IMPROVING RELIABILITY IN PREDICTING THE DEGRADATION OF BUILDING ASSETS

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Degree of Doctor of Philosophy

Department of Civil Engineering

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DECLARATION

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Names of the supervisors: [i] Prof. W.P.S. Dias (UoM)

[ii] Prof. Sujeeva Setunge (RMIT)

[iii] Prof. H. M. Y. C. Mallikarachchi (UoM)

Signatures of the supervisors: [i] Date: 22nd December 2023

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Abstract

Predictive modelling of building component degradation optimises project management and maintenance costs. Typically, the visual inspection-based generic condition ratings of building components are collected over time and analysed to determine age-related degradation trends and corresponding life cycle costs. Using two datasets, this research proposes two new approaches: (i) deficiency-based (as opposed to generic) condition ratings of building components from seven local councils in Sri Lanka were analysed to develop Markov models at the component level (engineering-based approach); (ii) nominal replacement costs and times for building components assigned by estimators from the City of Melbourne were used to arrive at degradation rates for component groups through a novel concept of cumulative lost value ratio (CLVR) (monetary-based approach).

In the engineering-based approach, snapshot data were collected using both deficiency-based and generic deterioration-based condition scales, and the Markov Chain Monte Carlo technique was used to develop reliability-based models. The results showed that deficiency-based models were more accurate and reliable. The monetary-based approach explored the CLVR concept and the validity of using Markov models for component groups, where stochasticity is based on component mix rather than degradation process randomness.

The study's theoretical contribution was to interpret "degradation" in terms of curable and incurable deterioration from a maintenance perspective, estimate component maintenance-free ages using data screening, establish new monetary indices such as LVR and CLVR, evaluate the impact of influencing factors using GRG NLO categorisation, and utilise a monetary-based degradation forecasting paradigm utilising nominal cost data as an alternative to using physical condition data. In practice, the deficiency-based approach will directly improve predictive maintenance reliability, lead to longer maintenance intervals, convert deficiency-based ratings to cost-based ratings using the LVR-based index, and bundle maintenance through categorisation via degradation patterns. The monetary-based approach will eliminate inconsistent physical condition assessments and enable more building assets to be modelled.

Keywords: Building components; Deficiency; Degradation; Markov modelling; Influencing factors

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LIST OF ABBREVIATIONS

Abbreviation	Description
AC	Air Conditioning
AE	Absolute Error
AI	Artificial Intelligence
AUD	The Australian Dollar
BC	Building Component
BFA	Building Functional Area
BII	Building Investment Index
BIM	Building Information Modelling
BIoT	Building Internet of Things
BN	Building Name
BPN	Back Propagation artificial Neural network
BT	Building Type
CAMS	Central Asset Management System
CG	Component Group
CI	Condition Index
CLV	Cumulative Lost Value
CLVR	Cumulative Lost Value Ratio
$\overline{CLVR}$	Mean Cumulative Lost Value Ratio
[CLVR]	Range of Mean Cumulative Lost Value Ratios of the interquartile range
CP	Condition Population
CRV	Current Replacement Value
CT	Component Type
DNN	Deep Neural Network
DoF	Degrees of Freedom
e.g.	For example
et al.	And other people
FAT	Functional Area Type

FCI	Facility Condition Index
FOR	Factored Overall Rating
GIS	Geographic Information System
GN	Grama Niladhari
GRG NLO	Generalised Reduced Gradient Non-Linear Optimisation
HVAC	Heating, Ventilation and Air Conditioning
ID	Identification
i.e.	In other words
ISO	International Organisation for Standardisation
IVI	Infrastructure Value Index
LCC	Life Cycle Cost
LIME	Local Interpretable Model-agnostic Explanations
LVR	Lost Value Ratio
MAE	Mean Absolute Error
MARIR	Mean of the Absolute Relative Importance Ratios
MCMC	Markov chain Monte Carlo
MEP	Mechanical, Electrical and Plumbing
ML	Machine Learning
MLR	Multiple Linear Regression
MR	Multiple Regression
μ(CLVR)	Mean Cumulative Lost Value Ratio of the interquartile range
NPV	Net Present Value
OR	Overall Rating
p-value	Probability value
QS	Quantity Surveyor
RCC	Reinforced Cement Concrete
ReLU	Rectified Linear Unit
RF	Random Forest
RILEM	Réunion Internationale des Laboratoires et Experts des Matériaux

RMIT	Royal Melbourne Institute of Technology
RQ	Research Question
$\overline{RVR}$	Mean Remaining Value Ratio
SLR	Simple Linear Regression
SNN	Simple Neural Network
USA	United States of America
USACERL	United States Army Construction Engineering Research Laboratories

LIST OF VARIABLES

LVR_n	LVR Index: Lost value ratio for condition n
$(Rc)_n$	Rectification cost at condition n
ic	Initial cost
P_{ij}	Transition probability from state 'i' to state 'j'
Y	A set 'Y 'of component conditions
M	Markov model
$\pi(P\|Y,M)$	Posterior distribution of P_{ij}
$L(Y\| P,M)$	Likelihood to observe a set Y of component conditions
$\pi_0(P)$	Prior distribution of P_{ij}
t	Component age in years
T	Largest age found in the dataset
J	Number of condition states
$N_i^{\ t}$	Number of components in condition i at year t
$C_i^{\ t}$	Probability of condition i at year t
r^0	Initial raw vector
r^1	Distribution after the first-time step
r^t	Distribution after t time steps
$CLVR(t)$	CLVR Index: Cumulative lost value ratio at time step t
$(rc)_t$	Replacement (or partial replacement) cost at time t
$\overline{CLVR}(t)$	Mean cumulative lost value ratio at time step t
k	k number of sites
$\overline{RVR}(t)$	Mean remaining value ratio at time step t
$\mu(CLVR)(t)$	Mean cumulative lost value ratio of the interquartile range at time step t
β	Proportion of the k sites that fall within and inclusive of the 25th and 75th percentiles
$k\_0.25(t)$	25th percentile value of the data at time step t
$k\_0.75(t)$	75th percentile value of the data at time step t

$[CLVR](t)$	Range of mean cumulative lost value ratios of the interquartile range at time step *t*
$CP_i(t)$	Condition Population: Number of sites with $CLVR(t)$ within a CLVR band(i)
X^2	Chi square
$observed_{(i)}$	Number of components observed in condition *i*
$predicted_{(i)}$	Number of components predicted in condition *i*
n_i	Number of observations in year *i*
$OR\_observed$	Observed overall rating
$OR\_predicted$	Predicted overall rating
$(OR)_t$	Overall rating at time step *t*
C_i	Condition rating *i*
P_i	Probability of being in condition *i*
$(FOR)_t$	Factored overall rating at time step *t*
N_t	Number of observations at time step *t*
$(FOR\_observed)_t$	Factored overall rating observed at time step *t*
$(FOR\_predicted)_t$	Factored overall rating predicted at time step *t*
y	Dependent variable
x_1	First independent variable
x_2	Second independent variable
a_1	Intercept
a_2	Slope of the dependent variable x_1
a_3	Slope of the dependent variable x_2
ε_i	Residual terms of the model
$(AE)_i$	Absolute error for condition rating *i*
$(C_i\_observed)$	Observed condition rating *i*
$(C_i\_predicted)$	Predicted condition rating *i*
n	Total number of observations
TP	True positive
TN	True negative
FP	False positive

FN	False negative
MARIR	Mean of the absolute relative importance ratios

LIST OF APPENDICES