13

Applying an Artificial Neural Network to Predicting Effort and Errors for Embedded Software Development Projects

Kazunori Iwata[1], Toyoshiro Nakashima[2], Yoshiyuki Anan[3] and Naohiro Ishii[4]

[1]*Dept. of Business Administration, Aichi University*
[2]*Dept. of Culture-Information Studies, Sugiyama Jogakuen University*
[3]*Base Business Division, Omron Software Co., Ltd.*
[4]*Dept. of Information Science, Aichi Institute of Technology*
Japan

1. Introduction

Recently, growth in the information industry has caused a wide range of uses for information devices, and the associated need for more complex embedded software, that provides these devices with the latest performance and function enhancements (Hirayama (2004); Nakamoto et al. (1997)). Consequently, it is increasingly important for embedded software-development corporations to ascertain how to develop software efficiently, whilst guaranteeing delivery time and quality, and keeping development low costs (Boehm (1976); Tamaru (2004); Watanabe (2004)). Hence, companies and divisions involved in the development of such software are focusing on various types of improvement, particularly process improvement. Predicting effort requirements of new projects and guaranteeing quality of software are especially important, because the prediction relates directly to costs, while the quality reflects on the reliability of the corporation Komiyama (2003); N. (2004); Nakashima (2004); Ogasawara & Kojima (2003); Takagi (2003). In the field of embedded software, development techniques, management techniques, tools, testing techniques, reuse techniques, real-time operating systems and so on, have already been studied. However, there is little research on the relationship between the scale of the development and the number of errors, based of data accumulated from past projects. As a result, previously we described the prediction of the total scale using multiple regression analysis (Iwata et al. (2006b); Nakashima et al. (2006)) and collaborative filtering (Iwata et al. (2006a)). In this Chapter we therefore, propose a method for creating effort and errors prediction model using an Artificial Neural Network (ANN) for complementing missing values (Iwata et al. (2006a)). The proposed method calculates the amount of effort and the number of errors by the following 3 steps. The first step, the similarity between the complementary project data, which include missing values, and the complete project data is calculated. Next, applies collaborative filtering using the method Tsunoda et al. (Tsunoda et al. (2005)) to complement missing values in the data and thus produce sufficient amount of data. In the final step, the prediction target project effort (or errors) is calculated

using the model that is derived from the ANN and with this data. However, the ANN has a large margin of errors for some projects. We therefore, propose a method to reduce the margin of errors model. Finally, we also compare the accuracy of the proposed ANN model with that of a multiple regression analysis model using Welch's t-test (Student (1908); Welch (1947)).
The rest of the Chapter is organized as follows. In Section 2, we explain software development management and discuss current problems and the objectives which this study is trying to achieve, and illustrate software development process and selection of data to establish the model in Section 3. Then, Section 4 explains a collaborative filtering to complement missing values. In Section 5 we expound models to predict effort and errors. In section 6 describes evaluation experiment. Section 7 concludes.

2. Software project management and issues

The embedded software for financial institutions developed by "OMRON software Co." is based on the basic software customized for an individual customer's need to install it at various sites. To minimize the customization needed during the development of basic software, parameters are embedded to control the system. This engineering technique assures productivity and quality. This type of approach is actively taken during the process of software development. While using this type of technique, the pressures related to delivery time and quality are more and more intense. This requires improving further the quality and cost during software development. Hence, we have already studied costs of the processes by using analysis(Iwata et al. (2006b); Nakashima et al. (2006)) and collaborative filtering(Iwata et al. (2006a)). To cope with this situation, the tools that can manage the progress status or results in the database are used to improve the quality and productivity. However, the more the volume of software development project increases the more the errors increase. By analyzing the database, we determine the relationship between the volume of software development project and the errors.

3. Software development processes and selection of data

In software development division of "OMRON software Co.", the waterfall model(Boehm (1976)) is used as the basic development-process model. A general description of this model is given in Table 1.
Regarding the data related to project productivity or quality, data for such things as internal effort and size information etc. are recorded as shown in Table 2 and Table 3, for 3 points in time:

1. At the beginning of the project.
2. During the project.
3. At the end of the project.

Before analyzing data, we examined the data and decided which data should be selected to make the model. Table 2 and Table 3 show the latter data and the results of the selection.

3.1 Data sets for creating models

Using the following data, we create models to predict both the planning effort (Eff) and errors (Err).

Eff**:** "The amount of effort", which needs be predicted.

	Process	Contents of work
1	Conceptual design(CD)	This is so-called "system engineering work". They analyze customer requirements and detail the areas to be addressed as development factors.
2	Design	According to the development factors defined in CD process, designing of software functionality, combining of software modules, and writing of source code are performed.
3	Debugging	Verify the outcome of the design process with the actual machine to see if it is designed according to the design. The same designer in design process is assigned to debug.
4	Test	After finishing debugging, double-check the software to confirm that it satisfies customer's requirements. A different person (not those assigned to design and debug) is assigned to do this.

Table 1. Software Development Process

Items	Data	Selection	Reason
Internal effort	Effort for each planned process and actual performance	Selected	The data are acquired by effort management system. These data are quantitative and accuracy is good.
Project-scale information	Number of lines in new, modified, original and reused software	Selected	These data are quantitative and accuracy is good.
Effort information	Actual effort in each process	Rejected	The data are acquired at the end of the project. Hence, they can not use to predict effort and errors at the beginning of the project.
	Effort for redo in each process	Rejected	The definition of redo is not consistent. The accuracy is poor.

