# Evaluation of Building Performance Using Artificial Neural Network: Study on Service Life Planning in Achieving Sustainability

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## Abstract

Construction process has often been described as a highly complex because of the number of disciplines involved from conceptual and design to construction stage. Once completed, the environmental change and usage of the building test the quality of the design and workmanship as well as the suitability of material used. The degradation of buildings are influenced by a whole set of factors such as environmental degradation agents, quality of material, protective treatment, design of buildings, quality of work and maintenance. This paper describes the global issue of sustainability, data collection and potential applications of an analysis using artificial neural network in predicting service life for an ongoing research on affordable quality housing at Universiti Teknologi Malaysia.

**Keywords:** Degradation factors, sustainability, service life prediction, artificial neural network.

## 1 Introduction

Demands for low cost housing provided by the government are increasing every year. The increase of demands is due to migration of population from urban areas to industrial cities. From the first Malaysia Plan that was implemented in 1966 the first formal and structured housing programs were undertaken to provide low cost housing. However, the maintenance cost of these low cost housings is imposing great burden to the government due to financial constraint. Study on low cost residential housing in Malaysia found that most of these buildings are occupied without regular or scheduled maintenance [1]. For an efficient operating and maintenance program to take place, the evaluation of building and its components performance is very important as it reflects the service life of its components.

Artificial neural network has become increasingly common in diverse fields such as diagnosing, forecasting, extracting, identification, and control along with advanced computer technologies. In this study, artificial neural network is used to assess and predict the service life of existing buildings and its component. Back-propagation learning algorithm is used as learning model in this paper. This learning model is among the most efficient tools in engineering applications [2-3]. The environment load factors, workmanship, building materials, usage and level of maintenance are used as input variables in training process of the neural network model. The environmental and building assessments data were collected from different location in Malaysia. This paper focuses on the potential application of neural network for evaluating and predicting the service life of timber as one of building materials.

## 2 Sustainability and Service Life Planning

Sustainability is a global concept to answer global problems. Sustainability is defined as balancing and safeguarding of the future's social, economy, and environment to meet the needs of today without compromising the ability of future generations to meet their own needs. Service life of a building should be designed to exceed design life by meeting eco performance requirements without disturbing what we have today for the future generation. Sustainable building aims to take into consideration the environmental, economic, and social impacts of a construction project.

It is established that the quality and reliability of performance of a building components decrease with time and also are affected by several other factors such as exposure to the environment, workmanship, building materials, usage and level of maintenance. These factors accelerate aging process of the buildings and thus shorten its life span. However, these issues are normally not being identified earlier during the design stage and material selection of building construction.

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.

Service life equations might be derived from an assessment of existing buildings and also from a statistical analysis of variables such as the building components condition, age of building or building parts, maintenance interval and environmental factors. The factor method as in ISO 15686 is used to modify a reference service life (RSL) to obtain an estimated service life (ESL) of the building components which takes into a consideration on a number of factors. These factors are represented as follows [4]:

$$ESL = RSL * A * B * C * D * E * F * G \qquad (1)$$

where:

A. Quality of component
B. Design level
C. Work execution level
D. Indoor environment
E. Outdoor environment
F. In use condition
G. Maintenance level

# 3 Neural Network

Neural network consists of small processing units called nodes, which operate in parallel, and these nodes are densely interconnected by elements called weights. The network structure consists of an input layer, an output layer, and a hidden layer. A weight is a connected strength between the node within the upper layer and the lower layer. The weight repeatedly modifies during the learning process until the difference between output value and target value is less than the defaults.

The artificial neurons can be arranged in a network in a variety of ways by changing the type of connectivity, the number of neurons and the number of layers. The network learns the memory patterns and gathers patterns from the training examples cyclically. The network is well trained until the error comes to a minimum value or allowable limit. The network, which was trained numerous times, obtains the recognition knowledge that was presented by the final weighted matrix and threshold vector. Neural network can identify and learn correlative pattern between set of input data and corresponding target values. One trained, the new input pattern can be put to forecast another output.

## 3.1 Data Acquisition

The Malaysian environmental loads in this study are characterized into six zones: rural, urban, industrial, coastal, highland and island. These six different zones imposed different impacts on the durability of buildings and its components. The industrial growth in Malaysia since 1980’s has also led to an increase in the atmospheric pollutions.

