ORIGINAL ARTICLE

A STUDY OF PSYCHOPHYSICAL FACTOR (HEART RATE) FOR DRIVER FATIGUE USING REGRESSION MODEL

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ABSTRACT

Driving activity has become more important as this medium being practical, it is also cheaper and faster in connecting human from one to another place. However, in some occurrence, it can cause accidents as they become fatigued while driving. Driver fatigue is one of the top contributors to the road accidents and can be dangerous as other road safety issues such as drink driving. Worst is, there are no laws regulating driver fatigue. Therefore, the main purpose of this study is to develop the regression model of apsychophysical factor for drivers' fatigue which can predict the relationship between the process input parameters and output responses. The study was participated by ten subjects. The heart rate was taken and recorded using heart rate monitor. Design Expert 8.0.6 software was used for the regression analysis. The modeling validation runs werewithin the 90% prediction intervals of the developed model and the residual errors were less than 10%. The R^2 value is 0.9400 whichmeans that the linear regression line passed exactly through all points. The significant parameters that influenced the heart rate were also identified. The parameters are time exposure, type of road, and gender.

Keywords: Psychophysical, fatigue, regression modeling, heart rate

INTRODUCTION

Fatigue can be defined as extreme tiredness brought about by not enough rest over a period of time whether from mental or physical exertion or illness. For a good quality of sleep each night people needs between seven or eight hours. People with the fewer hours of sleep can cause sleep debt risk or sleep deficit, which can impair reaction time and decision making when they are behind the wheel. Indirectly, increases the risk of being involved in an accident. If a driver falls asleep for just four seconds while traveling at a speed of 100 km/h the car will have gone 111 meters without a driver in control¹. At high speed, a crash is likely with a high risk of death or severeinjuries.

The Royal Malaysian Police (RMP) is one of the agencies responsible for collecting accident data in Malaysia and all road accidents must be reported to the police. Based on provisional data by the RMP, there were 6,674 road fatalities and 476,196 road accidents have been reported in 2014². From the number of accidents reported, some of the crashes were caused by the factor of fatigue. The in-depth crash investigations on some crash cases carried out by Malaysia Institute of Road Safety (MIROS) (2015), found that risky driving, speeding, and fatigue are main causes of traffic accidents in Malaysia from 2007 to 2010 as shown in Table 1³. While from 2011 through 2013, it was reported that fatigue was the fifth contributing factor of road accidents as represented in Table 2³. There is no data

reported for 2014 until 2016.Hence, early detection of driver fatigue is very important in order to reduce the number of accidents.

Table 1 - Crash contributing factors from2007 through 20103

Main crash contributing factors	Number	%
out of 439 cases		
Risky Driving	121	28
Speeding	93	21
Fatigue	70	16
Safety, Health, and Environment	38	9
Road Defects	36	8
Driving Under the Influence	24	5
Brake Defects	20	5
Conspicuousness	18	4
Tyre Defects	14	3
Overloading	11	3

Table 2 - Crash contributing factors from2011 through 2013³

2011 (11104311 2015		
Main crash contributing factors	Number	%
out of 439 cases		
Risky Driving	75	29
Speeding	68	26
Conspicuousness	55	21
Road Defects	27	10
Fatigue	17	7
Brake Defects	6	2
Tyre Defects	4	2
Driving Under the Influence	3	1
Safety, Health, and Environment	2	1
Overloading	2	1

Previous research has found physiological signals of thedriver such as heart rate are good indicators of drowsiness. As the stress response of organs occurs during fatigue. thecardiovascular nervous system will adapt or set up appropriately. Hence, the beginning of fatigue causes changes in the bio-electrical signals, such as the electrocardiogram (ECG), are cording of electrical signals produced by the electro-dynamic functioning of the heart⁴. The previous study has shown that the ECG signal and its derived information, which consist of the information of the heart rate (HR), heart rate variability (HRV) and frequency of breath, haveaconnection with fatigue. However, this study only focuses on heart rate. Heart rate is the number of heartbeats, generally expressed as beats per minute (bpm)⁴. According to Sun et al.⁵based on the previous study entitled Performance Decrement during Prolonged Night Driving by Riemersma et al.⁶ report that the HR of drivers would decrease during long-time night driving⁴⁻⁶. Besides, the HR reflected the physical and mental level under different task requirement and thus could be used as fatigue monitoring and detection. The previous study also had considered that the changes of HR could be influenced byfatigue. Hence, this study focused on the heart rate monitor for psychophysical factor as it gives effect on fatigue level of the drivers. Psychophysical originally is from the word psychophysics which describes as one method that can be used to estimate acceptable load under avariety of force, repetition, posture and duration conditions⁷.