Table 2. Classifications and Selection of Data 1

Items	Data	Selection	Reason
Products information	Product classification and product models	Selected	It is necessary to make characteristics of the products and development process be reflected in the model.
	Customer name and sub project name	Rejected	The data is qualitative and it is difficult to obtain accurate data.
	Development type(new or modification)	Rejected	Because there are only two types, it is not appropriate as parameter for the model.
	Delivery time	Rejected	Because the delivery time is seldom changed, this is not selected.
Outsourcing	The estimation of outsourcing amount and actual situation	Rejected	Because outsourcing amount includes sales aspects, this is not appropriate for actual project error status.
	The estimation of outsourcing effort and actual situation	Rejected	Because this is estimated by outsourcing amount and includes sales aspects, this is not selected.
Quality information	The number of problems in each process	Selected	It is necessary to find relationship between a project and errors. These data consist of "Total Error", "Error in CD and Design", "Error in Debugging" and "Error in Test".

Table 3. Classifications and Selection of Data 2

Err: "The number of errors" in a project.

V_{new}: "Volume of newly added", which denotes the number of steps in the newly generated functions of the target project.

V_{modify}: "Volume of modification", which denotes the number of steps modifying and adding to existing functions to use the target project.

V_{survey}: "Volume of original project", which denotes the original number of steps in the modified functions, and the number of steps deleted from the functions.

V_{reuse}: "Volume of reuse", which denotes the number of steps in functions of which only an external method of has been confirmed and which are applied to the target project design without confirming the internal contents.

4. Collaborative filtering

4.1 Conventional collaborative filtering and complementing values

Collaborative filtering is used as a basic technique in a system (here referred to as a "recommendation system"), that recommends items from a number of available options by matching user preferences (Breese et al. (2000); Tsunoda et al. (2005)). The items are any objects, for which the degree of preference changes according to the user, such as articles, web pages, books, songs, movies, and so on. A recommendation system based on collaborative filtering includes the following two steps:

1. Calculating similarity among users (user evaluation values are used in the calculation).
2. Determining items to be recommended (calculated values for the items are based on similarity). Herein, it is assumed that the preferences of users that are highly similar, will also be similar, and that new items are recommended to users.

This Chapter applies the method of conceptualizing from a recommendation system based on collaborative filtering to complement missing values, and references the effort and errors prediction method proposed by Tsunoda et al., (Tsunoda et al. (2005)). In other words, in this Chapter we calculate missing values based on the assumption that "if a project has any missing values, the values are similar to those of other projects that show striking similarities, because highly similar projects output similar values for each item.". We use metrics to calculate the similarity among projects instead of user evaluation values. However, the range of a metric is different for each class, in contrast to user evaluation values that are all within a fixed range. Hence, the values by each metric are normalized to set its range. Moreover, the values by each metric rely on the scale of the project, and the dispersion of the average values by each metric is extremely large. Because of this, errors will be magnified if the scale of the project is not considered when calculating missing values. Therefore, to calculate missing values, we use revised values corresponding to the scale of the project, and do not use those projects that are too far apart on the scale, even if the similarity is high.

4.2 Complement method for missing value

In this Chapter, the matrix $m \times n$ denotes a data set including missing values. $p_i \in \{p_1, p_2, \ldots, p_m\}$ indicates the ith project, and $m_j \in \{m_1, m_2, \ldots, m_n\}$ indicates the jth metric. $v_{i,j} \in \{v_{1,1}, v_{1,2}, \ldots, v_{m,n}\}$ means the value of the measurement in the jth matrix m_j in the ith project p_i. When $v_{i,j}$ is the missing value, it is denoted as $v_{i,j} = \phi$.

	m_1	m_2	$\cdots$	m_j	$\cdots$	m_b	$\cdots$	m_n
p_1	$v_{1,1}$	$v_{1,2}$	$\cdots$	$v_{1,j}$	$\cdots$	$v_{1,b}$	$\cdots$	$v_{1,n}$
p_2	$v_{2,1}$	$v_{2,2}$	$\cdots$	$v_{2,j}$	$\cdots$	$v_{2,b}$	$\cdots$	$v_{2,n}$
$\cdots$	$\cdots$	$\cdots$		$\cdots$		$\cdots$		$\cdots$
p_i	$v_{i,1}$	$v_{i,2}$	$\cdots$	$v_{i,j}$	$\cdots$	$v_{i,b}$	$\cdots$	$v_{i,n}$
$\cdots$	$\cdots$	$\cdots$		$\cdots$		$\cdots$		$\cdots$
p_a	$v_{a,1}$	$v_{a,2}$	$\cdots$	$v_{a,j}$	$\cdots$	$v_{a,b}$	$\cdots$	$v_{a,n}$
$\cdots$	$\cdots$	$\cdots$		$\cdots$		$\cdots$		$\cdots$
p_m	$v_{m,1}$	$v_{m,2}$	$\cdots$	$v_{m,j}$	$\cdots$	$v_{m,b}$	$\cdots$	$v_{m,n}$

Fig. 1. Matrix $m \times n$ Used in Prediction

Let the value of the bth metric m_b in the ath project p_a be a missing value $v_{a,b} = \phi$ and $\widehat{v}_{a,b}$ mean the prediction value for the metric value $v_{a,b}$.
In calculating $\widehat{v}_{a,b}$ the following three steps are processed.

