



CRC for Construction Innovation (2007) *Final : report learning system for life prediction of infrastructure*. CRC for Construction Innovation, Brisbane , Qld. □ □

The Participants of the CRC for Construction Innovation have delegated authority to the CEO of the CRC to give Participants permission to publish material created by the CRC for Construction Innovation. This delegation is contained in Clause 30 of the Agreement for the Establishment and Operation of the Cooperative Research Centre for Construction Innovation. The CEO of the CRC for Construction Innovation gives permission to the Queensland University of Technology to publish the papers/publications provided in the collection in QUT ePrints provided that the publications are published in full. Icon.Net Pty Ltd retains copyright to the publications. Any other usage is prohibited without the express permission of the CEO of the CRC. The CRC warrants that Icon.Net Pty Ltd holds copyright to all papers/reports/publications produced by the CRC for Construction Innovation.



CRC Construction Innovation
B U I L D I N G O U R F U T U R E

Final Report Learning System for Life Prediction of Infrastructure

Research Project No: 2005-003-B-12

The research described in this report was carried out by:

| | |
|--------------------|--|
| Project Leader | Penny Corrigan |
| Researchers | Angela Bradbury Ivan Cole Robin Drogemuller Stephen Egan Wayne Ganther Tim Muster David Paterson Gerry Trinidad Natalie Sherman Andrew Martin Wan Yee Chan Richi Nayak Esther Ge |
| Project Affiliates | Peter Hope Michael Ball Frank Turvey Lee Wade Wayne Muller Lex Vanderstaay |

Research Program: B
Sustainable Built Assets

Project: 2005-2003-B
Learning System for Life Prediction of Infrastructure

Date: November 2007

Leaders in Construction and Property Research

Distribution List

Cooperative Research Centre for Construction Innovation
Authors

Disclaimer

The Client makes use of this Report or any information provided by the Cooperative Research Centre for **Construction Innovation** in relation to the Consultancy Services at its own risk. Construction Innovation will not be responsible for the results of any actions taken by the Client or third parties on the basis of the information in this Report or other information provided by Construction Innovation nor for any errors or omissions that may be contained in this Report. Construction Innovation expressly disclaims any liability or responsibility to any person in respect of any thing done or omitted to be done by any person in reliance on this Report or any information provided.

© 2007 Icon.Net Pty Ltd

To the extent permitted by law, all rights are reserved and no part of this publication covered by copyright may be reproduced or copied in any form or by any means except with the written permission of Icon.Net Pty Ltd.

Please direct all enquiries to:

Chief Executive Officer
Cooperative Research Centre for Construction Innovation
9th Floor, L Block, QUT, 2 George St
Brisbane Qld 4000
AUSTRALIA
T: 61 7 3138 9291
F: 61 7 3138 9151
E: enquiries@construction-innovation.info
W: www.construction-innovation.info

Table of Contents

| | |
|--|-----------|
| List of Tables | iv |
| List of Figures | vii |
| EXECUTIVE SUMMARY | 1 |
| 1 INTRODUCTION | 2 |
| 1.1 Background | 2 |
| 1.2 Project Aims and Outcomes | 5 |
| 1.2.1 QDPW Program | 5 |
| 1.2.2 QDMR Program | 6 |
| 1.2.3 Report Outline | 6 |
| 2. BRIDGE PROGRAM DEVELOPMENT | 7 |
| 2.1 Introduction | 7 |
| 2.2 Effect of Bridge Height | 7 |
| 2.2.1 Calculation of Salt Concentration | 7 |
| 2.2.2 Comparison with Salt levels on Gateway Bridge | 9 |
| 2.2.3 Conclusions | 10 |
| 2.3 Natural Cleaning of Bridge Components | 11 |
| 2.3.1 Washing by Rain | 11 |
| 2.3.2 Rainfall intensity and duration needed for bridge cleaning | 13 |
| 2.3.3 Relationship Between Runoff and Cleaning | 13 |
| 2.4 Modifications to Bridge Program | 15 |
| 2.5 β -Testing of Software | 19 |
| 2.6 References | 20 |
| 3. BUILDING COMPONENTS AND HOLISTIC MODEL MODIFICATIONS | 21 |
| 3.1 Introduction | 21 |
| 3.2 Component Selection | 21 |
| 3.3 Holistic Model | 22 |
| 3.3.1 Holistic Model Modules | 24 |
| 3.3.1.1 <i>Salinity Retention</i> | 24 |
| 3.3.1.2 <i>State of surface of building component</i> | 25 |
| 3.3.1.3 <i>Damage to Components</i> | 25 |
| <i>Uncoated Metals</i> | 25 |
| <i>Coated Materials</i> | 26 |
| 3.4 Model Modifications for Components | 27 |
| 3.4.1 Gutters | 27 |
| 3.4.1.1 <i>Corrosion risk</i> | 27 |
| 3.4.1.2 <i>Module Modifications</i> | 27 |
| 3.4.2 Down pipes | 28 |
| 3.4.2.1 <i>Corrosion risk and Important Parameters</i> | 28 |
| 3.4.2.2 <i>Module Modifications</i> | 29 |
| Deposition of salt | 29 |
| State of Surface | 29 |
| Mass loss calculations | 31 |
| 3.4.3 Roof Sheeting | 32 |
| 3.4.3.1 <i>Corrosion risk and Important Parameters</i> | 32 |
| 3.4.3.2 <i>Module Modifications</i> | 34 |
| Deposition of salt | 34 |
| State of Surface | 34 |
| Mass loss calculations | 34 |
| 3.4.4 Roof Fasteners | 35 |

| | | | |
|-----|---------|---|-----------|
| | 3.4.4.1 | Corrosion risk and Important Parameters..... | 35 |
| | 3.4.4.2 | Module Modifications..... | 37 |
| | | Deposition of salt..... | 37 |
| | | State of Surface..... | 38 |
| | 3.4.5 | Ridge Capping and Flashing..... | 40 |
| | 3.4.5.1 | Corrosion risk and Important Parameters..... | 40 |
| | 3.4.5.2 | Module Modifications..... | 41 |
| | | Deposition of salt..... | 41 |
| | | State of Surface..... | 41 |
| | | Mass loss calculations..... | 41 |
| | 3.4.6 | Window frames..... | 42 |
| | 3.4.6.1 | Corrosion risk and Important Parameters..... | 42 |
| | 3.4.6.2 | Module Modifications..... | 43 |
| | | Deposition of salt..... | 43 |
| | | State of Surface..... | 43 |
| | 3.4.7 | Steel Supports..... | 43 |
| | 3.4.7.1 | Corrosion risk and Important Parameters..... | 43 |
| | 3.4.7.2 | Module Modifications..... | 45 |
| | | Deposition of salt..... | 45 |
| | | State of Surface..... | 45 |
| | 3.4.8 | Sub-floor members, stumps and support wires..... | 45 |
| | 3.4.8.1 | Corrosion risk and Important Parameters..... | 45 |
| | 3.4.8.2 | Module Modifications..... | 47 |
| | | Deposition of salt..... | 47 |
| | | State of Surface..... | 47 |
| | 3.4.9 | Gang nail plates..... | 48 |
| | 3.4.9.1 | Corrosion risk and Important Parameters..... | 48 |
| 3.5 | | Testing of Model..... | 48 |
| | 3.5.1 | Failure Conditions..... | 50 |
| | 3.5.2 | Results..... | 50 |
| 3.6 | | Dose Tests for Corrosion Rates of New Materials..... | 54 |
| | 3.6.1 | Experimental Set-Up..... | 54 |
| | 3.6.2 | Results..... | 55 |
| 3.7 | | References..... | 58 |
| 4. | | COLORBOND DEGRADATION MODELLING..... | 59 |
| | 4.1 | Introduction..... | 59 |
| | 4.2 | The Leaching of Corrosion Inhibitors from Colorbond®..... | 59 |
| | 4.2.1 | The action of chromate..... | 60 |
| | 4.3 | The Weathering of Polymers..... | 66 |
| | 4.4 | Implementation of Model..... | 66 |
| | 4.4.1 | Influence of salt concentration on leaching rate..... | 68 |
| | 4.4.2 | Degradation of damaged (with pinholes) Colorbond® topcoats..... | 68 |
| | 4.4.3 | Degradation of undamaged Colorbond® backcoats..... | 70 |
| | 4.4.4 | Models for the Accumulation of Salts and the Time of Wetness in Gutters (re-worked)..... | 71 |
| | 4.5 | Electrochemical Impedance Spectroscopy (EIS) of Colorbond®..... | 76 |
| | 4.5.1 | Introduction to EIS..... | 76 |
| | 4.5.2 | Experimental Details..... | 78 |
| | 4.5.3 | Results for unexposed Colorbond®..... | 78 |
| | 4.5.4 | Estimates of corrosion rate based upon polarization resistance..... | 80 |
| | 4.6 | Conclusions..... | 85 |
| | 4.7 | References..... | 85 |
| 5. | | SCHOOL SURVEY DATABASE..... | 87 |
| | 5.1 | Introduction..... | 87 |
| | 5.2 | Survey Methodology..... | 87 |
| | 5.2.1 | Material Rating Used in Survey..... | 93 |
| | 5.3 | Survey Results..... | 93 |
| | 5.3.1 | Analysis of Data..... | 93 |
| | 5.3.1.1 | Colorbond® Components..... | 94 |
| | 5.3.1.2 | Zincalume Components..... | 94 |

| | | |
|-----|--|------------|
| | 5.3.1.3 Galvanised Components | 95 |
| | 5.3.1.4 Aluminium Components..... | 95 |
| | 5.3.2 Database..... | 96 |
| 6. | DATA MINING..... | 98 |
| 6.1 | Introduction | 98 |
| | 6.1.1 Background Information on Data Mining | 100 |
| | 6.1.1.1 Basic Data Mining Tasks | 100 |
| | 6.1.1.2 Knowledge Discovery and Data Mining Process Model..... | 101 |
| | 6.1.2 Related Data Mining Applications..... | 103 |
| 6.2 | Data Analysis and Representation | 104 |
| | 6.2.1 Data Acquisition | 105 |
| | 6.2.1.1 Delphi Survey | 105 |
| | 6.2.1.2 Holistic-I..... | 106 |
| | 6.2.1.3 Holistic-II..... | 107 |
| | 6.2.1.4 Holistic-III..... | 107 |
| | 6.2.1.5 School Survey Data Set | 108 |
| | 6.2.2 Data Preprocessing | 109 |
| | 6.2.2.1 Data Cleaning..... | 109 |
| | 6.2.2.2 Data Reduction..... | 109 |
| | 6.2.3 Data Analysis | 111 |
| 6.3 | Query Based Learning System..... | 111 |
| | 6.3.1 Motivations for QBLS | 112 |
| | 6.3.2 Overview of QBLS | 112 |
| | 6.3.3 Phases of QBLS | 113 |
| | 6.3.4 Query Based Feature Selection..... | 113 |
| | 6.3.4.1 Categorisation of features | 114 |
| | 6.3.5 Domain Knowledge Base | 115 |
| 6.4 | Predictor Selection..... | 115 |
| | 6.4.1 Methods Selection | 116 |
| | 6.4.2 Experiments using Classification Methods | 116 |
| | 6.4.3 Experiments using Regression Methods | 117 |
| | 6.4.4 Predictors constructed using M5 | 119 |
| | 6.4.5 Improvement of Performance | 120 |
| 6.5 | Overall Solution | 122 |
| | 6.5.1 Overview of the System | 122 |
| | 6.5.2 Representation of the Knowledge Base | 123 |
| | 6.5.3 An Example of Prediction using the System..... | 124 |
| 6.6 | Conclusions | 126 |
| 6.7 | References | 126 |
| 7. | LIFE PREDICTION PROGRAM FOR BUILDING COMPONENTS | 128 |
| 7.1 | Component Selection and Options..... | 129 |
| 7.2 | β – Testing of Software..... | 132 |

List of Tables

| | |
|---|----|
| Table 2.1. Chloride levels on the Gateway Bridge..... | 9 |
| Table 2.2. Values derived for η (rainfall reduction factor)..... | 13 |
| Table 2.3. Values for initial loss ϕ_{3i} (in mm) and a continuing loss ϕ_{3c} (in mm/hr) | 13 |
| Table 2.4. Parameter values for the different bridge components..... | 15 |
| Table 2.5. Representative locations in the different geographic classifications | 16 |
| Table 2.6. Accumulated salt factor formulae for different Queensland regions | 17 |
| Table 2.7. Parameters for calculating salt accumulation factor..... | 17 |
| Table 2.8. Classifications Risk Rating on Level of Salt Accumulated..... | 19 |
| Table 3.1. Values of ψ defined for various parameter combinations | 25 |
| Table 3.2. Constants for galvanised steel mass loss in State 2..... | 26 |
| Table 3.3. Constants for galvanised steel mass loss in State 3..... | 26 |
| Table 3.4. Constants for Zinalume mass loss in State 2..... | 26 |
| Table 3.5. Constants for Zinalume mass loss in State 3..... | 26 |
| Table 3.6. Possible cases for downpipes..... | 29 |
| Table 3.7. Calculations for extended drying times depending on state of downpipe. | 30 |
| Table 3.8. Application of mass loss rules depending on case | 32 |
| Table 3.9. Cases for roof sheeting..... | 33 |
| Table 3.10. Effect of case on various parameters | 34 |
| Table 3.11. pH measurements of leaf litter solutions/suspensions..... | 35 |
| Table 3.12 Possible cases for roof fasteners..... | 37 |
| Table 3.13: Values for δ , a constant dependent on the time of day and season | 39 |
| Table 3.14. Solar radiation zones..... | 39 |
| Table 3.15 Possible cases for ridge capping and flashing | 41 |
| Table 3.16 Compatibility factors for possible material combinations | 42 |
| Table 3.17. Possible cases for windows | 43 |
| Table 3.18. Possible cases for steel supports | 45 |
| Table 3.19. The ventilation factors for subfloor members..... | 46 |

| | |
|---|-----|
| Table 3.20. Possible cases for subfloor members | 47 |
| Table 3.21. All parameters and cases determined for specified components | 49 |
| Table 3.22. Results of running revised models for components using climate conditions near Cairns .. | 51 |
| Table 3.23. Test variables for each type of metal | 54 |
| Table 3.24. Schedule for spraying | 55 |
| Table 3.25. Mass loss results for all samples | 56 |
| Table 4.1. Experimental details of leaching studies | 60 |
| Table 4.2. A comparison of old and new implementations for the calculation of salt concentration and time-of-wetness in gutters..... | 72 |
| Table 4.3. Analytical analysis of aqueous solutions obtained from (i) leaf matter in dirty gutters and (ii) solutions prepared from identical amounts of tree matter only. Further experimental detail is given in the text | 76 |
| Table 4.4. Typical values for Rp measured on Colorbond backcoats are:..... | 81 |
| Table 4.5. Modelling results for the backcoat of a clean and well-drained gutter. A comparison of EIS measured corrosion rates, estimated corrosion rates for the equivalent time period (from model) and the estimated time to failure (given as the time to totally remove the protective zincalume) .. | 82 |
| Table 4.6. Modelling results for the backcoat of a dirty and poorly maintained gutter. A comparison of EIS measured corrosion rates, estimated corrosion rates for the equivalent time period (from model) and the estimated time to failure (given as the time to totally remove the protective zincalume) | 83 |
| Table 4.7. Modelling results for the backcoat of a dirty and poorly maintained gutter. A comparison of EIS measured corrosion rates, estimated corrosion rates for the equivalent time period (from model) and the estimated time to failure (given as the time to totally remove the protective zincalume) | 84 |
| Table 5.1. Queensland School Details | 89 |
| Table 5.2. Victorian School Details | 90 |
| Table 5.3. Definition of Rating used for Components..... | 91 |
| Table 5.4. Parameter Values for Colorbond® components | 94 |
| Table 5.5. Parameters for Zincalume components | 95 |
| Table 5.6. Parameters for Galvanised components | 95 |
| Table 5.7. Parameters for Galvanised components..... | 96 |
| Table 5.8. Database of Service life determined from Survey data..... | 97 |
| Table 6.1. Details of Datasets | 105 |

| | |
|---|-----|
| Table 6.2. Details of Delphi Survey..... | 106 |
| Table 6.3. Details of Holistic-I..... | 106 |
| Table 6.4. Details of Holistic-II..... | 107 |
| Table 6.5. Details of Holistic-III..... | 108 |
| Table 6.6. Details of Datasets..... | 117 |
| Table 6.7. Classification Accuracy of Naïve Bayes & DT (C4.5)..... | 117 |
| Table 6.8. Correlation Coefficient of KNN, NN, SVM & M5..... | 118 |
| Table 6.9. Correlation Coefficient of M5, M5 + KNN and Bagging..... | 121 |
| Table 6.10: Mean Absolute Error of M5, M5 + KNN and Bagging..... | 121 |
| Table 6.11. Salt Deposition Knowledge..... | 123 |
| Table 6.12. Rainfall Knowledge..... | 123 |
| Table 6.13. Generalised Rules..... | 124 |

List of Figures

| | |
|---|----|
| Figure 1.1. GUI developed in previous project for life prediction of gutters in Queensland schools..... | 4 |
| Figure 1.2. Bridge zones developed from CFD analysis..... | 5 |
| Figure 1.3. User interface for bridge program for calculation of salt deposition..... | 7 |
| Figure 2.1. Atmospheric salt concentration near the coast | 8 |
| Figure 2.2. Atmospheric salt concentration 2-50km from the coast..... | 8 |
| Figure 2.3. Salt variation with height for flow over smooth terrain. | 10 |
| Figure 2.4. Bureau of Meteorology data on Queensland rainfall | 11 |
| Figure 2.5. Rainfall on the bridges at a) Gladstone Port Overpass , b) Ward River. The colours represent rainfall intensity, with blue as low intensity and red as high intensity (rain coming in through the left boundary has been ignored). The black lines are tracks of individual raindrops. | 12 |
| Figure 2.6 Pollution levels on the rain-washed part of the surface, together with a fitted exponential decay rate. | 14 |
| Figure 2.7. Map of Queensland showing the areas designated for salt accumulation calculations | 16 |
| Figure 2.8. The user interface for the salt deposition on bridges program..... | 19 |
| Figure 2.9. Detail from the user interface for the salt deposition on bridges program showing the risk factor..... | 19 |
| Figure 3.1. Definition of scale domains for holistic model. | 22 |
| Figure 3.2 Structure of the modules of the holistic model for predicting corrosion | 23 |
| Figure 3.3 Factors affecting service life of metallic components and how they relate to modules of the holistic model..... | 23 |
| Figure 3.4 Underside of gutter showing significant corrosion. | 27 |
| Figure 3.5 Rusting and deterioration on downpipe showing that problems are commonly associated with the joints..... | 28 |
| Figure 3.6 Sections of downpipe considered as separate cases..... | 28 |
| Figure 3.7. Instrumentation installed in the downpipe | 30 |
| Figure 3.8. Sample of Data from the instrumented downpipe..... | 31 |
| Figure 3.9. Galvanised Kliplok roof sheeting showing extensive red rust. | 32 |
| Figure 3.10 Underside of roof sheeting showing significant white corrosion product and some red rust. | 33 |
| Figure 3.11 Heads of roof fasteners showing red rust and white corrosion product. | 35 |

| | |
|---|----|
| Figure 3.12 Fastener shanks showing red rust. | 36 |
| Figure 3.13 Roof fastener cases being considered: fixed to timber or fixed to steel..... | 36 |
| Figure 3.14. The various sections of a roof fastener..... | 36 |
| Figure 3.15. Illustration of metal ridge capping. | 40 |
| Figure 3.16. Flashing between wall and roof. | 40 |
| Figure 3.17. Example of metal window frames. | 42 |
| Figure 3.18. Galvanised post (right) and close up (left) showing signs of white corrosion product. | 44 |
| Figure 3.19. The three cases for embedding of steel supports in concrete..... | 44 |
| Figure 3.20. Significant deterioration of sub-floor metallic components on modular classroom..... | 46 |
| Figure 3.21. Gang nail plates showing some red rust and white corrosion product..... | 48 |
| Figure 4.1. Photographs of the seven cells after two leaching cycles. | 61 |
| Figure 4.2. Photographs of the seven leaching cells after seven leaching cycles. | 62 |
| Figure 4.3. The leaching rate of chromium as a function of time from the cut edge of Colorbond XRW. | 63 |
| Figure 4.4. Leaching of chromate from paint films with various damage sites..... | 63 |
| Figure 4.5. (a) Concentrations of Strontium and Chromium during the first 48 hours of leaching from the cut-edge of Colorbond XRW in 50 mL aqueous solution at pH 2. (b) Cr:Sr ratio for leaching from the cut-edge over a longer time period. | 64 |
| Figure 4.6. Leaching data for strontium and chromium from cell 5 (topcoat with pinhole defects) as a function of leaching time. Note that a return to zero concentration occurs when the pH 2 leaching solution is refreshed. | 65 |
| Figure 4.7. Chromium concentrations removed from Colorbond after short time periods and those estimated from strontium ion concentration after longer time periods. | 65 |
| Figure 4.8. Relationships between simple climatic parameters (average daily maximum temperature and average daily relative humidity [9am and 3pm]) and the solar weathering index of Martin [5]. | 67 |
| Figure 4.9. Correlations between the concentration (in mol L ⁻¹) of strontium released into solution and those of zincalume and steel in aqueous solution acidified to pH 2 using HCl..... | 69 |
| Figure 4.10. Correlations between the concentration of strontium released into solution and those of zincalume and steel in aqueous solution acidified to pH 2 using HCl..... | 70 |
| Figure 4.11. The relationship between roof area and gutter area. Roof area = L/0.1 (or 10 × L) times the gutter area. | 71 |
| Figure 4.12. Estimations of the accumulation of salt in gutters at Brookfield State School calculated from rainfall runoff and accumulation using the old model. | 74 |

| | |
|--|-----|
| Figure 4.13. Accumulated chloride in a clean gutter over a one year period predicted using the revised methodology and assuming a collection length of 5m. | 75 |
| Figure 4.14. Accumulated chloride in a dirty gutter over a one year period predicted using the revised methodology and assuming a collection length of 5m. | 75 |
| Figure 4.15. Common equivalent circuits used to describe a metal-coating-solution interface using EIS measurements. | 77 |
| Figure 4.16. Typical fit of data to model 'C'. $R_s = 29.5 \Omega$, $C_c = 8.45 \times 10^{-9} \text{ F}$, $R_c = 585.2 \Omega$, $\text{CPE-T} = \text{Cdl} = 1.11 \times 10^{-8} \text{ F}$ (where $\text{CPE-P} = 1$) and $R_p = 5.34 \times 10^7 \Omega$. Surface area = 18.4 cm ² | 79 |
| Figure 4.17. Typical fit of data to model 'C'. $R_s = 358.5 \Omega$, $C_c = 1.038 \times 10^{-8} \text{ F}$, $R_c = 18930 \Omega$, $\text{CPE-T} = \text{Cdl} = 3.74 \times 10^{-8} \text{ F}$ (where $\text{CPE-P} = 1$) and $R_p = 3.42 \times 10^6 \Omega$. Surface area = 12.6 cm ² | 79 |
| Figure 4.18. Colorbond measurements using the portable EIS equipment. | 80 |
| Figure 5.1 Locations of the different areas surveyed, chosen to give a range of climates. | 88 |
| Figure 5.2. The Colorbond data for roofs in graphical form. | 93 |
| Figure 6.1. Training of the Model. | 99 |
| Figure 6.2. Using the Trained Model. | 99 |
| Figure 6.3. Query Based Learning System. | 100 |
| Figure 6.4. Phases of the CRISP-DM Process Model. | 103 |
| Figure 6.5. Query Based Learning System. | 112 |
| Figure 6.6: Correlation Coefficient of KNN, NN, SVM & M5. | 118 |
| Figure 6.7. M5 + KNN Algorithm. | 120 |
| Figure 6.8. Correlation Coefficient of M5, M5+KNN and Bagging (D=Delphi, H-I=Holistic-I, H-II= Holistic-II, H-III_G=Holistic-III for Galvanized Steel, H-III_Z=Holistic-III for Zinalume). | 121 |
| Figure 6.9. Mean Absolute Error of M5, M5+KNN and Bagging, (D=Delphi, H-I=Holistic-I, H-II= Holistic-II, H-III_G=Holistic-III for Galvanized Steel, H-III_Z=Holistic-III for Zinalume). | 122 |
| Figure 6.10. Overview of System. | 123 |
| Figure 6.11. User Interface of System. | 125 |
| Figure 7.1. User interface for life prediction program for building components. | 129 |
| Figure 7.2. Panel for inputting choice of component. | 129 |
| Figure 7.3. Panel for selecting Material type – only those relevant to the selected component are available. | 130 |
| Figure 7.4. More Options panel only allows input of data relevant to selected component. | 130 |
| Figure 7.5. Panel for information required for accessing Delphi data set. | 131 |

| | |
|---|-----|
| Figure 7.6. Panel for Maintenance database information and the Predict button..... | 131 |
| Figure 7.7. How prediction data is presented | 131 |
| Figure 7.8 . Warning dialog box that appears if not all required information is selected..... | 132 |

EXECUTIVE SUMMARY

The project has further developed two programs for the industry partners related to service life prediction and salt deposition.

The program for Queensland Department of Main Roads which predicts salt deposition on different bridge structures at any point in Queensland has been further refined by looking at more variables. It was found that the height of the bridge significantly affects the salt deposition levels only when very close to the coast. However the effect of natural cleaning of salt by rainfall was incorporated into the program. The user interface allows selection of a location in Queensland, followed by a bridge component. The program then predicts the annual salt deposition rate and rates the likely severity of the environment.

The service life prediction program for the Queensland Department of Public Works has been expanded to include 10 common building components, in a variety of environments. Data mining procedures have been used to develop the program and increase the usefulness of the application. A Query Based Learning System (QBLS) has been developed which is based on a data-centric model with extensions to provide support for user interaction. The program is based on number of sources of information about the service life of building components. These include the Delphi survey, the CSIRO Holistic model and a school survey. During the project, the Holistic model was modified for each building component and databases generated for the locations of all Queensland schools. Experiments were carried out to verify and provide parameters for the modelling. These included instrumentation of a downpipe, measurements on pH and chloride levels in leaf litter, EIS measurements and chromate leaching from Colorbond materials and dose tests to measure corrosion rates of new materials.

A further database was also generated for inclusion in the program through a large school survey. Over 30 schools in a range of environments from tropical coastal to temperate inland were visited and the condition of the building components rated on a scale of 0-5. The data was analysed and used to calculate an average service life for each component/material combination in the environments, where sufficient examples were available.

1 INTRODUCTION

1.1 Background

The ability to accurately predict the lifetime of building components is crucial to optimising building design, material selection and scheduling of required maintenance. This project follows on from CRC Project 2002-059-B Case Based Reasoning in Construction and Infrastructure Projects. This developed two pieces of software. The first was an illustration of how the principles of case based reasoning could be applied to a program that predicted the service life of roofs and gutters. This was developed for the Queensland Department of Public Works and related specifically to government schools in Queensland. The program accessed several sources of information on service life including databases formulated from the CSIRO holistic model for corrosion (modified for gutters) and a database populated through a Delphi survey of expert opinion (CRC Project 2002-010-B). Databases were searched for case matches using similarity rules developed for the program. The prototype program had no method of choosing the best option from several retrieved, and no process for saving the retrieved information as a new case – an essential part of case-based reasoning. Figure 1.1 shows the user interface developed for the program and illustrates the important factors in determining service life of building components.

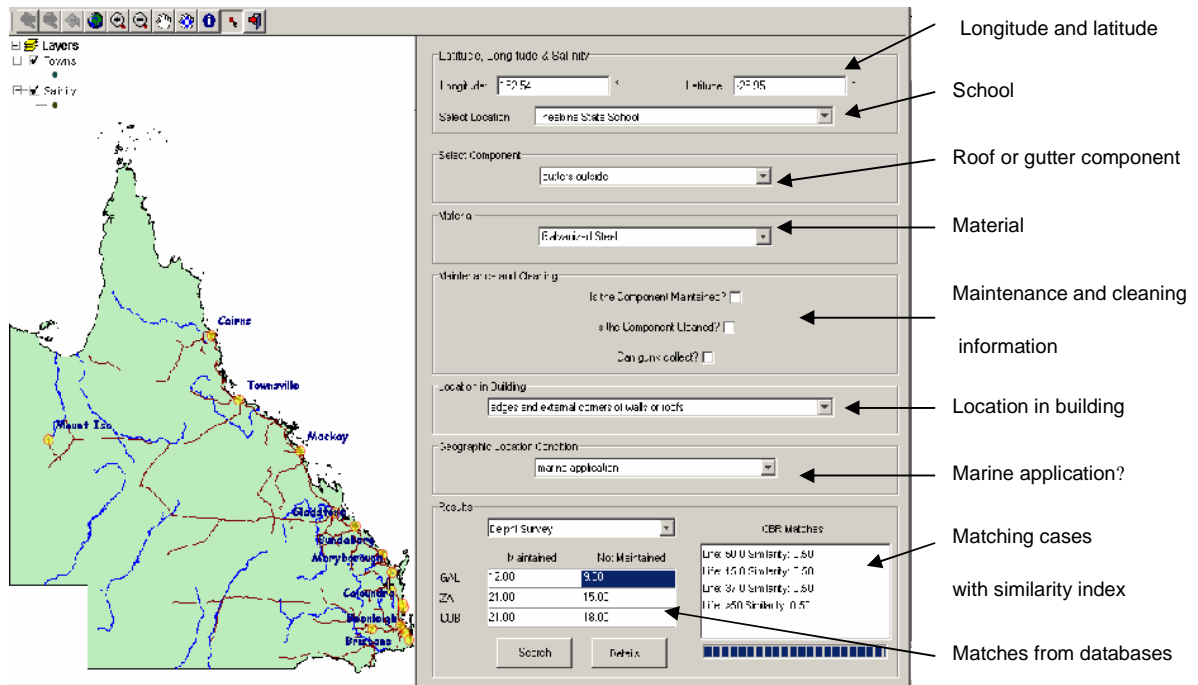
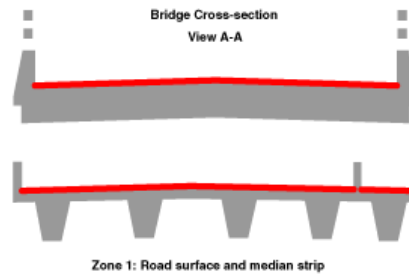


Figure 1.1. GUI developed in previous project for life prediction of gutters in Queensland schools

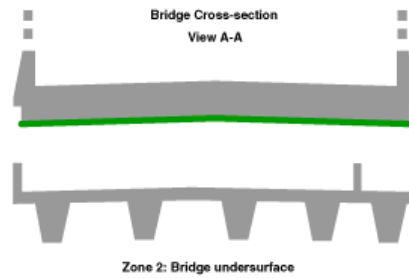
The second program was developed for the industry partners at the Queensland Department of Main Roads who had an interest in the life prediction of metal components of bridge structures. Several common bridge structures were analysed to extract bridge elements that could be used as case definitions in the future as the basis of a similar case based reasoning prediction program. Figure 1.2 illustrates the nine bridge elements chosen after

Computational Fluid Dynamics analysis of the bridge structures with respect to salt deposition.

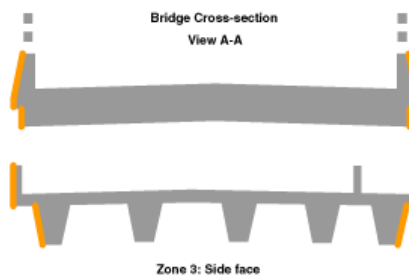
1. Road surface and median strip



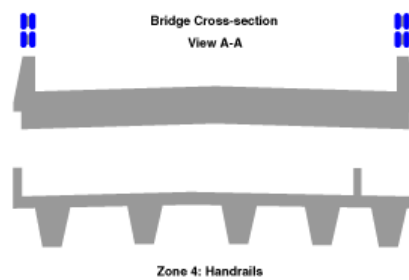
2. Bridge under-surface



3. Side face



4. Handrails



5. Side of support beams

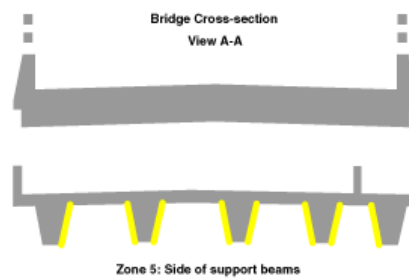
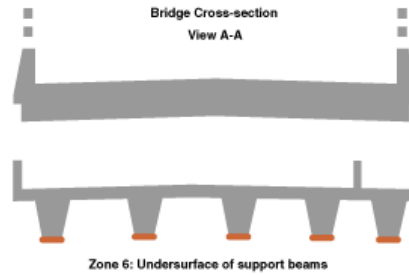
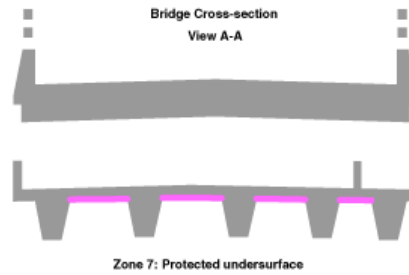


Figure 1.2. Bridge zones developed from CFD analysis

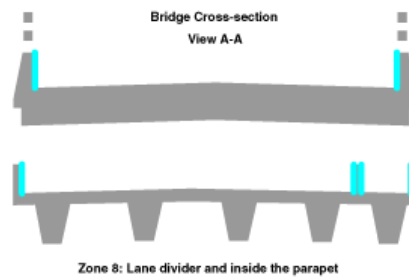
6.Under-surface of support beams



7.Protected under-surface



8.Lane divider and inside the parapet



9.On top of the parapet and under the side overhang

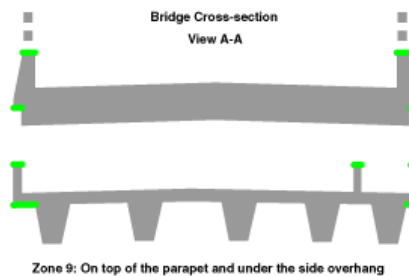


Figure 1.2(cont). Bridge zones developed from CFD analysis

Metal corrosion is largely governed by the amount of salt and water on the surface of a component so a program was developed that predicts the salt deposition on the different bridge elements for any location in Queensland. Figure 1.3 illustrates the user interface for the program. A drop down menu facilitates choice of the bridge zones and the salt deposition is displayed for the zone selected. The zoom facility on the map of Queensland has also been employed.

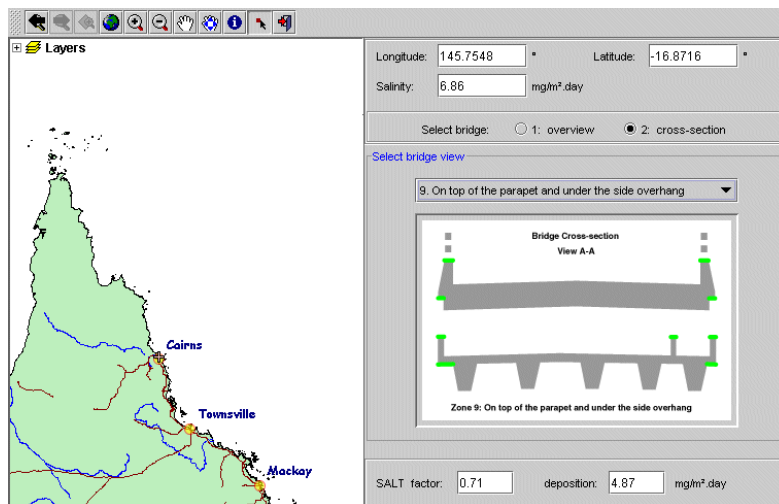


Figure 1.3. User interface for bridge program for calculation of salt deposition

1.2 Project Aims and Outcomes

The initial programs were prototype programs to show the usefulness of the concept. This phase of the work aimed to further develop both programs.

1.2.1 QDPW Program

Whilst the Delphi database utilised by the QDPW program contained information about a number of common metal building components the database derived for the CSIRO Holistic model was based purely on gutters. One of the aims of the project was to expand the number of building components to ten, choosing those of relevance to Queensland schools. This necessitated modifying the holistic model to take into account the various attributes and combinations of attributes that could occur for these components.

Originally it was planned to utilise the Queensland Department of Public Works database of maintenance activities to develop a lifetime database giving information based on current usage and updating as more events were entered by the actual maintainers reflecting ongoing upkeep of the schools' infrastructure. Maintenance information is seen as being a particularly useful source of data about service life of building components as it relates to actual performance of materials in the working environment.

Access was granted to a number of databases recording maintenance activities in Queensland Government Housing. However, analysis of the information indicated that entries did not give information in fine enough detail to enable extraction of data for the individual building components being considered in the current work.

An alternative approach was devised to estimate the performance of materials in the field. This involved a survey of a range of schools with inspection of the chosen building components in the project. These were given a rating indicating the current condition of the structure and the age of the buildings was also ascertained. Where sufficient examples were collected the data was analysed and the information collated in a database. The data

collected was also used to validate the modifications made to the holistic model for the different building components.

In the previous project a model was proposed for the degradation of Colorbond®, a new material not previously included in the Holistic model. Further work has been carried out to validate and update this model in this part of the project.

Thus the expanded program created for QDPW contains three databases: Delphi database, Holistic model for ten components, and a survey database.

These sources of information should be viewed as complementary rather than as discrete alternatives. They form different data sources of service life information. The problem is how they could be combined to determine the most appropriate answer for any given situation. The focus in this phase of the project has shifted from Case-Based Reasoning to data mining (partly due to changes in project partners). However, data mining is considered to be an ideal method that links together the different data sources and provides intelligent decisions. Data mining algorithms have been devised for the different databases and the results are presented to the program user.

1.2.2 QDMR Program

The bridge application for QDMR has been developed further by looking at other factors that will affect the levels of salt accumulating on the bridge structures. In particular the effects of the height of the bridge above water level and natural wash-off on the salt deposition levels have been analysed and incorporated into the program.

1.2.3 Report Outline

The improvements made to the bridge program for QDMR are discussed in detail in Chapter 2.

Chapter 3 looks at the selection, parameterisation and modelling for the extended number of building components.

The work done on validating the Colorbond® degradation model is discussed in Chapter 4

The methodology and data collected in the school survey is detailed in Chapter 5, along with the analysis and formation of the database.

Chapter 6 looks at the data mining techniques and how these were applied to the databases in the project.

The updated expanded program for prediction of service life of ten building components is presented in Chapter 7.

2. BRIDGE PROGRAM DEVELOPMENT

2.1 Introduction

Maintenance of bridge structures is a major issue for the Queensland Department of Main Roads. In the previous phase of this CRC project an initial approach was made towards the development of a program for lifetime prediction of metallic bridge components. This involved the analysis (using CFD) of five representative bridge structures with respect to salt deposition (a major contributor to metallic corrosion) to determine common elements to be used as “cases” - those defined for buildings are not applicable. These are illustrated in Figure 1.2. A program was developed to predict the salt deposition on these common elements at any point in Queensland. This program has been further refined by including more variables in the calculations. In particular, the effect of the height of the bridge above water level and the natural washing effect of runoff have been considered in the accumulation of salt calculations.

2.2 Effect of Bridge Height

2.2.1 Calculation of Salt Concentration

The effect of bridge height was considered in two separate parts: close to the coast and further inland, because the salt levels vary quite rapidly close to the coast, but the rate of change drops off quite rapidly further inland.

The computed variation of atmospheric salt concentration with height is shown in Figure 2.1 and 2.2.

Figure 2.1 shows the computed salt concentration as a function of height near the coast, at distances of 20, 50, 100 and 200 metres from the high water mark. Figure 2.2 shows the computed salt concentration as a function of height further from the coast, at distances of 2, 5 and 50 kilometres from the coast. Salt concentration profiles even further from the coast resemble those at 50 km. Salt concentrations below a height of 20 m in Figure 2.2 are not reliable because of the limitations of CFD grid resolution.

In Figure 2.2, the drop-off in salt concentration at heights below 25 metres is due to the effects of vegetation and topographic roughness but this decrease in concentration cannot be accurately computed. An average roughness calculated from topographic, urban and vegetation roughnesses is used. Vegetation and urban structures remove salt from the air and the combination of steep terrain and vegetation can remove even more.

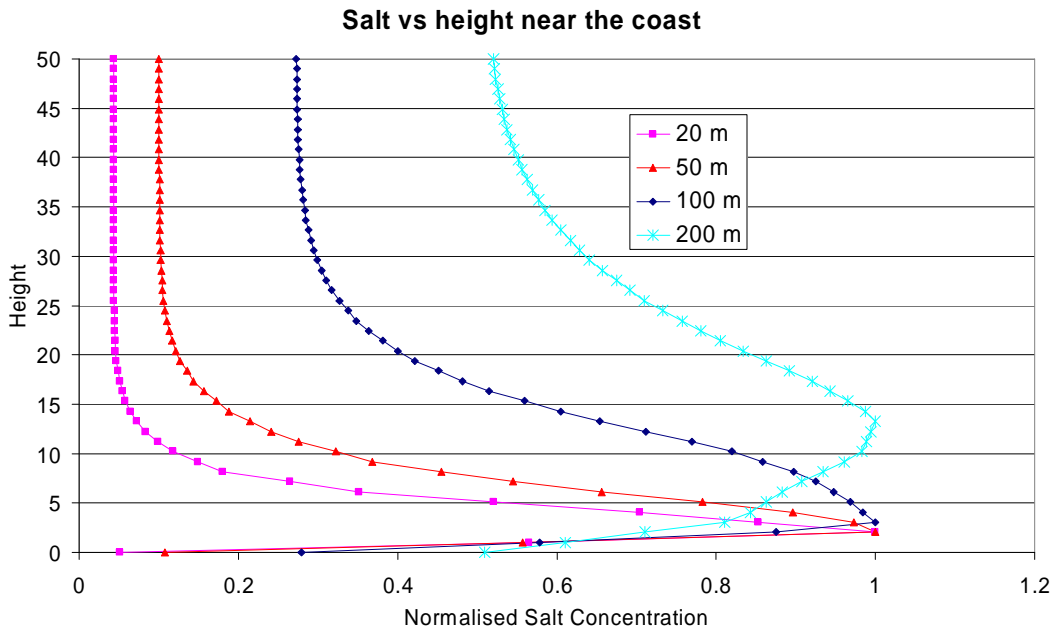


Figure 2.1. Atmospheric salt concentration near the coast

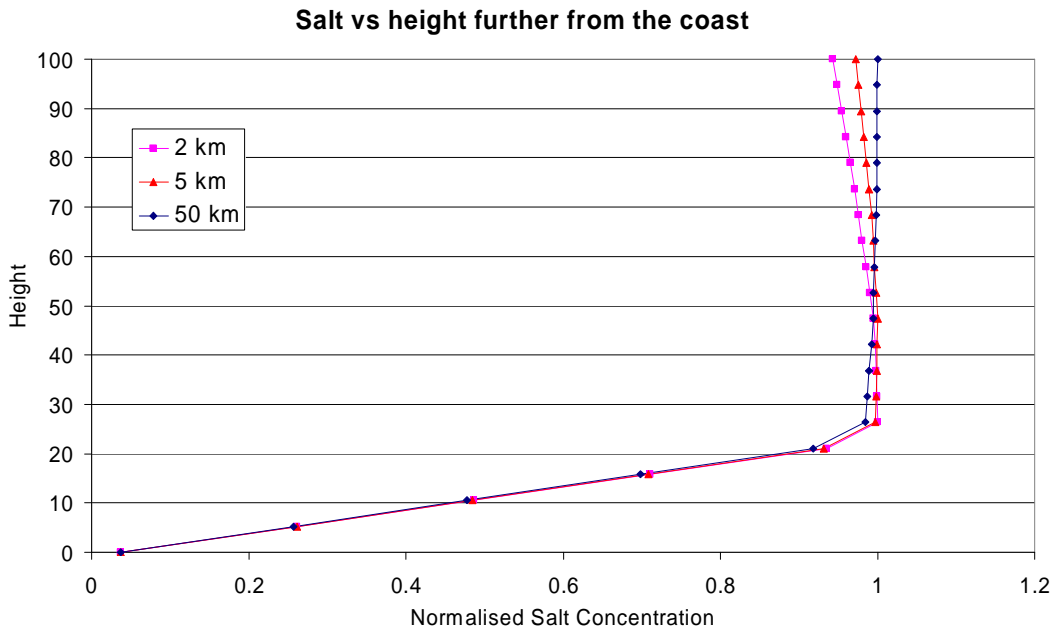


Figure 2.2. Atmospheric salt concentration 2-50km from the coast

Above 25 metres, the variation with height is due to a balance between gravity and air turbulence. Gravity brings salt-containing aerosols down towards the ground. This leads to a high concentration at lower heights. On the other hand, air turbulence tends to even out concentration and does so by reducing the concentration at lower levels and increasing them at upper levels. The result is a balance between gravity and turbulence that leads to an exponential decay of salt concentration with height (up to cloudbase) for each aerosol size.

By 50 km from the coast, all the coarser aerosols have already settled out, leaving only the fine aerosols that are almost unaffected by gravity so, above the influence of the vegetation and topography, the air turbulence gives these a concentration that is independent of height. At 2 km from the coast, some larger aerosols remain and gravity drags these downward resulting in a higher concentration at 25 to 50 metres high.

In Figure 2.1, the salt concentration profile 20 metres from the high water mark (pink data series) indicates the peak salt concentration is at a height of only 2 metres or so. This is because the salt is generated by ocean waves and these are not very high. The salt from the coastal waves has not yet diffused up to higher levels of the atmosphere. However, there is some salt at heights above 20 metres, and that is the salt that was generated way out at sea, independently of the waves at and near the coast.

Several things happen as the salt aerosol travels further distances from the coast. At 200 metres from the high water mark (light blue data series in Figure 2.1), the vegetation, urban and topographic roughness have strained salt from the lower 10 metres of the atmosphere. Salt from the coast has diffused upwards. The heaviest salt aerosol particles have settled out, leading to a more uniform variation of concentration with height.

Also, as the heaviest salt aerosol particles have settled out, so the relative proportion of the salt from the open ocean has increased, and this accounts for most of the increase in salt concentration at a height of 50 metres in Figure 2.1.

Local variations in vegetation, urban usage and topography will affect the salt variation with height at any given location. In smooth terrain with stunted vegetation and no urban development the height of peak salt will be lower. In rough terrain or with high-rise buildings or dense forest the height of peak salt will be higher. The one exception to that second statement is when the location is on the side of or top of an escarpment facing the ocean, then the height of peak salt will be lower.

2.2.2 Comparison with Salt levels on Gateway Bridge

The project partner, Queensland Department of Main Roads, was able to provide some chloride measurements taken at different heights on the Gateway Bridge over the Brisbane River. These measurements are listed in Table 2.1. The chloride concentration is in kg/m^3 .

Table 2.1. Chloride levels on the Gateway Bridge

| Core number | Height (m) | Chloride at 15 mm deep (kgm^{-3}). |
|-------------|------------|---|
| 7-6 | 1.40 | 0.69 |
| 6-4 | 1.425 | 0.57 |
| 6-2 | 1.50 | 0.54 |
| 7-4 | 4.65 | 0.26 |
| 6-6 | 4.95 | 0.29 |
| 6-8 | 8.97 | 0.30 |
| 7-2 | 9.80 | 0.22 |

Other relevant parameters include the distance from the coast (7.1km) and the type of terrain between the bridge and the coast: smooth, with no major obstructions.

Unfortunately, no direct comparison with computed results for this distance from the coast for the low ground roughness appropriate for the Gateway Bridge is feasible because it is not

possible to easily compute salt concentrations below a height of 20 metres at distances further than 1 km from the coast, see Figure 2.3.

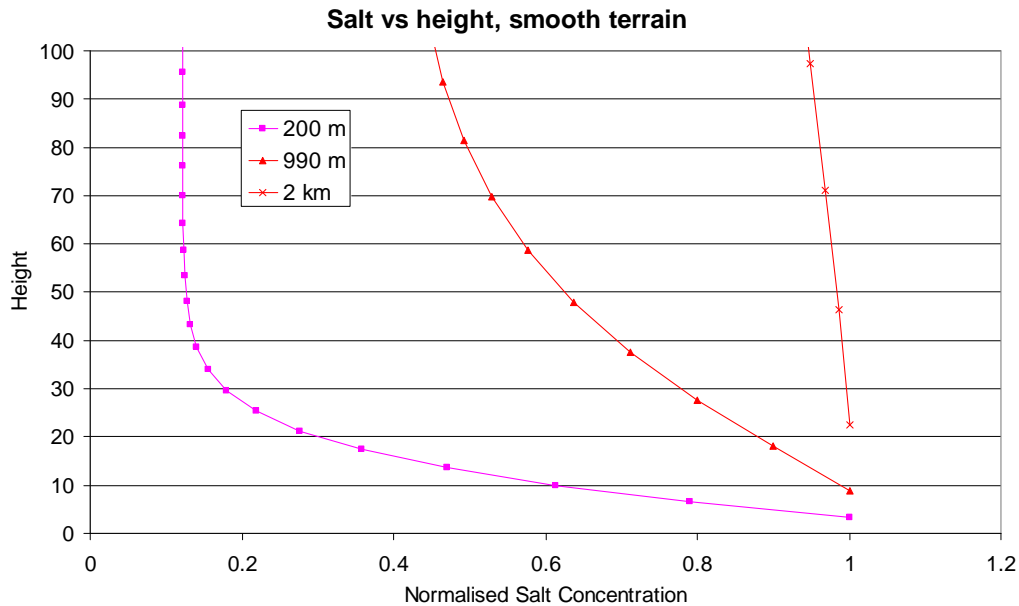


Figure 2.3. Salt variation with height for flow over smooth terrain.

Computed results for this location suggest that salt concentration in the air only decreases a small amount with height, no more than about 2% in 10 metres of height. This is consistent with the salt readings at heights of 4.65 metres and above. The significantly larger salt concentrations at 1.4 to 1.5 metres on the bridge are most probably due to splash and the bursting of bubbles created by ship propulsion systems. There is a significant amount of water traffic on the Brisbane River at this point, and the affects of this are not factored into the original calculations.

2.2.3 Conclusions

Adjacent to the coast, the salt concentration is largest at heights below 5 metres, unless salt at this height is blocked by high vegetation, rough terrain or urban development.

Under conditions of typical roughness (vegetation, terrain and urban), this height of peak salt concentration has moved up to about 14 metres at 200 m from the coast, and about 25 metres further than 2 km from the coast. The variation of salt concentration with height in the atmosphere gets less as the distance from the coast increases and the large droplets of salt water generated by salt spray at the coast settle out.

