1. INTRODUCTION

1.1. Background

Since the UN Conference on Environment and Development (UNCED) that was held in Rio de Janeiro, Brazil in 1992 and resulted in an agenda for global sustainable development, Agenda 21, *"there has been an ever-increasing focus on the needs to determine durability and service life of materials, components, installations, structures and buildings based on the following two important aspects:*

- *Environmental issues – scarcity of material and energy resources and the building and construction sector as a big consumer of these resources, and the environmental impact caused by buildings*

- *Economic issues – the total value of the built environment on a national level and the value of each specific unit (buildings, structures, roads, bridges, quays, etc.) for the owners (government, private sector or individuals). The conditions of the built environment, the annual costs of management and maintenance and the life cycle costs are of major importance be it for the economy of a country, or maintaining competitiveness within an industry or corporation."* (Hövde and Moser, 2004, p.11).

Sustainable development is defined as *"development that meets the needs of the present without compromising the ability of future generations to meet their own needs"* (Brundtland Report, 1987, cited by International Council for Research and Innovation in Building and Construction 1999, p.17). In the quest for sustainable buildings, the prediction of service life for building materials and components is dependant on the quantification of durability and degradation. This has lead to the establishment of the joint CIB W080/RILEM 175-SLM 'Service Life Methodologies' working committee on 'Prediction of service life of building materials and components' by the International Council for Research and Innovation in Building and Construction (CIB) in partnership with a Technical Committee of the International Association for Building Materials and Structures (RILEM). In March 2004, CIB W080/RILEM 175-SLM published State of the Art Reports on Methods for Service Life Prediction, CIB Report Publication 294 (Hövde and Moser, 2004), where two methods for service life prediction are proposed, the Factor Method and the Engineering Design Method. In the evaluation of the Factor Method, which is the recommended method, Hövde and Moser (2004, p.40) cites Rudbeck (1999), who made an extensive discussion of the Factor Method for service life prediction and concluded that the Markovian model would be the recommended method for service life prediction of building components if the Markov transition probability matrices can be developed and validated.

The thesis deals with the application of Artificial Intelligence (AI) to develop of transition probability matrices for the Markov Chain for service life prediction. Factors influencing degradation and durability are discussed in broad outline, followed by the application of fuzzy logic AI to develop Markov Chain transition probability matrices. The proposed methodology is tested against historical performance data from a set of academic hospitals, followed by some applications of the model.

It is based on research over a period of more than 20 years in the field of structural engineering and maintenance management. Since 1997 project work in close collaboration with the Division Building and Construction Technology of the Council for Scientific and Industrial Research (CSIR), focussed on the development of a building maintenance management system for the provincial government sector in South Africa that culminated in a software system calculating maintenance budget requirements based on condition assessments.

In general, buildings represent substantial investments and building performance over time is of utmost importance, not only to the building owner, but also to the occupants and the community at large. As Lee (1981, p.1) pointed out, *"dilapidated and unhealthy buildings in a decaying environment depress the quality of life and contribute in some measure to antisocial behaviour."*

Developing countries are in a race against time to eradicate poverty and famine, and provide shelter. If drastic steps are not taken sooner than later, existing building stocks in many countries will not be able to provide the required support for sustainable growth and development. Rehabilitation and replacement of buildings and loss of service life due to neglect are unnecessary expenditures depriving a developing economy from scarce resources for progress. Considering that buildings form such a substantial part of the wealth of countries, service life prediction is a powerful and essential management tool, which should be developed and refined to ensure extended service life and properly maintained building infrastructure.

The building owner's objective should be to optimise the return on the investment by extending the service life of the building, which is determined by a minimum performance level. Building performance can be expressed in many ways, the most common being condition.

A building is a complicated three-dimensional configuration of a diverse range of fabrics, materials or components, each with its own characteristics, which interacts differently to the environment, could be old or new, raw or processed, come in different forms, shapes, sizes and finishes, and its applications could vary considerably. Condition changes over time as the environment impacts on the building or component. Hypothetically, this change in condition of a building or component over time can be illustrated by the curve in Figure 1-1 below.

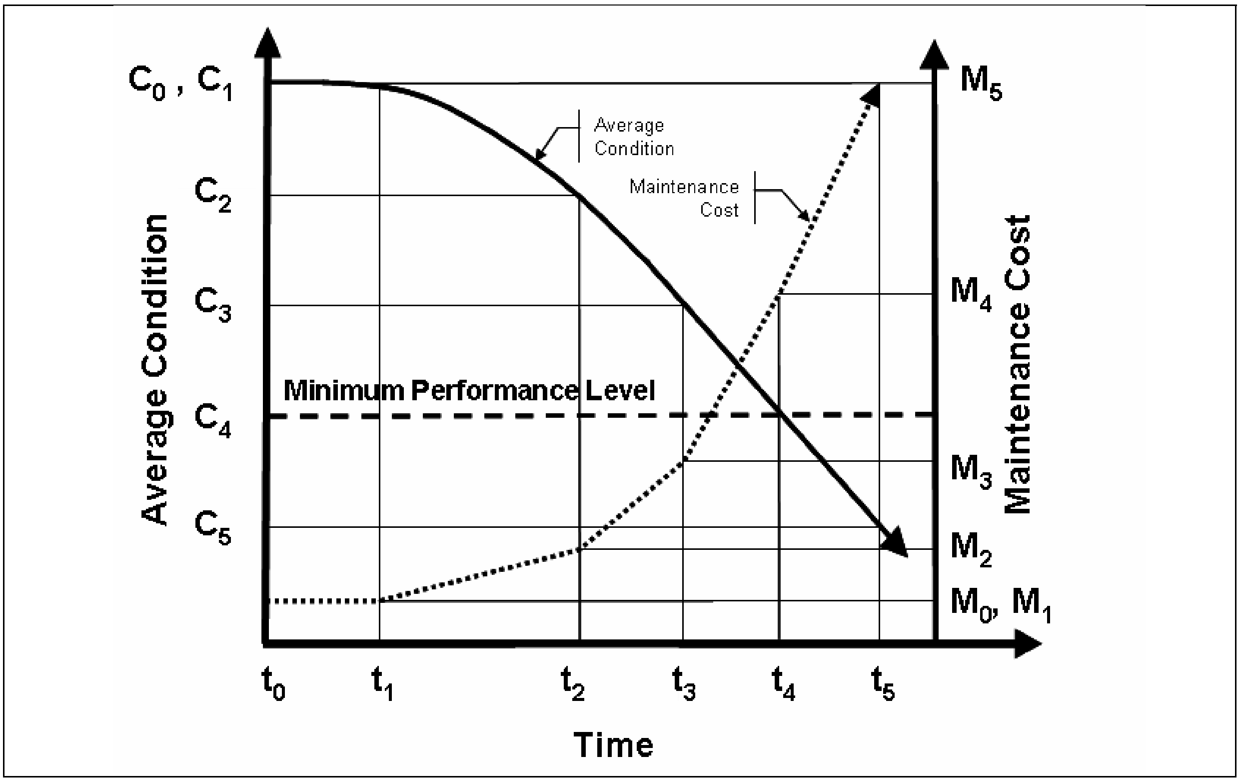


Figure 1-1: Hypothetical curve illustrating relationship between average condition and maintenance cost over time

Assuming normal degradation over time, no maintenance or rehabilitation and no premature failure, the condition profile of the component, that is the percentage of the component in various condition categories, will change or deteriorate. In other words, different portions of a component could be in different conditions at the same point in time. Likewise, the extent of required maintenance actions would range from preventative maintenance to condition-based maintenance, repairs, rehabilitation and eventually replacement, increasing in severity and cost, as illustrated in Figure 1-1 above.

If the minimum performance level for a particular building is an average condition of say C_4, the service life of the building will be t_4 - t_0. The higher the required or desired performance level, the shorter the service life and the lower the maintenance cost, and vice versa.

1.2. Problem Statement

The global importance of and need for sustainable socio-economic development demand an informed decision-making process from the built environment. Resources and non-renewable resources in particular, should be used as responsible and best possible to ensure optimum service life and life cycle costs. Optimum service life and life cycle costs depend on the ability to quantify (calculate) the changes in condition of building fabric and components over time in any given physical and operational environment.

If the change in condition over time can be defined mathematically, it will be possible to calculate the service life and remaining service life of buildings and components, and the consequences and risks of maintenance budget allocations and decisions to defer maintenance. The ability to predict changes in the condition profile of buildings or components is essential for cost-effective maintenance and rehabilitation decisions.

The prediction of the service life of a building or component requires a thorough understanding of the degradation process and the changes in condition over time. A simulation model for the degradation process should be based on actual performance data and provide for all the variables influencing the degradation process. In South Africa, reliable, continuous and consistent data on the historical performance of building materials and components are almost nonexistent. It is only since the mid 1990's that the need for condition assessments was recognised, unfortunately by far too few decision-makers, who still do not appreciate the value of regular and consistent condition assessments, while data remains scarce and inconsistent.

This scarcity of data does not mean that a model to simulate degradation cannot be developed and successfully implemented. The Factor Method (ISO 15686-1:2000), the current state of the art for building service life prediction, provides an empirical estimation of service life by applying seven factors to a reference service life. Although it is a simple technique, the valuation of these factors requires a thorough understanding of the variability and impact of individual and combined factors (e.g. 0.8 negative, 1.0 neutral and 1.2 positive). Calibration of these factor values with assessed performance over time is not clearly defined. The Factor Method calculates the estimated service life and does not provide information on the degradation process, change in condition or condition profile.

A number of studies (Coombes *et al*, 2002; Lounis *et al,* 1998a, p.1; Madanat *et al,* 1995, p.120; Morcous *et al,* 2003, p.353; Rudbeck, 1999 cited by Hövde, 2004, p.40) identified the Markov Chain, a stochastic approach used for simulating the transition from one state (condition) to another over time, as the preferred method for predicting service life and calculating changes in condition. The population of the Markov transitional probability matrix is a problem due to the lack of reliable and consistent historical performance data on the actual degradation rate of materials and components. According to Madanat *et al* (1995, p.120) *"existing approaches used to estimate these transition probabilities from inspection data are mostly ad hoc and suffer from important methodological limitations."*

The development of a reliable and consistent database through regular field assessments is however a very slow process. In general, the best available source of information on degradation is the knowledge and reasoning of experts on material degradation in the built environment. However, as Negnevisky (2002, p.15) stated, "*A major drawback is that human experts cannot always express their knowledge in terms of rules or explain the line of their reasoning. … experts do not usually think in probability values, but in terms as often, generally, sometimes, occasionally and rarely."* On the interim, a system is needed to translate the verbally expressed knowledge and reasoning of experts into probability values, while using the assessment database as it grows to calibrate, learn and improve the system's reliability and ability to simulate the degradation process, providing for various combinations of the factors effecting degradation.

Problem Statement No. 1:

The 'state-of-the-art' Factor Method for service life prediction only calculates the estimated service life of a building or component, and cannot quantify changes in condition over time or determine the effect of maintenance level on service life.

Problem Statement No. 2:

The application of the Markov Chain to predict service life, quantify changes in condition over time and determine the effect of maintenance levels on service life, is restricted by the limited availability of historic performance data on degradation of building materials to develop transition probability matrices for the Markov Chain.

Problem Statement No. 3:

Experts do not usually think in probability values and cannot always express their knowledge or explain their reasoning in terms of rules. This expert knowledge and reasoning need to be translated into probability values to develop transitional probability matrices for the Markov Chain to predict the change in condition or performance over time and service life of a building or component.

Problem Statement No. 4:

Many buildings are under-maintained because decision-makers are ignorant of the consequences of reduced service life due to inappropriate maintenance levels, deferred maintenance and maintenance budgets cuts.

1.3. Hypotheses

Hypothesis No. 1:

The Markov Chain can be used to calculate the estimated service life of a building or component, quantify changes in condition over time and determine the effect of maintenance levels on service life.

Hypothesis No. 2:

The limited availability of historic performance data on degradation of building materials can be supplemented with expert knowledge and reasoning, to develop transition probability matrices for the Markov Chain.

Hypothesis No. 3:

Expert knowledge and reasoning can be expressed in terms of 'IF-THEN' rules, and translated into probability values for the transitional probability matrices of the Markov Chain through the application of Fuzzy Logic Artificial Intelligence.

Hypothesis No. 4:

The reduction in service life due to inappropriate maintenance levels, deferred maintenance and maintenance budgets cuts can be quantified through the application of the proposed Markov Chain model.

1.4. Objective of the Thesis

The objective of this thesis is to develop a model, which translates expert knowledge and reasoning into probability values through the application of Fuzzy Logic Artificial Intelligence to supplement limited historical performance data on degradation of building materials for the development of Markov Chain transitional probability matrices to predict service life, condition changes over time, and consequences of maintenance levels on service life of buildings.

1.5. Scope of the Thesis

This thesis covers the following areas:

- Identification of durability factors and degradation agents influencing the degradation process.
- The use of fuzzy logic AI applications to translate expert knowledge and reasoning into probability values to populate the transition probability matrix of the Markov Chain.
- The application of the Markov Chain to predict the change in condition of a building or component.
- The application of the Markov Chain to predict the service life of a building or component.
- The application of the Markov Chain to predict the effect of maintenance levels on the service life of a building or component.

The following issues are not covered in this thesis:

- Although degradation agents and factors are identified, these agents are not discussed in detail.
- The philosophy and appropriateness of the Factor Method, which is accepted as the current international "State of the Art", or the Engineering Method for service life prediction.
- The theory of the Markov Chain and other statistical methodologies.
- Although a neuro-fuzzy system was used for the development of the Markov Chain transitional probability matrix values, the learning ability of the system's neural network component has not been activated for the purpose of this thesis, because available historical performance data required for learning purposes is still too limited and inconsistent.
- The theory of neural networks and other artificial intelligence applications.

1.6. Methodology

During the development of a method to calculate a condition-based maintenance budget for buildings and quantify the consequences of deferred maintenance, the need to quantify the change in condition over time was identified.. The search for potential solutions involved literature surveys (both internet and libraries), attendance of international conferences and interfacing with domain experts, which made the exploration of the existing knowledge base possible to gain a better understanding of the problem and identify potential solutions such as the Markov Chain and Factor Method.

Although the 'state of the art' Factor Method, which calculates an empirical estimated service life, does not provide information on the change in condition over time, it provided a better understanding of the degradation and durability factors that influence changes in condition.

Available South African historic performance data on degradation and durability of building components, required to populate the Markovian transition probability matrices, was however too limited and inconsistent to develop a reliable model. The only alternative potential source of transitional probabilities was expert knowledge and reasoning, but needed to be translated into probability values, which led to the exploration of Artificial Intelligence applications and identification of the Neuro-Fuzzy application. Other AI applications, such as expert systems, fuzzy logic systems, artificial neural networks and genetic algorithms were also explored and dismissed. The Neuro-Fuzzy application was selected as the most appropriate system because it can deal with linguistic variables and fuzzy IF-THEN rules of the expert thought process (fuzzy logic) and is capable of learning (artificial neural networks) at the same time.

The fuzzy logic AI application however comprises of a large number of rules and requires the use of a software system. Demo versions of a number of software systems, available as free downloads on the internet, were identified and tested. The FuzzyTECH 5.55c professional edition system, developed by Inform GmbH of Germany was selected as the most suitable of the systems tested and a licence was obtained for the use of the software.

The various degradation and durability factors, similar to the Factor Method, were identified and defined in linguistic terms based on a five point rating system similar to a system used for condition assessments. This was followed by the development of a structure for the fuzzy logic system and IF-THEN rules and degrees of support based on the expert thought process and knowledge providing for all possible combinations and levels of the degradation and durability factors and the current condition, allowing the user to simulate any possible scenario. A three-dimensional plot of condition, maintenance level and degradation rate is produced and expert knowledge is used to adjust the degrees of support of the IF-THEN rules in the Neuro-Fuzzy model to provide realistic degradation rates. The Neuro-Fuzzy model's revised output, expressed as degradation rate, is fed into the Markovian transitional probability matrix to simulate the change in condition over time.

The output of the Markovian model provides the percentages of the building or component in each condition category, at any point in time, also referred to as condition profile. From this condition profile, the average condition of the building or component is calculated and plot against time to provide typical curves for different maintenance levels. By selecting an appropriate performance level expressed as minimum desirable condition the predicted service life of the building or component for different maintenance levels can be obtained.