It well known that interactions between building materials and pollutants are very complex and many variables are involved. Deposition of pollutants on the surfaces of building components 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.

Sulphur dioxide, $SO_2$ is connected with atmospheric corrosion and considered as a major contributor to acid rain. $SO_2$ is easily adsorbed on material surfaces, and the deposition may be wet or dry. The transformation reactions may take place both in gas phase and in aerosol phase. $SO_2$ exists for quite a few materials in the dose response functions. For most of the materials, $SO_2$ is the main corrosive agent in the air [5].

In 1996, most of the countries in Asia were struck by monetary crisis including Malaysia. This economic phenomenon affected the $SO_2$ concentrations in the atmosphere where from year 1996 to 2000 the concentration of $SO_2$ had declined. Many factories reduce their operation and production during the economic recession period. Other reason for the reduction in the $SO_2$ concentration could be due to improvements in industrial processes and combustion techniques used in factories. Figure 1 shows the $SO_2$ concentration figure from year 1998 to 2000.

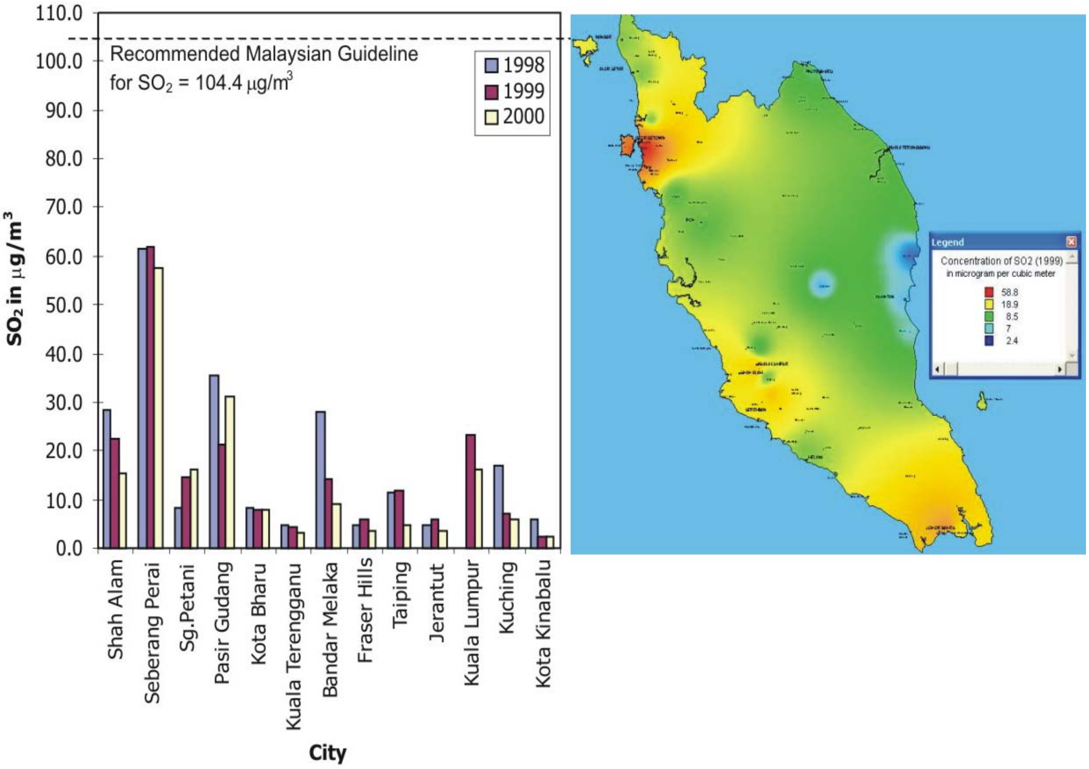


Figure 1: Yearly $SO_2$ concentration at Malaysia's Peninsular in $\mu g/m^3$

From the study, the concentrations of $SO_2$ for the six zones in Malaysia are listed as in Table 1. These figures indicate that $SO_2$ concentration characteristic for Malaysia is not too diverse.