The objective of this study is to formulate and validate the regression models of psychophysical factor (heart rate) using ergonomics approach in solving the driver fatigue. The modeling work is based on the regression analysis in the form of the polynomial equation, which defines the relationship between the input parameters and output responses. The aim of thepolynomial function is to explain the relationship within the range of the independent variables determined during the development of the function. A least square technique is used to select the polynomial equation to represent the model. This technique used to minimize the residual error measured by the sum of square deviations between the actual and predicted responses. The regression coefficients of the model should be calculated in order to test the statistical significance, which can be carried out by using analysis of variance (ANOVA). The tests for significance of the model, thesignificance of individual model coefficient, and lack of fit are performed by ANOVA⁸. The regression analysis in modeling and optimization has been applied and highly demand in various fields, from food products to electronic technologyas it is being practical, economy and relative ease of use $^{9\cdot11}$. Published work of regression modeling on driver fatigue and

ergonomics study is lacking. A wide range of factors affecting fatigue is still not modeled¹² and psychophysical and biomechanical factors are one of them.

METHODS

Subject and Population

The subjects are normal and have healthy bodies. Besides that, all the subjects told that they are refrained from drinking coffee, tea or alcohol, smoking, and free from taking any medicine. The health evaluation has been done 24 hours before the experiment to ensure they have enough habitual amount of sleep at night before the experiment in order to avoid sleep deprivation¹³. There were ten (five males and five females) healthy and experiences drivers served as the subjects for this study. The subjects represented three populations of each gender; big, average, and small. However, theonly average population is been discussed in this paper.

Questionnaire and Respond Analysis

In this experiment, the questionnaires were distributed to the subjects as to investigate the driving experience while undertaken the experiment. The questionnaire consists of three parts; personal information, driver's comfort experience throughout the type of road conditions, and driver physical comfort. The subjects are required to answer the questionnaire before and after the experiment.

Test Apparatus and Protocol

Proton Saga FLX 1.3L engine with automatic transmission was used as the test vehicle. This car was chosen, as it is a national car, which also a well-known national symbol of Malaysia. Besides, Proton Saga FLX has been choosing based on themajority of Malaysian population used it as Proton Saga can be categorized as affordable cars or economic cars¹⁴. Polar Watch S610i has been used in this research as the heart rate monitor. This device displays the heart rate as beat per minute (bpm) and percentage (%) of maximum heart rate (HRmax, average heart rate, and exercise duration. Besides, this device can predict the maximal oxygen uptake. Figure 1 shows the Polar watch S610i used to record the heart rate of thesubject during this study.



Figure 1 - Polar watch S610i

Regression Analysis

In developing and formulating the regression modeling, regression data analysis was carried out through this study. The regression analysis is suitable and the application of regression analysis in modeling and optimization has been proven in various fields. This analysis interprets the relationship between one or more output responses with the significant input factors. Design Expert 8.0.6 software was used to carry out this analysis. Several steps have been followed in order to analyze the data collected¹⁵. The output responses data for each experimental run were entered into the respective run number matrix. The software recognizes which models choose for further analysis. The identification and selection are based on the sequential sum of square. Through this analysis, the models were compared to he statistical significance of adding model terms to those already in the model. The highest degree model that has a p-value less than 0.10 should be chosen as the model to represent the model. Then, the significant of the model, significant parameter and interaction factors of the selected model were determined using the ANOVA. The Prob>F value is small or less than 0.1 indicates that the model or factors have a significant effect on the output response. This final equation of the model then been validated by using quantitative validations to analyse the results and the validation runs must meet this two following conditions; (1) The validation run outcome based on specific output parameters within 90% of its predictive interval, (2) The accuracy of a process model can be assessed by using residual error method with respect to the validation run¹⁶. The residual error is the percentage difference between the validation run value and predicted value over the predicted value. The residual error was calculated through the Design-Expert software capability, and the percentage value should be less than 10% to represent the accuracy of the model.

