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An Artificial Neural Network Approach in Service Life Prediction of Building Components in Malaysia Based on Local Environment and Building Service Load

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Abstract
The degradation of building and its components are influenced by whole set of factors such as environmental degradation agents, quality of material, protective treatment, design of building, quality of work and maintenance. Selection of suitable materials for the building components can prolong the service life of particular building components and in certain cases require less maintenance and replacement activity. Emphasis on material characterisations at the design stage is limited because most of the time great emphasis is given on delivering with lowest initial building cost rather than lowest life cycle cost. In this study, an artificial neural network is used to predict the service life of building materials with the basis study on deterioration of building components affected by its surrounding environment and factors that accelerate its aging process. The advantages of artificial neural network is employing as a prediction tool. The back-propagation learning algorithm is used as learning model. The environment load factors, workmanship, design, usage and level of maintenance are used as input variables in training process of the neural network model. The results are encouraging and potentially useful for further application of the service life prediction.

Keywords
Service Life Prediction, Artificial Neural Network, Degradation, Environment, Building Service Load

1. Introduction

Demands for low cost housing provided by the government are increasing every year. The increase of demands is triggered by migration of population from urban areas to rural and industrial cities. From the first Malaysia Plan that was implemented in 1966 the first formal and structured housing programs have been undertaken to provide low cost housing. Multi-million-ringgit has invested in providing low cost multi storey housing. However, the maintenance cost of these low cost housings is imposing great burden to the government due to financial constraint. With little attention paid on what happen during the building's life span, it is not surprising that most public housing management faces lack of funding for operational, maintenance and replacement of building components. Expenses and care during the life span were not taken into consideration during initial stage because of its non-immediate effect to the client especially if the client was not involved in maintaining these housing (Tapsir, 2001). This condition will become worst if the strategy in building construction on sufficing the housing demand do not include a view of how the building will deteriorate in local environment throughout its service life. If such strategy is not taken immediately, it could be faced next 25 to 30 years the country will spend a major portion of funding in maintaining, repairing or replacing of these housing.

In considering implementation of sustainable development through sustainable construction, there is a need in expertise and availability of predicted service life data of local building materials. This will ensure that any component and material employed in their construction achieved its economic service life. With implementation of such strategy in the early design stage the owner will plan the required service life cost with scheduled maintenance and thus the tenant would be ensured with assurance of safety and healthy living.

A typical problem is facing by designer in estimating the service life of a building component. Even, if there is specific service life data of component available, the in-use condition specific to the design usually are different. The environmental loads are at least partially overlooked, misunderstood or under-estimated in construction phase. There are many research have been done to elaborate and span the gap between required performance and factors that decreasing its performance during its service life. This study tries to propose and employ a prediction process using the advantages of artificial neural network which is based on the performance of in-use building components, the local environmental load factors that accelerate the degradation process and the building service load.

2. Service Life Prediction

The service life planning as defined in ISO 15686 is a design process, which seeks to ensure the service life of a building will equal or exceed its design life while taking into account the life cycle cost of the building. Service life prediction is a method which is constituted in the service life planning process and integrated with life cycle cost analysis to allow the effective reduction in cost of ownership based on material selection, maintenance planning and value engineering. It is done through data on life span of its components and considering effect of environment due to its aging process.

Bridging the gap on estimating the service life and design life of building materials are the object of research all over the world. Moser and Edvardsen, 2002 have classified the methodology in predicting the service life in to three types. Those are factorial method, probabilistic method and engineering method. Factorial method is carried out by adjusting the design life which is considering number of factors i.e. inherited quality of particular member, exposure to environment and in use condition. Probabilistic is developed in order to take into account the actual complexity of degradation process but most of the researchers were focused their study only on specific material such as concrete on bridge structure. Engineering method is carried out as extend of factorial method while the factors are employed as function rather then a static variable.

3. Data Acquisition

The interactions between building materials and pollutants are very complex and many variables are involved. More often than not, construction deterioration is due to environmental loading with the result of reduced durability. Malaysia that located in warm regions with high relative humidity and a high frequency of precipitation, with a rapid growth in population, economic development and industrial productivity is experiencing a considerable increase in air pollution. Some of the environmental loads include moisture, temperature, humidity and concentration of pollution in the atmosphere.

3.1 Environment

Data on environment are gathered from monthly measurement of wet deposition of the atmospheric pollutant and the climate measurement i.e. rain, temperature and relative humidity from Jabatan Metereologi Malaysia (JMM). The environment data is available from 1996 to 2005. For the purpose of characterization of different zone, statistical process is carried out. GIS maps are generated to estimate the level of pollution using inverse distance weighting (IDW) method for the location without environment data.