| Locations | Concentration of $SO_2$ ($\mu g/m^3$) |
|---|---|
| Highland | $< 10\ \mu g/m^3$ |
| Coastal | $< 10\ \mu g/m^3$ |
| Island | $< 10\ \mu g/m^3$ |
| Urban | $10 - 20\ \mu g/m^3$ |
| Rural | $< 5\ \mu g/m^3$ |
| Industrial | $> 20\ \mu g/m^3$ |

Table 1: The different concentration of $SO_2$ in $\mu g/m^3$ for 6 zones in Malaysia

Building assessments were carried out on more than 400 buildings around Malaysia and up to 7400 building components to be used as input variables in the neural network model. The buildings age in this study varies between 5 to 54 years where as the building components age is between 1 to 54 years old. Conditional rating approach was used where the building components are rated and assessed by its performance degree. The performance degrees used in this study are ranging from 1 to 5 where it represents the physical condition of the building components. The collected data is then stored in database for grouping and categorising.

Statistical analysis was carried out and a number of statistical models were developed. The statistical analysis of the collected data indicated that the correlations are statistically significant that is less than the 5% *p-level* between the degradation factors and the rating condition of the building components.

## 3.2 Model Development

The neural network model consisted of 11 input variables and a single output variable as illustrated in Figure 2. The neurons of the network are structured in multiple layers, namely, input, hidden, and output layers. It was decided to use only one hidden layer.

The data were drawn from statistical analysis of performance condition of the assessed building. In this paper building components made of timber in coastal area were used in the neural network model. There are 294 timber data from the assessed buildings. Pre-processing process was done to select the data, which comprise of the following steps:

1. Data brushing to examine and clean the data from outliers or unrealistic data, which do not appear to follow the characteristic distribution of the rest of the data and should not be modelled. Figure 3 shows the brushed data, which are presented as black spot.
2. Data conversion to convert and normalised the data format required by neural network model. Those data normalised to the range of 0 to 1 using a simple linear scaling method as the following equation [6].

$$I = (D - D_{min})/(D_{max} - D_{min}) \qquad (2)$$

where I is the normalized value of the input D, $D_{max}$ and $D_{min}$ are the maximum and minimum values in the range of D, respectively.