Under conditions of fairly low roughness, as in the area between the Gateway Bridge and the coast, it is not easy to say at what height the peak salt concentration is except to say that it is at a height of less than 22 metres at the position of the Gateway Bridge. At that distance from the coast the salt concentration is fairly constant with height.

Measurements of the salt concentration on the Gateway Bridge suggest that at heights of about 1.5 metres the salt spray from the river is increasing the amount of salt deposited above the ambient levels in the atmosphere.

Due to the fact that the height of the bridge will only have a significant impact on the salt deposition levels very close to the coast, these were not factored into the program revisions.

2.3 Natural Cleaning of Bridge Components

All the salt that is deposited on a structure does not necessarily remain there. Natural occurrences, in particular rain, may remove some of the deposited salt. The rate at which this occurs will depend on the amount of the rain, the material of the structure, the orientation and natural sheltering. Rainfall varies significantly across the state of Queensland (see Figure 2.4) so the wash-off of salt will also vary considerably depending on the location.

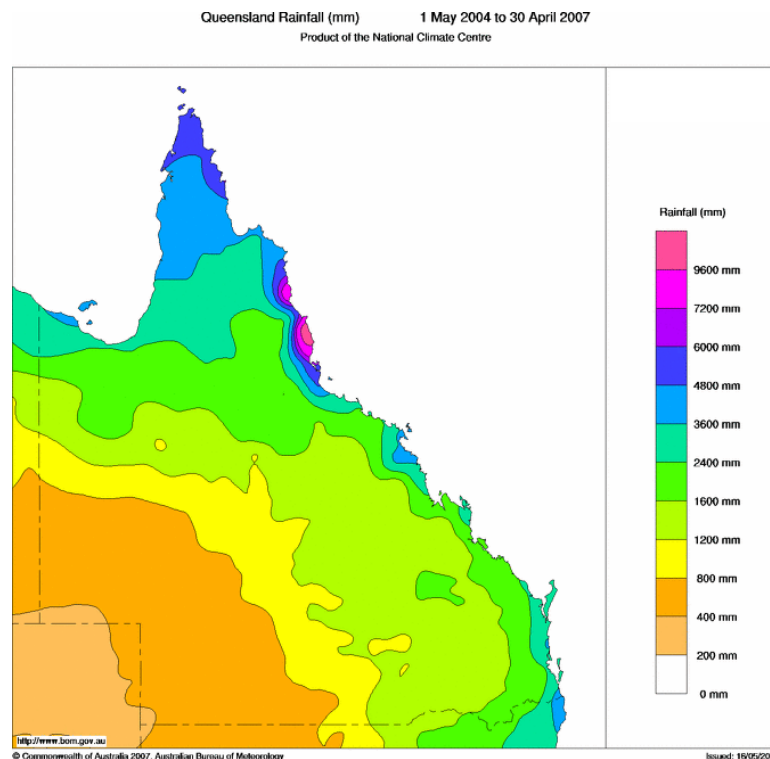


Figure 2.4. Bureau of Meteorology data on Queensland rainfall

Other natural mechanisms for salt removal include wind and condensation. Studies have shown that these mechanisms are unlikely to contribute markedly to the cleaning of bridges and these mechanisms have not been included in the calculations. (Muster and Cole, 2005; Cole et al., 2004)

2.3.1 Washing by Rain

Results of computer simulations of rain falling on bridge superstructures (Gladstone Overpass and Ward River) are shown in Figure 2.5. 50,000 raindrops with a mean diameter of 2.1 mm (terminal velocity 6.7 m/s) in a rain-shower of intensity 15.7 mm/hr were released

above the bridges. The assumed wind speed is 4.4 m/s at the Gladstone Overpass and 4.0 m/s at Ward River) The size distribution of raindrops was “Best’s raindrop distribution” as reported in Seinfeld & Pandis (1998). This is equivalent to a Rosin-Rammler distribution with size 2.48 mm and power 2.25.

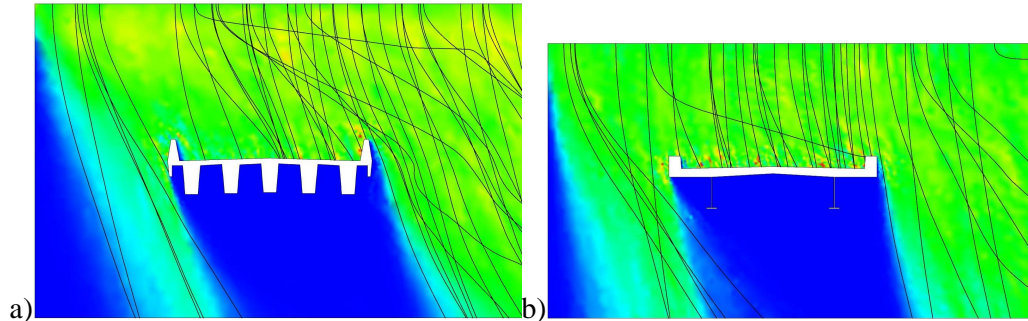


Figure 2.5. Rainfall on the bridges at a) Gladstone Port Overpass , b) Ward River. The colours represent rainfall intensity, with blue as low intensity and red as high intensity (rain coming in through the left boundary has been ignored). The black lines are tracks of individual raindrops.

As expected, these simulations show that the bridge components that are oriented upwards and outwards on the sides of the bridge get very wet when the rainfall is heavy enough. The bridge components under the bridge superstructure, and those on the side of the bridge opposite where the rain is coming from can get slightly damp, but not enough for rain-washing.

The direction from which the rain comes results from a combination of the wind due to synoptic pressure systems (highs and lows) and wind generated by the rainstorm itself. The heavier the rain, the more the wind is generated by the rainstorm and the more this governs the wind direction. The wind generated by the rainstorm can be in any direction so it is reasonable to say that cleaning by rain can occur on all sides of the structure.

There are locations on the superstructure where the rain drips off. These areas are very prone to corrosion, salt can build up there and the longer than normal presence of water makes it a very corrosive micro-environment. This applies particularly to zone 6 of the Ward River Bridge, and the bottom edges of handrail and crash barrier components on other bridges. The parts of the piers under the centre of the superstructure are shielded from the rain and so the salt is not cleaned off there. The surfaces of the piers under the edges of the superstructure are cleaned by rain.

A rainfall reduction factor (η) is introduced to account for the different effects of rain and the actual rain impacting on a surface is simply η multiplied by the measured rainfall. Thus for fully exposed positions, such as the road surface and top of the parapet, $\eta = 1$, for positions, such as the side face, some rain which is off the vertical is blocked by the opposite side of the parapet and so $\eta = 0.8$. In the case of the hand rails, the undersurface is taken, as this is the worst case. Here rain impact will be limited but there will be some run off effect from the top of the rail so $\eta = 0.3$. For the side position of the support beams, limited rain deposition will occur in high winds when the rain is at an acute angle to the vertical. These factors are summarised in Table 2.2.

Table 2.2. Values derived for η (rainfall reduction factor)

| No | Element | η | Reasoning |
|----|---|--------|-------------------------------|
| 1 | Road Surface | 1 | Fully exposed |
| 2 | Bridge Underside | 0 | Fully sheltered |
| 3 | Side face | 0.8 | Some sheltering |
| 4 | Hand rails | 0.3 | Underside taken as worst case |
| 5 | Side of Support Beams | 0.05 | Very limited rain deposition |
| 6 | Undersurface of support beams | 0 | Fully sheltered |
| 7 | Protected undersurface | 0 | Fully sheltered |
| 8 | Lane divider and inside the parapet | 0.8 | Some sheltering |
| 9 | On top of the parapet and under the side overhang | 1 | Fully exposed |

2.3.2 Rainfall intensity and duration needed for bridge cleaning

Not all the rain falling on a structure runs off. Some adheres to the surface and some soaks into the surface. This can be treated on individual surfaces as an initial loss ϕ_i (in mm) and a continuing loss ϕ_c (in mm/hr). If the rainfall rate is R in mm/hr then the runoff $\phi_o(t)$ is given by:

$$\phi_o(t) = \max(0, (R - \phi_c)t - \phi_i). \quad \dots\text{Eqn (2.1)}$$

Tests conducted at CSIRO were used to determine values for ϕ_c and ϕ_i for various materials. Because rainfall data is generally only available in three hourly intervals, these figures needed to be adjusted. Using a set of data from Brisbane where rain intervals of one minute were available, new rain washing factors were calculated and these are listed in Table 2.3.

Table 2.3. Values for initial loss ϕ_{3i} (in mm) and a continuing loss ϕ_{3c} (in mm/hr)

| Material | ϕ_{3c} (mm/hr) | ϕ_{3i} (mm) |
|------------------------------|---------------------|------------------|
| Painted concrete (or steel) | 0 | 0.04 |
| Bare metal, uncorroded | 0.43 | 0.17 |
| Bare concrete, smooth finish | 0.61 | 0.092 |
| Bare concrete, rough finish | 1.2 | 0.31 |

2.3.3 Relationship Between Runoff and Cleaning

In previous work relating to the holistic model of corrosion, the effect of rain on cleaning a fresh plate has been approximated, to the first order, by (Cole et al, 2007)

$$S_f = S_i \times e^{-\alpha R} \quad \text{if } R_i - R_c > 0 \quad \dots\text{Eqn (2.2)}$$

or

$$S_f = S_i \quad \text{if } R_i - R_c < 0 \quad \dots\text{Eqn (2.3)}$$

Where S_i is the initial salt content and S_f is the final salt content (after rainfall), R_i is the rainfall rate (in mm/hr) in a particular rainfall event and R_c is the critical rainfall rate (in mm/hr) required to guarantee runoff and cleaning. α is a constant that has been estimated from simulation to be 1.5 (Cole and Paterson, 2007).

In experimental studies it was found that runoff is not even, with individual drops needing to coalesce to reach a critical size before running down the plate and cleaning a path. Figure 2.6 shows the stepped shape of the pollution level curve due to this uneven cleaning. It can be approximated to an exponential decay rate. Depending on the rainfall rate, the size of the timestep will vary.

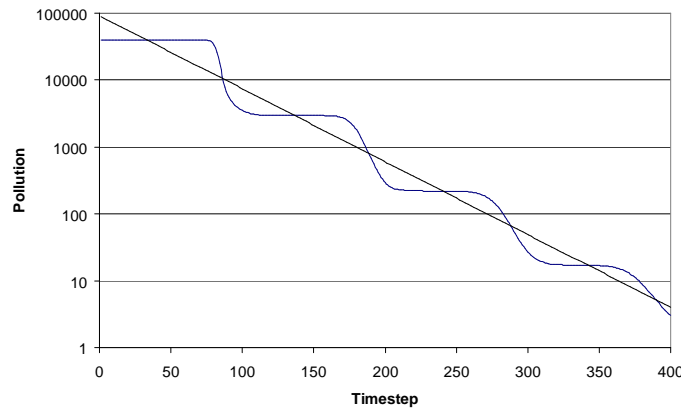


Figure 2.6 Pollution levels on the rain-washed part of the surface, together with a fitted exponential decay rate.

Equations 2.2 and 2.3 can be simplified if the run off is considered rather than the rainfall rate.

Then

$$S_f = S_i \times e^{-\alpha\phi} \quad \dots\text{Eqn (2.4)}$$

Where ϕ is the run off given in Equation (2.1).

The current corrosion model considers three hourly intervals so in that time span the runoff is given by:

$$\phi_o(3) = \max(0, (\eta R - \phi_{3c}) - \phi_{3i}). \quad \dots\text{Eqn (2.5)}$$

Where η is the geometric factor introduced that accounts for the different levels of rain falling on the component relative to rainfall onto a flat surface (see Table 2.2).

Thus the correct exponential decay factor is either 0 or $\alpha(\eta R - \phi_{3c}) - \phi_{3i}$, which thus has two terms $3\alpha\eta R - \alpha(\phi_{3c} + \phi_{3i})$ so this can be simplified as $\psi R - \phi$. So

$$S_f = S_i \times e^{-\psi R - \phi} \quad \dots\text{Eqn(2.6)}$$

The parameters for the different components are given in Table 2.4.

Thus for any given bridge element at a particular location with known rainfall the salt accumulation can be calculated, taking into account the amount deposited and the amount removed through rain washing.

Table 2.4. Parameter values for the different bridge components.

| Element | Material | η | Ψ | $\Phi=\alpha(\Phi_{3c}+\Phi_{3i})$ |
|--|-------------------------------|--------|--------|------------------------------------|
| 1.Road Surface | Painted concrete | 1 | 1.5 | 0.06 |
| 2.Bridge Underside | Bare concrete Rough Finish | 0 | 0 | 2.25 |
| 3. Side face | Bare Concrete – Smooth finish | 0.8 | 1.2 | 1.050 |
| 4.Hand rails | Bare metal -uncorroded | 0.3 | 0.45 | 0.9 |
| 5.Side of Support Beams | Bare concrete Rough Finish | 0.05 | 0.075 | 2.25 |
| 6.Undersurface of support beams | Bare concrete Rough Finish | 0 | 0 | 2.25 |
| 7.Protected undersurface | Bare concrete Rough Finish | 0 | 0 | 2.25 |
| 8. Lane divider and inside the parapet | Bare Concrete – Smooth finish | 0.8 | 1.2 | 1.05 |
| 9. On top of the parapet and under the side overhang | Bare Concrete – Smooth finish | 1 | 1.5 | 1.05 |

2.4 Modifications to Bridge Program

The bridge salt program does not have the ability to calculate directly the values of salt deposition or of salt retention as the run time would be too lengthy. Rather it looks up values from Tables which have been precalculated using the Holistic Model. Thus in order to incorporate the effect of cleaning into the bridge model it is necessary to have parameters defining the effect of rain washing. An accumulated salt factor was introduced that incorporated the effects of rain and runoff in washing salt from the bridge structure in any particular location. Thus the formulae for accumulation of salt are:

- seasonal ($mg/m^2 \cdot season$)

$$accumulated\ salt_{seasonal} = \frac{D * 90 * A}{100} \quad \dots Eqn(2.7)$$

- D - daily deposition rate in $mg/m^2 \cdot day$
- A - accumulated salt factor in %

- annual ($mg/m^2 \cdot year$)

$$accumulated\ salt_{annual} = Minimum \left(SAL, \sum_{season=summer}^{spring} accumulated\ salt_{season} \right) \quad \dots Eqn(2.8)$$

- SAL - annual salinity at bridge location

Note that the annual accumulated salt cannot exceed the annual base salinity at the bridge location.

The holistic model is then used to derive the parameter A. The value of A was derived for three different locations and 2 different levels of salinity. The Climate map of Figure 2.4 was simplified into 3 zones as shown in Figure 2.7.

- Northern Zone – rainfall greater than 3600mm per year and up to 9000mm
- Southern Zone – rainfall >1600mm per year and < 3600mm
- Inland – rainfall less than 1600mm



Figure 2.7. Map of Queensland showing the areas designated for salt accumulation calculations

For each climate zone two salinity zones were used, defined as:

- High salinity - average daily salinity was greater than 10 mg/m².day
- Low Salinity - average daily salinity was less than 10 mg/m².day

For each of these six geographic classification, A was derived as a function of ψ and ϕ with ψ varying 0 to 9 and ϕ from 0 to 5. A was derived for each of the locations given in Table 2.5.

Table 2.5. Representative locations in the different geographic classifications

| Region | Salinity | Location 1 | Location 2 |
|----------|----------|------------|-------------------|
| Northern | High | Cooktown | |
| | Low | White Rock | West Cairns |
| Southern | High | Pinkenba | |
| | Low | Brisbane | Nudgee |
| Inland | Low | BoxHill | Box Creek, Morven |

However, in order to run the salt deposition program, the variation of A on ψ and ϕ was parameterised. The derivations of the accumulated salt factor A from ψ and ϕ are listed in Table 2.6 for the different regions in Queensland. The values for the parameters L, F, C, E and R are given for the different seasons and Queensland locations in Table 2.7. These parameters were derived from the data in Location 1 for each zone and verified for those listed as Location 2.

Table 2.6. Accumulated salt factor formulae for different Queensland regions

| Φ | Location | Accumulated salt factor (A) - % |
|--------|--------------|--|
| = 0 | ALL | $L * (5 * F - \Psi) + E * (\exp - (C * \Psi))$ |
| > 0 | North | $L * (1 + \Phi * R)(5 * F - \Psi) + E * (1 + \Phi * R) * (\exp - (C * \Psi))$ |
| | South Inland | $L * (1 + \Phi^\sigma * R)(5 * F - \Psi) + E * (1 + \Phi^\sigma * R) * (\exp(G * \Phi^\sigma) - (C * \Psi))$ |

The values for the parameters L, F, C, E and R are given for the different seasons and Queensland locations in Table 2.7.

Table 2.7. Parameters for calculating salt accumulation factor

| Location | Salinity | Ψ | Parameters | Summer | Autumn | Winter | Spring |
|----------|----------|----------|------------|--------|--------|--------|--------|
| North | High | <1 | L | 0.035 | 0.23 | 0.35 | 0.29 |
| | | | F | 1.2 | 1.2 | 1.2 | 1.2 |
| | | | E | 0.32 | 3.1 | 6.65 | 3.17 |
| | | | C | 9 | 9 | 9 | 9 |
| | | | R | 5 | 7 | 2 | 3.1 |
| | | ≥ 1 | L | 0.035 | 0.23 | 0.35 | 0.29 |
| | | | F | 1.2 | 1.2 | 1.2 | 1.2 |
| | | | E | 0.32 | 3.1 | 6.65 | 3.17 |
| | | | C | 9 | 9 | 9 | 9 |
| | | | R | 0.26 | 0.55 | 0.8 | 0.5 |
| North | Low | <1 | L | 0.027 | 0.28 | 0.8 | 0.21 |
| | | | F | 1.2 | 1.2 | 1.2 | 1.2 |
| | | | E | 1.1 | 5.3 | 27 | 8 |
| | | | C | 9 | 9 | 9 | 9 |
| | | | R | 20 | 11 | 3 | 9 |
| | | ≥ 1 | L | 0.027 | 0.28 | 0.8 | 0.21 |
| | | | F | 1.2 | 1.2 | 1.2 | 1.2 |
| | | | E | 1.1 | 5.3 | 27 | 8 |
| | | | C | 9 | 9 | 9 | 9 |
| | | | R | 1.7 | 1.05 | 1.9 | 1.6 |
| South | High | <1 | L | 0.038 | 0.174 | 0.4 | 0.19 |
| | | | F | 1.2 | 1.2 | 1.2 | 1.2 |
| | | | E | 1.3 | 5.9 | 15.3 | 8 |
| | | | C | 9 | 9 | 9 | 9 |
| | | | R | 15 | 10 | 5 | 9 |
| | | | G | 2.2 | 0.9 | 0.28 | 0.8 |
| | | | σ | 0.05 | 0.1 | 0.2 | 0.07 |
| | | | ≥ 1 | L | 0.038 | 0.174 | 0.4 |
| | | F | | 1.2 | 1.2 | 1.2 | 1.2 |
| | | E | | 1.3 | 5.9 | 15.3 | 8 |
| | | C | | 9 | 9 | 9 | 9 |
| | | R | | 1 | 1 | 1.5 | 1.6 |
| | | σ | | 2.2 | 2 | 1.5 | 1.7 |

| | | | | | | | |
|--------|-----|----------|----------|-------|-------|-------|-------|
| | Low | <1 | L | 0.046 | 0.174 | 0.426 | 0.125 |
| | | | F | 1.2 | 1.2 | 1.2 | 1.2 |
| | | | E | 1.65 | 6.5 | 15.6 | 5.8 |
| | | | C | 9 | 9 | 9 | 9 |
| | | | R | 20 | 10 | 4 | 10 |
| | | | G | 1.7 | 0.7 | 0.3 | 1 |
| | | | σ | 0.05 | 0.12 | 0.25 | 0.08 |
| | | ≥ 1 | L | 0.046 | 0.174 | 0.426 | 0.125 |
| | | | F | 1.2 | 1.2 | 1.2 | 1.2 |
| | | | E | 1.65 | 6.5 | 15.6 | 5.8 |
| | | | C | 9 | 9 | 9 | 9 |
| | | | R | 0.7 | 1.1 | 1.4 | 1.4 |
| | | | G | 1 | 0.78 | 1 | 1 |
| | | | σ | 1.57 | 1.65 | 1.35 | 1.51 |
| Inland | Low | <1 | L | 0.07 | 0.27 | 0.24 | 0.13 |
| | | | F | 1.2 | 1.2 | 1.2 | 1.2 |
| | | | E | 3.35 | 12.2 | 11.3 | 7.1 |
| | | | C | 9 | 9 | 9 | 9 |
| | | | R | 12 | 9 | 11 | 12 |
| | | | G | 1.8 | 0.5 | 0.6 | 0.9 |
| | | | σ | 0.1 | 0.1 | 0.1 | 0.1 |
| | | ≥ 1 | L | 0.07 | 0.27 | 0.24 | 0.13 |
| | | | F | 1.2 | 1.2 | 1.2 | 1.2 |
| | | | E | 3.35 | 12.2 | 11.3 | 7.1 |
| | | | C | 9 | 9 | 9 | 9 |
| | | | R | 1 | 1.7 | 3 | 2 |
| | | | G | 1 | 0.5 | 0.6 | 1 |
| | | | σ | 1.51 | 1.85 | 1.5 | 1.49 |

Thus in estimating the accumulated salt at any location and for any bridge position, the values of ψ and ϕ are calculated (these are defined for the different bridge components and are independent of geographic location) and depend on the equations,

$$\phi = \alpha (\phi_{3c} + \phi_{3i}) \quad \dots \text{Eqn(2.9)}$$

$$\psi = \alpha \eta \quad \dots \text{Eqn(2.10)}$$

The updated user interface for the bridge program is shown in Figure 2.8. This shows that down towards the bottom of the screen, the salt deposited on the bridge component ($\text{mg/m}^2 \cdot \text{day}$) has now been augmented by a box showing salt accumulated on the bridge component (in $\text{mg/m}^2 \cdot \text{year}$), calculated as discussed above. A risk rating is given as shown in more detail in Figure 2.9 which classifies the risk according to the amount of salt accumulating as shown in Table 2.8.

Table 2.8. Classifications Risk Rating on Level of Salt Accumulated

| Risk Rating | Salt Level (mg/m ² .year) |
|-------------|--------------------------------------|
| Very Low | < 500 |
| Low | 500 – 1000 |
| Moderate | 1000 – 3000 |
| High | 3000 – 5000 |
| Very High | > 5000 |

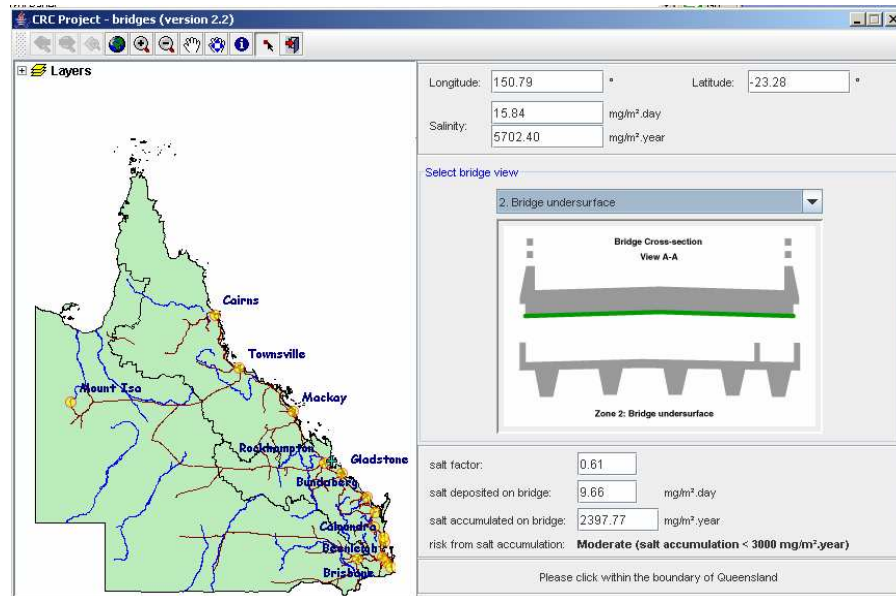


Figure 2.8. The user interface for the salt deposition on bridges program

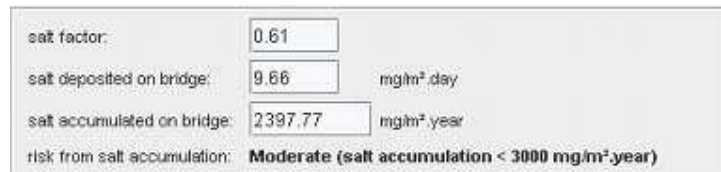


Figure 2.9. Detail from the user interface for the salt deposition on bridges program showing the risk factor

More detailed user instructions for the program are given in Appendix A.

2.5 β -Testing of Software

The Bridge Program was provided to the industry partners for β -testing. The feedback received was positive, saying it appeared user friendly and straightforward.

Some suggestions as to modifications included:

- the provision of an easy lookup matrix of high-low estimates for each element of the bridge.
- The rearrangement of the bridge elements in accordance with levels of risk., starting with handrails (high risk) and ending with road surface (low risk). This may assist the design team to more easily understand potentially higher risk elements.
- One user would like to see an index of salt corrosive risk to metal surfaces in generic terms - i.e. vertical, horizontal, rain exposed, sheltered, altitude, distance from coast, distance from equator, proximity to intervening variables such as other airborne dust, chemicals that may reduce the life of metal coatings etc. Generic data allows industry; manufactures and designers to contextualise their work in accordance with the risk of corrosion.

Overall the feedback was positive and useful and a workshop will be organised to show the software to a wider group of potential users.

2.6 References

Bureau of Meteorology, http://www.bom.gov.au/cgi-bin/silo/rain_maps.cgi

Cole, I, Corrigan, P, Chan WY., Ganther, W., Muster, T., Paterson, D., Trinidad, G., Carse., A. (2005) "Report No 2002-059-B No 9 Salt Deposition on Queensland Bridges, CRC for Construction Innovation

Cole, I. S.; Lau, D.; Chan, F.; Paterson, D. A. (2004) "Experimental Studies of salts removal from metal surfaces by wind and rain", *Corros. Engrg. Sci. Technol.* 2004, 39(4), 333–338.

Cole, I.S. and Paterson, D.A. (2007) "Holistic model for atmospheric corrosion Part 7 – Cleaning of salt from metal surfaces" *Corros. Engrg. Sci Technol.* 2007, 42(2), 106–111.

Muster, T. H.; Cole, I. S., (2005) "Attachment efficiencies of salt aerosols onto infrastructure and implications for atmospheric corrosion", *J. Electrochem. Soc.* 152(3), B125–B131

Seinfeld J.H. and Pandis S.N. "Atmospheric chemistry and physics – from air pollution to climate change", 1979, New York, NY Wiley Interscience

3. BUILDING COMPONENTS AND HOLISTIC MODEL MODIFICATIONS

3.1 Introduction

One aim of this project was to expand the life prediction program developed previously for gutters to include a greater range of building components. In this chapter the choice of building components will be discussed along modifications required to adapt the holistic model for the different components. The model is required to generate the database for the new components for inclusion in the life prediction program.

3.2 Component Selection

In order to select components to use in the current program of work, criteria for selection is needed to include specific components. The basis of these criteria is on three parameters.

- The possibility of corrosion of the component occurring. Components with higher possibility of corrosion are more likely to be included.
- The cost of maintenance or replacement required if corrosion occurs. Structural concerns are also considered here.
- Health and Safety: where a component would not need to be replaced even if it corrodes, but for health and safety reasons the component should be maintained it may be included in this work.

The following list of components was selected for inclusion in the program.

1. Gutters
 2. Down pipes
 3. Roof Sheeting (exposed and sheltered)
 4. Fasteners (exposed and sheltered)
 5. Ridge capping
 6. Flashings
 7. Window frames
 8. Steel Supports (vertical/horizontal, sheltered/exposed)
 9. Sub-floor members, stumps and support wires
 10. Gang nail plates and strapping (sheltered)
- Others left out at present include Brick ties and Lintels.

Following an overview of the holistic model these selected components will be analysed in detail and the modifications and parameters required to use the holistic model to predict corrosion of these components will be detailed. Photographs used to illustrate corrosion problems were taken during two surveys conducted on schools in this and the previous project.

3.3 Holistic Model

CSIRO have developed a holistic model of metallic corrosion. (Cole et al, 2003, Cole et al, 2004b, Cole and Paterson, 2004, Cole et al, 2004c, Cole et al, 2004d, Cole et al, 2004e, Cole and Paterson, 2006). The holistic approach defines processes controlling atmospheric corrosion on a range of scales, from macro through meso to local, micro, micron and lastly electrochemical (Figure 3.1) (Cole et al, 2003). These scales are defined in line with EOTA (1997) so that “macro” refers to gross meteorological conditions (polar, subtropical etc.), “meso” refers to regions with dimensions up to 100 km², “local” is in the immediate vicinity of a building, while “micro” refers to the absolute proximity of a material surface. “Surface response” refers to largely physical responses of a surface such as deposition and retention of pollutants or condensation and evaporation. “Micron” refers to interactions within the metal/oxide/electrolyte interfaces. In this approach, models on different dimensional scales are linked together so that the models on the micron level are informed by models on the macro, meso, micro and surface response regimes. Figure 3.2 illustrates the modules of the holistic model which are divided into three broad groups: microclimate, material-environment interactions and damage modules.

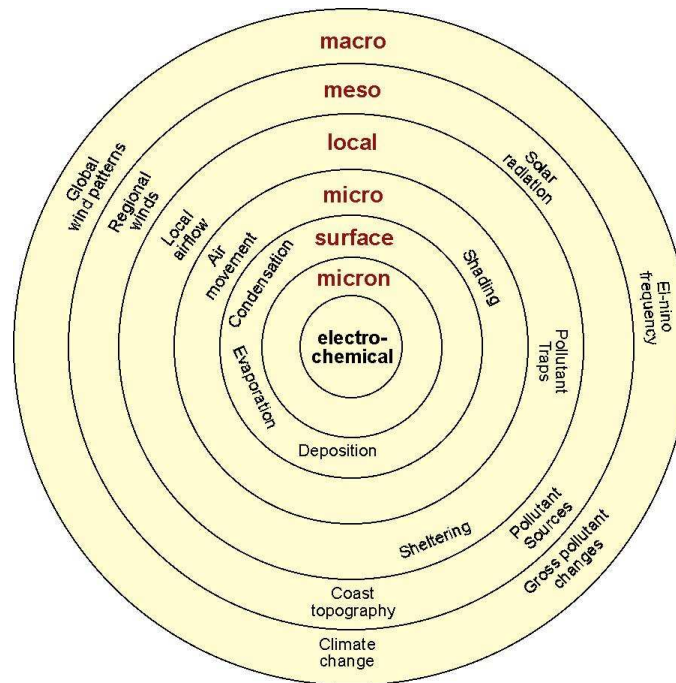


Figure 3.1. Definition of scale domains for holistic model.

CSIRO HOLISTIC MODELS

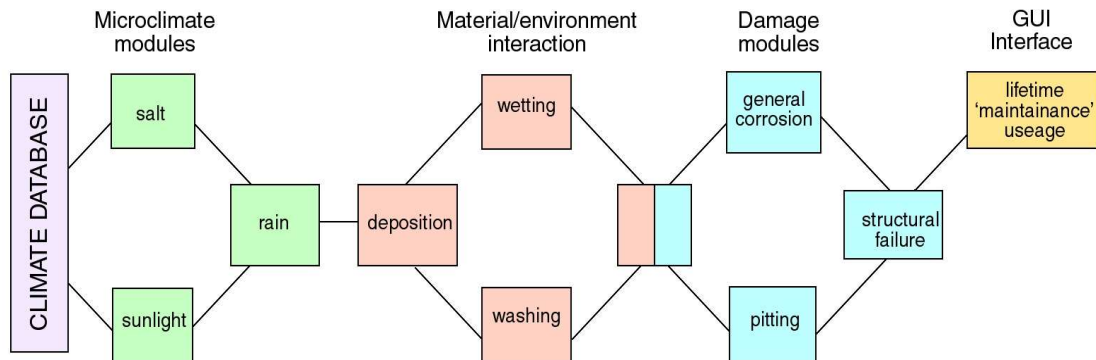


Figure 3.2 Structure of the modules of the holistic model for predicting corrosion

Adaptations were made to the basic holistic model in order to predict service life for a range of metallic building components. These included roofs, gutters, ridge caps, flashing, windows, fasteners, downpipes and steel supports.

Figure 3.3 illustrates the different factors affecting the service life of a building component. These are shown on the right hand side of the diagram. The different modules of the holistic model that may need modification for factors specific to different building components are shown on the left side of the diagram with arrows indicating which factors are likely to affect which modules.

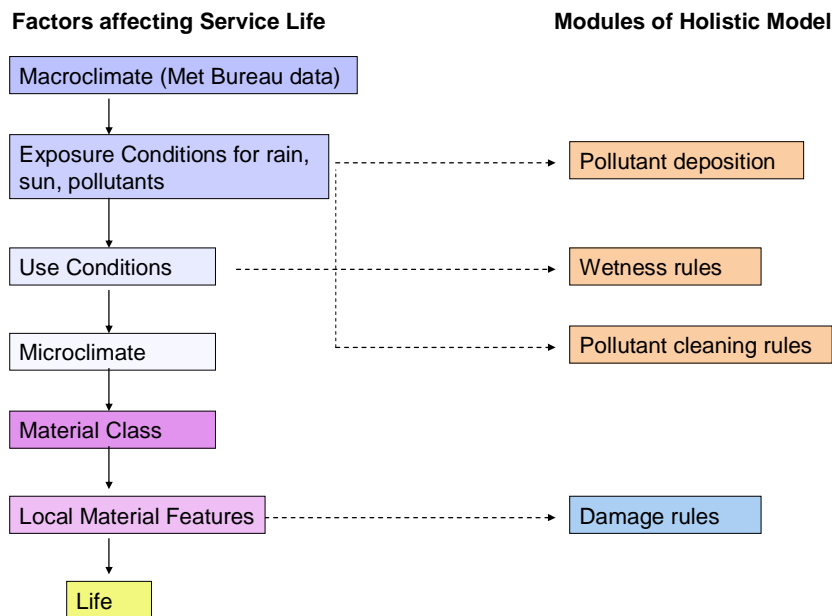


Figure 3.3 Factors affecting service life of metallic components and how they relate to modules of the holistic model.

A building component will be situated on a building experiencing climate depending on its geographic location. This can be referenced from the Bureau of Meteorology. The climatic conditions experienced by the building component eg, rain, sunlight and pollutant depositions may be altered by its positioning on the building and whether it is in an open, exposed position or sheltered in some way – either from the rain, sun, or pollutant bearing winds or combinations of these. For complex forms such as dwellings, deposition efficiency will vary across a structure, with deposition being highest at the edges of the structure where turbulence is highest. These parameters will impact on the modules in the holistic model dealing with pollutant (salt) deposition and removal (natural cleaning or washing).

The microclimate conditions experienced by a component can also be influenced by maintenance and cleaning (use conditions) especially if the component is in a dirt accumulation zone. The accumulation of dirt and leaf litter can dramatically increase the time it takes for a component to dry after rainfall and the time-of-wetness is a significant parameter in the wetting module of the holistic model. In the basic model, a surface is considered to be dry 3 hours after rainfall. The time to dry was experimentally determined for dirty gutters (Cole et al, 2005) and found to be at least 19 hours. All these factors (exposure and use conditions) determine the microclimate experienced by the building component.

How the microclimate affects the building component will depend on the material of the component eg galvanised steel, Colorbond, zincalume, aluminium, etc. and any local material features eg material incompatibilities where components are joined etc. These factors are considered in the damage modules of the holistic model. The ultimate outcome of how the microclimate affects the material and local features is the corrosion rate which determines the service life of the component.

3.3.1 Holistic Model Modules

The holistic model as shown in Figure 3.2 contains a number of modules that:

- a) predict the salinity at a location,
- b) predict the climate at a location,
- c) predict salinity retention on a component on a building,
- d) predict the state of a surface on a component on a building,
- e) predict the damage of the component on the building.

For all components, a) and b) remain unchanged as these relate to the macroenvironment at a particular location.

3.3.1.1 Salinity Retention

In calculating whether salt will be retained on a surface in the event of rain it is assumed that salt cleans off a surface according to the following relationships:

$$D_i \text{ after wash} = \Phi + \psi * D_{i-1} \quad \text{..Eqn (3.1)}$$

Where D_i is the retained salt after a rain event and D_{i-1} is the deposited salt prior to a rain event. Φ is taken as 1 and the values of ψ are given in Table 3.1. Here LMI, SMI and HMI refer to low, medium and high moisture index which is a parameter which describes the rate of evaporation and O refers to open exposure and S to sheltered.

Table 3.1. Values of ψ defined for various parameter combinations

| Moisture Index | Open/Sheltered | ψ |
|----------------|----------------|--------|
| LMI | O | 0.1 |
| | S | 0.6 |
| SMI | O | 0.5 |
| | S | 0.6 |
| HMI | O | 0.5 |
| | S | 0.6 |

3.3.1.2 State of surface of building component

Three states of a surface are defined

- a) S1 – dry
- b) S2 –wet from wetting of hygroscopic salts
- c) S3 - wet from rain

The holistic model calculates state on a three hour interval. The standard model assumes that a surface is in state 3 whenever rain is occurring but once the rain has ceased, it is dry before the next 3 hour period .If the rain ceased in the middle of the last time period this implies drying takes no more than 1.5 hours. Studies have indicated that this is a reasonable assumption for all cases, except where dirt and debris can accumulate. In these cases State 3 is extended and determined from experimental measurements.

3.3.1.3 Damage to Components

The damage to components is also calculated each three hours from a knowledge of the state of the component, the retained salinity and climatic parameters. Two different approaches are used for a) uncoated metals (steel, galvanised steel and zincalume) and b) coated steel eg. Colorbond.

Uncoated Metals

The standard holistic methods is used in which the corrosion rate is calculated each three hours according to the following equations:

$$Ms_1 = 0 \quad \dots \text{Eqn (3.2)}$$

$$Ms_2 = \zeta * M_2 \quad \dots \text{Eqn (3.3)}$$

Where M_2 depends on RH

For $35 < RH < 75$

$$M_2 = 3 + \Phi * D^\Phi \quad \dots \text{Eqn (3.4)}$$

Where D is the retained salt and the values of the constants are given in the Tables 3.2 – 3.5.

For $RH > 75$

$$M_2 = \Theta + \Omega * D^\Psi \quad \dots \text{Eqn (3.5)}$$

For State 3

$$M_{S_3} = \zeta * M_3$$

...Eqn (3.6)

In the case of M_3 , the rate of mass loss varies on the basis of the component case as this depend on the state of the component.

Table 3.2. Constants for galvanised steel mass loss in State 2

| | |
|---------------|-------|
| Θ | 0.02 |
| Ω | 0.027 |
| Ψ | 0.5 |
| \mathcal{Z} | 0.02 |
| θ | 0.027 |
| Φ | 0.5 |
| ζ | 1 |

Table 3.3. Constants for galvanised steel mass loss in State 3

| | |
|-------------------|---------|
| | ζ |
| open | 1 |
| sheltered | 2 |
| Partial sheltered | 1.5 |

Table 3.4. Constants for Zinalume mass loss in State 2.

| | |
|---------------|-------|
| Θ | 0.027 |
| Ω | 0.004 |
| Ψ | 0.5 |
| \mathcal{Z} | 0.0 |
| θ | 0.002 |
| Φ | 0.5 |
| ζ | 1 |

Table 3.5. Constants for Zinalume mass loss in State 3

| | |
|-------------------|---------|
| | ζ |
| open | 1 |
| sheltered | 2 |
| Partial sheltered | 1.5 |

Coated Materials

The application of paint to galvanised steel and zinalume is not modelled because the paint application is carried out after the component installation and quality control on such paint films is poor. Colorbond® is a product of Bluescope steel and has been proven to have exceptional performance in most locations across Australia. It is now commonly used in roofs, gutters and downpipes. A common illustrative grade of Colorbond® is steel sheet (low carbon steel) with a coating of zinalume AZ 150 (150 g m⁻²), which is overcoated on both sides with a 5 µm chromate-containing epoxy primer. The one-sided product has a 20 µm thick UV-resistant topcoat and a 5 µm grey backing coat covering the primer (Bluescope Steel, 2005). Colorbond® was introduced as a material into the holistic model for the previous phase of the project based on gutters and a model for the degradation of Colorbond® was proposed. In this phase of the project this model has been refined and validated with a range of measurements. This work is reported on in detail in Chapter 4.

3.4 Model Modifications for Components

3.4.1 Gutters

3.4.1.1 Corrosion risk

The corrosion risk of gutters is high due to the water flow from the roof and long drying times if leaf litter etc. is allowed to accumulate. Gutters tend to be wet often both from rain and overnight condensation from roof. Maintenance (removal of leaf litter etc.) is a crucial issue for corrosion risk as this significantly affects the drying time of gutters. (CRC report 2002-059-B No 16). Sheltered corrosion is also a problem for the underside of gutters where salt deposition is not removed by natural water flow. Poor installation practice can lead to cuts in the gutters or inappropriate choice of fasteners.

An example of gutter corrosion is shown in Figure 3.4.



Figure 3.4 Underside of gutter showing significant corrosion.

Materials: There are 3 types of material that can be considered namely *galvanised*, *zincalume* and *Colorbond*.

3.4.1.2 Module Modifications

Model modifications for gutters were detailed in the previous phase of the project. (CRC report 2002-059-B No 16)

3.4.2 Down pipes

3.4.2.1 Corrosion risk and Important Parameters

Figure 3.5 illustrates some of the problems associated with downpipes and the joints that are necessary in construction.



Figure 3.5 Rusting and deterioration on downpipe showing that problems are commonly associated with the joints.

The important parameters for corrosion in downpipes are similar to those for gutters. They are also a component where dirt can accumulate so maintenance (or lack of it) can strongly influence the service life. Blockages in the downpipe may occur which will affect the drying time of the internal faces of the downpipe above the blockage. Blockage locations considered are *above*, *at* or *below* blockage. The interior and the exterior of the downpipe are considered separately. Downpipes are commonly situated on the edge of the building so edge effects need to be considered. The separate downpipe parts being considered are illustrated in Figure 3.6.

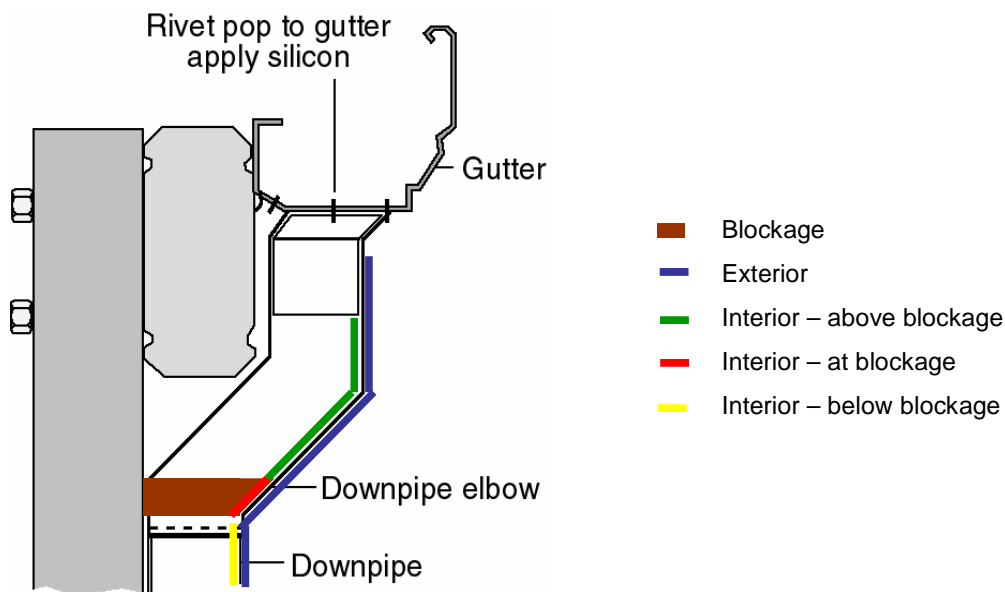


Figure 3.6 Sections of downpipe considered as separate cases.

Exposure: The exposure for downpipes will be in the *open* and *sheltered*. For sheltered exposure only the interior of the downpipes will be considered.

Materials: There are 3 types of material that can be considered namely *galvanised*, *zincalume* and *Colorbond*.

For each material considered, there are 5 different possible scenarios that would be considered and are as listed in Table 3.6.

Table 3.6. Possible cases for downpipes

| Case | Exposure | Location | Blockage | Blocked Location |
|------|--------------------------|----------|----------|------------------|
| 1 | In the open (exposed) | Exterior | No | N/A |
| 2 | | Interior | Yes | Above blockage |
| 3 | | | | At blockage |
| 4 | | | | Below blockage |
| 5 | Sheltered | Exterior | No | N/A |

Note: if the downpipes is clean then the assumption is there is no blockage.

3.4.2.2 Module Modifications

Deposition of salt

The deposition of salt is on the *front* of the building around the *edges*.

The rate of salt deposition (δ) is defined as follows:

$$\delta = \beta * \chi * \alpha \quad \dots\dots\text{Eqn}(3.7)$$

where β is a factor defining the effect of the face of a building,

χ is a factor defining the position on the face, and

α is the salt deposition in mg/m^2 for exterior exposure.

For downpipes $\beta = 0.6$ and $\chi = 3$.

State of Surface

For downpipes, the rule for state 3 (wet from rain) classification is similar to the previous implementation for gutters. The surface is considered to be in state 3 if the surface is not sheltered and it is raining. It is assumed to be raining if in a 3-hours period the rainfall > 0 . If the amount of rain in a 3-hours period is more than X mm then the surface remains wet for an additional N hours. The counting of N hours starts from the first occurrence of rain $> X$ mm. The counting is not reset even if there are intermittent rain $> X$ mm within the N hours period. This is the case when there is no blockage in the downpipes. However if there is blockage in the downpipes and rain $> X$ mm then the surface stays in state 3 a further additional time depending on the type of blockage. This is summarised in Table 3.7.

Table 3.7. Calculations for extended drying times depending on state of downpipe.

| Blockage | Rain > X mm | Extended hours in state 3 |
|----------------------|---------------|---------------------------|
| Yes/No | No | zero (0) |
| No | Yes | N |
| Yes – below blockage | Yes | $N + m_1$ |
| Yes – at blockage | Yes | $N + m_2$ |
| Yes – above blockage | Yes | $N + m_3$ |

The surface being considered wet for additional hours when rain > X mm is only applicable to the interior of the downpipes and not the exterior.

As with the gutters, a downpipe was instrumented with sensors to determine the length of time the surface remains wet after rain when there is a blockage in the drainpipe. The instrumentation is shown in Figure 3.7.

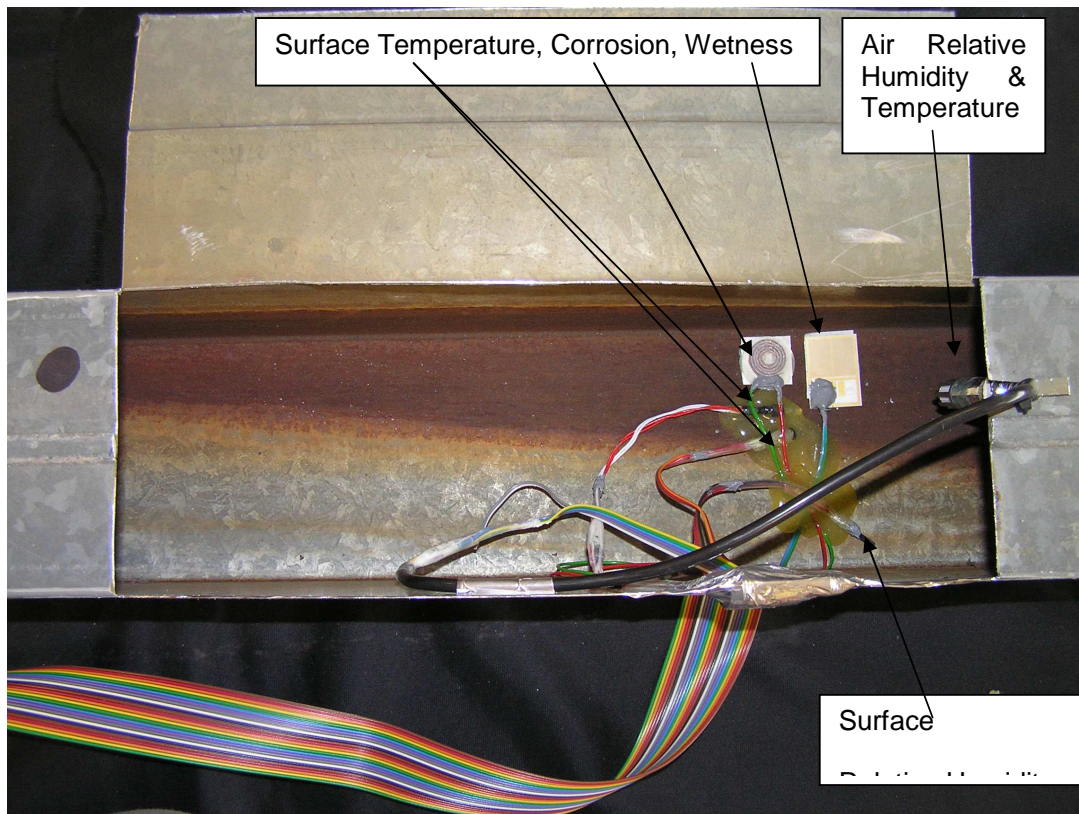


Figure 3.7. Instrumentation installed in the downpipe

Data has been collected from the downpipe over a number of months. Due to the extreme environment created in the downpipe the reliability of the sensors is not as good as would be liked. The relative humidity (RH) sensors are the least reliable as they do not work and are damaged when they get wet. The RH sensors can recover when they are dried but the reading becomes unreliable. Even with these problems the data collected does provide some interesting trends. A sample of the data collected is shown in Figure 3.8.