The model was tested and calibrated on a set of six South African academic hospitals. The selection of these six hospitals was based on the following criteria:

- The proposed model should be able to deal with any building, and the first criterion was to find a building representative of the population of buildings.
- The next criterion was to find a representative sample of buildings that had to be similar in construction (structure, materials and finishes), type (hospital), usage (academic), utilisation, management regime, size and age to allow valid comparisons.
- The third criterion was the existence of reliable historic performance data - the condition of the buildings had to be assessed more than once using the same assessment ratings and process.

The only buildings in South Africa complying with all these criteria are the major academic hospitals, because field assessment data was available for more than one assessment, the hospitals are of similar age and construction, have similar operational environments and internal climates, no major structural changes have been undertaken since construction and an academic hospital offers a good representation of the built environment as they contain most types and usages of buildings (e.g. healthcare, accommodation, offices, teaching & lecturing, workshops, laundries, kitchens, storage, commercial, recreational facilities, M&E plant and installations, and ICT systems, etc.).

During 1995, the National Department of Health commissioned the CSIR to do a National Health Facilities Audit of all the public hospitals in South Africa, which was subsequently followed by a number of similar audits by Provincial Health Departments in collaboration with the CSIR. According to the Health Systems Trust, a South African organisation specialising in health statistics, there are currently 396 public hospitals in South Africa, which vary in construction, type, usage, utilisation, size, location (urban and rural) and age. Eleven of these hospitals are academic hospitals (where doctors are trained), two of which are brand new (no condition assessments have been done to date) while three are old hospitals with a wide range of building and construction types, sizes, and ages. The remaining six hospitals comply with the criteria and were therefore selected as representative samples of the population of buildings. These six hospitals will remain unidentified for the purpose of this thesis due to the political sensitivity around the condition of public health care facilities in South Africa.

Hospital A, a large academic hospital (240,000 m^2 and 2,000 beds) and subject of a current investigation towards redevelopment options, was selected as pilot site, while the other five hospitals were used as control sites. The average assessed conditions of Hospital A, obtained from two field assessments 20 and 30 years after construction, were plotted on the performance over time graph. Based on the current investigation, which included interviews with key role-players in the maintenance and management of the hospital, the maintenance level has been rated as low. With minor adjustments to the model, the low maintenance level curve correlated with the assessed performance of Hospital A. The assessed average conditions of the five control hospitals were then transferred to the graph as control.

There is a good correlation between the transitional probability matrices developed for the proposed model and other Markov applications in concrete bridge deck deterioration and roof maintenance models, where the transition probabilities were based on assessment data collected over extended periods, which makes the correlation more significant.

The proposed model, based on the Markov Chain approach, translates expert knowledge and reasoning into probability values through the application of Fuzzy Logic Artificial Intelligence to supplement limited historical performance data on degradation of building materials for the development of Markov Chain transitional probability matrices to predict service life, condition changes over time, and consequences of maintenance levels on service life of buildings. Degradation and durability factors similar to those identified in the state-of-the–art 'Factor Method' for service life prediction are taken into consideration.

The model also brings the current condition into the equation, which gives it an added dimension, especially when dealing with existing buildings where the remaining service life could be a crucial factor in investment decisions. The ability to predict changes in condition profiles and average condition makes scenario analysis and quantification of the consequences of maintenance levels and deferred maintenance possible leading to an informed decision-making process.

1.7. Terminology and Abbreviations

1.7.1. Terminology

"Degradation	*Reduction over time in performance of a building or a building part*
Durability	*Capability of a building or a building part to perform its required function over a specified period of time under the influence of the agents anticipated in service*
Life cycle	*Successive periods of a building component, starting with the design, the construction, the use, the maintenance, the demolition and reuse*
Maintenance	*Combination of all technical and associated administrative activities during the service period that are meant to retain an item in a state in which it can perform its required function*
Performance (in use)	*Ability of a building or a building part to fulfil its functions under the intended use conditions*
Predicted service life	*Service life predicted from recorded performance over time as obtained, for instance, in ageing tests*
Preservation	*Activities that are meant to maintain the present capacity of a building component (conservation, protection)*
Preventive maintenance	*Maintenance activities performed to avoid failure*
Reference service life	*Service life for a building or a building part for use as a basis for estimating service life*
Service life	*the period after installation during which a building or its parts meet or exceeds the performance requirements*

Service life prediction	*A generic methodology which, for a certain or any reasonable performance requirement, facilitates a prediction on the service life distribution of a building or its parts for the use in a certain or in any reasonable environment"* (Jernberg *et al*, 2004, p.6-10)

1.7.2. Abbreviations

AI	Artificial Intelligence
BELCAM	Building Envelope Life Cycle Asset Management Project (NRCC)
BS	British Standard
CIB	International Council for Research and Innovation in Building and Construction
CS	Canadian Standard
CSIR	Council for Scientific and Industrial Research (South Africa)
ESL	Estimated Service Life
ESLC	Estimated Service Life of a Component
ISO	International Organisation for Standardisation
NRCC	National Research Council Canada
RILEM	International Association for Building Materials and Structures
RSL	Reference Service Life
SLP	Service Life Prediction
TRH4	Technical Recommendations for Highways (CSIR)

1.8. Organisation of the Thesis

This thesis is organised in the following way:

In Chapter 1, the background to the research, problem statement, hypothesis, objective and scope of the thesis, and the methodology are discussed.

Chapter 2 covers the literature review, which covers sustainable development, service life and durability issues, degradation, the Factor Method, Markov Chain, and artificial intelligence applications.

Chapter 3 deals with the research methodology and covers degradation and durability factors, condition, and degradation rate, assessment requirements, the application of artificial intelligence to simulate the degradation process, and the development of the Markov Chain transitional probability matrix for service life prediction.

The results are discussed in Chapter 4, followed by conclusions and recommendations in Chapter 5.

This is followed by the references used in the preparation of the thesis and appendices.

2. LITERATURE REVIEW

2.1. Introduction

The literature review, based on material obtained from libraries, conference proceedings and internet searches, covers sustainable development in the built environment, service life and durability of building materials, degradation agents influencing degradation of building materials, the application of the Markov model to predict changes in condition and the use of artificial intelligence applications in combination with the Markov model.

2.2. Sustainable Development

Since the formulation of Agenda 21 for global sustainable development at the UN Conference on Environment and Development held in Rio de Janeiro, Brazil, in 1992, the international focus on research in the built environment has shifted to durability and sustainability issues, particularly Service Life Prediction (SLP). The Brundtland Report (1987) cited by CIB (1999, p.17) defined sustainable development as *"development that meets the needs of the present without compromising the ability of future generations to meet their own needs."*

> *The pursuit of sustainable development throws the built environment and the construction industry into sharp relief. This sector of society is of such vital innate importance that most other industrial areas of the world society simply fade in comparison. Proper housing and the necessary infrastructure for transport, communication, water supply and sanitation, energy, commercial and industrial activities to meet the needs of the growing world population pose the major challenge. The Habitat II Agenda lays stress on the fact that the construction industry is a major contributor to socio-economic development in every country. The construction industry and the built environment must be counted as two of the key areas if we are to attain a sustainable development in our societies.* (CIB, 1999, p.17).

Haagenrud (Jernberg, Lacasse, Haagenrud, and Sjöström, 2004, p.2-1) noted that more than 50% of developed countries' real capital is represented by building stock and infrastructure. The current deteriorating state of the built environment after the *"build and let decay"* age during the past 30 years, has created *"an enormous economic, cultural and environmental problem"* resulting in the demand for reliable service life data becoming a driving force to continued research in this area.

Hövde (Hövde and Moser, 2004, p.9) points out that internationally the built environment is responsible for vast consumption of material and energy, many non-renewable, and waste to landfill deposits, and *"... even a limited reduction in the values for material and energy consumption, or waste, nonetheless represents significant values that have potential for greatly affecting the sustainability of building and construction activities."* This view is supported by Haagenrud (Jernberg *et al.*, 2004, p.2-1) who stated that the *"wasteful consumption of energy and materials linked to the degrading built environment makes this a major environmental problem in the context of sustainable development."*

According to Hövde (Hövde and Moser, 2004, p.9) the need to determine durability and service life is based on the following two aspects:

- **Environmental issues –** scarcity of material and energy resources and the building and construction sector as a big consumer of these resources, and the environmental impact caused by buildings
- **Economic issues** – the total value of the built environment on a national level and the value of each specific unit (buildings, structures, roads, bridges, quays, etc.) for the owners (government, private sector or individuals). The conditions of the built environment, the annual costs of management and maintenance and the life cycle costs are of major importance be it for the economy of a country, or maintaining competitiveness within an industry or corporation.
-

He concludes that *"an ability to understand what influences durability and service life of materials, components and structures, to develop more durable materials and components and to establish reliable methods for testing of durability and for prediction of the service life"* could contribute towards addressing environmental problems in the context of sustainable development.

According to Jernberg *et al* (2004, p.3) the development of service life prediction methodologies has now reached the point where *"the possibility of standardising methodologies and incorporating predictions of the service lives of materials and components into the design process for whole buildings is being given serious attention."*

During 1982, the International Council for Research and Innovation in Building and Construction (CIB) and the International Association for Building Materials and Structures (RILEM) established a joint activity on the Prediction of Service Life of Building Materials and Components, denoted W080 and 71-PSL (Prediction of Service Life) within CIB and RILEM, respectively. Between 1982 and 1986, the focus was on describing the state of the art of the research area, and proposed a generic methodology for the prediction of service life. During the period 1987 to 1990 the work centred on developing methodologies for generating data from long-term ageing studies of materials and components in actual, 'in-use', conditions. The focus then shifted to prediction of service life of building materials and components during the third period between 1991 and 1996, followed by additional information subsequently provided in the period between 1997 and 2002. The work of the present committee will continue to refine existing prediction and service life techniques, tools and methods. *"However, the new committee will make efforts towards further development of service life prediction methods in the context of emerging information technologies (IT)."* (Jernberg *et al*, 2004, p.4)

Several initiatives and activities at both the international and national level that illustrate the importance of these issues are listed by Hövde (Hövde and Moser, 2004, p.11-13) and include the following:

- Agenda 21 for a global sustainable development initiated at the UN Conference on Environment and Development (UNCED), Rio de Janeiro, Brazil, in 1992.
- International research and development activities within CIB, in partnership with RILEM.
- RILEM's publication of a Recommendation for prediction of service life of building materials and components which was the basis for the development of standards for service life prediction within the International Organization for Standardization (ISO).
- International Standardization Organisation's (ISO) publication of ISO 6241, a standard describing the principles for preparation of performance standards in buildings and factors that must be considered, ISO 15686-1:2000, Buildings and Constructed Assets – Service Life Planning – Part 1: General Principles, and ISO 15686-2:2001, Buildings and Constructed Assets – Service Life Planning – Part 2: Service Life Prediction Procedures.
- The Construction Products Directive (CPD) (Directive 89/106/EEC adopted by the Commission of the European Union in 1988.
- Development of European Standards within the European Committee for Standardization (CEN).
- The establishment of the European Organization for Technical Approvals (EOTA) under the provisions of the EU Council Directive 89/106/EEC (Construction Products Directive) and publication of a document that describes how to assess the working life of products related to durability.
- The publication of a Guidance Paper regarding durability and the Construction Products Directive in 1999 by the EU Commission.

- Work that has been carried out for decades in Japan on how to deal with methods to predict the durability and service life of materials and buildings both in the planning and the management phase of a building.
- Results of a national study regarding needs for research and development to upgrade the civil infrastructure published in 1993 in the U.S.
- Initiatives in countries such as New Zealand (Building Code published in 1992, introducing quantitative requirements for the service life of building components), the United Kingdom (a national standard for prediction of durability and service life of buildings and building elements, products and components published in 1992), and similar standards in Canada (1995) and Norway (1994 and 1995).

The immense importance of service life prediction towards the development of a sustainable built environment is quite evident from the above-mentioned international initiatives. However, service life prediction goes far beyond a mere prediction of service life, it forms the backbone of sustainable development.

According to Kirkham *et al* (2004a) and Kirkham *et al* (2004b) the emergence of Private Finance Initiative (PFI) and Public Private Partnerships (PPP) *"procurement routes in particular have focused clients and designers to think 'whole life cycle' rather than on a short-term basis."* This paradigm shift *"has placed a heavy emphasis upon the need to manage projects effectively based upon sound risk management and quantification techniques as well as robust and articulate methods of appraising the long-term cost effectiveness of design decisions."*

> *This shift of emphasis within the UK has been lead in part by a government commitment to challenge the way organisations deliver services, and has placed on them a duty to continuously improve in order to provide the services that people require economically, efficiently and effectively. This concept of "best value" has dominated public sector capital investment policy in the UK since the 1990s. This has been the case particularly in large buildings and civil infrastructure projects such as hospitals, prisons and highways. As a result of the fundamental revisions in public procurement policy that have subsequently taken place, interest and demand for the use of Whole Life Cycle Costing (WLCC) techniques has risen to unprecedented levels.* (Kirkham *et al,* 2004a)

In the South African context the implementation of PFI's and PPP's is a slow process linked to the political processes peculiar to South Africa. There is however a move towards a performance based or outcomes based contract. Routine road maintenance has gone a long way down this route and there is a very strong social motive for human capital development and development of SMME's.

Unfortunately this process has not moved fully to outcomes based contracting or PPP's and only hybrids are in place. The biggest problem is sustainability of budgets. At local authority level problems are even bigger due to insufficient and incompetent human resources and funding, which is unique to the South African environment. In the South African context this is a study field on its own and it will be difficult to address this within the scope of this thesis.

2.3. Service Life and Durability of Building Materials and Components

Service Life is defined by ISO 15686-1:2000 as the *"period of time after installation during which a building or its parts meet or exceeds the performance requirements"* which is the *"minimum acceptable level of a critical property"* or *"inherent or acquired attribute of a building or a part of a building that has an acceptable value if its required function is to be fulfilled."* Moser (Hövde and Moser, 2004, p.60) defines service life as *"the point in time, when the foreseen function is no longer fulfilled."*

The objective of service life planning, as stated by ISO 15686-1 (2000, p.7) *"is to assure, as far as possible, that the estimated service life of the building or component will be at least as long as its design life."* Service life prediction is defined as *"A generic methodology which, for a certain or any reasonable performance requirement, facilitates a prediction on the service life distribution of a building or its parts for the use in a certain or in any reasonable environment"* (Jernberg *et al*, 2004, p.10).

According to Jernberg *et al* (2004, p.1-1) the objective of service life analysis is to establish and explain the performance-over-time functions, which *"describe how the measured values of some chosen performance characteristics are expected to vary with time. Performance characteristics are measurable, physical quantities corresponding to the critical properties identified for the component in its application. With performance-over-time functions established for the range of in-use conditions considered and agreed performance criteria, all essentials are known to make a service life prediction."*

They used Figure 2-1 below to show some hypothetical performance-over-time functions for a component in a certain service environment, which describes statistical distributions of performance characteristics. The use of a performance criterion suggests a minimum acceptable performance standard, which means that although the building or component might still be functional or operational below this value, the performance might no longer be acceptable for the intended function.

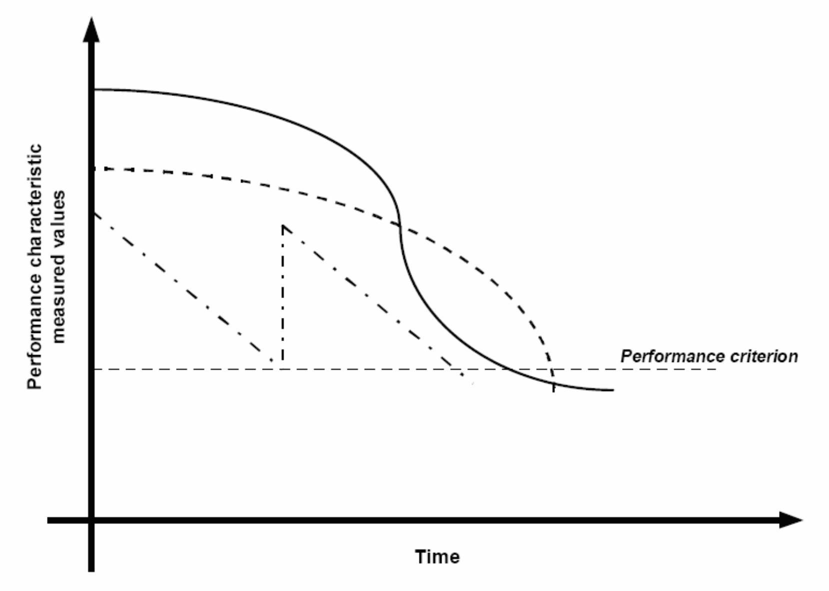


Figure 2-1: Hypothetical performance over time functions (Jernberg *et al*, 2004, p.1-1)

The design life of hospitals varies between 50 to 60 years, according to the Capital Investment Manual: Business Case Guide (1995, p.37) and the Design Brief Working Group (2002). Aikivuori (1999), cited by Moser (Hövde and Moser, 2004, p.59), claimed that the limiting factor for service life is in most cases not durability. This is especially true in the case of health care facilities, where development and innovation in modern medical and health care technology often render buildings or components obsolete before it has reached the end of its service life.

