Lumbar Moment Estimation of Engine Drivers in a Static Sitting Working Position by using Multiple Linear Regression

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ABSTRACT

The paper presents a simpler and more precise model of lumbar moment prediction based on single linear, or multiple linear regression with two predictors. The body mass index (BMI) as the predictor contains two of the most important static anthropometric measures, height and mass, whose separated role in lumbar moment prediction, as well as their mutual relations, have not been sufficiently investigated. This study analysed mass, height, age and BMI as lumbar moment predictors, on a sample of 50 Croatian male engine drivers. Two prediction models were compared: (1) multiple linear regression prediction with mass and height as predictors; (2) single linear regression with mass as the only predictor. Results confirmed the multiple regression model as the best one ($R^2 = 0.9015$ with standard error of prediction 1.26), having the mass of the best predictor. Surprisingly, the single regression model with mass as predictor explained only 3.6% of lumbar moment variance less than multiple regression model, with related standard error of prediction 1.46 (mean percentage value of the relative error was only 0.8% higher than at multiple regression model). The obtained findings suggest high prediction potential of mass and height that should be verified on various subject samples.

KEYWORDS

lumbar moment; engine driver; static siting position; multiple linear regression; predictors.

1. INTRODUCTION

In the transport of both cargo and passengers, depending on the local capacity and condition of the railway infrastructure, different measures of implementation are being investigated in different EU member states, in order to motivate people to switch to public transport from using their own car [1], which is one of the most important measures to meet the challenges of the 2050 Green Deal [2]. The levels (Level 0–Level 3) and operation modes are fundamental concepts [3] of the ETCS system (European Train Control System). As long as the engine driver has to be constantly in the cabin of the locomotive or railcar (current practice is up to and including ETCS Level 2), the estimation of the physical workload in a static sitting working position is a relevant research topic.

The engine drivers' task demand depends dominantly on the change of speed, unlike road vehicle drivers who can at the same time change both gears and direction. Fuller [4] recognised the fact that the choice of speed is the primary solution of the problem of keeping the difficulty of the task within the selected limits, and the limits are subject to the motivation influences. Therefore, the choice, maintenance or change of speed is the most important task in the engine driver's performance, with the most important possible impact on the safety of the traffic process. The success of the engine driver's performance as well as his physical effort measured by the amount of lumbar moment will be influenced by, among other factors, whether the

grouped related commands related to change of speed (multipurpose controller for manual serving of the braking module and/or accelerator module, as well as "dead-man" function) is placed in the maximum or normal hand reach. According to the guidelines of the Rail Safety and Standards Board from Great Britain [5] the actual priorities during scientific research that can be related to safety include, among other important factors, the design of the driver's cab.

The hypothesis investigated in this paper states that there is a simple and more precise model of lumbar moment prediction (than the previous ones) based on single or multiple linear regression method, which contains a maximum of two predictors.

In a previous study [6], prediction of the lumbar moment value M_{ly} at the level of vertebra L4/L5 with the predictor of the body mass index (BMI) has been determined in the hypothetically most unfavourable static seating working position of engine drivers, as a measure for the driver's physical workload. Regression equation $M_{ly}(BMI)$ has an acceptable correlation dependence of medium strength, with correlation coefficient $r = 0.764$ (*Equation 1*).

$$M_{ly}(BMI) = 0.7847 \cdot BMI + 3.0787 \tag{1}$$

The most unfavourable static seating equilibrium working position (with a completely upright torso and head) implies both engine driver's hands stretched out horizontally which mimic the hypothetical most unfavourable situation when, in reality in Croatia, in older models of locomotives and railcars, frequently used and manually served commands are placed within the maximum arm reach. Therefore, regression *Equation 1* refers to the stick biomechanical 2D model of an engine driver in sagittal plane, in the least favourable hypothetical static sitting working position.

It is widely recognised that the performance and all types of driver workload are related, and this relationship is individual and non-linear. According to the open dynamic TCI model of "task demand – driver's capability" interface [4], if "human factors" significantly affect the "task demand" and consequently the engine driver's performance through the speed selection, it is obviously related to the availability and placement of frequently used speed change commands on the control panel, such as the above-mentioned multipurpose controller for manual serving.

