Predicting the service life of buildings and components

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The prediction of the service life of buildings and engineered structures is complex. Such predictions are usually carried out on a component-by-component basis, but must incorporate variations in component design, material type, usage and environment. Extensive databases of life prediction are required to cover the vast number of components/environments/usage combinations that exist in buildings or engineered structures. This study investigated the diverse methods used to model the life of components in structures, including data mining of maintenance and service records, expert opinion surveys (Delphi surveys), multiscale process modelling, and sensing. These methods were analysed in terms of the issues identified above and their applicability to meet the differing uses of life prediction data. Detailed case studies are presented and the strengths and weaknesses of the methods are analysed with respect to the final uses of life prediction.

1. Introduction

The estimation of the service life of buildings or their individual components is a complex process. Materials degrade through exposure to the environment, with a range of environmental factors having varying impact on different materials. Service life predictions are usually carried out on a component-by-component basis and these must incorporate variations in component design, material type, usage and environment.

Looking at service life on a component-by-component basis requires the development of large databases of component life under a diverse range of conditions. The end-use of the service life prediction may also necessitate different levels of detail in these databases (Lounis *et al.*, 1998). The wide variety of uses for life prediction information include the following situations.

- (a) Life prediction of known products in known environments: this is important for the manufacturer who provides guarantees on his product, and the designer for material selection.
- (b) Comparative materials selection based on life estimates of known materials in known environments: this has always been important for the designer but is increasing in importance as online life-cycle assessment tools allow selection of a variety of designs and material types.
- (c) Comparative life prediction in new environments: as for points (a) and (b) above.
- (d) Effect of design changes on component life: as for points (a) and (b).

- (e) Estimation of maintenance schedules of already built facilities: critical for the maintainer and the portfolio manager of buildings.
- (f) Estimation of maintenance schedules from the design of facilities: this is important for the designer, maintainer and owner of buildings.
- (g) Effect of workmanship and human factors on maintenance and component life: critical for the builder, owner and maintainer of buildings.
- (h) Prediction of remaining life of inspected facilities: critical for owners or managers of a portfolio of buildings.

Thus, the generic problem of life prediction can be seen as how to use a wide variety of information sources (historic data, survey information, modelling, expert opinion, etc.) to generate information on an enormous number of conditions. Buried within this overall question are a number of subsidiary questions.

- (a) What are the different classes of information available and what are the different methodologies to be followed in their use?
- (b) How can project service life from a known case be transferred to an unknown case where not all the conditions are the same?

2. Classes of information

The degree of knowledge available for any case can be classified into four levels, with increasing levels of uncertainty.

- (a) Well known and documented situations.

- (b) Known but not documented.
- (c) Life and damage rate are not known but are predictable from damage causes (environmental and human) even if this prediction is complicated.
- (d) Damage causes and damage progression are not predictable but can be measured.

The most reliable prediction can be made if the situation is well known and documented. This is the case where code books or databases have been derived from years of observation and measurements. The next step down from this is where the situation is understood but has not been documented. This may be reflected in expert knowledge that may be extracted by surveying expert opinion or information buried in maintenance records that may be extracted by data mining. However, these forms of knowledge are not able to deal with new situations. Where the factors that cause damage are known, and these causes are predictable, then modelling can be used to predict the progression of damage. This works well when there is a strong relationship between the damage and the damage causes. This class would include data derived from service life models.

If the known causes of damage cannot be well defined but are able to be measured then sensor-based approaches can be used to predict damage. This method is particularly relevant when the onset of damage is controlled by human factors, such as building usage or workmanship. It is very difficult to predict human errors, but areas of risk can be monitored by sensing. In addition, life estimation can also be based on accelerated testing. In principle, this is a special case of condition (a) with the particular issue of how can a well-documented measure of component life developed in one situation (accelerated testing) be applied in another (real service conditions).

3. Methods to estimate component life

Several of the methods outlined in the previous section have been investigated by the authors and a team of researchers at CSIRO Materials Science and Engineering (CMSE), with particular emphasis on metallic components in infrastructure and aerospace applications.

