THE APPLICATION OF NEURO-FUZZY METHODOLOGY TO MAINTENANCE OF BUILDINGS

J.J. Mc Duling[1], C.E. Cloete[2], E. Horak[3]

[1] PhD Candidate, Department Civil Engineering and Biosystems, Faculty of Engineering, Built Environment and Information Technology, University of Pretoria, South Africa
[2] Professor, Department Construction Economics, Faculty of Engineering, Built Environment and Information Technology, University of Pretoria, South Africa
[3] Professor, Head of Department, Civil and Biosystems Engineering, Faculty of Engineering, Built Environment and Information Technology, University of Pretoria, South Africa

Short Abstract

The ability to quantify changes in condition over time is important to ensure sustainable development in the built environment. The current 'state of the art' Factor Method (ISO 15686-1:2000) for service life prediction calculates an estimated service life, but not changes in condition. The application of the Markov Chain, a stochastic approach used to simulate the transition from one condition to another over time, is restricted by limited availability of historic performance data on degradation and durability of building materials required to populate Markovian transition probability matrices.

This paper looks at the application of neuro-fuzzy artificial intelligence to translate expert knowledge into probability values to supplement historic performance data for the development of Markovian transitional probability matrices, towards prediction of service life, condition changes over time, and consequences of maintenance levels on service life of buildings. Expert knowledge is used to express durability and degradation factors in "IF-THEN" rules, which are translated into crisp probability values with neuro-fuzzy artificial intelligence to populate the Markovian transitional probability matrices.

Keywords: Building maintenance, condition changes, Markov Chain, neuro-fuzzy artificial intelligence, service life prediction

Introduction

Since the 1992 UN Conference on Environment and Development (UNCED) in Rio de Janeiro, Brazil, which resulted in an agenda for global sustainable development, *"there has been an ever-increasing focus on the needs to determine durability and service life of materials"* and buildings based on environmental and economic issues. (Hövde and Moser, 2004, p.11).

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, which depend on the ability to quantify 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 current state of the art method for building service life prediction, the Factor Method (ISO 15686-1:2000), applies seven factors to a reference service life to estimate an empirical service life. Although the Factor Method calculates the estimated service life, it 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 and Moser, 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. Lounis et al (1998) cited by Moser (Hövde and Moser, 2004, p.66) stated:

> *"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."*

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.

Degradation Process

A building is a complicated three-dimensional human-made configuration of a diverse range of fabrics, materials and components, each with its own characteristics, which interacts differently to the influences of its environment, could be old or brand new, raw or processed, come in different forms, shapes, sizes and finishes, and its applications could vary considerably. The environment acts on a building or component through mechanical, electromagnetic, thermal, chemical and biological agents causing degradation over time. The degradation process, as illustrated in Figure 1 below, is a continuous interaction between durability factors, which counters degradation, and degradation factors, which promotes or cause degradation. These factors are the same as used in the 'state of the art' Factor Method.

