Journal of Engineering and Technology

ISSN 2180-3811 eISSN 2289-814X https://jet.utem.edu.my/jet/index

# MATHEMATICAL MODEL OF PHYSICAL FACTORS LEADING TO DRIVER FATIGUE DURING PROLONGED DRIVING

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**Article history:**
Received Date: 28 June 2022
Revised Date: 22 August 2022
Accepted Date: 12 September 2022

Keywords: Electromyograpy (EMG), Mathematical model, Muscle Fatigue, Regression

**Abstract**— Prolonged driving in a monotonous environment leads to drowsiness, hinders the driver's performance, and increasees muscle fatigue. This often results in vehicle crashes and loss of life. The aim of this study was to develop a mathematical model of the physical factors that affect driver fatigue during driving. The first objective was to identify how the physical factors of body mass index (BMI), age, and years of driving affect driver muscle fatigue during prolonged driving. The second objective was to formulate and validate a mathematical model of muscle fatigue and these three physical factors of the driver. Electromyography (EMG) signals from the trapezius muscles of ten healthy subjects were recorded for two hours of driving with a 90km/h speed limit. From the EMG signals, the median frequency (MDF) was extracted, and the slope of the coefficient was computed using linear regression. A mathematical model was developed in which the slope coefficient was set as the output and the physical factors of the driver were set as the input variables. Based on the results, it was concluded that BMI was the physical factor that most significantly influenced driver muscle fatigue during prolonged driving. This study successfully developed a mathematical model of the second-order polynomial of muscle fatigue and BMI ($p<0.05$ and $R^2 = 0.85$). The model was successfully validated using the regression method, whereby the residual error was less than 10%.

## I. Introduction

Malaysia is a developing country that could gain income from greater productivity, which requires its citizens to move further and faster [1]. Driving has become an increasingly important way of transporting goods and people from one place to another [2]. However, while the increase in driving activity has offered major benefits, it has also had negative effects, such as the increasing number of road accidents. A report from selected hospitals in Malaysia reported that an annual average of 70% of the major trauma cases are due to road traffic collisions [3]. According to Syazmin et al. (2020), more than half a million road traffic accidents were recorded by the Malaysian Institute of Road Safety Research. In addition, despite having nearly the same total geographical area as Japan, Malaysia recorded an average of 24 fatalities per 100,000 people in 2015, five times the rate reported in Japan [4]. One of the key factors in road accidents is driver fatigue [5].

Monotonous driving environments involve fewer spatial references, a large volume of traffic, and a wide, flat pavement. These circumstances require the driver to sustain their attention during prolonged driving, which will decrease alertness and performance [6]. Mohamad et al. (2010) also concluded that a long driving duration was associated with fatigue [7]. Driving fatigue is characterized as drowsiness caused by prolonged driving, tiredness, and a decrease in attentiveness, all of which limit one's capability and willingness to perform the driving activity [8]. Slower reaction times, a lack of attention, and a loss of vehicle speed control are all indicators of driver weariness. Research has defined fatigue as the lack of ability to exert additional force or power [9]. In previous research, the median frequency (MDF) and mean frequency (MNF) have been obtained based on the Fourier Transform of EMG signals and used for muscle fatigue assessment [10-12]. EMG is an experimental technique concerned with the development, recording, and analysis of myoelectric signals. These signals are formed by physiological variations in the state of the muscle fiber membranes [13]. The slope coefficient of the MDF provides an important index in muscle fatigue assessment [14].

Ani et al. (2017) developed and validated a mathematical model of driver fatigue using driving duration, road type, gender, the relation between gender and road type, as well as the relation between driving duration and road type as the input parameters [15]. Meanwhile, Fu et al. (2016) developed a mathematical model based on the Hidden Markov Model (HMM) that used EMG, Electroencephalograms (EEG), and respiration signals, as well as contextual information such as the driver's sleep quality, driving conditions, and circadian rhythm [6]. Lastly, Wang et al. (2017) developed a model for driver fatigue based on ECG and EMG data using non-contact sensors [16]. To date, no research has been undertaken to develop a mathematical model based on the physical factors of body mass index (BMI), age, and years of driving (YOD) to determine muscle fatigue during driving.