3.1 Data mining

The maintenance records of large collections of buildings (e.g. those of public housing authorities) could theoretically be used to provide knowledge of the service life of those actual buildings. Data mining provides techniques and algorithms for extracting information from large databases. The authors have investigated the use of data mining to extract service life information from maintenance records of public authorities in Australia; however, in general, the records did not contain sufficient detail to permit this analysis. Information was of a very broad nature, with individual building components of interest to the researchers (e.g. aluminium window frames,

downpipes) not being designated. Material type was also not included in the records, or reasons for maintenance or degree of damage.

With far more detailed recording of maintenance activities, data mining could potentially provide valuable information for estimating service life. However, the level of detail required is far in excess of that currently gathered in the maintenance units of public infrastructure owners, and would impose a time burden for entry of data on these authorities. More recently, surveys have addressed this need for greater detail, with perhaps the benchmark being set by Vanier and Kyle (2001) in a survey of 600 roofs in seven climate zones across Canada. This survey used a specially designed data collection tool that facilitated the inclusion of so-called 'tombstone information' (location, roof type, area, roof and building age, CAD drawings etc.), as well as data on condition, and distress type, severity and quantity for the different elements of the roof fabric. The survey defined the condition of a roof in terms of a 'state', where state 7 was a roof in excellent condition and state 1 was a roof requiring immediate replacement. The survey found relatively few roofs that were in an advanced state of disrepair (state 1 or 2). This observation raises the generic problem of how to estimate the time to move from one state to another. One method is that of transition probabilities, (the probability that in a given time the state of a member will move say from state 2 to state 1) which has been developed by Lounis *et al.* (1998) from field surveys.

If detailed maintenance data were available then the problem arises of how data that defines the condition at specific times and locations can be used to estimate the final life of a building at a different time and location. Some researchers have used case-based reasoning (CBR) to address this problem by matching lifetimes in maintenance databases to those required for prediction (Kyle 2001). In CBR, the characteristics of the buildings in the maintenance database are searched to select those with the most similar characteristics to the building of interest, and then it is assumed that the lifetime of the building of interest is a weighted combination of the lifetime of the similar buildings (Kyle 2001).

3.2 Expert opinion

People working in the field build up a great deal of knowledge of how different materials and components behave in different environments. This 'expert opinion' is not documented and so is difficult to apply, and does not deal well with new situations. An accepted method of quantifying expert opinion is the use of a 'Delphi survey'. A project applying the principles of a Delphi survey to collect expert opinion on the durability of building components has been carried out under funding from the Cooperative Research Centre for Construction Innovation (Cole *et al.*, 2004a).

A Delphi survey is a structured group interaction process and is an established technique for obtaining consensus (Duffield, 1993). It offers an established protocol to refine responses to a number of 'rounds' of opinion collection through feedback loops.

3.2.1 Application of Delphi survey to building components

Building component life depends on a wide range of factors, not just the material properties but also the service environment, the quality of installation and of maintenance. Delphi surveys can survey a range of professionals with different expertise and backgrounds to address these diverse factors. For example, builders and architects have practical knowledge of component performance and how performance may relate to design and construction issues, while building material suppliers have a detailed knowledge of their specific product's performance within their established markets. Academics and scientists bring a wider understanding of the general principles of materials durability.

Cole *et al.* (2004a) carried out a Delphi survey to estimate the life of metal components in Australian domestic and light commercial dwellings. Over 30 different building components were chosen as the basis of the survey, ranging from nails and ducting through to roofing, window frames and door handles. 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.

Respondents were asked to fill in a web-based questionnaire that required component life in a variety of conditions to selected within given intervals, such as 15–20 years. The survey was conducted in two stages. In the first stage, there were 66 responses coming from researchers into materials and building, technical experts in building material companies, material specifiers, architects and builders. The aggregated responses to individual questions were classified into four classes based on a simple rule relating the consistency of the responses.

- (a) Class 1. One interval contained more than 50% of responses.
- (b) Class 2. Two adjacent intervals contained more than 50% of responses.
- (c) Class 3. Three adjacent intervals contained more than 50% of responses.
- (d) Class 4. None of the above.

An example of the results for one component/material/environment combination is shown in Figure 1. It is an example of a class 2 response. After the first stage, approximately 80% of questions had a consistent answer (class

1 or 2) from the survey group. The second round of the survey was used to gain additional information for categories (20% of questions) that initially fell into class 3 or 4 due to lack of consistency. After the second round of the survey, 75% of these remaining questions then had a consistent answer. At the end of the second round the information was collected into a database – a table for users to look up predicted lifetimes for metallic components in a comparable environment. The predicted life is stored in the table in two forms: the mode and the mean, as well as a standard deviation for the mean value.