Deposition of pollutants on the building surface depends on atmospheric concentrations of the pollutants, the climate and microclimate around the surface. Once the pollutants are on the surface, interactions will vary depending on the amount of exposure, the reactivity of different materials and the amount of moisture present. SO_2 is connected with atmospheric corrosion with other atmospheric corrosion agent including nitrogen oxides, carbon dioxide, ozone and sea salt from sea sprays. SO_2 is considered as a major contributor to acid rain. SO_2 is easily absorbed on material surfaces, and the deposition may be wet or dry. For most of the materials, SO_2 is the main corrosive agent in the air (Haagenrud, 1997). Research has discovered that when nitrogen dioxide is present with SO_2, increased corrosion rates occur. This is because the nitrogen dioxide oxidizes the SO_2 to sulphite thereby promoting further SO_2 absorption.

Moisture conditions are strongly correlated with relative humidity and temperature in absorption process deep in to the exposure building components. The moisture or wetness of surface is depended not only on relative humidity but also on other parameters such as salt deposition, sunlight radiation, wind, and absorption of ambient heat (Chotimongkol, 2003). The decrease in acidity of rainwater is generally larger from the drop of SO_2 and H^+ concentrations. Malaysia is experiencing the decrease of sulphate in the form of wet deposition during rainy season and it is observed increase on dry season per mg/l unit of its deposition. Figure 1 show the wet deposition of sulphate for several areas in Malaysia. It shows that on December to February, the concentration of sulphate decrease significantly as rainy season is experienced on that regions.

The relative humidity for all regions in Malaysia is greater then 50%, the average temperature 27^{o}C and the average yearly time of wetness (TOW) equal to 0.783 fractional hours. The calculated TOW as on ISO 9223 which is based on duration of their action on the metal surface is classified the wetness to T5. The most understandable influence of temperature is on the rate of the chemical reaction. If building component's surface temperature falls below the dew point, the surface becomes moist and in the presence of corrosive pollutants it becomes conducive to certain types of damage to the most of materials.

3.2 Pollution Characterization

The pollution characterization of selected area will represent the condition of all regions in Malaysia. The different characteristics of selected areas of study are dominated by several environmental parameters such as temperature, humidity, amount of precipitation, deposition of pollutant in the wet or dry form deposition and the level of acidity of the rain water. Even in the same equatorial zone, there are different characteristics of environmental parameters where some of them dominant compared to others. The coastal area is expected to be affected by particles of sea salt e.g. chlorides carried by wind and deposited on the surface of building components. This condition is believed will longer the time of wetness of the moisture layer on the surface of the building components. Urban area is subjected to normal precipitation patterns and typical urban contaminants emitted by traffic. Industrial area is identified with heavy industrial manufacturing facilities with high concentration of SO_2. Highland area is subjected to the high humidity and below average daily temperature. The environmental data as climate and pollution data are collected from those different regions.

