

Architecture of Ensemble Neural Networks for Risk Analysis

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Assembling of neural networks referred to as "Ensemble neural networks" consist with many small "expert networks" that learn small parts of the complex problem, which are established by decomposing it into its sub levels. Ensemble neural network architecture has been proposed to solve complex problems with large numbers of variables. In this paper, this architecture is used to analyze maintainability risks of high-rise buildings. An ensemble neural network that consists with four expert networks to represent four building elements namely roof, façade, basement and internal areas is developed to forecast the maintenance efficiency (ME) of buildings. The model is tested and the results showed good performance. The model is further validated using a real case study.

Key Words: ensemble neural networks, maintenance, risk analysis, artificial neural networks, buildings

Introduction

The risks analysis problem often need to handle number of variables and thus its analysis has become a complex problem. Typically a complex problem would require a network dealing with larger number of inputs covering different dimensions of the problem domain. However, as the network becomes larger the requirement on the data set that is needed to train the network grows high or almost exponentially in terms of number of distinct data points (Walczak, 2001; Huang *et al.*, 2005). For most application domain however compiling a large representative dataset becomes difficult task at its best. This issue is most significant to this problem since the availability of sources to collect data is highly constrained. On the other hand when a smaller than required dataset is used, the network becomes incompletely training, only where part of the problem is learned and the generalization capabilities of the network is compromised.

In the recent past, many researchers have attempted solving this problem. One of such successful attempts has been the use of an ensemble neural networks model where a larger neural network is represented as an ensemble several independent and smaller expert networks (Jacobs, *et al*., 1991a&b; Fu, 2003; Krasnopolsky, 2007). Each of these smaller networks is expected only to learn the solution for a sub-problem within larger problem domain and therefore can be trained with a relatively smaller training data set. Outputs of the smaller networks are then combined together to form the final output which can be trained to represent the solution for the larger problem domain.

In this paper, risk analysis in maintainability of high-rise buildings is discussed with the application of ensemble network due to (1) large numbers of maintainability risk factors in these buildings and (2) difficulty to obtain a single data set by eliciting experts knowledge.

The maintainability of buildings can be stated as "ensuring efficiency in relation to the maintenance functions of a building to maintain its performance throughout the usable life cycle" (Chew *et al.*, 2004; Buys and Nkado, 2006). The measuring of the maintenance efficiency (ME) is not straightforward as there are no standard tools available for the purpose. Many indicators used at different levels to compute the ME. These indicators can be categorized as (1) cost efficiency, (2) technical efficiency, (3) safety and environmental efficiency and (4) other factors such as human comfort(Marquez and Herguedas, 2004; Parida and Chattopadhyay, 2007; Ali, 2009; Bahr and Lennerts, 2010). Measuring the ME using cost terms is a direct method. On the other hand, most of the other indicators can be converted into costs terms, by considering their financial values. Therefore, in this research study, the ME is modelled using "whole life maintenance cost" as the primary indicator. However, the ME can be varied by the inherent risks originated by the characteristics of design, construction and maintenance parameters.

Summarizing the findings of various research studies on this area, these risks can be grouped into seven factors such as (1) accessibility for maintenance, (2) characteristics of building materials and components, (3) design detailing, (4) environmental conditions, (5) requirement for maintenance, (6) constructability and construction quality, and (7) maintenance management process (Assaf *et al*., 1995; Al-Hammad *et al*., 1997; El-Haram and Horner, 2002; Chew *et al*., 2004; Cholasuke *et al*., 2004; Chong and Low, 2006; Flores-Colen, *et al*., 2008; McDuling *et al*., 2008; De Silva and Ranasinghe, 2010). They were established by identifying the causes of maintainability problems.