There appears to be a similarity between the approach used to determine design periods and strategies for roads and service life prediction for buildings. In Figure 2-2 below, the CSIR (1985, p.6) produced generalised performance over time curves for roads in South Africa, clearly showing the effect of maintenance and rehabilitation on the performance of the road, in this case riding quality.

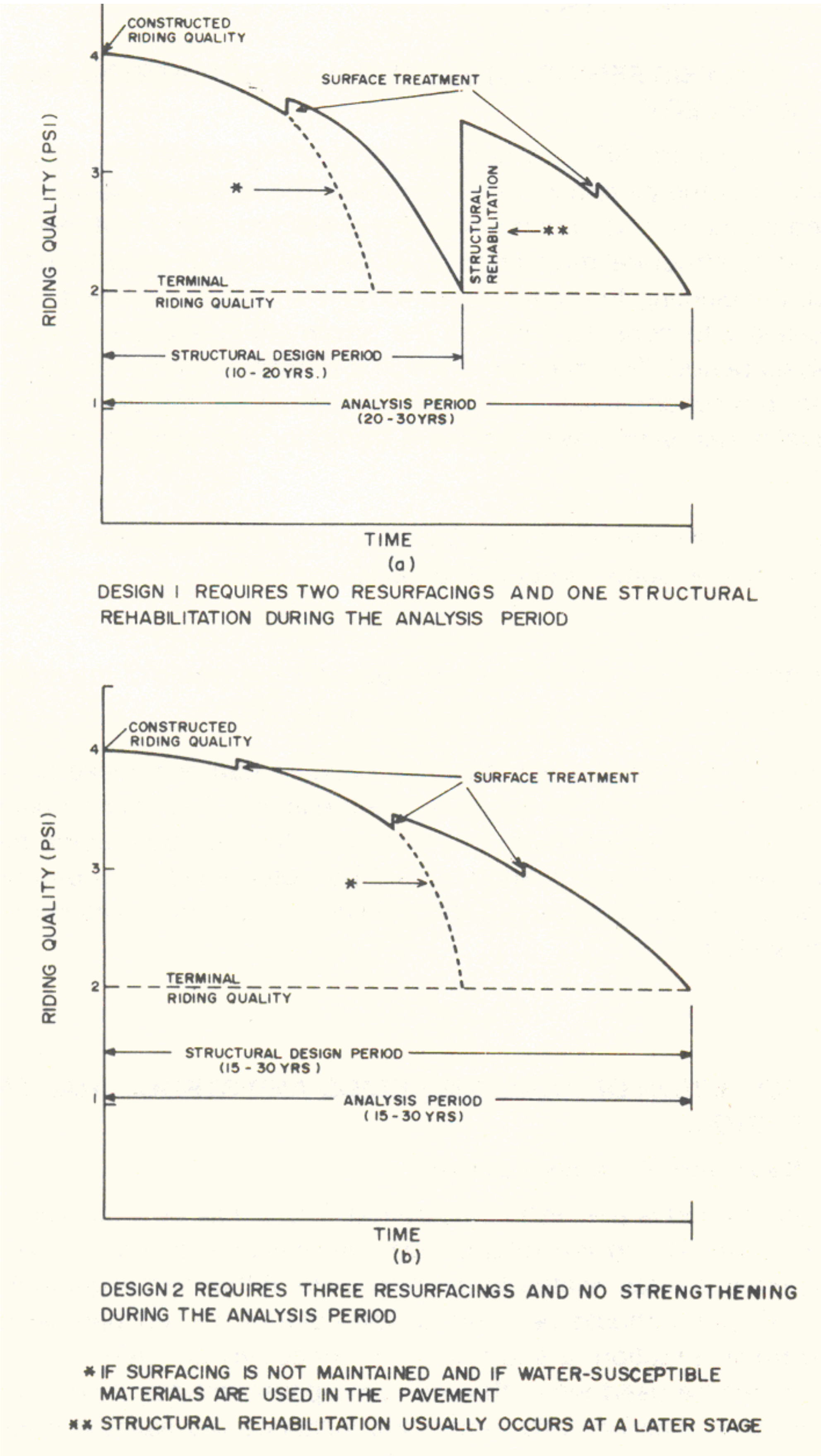


Figure 2-2: Typical performance over time curves for roads (CSIR, 1985, p.6)

The minimum performance level is defined as terminal riding quality, which corresponds to the performance criterion in Figure 2-1 above by Jernberg *et al* (2004). The riding quality unit is present serviceability index (PSI), measured on a scale from 5 to 0, with the terminal riding quality varying between 2.5 and 1.5 PSI. It is interesting to note the use of two periods: the structural design period and the analysis period. Structural design period is defined as *"the period during which it is predicted with a high degree of confidence that no structural maintenance will be required"*, while the analysis period is *"a convenient planning period during which full reconstruction of the pavement is undesirable."*

Haagenrud in Jernberg *et al* (2004, p.2-6) states that chemical or physical deterioration or corrosion in most cases cause materials degradation and loss of characteristic properties, as described by performance over time functions.

Hövde (Hövde and Moser, 2004) devotes a whole chapter to the need for service life prediction tools. Some of the specific requirements for service life prediction in Europe, New Zeeland, Canada, EU, ISO and EOTA are presented. Typical design service life categories for buildings from the Canadian, European, ISO and EOTA codes and guidelines are shown. He concludes, *"Life Cycle Assessment (LCA) can be an important tool that is typically used for establishing more sustainable construction activities and achieving sustainable buildings. (….) The introduction of LCA into the building and construction sector will therefore increase the need for service life prediction of construction products."*

Durability is defined as the *"capability of a building or its parts to perform its required function over a specified period of time under the influence of the agents anticipated"* (ISO 15686-1:2000). According to Hövde (Hövde and Moser, 2004, p.9) sustainability, service life, cost of repair and refurbishment, and environmental impact are influenced by durability.

Moser (Hövde and Moser, 2004, p.59) cites Aikivuori (1999), who pointed out *"that service life limited by durability is seldom reached, as components are refurbished earlier due to other reasons. In most cases the limiting factor for service life is not durability."*

2.4. Degradation

The Oxford Dictionary defines degradation as a term used to describe the process to *"break down or deteriorate chemically,"* and according to ISO 15686-1:2000(E) it is *"changes over time in the composition, microstructure and properties of a component or material which reduce its performance"*. According to Jernberg *et al* (2004, p.7) it is the reduction in the ability of a building or component over time to fulfil its functions under the intended use conditions.

Degradation is, according to Hövde and Moser (2004, p.62), and Mishalani and Madanat (2002, p.139), regarded as a stochastic process. Jernberg *et al* (2004, p.1-12) states that a performance-over-time function *"is a complicated, non-linear, multivariate function of time as well as of agent intensities or combinations of such agent intensities."*

2.4.1. <u>Degradation Agents</u>

According to Jernberg *et al* (2004, p.1-18) the origin of external degradation agents is either the atmosphere or ground, which *"mostly involves complicated chemical and/or physical processes governed by a great number of degradation agents"* while occupancy, design and installations are the main sources of internal degradation agents. It is also possible that a design consequence could result in an agent acting externally, while 'external' agents could influence internal degradation.

The nature and class of degradation agents affecting the service life of building materials and components are identified by Jernberg *et al* (2004, p.1-5) in Table 2-1 below.

Nature	Class
Mechanical agents	Gravitation, forces and imposed or restrained deformations, kinetic energy, vibrations and noises
Electromagnetic agents	Radiation, electricity, magnetism
Thermal agents	Extreme levels or fast alterations of temperature
Chemical agents	Water and solvents, oxidising and reducing agents, acids, bases, salts, chemically neutral
Biological agents	Vegetable, microbial and animal

Table 2-1: Degradation agents affecting the service life of building materials and components (Jernberg *et al*, 2004, p.1-5)

Jernberg *et al* (2004, p.1-6) also states that although limitations of the knowledge available will always exist, identification of all reasonable possible degradation mechanisms and effects by which the identified degradation agents are known or believed to induce changes in the properties and performance of the component should be identified. An important consideration highlighted by Jernberg *et al* (2004, p.1-19) is combined degradation agents and combination of degradation agents:

> *Some agents are combined by more than one co-existing factor, e.g. an imposed force such as freeze-thaw stress is due to cycling temperature and to the presence of water. At the same time, water solely is a chemical agent. Temperature itself is the thermal agent, while for many chemical reactions the temperature is decisive for the reaction rate. Other agents of the same or different nature can give rise to significant synergistic effects, e.g. sulphur dioxide together with nitric oxides, and UV radiation together with oxygen (photo oxidation).*

Chemical and physical incompatibility between dissimilar components is another important issue that should be considered. *"Incompatibility includes, for example, corrosion caused by contact between dissimilar metals or stress caused by different thermal expansion coefficients of rigidly connected dissimilar components."* (Jernberg *et al*, 2004, p.1-20)

2.4.2. Climate

According to Eurin *et al* (1985) cited by Jernberg *et al* (2004, p.1-18) *"every attempt in practice to measure and describe the degradation environment is an approximation and simplification."*

Haagenrud from the Norwegian Institute for Air Research (NILU) in Jernberg *et al* (2004, p.2-9 and 2-19 to 2-46) elaborates on the characterisation of key environmental degradation factors and discusses climatic ranges in detail. In Figure 2-3 below, he illustrates the different levels of climatic classification based on macro, meso and microclimate. *"This division means a definition of different scales describing the variations in the meteorological variables. There exist no common and exact definitions of the different scales."*

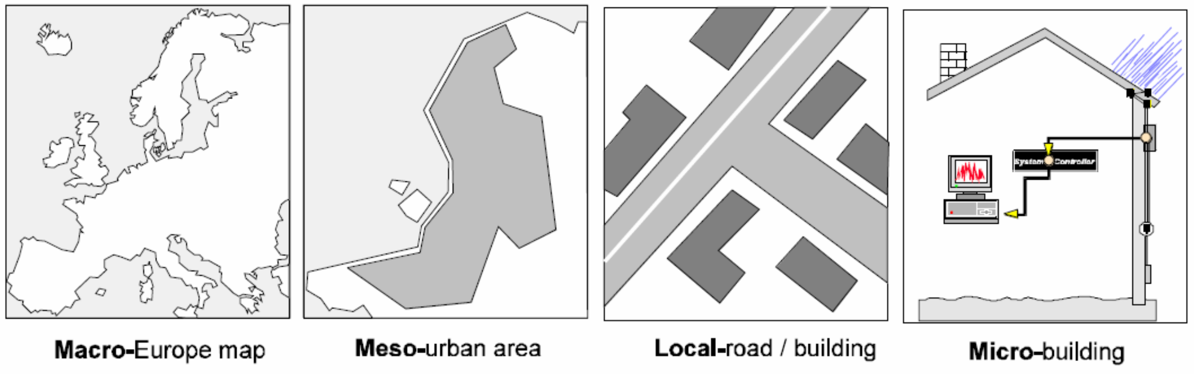


Figure 2-3: Exposure environment on different geographical scales (Source: Jernberg *et al*, 2004, p.2-9)

The macroclimate describes the gross meteorological conditions *"in terms like polar climate, subtropical climate and tropical climate. The descriptions are based on measurement of meteorological agents such as air temperature, precipitation etc."* The meso climate takes "the effects of the terrain and of the built environment" into account, while *"the climatological description is still based on the standard meteorological measurements."* The local scale describes, *"The local conditions in the building proximity, such as for example in the streets around the building."* The meteorological variables in the absolute proximity of a material surface are described by the microclimate, which *"is crucial to understanding and estimating material degradation. The most important variables describing microclimate include relative humidity, surface moisture, surface temperature, irradiation and deposition of air pollutants. ... The actual in-use condition relevant to materials degradation is the microclimate, i.e. the prevailing environmental condition in a layer adjacent to a component surface. ... As weather does not repeat itself — i.e. every year is not a standard year — one has to be cautious in drawing conclusions from one exposure period to another."* (Jernberg *et al*, 2004, p.2-9)

Haagenrud (Jernberg *et al*, 2004, p.2-8) states that the choice of degradation indicators and establishment of performance requirements are limited due to the currently available dose-response functions.

> *Another major barrier to reliable predictions of service life and/or maintenance intervals is insufficient knowledge of the relevant exposure environment. However, substantial knowledge and data exist on the environmental exposure conditions on the macro and meso level. It is a serious problem that these tend to be in a generalised form such as a contour map of average data, for example mean temperature, humidity etc., while researchers and designers need to consider the specific form, for instance time of*

wetness .... and also the local- and micro-environmental conditions of the building. A third barrier is just this adaptation of data and knowledge to the local and micro environmental conditions. The complexities of a structure can result in very different climatic and environmental conditions on a single structure and greatly affecting damage rates.

According to Durango and Madanat (2002, p.765) there exists an uncertainty in generating a set of parameters for a deterioration model, reflecting the effect of deterioration (degradation) factors, which can be attributed to:

a.) Exogenous factors: Uncertainty in predicting the environmental and level of utilisation factors produces uncertainty in the parameters of the deterioration model.
b.) Endogenous factors: Unknown variability in facility design and materials can make similar facilities respond differently to the same exogenous conditions.
c.) Statistical factors: Limited size and variability of data used to generate deterioration models are often complemented by experience (expert opinion).

On the impact of the climate on road materials in South Africa Weinert (1980, p.19) states the influence of the environment on the life and performance of a road is often greater than realized. Observed variations in the performance of weathered dolerite used in road construction in different parts of the South Africa eventually culminated into the development of Weinert's climatic N-value, which is expressed by the following formula:

$$\mathbf{N} = \frac{12E_J}{P_a}$$

where E_J is the computed evaporation from a shallow free water surface during January (warmest month), and P_a is the total annual precipitation

There was a marked difference in the performance of dolerite when used in road pavements to the east and west of an imaginary north-south line running from Port Elizabeth through Bloemfontein to Mafikeng. This line has an N-value of 5 as shown in Figure 2-4 below. To the east of this line where $N < 5$ the performance was unsatisfactory, while to the west where $N > 5$ the performance was satisfactory.

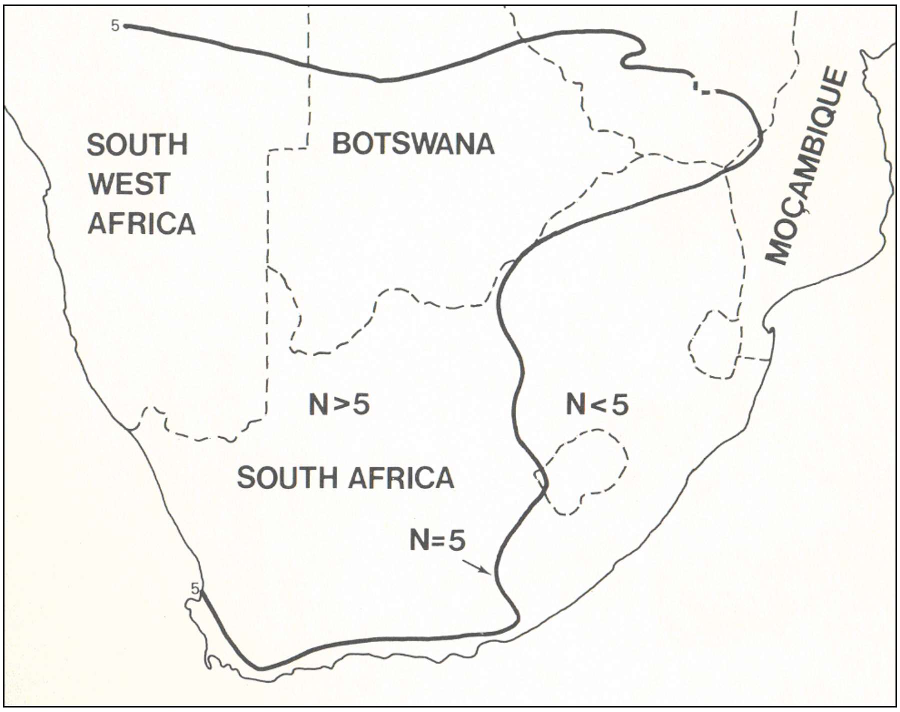


Figure 2-4: Weinert's Climatic N-values (Source: Brink, 1978, p.31)

Brink (1978, p.30) also refers to Weinert who *"has demonstrated that mechanical disintegration is the predominant mode of rock weathering in areas where his climatic N-value is greater than 5, whereas chemical decomposition predominates where the N-value is less than 5."*

On climatic regions and the design of road pavements the CSIR (1985, p.26) states that the environment under which a road functions is defined by the climatic conditions (moisture and temperature) and must be taken into account in the structural design of the pavement. The influence of the climate on the equilibrium moisture content and the weathering, durability and stability of natural road building materials is discussed. The climatic conditions should always be considered and the use of excessively water-susceptible or temperature-sensitive materials in adverse conditions should be avoided.