The first objective of this paper was to identify the physical factors that contribute to driver muscle fatigue during prolonged driving. Secondly, the researchers aimed to develop and validate a mathematical model of muscle fatigue with respect to the driver's physical information. According to Barbosa et al. (2003), a mathematical model is defined as a representative of the behavior of a real device or object in mathematical terms [17]. This paper is organized as follows: Section 2 explains the methodology. The results and formulated mathematical model are presented and discussed in Section 3. Finally, the conclusion is explained in Section 4.

## II. Methodology

### A. Subjects

Ten healthy subjects (five males and five females; age: 30.8±5.77 years; height: 164.4±6.06 cm, mass: 64.2±12.70 kg) with no record of sleep-related problems volunteered for this experiment. All the volunteers had to have at least two years of driving experience. The subjects were prohibited from taking coffee, tea, or other energy drinks before or during the experiment. The nature of the study and the experimental procedure were fully explained to the subjects. The study was approved by the Ethics Committee of the International Islamic University Malaysia (ID No: IREC 2020-069) and written consent was obtained from all the subjects before the onset of the experimental procedure.

### B. Experimental procedure

EMG signals were recorded using a BITalino biosignal acquisition board and acquired at a sampling rate of 1,000Hz. Before the EMG electrodes were placed over the muscle, the skin surface needed to be cleaned to remove any dry skin and dirt by applying an alcohol swab (Isopropyl, approximately 70%) and allowing the surface to dry. The electrodes were placed on the left trapezius muscle of the driver and the location of the electrodes followed the SENIAM standard [18]. The reference electrode was placed on the bony surface of the C7 vertebra, as shown in Figure 1.

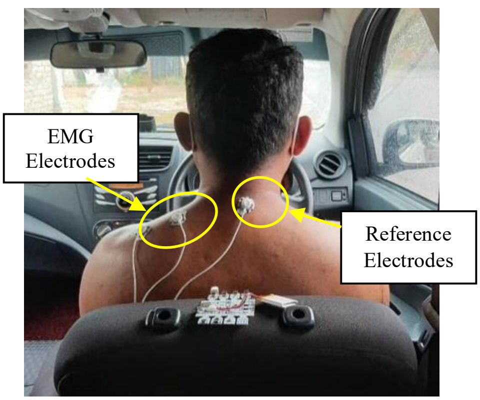


Figure 1: Location of EMG sensor over the driver's muscle

The experiment took place on a highway route on the East Coast Expressway Phase 2, Malaysia. This route was a monotonous environment (straight, downhill, and bumpy; some slanted ramps). A Perodua Axia with automatic transmission was used as the test vehicle. The subjects needed to drive for two hours and maintain a driving speed of 90km/h. Before starting the experiment, the seat inclination angle was set to 10 degrees using MPU6050, the accelerometer and gyroscope sensor. The seat inclination angle followed the optimum driver's seat angle suggested by Ferrari et al. (2001), Majid et al. (2013), and Li et al. (2015) [19-21]. The physical data of all subjects were recorded (weight, height, BMI, age, and years of driving). To minimize artefacts, the subjects were recommended to minimize any movement of their left hand because this would affect the EMG signals [6]. The subjects were given a five-minute test drive to familiarize themselves with the road and the car. The EMG signals were recorded throughout the experiment.

### C. Data Preprocessing

Having been collected, the EMG signals were further analyzed using MATLAB software. The signals were filtered using a fourth-order Butterworth band pass filter with a range of 20-500Hz. The signals had to be filtered to remove noise at the high-end cut-off and motion artefacts at the low-end cut-off. The median frequency was computed using a window size of 250 samples and an increment of 125 samples, as suggested by Thongpanja et al. (2013) [22]. The median frequency was calculated by dividing the EMG total power spectrum into two equal halves using the Equation (1):

$$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^{M} P_j = \frac{1}{2}\sum_{j=1}^{M} P_j \qquad (1)$$

where:
$P_j$ = EMG power spectrum at the frequency bin $_j$
$M$ = length of the frequency bin

