Importance of the Pre-Requisite Subject

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ABSTRACT

In this paper, it describes how the pre-requisite subjects influence the student's performance in Heat transfer subject in University Malaysia Pahang (UMP). The Pre-requisite for Heat transfer in UMP are Thermodynamics I and Thermodynamics II. Randomly 30 mechanical engineering students were picked to analysis their performance from Thermodynamics I to Heat transfer. Regression analysis and Neural Network were used to prove the effect of prerequisite subject toward Heat transfer. The analysis shows that Thermodynamics I highly affect the performance of Heat transfer. The results show that the students who excellent in Thermodynamics I, their performance in Thermodynamics II also the same and goes to Heat transfer. Those students who scored badly in their Thermodynamics I, the results for the Thermodynamics II and Heat transfer are similar to Thermodynamics I. This shows the foundation must be solid, if the students want to do better in Heat transfer.

INTRODUCTION

Pre-requisite means course required as preparation for entry into a more advanced academic course or program [1]. Regression analysis is a technique used for the modeling and analysis of numerical data consisting of values of a dependent variable (response variable) and of one or more independent variables (explanatory variables). The dependent variable in the regression equation is modelled as a function of the independent variables, corresponding parameters ("constants"), and an error term. The error term is treated as a random variable. It represents unexplained variation in the dependent variable. The parameters are estimated so as to give a "best fit" of the data. Most commonly the best fit is evaluated by using the least squares method, but other criteria have also been used [1].

Regression can be used for prediction (including forecasting of time-series data), inference, hypothesis testing, and modelling of causal relationships. These uses of regression rely heavily on the underlying assumptions being satisfied. Regression analysis has been criticized as being misused for these purposes in many cases where the appropriate assumptions cannot be verified to hold [1, 2]. One factor contributing to the misuse of regression is that it can take considerably more skill to critique a model than to fit a model [3].

However, when a sample consists of various groups of individuals such as males and females, or different intervention groups, regression analysis can be performed to examine whether the effects of independent variables on a dependent variable differ across groups, either in terms of intercept or slope. These groups can be considered from different populations (e.g., male population or female population), and the population is considered heterogeneous in that these subpopulations may require different population parameters to adequately capture their characteristics. Since this source of population heterogeneity is based on observed group memberships such as gender, the data can be analyzed using regression models by taking into consideration multiple groups. In the methodology literature, subpopulations that can be identified beforehand are called groups [4, 5].Model can account for all kinds of individual differences. Regression mixture models described here are a part of a general framework of finite mixture models [6] and can be viewed as a combination of the conventional regression model and the classic latent class model [7, 8]. It should be noted that there are various types of regression mixture models [7], but this only focus on the linear regression mixture model. The following sections will first describe some unique characteristics of the linear regression mixture model in comparison to the conventional linear regression model, including integration of covariates into the model. Second, a step-by-step regression mixture analysis of empirical data demonstrates how the linear regression mixture model may be used by incorporating population heterogeneity into the model.

Ko et al. [9] have introduced an unsupervised, self-organised neural network combined with an adaptive time-series AR modelling algorithm to monitor tool breakage in milling operations. The machining parameters and average peak force have been used to build the AR model and neural network. Lee and Lee [10] have used a neural network-based approach to show that by using the force ratio, flank wear can be predicted within 8% to 11.9% error and by using force increment, the prediction error can be kept within 10.3% of the actual wear. Choudhury et al. [11] have used an optical fiber to sense the dimensional changes of the work-piece and correlated it to the tool wear using a neural network approach. Dimla and Lister [12] have acquired the data of cutting force, vibration and measured wear during turning and a neural network has been trained to distinguish the tool state.

This paper will describe the influence of prerequisite subject toward Heat transfer. The analysis will be done using regression method and Neural Network.

REGRESSION METHOD

In linear regression, the model specification is that the dependent variable, yi is a linear combination of the parameters (but need not be linear in the independent variables). For example, in simple linear regression for modelling N data points there is one independent variable: xi, and two parameters, β0 and β1 [2]:

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i, \quad i = 1, \ldots, N \tag{1}$$

Results from the 30 mechanical engineering students were collected. There are mixed between female and male, no age different, different of background and all the students from same class. Regression analysis was done to check the most dominant variables (Thermodynamics I and Thermodynamics II) effect towards response (Heat transfer). Table 1 shows the marks of the students.