There were 11,625 maintenance records identified due to inferior quality in construction of houses built between 1982 to 1999 in Victoria, Australia (Mills *et al*., 2009). Ramly *et al*. (2006) reviewed 4,389 records from 36 public housing areas in Kuala Lumpur, and found that 47% were caused due to design faults. Failure to achieve the tightness requirements in buildings under tropical conditions is critical (Chew and De Silva, 2003; Chew *et al*., 2004; Wong and Hui, 2005). Consequences of being exposed to tropical weather conditions such as cracking, staining, biological colonization, dampness, etc., have shown a high profile (Chew and Tan, 2003; Flores-Colen *et al*., 2008; Lateef, 2009). However, most of these problems were common under other weather conditions (Mills *et al*., 2009). Among the causes for these defects, design deficiencies were indicated to be the highest and it is emphasised that these deficiencies can only be prevented by improving the designs (Low and Chong, 2004; De Silva and Ranasinghe, 2010).

Literature Review

Biological studies have shown that the human brain functions not as a single massive network, but as a collection of small networks. This realization gave birth to the ensemble neural networks, within which the several small networks (i.e. small tasks) are combined to generate the task. Therefore these networks are developed to handle large and complex real world problems which cannot be effectively solved by means of training a simple unitary network (Sharkey, 1996; Jiang and Tanner, 1999; Fu, 2003). Due to such nature of many real-world problems, many techniques are used to reduce the complexity of the problem. One such widely used method is "divide and conquer method" where a complex problem is divided into simpler sub-problems. That is breaking a problem into smaller sub-problems, each of which contributes to the combined solution is called "task decomposition" or sometimes is called "functional decomposition**".**

From the neural network (NN) perspective, combining the corresponding outputs of a number of trained networks is similar to creating a large network in which the trained NNs are sub-networks operating in parallel, and the combination-weights are the connection-weights of the output layer (Sharkey, 1996). Therefore, following two steps should be completed to develop an ensemble network as follows:-

Step 1: establish expert networks (ensemble members) which train differently;
Step 2: set up ensemble network connecting trained experts networks in Step 1.

Step 1- In this process, there are number of parameters to be manipulated to obtain set of networks which generalize differently. They include, network architecture, training data set and training algorithm. The same approach as for any NN can be used to select the topology and the algorithm for these expert networks as they behave as independent networks. The common approaches found in the literature to create these expert networks were as follows (Sharkey, 1996; Webb and Zheng, 2004; Valdovinos and S´anchez, 2006):

- Varying the data set – which is the most frequently used method. This involves altering the training data set that generally can be done with sampling data, disjoint training data sets, bagging, boosting and different data sources.
- Varying the architecture – which involves varying number of hidden units while holding the same data set.

- Varying the algorithm – which varies the training algorithm while holding the same data set.

Step 2 – Mainly two architectures are used including ensemble network architectures and modular network architectures to combine individual expert networks.

- Ensemble-Based Networks - In this network architecture, expert networks essentially accomplish the same task. The combining of these networks were commonly used (1) linear approach such as simple averaging and weighted averaging, (2) non-linear approaches and (3) Bayesian approaches where probability distribution of expert networks are combined (Sharkey, 1996; Webb and Zheng, 2004; Krasnopolsky, 2007).
- Modular Networks - Modular networks give broader interpretation than ensemble-based networks. They can be used to combine entirely different networks trained for various tasks. Among the various architectures used in modular networks, mixture of experts network which can combine outputs of separate expert networks to resolve the complex problem was used for various applications (Jacobs *et al*., 1991a). A separate gating network is used and it performs as a "multi-class" of classification task. A huge number of variations and improvements in the learning process of this network have been developed since the original concept paper by Jacobs *et al*. in 1991 (Jiang and Tanner, 1999; Sharkey, 1996; Liu and Yao, 1999; Valdovinos and S´anchez, 2006).

Methodology

Data Collection

Survey method was selected to gather data to develop the ensemble neural network model that can forecast maintenance efficiency of buildings. Data were collected into two different phases. In the first phase, maintainability problems and their causes were explored from the literature and the industry experts to derive risk factors of maintainability of high-rise buildings. At the second phase, experts' knowledge was elicited to quantify these risks. Data were gathered with respect to a sample of high-rise buildings. The facilities or building managers who are employed in these high-rise buildings are assumed to be substantive experts due to their vast experience and knowledge by managing such buildings which are considered to be complex and difficult to maintain.
During the 1st phase, eight leading experts were consulted to substantiate the identified risk factors from the literature. Author discussed the entire list of these factors with two experts to elicit their vast knowledge on this area. The each exercise took about two hours. The concept of "three card trick" was used by asking the most three (1) critical problems, (2) frequent problems to increase current maintenance cost, and (3) effective features that may be favour in reducing maintenance cost, with other experts. The method is selected due to its efficiency in capturing the most relevant information in a short timeframe (Wagner *et al*., 2001). Fifty eight maintainability problem causes were identified and grouped them under 10 risk factors (RF).