In Figure 2-5 below the three macroclimatic regions of Southern Africa is shown. In the western region, which has a dry climate with N > 5, mechanical degradation is dominant. The southern and central region is smaller and a transitional zone with a moderate climate, where both mechanical and chemical degradation take place. The eastern region has a wet climate with an N-value < 5, where chemical degradation is dominant. This demarcation is based on the weathering of natural road materials such as dolerite, which is a natural rock occurring throughout South Africa. Some of the materials used in the built environment are also natural materials and these three macroclimates could therefore also apply to these natural materials.

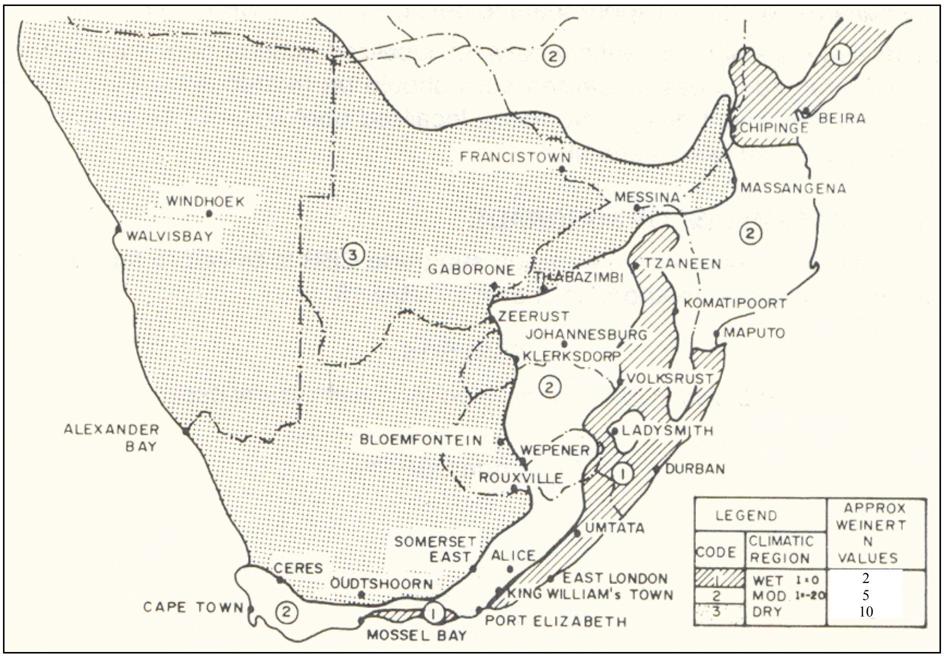


Figure 2-5: Macroclimatic Regions of Southern Africa (Source: CSIR, 1985, p.27)

The mean annual rainfall, evaporation and temperatures for South Africa are shown in Figures 2-6 to 2-8 below. It is interesting to note the correlation with the three macroclimatic zones shown in Figure 2-5 above.

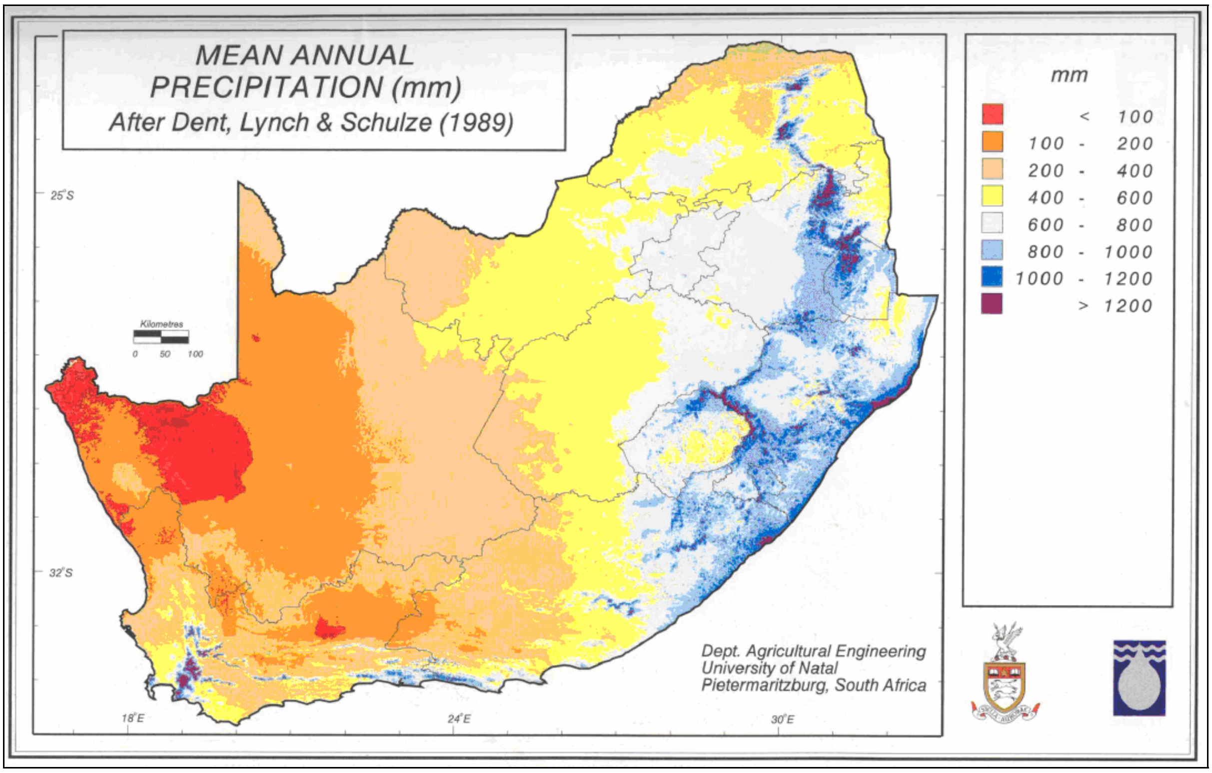


Figure 2-6: Mean Annual Precipitation for South Africa (source: University of Natal)

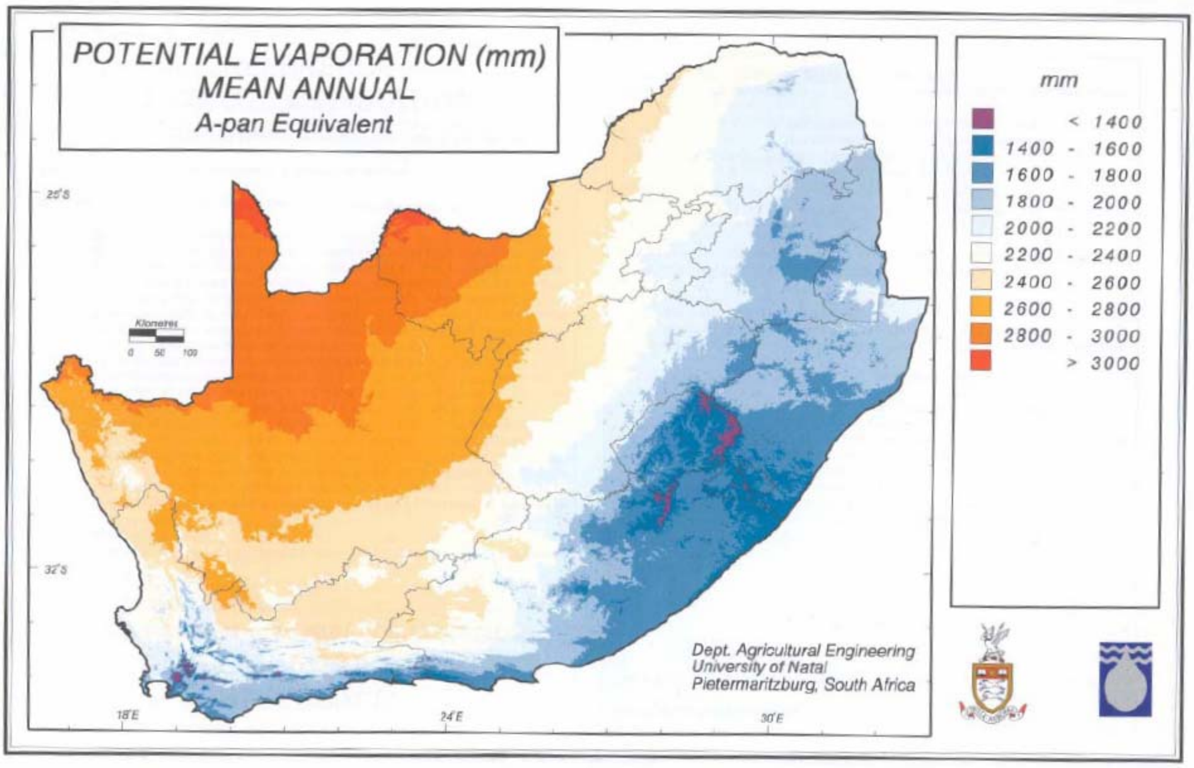


Figure 2-7: Mean Annual Potential Evaporation for South Africa (source: University of Natal)

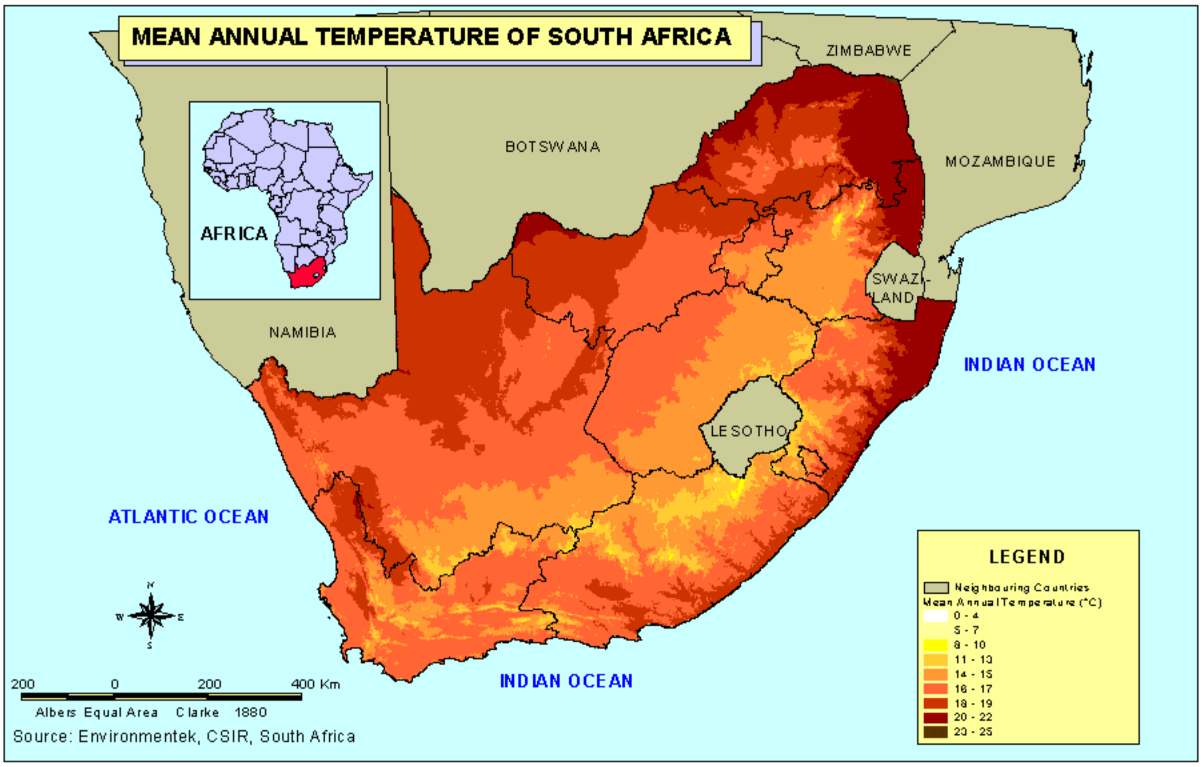
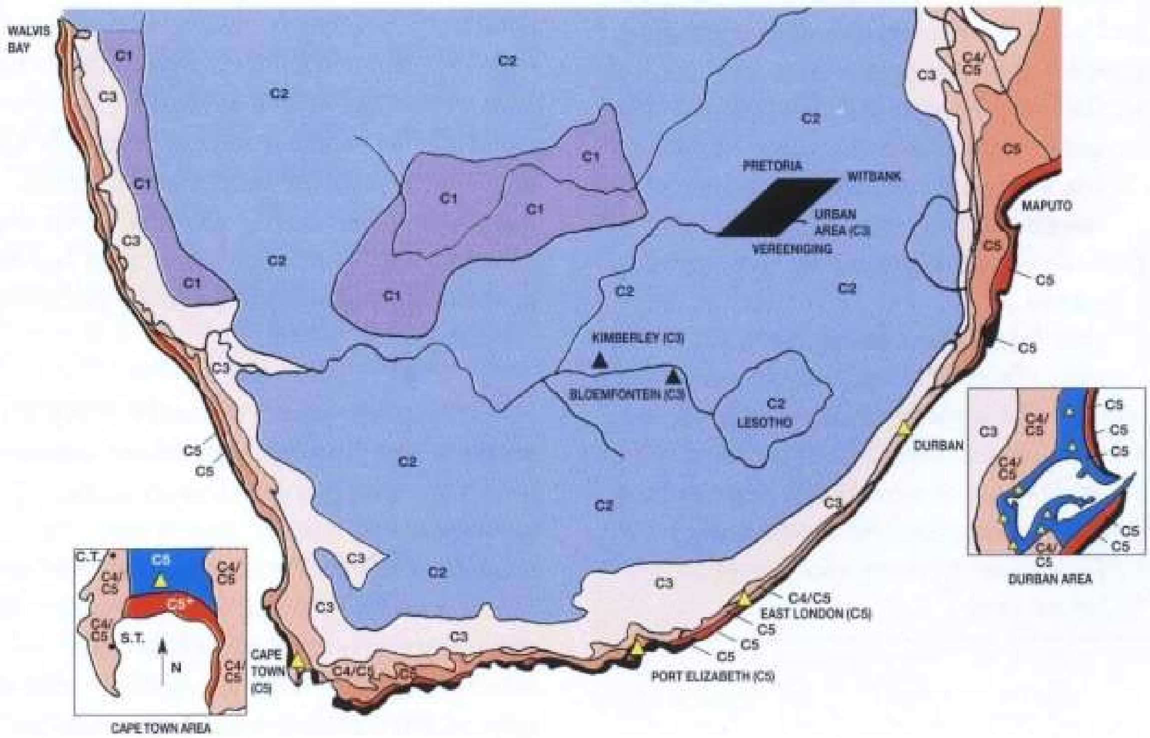


Figure 2-8: Mean Annual Temperatures (Source: CSIR)

In Figure 2-9 below a map indicating the atmospheric corrosion of zinc is shown as an example of the influence of the environment on the degradation of metals. The corrosion rate of uncoated mild steel is also given.