1. Metric normalization. The range of every metric range is $[0, 1]$ via normalization.
2. Calculation of similarity among projects.
3. Missing value calculation.

4.2.1 Metric normalization

The values of each metric are normalized to set the range for the metric. The range of every metric range is $[0, 1]$ via normalization. The normalized value for a metric of value $v_{i,j}$ is denoted as $f_n(v_{i,j})$, and $f_n(v_{i,j})$ is calculated by the Eq. (1).

$$f_n(v_{i,j}) \quad = \quad \frac{v_{i,j} - min(P_j)}{max(P_j) - min(P_j)} \tag{1}$$

where, P_j is the set of projects able to measure the value of the metric m_j and $max(P_j)$, $min(P_j)$ are the maximum and minimum values of $\{v_{k,j} | p_k \in P_j\}$, respectively.

4.2.2 Calculation of similarity among projects

The similarity between the missing value prediction target project p_a and another project p_i is described as $f_{sim}(p_a, p_i)$. The similarity calculation uses a vector calculation algorithm (Breese et al. (2000)).
The algorithm for calculating similarity is usually used to calculate the similarity between two documents (Salton & MacGill (1983)). In the algorithm, each vectors contain the frequency of words appearing in each document, and similarity is calculated using the cosine of the angles created by the vectors. Breese et al. (Breese et al. (2000)) proposed a recommendation system based on this algorithm, in which they equate a document with a user, the words with items, and the word frequency with the item evaluation value. In this Chapter, we calculate the similarity of projects by equating the user with the project, the item with the metric, and the item prediction value with the metric value similar to the method of Tsunoda et al. (Tsunoda et al. (2005)).
The similarity $f_{sim}(p_a, p_i)$ between the prediction target project p_a and the another project p_i is calculated as in Eq. (2).

$$f_{sim}(p_a, p_i) = \frac{\sum_{j \in M_a \cap M_i} f_n(v_{a,j}) \times f_n(v_{i,j})}{\sqrt{\sum_{j \in M_a \cap M_i} f_n(v_{a,j})^2} \sqrt{\sum_{j \in M_a \cap M_i} f_n(v_{i,j})^2}} \quad (2)$$

where, M_a and M_i are the set of non missing metrics measured in projects p_a and p_i respectively. The value range for the similarity $f_{sim}(p_a, p_i)$ is $[0, 1]$.

4.2.3 Missing value calculation

The prediction value $\widehat{v}_{a,b}$ of a missing value $v_{a,b}$ is calculated using the similarity $f_{sim}(p_a, p_i)$. It is necessary to consider the scale of projects in higher similarity to p_a to calculate $\widehat{v}_{a,b}$, because only the vector angles are used in the similarity calculation and vector size is not taken into account (Tsunoda et al. (2005)). Hence, for the calculation of missing values, the project scale reviser $amplifier : f_{amp}(p_a, p_i)$ is used as a weight. Furthermore, if $f_{amp}(p_a, p_i)$ exceeds the constant value $ampmax$, the project p_i is not used in the calculation of $\widehat{v}_{a,b}$, since the project scale is considered too different even if the similarity is high. $\widehat{v}_{a,b}$ is calculated from Eq. (3).

$$\widehat{v}_{a,b} = \frac{\sum_{i \in knP} v_{i,b} \times f_{amp}(p_a, p_i) \times f_{sim}(p_a, p_i)}{\sum_{i \in knP} f_{sim}(p_a, p_i)} \quad (3)$$

where, knP means a set that has the k projects with a high similarity to project p_a without the value of $amplifier$ exceeding $ampmax$. $f_{amp}(p_a, p_i)$ is calculated from Eq. (4).

$$f_{amp}(p_a, p_i) = \begin{cases} r_n & h = (2n-1) \\ \frac{r_n + r_{n+1}}{2} & h = 2n \end{cases} \quad (4)$$

where, h is the number of the product set of M_a and $M_i(|M_a \cap M_i|)$, and r_j equals $\frac{f_n(v_{a,j})}{f_n(v_{i,j})}$, that is, the ratio of the values of the metric m_j in projects p_a and p_i.

5. Effort and error prediction models

5.1 An artificial neural network model

Artificial Neural Networks (ANNs) are essentially simple mathematical models defining function.

$$f : X \to Y \quad (5)$$

where $X = \{x_i | 0 \leq x_i \leq 1, i \geq 1\}$ and $Y = \{y_i | 0 \leq y_i \leq 1, i \geq 1\}$.
ANNs are non-linear statistical data modeling tools and that can be used to model complex relationships between inputs and outputs. The basic model is illustrated in Fig. 2, in which the output is calculated as follows.

1. Calculating values for hidden nodes. The value of $Hidden\ Node_j$ is calculated using the following equation:

$$Hidden\ Node_j = f\left(\sum_i (w_{i,j} \times Input_i)\right) \tag{6}$$

where $f(x)$ equals $\frac{1}{1+\exp(-x)}$ and the $w_{i,j}$ is weight calculated by the learning algorithm.

2. Calculating $Output$ using $Hidden\ Node_j$ as follows:

$$Output = f\left(\sum_k (w'_k \times Hidden\ Node_k)\right) \tag{7}$$

where $f(x)$ equals $\frac{1}{1+\exp(-x)}$ and the w'_k is weight calculated by the learning algorithm.