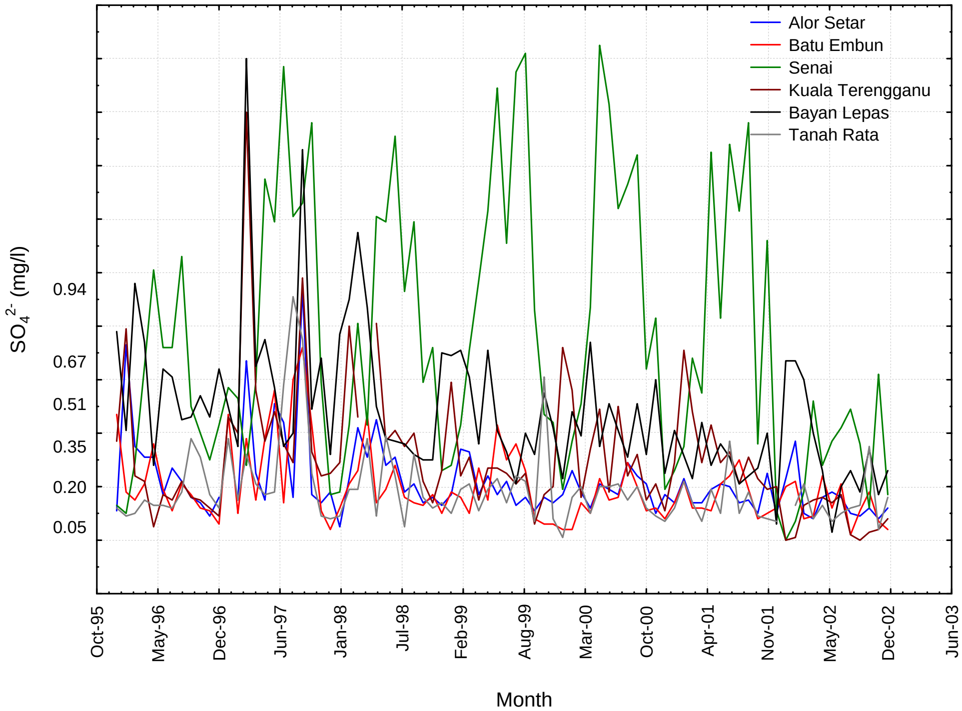

Figure 1: Sulphate wet deposition for several areas in peninsular Malaysia

Table 1 show the different characteristic of 6 different zones based on the wet deposition of pollution and their climatic condition. Even the ranges of the concentration of pollutant are slightly different, some of pollutant depositions are found dominant for particular zone. Sulphate deposition is observed dominant in Industrial area and it increases the acidity of rain water to the pH range under 5. Nitrate as result mostly from combustion of vehicles is experienced fairly same range for all zones. Chloride is a dominant pollutant agent for the coastal and island area.

Table 1: Pollution and environment characteristic for 6 different zones

Zone	pH		SO_4^{2-}		NO_3^-		Cl^-		RH		Temperature		Rain	
	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
Urban	4.51	5.27	0.15	0.34	0.04	0.14	0.44	0.79	78.6	83.9	27.0	28.1	0.139	0.183
Rural	4.87	5.18	0.14	0.34	0.04	0.15	0.27	0.52	85.5	88.3	26.2	27.3	0.160	0.210
Industrial	4.29	4.61	0.30	0.98	0.17	0.51	0.37	0.81	84.5	86.2	26.1	27.1	0.158	0.223
Coastal	4.85	5.23	0.08	0.53	0.05	0.14	0.50	1.69	81.3	84.6	26.9	28.0	0.155	0.276
Island	4.71	4.98	0.07	0.71	0.04	0.21	0.67	0.90	79.9	81.5	27.3	28.2	0.126	0.269
Highland	4.83	5.26	0.14	0.34	0.04	0.09	0.17	0.29	85.6	88.3	26.2	27.3	0.160	0.210

3.3 Building Assessment

Data collected from existing building from different characteristic i.e. building service load, location and environment. There are 20 components of building collected and grouped as structural and non-structural components from 7 different service types of buildings. The buildings age varies between 1 to 54 years where as the building components age is between 1 to 54 years old. Conditional rating approach is used in building assessment on the inspected buildings. There are 5 degradation factors taken on building assessment, those are exposure to the environment, design of the building's component, usage, workmanship, and maintenance condition.

4. Implementation of Artificial Neural Network

The ability of an artificial neural network to learn automatically from examples makes them attractive and exiting. Instead of following a set of rules specified by expertises or common mathematical model, the artificial neural network appears to learn the basic input–output relationship from the examples presented to it in a training set. In this study, an artificial neural network is used to predict the service life of building materials based on building components assessment and local environment condition. The back-propagation learning algorithm is used as a learning model in this paper.

4.1 Pre-processing

The pre-processing process is carried out to select the data which is prepared for the neural network model. It is comprised by examine and clean the outliers or unrealistic data from the raw data. Box plot and scatter-quantile graph are used to identify the outliers. This process will determine the service life of selected building materials based on its performance and deterioration level of assessed building components. Remaining data that have brushed typically will show same pattern with the performance building without maintenance. These data is then generalized before feed to the neural network model.

4.2 Model Development

A limited training set parameter and the corresponding simulations from the environmental and building load are available for each building materials. The Scaled Conjugated Gradient (SCG) and Levenberg-Marquardt (LM) algorithm are employed in this neural network model. These algorithms have some advantage features such as fast algorithm (especially for large networks), relatively small in memory requirement and performs well over wide variety of problem (Hagan and Menhaj 1998).

The training algorithms have the following structure; initializing the neural network parameters, initializing the weights and the biases, define the architecture of the neural network model and the parameters associated with the algorithm such as error goal and maximum number of epochs. In this study, the neural network model consists of 10 input variables and a single output variable as illustrated in Figure 2. Age of the building components are used as target or output in the training process. The neurons of the neural network model are structured in multiple layers, namely input, hidden, and output layers.

