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Student Performance Analysis using Artificial Intelligent Method

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***Abstract* -** Measuring of academic performance of students is challenging since student performance is product of socio-economic, psychological and environmental factors. This paper discussed the neural network method were used to measure student performance in Thermodynamic at Faculty of Mechanical Engineering, University Malaysia Pahang (UMP). Randomly 65 mechanical engineering students were picked to analysis their performance in these subjects with 5 variables which are Test1, Test 2, Final Examination, assignment and Quizzes. The analysis was done to measure the student performance in Thermodynamic I which final grade was used as the tools. The models show that Test 1 and Test 2 plays major role in the student final grade. Meanwhile assignments and quizzes play as a booster to their performances. The artificial intelligent model can be used for further investigate of the subject performance with include more predictor such as age, CGPA, gender and etc.

Keywords: Thermodynamics I, Statistical, Genetic Algorithms, Radial Basis Function Network (RBFN)

Introduction

All of the research reviews support the hypothesis that student performance depends on different socio-economic, psychological, environmental factors. The findings of research studies focused that student performance is affected by different factors such as learning abilities because new paradigm about learning assumes that all students can and should learn at higher levels but it should not be considered as constraint because there are other factors like race, gender, sex that can affect student's performance. [1].

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Yvonne Beaumont Walters *et al.* [2] further elaborated that student performance is very much dependent on SEB (socio economic back ground)as per their statement, "High school students' level of performance is with statistically significant differences, linked to their gender, grade level, school location, school type, student type and socio-economic background (SEB)." Gordon and David [3] focused on student's impatience (his time-discount behavior) that influences his own academic performance. 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]. 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.

Neural network is one of the tools to measure and evaluate the performance. Ko et al. [8] 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 [9] 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. [10] 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

[11] 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 focuses on the development of the model to predict the thermodynamics 1 outcome and to investigate and analyse the relationship between the few variables which are test 1, test 2, assignment, quizzes and final examination and outcome (Thermodynamics 1 result).

Artificial Intelligent

ANN can handle continuous as well as discrete data and have good generalization capability as with fuzzy expert systems. An ANN is a computational model of the brain. They assume that computation is distributed over several simple units called neurons, which are interconnected and operate in parallel thus known as parallel distributed processing systems or connectionist systems. Implicit knowledge is built into a neural network by training it. Several types of ANN structures and training algorithms have been proposed. The basic form of RBF architecture involves entirely three different layers. The input layers is made n, of source nodes while, the second layer is hidden layer of high enough dimension which senses a different purpose from that in a multilayer perception. The output layer supplies the response of the network to the activation patterns applied to the input layer. The tram formation from the input layer to hidden is nonlinear whereas the transformation from the hidden from unit to the output layer is linear. Genetic Algorithm (GA) was used to find the optimum weight, momentum and step size to be used in RBFN. Later the optimum weight will be fed to the RBFN. Then, train the network until the R.M.S.E reaches a satisfactory value. The training data acquired from Response Surface Method to RBFN mode, and the epoch number is 10,000 [19]. After 1,000 iterations, the RBFN is better enough to produce acceptable results. Transfer function used as sigmoid, while for the momentum used is 0.7.

Result and discussion

Randomly the student results were picked and total of 65 students selected to investigate their performance in Thermodynamics 1. The table 1 shows the results of the students and the prediction output by the neural network. The prediction models predict the final outcome of the Thermodynamics quite accurately. The set of measurements, immediately prior to a thermodynamic measurement, had been used for training the neural network. About 113 patterns were collected. About 90% of the data 101 patterns, were used to train the different network architectures, where remaining 12 patterns were used for testing to verify the prediction ability of each trained NN model. Since, Radial Basis Function Network (RBFN) learn relations and approximate function mapping limited by the extent of the training data, the best use of the trained RBFN models can be achieved in interpolation. Table 1 shows the RBFN output for prediction Thermodynamic 1, from the analysis of the results in Table 1, it is observed that the accuracy of the RBFN method was slightly superior when compared to the experimental results on account of Mean Average Error (MAE) as shown in Figure 2. Figure 3 shows the sensitivity test of the model. It clearly shows that final exam influences the student performance in Thermodynamic 1. Eventhough some students were excelling in their test 1 and test 2, but then their final outcome of the thermodynamic totally affected by their final examination. Other than the final examination, Test 1 and Test2 plays quite important role in student performance. Assignment and quizzes plays as a booster for the student performance. The prediction model are very important for the the educator to measure the outcome and investigate the relationship between the variables (Test 1, Test 2, assignment, quizzes and final examination) towards final outcome.

Table 1: Prediction results by the RBFN.