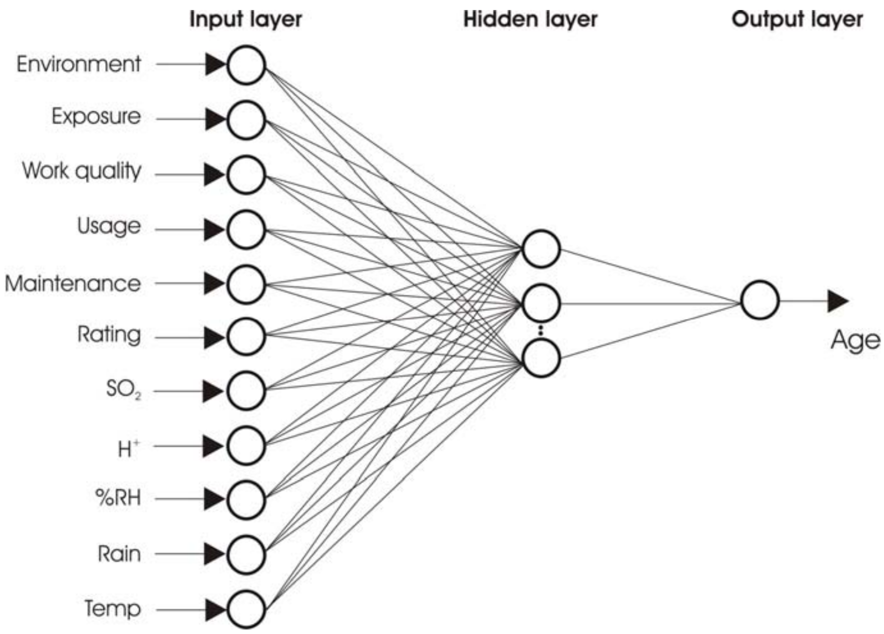


Figure 2: Neural network model

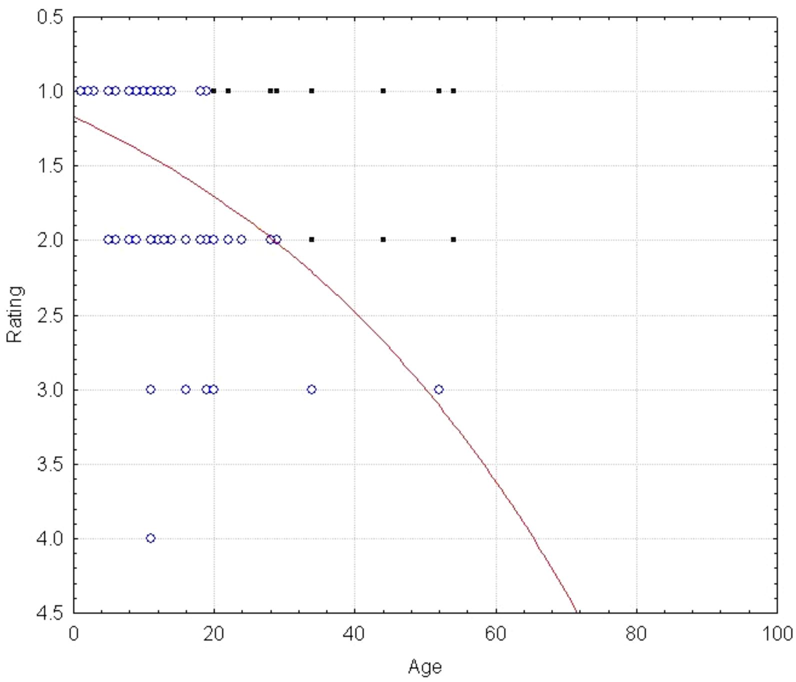


Figure 3: Brushed outliers

There are 255 data left in database after pre-processing process. The individual data sets are randomly divided into training and testing data sets. In total, 60% of the data (153 data) are used for training and the rest 40% are used for testing. Summary of the parameters are shown in Table 2.

| Parameter | Unit | Minimum | Maximum |
|---|---|---|---|
| Age | year | 1 | 54 |
| Environment | - | 1 | 3 |
| Exposure | - | 1 | 3 |
| Work Quality | - | 1 | 3 |
| Usage | - | 1 | 3 |
| Maintenance | - | 1 | 3 |
| Rating | - | 1 | 4 |
| $SO_2$ | $\mu g/m^3$ | 3.12 | 21.0 |
| $H^+$ | mol/l | 7.13 | 33.24 |
| RH | % | 81.90 | 87.90 |
| Rain | m/year | 0.180 | 0.305 |
| Temp | $^oC$ | 26.6 | 27.4 |

Table 2: Summary of parameters

Age of the building components are used as target or output in the training process. The parameter used for the training process are learning rate = 0.05 and randomised value in the range of –2 and 2 for the weight. The equation bellow is used to for estimating the number of neuron in hidden layer [7]:

$$N_{hid} = 0.5 \times (N_{in} + N_{out}) + \sqrt{N_{tpatt}} \qquad (3)$$

where $N_{hid}$ is the number of neuron in hidden layer, $N_{in}$ is the number of input parameter, $N_{out}$ is the number of output parameter and $N_{tpatt}$ is the number of training pattern.

## 3.3 Results

The scatter plot of neural network output and the training target data is compared as in Figure 4. The coefficient of correlation, *r*, for the training process of 0.8939 was achieved. This result indicates that neural network was successfully learning the complex relationship between input and output variables from the input pattern. The coefficient of correlation, *r* for the testing is 0.4405. Figure 5 shows the comparison of neural network simulation output and testing target data. The results show that neural network model utilized is able to recognize the input data and able to predict the testing data. However, the network model cannot achieve a high level of accuracy. It is suspected that this situation is due to the data characteristic. Moreover, data were randomly selected for testing process. There is a need to improve the neural network performance on data distribution and learning capability.