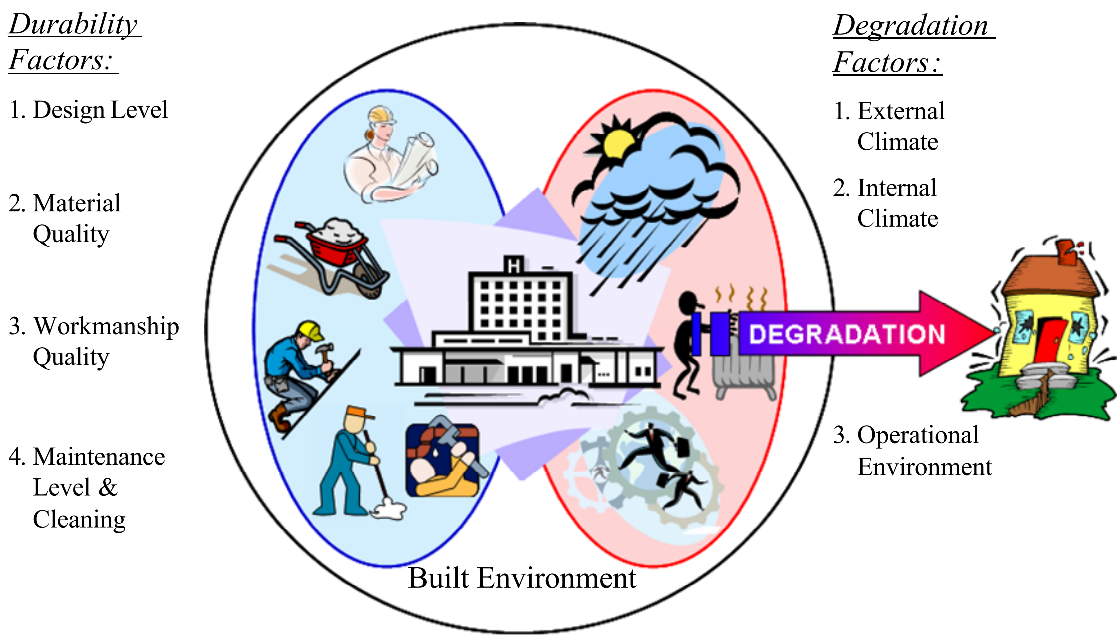

Figure 1 : Degradation Process (Mc Duling, 2005)

Durability is the ability of a building or component to resist the adverse effects of exposure to its environment. Degradation is determined by the environment, which can be divided into a physical and operational environment. The physical environment in and around the building or component comprises of a macroclimate (gross meteorological conditions), mesoclimate (terrain and local built environment) and microclimate (absolute proximity of a material surface). The operational environment or 'user culture' is determined by the level and extent of the utilisation of the building by the occupants. Mechanical processes play a major role in the operational environment. The level of maintenance and cleaning is sometimes also taken into consideration with utilisation to determine the operational environment of a building. In the case of the 'Factor Method' this approach could result in 'double counting', because maintenance level is a factor in its own right.

Neuro-Fuzzy Artificial Intelligence

According to Negnevisky (2002, p.1-21) *"Fuzzy logic is concerned with the use of fuzzy values that capture the meaning of words, human reasoning and decision making"*. It encodes and applies *"human knowledge in a form that accurately reflects an expert's understanding of difficult, complex problems."* An integrated neuro-fuzzy system has been selected to translate expert knowledge and reasoning into probability values because it *"can combine the parallel computation and learning abilities of neural networks with the human-like knowledge representation and explanation abilities of fuzzy systems. ... 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."* (Negnevisky, 2002, p.266-267). The Mamdani-style fuzzy inference technique is used and performed in four steps: fuzzification of the input variables, rule evaluation, aggregation of the rule outputs, and finally defuzzification.

Structure of the fuzzy logic system

The system structure in Figure 2 below identifies the fuzzy logic inference flow from the input variables to the output variables. The fuzzification in the input interfaces translates analogue inputs into fuzzy values. The fuzzy inference takes place in IF-THEN rule blocks, which contain the linguistic control rules. The output of these rule blocks is linguistic variables, which are translated into analogue variables through defuzzification in the output interfaces.