During then 2nd phase, the main survey was carried out to seek subjective judgments of experts to quantify RFs. Experts' knowledge was elicited into five systematic steps such as

1. Motivation: Briefed the research objectives and information to be elicited.
2. Structuring and Description: Walkthrough survey was carried out with the facilities manager to explore the existing maintainability issues and challenges, maintenance-free features/situations and the condition of the building component. Elements covered during this survey were roof, façade, basement and internal areas. Pre-identified maintainability risk factors were then introduced to understand the question and mapped them with existing condition of the building to remember the relevant information.
3. Discussion and Conditioning: Pre-set interview guidance was used to start the discussions by focusing the minds of experts to a common set of measuring rules to maintain the consistency of the experts' judgments. The identified 58 maintainability causes were discussed under 10 RFs.
4. Making Judgment: Experts were asked to make subjective judgments for ten questions given below.

5. Response Mode or Reporting: Direct estimates were taken using a numerical scale discussed in this paper.

The ten questions used to elicit subjective judgments from the experts are as follows:

What is your view on the performance of [Question 1 to 10] responsible to originate the current maintenance cost of [Section A to D]:

Question 1 – RF1:architectural and design, Question 2 – RF2:structural and detailing, Question 3 – RF3:services integration, Question 4 – RF4:accessibility for maintenance, Question 5 – RF5:requirements for maintenance, Question 6 – RF6:materials and spare parts for maintenance, Question 7 – RF7:constructability and construction/installation quality, Question 8 – RF8:maintenance process quality, Question 9 – RF9:characteristics, environment and exposure, Question 10 - ***-*** *RF10:user requirements and changes*

Section (A) – roof, Section (B) – façade, Section (C) – basement and/or ground floor, Section (D) – internal common areas

For the purpose of quantifying risk factors for this model, the estimates were obtained according to a continuous rating scale. Anchor points were commonly used with numerical and verbal scales (Meyer and Booker, 2001; Chandrashekaran and Gopalakrishnan, 2008; Dawes, 2008; Sachs and Tiong, 2009). In this study, three anchor points of the scale were given to estimate the performance as:-

1. extremely poor – lower point
2. extremely high– upper point
3. moderate– mid point

Further, minimum (1), maximum (7) and mid (4) numbers of the 7-point Likert scale were assigned to the verbal scales to minimize the ambiguity associated with these scales. The overall elicitation process took minimum of 2hrs-3hrs to get all the answers.

The Model

Building maintainability is a characteristic of building's design, construction and maintenance process to ensure its ME which can be varied by the inherent risks originated by the characteristics of design, construction and maintenance parameters. In this study, risks and the ME of the building was evaluated by decomposing the building into four components namely, roof, façade, basement and internal areas to remove the complexity of the task. Thus the respective ME of these building components are expressed in using the following model:

$$\sum_{c=1}^{4}(ME_B)_c = \sum_{c=1}^{4} f(R_1, R_2, \ldots R_{10})_c \tag{1}$$

Where ME_B is ME of the building c is building components: c1-roof, c2-façade, c3-basement and c4-internal areas and RF_i is risk factors.

