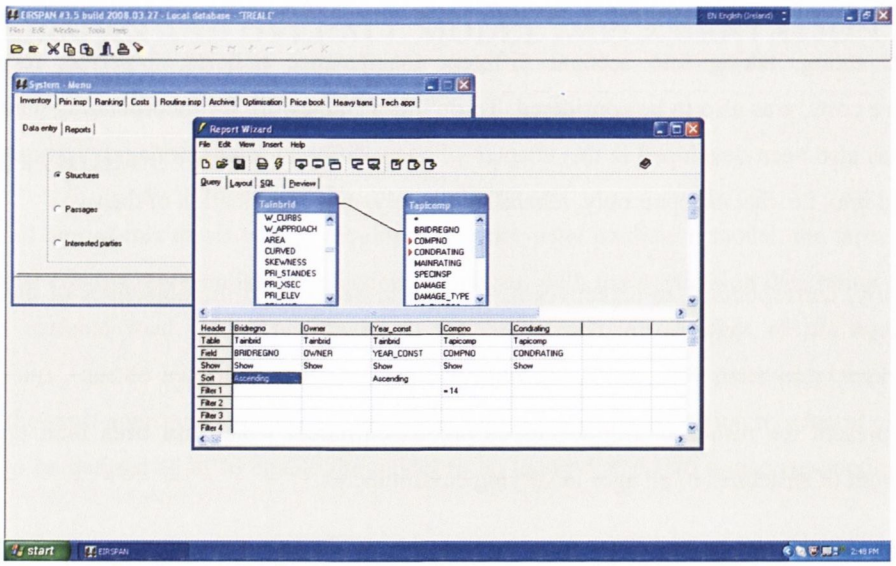

Figure 6.1: Screenshot of SHAZAM report wizard in EIRSPAN

However, whilst SHAZAM enables one to sort data in each field in ascending or descending order, according to a specific value, within a specific range and so forth, numerous problems with the required data extraction were found to exist. To begin with SHAZAM just gives either the latest overall condition rating for each component or else the history of condition ratings for each component. It does not allow the latest overall condition rating to be set at 0, and then give just the latest condition rating of other individual components. Instead it gives the chronological condition rating history of the two, three or four inspections that have been carried out on the component. Hence alternative, additional procedures have to be used to obtain a snapshot of elemental condition rating spread when the overall condition rating has been set to 0, 1, 2, 3, 4 or 5. This was necessary for example in determining the bridge elemental interdependency equation ascertained in Section 5.3.1.

Since SHAZAM does not give the user full access to all of the information hidden in its datafields, as much relevant information as possible needs to be extracted from the operational tables and exported as a .csv file. This can then be resaved as a .xls file and imported into Matlab where data-processing can ensue.

Another problem which was found to exist was that while EIRSPAN utilizes a six state system as outlined in Section 2.2, many elements were found to have no recorded state - a dash instead was indicated in the state space. This creates a major problem as Matlab reads these as NaN's (not a number) and cannot compute the required functions. Mathematically, this can be easily overcome by overwriting these NaN's with an arbitrary value such as 6 (since it is not already used for a condition state). The true problem though lies in the amount of potential information which is missing from the analysis as a result of these dashes. Upon investigation, sometimes they can be

explained by the fact that not all elements apply to all bridges. For instance of the 13 bridge components listed in Section 5.3.1, the footways and the riverbed may not always applicable. Likewise, not all bridges have intermediate piers or beams. However, for the majority of cases these dashes arise due to either incomplete inspection forms whereby the inspector either did not for whatever reason give the element a rating, or whereby a further opinion or inspection was deemed necessary. The analysis of textual remarks in the database may eliminate some of this 'missing' information, but would require a vast amount of work. Since as it stands, this 'missing' information results in vast quantities of information becoming unusable for programmable purposes, it is recommended that this point be clarified to the personnel responsible for inputting the information in the database. This problem however is recognized as a worldwide problem in the context of BMS and models requiring direct access to such databases (Kallen, 2007).

Likewise the date as it stands in the EIRSPAN database is represented as year.month.date and needs to be reformatted in Excel to discrete numbers in individual columns before Matlab can manipulate it – again it appears as a NaN.

Nevertheless, having selected the appropriate information from EIRSPAN, saving to a .csv file, converting to a .xls file and importing into Matlab the data can be manipulated and the required records obtained to fully calibrate the model for the Irish network. This entire model implementation and acquiring of relevant initial state vectors for the Markov deterioration model developed in this thesis shall be presented now in the following section.

6.3 EXPECTED CONDITION RATING RESULTS FROM MODEL

Since, as outlined in Section 5.4, a time-based or age-based model has been selected as a means of modelling and predicting future bridge behaviour, the year of construction or age of the bridge needs to be determined. This is necessary because as described in Section 5.4, transition matrix 1 corresponds to the first 10 years of chloride-induced corrosion deterioration, hence the structures to which it is applied to must be ten years old or less. Likewise, transition matrix 2 describes the expected deterioration pattern from years 11 to 20, therefore it must be applied to structures of that age.

Problems arise again here though for implementation purposes as it is found that of the 1555 concrete bridges, the age is only recorded for 842 or 54 % of them. Hence either inferences are made about the year of construction or age of the other 46% and arbitrary matrices applied then accordingly, or else the model can only be applied to 842 bridges instead of the full 1555. The spread of construction years across the 842 structures for which a construction year has been recorded then is depicted in Figure 6.2.

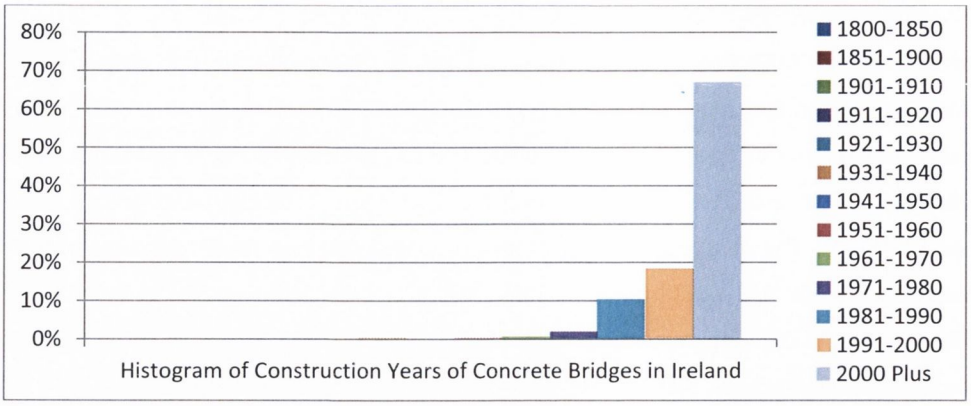

Figure 6.2: Histogram of known years of construction of Irish RC bridges.

It can be seen that as expected, the vast majority of the Irish bridge stock dates from 1990. This again validates the argument for the necessity of developing the deterioration and prediction models which have been outlined thus far and which have been the focus of this thesis, i.e. Ireland has at present a relatively new bridge stock which will mature and degenerate at the same time in perhaps ten to twenty years in the absence of appropriate maintenance and rehabilitation. Therefore their development is paramount. Especially when other countries such as Portugal (Horta and Lopes, 2012) are in a similar situation regarding their bridge stock.

Having ascertained the ages of bridges, the initial condition state vectors need to be obtained. Since the model was developed on an elemental basis, in keeping with the objective to establish a state-of-the-art modifiable, adaptable system as stated in Chapter 2, Markov transition matrices and initial state vectors need to be identified for the five principal bridge elements selected in Section 5.3.1. Furthermore, again in keeping with the intention of developing a state-of-the-art system for the Irish national road network, these matrices were calibrated for both inland and coastal regions. This has already been demonstrated and the matrices calibrated and listed in Chapter 5, but the relevant p_0, initial state vectors of condition state will be obtained from the EIRSPAN database here and both segments of the model put together.

In order to segregate the bridges into both environmental regions, the GPS coordinates were obtained from EIRSPAN and imported into ArcGIS where they were then sorted. Figure 6.3 below illustrates the location of all concrete bridges contained in the database. Note however that 23 rogue bridges have been removed as they were shown to be in the middle of the Irish Sea or Atlantic Ocean due to erroneous input of data.

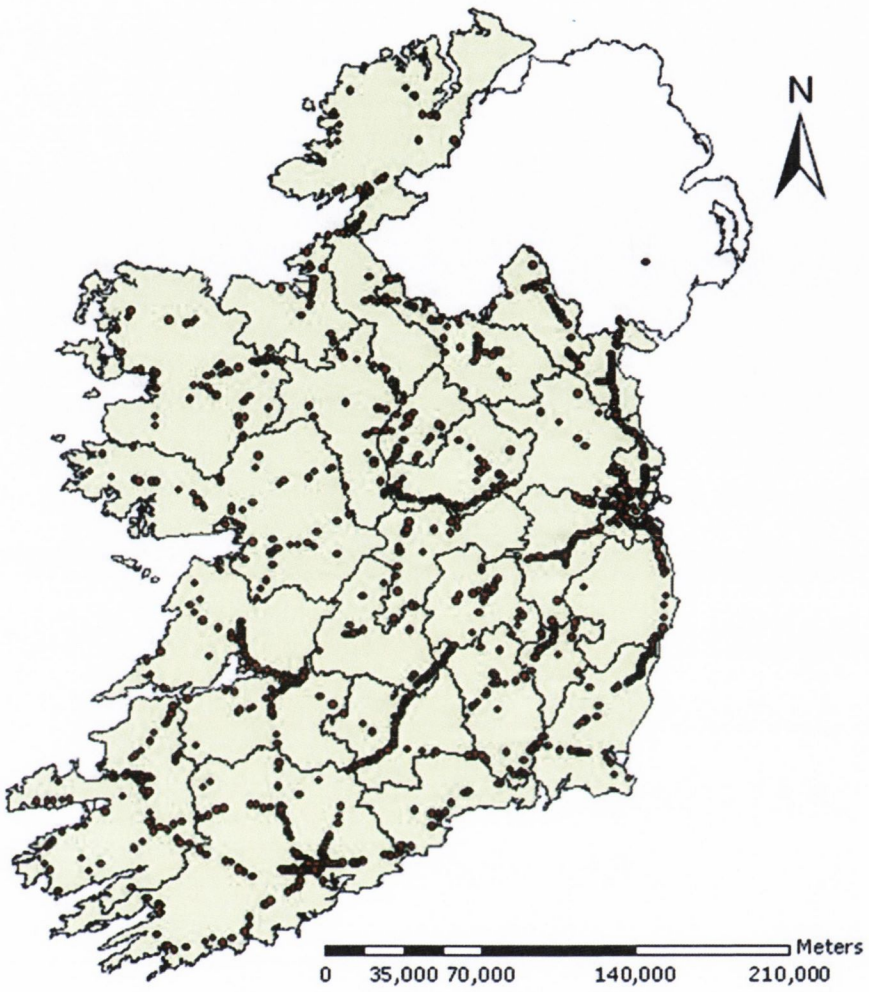

Figure 6.3: ArcGIS map showing all RC bridges in Ireland.

The following section now will list the initial state vectors as obtained from EIRSPAN, together with an outline description of the overall model implementation and application.

6.3.1 Model Implementation

Having obtained the p_0 vectors from each element through a combination of database sorting with EIRSPAN and ArcGIS, and then information manipulation with Matlab, the vectors now need to be combined with the appropriate Markov transition matrix to accurately predict future condition state. As previously mentioned, these p_0 vectors were calibrated for the five different elements of bridge wing, bridge abutment, bridge deck, bridge beam and bridge pier in two different environments, and will themselves will be listed in the following two sections for coastal and

inland structures respectively, the actual code integration and model methodology however will be illustrated here.

As stated in Section 5.4, the transition matrices have been calibrated to describe 10 year blocks in time of the life-cycle of an RC bridge subject to chloride-induced corrosion. Having inspected the EIRSPAN database, and the range of information available as to the construction years of the bridges, it was decided to have 10 year bins for the initial state vectors of bridges as far back as 1900, and from then on to employ two 50 year bins for structures with construction years in the ranges of 1850 to 1899, and 1800 to 1849 respectively. This is because there were very few concrete structures built at this time hence 50 year brackets were deemed sufficient. Prior to sorting them according to location, Table 6.1 below lists the number of structures in each bin. Note that the bin '2000 +' is utilized because in the version of EIRSPAN analyzed in this thesis, structures built, maintained or inspected after 2009 were not included in it. Hence upon updating the BMS with more information this bin would instead become '2000-09' and the next bin would become '2010-19'.

Age-group	Number
1800-49	2
1850-99	2
1900-09	0
1910-19	0
1920-29	1
1930-39	3
1940-49	2
1950-59	3
1960-69	6
1970-79	17
1980-89	88
1990-99	154
2000 +	564

Table 6.1: Construction Years of Irish bridges

For the first 10 years then, transition matrix 1 is applied to structures built from the year 2000 onwards, transition matrix 2 to structures built from 1990 to 1999, transition matrix 3 to structures built from 1980 to 1989 and so forth. It can be seen that while there are 10 matrices, there are actually 13 initial state distribution vectors, of which the last 2 are of 50 years duration each. Since

there are more initial state vectors than transition matrices, the last matrix, transition matrix 10 becomes an absorbing matrix. Hence, it describes the expected deterioration pattern of all structures built before 1910. This is in keeping with findings by Guignier and Madanat (1999), who found that after 73 years, the transition matrices became time-homogeneous as the deterioration matrix had reached its lower bound. Consequently, expecting the bridges to follow a certain deterioration pattern after 90 years is deemed reasonable. Note also that after the first 10 year period, the structures jump to the next matrix and now structures built from the year 2000 onwards are described by transition matrix 2 since they are expected to be at that stage of deterioration. Transition matrix 3 is now used to describe the expected structural deterioration of bridges built during the period 1990 to 1999. The process continues like such with new structures added to the database always deteriorating according to transition matrix 1. Hence for the first 10 years, transition matrices 1:9 are applied to the relevant p_0 vectors, i.e. vectors 13:5 respectively, with transition matrix 10 applied to all structures older than 90 years, i.e. vectors 4:1. For t = 11:20 years then transition matrices 1:8 are applied to P1 vectors 1:8 respectively (these are condition state distribution vectors derived from p_0 vectors 13:6 after 10 years), with transition matrix 10 applied to all structures older than 90 years, i.e. P1 vectors 9:13.

The p_0 vectors were derived on an elemental level which when paired with the appropriate transition matrix as listed in Section 5.5 and combined with the various age-groups will predict the deterioration pattern of each element individually. The individual elemental patterns then need to be combined according to Equation 5.1 and the overall bridge rating ascertained.

These elemental and consequently bridge expected condition ratings were derived for both coastal and inland environments and the results of both of these cases, together with a summed network expected condition rating is presented in the next section.

6.3.2 Future Bridge Prediction - Coastal Regions

For the purposes of obtaining 'coastal' bridges, a coastal boundary limit of 2 miles from the coast was assumed in this study. ArcGIS then identified 333 bridges within this region as shown in Figure 6.4. Note that certain estuary bridges are missing from this depiction due to the method in which the data was extracted from ArcGIS.

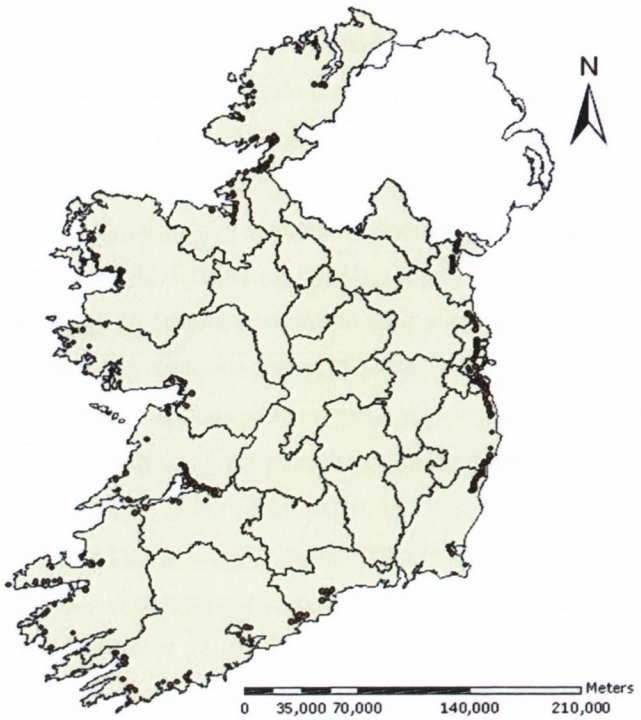

Figure 6.4: Coastal RC bridges on Irish National Roads.