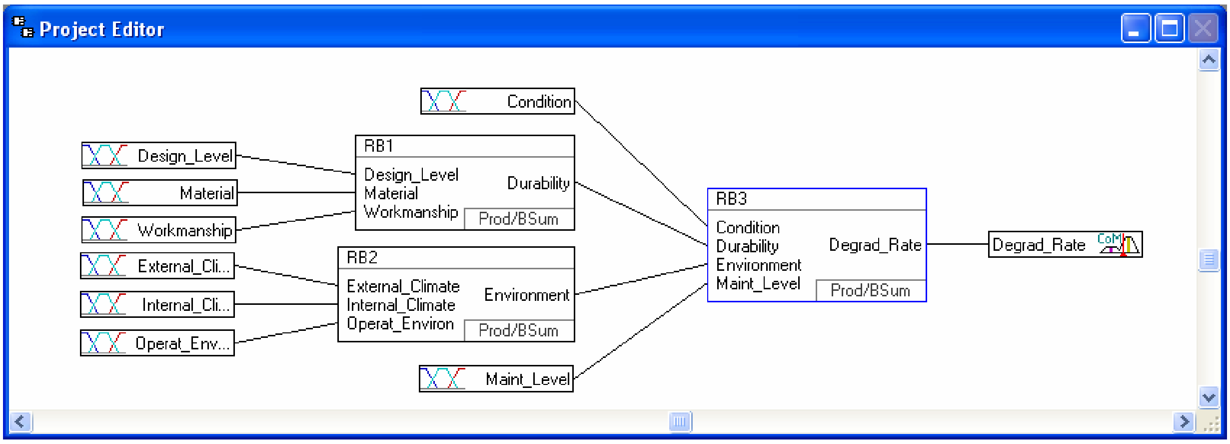

Figure 2: Structure of the Fuzzy Logic System (Mc Duling, 2005)

The input variables are the durability and degradation factors influencing the degradation of the material or component, defined in linguistic or fuzzy terms. These factors are similar to the factors used in the Factor Method, except for the valuation or rating of the factors. A five point colour-coded rating system is used based on a similar rating system used for condition assessments.

The input, intermediate and output variables are defined in Tables 1, 2 and 3 below:

No	Variable Name	Rating	Term Names	No	Variable Name	Rating	Term Names
1	Condition	1 2 3 4 5	Very Bad Bad Fair Good Very Good	5	Maintenance Level	1 2 3 4 5	Very Low Low Normal High Very High
2	Design Level	1 2 3 4 5	Very Low Low Medium High Very High	6	Material Quality	1 2 3 4 5	Very Low Low Medium High Very High
3	External Climate	0 1 2 3 4 5	Internal Element Very Aggressive Aggressive Slightly Aggressive Less Favourable Favourable	7	Operational Environment	1 2 3 4 5	Very Aggressive Aggressive Slightly Aggressive Less Favourable Favourable
4	Internal Climate	0 1 2 3 4 5	External Element Very Aggressive Aggressive Slightly Aggressive Less Favourable Favourable	8	Workmanship Quality	1 2 3 4 5	Very Low Low Medium High Very High

Table 1: Input Variables (Mc Duling, 2005)

No	Variable Name	Term Names
9	Durability	Very Low Low Medium High Very High
10	Environment	Very Aggressive Aggressive Slightly Aggressive Less Favourable Favourable

Table 2: Intermediate Variables (Mc Duling, 2005)

No	Variable Name	Defuzzification method	Unit	Rating	Term Names
11	Degradation Rate		Percentage	0 25 50 75 100	Very Slow Slow Medium Fast Very Fast

Table 3: Output Variable (Mc Duling, 2005)

The output variable, degradation rate, is expressed as the percentage of the material or component that changes from one condition to the next worst condition during one time interval. This interval, which could vary from material to material, is determined by the time required for the material to change from one condition to the next worst condition without jumping more than one-step at a time in order to keep the model as simple as possible and dictates the assessment frequency. The degradation rate is the transition probability required for the Markov process.

There are three rule blocks in the proposed system; an extract from Rule Block 3 (Figure 2) is shown in Table 4 below as an example of a typical rule block.