Returning to the methodological questions discussed above, the following conditions apply.

- (a) The Delphi survey did lead to consistent responses from the three groups of experts, with 78% of the sets of responses for each component falling in either class 1 or class 2 after stage 1 of the survey and 95% after stage 2.
- (b) The Delphi survey is internally consistent. For example, it would be expected that responses on commercial roofing material and domestic roofing material should be very similar, as in this case the use does not significantly change the life, and in fact in all conditions for all materials the difference between roof sheet life and gutter life for the different types of buildings was never more than four years and generally less than three.
- (c) The survey is consistent with basic physical and chemical principles and with results of data derived from other means. Again considering roofs, basic corrosion science indicates that roof life in a marine environment should be shorter than in an urban setting as is demonstrated by the survey. Roof life should also increase when the protection level of the component is increased; that is, the life of Colorbond > zincalume > galvanised. This is in fact observed. Furthermore, in Table 1 the life in the Delphi survey is compared with comparable values derived from

Figure 1. Graph of results from question in Delphi survey

experimental studies, process modelling and from maintenance records.

Thus the Delphi survey does appear to provide reasonable estimates of component life in known environments and could be used to select between known materials. It cannot in itself account for variations in environment, workmanship or usage.

3.3 Process models

Models based on the actual physical processes of material degradation can take into account local and usage factors that may influence these degradation processes and so can be a very accurate method of predicting the life of individual components. Such process models have been developed to predict the life of concrete (Akiyama *et al.*, 2010; Kranc and Sagues, 2001; Melchers *et al.*, 2008; Sagues, 2003; Torres-Acosta *et al.*, 2003), and metal products (Graedel, 1996; Lyon *et al.*, 1995; Spence and Haynie, 1990). In terms of reinforced concrete models it is generally agreed that total life consists of time to initiate corrosion, time for crack propagation after initiation until it reaches an unacceptable level (often taken as the first crack in the concrete, and residual lifetime from the first crack to final failure (Torres-Acosta and Martinez-Madrid, 2003). Time to initiation is generally modelled assuming that when a critical chloride content is reached at the surface, steel passivity (generated by the high pH of the alkaline concrete) can break down and corrosion can begin (Sagues, 2003). Chloride diffusion is assumed to be Fickian and the surface chloride concentration is assumed to be constant (Sagues, 2003). Kranc and Sagues (2001) model the corrosion propagation stage assuming that the steel is in the active state by modelling corrosion cells and oxygen diffusion to the rebar, as developed by and refined by Lin *et al.* 2010 (among others). A number of workers integrated these concepts together to give unified and often probabilistic models (Akiyama *et al.*, 2010; Melchers *et al.*, 2008; Torres-Acosta and Martinez-Madrid, 2003). The model of Akiyama *et al.* (2010) is

particularly interesting as it combines a model of airborne salinity, corrosion initiation (based on Fickian transport of chlorides), oxide growth and concrete cracking, and as such is one of the few corrosion lifetime models to consider explicitly geographic variations in chloride level. In fact it could be argued that in general the models of reinforced concrete structures do not include a number of microclimatic and surface parameters that could be of significance. These include the variation of salt deposition onto concrete structures as a function of component position and exposure, the retention of salt on concrete structures, the formation of moisture films on concrete structures and their effect on chloride diffusion into the concrete matrix.

In atmospheric corrosion a number of process models have been developed (Graedel, 1996; Lyon *et al.*, 1995; Spence and Haynie, 1990) to predict metal corrosion. One of the leading models is Graedel's 'GILDES' (gas, inter-face, liquid, deposition layer, electrodic regime and solid) model, which systematically looked at the chemical interactions across a range of interfaces. However, Graedel (1996) applied the model to relatively simple gaseous and interface regimes, and therefore a greater understanding of the external environment was required.

The holistic model of corrosion of Cole *et al.* (2003; 2004b; 2004c; 2004d; 2004e; Cole and Paterson, 2004; 2006) is one such process model that aims to incorporate a deep understanding of local environmental and usage factors.