We can use an ANN to create effort and error prediction models.

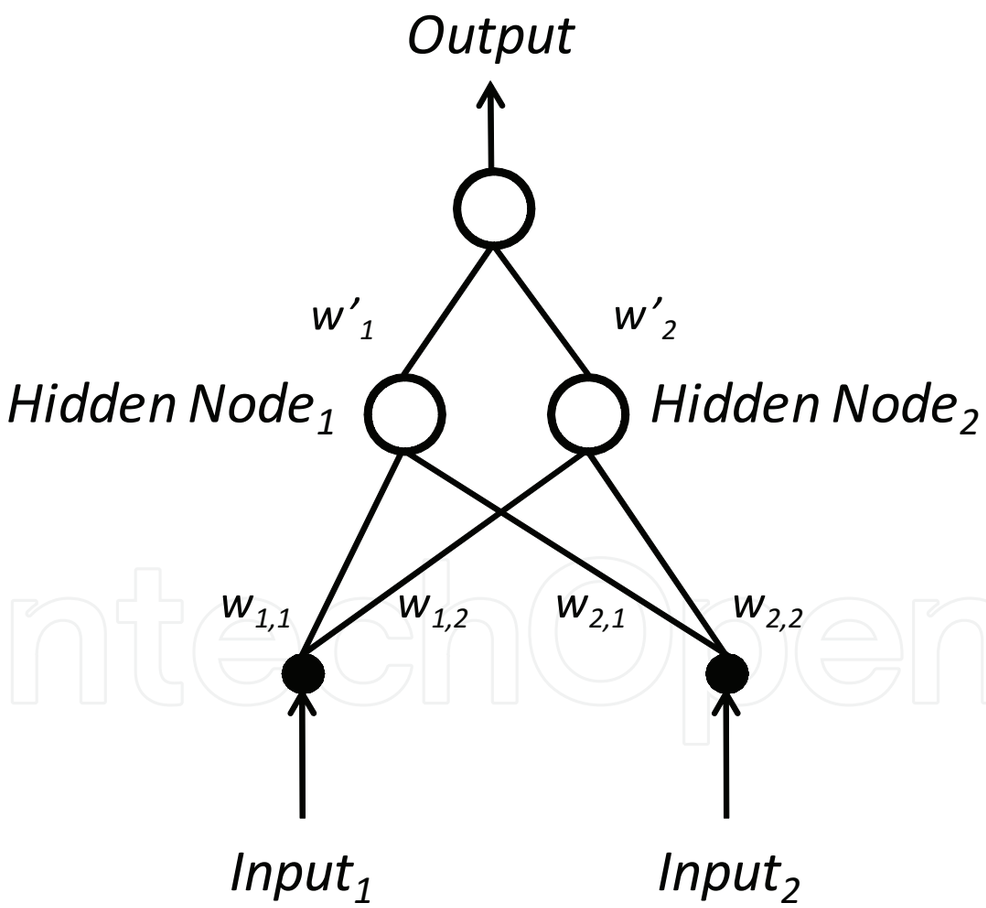


Fig. 2. Basic Artificial Neural Network

5.1.1 Normalization of data

In an ANN, a range of input values or output values is usually less than or equal to 1 and greater than or equal to 0. However, most selected data are grater than 1. Each data range is, therefore, converted to [0, 1] by normalization. The normalized value for t_{kind} is expressed as $f_n(t_{kind})$ (where $kind$ denotes Eff, Err, V_{new}, V_{modify}, V_{survey} and V_{reuse}). The normalized value $f_n(t_{kind})$ is calculated using Eq. (8) , which is the same as Eq. (1).

$$f_n(t_{kind}) = \frac{t_{kind} - min(T_{kind})}{max(T_{kind}) - min(T_{kind})} \tag{8}$$

where T_{kind} denotes the set of t_{kind}, and $max(T_{kind})$ and $min(T_{kind})$ denote the maximum and minimum values, respectively, of T_{kind}.

The normalization is flat and smooth, then, a small change in a normalized value influences a small-scale project to a greater degree than a large scale project.

For example, let $min(T_{Eff})$ equal 10, $max(T_{Eff})$ equal 300, t_{Eff1} equal 15, t_{Eff2} equal 250, predicted value for t_{Eff1} be $\widehat{t_{Eff1}}$ and t_{Eff2} be $\widehat{t_{Eff2}}$. If the prediction model has $+0.01$ error, then $f_{n_l}^{-1}(0.01) = 2.90$. The predicted values result in $\widehat{t_{Eff1}} = 17.90$ and $\widehat{t_{Eff2}} = 252.90$. Both cases has same errors, but their absolute of the relative errors (ARE) are follows:

$$ARE_{Eff1} = \left| \frac{\widehat{t_{Eff1}} - t_{Eff1}}{t_{Eff1}} \right| = \left| \frac{17.90 - 15}{15} \right| = 0.1933$$

$$ARE_{Eff2} = \left| \frac{\widehat{t_{Eff2}} - t_{Eff2}}{t_{Eff2}} \right| = \left| \frac{252.90 - 250}{250} \right| = 0.0116$$

The results indicate the absolute of the relative errors of former is greater than that of the latter. These distributions for the amount of effort and the number of errors indicate the small-scale projects are major and more than the large scale projects. Therefore, in order to improve prediction accuracy, it is important to reconstruct the normalizing way.