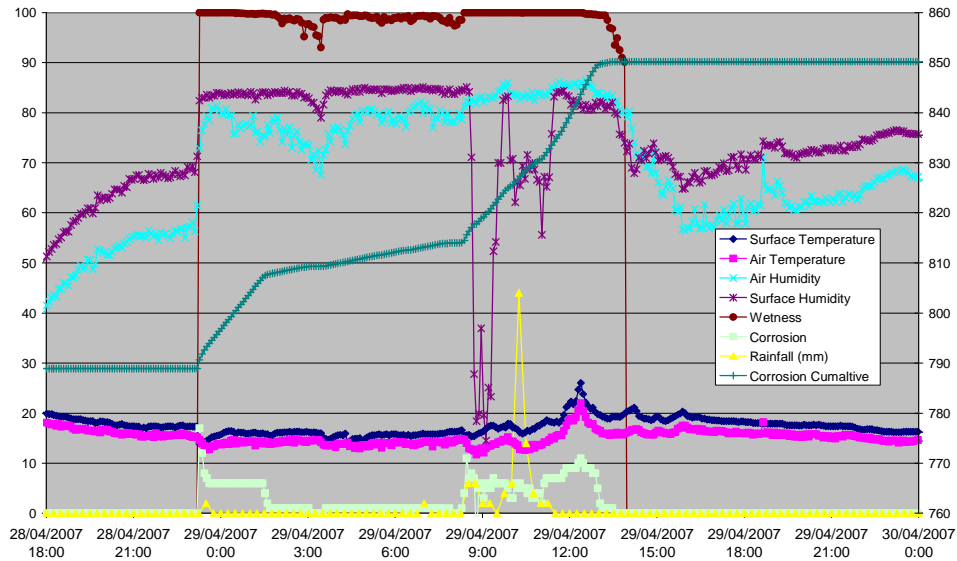


Figure 3.8. Sample of Data from the instrumented downpipe

The data shown in Figure 3.8 is complex but there are a few trends that are obvious. The yellow line is the rainfall readings from a weather station located within 250 metres of the downpipe, the readings have been multiplied by 10 so that there are clear on the graph, (a reading of 40 is actually 4mm). The rainfall readings are taken every 15 minutes and a rain depth of 0.2 mm is needed before the gauge reads, which means that light drizzle may not be recorded but could run off the roof and down the downpipe. Two main rain events occur in the graph. The first is before midnight on the 28/4 and the second is around 9am on the 29th. The rain event at 9am was a significant amount of rain and it can be seen that the surface humidity sensor has recorded incorrect readings probably due to being wet from the rain. It would have been expected that inside the enclosed area of the downpipe that the RH would have been closer to 100% than has been recorded. While the RH sensors are still recording trends in RH the sensors have probably been damaged by water at some stage and the readings, while showing the correct trends are most likely inaccurate. In future work, some protection will need to be installed to prevent the RH sensors from becoming wet.

The wetness sensor, brown line, shows that the downpipe is wet from the first rain event right through until just before 3pm on the 29th. While the wetness is fairly consistent through the period the corrosion sensor, (light green line instantaneous corrosion, dark green line cumulative corrosion) shows that the sensor is corroding at different rates probably with the different amounts of water flowing through the downpipe. This data was used to inform the parameter setting for the model.

Mass loss calculations

The state 3 mass loss calculations have been modified to account for the possibility of blockages increasing the rate of corrosion:

Two rules are postulated:

- $R1 - Ms3a = (\xi * Ms3)$ Eqn(3.8)

- $R2 - Ms3a = (\xi * Ms3) + \beta * D^\sigma$ Eqn(3.9)

Rule R1 is applied in the situation where there is no blockage in the downpipes that is case 1 and case 4. For cases 2, 3 and 4 where the downpipes is blocked the second rule R2 is applied. (Case definition is in Table 3.6). The application of the rule to the state 3 mass loss calculation is given in Table 3.8.

Table 3.8. Application of mass loss rules depending on case

| Case | State 3 mass loss calculation (Ms3a) |
|------|--------------------------------------|
| 1 | R1 |
| 2 | R2 |
| 3 | R2 |
| 4 | R2 |
| 5 | R1 |

If there is an edge, then the calculated mass loss $Ms2a$ for state 2 and $Ms3a$ for state 3 is multiplied by the edge mass loss accelerator factor Λ_i as follows:

- State 2 - $Ms2a' = \Lambda_2 * Ms2a$...Eqn(3.10)

- State 3 - $Ms3a' = \Lambda_3 * Ms3a$...Eqn(3.11)

Downpipes are by definition at the edge of a dwelling so the edge mass loss accelerator factor Λ_i does apply in both the state 2 and state 3 mass loss calculations.

3.4.3 Roof Sheeting

3.4.3.1 Corrosion risk and Important Parameters

Examples of roof sheeting corrosion are shown in Figure 3.9 and 3.10.



Figure 3.9. Galvanised Kliplok roof sheeting showing extensive red rust.



Figure 3.10 Underside of roof sheeting showing significant white corrosion product and some red rust.

Roof type; The type of the roof considered is *normal* or *very flat* roof. The roof type determines whether the surface remains in state 3 for additional hours when there is rain. It is recommended that roofs should be installed with a roof angle of $> 5^\circ$.

Exposure: Roofs are assumed to be fully exposed and not sheltered and hence roof sheeting is only considered for open exposure.

Condition of the roof: The condition of the roof sheeting is either *cleaned* or *not cleaned* which controls whether rule R1 or R2 (see downpipes) will be applied in the state 3 mass loss calculation. Rule R1 is applied when the roof sheeting is cleaned while R2 is applied when dirty.

Material type: There are 3 types of material that are considered namely *galvanised*, *zincalume* and *Colorbond*.

For each material considered, there are 8 different possible scenarios that would be considered and are as listed in Table 3.9.

Table 3.9. Cases for roof sheeting

| Case | Exposure | Salt deposition | Roof | Condition |
|------|--------------------------|-----------------|-----------|-------------|
| 1 | In the open (exposed) | edge | Normal | Cleaned |
| 2 | | | | Not cleaned |
| 3 | | | Very flat | Cleaned |
| 4 | | | | Not cleaned |
| 5 | | other positions | Normal | Cleaned |
| 6 | | | | Not cleaned |
| 7 | | | Very flat | Cleaned |
| 8 | | | | Not cleaned |

3.4.3.2 Module Modifications

Deposition of salt

The deposition of salt is on the *roof* of the building around the *edges* and other *positions* of the roof surface.

Equation 7 still applies and for downpipes $\beta = 0.4$ and $\chi = 3$.

State of Surface

Table 3.10 summarises the application of the state 3 extension rule, the edge mass loss acceleration factor and the state 3 mass loss calculation rule.

Table 3.10. Effect of case on various parameters

| Case | State 3 (additional hours) | Edge factor | <i>Ms3a</i> rule |
|------|-------------------------------|-------------|------------------|
| 1 | | Λ_i | R1 |
| 2 | | Λ_i | R2 |
| 3 | Yes | Λ_i | R1 |
| 4 | Yes | Λ_i | R2 |
| 5 | | | R1 |
| 6 | | | R2 |
| 7 | Yes | | R1 |
| 8 | Yes | | R2 |

For roof sheeting, the rule for state 3 classification is similar to downpipes except in this case the extension of state 3 by an additional N hours only applies when the roof is a *very flat roof* and the rain $> X$ mm.

Mass loss calculations

It was considered that leaf litter build up on roofing may affect the pH of rain water and hence the corrosivity of the water. Tests were carried out to determine if this was the case and whether extra factors would need to be included in the mass loss calculations. The pH measurements taken over time (for 50g of leaf litter pulverised and mixed with 1l distilled water) are listed in Table 3.11. A variety of trees were included in the tests, with leaf material taken from gutters and from trees.

The results suggest that pH changes need not be considered in the mass loss calculations.

Similar to downpipes, if there is an edge, then the calculated mass loss $Ms2a$ for state 2 and $Ms3a$ for state 3 is multiplied by the edge mass loss accelerator factor Λ_i (see downpipes).

Table 3.11. pH measurements of leaf litter solutions/suspensions

| Sample | pH | | | |
|--------|-----------|-------|--------|---------|
| | Initially | 1 day | 4 days | 22 days |
| LAG1 | 5.47 | 5.69 | 6.03 | 6.17 |
| GAT | 5.96 | 5.83 | 7.51 | 7.08 |
| EG | 5.26 | 5.26 | 6.20 | 6.16 |
| LAG2 | 5.95 | 6.00 | 7.08 | 7.38 |
| LAT1 | 4.14 | 4.28 | 4.00 | 4.38 |
| GAG | 6.72 | 6.45 | 7.15 | 7.36 |
| WMT | 5.18 | 5.12 | 5.19 | 5.56 |
| LAT2 | 4.26 | 4.35 | 4.36 | 4.39 |
| WMG | 6.49 | 6.64 | 7.12 | 6.94 |
| CT | 4.46 | 4.37 | 4.18 | 4.04 |
| CG | 6.10 | 6.15 | 6.69 | 6.81 |
| ET | 5.73 | | | |

Abbreviations:

- LAG1 = Liquid amber gutter sample 1
- LAT1 = Liquid amber tree sample 1
- LAG2 = Liquid amber gutter sample 2
- LAT2 = Liquid amber tree sample 2
- GAT = Golden ash tree sample
- GAG = Golden ash gutter sample
- EG = eucalyptus gutter sample
- ET = Eucalyptus tree sample
- CT = conifer tree sample
- CG = conifer gutter sample
- WMG = Willow myrtle gutter sample
- WMT = Willow myrtle tree sample

3.4.4 Roof Fasteners

3.4.4.1 Corrosion risk and Important Parameters

Roof fasteners are illustrated in Figure 3.11 and 3.12.



Figure 3.11 Heads of roof fasteners showing red rust and white corrosion product.



Figure 3.12 Fastener shanks showing red rust.

The parameters of relevance to roof fasteners are considered below.

Beam type: The type of the beam considered is *timber (T)* or *steel (S)* as illustrated in Figure 3.13.

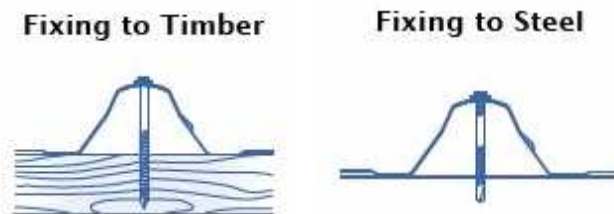


Figure 3.13 Roof fastener cases being considered: fixed to timber or fixed to steel.

Roof fastener sections: Figure 3.14 shows the 3 sections of the roof fastener that are considered. The first section (indicated as I in the figure) is the fastener head above the roof sheeting. The middle section (II) is the shank below the roof sheeting but has not been embedded in the beam. The last section (III) is the shank that has been embedded in the beam.

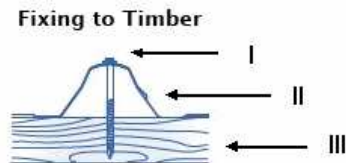


Figure 3.14. The various sections of a roof fastener

Roof type: The type of the roof considered is normal or very flat roof. The roof type determines whether the surface remains in state 3 for additional hours when there is rain.

Roof fastener/roof sheeting compatibility: There are 2 cases to be considered in terms of the compatibility between the roof fastener and roof sheeting, that is, either compatible or not compatible. If the roof fastener and roof sheeting are not compatibility then an acceleration factor is applied in the state 2 and state 3 mass loss calculations (see downpipes).

Material type: There are 3 types of material that are considered namely stainless steel, hot-dipped coated and zinc coated.

For each material considered, there are 16 different possible scenarios that would be considered and are listed in Table 3.12.

Table 3.12 Possible cases for roof fasteners

| Case | Face Position | Roof Type | Fastener/Roof sheet interaction | Fastener Section |
|------|-----------------|-----------|---------------------------------|------------------|
| 1 | edges | normal | compatible | I |
| 2 | | | | II |
| 3 | | | not compatible | I |
| 4 | | | | II |
| 5 | | very flat | compatible | I |
| 6 | | | | II |
| 7 | | | not compatible | I |
| 8 | | | | II |
| 9 | other positions | normal | compatible | I |
| 10 | | | | II |
| 11 | | | not compatible | I |
| 12 | | | | II |
| 13 | | very flat | compatible | I |
| 14 | | | | II |
| 15 | | | not compatible | I |
| 16 | | | | II |

NOTE: The last section (III) where the shank is embedded in the beam has been programmed previously and that will be used to generate the information for the database.

3.4.4.2 Module Modifications

Deposition of salt

The deposition of salt is on the *roof* of the building around the *edges* and *other positions* on the roof surface.

In calculating the salt deposition for the middle section of the roof fastener (II) an additional building envelope factor is required.

The rate of salt deposition (δ) is defined as follows:

$$\delta = \beta * \chi * \gamma * \alpha \quad \dots \text{Eqn(3.12)}$$

where β is a factor defining the effect of the face of a building,

χ is a factor defining the position on the face,

γ is the building envelope factor, and

α is the salt deposition in mg/m^2 for exterior exposure.

For fasteners $\beta = 0.4$, $\chi =$, and $\gamma = 10..$

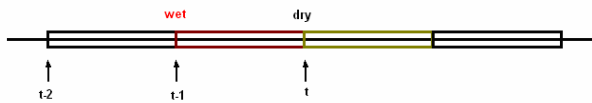
If the first section (I) of the roof fastener, ie. the head above the roof sheeting is considered then the salt deposition is that deposited in the open.

$$\delta = \alpha \quad \dots \text{Eqn(3.13)}$$

State of Surface

For a roof fastener, the state law requires a 3 hour period of daylight to dry. Daylight is considered to be between 6 am and 6 pm. This means if the rain event happens before 6 am and after 6 pm, that is, night time, then the surface continues to remain in state 3 until after the first 3 hour period without rain from 6 am to 6 pm. If the rain event is during daytime between 6 am and 6 pm then roof will only dry in the next 3 hour period without rain.

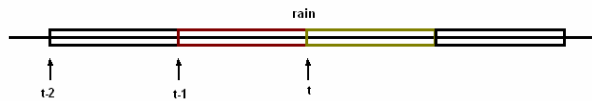
Scenario #1



If it is *dry* at time interval t then

1. check to see at time interval $(t - 1)$ the surface has stays wet for N hours
 - a. if *yes* then check if it is
 - *dry* then state at time interval t is *dry*
 - *wet* then
 - a. check to see if
 - i. $t > 6 \text{ am} \ \& \ t < 6 \text{ pm}$ (i.e. *day-time*) then state at time interval t is *dry*
 - ii. $t \leq 6 \text{ am} \ \& \ t \geq 6 \text{ pm}$ (i.e. *night-time*) then state at time interval t is *wet*
 - b. if *no* then do nothing but accumulate wet hours

Scenario #2



If it is *rain* at time interval t then state at time interval t is *wet* & time interval $(t + 1)$ will be scenario #1 again

Climate conditions in building envelopes

The *temperature* and *relative humidity* in the roof space are only applicable when the middle section of the roof fastener (II) is considered.

The temperature in the roof space T_{rs} is calculated as follows:

$$T_{rs} = T_{ad} + \beta(T_{ext} - T_{ad}) + \delta \quad \text{Eqn(3.14)}$$

where T_{ad} - average daily temperature and calculated as follows

$$T_{ad} = \sum_{hr=1}^8 T_{3hr} / 8 \quad \text{Eqn(3.15)}$$

T_{ext} - external temperature for that 3-hour period

δ - a constant dependent on time of day and season (values given in Table 3.13)

β - solar radiation zone

Table 3.13: Values for δ , a constant dependent on the time of day and season

| Time | 00:00 | 03:00 | 06:00 | 09:00 | 12:00 | 15:00 | 18:00 | 21:00 |
|--------|-------|-------|-------|-------|-------|-------|-------|-------|
| Summer | -3 | -3 | 0 | 15 | 30 | 15 | 5 | -3 |
| autumn | -3 | -3 | 0 | 10 | 20 | 10 | 3 | -3 |
| winter | -3 | -3 | 0 | 5 | 10 | 5 | 2 | -3 |
| spring | -3 | -3 | -3 | 10 | 20 | 15 | 5 | -3 |

The solar radiation zone is determined by the latitude of the location of interest and is as given in Table 3.14.

Table 3.14. Solar radiation zones

| Latitude | Solar radiation zone | Index |
|---|----------------------|-------|
| $> -25^\circ$ | High | 0.4 |
| $\geq -35^\circ \quad \Lambda \quad \leq -25^\circ$ | Medium | 0.5 |
| $< -35^\circ$ | Low | 0.6 |

The relative humidity in the roof space RH_{rs} is calculated in a similar way as temperature as follows:

$$RH_{rs} = RH_{ad} + \beta * (RH_{ext} - RH_{ad}) + \delta + \zeta \quad \text{Eqn(3.16)}$$

where RH_{ad} - average daily relative humidity and calculated as follows

$$RH_{ad} = \sum_{hr=1}^8 RH_{3hr} / 8 \quad \text{Eqn(3.17)}$$

RH_{ext} - external relative humidity for that 3-hour period

δ - a constant dependent on time of day and season

β - solar radiation zone

ζ - a factor to promote condensation

The factor to promote condensation is to be introduced at a given frequency at dawn for example 8 times per month. Dawn is taken to be at 6 am in the morning. The eight days on which this factor is applied is implemented using a random generator.

3.4.5 Ridge Capping and Flashing

3.4.5.1 Corrosion risk and Important Parameters

Ridge capping and flashing are considered together as the parameters affecting corrosion are identical. Ridge capping is the special tiles or metal sheeting that run along the top of the roof protecting the ridge joint from water ingress (illustrated in Figure 3.15).



Figure 3.15. Illustration of metal ridge capping.

A flashing is a strip of material, usually metal, that covers the junction between the roof sheeting and another surface, such as a pipe, chimney, roof light or a wall. This is illustrated in Figure 3.16.



Figure 3.16. Flashing between wall and roof.

Exposure: Roofs are assumed to be fully exposed and not sheltered and hence ridge capping and flashing are only considered for open exposure.

Material type: There are 3 types of ridge capping material that are considered namely *galvanized*, *zincalume* and *aluminium*.

Roof material type: There are 4 types of roof material possible with each material type for the ridge capping, namely *galvanized*, *zincalume*, *colorbond* and *aluminium*.

For each material considered, there are 8 different possible scenarios that would be considered and are listed in Table 3.15:

Table 3.15 Possible cases for ridge capping and flashing

| Case | Drainage | Exposure | Building Face | Face Position | Roof Material |
|------|----------|----------|---------------|-----------------|---------------|
| 1 | drained | open | roof | edges | galvanized |
| 2 | | | | | zincalume |
| 3 | | | | | colorbond |
| 4 | | | | | aluminum |
| 5 | | | | other positions | galvanized |
| 6 | | | | | zincalume |
| 7 | | | | | colorbond |
| 8 | | | | | aluminum |

3.4.5.2 Module Modifications

Deposition of salt

Similar to roof sheeting, the deposition of salt is on the *roof* of the building around the *edges* and other *positions* of the roof surface.

State of Surface

The drainage condition in ridge capping and flashing is always drained and hence there are no extended wet hours to state 3 when it rains. Thus the state 3 classification rule used is based on the original implementation.

Mass loss calculations

Similar to downpipes, if there is an edge, then the calculated mass loss $Ms2a$ for state 2 and $Ms3a$ for state 3 is multiplied by the *edge mass loss accelerator factor* Λ_i (see downpipes).

Material compatibility factor: Similar to the roof fastener, ridge capping and flashing has a compatibility factor. The compatibility factor is between the material of the ridge capping and flashing and the roof.

The compatibility factor between the two components is given in Table 3.16.

Table 3.16 Compatibility factors for possible material combinations

| Roof material | Galvanized | Zincalume | Aluminium |
|---------------|------------|-----------|-----------|
| Galvanized | 1 | 1 | 1 |
| Zincalume | 1.5 | 1 | 1 |
| Colorbond | 1 | 1 | 1 |
| Aluminium | 1.5 | 1.5 | 1 |

The damage rules for state 2 and state 3 are as given below:

$$Ms2a' = A * B * Ms2a \quad \text{Eqn(3.18)}$$

$$Ms3a' = A * B * Ms3a \quad \text{Eqn(3.19)}$$

where A – edge factor

B – material compatibility effect

3.4.6 Window frames

3.4.6.1 Corrosion risk and Important Parameters

Examples of corrosion of metal window frames are shown in Figure 3.17. The main material for window frames is painted or anodised aluminium 6060.



Figure 3.17. Example of metal window frames.

Drainage condition: Two cases are considered, that is, drained or not drained. Not drained will affect the classification of state 3 by extending the hours the surface is considered to still be wet.

Exposure: Similar to downpipes, the exposure for window frames will be in the *open* and *sheltered*. For *sheltered* exposure the drainage condition possible is '*drained*'. The case of '*not drained*' is not considered. For *open* exposure the deposition of salt is only considered at '*other positions*' of the building face.

Material type: There are 3 types of window frames material that are considered namely *aluminium, coated aluminium and galvanized steel.*

For each material considered, there are 12 different possible scenarios that would be considered and are listed in Table 3.17:

Table 3.17. Possible cases for windows

| Case | Building Face | Exposure | Face Position | Drainage |
|------|---------------|-----------|-----------------|-------------|
| 1 | front | open | other positions | drained |
| 2 | | | | not drained |
| 3 | side | | | drained |
| 4 | | | | not drained |
| 5 | back | | | drained |
| 6 | | | | not drained |
| 7 | front | sheltered | edges | drained |
| 8 | | | other positions | |
| 9 | side | | edges | |
| 10 | | | other positions | |
| 11 | back | | edges | |
| 12 | | | other positions | |

3.4.6.2 Module Modifications

Deposition of salt

For window frames the deposition of salt is on the *front, side* and *back* of the building around the *edges* and other *positions* of the roof surface.

Using this approach eliminates the need to implement separately the orientation factor which was described in previous documentation.

Face factors are defined for the different faces.

State of Surface

For window frames, the rule for state 3 classification is similar to downpipes except in this case the extension of state 3 by an additional N hours only applies when the drainage condition is *not drained* and the rain $> X$ mm.

3.4.7 Steel Supports

3.4.7.1 Corrosion risk and Important Parameters

The parameters to be considered will be similar to those for downpipes, except that the base may be embedded in cement or in contact with soil in the ground. An example of corrosion on a steel support is shown in Figure 3.18.



Figure 3.18. Galvanised post (right) and close up (left) showing signs of white corrosion product.

The workmanship on installation can significantly impact on the likely corrosion of the base of steel supports embedded in concrete. The recommended practice would have the concrete sloping away from the base to provide good drainage. In practice, the concrete may be level or even sloping up which will promote pooling of rainwater around the base of the support. These are illustrated in Figure 3.19a, b and c respectively.

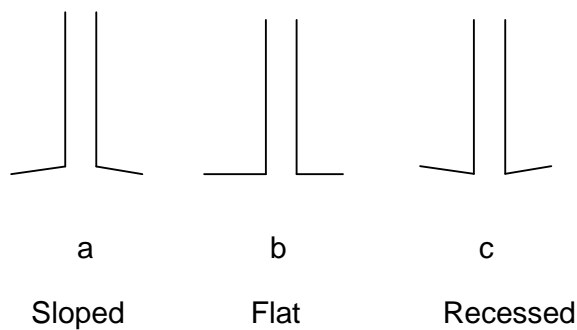


Figure 3.19. The three cases for embedding of steel supports in concrete

Drainage condition: Two cases are considered, that is, drained (Figure 3.19a) or not well drained (Figure 3.19 and c). Similar to window frames, not drained will affect the classification of state 3 by extending the hours the surface is considered still wet.

Exposure: Similar to window frames, the exposure for steel supports will be in the *open* and *sheltered*.

Material type: There are 2 types of steel supports material that are considered namely galvanized and zincalume.

For each material considered, there are 8 different possible scenarios that would be considered and are as listed in table 3.18.

Table 3.18. Possible cases for steel supports

| Case | Position | Exposure | Building Face | Face Position | Drainage |
|------|----------|-----------|---------------|-----------------|------------------|
| 1 | others | open | front | edges | drained |
| 2 | | | | | not well drained |
| 3 | | | | other positions | drained |
| 4 | | | | | not well drained |
| 5 | | sheltered | | edges | drained |
| 6 | | | | | not well drained |
| 7 | | | | other positions | drained |
| 8 | | | | | not well drained |

3.4.7.2 Module Modifications

Deposition of salt

For steel supports the deposition of salt is assumed on the *front* of the building around the *edges* and other *positions* of the surface.

State of Surface

For steel supports, the rule for state 3 classification is similar to window frames. The extension of state 3 by an additional N hours only applies when the drainage condition is *not drained* and the rain $> X$ mm.

3.4.8 Sub-floor members, stumps and support wires

3.4.8.1 Corrosion risk and Important Parameters

The main issue is likely to be the drainage and level of ventilation and natural drying that can occur. An example of sub-floor members showing significant corrosion is shown in Figure 3.20.



Figure 3.20. Significant deterioration of sub-floor metallic components on modular classroom.

Drainage condition: Two cases are considered, that is, drained or not well drained. Similar to steel supports frames, not drained affects the classification of state 2 by extending the hours the surface is considered still wet.

Ventilation factor: For subfloor member there is a ventilation factor which is dependent on the ventilation rates. There are 3 levels of ventilation and is classified as *high*, *medium* and *low*. The ventilation condition in turn affects the time a surface remains wet after wetness from a salt wetting period that is a state 2 condition.

A ventilation factor is a constant which is associated with each level of ventilation as shown in Table 3.19.

Table 3.19. The ventilation factors for subfloor members

| Ventilation level | Factor |
|-------------------|--------|
| High | 1 |
| Medium | 0.5 |
| Low | 0.2 |

Exposure: The subfloor being located inside the building, it is assumed to be fully sheltered and not exposed and hence the subfloor members are only considered for sheltered exposure.

Material type: There are 3 types of subfloor members material that are considered namely *galvanized*, *zincalume* and *bare steel*.

For each material considered, there are 6 different possible scenarios that would be considered and are as listed in Table 3.20.

Table 3.20. Possible cases for subfloor members

| Case | Position | Exposure | Building Face | Drainage | Ventilation |
|------|----------|-----------|---------------|------------------|-------------|
| 1 | others | sheltered | front | drained | high |
| 2 | | | | | medium |
| 3 | | | | | low |
| 4 | | | | not well drained | high |
| 5 | | | | | medium |
| 6 | | | | | low |

3.4.8.2 Module Modifications

Deposition of salt

For subfloor members the deposition of salt is the *front* of the building with no face position considered.

The figure below shows the data entry screen for entering the face factor, the factors for the different level of ventilations and also the formula for calculating the rate of salt deposition for subfloor members.

The rate of salt deposition is defined as:

$$\delta = \beta * \nu * \alpha \quad \dots \text{Eqn(3.20)}$$

where β is a factor defining the effect of the face of a building,

ν is the ventilation factor, and

α is the salt deposition in mg/m^2 for exterior exposure.

β is defined as 0.6 for sub-floor members and ν takes the values defined in Table 18.

State of Surface

The implementation of the state 2 classification rule for subfloor members is similar to that of state 3 classification in other components.

The extension of the surface in state 2 by N additional hours only applies if both the surface is classified as in state 2 using the condition $RH_s > \epsilon$ and the drainage condition is *not drained*. The number of additional hours that a surface remains as wet will depend on the ventilation level. The value of ϵ depends on the salt deposition D according to the list below:

$$0 < D < 6 \quad \epsilon = 100,$$

$$6 \leq D < 21 \quad \epsilon = 75$$

$$21 \leq D \quad \epsilon = 35$$

where D is in mg/m^2 .

The extended wet hours for the different ventilation rates are: 0 (high), 24 (medium) and 48 (low).

3.4.9 Gang nail plates

3.4.9.1 Corrosion risk and Important Parameters

Gang nail plates are metal plates with rows of sharp points that are hammered into butt-jointed timber to secure the join. This is shown in Figure 3.21.



Figure 3.21. Gang nail plates showing some red rust and white corrosion product

The critical issue with gang nail plates is the different timbers that may be used as the substrate. The model modifications are covered in roof fasteners.

3.5 Testing of Model

The different cases determined for all of the specified components are listed in Table 3.21. The models for the different building elements are tested using data in the vicinity of Cairns where the salinity is 4.0 and 40 mg/m².day respectively for Benign and Marine conditions, average humidity is 74% and rainfall 1764 mils.

Table 3.21. All parameters and cases determined for specified components

| COMPONENT | PARAMETERS | CASES | MATERIALS |
|--------------------------------|--------------------------|--|--|
| Gutters | Gutter segment | <ul style="list-style-type: none"> ●Internal sides ●Internal Bottom ●External Bottom | Galvanised steel Zincalume Colorbond |
| | Rain exposure | <ul style="list-style-type: none"> ●open ●sheltered | |
| | Maintenance | <ul style="list-style-type: none"> ●Cleaned ●Not cleaned | |
| Downpipes | Downpipe region | Interior Exterior | Galvanised steel Zincalume Colorbond |
| | Edges | <ul style="list-style-type: none"> ●Edge ●Not edge | |
| | Blocked | <ul style="list-style-type: none"> ●blocked above blockage at blockage below blockage ●Not blocked | |
| | Rain exposure | <ul style="list-style-type: none"> ●exposed ●sheltered | |
| roof sheeting | Roof angle | <ul style="list-style-type: none"> ●normal (drained) ●very low (not drained) | Galvanised steel Zincalume Colorbond |
| | Maintenance | <ul style="list-style-type: none"> ●Cleaned ●Not cleaned | |
| fasteners | Roof fastener | <ul style="list-style-type: none"> ●Well drained ●flat roof | Stainless steel Hot-dip coated zinc-coated |
| | Fastener part | <ul style="list-style-type: none"> ●head above sheet ●exposed shank ●shank in beam | |
| | Beam type | <ul style="list-style-type: none"> ●Timber ●Steel | |
| ridge capping | Edges | <ul style="list-style-type: none"> ●Edge ●Not edge | Galvanised steel Zincalume Colorbond Aluminium |
| | Material compatibility | <ul style="list-style-type: none"> ●Material compatibility effect (4x4 matrix) | |
| flashing | Edges | <ul style="list-style-type: none"> ●Edge ●Not edge | Galvanised steel Zincalume Colorbond Aluminium |
| | Material compatibility | <ul style="list-style-type: none"> ●Material compatibility effect (4x4 matrix) | |
| window frames | Building face | <ul style="list-style-type: none"> ●Front ●Side ●Back | Aluminium (anodised) Coated aluminium Galvanised steel |
| | Rain exposure | <ul style="list-style-type: none"> ●exposed ●sheltered | |
| | Drainage | <ul style="list-style-type: none"> ●Not drained ●drained | |
| | Edge | <ul style="list-style-type: none"> ●Edge ●Not edge | |
| steel supports | Rain exposure | <ul style="list-style-type: none"> ● exposed ●sheltered | Galvanised steel zincalume |
| | Drainage | <ul style="list-style-type: none"> ●drained ●not drained | |
| sub-floor members | Ventilation rate | <ul style="list-style-type: none"> ●high ●medium ●low | Galvanised steel Zincalume bare steel |
| | Drainage | <ul style="list-style-type: none"> ●drained ●not drained | |
| gang nail plates and strapping | Rain exposure | <ul style="list-style-type: none"> ●exposed ●sheltered | Galvanised steel Zincalume |
| | Timber/metal interaction | | |

3.5.1 Failure Conditions

The model generates a mass loss per year so that in order to calculate a predicted life then equation 3.21 is used to calculate the mass loss over a number of years.

$$ML = AI * T^n \quad \dots \text{Eqn(3.21)}$$

where ML is mass loss over n years and AI is the mass loss in one year.

The end point or failure varies for the material under consideration and is defined as:

ML= 165 for galvanized

ML= 90 for zincalume

ML= 15 for aluminium

3.5.2 Results

The results for the different building elements in the different cases are listed for the two environments (Benign and Marine) using the salinity, average humidity and rainfall for near Cairns. These are shown in Table 3.22.

The results generated using the different component models are of the same order as experimental results and those found in the Delphi survey, but all have been derived independently.

Table 3.22. Results of running revised models for components using climate conditions near Cairns

| Component | Material | Environment | Parameters | Case | Annual loss | life | n |
|---------------|--------------|-------------|---------------------------------|------------------|-------------|------|-----|
| Roof | galvanised | Benign | Open-Edges-normal | Clean | 6.4 | >50 | 0.5 |
| Roof | galvanised | Benign | Open-edges-normal | Not clean | 22 | 29 | 0.6 |
| Roof | Galvanized | Marine | Open-edges-normal | clean | 35 | 13 | 0.6 |
| Roof | Galvanized | Marine | Open-edges -normal | Not clean | 118 | 2 | 0.6 |
| Gutters | Galvanised | Marine | Open-front face-edge-edge | | 39 | 11 | 0.6 |
| Gutters | Galvanised | Benign | Open-front –face edge-edge | | 11 | >50 | 0.5 |
| Gutters | Galvanised | Marine | Sheltered-front face-edge | | 99 | 3 | 0.6 |
| Gutters | Galvanised | Benign | Sheltered-front face-edge | | 22 | 29 | 0.6 |
| Gutters | Galvanised | Marine | Open-front face –bottom -edge | Cleaned | 59 | 6 | 0.6 |
| Gutters | Galvanised | Benign | Open-front face –bottom -edge | cleaned | 11 | >50 | 0.5 |
| Downpipes | Galvanised | Marine | Open-exterior-edge | | 49 | 8 | 0.6 |
| Downpipes | Galvanised | Benign | Open-exterior-edge | | 7 | >50 | 0.5 |
| Downpipes | Galvanised | Marine | Sheltered-exterior-edge | | 123 | 2 | 0.6 |
| Downpipes | Galvanised | Benign | Sheltered-exterior-edge | | 24 | 25 | 0.5 |
| Downpipes | Galvanised | Marine | Open-interior -edge | | 51 | 7 | 0.6 |
| Downpipes | Galvanised | Benign | Open-interior-edge | | 11 | >50 | 0.5 |
| Downpipes | Galvanised | Marine | Open-interior-edge | Blocked | 137 | 1 | 0.6 |
| Downpipes | Galvanised | benign | Open-interior-edge | blocked | 33 | 15 | 0.5 |
| Ridge Cap | Galvanised | Marine | Open-edge | galvanised | 36 | 13 | 0.6 |
| Ridge Cap | Galvanised | Benign | Open-edge | galvanised | 12 | >50 | 0.5 |
| Ridge Cap | Galvanised | Marine | Open-edge | zincalume | 52 | 7 | 0.6 |
| Ridge Cap | Galvanised | Benign | Open-edge | zincalume | 17 | 43 | 0.6 |
| Steel Support | Galvanised | Marine | Open-other positions | drained | 44 | 9 | 0.6 |
| Steel Support | Galvanised | Benign | Open-other positions | drained | 8.4 | >50 | 0.5 |
| Steel Support | Galvanised | Marine | Sheltered-edge | drained | 122 | 2 | 0.7 |
| Steel Support | Galvanised | Benign | Sheltered-edge | drained | 23 | 27 | 0.6 |
| Steel Support | Galvanised | Marine | Open-other positions | Not well drained | | | |
| Steel Support | Galvanised | Benign | Open-other positions | Not well drained | 36 | 13 | 0.6 |
| fasteners | Hot dip-head | marine | Open-edge head above roof sheet | compatible | 53 | 32 | 0.7 |

Table 3.22(cont). Results of running revised models for components using climate conditions near Cairns

| Component | Material | Environment | Parameters | Case | Annual loss | life | n |
|-----------|-------------------|-------------|---|----------------|-------------|------|-----|
| fasteners | Hot dip-head | benign | Open-edge head above roof sheet | compatible | 16 | >50 | 0.7 |
| fasteners | Hot dip -head | marine | Open-edge head above roof sheet | Non-compatible | 136 | 8 | 0.7 |
| | | benign | Open-edge head above roof sheet | Non-compatible | 37 | 38 | 0.7 |
| fasteners | Zinc plated -head | marine | Open-edge head above roof sheet | compatible | 53 | 5 | 0.7 |
| | | benign | Open-edge head above roof sheet | compatible | 16 | 28 | 0.7 |
| fasteners | zincplated -head | marine | Open-edge head above roof sheet | Non-compatible | 136 | 6 | 0.7 |
| fasteners | zincplated -head | benign | Open-edge head above roof sheet | Non-compatible | 37 | 1 | 0.7 |
| fasteners | Hot dip-head | marine | Open-edge , shank below roof but not embedded in beam | Compatible | 159 | 6 | 0.7 |
| fasteners | Hot dip-head | benign | Open-edge shank below roof but not embedded in beam | Compatible | 39.8 | 48 | 0.7 |
| Roof | Zincalume | Benign | Open –edges-normal | Clean | 4.8 | >50 | 0.5 |
| Roof | Zincalume | Benign | Open –edges-normal | Not clean | 8.2 | >50 | 0.5 |
| Roof | zincalume | Marine | Open –edges-normal | clean | 10 | 39 | 0.6 |
| Roof | Zincalume | Marine | Open –edges-normal | Not clean | 24 | 9 | 0.6 |
| Gutters | Zincalume | Marine | Open –edge -edge | | 11 | 33 | 0.6 |
| Gutters | Zincalume | Benign | Open-edge-edsge | | 6.8 | 50 | 0.5 |
| Gutters | Zincalume | Marine | Sheltered-front face-edge | | 11 | 33 | 0.6 |
| Gutters | Zincalume | Benign | Sheltered-front face -edge | | 2.2 | 50 | 0.5 |
| Gutters | Zincalume | Marine | Open-front face –bottom -edge | clean | 11 | 33 | 0.6 |
| Gutters | Zincalume | Benign | Open-front face –bottom -edge | clean | 6.8 | 50 | 0.5 |
| Downpipes | Zincalume | Marine | Open-exterior-edge | | 14 | 22 | 0.6 |
| Downpipes | Zincalume | Benign | Open-exterior-edge | | 6.6 | >50 | 0.5 |
| Downpipes | Zincalume | Marine | Sheltered-exterior-edge | | 25 | 8 | 0.6 |
| Downpipes | Zincalume | Benign | Sheltered-exterior-edge | | 6.9 | >50 | 0.5 |
| Downpipes | Zincalume | Marine | Open-interior-edge | cleaned | 14 | 22 | 0.6 |
| Downpipes | Zincalume | Benign | Open-interior -edge | cleaned | 6.6 | >50 | 0.5 |
| Downpipes | Zincalume | Marine | Open –interior-edge | Blocked | 31 | 6 | 0.6 |
| Downpipes | Zincalume | benign | Open-interior-edge | blocked | 11 | 33 | 0.6 |
| Ridge Cap | Zincalume | Marine | Open-edge | Zincalume | 13.5 | 24 | 0.6 |

Table 3.22(cont). Results of running revised models for components using climate conditions near Cairns

| Component | Material | Environment | Parameters | Case | Annual loss | life | n |
|------------------|-----------------|--------------------|---------------------------------|------------------|--------------------|-------------|----------|
| Ridge Cap | Zincalume | Benign | Open-edge | zincalume | 9.5 | >50 | 0.5 |
| Steel Support | Zincalume | Marine | Open-other positions | drained | 9 | >50 | 0.5 |
| Steel Support | Zincalume | Benign | Open-other positions | drained | 5 | >50 | 0.5 |
| Steel Support | Zincalume | Marine | Sheltered-edge | drained | 22.4 | 10 | 0.6 |
| Steel Support | Zincalume | Benign | Sheltered-edge | drained | 6.5 | >50 | 0.5 |
| Steel Support | Zincalume | Marine | Open-other positions | Not well drained | 22 | 10 | 0.6 |
| Steel Support | Zincalume | Benign | Open-other positions | Not well drained | 8.7 | >50 | 0.5 |
| Window | Aluminium | Marine | Open-front face -other position | drained | 0.89 | 35 | 0.8 |
| Window | Aluminium | Benign | Open-front face -other position | drained | 0.27 | >50 | 0.8 |
| Window | Aluminium | Marine | Open-front face -other position | Not drained | 0.39 | >50 | 0.8 |
| Window | Aluminium | Benign | Open-front face -other position | Not drained | 0.27 | >50 | 0.8 |
| Window | Aluminium | Marine | Sheltered-front face -edge | Drained | 1.37 | 20 | 0.8 |
| Window | Aluminium | Benign | Sheltered -front face edge | drained | 0.30 | >50 | 0.8 |

3.6 Dose Tests for Corrosion Rates of New Materials

A number of the new components commonly use materials not previously considered in the Holistic model calculations. Dose tests were carried out to enable the Holistic models to incorporate these new materials. The variables that are likely to influence corrosion rate include:

1. Salt dosage
2. RH
3. pH

3.6.1 Experimental Set-Up

A matrix of tests was constructed around these variables, as defined by Table 3.23.

The following metals were characterized by salt dosing experiments:

- Aluminium AA6060-T5
- Anodised aluminium AA6060-T5
- Copper steel
- Zinalume®
- Zintane 83 rolled zinc

Table 3.23. Test variables for each type of metal.

| Test | RH/Temp. | pH | Average salt deposition rate (mg/m ² .day) | Notes |
|------|-----------|-----|---|---|
| 1 | 40 / 30 | 7.0 | 15 (4.73 mg/3 weeks) | 4% salt solution, total mass liquid = 39.375 mg seawater. |
| 2 | 40 / 30 | 7.0 | 45 (4.73 mg/week) | 118.125 mg seawater. |
| 3 | 40 / 30 | 7.0 | 120 (12.6 mg/week) | 315 mg seawater. |
| 4 | 60 / 30 | 7.0 | 15 (4.73 mg/3 weeks) | |
| 5 | 60 / 30 | 7.0 | 45 (4.73 mg/week) | |
| 6 | 60 / 30 | 7.0 | 120 (12.6 mg/week) | |
| 7 | 90 / 30 | 7.0 | 15 (4.73 mg/3 weeks) | |
| 8 | 90 / 30 | 7.0 | 45 (4.73 mg/week) | |
| 9 | 90 / 30 | 7.0 | 120 (12.6 mg/week) | |
| 10 | Immersion | 7.0 | Seawater | |
| 11 | Immersion | 6.0 | Seawater | Add H ₂ SO ₄ to adjust pH. |
| 12 | Immersion | 5.0 | Seawater | |

- All tests were done over a period of 12 weeks.
- Immersion tests were in individual containers for each metal and the solution volume to specimen area ratio exceeded 40mL per cm².
- The pH of immersion tests were readjusted each week.

The aluminium was prepared by washing with Neutracon non-ionic detergent and then rinsing in ethanol. The Zintane was cleaned with acetone (rubbed over with paper towel a few times), washed with Neutracon non-ionic detergent and then given an ethanol rinse. The copper steel was prepared by etching in an HCl/H₂O solution as described in the Wet Chemistry Lab procedures document. All samples are dried in a 110 degree C oven ready for use.

The first spray was on 9/1/2007 and the final spray was on 28/3/2007, a total of 12 weeks.

The immersion tests began on 10/1/2007 and ended on 6/3/2007, a total of 8 weeks. For these tests every week the pH was recorded and adjusted back to 5, 6 or 7 with the addition of H₂SO₄. Care was taken when this was done as sometimes only one drop was required using a pasteur pipette.

The schedule for spraying is shown as follows in Table 3.24. Spraying occurs in all the combinations above except for where an 'x' is shown.

Table 3.24. Schedule for spraying

| Week | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|-------------|----------|----------|----------|----------|----------|----------|----------|----------|----------|-----------|-----------|-----------|
| Test 1 | | x | x | | x | x | | x | x | | x | x |
| Test 2 | | | | | | | | | | | | |
| Test 3 | | | | | | | | | | | | |
| Test 4 | | x | x | | x | x | | x | x | | x | x |
| Test 5 | | | | | | | | | | | | |
| Test 6 | | | | | | | | | | | | |
| Test 7 | | x | x | | x | x | | x | x | | x | x |
| Test 8 | | | | | | | | | | | | |
| Test 9 | | | | | | | | | | | | |

The schedule for the spraying was to remove the samples from the chambers one test at a time and photograph each sample on the front side. Each sample was then sprayed according to the dosage required for that test number and placed back on the tray sprayed side up. When all the samples from one test were photographed and sprayed they were returned to the chamber. This was repeated for remaining tests according to the matrix above.

3.6.2 Results

The following table lists all the mass loss data after exposure from salt dosage tests or immersion tests. The average loss is given for each test along with the standard deviation.

The results of these tests have been used in the modification of the models for these new materials where relevant.

Table 3.25. Mass loss results for all samples

| Sample | Test | Avg loss (µm) | Std Dev |
|-----------------|-------------|----------------------|----------------|
| AA6060-T5 | 1 | 0.024 | 0.004227 |
| | 2 | -0.004 | 0.006227 |
| | 3 | 0.018 | 0.01973 |
| | 4 | -0.018 | 0.013662 |
| | 5 | -0.006 | 0.015276 |
| | 6 | 0.033 | 0.051198 |
| | 7 | 0.017 | 0.02106 |
| | 8 | 0.026 | 0.028393 |
| | 9 | 0.037 | 0.01012 |
| | 10 | 0.108 | 0.007332 |
| | 11 | 0.068 | 0.029394 |
| | 12 | 0.055 | 0.008238 |
| Anodised Al | 1 | -2.316 | 0.312272 |
| | 2 | -2.440 | 0.384018 |
| | 3 | -1.674 | 0.464912 |
| | 4 | -1.937 | 0.213959 |
| | 5 | -1.711 | 0.590815 |
| | 6 | -1.783 | 0.211424 |
| | 7 | -2.690 | 0.215921 |
| | 8 | -1.627 | 0.148174 |
| | 9 | -1.725 | 0.01293 |
| | 10 | -1.526 | 0.306318 |
| | 11 | -2.111 | 0.211909 |
| | 12 | -2.186 | 0.211171 |
| Cu-steel | 1 | 1.216 | 0.148159 |
| | 2 | 1.362 | 0.197431 |
| | 3 | 2.603 | 0.701051 |
| | 4 | 6.611 | 0.207615 |
| | 5 | 8.387 | 0.355205 |
| | 6 | 10.840 | 0.642284 |
| | 7 | 24.754 | 6.41232 |
| | 8 | 39.986 | 1.97362 |
| | 9 | 42.780 | 4.736083 |
| | 10 | 7.278 | 0.271692 |
| | 11 | 8.646 | 0.612668 |
| | 12 | 9.339 | 1.026542 |
| Zincalume AZ150 | 1 | 0.074 | 0.014296 |
| | 2 | 0.157 | 0.021345 |
| | 3 | 0.375 | 0.02221 |
| | 4 | 0.152 | 0.013189 |
| | 5 | 0.307 | 0.030594 |
| | 6 | 0.615 | 0.07639 |
| | 7 | 0.715 | 0.029337 |
| | 8 | 1.409 | 0.134141 |
| | 9 | 1.718 | 0.175553 |
| | 10 | 0.987 | 0.01783 |
| | 11 | 1.267 | 0.026369 |
| | 12 | 1.612 | 0.076951 |
| Zintane Z83 | 1 | 0.208 | 0.019016 |
| | 2 | 0.280 | 0.03042 |
| | 3 | 0.418 | 0.033978 |
| | 4 | 0.882 | 0.043724 |
| | 5 | 1.500 | 0.273735 |
| | 6 | 0.969 | 0.142946 |
| | 7 | 1.247 | 0.20474 |
| | 8 | 2.076 | 0.126785 |
| | 9 | 3.069 | 0.13994 |
| | 10 | 0.642 | 0.024101 |

| Sample | Test | Avg loss (µm) | Std Dev |
|-----------------|------|---------------|----------|
| AA6060-T5 | 1 | 0.024 | 0.004227 |
| | 2 | -0.004 | 0.006227 |
| | 3 | 0.018 | 0.01973 |
| | 4 | -0.018 | 0.013662 |
| | 5 | -0.006 | 0.015276 |
| | 6 | 0.033 | 0.051198 |
| | 7 | 0.017 | 0.02106 |
| | 8 | 0.026 | 0.028393 |
| | 9 | 0.037 | 0.01012 |
| | 10 | 0.108 | 0.007332 |
| | 11 | 0.068 | 0.029394 |
| | 12 | 0.055 | 0.008238 |
| Anodised Al | 1 | -2.316 | 0.312272 |
| | 2 | -2.440 | 0.384018 |
| | 3 | -1.674 | 0.464912 |
| | 4 | -1.937 | 0.213959 |
| | 5 | -1.711 | 0.590815 |
| | 6 | -1.783 | 0.211424 |
| | 7 | -2.690 | 0.215921 |
| | 8 | -1.627 | 0.148174 |
| | 9 | -1.725 | 0.01293 |
| | 10 | -1.526 | 0.306318 |
| | 11 | -2.111 | 0.211909 |
| | 12 | -2.186 | 0.211171 |
| Cu-steel | 1 | 1.216 | 0.148159 |
| | 2 | 1.362 | 0.197431 |
| | 3 | 2.603 | 0.701051 |
| | 4 | 6.611 | 0.207615 |
| | 5 | 8.387 | 0.355205 |
| | 6 | 10.840 | 0.642284 |
| | 7 | 24.754 | 6.41232 |
| | 8 | 39.986 | 1.97362 |
| | 9 | 42.780 | 4.736083 |
| | 10 | 7.278 | 0.271692 |
| | 11 | 8.646 | 0.612668 |
| | 12 | 9.339 | 1.026542 |
| Zincalume AZ150 | 1 | 0.074 | 0.014296 |
| | 2 | 0.157 | 0.021345 |
| | 3 | 0.375 | 0.02221 |
| | 4 | 0.152 | 0.013189 |
| | 5 | 0.307 | 0.030594 |
| | 6 | 0.615 | 0.07639 |
| | 7 | 0.715 | 0.029337 |
| | 8 | 1.409 | 0.134141 |
| | 9 | 1.718 | 0.175553 |
| | 10 | 0.987 | 0.01783 |
| | 11 | 1.267 | 0.026369 |
| | 12 | 1.612 | 0.076951 |
| Zintane Z83 | 1 | 0.208 | 0.019016 |
| | 2 | 0.280 | 0.03042 |
| | 3 | 0.418 | 0.033978 |
| | 4 | 0.882 | 0.043724 |
| | 5 | 1.500 | 0.273735 |
| | 6 | 0.969 | 0.142946 |
| | 7 | 1.247 | 0.20474 |
| | 8 | 2.076 | 0.126785 |
| | 9 | 3.069 | 0.13994 |
| | 11 | 0.984 | 0.056273 |
| | 12 | 2.660 | 0.1015 |

3.7 References

- Cole, I.S., Trinidad, G., Bradbury, A., McFallen, S., Chen, S.-E., MacKee, J., Gilbert, D., and Shutt, G., 2004a, "Final Report of Delphi study," CRC Report 2002-020-B, 2004.
- Cole, I.S., Paterson, D.A. and Ganther, W.D., 2003, "Holistic model for atmospheric corrosion - Part 1 Theoretical framework for production, transportation and deposition of marine salts", *Corros Eng Sci Techn* (2) 129-134.
- Cole, I.S., Chan, W.Y., Trinidad, G.S. and Paterson, D.A., 2004b, "Holistic model for atmospheric corrosion - Part 4- Geographic Information system for predicting airborne salinity", *Corros Eng Sci Techn* 39(1): 89-96
- Cole, I.S. and Paterson, D.A. "Holistic model for atmospheric corrosion. 2004, Part 5. Factors controlling deposition of salt aerosol on candles, plates and buildings." *Corrosion Engineering Science and Technology* 39, no. 2: 125-130
- Cole, I.S., Ganther, W.D., Sinclair, J.O., Lau, D., and Paterson, D.A., 2004c, "A study of the wetting of metal surfaces in order to understand the processes controlling atmospheric corrosion." *Journal of the Electrochemical Society* 151, no. 12: B627-B635
- Cole, I.S., Lau, D., Chan, F. & Paterson, D.A. 2004d, 'Experimental studies of salts removal from metal surfaces by wind and rain', *Corrosion Engg, Sci. & Technol.*, 39(4), 333-338
- Cole, I.S., Lau, D., and Paterson, D.A., 2004e, "Holistic model for atmospheric corrosion. Part 6 - From wet aerosol to salt deposit." *Corrosion Engineering Science and Technology* 39, no. 3, 209-218
- Cole, I.S. and Paterson, D.A., 2006, "Mathematical models of dependence of surface temperatures of exposed metal plates on environmental parameters" *Corrosion Engineering, Science and Technology*, 41 no. 1, 67-76
- Cole, I.S., Ball, M., Carse, A., Chan, W. Y., Corrigan, P.A., Ganther, W., Muster, T.H., Paterson, D, Trinidad, G., Maher, M.L., and Liew, P-S., "Case-Based Reasoning in Construction and Infrastructure Projects - Final Report," 2002-059-B, March 2005

4. COLORBOND DEGRADATION MODELLING

4.1 Introduction

In the previous phase of this project a model was developed for predicting the lifetime of painted metal components, with a particular emphasis on Colorbond® due to its prominent use throughout Australia. (Muster et al. 2005) Colorbond® is a product of Bluescope steel and has been proven to have exceptional performance in most locations across Australia. Although there are different grades of Colorbond®, the most common make-up for guttering is steel sheet (low carbon steel) with a coating of zincalume AZ 150 (150 g m⁻²), which is overcoated on both sides with a 5 µm chromate-containing epoxy primer. The one-sided product has a 20 µm thick UV-resistant topcoat and a 5 µm grey backing coat covering the primer (Bluescope Steel, 2005). Colorbond® gutters are assembled so that the backing coat forms the interior of the gutter and the coloured topcoat forms the outer gutter.