Corrosion of metals requires the presence of oxygen and electrolyte and is increased by the presence of salts and water. Thus, the basic holistic model combines processes that control atmospheric corrosion on a range of scales (Figure 2), from macro through meso to local, micro, micron and lastly electrochemical (Cole *et al.*, 2003), to estimate the corrosion rate of exposed plates by modelling the salt and water deposition.

Data Source	Environment	Mode: years	Mean: years	SD: years
Delphi	Marine	10–20	12	6
Experimental	Marine	5–10	14	12
Process model	Marine	5–10	9	5
Maintenance	Marine		16	
Delphi	Benign	30–50	35	13
Experimental	Benign	> 50	> 50	
Process model	Benign	> 50	> 50	
Maintenance	Benign		41	4

Table 1. Comparison of database and survey predictions for roof sheeting

3.3.1 Case Study: application of holistic model to life prediction of metal components

This model will be outlined in more detailed as a case study of the development and use of process models for life prediction. The model consists of a number of sub-models.

- (a) Climate.
 - (b) Microclimate
 - (i) pollutant sources, transport, deposition and retention
 - (ii) surface condition: surface relative humidity (RH), surface temperature.
 - (c) Surface response
 - (i) surface state
 - (ii) surface corrosion rate.
- (a) *Climate*. The climate model includes base data being 3 h meteorological data for Australia, Australia land use and topography, coastline and sea states.
- (b) *Microclimate*. The microclimate model has two major sub-modules as highlighted above.
- (i) Pollutant sources, transport, deposition and retention. In Australia, corrosion is promoted by the effects of marine aerosols, so this submodule analyses their production, transport, deposition and retention. A major source of aerosol production is through wind blowing over or across breaking

waves (so-called whitecaps) in the open ocean, with the extent of aerosol pick-up being proportional to the whitecap coverage (percentage or fraction of the ocean that is covered by breaking waves). The aerosol production and transport models are linked to a geographical information system (Cole *et al.*, 2004b) that allows the airborne salinity to be calculated in the vicinity of a building. The efficiency of aerosol deposition onto objects and dwellings depends on aerosol size, air speed and air turbulence which is incorporated into the model, increasing dramatically the deposition onto the edges of a building where air turbulence is high (Cole *et al.*, 2004a). To cause ongoing corrosion, pollutants must be retained on the surface, and research has indicated that the surface can be effectively cleaned by rain but not by wind (Cole *et al.*, 2004d). The efficiency of rain cleaning depends on the amount and intensity of rain in a given rain event (Cole *et al.*, 2007). For rain cleaning to be effective, rain droplets must reach a critical size so that they can roll down and off the surface, dissolving and removing pollutants in their path (Cole and Paterson, 2007).

- (ii) Surface condition: surface RH, surface temperature. This module uses the baseline climatic data to calculate the temperature and RH at the surface of a metal component. It does so with the same time interval (3 h) as the meteorological data. An exposed metal surface will be heated by the sun and in turn irradiate heat to the night sky so that the metal surface temperature will be significantly above ambient temperature during the day and below ambient on clear nights (Cole *et al.*, 2005). These surface temperature variations are calculated as a function of global radiation, wind speed, ambient temperature, and sky condition (Cole and Paterson, 2006). Given knowledge of plate surface temperature and ambient RH, the RH at the metal surface (RH_{surf}) can be calculated (Cole *et al.*, 2004c).

(c) Surface response

- (i) Surface state. This module calculates whether the surface is wet from rain, wet from the wetting of hygroscopic salts, drying or dry, as before using the same time basis as the meteorological data. Simple rules which account for the exposure of the metal surface are used to calculate if the surface is wet from rain. A surface (Cole *et al.*, 2004c) is assumed to be wet from the wetting of hygroscopic salts if the surface RH exceeds the deliquescence RH of any contaminating salts (DRH). The DRH

Figure 2. Schematic of multiscale model of corrosion

points vary, with salts associated with marine exposures MgCl and NaCl wetting at 35 and 75%, respectively, and those associated with industrial exposures such as $(\text{NH}_4)\text{HSO}_4$, $(\text{NH}_4)_2\text{H}(\text{SO}_4)_2$, NaNO_3 , $(\text{NH}_4)_2\text{SO}_4$ wetting at 40, 69, 74 and 80% RH. Once wet a surface will take some time to dry, with the drying time highly dependent on RH_{surf} , temperature and wind speed. Because of the strong diurnal cycle in surface temperature and RH, surfaces wet during the night will tend to remain wet until sunrise and with droplets evaporating after sunrise (Cole *et al.*, 2006). However the evaporation process itself will lower the surface temperature which will increase the drying times so that post-sunrise these may range from seconds to almost 4 h.