5.2 New normalization of data

In order to solve the problem, we adopt new normalizing way in the following equation:

$$f_{n_c}(t) = \sqrt{1 - (f_{n_l}(t) - 1)^2} \tag{9}$$

The comparison between Eq. (8) and Eq. (9) is shown in Figure 3 and 4. The Eq. (9) has a sharp inclination at the lower original data, then a small change at the lower original data get magnified.

Using the same assumption, the predicted values result in $\widehat{t_{Eff1}} = 15.56$ and $\widehat{t_{Eff2}} = 271.11$. Their absolute of the relative errors are in Eq. (10) and Eq. (11).

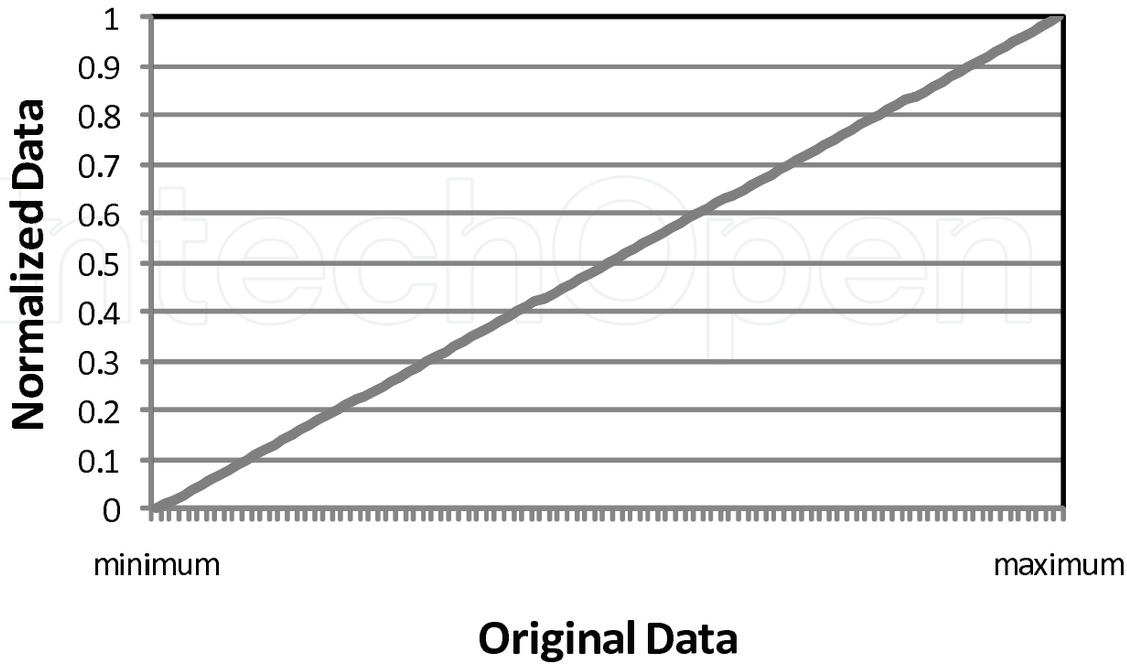


Fig. 3. Normalizing Results using Eq. (8)

$$ARE_{Eff1} = \left|\frac{15.56 - 15}{15}\right| = 0.0373 \quad (10)$$

$$ARE_{Eff2} = \left|\frac{271.11 - 250}{250}\right| = 0.0844 \quad (11)$$

The results show the absolute of the relative errors for the small-scale project is smaller than that of old normalization method and, in contrast, that for the large scale project is slightly larger than that of old normalization method. The more detailed comparison analyses are in Section 6.

5.2.1 Structure of model

In a feed-forward ANN, the information is moved from input nodes, through the hidden nodes to the output nodes. The number of hidden nodes is important, because if the number is too large, the network will over-training. The number of hidden nodes is, generally 2/3 of the number of input nodes or twice the number of input nodes. In this Chapter, we use 8 hidden nodes in our model which is illustrated in Fig. 5.