Note that the condition state of the structure must also be defined along with the age. As listed in Table 2.3, EIRSPAN utilises a six state condition rating system, but as mentioned above in Section 6.3, many of these ratings are missing. Hence this further reduces the number of elements available for use. For instance taking the case of a bridge deck in a coastal environment, of the 333 structures, 36 do not have a condition state assigned to them, hence 297 structures only can be used as an input to the model.

For clarity, the p_0 vectors for each element for each age-group are illustrated below in Figures 6.5 to 6.9. Note that numbers 1 to 13 along the x-axis refer to groups 1 to 13 accordingly, i.e. group 1 refers to structures built from 1800-1849, while group 13 refers to structures built from the year 2000 onwards.

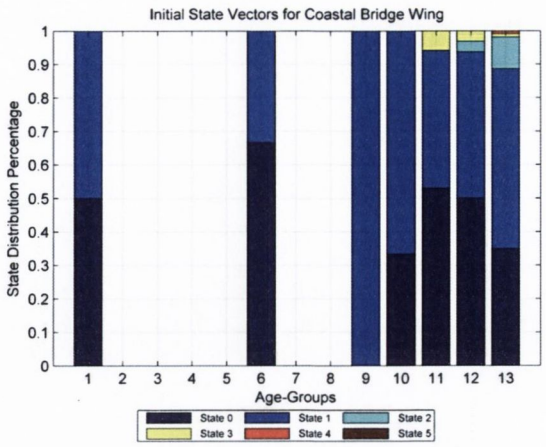

Figure 6.5: Initial state vectors for a bridge wing in a coastal environment.

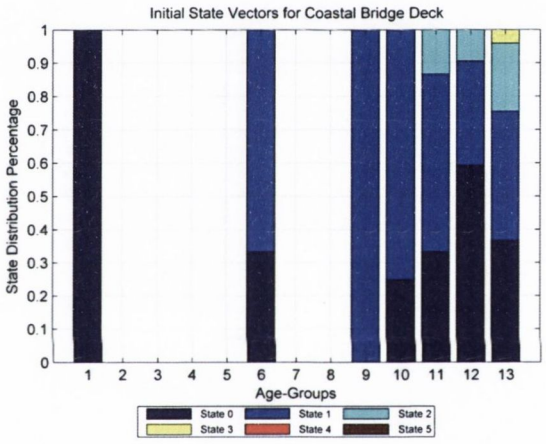

Figure 6.6: Initial state vectors for a bridge deck in a coastal environment.

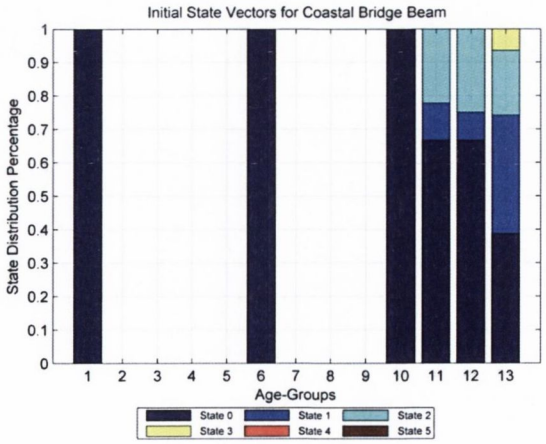

Figure 6.7: Initial state vectors for a bridge beam in a coastal environment.

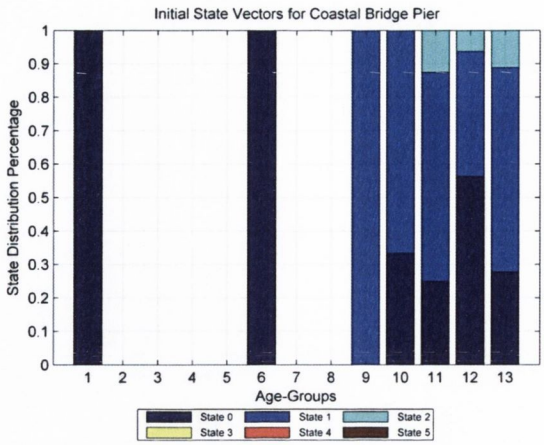

Figure 6.8: Initial state vectors for a bridge pier in a coastal environment.

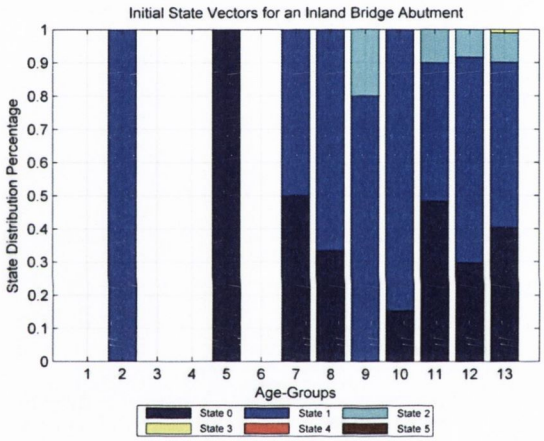

Figure 6.9: Initial state vectors for a bridge abutment in a coastal environment.

By combining these p_0 vectors together with the appropriate matrices outlined in Section 5.5, the expected condition rating over the 100 year period can be found. Note that when computing the overall expected condition rating for each element, as opposed to each age-bracket within that element, the expected condition distributions and ratings must be weighted each time by the number of structures in that age-bracket. This is necessary as otherwise, were the age-brackets weighted and aggregated equally, the network would be skewed for instance by the older groups '1800-49', '1850-99' and so forth, when it reality from Table 6.1, the group '2000 +' should have the most influence.

After combining the elements then as described in Equation 5.1, the expected aggregated condition rating of the coastal RC bridges can be obtained. This will be presented graphically in Section 6.3.4

together with the expected condition rating of the inland structures and consequently the expected network rating as a whole.

6.3.3 Future Bridge Prediction – Inland

The process of obtaining the inland initial state vectors is exactly the same as that outlined above for the coastal initial state vectors. Likewise, they are combined in the exact same fashion. Hence the P_0 vectors themselves will be shown below in Figures 6.10 to 6.14 for completeness sake only and then all results of expected future condition state will be discussed in the next section. Note that having removed the rogue bridges, there are 1222 bridges in the region designated 'inland' for the purposes of this thesis.

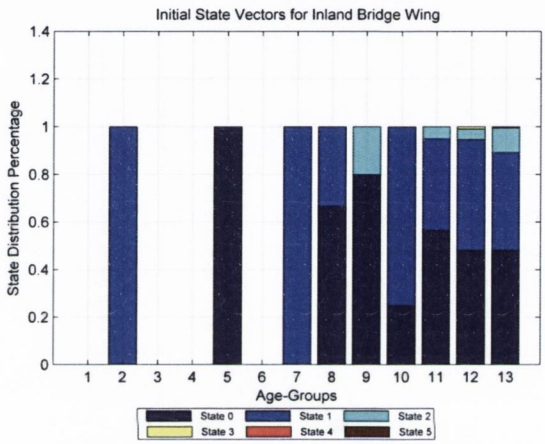

Figure 6.10: Initial state vectors for a bridge wing in an inland environment.

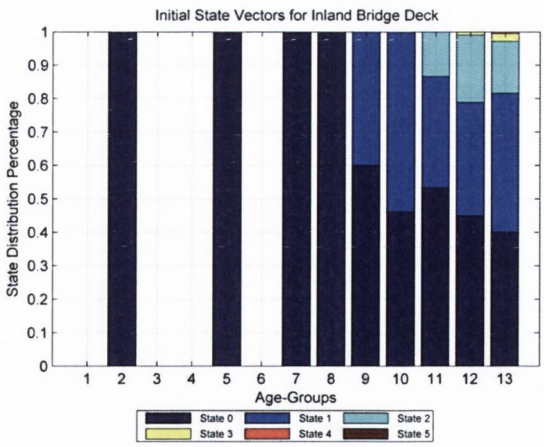

Figure 6.11: Initial state vectors for a bridge deck in an inland environment.

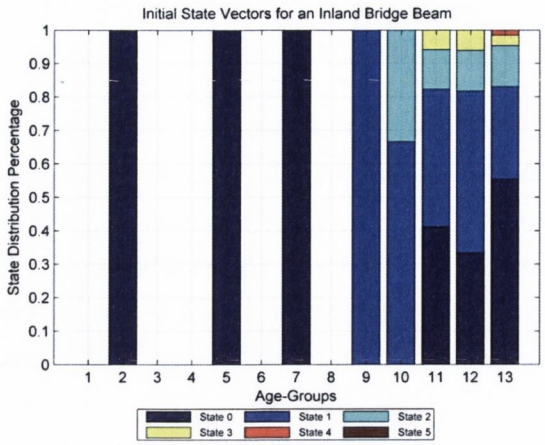

Figure 6.12: Initial state vectors for a bridge beam in an inland environment.

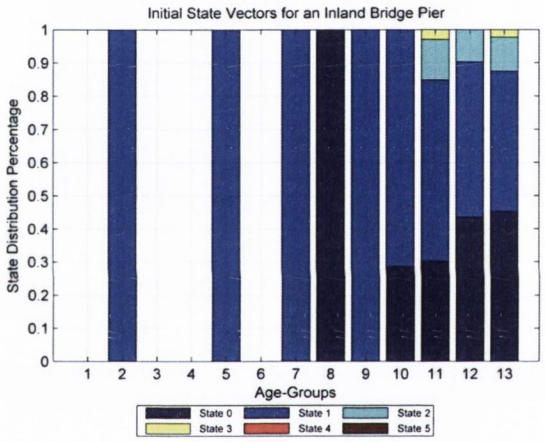

Figure 6.13: Initial state vectors for a bridge pier in an inland environment.

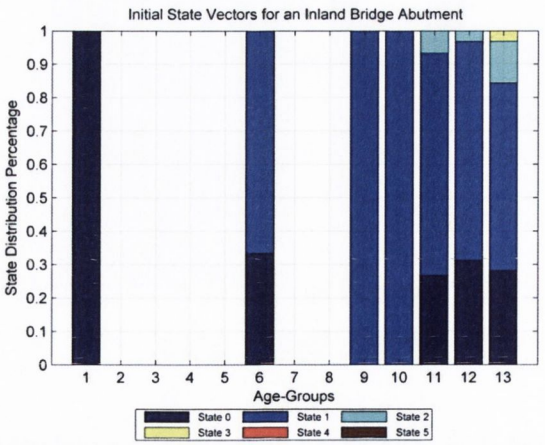

Figure 6.14: Initial state vectors for a bridge abutment in an inland environment.

The above figures show that there is a greater spread of age-groups in the inland case – as expected since there are almost four times as many structures in this group than are in the coastal group. On an elemental basis then it can also be seen that for the bridge wing, beam, pier and abutment there is little difference in condition rating spread between environments whereas for bridge decks, the coastal decks appear to have general worse condition rating.

6.3.4 Future Bridge Prediction – Combined

Combining the expected future condition ratings of the marine and inland structures yields an overall expected condition rating life-cycle curve for the Irish network, which is ultimately displayed below in Figure 6.15. In order to combine them, both the inland and marine structures are weighted according to the number of structures in that exposure category. This is illustrated in Equation 6.1.

$$E(t) = 0.214 \times E[marine] + 0.786\, E[inland] \qquad \textbf{Equation 6.1}$$

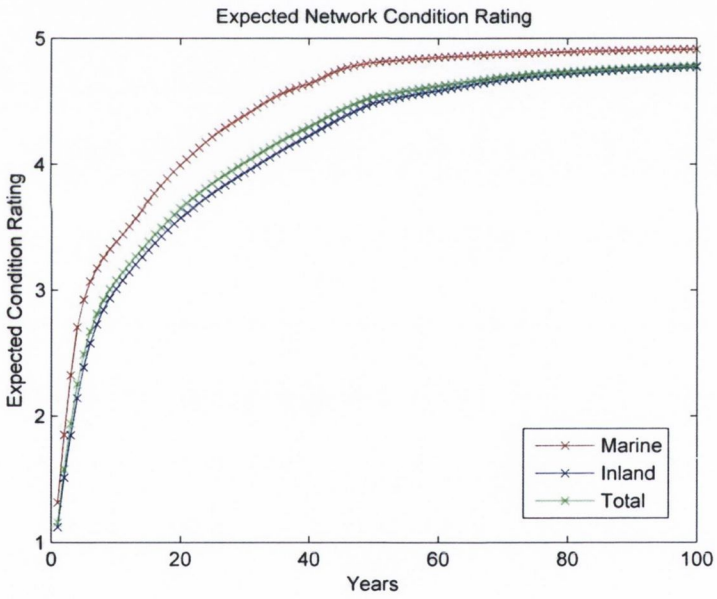

Figure 6.15: Expected condition state rating of RC bridges under model.

As expected, it can be seen that the overall network expected condition rating curve is most similar to that of the inland expected condition rating curve. For clarity, the expected condition rating of the overall network is tabulated for the first 20 years in Table 6.2 below. It is noted though that that structures appear to be transitioning between states extremely fast – for instance within the first 20 years, with a 0.42 jump in condition state between years 1 and 2 alone. This however is explained by the condition state definitions as defined in Table 4.9 when attempting to map deterioration due to chloride-induced corrosion to a 6 state system, and accordingly a real database. For

completeness, the initial overall condition rating was obtained through further aggregation of elemental p_0 vectors, aggregated over all age-groups. Note that the individual element contributions for the example illustrated in this thesis were taken for the case where a bridge structure consists of all five elements as listed in Table 5.11 and therefore the contributions were as in Equation 5.2. These aggregated vectors can be seen in Table 6.3 and Table 6.4 below. Furthermore, by comparing the expected condition rating in Table 6.2 for year 1 to the initial rating in Table 6.4 one can see that a jump in condition state of 0.42 was also observed in the first year. This can be explained by the number of structures in condition state 1 initially jumping or changing state to condition sate 2. Since condition state 1 has by definition a very short duration time (see Table 5.14), this changing of state creates a large effect on overall condition state. In order to change this lifecycle pattern, the inputs to the deterioration model can easily be modified – either in the form of different state definitions such as in those outlined in Table 4.9 or different parameter inputs as in Tables 5.12 and 5.13. This will result in different Markov transition probabilities and consequently different lifecycle curves.

Year #	E	Year #	E
1	1.15	11	3.14
2	1.57	12	3.20
3	1.94	13	3.27
4	2.25	14	3.33
5	2.49	15	3.39
6	2.67	16	3.44
7	2.81	17	3.50
8	2.92	18	3.55
9	3.00	19	3.60
10	3.07	20	3.64

Table 6.2: Expected condition rating for years 1:20.

	0	1	2	3	4	5	E
Wing Coastal	0.40	0.50	0.07	0.02	0.01	0	0.720
Pier Coastal	0.38	0.53	0.09	0	0	0	0.706
Deck Coastal	0.41	0.4	0.16	0.03	0	0	0.800
Beam Coastal	0.54	0.23	0.20	0.03	0	0	0.732
Abutment Coastal	0.29	0.60	0.09	0.02	0	0	0.843
Wing Inland	0.49	0.42	0.08	0.01	0	0	0.608
Pier Inland	0.41	0.47	0.1	0.02	0	0	0.717

Deck Inland	0.44	0.39	0.15	0.02	0	0	0.765
Beam Inland	0.47	0.36	0.12	0.04	0.01	0	0.756
Abutment Inland	0.38	0.52	0.09	0.01	0	0	0.717

Table 6.3: Elemental level initial state vectors when aggregated out over different age-groups.

	0	**1**	**2**	**3**	**4**	**5**	**E**
Coastal	0.40	0.45	0.12	0.02	0.01	0	0.771
Inland	0.43	0.43	0.12	0.02	0	0	0.720
Network	0.42	0.43	0.12	0.02	0.01	0	0.726

Table 6.4: Overall initial state vectors.