This chapter reports on experimental work to validate and refine the model for degradation of Colorbond®. This includes:

- (1) Experimental proving of the leaching of chromate inhibitors from Colorbond® materials.
- (2) Updated models for the accumulation of salts and the time of wetness for gutters, based upon field observations.
- (3) Electrochemical Impedance Spectroscopy investigations aimed at correlating the corrosion rates of weathered Colorbond® with those predicted by modeling.

4.2 The Leaching of Corrosion Inhibitors from Colorbond®

The leaching of chromate inhibitor from Colorbond was studied as a function of the following:

- 1) topcoat or backcoat
- 2) type of defect (circular defect, scribe or edge)
- 3) the size of the defect.

Seven samples were prepared as detailed in Table 4.1. Each sample was exposed to 50 mL of aqueous solution at pH 2 (pH adjusted using HCl) for varying periods of time. The dissolution of chromate corrosion inhibitor pigments into the aqueous solution was monitored.

Figure 4.1 and 4.2 show the appearance of each of the samples after two leaching cycles and seven leaching cycles, respectively.

Table 4.1. Experimental details of leaching studies.

| Sample | Exposed coating | Damage | Total area exposed to leaching solution (cm ²) | Exposed area of metal (cm ²) | Exposed area of primer (cm ²) |
|--------|-----------------|---------------------------------------|--|--|---|
| 1 | Topcoat | - | 18.2 | 0 | 0 |
| 2 | Backcoat | - | 18.2 | 0 | 0 |
| 3 | Edge | Eight 2 cm x 2cm | Topcoat =8 Edge =2.16 | Steel =1.92 Zincalume =0.128 | 0.032 |
| 4 | Topcoat | 3 x 70 µm wide scribes | 18.2 | 0.101 | 0.0144 |
| 5 | Topcoat | 10 x 100 µm diameter circular defects | 18.2 | 7.85 x 10 ⁻³ | 0.314 |
| 6 | Topcoat | 4 x 500 µm diameter circular defects | 18.2 | 7.85 x 10 ⁻³ | 0.628 |
| 7 | Topcoat | 1 x 2 mm diameter circular defect | 18.2 | 0.0314 | 0.628 |

4.2.1 The action of chromate

Solution concentrations were measured over a 43-day period. Over the length of the test Colorbond specimens were exposed to aqueous solutions at pH 2. Cell 1 showed no detectable trace of soluble chromium suggesting that the topcoat provides an effective barrier against degradation over short time frames. Cell 2, which exposes the backcoat of Colorbond to pH 2 solution, showed a release of 0.025 mg/L (0.0005 mol/L) into solution over the first 24 hours. At neutral pH, Scholes *et al.* (2006) showed that 200 µg/cm² of Cr could be released from a chromate inhibited primer over a 10-day period. The amount released in the first 24 hours from the backing coat amounted to less than 0.07 µg/cm². No chromium was detected in leaching for the remainder of the experiment.

Chromate release from cut edges was more significant than from planar faces of Colorbond. Cell 3 contained an edge length of 64 cm. Assuming a 5 µm thick primer, this equates to a primer area of 0.032 cm². In the first 24 hours the Cr release is estimated to be approximately 405 µg/cm², a release that more closely matches the reported value of Scholes *et al.* (2006). The release over the first 24 hours was modeled against Fick's second law of diffusion (Furman *et al.*, 2006), whereby a plot of log[dC/dt] (the concentration change over time) against log t gives a slope that represents the exponent of the inhibitor release. Fickian diffusion is represented by a slope equal to -0.5 (assuming a constant surface concentration of diffusing species) whilst anomalous diffusion is a collective term given to concentrations that do not change as t^{0.5}. Figure 4.3 shows that chromate is initially released from a cut edge with a slope of -0.85 = n-1, resulting in an exponent of t^{0.15}, indicating a rapid release of chromium. In contrast, strontium was found to release with an exponent of t^{0.55}, which is a close approximation of Fickian diffusion behaviour.

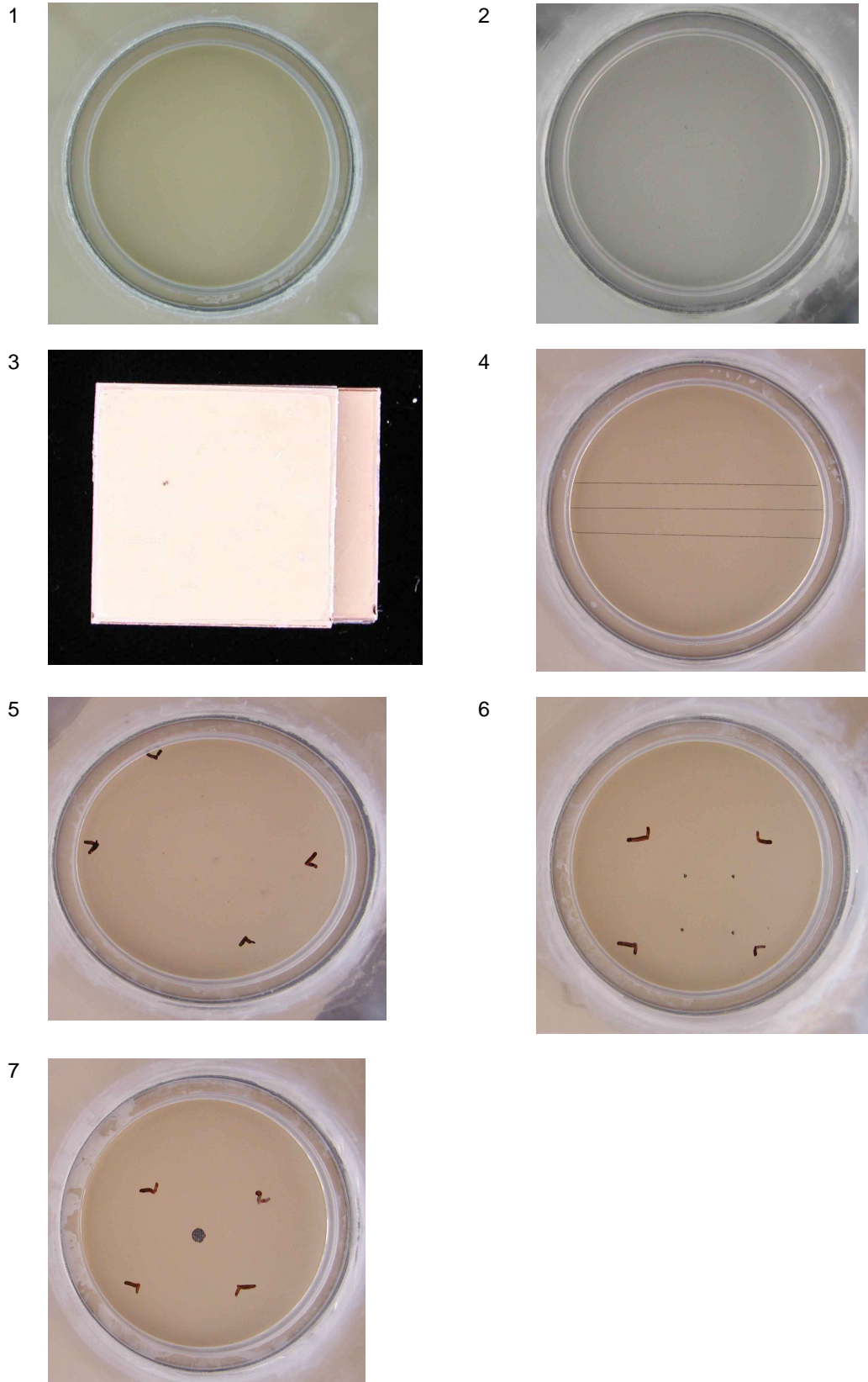


Figure 4.1. Photographs of the seven cells after two leaching cycles.

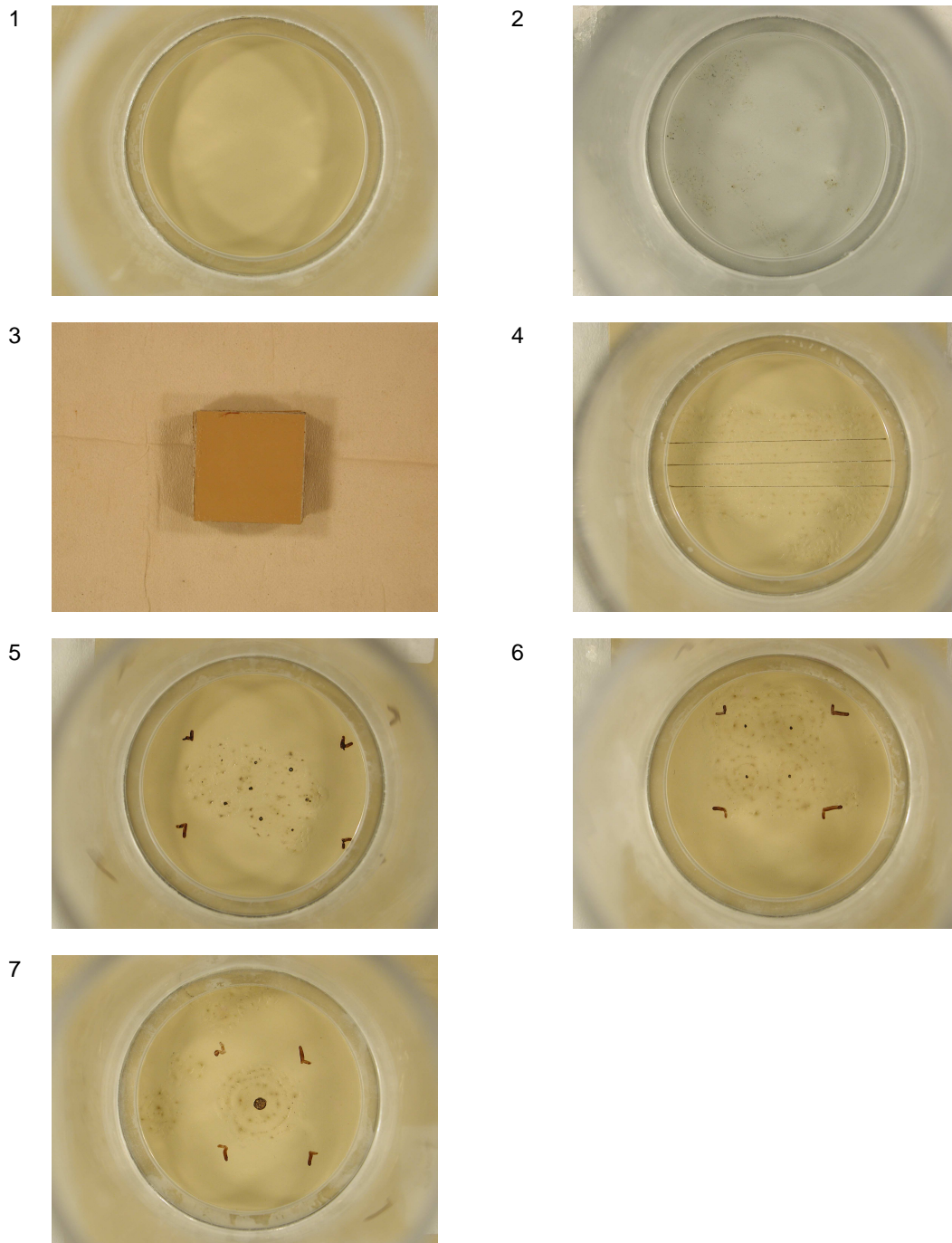


Figure 4.2. Photographs of the seven leaching cells after seven leaching cycles.

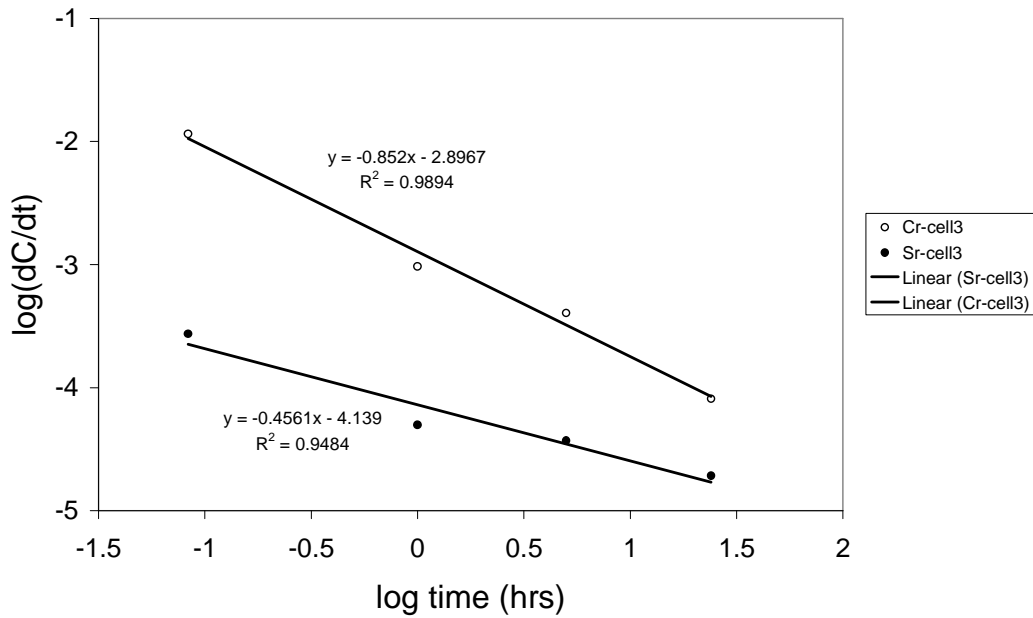


Figure 4.3. The leaching rate of chromium as a function of time from the cut edge of Colorbond XRW.

Figure 4.4 below shows that cell 7 (with a 2 mm diameter area of damage) produced a significant amount of soluble chromate after 5 minutes. A second sample taken after one hour showed no detectable chromium concentration. Cell 5 also showed some chromium in the initial sample but none thereafter. No soluble chromium was present on cell 6. Both cell 2 and cell 4 showed a gradual release of chromium for 5 to 24 hours, and thereafter no chromium was released into solution.

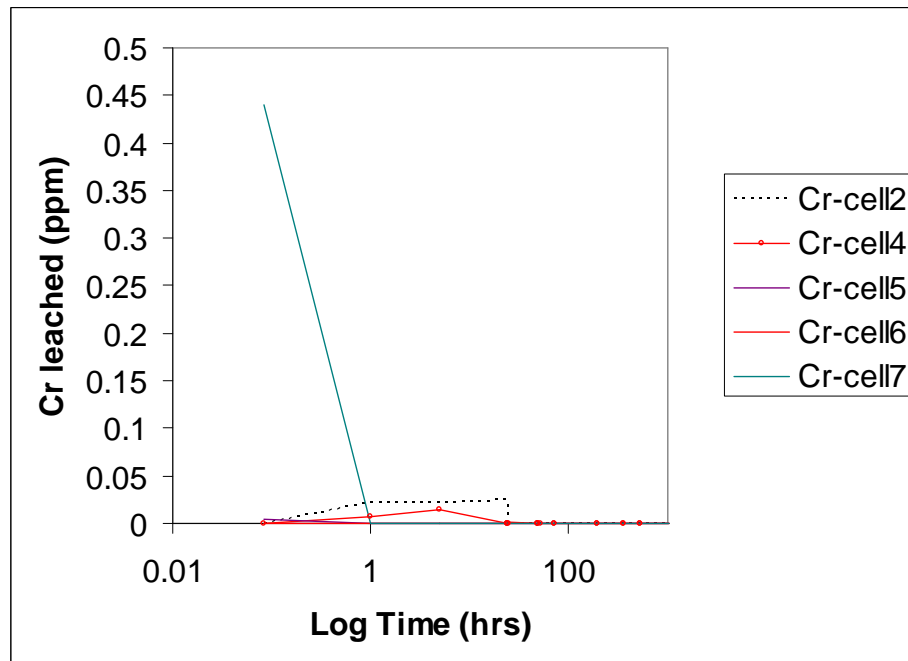


Figure 4.4. Leaching of chromate from paint films with various damage sites.

Cr(VI) species are known to have high aqueous solubility, however, Cr(III) species are likely to precipitate out of solution at more neutral pH's. Solubility of Cr(OH)₃ is reported to be

$10^{-30.27}$ at 17 °C in 0.1 M KCl (Bjerrum et al., 1958). Despite the low solubility, the low pH should ensure that Cr species are able to exist in solution. pH measurements of the final solutions showed increases during the experimental lifetime, which can lead to the precipitation of Cr(III) oxides. For this reason the chromium levels appeared to be initially high (where the time of solution contact with the sample was short) and then decreased at longer experimental times, as the concentration of metal ions in solution increased, which leads to increased pH levels through hydrolysis.

Strontium and zinc concentrations, unlike most other species measured appeared to be unaffected by the increase in pH. Therefore, the relationships existing between strontium and chromium concentrations in the measurements taken during the first 24 hours were extended to longer time periods. SrCrO₄ should ideally be dissolved to give a 1:1 ratio of Cr:Sr, however, as Figure 4.5 shows the initial release of chromium is significantly higher than for strontium. For the cut edge, the 1:1 ratio is obtained after longer leaching times, approximately greater than 300 hours.

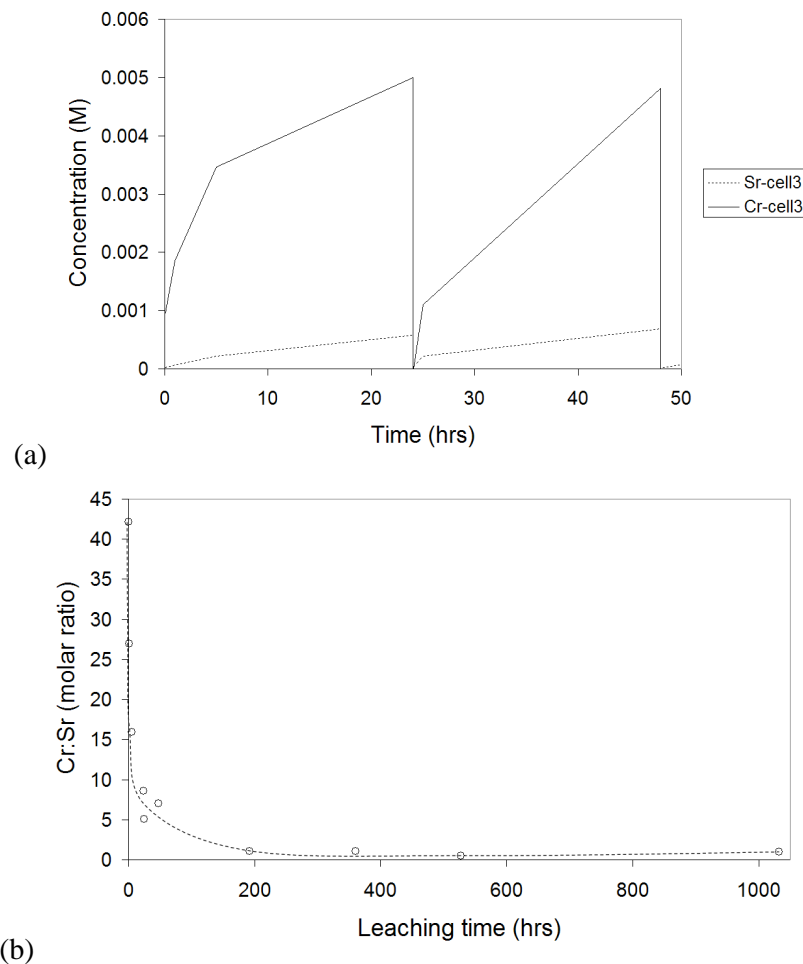


Figure 4.5. (a) Concentrations of Strontium and Chromium during the first 48 hours of leaching from the cut-edge of Colorbond XRW in 50 mL aqueous solution at pH 2. (b) Cr:Sr ratio for leaching from the cut-edge over a longer time period.

Estimations for the rate of chromate leaching were obtained from strontium chromate leaching data, which showed consist changes in concentration as a function of time, as shown in Figure 4.6.

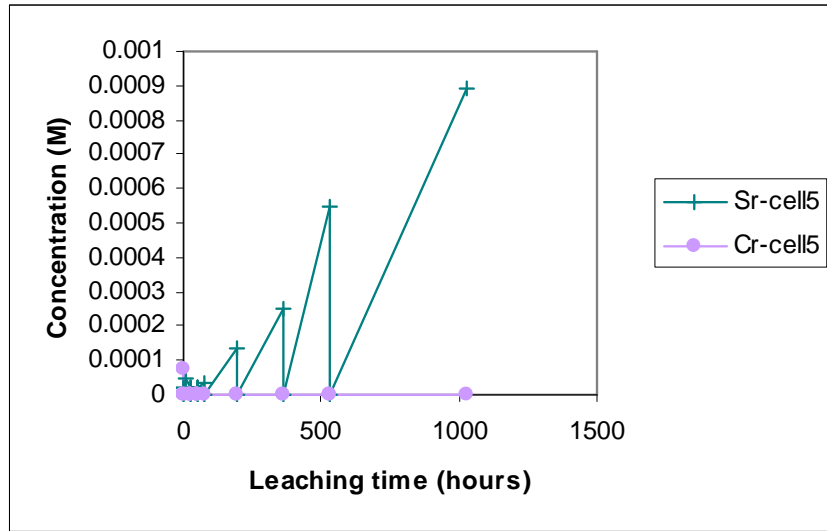


Figure 4.6. Leaching data for strontium and chromium from cell 5 (topcoat with pinhole defects) as a function of leaching time. Note that a return to zero concentration occurs when the pH 2 leaching solution is refreshed.

The rate of chromate depletion from a damaged topcoat (with a pinholes according to Cell 5) and undamaged backcoat of Colorbond materials was determined for the first 24 hour period, after which it was estimated from the solution concentrations of strontium ions. The resultant dependence upon time is given in Figure 4.7.

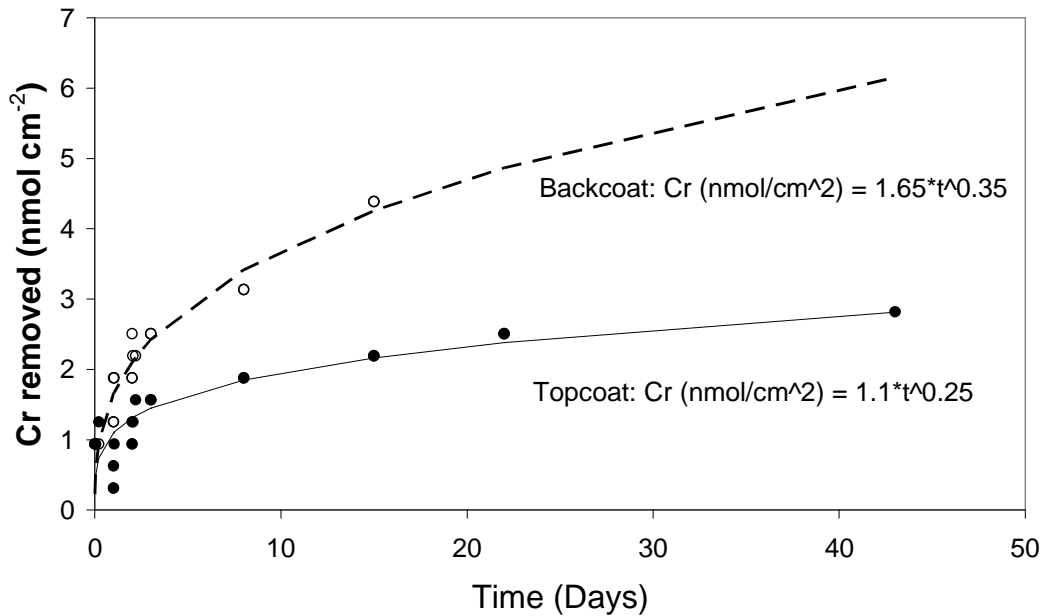


Figure 4.7. Chromium concentrations removed from Colorbond after short time periods and those estimated from strontium ion concentration after longer time periods.

The original model assumed that chromate was depleted with a dependence of $t^{0.5}$. It is now believed that $t^{0.25}$ or $t^{0.35}$ are more realistic dependencies, and hence an updated calibration has been made.

4.3 The Weathering of Polymers

Previous work by Martin and co-workers at the CSIRO accrued data on the solar irradiance, ultraviolet radiation and solar weathering performance of polymeric films Australia-wide [Martin, 1977]. The data from this work has been analysed and compared with climatic data from the Bureau of Meteorology. Climatic variables considered were the average maximum daily temperature, average relative humidity (9am and 3pm) and average rainfall. Previous work by Bauer (2000) demonstrated that solar irradiation data could be converted to a weathering index by considering the affects of daily temperature maximum's and relative humidity. Increases in temperature provide the polymer with energy, which increases the rate of photooxidation through an Arrhenius-type relationship with temperature. Relative humidity is known to influence the weathering of polymer and to promote photooxidation, however, it is not used in deriving the relationship between climatic conditions and the solar weathering index of Martin (1977). Rather, the increased rate of degradation in humid environments is dealt with elsewhere within the model, in terms of the rate at which the corrosion inhibitor is consumed within a polymeric film.

Figure 4.8 shows the dependence of the solar weathering index on average maximum daily temperature, average relative humidity (9am and 3pm) and a combined variable of average maximum daily temperature^k/average relative humidity (T^k/RH , which has an optimised regression of 0.75 where $k = 1.7$).

4.4 Implementation of Model

In the previous model the relative photooxidation rates with damage to colorbond was achieved through by matching the % failure data provided by Bauer (2000) with the failure ratings of Colorbond provided by King et al. (2001). Failure of the topcoat and backing coats leads to an increased loss of chromate from the primer. The total loss of chromate, L_{total} (mol) is given as:

$$L_{total} = L_{Cl}(1 + xt)(-0.0004 * LAT^2 + 0.0003.LAT) \text{ mol} \quad \dots \text{Eqn(4.1)}$$

where $x = 0.8$ for topcoat and 0.4 for backing coat, $t =$ time in years, $LAT =$ latitude in degrees.

In the current model the solar weathering index, W is given as:

$$W = 1.54 \frac{T_{av}^{1.7}}{RH_{av}} + 6.5 \quad \dots \text{Eqn(4.2)}$$

The value of W represents the rate of degradation of a painted sample due to irradiance from the sun and leads to a revised expression of the total loss of chromate:

$$L_{total} = L_{Cl}(1 + xt)W \text{ mol} \quad \dots \text{Eqn(4.3)}$$

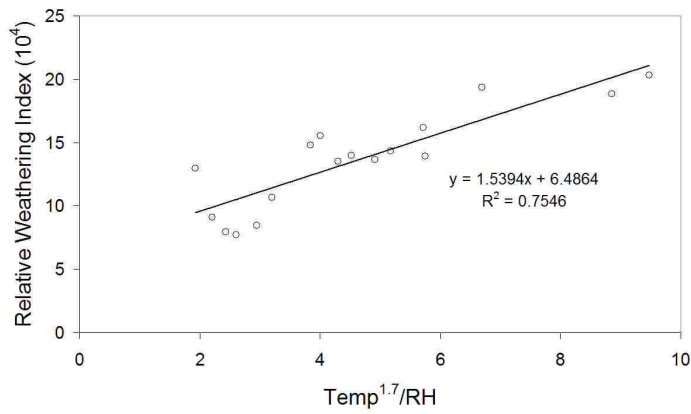
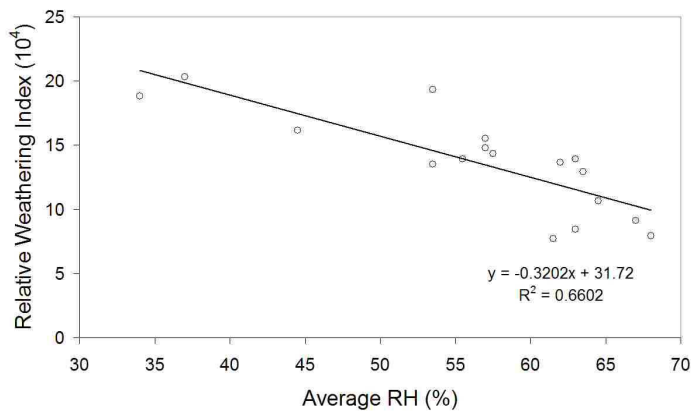
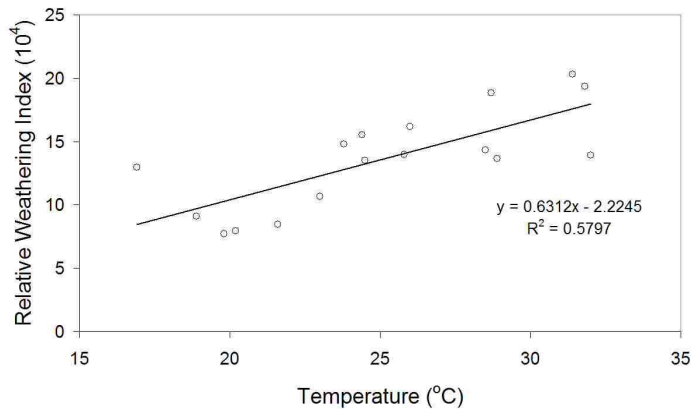


Figure 4.8. Relationships between simple climatic parameters (average daily maximum temperature and average daily relative humidity [9am and 3pm]) and the solar weathering index of Martin [5].

4.4.1 Influence of salt concentration on leaching rate

Chromate leaching has been shown to be a function of chloride concentration (Prosek and Thierry, 2004). Chloride anions are able to associate with soluble chromate and encourage dissolution of pigments. Prosek and Thierry (2004) found that 10 mmol L⁻¹ of NaCl increased chromate leaching by 30%. By increasing the NaCl concentration to 100 mmol L⁻¹ had minimal additional impact. The amount of chromate leached during a 3-hour period allowing for the influence of salt concentration is given as:

$$L_{Cl} = (L_t - L_{t-1}) * (1.2123[Cl]^{0.1544}) \quad \dots \text{Eqn(4.4)}$$

In the present model new data from chromate leaching experiments at pH 2 have developed relationships that link the rate of chromate removal to the rate at which the underlying metal is removed.

Annual rainfall in Australia generally varies from less than 200 mm up to 1500 mm. The percentage time of wetness can vary from less than 10% to over 60%, and up to 100% if the coated metal is dirty, with for instance leaf litter. Chromate was previously assumed to leach according to Fick's second law (i.e. $t^{0.5}$ dependence), however, data from Figure 4.7 indicates that leaching from Colorbond® follows a dependence closer to $t^{0.25}$ or $t^{0.35}$. The solubility and rate of chromate removal is pH dependent, as demonstrated by Sinko (2001). From Sinko, strontium chromate (SrCrO₄) was shown to have a pH-dependent saturation solubility given by:

$$C_{sat} = -0.5 \times pH + 4.5 \quad \dots \text{Eqn(4.5)}$$

Therefore, at pH 2 $C_{sat} = 3162$ mmol/L and at pH 6 $C_{sat} = 31.62$ mmol/L. The amount of chromate removed in the accelerated experiment can be approximated to be 100 times that at pH 6.

4.4.2 Degradation of damaged (with pinholes) Colorbond® topcoats

Several calculations are required to estimate the longevity of roofs. The approach is to estimate the amount of chromate removed in one year. The rate of loss of chromate, zinc and aluminium species has been estimated under laboratory conditions. Therefore, the amount lost in subsequent years can then be estimated and matched with the rates of zinc and aluminium loss given the amount of removed chromate. This model is not expected to hold where there is more significant damage to the topcoat.

1. The average annual maximum temperature and average annual relative humidity are used to calculate the solar weathering factor, based upon the work of Martin (1977), where:

$$W = \frac{1.54 \frac{T_{av}^{1.7}}{RH_{av}} + 6.5}{6.5} \quad \dots \text{Eqn(4.6)}$$

The weathering factor alters the rate at which chromate is leached during wet conditions. A value of $W=1$ exists where the average maximum temperature = 0 °C. The weathering factor for Australia largely varies between 1.1 in cooler climates (Melbourne) up to 3.1 for warmer climates (Longreach).

2. Chromate loss is a summation during the periods where the surface is deemed to be wet. These wet periods are obtained from the current holistic model. For each wet period (3 hr) the chromate loss is calculated as:

$$Cr_i = [(0.5 \times 3.422e - 4^{0.25W/6.5}) \times 1.2123 \times [Cl]^{0.1544}] \quad \dots \text{Eqn(4.7)}$$

3. Where [Cl] is the accumulated salinity (mg/m².day) for the 3-hr period in question. The chromate loss is in nmol/cm² and should be summed for a 1 yr period to obtain Cr_{1yr}.

4. The loss of chromate for each subsequent year is given as:

$$Cr_t = Cr_{1yr} \times t^{0.25W} \quad \text{where time (t) is in years.} \quad \dots \text{Eqn(4.8)}$$

5. The loss of zincalume from the topcoat is calculated by the following equation:

$$AlZn_{loss(\mu m)} = [(Cr_t \times 0.0643) + (Cr_t \times 0.3)] \times \frac{(0.00045[Cl_{av}]) + 0.02255}{0.182075} \quad \dots \text{Eqn(4.9)}$$

Where $(Cr_t \times 0.0643)$ accounts for the loss of zinc, $(Cr_t \times 0.3)$ accounts for the loss of aluminium and the remainder of the equation is the scaling factor that links the rate of zincalume loss from laboratory tests in 0.01 M chloride to the daily average salinity in the field (mg/m².day). Figure 4.9 below demonstrates the correlation between strontium chromate removal and that of the underlying zincalume and steel.

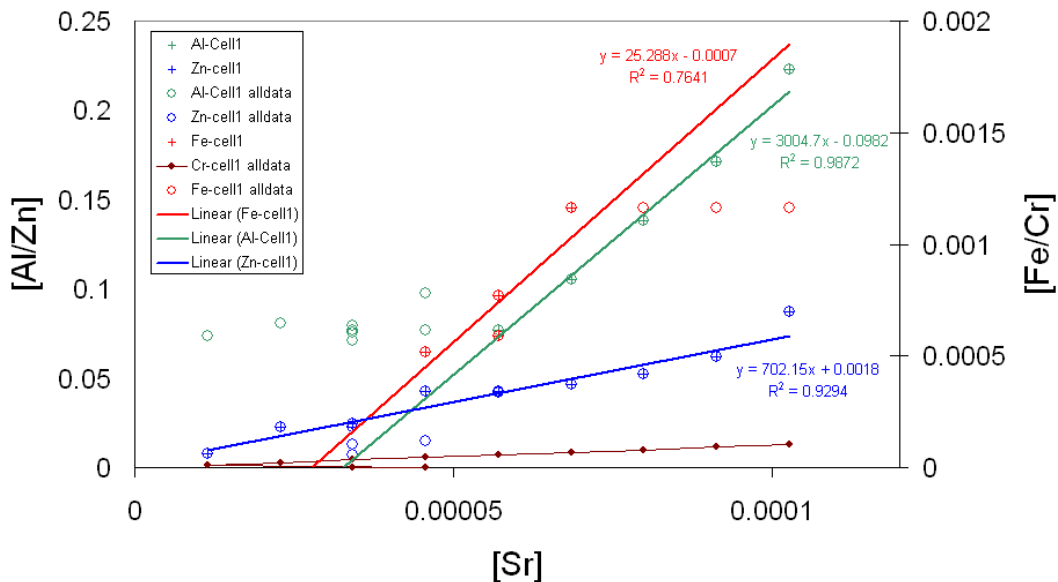


Figure 4.9. Correlations between the concentration (in mol L⁻¹) of strontium released into solution and those of zincalume and steel in aqueous solution acidified to pH 2 using HCl.

The onset of white rust can be estimated where AlZn losses exceed 2 μ m. The onset of red rust is achieved when a ZnAl thickness of 15 μ m has been reached.

4.4.3 Degradation of undamaged Colorbond® backcoats

The application of the weathering factor is the same for the backcoat as for the topcoat.

The governing equation relating to chromate removal from a backcoat is:

$$Cr_t = [(1.1 \times 3.422e - 4^{0.35W/6.5}) \times 1.2123 \times [Cl]^{0.1544}] \dots \text{Eqn(4.10)}$$

This again is the Cr loss estimated for a 3-hr period. A summation of the TOW for one year gives the chromate loss for one year (Cr_{1yr}).

1. The loss of chromate for each subsequent year is given as:
2. $Cr_t = Cr_{1yr} \times t^{0.35W}$ where time (t) is in years. ...Eqn(4.11)
3. The loss of zincalume from the backcoat is calculated by the following equation:

$$AlZn_{loss(\mu m)} = [(Cr_t \times 0.417) + (Cr_t \times 1.066)] \times \frac{(0.00045[Cl_{av}]) + 0.02255}{0.182075} \dots \text{Eqn(4.12)}$$

Where $Cr_t \times 0.417$ accounts for the loss of zinc, $Cr_t \times 1.066$ accounts for the loss of aluminium and the remainder of the equation is the scaling factor that links the rate of zincalume loss from laboratory tests in 0.01 M chloride to the daily average salinity in the field ($mg/m^2 \cdot day$).

Figure 4.10 below demonstrates the correlation between strontium chromate removal and that of the underlying zincalume and steel.

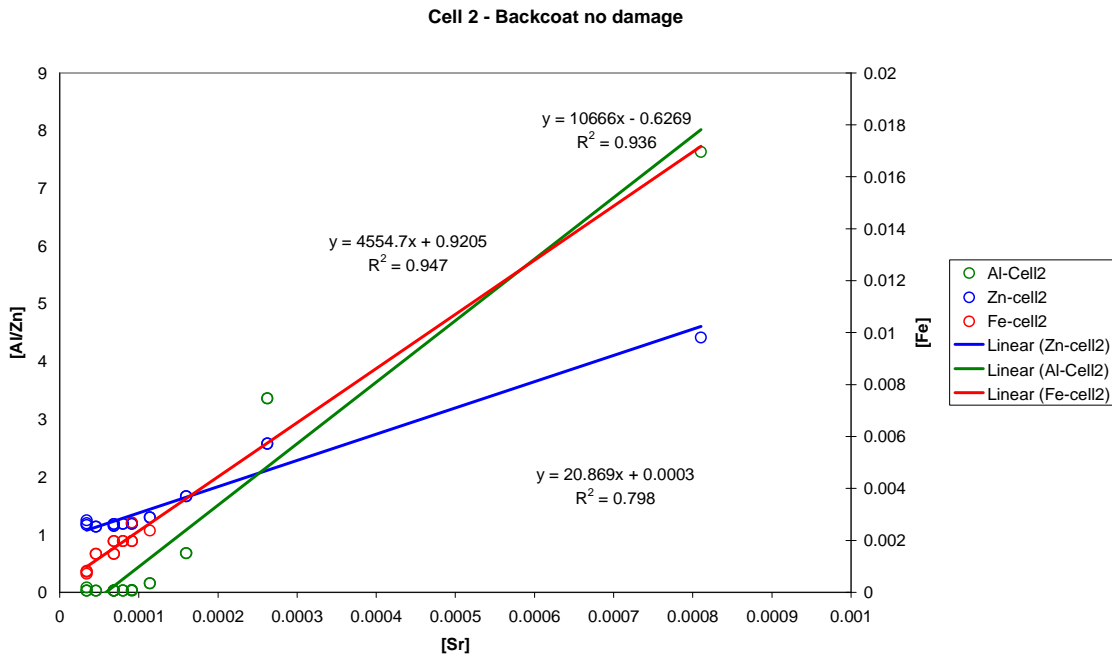


Figure 4.10. Correlations between the concentration of strontium released into solution and those of zincalume and steel in aqueous solution acidified to pH 2 using HCl.

4.4.4 Models for the Accumulation of Salts and the Time of Wetness in Gutters (re-worked)

The environmental conditions inside a gutter can vary significantly from those of openly exposed surfaces. The prime causes of these variations during roof surveys have been observed to be: (i) the presence of dirt or leaf litter in the gutter, or (ii) incorrectly installed or damaged gutters that retain pools of moisture.

For modeling purposes the time-of-wetness (TOW) experienced by gutters is assumed to be the same as an openly exposed roof only if it is clean and well-drained (i.e. the gutter is wet when the roof is wet). Work by Ganther (2005) showed that dirty gutters on the other hand can take up to ten days to dry once they have been wet. For modeling purposes a dirty or water-retaining gutter is assumed to be wet unless the relative humidity (RH) is less than the critical humidity (defined by the types of salts present) for greater than 240 hours. Please refer to the work of Cole et al. (2003) for rules concerning the critical relative humidity.

The accumulation of salt in gutters is modeled by assuming that all salt entering the gutters has its origins from the roof. As Figure 4.11 demonstrates, the amount of salt being deposited onto a roof (mg/m^2) can be translated to a salt concentration within the gutter with knowledge of the volume of moisture runoff (mm) and the collection length of the gutter (L). The width of the gutter is assumed to be 0.1 m.

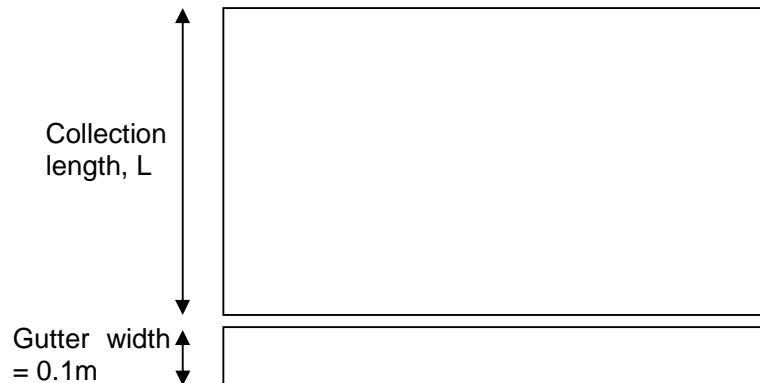


Figure 4.11. The relationship between roof area and gutter area. Roof area = $L/0.1$ (or $10 \times L$) times the gutter area.

Therefore, the following inputs must be specified for the calculation of TOW and salt concentration within gutters:

1. Clean and well-drained gutter
2. Dirty or water-retaining gutter
3. Input roof collection length (m).

Details of the implemented model for the calculation of TOW and salinity are contained in Table 4.2.

Table 4.2. A comparison of old and new implementations for the calculation of salt concentration and time-of-wetness in gutters.

| OLD IMPLEMENTATION | NEW IMPLEMENTATION |
|---|--|
| <p>1. Salt concentration CI</p> <ul style="list-style-type: none"> □ SAL_{ss} (mg/m².day) - seasonal values from previous implementation □ $\Delta CI = \frac{SAL_{ss}}{8}$ (mg/m².3hr) <p>2. Cumulative salt deposition $CI_{cum,t}$</p> $CI_{cum,t} = \begin{cases} \Delta CI & t = 0 \\ CI_{cum,t-1} * (1 - \epsilon) & t > 0 \quad R \geq \gamma \\ CI_{cum,t-1} + \Delta CI & t > 0 \quad R < \gamma \end{cases}$ <ul style="list-style-type: none"> □ rain-limit γ is 0.6 for interior and 0.19 for exterior □ wash-off- efficiency ϵ is 0.3 for interior and 0.05 for exterior | <p>At the $i+1^{th}$ 3-hour interval if rain cleaning occurs then</p> <p>Salt deposition is given by the Holistic model as follows:</p> <ul style="list-style-type: none"> □ $D_{i+1} = \phi + (\psi * D_i)$ <p>Salinity loss is calculated as follows:</p> <ul style="list-style-type: none"> □ $SAL_{loss} = D_{i+1} - D_i$ <p>Salinity increment is calculated as follows:</p> <ul style="list-style-type: none"> □ $\Delta CI = SAL_{loss} * L * 10$ <p>Rain depth in gutter is calculated as follows:</p> <ul style="list-style-type: none"> □ $R_g = Rain * L * 10$ <p>Fraction of SAL remaining is calculated as follows:</p> $SAL_{fraction} = 1 - \left(\frac{R_g - R_g^{limit}}{R_g} \right) \quad R_g > R_g^{limit}$ <ul style="list-style-type: none"> □ $R_g^{limit} = \begin{cases} 1 & \text{clean \& well drained gutter} \\ 5 & \text{dirty or water retaining gutter} \end{cases}$ <p>NOTE: if there is no rain cleaning occurs then</p> <ul style="list-style-type: none"> ○ $SAL_{fraction} = 1$ |

Salinity accumulated in gutter is calculated as follows:

$$\square \quad SAL_{i+1} = (SAL_i + \Delta CI) * SAL_{fraction}$$

3. Cumulative time-of-wetness (hours) $TOW_{cum,i}$

$$TOW_{cum,i} = \begin{cases} TOW_{cum,i-1} + 3 & S > 1 \\ TOW_{cum,i-1} & S = 1 \end{cases}$$

a) If gutter is clean & well drained then

$$TOW_{cum,i} = \begin{cases} TOW_{cum,i-1} + 3 & S > 1 \\ TOW_{cum,i-1} & S = 1 \end{cases}$$

b) If gutter is dirty or water retaining

$$TOW_{cum,i} = \begin{cases} TOW_{cum,i-1} & S = 1 \wedge \sum dryHours > 240 \\ TOW_{cum,i-1} + 3 & otherwise \end{cases}$$

An example of the performance of the model is given by the calculated data for Brookfield State School in Queensland (152.913, -27.495). Figure 4.12 shows the data inputs of rainfall, chloride loss (from the roof), the surface state (old model) and accumulated chloride (cum_Cl using old model).

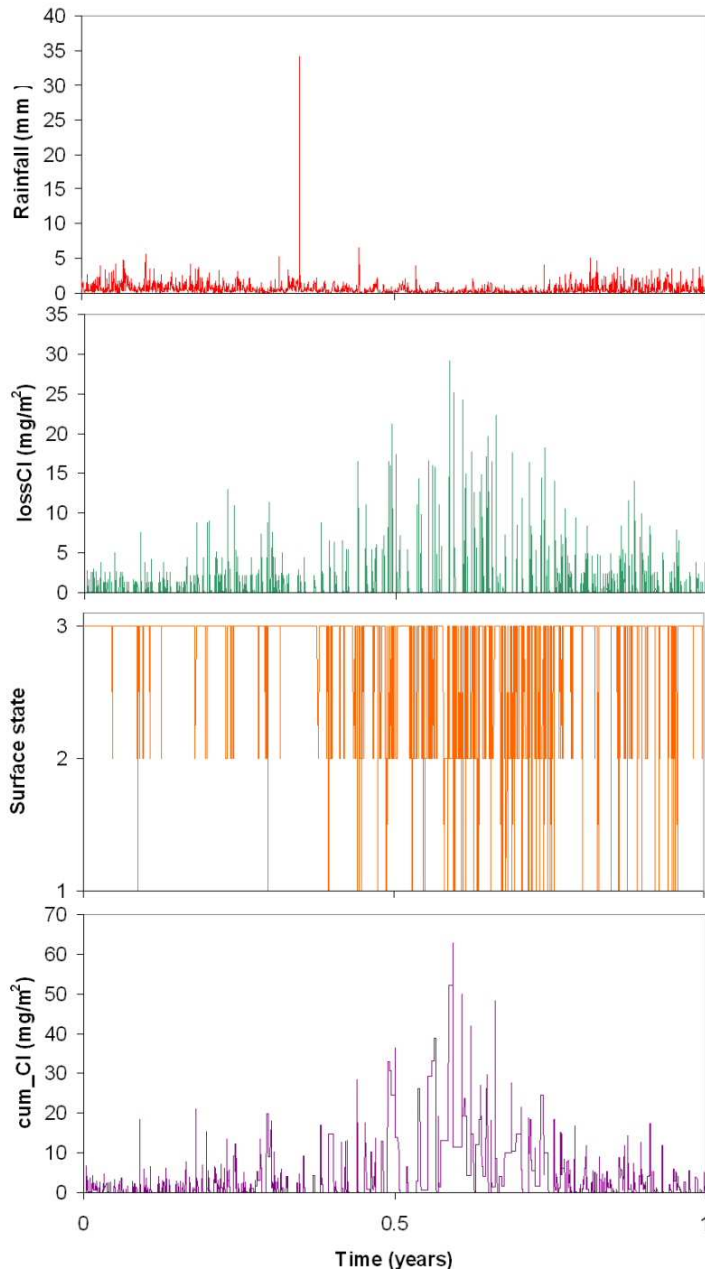


Figure 4.12. Estimations of the accumulation of salt in gutters at Brookfield State School calculated from rainfall runoff and accumulation using the old model.