RESULTS AND DISCUSSION

This section presents the results and discussions of this study regarding a development, formulating and validation of regression model for psychophysical factor (heart rate) using ergonomics approach for driver fatigue through regression analysis. The psychophysical factor (heart rate) has been proven as a factor leading to driver fatigue among the Malaysian. Thus, this study will develop the regression model based on this factor as to solve the driver fatigue problems.

Regression Modeling of Psychophysical Factor (Heart Rate, bpm)

All the data of the measurement of heart rate (HR) was recorded in Table 3. The table shows the data that used in formulating the regression modeling for the HR of the subjects. In this study, thirty-two experimental runs were carried out with three factors were studied as the input parameters; time exposure, type of road, and gender. While HR (bpm) as the output response in this experimental runs. Two HR measurement were recorded per sample and the average HR were calculated. This average values used as the output response of the process as reflected in Table 3.

Determination of Appropriate Polynomial Equation to Represent Regression Model

The sequential model sum of squares (SMSS), lack of fit test, and model summary statistic (R^2 value) in the Design-Expert software was carried out to determine the appropriate polynomial equations to represent the regression model for the HR as shown in Table 4, Table 5, and Table 6 respectively. All these analyses are carried out in order to determine the appropriate model to represent the relationship between the input parameter; type of road, gender, and time exposure, with the resultant or output response; heart rate (bpm) in this study. All analyses suggested the relationship between factors and output response can be modeled using a Linear equation.

Std	Run	Factor 1		Factor 2	Facto		Respon	
	_	A: Time Exposure, m	in B:	Type of Road	C: Gen	der	Heart Rate	e, bpm
1	1	15.00		Straight	Fema	le	112	
2	2	15.00		Straight	Fema	le	108	}
3	3	15.00		Straight	Male	5	110)
4	4	15.00		Straight	Male	5	101	
5	5	15.00		Winding	Fema	le	137	7
6	6	15.00		Winding	Fema	le	132	-
7	7	15.00		Winding	Male	5	128	}
8	8	15.00		Winding	Male	5	126)
9	9	15.00		Uphill	Fema	le	125)
10	10	15.00		Uphill	Fema	le	123	}
11	11	15.00		Uphill	Male	5	124	ļ
12	12	15.00		Uphill	Male	5	120)
13	13	15.00		Downhill	Fema	le	118	}
14	14	15.00		Downhill	Fema	le	119)
15	15	15.00		Downhill	Male	5	116)
16	16	15.00		Downhill	Male	5	114	ļ
17	17	30.00		Straight	Fema	le	88	
18	18	30.00		Straight	Fema	le	90	
19	19	30.00		Straight	Male	5	95	
20	20	30.00		Straight	Male	5	90	
21	21	30.00		Winding	Fema	le	119)
22	22	30.00		Winding	Fema	le	122	_
23	23	30.00		Winding	Male	5	118	}
24	24	30.00		Winding	Male	5	116)
25	25	30.00		Uphill	Fema	le	112	_
26	26	30.00		Uphill	Fema	le	113	}
27	27	30.00		Uphill	Male	5	114	ļ
28	28	30.00		Uphill	Male		111	
29	29	30.00		Downhill	Fema		111	
30	30	30.00		Downhill	Fema		104	
31	31	30.00		Downhill	Male		98	
32	32	30.00		Downhill	Male		101	
Abbre	viations	and Notes:	Std =	Standard,	bpm	= b	peats per	minut

Table 3 - Experimental runs and results of HR, bpm

Table 4 - Sequential model sum of squares (SMSS) analysis for HR model

Sequential Model Sum of Squares									
Source	Sum of Squares	df	Mean Square	F Value	<i>p</i> -value Prob> F				
Mean vs Total	4.084E+005	1	4.084E+005						
Linear vs Mean	4336.16	5	867.23	81.46	< 0.0001	Suggested			
2FI vs Linear	105.47	7	15.07	1.67	0.1763				
Quadratic vs 2FI	0.000	0				Aliased			
Residual	171.34	19	9.02						
Total	4.130E+005	32	12906.09						