## D. Regression

Using the median frequency of each subject, the slope of the linear regression was computed. The slope coefficient is also known as the muscle fatigue index and it is used to identify muscle fatigue trends [23]. The data from eight subjects were used as the training data and the data from the other two subjects were used as the test data for validation. The training data were analyzed using the regression technique. Data related to the physical factors of the driver, such as their BMI, age, and years of driving, were used as the input variable to develop the mathematical model. Meanwhile, the slope coefficient was used as the output of the model. Using each input variable, the model was analyzed using Analysis of Variance (ANOVA), in which the p-value should be less than 0.05. For each model, a p-value of less than 0.05 indicates that the model is significant as regards the output. In addition, the coefficient of determination ($R^2$) was computed, the values of which should be higher than or equal to 0.6 [24]. If the model fits the two conditions of p-value and $R^2$, it would be selected as the mathematical model to illustrate driver muscle fatigue during prolonged driving. Lastly, the model would need to be validated by calculating the residual error, as shown in Equation (2):

$$\% \, Residual \, Error = \frac{Predicted \, value - Actual \, value}{Predicted \, value} x \, 100 \quad (2)$$

The predicted value was the value calculated using the model developed; the actual value was the actual value of the test data. The residual error computed should be less than 10% for the model to be considered suitable for its intended use. This step was necessary to compare the prediction obtained from the model with the real-world value.

## III. Result and analysis

### A. Data preprocessing

Figure 2 shows the median frequency value for a representative subject. As the graph shows, after the 27,000th window, the MDF of the EMG signal tended to decrease and fluctuate. This was because the association between MDF values and fatigue decreased due to the reduction in the propagation velocity of the muscle's action potential [25].

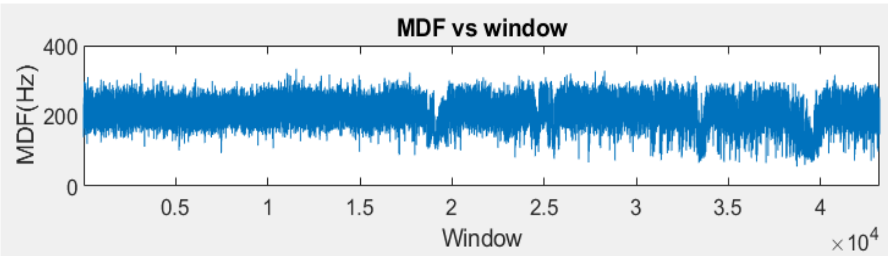


Figure 2: Graph of median frequency for a representative subject

### B. Regression

Based on the literature discussed earlier, muscle fatigue can be evaluated using the slope coefficient obtained from linear regression of the median frequency [26]. Thus, the median frequency computed previously was used to conduct further analysis to determine the effects of the driver's physical factors (BMI, age, and YOD). This was based on the slope coefficient, which represents the rate at which driver muscle fatigue occurred.

The slope coefficient of the median frequency of each subject was obtained using linear regression. Figure 3 below shows the result obtained through the linear regression of the median frequency for subject 001. Based on the results shown in the graph, it was confirmed that muscle fatigue happened because the slope coefficient value is negative, which represents a decrease in muscle power.

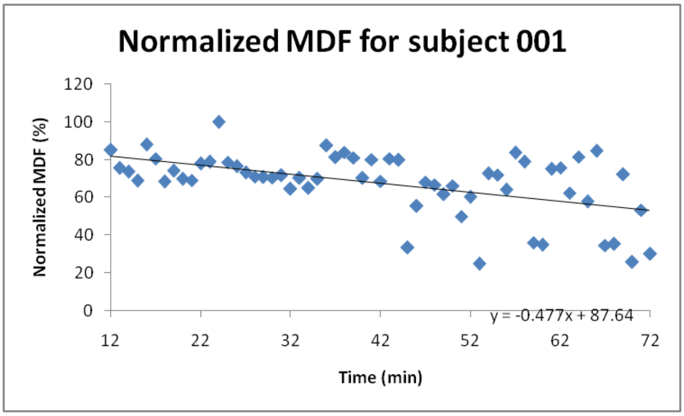


Figure 3: Normalized MDF linear regression for subject number one.