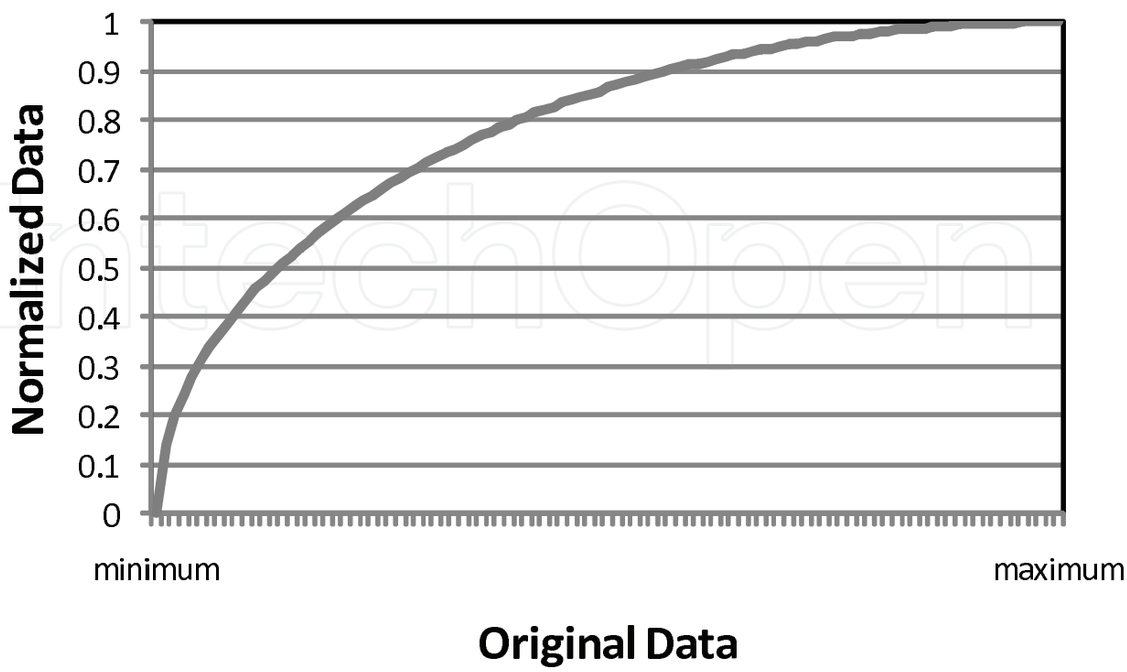


Fig. 4. Normalizing Results using Eq. (9)

5.3 Multiple regression analysis model

The multiple regression analysis (MRA) model is derived from Eq. (12), in which the notation adheres to the meanings defined in Subsection 3.1.

$$D = \alpha_1 \times S^2 + \alpha_2 \times S + \beta \tag{12}$$

where, D indicates Eff or Err, and S is calculated by Eq. (13).

$$S = V_{new} + V_{modify} + \theta_1 \times V_{survey} + \theta_2 \times V_{reuse} \tag{13}$$

where, θ_1 and θ_2 are less than 1, thus Eq. (13) emphasizes V_{new} and V_{modify}.

6. Evaluation experiment

6.1 Evaluation criteria

Equations (14) to (16) are used as evaluation criteria for the effort and errors prediction models. The smaller the value of each evaluation criterion, the higher is the relative accuracy in Eqs. (14) to (16). The accuracy value is expressed as X, and the predicted value as $\widehat{X}$. Also, the number of data is expressed as n.

1. Mean of Absolute Errors (MAE).
2. Standard Deviation of Absolute Errors ($SDAE$).

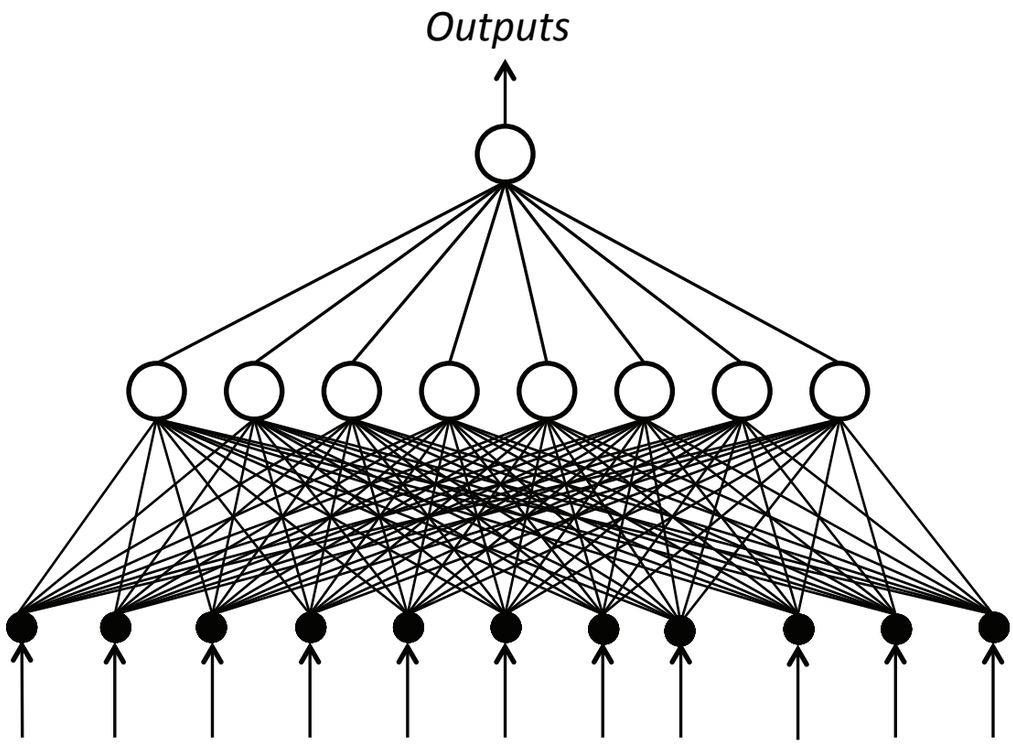


Fig. 5. Structure of Model

3. Mean of Relative Errors (MRE).
4. Standard Deviation of Relative Errors ($SDRE$).

$$MAE = \frac{1}{n}\sum|\widehat{X} - X| \tag{14}$$

$$SDAE = \sqrt{\frac{1}{n-1}\sum\left(|\widehat{X} - X| - MAE\right)^2} \tag{15}$$

$$MRE = \frac{1}{n}\sum\left|\frac{\widehat{X} - X}{X}\right| \tag{16}$$

$$SDRE = \sqrt{\frac{1}{n-1}\sum\left(\left|\frac{\widehat{X} - X}{X}\right| - MRE\right)^2} \tag{17}$$

6.2 Data used in evaluation experiment

The evaluation experiment uses the complemented data for projects including missing values by the method described in Subsection 4.2. This complemented project data is divided into

two random sets. One of the two sets is used as training data, while the other is test data. The training data is used the generation of the effort (or errors) prediction model generation, which is used to predict the effort (or errors)of the projects in the test data. The prediction criteria presented in Subsection 6.1 are then used to confirm whether the effort were accurately predicted or not by. Both data sets, that is, the training data and test data, are divided into 5 sections and these are used to repeat the experiment 5 times.