IF				THEN	
Condition	**Durability**	**Environment**	**Maintenance Level**	**DoS**	**Degradation Rate**
Fair	Medium	Slightly Aggressive	Very Low	0.50	Very Fast
Fair	Medium	Slightly Aggressive	Very Low	0.50	Medium
Fair	Medium	Slightly Aggressive	Low	0.25	Very Fast
Fair	Medium	Slightly Aggressive	Low	0.25	Fast
Fair	Medium	Slightly Aggressive	Low	0.50	Medium
Fair	Medium	Slightly Aggressive	Normal	0.25	Very Fast
Fair	Medium	Slightly Aggressive	Normal	0.75	Medium
Fair	Medium	Slightly Aggressive	High	0.25	Very Fast
Fair	Medium	Slightly Aggressive	High	0.50	Medium
Fair	Medium	Slightly Aggressive	High	0.25	Slow
Fair	Medium	Slightly Aggressive	Very High	0.25	Very Fast
Fair	Medium	Slightly Aggressive	Very High	0.50	Medium
Fair	Medium	Slightly Aggressive	Very High	0.25	Very Slow

Table 4: Extract from 'IF-THEN" Rule Block 3 (Mc Duling, 2005)

While the other variables were kept constant during the simulation, the maintenance level and condition ratings were adjusted to obtain degradation rates for various scenarios. The motivation for this is that design level, material, workmanship, and external and internal climate are largely predetermined during planning, design and construction, while operational environment could vary slightly but mostly stay relatively constant over the service life of the building or component. Subsequent to completion of construction, the degradation rate is controlled mainly by the maintenance level. There is also an increase in the rate of degradation as the condition deteriorates.

Transition from Artificial Intelligence to Markov Chain

Degradation rate is defined as that percentage of the building or component that will 'transit' or change to a condition of worse degradation in one time interval. In the case of buildings, this time interval is normally one year, but could be months, weeks or even days, depending on the reference service life of the component under consideration. Due to the influence of the degradation and durability factors on the building, the transition to a condition of worse degradation is probabilistic with the transitional probabilities depending on the current condition of the building. Therefore, degradation rate is defined as the transition from condition *i* to the next worse condition *j* in one time interval:

$\therefore$ Degradation rate = transitional probability P(ij)

A five -point condition rating system is used, with Condition 5 the initial condition, progressively worsening towards Condition 1, where the material or component has failed and needs to be replaced.

Based on the assumptions that under normal circumstances the condition will only deteriorate and not improve and a one year interval is short enough to ensure the change in condition will not jump more than one condition rating, or P(ij) = 0 when i < j and j < i - 1, the transitional probability matrix is defined as:

$$P = \begin{array}{c|ccccc|c} & [5] & [4] & [3] & [2] & [1] & \\ (5) & P(55) & P(54) & 0 & 0 & 0 & \sum P(5j) = 1 \\ (4) & 0 & P(44) & P(43) & 0 & 0 & \sum P(4j) = 1 \\ (3) & 0 & 0 & P(33) & P(32) & 0 & \sum P(3j) = 1 \\ (2) & 0 & 0 & 0 & P(22) & P(21) & \sum P(2j) = 1 \\ (1) & 0 & 0 & 0 & 0 & 1 & \sum P(1j) = 1 \end{array}$$

The transition probabilities P(54), P(43), P(32), and P(21) are obtained from the Neuro-fuzzy simulation, while P(5 5), P(44), P(33), and P(22) are obtained from $\sum P(ij) = 1$. These transition probabilities are then used to populate the Markov Transitional Probability Matrix.

Markov Transition Probability Matrix		Condition at time t = 1				
		5	4	3	2	1
Condition at time: t = 0	5	0.578	0.422	0	0	0
	4	0	0.516	0.484	0	0
	3	0	0	0.391	0.609	0
	2	0	0	0	0.453	0.547
	1	0	0	0	0	1

Table 5: Markov Transition Probability Matrix for 'base-line' Model (Mc Duling, 2005)

In the 'base-line' Neuro-fuzzy model, it was assumed that the variables in each rule block carried the same weight, and this resulted in deterioration rates being too high, as shown in Table 5 above. After evaluating the results and adjusting the weights based on expert knowledge and reasoning, more realistic values were obtained as shown in Table 6 below:

Markov Transition Probability Matrix		Condition at time t = 1				
		5	4	3	2	1
Condition at time t = 0	5	0.950	0.050	0	0	0
	4	0	0.915	0.085	0	0
	3	0	0	0.900	0.100	0
	2	0	0	0	0.875	0.125
	1	0	0	0	0	1