- (ii) Surface corrosion rate. For each state outlined above (and depending on retained salt level), a corrosion rate is determined from dose function tests in accelerated test chambers (Cole *et al.*, 2010). For example, the corrosion rate of a surface wetted by hygroscopic salts is estimated as mass loss (over 3 h) = $v + \beta \times S^\psi$ where mass loss is in g/m^2 , S is the salinity level (mg/m^2) on the surface, v , β and ψ are constants having values of 8.3×10^{-4} , 11.3×10^{-4} and 0.5. Thus from the data stream of states and retained salts a data stream of corrosion rates is estimated and then annual corrosion can be determined by summing the three-hourly corrosion rates. These annual corrosion rates have been used to generate corrosion maps of Australia, such as the one illustrated in Figure 3 for zinc.

3.3.2 Usage and maintenance factors

This generic model then needs to be modified to take into account factors pertinent to buildings and individual components. A schematic of how different factors are incorporated is shown in Figure 4. As an example, the fact that efficiency of aerosol deposition depends on air turbulence leads to marked variations in deposition across a building with heightened deposition onto building edges where air is more turbulent. The practical effect of this in the multi-scale model is that pollutant deposition onto gutters and downpipes is heightened with respect to the general deposition onto walls and roofs leading to correspondingly faster degradation rates of gutters and downpipes.

Further, usage and maintenance issues may affect the service life of a particular component and these can be factored into the model. For instance, downpipes have a number of different sections that will deteriorate at different rates. First, the downpipe is divided into the exterior surface or the interior surface. The exterior surface is further divided into

Figure 3. Map of Australia illustrating levels of corrosion for zinc (g/m^2 year). Values of counter lines are placed adjacent to lines

two: the section just below the roof eaves that is sheltered from rain, and the sections at the lower part of the wall that will be cleaned (though not from vertical rain). The interior of the downpipe is divided into two usage cases: maintained (in this application, equivalent to cleaned) and not maintained. If the downpipe is not maintained it may become blocked due to the accumulation of leaf litter and other debris, which then leads to three more classes (above, at and below the blockage).

The usage cases will change different parts of the model. For example, if the surface is covered in debris (leaf litter etc.) it will trap salts and significantly decrease the efficiency of rain cleaning. Further, the debris will also absorb moisture, prevent evaporation and thus increase the time of wetness within the interior of a blocked downpipe. In Table 2, some predictions

Figure 4. Schematic of factors affecting corrosion of components

from the model are compared with the Delphi survey and a condition survey. The table quotes the worst case and best case for the modified model. In general there is a reasonable agreement between the worst case holistic model and the other two methods.

The model can readily predict the life of specified products in known and new environments. What is currently unique about the model is that it combines a central core with models that can determine the effect of individual microclimate effects (e.g. in the case of guttering, how some surfaces are exposed to rain and so regularly cleaned while some are sheltered from rain but exposed to salt air allowing salt build up). It can be used to compare the life of components made from different materials and the effects of maintenance, as long as it can be defined in terms of changes to a material's response or local microclimate (as in the example of the effect of maintenance on downpipes). The model can be used to determine the required maintenance from designed facilities. It can, in principle, be used to calculate the impact of design and workmanship and human factors, again as long as these changes can be translated to changes in microclimate and material response. However, this last task is complex, but could be completed if the multi-scale model approach was integrated with that of building pathology. The estimation of maintenance of already built facilities and the prediction of remaining life are best accomplished with other techniques.

The development of the holistic model also indicates that if accurate predictions are to be made of component life, models must be able to take into account the different exposure conditions of different parts of a component and the effect of maintenance. This is well illustrated in Table 2 when the life of the least exposed part of the component could be five times that of the most exposed, while lack of maintenance can cut the modelled and observed component life by more than half. The development of models with this degree of differentiation is possible (as illustrated by the case study) but does require significant effort to construct the models and significant input with regard to both climatic conditions and maintenance practice. Engineering

judgement would need to be used to determine if such an investment is warranted or if one of the more general methods outlined previously could give information that resolves the required use (e.g. for general life prediction of known components in known situations, information from surveys may be sufficient).