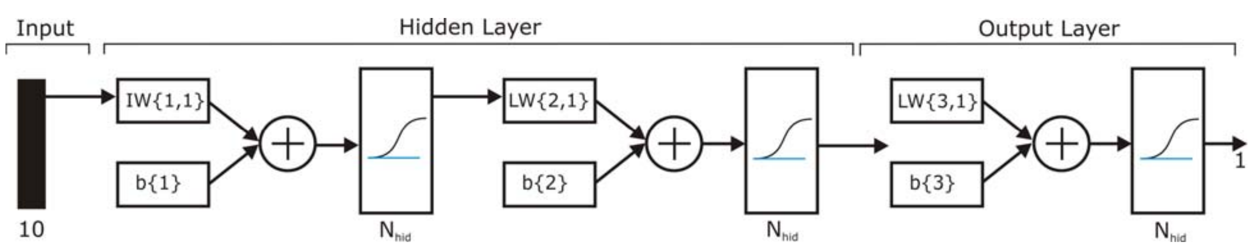

Figure 2: Architecture of the neural network model

The Input variables in this neural network model consists of 5 building service load variables (design, exposure, work quality, usage and maintenance), performance rate of building component, SO_2 level, H^+ level, time of wetness (TOW) and zone where the location of the assessed building components are assessed. In this paper building components made of steel are modelled. Summary of the input variables are shown in Table 2. Several training process is conducted to define the activation function for the given parameters and it is found the best suited activation functions are logistic sigmoid function for the hidden layer and output layer.

The variables for the training process are generalized using simple linear scaling method that will range the input variables from 0 to 1 and the goal value is set to 0.001. The equation 1 bellow is used to estimate the initial number of neuron in hidden layer (M. Lu, 2002):

$$N_{hid} = 0.5 \times (N_{in} + N_{out}) + \sqrt{N_{tpatt}} \tag{1}$$

where N_{hid} is the number of neuron in hidden layer, N_{in} is the number of the input variables, N_{out} is the number of the output variables and N_{tpatt} is the number of the training pattern. The mean square error (MSE) is used to evaluate the prediction performance of the neural network model following completion of the training session.

Table 2: Summary of variables

Variable	Minimum	Maximum	Variable	Minimum	Maximum
MatAge	1	44	Rating	1	4
Environment	1	3	SO_2	2.2	57.4
Exposure	1	3	H^+	6.1	41.8
WQuality	1	3	TOW	0.7	0.9
Usage	1	3	Zone	1	6
Maintenance	1	3	Valid N	1096	

4.3 Result and Discussion

The LM algorithm seems not suitable in this case even this algorithm is reported as the most efficient learning algorithm due to its extremely fast convergence (Hagan and Menhaj 1998). The SCG algorithm shows converged early and the accuracy in the testing results are quiet better compare to the LM algorithm testing results. In this case, the LM algorithm is too computational time consuming to deal with large neural network model.

Figure 3 shows the squared error calculated during every epoch. The results show that neural network model is able to recognize and map the input data and able to predict the testing data in a reasonable good accuracy. The scatter plot of neural network output and the training target data is compared as in Figure 4(a). The coefficient of correlation, *r*, for the training process of 0.9044 is achieved. This result indicates that neural network is successfully learning the complex relationship between input and output variables from the input pattern. The coefficient of correlation, *r* for the testing is 0.8812. Figure 4(b) shows the comparison of neural network simulation output and testing target data.