Table 6: Markov Transition Probability Matrix for revised Model (Mc Duling, 2005)

Calibration of the neuro-fuzzy model

Although there are currently approximately 27 tertiary hospitals and 380 other government hospitals in South Africa, only six academic hospitals were chosen as pilot and control sites to calibrate the model because they are of similar age, were all build within a seven year period during the 1970's, have similar construction types, design, material and workmanship levels and operational environments, and their condition have been assessed at least twice since 1995. In Figure 3 below the average assessed condition of the six hospitals are shown on performance over time curves for five levels of maintenance:

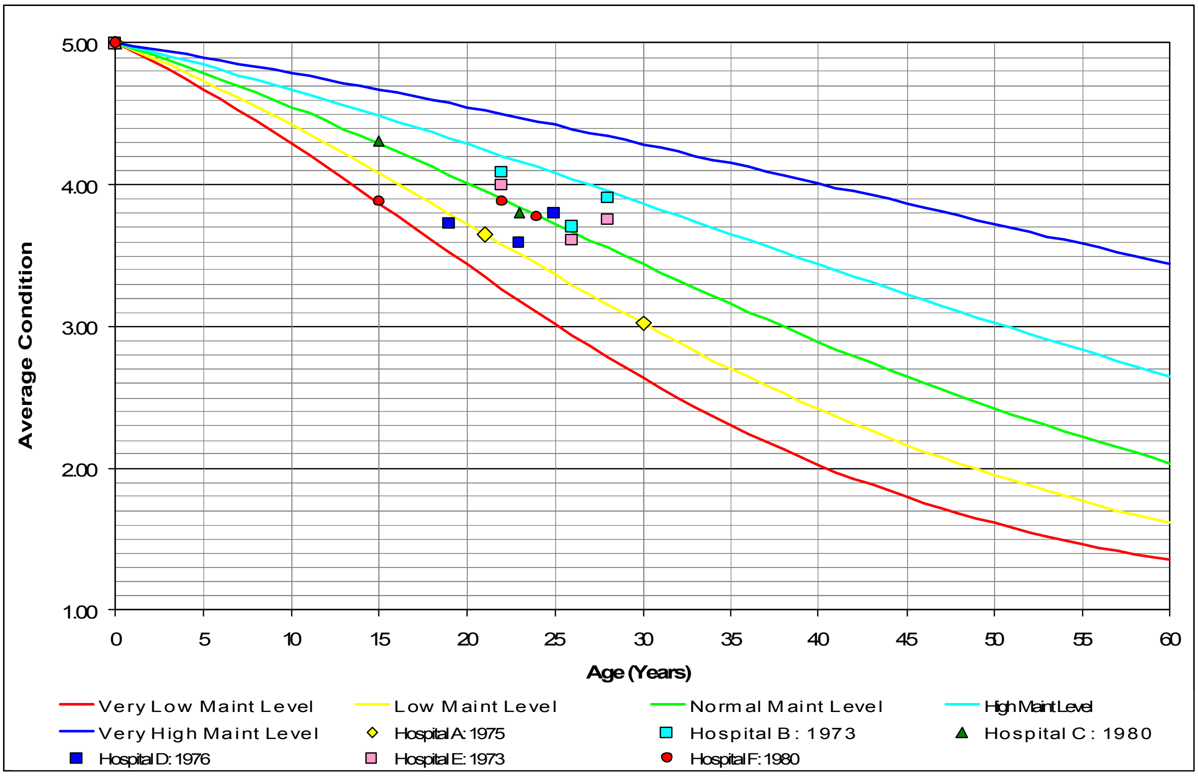

Figure 3: Performance over Time Curves (Mc Duling, 2005)

Service Life Prediction

For service life prediction, the condition of a building or component is a relatively easy to assess and ideal to use performance indicator. The minimum performance requirement for academic hospitals should be Condition 3. Below a level 3 the building or component is simply not able to provide an environment supportive of proper health care. There are areas in hospitals where the performance requirements are higher (e.g. operating theatres and intensive care units). For other building types, this performance standard may be different. The performance requirements for buildings and components should be determined by clearly defined and appropriate policies and codes.