Finally, it is recognized that there is of course another level of complexity. Real-life data has been used to implement the model developed in this thesis but this data as implemented thus far has been purely 'age-based', with no account taken for the fact that many structures have naturally been maintained and so should not be expected to deteriorate in the same fashion as a deteriorated, un-maintained, un-rehabilitated bridge, i.e. new materials with different characteristics to the original materials will have been employed. Furthermore the effect of loading on structures with time has not been considered. These however are considered to be assumptions of the developed model, which should not skew results too much. Firstly, if the structure has been repaired or maintained, short of it being fully replaced, in which case it would have been assigned a new registration ID, and new age of construction, hence not be the same structure anymore, it cannot be expected to further deteriorate then in the same fashion as if it were a new structure, parts of it naturally will still be deteriorating in the original manner. Secondly, the model thus far has taken account of deterioration only, but in the following chapter a tentative framework for incorporating maintenance and repair actions will be proposed. Note that this is not the main aim of this thesis, hence it is not all-encompassing, but nevertheless it will serve to act as guideline for future development.

Before this addition to the model is implemented however, the remainder of this chapter deals with objective number 8, i.e. the development of a data-cleaning procedure which could be used to elicit suitable transition probabilities from infrastructure inspection databases as soon as sufficient information becomes available. The difficulties of obtaining this information and the development of a data-cleaning procedure itself have already been detailed in Section 6.2. However, this data extraction process will be further expanded in this next section to derive the Markov transition matrices from the database through the use of percentage prediction as outlined in Section 2.1.2. Initially, the matrices will be calibrated as though maintenance has not occurred, i.e. structures

which have shown an improvement in condition rating will be discarded. Likewise, the same process will then be carried out accounting for maintenance actions also in order to be able to make a direct comparison between the transition matrices obtained under both methods, and by extension the transition matrices calculated for this model in Chapter 5.

By developing the procedure to calibrate the Markov transition matrices directly from the raw data, the framework has been put in place to obtain the transition probabilities from the data itself as soon as sufficient information becomes available. Therefore, objective number 8 can be considered fulfilled.

6.3.5 Future Bridge Prediction – All Elements equally weighted.

In order to ascertain the effect of the elemental bridge weighting system, the analysis as carried out above was repeated with all elemental weights set at 0.2 as opposed to those listed in Equation 5.2. To enable a comparison to be made, the results have been superimposed upon those as depicted in Figure 6.15 and listed in Table 6.4. As can be seen the expected condition state rating with all elements weighted equally appears most similar to that obtained when all elements are weighted differently. For clarity the expected condition ratings now for years 1 to 20 are listed in Table 6.7. Comparing to Table 6.4 however it is clear that minimal difference exists. In order to ensure that equifinality (Beven, 2006) is not occurring due to the various combinations of probabilities and condition states combining to give the same answer, Table 6.8 charts the probability of being in any condition state for the first 10 years under both methods. From this it can be seen that, as expected the weighting system does lead to different probability distributions of condition state, albeit by a minimal amount – the un-weighted system is represented in italics. This however can be accounted for as a direct result of the rapid transitioning of condition states and the fact that many structural elements are missing age-groups and have very similar initial state vectors – as illustrated in Table 6.5. Hence for the example presented in this thesis, the importance of the elemental weighting system is not easily evident. However should different figures and initial state vectors be employed in another instance of the model, the difference is expected to become more apparent.

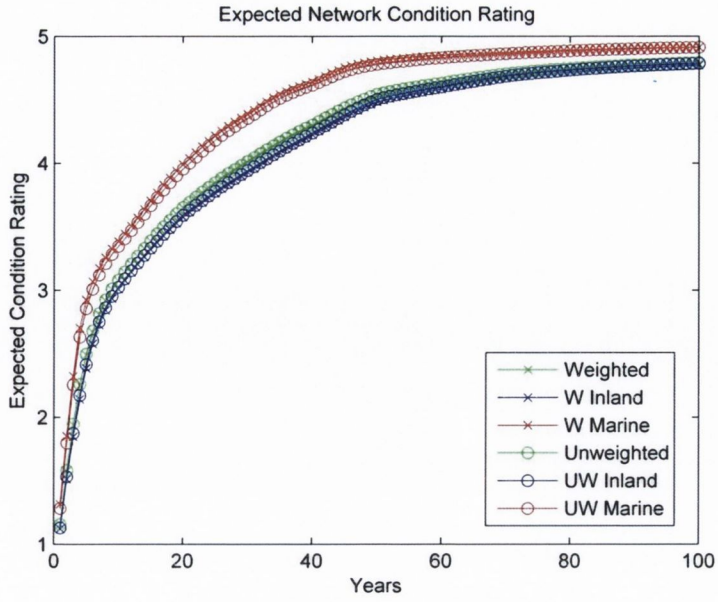

Figure 6.16: Expected condition state rating of RC bridges under model with all elements equally weighted.

Year #	E	Year #	E
1	1.16	11	3.14
2	1.58	12	3.21
3	1.95	13	3.27
4	2.26	14	3.33
5	2.50	15	3.39
6	2.68	16	3.44
7	2.82	17	3.50
8	2.92	18	3.55
9	3.00	19	3.60
10	3.08	20	3.65

Table 6.7: Expected condition rating for years 1:20, all bridge elements equally weighted.

Year	P_{00}	P_{11}	P_{22}	P_{33}	P_{44}	P_{55}
1	0.414	0.121	0.348	0.098	0.010	0.001
	(0.419)	*(0.116)*	*(0.354)*	*(0.095)*	*(0.010)*	*(0.001)*
2	0.405	0.064	0.129	0.329	0.059	0.006
	(0.409)	*(0.060)*	*(0.127)*	*(0.336)*	*(0.057)*	*(0.006)*
3	0.396	0.039	0.070	0.228	0.222	0.037

	(0.400)	*(0.036)*	*(0.067)*	*(0.231)*	*(0.256)*	*(0.036)*
4	0.387	0.027	0.042	0.164	0.212	0.155
	(0.391)	*(0.025)*	*(0.039)*	*(0.163)*	*(0.223)*	*(0.155)*
5	0.378	0.020	0.028	0.116	0.189	0.261
	(0.382)	*(0.019)*	*(0.026)*	*(0.113)*	*(0.191)*	*(0.265)*
6	0.370	0.016	0.020	0.082	0.155	0.349
	(0.272)	*(0.016)*	*(0.019)*	*(0.078)*	*(0.154)*	*(0.354)*
7	0.362	0.014	0.016	0.059	0.124	0.418
	(0.365)	*(0.014)*	*(0.016)*	*(0.056)*	*(0.122)*	*(0.423)*
8	0.354	0.013	0.014	0.044	0.098	0.470
	(0.357)	*(0.013)*	*(0.013)*	*(0.042)*	*(0.095)*	*(0.475)*
9	0.346	0.012	0012	0.034	0.078	0.511
	(0.349)	*(0.012)*	*(0.012)*	*(0.033)*	*(0.075)*	*(0.515)*
10	0.339	0.011	0.011	0.028	0.063	0.542
	(0.341)	*(0.011)*	*(0.011)*	*(0.027)*	*(0.061)*	*(0.545)*

Table 6.8: Expected probability distribution of condition states for years 1:10, all bridge elements equally weighted.

6.4 MATRICES AS OBTAINED DIRECTLY FROM DATABASE

Percentage prediction was used to obtain the Markov transition probabilities directly from the data. This method has been discussed previously in Section 2.1.2, but to reiterate, it is an approach which has been employed many times in the literature (Costello et al., 2011; Crespi et al., 2010; Morcous et al., 2003; Orcesi and Cremona, 2011) and essentially involves dividing the number of structures or elements transitioning from state *i* to state *j*, over the number of structures or elements in that state initially.

As stated earlier in Section 6.2 however, many difficulties were encountered due to the amount of unrecorded states for the structures. This is clear from the elemental transition matrices tabulated and described below as it can be seen that the transition probabilities had to be estimated on highly limited data in some cases. This would naturally give rise to highly subjective distributions of future condition state were these transition probabilities to be used in the model developed in this thesis.

Another problem when obtaining transition probabilities in this fashion is that in order for the probabilities to be robust, they should be estimated from state observation pairs spaced evenly apart, i.e. for example 2 years plus or minus an error period such as that used in Thompson &

Sobanjo (2010). Otherwise, as noted in Tsuda et al. (2005), the Markov transition probabilities will be inaccurate as they are highly dependent on the inspection interval. EIRSPAN unfortunately has not been in existence long enough, nor the structures inspected regularly enough for sufficient information to be obtained accurately from it. This is true for the majority of BMS internationally. The Irish situation is depicted in Figure 6.17 where it can be seen that the vast majority of structures have been inspected only every 6 years. In itself this has arisen because the rule of thumb is for structures to be inspected every 6 years minus the present condition rating of the structure (NRA, 2008) so for 'as new' structures, it is perfectly valid. Note that the bridges which have repeat inspections either that year or the next are as a result of either special inspections or maintenance operations on those bridges.

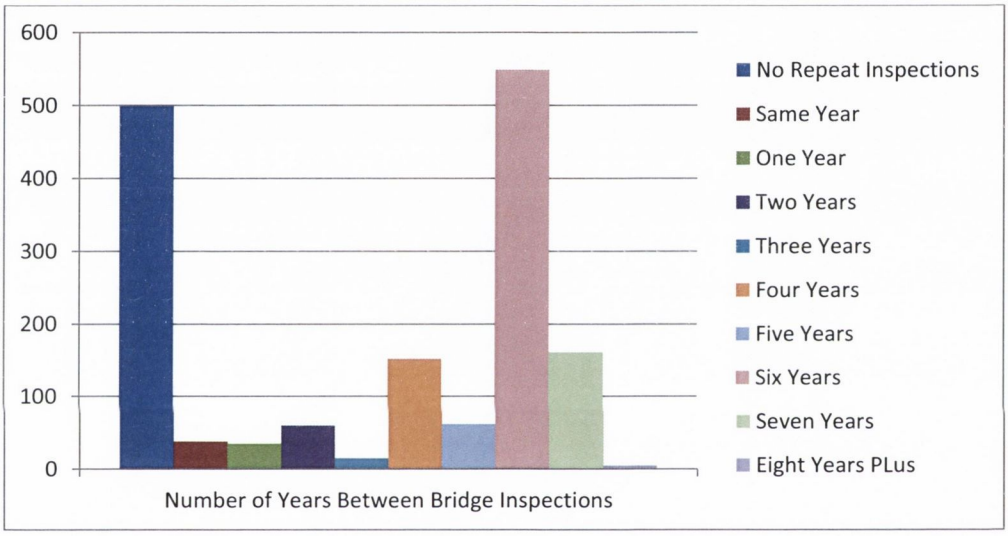

Figure 6.17: Graph depicting number of years between bridge inspections on RC stock.

In estimating transition probabilities directly though, it would be much more appropriate if the structures were all inspected at regular, evenly-spaced intervals. Note that common practice in the United States is to inspect every 2 years but for the purposes of developing deterioration models directly from historical data, it appears to make more sense to use 5 or 6 year windows, since in a 2-year transition sequence the probability of transitioning by more than one state is negligible, which results in there being a very small probability of structures being in higher states of deterioration after a duration of time. Were the structures to be observed over a longer period of time, the transition probabilities themselves would be much more directly usable. This problem was also mentioned by Thompson et al. (2010). In this paper they developed a procedure to deal with this whereby they compute the 2, 3 or 4 year transition probability from the bridge records, convert it back to a 1-year transition probability and then in turn, reconvert it to a 5-year transition probability. However, the procedure they employ is akin to that used in PONTIS the US system and described in Section 2.1.2 and as stated results in possible negative probabilities which have in

turn to be renormalized or considered which affects the accuracy of the obtained results. This was in fact one of the reasons which necessitated this research and the development of a procedure to find more appropriate transition probabilities.

Due to the lack of data surrounding structures that have both repeat inspections and a recorded state however, all state transitions between inspections shall be used for the purposes of determining the transition probability matrices below, regardless of the duration of inspection interval.

6.4.1 Element Matrices from EIRSPAN records allowing for Deterioration Only

In keeping with the elemental deterioration matrices as developed earlier in Chapter 5 of this thesis, the matrices developed below are for the bridge wing, bridge deck, bridge beam, bridge abutment and bridge pier respectively. All records were utilised and since the data was limited as mentioned previously and as shown by the lack of repeat inspections listed in Table 6.9, structures were not segregated into marine and inland environments as was done for the matrices developed from the analytical models in Chapter 5.

Element	# No Repeat Inspection	# Two Inspections	# Three Inspections	# Four Inspections
Wing	645	890	107	9
Abutment	645	890	107	9
Pier	645	890	107	9
Deck	645	890	107	9
Beam	645	890	107	9

Table 6.9: Investigation of Number of Inspections on Bridge Elements.

In order to calibrate these matrices, the number of observed pairs of bridge inspection condition ratings on each bridge was obtained from EIRSPAN. The observations containing NaN's or invalid condition states were then discounted. These were then segregated according to whether or not maintaining actions were to be allowed or not. This information is as depicted in Table 6.10 and it can be seen that for the bridge beam and bridge pier in particular, the number of transition pairs available from which to infer information was quite limited.

The matrices were calibrated by simply dividing the number of state transitions by the number of transitions in that row and are as depicted in Figure 6.18. Note that this corresponds to the percentage prediction method as outlined in Section 2.2.2.

Element	# Observed Pairs	# Invalid Condition States	# Valid Transition Pairs	# Deterioration Only	# Maintenance allowed
Wing	1131	206	925	764	161
Abutment	1131	198	933	776	157
Pier	1131	738	393	340	53
Deck	1131	222	909	745	164
Beam	1131	924	207	179	28

Table 6.10: Investigation of EIRSPAN condition rating database.

P_{00}	P_{11}	P_{22}	P_{33}	P_{44}	P_{55}
0.704	0.252	0.035	0.004	0.005	0
0	0.89	0.099	0.011	0	0
0	0	1	0	0	0
0	0	0	1	0	0
0	0	0	0	0	0
0	0	0	0	0	0

(i) Wing

P_{00}	P_{11}	P_{22}	P_{33}	P_{44}	P_{55}
0.702	0.254	0.039	0.005	0	0
0	0.91	0.082	0	0.008	0
0	0	0.96	0.04	0	0
0	0	0	1	0	0
0	0	0	0	0	0
0	0	0	0	0	0

(ii) Pier

P_{00}	P_{11}	P_{22}	P_{33}	P_{44}	P_{55}
0.635	0.333	0.03	0.002	0	0
0	0.933	0.06	0.007	0	0
0	0	0.958	0.042	0	0
0	0	0	1	0	0
0	0	0	0	0	0
0	0	0	0	0	0

(iii) Abutment

P_{00}	P_{11}	P_{22}	P_{33}	P_{44}	P_{55}
0.722	0.206	0.067	0.005	0	0
0	0.853	0.128	0.019	0	0
0	0	0.901	0.088	0.011	0
0	0	0	0.75	0.25	0
0	0	0	0	1	0
0	0	0	0	0	0

(iv) Deck

P_{00}	P_{11}	P_{22}	P_{33}	P_{44}	P_{55}
0.765	0.127	0.098	0.01	0	0
0	0.837	0.116	0.046	0	0
0	0	0.846	0.154	0	0
0	0	0	1	0	0
0	0	0	0	1	0
0	0	0	0	0	0

(v) Beam

Figure 6.18: Elemental level transition probability matrices from EIRSPAN allowing for deterioration only.

Note that unlike the transition matrices calibrated earlier in Chapter 5, these are independent of time and do not account for either age effects or specific effects. Hence they are rather simplistic and the results cannot be expected to be all-encompassing as many possible state transitions are

missing due to a lack of observations in the relatively new Irish database. In an attempt to compare both methods however, they shall be applied to relevant elemental initial state vectors and the expected condition rating over the same 100-year period computed. These p_0 initial state vectors are different to those employed in Section 6.3 as again age is not considered. For completeness they are instead as listed in Table 6.11. Like earlier in Section 6.3, the expected condition rating is derived from the individual elemental deterioration curves of the bridge elements and aggregated using Equation 5.2. This life-cycle curve is then presented below in Figure 6.19 in graphic format.

	0	**1**	**2**	**3**	**4**	**5**
Wing	0.6	0.326	0.068	0.004	0.002	0
Abutment	0.534	0.393	0.067	0.006	0	0
Pier	0.635	0.30	0.056	0.008	0.01	0
Deck	0.565	0.30	0.123	0.011	0.001	0
Beam	0.658	0.209	0.089	0.041	0.003	0

Table 6.11: Initial elemental condition state vectors as considered independent of age.