Figure 4.13 and 4.14 show the revised chloride accumulation for clean and dirty gutters, respectively.

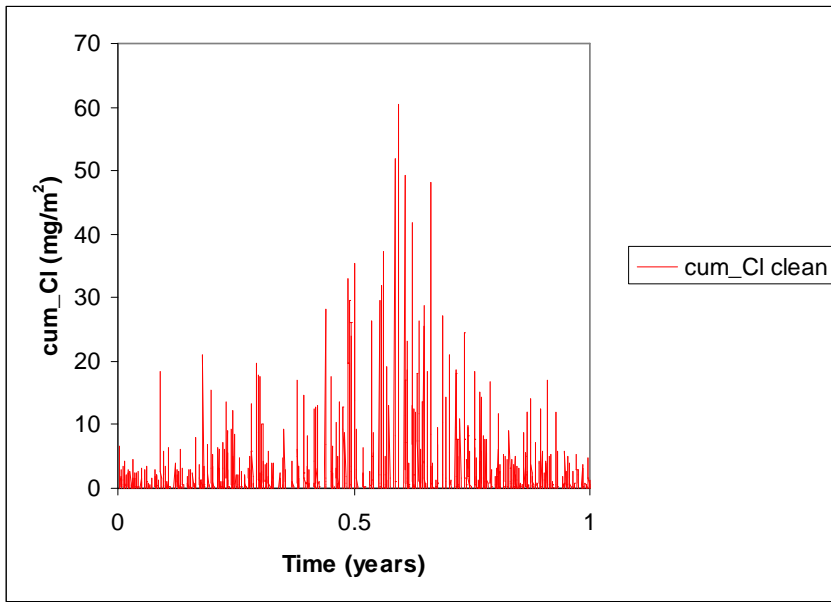


Figure 4.13. Accumulated chloride in a clean gutter over a one year period predicted using the revised methodology and assuming a collection length of 5m.

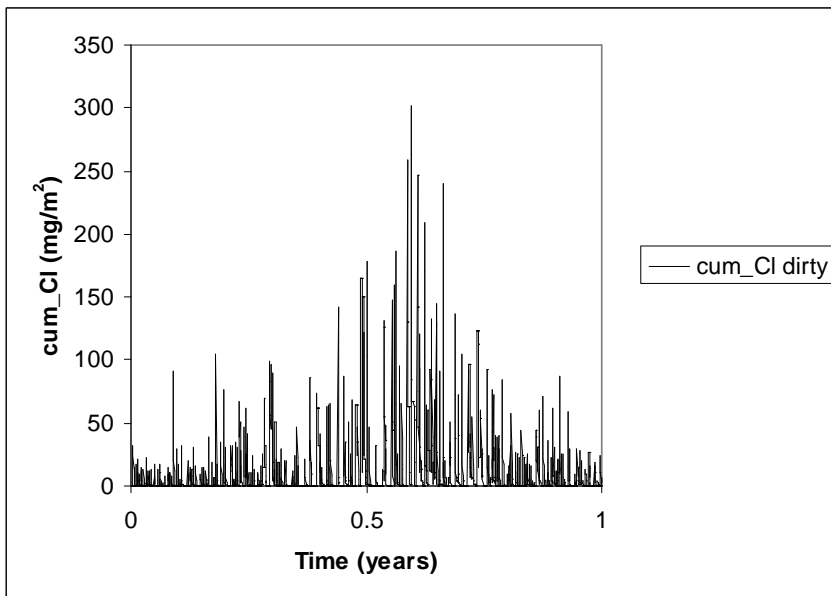


Figure 4.14. Accumulated chloride in a dirty gutter over a one year period predicted using the revised methodology and assuming a collection length of 5m.

There is a large difference in the levels of accumulated salt in gutters. The old model has an average accumulated salt concentration of 10.7 mg/m^2 whilst the new model calculates an average of 1.15 mg/m^2 for clean and well-drained gutters and 11.46 mg/m^2 for dirty gutters. The lower salt levels are likely to increase the working life of gutters. However, the presence of dirt in gutters and incorrectly installed gutters keeps them wet for longer periods of time. Typically open roofs can dry within 30 minute periods whilst dirty gutters have been shown to stay wet for over 10 days, even though the relative humidity can remain below a critical level

in which salts are able to wet. For a dirty gutter at Brookfield state school it was estimated that it stayed wet for 354 days per year.

The levels of chloride predicted using the new methodology have been observed experimentally, where a series of samples were taken from dirty gutters and analysed for their chloride content (Table 4.3). Here a fixed mass (100 g) of dried leaf/dirt matter or free tree matter was mixed with 500 ml of high purity water and allowed to incubate in a shallow tray for approximately 30 days. After this time the samples were filtered and the filtrate analysed using inductively couple plasma (ICP) atomic emission spectrometry (AES). (The same specimens were used for pH measurements in Chapter 3) Table 4.3 demonstrates that the amount of chloride ions available in a gutter is significantly reduced for most of the specimens tested. This indicates that chloride ions readily get washed from gutters due to a more consistent contact with aqueous solution and greater dilution due to increased thicknesses in water layers.

Table 4.3. Analytical analysis of aqueous solutions obtained from (i) leaf matter in dirty gutters and (ii) solutions prepared from identical amounts of tree matter only. Further experimental detail is given in the text.

| Specimen | Chloride Concentration (ppm) |
|----------------------------|------------------------------|
| Willow Myrtle (gutter) | 30 |
| Willow Myrtle (tree only) | 190 |
| Liquid Amber 1 (gutter) | 53 |
| Liquid Amber 1 (tree only) | 190 |
| Liquid Amber 2 (gutter) | 85 |
| Liquid Amber 2 (tree only) | 210 |
| Golden Ash (gutter) | 120 |
| Golden Ash (tree only) | 213 |
| Eucalypt (gutter) | 120 |
| Eucalypt (tree only) | 80 |
| Condifer (gutter) | 5 |
| Conifer (tree only) | 418 |

4.5 Electrochemical Impedance Spectroscopy (EIS) of Colorbond®

4.5.1 Introduction to EIS

The impedance describes the frequency-dependent relationship between voltage and current. It is comprised of real and imaginary parts.

$$Z(\omega) = Z_{Re} - jZ_{Im} \quad \dots\text{Eqn(4.13)}$$

where Z_{Re} is real, for example the resistance, R , and Z_{Im} is imaginary = reactance (X_C) = $1/\omega C$.

The magnitude of $|Z|$ is given by:

$$|Z|^2 = Z_{Re}^2 + Z_{Im}^2 \quad \dots\text{Eqn(4.14)}$$

The phase angle (ϕ) is given by:

$$\tan \phi = Z_{Im} / Z_{Re} \quad \dots \text{Eqn(4.15)}$$

For pure resistance, $\phi = 0$, for pure capacitance $\phi = \pi/2$.

The total impedance of a corroding metal is given as:

$$Z_{total} = Z_{metal-film} + Z_{film} + Z_{film-solution} \quad \dots \text{Eqn(4.16)}$$

As these elements are connected in series the largest impedance will dominate (MacDonald and McKubre, 1987). Dipolar properties are measured at high frequencies, bulk properties at intermediate frequencies and surface properties at low frequency (Amirudin and Thierry, 1995)

The data generated from EIS measurements was fitted to a common equivalent circuit for a metal-paint-electrolyte system. The models were considered to be relevant to the Colorbond® system: A, B and C, in Figure 4.15.

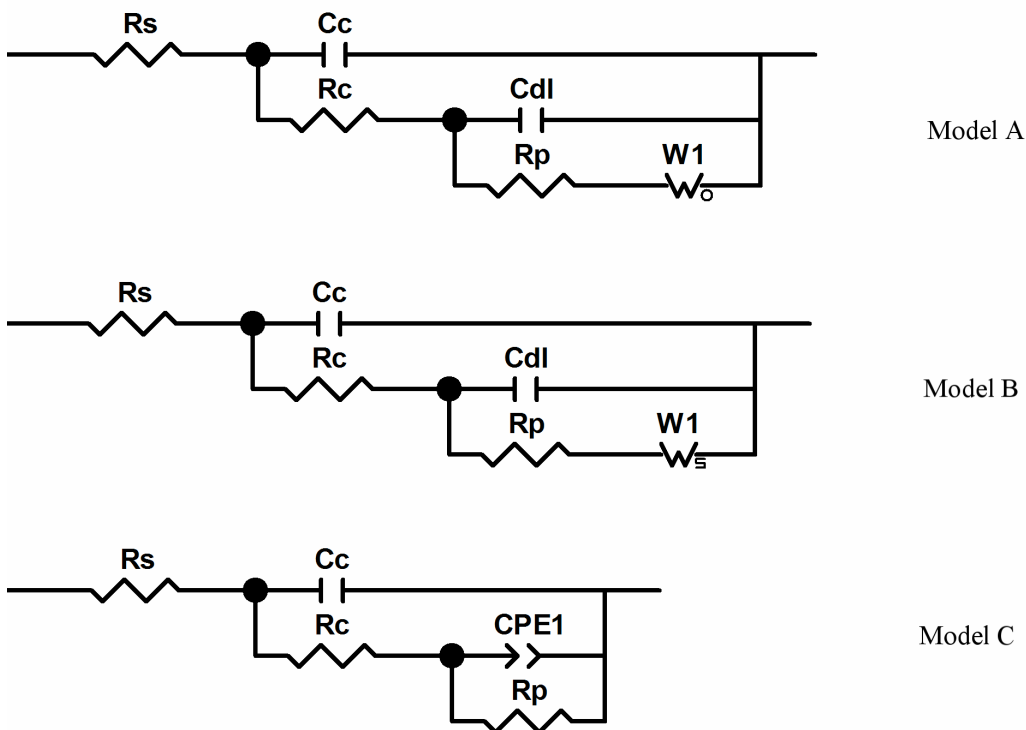


Figure 4.15. Common equivalent circuits used to describe a metal-coating-solution interface using EIS measurements.

Model 'C' was chosen as a standard analysis for the performance of coatings.

The constant phase element has the form given in equation x, whereby a constant phase element can be used in the place of the double-layer capacitance (Kendig et al., 1996).

$$Z = \frac{1}{T(i\omega)^P} \quad \dots \text{Eqn(4.17)}$$

where T and P are the Constant Phase constants.

The constant phase is the equivalent of a capacitor where P equals 1. If CPE- P equals 0.5, a 45 degree line is produced on the complex plane impedance graph. When a CPE is placed in parallel to a resistor, a Cole-Element (depressed semi-circle) is produced similar to that of the short-circuited Warburg impedance.

The CPE element is most commonly used in the place of a capacitor to compensate for non-homogeneity in the system. For example, a rough or porous surface can cause a double-layer capacitance to appear as a constant phase element with a CPE- P value between 0.9 and 1.

A CPE with CPE- P value of 0.5 can be used to produce an Infinite Length Warburg element. A Warburg element occurs when charge carrier diffuses through a material. Lower frequencies correspond to diffusion deeper into the material. If the material is thin, low frequencies will penetrate the entire thickness, creating a Finite Length Warburg element. If the material is thick enough so that the lowest frequencies applied do not fully penetrate the layer, it must be interpreted as infinite. The CPE produces the same spectrum as the 'high frequency' portion of a Finite Length Warburg when $CPE-T = \sqrt{W-T} / W-R$.

QPE = Constant Phase Element #2

$$Z = 1 / [l * wQ]^n \quad \dots \text{Eqn}(18)$$

Parameters: CPE- Q , CPE- n

This Constant Phase element has the equation format used by Dr. Bernard Boukamp in his EQUIVCRT program. It will fit exactly the same spectrums as the CPE element, but the Q parameter values will be different from the T parameter values in Constant Phase Element #1.

The Q parameter is inside the exponent, while the T value is outside the exponent. The n and P parameters are identical. The Q and T parameters may translated using the equation $T = (Q)^n$.

4.5.2 Experimental Details

EIS measurements were performed using a CompactStat electrochemical interface (Ivium Technologies). A cylindrical Perspex cell (typically 4 cm diameter) was used to contain a reservoir of 0.1 M sodium chloride over the surface of the Colorbond specimen. Each test required both a counter electrode (platinum or stainless steel) and a reference electrode (standard calomel electrode or silver/silver chloride). The magnitude of the solution resistance, R_s and the impedance associated with the platinum counter electrode was investigated using a three electrode system consisting of two identical platinum mesh counter electrodes and a Ag/AgCl reference electrode. 0.1 M NaCl was added to the three electrode system and a 15 mV AC potential was applied as a function of frequency.

4.5.3 Results for unexposed Colorbond®

The solution resistance determined at high frequency was $29.5 \pm 2.5 \Omega$ for a typical cell configuration used for gutter performance testing.

At the interface between the electrode and the counter electrode an electrical double-layer exists, which creates a capacitive impedance. Normal values for the capacitance are of the

order of $30 \mu\text{F cm}^{-2}$, although these values are highly dependent upon the characteristics of the metal. Figure 4.16 shows typical data for an undamaged topcoat.

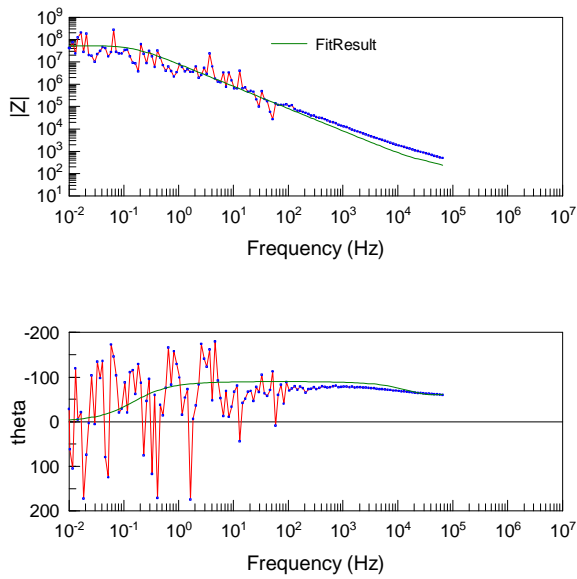


Figure 4.16. Typical fit of data to model 'C'. $R_s = 29.5 \Omega$, $C_c = 8.45 \times 10^{-9} \text{ F}$, $R_c = 585.2 \Omega$, $\text{CPE-T} = \text{Cdl} = 1.11 \times 10^{-8} \text{ F}$ (where $\text{CPE-P} = 1$) and $R_p = 5.34 \times 10^7 \Omega$. Surface area = 18.4 cm^2 .

The undamaged backcoat was analysed according to model 'C', as shown in Figure 4.17.

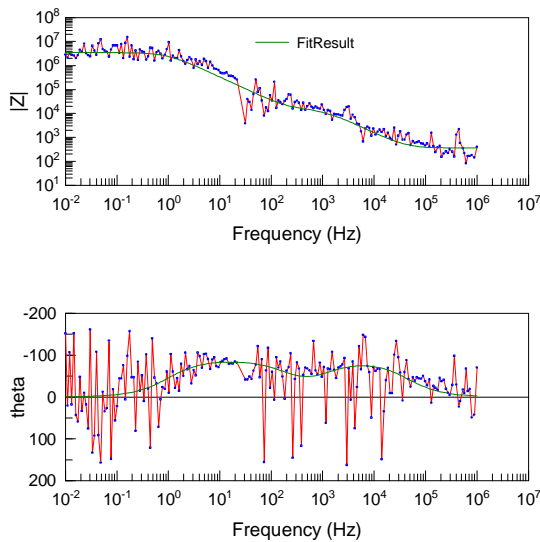
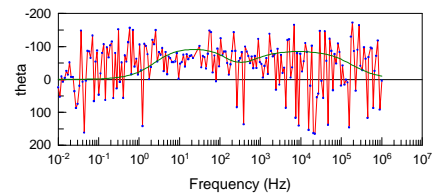
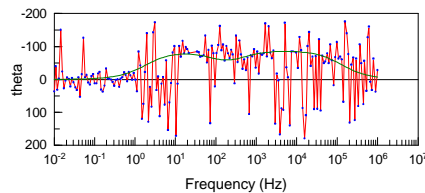
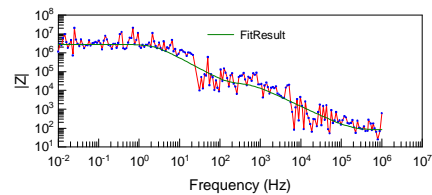
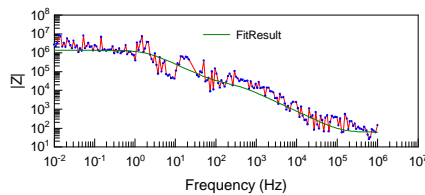


Figure 4.17. Typical fit of data to model 'C'. $R_s = 358.5 \Omega$, $C_c = 1.038 \times 10^{-8} \text{ F}$, $R_c = 18930 \Omega$, $\text{CPE-T} = \text{Cdl} = 3.74 \times 10^{-8} \text{ F}$ (where $\text{CPE-P} = 1$) and $R_p = 3.42 \times 10^6 \Omega$. Surface area = 12.6 cm^2 .

The following data (Figure 4.18) was recorded using the portable EIS measurement equipment. Colorbond XRW was allowed to equilibrate in 0.1M NaCl for 48 hours. The data obtained using both laboratory and portable equipment yielded similar results.

| | Rs(+) | Cc(+) | Rc(+) | CPE1-T(+) | CPE1-P(+) | Rp(+) | Estimated I _{corr} (A cm ⁻²) |
|---------------------|-------|----------|-------|-----------|-----------|----------|---|
| XRW backcoat 48 hrs | 60.45 | 2.03E-08 | 34967 | 4.58E-08 | 0.99059 | 1.31E+06 | 2.4044E-07 |
| XRW topcoat 48 hrs | 80.84 | 1.10E-08 | 34640 | 1.00E-08 | 1.162 | 2.64E+06 | 1.19085E-07 |



Undamaged Colorbond XRW backcoat

Undamaged Colorbond XRW topcoat

Figure 4.18. Colorbond measurements using the portable EIS equipment.

4.5.4 Estimates of corrosion rate based upon polarization resistance

The corrosion current can be related to the Tafel slopes using the Stearn-Geary relationship:

$$i_{corr} = \left(\frac{1}{2.303R_p} \right) \frac{b_a b_c}{b_a + b_c} \quad \dots \text{Eqn(18)}$$

Where R_p is the polarization resistance ($\Omega \text{ cm}^{-2}$) and b_a and b_c are the Tafel slopes for anodic and cathodic polarization, respectively. Since the values of b_a and b_c are not accurately known the exact estimation of corrosion currents is uncertain. It has been shown previously that useful estimation can be obtained by assuming that the corrosion current is equal to the reciprocal of the polarization resistance multiplied by 0.025 V. Table 4.4 presents some typical values for the corrosion rate taken from field measurements at Queensland Schools, as details in Appendix B. The results show that the rate of corrosion increases according to

the relative age of the component. This can be attributed to a break down in the performance of the paint film and an increase in the amount of under-paint corrosion at longer exposure times.

Table 4.4. Typical values for Rp measured on Colorbond backcoats are:

| Sample | Rp ($\Omega \text{ cm}^{-2}$) | Icorr (A cm^{-2}) | Mass loss ($\mu\text{m yr}^{-1}$) |
|---------------|---|--|---|
| Undamaged | 2.71×10^5 | 9.21×10^{-8} | 1.2 |
| 7 years | 3.29×10^3 | 7.59×10^{-6} | 98.9 |
| 29 years | 9.08×10^2 | 2.75×10^{-5} | 358.3 |

Tables 4.5 and 4.6 detail the ability of modeled corrosion rates to predict those measured in the field. The results for a Colorbond backcoat are presented for the case of both clean and dirty gutters. In most cases the EIS measured corrosion rate falls between the predicted rates for clean and wet gutters. It should be noted that the corrosion rate estimated by the model does not change from year to year, rather damage is assumed to occur at a specific site. The data from Table 4.4, which suggests that rates increase significantly are not compensated on an area basis. That is, it is assumed that the high rates measured after 29 years would be obtained from a much larger metal-solution contact area due to paint delamination. At present there has been no investigation regarding these increases in surface area. The key result from Tables 4.5 and 4.6 are however the correctly predicted magnitudes of corrosion and the reproducibility of the model to differentiate between high and low corrosivity sites.

Table 4.5. Modelling results for the backcoat of a clean and well-drained gutter. A comparison of EIS measured corrosion rates, estimated corrosion rates for the equivalent time period (from model) and the estimated time to failure (given as the time to totally remove the protective zincalume).

| Location | Age | Micron zincalume loss (fully wet & salt @ 3545 mg/m ²) | TO W | Average salinity: clean gutter (mg/m ²) | T _{av} | RH _{av} | W | Fraction of Cr removed in 1 yr (10 yrs) | Estimated depth loss from EIS (µm/yr) | Estimated previous model (µm/yr) | Estimated Well-drained backcoat (µm/yr) | Time to failure (yrs) |
|--------------------------|-----|--|------|---|-----------------|------------------|------|---|---------------------------------------|----------------------------------|---|-----------------------|
| Brookfield SS (clean) | 7 | 98.99334706 | 37 | 1.15 | 26 | 60 | 2.00 | 0.01 (0.07) | 0.0367 | 0.64 | 0.26 | 88 |
| Chapel Hill SS (clean) | 29 | 358.9853378 | 37 | 1.18 | 26 | 60 | 2.00 | 0.01 (0.07) | 0.133 | 0.64 | 0.17 | 87 |
| Townsville house (clean) | 5 | 812.0397769 | 51 | 4.19 | 28.9 | 62 | 2.16 | 0.02 (0.11) | 0.414 | 1.49 | 0.48 | 41 |
| Townsville house (dirty) | 5 | 1433.429207 | 51 | 4.19 | 28.9 | 62 | 2.16 | 0.02 (0.11) | 0.731 | 1.49 | 0.48 | 41 |
| Payne Road (dirty) | 9 | 1459.472987 | 37 | 1.14 | 26 | 60 | 2.00 | 0.01 (0.07) | 0.540 | 0.63 | 0.24 | 88 |
| The Willows (dirty) | 10 | 313.5420691 | 51 | 0.866 | 28.9 | 62 | 2.16 | 0.01 (0.09) | 0.160 | 0.54 | 0.29 | 61 |

Table 4.6. Modelling results for the backcoat of a dirty and poorly maintained gutter. A comparison of EIS measured corrosion rates, estimated corrosion rates for the equivalent time period (from model) and the estimated time to failure (given as the time to totally remove the protective zincalume).

| Location | Age | Micron zincalume loss (fully wet & salt @ 3545 mg/m ²) | TOW | Average salinity: clean gutter (mg/m ²) | T _{av} | RH _{av} | W | Fraction of Cr removed in 1 yr (10 yrs) | Estimated depth loss from EIS (µm/yr) | Estimated previous model (µm/yr) | Estimated Well-drained backcoat (µm/yr) | Time to failure (yrs) |
|--------------------------|-----|--|-----|---|-----------------|------------------|------|---|---------------------------------------|----------------------------------|---|-----------------------|
| Brookfield SS (clean) | 7 | 98.99334706 | 37 | 1.15 | 26 | 60 | 2.00 | 0.01 (0.07) | 0.0367 | 0.64 | 0.26 | 88 |
| Chapel Hill SS (clean) | 29 | 358.9853378 | 37 | 1.18 | 26 | 60 | 2.00 | 0.01 (0.07) | 0.133 | 0.64 | 0.17 | 87 |
| Townsville house (clean) | 5 | 812.0397769 | 51 | 4.19 | 28.9 | 62 | 2.16 | 0.02 (0.11) | 0.414 | 1.49 | 0.48 | 41 |
| Townsville house (dirty) | 5 | 1433.429207 | 51 | 4.19 | 28.9 | 62 | 2.16 | 0.02 (0.11) | 0.731 | 1.49 | 0.48 | 41 |
| Payne Road (dirty) | 9 | 1459.472987 | 37 | 1.14 | 26 | 60 | 2.00 | 0.01 (0.07) | 0.540 | 0.63 | 0.24 | 88 |
| The Willows (dirty) | 10 | 313.5420691 | 51 | 0.866 | 28.9 | 62 | 2.16 | 0.01 (0.09) | 0.160 | 0.54 | 0.29 | 61 |

Table 4.7. Modelling results for the backcoat of a dirty and poorly maintained gutter. A comparison of EIS measured corrosion rates, estimated corrosion rates for the equivalent time period (from model) and the estimated time to failure (given as the time to totally remove the protective zincalume).

| Location | Age | Micron zincalume loss (fully wet & salt @ 3545 mg/m ²) | TOW | Average salinity: dirty gutter (mg/m ²) | T _{av} | RH _{av} | W | Fraction of Cr removed in 1 yr (10 yrs) | Estimated depth loss from EIS (µm) | Estimated previous model (µm/yr) | Estimated loss (µm/yr) Dirty backcoat (100% TOW) | Time to failure (yrs) |
|--------------------------|-----|--|-----|---|-----------------|------------------|------|---|------------------------------------|----------------------------------|--|-----------------------|
| Brookfield SS (clean) | 7 | 98.99 | 100 | 11.46 | 26 | 60 | 2.00 | 0.02 (0.11) | 0.0367 | 0.64 | 0.51 | 35 |
| Chapel Hill SS (clean) | 29 | 358.99 | 100 | 11.72 | 26 | 60 | 2.00 | 0.02 (0.11) | 0.133 | 0.64 | 0.32 | 35 |
| Townsville house (clean) | 5 | 812.04 | 100 | 41.72 | 28.9 | 62 | 2.16 | 0.03 (0.17) | 0.414 | 1.49 | 1.25 | 12 |
| Townsville house (dirty) | 5 | 1433.43 | 100 | 41.72 | 28.9 | 62 | 2.16 | 0.03 (0.17) | 0.731 | 1.49 | 1.25 | 12 |
| Payne Road (dirty) | 9 | 1459.47 | 100 | 11.41 | 26 | 60 | 2.00 | 0.02 (0.12) | 0.540 | 0.63 | 0.46 | 35 |
| The Willows (dirty) | 10 | 313.54 | 100 | 8.627 | 28.9 | 62 | 2.16 | 0.02 (0.13) | 0.160 | 0.54 | 0.52 | 29 |

4.6 Conclusions

The model for predicting the longevity of Painted Metal Components has been updated and improved. The rates of corrosion predicted by the model have been validated to some extent by field measurements using Electrochemical Impedance Spectroscopy. The field measurements were limited to several schools in coastal areas of Queensland, and therefore, further validation would be required to ensure its accuracy for wider Australia. There are numerous factors that control the rate of degradation of painted components and some of these factors have yet to be investigated. For instance, the rate of delamination of paint and how this influences the removal of corrosion inhibitor and advance of corrosion damage. The performance of the currently presented model in predicting damage should ultimately be validated through further long-term experimental studies, which would be required to demonstrate statistical significance in its predictions.

4.7 References

- Amirudin and Thierry, 1995. Application of electrochemical impedance spectroscopy to study the degradation of polymer-coated metals. *Prog. Org. Coat.*, 26(1), 1-28.
- Bauer, D.R., 2000. Global exposure models for automotive coating photo-oxidation. *Polymer Degradation and Stability*, 69, 297-306.
- Bjerrum, J., Schwarzenbach, G., Gunnar Sillen, L. Stability constants of metal-ion complexes, with solubility products of inorganic substances. K.W. Skyes (Ed.). The Chemical Society, London, 1958.
- Cole, I.S., Paterson, D.A. and Ganther, W.D., 2003. A holistic model for atmospheric corrosion: part 1- theoretical framework for the production, transportation and deposition of marine salts. *Corrosion Engineering, Science and Technology*, 38 (2), 129-134.
- Furman, S.A., Scholes, F.H., Hughes, A.E., Lau, D. 2006. Chromate leaching from inhibited primers II: modelling of leaching. *Progress in Organic Coatings*, 56, 33-38.
- Ganther, W. 2005. Report on gutter sensing. Instrumentation of Roof Gutter to Determine Time of Wetness. Report No 2002-059-B No 11.
- Kendig, M., Jeanjaquet, S., Brown, R., Thomas, F., 1996. Rapid electrochemical assessment of paint. *J. Coat. Tech.*, 68(863), 39-47.
- King, G.A., Kao, P., Norberg, P., O'Brien, D.J., 2001. Metals and coated metal products in marine environments. CSIRO Building, Construction and Engineering, Internal report, BCE Doc. 01-259.
- Martin, K. 1977. Solar weathering indices for Australian Sites. Division of Building Research Technical Paper No. 18. CSIRO, 1977.
- Muster et al. 2005. Colorbond degradation model. CRC Construction Innovation Report No. 2002-059-B No.12.
- Prosek, T., Thierry, D., 2004. A model for the release of chromate from organic coatings. *Progress in Organic Coatings*, 49, 209-217.

Scholes, F.H., Furman, S.A., Hughes, A.E., Nikpour, T., Wright, N., Curtis, P.R., Macrae, C.M., Intem, S., Hill, A.J., 2006. Chromate leaching from inhibited primers I: characterisation of leaching. *Progress in Organic Coatings*, 56, 23-32.

Sinko, J., 2001. Challenges of chromate inhibitor pigments replacement in organic coatings. *Progress in Organic Coatings*, 42, 267-282.

5. SCHOOL SURVEY DATABASE

5.1 Introduction

This project is developing a program to access a number of sources of data on service lifetimes of metallic building components. Originally it was planned to utilise the Queensland Department of Public Works database of maintenance activities to develop a lifetime database giving information based on current usage, with the possibility of updating as more events were entered by the actual maintainers reflecting ongoing upkeep of the schools' infrastructure. Maintenance information is seen as being a particularly useful source of data about service life of building components as it relates to actual performance of materials in the working environment.

Access was granted to a number of databases recording maintenance activities in Queensland Government Housing. However, analysis of the information indicated that entries did not give information in fine enough detail to enable extraction of data for the individual building components being considered in the current work. For example, there is an activity code for roof replacement, but the only code that specifically refers to windows is for installation of window locks and has no information about the condition of the windows. Similarly there are no specific entries relating to fasteners or steel supports etc.

An alternative approach was devised to estimate the performance of materials in the field. This involved a survey of a range of schools with inspection of the building components of relevance to the current work. These were given a rating indicating the current condition of the structure and the age of the buildings was also ascertained. This data collected was also used to validate the modifications made to the holistic model for the different building components.

5.2 Survey Methodology

Schools were chosen to give a wide range of climates and corrosivity levels (related to salt levels). At least three schools in each category were chosen, where possible with different ages.

Three climates were looked at:

- Tropical (Townsville)
- Subtropical (Brisbane and Sunshine Coast)
- Temperate (Melbourne and southern coast of Victoria).

Figure 5.1 shows the locations of the school areas surveyed in the Eastern part of Australia.

Within these climates corrosive severity levels can be classified as

- Severe marine (within 3km of the coast)
- Coastal (3-10km from coast)
- Inland (>10km from coast)

Ideally all three corrosivity levels in each of the three climate types would be surveyed, but this was not possible. The categories looked at are:

- Tropical Coastal
- Subtropical Marine
- Subtropical inland
- Temperate Marine
- Temperate Inland

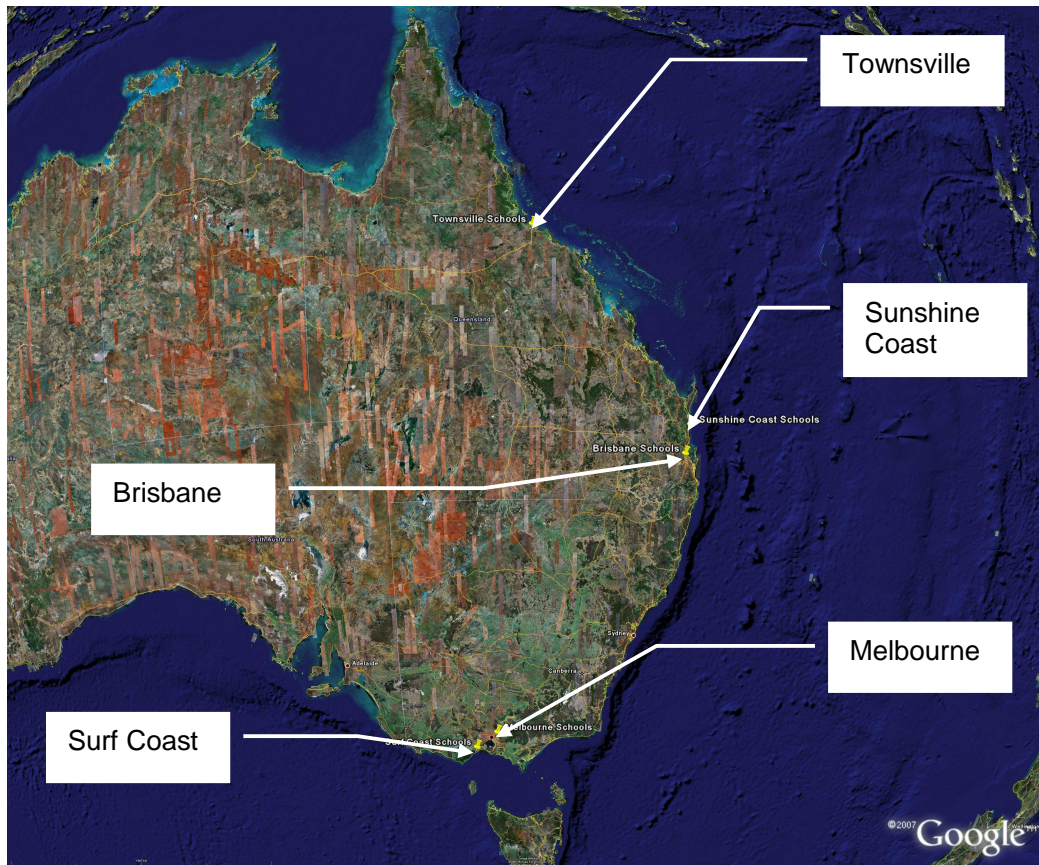


Figure 5.1 Locations of the different areas surveyed, chosen to give a range of climates

A list of all the Queensland schools surveyed is given in Table 5.1 along with details such as longitude and latitude and distance from the ocean. In some cases two figures are given indicating the distance from a sheltered beach on an inlet and the actual distance from the nearest ocean beach. Similar details are given for the Victorian schools visited in Table 5.2.

Not all the schools visited had the full array of metal components of interest. In particular it was difficult to gain information for the sub-floor components, as many schools had wooden and concrete footings rather than metal. These were more prevalent on portable classrooms but they were not included in the survey as their location history is unknown and the condition of metal components may have been affected by previous environments.

At each school, the relevant building components on a number of buildings were identified as to material and the condition rated, noting the orientation and degree of sheltering etc.

Table 5.1. Queensland School Details

| School Code | School Name | Year opened | Address Line 1 | Address Line 2 | Post Code | Latitude | Longitude | Distance from Coast |
|-------------|----------------------------------|-------------|-----------------------------------|------------------|-----------|-----------|-----------|---------------------|
| | <i>Sunshine Coast</i> | | | | | (Degrees) | (Degrees) | (KM) |
| 1888 | Buddina State School | 1979 | Cnr Tumut Street and Iluka Avenue | Buddina | 4575 | 153.1329 | -26.7018 | 0.3 |
| 2165 | Coolum State High School | | Havana Road | Coolum | 4573 | 153.0856 | -26.5005 | 1.0 |
| 1571 | Coolum State School | 1917 | School Road | Coolum Beach | 4573 | 153.0771 | -26.5349 | 1.6 |
| 1818 | Mooloolaba State School | 1930 | Cnr Meta & Douglas Streets | Mooloolaba | 4557 | 153.1146 | -26.6782 | 0.3** |
| 2190 | Mountain Creek State High School | 1995 | Lady Musgrave Drive | Mountain Creek | 4557 | 153.1031 | -26.6867 | 2-3* |
| 1999 | Mountain Creek State School | 1994 | Lady Musgrave Drive | Mountain Creek | 4557 | 153.1027 | -26.6903 | 2-3* |
| 1991 | Pacific Paradise State School | 1992 | 14-24 Menzies Drive | Pacific Paradise | 4564 | 153.0810 | -26.6126 | 2.0 |
| 2108 | Sunshine Beach State High School | 1992 | 45 Ben Lexcen Drive | Sunshine Beach | 4567 | 153.0996 | -26.4085 | 1.2 |
| 1917 | Sunshine Beach State School | 1982 | David Low Way | Sunshine Beach | 4567 | 153.1011 | -26.4018 | 1.2 |
| | <i>Townsville</i> | | | | | | | |
| 2186 | William Ross State High School | 1991 | Mervyn Crossman Drive | Annandale | 4814 | 146.7999 | -19.3174 | 7 |
| 2120 | Heatley Secondary College | 1968 | Cnr Hanlon Street and Fulham Road | Heatley | 4814 | 146.7557 | -19.2899 | 7 |
| 305 | Heatley State School | 1971 | 410 Fulham Road | Heatley | 4814 | 146.7557 | -19.2899 | 7 |
| 1862 | Kirwan State School | 1977 | 21 Burnda Street | Kirwan | 4817 | 146.7335 | -19.2990 | 9 |
| 2146 | Kirwan State High School | 1979 | Hudson Street | Kirwan | 4817 | 146.7321 | -19.3086 | 10 |
| 287 | The Willows State School | 1997 | Bilberry Street | Kirwan | 4817 | 146.7241 | -19.3066 | 10 |
| | <i>Brisbane</i> | | | | | | | |
| 923 | Kenmore State School | | 2052 Moggill Road | Kenmore | 4069 | 152.9394 | -27.5093 | 25-53* |
| 1872 | Chapel Hill State School | 1978 | Ironbark Road | Chapel Hill | 4069 | 152.9435 | -27.5006 | 25-53* |
| 16 | Brookfield State School | | Boscombe Road | Brookfield | 4069 | 152.9136 | -27.4962 | 25-53* |
| 2053 | The Gap State High School | | 1020 Waterworks Road | The Gap | 4061 | 152.9502 | -27.4461 | 20-50* |
| 1302 | The Gap State School | 1912 | Cnr Waterworks & Settlement Roads | The Gap | 4061 | 152.9443 | -27.4427 | 20-50* |
| 286 | Payne Road State School | 1970 | 171 Payne Road | The Gap | 4061 | 152.9516 | -27.4483 | 20-50* |
| 1887 | Hilder Road State School | 1980 | Cnr Kaloma and Hilder Roads | The Gap | 4061 | 152.9378 | -27.4382 | 20-50* |

* near sheltered beach and open ocean ie. 25-53 is 25KM to sheltered beach and 53KM to open ocean** slightly sheltered beach

Table 5.2. Victorian School Details

| School Code | School Name | Year opened | Address Line 1 | Address Line 2 | Post Code | Latitude | Longitude | Distance from Coast |
|-------------|----------------------------------|-------------|-------------------|----------------|-----------|-----------|-----------|---------------------|
| | <i>Surf Coast</i> | | | | | (Degrees) | (Degrees) | (KM) |
| 4332 | Anglesea Primary School | | Camp Rd | Anglesea | 3230 | | | 1 |
| 1574 | Barwon Heads Primary School | 1950 | Golf Links Rd | Barwon Heads | 3227 | | | 1 |
| 3368 | Torquay Primary School | 2000 | P O Box 51 | Torquay | 3228 | | | 1.5 |
| 2162 | Lorne - Aireys Inlet P-12 School | 1879 | Grove Road | Lorne | 3232 | | | 0.4 |
| | <i>Melbourne (Blackburn)</i> | | | | | | | |
| 4717 | Box Hill North Primary School | 1955 | Elizabeth St | Box Hill North | | | | 16-70* |
| 2923 | Blackburn Primary School | 1889 | 185 Whitehorse Rd | Blackburn | 3130 | | | 16-70* |
| 4860 | Blackburn Lake Primary School | 1964 | Florence St | Blackburn | 3130 | | | 16-70* |
| 4863 | Laburnum Primary School | 1964 | Janet St | Blackburn | 3130 | | | 16-70* |

* near sheltered beach and open ocean ie. 25-53 is 25KM to sheltered beach and 53KM to open ocean

** slightly sheltered beach

Table 5.3. Definition of Rating used for Components

| Damage Rating | | 0 | 1 | 2 | 3 | 4 | 5 |
|---|------------------------------------|---------------|--|--|---|--|--|
| Component | Material | As New | Shows signs of Age | Needs maintenance | Significant Maintenance required | Planning for replacement | Needs replacement |
| Roof Sheeting Ridge Cap Flashings Gang Nails Steel Supports | Coated Steel | No Damage | Some loss of paint gloss/coating (Top coat only on multi-coat systems), dulling of surface | Loss of paint (chips lost, peeling, undercoat may still be intact), White corrosion product less than 50%, red rust on cut edges | Some red rust present, less than 50% of a particular area, White corrosion product greater than 50% | 50- 100% red rust | Perforation |
| | Aluminium | No Damage | Dulling of Surface | White and/or Grey Corrosion Product <50% coverage and/or signs of pitting | Pitting/Black Corrosion Product <50% coverage, No perforation | Significant pitting >50% coverage, No perforation | Perforation |
| Fasteners | | No Damage | Some loss of paint coating (if applied), often mechanical damage during installation | White corrosion product (more than 25%) on less than 50% of fasteners | Red rust present, on any fasteners but more than spotting | Red rust (>25%) present on all fasteners | 100% Red rust, on more than 50% of fasteners |
| Gutters Down Pipes | Coated Steel (For AI see above) | No Damage | Some loss of paint gloss/coating (Top coat only on multi-coat systems), dulling of surface | Loss of paint (chips lost, peeling, undercoat may still be intact), White corrosion product less than 50%, red rust on cut edges or spotting | Some red rust present, less than 50% of a particular area, White corrosion product greater than 50% | Red Rust >50% of Inside bottom of Gutter or Downpipe | Perforation |

Table 5.4. (cont) Definition of Rating used for Components

| Damage Rating | | 0 | 1 | 2 | 3 | 4 | 5 |
|----------------------|-------------------|---------------|--|--|---|---------------------------------|-------------------------------|
| Component | Material | As New | Shows signs of Age | Needs maintenance | Significant Maintenance required | Planning for replacement | Needs replacement |
| Windows | Bare and Anodised | No Damage | Loss of new look, loss of gloss or staining | Corrosion Product present <10%, at joins or other | White corrosion product less than 50%, | > 50% WCP | Perforation or loss of window |
| | Painted | No Damage | Some loss of paint gloss/coating (Top coat only on multi | Undercutting of paint, White Corrosion Product present <10%, at joins or other | Loss of paint (chips lost, peeling), White corrosion product less than 50%, | >50% paint loss and > 50% WCP | function, Jamming etc. |

5.2.1 Material Rating Used in Survey

The components in the survey were rated using the following scheme:

- 0. As new
- 1. Shows signs of age
- 2. Needs maintenance
- 3. Significant maintenance required
- 4. Planning for replacement
- 5. Needs replacement

How these different categories relate to the conditions of the components is detailed in Table 5.3.

5.3 Survey Results

The raw data for all the schools surveyed was collated in a database. This was then rearranged into component databases categorised for the different environments.

The information for Colorbond® roofs is graphed in Figure 6.

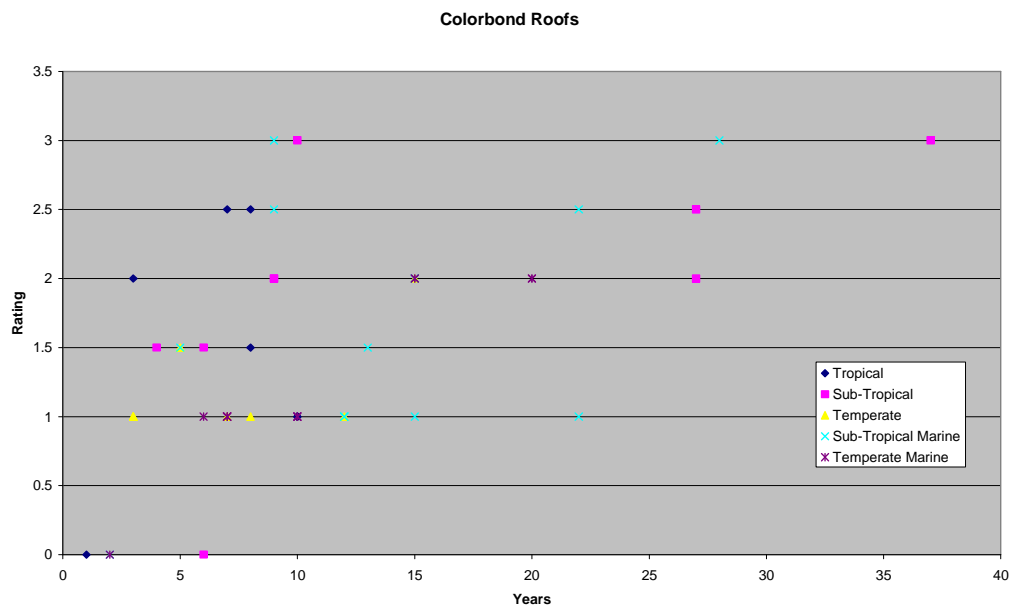


Figure 5.2. The Colorbond data for roofs in graphical form.

5.3.1 Analysis of Data

The data for the different components were graphed separately for each material with two rates of corrosion being designated: normal and accelerated. In some cases there were very limited data points, but the points were used to estimate a line of best fit.

The data for the different components were graphed separately for each material and environment type. In some cases there were very limited data points, but the points were used to estimate an exponential line of best fit using equation 5.1.

$$\text{Damage} = A * \ln(\text{life}) - B$$

...Eqn (5.1)

Where Damage is the rating system (from 0-5)

life is the age of the component in years

A, B are constants

In some cases there appeared to be two rates of material aging so these were separated in two sets of data: “normal” and “accelerated”.

Equation 1 was used to estimate the service life of all the components surveyed. A and B were determined for the different materials and environments.

5.3.1.1 Colorbond® Components

For Colorbond® the formula was used to estimate the time to reach Rating 3 and then 10 years was added. Table 5.4 shows the values estimated for A and B from the survey data.

Table 5.4. Parameter Values for Colorbond® components

| Component | Environment | A | B |
|------------------|----------------------|----------|----------|
| Roof | Normal | 1.27 | -1.84 |
| Roof | Accelerated | 1.30 | -0.38 |
| Roof | Tropical | 1.18 | -1.5 |
| Roof | Tropical accelerated | 1.3 | 0 |
| Downpipes | normal | 1.13 | -0.95 |
| Down pipes | accelerated | 1.39 | 0 |
| Gutters | normal | 1.2 | -1.9 |
| Gutters | tropical | 0.99 | -0.043 |
| Gutters | accelerated | 1.30 | -0.67 |

5.3.1.2 Zinalume Components

Equation (5.1) was used to calculate the years to reach Rating 3 and then D was added to give service life. Values for A, B and D are given in Table 5.5.

Table 5.5. Parameters for Zinalume components

| Component | Environment | A | B | D |
|------------|---------------------|------|--------|---|
| Roof | Sub tropical normal | 1.28 | -1.80 | 9 |
| Roof | accelerated | 1.28 | -0.50 | 9 |
| Roof | tropical | 1.28 | -1.43 | 9 |
| Roof | temperate | 1.28 | -1.43 | 9 |
| Downpipes | normal | 1.25 | -2.2 | 9 |
| Down pipes | accelerated | 1.31 | -0.37 | 6 |
| Gutters | normal | 1.26 | -1.29 | 9 |
| Gutters | accelerated | 1.31 | -0.075 | 6 |
| Ridge cap | normal | 1.18 | -1.2 | 9 |

5.3.1.3 Galvanised Components

Equation (5.1) was used to calculate the years to reach Rating 3 and then D was added to give service life. Values for A, B and D are given in Table 5.6.

Table 5.6. Parameters for Galvanised components

| Component | Environment | A | B | D |
|------------|-------------|------|-------|---|
| Roof | normal | 1.1 | -0.64 | 8 |
| Roof | accelerated | 1.3 | -0.48 | 8 |
| Downpipes | normal | 1.1 | -1.58 | 8 |
| Down pipes | accelerated | 1.31 | -0.37 | 5 |
| Gutters | normal | 2.52 | -4.9 | 8 |
| Flashing | normal | 1.1 | -1.1 | 8 |
| Flashing | accelerated | 1.22 | -0.18 | 8 |
| Fasteners | normal | 1.36 | -1.1 | * |
| Fasteners | accelerated | 1.38 | -0.06 | * |

* For fasteners the formulae were used to calculate the time to reach Rating 5 to give the predicted service life. Therefore D is not applicable

5.3.1.4 Aluminium Components

Equation (1) was used to calculate the years to reach Rating 3 and then D was added to give service life. Values for A, B and D are given in Table 5.7.

Table 5.7. Parameters for Galvanised components

| Component | Environment | A | B | D |
|------------------|--------------------|----------|----------|----------|
| Windows | normal | 0.92 | -0.68 | 10 |
| Windows | accelerated | 1.0 | -0.04 | 10 |
| Powder coated | normal | 0.53 | -0.05 | 10 |
| Powder coated | accelerated | 0.89 | -0.14 | 10 |
| Fasteners | normal | 1.36 | -1.1 | 5 |
| Fasteners | accelerated | 1.36 | -0.06 | 5 |

5.3.2 Database

The results of applying these formulae to the components surveyed to estimate the remaining life is consolidated into Table 5.8. Service life determined to be more the 50 years is quoted as >50 in all cases.