Abbreviations and Notes: df = degree of freedom, F= indicate One way ANOVA test, FI = factor of interaction

Source	Sum of Squares	df	Mean Square	F Value	<i>p</i> -value Prob> F	
Linear	146.31	10	14.63	1.79	0.1434	Suggested
2FI	40.84	3	13.61	1.67	0.2135	
Quadratic	40.84	3	13.61	1.67	0.2135	Aliased
Pure Error	130.50	16	8.16			

Abbreviations and Notes: df = degree of freedom, F= indicate One way ANOVA test, FI = factor of interaction

Source	Std. Dev.	R- Squared	Adjusted R-Squared	Predicted R-Squared	PRESS	
Linear	3.26	0.9400	0.9285	0.9091	419.31	Suggested
2FI	3.00	0.9629	0.9394	0.8946	486.03	
Quadratic					+	Aliased
Cubic	2.86	0.9717	0.9452	0.8868	522.00	Aliased

Table 6 - Model summary statistic (R^2 Value)

Abbreviations and Notes: Std Dev = standard deviation, FI = factor of interaction, PRESS = prediction sum of squares

The SMSS analysis making acomparison of models that show the statistical significance of adding model terms to those already in the model. The model to represent the process is chosen based on the highest degree model that has a p-value less than $0.10^{8,17}$.

Lack of fit test analysis assesses how well each of the polynomial models fit the data. This is done by comparing the residual error to the pure error from replicated design points. As the residual error value larger than the pure error, more appropriate modeling can be removed.Models with significant lack of fit of Prob-F value 0.10 or less should not be selected^{8, 17}.

The model summary statistic calculated the coefficient method of determination (R^2) by using the Pearson product moment correlation coefficient method, R. This value shows how well a regression line represents the data. The coefficient of determination value must be in the range of 0< R^2 <1, where thevalue of 1 indicates that the regression line passes exactly through all points. Hence, the regression line would be able to explain all of the variation. While the R^2 value of 0 indicates that no correlation at all between both variables being investigated^{18,19}.

In this study, the relationship between the input parameters with responses can be modeledusing the linear model as the R^2 value is 0.9400, which is close to thevalue of 1. Besides, the Predicted R^2 value, 0.9091 is close to the value of R^2 , which means that the model provides the valid predictions. Predicted R^2 value is the value that indicates how well a regression model predicts responses for new observations. In addition, the PRESS value for thelinear model, 419.31 is smaller than others. PRESS value indicates the model's predictive ability. The smaller PRESS value means the better model's predictive ability^{19,20}.

ANOVA for Response Surface Linear Model

Table 7 represents the ANOVA analysis of the linear model. The Model F-value of 81.46 signifies that the model is significant. From the table, a chance of a "Model F-value" this large occurs due to noise is only a 0.01%. The accuracy and significant of this model are also supported by the lack of fit analysis. The "Lack of Fit F-value" of 1.79 implies the lack of fit is not significant relative to the pure error. There is a 14.34% probability that a "Lack of Fit F-value" this large could happencaused by noise.

ANOVA for Response Surface Linear Model								
Source	Sum of	df	Mean	F	p-value			
	Squares		Square	Value	Prob> F			
Model	4336.16	5	867.23	81.46	< 0.0001	significant		
A-Time Exposure	1391.28	1	1391.28	130.68	< 0.0001			
B-Type of Road	2863.59	3	954.53	89.66	< 0.0001			
C-Gender	81.28	1	81.28	7.63	0.0104			
Residual	276.81	26	10.65					
Lack of Fit	146.31	10	14.63	1.79	0.1434	not significant		
Pure Error	130.50	16	8.16			C C		
Cor Total	4612.97	31						

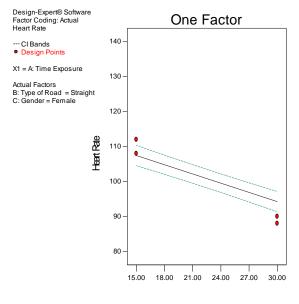
Table 7 - ANOVA analysis of the linear model of HR

Abbreviations and Notes: df = degree of freedom, Cor = correlation, ANOVA = analysis of variance