ATMOSPHERIC CORROSION OF ZINC



CATEGORY	DESCRIPTION	LEGEND	SEVERITY OF CORROSION	CORROSION RATE UNCOATED MILD STEEL	ZINC COATING LOSS
C5+	USUALLY LESS THAN 50m FROM H.W.M.		SEVERE MARINE	+300µm/ YEAR	> 30µm/ YEAR
C5	USUALLY 50m TO 1km FROM H.W.M.		MARINE	200 - 300 µm/YEAR	15 - 30 µm/ YEAR
C4/C5	1km TO 40km FROM SEA		AVERAGE MARINE	20 - 200 µm/YEAR	2 - 15 µm/ YEAR
C3	40km TO 100km FROM SEA		MILDLY MARINE	10 - 20 µm/YEAR	1 - 2 µm/ YEAR
C2	INLAND		RURAL	LESS THAN 10µm/YEAR	< 0.8 µm/ YEAR
C1	INLAND		DESERT	LESS THAN 5µm/YEAR	< 0.5 µm/ YEAR
C3	URBAN INLAND		INDUSTRIAL	10 - 30 µm/YEAR	1 - 3 µm/ YEAR
C5	URBAN COASTAL		MARINE INDUSTRIAL	50 - 150 µm/YEAR	5 - 15 µm/ YEAR

H.W.M - HIGH WATER MARK

Figure 2-9: Atmospheric corrosion of zinc

(Source: [web page], http://www.ckit.co.za/Secure/Conveyor/Troughed/corrosion%20protection/Steel%20Protection/Steel%20Protection%20-%2013%20Corrosion%20Resistance.htm. Date accessed: 18 November 2005)

2.4.3. Evaluation of degradation

Hövde (Hövde and Moser, 2004, p.23) cites BS 7543:1992, Guide to Durability of Buildings and Building Elements, Products and Components, which states that:

> *Prediction of durability is subject to many variables and cannot be an exact science. Accelerated testing of components by itself can seldom be used to give an accurate basis for predicting service life. …*
>
> *Whatever method is used to assess it, the predicted service life is unlikely to be a precise figure because the effect of an action in any building is not likely to be accurately predictable. More reliable predictions can be made when there is a correlation between the results of different assessments.*
>
> *The interpretation of data from tests requires skill and experience and knowledge of building maintenance. It is often necessary to rely on an informed opinion for service life prediction.*

Hövde (Hövde and Moser, 2004, p.25) also cites Canadian Standard CS 478-95, which states, *"the predicted service life of any building component, including repaired as well as new components, is approximate based on the assumed environmental conditions and on installation, operating and maintenance procedures."*

Change in condition over time seems to be a common accepted method to evaluate degradation (Mishalani and Madanat (2002, p.139); Coombes *et al* (2002); Morcous *et al* (2003, p.353)). Jernberg *et al* (2004, p.1-30) states that the purpose of the investigation determines the information required, which usually includes the change in material properties over time, the cause of failure and the effect thereof. The following example of evaluation levels for condition is presented:

- Condition 0: Intact, no changes
- Condition 1: Minor damages, some maintenance is suggested
- Condition 2: Malfunction, maintenance needed as soon as possible
- Condition 3: Out of order, replace or repair immediately

Another example of degradation evaluation used for the BELCAM project by the NRCC is presented by Lounis *et al* (1998a, p. 9) in Table 2-2 below.

Condition rating	Condition/state description	Damage (%)
7	Excellent : No noticeable distresses/anomalies.	0-10
6	Very Good: Minor anomalies (e.g. small blisters)	11-25
5	Good: Presence of some distresses (ridges).	26-40
4	Fair: Moderate deterioration; Water tightness is still adequate.	41-55
3	Poor: Major deterioration; Potential loss of water tightness	56-70
2	Very Poor: Extensive deterioration; Localized water leakage	71-85
1	Failed: Extensive water leakage.	>85

Table 2-2: Condition Assessment of Built-up Roofing Membranes (BELCAM Project)

Morcous *et al* (2003, p.354) cites Lipkus (1994) and Thompson *et al* (1998) for a 1 to 5 rating system used for bridge decks, where state 1 represents the condition of a new undamaged element, state 5 represents a severely deteriorated element, and states 2, 3, and 4 represent intermediate levels of damage. A 1 to 6 system used by the Ministe´re des Transports du Que´bec (MTQ) is also presented.

Madanat *et al* (1995) and Madanat *et al* (1997) present examples of road pavement (1 to 8) and bridge deck (0 to 9) condition ratings.

During 1995 and 1996 the CSIR was commissioned by the National Department of Health to undertake the National Health Facilities Audit (NHFA). For this project, which looked at the condition, suitability and other characteristics of health facilities in South Africa, the CSIR used a five-point rating system to assess the condition and suitability. The original ratings have since been adjusted and redefined, see Table 2-3 below, and used with great success in subsequent audits of health and other government facilities. The objective was to define the ratings in such a way as to ensure common interpretation by assessment staff and users of the information generated by the process. The introduction of colour coding attached to the ratings ensured maximum user friendliness, especially to people without a built environment background (such as medical, education, financial, etc.) and improved communication, which was identified by Mc Duling (2003) as one of the major problems in the built environment.

CONDITION RATING	Condition	Action Required	Description
5	Very Good	Planned Preventative Maintenance	The component or building is either new or has recently been maintained, does not exhibit any signs of deterioration
4	Good	Condition-based Maintenance	The component or building exhibits superficial wear and tear, minor defects, minor signs of deterioration to surface finishes and requires maintenance/servicing. It can be reinstated with routine scheduled or unscheduled maintenance/servicing.
3	Fair	Repairs Required	Significant sections or component require repair, usually by a specialist. The component or building has been subjected to abnormal use or abuse, and its poor state of repair is beginning to affect surrounding elements. Backlog maintenance work exists.
2	Bad	Rehabilitation Required	Substantial sections or component have deteriorated badly,suffered structual damage or require renovations. There is a serious risk of imminent failure. The state of repair has a substantial impact on surrounding elements or creates a potential health or safety risk.
1	Very Bad	Replacement Required	The component or building has failed, is not operational or deteriorated to the extent that does not justify repairs, but should rather be replaced. The condition of the element actively contributes to the degradation of surrounding elements or creates a safety, health or life risk.

Table 2-3: Condition Ratings (Abbott & Mc Duling, 2004)

2.5. The Factor Method

Hövde (Hövde and Moser, 2004, p.29) refers to the Japanese Principal Guide for service life planning of buildings, based on decades of development and published in 1989, followed in 1993 by a shorter version in English (AIJ 1993), which promoted the use of the Factor Method for service life prediction. The Guide identifies the following classification concerning the deterioration factors:

a) Items relating to the inherent (durability) characteristics of performance over time:

1) Performance of materials

2) Quality of designing

3) Quality of construction work

4) Quality of maintenance and management

b) Items relating to the environmental deterioration factor:

1) Site and environmental conditions

2) Condition of building

The starting point of the factor method is the reference service life, which is defined as *"a documented period in years that the component or assembly can be expected to last in a reference case under certain service conditions."* (Jernberg *et al*, 2004, p.1-15). According to Hövde (Hövde and Moser, 2004) there are three different types of service life prediction methods: research or probabilistic methods, deterministic methods and engineering methods. The Factor Method for the calculation of the Estimated Service Life of a Component (ESLC), as defined in ISO 15686–1:2000, is based on the deterministic approach and given by the following formula:

ESLC = RSLC x factor A x factor B x factor C x factor D x factor E x factor F x factor G.

- factor A: quality of components
- factor B: design level
- factor C: work execution level
- factor D: indoor environment
- factor E: outdoor environment
- factor F: in-use conditions
- factor G: maintenance level,

where RSLC is the Reference Service Life of the Component.

Factor A: Quality of components: It is a measure of the quality of the design, the materials used, the manufacturing and assembly of the component as supplied to site.

Factor B: Design level: It is a measure of the level of protection and shelter or exposure to degradation agents offered to the component by the design in terms of installation.

Factor C: Work execution level: This factor is determined by the quality of workmanship and control of the site work based on the likelihood of achieving the manufacturers' recommendations and the specified level of workmanship, *"including issues such as storage, protection during installation, ease of installation, number of trades required for each activity, site applied coatings etc."* and the level of control on site.

Factor D: Indoor environment: This factor is a measure of the exposure to and severity of internal degradation agents, based on the use of the building or space providing for locations subject to wetting, steam and temperature, such as kitchens, bathrooms and cold rooms.

Factor E: Outdoor environment: This factor is a measure of the exposure to and severity of external environment degradation agents, and although an assessment at meso level may be adequate, the impact of the macro- and microclimates should also be taken into consideration.

Factor F: Maintenance level: The assessment of this factor is based on the planned or actual level of maintenance and the likelihood of that being achieved for the type of building under consideration. Accessibility and requirement for special equipment for access, and the expertise of cleaning should also be taken into account. (Jernberg *et al*, 2004, p.1-16)

The quality of the fabric, material and workmanship in the initial construction and subsequent maintenance also has a major affect on the resistance of the building to the environment. It is interesting to note that according to Seeley (1987, p.6 - 7) hospitals built in Britain during the 1960's and 1970's can cost up to three or four times as much to maintain as older hospitals because of the experimental methods by which many were constructed. He also points out that the appalling state of repair of many of Britain's school buildings is *"rooted in the educational building boom of the 1960's when decades of common sense in materials and detailing were discarded in favour of non-durable and inadequately researched materials, poor and sometimes 'unbuildable' detailing, and lax supervision of construction."*

Human processes are a very important influence on degradation of public buildings. According to Lee (1981, p.1):

> *The built environment expresses in physical form the complex social and economic factors which give structure and life to a community. The condition and quality of buildings reflect public pride or indifference, the level of prosperity in the area, social values and behaviour and all the many influences both past and present, which combine to give a community its unique character. There can be little doubt that dilapidated and unhealthy buildings in a decaying environment depress the quality of life and contribute in some measure to antisocial behaviour.*

This also applies to South Africa, where cultural differences and perceptions are prominent. There is a general lack of understanding of the need for maintenance, aggravated by a culture of vandalism stemming from the apartheids era when vandalism of public buildings (houses, schools and hospitals in particular) was part of the freedom struggle.

The factor method considers each of the variables that are likely to affect service life, but provides only an empirical estimate of the service life based on what information is available. Hövde (Hövde and Moser, 2004, p.38) refers to Aarseth and Hövde (1999) who applied a *"step-by-step"* principle, which *"enables a stochastic handling of the modifying factors in the ISO factor method by performing a triple estimate for each factor. After the statistical calculation the estimated service life is expressed as three figures: the expected value plus/minus one standard deviation."*

Moser (Hövde and Moser, 2004, p.81) has also carried out an evaluation and improvement of the factor method by use of statistical methods. He applied an individual statistical treatment of each factor and employs variables with density-functions instead of plain figures.

> *The variables are based on data given by the manufacturer, by tests, by experience, by expert opinion, and others. Reliable data from expert opinion can be derived by application of the so-called recursive Delphi method. Experts are required to estimate the minimum (say 5%), the average (50%) and the maximum (say 95%) fractals of the variable considered. These estimates are fitted into density distributions of any kind such as: standard, symmetric, asymmetric, custom-defined, or others (or even deterministic, here for design level).*

Hövde (Hövde and Moser, 2004, p.39) cites Rudbeck (1999) who states that *"From a statistical point of view"* Moser's statistical approach *"seems to be the most reliable."* According to Hövde (Hövde and Moser, 2004, p.41) the lack of knowledge of the Factor method among practitioners has limited *"widespread practical application of the method."* Moser (Hövde and Moser, 2004, p.62) summarised the main shortcomings of the Factor Method as follows:

- The plain multiplication of factors, which in reality might have a different weight,
- The result being a single figure instead of a result to reflect variance of reality,
- The data still to be accumulated,
- The lack of a direct relation to data gathered e.g. on environment, climate, installation quality, in use conditions, etc. The factors are usually set basing directly on the behaviour of the component in a given set of conditions, rather than basing on the influence of individual parameters such as regimes of rainfall, temperature, wetting time, type of use, etc.
- Considering the efforts in gathering input data, the simple figure result of the factor method, when executed as set out in ISO 15686, seems not to be adequate.

2.6. The Markov Chain

"The Markov Chain is used in the analysis of time dependent systems." (Van As, 2001, p.17-1). A number of studies (Morcous *et al,* 2003, p.353; Lounis *et al,* 1998a, p.1; Rudbeck, 1999 cited by Hövde and Moser, 2004, p.40; Madanat *et al,* 1995, p.120) identified the Markov Chain, a stochastic approach used for simulating the transition from one state (condition) to another over time, as the preferred method to predict service life. According to Kyle *et al* (2002a) *"Markov Chain models are one of the most promising technologies to determine the remaining service life."* Populating the Markov transition probability matrix however remains a challenge (Morcous *et al,* 2003, p.354; Zhang *et al,* 2005).

> *In many processes, significant dependence exists between successive trails or steps that can be identified in a physical process. The state of such systems invariably depends on some parameter, for example time or space. The transition from one state to another, or its corresponding transitional probability, may generally depend on the prior states. If, however, the transitional probability depends only on the current state, the process of change is said to be memoryless and may be modelled by the Markov process.* (Van As, 2001, p.17-1)

2.6.1. Transitional Probability

According to Van As (2000), the transitional probability that a system with *m* possible states will change from state *i* at time t_m to state *j* at time t_n is:

$P_{mn}(ij) = P[X_n = j \,/\, X_m = i]$ $\quad$ *for* $n > m$, where *X* donates the state of the system

If $P_{mn}(ij)$ depends only on the difference in times $k = t_n - t_m$, the Markov Chain is said to be homogeneous and the *k*-step transition probability is then given by:

$P_k(ij) = P[X_k = j \,/\, X_o = i]$ $\quad$ *for* $k > 0$

"This step represents the conditional probability that a homogeneous Markov Chain will change state from state i to state j in k time steps. The one-step transitional probabilities, P(ij), can be summarized in a matrix of m states, called the transitional probability matrix (in which the probabilities in each row add up to 1):"

$$P = \begin{array}{c|cccc|c} & [1] & [2] & \ldots.. & [m] & \\ (1) & P(11) & P(12) & \ldots.. & P(1m) & \\ (2) & P(21) & P(22) & \ldots.. & P(2m) & \\ \ldots & \ldots & \ldots & \ldots.. & \ldots & \\ (m) & P(m1) & P(m2) & \ldots.. & P(mm) & \end{array} \qquad \begin{array}{l} \\ \sum P(1j) = 1 \\ \sum P(2j) = 1 \\ \ldots \\ \sum P(mj) = 1 \end{array}$$

"This matrix represents the probability that a system will change from state i (indicated by round brackets) to state j (indicated by square brackets) in one-step. This process is only homogeneous if the process is independent of the time or the step number."

Van As (2000) states that the probabilities of the initial states of the system are required as additional information for a homogeneous Markov chain:

$$P(0) = [P_0(1), P_0(2) \ldots P_0(m)]$$

Where $P_0(i)$ is the probability that the system is initially in state *i*. In the special case for which the initial state is known to be *i*, $P_0(i) = 1$ and the other probabilities are 0. After one transition, the probability that the system will move from state *i* to state *j* can be determined by using the following event table:

Time 0 states		Transition	Time 1 states	
State *i*	$P_0(i)$	*P(ij)*	State *j*	$P_1(j)$
1	$P_0(1)$	P(1j)	j	$P_1(j) = P_0(1).\ P(1j)$
2	$P_0(2)$	P(2j)	j	$P_1(j) = P_0(2).\ P(2j)$
…	…	…	…	…
m	$P_0(m)$	P(mj)	j	$P_1(j) = P_0(m).\ P(mj)$

The probability that the system will be in state *j* is then determined as the summation:

$$P_1(j) = \sum_{j=1}^{m} P_0(i).P(ij)$$

In matrix notation, the single stage state probability is a vector of probabilities:

$$\mathbf{P}(1) = \mathbf{P}(0).\mathbf{P}$$

Van As (2000) concludes that by repeating the process, it can be shown that the n-stage probability vector is given by:

$$\begin{aligned}\mathbf{P}(n) &= \mathbf{P}(n-1).\mathbf{P}\\ &= \mathbf{P}(n-2).\mathbf{P}.\mathbf{P}\\ &= \mathbf{P}(0).\mathbf{P}^n\end{aligned}$$

2.6.2. Application of the Markov model

According to Davison and Hinkley (1999, p.1) *"The explicit recognition of uncertainty is central to the statistical sciences. Notions such as prior information, probability models, likelihood, standard errors and confidence limits are all intended to formalize uncertainty and thereby make allowance for it. In simple situations, the uncertainty of an estimate may be gauged by analytical calculation based on an assumed probability model for the available data. But in more complicated problems this approach can be tedious and difficult, and its results are potentially misleading if inappropriate assumptions or simplifications have been made."* This is very relevant for building degradation analysis where the opinion of the domain expert and inconsistent field data are often the only source of available data.