Test 1	Test 2	Quiz	Assignment	Final Exam	Final Mark	Prediction output
53.3	100.0	10.0	6.0	91.2	83.2	81.6
26.6	96.6	8.0	7.0	86.2	75.0	76.2
20.0	71.6	8.0	7.5	47.5	55.2	55.2
66.6	80.0	8.0	6.0	57.5	66.5	66.5
80.0	85.0	8.0	6.5	87.5	83.1	81.5
56.6	71.6	10.0	7.5	66.2	72.1	72.5
23.3	53.3	8.0	7.0	66.2	60.1	60.2
26.6	88.3	7.0	7.5	66.2	65.3	65.8
66.6	93.3	10.0	6.0	76.2	78.0	78.2
83.3	93.3	9.0	7.0	65.0	75.8	76.8
36.6	80.0	9.0	6.0	63.7	65.6	65.4
30.0	90.0	6.0	6.0	21.2	46.0	46.1
63.3	100.0	8.0	7.0	67.5	73.4	74.7

66.6	85.0	7.0	6.0	58.7	66.5	66.6
70.0	100.0	8.0	6.0	72.5	76.0	76.4
63.3	86.6	8.0	6.0	70.0	72.0	72.7
36.6	56.6	10.0	6.5	55.0	60.2	59.9
63.3	93.3	8.0	6.0	82.5	77.4	78.4
33.3	93.3	10.0	7.5	52.5	65.0	65.7
40.0	86.6	8.0	7.0	63.7	67.1	67.3
70.0	90.0	7.0	7.1	76.2	77.5	77.2
50.0	100.0	10.0	5.6	75.0	75.8	75.7
40.0	51.6	10.0	6.6	60.0	61.7	62.2
76.6	100.0	10.0	6.9	90.0	87.0	84.0
33.3	40.0	10.0	7.5	35.0	50.1	51.0
50.0	100.0	10.0	5.0	76.2	75.0	75.5
46.6	100.0	10.0	6.0	81.2	77.5	77.9
60.0	75.0	10.0	6.0	56.2	66.4	66.5
70.0	96.6	10.0	6.5	72.5	77.4	78.2
43.3	100.0	10.0	6.0	67.5	71.4	72.3
56.6	58.3	10.0	7.5	32.5	55.2	55.6
70.0	96.6	10.0	7.5	75.0	80.0	80.1
23.3	96.6	10.0	7.5	56.2	65.5	66.2
23.3	85.0	10.0	7.5	51.2	63.1	62.3
63.3	95.0	10.0	8.0	90.0	85.4	83.5
50.0	86.6	10.0	6.5	63.7	70.0	70.7
30.0	96.6	10.0	7.0	58.7	68.4	67.4
70.0	96.6	6.0	7.7	62.5	71.3	72.0
43.3	100.0	10.0	6.9	63.7	71.5	72.0
56.6	80.0	10.0	7.0	77.5	75.8	77.1
83.3	100.0	10.0	6.7	85.0	85.7	83.4
20.0	68.3	10.0	6.9	63.7	63.1	63.6
70.0	86.6	10.0	6.0	58.7	70.5	71.1
40.0	93.3	8.9	7.2	58.7	67.8	67.5
83.3	93.3	9.3	7.2	88.7	85.7	83.9
33.3	80.0	8.5	5.7	72.5	68.1	67.9
70.0	88.3	8.7	6.7	76.8	78.1	78.1
56.6	95.0	9.5	5.9	72.5	74.9	75.1
40.0	93.3	8.7	7.2	60.0	67.1	67.8
33.3	88.3	9.0	6.9	76.2	72.8	73.1
36.6	93.3	8.7	7.2	61.2	67.0	67.8
70.0	93.3	9.3	6.9	76.2	80.2	79.1
40.0	86.6	8.7	7.2	60.0	67.2	66.8
33.3	66.6	8.3	5.9	41.2	54.7	52.1
53.3	88.3	8.1	6.2	40.0	59.9	57.7
40.0	73.3	8.1	6.9	27.5	50.3	50.1
23.3	85.0	8.7	5.6	58.1	61.6	60.3
16.6	93.3	8.4	6.4	62.5	64.7	63.2
30.0	80.0	9.2	6.7	46.8	60.1	58.1
70.0	93.3	9.1	6.7	75.6	79.8	78.5
10.0	93.3	8.0	3.5	11.2	40.3	43.8
40.0	93.3	8.5	6.9	42.5	60.6	59.1
96.6	88.3	8.1	6.5	65.0	76.3	76.7
36.6	93.3	8.9	7.2	31.2	55.3	55.2
63.3	93.3	9.0	6.5	65.6	73.2	73.4