In Figure 4 below, the predicted service life for an academic hospital can be read from the graph for various levels of maintenance. In a similar way, curves for other types of buildings or components can be developed for the whole range of durability and degradation factors. By doing regular condition assessments during the service life of the building or component, 'progress' can be measured against these curves and the necessary corrective actions can be implemented in time to either ensure that the desired service life is achieved or exceeded.

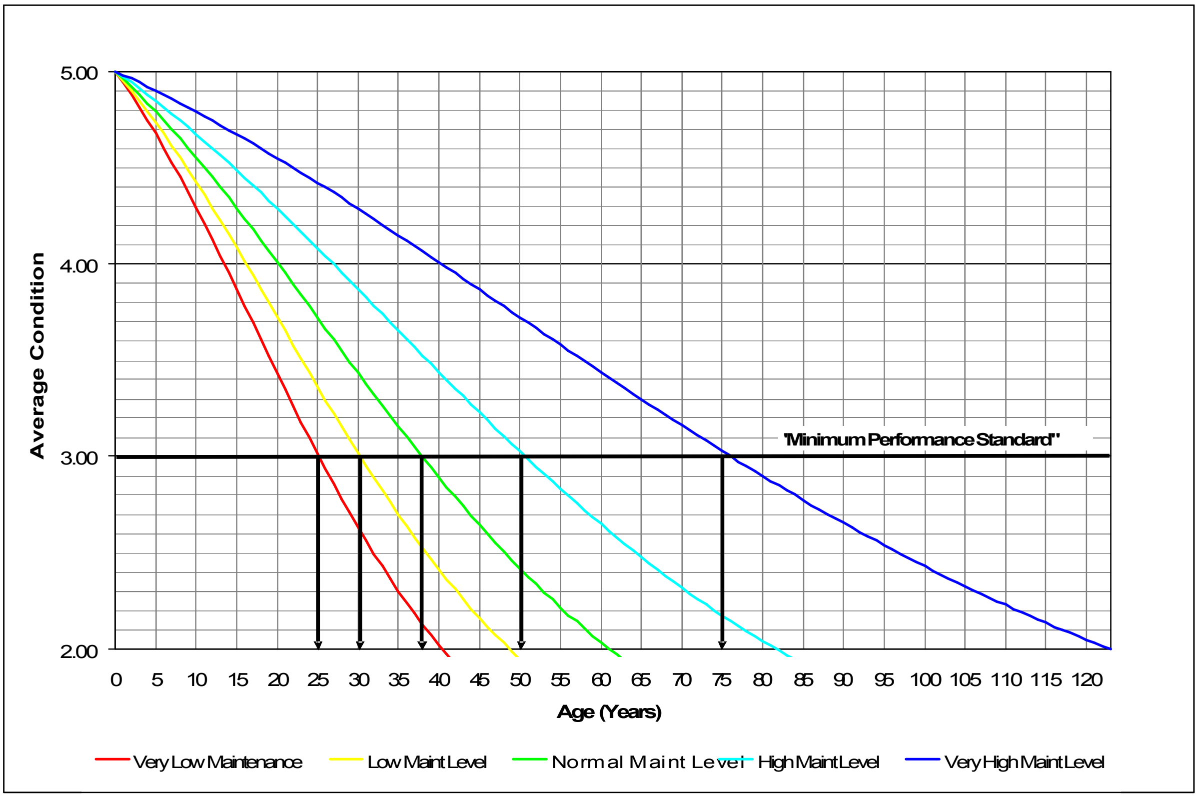

Figure 4: Service Life Prediction Graph for Academic Hospitals in South Africa (Mc Duling, 2005)

Conclusion

The proposed model, based on the Markov Chain approach, translates expert knowledge and reasoning into probability values through the application of Neuro-Fuzzy 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.