It is clear though that the yellow curve in Figure 6.19 as obtained from the EIRSPAN 'deterioration only' matrices presents a very different figure to the total deterioration curve illustrated in Figure 6.15 and represented below for clarity. The curves in Figure 6.15 depict a much greater state of degradation after the 100-year period, with an average network condition rating approaching 5, the worst state. On the other hand it can be seen here that using the matrices as calibrated directly from EIRSPAN gives a limiting network value of 3. This results as a direct consequence of there being no recorded information beyond state 3 for the pier, wing, abutment or beam. Therefore, as it stands, these matrices are unusable. This problem meanwhile is not uniquely an Irish one and in a recent study by Thompson (2012) it was found that when investigating the PONTIS database, fewer than half of the elements produced usable models when all elements were modeled separately. The rest simply were too uncommon to present a clear progression of deterioration through all possible states.

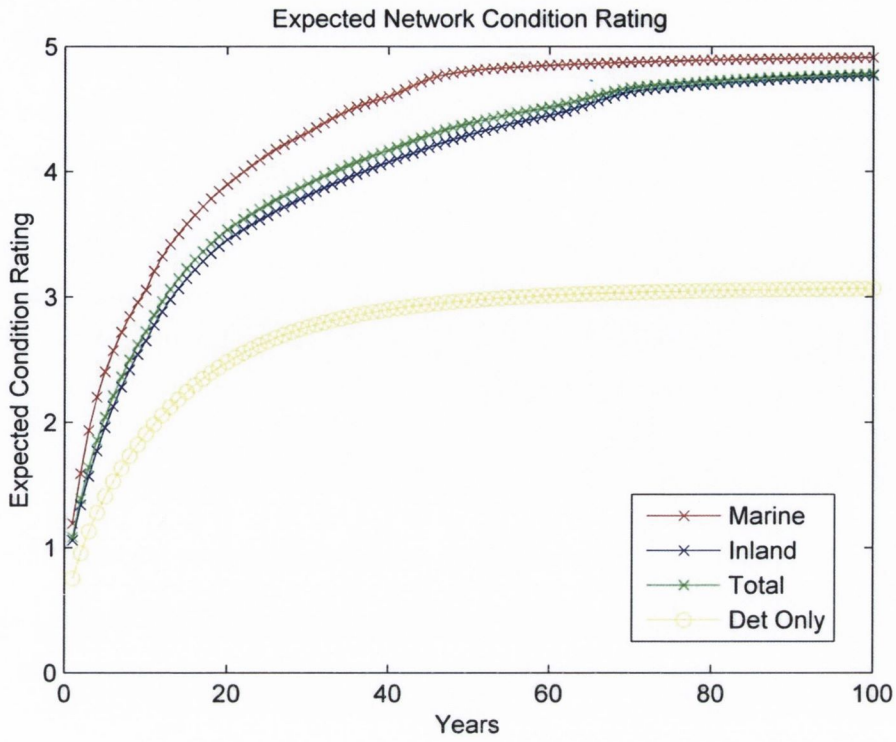

Figure 6.19: Expected condition rating of RC bridge using EIRSPAN deterioration only transition matrices.

Clearly a true comparison between the matrices developed from analytical deterioration models of chloride-induced corrosion, and the deterioration only matrices from inspection is not feasible currently. Nonetheless, the procedure has been put in place and the framework implemented for the transition probabilities to be derived in such a manner if and when sufficient information becomes available. Note that the Canadian systems have also been developed in this manner, i.e. they already have in-built Bayesian updating procedures which will directly update the deterioration models and transition probabilities on the basis of repeat inspections (Evans and Ellis, 2012).

So far this thesis has dealt solely with deterioration. In an attempt to quantify the effects maintenance and rehabilitation works have had on the Irish bridge network however, the next section will illustrate the transition matrices as derived from EIRSPAN if improvements in condition state, i.e. maintenance actions are considered. These then will be used to present a graph similar to Figure 6.19 but will demonstrate the effect maintenance has on network condition and the need to research and investigate it thoroughly.

6.4.2 Element Matrices from EIRSPAN Records allowing for Maintenance

The matrices presented below in Figure 6.20 have been derived in exactly the same fashion as those in Figure 6.18 except that improvements in condition state have now been taken into account. Like the deterioration only matrices in Figure 6.18, it can be seen that there are numerous empty rows and columns, thereby limiting the applicability of these matrices. Furthermore it can be seen that the proportion of structures being repaired from a 2 or a 1 to a 0 is relatively constant at 0.15 to 0.2 for all elements bar the bridge wing which has a lower probability of being maintained from a 1 to a 1 than the other elements but a higher probability of being maintained from a 2 to a 0 than the other elements. In general, from inspecting the matrices below, it appears that the different bridge elements are all maintained at a relatively similar rate, i.e. equal importance is placed on each element concerning the timing of repairs.

P_{00}	P_{11}	P_{22}	P_{33}	P_{44}	P_{55}
0.704	0.252	0.035	0.004	0.005	0
0.108	0.794	0.088	0.01	0	0
0.254	0.373	0.373	0	0	0
0	0.5	0.25	0.25	0	0
0	0	0.5	0.5	0	0
0	0	0	0	0	0

(i) Wing

P_{00}	P_{11}	P_{22}	P_{33}	P_{44}	P_{55}
0.703	0.254	0.039	0.004	0	0
0.223	0.707	0.064	0	0.006	0
0.216	0.384	0.384	0.016	0	0
0	0.167	0.583	0.25	0	0
0.5	0.5	0	0	0	0
1	0	0	0	0	0

(ii) Pier

P_{00}	P_{11}	P_{22}	P_{33}	P_{44}	P_{55}
0.635	0.333	0.03	0.002	0	0
0.141	0.801	0.051	0.006	0	0
0.14	0.444	0.398	0.017	0	0
0.1	0.2	0.6	0.1	0	0
0.333	0	0.333	0.333	0	0
0	0	0	0	0	0

(i) Abutment

P_{00}	P_{11}	P_{22}	P_{33}	P_{44}	P_{55}
0.722	0.206	0.067	0.005	0	0
0.183	0.697	0.105	0.015	0	0
0.131	0.349	0.469	0.045	0.006	0
0.414	0.138	0.31	0.103	0.034	0
0.143	0.286	0.286	0.143	0.143	0
0	0	0	0	0	0

(ii) Deck

P_{00}	P_{11}	P_{22}	P_{33}	P_{44}	P_{55}
0.765	0.127	0.098	0.01	0	0
0.14	0.72	0.1	0.04	0	0
0.139	0.256	0.512	0.093	0	0
0	0	0.364	0.636	0	0
0	0	0	0	1	0
0	0	0	0	0	0

(v) Beam

Figure 6.20: Elemental level transition probability matrices from EIRSPAN allowing for maintenance.

Figure 6.21 presents the expected network condition rating over the 100-year return period if the matrices incorporating maintenance effects are used. Again the results from Figure 6.15, i.e. those obtained using the deterioration model outlined in this thesis are also included for comparison purposes. Since the average condition rating is now much lower, for clarity the lifecycle curve obtained using the transition matrices as derived from EIRSPAN alone will be presented separately in Figure 6.22. In marked contrast to Figure 6.19, the limiting value is clearly much lower than that obtained using deterioration only matrices. Furthermore, it reaches this limiting value after approximately 10 years. However, matrices which take account of maintenance actions cannot be used directly to predict future state or plan for future budgetary needs as it is not evident precisely what kind of actions are being undertaken at what time. Therefore all that really can be concluded from Figure 6.21 is that should the NRA continue to maintain their bridge stock in a similar fashion to that conducted so far, the bridge stock would be expected to remain relatively stable over the specified period.

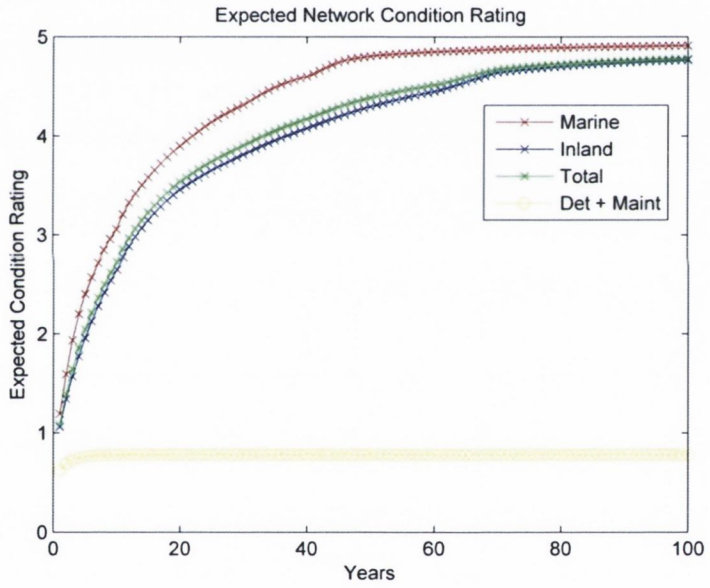

Figure 6.21: Expected condition rating of RC bridge using EIRSPAN transition matrices allowing for both deterioration and maintenance.

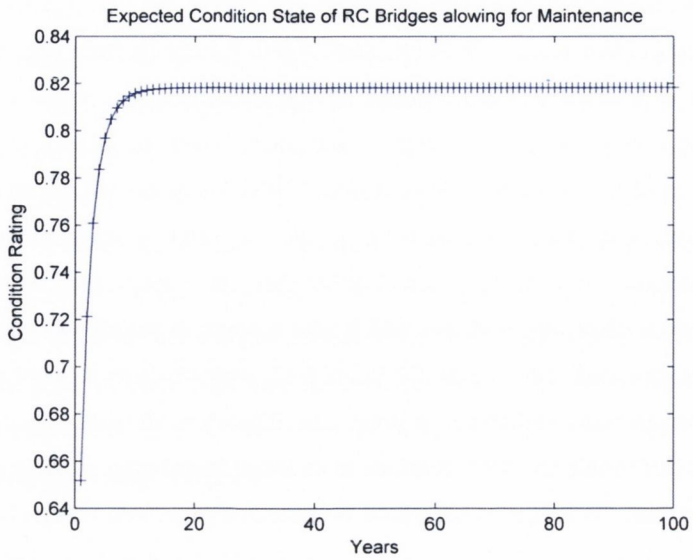

Figure 6.22: Expected condition rating of RC bridge using EIRSPAN transition matrices accounting for maintenance actions also.

As stated previously, the main aim of this thesis was not to conduct an in depth analysis of maintenance and repair actions, but rather instead, for robustness of the developed methodology to consider the implication of its effect on a network of structures. Figure 6.22 briefly illustrates the effect of it, i.e. the bridges do not deteriorate as rapidly or much but naturally this also has budgetary implications. Hence the next section will consider briefly the effects of alternative repair strategies in terms of both relative cost and overall bridge network rating.

6.5 INCORPORATION OF MAINTENANCE EFFECTS

As stated in Section 2.1 the three idealised requirements of a BMS are (i) data storage, (ii) the prediction of the future state of structures and (iii) the prioritisation of maintenance and repair. Up until this point, this thesis has dealt solely with fulfilling requirement (ii) i.e. that of assuring the accurate prediction of the future state of structures. Part (iii) then involves the incorporation of maintenance and rehabilitation actions into the structure lifecycle. However, as stated at the very outset, maintenance effects as a whole are not the primary focus of this thesis, as in itself this is a vast area. Instead, this section merely serves to highlight and give a brief introduction to the importance of maintenance and the consequences of applying different rehabilitation policies at different times. As stated in Section 2.5, the objective therefore is to consider the effects of maintenance and repair on equilibrium network condition rating, taking into account different maintenance policies, imperfect repairs and alternative costs.

To do this a framework for incorporating maintenance effects has been developed whereby different repair strategies and options will be looked into, i.e. that of repair only, rehabilitation only, or a combination of the two. To act as a basis and means for comparison, relative costs will be employed. These are subjective. However, the purpose is purely to demonstrate the importance and effect of alternative, potential maintenance strategies, as the development of more accurate costing models which would incorporate such factors as user delay costs and penalty costs for reduced service is something which needs to be looked into in further work. The effect however of various percentage repair and percentage repair effectiveness will be looked into.

6.5.1 Maintenance Implementation

As in Lounis (2006) and Orcesi and Cremona (2006), maintenance actions are implemented as a set of possible actions that could feasibly occur if an element is in a particular state. Hence they are different for each bridge type and each bridge element. Furthermore, this means that certain transitions are not accounted for on the basis that they correspond to maintenance actions rarely, if ever implemented by authorities (Orcesi and Cremona, 2006).

For the purposes of demonstrating the method developed in this thesis these rehabilitation actions therefore will be considered below for the example of an inland bridge deck over a 50-year period which deteriorates in time according to the non – homogeneous Markov transition matrices listed in Table 5.20. This 50-year period was chosen as it was deemed to be a sufficient amount of time over which to illustrate the effects of maintenance actions on a network of bridges or bridge elements. As a means of including the uncertainty of maintenance being carried out then, a probability of repair is also incorporated into these transition matrices for different, viable state transitions. Additionally, the idea of imperfect repair is allowed for in the methodology by including a percentage efficiency of repair into the model, i.e. not all elements are assumed to transition to the state intended at the outset of repair. These probabilities have been calibrated by an 'expert judgment' process which takes the likelihood and severity of the transition in question into account.

The process was implemented by incorporating the probability of the maintenance action into the deterioration only transition matrix. The possible preservation actions are outlined and a probability for each repair action, together with a repair efficiency percentage specified for each element. Having accounted for the probability of maintenance and repair, the structure is expected to continue to deteriorate otherwise, hence the probability of deterioration in this aggregated 'Maintenance Matrix' is split according to the initial expectations when maintenance was not considered. For clarity, this method is illustrated in Figure 6.23. For instance, prior to maintenance being performed, there was a 90% chance of a structure remaining in state 2 after the time period in question if it had started in state 2, and a 10% chance of it deteriorating further to state 3. A possible maintenance action has been defined as having a 65% probability of the structure being

maintained to state 0 from state 2, with 92% efficiency. Consequently, there is now a 35% probability of deterioration. This 35% is then split according to the original 9:1 ratio (90% chance of remaining in state 2, 10% chance of deteriorating further), thereby giving a probability of 31.5% of the structure remaining in state 2 after the time period, and a probability of 3.65% of it deteriorating further to state 3.

Deterioration Only Matrix						Possible Maintenance Actions
0.72	0.28	0	0	0	0	
0	0.85	0.15	0	0	0	
0	0	0.9	0.1	0	0	P_{20}. 65% Efficiency - 92%
0	0	0	0.75	0.25	0	P_{30}. 65% Efficiency - 92%
0	0	0	0	0.8	0.2	P_{40}. 90% Efficiency - 94%
0	0	0	0	0	1	P_{50}. 95% Efficiency - 95%
Incorporating Maintenance Effects						**Comments**
0.72	0.28	0	0	0	0	Deterioration Only
0	0.85	0.15	0	0	0	Deterioration Only
0.6	0.05	0.315	0.036	0.	0	35% Probability of Det.
0.6	0.05	0	0.26	0.09	0	35% Probability of Det.
0.85	0.05	0	0	0.08	0.02	10% Probability of Det.
0.9	0.05	0	0	0	0.05	5% Probability of Det.

Figure 6.23: Illustration of maintenance incorporation into Markov transition matrices.

Note that the necessity of incorporating maintenance into infrastructural management systems is exactly what validates the argument for using Markov chains as opposed to directly using deterioration models only. This has also been stated in Roelfstra et al. (2004) when they claim that the strength of Markov chains is with the optimization of possible preservation actions. Optimization of such preservation actions is beyond the scope of this thesis but nevertheless, the model basis is seen to allow for the incorporation of optimization. Moreover, since this method of incorporating maintenance is done at elemental level, the deterioration pattern of individual structures can also be looked into in more detail. Hence it can also be considered project-level management as opposed to network-level management. This ensures that the developed model is state-of-the art.

The next section outlines now the results of applying different maintenance policies at different points in time to the network of bridges in question.

6.5.2 Results of Different Policies

A method of incorporating maintenance effects into a transition probability matrix has been outlined in Figure 6.23 and on the basis of this, four different maintenance policies have been identified for analysis in this thesis. The first two involve a combination of both repair and rehabilitation or replacement actions at varying probabilities and efficiency percentages of repair. The latter two then consider the effect of purely repairing or replacing the bridge deck or element in question only. Figure 6.24 outlines these policies respectively.