Table 1: Marks for the subjects.

Student	Thermodynamics1	Thermodynamics2	Heat transfer
1	85	83	85
2	51	50	53
3	67	65	69
4	55	61	55
5	44	51	51
6	64	63	55
7	42	50	49
8	54	63	60
9	58	50	58
10	52	61	60
11	69	77	77
12	58	64	68
13	57	61	68
14	71	68	60
15	61	70	73
16	53	66	62
17	60	71	59
18	45	55	57
19	47	60	56
20	62	77	69
21	45	60	53

22	40	52	37
23	53	70	62
24	53	61	70
25	56	60	73
26	51	63	69
27	44	62	57
28	40	58	52
29	62	80	71
30	47	63	46

MULTILAYER PERCEPTIONS NEURAL NETWORK

In the current application, the objective is to use the supervised network with multilayer perceptrons and train with the back-propagation algorithm (with momentum). The components of the input pattern consist of the control variables used in the student performance (Thermodynamics I and Thermodynamics II), whereas the components of the output pattern represent the responses from sensors (Heat transfer). During the training process, initially all patterns in the training set were presented to the network and the corresponding error parameter (sum of squared errors over the neurons in the output layer) was found for each of them. Then the pattern with the maximum error was found which was used for changing the synaptic weights. Once the weights were changed, all the training patterns were again fed to the network and the pattern with the maximum error was then found. This process was continued till the maximum error in the training set became less than the allowable error specified by the user. This method has the advantage of avoiding a large number of computations, as only the pattern with the maximum error was used for changing the weights. Fig.1 shows the neural network computational mode with 2-5-1 structure.

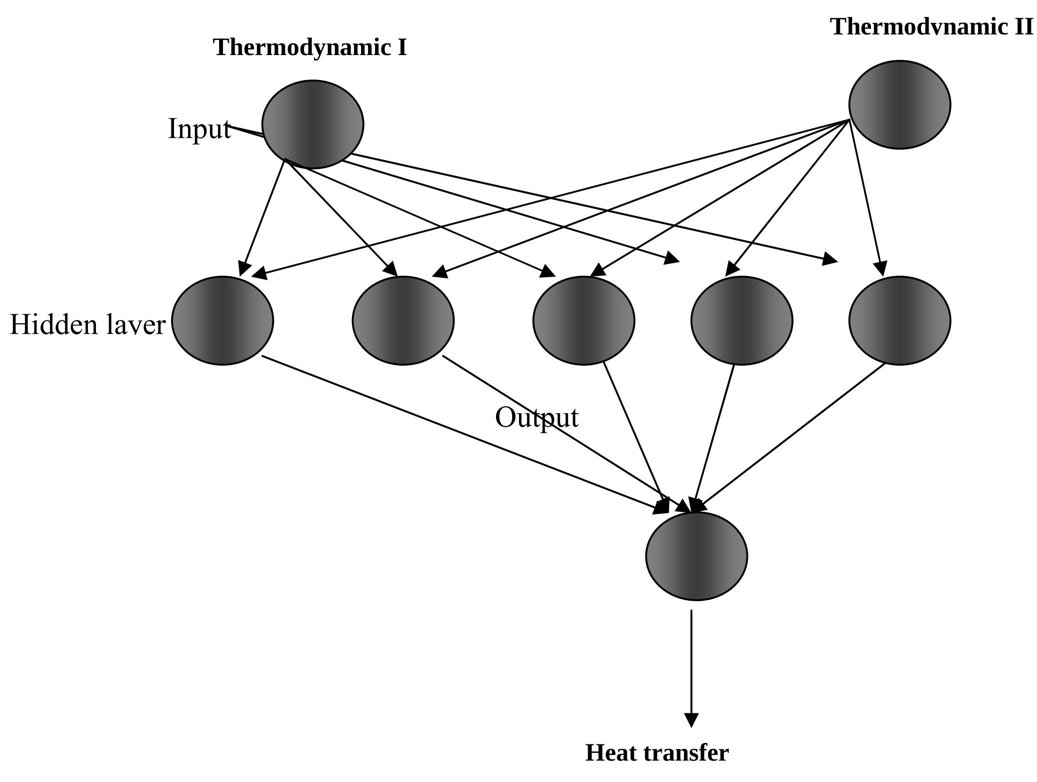

Fig. 1: Neural Network with 2-5-1 structure.