Due to the limited availability of reliable historic performance data, expert knowledge and reasoning were used to develop initial transition probability matrices for the proposed model. However, the initial model produced unrealistic results and available historic performance data was used to calibrate the model. After calibration, the model produced realistic results, which compared well with historic performance data for other hospitals.

According to Lounis et al (1998b, p.5) *"The development of the Markovian model requires a relatively limited amount of historical performance data at two or more points in time."* This statement is supported by the results of the proposed model. But, instead of using the limited available historic performance data to develop the Markovian transition probability matrices, the proposed model reverses the process by using expert knowledge and reasoning, and supplements it with available historic performance data to calibrate the model.

Comprehensive historic performance data on the actual degradation process takes years to collect. Until sufficient historic performance data has been collected, expert knowledge and reasoning can be used to supplement or even substitute historic performance data. Historic performance data should however not be used indiscriminately. The degradation and durability factors could vary considerably between assessments and these potential variations should be taken into consideration.

It was illustrated how expert knowledge and reasoning can easily be expressed in terms of 'IF-THEN' rules and translated into crisp probability values through Neuro-Fuzzy Artificial Intelligence, which deals with vague, imprecise and uncertain knowledge and data.

REFERENCES

1. Coombes, P.J., Micevski, T., and Kuczera, G., 2002. *"Deterioration, Depreciation and Serviceability of Stormwater Pipes."* Stormwater Industry Association 2002 Conference on Urban Stormwater Management, Orange NSW, Australia, 23-24 April 2002. [web page], http://www.eng.newcastle.edu.au/~cegak/Coombes/Assetmanagement.pdf. Date accessed: 20 November 2005.

2. Hövde, P.J., and Moser, K., 2004. State of the Art Reports, CIB W080 / RILEM 175-SLM *Service Life Methodologies Prediction of Service Life for Buildings and Components*, CIB Report, Publication 294, March 2004. International Council for Research and Innovation in Building and Construction. [web page], http//www.cibworld.nl. Date accessed: 05 November 2005.

3. International Organization for Standardization, 2000. *ISO 15686-1, Buildings and constructed assets - Service life planning - Part 1: General principles*, Geneva, Switzerland: International Organization for Standardization.

4. Lounis, Z., Lacasse, M.A., Vanier, D.J., and Kyle, B.R., 1998a. *Towards Standardization of Service Life Prediction of Roofing Membranes*. In: Wallace, T. J., and Rossiter, W.J. Jr., eds, Roofing Research and Standards Development, 4th Volume, ASTM STP 1349. American Society for Testing and Materials. [web page], http://www.nrc.ca/irc/fulltext/nrcc42034.pdf. Date accessed: 05 November 2005.

5. Madanat, S., Mishalani, R., and Wan Ibrahim, W.H., 1995. Estimation of Infrastructure Transition Probabilities from Condition Rating Data. *Journal of Infrastructure Systems*, Vol. 1, No. 2, June 1995, p.120–125. [web page], http://www.ce.berkeley.edu/trans/Madanat/. Date accessed: 20 November 2005.

6. Mc Duling, J.J., 2005. Towards the Development of Transition Probability Matrices in the Markovian Model for the Predicted Service Life of Buildings, PhD Thesis, Department of Civil and Biosystems Engineering, Faculty of Engineering, Built Environment and Information Technology, University of Pretoria, South Africa.

7. Morcous, G., Lounis, Z., and Mirza, M.S., 2003. *"Identification of environmental categories for Markovian Deterioration Models for Bridge Decks."* Journal of Bridge Engineering. Vol 8, (6), Nov/Dec., November 01, 2003, p.353-361.

8. Negnevitsky, M., 2002. *Artificial Intelligence, A Guide to Intelligent Systems*. Essex, England, Addison-Wesley.