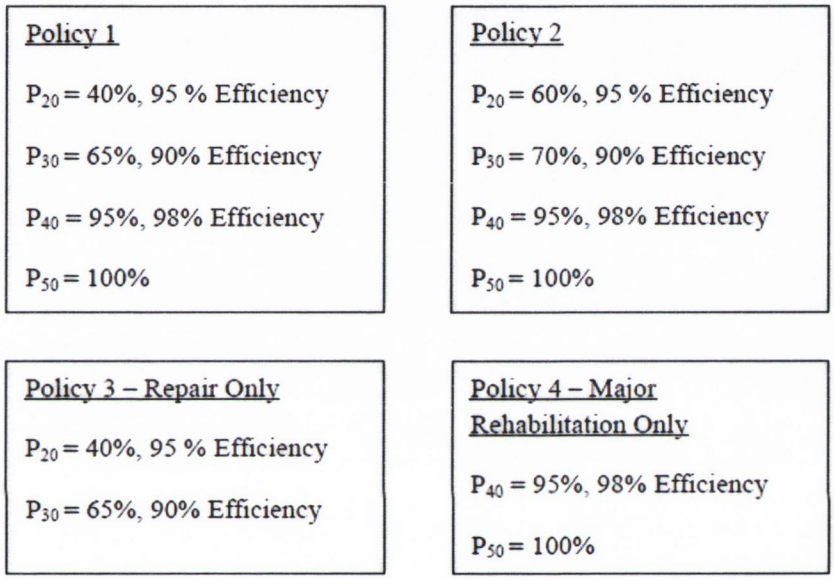

Figure 6.24: Maintenance policies under investigation

Note that for the policies outlined above and therefore for the remainder of the discussion in this chapter, repair refers to the more routine repairs as signified by a repair from a condition state 2 or 3, while a major rehabilitation action refers to a more serious repair from a 4 or 5.

Different time intervals are also considered in this section, i.e. the effect of applying the maintenance policies at varying regular intervals. It is expected that the most appropriate maintenance interval will be the longer duration interval of every 10 years in agreement with Thompson (2012) who states that '' *while deterioration actions can occur every year, preservation actions occur infrequently, often at intervals of 10-30 years*''. For completeness, intervals of (i) every year, (ii) every 5 years and (iii) every 10 years will be considered. The results of applying the policies as outlined in Figure 7.2 thus at these varying intervals are as illustrated in Figure 6.25 to Figure 6.28 below. Costs have not been included in this section as the aim is to differentiate solely between different policies. Nominal costs will however be included in the next section in order to gauge a balance between infrastructural condition state and budget requirements.

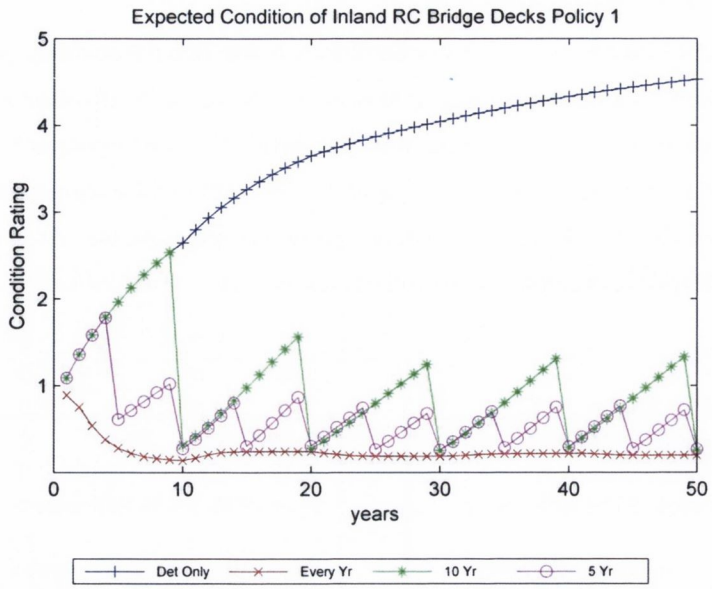

Figure 6.25: Expected condition of 'inland' RC bridge deck under maintenance policy 1.

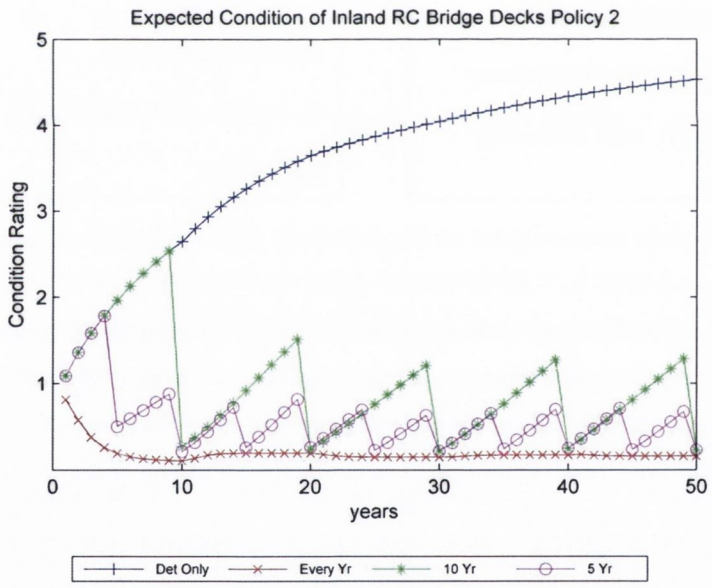

Figure 6.26: Expected condition of 'inland' RC Bridge deck under maintenance policy 2.

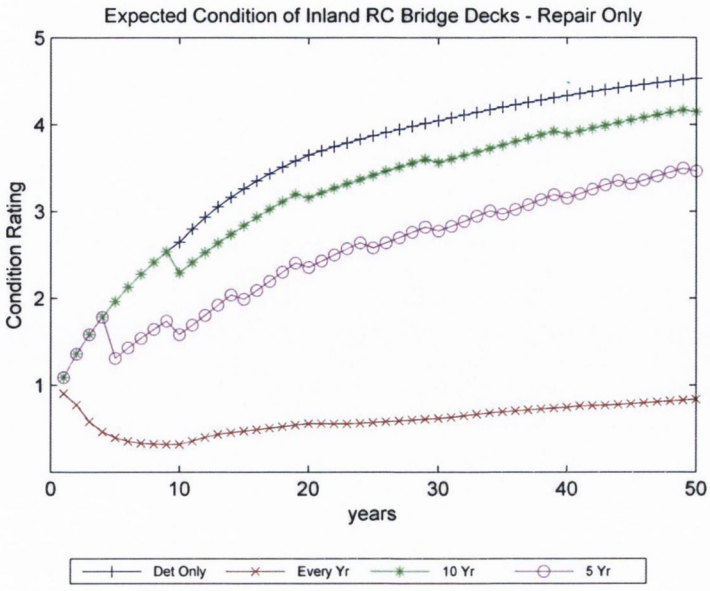

Figure 6.27: Expected condition of 'inland' RC bridge deck under maintenance policy 3.

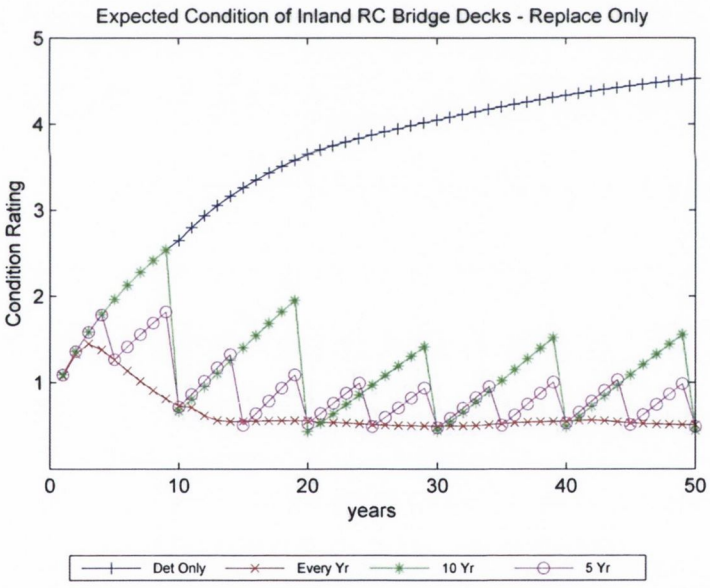

Figure 6.28: Expected condition of 'inland' RC bridge deck under maintenance policy 4.

Figure 6.25 to Figure 6.28 above illustrate the expected condition rating of inland bridge deck elements over a 50 year period. For each policy the maintenance has been carried out at three different time intervals of 1 year, 5 years and 10 years respectively. In each instance, the blue line (marked with a cross) corresponds to deterioration only, i.e. it simulates the expected performance of the structural element in the absence of any maintaining actions. Note that this 'deterioration only' matrix has been calibrated already in this thesis and is outlined in Chapter 4. The red line

(marked with an x) then corresponds to maintenance carried out every year, the magenta line (marked with a circle) to maintenance at 5 year intervals and the green line (marked with an asterisk) to 10 year intervals. It can be seen that policies 1 and 2 in Figure 6.25 and Figure 6.26 appear to give quite similar graphs, thereby indicating that the probability of repair percentage may not necessarily be that important when the percentage efficiency of repair is the same or similar. A further comparison will therefore be made between these policies directly on the same graph in order to ascertain if there is a difference. Histograms of expected distribution state at an arbitrary year will also be depicted later on in this section to further illustrate the differences in expected condition rating of structures between policies. Ultimately though, relative costs will need to be incorporated to make a legitimate assessment. Concerning the 'repair only' policy illustrated in Figure 6.27, it is evident that the structures are all deteriorating, albeit at different rates depending on the maintenance interval. Lastly, the 'major rehabilitation only' policy in Figure 6.28 shows the stock overall remaining in a much better average condition state as expected than if a 'repair only' policy is implemented. As an aside, it is interesting to note that were the maintenance actions carried out every year, a 'repair only' policy would actually be sufficient to achieve a stable, well-maintained bridge stock. However this would naturally incur a greater monetary cost, hence it will be looked into in the next section.

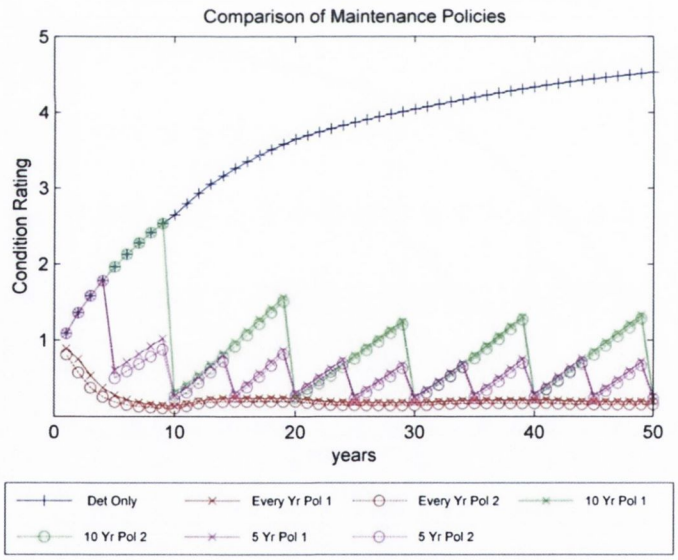

Figure 6.29: Comparison of maintenance policies 1 and 2.

From Figure 6.29 it appears that although policies 1 and 2 are very similar, there is a slight difference with the second maintenance policy giving an average lower expected condition state rating as expected since it maintains to a higher probability, i.e. P_{20} is now 60 % as opposed to 40% and P_{30} is now 70% instead of 65%. For further comparison of the policies as listed in Figure 6.24 however, Figure 6.30 to Figure 6.32 below graph the expected condition rating of each policy under their respective policy application times, i.e. every year, every 5 years and every 10 years.

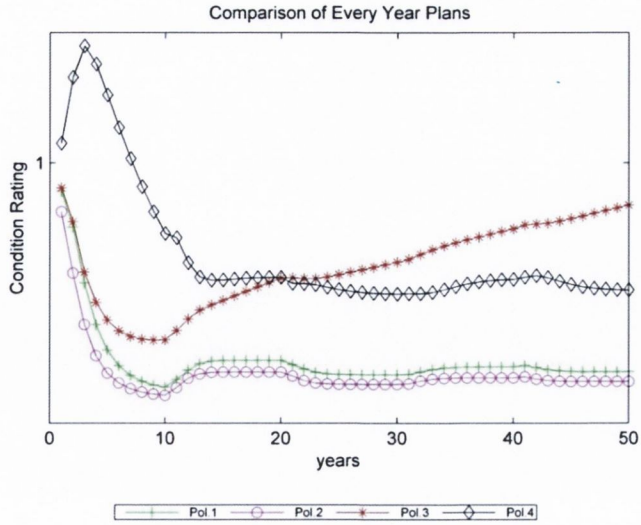

Figure 6.30: Comparison of maintenance polices as implemented every year.

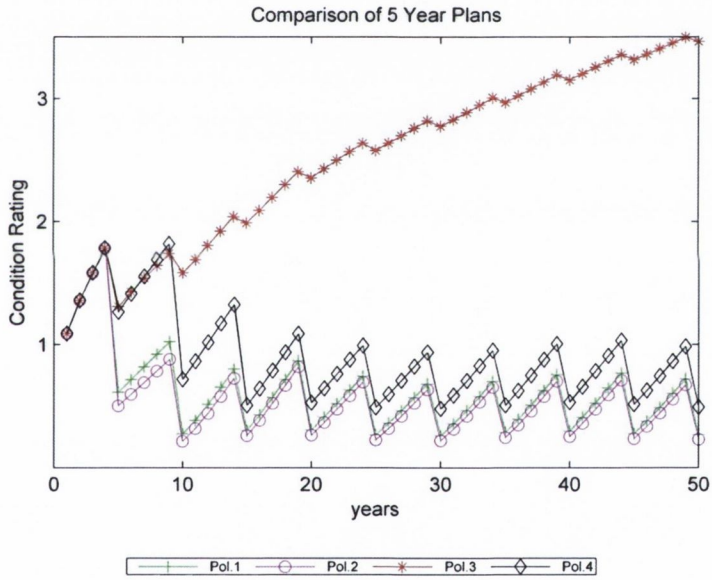

Figure 6.31: Comparison of maintenance polices as implemented at 5-year intervals.

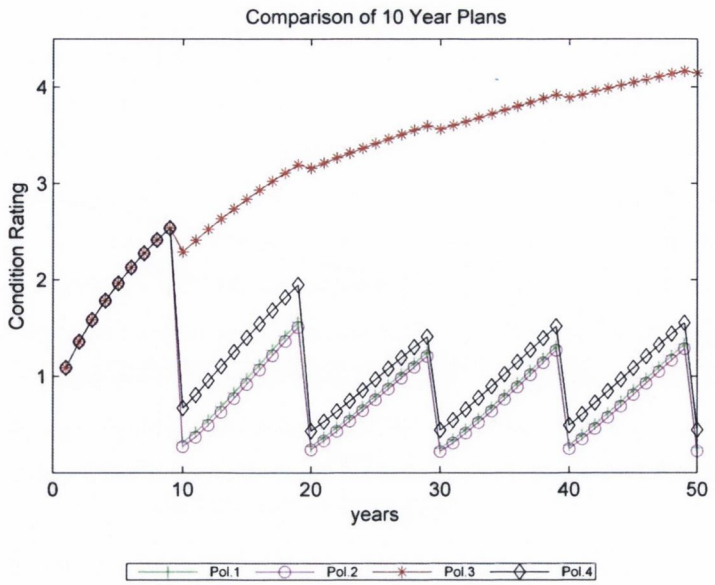

Figure 6.32: Comparison of maintenance polices as implemented at 10-year intervals.

It can be seen above that policy 2 does indeed give a lower expected condition rating than policy 1 regardless of inspection interval. Again this is as expected since the structures are repaired to a higher probability, albeit with the same percentage efficiency. Furthermore, as expected also, Policy 3, i.e. that of repair only gives the worst condition rating for maintenance as implemented at 5 and 10 year intervals, but interestingly, the policy of major rehabilitation only gives a much higher condition rating for the first 10 years or so if maintenance is implemented every year. Again though, upon investigating, this is as expected since the rehabilitation policy only occurs when a structure reaches a condition state 4 or 5, which is very unlikely to happen for the first few years. As structures age and degenerate however, it can be seen from Figure 6.30 that the rehabilitation policy, i.e. that of replacement gives a lower overall condition rating again than policy 3, that of repair only (from lower condition states). As expected also, the combination of both repair and rehabilitation actions, i.e. policies 1 and 2 give a lower expected condition rating than either policy 3 or policy 4 which take just repair and rehabilitation respectively into account.