ME is calculated using a cost indicator of the ratio of equivalent annuity values of maintenance cost and its initial construction cost. The equivalent annuity value is also known as sinking fund that combines all costs into a single annual cost over the analysis period. This is mathematically expressed as:

$$MEI = \frac{(MC_R)_{EAV}}{(IC)_{EAV}} \tag{2}$$

Step 1: Expert Networks

The computation process of a single element (neuron) in the neural network can be expressed as in the equations 3:

$$y_k = \sum_{k=1}^{K} F_j(x_j w_{jk}) \tag{3}$$

where y_k is the network output of the k^{th} training data set, x is network inputs, w are the weights associated to each connection and j is the number of neurons. It must be noted that equation (3) represents a linear function on the input space spanned by the set of risk factors (x) and F is the *Sigmoid* transfer function,

$$F(z) = \frac{1}{1+e^{-z}} \quad (4)$$

In the backward pass of the network, the process starts at the output layer by passing the error signal E_{net} which is the difference between network output (y_k) and the desired output (t_k) as,

$$E_{net} = \frac{1}{2K}\sum_{k=1}^{K}(y_k - t_k)^2 = \frac{1}{2K}\sum_{k=1}^{K}(\varepsilon_k)^2 \quad (5)$$

where K is the number of training samples. E_{net} should be kept at the minimum level. Mean Squared Error (MSE) minimization processed was used for this task.

Four networks were developed to represent the particular component of the building; such as roof, façade etc. These individual networks were trained as a classification problem, using multi-layer feed-forward networks (Equation 5), as multi-layer perception is one of the most popular connectionist models applied in the literature (Chew *et al*., 2004; Valdovinos, and S´anchez, 2006; Hu, 2008). Good performances of these networks have showed their accuracy as:

- low network errors - roof=3.74918e-3, faced= 2.12403e-3, basement= 5.75240e-3, internal= 2.91361e-2) and
- low generalization errors -i.e. roof= 0.00265, facade= 0.00132, basement= 0.00542, internal= 0.03130 and ensemble network= 0.00214).

Step 2: Ensemble Network

The output of the four expert networks: roof, façade, internal areas, basement and common risk factors were used to get the ME of the building (Figure 1). The common risk factors (RF8, RF9 and RF10) in the expert networks were fed directly as common variables (Figure 1).

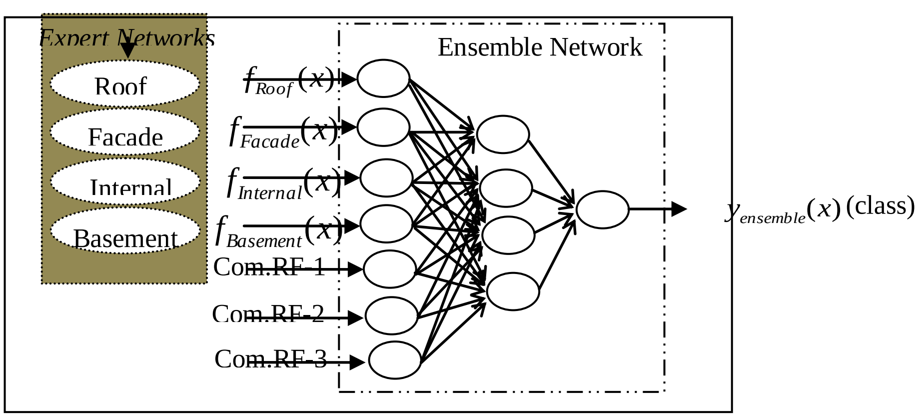

Figure 1: Architecture of the ensemble

In combining these expert networks, ensemble network output of k^{th} training data set can be expressed as (Sharkey, 1996):

$$y_{ensemble}(x)_k = \sum_{i=1}^{N} f_i(x).w_{ik} + \sum_{j=1}^{n} x_j w_{jk} \quad (6)$$

where $f_i(x)$ is the output of the i th expert network, w_i is the corresponding non-negative real values combination weight, N is the number of expert networks and *n* is the number of common variables.

Assuming that there is a linear relationship between the network output and the generalization error, the ensemble error can be established using straight-forward Mean Squared Error (MSE) method in input-output mapping (Ahmad and Zhang, 2002),

$$E_{ens} = E\{\sum_{i=1}^{N}(y_k - y_k(x))^2\} \tag{7}$$

The trained ensemble network was shown low network error (i.e.1.84059e-3) and generalization error (i.e. 0.00214) and thus considered as an accurate model.