Table 5.8. Database of Service life determined from Survey data.

| Component | Material | Environment | Severity | Life (years) |
|------------------|-----------------|----------------------------|-----------------|---------------------|
| roof | galvanised | All | normal | 35 |
| roof | galvanised | All | accelerated | 23 |
| downpipes | galvanised | All | normal | >50 |
| downpipes | galvanised | All | accelerated | 18 |
| gutters | galvanised | All | normal | 31 |
| flashing | galvanised | All | normal | 50 |
| flashing | galvanised | All | accelerated | 19 |
| | | | | |
| roof | zincalume | Sub-tropical | normal | >50 |
| roof | zincalume | Tropical | Normal | 41 |
| roof | zincalume | Temperate | Normal | 41 |
| roof | zincalume | All | accelerated | 24 |
| downpipes | zincalume | All | normal | >50 |
| downpipes | zincalume | All | accelerated | 18 |
| gutters | zincalume | All | normal | 39 |
| gutters | zincalume | All | accelerated | 15 |
| ridge cap | zincalume | All | normal | 44 |
| | | | | |
| window | Al anodized | All | normal | >50 |
| window | Al anodized | All | accelerated | 31 |
| window | Powder coated | All | normal | >50 |
| window | Powder coated | All | accelerated | 48 |
| | | | | |
| roof | Colorbond | Temperate and Sub-tropical | normal | >50 |
| roof | Colorbond | Temperate and Sub-tropical | accelerated | 25 |
| roof | Colorbond | Tropical | normal | >50 |
| roof | Colorbond | Tropical | accelerated | 22 |
| gutters | Colorbond | Temperate and Sub-tropical | normal | >50 |
| gutters | Colorbond | Tropical | normal | 34 |
| gutters | Colorbond | All | accelerated | 29 |
| downpipes | Colorbond | All | normal | 45 |
| downpipes | Colorbond | All | accelerated | 21 |
| | | | | |
| fasteners | galvanised | All | accelerated | 38 |
| fasteners | galvanised | All | normal | >50 |

6. DATA MINING

6.1 Introduction

Chapters 3 and 4 have detailed the development of the Holistic Model data sets for 10 components and their most common materials. Chapter 5 discussed the formulation of a data set based on a school survey looking at how the various components had aged in their environments. The data sets used in the previous Case-Based Reasoning program: the Delphi survey data set created in a previous CRC project (Cole et al, 2004) and a Roof Maintenance data set are also still available. (The Delphi data set is explained in more detail in Appendix C)

These sources of information should be viewed as complementary rather than as discrete alternatives. They form different data sources of service life information. The problem is how they could be combined to determine the most appropriate answer for any given situation. The focus in this phase of the project has shifted from Case-Based Reasoning to data mining (partly due to changes in project partners). However, data mining is considered to be an ideal method that links together the different data sources and provides intelligent decisions.

Data mining (DM) has been driven by the need to solve practical problems since its inception (Melli et al., 2006). In order to achieve a greater usability of the data mining models, there are three main phases in the lifecycle of a data mining project: (1) training of the model, (2) evaluation (or testing) of the model and (3) using the final trained model in practice. The third phase is usually carried out by the business managers or a typical user of the system. A number of Knowledge Discovery and Data Mining (KDDM) process models have been established to organise the lifecycle of a data mining project within a common framework. However, the existing KDDM process models end up with the deployment phase and do not consider the use of the trained model in practice. This has led to a gap of knowledge that may limit widespread use of the trained model.

DM has been successfully applied in many areas such as business, marketing, medical and financial fields (Kantardzic and Zurada, 2005). Civil engineering is one of the areas where a variety of successful real-world data mining applications are reported in building construction (Melham and Cheng, 2003; Leu et al., 2001; Furuta et al., 1995; Morcoux et al., 2002a; Morcoux et al., 2002b, Mita and Hagiwara, 2003; KamrunNahar and Urquidi-MacDonald, 2005; Brence and Brown, 2002; Skomorokhov, 2000; Kessler et al., 1994; Melhem et al., 2003). One such application is metallic corrosion prediction in buildings. The corrosion prediction applications can be classified into two main categories: 1) building the predictive models using various traditional data mining techniques; and 2) improving the prediction accuracy using new hybrid methods.

All of these predictive models in the above two categories assume that the inputs that users will provide in using the model are the same as the input features used for training the models. However, if users have information of limited inputs only, the predicted results will not be as good as they were during the training and evaluation phases of the data mining system. In other words, the performance of the predictive model degrades due to the absence of many input values. For example, a predictive data mining model is built to predict the "Service Life" of the building components based on the input features such as "Location", "Component", "Material", "Salt Deposition", and "Mass Loss" (shown as Figure 6.1). Suppose builders (typical users of the predictive model or tool) want to know the service life of a "Gutter" with "Galvanized Steel" at a location (shown as Figure 6.2). However, the user does not know the "Salt Deposition" and "Mass Loss" in that location. The user query will include two missing values. In such a case, the predicted service life by the predictive data mining

tool may not be as accurate as the service life tested in the evaluation phase of the predictive model, especially when the missing features play key roles in building the model. On the other hand, if the “Salt Deposition” and “Mass Loss” features are excluded from the model building, the performance of the model may not be acceptable. Hence, a major problem that still needs to be solved is how to select appropriate features to build the model for a real situation when users have information on limited inputs only.

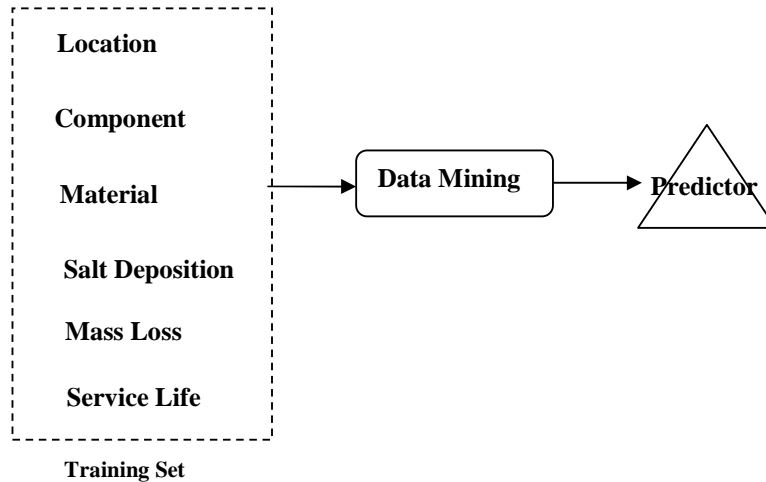


Figure 6.1. Training of the Model

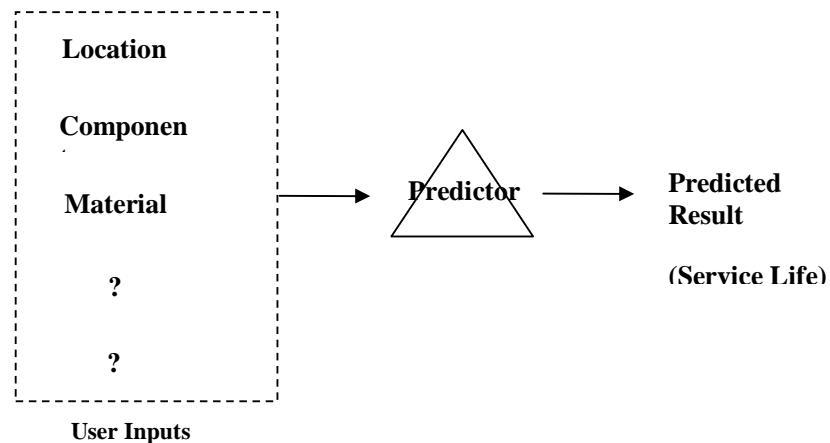


Figure 6.2. Using the Trained Model

This research proposes a learning system framework, namely the Query Based Learning System (QBLs), for improving the performance of predictive models in practice where not all inputs are available for querying to the system.

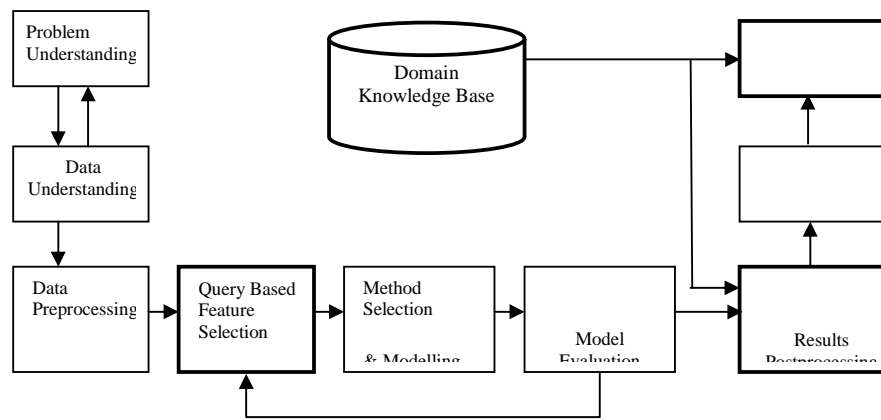


Figure 6.3. Query Based Learning System

The QBLs model consists of nine phases (as shown in Figure 6.3), which are structured as sequences of predefined steps. The arrows indicate the most important and frequent dependencies between phases. A domain knowledge base is involved in the results post-processing and the use of model phase. More specifically, the domain knowledge is used for pre-processing the incomplete queries and post-processing the inconsistent results. Based on this model, a practical system is developed for predicting the lifetime of metallic components. The system is evaluated on the data provided by CSIRO.

6.1.1 Background Information on Data Mining

Data mining, also referred to as knowledge discovery, is a powerful new technology with great potential to help companies to focus on the most important information in their data warehouses or database. It extracts hidden valued information from large databases (Fayyad et al, 1995a; Chapple, 2006). Through the use of automatic or semiautomatic algorithms, data mining extracts patterns from the data and transfers the data to knowledge. Data mining techniques can be applied to many applications, answering various types of business questions such as cross-selling, fraud detection and banking (Kantardzic and Zurada, 2005). A poll about successful data mining applications in 2005 was presented on KDnuggets website (2005), which shows that the most common applications are still the traditional areas of Banking, Direct Marketing, and Fraud detection.

6.1.1.1 Basic Data Mining Tasks

Based on the nature of data mining problems, the data mining tasks can be grouped into the following main categories: classification, regression, clustering and association rules.

Classification

Classification is one of the most popular data mining tasks. Classification assigns tuples in the dataset into predefined classes based on a target attribute. Each tuple contains a set of attributes, one of which is the target attribute and others can be chosen as input attributes. The purpose is to find a model that describes the target attribute as a function of input attributes. Classification can be considered as supervised learning since it requires a target to learn.

Prediction can be viewed as a type of classification when the target is a categorical attribute; namely, prediction can be thought of as classifying an attribute value into one of a set of possible classes.

Typical classification algorithms include K Nearest Neighbors (Aha et al, 1991), decision trees (Quinlan, 1986), neural network (Resampling Stats??), Naïve Bayes (Fayyad et al., 1995b) and support vector machine (Vapnik, 1995).

Regression

The regression task is similar to classification. The main difference is that the target attribute is a continuous value. Just as prediction for class values can be viewed as a classification problem, numeric prediction can be regarded as a regression problem. Therefore, the proposed research problem belongs to this category.

Although all classification algorithms can automatically deal with continuous values (they usually divide them into ranges, e.g. decision trees), most of them can not be used to solve a regression problem directly (e.g. decision trees and Naïve Bayes) unless numeric target is discretised to nominal type. However, the discretisation level chosen dramatically affects the learning of the problem and, not incidentally, the utility of the results. Therefore, the best solution to a regression problem is regression techniques. Linear regression and logistic regression are the most popular regression methods. Other regression techniques include regression trees (Breiman et al., 1984), model trees (Quinlan, 1993), neural networks and support vector machine (Vapnik, 1984), in which a neural network and support vector machine can also be applied to the classification problem.

Clustering & Association Rules

Clustering and association rules are another two popular data mining tasks. Clustering partitions or segments the data into groups (clusters). The most similar data are grouped into the same group. It is similar to classification except the groups are not predefined, but rather based on a set of attributes. From this point of view, clustering is an unsupervised learning.

Association rules, also called market basket analysis, refer to the data mining task of finding the relationships between data items. The form of an association rule is $X \Rightarrow Y$, where X and Y are sets of items called itemsets. Support and confidence are used to measure an association rule, in which support is the percentage of transactions in the database that contain $X \cup Y$ and confidence is the ratio of the number of transactions that contain $X \cup Y$ to the number of transactions that contain X (Dunham, 2003). The common usage of association rules is to identify common sets of items and rules for the purpose of cross-selling (Chapple, 2006).

6.1.1.2 Knowledge Discovery and Data Mining Process Model

A Knowledge Discovery and Data Mining (KDDM) process model consists of a set of processing steps to be followed by practitioners when executing KDDM projects. The concept of a KDDM process model was originally discussed during the first workshop on KDD in 1989 (Piatetsky-Shapiro, 1991). The main reason for defining and implementing KDDM process models is to ensure that the end product will be useful to the user (Fayyad et al, 1996a). The basic structure of the model was proposed by Fayyad et al. (1996b). Since then, several different KDDM models have been developed in both academia and industry. The human-centric and data-centric models are two major types of process models. The human-centric model emphasised the interactive involvement of a data analyst during the process, and the data-centric model emphasised the iterative and interactive nature of the data analysis tasks (Fayyad et al., 1996b). Kurgan et al. (2006) conducted a survey of

knowledge discovery and data mining process models, presenting a historical overview and a comprehensive comparison of several leading process models.

The CRISP-DM (CRoss-Industry Standard Process for Data Mining) (2003) process model is currently the most popular and broadly adopted data-centric model. It was first proposed in early 1996 by a consortium of three companies: SPSS (then ISL), NCR and DaimlerChrysler (then Daimler-Benz). It was later sponsored by the European Commission research fund. This model is very industry-oriented and enjoys strong industrial support. In fact it has already been assessed as meeting industrial needs (Kurgan et al., 2006).

The CRISP-DM model consists of six phases, as shown in Figure 6.4. The centre of the CRISP-DM model is the data. The possible relationships between all data mining phases most importantly depend on the data. The arrows indicate the most important and frequent dependencies between phases. The outer circle in the figure symbolises the cyclic nature of data mining itself. A data mining process continues after a solution has been deployed. The lessons learned during the process can trigger new, often more focused business questions.

Below follows a brief outline of the phases:

Business Understanding

This initial phase focuses on understanding business objectives and requirements, which are converted into a data mining problem definition.

Data Understanding

The data understanding phase includes data collection, identification of data quality problems, data exploration and detection of interesting subsets.

Data Preparation

The data preparation phase covers all activities about preparation of the final dataset which will be fed into the modeling tool(s). The tasks include table, record, and attribute selection as well as data transformation and cleaning.

Modeling

The modeling phase selects and applies various data mining techniques to the prepared data and generates the knowledge (patterns) from data or constructs the model from data.

Evaluation

The evaluation phase evaluates the generated knowledge/model from the business perspective, to be certain it properly achieves the business objectives.

Deployment

The deployment phase includes presentation of the discovered knowledge, generation of a report or implementation of deployment in order to actually make use of the created models.

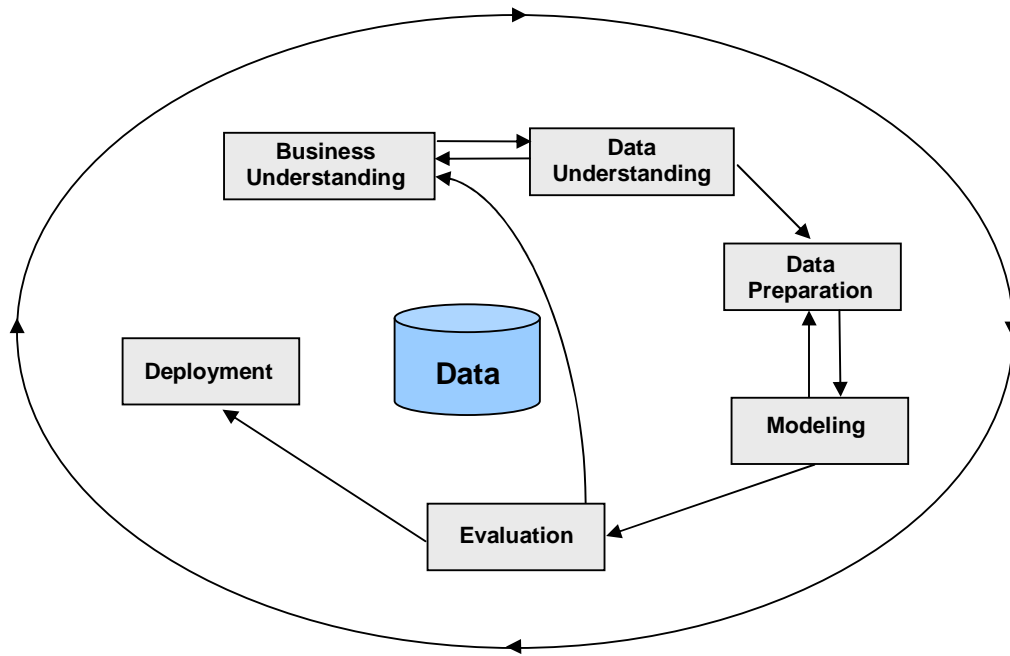


Figure 6.4. Phases of the CRISP-DM Process Model

In general, data-centric models are structured as sequences of steps that focus on performing manipulation and analysis of data and information surrounding the data. In such models, the user's role is to ensure that specific objectives for each step are met (Kurgan et al., 2006). Therefore, one major limitation of such models is their lack of user interaction. As the main purpose of KDDM process models is to ensure that the end product will be useful to the user, the success of a process model depends upon providing results to suit user needs. This success could be achieved when the user interacts with the process model by constraining the process to suit his/her needs. Another limitation is such models do not consider the use of model phase, which is usually carried out by the customer after the model is deployed. The problems or user needs sometimes arise during this phase as described earlier. Such problems/needs will trigger new, often more constrained data mining processes.

6.1.2 Related Data Mining Applications

A number of successful corrosion prediction applications in civil engineering have been reported.

Furuta et al. (1995) developed a practical decision support system for structural damage assessment due to corrosion using the Neural Network. This system aimed to aid inexperienced inspectors to judge whether a certain bridge should be repaired or not. It proved the learning ability of the Neural Network in damage assessment.

Morcous et al. (2002a) proposed a case-based reasoning system for modeling infrastructure deterioration (CBRMID). It was a CBR system developed to provide government agencies with practical, accurate, and versatile deterioration models. The architecture of CBRMID was described in terms of case representation, case retrieval, case adaptation, and case accumulation. Later Morcous et al. (2002b) presented an application example generated using CBRMID for modeling the deterioration of concrete bridge decks.

Melhem and Cheng (2003) first used KNN and the decision tree for estimating the remaining service life of bridge decks. Their work showed the prediction accuracy generated by KNN (50%) was higher than that produced by C4.5 (41.8%). However, both of these values were considered low from a machine learning standpoint. They attributed this to the fact that the deterioration model used to compute the remaining service life turned out to be inadequate. Later Melhem et al. (2003) investigated the use of wrapper methods to improve the prediction accuracy of the decision tree algorithm for the application of bridge decks. Bagging, boosting and automatic feature selection were chosen to compare the results. Their experiments showed all three methods could provide improvement to the decision tree. However, the improvement obtained by the feature selection method can be misleading because the attributes selected were not the ones most important to the problem domain. Therefore, what may be an improvement from the machine learning or data mining viewpoint, can turn out to be a mistake from an engineering perspective. They concluded that the general purpose feature selection was not recommended in this case.

Skomorokhov (2000) presented a rule extraction algorithm for a real life problem, which is to find automatic rules to describe the corrosion rate of steel in sodium as a function of alloy additions. The input data were experimental data of corrosion rate measured for different steel samples. The output is a set of IF-THEN rules, which describe the dependence of corrosion rate on alloy additions.

Brence and Brown (2002) described the use of data mining (multiple linear regression, regression trees, polynomial networks and ordinal logistic regression) to predict corrosion damage from non-destructive test (NDT) data with aircraft. Their results showed that while a variety of modeling techniques can predict corrosion with reasonable accuracy, regression trees are particularly effective in uncovering the complexity of the corrosion-NDT relationship.

Others like Kessler et al. (1994) improved prediction of the corrosion behaviour of car body steel using a Kohonen self organising map. Leu et al. (2001) presented a data mining approach to the prediction of tunnel support stability using artificial neural networks. Mita and Hagiwara (2003) proposed a method using the support vector machine to detect local damage in a building structure with a limited number of sensors. KamrunNahar and Urquidi-Macdonald (2005) used Neural Network to predict the corrosion behaviour and in turn, the life of metals and alloys over extended periods of time in specific environments.

Although the above applications utilise various data mining techniques to predict the corrosion or service life of building components, they can be classified into two main groups: 1) Building the models using various traditional data mining techniques (Melham and Cheng, 2003; Leu et al., 2001; Furuta et al., 1995; Morcous et al., 2002a; Morcous et al., 2002b, Mita and Hagiwara, 2003; KamrunNahar and Urquidi-MacDonald, 2005; Brence and Brown, 2002; Skomorokhov, 2000) and 2) Improving the prediction accuracy using new hybrid methods (Kessler et al., 1994; Melhem et al., 2003). None of them involves solving the problem of reduced performance in a real situation when users only have knowledge of limited inputs.

6.2 Data Analysis and Representation

This section describes the datasets to be used in this project, data pre-processing and existing problems to be solved.

6.2.1 Data Acquisition

The objective is to predict the service life of metallic components in Queensland school buildings. The datasets include two different sources of service life information: the Delphi Survey and Holistic Corrosion Model, in which the Holistic Model includes three datasets named Holistic-I, Holistic-II and Holistic-III for different components and materials respectively. The Delphi Survey, conducted by the CSIRO, includes the estimation of service life for a range of metallic components by experts in the field such as builders, architects, academics and scientists. The Holistic Model is based on a theoretical understanding of the basic corrosion processes. It provides the required knowledge for computing the lifetime of metallic components through grounded theories and principles. Details of these datasets are presented in Table 6.1.

Table 6.1. Details of Datasets

| Data Set | Number of cases | Number of attributes | Building Component | Building Material | Target attribute |
|---------------|-----------------|----------------------|------------------------------|---|-------------------------|
| Delphi Survey | 683 | 10 | Roofs, Gutters, Others | Galvanized Steel, Zincalume, Colorbond, Others | Mean |
| Holistic-I | 9640 | 11 | Gutters | Galvanized Steel and Zincalume | MLannual |
| Holistic-II | 4780 | 22 | Gutters | Colorbond | Life of gutter at 600um |
| Holistic-III | 1297 | 18 | Roofs | Galvanized Steel and Zincalume | Zincalume Life |
| | | | | | Galvanized Life |

6.2.1.1 Delphi Survey

The Delphi Survey dataset contains the predicted life information for over 30 components and 29 materials, for marine, industrial and benign environments of both service (with and without maintenance) and aesthetic life. They are knowledge of domain experts. The output of this dataset is an estimated service life of metallic components. As the Delphi dataset is the result of surveys, the final dataset was examined in three ways to determine its accuracy and reliability. These were analysis for internal consistency of the data, analysis for consistency with expected trends based on knowledge of materials performance and correlation with existing databases on component performance. In all of these comparisons, the Delphi dataset showed good agreement (Cole et al., 2005). Table 6.2 contains the details of the Delphi Survey dataset.

Table 6.2. Details of Delphi Survey

| Attribute ID | Attribute Name | Type | Description |
|--------------|----------------|---------|---|
| 1 | Building type | Nominal | e.g. Commercial, Residential |
| 2 | Component | Nominal | e.g. Gutters, Roof, Door Handles |
| 3 | Measure | Nominal | e.g. Service Life, Aesthetic Life |
| 4 | Environment | Nominal | e.g. Benign, Industrial, Marine |
| 5 | Material | Nominal | e.g. Aluminium, Galvanised Steel, Zinalume |
| 6 | Maintenance | Boolean | Yes / No |
| 7 | Mode (years) | Nominal | The range of Service Life, Aesthetic Life or Time to First Maintenance (e.g. <5 means less than 5 years, 5-10 means from 5 to 10 years) |
| 8 | SD (years) | Numeric | standard deviation for the mean |
| 9 | Mean (years) | Numeric | The average years of Service Life, Aesthetic Life or Time to First Maintenance |
| 10 | Criteria | Nominal | How good the agreement was in the responses from the survey Rated 1,2,3,4 |

6.2.1.2 Holistic-I

The Holistic-I dataset contains theoretical information of corrosion for gutters with Galvanized Steel and Zinalume in Queensland schools. The overall model is a reflection of the influence of climatic conditions and material/environment interactions on corrosion. Table 6.3 contains the details of the Holistic-I dataset. The output of this dataset is the annual mass loss of Zinalume or Galvanized Steel. Once the mass loss of material is determined, its service life is measured with formula 6.1 (Cole et al., 2005).

$$Service\ life = \min\left(\exp\left(\frac{\log\left(\frac{effective_coating_mass}{ML_{annual} \times 1.5}\right)}{n}\right), 100\right) \quad \dots\ Eqn(6.1)$$

Where ML_{annual} is the annual mass loss (last attribute of Holistic-I dataset), $effective_coating_mass = 56.25$ for Zinalume and 103.13 for Galvanized, $n = 0.60$ for Zinalume and 0.62 for Galvanized.

Table 6.3. Details of Holistic-I

| Attribute ID | Attribute Name | Type | Description |
|--------------|--------------------|---------|--|
| 1 | LocID | Numeric | Location ID for each school |
| 2 | XLong | Numeric | Longitude and Latitude of school |
| 3 | YLat | Numeric | |
| 4 | Location | Nominal | School name |
| 5 | State | Nominal | QLD |
| 6 | SALannual | Numeric | Annual salt accumulation |
| 7 | Building Type | Nominal | Gutters |
| 8 | Material | Nominal | Zinalume or Galvanized |
| 9 | Gutter Position | Nominal | Bottom-interior, outside or sides-interior |
| 10 | Gutter Maintenance | Boolean | Cleaned or not cleaned |
| 11 | MLannual | Numeric | Annual Mass Loss of Zinalume/Galvanized |

6.2.1.3 Holistic-II

The Holistic-II dataset is for gutters with Colorbond material in Queensland schools. This model is also generated with theoretical information. But the rules for the degradation of Colorbond are devised separately. The output of this dataset is the service life of gutters with Colorbond material. Table 6.4 presents the details of the Holistic-II dataset.

Table 6.4. Details of Holistic-II

| Attribute ID | Attribute Name | Type | Description |
|--------------|----------------------------------|---------|--|
| 1 | LocID | Numeric | Location ID for each school |
| 2 | XLong | Numeric | Longitude and Latitude of school |
| 3 | YLat | Numeric | |
| 4 | SALannual | Numeric | Annual salt accumulation |
| 5 | Building Type | Nominal | Gutters |
| 6 | Position | Nominal | Facade of buildings |
| 7 | Exposure | Nominal | Open or sheltered |
| 8 | Material | Nominal | Colorbond |
| 9 | PositionVsExposure | Nominal | Openly exposed to rain and sky or sheltered from rain and sky |
| 10 | Building Face | Nominal | Front face |
| 11 | BuildingFacePos | Nominal | Edges |
| 12 | Gutter Type | Nominal | One-sided topcoat or two-sided topcoat |
| 13 | rain_annual_mm | Numeric | Annual rainfall |
| 14 | cum_MZa_2ndYear | Numeric | Cumulative Zincalume mass loss of 2nd year |
| 15 | cum_dSTEEL_2ndYear | Numeric | Cumulative Steel corrosion of 2nd year |
| 16 | remCr | Numeric | The amount of chromate remaining in the 25um area surrounding the defect |
| 17 | normCr | Numeric | |
| 18 | accelerated_corrosion_rate | Numeric | An increased corrosion rate of Zincalume |
| 19 | Time to White Rust of Zincalume | Numeric | Time to occur Zincalume Mass Loss |
| 20 | Time to penetration of Zincalume | Numeric | Time to penetrate Zincalume coating |
| 21 | Time to onset of Red Rust | Numeric | Time to occur Steel Mass Loss |
| 22 | Life of gutter at 600um | Numeric | Service life of gutter |

6.2.1.4 Holistic-III

The Holistic-III dataset contains life information of roof components for schools in Queensland. They are the results of analysing over 10000 records with regard to significant maintenance. The output of this dataset is service life of roofs with Zincalume and Galvanized Steel materials. Table 6.5 presents the details of the Holistic-III dataset.

Table 6.5. Details of Holistic-III

| Attribute ID | Attribute Name | Type | Description |
|--------------|--------------------|---------|--|
| 1 | Centre Code | Numeric | Identification for each school |
| 2 | Centre Name | Nominal | School name |
| 3 | Longitude | Numeric | Geographic location of school |
| 4 | Latitude | Numeric | |
| 5 | Salt Deposition | Numeric | A parameter pertinent to corrosion |
| 6 | Zinc Mass Loss | Numeric | Damage to Zinc, Steel and Zinalume |
| 7 | Steel Mass Loss | Numeric | |
| 8 | Zinalume Mass Loss | Numeric | |
| 9 | Marine | Boolean | True / False |
| 10 | Nzinc | Numeric | A constant that depends on Zinc Mass Loss |
| 11 | Nsteel | Numeric | A constant that depends on Steel Mass Loss |
| 12 | L | Numeric | Calculated based upon Zinc Mass Loss |
| 13 | M | Numeric | Calculated based upon Steel Mass Loss |
| 14 | N | Numeric | Calculated based upon Zinalume Mass Loss |
| 15 | Zinc Life | Numeric | Calculated based upon Nzinc and L |
| 16 | Steel Life | Numeric | Calculated based upon Nsteel and M |
| 17 | Zinalume Life | Numeric | Calculated based upon N |
| 18 | Galvanized Life | Numeric | Calculated based upon Zinc Life and Steel Life |

In general, the Delphi Survey is expert opinions while Holistic-I, -II and -III are theoretical. They form four important sources of information for predicting the lifetime of metallic components. They are independent but complementary to each other. The Delphi Survey can be used for analysing correlation with the other three datasets on component performance and consistency with expected trends based on knowledge of materials performance, while Holistic-I, -II and -III provide theoretical proof for prediction. Holistic-I, -II and -III relate to different component types with different materials while Delphi contains all component types with all materials. More specifically, Holistic-I is for gutters with Galvanized Steel and Zinalume, Holistic-II is for gutters with Colorbond, Holistic-III is for roofs with Galvanized Steel and Zinalume and Delphi is for a range of components including roofs and gutters with different materials including Galvanized Steel, Zinalume and Colorbond. There is no overlap of predicted outcomes from Holistic-I, -II and -III while the predicted outcome from them can be compared with the outcomes from Delphi.

6.1.2.5 School Survey Data Set

The data set derived from the school survey was not large enough to warrant data mining techniques. It is accessed in the post-processing phase by normal table lookup techniques.

6.2.2 Data Preprocessing

Data quality is a key aspect in performing data mining on real-world data. Raw data generally include many noisy, inconsistent and missing values and redundant information. This section describes how data is pre-processed in terms of data cleaning and data reduction.

6.2.2.1 Data Cleaning

Data cleaning consists of dealing with missing data and inconsistent data. In our datasets, the percentage of missing values is very low. For the Delphi Survey, only the attribute 'mode' has 8% missing values while all other attributes have no missing values. For Holistic-I, only the attribute 'Gutter Maintenance' has 51% missing values. For Holistic-II and -III, all attributes have no missing values. Due to the low percentage of missing values, we do not apply cleaning on the missing values. Inconsistent data were also dealt with during the data cleaning phase. An example for inconsistent data is the use of lowercases and capitals such as 'Steel' and 'steel'. More examples are different spellings but the same meaning like 'Galvanised' and 'Galvanized' or different words but the same meaning like 'Steel in Hardwood' and 'Steel-Hardwood'. More spaces included in values like 'Residential ' and 'Residential ' is another reason to cause inconsistency. The data mining tool will treat those kinds of values as different values and hence will influence the predicted results. All such kind of inconsistency is recovered during the data cleaning phase. For example, the 'Material' attribute in the Delphi Survey originally consists of 36 values. After cleaning, there are total 29 different values (instances of Material) in the data set.

6.2.2.2 Data Reduction

Data reduction includes dimension reduction and instance selection. This section describes these two tasks for each of the datasets.

Delphi

The original Delphi dataset has ten attributes. They are 'Building type', 'Component', 'Measure', 'Environment', 'Material', 'Maintenance', 'Mode', 'Mean', 'SD' and 'Criteria'. The estimated service life was stored in two forms: the mode and the mean as well as a standard deviation (SD) for the mean. The mode is the range (e.g. 5-10) of 'service life', 'aesthetic life' or 'time to first maintenance'. The mean is the average year of 'service life', 'aesthetic life' or 'time to first maintenance'. As we want a real value to be the final predicted result, the attribute 'mean' is chosen as the target attribute and hence the 'Mode' is removed since 'Mean' and 'Mode' are different forms for the same information. 'SD' can not be considered as input because it is a part of output. 'Criteria' relates to how good the agreement was in the response from the Delphi Survey. It is not useful in mining and should be removed. This dataset contains life information of service life, aesthetic life and time to first maintenance. As we are only interested in service life, those instances whose value of 'Measure' is not equal to 'Service Life' are removed. After removing those instances, the attribute 'Measure' becomes unary and hence should be removed. The remaining attributes that are included in analysis are as follows:

Building type | Component | Environment | Material | Maintenance | Mean

Holistic-I

The original Holistic-I dataset has 11 attributes, in which 'LocID' and 'Location' are identification information and 'State' and 'Building Type' only have one value. After removing those irrelevant attributes, the attributes are as follows:

XLong | YLat | SALannual | Material | Gutter Position | Gutter Maintenance | MLannual

As we described in Section 6.2.1.2, the service life is calculated based upon 'MLannual'. We create a target variable named 'Service Life' and remove the false predictor 'MLannual'. Therefore, the attributes are as follows:

XLong | YLat | SALannual | Material | Gutter Position | Gutter Maintenance | Service Life

Holistic-II

The original Holistic-II dataset has 22 attributes, in which 'LocID' is identification information and 'Building Type', 'Position', 'Material', 'Building Face' and 'BuildingFacePos' only have one value. 'Exposure' and 'PositionVsExposure' are two attributes which are correlated to each other. For example, when 'Exposure' is equal to 'open', 'PositionVsExposure' must be equal to 'openly exposed to rain and sky'. Therefore, they are redundant to each other and one of them should be removed. After removing these irrelevant attributes, the attributes are as follows:

XLong | YLat | SALannual | Exposure | Gutter Type | rain_annual_mm | cum_MZa_2ndYear | cum_dSTEEL_2ndYear | remCr | normCr | accelerated_corrosion_rate | Time to White Rust of Zinalume | Time to penetration of Zinalume | Time to onset of Red Rust | Life of gutter at 600um

'Life of gutter at 600um' is the target attribute.

Holistic-III

The Holistic-III dataset is divided into two parts in terms of different target attributes: one is for 'Zinalume Life' named Holistic-III_Zi and the other is for 'Galvanized Life' named Holistic-III_Ga. The attribute 'Centre Code' and 'Centre Name' are ignored since they are identification information. After that, their attributes are as follows:

Holistic-III_Zi:

Longitude | Latitude | Salt Deposition | Zinalume Mass Loss | Marine | N | Zinalume Life

Holistic-III_Ga:

Longitude | Latitude | Salt Deposition | Zinc Mass Loss | Steel Mass Loss | Marine | Nzinc | Nsteel | L | M | Zinc Life | Steel Life | Galvanized Life

6.2.3 Data Analysis

After data pre-processing, the datasets were analysed in terms of the type of features and their availability of values as user inputs in order to determine the learning method and the input attributes. For all datasets, both discrete and continuous features exist. Therefore, a learning method for handling both discrete and continuous data is required.

The data mining system lifecycle includes three main phases: (1) training of the model, (2) evaluation (or testing) of the model and (3) using the trained model in practice. If the user can not provide the same inputs as used for training the model in the use of the model phase, the performance of the predictive model degrades due to the absence of many input values. Therefore, the availability of features in the use of model phase is an important aspect to influence the model performance. Based on the availability of features in the use of the model phase, we simply divide all features into two groups: *available features* which are features that can be provided by users and *unavailable features* which are features that can not be provided by users. Our datasets contain some unavailable features. More specifically, all features in Delphi are available features while in Holistic-I, 'SALannual' is an unavailable feature; in Holistic-II, all other features except 'XLong', 'YLat', 'Exposure' and 'Gutter Type' are unavailable and in Holistic-III, only 'Longitude', 'Latitude' and 'Marine' are available to users. Hence, how to deal with these unavailable features is a research issue to be addressed. The literature on related data mining applications shows that most research work [9-19] aims to build the predictive models and improve the prediction accuracy. None of the existing work involves solving the problem of the reduced performance of the predictive model when the model is trained with some unavailable features.

Moreover, our datasets include multiple data sources of service life information. These sources can not be combined and the models are required to be constructed independently from each of them. However, the predicted results from different models can be compared to each other. For example, both Delphi and Holistic-II can be used to predict the lifetime of gutters with Colorbond material. The results from Delphi and Holistic-II may be inconsistent. Hence, we used the knowledge base based on the expert knowledge to choose the most appropriate answer for a given situation in case of inconsistencies in the results of different models.

The detailed explanation given for the data mining of the original data sets has also been applied to the expanded data sets created using the Holistic model for the new components included in the program.

6.3 Query Based Learning System

As discussed previously, the current KDDM process models are data-oriented rather than user-oriented. The data-oriented process models emphasise the data analysis tasks surrounding the data and lack the interactive involvement of users during the process. Hence, they do not suffice to address the problems that are due to user interaction during the use of the model phase. This section will propose a user-oriented learning system, namely the Query Based Learning System (QBLS), which is based on a data-centric model with extensions to provide support for user interaction.

6.3.1 Motivations for QBLS

Due to user interaction, problems arise during the use of the model phase. One such problem is the availability of features in the use of the models. Neither keeping both available and unavailable features nor simply removing unavailable features is a good solution. A suitable feature selection algorithm is required to minimise the number of unavailable features and maximise the classification accuracy. Meanwhile, when the user can not input the values of those unavailable features for querying to the system, some pre-processing should be done for missing input values. Moreover, the data mining process is usually carried out by a data analyst and the knowledge or model generated from the data mining process is too complex to be understood by the user. In order to ensure the end product (knowledge or model) will be useful to the user, some post-processing is needed, such as interpreting the discovered knowledge in such a way that the user can use it. In our case, post-processing can eliminate the conflicting results from multiple data sources. Hence, we propose a new learning system framework, called the Query Based Learning System (QBLS), which is based on the data-centric process model. A domain knowledge base is introduced for pre-processing missing input values and post-processing inconsistent results.

6.3.2 Overview of QBLS

The QBLS is developed based on an industry standard data mining process model, CRISP-DM (Cross Industry Standard Process for Data Mining) (2003). Four procedures that are different from the CRISP-DM are highlighted in Figure 6.5. The three procedures - Query Based Feature Selection, Results Post-processing and the Use of Model - are critical for the success of the proposed QBLS model. The Query Based Feature Selection is separated from the data pre-processing step as it has the involvement of users or domain experts and hence is different from the usual feature selection. The Results Post-processing and the Use of Model phase are added into the model in order to ensure the results are useful to users. An external domain knowledge base is involved in results post-processing and missing inputs pre-processing in the Use of Model phase. The next section will discuss each phase of the QBLS model.

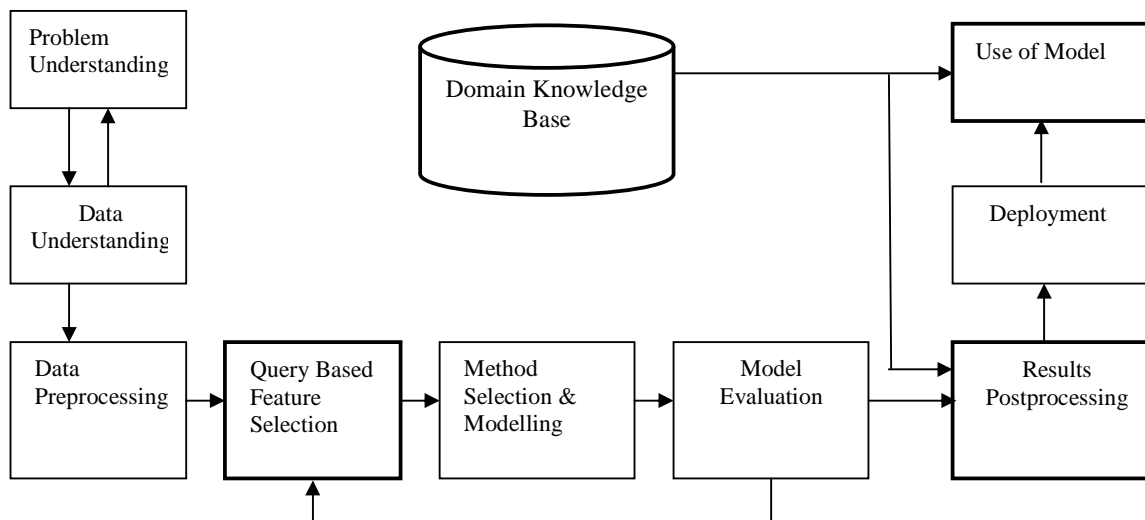


Figure 6.5. Query Based Learning System

6.3.3 Phases of QBLS

The Problem Understanding phase, like the Business Understanding phase in the CRISP-DM model, focuses on understanding the project objectives and requirements and then converting them into a data mining problem definition.

The Data Understanding phase is for identifying data quality problems and exploring the interesting subsets of data.

The Data Pre-processing phase involves preparing the datasets for applying the Query Base Feature Selection algorithm, which includes data cleaning and data reduction.

The Query Based Feature Selection phase involves selecting the final features of the dataset, which will be used to build the model. The basic idea of this phase is to select a minimum subset of relevant features with which the predictive model provides an acceptable performance, as well as, to make the selected features available to users when the model is used in practice.

The Method Selection and Modeling phase is for selecting and applying various data mining techniques to the prepared data. The models are constructed in this phase.

The Model Evaluation phase includes performance measures from both a technical perspective and business perspective.

The Results Post-processing phase includes interpretation of the mined patterns/ discovered knowledge and elimination of unreasonable results to ensure the end product will be useful.

The Deployment phase covers presentation of the generated knowledge in a customer-oriented way or deploying the created model as a customer-oriented system.

The Use of Model phase involves using the deployed system in practice. In many cases, it will be the customer, not the data analyst, who will carry out this phase. The user needs in this phase will trigger new, often more constrained data mining processes.

6.3.4 Query Based Feature Selection

The first step of QBFS involves removing the features such as features for identification. Let $A = \{a_1, a_2, \dots, a_k, a_{k+1}, \dots, a_m, a_{m+1}, \dots, a_n\}$ be a set of remaining features in a dataset. The remaining features are clustered into three groups according to their easy availability to users as follows:

- Group 1 ($a_1 - a_k$): Features that the user can easily provide while using the model
- Group 2 ($a_{k+1} - a_m$): Features that can not be provided by the user but can be obtained from the external domain knowledge
- Group 3 ($a_{m+1} - a_n$): Features that can not be provided by the user or obtained from domain knowledge

Group 1 will be included in the final model because features in Group 1 are not only useful in mining but also can be provided by users while they are using the model. Group 3 will be rejected because they can not be provided in model use although they have mining value. If we include the features of Group 3 in the final model, their values in new data will be missing. As a result, the generalization accuracy will decrease. A decision has to be made for features in Group 2, as they can not be provided by users but they can be obtained from external

domain knowledge. If we include all the features of Group 2, the measurements to obtain some of these values may be too complex and computationally expensive. If we exclude those features, the performance of the model may not be accepted by users.

The datasets include four different sources of service life information from the Delphi Survey, Holistic-I, -II and -III, where Holistic-III was divided into two parts in terms of different target features. The multiple sources are independent but complementary to each other. Holistic-I, -II and -III relate to different component types with different materials while Delphi contains all component types with all materials. Each data source contains completely different features in which some can not be provided by users or domain knowledge.

6.3.4.1 Categorisation of features

Features of each data source are divided into three groups.

Holistic-I

Group 1: { XLong, YLat, Material, Gutter Position, Gutter Maintenance }

Group 2: { SALannual }

There is no feature in Group 3.

Holistic-II

Group 1: { XLong, YLat, Exposure, Gutter Type }

Group 2: { SALannual, rain_annual_mm, cum_MZa_2ndYear, cum_dSTEEL_2ndYear, remCr, normCr, accelerated_corrosion_rate }

Group 3: { Time to White Rust of Zinalume, Time to penetration of Zinalume, Time to onset of Red Rust }

Holistic-III_Zi

Group 1: { Longitude, Latitude, Marine }

Group 2: { Salt Deposition }

Group 3: { Zinalume Mass Loss, N }

Holistic-III_Ga

Group 1: { Longitude, Latitude, Marine }

Group 2: { Salt Deposition }

Group 3: { Zinc Mass Loss, Steel Mass Loss, Nzinc, Nsteel, L, M, Zinc Life, Steel Life }

Delphi

Group 1: { Building type, Component, Environment, Material, Maintenance }

There is no feature in Groups 2 and 3.

6.3.5 Domain Knowledge Base

Domain knowledge can be included in the process of data mining from the beginning of the problem understanding to the end when the result inferred by the predictive model is presented to the users while used in practice. It is necessary to understand the project objectives and requirements and then convert them into a data mining problem definition. In the proposed process model, QBLS, a domain knowledge base is used especially for results post-processing and missing input values pre-processing in the Use of Model phase. Some features included in the final model may not be directly provided by users but can be inferred by the domain knowledge base. For example, "annual rainfall" is an important factor in determining the service life of building components in civil engineering. However, while using the data mining model to predict the service life of a building component, the user will most likely provide the location and material as an input. The user may not be aware of the exact value of rainfall in the area. However, a domain knowledge base will have such information. This information can now be treated as one of the input values for the model.

Furthermore, the domain knowledge base can be used in reinforcing the outputs inferred by the predictive model. Since the real-life data mining models are for solving practical problems, the final results should be significant to users. However, mining errors are inevitable even for a perfect model. The domain knowledge base is used to confirm that the results predicted by the data mining system do abide by the rules of the domain and/or domain experts. For example, it is domain knowledge in civil engineering that (1) a roof in a severe marine location will not last longer than one in a benign environment, and (2) a stainless steel roof should last longer than one with galvanized steel. Such in-built rules will be checked to ensure the correctness of the results processed by the models.

In general, the external domain knowledge base assists to deal with the vague queries in use of the model phase and with eliminating illogical outcomes in post-processing. The domain knowledge base is extensible with the use of the system in real-life practice.

6.4 Predictor Selection

This section will explore various predictive data mining techniques to apply to the selected features for building the predictors to determine the service life of metallic components in buildings. The primary objective is to find the best method for the building service life prediction problem. For this purpose, two types of data mining methods, namely classification methods and regression methods are applied for comparison. The following sections will discuss each of the methods involved and present the experimental results conducted to achieve the research objective. An integrated method of combining M5 and KNN will also be provided for improving the performance of predictors.

6.4.1 Methods Selection

There are various data mining methods such as Naïve Bayes (Fayyad et al., 1995b), K Nearest Neighbors (KNN) (Aha et al., 1991), regression modelling, support vector modelling (SVM) (Vapnik, 1995), decision tree (DT) (Quinlan, 1986) and neural network (NN) (Resample, 2003) that can be considered to undertake prediction tasks. These methods can be categorised into two groups, namely classification methods and regression methods, based on the type of target feature. Classification methods require categorical class as the target feature while regression methods work for numeric prediction. Typical classification methods include Naïve Bayes, KNN, DT, NN, and SVM. Naïve Bayes is a statistical-based algorithm. It is useful in predicting the probability that a sample belongs to a particular class or grouping (Fayyad et al., 1995b). KNN is based on the use of distance measures. Both DT (Quinlan, 1986) and NN are very popular methods in data mining. DT is easy to understand and better in classification problems while NN can not produce comprehensible models in general and is more efficient for predicting numerical targets. SVM is relatively new method. It can solve the problem of efficient learning from a limited training set. For Naïve Bayes and DT, before they are applied to do numeric prediction tasks, the target feature needs to be discretised to a nominal type. Others like KNN, NN and SVM can predict the continuous value directly.

Linear regression, logistic regression, regression trees, KNN, M5 model trees (Quinlan, 1992), NN and SVM are typical regression methods. Linear regression and logistic regression are statistical-based algorithms and they are the most popular regression techniques. Model trees and regression trees are tree-based algorithms and efficient for large datasets. Model trees are generally much smaller than regression trees and prove to be more accurate (Quinlan, 1997).

For comparison purposes, experiments were conducted on both classification and regression methods. Naïve Bayes and DT (C4.5) were chosen as representative classification methods as they are statistical-based and tree-based algorithms respectively. Linear regression, KNN, M5 model trees, NN and SVM were also chosen as representative regression methods as they are based on different theory. All the experiments were conducted in a WEKA environment and tenfold cross validation (10-CV) was used throughout the experiments described in this chapter.

The n -fold cross validation (n -CV) is a popular method used to test the performance. The idea behind n -fold cross validation is that a dataset is randomly evenly divided into n parts, $n-1$ parts of which are used as a training set for building a predictive model and the remainder is used as a test set. This process is repeated n times. Each time a different one of n parts is chosen as the test set. The performance is reported as average of n runs.

6.4.2 Experiments using Classification Methods

The first experiments were conducted using classification methods, that is, Naïve Bayes and DT (C4.5). The MDL discretisation method (Fayyad and Irani, 1992) was applied first to discretise the target feature to a nominal type. Table 6.6 shows the number of target classes after discretisation and the percentage of numerical and categorical attributes in datasets. Table 6.7 presents the classification accuracy of Naive Bayes and C4.5.

Table 6.6. Details of Datasets

| Dataset | No. of Cases | No. of Target Classes | No. of Input Attributes | Numerical Attributes (%) | Categorical Attributes (%) |
|-----------------|--------------|-----------------------|-------------------------|--------------------------|----------------------------|
| Delphi Survey | 683 | 10 | 7 | 0% | 100% |
| Holistic-I | 9640 | 10 | 6 | 50% | 50% |
| Holistic-II | 4780 | 10 | 13 | 76.92% | 23.08% |
| Holistic-III_Ga | 1297 | 10 | 12 | 91.67% | 8.33% |
| Holistic-III_Zi | 1297 | 9 | 6 | 83.33% | 16.67% |

Table 6.7. Classification Accuracy of Naïve Bayes & DT (C4.5)

| Dataset | Classification Accuracy | |
|-----------------|-------------------------|-----------|
| | Naive Bayes | DT (C4.5) |
| Delphi Survey | 30.0587% | 36.217% |
| Holistic-I | 89.744% | 90.125% |
| Holistic-II | 94.728% | 96.548% |
| Holistic-III_Ga | 93.138% | 94.603% |
| Holistic-III_Zi | 91.904% | 93.215% |

The results from Table 6.7 show that for Naive Bayes and C4.5, classification accuracy is around 90% except for the Delphi Survey. Both Naive Bayes and C4.5 are not good for the Delphi Survey (only 30.0587% and 36.217% classification accuracy - that means more than half the cases are not correctly classified). The highest accuracy is for Holistic-II (94.728% from Naïve Bayes and 96.548% from C4.5). Decision tree is a good classification method but seems less appropriate for estimation tasks where the goal is to predict the value of a continuous attribute. Transforming our prediction problem to a classification problem by discretising continuous values to categorical values proved not suitable on our datasets, especially for the Delphi Survey.

Moreover, we can observe from Table 6.6 that the numbers of classes for all datasets are almost the same while the number of cases varies from 683 to 9640. There are ten classes while only 683 cases in the Delphi Survey. Therefore, it may be true that the decision tree is prone to errors in classification problems with many classes and a relatively small training set.