6.3 Results and discussion

A total of 73 projects were used in the experiment, of which 53 included missing values. Missing values were added to these 53 projects. For each method, averages of the experiments results for the 5 experiments are shown in Table 5.

	MAE	$SDAE$	MRE	$SDRE$	
ANN Model	17.440	37.679	0.69892	0.67254	
MRA Model	30.825	55.643	0.98884	0.98928	

Table 4. Experimental Results for Errors Prediction

	MAE	$SDAE$	MRE	$SDRE$
ANN Model	11.345	17.403	0.25536	0.33830
MRA Model	24.962	11.941	0.89056	0.91893

Table 5. Experimental Results for Efforts Prediction

6.3.1 Validation analysis of the accuracy of the models

We compare the accuracy of the ANN model with that of the regression analysis model using Welch's t-test (Welch (1947)). The t-test (called Student's t-test)(Student (1908)) is used as a test of the null hypothesis that the means of two normally distributed populations are equal. Welch's t-test is used when the variances of two samples are assumed to be different to test the null hypothesis that the means of non two normally distributed populations are equal if the two sample sizes are equal (Aoki (n.d.)). The t statistic to test whether the means are different is calculated as follows:

$$t_0 = \frac{\left|\overline{X} - \overline{Y}\right|}{\sqrt{\frac{s_x}{n_x} + \frac{s_y}{n_y}}} \tag{18}$$

where $\overline{X}$ and $\overline{Y}$ are the sample means, s_x and s_y are the sample standard deviations and n_x and n_y are the sample sizes. For use in significance testing, the distribution of the test statistic is approximated as an ordinary Student's t-distribution with the following degrees of freedom:

$$\nu = \frac{\left(\frac{s_x}{n_x} + \frac{s_y}{n_y}\right)^2}{\frac{s_x^2}{n_x^2(n_x-1)} + \frac{s_y^2}{n_y^2(n_y-1)}} \tag{19}$$

Thus once the a t-value and degrees of freedom have been determined, a p-value can be found using a table of values from the Student's t-distribution. If the p-value is smaller than or equal

to the significance level, then the null hypothesis is rejected. The significance levels are usually 0.05 and 0.01, are represented by the Greek symbol, α.
The null hypothesis, in these cases, is "there is no difference between the means of the prediction errors for the ANN model and the MRA model". The results of the t-test for absolute errors and relative errors are given in Tables 6 and 7,
are given in Tables 8 and 9, respectively.

	ANN Model	MRA Model
Mean ($\overline{X}$)	17.440	30.825
Standard deviation(s)	37.679	55.643
Sample size (n)	189	189
Degrees of freedom (ν)	362.565	
t value (t_0)	19.0483	
p value	2.2×10^{-16}	

Table 6. Results of t-test for MAE for Effort

	ANN Model	MRA Model
Mean ($\overline{X}$)	0.69892	0.98884
Standard deviation(s)	0.67254	0.98928
Sample size (n)	189	189
Degrees of freedom (ν)	362.82	
t value (t_0)	3.0918	
p value	0.002143	

Table 7. Results of t-test for MRE for Effort

	ANN Model	MRA Model
Mean ($\overline{X}$)	11.345	24.962
Standard deviation(s)	17.403	11.941
Sample size (n)	189	189
Degrees of freedom (ν)	363.409	
t value (t_0)	34.5583	
p value	2.2×10^{-16}	

Table 8. Results of t-test for MAE for Errors

	ANN Model	MRA Model
Mean ($\overline{X}$)	0.25536	0.89056
Standard deviation(s)	0.33830	0.91893
Sample size (n)	189	189
Degrees of freedom (ν)	309.901	
t value (t_0)	7.7881	
p value	1.031×10^{-13}	

Table 9. Results of t-test for MRE for Errors

The results indicate that the means of the absolute (or relative)errors between ANN models and MRA model shows a statistically significant difference, because the p-values are less than 0.01.

7. Conclusion

In this Chapter, we have established effort and errors prediction models using artificial neural networks for complementing missing values. The proposed method calculated the amount of effort and the number of errors by the following 3 steps.

1. Calculating the similarity between the complementary projects data (which include missing values) and the complete project data,
2. Applying collaborative filtering to complement missing values in the data and thus produce sufficient amount of data,
3. Creating models to predict target project effort (or errors) by the ANN and with this data.

In addition, we carried out an evaluation experiment that compared the accuracy of the ANN model with that of the MRA model using Welch's t-test. The results of the comparison indicate that the ANN model is more accurate than the MRA model, because the mean errors of the ANN are statistically significantly lower.
Our future works are the following:

1. In this study, we used a basic artificial neural network. More complex models need to be considered to improve the accuracy by avoiding over-training.
2. We implemented a model to predict the final amount of effort and number of errors in new projects. It is also important to predict effort and errors mid-way in the development process of a project.
3. We used all the data in implementing the model. However, the data include exceptions and there are harmful to the model. Data needs to be clustered in order to to identify these exceptions.
4. Finally, more data needs to be collected from completed projects.