Therefore, a possible reason for the changed driver's performance level in the least favourable hypothetical static equilibrium of the driver's working position may be physical load of the driver due to his own increased mass. The excessive body mass in relation to the engine driver's height is expressed by the amount of *BMI* (*Equation 2*). The *BMI* contains two most important static anthropometric measures, the standing height *h* and the body mass *m*. *BMI* is not a best choice for a predictor, because the amount of *BMI* is not related to the distribution of mass in the human body.

$$BMI = \frac{m}{h^2} \tag{2}$$

However, the separate or possible joint influence of height and mass in the static sitting position on the amount of lumbar moment has not been sufficiently investigated, and that fact is the second reason why BMI was not the best choice for a predictor in the previous research using the single linear regression method. BMI contains the two most important static anthropometers, mass and height, which are not functionally related, but are clearly stochastically related with positive moderate correlation. Therefore, the selection of mass, height and BMI as predictors will be analysed and discussed in the chapter under the title "Selection and Analysis of Potential Predictors".

Our own previous research [7] confirms that after the age of 30, the percentage of obese and overweight engine drivers (BMI ≥ 25) increases significantly (after the age of 30, the BMI percentage is in the range between 72.3% and 92.31%, which depends on the age group). The studies carried out during 2011 in Slovenia [8], targeting 245 employees at the railways, indicate 66.9% of overweight or obese workers, with no significant differences between the two groups of workers regarding the nature of their work (white or blue-collar workers). In a study on 118 subjects, the influence of BMI on seat comfort was studied [9]. Relationships between BMI and the size of the backrest contact surface, pressure change and maximum pressure were determined. The reason for the

significantly higher percentage of overweight and obese engine drivers in Croatia can be related to the shift work schedule, which implies irregular shifts that include night work, as well as unhealthy dry food. It is important that BMI as a predictor candidate has an adequate variability (mostly analysed by the coefficient of variation *CV*), otherwise it cannot correlate properly with other variables, including the lumbar moment.

Back in 1984, it was established that the lumbar moment and intra-abdominal pressure can be used to estimate human physical effort in static body positions [10].

This additional study had been based on previously measured static and kinematic anthropometric measurements for 50 male engine drivers from Croatia [6]. In the simplified calculation i.e. prediction of the lumbar moment Mly, predictors can be variables mass, height, BMI and age. Instead of additionally measuring several segments of arm length (hands, forearms and upper arms) for 50 research participants and subsequently calculating segmental masses for hands, forearms and upper arms (see Chapter 4), it is possible to obtain an even simpler calculation of the predicted M_{ly} by using a regression equation model with one (*m* or *h*) or two predictors (*m* and *h*), while measuring these predictors is simple and fast.

Measurements of mass and height can be performed with a calibrated digital scale with mechanical altimeter Tanita WB 3000 (digital scales accuracy class III) in the Laboratory for Applied Ergonomics in Traffic and Transport [11]. The above-mentioned device is not expensive and it enables a relatively quick measurement of the two most important anthropometric measures, mass *m* and height *h*, which were also predictor candidates. The latest trends indicate the use of more modern but also more expensive devices such as 3D body scanners [12]. Anthropometric measurements obtained by using this measurement are more accurate, precise and repeatable, and can be applied for the ergonomic design of a sitting workplace.

2. METHOD

Participants. Fifty (50) male engine drivers from Croatia, in the age range from 28 to 53 (8% were left-handed) participated in anthropometric measurements. In 2012, when the study was conducted, the engine drivers population in the Republic of Croatia included 1,357 male engine drivers (there were no female engine drivers at all). Participants have been selected by taking into account regional representativeness of the population, so engine drivers were measured in seven Croatian railway centres in various regions: Zagreb, Karlovac, Varaždin, Slavonski Brod, Knin, Rijeka and Zadar.

Instruments. Anthropometric measurements have been performed with large and small Lafayette Instrument anthropometers (accuracy class II, sliding anthropometric callipers designed to measure a straight-line distance between two landmarks with an accuracy of 1 mm) and calibrated digital scales with the mechanical altimeter Tanita WB 3000 (digital scales accuracy class III).

Procedure. The anthropometric measurements were conducted at the same time of the day, between 11:00 a.m. and 3:00 p.m. It was always done by the same person, one of the co-authors of the paper. All length-based anthropometric measures were measured with the precision of the whole number of centimetres, while mass *m* was measured with the precision of one decimal place (in kilograms). For certain length-based anthropometric measures (hand, forearm, upper arm), the measurement procedure depended on the hand dominance: for right-handed subjects, the anthropometric measures were measured on the non-dominant left side of the body, whereas for the left-handed subjects the anthropometric measures were measured on the non-dominant, right side of the body.