6.4.3 Experiments using Regression Methods

The second experiments were conducted using regression methods, that is, linear regression, KNN, M5, NN and SVM. The average correlation coefficients over 10-CV of these algorithms on our datasets are reported in Table 6.8.

The results in Table 6.8 show that good results are achieved for all methods. Most of the correlation coefficients (CCs) are above 0.95. The lowest CC is 0.797 (KNN for Delphi Survey) and the highest is 1 (NN and M5 for Holistic-II). NN works best for all datasets, getting very high CC for all datasets. This result proves that NN is very efficient for handling numerical values and well-suited for predicting a numerical target because most of the attributes in our datasets are numerical values (the last two columns of Table 6.6 show the percentage of numerical and categorical attributes - it is obvious that almost all datasets have more than 50% numerical attributes). The correlation coefficients of SVM are closer to NN, only the value for Holistic-I is much reduced. The results from KNN are also similar to

NN, even better for Holistic-I. KNN obtained the worst result for the Delphi Survey. This may prove that KNN is quite effective if the training set is large. There are 9640 cases in Holistic-I, 4780 cases in Holistic-II, 1297 cases in Holistic-III while only 683 cases in the Delphi Survey. M5 is learned efficiently as NN. Especially, it is better for the Delphi Survey than NN.

Table 6.8. Correlation Coefficient of KNN, NN, SVM & M5

| Dataset | Correlation Coefficient (CC) | | | | |
|-----------------|------------------------------|--------|--------|--------|--------|
| | Linear regression | KNN | NN | SVM | M5 |
| Delphi Survey | 0.9320 | 0.7970 | 0.9299 | 0.9280 | 0.9333 |
| Holistic-I | 0.8679 | 0.9960 | 0.9790 | 0.8412 | 0.9892 |
| Holistic-II | 0.9999 | 0.9962 | 1 | 0.9999 | 1 |
| Holistic-III_Ga | 0.9678 | 0.9915 | 0.9994 | 0.9737 | 0.9883 |
| Holistic-III_Zi | 0.9038 | 0.9886 | 0.9990 | 0.9889 | 0.9971 |

From the view of each dataset, Holistic-II gets the best result. That is because Holistic-II contains more valuable features than others for predicting service life. The CC from all methods for Holistic-II is very high (the highest reaches 1 while the lowest is also 0.9962). The results for the Delphi Survey are the worst (the highest is only 0.9333 while the lowest is 0.797).

All results indicate those methods which can deal with continuous values directly such as KNN, NN, SVM and M5 are better than those that have to discretise continuous values such as Naïve Bayes and DT. However, the interesting fact is that no one method is always best for all five datasets. In order to clearly show the best method for each dataset, the information in Table 6.8 is presented graphically in Figure 6.6

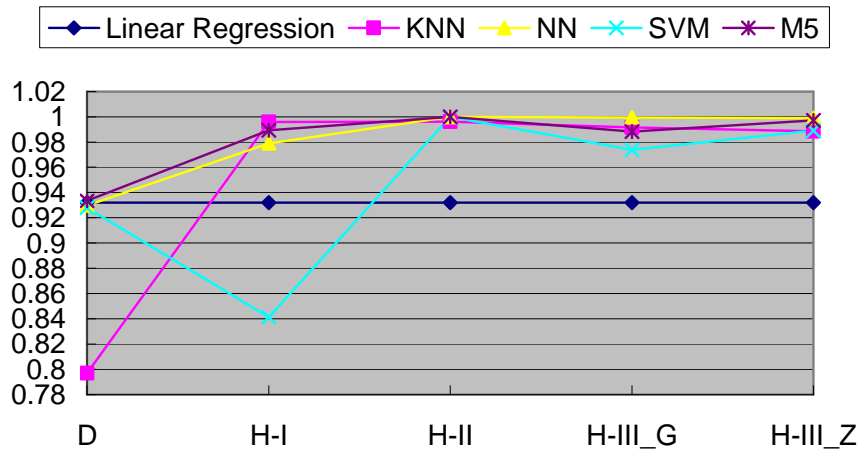


Figure 6.6: Correlation Coefficient of KNN, NN, SVM & M5

Figure 6.6 clearly indicates that M5 is the best method for the Delphi Survey (CC is 0.9333), KNN is the best method for Holistic-I (CC is 0.9960), NN and M5 are the best methods for Holistic-II (CC is 1) and NN is the best method for Holistic-III (CC is 0.999). Considering the

balance of accuracy and comprehensibility of predictors, M5 was chosen as the final learning method.

6.4.4 Predictors constructed using M5

Having chosen M5 as the learning method, it was then applied on the features selected by QBFS to build the predictors for each of the datasets. As the whole predictive model for each of the datasets is very large, a part of the M5 model tree output for Holistic-I is given as an example.

Predictor for Holistic-I

Part of M5 pruned model tree:

GutterMaintenance=cleaned <= 0.5 : LM1 (2410/2.632%)

GutterMaintenance=cleaned > 0.5 :

| *GutterPosition=sides-interior,outside* <= 0.5 :

| | *XLong* <= 151.184 :

| | | *XLong* <= 145.486 :

| | | | *XLong* <= 141.351 :

| | | | | *YLat* <= -21.646 :

| | | | | | *XLong* <= 139.491 : LM2 (4/0%)

| | | | | | *XLong* > 139.491 : LM3 (4/3.365%)

| | | | | *YLat* > -21.646 :

| | | | | | *XLong* <= 140.027 : LM4 (22/4.599%)

LM num: 1

ServiceLife =

-0.0116 * *XLong*

- 0.0064 * *YLat*

- 0.0002 * *SALannual*

+ 0.0085 * *Material=Zincalume*

+ 0.0689 * *GutterPosition=sides-interior,outside*

+ 0.039 * *GutterPosition=outside*

+ 0.0345 * *GutterMaintenance=cleaned*

+ 1.9424

...Eqn(6.2)

This is a part of the M5 model tree output using the attributes 'XLong', 'YLat', 'SALannual', 'Material', 'GutterPosition' and 'GutterMaintenance' for Holistic-I. The first part of the output

shows the tree structure of the model. The output on a leaf node is a reference to a function. For example, there is a rule in the tree:

GutterMaintenance=cleaned <= 0.5 : LM1 (2410/2.632%)

This means that if this rule is true, then the output, 'ServiceLife' in this case, is decided by the linear regression equation with label LM1, namely the second part of the output above (Equation 6.2). The numerical values in parentheses (2410/2.632%) tell us 2410 instances satisfy the rule and 2.632% in the training set do not satisfy the rule.

To evaluate Equation 6.2, simply replace all numerical attributes (XLong, YLat and SALannual in this example) with their value for the particular instance and replace categorical expressions (such as Material=Zincalume) with the value 1 if the attribute is equal to any of the listed attributes (they are comma-delimited) or with 0 if they are false. This is the same in the model tree; any rules that involve categorical values, such as

GutterMaintenance=cleaned <= 0.5

Simply replace 'GutterMaintenance=cleaned' with the value 1 if 'GutterMaintenance' is equal to 'cleaned' or with 0 if it is false.

6.4.5 Improvement of Performance

The QBFS feature selection algorithm may result in some useful features being rejected; as a result, this may reduce the performance of the predictive models. The model-based learning (M5) is combined with the instance-based learning (Quinlan, 1993) to improve the performance. This method first uses the instance-based approach to find a set of instances similar to the target instance. Then, the class values of similar instances are adjusted using the value predicted by the model tree before they are combined. The detailed algorithm is given in Figure 6.7. We use the KNN ($K=3$) for the instance-based method.

Input:

- T : the Training Set
- M : A predictive model constructed by the model-based method
- U : an unseen instance

Output:

$V(U)$: predicted class value for U

1. $M(U) \leftarrow$ the value predicted for U by M
2. Let $P \leftarrow \{P_1, P_2, \dots, P_k\}$ be a subset of instances similar to U by using the instance-based method
3. Let $VP \leftarrow \{V(P_1), V(P_2), \dots, V(P_k)\}$ be a subset of class values for P
4. For $i=1$ to k

$M(P_i) \leftarrow$ the value predicted for P_i by M

$diff(i) = M(P_i) - M(U)$

$V(P_i)' = V(P_i) - diff(i)$

5. $V(U) = \frac{\sum_{i=1}^k V(P_i)'}{k}$

Figure 6.7. M5 + KNN Algorithm

Therefore, the final predictors are built using M5+KNN on the features selected by QBFS. The performance of this M5+KNN combined model is compared with the M5 model and the ensemble model with bagging (Breiman, 1996). Correlation coefficient and Mean Absolute Error of M5, M5+KNN and bagging are presented in Table 6.9 and Table 6.10.

Table 6.9. Correlation Coefficient of M5, M5 + KNN and Bagging

| Dataset | Correlation Coefficient (CC) | | |
|-----------------|------------------------------|----------|---------|
| | M5 | M5 + KNN | Bagging |
| Delphi Survey | 0.9198 | 0.94555 | 0.9467 |
| Holistic-I | 0.9790 | 0.97990 | 0.9904 |
| Holistic-II | 0.9103 | 0.97628 | 0.9158 |
| Holistic-III_Ga | 0.9421 | 0.97520 | 0.9416 |
| Holistic-III_Zi | 0.8692 | 0.94859 | 0.8770 |

Table 6.10: Mean Absolute Error of M5, M5 + KNN and Bagging

| Dataset | Mean Absolute Error | | |
|-----------------|---------------------|----------|---------|
| | M5 | M5 + KNN | Bagging |
| Delphi Survey | 3.3272 | 2.7526 | 2.7686 |
| Holistic-I | 0.9113 | 0.5094 | 3.0823 |
| Holistic-II | 2.3758 | 1.1414 | 2.3177 |
| Holistic-III_Ga | 2.1044 | 0.9857 | 2.1486 |
| Holistic-III_Zi | 2.9378 | 1.2025 | 2.9157 |

The same information is presented graphically in Figures 6.8 and 6.9. From Figures 6.8 and 6.9, we can observe that the better correlation coefficient and lower mean absolute error are obtained by combining the M5 and KNN learning methods. The method seems to provide significant improvement for relatively weaker models such as the Holistic-II and Holistic-III_Zi, whereas the improvement for the near-perfect models such as Holistic-I, is not so obvious. The combined M5+KNN model also outperforms the ensemble model with bagging. Bagging can not always improve the performance such as for Holistic-I as shown in Figure 6.8 and 6.9.

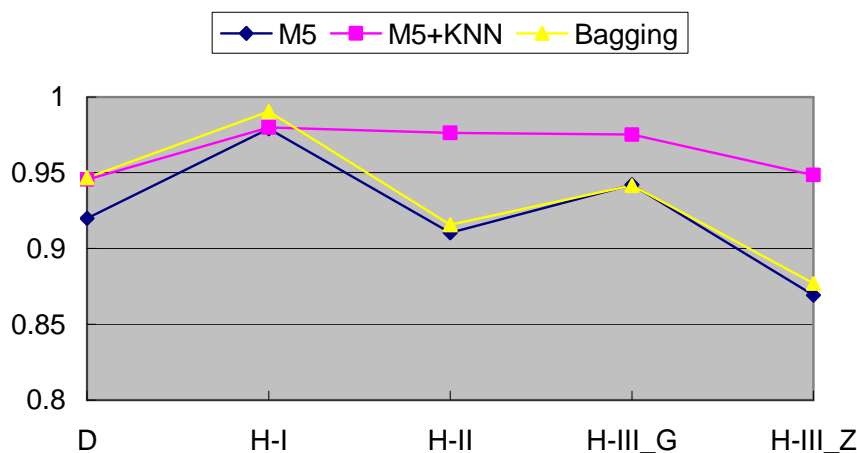


Figure 6.8. Correlation Coefficient of M5, M5+KNN and Bagging (D=Delphi, H-I=Holistic-I, H-II= Holistic-II, H-III_G=Holistic-III for Galvanized Steel, H-III_Z=Holistic-III for Zincolume)

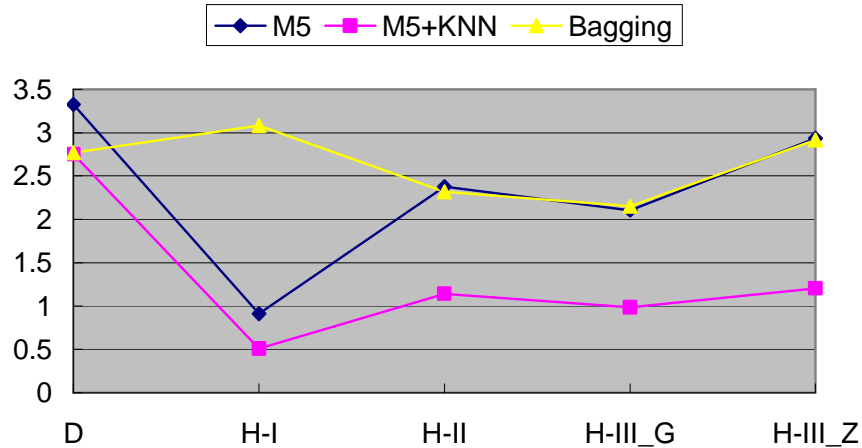


Figure 6.9. Mean Absolute Error of M5, M5+KNN and Bagging, (D=Delphi, H-I=Holistic-I, H-II= Holistic-II, H-III_G=Holistic-III for Galvanized Steel, H-III_Z=Holistic-III for Zincalume)

6.5 Overall Solution

In the previous section, we proposed a learning system framework, the QBLS model. We also presented a summary of experimental results for choosing the best learning method. Based on the theoretical framework and practical experiments, we propose an overall solution to predict the service life of metallic components in Queensland schools. This section will describe the solution in detail and provide an example of prediction using the developed system.

6.5.1 Overview of the System

The overview of the system is given in Figure 6.10. This system basically consists of three main parts: feature selection, predictors and domain knowledge. The Query Based Feature Selection is first applied to the datasets to select a minimum subset of features which can be provided by users. Then, a hybrid method M5+KNN is applied on the selected features to build the predictors for all of the datasets. The predictors are used to carry out prediction for user input queries. The domain knowledge base consists of three parts: salt deposition knowledge, rainfall knowledge and generalised rules extracted from domain expert opinions. Because the features selected to build the predictors include features of 'Salt Deposition' and 'Rainfall Annual', the salt deposition and rainfall database is included in the knowledge base, which is for pre-processing user inputs. Generalised rules are used in post-processing the predicted results, for example, solving the inconsistency in predicted results.

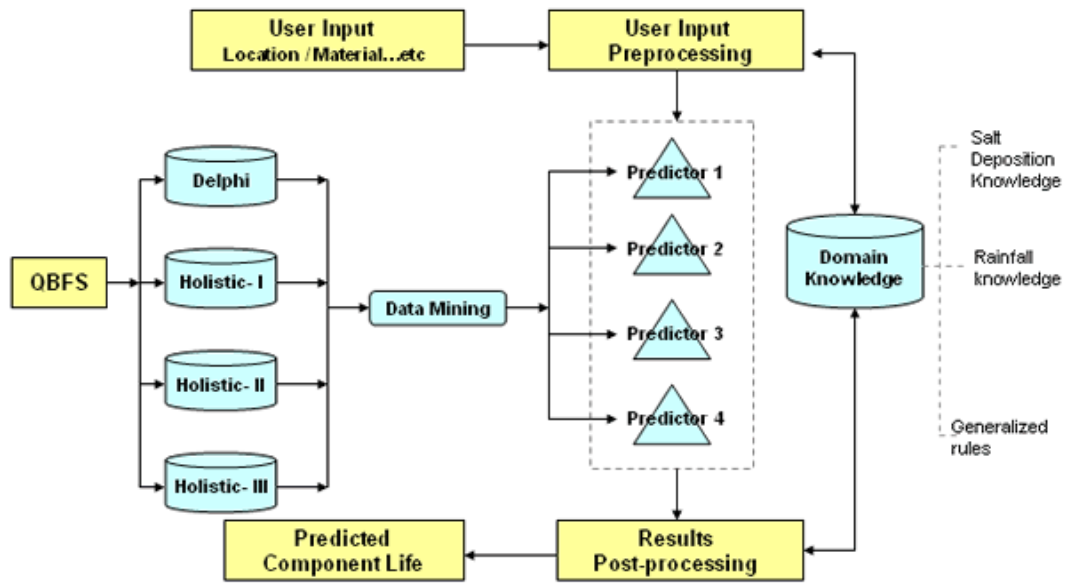


Figure 6.10. Overview of System

6.5.2 Representation of the Knowledge Base

Construction of the knowledge base, consisting of the salt deposition, annual rainfall and generalised rules, has been generated for the purpose of pre-processing vague queries and post-processing inconsistent results. The knowledge is represented as items in the database. Some of the salt deposition knowledge in the generated knowledge base is presented in Table 6.11.

Table 6.11. Salt Deposition Knowledge

| XLong | YLat | Salt Deposition |
|---------|----------|-----------------|
| 151.986 | -28.0373 | 3.80842 |
| 153.007 | -27.3206 | 4.42054 |
| 147.633 | -22.8372 | 3.77518 |

Some of the rainfall knowledge in the generated knowledge base is presented in Table 6.12.

Table 6.12. Rainfall Knowledge

| XLong | YLat | Rain Annual (mm) |
|---------|----------|------------------|
| 151.986 | -28.0373 | 1595 |
| 153.007 | -27.3206 | 1595 |
| 147.633 | -22.8372 | 783 |

And some of the generalised rules in the generated knowledge base are presented in Table 6.13.

Table 6.13. Generalised Rules

| Component | Environment | Material | Min (years) | Max (years) |
|-----------|-------------|------------------|-------------|-------------|
| Gutters | Marine | Galvanised Steel | 5 | 15 |
| Gutters | Benign | Galvanised Steel | 30 | 50 |
| Gutters | Benign | Colorbond | 20 | 50 |
| Roof | Marine | Colorbond | 15 | 30 |

Once the knowledge base is created, it can be used for pre-processing the user inputs and post-processing the predicted results.

As the location (longitude and latitude) that users input may not exactly match the salt deposition and rainfall knowledge, a similarity principle is employed to obtain the value of salt deposition and rainfall. The similarity principle means that the nearest geographic location will have the most similar value for salt deposition and annual rainfall. The distance D between two points on the surface on the earth is computed by the formula 2 (Cole et al., 2005).

$$D = R \times \cos^{-1} \left\{ \left[\sin \left(\frac{latitude_1}{57.2956} \right) \times \sin \left(\frac{latitude_2}{57.2956} \right) \right] + \left[\cos \left(\frac{latitude_1}{57.2956} \right) \times \cos \left(\frac{latitude_2}{57.2956} \right) \times \cos \left(\frac{longitude_2}{57.2956} - \frac{longitude_1}{57.2956} \right) \right] \right\} \quad \dots \text{Eqn(6.3)}$$

Where:

The location of the first point is given by (longitude₁, latitude₁);

The location of the second point is given by (longitude₂, latitude₂);

And longitudes and latitudes are measure in decimal degrees;

R is the radius of the earth taken as 6378.7 km.

To covert latitude or longitude from decimal degrees to radians, the latitude and longitude values are divided by $180/\pi \approx 57.2956$ (taking π to be 3.1416).

Once the user inputs longitude and latitude, the system will find the nearest location from the knowledge base and then get the value of salt deposition and rainfall. These values can then be treated as user inputs for the predictors.

In terms of predicted results, the system checks them with the generalised rules. If the component, material and environment are matched and the predicted service life is in the range, the results are reasonable. Otherwise we suggest that the result does not abide by the generalised rules.

6.5.3 An Example of Prediction using the System

A prediction system has been developed in this research project. Figure 6.11 shows the user interface of the system.

Figure 6.11. User Interface of System

As shown in the user interface, the location, component and material are compulsory inputs for querying to the system. (The location can also be entered by choosing a Queensland school). Based on these inputs more options become available which require selections to be made. Based on these required inputs, different predictors will be used to do the prediction. Here we provide an example for using the system. Suppose the user wants to know the service life of gutters with galvanized steel in location (151, -28). He/she first inputs (151, -28) as location, gutters as component and galvanized steel as material. The location inputs can also be directly selected from the geo-spatial database using the GIS system. Then Holistic-I and Delphi options are activated for more inputs needed by these two predictors. After the user inputs the gutter position, maintenance and environment etcetera, the system automatically gets values from domain knowledge for other features needed by the predictors. For example, the Holistic-I predictor requires salt deposition in this location as an input as well. The system gets the salt deposition from the salt database and predicts the service life is 14.5004 years from the Holistic-I predictor. A similar process is done by the Delphi predictor and the predicted service life is 14.4165 years. The results for this example are quite consistent. However, sometimes the results from different predictors will conflict with each other. An example of such a case is the service life of roof with Zincalume in

location (153.0310, -27.4315). The predicted result from the Delphi predictor is 51.877 years while from the Holistic-III predictor is only 29.928 years. In such a case, domain knowledge is also used to eliminate unreasonable results.

6.6 Conclusions

The main objective of this research is to develop a prediction tool for accurately estimating the service life of metallic components and hence provide economic benefits to industry partners of this project. To achieve this objective, we have proposed a user-oriented learning system framework, namely QBLs, for solving the problem of using the data mining models in a real-world situation where the user can not provide all the inputs with which the model is built. A practical prediction system is developed based on the QBLs framework, which provides high accuracy in practice where not all inputs are available for querying to the system.

6.7 References

- Aha, D. W., Kibler, D. and Albert, M. K., (1991) "Instance-Based Learning Algorithms," *Machine Learning*, vol. 6, pp. 37 - 66.
- Breiman, L., (1996) "Bagging Predictors," *Machine Learning*, vol. 24, pp. 123-140.
- Breiman, L., Friedman, J. H., Olshen, R. A. and Stone, C. J., (1984) "Classification and Regression Tree".
- Brence, J. R., and Brown, D. E., (2002) "Data mining corrosion from eddy current non-destructive tests," *Computers & Industrial Engineering*, vol. 43, pp. 821-840.
- Chapple, M., (2006) "Data Mining: An Introduction," vol. 2006.
- Cole, I.S., Ball, M., Carse, A., Chan, W. Y., Corrigan, P., Ganther, W., Muster, T., Paterson, D., Trinidad, G., Maher, M. L. and Liew, P.S, (2005) "Case-Based Reasoning in Construction and Infrastructure Projects - Final Report," 2002-059-B, March 2005.
- Cole, I.S., Trinidad, G., Bradbury, A., McFallen, S., Chen, S.-E., MacKee, J., Gilbert, D. and Shutt, G.(2004) "Final Report of Delphi study," CRC Report 2002-020-B.
- CRISP-DM, "Cross Industry Standard Process for Data Mining", 2003.
- Dunham, M. H., (2003) *Data mining introductory and advanced topics*: Upper Saddle River, NJ : Prentice Hall/Pearson Education.
- Fayyad, U. M. and Irani, K. B., (1992) "On the Handling of Continuous-Valued Attributes in Decision Tree Generation," *Machine Learning*, vol. 8, pp. 87—102.
- Fayyad, U. M., Piatetsky-Shapiro, G. and Smyth, P., (1995a) "From Data Mining to Knowledge Discovery: An Overview," in *Advances in Knowledge Discovery and Data Mining*, U. M. Fayyad, G. Piatetsky-Shapiro, P. Smyth, and R. Uthurusamy, Eds. Menlo Park: AAAI Press, pp. 1 - 34.

- Fayyad, U. M., Piatetsky-Shapiro, G. and Smyth, P., (1995b) "Bayesian Networks for Knowledge Discovery," in *Advances in Knowledge Discovery and Data Mining*, U. M. Fayyad, G. Piatetsky-Shapiro, P. Smyth, and R. Uthurusamy, Eds. Menlo Park: AAAI Press, pp. 273 - 305.
- Fayyad, U. M., Piatetsky-Shapiro, G. and Smyth, P., (1996a) "Knowledge discovery and data mining: towards a unifying framework," presented at Proceedings of the 2nd International Conference on Knowledge Discovery and Data Mining, Portland.
- Fayyad, U. M., Piatetsky-Shapiro, G., Smyth, P. and Uthurusamy, R., (1996b) *Advances in Knowledge Discovery and Data Mining*: AAAI Press.
- Furuta, H., Deguchi, T. and Kushida, M., (1995) "Neural network analysis of structural damage due to corrosion," presented at Proceedings of ISUMA - NAFIPS '95 The Third International Symposium on Uncertainty Modeling and Analysis and Annual Conference of the North American Fuzzy Information Processing Society.
- KamrunNahar, M., and Urquidi-Macdonald, M., (2005) "Data mining of experimental corrosion data using Neural Network," presented at 208th Meeting of the Electrochemical Society, Oct 16-21 2005, Los Angeles, CA, United States.
- Kantardzic, M. and Zurada, J. , (2005) *Next Generation of Data-Mining Applications*: Wiley-IEEE Press.
- KDnuggets, (2005) "Successful Data Mining Applications,".
- Kessler, W., Kessler, R. W., Kraus, M., Kubler, R. and Weinberger, K., (1994) "Improved prediction of the corrosion behaviour of car body steel using a Kohonen self organising map," presented at Advances in Neural Networks for Control and Systems, IEE Colloquium.
- Kurgan, L. A., Alberta, K. and Musilek, P., (2006) "A survey of Knowledge Discovery and Data Mining process models," *The Knowledge Engineering Review*, vol. 21, pp. 1 - 24.
- Leu, S.-S., Chen, C.-N. and Chang, S.-L., (2001) "Data mining for tunnel support stability: neural network approach," *Automation in Construction*, vol. 10, pp. 429-441.
- Melhem, H. G. and Cheng, Y. (2003) "Prediction of remaining service life of bridge decks using machine learning," *Journal of Computing in Civil Engineering*, vol. 17, pp. 1-9.
- Melhem, H. G., Cheng, Y., Kossler, D. and Scherschligt, D., (2003) "Wrapper Methods for Inductive Learning: Example Application to Bridge Decks," *Journal of Computing in Civil Engineering*, vol. 17, pp. 46-57.
- Melli, G., Zaiane, O.R., and Kitts, B. (2006) "Introduction to the special issue on successful real-world data mining applications," *SIGKDD Explor. Newsl.*, vol. 8, pp. 1-2.
- Mita, A. and Hagiwara, H., (2003) "Damage Diagnosis of a Building Structure Using Support Vector Machine and Modal Frequency Patterns," presented at Smart Structures and Materials 2003: Smart Systems and Nondestructive Evaluation for Civil Infrastructures, Mar 3-6 2003, San Diego, CA, United States.
- Morcous, G., Rivard, H., and Hanna, A. M., (2002a) "Case-Based Reasoning System for Modeling Infrastructure Deterioration," *Journal of Computing in Civil Engineering*, vol. 16, pp. 104-114.

- Morcous, G., Rivard, H., ASCE, A., Hanna, A.M., A. M. and ASCE, F., (2002b) "Modeling Bridge Deterioration Using Case-based Reasoning," *Journal of Infrastructure Systems*, vol. 8, pp. 86-95.
- Piatetsky-Shapiro, G., (1991) "Knowledge discovery in real databases: A report on the IJCAI-89 Workshop," *AI Magazine*, vol. 11, pp. 68 - 70.
- Quinlan, J. R., (1986) "Induction of decision trees," *Machine Learning*, vol. 1, pp. 81-106.
- Quinlan, J. R., (1992) "Learning with Continuous Classes," presented at 5th Australian Joint Conference on Artificial Intelligence.
- Quinlan, J. R., (1993) "Combining instance-based and model-based learning," presented at Proceedings of the Tenth International Conference on Machine Learning, Amherst, Massachusetts.
- Resampling and Stats, "Neural Networks Classification," vol. 2006, 2003.
- Skomorokhov, A. O., (2000) "A knowledge discovery method - APL implementation and application," presented at Proceedings of the APL Berlin 2000 Conference, Jul 24-27 2000, Berlin, Germany.
- Vapnik, V. N., (1995) *The Nature of Statistical Learning Theory*. New York: Springer-Verlag.

7. LIFE PREDICTION PROGRAM FOR BUILDING COMPONENTS

The data mining program with its user interface has been integrated into the GIS user interface that was implemented for the original phase of the project allowing for selection of any point in Queensland. This is illustrated in Figure 7.1.

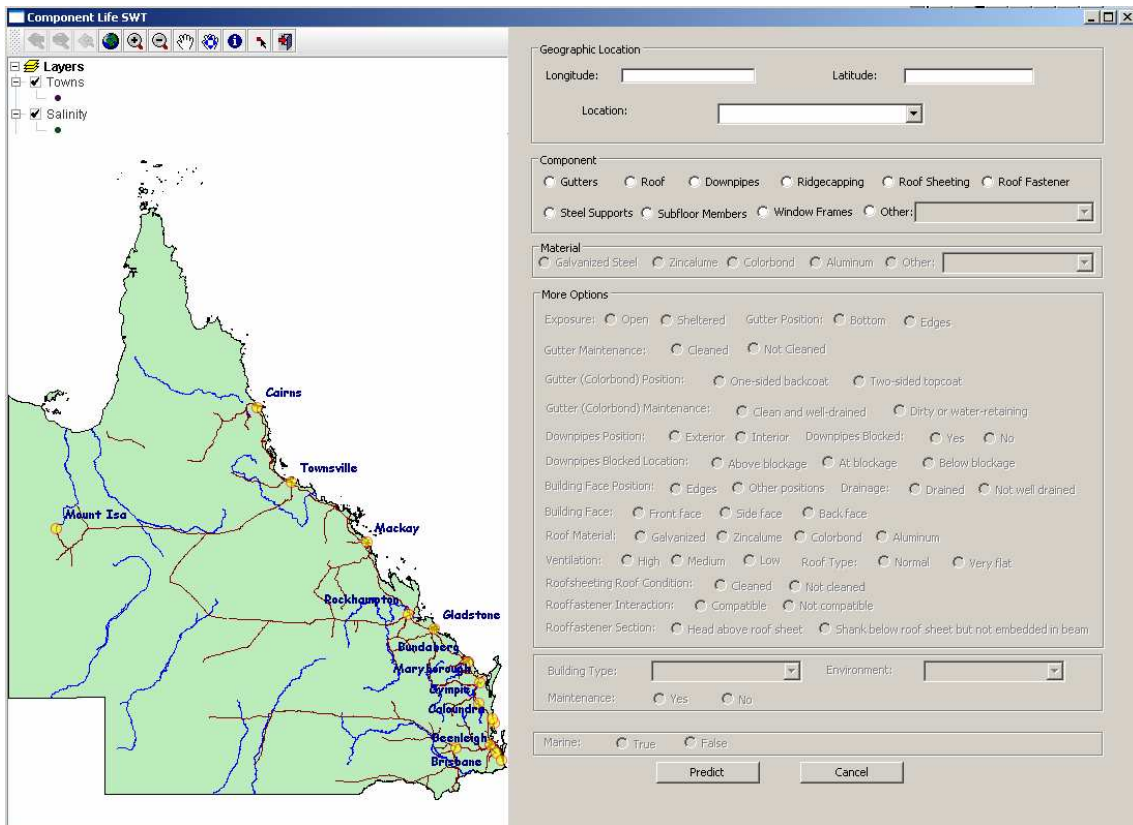


Figure 7.1. User interface for life prediction program for building components.

Thus the user can either enter a point in Queensland using the map (with zoom) feature or select a particular school. All current government schools in Queensland are listed in the pull-down menu. A brief overview of the options available in using the program is given in the following section but a more detailed explanation of the GIS feature and component selection is given in Appendix D.

7.1 Component Selection and Options

The new components added to the Holistic model database have been included for selection. These are the focus of the program. A dropdown menu to the right also allows selection of the building components included in the Delphi survey but not included in the expanded modelling. (Figure 7.2)

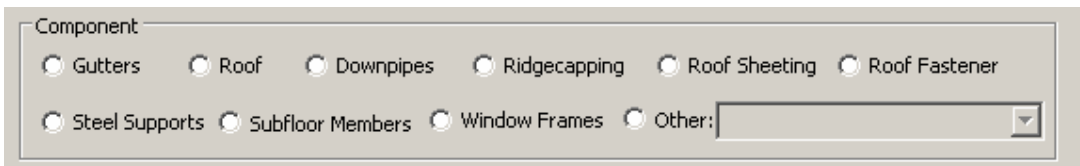


Figure 7.2. Panel for inputting choice of component

Designation of the component then allows selection of material with materials not relevant to the component remaining grey and unavailable (Figure 7.3).

Figure 7.3. Panel for selecting Material type – only those relevant to the selected component are available

Once the material has been selected then more options become available in the box beneath and choices must be entered. The options available reflect the likely environments for the particular components and the cases that have been modelled and form part of the Holistic data set (Figure 7.4). Selection of an option which limits the possibilities for other parameters will change the interface accordingly.

Figure 7.4. More Options panel only allows input of data relevant to selected component

If a component has been chosen that is included in the Delphi database then the next main box requests information necessary for retrieval of that information Figure 7.5. If the component is not available then that area of the input screen remains grey and can not be accessed.

Figure 7.5. Panel for information required for accessing Delphi data set

Similarly if Roof has been selected then this accesses the Previous dataset from Maintenance records, and the bottom panel becomes available and prompts for information (Figure 7.6).

Figure 7.6. Panel for Maintenance database information and the Predict button

Once all information has been entered, the user can select the 'Predict' button (Figure 7.6).and a dialog box appears with a number of predictions, depending on the number of databases that the component appears in. Delphi, Holistic-I and School Survey are the main sources with Roofs also accessing the previous data set from the earlier version of the program

| Name of Data | Predicted Life from MS+KNN Model (Years) |
|--------------|--|
| Holistic-I | 33.7376 |
| Survey Data | 44 |
| | |
| | |

Figure 7.7. How prediction data is presented

Failure to select one of required options results in the appearance of a warning dialog which prompts the user to select an option.

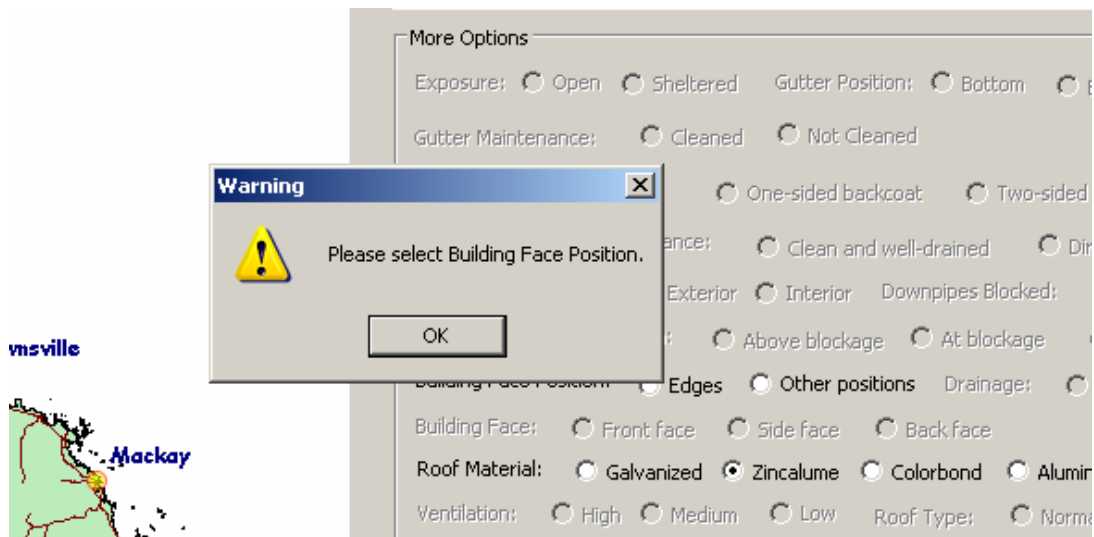


Figure 7.8 . Warning dialog box that appears if not all required information is selected

7.2 β – Testing of Software

Industry partners used the software and reported back on the usefulness of the program. It was generally felt to have the focus required. Some difficulties and bugs in the program were noted:

- The program gives up to three predictions for component life – sometimes with wide variation. Some method of presenting a more definitive result would be better eg a range, rather than specific year. (Holistic and Delphi results do not need the number of significant figures currently quoted).
- Roof and Roof Sheeting are synonymous and could be amalgamated. Roof only accesses the Maintenance database – the designation of Marine or Benign could be removed from the user and based on Annual Salt Deposition. Marine is > 30 units???
- Colorbond® can not be selected as a material for downpipes.
- Values returned for the Holistic data mining could be ‘gated’ with answers only given between 2 and 50 and outliers reported as <2 or >50 whichever is appropriate.
- The label on the service life in the Prediction life is not very meaningful for users- “Predicted Life from M5+KNN Model (Years)”. This could probably be changed to “Predicted Life (Years)”

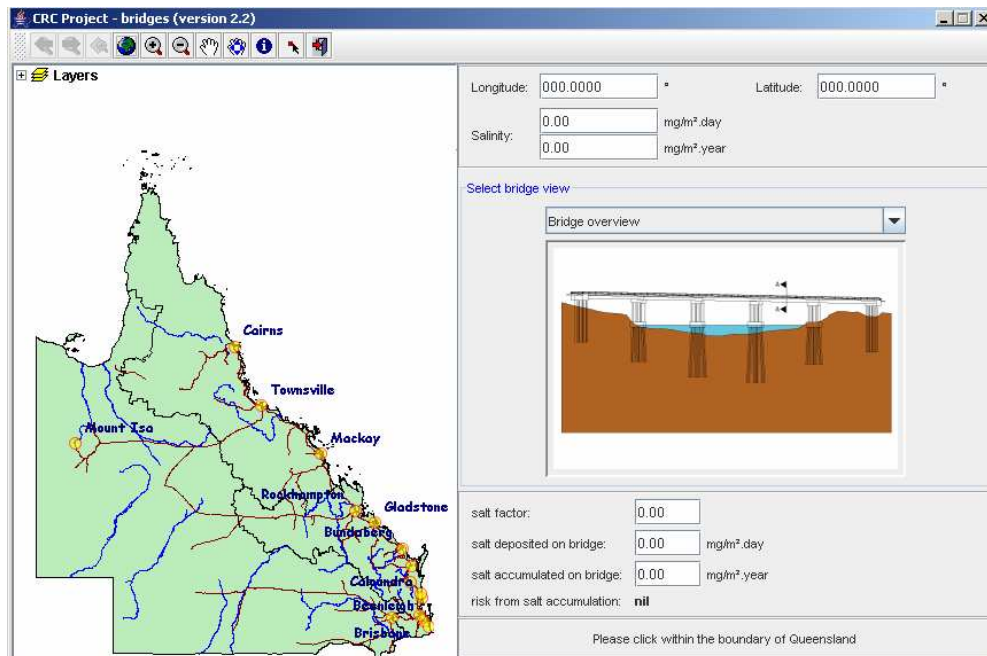
Overall the feedback was positive and useful and a workshop will be organised to show the software to a wider group of potential users.

Appendix A - User Guide for Bridges Program (V2,2007)

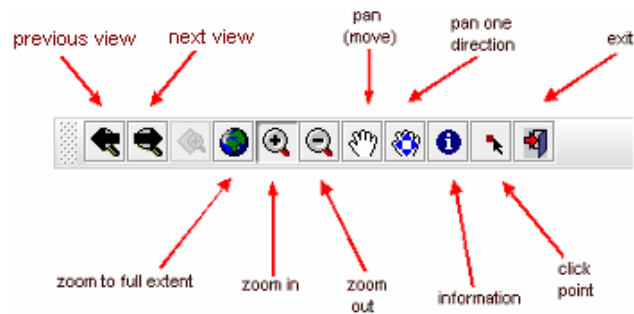
The user interface (GUI) for the Bridges program is very similar to the previous version. The information displayed in this version is slightly different. In this version the program calculates the salt accumulated by applying an accumulation factor onto the daily deposition rate, which takes into account the geometry of the bridge component and how much of accumulated salt will be removed by rainfall.





Running the program

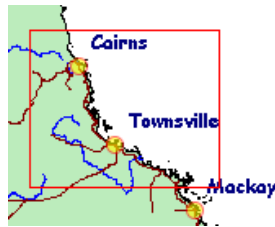
1. Copy the directory **bridges** from the CD to your computer C: or D: drive.
2. Double-click to open the **bridges** directory.
3. Double-click the file **Bridges.cmd** to run the program. A dos screen appears and moments later the bridge program with an initial screen as shown in the figure below appears.




4. Run the program by clicking any buttons on the toolbar shown below. The function of each button is explained in the diagram.




- a) If the map has been zoomed in and out several times, the previous  and next  buttons allows the user to move backward and forward to view previously zoomed level of the map.
- b) The third button has been *disabled*.
- c) The *fifth* button to the *tenth* button requires the user to click on the button ***first*** and then anywhere on the map.
- d) Moving the mouse cursor over a button to display its functionality.
- e) The fourth, fifth and sixth buttons have zoom functionalities. Zoom functions: *zoom-in*  and *zoom-out*  can be executed either by just clicking on the map or clicking and dragging over an area as shown in the figure below.




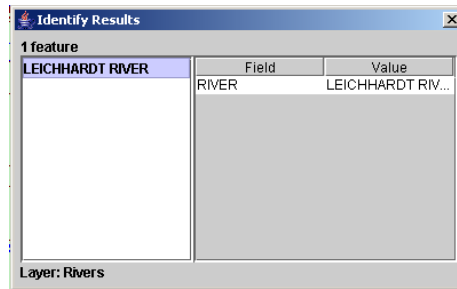
The zoom function *zoom-to-full-extent*  resets the content of the map viewer to its default zoom level.


- f) The *pan* function  moves the map in any one of the four directions shown in the figure below.




While the first *pan* function  follows the movement of the mouse cursor.

- g) The *identity* function  displays the underlying information (if any) at the point on the map where it is clicked.






- h) Click the button  followed by clicking anywhere on the map of Queensland. The *location coordinates* and the *daily* and *annual salinity* at the clicked point will be displayed.

| | | | | | |
|------------|---------|-------------------------|-----------|--------|---|
| Longitude: | 146.67 | ° | Latitude: | -20.23 | ° |
| Salinity: | 4.59 | mg/m ² .day | | | |
| | 1652.40 | mg/m ² .year | | | |

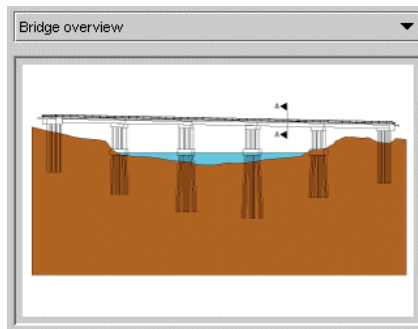
The point where the mouse was clicked is marked by the symbol  as shown in the figure below.



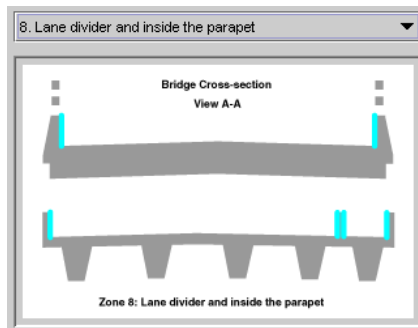
The shape of mouse cursor will change from an arrow  to a cross  if the area is clickable.

- i) The *exit* function  terminates the bridges program and cleans up.
5. The program allows the users to view different cross-sections of the bridge. There are nine different cross-sections of the bridge that can be analysed and the program is defaulted to display the complete view of the bridge on initial start-up.

a) complete view of the bridge



b) cross-section of the bridge

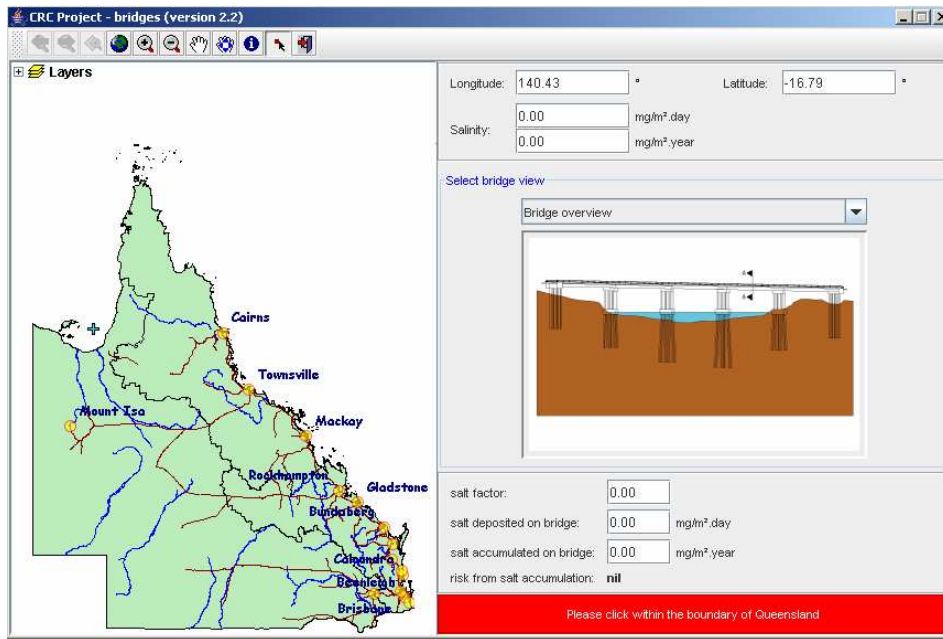


6. If one of the cross-section of the bridge is selected, the program displays the associated *salt factor* and calculated the *salt daily deposition* and *annual accumulation* on that section of the bridge. The risk associated with the levels of salt accumulation is also given in terms of very low, low, moderate, high and very high.

| | | |
|------------------------------|---|-------------------------|
| sat factor: | <input type="text" value="0.61"/> | |
| sat deposited on bridge: | <input type="text" value="9.66"/> | mg/m ² .day |
| sat accumulated on bridge: | <input type="text" value="2397.77"/> | mg/m ² .year |
| risk from salt accumulation: | Moderate (salt accumulation < 3000 mg/m².year) | |

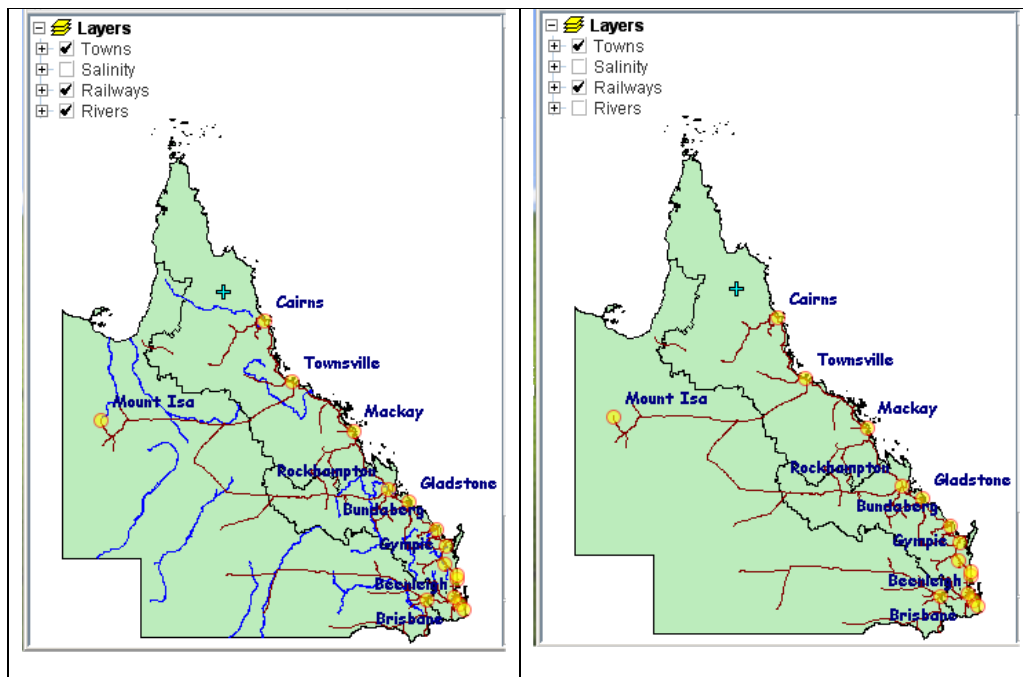
The bridge overview does not have any salt related information. If this is selected, the salt information is reset to zero (0).

7. If the point clicked is not within the boundary of Queensland the program resets all information (except the coordinates of the clicked point) located on the right side of the screen.



The salinity information of the clicked location displayed at the top of the screen is reset to zero (0). The error panel at the bottom of the screen will be highlighted in red with a warning message. The bridge view panel will be reset displaying the overview of the bridge instead and the associated salinity information reset to zero.

- The information on the map can be altered by toggling a layer on or off. For example, the figure below on the left displays the Towns, Railways and River layers while on the right only the Towns and Railways layers are displayed.



Appendix B - EIS Testing of Exposed Colorbond® Panels

The following data was obtained by testing the current status of gutters at various field locations using a portable EIS analysis.

Brookfield State School, Qld.

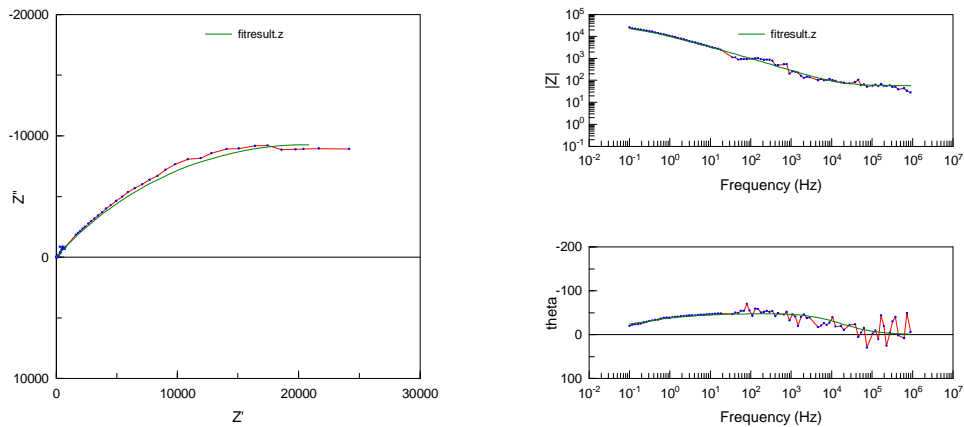
Latitude: 27°29'42.74S

Longitude: 152°54'47.87E

Product: Colorbond backcoat

Age: 7 years.

| | Rs(+) | Cc(+) | Rc(+) | CPE1-T(+) | CPE1-P(+) | Rp(+) | Estimated Icorr (A cm-2) |
|------------|-------|----------|-------|-----------|-----------|-------|--------------------------|
| Brookfield | 58.44 | 1.38E-07 | 3.508 | 3.07E-05 | 0.5352 | 41384 | 7.59132E-06 |



FigureB1. Left: Nyquist plot, Right (top): Bode plot, Right (bottom): Phase plot.