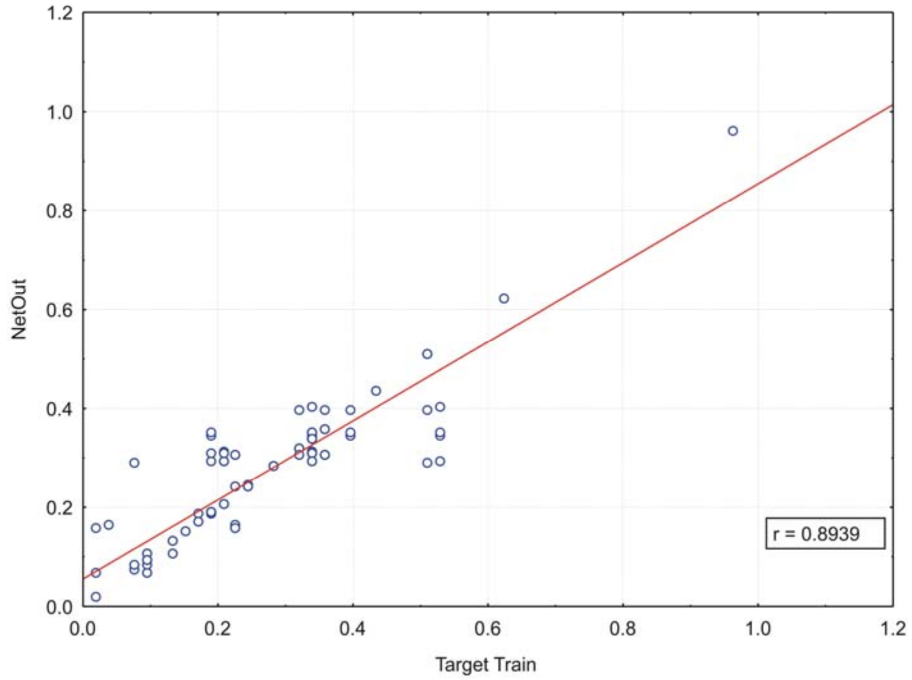


Figure 4: Comparison neural network output and training target data

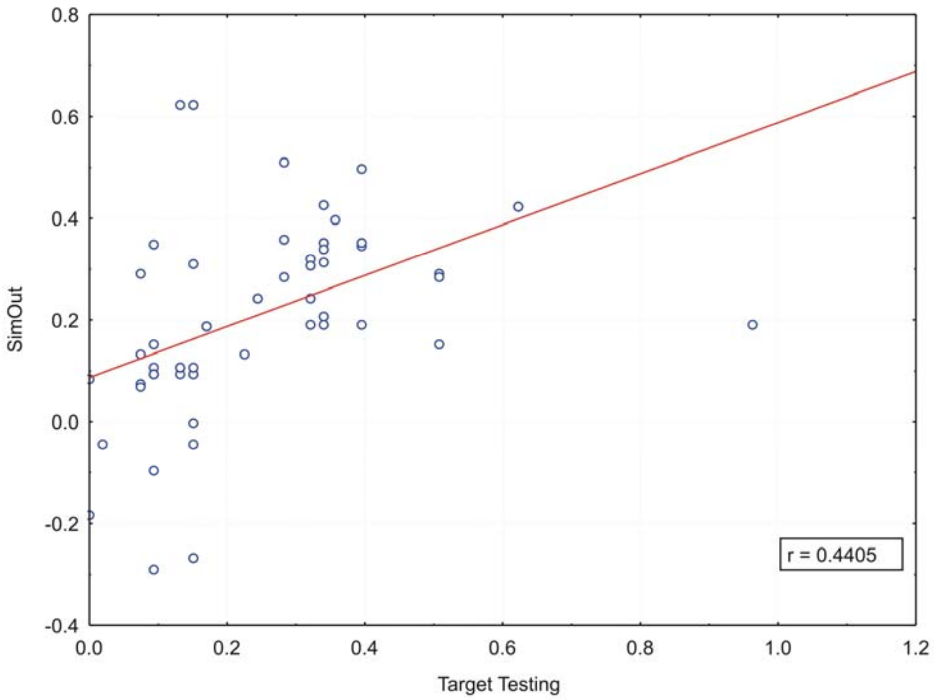


Figure 5: Comparison of neural network and testing target data

# 4 Conclusion

The back-propagation training method used within neural network model was able to predict the service life of timber as material to form building components for coastal area in Malaysia. There is a need to improve the neural network performance on data distribution and learning capability. Further analysis is on going to overcome the best performance of results in predicting the service life of other local building materials.

# 5 Acknowledgement

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