The value of *p*-value less than 0.1 indicate model terms are significant. In this case, time exposure, type of road, and gender are significant influencing factors of the resultant heart rate. As the time exposure increases from 15 minutes to 30 minutes, average heart rate reduced from 110 bpm to 89 bpm as shown in Figure 2. This result supported with the previous

study by Sun et al.⁴ who reported a decrease in heart rate with the increase in time exposure⁵. There was a decreasing trend of HR from early experiment to the end of the experiment. This trends clearly shows the variation from non-fatigue to fatigue stage. The decreasing trend of HRis occurred due to an insufficient supply of

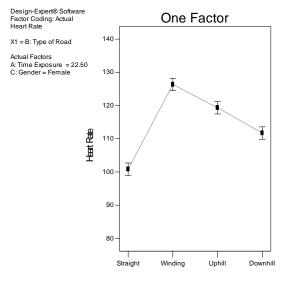
oxygen or called hypoxia as metabolic reactions fuelling heart contraction are restricted^{21,22}.



A: Time Exposure

Figure 2 - Behaviour of HR in response to variation of time exposure

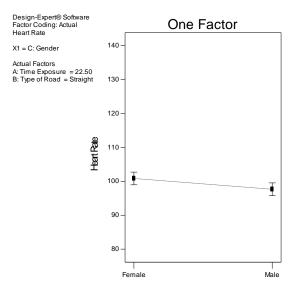
As shown in Figure 3, the HR changes when the subjects drive through different road conditions. The result shows that the straight road produced the lowest HR among others road condition. While the highest HR happened when driving through winding road which is 126 bpm of the female subjects. This happened due to the subjects cautious when turns at thewinding road. A published study by Proma et al.²³supported the result as they reported that the heart rate is found to change significantly under differentroad conditions with different monotony²³.



B: Type of Road

Figure 3 - Behaviour of HR in response to variation of type of road

As reflected in Figure 4, the HR decreases as the gender changes from female to male subjects. The HR changes from 101 bpm to 98 bpm as the gender change. Female subjects produced more HR than male subjects. This is reflected by the ANOVA analysis in Table 6 where the linear term of gender is a significant term. Besides, the previous studies by Theobald and Wändell²⁴, Zhang²⁵and Valentini and Parati²⁶claimed that male heart rates were lower than those of females. These studies supported the result of this experiment.



C: Gender

Figure 4 - Behaviour of HR in response to variation of gender

Polynomial Equation

Based on surface response modeling, the linear polynomial equation was developed. The purpose of the linear polynomial equation is to relate the input parameters to the resultant of the HR as shown in Table 8. The predictions of the response or resultant for the given levels of each factor can be made by using the equation.

In this equation, the type of road and gender is the constant variables, which the value cannot be changed once it has been assigned a value. While the time exposure is the independent variable or manipulated avariable in this equation. This variable can change and varies over the course of the investigation.

Parameter/Factor	Equation
Type of Road: Straight Gender: Female	Heart Rate = +120.62500 - 0.87917 * Time Exposure
Type of Road: Straight Gender: Male	Heart Rate = +117.43750 - 0.87917 * Time Exposure
Type of Road: Winding Gender: Female	Heart Rate = +146.12500 - 0.87917 * Time Exposure
Type of Road: Winding Gender: Male	Heart Rate = +142.93750 - 0.87917 * Time Exposure
Type of Road: Uphill Gender: Female	Heart Rate = +139.12500 - 0.87917 * Time Exposure
Type of Road: Uphill Gender: Male	Heart Rate = +135.93750 - 0.87917 * Time Exposure
Type of Road: Downhill Gender: Female	Heart Rate = +131.50000 - 0.87917 * Time Exposure
Type of Road: Downhill Gender: Male	Heart Rate = +128.31250 - 0.87917 * Time Exposure

Table 8 - Polynomial equation for the heart rate in term of actual model

Regression Model Validation

The analysis continued with the regression model validation activity to quantify the accuracy of the model through the comparison of experimental data with the prediction of the model²⁷. This validation is carried out to determine if the developed response surface model can predict the HR behavior was successfully performed. Three sets of process

parameters were chosen as validation runs by using the point prediction capability of the Design-Expert software. The predicted HR values together with their 90% prediction interval values and the residual error were calculated automatically using the software capability in order to ensure the accuracy of the model. Table 9 shows the validation results of the three sets of parameter settings.