## C. ANOVA analysis

The first objective of this research was to identify how certain physical factors of the driver were related to muscle fatigue. The selected factors were BMI, age, and years of driving. Before the experiment was conducted, the subjects needed to provide these three parameters through a questionnaire. Using ANOVA, the significance of each physical factor was analyzed and determined by polynomial regression. The model with a p-value of less than 0.05 and a coefficient of determination ($R^2$) greater than 0.6 would be selected as the most appropriate model of driver fatigue during prolonged driving.

As mentioned earlier, the slope coefficient represents important features in muscle fatigue assessment. This coefficient indicates how fast muscle fatigue will occur and it can be used to represent muscle fatigue endurance. The input parameters to analyze were the driver's BMI, age, and years of driving. The slope coefficients of the median frequency for each subject were used as the output response of the second-order and third-order polynomial regression. Each physical factor was analyzed using ANOVA. Table 1 below summarizes the ANOVA analysis results using the MDF slope coefficients.

Table 1: ANOVA analysis of the physical factors of muscle fatigue using MDF slope

| | Second-order polynomial | | | Third-order polynomial | | |
|---|---|---|---|---|---|---|
| Physical factor | $R^2$ | p-value | MSE | $R^2$ | p-value | MSE |
| BMI | 0.85 | 0.0081 | 0.0046 | 0.92 | 0.0011 | 0.0029 |
| Age | 0.41 | 0.2690 | 0.0187 | 0.45 | 0.4548 | 0.0218 |
| YOD | 0.35 | 0.3453 | 0.0207 | 0.54 | 0.3353 | 0.0184 |

The results indicate that age and years of driving were not statistically related to the slope coefficient of the MDF because the p-values are greater than 0.05. On the other hand, for BMI, the p-value is less than 0.05 and the $R^2$ value is greater than 0.6. This suggests a relationship between BMI and the muscle fatigue rate using the slope coefficient of the MDF.

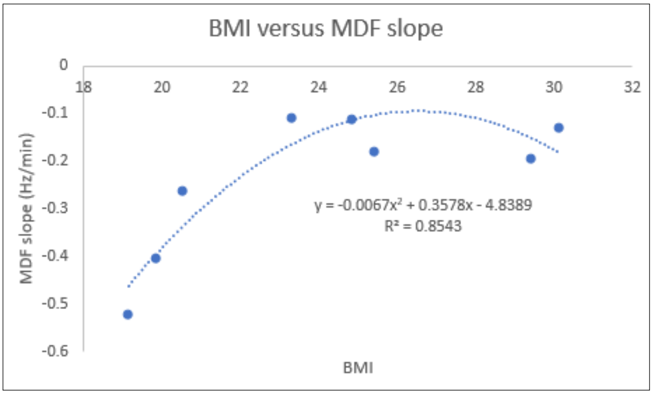


Figure 4: Second-order polynomial regression graph for BMI

Figure 4 shows the second-order polynomial regression graph for the BMI of eight subjects. The actual data were found to be close to the regression line. That is, the $R^2$

value is 0.85, which indicates that 85% of the dependent variable can be explained by the independent variable. Table 2 below summarizes the ANOVA analysis. The significance F, also known as the p-value, is less than 0.05, indicating the good fit of the data. The p-values for the individual input variables (BMI and $BMI^2$) are also less than 0.05, indicating that the quadratic coefficient was significant.

For the third-order polynomial regression of BMI versus the MDF slope, the $R^2$ value and p-value were also a good fit for the data. Based on the individual input variable ANOVA results, the third-order coefficient was significant because the p-value is less than 0.05. Table 3 below summarizes the ANOVA analysis of the third-order polynomial of BMI versus the MDF slope.