These expected condition ratings will need to be weighed against the cost of either policy relative to the other in the next section in order to ascertain the more appropriate policy.

The histograms depicted in Figure 6.33 to Figure 6.36 below represent the above information again in a different manner. This time, an arbitrary year – year 21, has been selected and the expected condition state distribution has been depicted. Note that Figures 6.25 to 6.28 earlier have graphed the expected condition rating for the 50 year period earlier, hence it can be seen that the general deterioration pattern between policies is the same regardless of the year chosen. Thus, these

histograms enable another depiction of the difference between policies. Tables 6.12 to Table 6.15 merely serve to quantify the percentages in each condition state respectively.

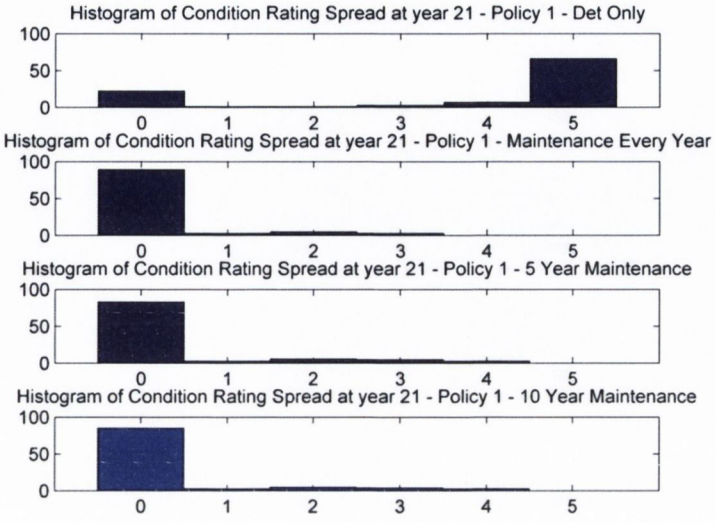

Figure 6.33: Histogram of expected condition rating spread under policy 1 with varying time intervals.

%	0	1	2	3	4	5
Det. only	22	1	1	3	7	66
Every year	89	3	5	3	0	0
Every 5 years	83	3	6	5	3	0
Every 10 years	85	3	5	4	3	0

Table 6.12: Expected condition rating distribution at year 21 under policy 1.

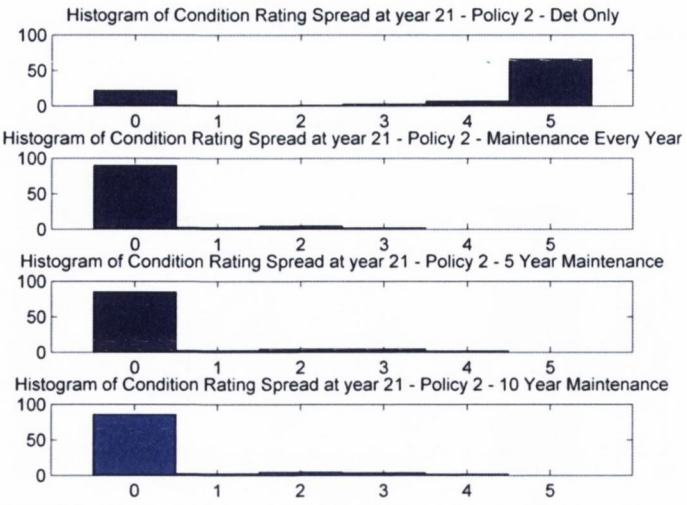

Figure 6.34: Histogram of expected condition rating spread under policy 2 with varying time intervals.

%	0	1	2	3	4	5
Det. only	22	1	1	3	7	66
Every year	90	3	5	2	0	0
Every 5 years	85	3	5	5	2	0
Every 10 years	86	3	5	4	2	0

Table 6.13: Expected condition rating distribution at year 21 under policy 2.

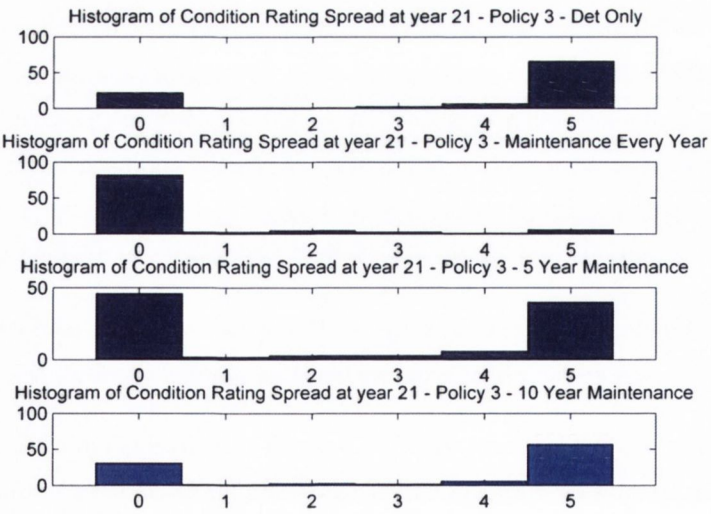

Figure 6.35: Histogram of expected condition rating spread under policy 3 with varying time intervals.

%	0	1	2	3	4	5
Det. only	22	1	1	3	7	66
Every year	82	3	5	3	1	6
Every 5 years	46	2	3	3	6	40
Every 10 years	31	1	3	2	6	57

Table 6.14: Expected condition rating distribution at year 21 under policy 3.

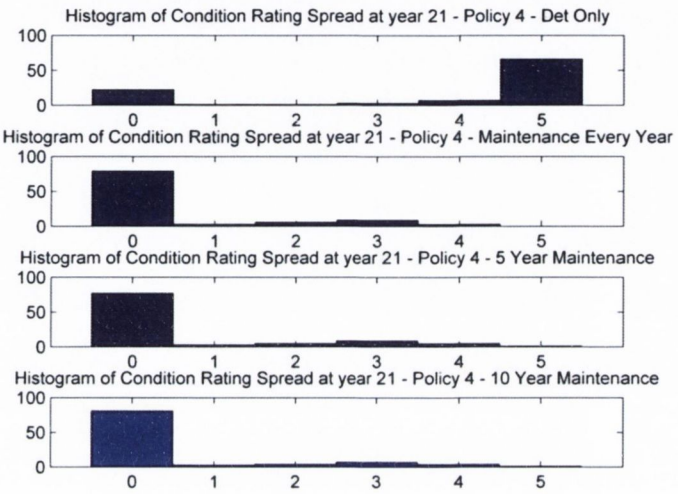

Figure 6.36: Histogram of expected condition rating spread under policy 4 with varying time intervals.

%	0	1	2	3	4	5
Det. only	22	1	1	3	7	66
Every year	79	3	6	9	3	0
Every 5 years	77	3	5	9	5	1
Every 10 years	81	3	4	7	4	1

Table 6.15: Expected condition rating distribution at year 21 under policy 4.

As expected from Figure 6.29, policy 2 appears to give a slightly better expected condition rating at year 21 when Table 6.12 is compared to Table 6.13. Again though, as stated earlier, costs need to be implemented before it can be ascertained whether or not it is in fact a better maintenance alternative than Policy 1 – if for instance the cost of policy 2 was much more expensive than policy 1 due to the higher probability of maintenance being performed, the management authorities in question may deem it more beneficial overall to implement policy 1. Also, as mentioned earlier it is again clear from looking at Table 6.14 and Table 6.15 that Policy 4, i.e. that of major rehabilitation gives a much better expected condition state distribution than Policy 3, that of repair only – at 5-

year maintenance intervals, it can be expected that 77% of the bridge stock will be in condition state 0 under policy 4 versus 46% under policy 3.

Overall however, while suggestions can be inferred on the basis of the above comparison of policies, relative costs need to be incorporated in order to make a more complete proposition of future bridge or elements condition state as a result of varying maintenance management strategies as for example, major rehabilitation, while effective in terms of improvement in overall condition state, is extremely costly. Hence, this next section shall attempt to incorporate this.

6.5.3 Results of Different Policies allowing for Nominal Costs

So far the various maintenance alternatives have been evaluated purely on the basis of expected condition rating. It is evident however that another dimension to the problem exists i.e. that of limited budgets for such repairs. To deal with this the idea of relative costs have been assigned to the potential repairs as was also applied in Orcesi and Cremona (2006). These are as laid out in Table 6.16 and again, an alternative for each maintenance transition has been listed to briefly compare the effect the relative cost has on the overall expected cost. Note too that transitions such as state 2 to state 1 and state 3 to state 1 and so forth are also possible since imperfect repair has been considered, the relative cost of these transitions shall be deemed to be the same as the perfect repair, since essentially it is not considered to be as a result of a different type of repair, rather instead the result of an imperfect maintenance action.

	Relative Cost
Policy 1	
2 - 0	0.1
3 - 0	0.3
4 - 0	0.65
5 - 0	1
Policy 2	
2 - 0	0.2
3 - 0	0.45
4 - 0	0.8
5 - 0	1

Table 6.16: Relative costs of various maintenance alternatives.

Addition of Relative Costs to Maintenance Alternatives

In order to introduce the idea of relative cost to the problem, a matrix was set up to represent and store the arbitrary values defined in Table 6.16. This then was multiplied by the maintenance transition probability matrix such as that depicted in Table 6.12 to obtain a probability cost matrix for each maintenance action. The expected distribution of condition state after time t was then multiplied by this probability cost matrix and computed on a yearly basis for all structure age-groups. When weighted by the number of structures in each age-bracket as outlined in Section 6.2 to avoid skewing of the results by different numbers of structures in n different age-brackets, the total cost can then be obtained by aggregating the total cost over the simulated 50-year period for each age-bracket. This is represented in Equation 6.2 below where T = the relative cost matrix, M = maintenance transition probability matrix, C = the probability cost matrix and $P(t)_n$ is the expected distribution of condition state at year t of age-group n.

$$\sum_{t=1}^{50}\sum_{n=1}^{13}[P(t)_n][C] \quad where \quad [C]=[T][M] \qquad \textbf{Equation 6.2}$$

The total relative costs then for each maintenance policy as listed in Table 6.13 under both relative cost scenarios in Table 6.16, for each inspection year, are depicted in Figure 6.37 to Figure 6.44 below. Note again that these costs are purely arbitrary and serve just a relative purpose for basic comparison of policies. They do not include such things as set-up costs, traffic delay costs, user delay costs etc. However, a penalty function will be introduced later to give an indication of their effect.

Concerning Figures 6.37 and 6.38 it can be seen that the general deterioration pattern each year is very similar as expected. Furthermore, after 2 to 3 years in the case of repairing at 5 year or 10 year intervals, the deck condition level quickly reaches a limiting value and stays relatively stationary around that value for the remainder of the time period under investigation. Conversely, Figures 6.39 and 6.40 show that repair policies 3 and 4 are not as stable, especially with increased time.

For relative cost scenario 2 then Figures 6.41 and 6.42 are again, as expected, very similar, both to each other and also to relative cost scenario 2. Likewise Figures 6.43 and 6.44 are very similar to Figures 6.39 and 6.40 respectively, albeit the relative maintenance cost has increased.

Overall, it is clear that in terms of expected network condition rating they are biased towards maintaining the bridge stock more often. As expected also, the cost of maintaining per inspection is less since the inspections are carried out on a more frequent basis, therefore ensuring a better maintained bridge stock requiring less maintenance. However, instead of year of inspection costs, it

is the total costs over the 50-year period which needs to be weighed against the overall expected network rating in an effort to rank the most appropriate solution. This shall be illustrated below in Figure 6.45 and Figure 6.46 for both cost scenarios and all four polices. However Figure 6.37 to Figure 6.44 have been included in this thesis in order to demonstrate that the relationship between expected overall condition rating and relative cost is non-linear and that the information from the combined graphs cannot be extrapolated out to infer conjectures. For clarity, Table 6.17 in the next section lists the information shown in Figure 6.45 and Figure 6.46.

Relative Cost Scenario 1

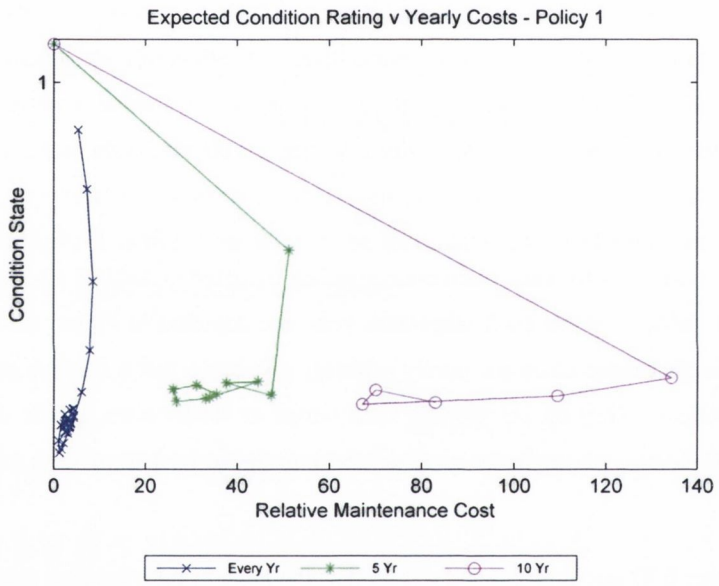

Figure 6.37: Expected overall condition rating v. total relative maintenance cost for policy 1under cost scenario 1.

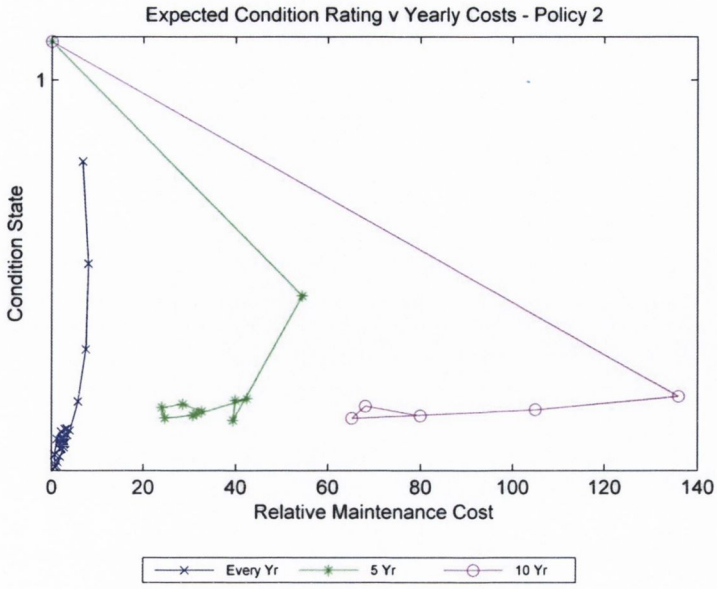

Figure 6.4: Expected overall condition rating v. total relative maintenance cost for policy 2 under cost scenario 1.

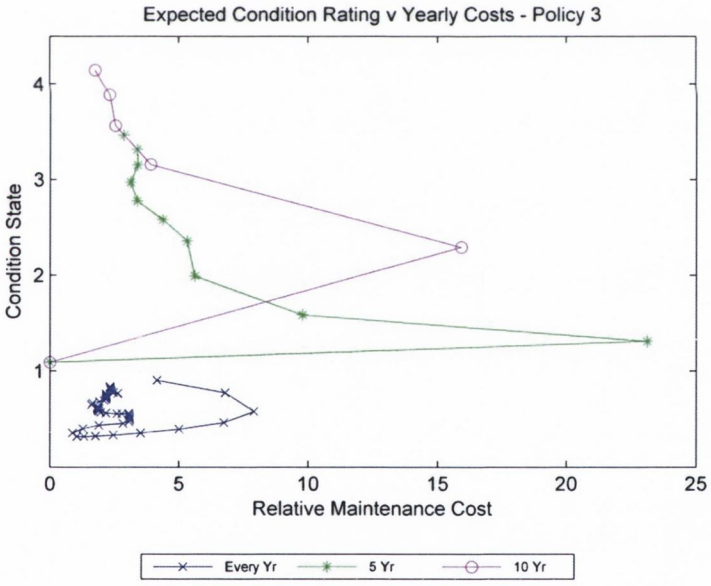

Figure 6.39: Expected overall condition rating v. total relative maintenance cost for policy 3 under cost scenario 1.