8. References

Aoki, S. (n.d.). In testing whether the means of two populations are different(in Japanese), `http://aoki2.si.gunma-u.ac.jp/lecture/BF/index.html`.

Boehm, B. (1976). Software engineering, *IEEE Trans. Software Eng.* C-25(12): 1226–1241.

Breese, J., Heckerman, D. & Kadie, C. (2000). Empirical analysis of predictive algorithms for collaborative filtering, *Proc. 14th Conf. on Uncertainty in Artificial Intelligence, Wisconsin* pp. 337–386.

Hirayama, M. (2004). Current state of embedded software(in japanese), *Journal of Information Processing Society of Japan(IPSJ)* 45(7): 677–681.

Iwata, K., Anan, Y., Nakashima, T. & Ishii, N. (2006a). Effort prediction model using similarity for embedded software development, *Lecture Notes in Computer Science, Springer* 3981: 40–48.

Iwata, K., Anan, Y., Nakashima, T. & Ishii, N. (2006b). Improving accuracy of multiple regression analysis for effort prediction model, *Proceedings of 5th IEEE/ACIS International Conference on Computer and Information Science – ICIS 2006* pp. 48–55.

Komiyama, T. (2003). Development of foundation for effective and efficient software process improvement(in japanese), *Journal of Information Processing Society of Japan(IPSJ)* 44(4): 341–347.

N., U. (2004). Modeling techniques for designing embedded software (in japanese), *Journal of Information Processing Society of Japan(IPSJ)* 45(7): 682–692.

Nakamoto, Y., Takada, H. & Tamaru, K. (1997). Current state and trend in embedded systems(in japanese), *Journal of Information Processing Society of Japan(IPSJ)* 38(10): 871–878.

Nakashima, S. (2004). Introduction to model-checking of embedded software(in japanese), *Journal of Information Processing Society of Japan(IPSJ)* 45(7): 690–693.

Nakashima, T., Iwata, K., Anan, Y. & Ishii, N. (2006). Studies on project management models for embedded software development projects, *Proceedings of 4th International Conference on Software Engineering Research, Management Applications – SERA 2006* pp. 363–370.

Ogasawara, H. & Kojima, S. (2003). Process improvement activities that put importance on stay power(in japanese), *Journal of Information Processing Society of Japan(IPSJ)* 44(4): 334–340.

Salton, G. & MacGill, M. (1983). *Introduction to Modern Information Retrieval*, Mcgraw-Hill College.

Student (1908). The probable error of a mean, *Biometrika* 6(1): 1–25.

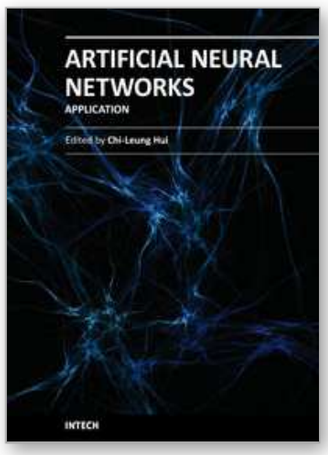
Takagi, Y. (2003). A case study of the success factor in large-scale software system development project(in japanese), *Journal of Information Processing Society of Japan(IPSJ)* 44(4): 348–356.

Tamaru, K. (2004). Trends in software development platform for embedded systems(in japanese), *Journal of Information Processing Society of Japan(IPSJ)* 45(7): 699–703.

Tsunoda, M., Ohsugi, N., Monden, A., Matsumoto, K. & Sato, S. (2005). Software development effort prediction based on collaborative filtering(in japanese), *Journal of Information Processing Society of Japan(IPSJ)* 46(5): 1155–1164.

Watanabe, H. (2004). Product line technology for software development(in japanese), *Journal of Information Processing Society of Japan(IPSJ)* 45(7): 694–698.

Welch, B. L. (1947). The generalization of student's problem when several different population variances are involved, *Biometrika* 34(28).



Artificial Neural Networks - Application

Edited by Dr. Chi Leung Patrick Hui

ISBN 978-953-307-188-6
Hard cover, 586 pages
Publisher InTech
Published online 11, April, 2011
Published in print edition April, 2011

This book covers 27 articles in the applications of artificial neural networks (ANN) in various disciplines which includes business, chemical technology, computing, engineering, environmental science, science and nanotechnology. They modeled the ANN with verification in different areas. They demonstrated that the ANN is very useful model and the ANN could be applied in problem solving and machine learning. This book is suitable for all professionals and scientists in understanding how ANN is applied in various areas.

InTech Europe
University Campus STeP Ri
Slavka Krautzeka 83/A
51000 Rijeka, Croatia
Phone: +385 (51) 770 447
Fax: +385 (51) 686 166
www.intechopen.com

InTech China
Unit 405, Office Block, Hotel Equatorial Shanghai
No.65, Yan An Road (West), Shanghai, 200040, China
中国上海市延安西路65号上海国际贵都大饭店办公楼405单元
Phone: +86-21-62489820
Fax: +86-21-62489821

IntechOpen