Chapel Hill State School, Qld.

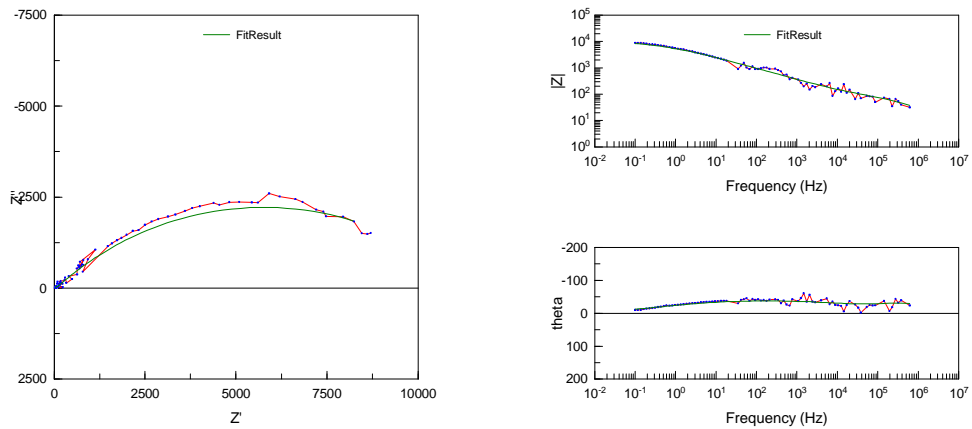
Latitude: 27°29'58.20S

Longitude: 152°56'37.69E

Product: Colorbond backcoat

Age: 29 years.

| | Rs(+) | Cc(+) | Rc(+) | CPE1-T(+) | CPE1-P(+) | Rp(+) | Estimated Icorr (A cm-2) |
|----------------|-------|----------|-------|-----------|-----------|-------|--------------------------|
| Chapel Hill SS | 24.28 | 1.03E-08 | 35.24 | 4.87E-05 | 0.47193 | 11412 | 2.75289E-05 |



FigureB2. Left: Nyquist plot, Right (top): Bode plot, Right (bottom): Phase plot.

Monitored house, Townsville, Qld.

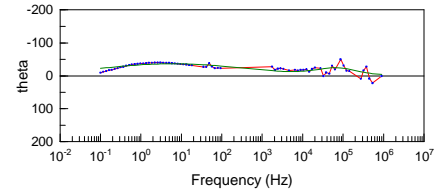
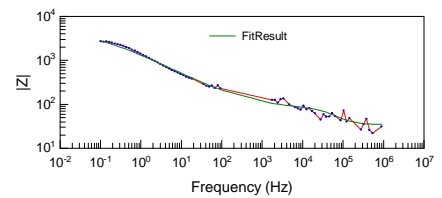
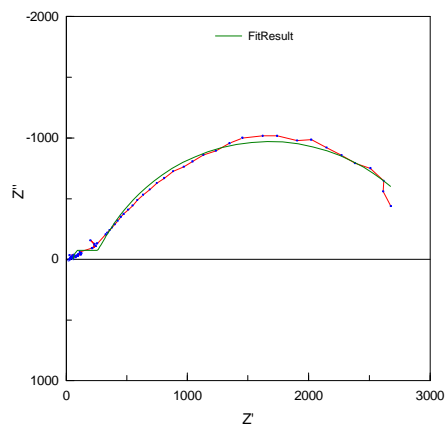
Latitude: 19°15'16.37S

Longitude: 146°48'54.34E

Product: Colorbond backcoat

Age: 5 years.

| | Rs(+) | Cc(+) | Rc(+) | CPE1-T(+) | CPE1-P(+) | Rp(+) | Estimated Icorr (A cm-2) |
|-----------------|-------|----------|-------|-----------|-----------|-------|--------------------------|
| Michelles house | 34.84 | 7.08E-08 | 45.35 | 0.000255 | 0.50704 | 5045 | 6.22714E-05 |



FiguresB3. Left: Nyquist plot, Right (top): Bode plot, Right (bottom): Phase plot.

Payne Road State School, Brisbane, Qld.

Latitude: 27°26'53.51S

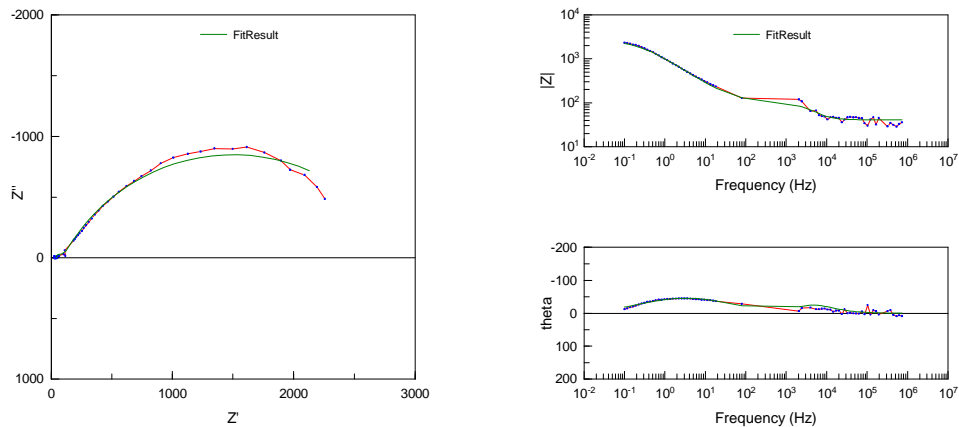
Longitude: 152°57'05.81E

Product: Colorbond backcoat

Age: 9 years.

State: Near the down pipe of a gutter full of leaves. Wet for the majority of time. There was visible damage to the backcoat, with approximately 30 % coating loss.

| | Rs(+) | Cc(+) | Rc(+) | CPE1-T(+) | CPE1-P(+) | Rp(+) | Estimated Icorr (A cm-2) |
|------------|-------|----------|-------|-----------|-----------|-------|--------------------------|
| Payne Road | 40.82 | 8.49E-07 | 56.55 | 0.00024 | 0.69072 | 2807 | 0.00011192 |



FigureB4. Left: Nyquist plot, Right (top): Bode plot, Right (bottom): Phase plot.

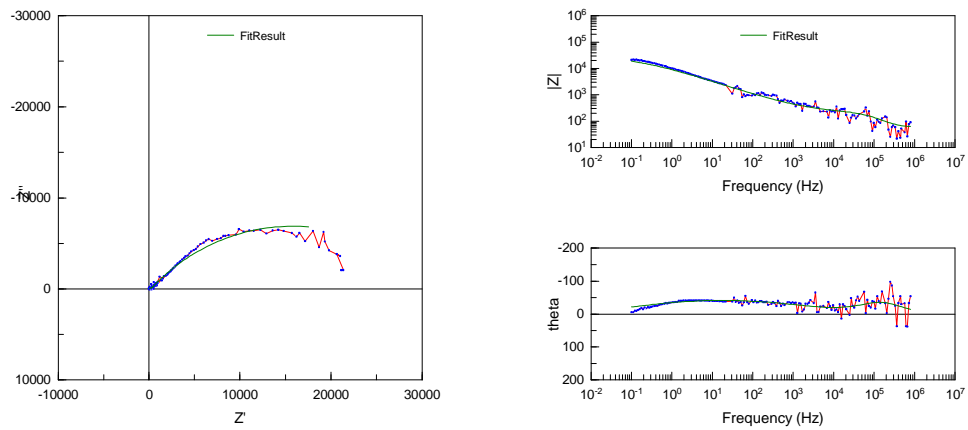
Sandringham College Highett Campus, Vic

Product: Colorbond backcoat

Age: 20 years.

State: ½" of leaf litter. Wet prior to testing.

| | Rs(+) | Cc(+) | Rc(+) | CPE1-T(+) | CPE1-P(+) | Rp(+) | Estimated Icorr (A cm-2) |
|--------------|-------|----------|-------|-----------|-----------|-------|--------------------------|
| Sandringham1 | 58.82 | 1.26E-08 | 147.8 | 3.39E-05 | 0.52814 | 31268 | 1.00473E-05 |



FigureB5. Left: Nyquist plot, Right (top): Bode plot, Right (bottom): Phase plot.

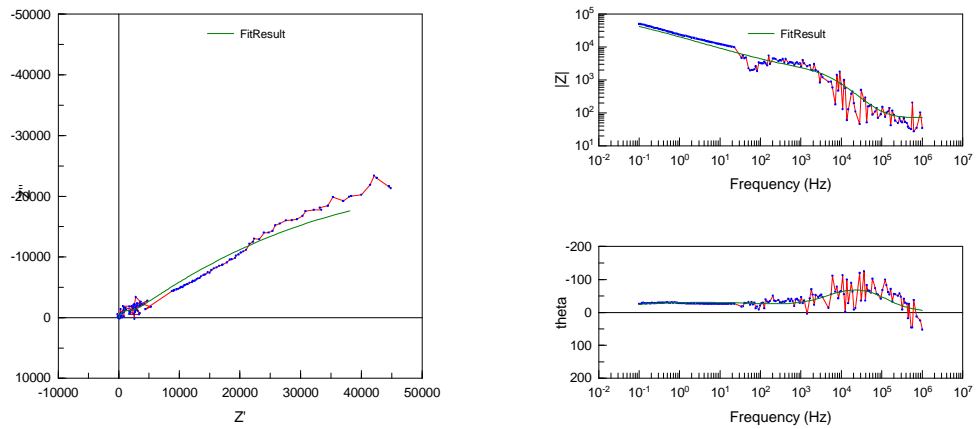
Sandringham College Highett Campus, Vic

Product: Colorbond backcoat

Age: 20 years.

State: No leaf litter, well drained.

| | Rs(+) | Cc(+) | Rc(+) | CPE1-T(+) | CPE1-P(+) | Rp(+) | Estimated Icorr (A cm-2) |
|--------------|-------|----------|-------|-----------|-----------|----------|--------------------------|
| Sandringham2 | 71.66 | 1.91E-08 | 1517 | 2.13E-05 | 0.41606 | 1.21E+05 | 2.59851E-06 |



FigureB6. Left: Nyquist plot, Right (top): Bode plot, Right (bottom): Phase plot.

Sandringham College Highett Campus, Vic

Latitude: 37°57'03.12S

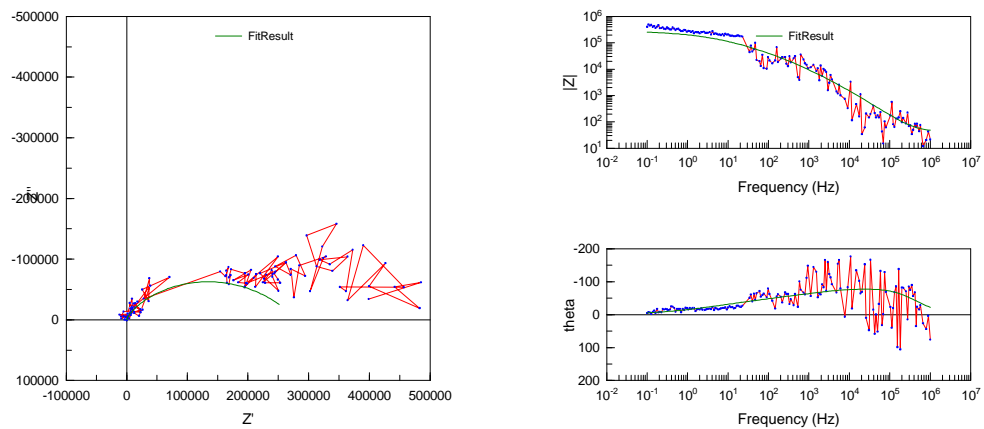
Longitude: 145°01'18.50E

Product: Colorbond backcoat

Age: 1 years.

State: Leaf litter (eucalyptus), wet.

| | Rs(+) | Cc(+) | Rc(+) | CPE1-T(+) | CPE1-P(+) | Rp(+) | Estimated Icorr (A cm-2) |
|--------------|-------|----------|-------|-----------|-----------|----------|--------------------------|
| Sandringham3 | 44.59 | 8.25E-09 | 51.58 | 6.92E-07 | 0.51146 | 2.81E+05 | 1.11872E-06 |



FigureB7. Left: Nyquist plot, Right (top): Bode plot, Right (bottom): Phase plot.

Sunshine Beach State School, Sunshine Coast, Qld.

Latitude: 26°24'07.90S

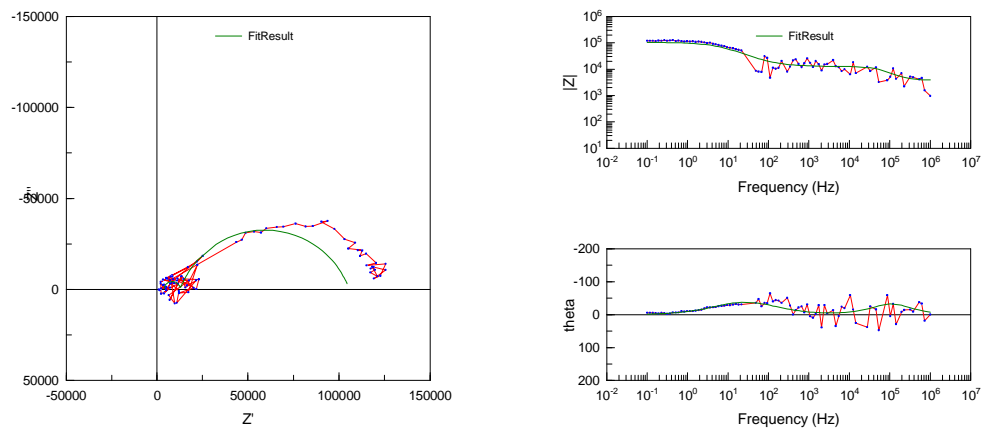
Longitude: 153°06'04.87E

Product: Colorbond topcoat

Age: 16 years.

State: Leaf litter, damp.

| | Rs(+) | Cc(+) | Rc(+) | CPE1-T(+) | CPE1-P(+) | Rp(+) | Estimated Icorr (A cm-2) |
|----------------|-------|----------|-------|-----------|-----------|-------|--------------------------|
| Sunshine Beach | 3846 | 3.02E-10 | 8837 | 5.70E-07 | 0.77946 | 93045 | 3.37642E-06 |



FigureB8. Left: Nyquist plot, Right (top): Bode plot, Right (bottom): Phase plot.

The Willows State School, Townsville, Qld.

Latitude: 19°18'16.41 S

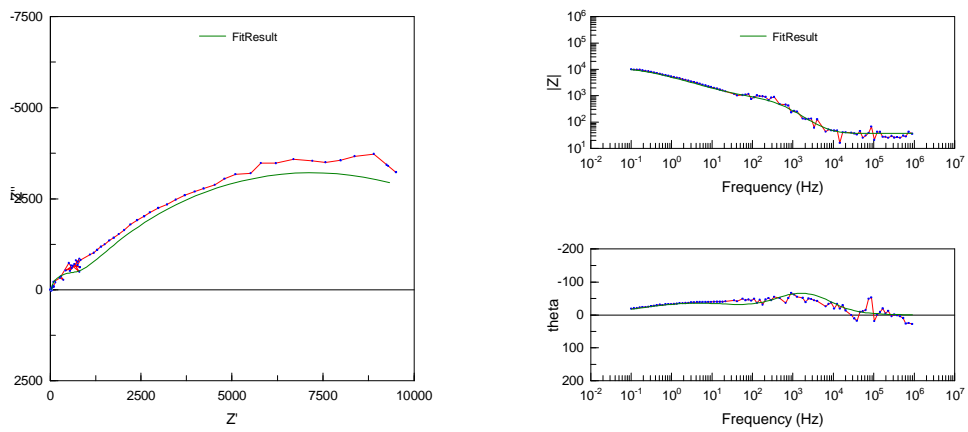
Longitude: 146°43'18.58 E

Product: Colorbond backcoat

Age: 10 years.

State: Leaf litter, dry.

| | Rs(+) | Cc(+) | Rc(+) | CPE1-T(+) | CPE1-P(+) | Rp(+) | Estimated Icorr (A cm-2) |
|--------------------|-------|----------|-------|-----------|-----------|-------|--------------------------|
| The Willows leaves | 36.68 | 5.72E-07 | 704.8 | 5.87E-05 | 0.57612 | 13066 | 2.4044E-05 |



FigureB9. Left: Nyquist plot, Right (top): Bode plot, Right (bottom): Phase plot.

Site 1 – Naval Base (Flinders)

Latitude: 38°28'58.78 S

Longitude: 145°01'07.41 E

B5

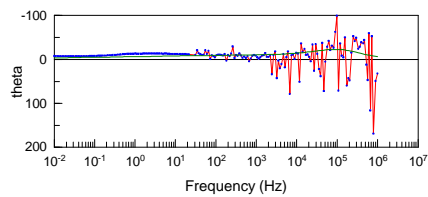
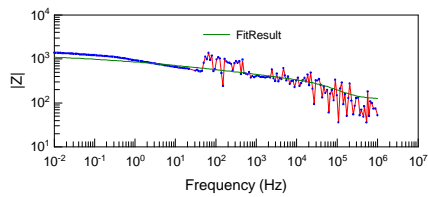
Site 1

10 years

Sheltered

Backcoat

| | Rs(+) | Cc(+) | Rc(+) | CPE1-T(+) | CPE1-P(+) | Rp(+) | Estimated Icorr (A cm-2) |
|---------|-------|----------|----------|-----------|-----------|-------|--------------------------|
| B5110Sb | 125 | 1.05E-08 | 9.82E-05 | 0.000401 | 0.19943 | 1241 | 0.00025315 |





Site 3 – CSIRO (Highett)

Latitude: 37°56'58.43 S

Longitude: 145°02'25.67 E

B535Sb

Colorbond B5

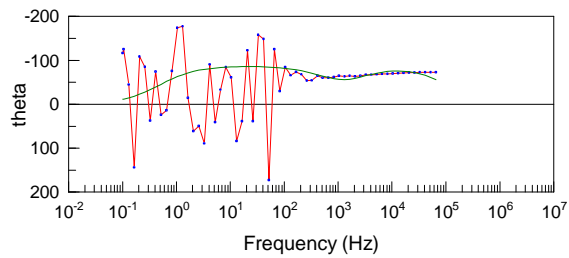
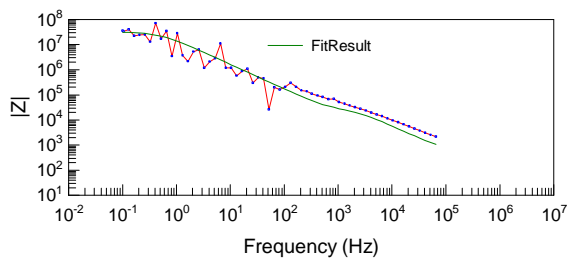
Site3

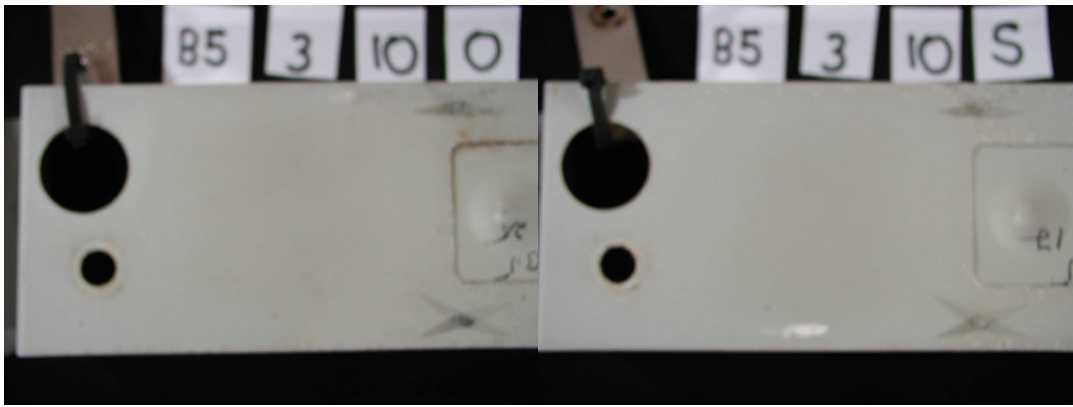
5 years

Sheltered/Open

Backcoat

| | Rs(+) | Cc(+) | Rc(+) | CPE1-T(+) | CPE1-P(+) | Rp(+) | Estimated Icorr (A cm-2) |
|--------|-------|----------|-------|-----------|-----------|----------|--------------------------|
| B535Sb | 279.2 | 1.25E-09 | 8219 | 1.80E-08 | 0.7548 | 6.32E+06 | 4.97127E-08 |
| B535Ob | 573.4 | 2.74E-09 | 36140 | 7.63E-09 | 0.97904 | 3.17E+07 | 9.90726E-09 |





Appendix C – Delphi Database

In an earlier CRC-CI project, a Delphi survey was conducted to provide expert opinion on the life of metallic building components (Cole at al, 2004a). A Delphi survey is a structured group interaction process that is directed in 'rounds' of opinion collection and feedback. Opinion collection is achieved by conducting a series of surveys using questionnaires. Thirty different components were included in the survey, chosen to be representative of the wider range of components in the same building environments. A range of materials, coatings, environments and failure modes relevant to the components were considered. Thus, the survey included both service life (with and without maintenance) and aesthetic life, and time to first maintenance. It included marine, industrial and benign environments, and covered both commercial and residential buildings.

The primary respondents to the survey were professionals, such as builders and architects, selected on the basis of their practical experience and theoretical knowledge. Building material suppliers were also invited to participate in the survey for their intimate knowledge of their specific products. Academics and scientist were also included because it is believed that they understand scientific principles in areas that are related to material durability, and so their expertise was relevant to the construction of a durability model.

The survey was conducted in two stages. In the first stage, there were a total of 66 responses, with the number of the responses to each of the survey parts ranging from 9 to 18. The questions were placed in four classes depending on the degree of consensus in responses to the particular question. The classification is illustrated in Figure C.1 where a) shows a class 1 response with >50% of respondents agreeing on a predicted life range, and b) shows a class 4 response, with virtually no agreement between respondents

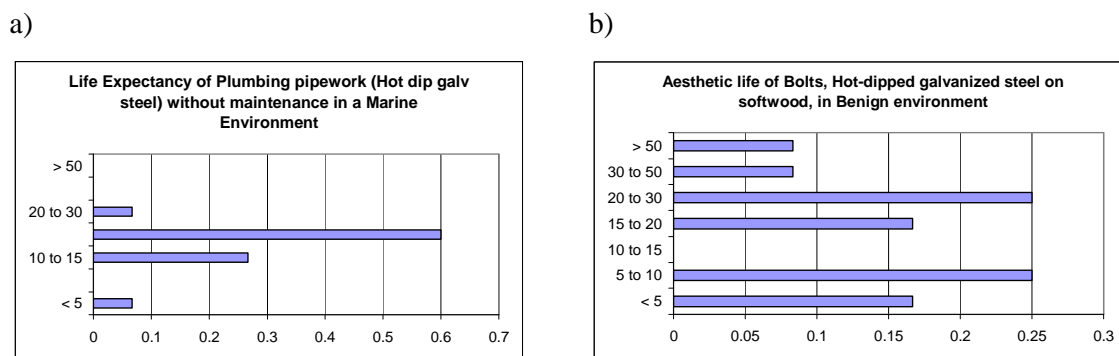


Figure C.1. Illustration of two of the classes of response in the Delphi survey a) class 1, b) class 4

After the first stage, approximately 80% of questions had a consistent answer from the survey group. In Stage 2, 10% of questions were further investigated, with 75% of these remaining questions then having a consistent answer. The responses to each question were analysed to give a mode (most frequent interval), a mean value and a standard deviation of the mean, and these were tabulated in the database.

The final database was examined in three ways to determine its accuracy and reliability. These were analyses for internal consistency of the data, for consistency with expected trends based on knowledge of materials performance and environmental severity, and for correlation with existing databases on component performance. In all cases, the Delphi survey data appear reliable.

The components included in the Delphi survey are listed below, classified into the microclimates positions (Table C1)

Table C1 Components and environments used in Delphi Survey

| Microclimate | Component |
|-----------------------------|-----------------------------------|
| Fully exposed – external | roof sheeting |
| | Flashings |
| | Gutters |
| | wall cladding |
| Partially exposed – facades | windows -frames -all types (e.g.) |
| | awning |
| | doors |
| | bolts |
| | nails |
| | lintels |
| Roof space | sarking |
| | roof strap – storm fixing |
| | purlins |
| | gang nails |
| Wall cavity | purlins/girts |
| | bracing |
| | nails |
| | brick ties |
| | bolts |
| Subfloor | plumbing pipework |
| | metal deck for concrete floor |
| | universal section |
| | pile |
| Internal | bathroom taps |
| | laundry sink |
| | bathroom sink |
| | door handle |
| | curtain rail |
| | suspended ceiling -support |
| | air grilles |
| stairs | |

Other Attributes and their possible values are also shown in Table C2.

Table C2 Other Attributes assessed in Delphi Survey

| Attribute Name | Values |
|----------------|--|
| Building type | Commercial, Residential |
| Measure | Service Life, Aesthetic Life |
| Environment | Benign, Industrial, Marine |
| Material | Aluminium, Galvanised Steel, Zinalume, Colorbond, Powder coated Aluminium, Stainless Steel, Polished Bras, Copper, Lead, Hot-dipped galvanized, coated steel, anodized aluminium |
| Maintenance | Yes / No |

Table C.3 Example of entries in Delphi Database

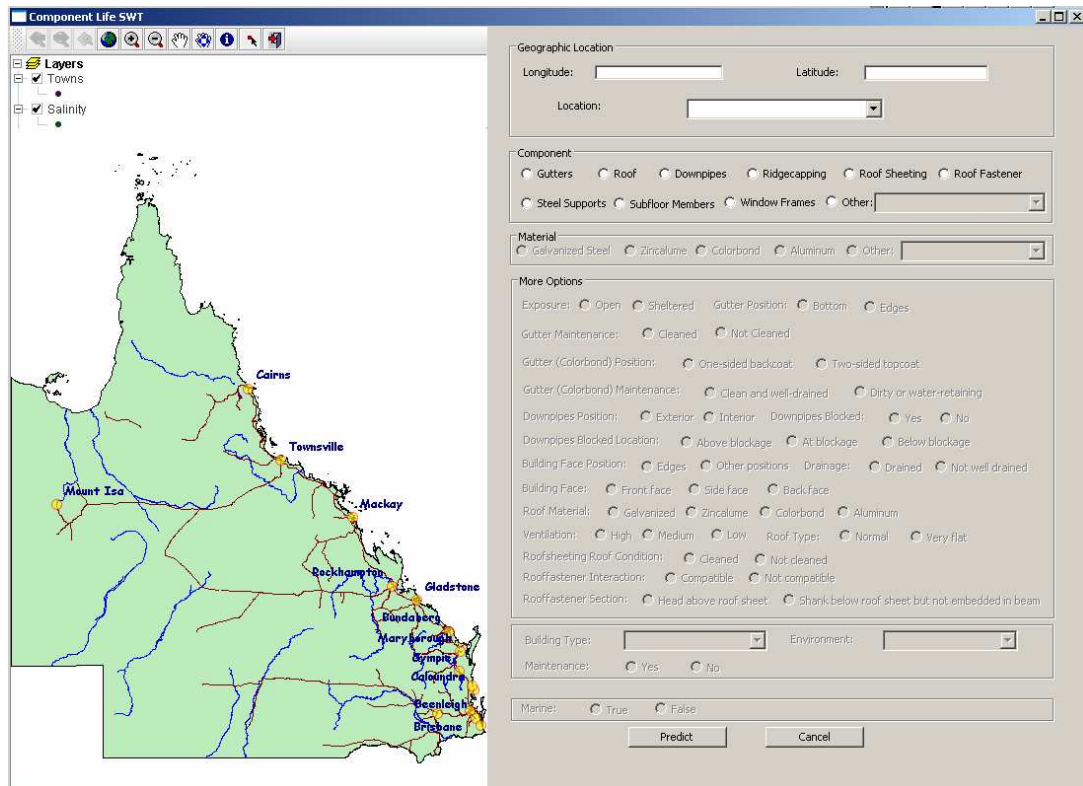
| Building Type | Component | Measure | Environment | Material | Maintenance | Mode (years) | SD (years) | Mean (Years) | Criteria |
|----------------------|------------------|---------------------------|--------------------|------------------|--------------------|---------------------|-------------------|---------------------|-----------------|
| Commercial | Gutters | Service Life | Marine | Galvanised Steel | No | 5-10 | 5 | 9 | 2 |
| Commercial | Gutters | Time to First Maintenance | Marine | Galvanised Steel | Yes | <5 | 4 | 6 | 2 |
| Commercial | Gutters | Aesthetic Life | Marine | Galvanised Steel | Yes | 10-15 | 6 | 11 | 2 |
| Commercial | Gutters | Service Life | Industrial | Galvanised Steel | Yes | 10-15 | 9 | 15 | 2 |
| Commercial | Gutters | Service Life | Industrial | Galvanised Steel | No | 5-10 | 5 | 10 | 2 |
| Commercial | Gutters | Time to First Maintenance | Industrial | Galvanised Steel | Yes | 5-10 | 5 | 8 | 2 |
| Commercial | Gutters | Aesthetic Life | Industrial | Galvanised Steel | Yes | 5-10 | 6 | 10 | 2 |
| Commercial | Gutters | Service Life | Benign | Galvanised Steel | Yes | 30-50 | 16 | 32 | 2 |
| Commercial | Gutters | Time to First Maintenance | Benign | Galvanised Steel | Yes | 10-15 | 15 | 17 | 2 |
| Commercial | Gutters | Aesthetic Life | Benign | Galvanised Steel | Yes | 20-30- | 13 | 22 | 2 |
| Commercial | Gutters | Service Life | Marine | Colorbond® | No | 5-10 | 12 | 18 | 2 |
| Commercial | Gutters | Time to First Maintenance | Marine | Colorbond® | Yes | 5-10 | 7 | 10 | 2 |
| Commercial | Gutters | Service Life | Industrial | Colorbond® | Yes | 15-20 | 14 | 26 | 2 |
| Commercial | Gutters | Service Life | Industrial | Colorbond® | No | 10-15 | 12 | 21 | 2 |
| Commercial | Gutters | Time to First Maintenance | Industrial | Colorbond® | Yes | 5-10 | 7 | 12 | 2 |
| Commercial | Gutters | Aesthetic Life | Industrial | Colorbond® | Yes | 15-20 | 10 | 17 | 2 |
| Commercial | Gutters | Service Life | Benign | Colorbond® | Yes | 30-50 | 16 | 36 | 2 |
| Commercial | Gutters | Service Life | Benign | Colorbond® | No | 30-50 | 16 | 35 | 2 |
| Commercial | Gutters | Aesthetic Life | Benign | Colorbond® | Yes | 30-50 | 14 | 29 | 2 |
| Commercial | Gutters | Service Life | Marine | Zincalume | No | 10-15 | 11 | 15 | 2 |
| Commercial | Gutters | Time to First Maintenance | Marine | Zincalume | Yes | 5-10 | 8 | 10 | 2 |
| Commercial | Gutters | Service Life | Industrial | Zincalume | Yes | 15-20 | 10 | 24 | 2 |

Appendix D User Guide for Life Prediction Program

Loading and Opening Program

Load installer onto computer and run installation. (If the computer already has Java installed this may cause an error message unless the most recent version is available. This version can be freely downloaded from java.com)

Go to the directory that the installer has loaded the program into and run CRC program. The following user interface appears (it may take several minutes).



Choosing Location

The desired location in Queensland can be selected in two ways:

1. In the Location box a dropdown menu has all the Queensland schools available for selection. Selecting a school fills in the appropriate Longitude and Latitude coordinates.

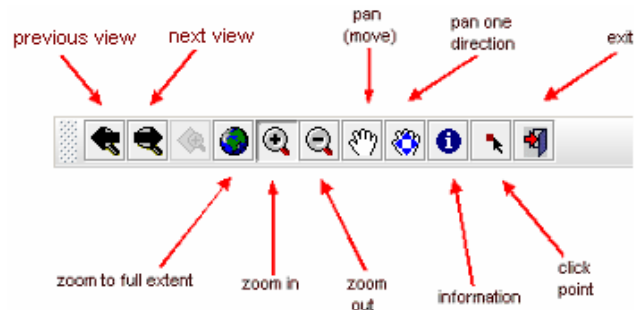
Geographic Location





Longitude: Latitude:

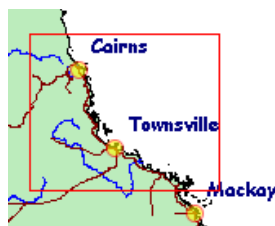
Location:

- The GIS on the left hand side of the screen can be used to select a point on the map of Queensland.


Run the program by clicking any buttons on the toolbar shown below. The function of each button is explained in the diagram.




- If the map has been zoomed in and out several times, the previous  and next  buttons allows the user to move backward and forward to view previously zoomed level of the map.
- The third button has been *disabled*.
- The *fifth* button to the *tenth* button requires the user to click on the button *first* and then anywhere on the map.
- Moving the mouse cursor over a button to display its functionality.
- The fourth, fifth and sixth buttons have zoom functionalities. Zoom functions: *zoom-in*  and *zoom-out*  can be executed either by just clicking on the map or clicking and dragging over an area as shown in the figure below.




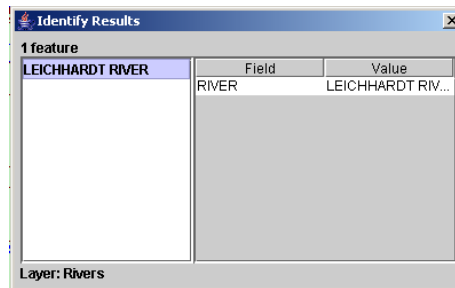
The zoom function *zoom-to-full-extent*  resets the content of the map viewer to its default zoom level.


- f. The *pan* function  moves the map in any one of the four directions shown in the figure below.



While the first *pan* function  follows the movement of the mouse cursor.

- g. The *identity* function  displays the underlying information (if any) at the point on the map where it is clicked.




- h. Click the button  followed by clicking anywhere on the map of Queensland. The *location coordinates* at the clicked point will be displayed in the Geographic Location box.



Geographic Location

Longitude: Latitude:

Location:

The point where the mouse was clicked is marked by the symbol  as shown in the figure below.



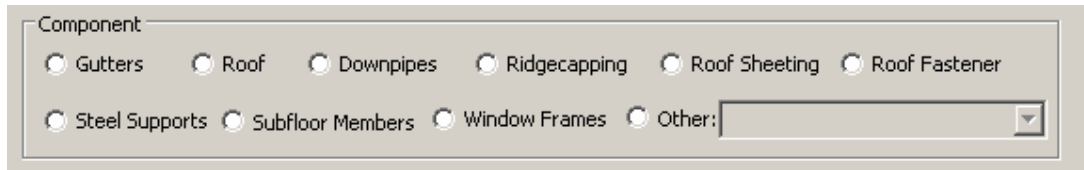
The shape of mouse cursor will change from an arrow  to a cross  if the area is clickable.

- i. The *exit* function  terminates the component program and cleans up.

(If a school has been selected and the GIS is used to choose a point, the school name does not disappear but the coordinates are overridden.)

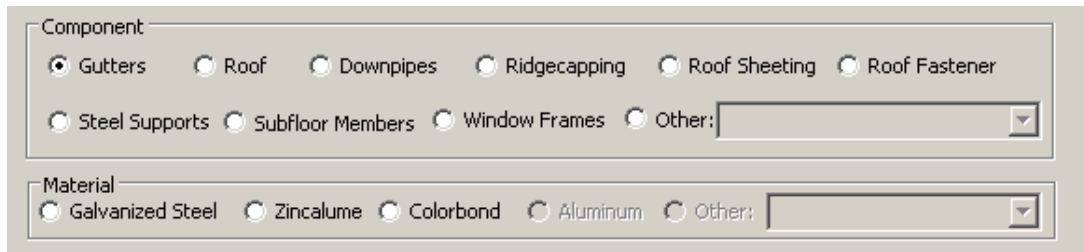
Component and Option Selection

The new components added to the Holistic model database have been included for selection. These are the focus of the program. A dropdown menu to the right also allows selection of the building components included in the Delphi survey but not included in the expanded modelling.



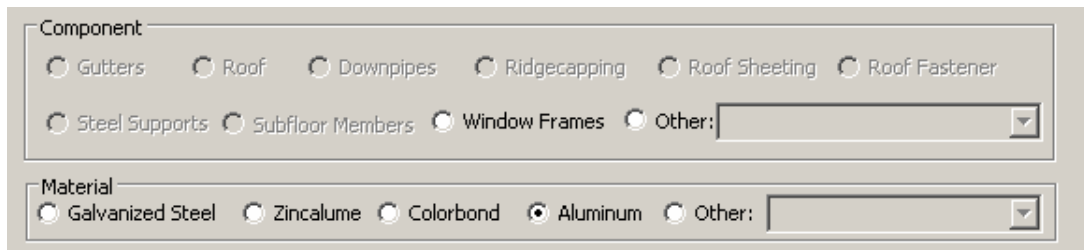
A screenshot of a software interface for component selection. It features a section titled "Component" with a list of radio buttons: Gutters, Roof, Downpipes, Ridgescaping, Roof Sheeting, Roof Fastener, Steel Supports, Subfloor Members, Window Frames, and Other: [dropdown menu]. All radio buttons are currently unselected.

Designation of the component then allows selection of material with materials not relevant to the component remaining grey and unavailable. Eg gutters are only considered in Galvanized steel, Zinalume and Colorbond.



A screenshot of the software interface showing both component and material selection. In the "Component" section, "Gutters" is selected. In the "Material" section, "Galvanized Steel" is selected. Other materials like "Zinalume" and "Colorbond" are visible but appear greyed out.

However, once a Material has been selected the other materials do become available. Changing the selection to a material not relevant to the chosen component will void that selection and the components available for that material are presented as options. Eg, selection of Material: Aluminium only presents Window Frames and Other for selection.



A screenshot of the software interface showing "Aluminum" selected in the "Material" section. In the "Component" section, "Window Frames" and "Other:" are now selected, while other components like "Gutters" and "Roof" are greyed out.

Once the component and material have been selected then more options become available in the box beneath and choices must be entered. The options available reflect the likely

environments for the particular components and the cases that have been modelled and form part of the Holistic data set.

The image shows a software interface with three main sections: Component, Material, and More Options. Each section contains radio buttons for selection and dropdown menus for 'Other' categories.

- Component:** Radio buttons for Gutters, Roof, Downpipes, Ridgescaping, Roof Sheeting, Roof Fastener, Steel Supports (selected), Subfloor Members, Window Frames, and Other: [dropdown].
- Material:** Radio buttons for Galvanized Steel, Zincalume (selected), Colorbond, Aluminum, and Other: [dropdown].
- More Options:** A collection of radio buttons for various parameters:
 - Exposure: Open, Sheltered
 - Gutter Position: Bottom, Edges
 - Gutter Maintenance: Cleaned, Not Cleaned
 - Gutter (Colorbond) Position: One-sided backcoat, Two-sided topcoat
 - Gutter (Colorbond) Maintenance: Clean and well-drained, Dirty or water-retaining
 - Downpipes Position: Exterior, Interior
 - Downpipes Blocked: Yes, No
 - Downpipes Blocked Location: Above blockage, At blockage, Below blockage
 - Building Face Position: Edges, Other positions
 - Drainage: Drained, Not well drained
 - Building Face: Front face, Side face, Back face
 - Roof Material: Galvanized, Zincalume, Colorbond, Aluminum
 - Ventilation: High, Medium, Low
 - Roof Type: Normal, Very flat
 - Roofsheeting Roof Condition: Cleaned, Not cleaned
 - Rooffastener Interaction: Compatible, Not compatible
 - Rooffastener Section: Head above roof sheet, Shank below roof sheet but not embedded in beam

Exposure has two options: open and sheltered. A sheltered environment where the component is not exposed to rain allows the build up of salt and is a more corrosive environment.

Building Face Position relates to where on the face of the building the component is situated, the edges experience a different environment from other positions on the face.

Drainage (for steel supports) relates to the construction and whether the ground installation is sloped for drainage.

If a selection is made that negates previous choices then that option will be removed (go grey). For example the cases designated for window frames are shown in the following table.

| Case | Building Face | Exposure | Face Position | Drainage |
|------|---------------|-----------|-----------------|-------------|
| 1 | front | open | other positions | drained |
| 2 | | | | not drained |
| 3 | side | | | drained |
| 4 | | | | not drained |
| 5 | back | | | drained |
| 6 | | | | not drained |
| 7 | front | sheltered | edges | drained |
| 8 | | | other positions | |
| 9 | side | | edges | |
| 10 | | | other positions | |
| 11 | back | | edges | |
| 12 | | | other positions | |

It will be seen that although there are two exposure options, the *sheltered* alternative does not allow *not drained*, and the *open* exposure does not allow *edge* positions. If *not drained* is selected – the options for *exposure* and *Building Face Position* are removed.

Component

Gutters
 Roof
 Downpipes
 Ridgescaping
 Roof Sheeting
 Roof Fastener
 Steel Supports
 Subfloor Members
 Window Frames
 Other:

Material

Galvanized Steel
 Zincalume
 Colorbond
 Aluminum
 Other:

More Options

Exposure: Open Sheltered
Gutter Position: Bottom Edges
Gutter Maintenance: Cleaned Not Cleaned
Gutter (Colorbond) Position: One-sided backcoat Two-sided topcoat
Gutter (Colorbond) Maintenance: Clean and well-drained Dirty or water-retaining
Downpipes Position: Exterior Interior
Downpipes Blocked: Yes No
Downpipes Blocked Location: Above blockage At blockage Below blockage
Building Face Position: Edges Other positions
Drainage: Drained Not well drained
Building Face: Front face Side face Back face
Roof Material: Galvanized Zincalume Colorbond Aluminum
Ventilation: High Medium Low
Roof Type: Normal Very flat
Roofsheeting Roof Condition: Cleaned Not cleaned
Rooffastener Interaction: Compatible Not compatible
Rooffastener Section: Head above roof sheet Shank below roof sheet but not embedded in beam

Component

Gutters
 Roof
 Downpipes
 Ridgecapping
 Roof Sheeting
 Roof Fastener
 Steel Supports
 Subfloor Members
 Window Frames
 Other: Railings

Material

Galvanized Steel
 Zincalume
 Colorbond
 Aluminum
 Other:

More Options

Exposure: Open Sheltered
Gutter Position: Bottom Edges
Gutter Maintenance: Cleaned Not Cleaned
Gutter (Colorbond) Position: One-sided backcoat Two-sided topcoat
Gutter (Colorbond) Maintenance: Clean and well-drained Dirty or water-retaining
Downpipes Position: Exterior Interior
Downpipes Blocked: Yes No
Downpipes Blocked Location: Above blockage At blockage Below blockage
Building Face Position: Edges Other positions
Drainage: Drained Not well drained
Building Face: Front face Side face Back face
Roof Material: Galvanized Zincalume Colorbond Aluminum
Ventilation: High Medium Low
Roof Type: Normal Very flat
Roofsheeting Roof Condition: Cleaned Not cleaned
Rooffastener Interaction: Compatible Not compatible
Rooffastener Section: Head above roof sheet Shank below roof sheet but not embedded in beam

If a component has been chosen that is included in the Delphi database then the next main box requests information necessary for retrieval of that information. If the component is not available then that area of the input screen remains grey and can not be accessed.

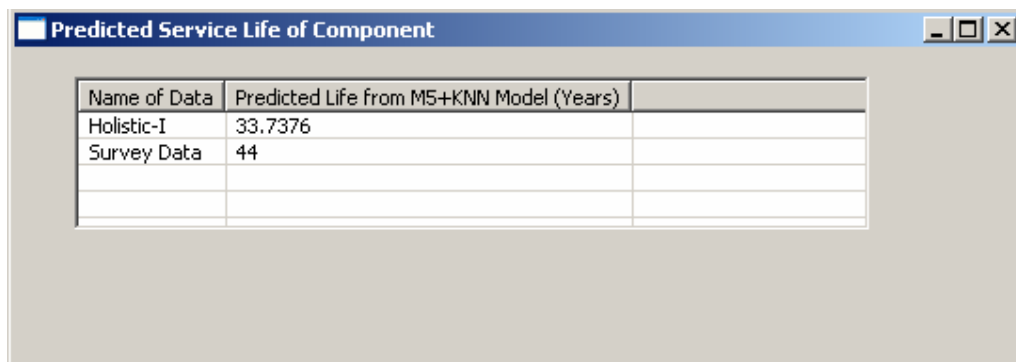
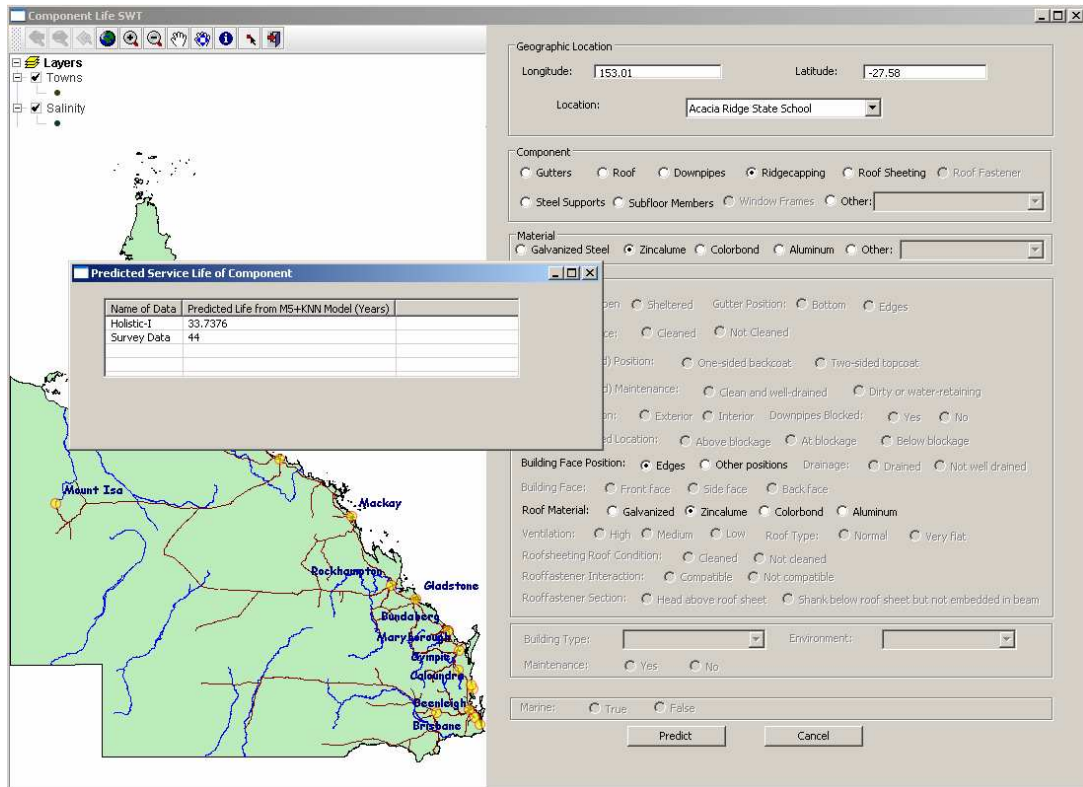
Building Type:
Environment:
Maintenance: Yes No

Similarly if Roof has been selected then this accesses the Previous dataset from Maintenance records, and the bottom panel becomes available and prompts for information.

Marine: True False

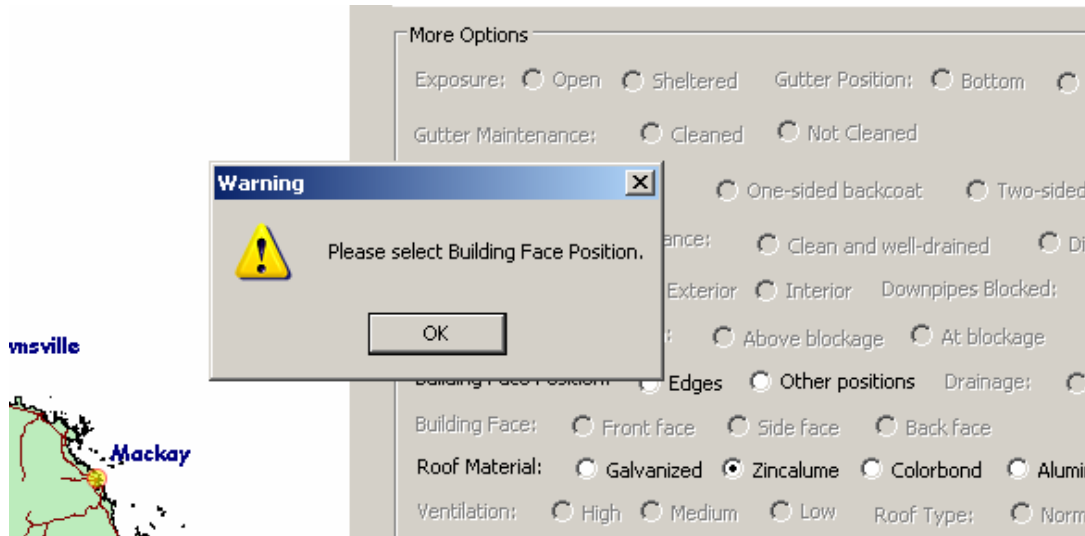
Prediction

Once all information has been entered, the user can select the 'Predict' button (shown in the previous diagram) and a dialog box appears with a number of predictions, depending on the number of databases that the component appears in. Delphi, Holistic-I and School Survey are the main sources with Roofs also accessing the previous data set from the earlier version of the program




The prediction box can be removed by clicking the  icon in the top right hand corner.

Failure to select one of required options results in the appearance of a warning dialog box which prompts the user to select that option.



Clicking OK removes the dialog box and the program continues.

The prediction program can be closed by the  icon in the top right hand corner of the program screen.

Marine Environment

Only four schools:

- Slade Point State School
- Mission Beach State School
- Mooloolaba State School
- Broadbeach State School

have annual salt levels that classify them as being in a Marine environment.



**Cooperative Research Centre
for Construction Innovation**

9th Floor, L Block
QUT Gardens Point
2 George Street
BRISBANE QLD 4001
AUSTRALIA

Tel: +61 7 3138 9291

Fax: +61 7 3138 9151

Email:
enquiries@construction-innovation.info

Web:
www.construction-innovation.info



Established and supported
under the Australian
Government's Cooperative
Research Centres Program