Moser (Hövde and Moser, 2004, p.62) stated, *"The Markov model assumes deterioration to be a stochastic process governed by random variables. The structure may be split into a number of components, which deteriorate randomly. The main parameters of the deterioration are established for each component, together with the deterioration variables versus time."*

Moser (Hövde and Moser, 2004, p.66) cited Lounis, Z., Lacasse, M.A., Siemes, A.J.M., and Moser, K. (1998), who stated that:

> *The Markov model considers steadily degrading systems, where for each property, during each time period, a probability of deterioration is defined. This method thus requires sophisticated inputs in the form of probabilities, which are not easily estimated, as they cannot be read directly off the real behaviour of the structure in the field. The Markov model requires an in depth knowledge of the system dealt with or on the other hand has to rely on significant simplifications.*

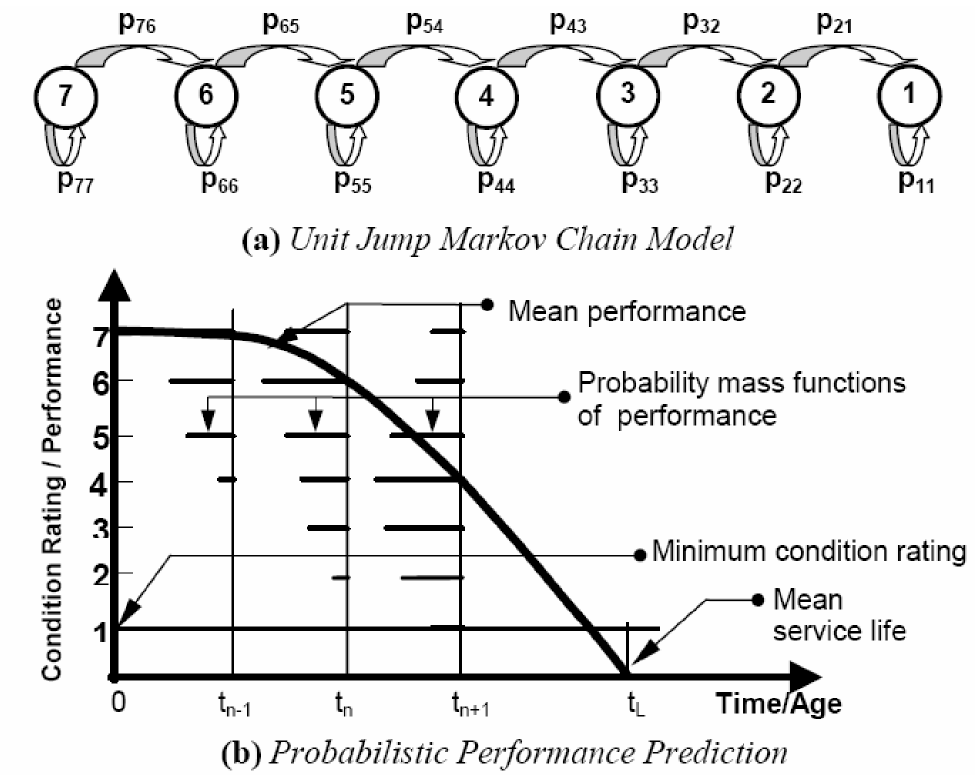


Figure 2-10: Markov deterioration function (Lounis *et al*, 1998, p.5)

In Figure 2-10 above, Lounis *et al* (1998) illustrates the Markov deterioration function. It is assumed that the condition rating can only jump one rating from its current rating to a more deteriorated rating in one time interval or it can stay in its current rating. This implies that the condition can only get worse or stay the same, but cannot improve without deliberate intervention (such as maintenance, repairs, rehabilitation or replacement). In Figure 2-10 (a) p_{77} is the probability that the component under consideration will remain in condition 7 during the interval under consideration, while p_{76} represents the probability that the condition will deteriorate from condition 7 to condition 6 during the same interval.

The following two recent research projects established the Markov Chain as a recognised method for service life prediction:

a.) Service Life Prediction of Roofing Membranes – BELCAM Project

The Building Envelope Life Cycle Asset Management (BELCAM) Project by the NRCC in Canada can be regarded as one of the milestones in the development of service life prediction methods. According to Kyle *et al* (2002a) *"The objectives of the Building Envelope Life Cycle Asset Management (BELCAM) Project were to develop techniques to predict the remaining service life of building envelope components and procedures to optimize their maintenance."* The use of visual inspection techniques to investigate the service life of multi-component systems was a BELCAM first. *"Data were collected on 2800 roof sections from a wide range of systems and climatic regions across Canada"* … *"since the domain of the entire building envelope was too large for the budget of the project."* … *"Markov Chain modelling was used to predict the change in conditions of representative samples; deterioration curves were generated to predict the change in condition, and remaining service life of specific components of the roofing system could be estimated from these data."*

> *Industry will require years if not decades of data collection to have enough data to develop Markov Chain-based service life models in all the important domains. This three-year project barely produced enough data to generate service life curves for the generalized cases for specific types of low slope roofs. In addition, insufficient multi-year data was collected in the term of the project for two principal reasons: (1) there is very little change in the performance in this time frame to warrant annual inspections and (2) inspections are too expensive to carry out annually for every asset type in a large portfolio. In place of multi-year*

> *data, a technique using random sampling of data was used to generate the required deterioration curves.* (Kyle *et al,* 2002a)

Kyle *et al* (2002a) *also* cites Vanier (2001) who recommended *"generalized models for deterioration as temporary substitutes"* should be developed until sufficient data are available.

According to Lounis *et al* (1998b, p.3) *"The performance prediction is based on a probabilistic Markovian model (Ross, 1996) that captures the time-dependence, uncertainty and variability associated with the roof section performance (or condition rating). This model is developed from in-field performance data collected during roofing inspections, considering the system and material types, environmental conditions, age, workmanship quality and maintenance level. "*

Figure 2-10 above illustrates the probabilistic prediction of the performance, *"which indicates the evolution with time of the probability mass function of the roofing performance. Initially, the probability mass is close to condition rating 7. As the roofing component ages and deteriorates, this probability mass shifts from states of high condition ratings to those with lower ratings."*

> *"The transition probability matrix is determined from the historical performance data collected during inspections. The proposed model enables the forecast of future performance of roofing systems throughout their entire service lives. The performance of roofing components and systems is dependent upon several explanatory variables, including age, environmental conditions, material type, quality of work executed and materials used as well as the amount and quality of maintenance. In order to validate the Markov chain model, it is necessary to develop transition probability matrices for roofing components and systems according to their classification with regard to these explanatory variables.*
>
> *The development of the Markovian model requires a relatively limited amount of historical performance data at two or more points in time. If the probability of a roofing component decaying by more than one state in one transition period is assumed negligible, the transition probability matrix is greatly simplified, and the deterioration process may be modelled by the unit-jump Markov chain shown in"* Figure 2-10(a). (Lounis *et al*, 1998b, p.5)

One of the biggest problems in building maintenance is the lack of reliable and consistent historical performance data. If the model does require data at only "two or more points in time", the application of the Markovian model becomes more viable in view of the lack of data.

To ensure negligible probability of decay by more than one state in one transition period, the length of the transition period should be appropriate. Historical performance data under 'normal' conditions, manufacturer or supplier information, and expert opinion could be used to determine suitable transition periods, which could vary from months to any number of years, depending on the component or fabric.

Zhang *et al* (2005) looked at "Uncertainty Analysis in Using Markov Chain Model to Predict Roof Life Cycle Performance" based on earlier work by Van Winden and Dekker (1998) and the BELCAM Project (Lounis *et al*, 1999). It was found that the predictions based on Markov model might be sensitive to deviation caused by parameter variance. The complex and probabilistic nature of the degradation process simulation due to the uncertain environmental factors in the service life duration and the variability of the factors is pointed out. *"Hence it is desirable to simulate and predict this process in the framework of stochastic models. However, the validation and parameter identification of a stochastic model depends on the availability and format of data, coming either from controlled experiments or field tests."* Two very important issues are discussed in some detail. Firstly, the issue of the service life span, accelerated degradation experiments, making *"inference on the real service life through the lab testing results"* and the limited accessibility to field data. Secondly, the consistency and objectivity of the inspection/assessment process are mentioned.

The seven-point condition rating system of the BELCAM project was used. According to Zhang *et al* (2005, p.5) the requirement that *"the observed roofing systems should be of the same kind and expose to similar circumstances, is too restrictive to make it a realistic method. Another difficulty is that inspected data under certain maintenance policy may never reach certain states. ... It is more practical to infer parameters from a service life curve, coming either from lab test or expert opinion. When it comes to expert opinion, intuition is to let experts directly estimate the coefficient in Markov chain model. However, this estimation requires the expert to be familiar with both the assumptions of Markov chain model and the specific transition behavior."*

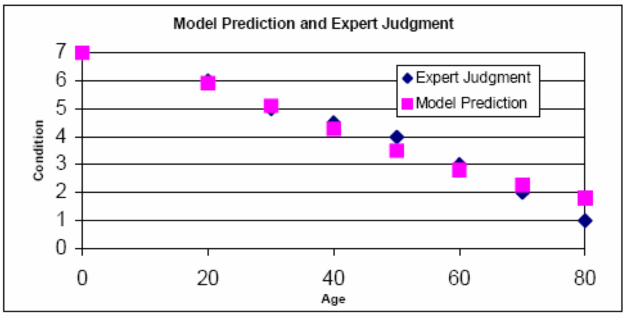


Figure 2-11: Expert Judgment Data and Model Prediction (Zhang *et al*, 2005, p.5)

Figure 2-11 illustrates a comparison between expert judgment on service life condition under natural degradation and model prediction, from which the matrix as shown in Figure 2-12 is derived.

$$P = \begin{pmatrix} 0.95 & 0.05 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.93 & 0.07 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.91 & 0.09 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.88 & 0.12 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.83 & 0.17 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.75 & 0.25 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

Figure 2-12: Markov Chain Transition Probability Matrix (Zhang *et al*, 2005, p.5)

b.) Identification of Environmental Categories for Markovian Deterioration Models of Bridge Decks by Morcous *et al* (2003).

Morcous *et al* (2003, p.353–361) discuss the application of Markovian deterioration models to identify environmental categories for bridge decks in Canada. It was found that *"the categories used to describe the various possible environments for a bridge element are neither accurately defined nor explicitly linked to the external factors affecting the element deterioration."*

	1	2	3	4	5
1	0.98	0.02	0	0	0
2	0	0.97	0.03	0	0
3	0	0	0.97	0.03	0
4	0	0	0	0.96	0.04
5	0	0	0	0	1

Benign environment

	1	2	3	4	5
1	0.95	0.05	0	0	0
2	0	0.94	0.06	0	0
3	0	0	0.94	0.06	0
4	0	0	0	0.92	0.08
5	0	0	0	0	1

Low environment

	1	2	3	4	5
1	0.93	0.07	0	0	0
2	0	0.92	0.08	0	0
3	0	0	0.91	0.09	0
4	0	0	0	0.90	0.10
5	0	0	0	0	1

Moderate environment

	1	2	3	4	5
1	0.87	0.13	0	0	0
2	0	0.86	0.14	0	0
3	0	0	0.85	0.15	0
4	0	0	0	0.83	0.17
5	0	0	0	0	1

Severe environment

Figure 2-13: Transition probability matrices of concrete bridge decks with asphalt concrete overlay for the four environments (Morcous *et al*, 2004, p.355)

A set of transition probability matrices for various climatic environments, based on data obtained from the Ministére des Transports du Québec, is developed as shown in Figure 2-13 above. Two important principles are displayed in these graphs: first, condition cannot improve ($p_{ij} = 0$ where $i > j$) without rehabilitation, and second: condition changes only one-step per time interval ($p_{ij} = 0$ where $j > i + 1$).

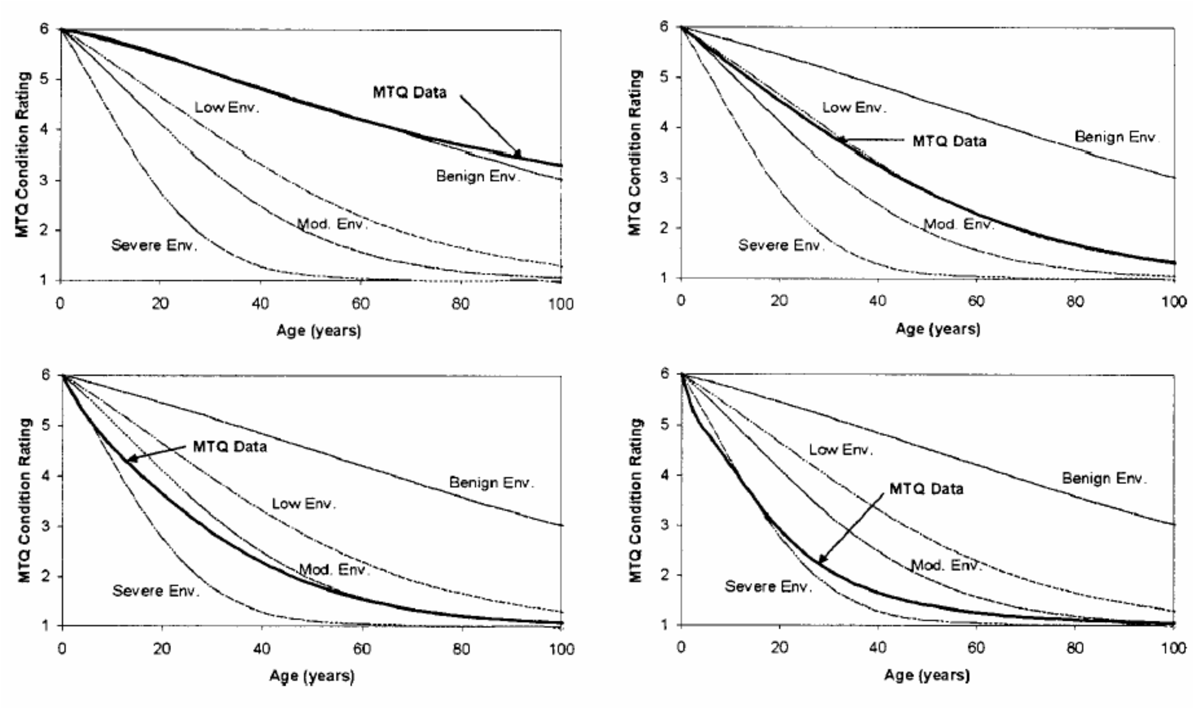


Figure 2-14: Genetic algorithm-generated deterioration curves for the four environmental categories (Morcous *et al*, 2004, p.359)

> Genetic algorithms are used *"to determine the combinations of deterioration parameters that best fit each environmental condition."* Performance over time curves for each of the four environmental categories, showing the change in condition over time, are presented in Figure 2-14 above.

Kirkham and Boussabaine (2004) proposed a stochastic approach to the forecasting of the residual service life of NHS hospital buildings. The results from their proposed model, based upon a combination of weighted average techniques and a Markov property; the minimum of exponentials, were compared with those obtained by means of existing deterministic methods and revealed an average percentage difference of 56.26%. *"This confirms the notion that stochastic approaches in combination with elemental weightings could yield greater accuracy. Whilst the results obtained can be used primarily to determine the overall residual service life of a hospital building, the model also allows the condition state transition probabilities to be calculated at a given time. On the macro level, this information can be used for optimization of maintenance strategies."*

Some other documented examples of Markov applications briefly cited by Moser (Hövde and Moser, 2004, p.63) are listed below:

a.) Development of prediction models for sewer deterioration

Abraham and Wirahadikusumh (1999) explored the probability-based Markovian approach for modelling deterioration of sewer lines. They used expert opinions from engineers for validating the deterioration models, which enabled the comparison of predicted values with actual field observations.

b.) Sewer lines

"A somewhat simplified deterioration model" has been applied to sewer lines by Kaempfer *et al* (2002). They assessed the condition of sewer pipes, using a five-point scale for different damage classes, ranging from very serious to negligible. *"... aging curves were derived from the available inspection data and the construction year for each status class. ... The average residual service life of the sewer section is represented by a vertical line between the real age of the sewer section and the point of intersection with the aging curve of intervention status class. The different intersections on the horizontal line with the aging curves of different status classes indicate the ages at which the section is likely to drop to the next class or, going back in time, came from the previous class."*

c.) Service life of bridge elements

Ansell *et al* (2002) reported a Markov approach in estimating the service life of bridge elements in Sweden. *"Deterioration of bridge elements can be analysed numerically using the Markov chain theory. The deterioration of a particular structural member must be defined by a number of states, in this case given by the assessed condition classes. The numerical method used, is based on an iterative stepwise combination of the matrix elements until the error between a known deterioration average curve and a curve given by the Markov chain is minimised."*

Other documented examples of Markov applications include the following:

a.) Highway pavement management

Puterman (1994, p.5) discusses the development of a pavement management system by the Arizona Department of Transportation *"based on a Markov decision process model to improve allocation of its limited resources while ensuring that the quality of its roadways was preserved"*. A dynamic long-term model was used to *"identify maintenance policies which minimize long-run average costs subject to constraints on road quality."* The model was applied to 7,400 one-mile sections based on *"road type, traffic density, and regional environment."* The model provided for condition, associated maintenance actions, expected yearly deterioration, and costs for each maintenance action.