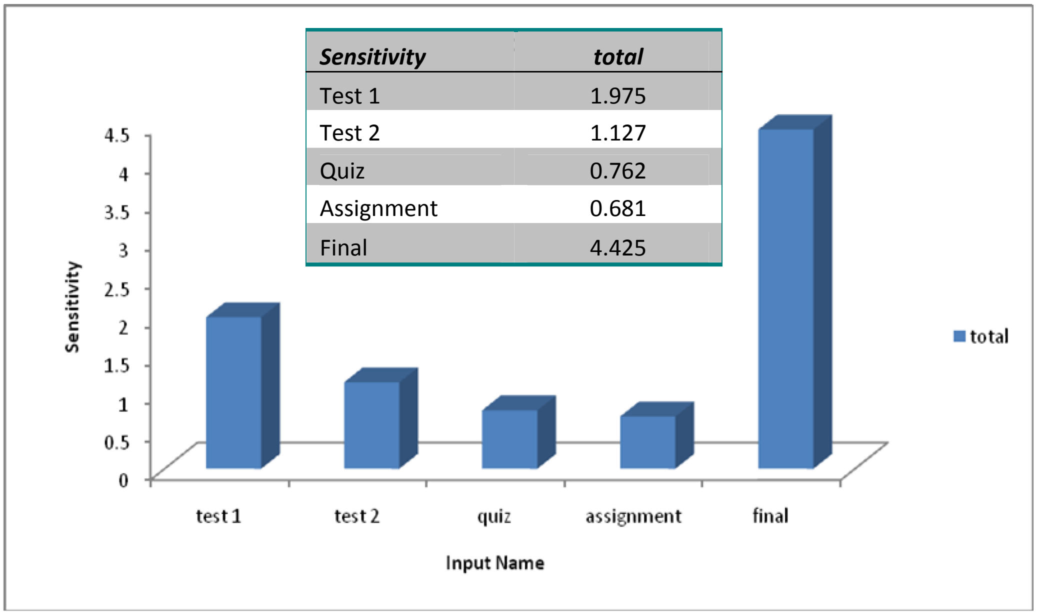

Figure 2: The sensitivity Test

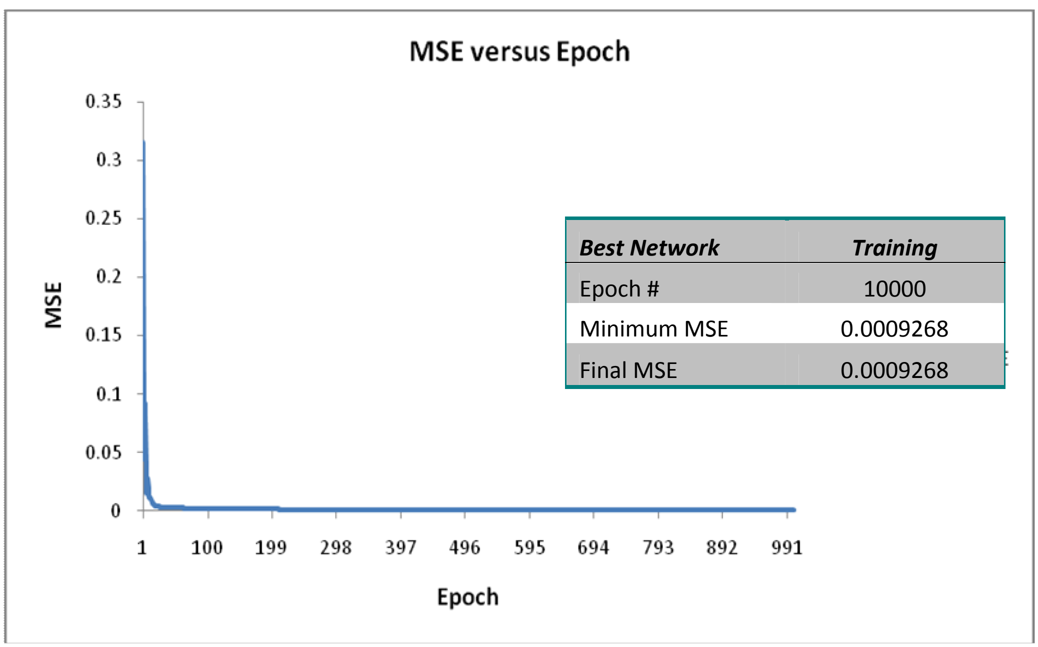

Figure 2: The RBFN training output.

Conclusion

The artificial intelligent are excellent tools to measure and analyse the student performance. The overall goal of the proposed study was to develop methodologies using Radial Basis Function Network for predicting the effects of the test 1, test 2, assignments, quizzes and final examination on thermodynamics 1 as follows:

- RBFN proved to be an efficient tool to optimize and investigate the student performance in thermodynamics 1. The use of RBFN in modelling of student performance allows for considering process details that analytical models cannot handle and for predicting variables.
- Final Examination plays a very important role for the student performance in thermodynamics

1 follow by test 1 and test 2. Assignment and quizzes plays as a booster to the student performance.

- Finally, the simulations results show that RBFN can be very successively used for investigate student performance whereas it can give the detail relationships between the variables and the outcome. This means that it can solve many problems that have mathematical and time difficulties.

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