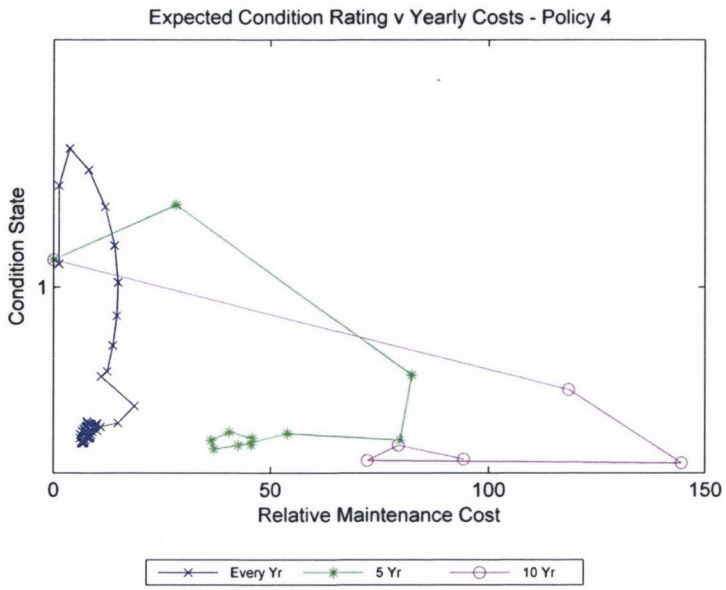

Figure 6.40: Expected overall condition rating v. total relative maintenance cost for policy 4 under cost scenario 1.

Relative Cost Scenario 2

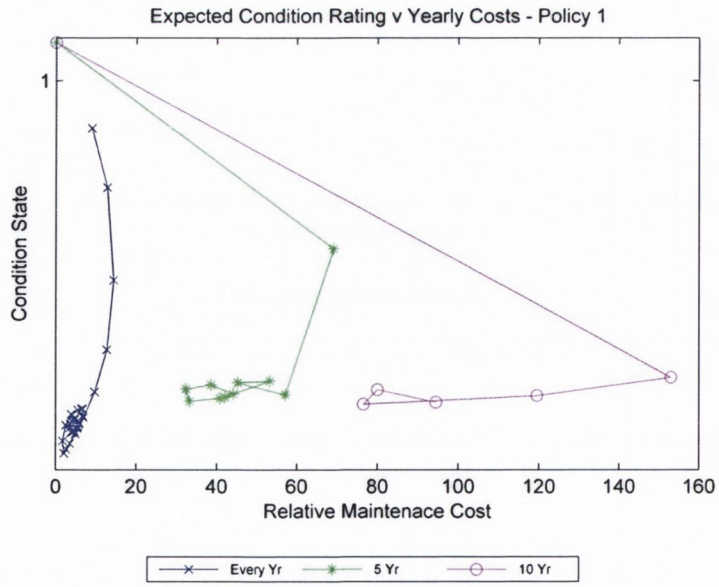

Figure 6.41: Expected overall condition rating v. total relative maintenance cost for policy 1 under cost scenario 2.

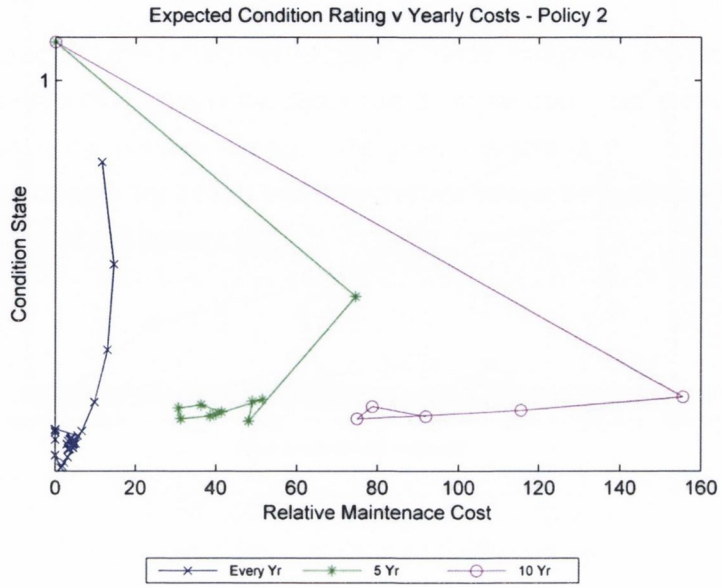

Figure 6.42: Expected overall condition rating v. total relative maintenance cost for policy 2 under cost scenario 2.

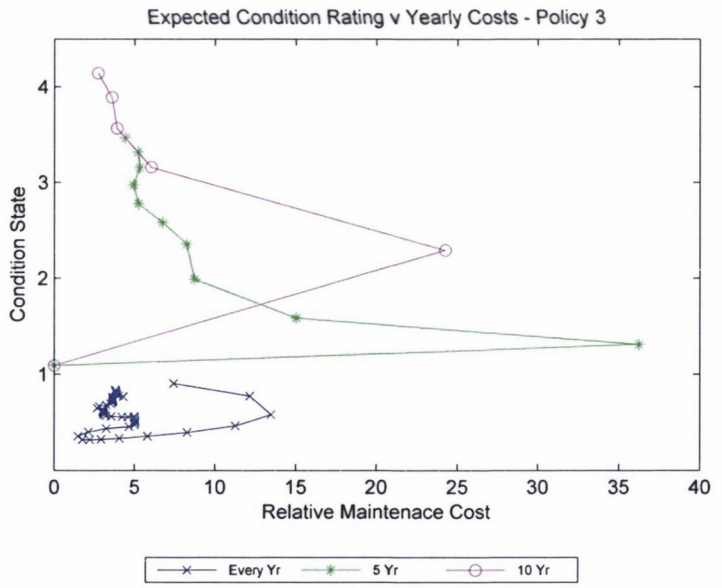

Figure 6.43: Expected overall condition rating v. total relative maintenance cost for policy 3 under cost scenario 2.

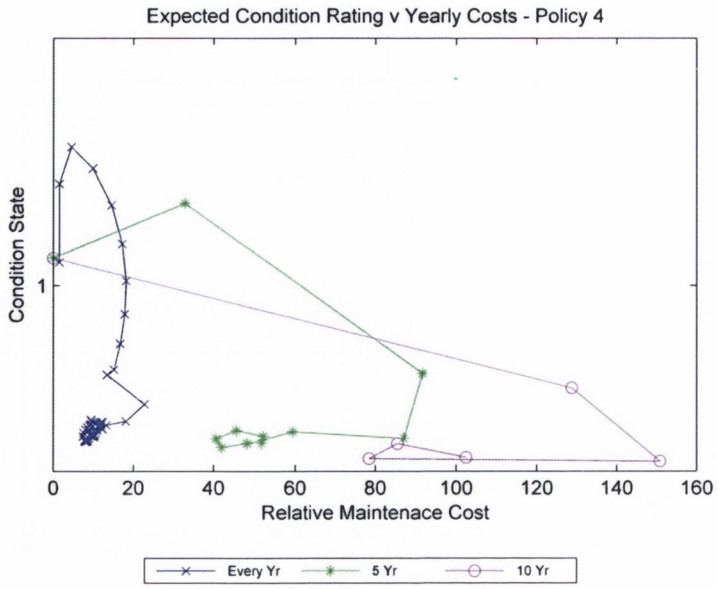

Figure 6.44: Expected overall condition rating v. total relative maintenance cost for policy 4 under cost scenario 2.

In Figure 6.45 and Figure 6.46, the total costs can be compared to the total expected condition state under all policies and all maintenance intervals. In Figure 6.45, policies 1 and 2 give roughly the same total expected condition state as expected, but at a slightly higher lifetime maintenance cost. Policy 4 then, that of rehabilitation only, gives a higher expected lifetime condition state than the combination policies 1 and 2, but at a much higher relative maintenance cost, hence it can be concluded that for the relative costs at least considered here, it is a non-viable policy since it is neither optimal in terms of summed lifetime condition state or summed lifetime maintenance costs. Likewise, policy 3 - that of repair only, is by far the cheapest option, but leads to an enormous increase in total lifetime expected condition state. Hence it too can be considered non-viable.

Concerning the repair intervals then the 10-year maintenance gives the highest total cost in all cases except policy 3. This is as expected since policy 3 corresponds to repair only and does not consider rehabilitation. Hence not that many maintenance actions will be carried out since the majority of structures when only inspected and maintained at 10 year intervals will deteriorate too rapidly for repair actions to be applicable. Again this rapid deterioration is evident in the high total expected condition rate for policy 3.

In all, from Figure 6.45, it appears that performing maintenance policy 2 every year gives the best balance between summed lifetime expected condition state and summed lifetime maintenance cost. If maintaining every year though, all three policies do give quite similar results. This is as expected since the only reason policy 1 and policy 3 should differ is that random deterioration applies and

that there isn't perfect repair. Policy 2 and policies 1 and 3 then differ as different percentage repairs are considered under both policies.

As expected, Figure 6.45 gives a very similar graph to Figure except that now the costs are shifted slightly towards the right, reflecting the higher cost of maintenance since the relative costs hare now higher than in the previous example. The general pattern though is still the same, i.e. performing maintenance policy 2 every year gives the best balance between total lifetime expected condition state and total maintenance cost.

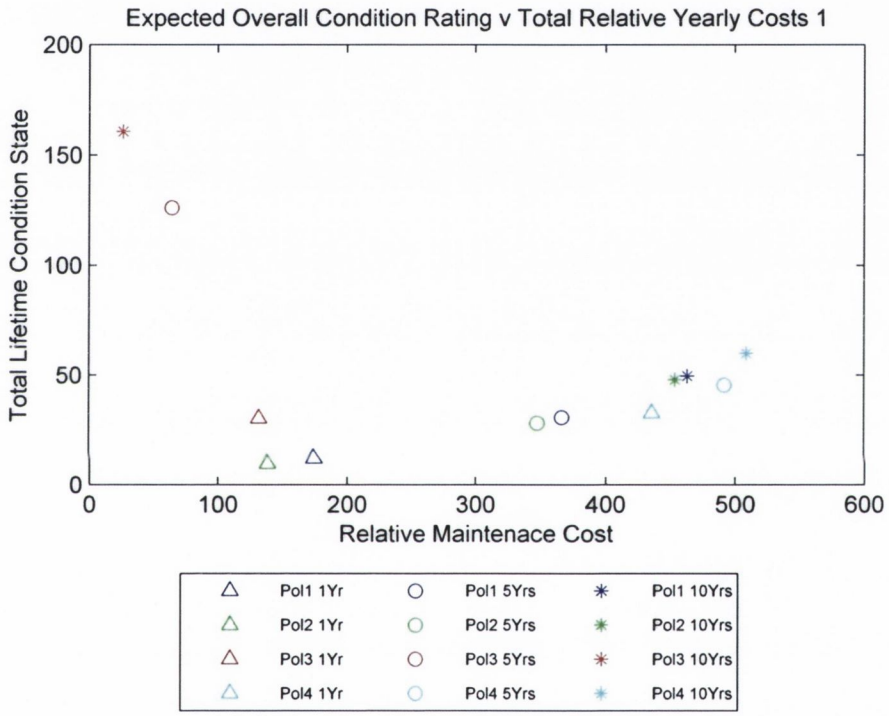

Figure 6.45: Expected overall condition rating v. total relative maintenance cost for all maintenance policies under cost scenario 1.

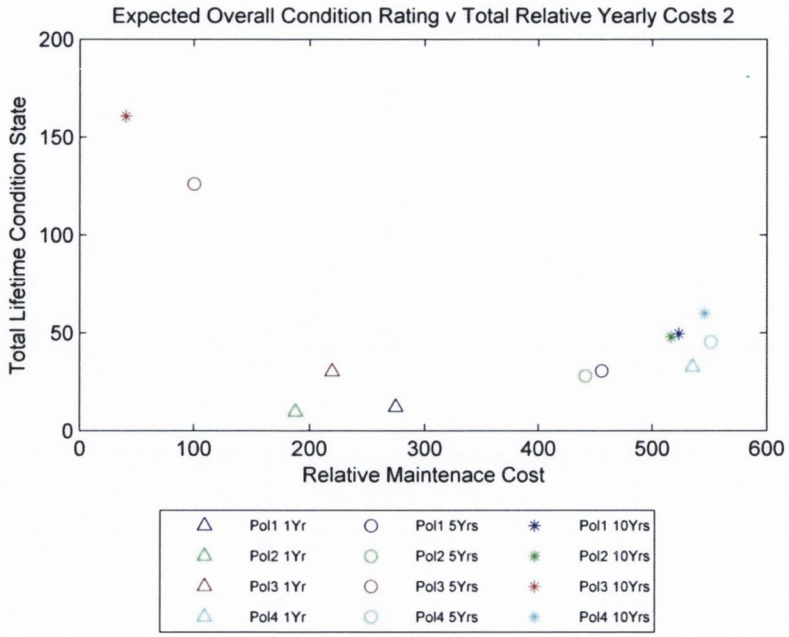

Figure 6.46: Expected overall condition rating v. total relative maintenance cost for all maintenance policies under cost scenario 2.

Clearly this analysis cannot be taken as conclusive. It considers arbitrary costs only and while they serve to illustrate the importance of different maintenance strategies and the effect they have on the overall network, conclusive decisions cannot be drawn from them. Further study is needed to quantify these costs properly by including such things as user delay cots, traffic disruption costs, the cost of inspection and so forth. However, in an attempt to consider the impact such additional costs may have on the outcome, given that the above analysis and discussion alludes that maintaining the bridge stock every year looks to be the most cost-effective measure, a penalty cost function has been incorporated into the model to allow for the fact that bridge inspections themselves are quite costly and that it is most probably not cost-effective to do so. This shall now be outlined in an effort to make a more reasonable comparison between policies.

Inclusion of Penalty Cost

This penalty cost function included here weights the relative cost of each policy by comparing it to the cost of carrying out an inspection and maintenance policy at 10 year intervals. Hence the cost of repairing at 5 year intervals is multiplied by two, while the cost of repairing every year is multiplied by 10. Note this is clearly a simplification but it is indicative of the costs which would be accrued. Figure 6.47 and Figure 6.48 represent now an updated portrayal of Figure 6.45 and Figure 6.46. For clarity Table 6.17 represents the information shown in both these graphs with the included penalty cost function to the previous information shown in Figure 6.45 and 6.46 where the

penalty cost had yet to be incorporated. As expected, repairing at 5 and 10 year intervals now appears much more beneficial. This is also evident from Table 6.17. For both cost policy 1 and cost policy 2 though, Figure 6.47 and Figure 6.48 both indicate that performing repair policies 1 and 2 at intervals of 5 to 10 years are most beneficial in a cost-benefit approach, the inspection interval dependant on whether low cost or low total lifetime condition state is more desirable. Again though, in the absence of more accurate costs, comprehensive maintenance decisions cannot be made.

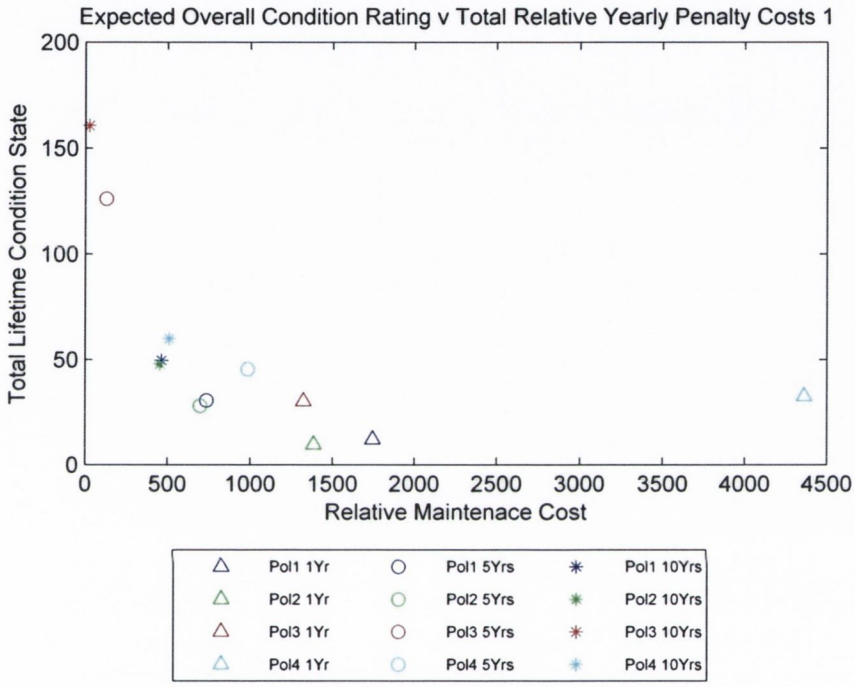

Figure 6.47: Expected overall condition rating v. total relative maintenance cost for all maintenance policies under cost scenario 1 using penalty costs.