> *Transition probabilities specify the likelihood of yearly changes in road condition under the various maintenance actions. These were estimated using existing data, under the assumption that each dimension of the state description varied independently. Since in each state only a limited number of subsequent states could occur, most of the transition probabilities (97%) were zero.*

According to Puterman, the saving in the first year of implementation, 1980, was $14 million, *"nearly a third of Arizona's maintenance budget with no decline in road quality."*

b.) Stormwater pipes

Coombes *et al* (2002) looked at deterioration, depreciation and serviceability of stormwater pipe networks in Newcastle, Australia, and presented a Markov model for the structural deterioration of stormwater pipes. Bayesian techniques are used to calibrate the model with structural condition assessment data. It was found that the deterioration process was influenced by *"diameter, construction material, soil type and exposure classification"*. The model is also presented as a *"rational approach to assessing depreciation"* as required by Australian Accounting Standard AAS27.

c.) Bridge decks and infrastructure:

Madanat *et al* (1995) and Madanat *et al* (1997) worked on transition probabilities for bridge decks. It is pointed out that inspection data *"suffer from important methodological limitations."* Inspection ratings are *"discrete ordinal measurements ... instead of continuous condition indices"* and do not account *"for the presence of heterogeneity in the panel data." ... which may lead to biased coefficient estimates."*

Incremental deterioration models, which *"predicts changes in condition that are added to previous condition to estimate the new condition"* have been developed and claimed to be *"more realistic representations of the deterioration process than models which predict condition directly because they take the form of difference equations (or differential equations for the continuous time case) where condition at a point in time is a function of both condition at a previous point in time and other explanatory variables such as age, traffic, weather, and maintenance."*

The "expected-value" method for estimating transitional probabilities for the Markovian model is discussed and pointed out that the deterioration process *"is not explicitly modelled"* and *"the latent nature of infrastructure deterioration"* is not recognised. Corrosion of concrete reinforcement is presented as an example of latent deterioration, which is a very important and often neglected consideration.

In Madanat *et al* (1995, p.124) and Madanat *et al* (1997, p.6) the role of age in the deterioration process is also highlighted. It is agued, quite correctly, that older bridge decks deteriorate faster than new bridge decks, which *"clearly illustrates the nonstationarity of the deterioration process."*

In Madanat *et al* (1997, p.4 - 5) the issue of state dependence is discussed. It is stated that the assumption that deterioration might not be independent of history in the case of *"some types of facilities in which early stress initiation leads to accelerated deterioration in later stages of their lives. ... In the context of deterioration modelling, the Markovian assumption states that the probability that the facility's condition drops to a lower state in a given time period is independent of its deterioration in previous time periods."* Due to the influence of past deterioration, it is argued that the transition process is a *"function of past experience",* which is referred to as *"state dependence"*.

State dependence could be due to historical deterioration, called true state dependence, or differences in *"certain unmeasured characteristics that influence deterioration but are not influenced by history"* or heterogeneity. True state dependence invalidates the Markovian assumption, while *"heterogeneity, if properly accounted for in the model, does not."*

2.7. Artificial Intelligence Applications

2.7.1. <u>Introduction</u>

The fundamental question of artificial intelligence is *"Can machines think?"* Negnevisky (2002, p.2) quotes Boden (2000) who states that *"the goal of Artificial Intelligence (AI) as a science is to make machines do things that would require intelligence if done by humans."*

According to Negnevisky (2002, p.1) *"The first work recognised in the field of artificial intelligence (AI) was presented by Warren McCulloch and Walter Pitts in 1943"*, who *"proposed a model of artificial neural networks in which each neuron was postulated as being in binary state."* Neural networks *"can learn, adapt to changes in a problem's environment, establish patterns in situations where rules are not known, and deal with fuzzy or incomplete information. However, they lack explanation facilities and usually act as a black box."* Negnevisky (2002, p.14)

He also discusses the development of the expert system (1970's to mid 1980's), which goal it is to incorporate the "domain expert's" expertise into a computer program to make it perform at a human expert level. This is of course very relevant to service life prediction, where there are many experts but very little historical performance data available, and the opinion of these experts are very often the only means to compensate for the lack of consistent reliable statistics. *"A major drawback is that human experts cannot always express their knowledge in terms of rules or explain the line of their reasoning."*

Genetic algorithms, evolutionary strategies, and genetic programming, all evolutionary artificial intelligence applications, are *"based on the computational models of natural selection and genetics"*. Negnevisky (2002, p.14) points out that *"an evolutionary strategies approach can be considered as an alternative to the engineer's intuition. Evolutionary strategies use a numerical optimisation procedure, similar to a focused Monte Carlo search."*

Another very important technology dealing with vague, imprecise and uncertain knowledge and data is fuzzy logic. Most methods of handling imprecision in classic expert systems are based on the probability concept. ... However, experts do not usually think in probability values, but in terms as often, generally, sometimes, occasionally and rarely. Fuzzy logic is concerned with the use of fuzzy values that capture the meaning of words, human reasoning and decision making. As a method to encode and apply human knowledge in a form that accurately reflects an expert's understanding of difficult, complex problems, fuzzy logic provides the way to break through the computational bottlenecks of traditional expert systems." (Negnevisky, 2002, p.1-21)

From the above, the following artificial intelligence applications have been identified:

- Rule-based expert systems,
- Fuzzy logic systems,
- Frame-based expert systems,
- Artificial neural networks (ANN),
- Genetic algorithms (evolutionary computation), and
- Hybrid intelligent systems:
  - Neural expert systems,
  - Neuro-fuzzy systems,
  - Adaptive Neuro-fuzzy Inference System (ANFIS),
  - Evolutionary neural networks, and
  - Fuzzy evolutionary systems.

For the purpose of this thesis, only the Fuzzy logic, Artificial Neural Networks (ANN) and Neuro-fuzzy systems will be looked at in brief.

2.7.2. Fuzzy Logic

In a discussion on the differences between stochastic uncertainty and linguistic uncertainty Von Altrock (1995, p.8 - 11) points out that *"Stochastic uncertainty deals with the uncertainty of whether a certain event will take place, and probability theory lets you model this. In contrast, lexical uncertainty deals with the uncertainty of the definition of the event itself. Probability theory cannot be used to model this because the combination of subjective categories in human decision processes does not follow its axioms."*

According to Negnevisky (2002, p.87-90) fuzzy logic is logic that describes fuzziness in contrast to Boolean or conventional logic which uses sharp distinctions. *"Fuzzy logic is the theory of fuzzy sets, sets that calibrate vagueness. Fuzzy logic is based on the idea that all things admit of degrees."* He continues by stating, *"Unlike two-valued Boolean logic, fuzzy logic is multi-valued. It deals with degrees of membership and degrees of truth. Fuzzy logic uses the continuum of logical values between 0 (completely false) and 1 (completely true). Instead of just black and white, it employs the spectrum of colours, accepting that things can be partly true and partly false at the same time. ... The basic idea of the fuzzy set theory is that an element belongs to a fuzzy set with a certain degree of membership."*

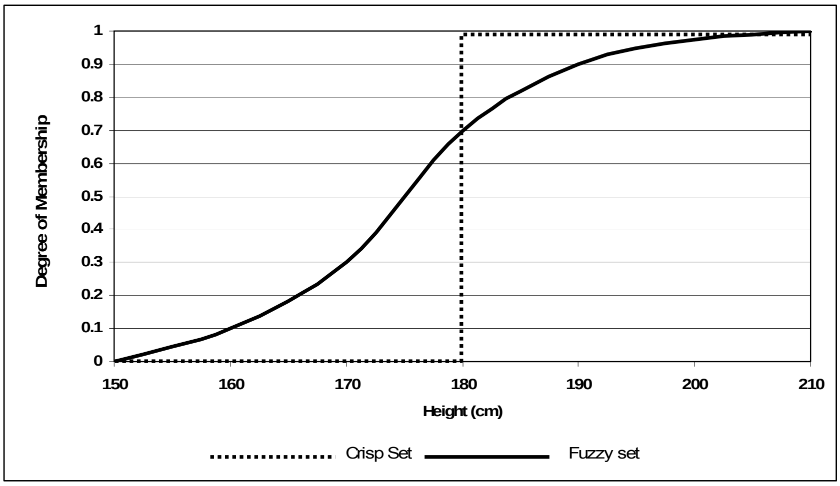


Figure 2-15: Examples of crisp and fuzzy sets (after Negnevisky, 2002)

The horizontal axis represents the universe of discourse (the range of all possible values applicable to a chosen variable), while the vertical axis represents the membership value of the fuzzy set. A fuzzy set is capable of providing a graceful transition across a boundary and *"can be simply defined as a set with fuzzy boundaries."*

In the classical set theory, if X is the universe of discourse and x its elements, then the "crisp set A of X or characteristic function of A is defined as function $f_A(x)$:

$f_A(x)$: X → 0, 1,

where

$$f_A(x) = \begin{cases} 1, & \text{if } x \in A \\ 0, & \text{if } x \notin A \end{cases}$$

This set maps universe X to a set of two elements. For any element x of universe X, characteristic function $f_A(x)$ is equal to 1 if x is an element of set A, and is equal to 0 if x is not an element of A.
In the fuzzy theory, fuzzy set A of universe X is defined by function, $\mu_A(x)$ called the membership function of set A

$\mu_A(x) : X \rightarrow [0,1]$,
where
$\mu_A(x) = 1$ *if x is totally in A;*
$\mu_A(x) = 0$ *if x is not in A;*
$0 < \mu_A(x) < 1$ *if x is partially in A*

This set allows a continuum of possible choices. For any element x of universe X, membership function $\mu_A(x)$ equals the degree to which x is an element of set A. This degree, a value between 0 and 1, represents the degree of membership, also called membership value, of element x in set A." (Negnevisky, 2002, p.92)

According to Negnevisky (2002, p.92) a number of methods learned from knowledge acquisition such as the knowledge of single expert, multiple experts or artificial neural networks can be applied to determine the membership function.

"If X is the reference super set and A is a subset of X, then A is said to be a fuzzy subset of X if, and only if,

$$A = \{(x, \mu_A(x)\} \quad x \in X, \mu_A(x) : X \rightarrow [0,1]$$

Fuzzy subset A of the finite reference super set X can be expressed as,

$$A = \{(x_1, \mu_A(x_1)\},\{(x_2, \mu_A(x_2)\}, \ldots,\{(x_n, \mu_A(x_n)\}$$

However it is more convenient to represent A as,

$$A = \{\mu_A(x_1)/ x_1\}, \{\mu_A(x_2)/ x_2\}, \ldots ,\{\mu_A(x_n)/ x_n\},$$

where the separating symbol / is used to associate the membership value with its coordinate on the horizontal axis." Negnevisky (2002, p.93 - 94)

"A fuzzy rule can be defined as a conditional statement in the form:

IF x is A

THEN y is B

Where x and y are linguistic variables; and A and B are linguistic values determined by fuzzy sets on the universe of discourses X and Y, respectively. ... Fuzzy reasoning includes two distinct parts: evaluating the rule antecedent (the IF part of the rule) and implication or applying the result to the consequent (the THEN part of the rule)." If in fuzzy systems *"the antecedent is true to some degree of membership, then the consequent is also true to that same degree."* (Negnevisky, 2002, p.103-104).

According to Von Altrock (1995) the rule blocks contain the control strategy of a fuzzy logic system. All rules for the same combination of variables are confined in a rule block. The rules' 'IF' part describes the situation, for which the rules are designed. The 'THEN' part describes the response of the fuzzy system in this situation. The degree of support (DoS) is used to weigh each rule according to its importance.

Negnevisky (2002, p.106) defines fuzzy inference *"as a process of mapping from a given input to an output, using the theory of fuzzy sets. ... The most commonly used fuzzy inference technique is the so-called Mamdani method,"* which applies *"a set of fuzzy rules supplied by experienced human operators. ... The Mamdani-style fuzzy inference process is performed in four steps: fuzzification of the input variables, rule evaluation, aggregation of the rule outputs, and finally defuzzification."*

Step 1: Fuzzification

The degree to which the inputs the crisp inputs, x1 and y1, a numerical value limited to the universe of discourse X and Y respectively, belong to each of the appropriate fuzzy sets is firstly determined. *"The ranges of the universe of discourses can be determined by expert judgments. .... While some of the inputs can be measured directly (height; weight, speed, distance, temperature, pressure etc.), some of them can be based only on expert estimate."* The crisp inputs, x1 and y1, are fuzzified against the appropriate linguistic fuzzy sets over all the membership functions used by the fuzzy rules. (Negnevisky, 2002, p.107)

Step 2: Rule evaluation

Next, the fuzzified inputs are applied to the antecedents of the fuzzy rules. The fuzzy operator (AND or OR) is used to obtain a single number (the truth-value) that represents the result of the antecedent evaluation when a given fuzzy rule has multiple antecedents, which is then applied to the consequent membership function. The OR fuzzy operation is used to evaluate the disjunction of the rule antecedents.

This is followed by clipping or scaling of the consequent membership function to the level of the truth-value of the rule antecedent through the application of the result of the antecedent evaluation to the membership function of the consequent. Clipping slices the top of the membership function and loses some information, but *"involves less complex and faster mathematics, and generates an aggregated output surface that is easier to defuzzify."*

"While clipping is a frequently used method, scaling or correlation product offers a better approach for preserving the original shape of the fuzzy set. The original membership function of the rule consequent is adjusted by multiplying all its membership degrees by the truth value of the rule antecedent This method, which generally loses less information, can be very useful in fuzzy expert systems." (Negnevisky, 2002, p.107)

Step 3: Aggregation of the rule outputs

The next step, aggregation, combines all rule consequents previously clipped or scaled into a single fuzzy set. *"Thus, the input of the aggregation process is the list of clipped or scaled consequent membership functions, and the output is one fuzzy set for each output variable."* (Negnevisky, 2002, p.110)

Step 4: Defuzzification

Defuzzification is the retranslation of the fuzzy output into a crisp value through membership functions, and there are several defuzzification methods such as Centre of Maximum (CoM) method, Centre of Area (CoA) or Centre of Gravity (CoG) method, Fast Centre of Area (Fast CoA) method, Mean of Maximum (MoM) method and Hyper Centre of Maximum (Hyper CoM) method (Von Altrock, 1995, p.235-244). According to Negnevisky (2002, p.111) *"probably the most popular one is the centroid technique. It finds the point where a vertical line would slice the aggregate set into two equal masses. Mathematically this centre of gravity (COG) can be expressed as*

$$\mathrm{COG} = \frac{\int_a^b \mu_A(x)x\,dx}{\int_a^b \mu_A(x)\,dx}$$

A centroid defuzzification method finds a point representing the centre of gravity of the fuzzy set, A, on the interval, ab."

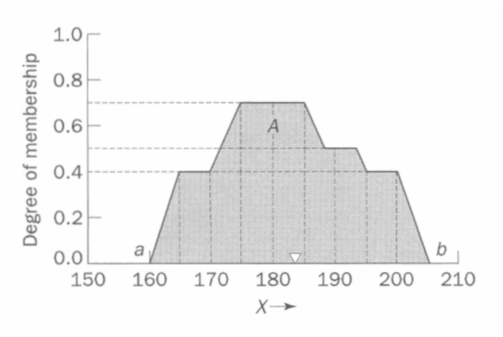


Figure 2-16: The centroid method of defuzzification (Negnevisky, 2002, p.111)

According to Von Altrock (1995, p.225-246) a disadvantage of the Centre-of-Area defuzzification method is its high computational effort and most software development tools and fuzzy logic processors use the so-called fast-CoA, which *"computes the individual areas under the membership functions during compilation to avoid numerical integration during run time. This approach neglects the overlapping of the areas; hence it is only an approximation of the 'real' CoA."* The Centre-of-Maximum (CoM) method *"first determines the most typical value for each term and then computes the best compromise of the fuzzy logic inference result. ... To obtain the best compromising value for the result of the fuzzy logic inference ... as a real number, the inference results are considered 'weights' at the positions of the most typical values of the terms. The best compromise is where the defuzzified (crisp) value balances the weights."* Where the result of the fuzzy logic inference is that no evidence exists, the Centre-of-Maximum defuzzification approach does not work and a compromise between two good solutions can lead to a bad result.

The Mean-of-Maximum Method (MoM) computes a system output only for the term with the highest resulting degree of validity, such as pattern recognition applications. In decision support systems, the choice of defuzzification method depends on the context of the decision. CoM is used for quantitative decisions, such as budget allocation or project prioritization, while MoM is used for qualitative decisions, such as credit card fraud detection or credit worthiness evaluation.