RESULTS AND DISCUSSION

The regression equation as below:
Heat transfer = 8.04 + 0.498 Thermodynamics I + 0.408 Thermodynamics II (2)

Equation 2 shows that Thermodynamics I is more dominant compare with Thermodynamics II. One can notice that, increase in Thermodynamics I and Thermodynamics II it will increase the result in Heat transfer. Table 2 show that Thermodynamics really significantly effect the heat transfer. It means, those have a very good foundation in Thermodynamics I, they can do better in Heat transfer. The p-value in the Analysis of Variance Table 2 (0.000) indicates that the relationship between Thermodynamics I and Thermodynamics II is statistically significant at an a-level of 0.05. This is also shown by the p-value for the estimated coefficient of Thermodynamics I, which is 0.008 as shown in Table 3.

Table 2: Analysis of Variance

Source	DF	SS	MS	F	P
Regression	2	1873.87	936.93	22.64	0
Residual Error	27	1117.6	41.39		
Total	29	2991.47			

Table 3: Estimated coefficient

Predictor	Coef	SE Coef	T	P
Constant	8.043	8.771	0.92	0.367
Thermodynamics1	0.498	0.1734	2.87	0.008
Thermodynamics2	0.4079	0.2032	2.01	0.055

Fig. 2 shows the sensitivity test. The test shows that Thermodynamics I is the main effect for the heat transfer. The results for the sensitivity test and regression analysis show the same results.

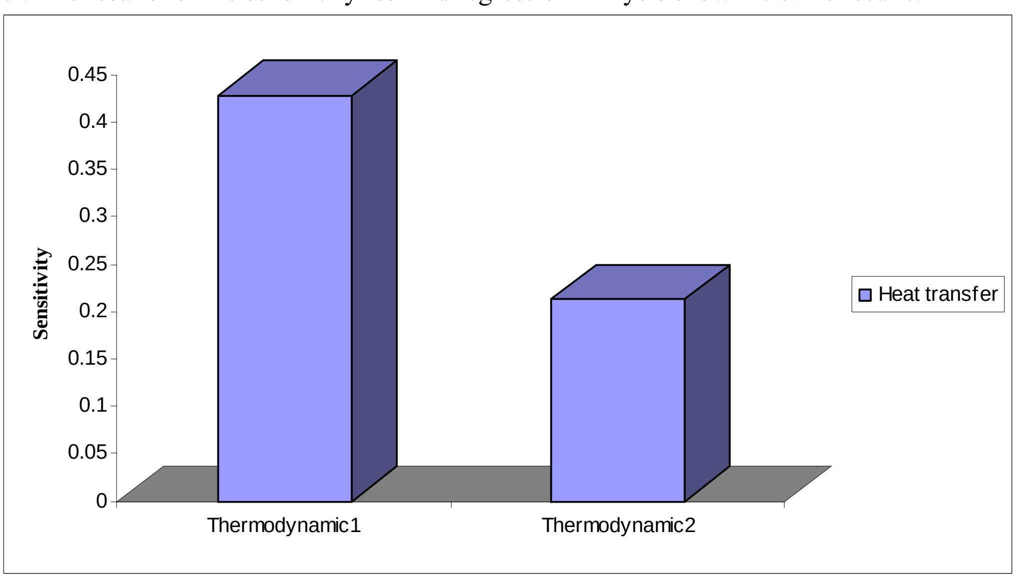

Fig.2: Sensitivity Test

CONCLUSION

The regression analysis and Neural Network is very useful tool to do analysis in term of measure student performance and importance of prerequisite subject. The results prove that Thermodynamics I effect lot the student performance in Heat transfer. The foundation subject must be very strong, if the students want to perform better in Thermodynamics II and Heat transfer.

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