Model Application and Discussion

A high-rise building owned by a local bank was selected as a case study to validate the model. It is a 15 years old building developed for a bank and customer activities. It has a basement floor which is used as the car park and machine rooms. The building was developed and constructed by a local engineering firm. It has a good architectural view created by the steps of the vertical façade. The flushed windows are provided at the façade to acquire the advantage of the surrounding beauty shaped by a lake. The building is managed by a private company appointed by the management of the bank. This company has a maintenance manager and the technical staff to carry out the maintenance work.

The whole life maintenance cost of this building is US $ 5,127,000 (SL Rs. 563,970,567). The cost items considered in this case are small repairs such as replacing of ceiling boards; tiles; repairing of window fittings; skirting etc., major repairs that include waterproofing, painting, etc., building materials and construction work, testing and consultancies, insurances, administration and other overheads. The expert's judgments for risk factors under (1) existing scenario and (2) and the improved scenario to be expected the maximum maintenance efficiency were elicited. According to the expert, current risk conditions could be further reduced if some deficiencies in architecture, accessibility for maintenance, lack of thoughts for future maintenance requirements, inefficiencies in the existing maintenance programme, difficulties given by the building's characteristics under exposure conditions and user requirements would be removed. Thus, further improvements of roof (1st, 2nd and 7th factors), façade (1-3, 5-7 factors), basement (2nd, 3rd,5th and 7th factors) and internal areas (3rd, 6th and 7th factors) were proposed as given in Table 1. Further, performances of 8th and 10th factors were improved. Ninth factor was unchanged due to its characteristics of building such as size, complex features and location to be required for its nature of business.

Table 1

Performances of risks factors for two scenarios

No	**Risk Factor**	**Roof**		**Façade**		**Basement**		**Internal**	
		E	M	E	M	E	M	E	M
1	Structural and detailing	M	G	SG	G	P		SG	
2	Architecture and design	SG	G	M	G	SG	G	G	
3	Services integration	G		SG	G	M	G	P	G
4	Accessibility	G		M		G		G	
5	Materials and spare parts	SG		SG	G	M	VG	G	
6	Maintenance requirements	G		G	VG	G		G	VG
7	Construction quality	SG	G	SG	G	SP	G	SG	G
8	Maintenance process quality	M	VG	M	VG	M	VG	M	VG
9	Characteristics, environment and exposure	SG		SG		SG		SG	
10	User requirement and changes	M	SG	M	SG	M	SG	M	SG

Title: E-Existing, M-Maximum

E-Excellent, G-Good, SG-Somewhat Good, M-Moderate, SP-Somewhat Poor, P-Poor, VP-Very Poor

Results of the model indicated the *MEI* was improved from “Very Low” to “Very High”. The results were further validated by the expert, after having a detailed discussion. Therefore, if risks would have been managed, ME of this building could be improved, irrespective of the type, business and size of the building. This is a good indication that any type of building can be well maintained with lesser maintenance costs, if the building was designed, constructed and managed properly by controlling their maintainability risks.

Conclusions

The ensemble neural network architecture has provided the best framework for predicting the maintenance efficiency of buildings. This network architecture is made of an ensemble of small, independent neural networks (referred to as “expert networks”), where each network can be assigned and trained to make a prediction relating to a different component in the building. This provided effective way of handling two native issues; the lack of a large representative training data sample and the un-known correlation among the input variables. In the model proposed in this paper, four different expert networks were used to represent major building components of roof, façade, basement and internal common areas of the building. Outputs of the expert networks were then combined to forecast the overall maintenance efficiency using an indicator of *MEI*. Low error terms of the trained neural network models showed it capacity for generate accurate results.

The ensemble neural network model was then used to determine the *MEI* of a real case study under two different scenarios as (1) existing risk condition and (2) improved risk condition. The results showed a significant improvement in the *MEI* under “improved risk conditions”. This indicated that the better management of maintainability risks can enhance e its efficiency.

It is an immense need to promote importance of the risk analysis in maintainability of building to enhance maintainable buildings. Thus, the cutting-edge of risk analysis need to focus on developing and promoting effective risk analysis frameworks and models to the industry. The proposed NN architecture is a momentum to create an impact in promoting this.

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