3.4 Sensor monitoring

If the known causes of damage are variable and cannot be predicted, measurement by sensors of corrosion-producing elements offers an alternative route to monitoring likely damage. Corrosion frequently develops from non-predictable causes such as poor workmanship or accidental spills. Modelling cannot easily accommodate these variations, but sensors can pick up changes in the environments resulting from these occurrences. CMSE has developed corrosion sensor technologies and a sensor-driven intelligent vehicle health-monitoring system (Cole *et al.*, 2008) for aircraft. This is an agent-based system that uses sensed microclimate and corrosion data with an innovative analysis that forms regularly updated relationships to diagnose the current state of corrosion and predict its future progression. A schematic of the system architecture is shown in Figure 5. It could easily be adapted for building or infrastructure monitoring.

In order to make the system robust, readily extendable and to minimise communication traffic, the system architecture is based on the use of local sensing 'agents'. Clusters of sensors in small local regions of the aircraft measure local microclimate factors, including temperature, humidity, surface wetness and conductivity of surface moisture. Each sensor cluster also includes a galvanic corrosion sensor, fabricated from mated strips of copper and aluminium alloy. Each agent forms an autonomous sensing unit by including data acquisition, processing and communications capability within each sensor cluster.

Agents communicate with a central processor (IT platform) that contains global knowledge of the aircraft structure in software constructs known as intelligent objects. Typically an intelligent object will represent a structural component or

	Model (worst case): years	Model (best case): years	Delphi: years	Condition survey: years
Benign – maintained	25	> 50	33	> 50
Marine – maintained	11	> 50	11	
Benign – not maintained	15		21	18
Marine – not maintained	1		10	

Table 2. Comparison of modified holistic model, Delphi and condition survey for downpipes

Figure 5. Schematic of the system architecture, with local agents that consist of a group of sensors and processing hardware communicating with a central processor

sub-structure, and it will contain information about the geometry and materials of the object, as well as defining relationships and connections with other objects to form the complete aircraft structure.

The data streams from the microclimate and damage sensors are used to define a model linking microclimate and damage. This relationship is then used to predict the future progression of damage over immediate time spans (up to 6 months). The model is derived by a novel approach that combines a structure derived from physics-based models with statistical optimisation procedures applied to the data streams. The model is continuously modified while the system is in use. To predict damage beyond immediate time spans, methods based on system learning (both within an aircraft and across a fleet) are being developed.

Figure 6. Comparison of models generated at different times with measured damage (cumulative corrosion sensor current in μamp) on a bimetallic sensor at outdoor position 1

Prediction model	Days of accuracy ($\pm 20\%$)
Day 1	14
Day 10	146
Day 30	222

Table 3. Length of time models maintain accuracy

One of the features of this system is its capability to predict corrosion damage at some points that do not have a sensor array attached, by matching the materials, geometry and local microclimate to those at sensed points and making modifications to allow for specific features such as fastener holes. These 'unsensed' points can be monitored by the creation of 'virtual agents' within the IT platform, which generate diagnostic information using the data from appropriate real agents.

One of the difficulties with this approach is that the damage sensors do not actually measure corrosion of the underlying structure, and so laboratory experiments have been used to relate the readings from the corrosion sensors to corrosion damage on a number of aerospace metals.

The method has now been tested and refined across a variety of different test conditions from accelerated laboratory tests, long-term simulation testing, environmental exposures and on-board aircraft. The results from analysing the data collected from an outdoor exposure panel are shown in Figure 6. Models were derived from data sets commencing after 1, 10, 30 or 59 days, and the determined lengths of accuracy of these models are listed in Table 3. Except for the initial model, the modelling predictions remain accurate for more than 4 months. Models derived when damage levels are very low appear to have limited applicability, but this limitation is overcome in practice by the method, embedded in the software, of continuously regenerating the model, rather than the stepwise process used in these illustrations.

4. Conclusions

The paper outlines the different types of information that can be constructed to define the service life of components. As indicated, depending on the source of the information, it will contain different levels of detail and thus be suitable for different purposes. Some of the purposes, such as predicting the effect of design on service life, will require rich information such as the effect of component geometry, service issues and microclimate on service life. Other purposes, such as knowledge of known products in known environments, will require relatively shallow data that can be derived from simple data such as those formed by expert opinion.

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