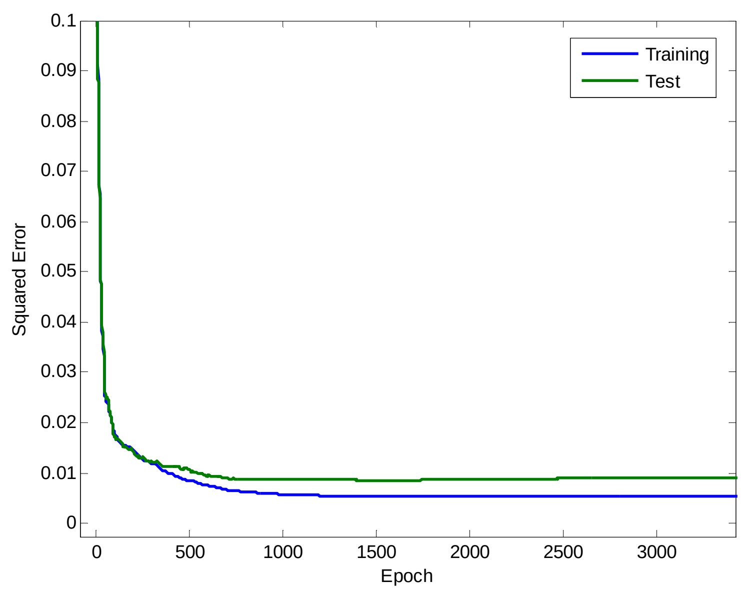

Figure 3: The squared error calculated for each epoch

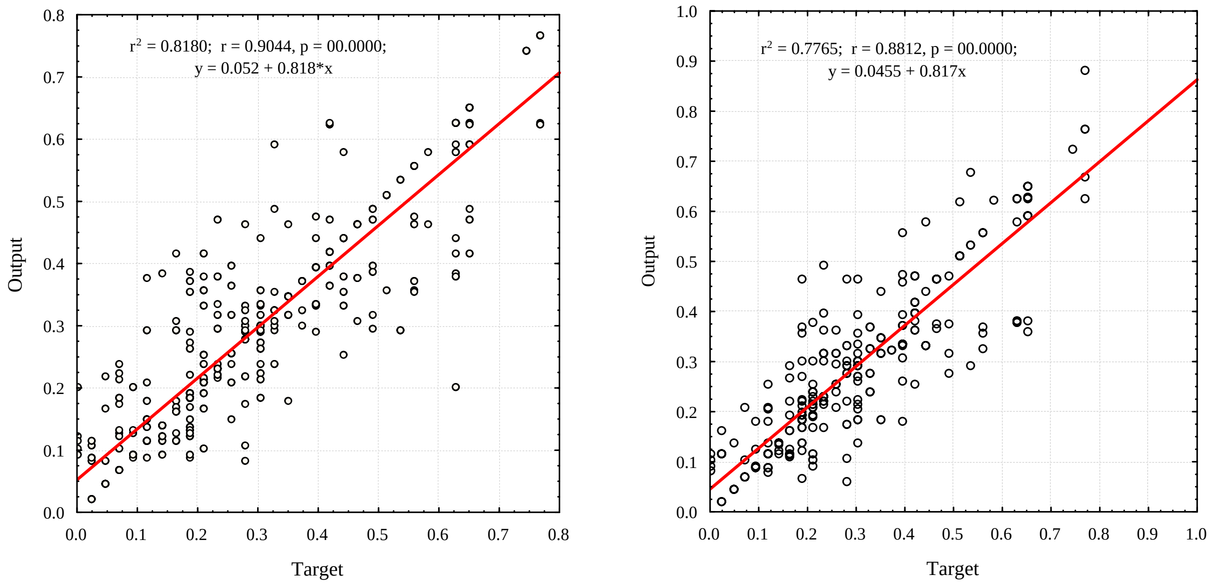

Figure 4: Comparison neural network output with training and testing target

4.3.1 Validation

The outcome of the research is encouraging. The neural network model worked fairly well. This neural network model also demonstrates stable performance in its application to unknown data, which is important for future application. The other validation process is based on the service life of steel building components which is generated from fitting equation between rating of its performance and its age. Table 3 shows the fitting equation that represents the correlation between performance and age of steel building component in different zone.

Table 3: Fitting equation for different zone service life of steel material's building components

Steel	Service Life Range		r	p	Fitting		r^2
					Exponential	Linear	
Coastal	41	58	0.934	< 0.05	y=0.8927exp(0.0363x)	y=0.7192+0.0624x	0.872
Highland	43	71	0.779	< 0.05	y=0.9937exp(0.0406x)	y=0.8216+0.0586x	0.606
Industrial	31	46	0.865	< 0.05	y=0.7168exp(0.0626x)	y=0.4598+0.0971x	0.747
Island	48	71	0.773	< 0.05	y=0.9727exp(0.0343x)	y=0.861+0.0584x	0.597
Rural	52	79	0.830	< 0.05	y=0.8259exp(0.0349x)	y=0.6937+0.054x	0.688
Urban	41	62	0.835	< 0.05	y=0.8487exp(0.0433x)	y=0.6956+0.0696x	0.697

4.3.2 Accuracy

The average error of prediction using the neural network model is 24.4% ± 7 at 95% confidence level. This is based on testing of generalized raw data which were not included in the training of the neural network model. The possible sources of error consist of the field data is actually a time-averaged value determined by the immediate environmental parameters and the prediction in this study is obtained using the annual average of the environmental parameters. The limited number of factors in the prediction model is other source of problem. Only ten parameters is included i.e. time of wetness, acidity, sulphur dioxide concentration, zone, level of performance of the building components and 5 building's degradation factors from its service load. In reality, many environmental, materials, and structural factors but are not used regarding insignificant effect to the degradation process. There are very limited amounts of field data available for.

5. Conclusion

The back-propagation training method used within the neural network model is able to predict the service life of steel material of building components in Malaysia. Even its result seems encouraging there is a need to improve the neural network performance and its learning capability. Further analysis is on going to overcome the best performance of results in predicting the service life of other local building materials.

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