Input Parameters		Prediction 90% Pl (bpm) low		90% Pl Hi (bpm)	Actual	Error (%)	
Time Exposure	Type of Road	Gender	- (bpiii)	(bpm)	(חוקס)	(bpm)	
15.00	Straight	Female	107.000	101.000	104.000	112.000	4.673
22.50	Straight	Female	101.000	95.000	107.000	103.000	1.980
30.00	Downhill	Male	102.000	96.000	108.000	98.000	3.922

Table 9 - Validation data of HR

Abbreviations and Notes: bpm = beats per minute, PI = prediction interval, Hi = high, value Actual (bpm) is based on actual experiment, value Prediction (bpm) is based on polynomial equation

The results indicate that actual HR data from the validation runs fall within the 90% prediction interval and the residual errorsare less than 10%. The residual error values are ranging from 1.980% to 4.673%. The result has met both quantitative validation conditions as mentioned in section 3. Hence, it can be concluded that the model is accurate enough to predict the resultant HR within 90% CI and the residual error relative to predicted values are less than 10%. Note that, the assumption of classical linear regression models (CLRM) is not discussed by the authors as this study carried out the validation analysis using point prediction capability of Design-Expert software.

CONCLUSION

paper formulated and developed This а regression model of psychophysical factor (heart rate) that contributes to driver fatigue among Malaysian. All objectives were successfully achieved through this study. Through this study, the regression model in the form of thepolynomial equation was successfully developed to relate the relationship between the HR input process parameters; time exposure, type of road, and gender, and one output response; HR. The model validation found that the HR output of the modeling validation run falls within the 90% prediction intervals of the

developed model and the residual error values were less than 10%. This study identified the significant parameters that affected the HR through ANOVA analysis during the development of the model. HR was influenced by the time exposure, type of road, and gender. The result shows that the HR of the subjects highest when the driving through winding road at the first 15 minutes and the subjects are female. Besides, the author believes that HR monitoring study can be used as the method of early driver fatigue detection as the fatigue levels or stages can be identified early. The authors believe that the development of psychophysical factor models for the driver fatigue problem among Malaysian using regression analysis is a new contribution to the body of knowledge. This development of regression models has founded the significant factors or parameters and interaction between factors which, influenced the psychophysical factors. There are a large scope and many factors which cause the driver fatigue problem such as environment, weather, lighting, noise, and others to study in future using the same methodology. There is an opportunity for the industrial area, organization, and road safety practitioners to be reviewed in depth. A more comprehensive study could be done by involving a larger number of drivers, adults, and elderly people from different populations in order to compare the different result of the study. Besides, the type of vehicles or car can be variety and the duration of the experiment can be longer as to compare with existing result.

ABBREVIATIONS

MIROS- Malaysia Institute of Road Safety, HR-Heart rate, bpm- Beats per minute, ANOVA-Analysis of variance.

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COMPETING INTERESTS

There is no conflict of interest.

REFERENCES

- 1. Royal Commission. Report of the Royal Commission to Enhance the Operation and Management of the Royal Malaysian Police. Government of Malaysia, Kuala Lumpur, 2015.
- 2. OECD/ITF. Malaysia in Road Safety Annual Report 2015. OECD Publishing, Paris. Available from: http://dx.doi.org/10.1787/irtad-2015-29-en. (Accessed 15 June 2016).