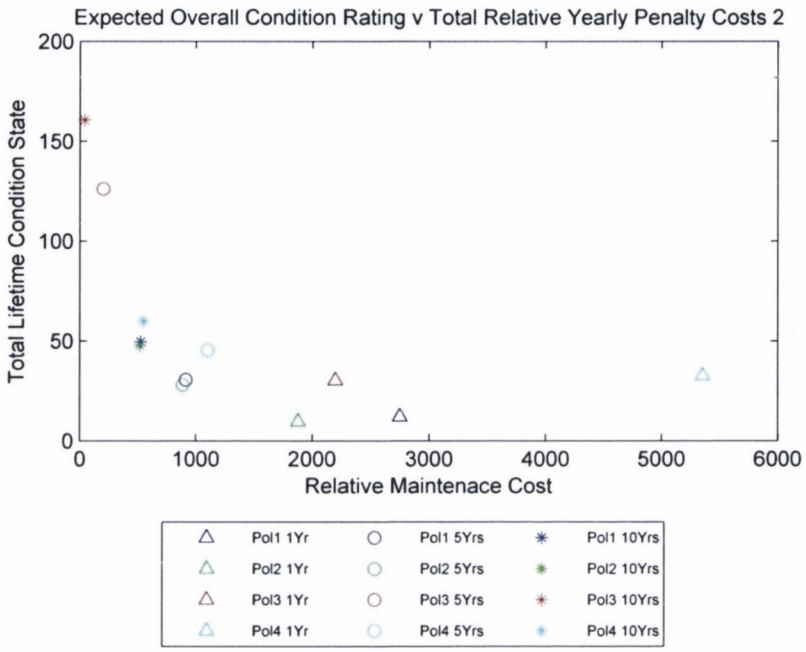

Figure 6.48: Expected overall condition rating v. total relative maintenance cost for all maintenance policies under cost scenario 2 using penalty costs.

	Expected Lifecycle Cost	Cost Policy 1	Cost Policy 1 with Penalty	Cost Policy 2	Cost Policy 2 with Penalty
Policy 1					
Every year	12.02	174.54	1745.4	274.87	2748.7
5 years	30.65	367.13	734.26	455.87	911.74
10 years	49.55	463.83	463.83	523.36	523.36
Policy 2					
Every year	9.6	138.43	1384.3	187.85	1878.5
5 years	28.06	348.40	696.81	441.31	882.63
10 years	47.83	453.97	453.97	516.52	516.52
Policy 3					
Every year	30.17	132.35	1323.5	220	2200.2
5 years	126.11	64.43	128.85	100.2	200.4
10 years	160.58	26.44	26.44	40.48	40.48
Policy 4					
Every year	32.6	436.38	4363.8	535.38	5353.3
5 years	45.40	492.14	984.28	551.33	1101.7
10 years	59.81	508.91	508.91	546.01	546.01

Table 7.17: Expected relative cost of each maintenance alternative.

6.6 CONCLUSION

This chapter has outlined the overall implementation of the model developed in this thesis. In keeping with the objectives as listed at the outset, this model has been developed on an elemental basis and these elemental ratings aggregated using a weighting system as suggested from analysis of the EIRSPAN database. For completeness the analysis was also carried out as though all elements had equal weighting on the overall structure and while it was found to differ only slightly in the example presented in this chapter, this was deemed to be as a direct consequence of all elements deteriorating in a similar manner in this instance and also being in a similar condition at the outset.

Additionally, since it considers both inland and coastal environmental regions, the model has been calibrated directly for the Irish network. The results of both of these regions individually have also been combined to give an expected life-cycle for the entire Irish bridge network over the pre-specified 100-year period. Note that while the example given has been that of bridges in Ireland, the system methodology itself is easily modified to allow for its application to alternative kinds of bridges in other environments by using different parameters in the deterioration model and employing an elemental weighting system as suggested from inspection information pertaining to the country in question.

Furthermore a framework has been put in place by which the transition probabilities themselves can be obtained from the EIRSPAN database as soon as sufficient information becomes available. However a few points to note when using real data are that firstly, real data ignores age effects and secondly, it cannot make allowances for uncharted maintenance, hence it can be biased towards a new bridge stock in the former case since they are far greater in number, and biased unequivocally in the latter case. Therefore this suggests that the elemental deterioration models developed in this thesis should not just only be used until such time as sufficient real-time data becomes available, but rather indefinitely.

In an attempt to further develop the methodology derived and defined in this thesis then, a maintenance framework was also incorporated into the model. The main point of this was to demonstrate the robustness of the developed methodology to allow for the incorporation of maintenance actions. Different policies have been considered which all take into account the idea of imperfect repair. Varying repair intervals have also been taken into account and a relative cost rating with penalty function for increased inspection rate introduced in an effort to rank the alternative policies. Ultimately though, in the absence of accurate costs and specific maintenance actions, a comprehensive maintenance management policy cannot be derived at present. Nevertheless, a framework which can be easily modified has been proposed. This has as

demonstrated, the capability to be incorporated into either a new or existing BMS and by entering specific maintenance actions with associated costs for each structural bridge element, conclusive management methodologies can be obtained.

In conclusion then, further work is required in a few areas of this maintenance management protocol. Firstly, as stated many times in this chapter, more exact cost models allowing for additional costs such as user-delay, traffic delay and the cost of inspection are necessary. Secondly, the balance between expected network condition state and expected maintenance cost has been looked at in this chapter, but only in an elementary manner. Instead, in future work, the budget will need to be incorporated as a constraint into the model and the entire process can then be optimized by setting either the network condition state or the budget requirements as the constraint in the process.

CHAPTER 7 - CONCLUSIONS

7 CONCLUSIONS

7.1 INTRODUCTION

Much research has been undertaken worldwide already in the field of bridge maintenance management as is evident from the review and analysis of current systems and practice presented in Chapter 2. It is clear however that much work still needs to be undertaken to ensure accurate prediction of future network condition state – paramount for scheduling maintenance and repair at optimal times and allocating sufficient resources to carry out the necessary work. The provision of such maintenance management and planning tools is especially important for a country such as Ireland which consists of a relatively new bridge stock which will suffer the debilitating effects of deterioration all at once if adequate protocol is not firstly developed to ensure that maintenance and repair is correctly prioritised in time. Consequently this thesis outlined the development of a new bridge network lifecycle management tool suitable for incorporation into a BMS. The objectives of this thesis then as outlined in Section 2.5 were defined as:

1. To develop the system methodology, particularly the most appropriate manner of modelling future bridge condition, given the fact that the module needs to ideally be incorporated as part of a BMS. This includes ascertaining the most appropriate optimization procedure.
2. To implement a more robust solver for use in transition probability estimation, given that many of those in use at the present time are unsuitable.
3. To determine how best to calibrate suitable transition matrices in the absence of sufficient quantities of inspection data, specifically, the incorporation of physically-based, analytical models into prediction systems.
4. To investigate the phenomenon of chloride-induced corrosion of reinforced concrete and particularly the most suitable analytical models for use in predicting future condition state in a cracking-limit state, service life model.
5. To 'calibrate' in effect such systems for use with regard to the Irish Bridge network, i.e. conduct a literature review and sensitivity analysis of the most appropriate parameter values.
6. To develop the system on an elemental basis, i.e. to build up the overall bridge condition rating as a function of its minor elements and to consider the overall condition rating then as dependant on the correlations between these elements. In this respect, the system will be most robust and adaptable for other kinds of structures in alternative locations.
7. To consider the effects of maintenance and repair on equilibrium network condition rating, taking into account different maintenance policies, imperfect repairs and alternative costs.
8. To develop a data-cleaning procedure which could be used to elicit suitable transition probabilities from infrastructure inspection databases as soon as sufficient information becomes available.

The developments and conclusions of this thesis with regard to the objectives outlined above are summarized in the following sections.

7.2 DEVELOPMENT OF SYSTEM METHODOLOGY

In keeping with the intention of designing the prediction tool so as to be able to incorporate it into either a new or existing BMS, a Markovian basis was selected for the model. This was because the discrete states of condition assigned to structures upon inspection corresponded to the predefined states of condition necessary for a Markov chain. Having investigated both homogeneous and non-homogeneous chains, non-homogeneous chains were found to be far more accurate and were selected to model and predict future structure behavior. Additionally, a non-linear minimization procedure was found to be most appropriate as an optimization routine for obtaining the Markovian transition probabilities given the end purpose of incorporating the tool into a BMS. Specifically, a minimization of absolute expected condition state distribution was found to be the most accurate.

7.3 SOLVER INVESTIGATION

Given the fact that many of the optimization algorithms in use in systems at the current time are unsuitable and can give rise to either negative probabilities or solutions on the bound constraints of the problem, a robust, previously unimplemented solver in the field – Cross Entropy was investigated in this thesis. Specifically, it was found to be more appropriate for use than some other commonly used algorithms, as it avoided converging to probabilities of 0.0 and 1.0. Since such probabilities would give rise to inconsistent distributions of condition state and consequently inaccurate maintenance requirements and budget specifications, it is of the utmost importance to point out that Cross Entropy does not tend to such solutions. In implementing this algorithm a modification was made whereby the original algorithm itself was modified to allow for further accuracy and precision.

7.4 INCORPORATION OF ANALYTICAL MODELS INTO PREDICTION SYSTEM

Ideally, given adequate quantities of inspection information the transition probabilities required for a Markov model would be obtained directly from the raw data. However, the majority of countries do not as yet have access to such data. As a result, these probabilities are often estimated using 'expert judgement' procedures, though these have been shown to overestimate the time to failure of bridge components. Statistical models have also been incorporated as a means of predicting future

structural deterioration. These are often purely statistical in theory though and do not correspond to actual degradation mechanisms. This thesis has therefore identified a framework for developing life-cycle curves from analytical deterioration models of specific mechanisms. For application purposes chloride-induced corrosion was chosen as the investigated mechanism but the procedure is easily modifiable to allow for the addition and inclusion of alternative types of deterioration. This thesis focused on ascertaining the most suitable analytical models for use in a cracking limit state, service-life model of chloride-induced corrosion. In doing so, a previously proposed and widely cited formula for one of the deterioration phases of chloride-induced corrosion - the time-to-first-crack, was modified to allow for an earlier error in the formula. Note that while this modified version appeared to give results which were much more in line with observed, experimental results, more research should be carried out to further validate the model. This was encapsulated into the developed prediction tool along with two other formulae, to respectively represent the multiphase deterioration of this mechanism. Life-cycle curves of expected structure behavior were then simulated. The Markov matrices are then calibrated from these life-cycle curves and thus represent real-life behavior. Different methods of obtaining the relevant transition probabilities from these life-cycle curves were investigated and a time-based manner, i.e. dependent on structure age and expected deterioration pattern at that time was implemented.

7.5 SENSITIVITY ANALYSIS OF DETERIORATION MODEL

A sensitivity analysis of the implemented deterioration model was performed to examine the robustness of the method. Both variability in chosen parameter distributions, as well as the inherent variation within a specified parameter distribution were investigated. In general it was found that, as expected the surface chloride content C_s, and the critical chloride content C_{cr} had the most effect on the computed time to initiation. In particular, it was noted that care must be exercised when choosing stochastic parameters for distributions of these parameters as there is potential for unrealistic values to occur which can have a profound impact on the results. As also expected, the cover depth, C, was also found to have a considerable impact on the computed time to initiation, with increasing cover resulting in an increased time to corrosion initiation. Following on from this study then, parameters relative to Irish conditions were selected to allow for accurate prediction from an Irish perspective.

7.6 ELEMENTAL DEVELOPMENT OF PREDICTION TOOL

From an analysis of the EIRSPAN database, the effect of each bridge element on the overall structural rating was numerically evaluated and weighting coefficients derived. This therefore means that the methodology can be easily adapted to other countries and other types of bridges etc. The overall rating is then developed in an incremental, elemental level manner, with each element

deteriorating according to pre-specified but adjustable parameter values. Furthermore, system development on such an elemental level means that parameters such as age and environment have also been taken into consideration. For application purposes, both coastal and inland regions have been considered in this thesis but many more subsets of the bridge stock could be identified and relevant Markov transition matrices derived. This reiterates the robustness of the developed framework. For completeness, an example of the application of the prediction tool to the Irish bridge network has been given.

7.7 EFFECTS OF MAINTENANCE AND REPAIR

While not an exhaustive study into the application and effects of optimal maintenance and repair actions, this thesis has demonstrated the importance of maintenance and the effect it has on a bridge network. Different policies have been considered which take into account the idea of imperfect repair. Varying repair intervals have also been taken into account and a relative cost rating with penalty function for increased inspection rate introduced in an effort to rank the alternative policies. Ultimately though, in the absence of accurate costs and specific maintenance actions, a comprehensive maintenance management policy cannot be derived at present. Nevertheless, a framework which can be easily modified has been proposed. This has, as demonstrated, the capability to be incorporated into either a new or existing BMS and by entering specific maintenance actions with associated costs for each structural bridge element, conclusive management methodologies can be obtained.

7.8 DATA ELICITATION PROCEDURE

A framework has also been put in place by which the transition probabilities themselves can be obtained from the EIRSPAN database as soon as the database is sufficiently populated. However, a few points to note when using real data are that firstly, real data ignores age effects and secondly, it cannot make allowances for uncharted maintenance, hence it can be biased towards a new bridge stock in the former case since they are far greater in number, and biased unequivocally in the latter case. Therefore this suggests that the elemental deterioration models developed in this thesis should perhaps not just only be used until such time as sufficient real-time data becomes available, but rather afterward as well for increased prediction power.

7.9 SUGGESTIONS FOR FURTHER WORK

Based on the developments of this thesis, further research is recommended in the following areas:

1. OPC has been the material of choice for the purposes of the chloride-induced deterioration model implemented here. However, the model should be implemented for varying mixes of

concrete considering differing water cement ratios, and especially, the addition of partial cement replacements such as PFA and GGBS, given their prevalent use. Accordingly, with the development and calibration of life-cycle curves of expected future condition state, a relative comparison of lifetime behaviour could then be drawn.

2. The modified El-Maaddawy method for predicting the time-to-first-crack analytically should be further validated against corrosion-cracking experiments to ensure its robustness.

3. The bridge stock could be further segregated to account for more environmental variation and localisations. Additional forms of deterioration should also be accounted for such as carbonation and freeze-thaw action. The overall expected condition rating will then be a weighted function of a combination of these mechanism in a similar fashion to it being a weighted function of climatic regions and age-groups as illustrated in this thesis. Furthermore, the framework should also be expanded to allow for the inclusion of varying bridge materials and bridge types such as steel and masonry arch.

4. Further work is required in quite a few areas of the maintenance management protocol. Firstly, specific maintenance actions with associated costs instead of arbitrary actions with nominal costs need to be accounted for. Secondly, the balance between expected network condition state and expected maintenance cost has been looked at, but only in an elementary manner. In future work, the budget will need to be incorporated as a constraint into the model and the entire process can then be optimized by setting either the network condition state or the budget requirements as the constraint in the process.

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APPENDIX A – LIST OF JOURNAL AND CONFERENCE PAPERS

PAPER LIST

Journal Papers:

Reale, T. and O'Connor, A.J. (2012). ''Cross-Entropy as an Optimization Method for Bridge Condition Transition Probability Determination.'' *ASCE Journal of Transportation Engineering.* 138(6): 741-750.

Reale, T. and O'Connor, A.J. (2012). '' A Review and Comparative Analysis of Corrosion-induced Time to First Crack Models.'' *Construction and Building Materials.* (36) 475-483.

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Reale, T. and O'Connor, A.J. (2012). '' Future State Prediction of Reinforced-Concrete Bridges allowing for Chloride-induced Deterioration'' *BCRI 2012, Dubin, Spetember 6-7.*

Reale, T. and O'Connor, A.J. (2012). ''Bridge Maintenance Planning using Cross-Entropy and Non-Stationary Markov Chains.'' *IABMAS 2012, Lake Como, Italy, July 8-12, 2012.*

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