2.7.3. Artificial Neural Networks (ANN)

"A neural network can be defined as a model of reasoning based on the human brain." The human brain consists of a densely interconnected set of nerve cells, called neurons, with synapses or connections between them. A neural network exhibits plasticity, which means that *"connections between neurons leading to the 'right answer' are strengthened while those leading to the' wrong answer' weaken. As a result, neural networks have the ability to learn through experience."*

"An artificial neural network consists of a number of very simple and highly interconnected processors, also called neurons, which are analogous to the biological neurons in the brain." (Negnevisky, 2002, p.164)

A neuron as shown in Figure 2-18 below is an elementary information-processing unit. It can receive several weighted input signals x_1 to x_n and produce a single output Y. The input signals could be raw data or output signals from other neurons and the output Y could be the end result or an input signal to other neurons.

The basic structure of an artificial neural network is shown in Figure 2-19 below. *"The neurons are connected by weighted links passing signals from one neuron to another. Each neuron receives a number of input signals through its connections; however, never produces more than one output signal.… Weights are the basic means of long-term memory in ANN's. They express the strength, or in other words importance, of each neuron input. A neural network 'learns' through repeated adjustments of these weights."* (Negnevisky, 2002, p.165)

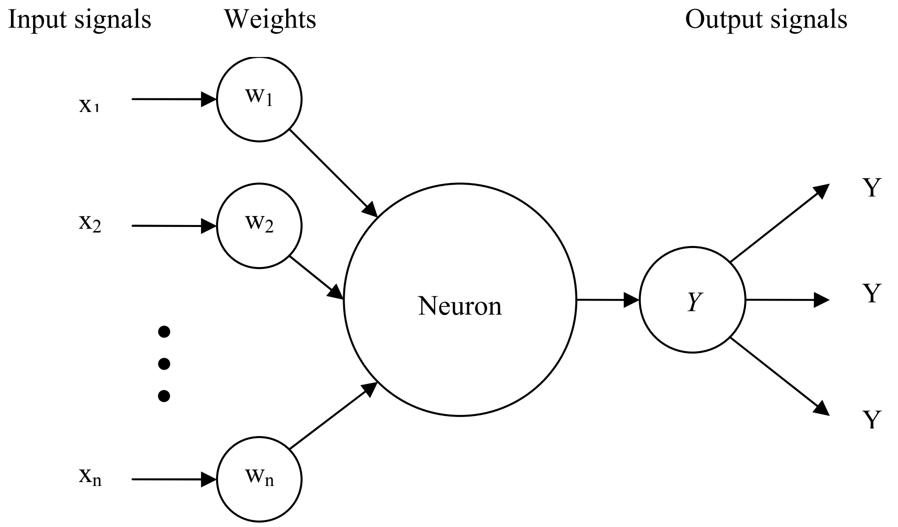


Figure 2-17: Diagram of Neuron (Negnevisky, 2002, p.166)

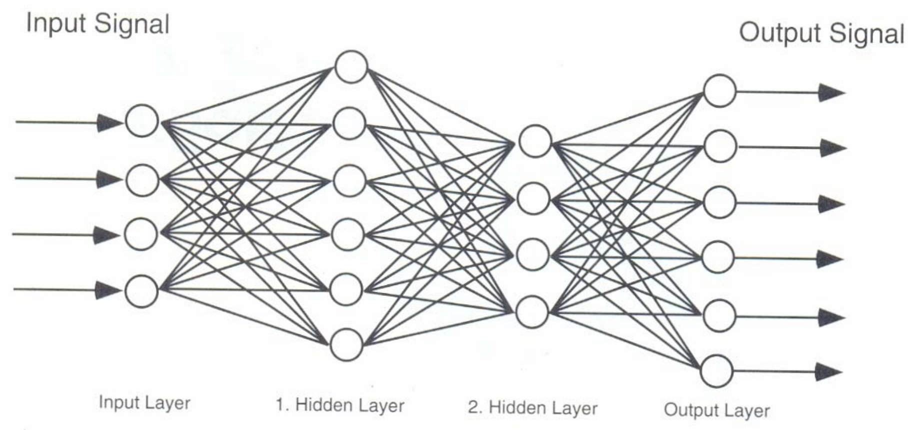


Figure 2-18: Basic structure of an artificial neural network (Von Altrock, 1995, p.64)

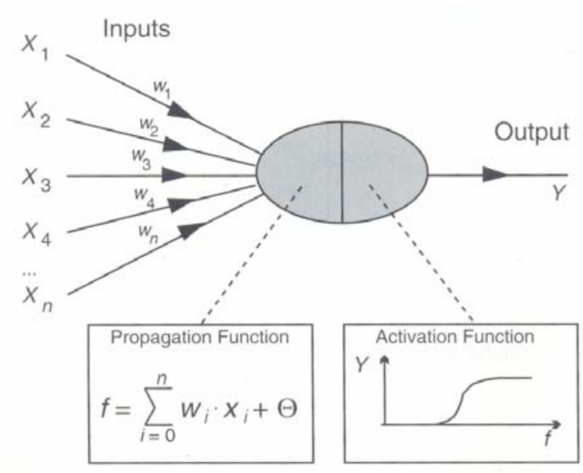


Figure 2-19: Simple mathematical model of a neuron (Von Altrock, 1995, p.66)

According to Negnevisky (2002, p.167) the neuron activation function is given by:

$$X = \sum_{i=1}^{n} x_i w_i \qquad\qquad Y = \begin{cases} +1 & \text{if } X \geq \theta \\ -1 & \text{if } X < \theta \end{cases}$$

"Where X is the net weighted input to the neuron, x_i is the value of input i, w_i is the weight of input i, n is the number of neuron inputs, and Y is the output of the neuron" and θ is a threshold value. *"This type of activation function is called a sign function. ... and can be represented as:"*

$$Y = sign\left[\sum_{i=1}^{n} x_i w_i - \theta\right]$$

According to Negnevisky (2002, p.169) the perceptron, the simplest form of a neural network and training algorithm introduced by Frank Rosenblatt in 1958, learns *"by making small adjustments in the weights"* of input signals *"to reduce the difference between the actual and desired outputs of the perceptron."*

The learning process comprises of an initially random assignment of weights, which are then adjusted to obtain outputs consistent with training examples or actual data from field assessments, pilot studies or testing (accelerated or long-term).

2.7.4. Neuro-Fuzzy Systems

On Neuro-Fuzzy systems, the combination of fuzzy logic and neural networks, Negnevisky (2002, p.266-267) stated:

> *Fuzzy logic and neural networks are natural complementary tools in building intelligent systems. While neural networks are low-level computational structures that perform well when dealing with raw data, fuzzy logic deals with reasoning on a higher level, using linguistic information acquired from domain experts. However, fuzzy systems lack the ability to learn and cannot adjust themselves to a new environment. On the other hand, although neural networks can learn, they are opaque to the user. The merger of a neural network with a fuzzy system into one integrated system therefore offers a promising approach to building intelligent systems. Integrated neuro-fuzzy systems can combine the parallel computation and learning abilities of neural networks with the human-like knowledge representation and explanation abilities of fuzzy systems. As a result, neural networks become more transparent, while fuzzy systems become capable of learning.*
>
> *A neuro-fuzzy system is, in fact, a neural network that is functionally equivalent to a fuzzy inference model. It can be trained to develop IF-THEN fuzzy rules and determine membership functions for input and output variables of the system. Expert knowledge can be easily incorporated into the structure of the neuro-fuzzy system.*

Neuro-Fuzzy is therefore the ideal application in the situation where system input initially depends mainly on expert knowledge while historical performance data is being collected, which is then used for system 'learning'.

"The structure of a neuro-fuzzy system is similar to a multi-layer neural network. In general, a neuro-fuzzy system has input and output layers, and three hidden layers that represent membership functions and fuzzy rules." (Negnevisky, 2002, p.267). Figure 3-21 shows a Mamdani fuzzy inference model and Figure 3-22 the corresponding Neuro-fuzzy system.

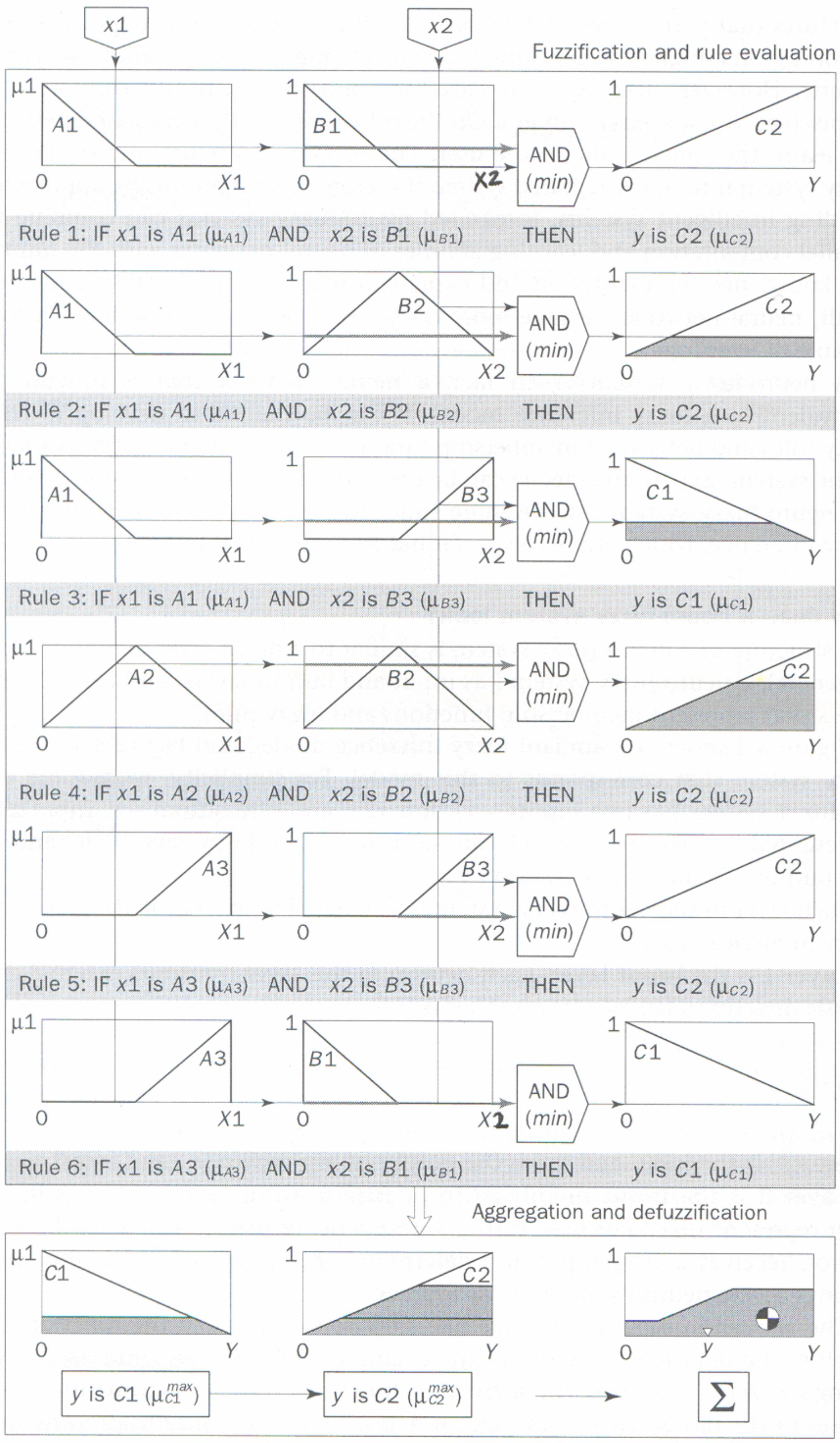


Figure 2-20: Mamdani fuzzy inference system (Negnevisky, 2002, p.268)

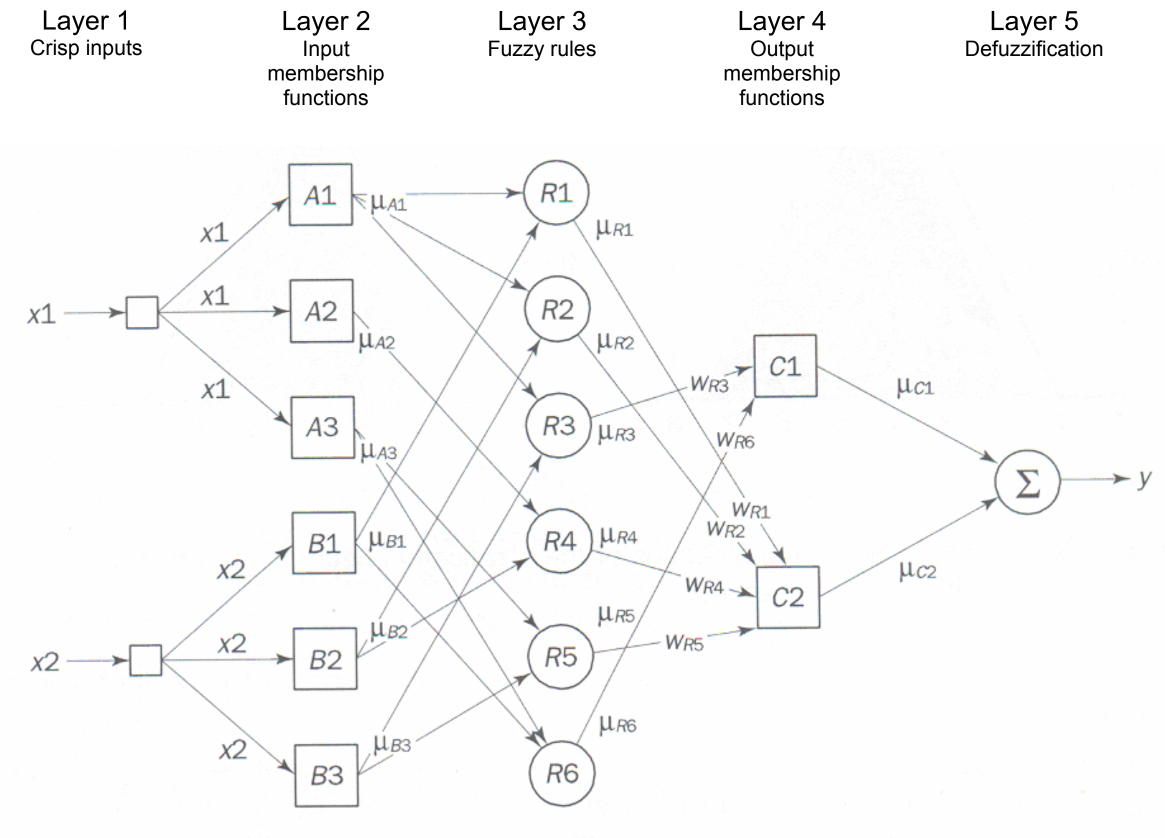


Figure 2-21: Neuro-fuzzy equivalent system (Negnevisky, 2002, p. 269)

According to Negnevisky (2002, p.271-272):

> *A neuro-fuzzy system is essentially a multi-layer neural network, and thus it can apply standard learning algorithms developed for neural networks, ... When a training input-output example is presented to the system, the back-propagation algorithm computes the system output and compares it with the desired output of the training example. The difference (also called the error) is propagated backwards through the network from the output layer to the input layer.*

2.7.5. Examples of relevant Artificial Intelligence Applications

- Assessment of the service life of bridges:

  Liang *et al* (2001, p.133), also cited by Moser (Hövde and Moser, 2004, p.78), developed a multiple layer fuzzy evaluation model for evaluating the damage state of existing reinforced concrete bridges. *"In addition, the evaluated results may also be used as a design reference for service life in future bridge building. The evaluated model may be divided into the degrees of grades I, II, III, IV, and V, which are described as nondamage (sic), light damage, moderate damage, sever (sic) damage, and unfit for service, respectively."*

- Fuzzy logic in building cost models:

  Baguley *et al* (2002) examined *"current cost modelling practices and methods, as well as fuzzy logic as a way of reducing the data in building cost models. ... using principally expert knowledge."*

- Neurofuzzy system for predicting cost and duration of construction projects:

  Boussabaine *et al* (1997) investigated *"the feasibility of developing a neurofuzzy system for predicting cost and duration of construction projects. ... The hypothesis of this study envisages that combining these methodologies would improve and benefit cost and time estimation of construction projects.* It is concluded that: *"Neurofuzzy systems offer several advantages over traditional methods for the prediction of construction projects cost and duration."*