- Road Facts. Statistic of Accident in Malaysia. Available from: http://www.miros.gov.my/1/page.php?i d=17&k=StatisticAccident (Accessed 14 Nov 2015)
- 4. Jasiulewicz-Kaczmarek, M.&Drożyner, P. Social dimension of sustainable development-safety and ergonomics in maintenance activities. International Conference on Universal Access in Human-Computer Interaction. Springer, Berlin, Heidelberg. 2013; 175-184.
- 5. Sun, Y. Yu, X.Berilla, J. Liu, Z.&Wu, G. An in-vehicle physiological signal monitoring system for driver fatigue detection. 3rd International Conference on Road Safety and Simulation 2011.
- Riemersma, JB. Sanders, AF.Wildervanck, C.& Gaillard, AW. Performance decrement during prolonged night driving. Vigilance 1977 (pp. 41-58). Springer US.
- Lal, SK.& Craig, A. Driver fatigue: electroencephalography & psychological assessment. Psychophysiology. 2002; 39(3):313-21.
- 8. Rahman, MN. Modelling of physical vapour deposition (PVD) process on cutting tool using response surface methodology (RSM). Doctoral dissertation, Coventry University2009.
- 9. Deshpande, RP.Chinnan, MS. &McWatters, KH. Optimization of a chocolate-flavored, peanut-soy beverage using response surface methodology (RSM) as applied to consumer acceptability data. LWT-Food Science and Technology.2008;41(8):1485-92.
- 10. Lotfy, WA.Ghanem, KM. & El-Helow, ER. Citric acid production by a novel Aspergillus nigerisolate: II. Optimization of process parameters through statistical experimental designs. *Bioresource technology*. 2007;98(18):3470-7.
- 11. Axelevitch, A. & Golan, G. Modeling and Optimization of Film Deposition by Magnetron Sputtering. *Journal of Uncertain Systems*. 2007; 1(4):277-90.
- 12. Dinges, DF. Critical research issues in development of biomathematical models of fatigue and performance. Aviation, space, and environmental medicine. 2004;75(3):A181-91.

- Wickens, CD. Gordon, SE. Liu, Y. & Lee, J. An introduction to human factors engineering. 2003.
- Malaysian Automotive Association (MAA). Malaysia Vehicles Sales Data for October 2016 by brand. MAA Vehicles Data Report. 2016.
- 15. Vaughn, NA. & Polnaszek, C. Design-Expert® software. Stat-Ease, Inc, Minneapolis, MN. 2007.
- 16. Baluch, NH. Abdullah, CS. & Mohtar, S. Maintenance management performance-An overview towards evaluating Malaysian palm oil mill. *The Asian Journal of Technology Management*. 2010.
- Amrana, M.Salmaha, S.Sanusia, M.Yuhazria, M.Mohamada,N.Asyadi'Azama, M.Abdullaha, Z. &Mohamada, E. Surface Roughness Optimization in Drilling Process Using Response Surface Method (RSM). J. Tech. 2014;66:3.
- Milton, SJ.McTeer, PM. & Corbet, JJ. Introduction to Statistics. Boston: McGraw-Hill. 1997.
- 19. Draper, NR.&Smith, H. Applied regression analysis. *John Wiley & Sons*. 2014.
- 20. Neter, J.Kutner, MH.Nachtsheim, CJ. &Wasserman W. Applied linear statistical models. *Chicago: Irwin.* 1996.
- Yancy, CW. Jessup, M. Bozkurt, B. Butler, J. Casey, DE.Drazner, MH.Fonarow, GC.Geraci, SA.Horwich, T.Januzzi, JL.& Johnson, MR. 2013 ACCF/AHA guideline for the management of heart failure. *Circulation*. 2013;CIR-0b013e31829e8776.
- 22. Saladin, KS. &Porth, CM. Salivary glands. Anatomy and Physiology: The Unit of Form and Function.6th ed. Oxford University Press, New York, 892-898, 1998.
- 23. Proma, FA.Yesmin, T.Hasin, MA. & Ahsan, A. Measurement of TPM Losses Due To Skill Level Difference of Workers: Case Study of A Pharmaceutical Company. Proceeding of International Conference on Industrial Engineering and Operations Management 2010; (pp. 9-10).
- 24. Theobald, H. & Wandell, PE. Effect of heart rate on long-term mortality among

men and women. *Actacardiologica*. 2007;62(3):275-9.

- 25. Zhang J. Effect of age and sex on heart rate variability in healthy subjects. Journal of manipulative and physiological therapeutics. 2007;30(5):374-9.
- 26. Valentini, M. & Parati, G. Variables influencing heart rate. *Progress in cardiovascular diseases*. 2009;52(1):11-9.
- 27. Oosterveer P. Promoting sustainable palm oil: viewed from a global networks and flows perspective. *Journal of Cleaner Production*. 2015;107:146-53.