Table 2: Summary output of ANOVA analysis for the second-order polynomial of BMI and MDF slope

| | df | SS | MS | Significance F |
|---|---|---|---|---|
| Regression | 2 | 0.1350 | 0.0675 | 0.0081 |
| Residual | 5 | 0.0230 | 0.0046 | |
| Total | 7 | 0.1580 | | |

| | Coefficients | P-value | Lower 95% | Upper 95% |
|---|---|---|---|---|
| Intercept | -4.8389 | 0.0091 | -7.8495 | -1.8283 |
| BMI | 0.3578 | 0.0142 | 0.1083 | 0.6073 |
| $BMI^2$ | -0.0068 | 0.0187 | -0.0118 | -0.0017 |

Table 3: Summary output of ANOVA analysis for the third-order polynomial of BMI and MDF slope.

| | df | SS | MS | Significance F |
|---|---|---|---|---|
| Regression | 3 | 0.1560 | 0.0520 | 0.0003 |
| Residual | 4 | 0.0020 | 0.0005 | |
| Total | 7 | 0.1580 | | |

| | Coefficients | P-value | Lower 95% | Upper 95% |
|---|---|---|---|---|
| Intercept | -37.6242 | 0.0018 | -51.7911 | -23.4574 |
| BMI | 4.4667 | 0.0022 | 2.6941 | 6.2393 |
| $BMI^2$ | -0.1760 | 0.0026 | -0.2489 | -0.1030 |
| $BMI^3$ | 0.0023 | 0.0030 | 0.0013 | 0.0033 |

### D. Model validation

The last step in developing a mathematical model is its validation. Model validation refers to the process of confirming that the model is an accurate representation of the real world from the perspective of intended use. This is done by comparing another set of actual data from the experiment conducted with the data predicted by the new model [15]. A model is considered suitable for its intended use when the residual error is less than 10%. This step is important to examine the model's real-world accuracy. Table 4 shows the model validation and residual error results.

Table 4: Validation result of the newly developed mathematical model

| BMI | Prediction | Actual | Residual | Error (%) |
|---|---|---|---|---|
| 18.61 | -0.516 | -0.477 | 0.039 | 7.55 |
| 22.49 | -0.204 | -0.208 | 0.004 | 1.96 |

Third-order polynomial model

| BMI | Prediction | Actual | Residual | Error (%) |
|---|---|---|---|---|
| 18.61 | -0.671 | -0.477 | 0.194 | 28.91 |
| 22.49 | -0.107 | -0.208 | 0.101 | 94.39 |

Based on the results, the residual error for the second-order polynomial model was less than 10%, indicating that the model developed was successfully validated and thus suitable for its intended purpose. The third-order polynomial model was not successfully validated because the residual error was larger than 10%. In conclusion, of the three physical factors of the driver investigated, only BMI was related to muscle fatigue. The mathematical model of driver fatigue during prolonged driving was successfully developed using second-order polynomial regression which follows Equation (3):

$$Rate\ of\ muscle\ fatigue = -4.8390 + 0.3578\,BMI - 0.00675\,BMI^2 \quad (3)$$

## IV. Conclusion

The current study aimed to develop a mathematical model of the physical factors that cause driver fatigue during driving. Based on the regression analysis, the physical factors of the driver (BMI, age, and YOD) that most significantly affect muscle fatigue were identified using ANOVA. However, the results showed that only BMI was significantly related to muscle fatigue. Thereafter, the mathematical model of the second-order polynomial of BMI and muscle fatigue was successfully developed since the p-value was less than 0.05 and the $R^2$ value was 0.85. The model was validated since the residual error was less than 10%.

In the future, it is suggested that the sample size should be increased to make the developed model more accurate and effective. In addition, a broader range of age, health conditions, and BMI should be obtained from the study population. Other factors contributing to muscle fatigue - such as different types of road, driving times, and types of car - also need to be studied. The outcomes of this work may serve as an important guide and safety measure that could be used when studying driver muscle fatigue to reduce fatigue, avoid musculoskeletal disorders, and prevent accidents.

## V. Acknowledgments

This work was funded by International Islamic University Malaysia (IIUM) Research Acculturation Grant Scheme (IRAGS)(IRAGS18-023-0024). Noor Azlyn Ab Ghafar is supported by the Malaysian Ministry of Higher Education.

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