Data analysis design. In order to reach the proposed research goal, the following data analysis procedures were conducted:

1) Potential predictors of lumbar moment values were analysed in terms of their distribution features that constitute the presumptions for single and multiple regression – variability and distribution normality (with the focus on asymmetry)
2) Potential predictors of lumbar moment values were selected by considering their distribution features and the correlation coefficients between predictors and lumbar moment values, but also among the predictors (with previous non-linearity relation checking by Pearson and Spearman correlations comparison)

3) Calculation of lumbar moment values via single and multiple linear regression equations, based on the selected predictors

4) Calculation and mutual comparison of two indicators of regression fit: (i) standard error of prediction and (ii) mean percentage value of the relative error of calculated lumbar moment.

3. ANALYSIS AND SELECTION OF POTENTIAL PREDICTORS

Before proposing two optimal predictors for lumbar moment by using the correlation matrix of all available variable candidates, distribution-based assumptions for single and multiple regression have been verified. Distribution-based statistics that have been analysed are mean M, standard deviation sd, coefficient of variation CV calculated via *Equation 3*, distribution normality test significance and skewness test statistics. They are presented in *Table 1* and related explanations are given below *Table 1*.

Table 1 – Descriptive statistics for testing single or multiple linear regression assumptions for male engine drivers

	Variables that are candidates for predictors			
	Mass *m*	Height *h*	Age	*BMI*
	[kg]	[cm]	[years]	[kg/m²]
M	94.5	180.4	44.9	29.0
sd	14.6	6.2	6.2	3.8
CV [%]	15.4	3.4	13.8	13.2
Significance of distribution normality tests p	>0.2	>0.2	<0.01	>0.2
Skewness coefficient *SC*	0.195	0.058	-0.982	0.569
Standard error of skewness coefficient SE_{SC}	0.337	0.337	0.337	0.337
SC/ SE_{SC}	0.578	0.173	-2.917	1.691

$$CV = \frac{sd}{M} 100 \tag{3}$$

Skewness coefficient *SC* is calculated (for each variable *x*) in the next *Equation 4*. Calculated values of the *SC* as shown in *Table 1* can be positive or negative, if the variable distribution is asymmetric.

$$SC = \frac{n}{(n-1)(n-2)} \sum \left(\frac{x_i - M}{s} \right)^3 \tag{4}$$

Positive values of the skewness coefficient (*SC*) shown in *Table 1* mean that the distribution concentrated around central tendency measure (median *C*) has a certain number of significantly higher results, i.e. a long tail on the right side of the distribution. Therefore the mean value *M* will be greater than the median value C for the variables *m*, *h* and *BMI*. The negative *SC* value shown in *Table 1* for the age variable means that age shows a negatively asymmetric distribution.

Standard error of the skewness coefficient SE_{SC} calculated (for each variable *x*) in *Equation 5* depends only on the sample size, so it has the same value for all analysed variables $SE_{SC} = 0.337$ as shown in *Table 1*.

$$SE_{SC} = \sqrt{\frac{6 \cdot n \cdot (n-1)}{(n-2) \cdot (n+1) \cdot (n+3)}} \tag{5}$$

In order to prove that the obtained *SC* reflects the actual existing distribution skewness in the whole population of Croatian engine drivers, we need to test SC significance. To test the related null-hypotheses, z-statistics was used:

$$z_{SC} = \frac{SC}{SE_{SC}} \tag{6}$$

Since z_{SC} is distributed according to standard normal distribution, the obtained skewness of the analysed variable will be significant on 95% or 99% level when the calculated z_{SC} in *Equation 6* is absolutely greater

than 1.96 or 2.58, respectively. An additional reason to test asymmetry significance is to find the source of possible distribution normality deflection of the observed variable. If the asymmetry significance has been confirmed, it can cause problems in correlation calculus and interpretation when correlated variables show the opposite significant distribution asymmetry.

The results of the analysis from *Table 1* show several distribution characteristics that are relevant for correlation and regression calculation:

- *CV* values indicate good but not optimal variability for correlation calculation, especially for height *h*. Namely, reduced variability will cause reduced covariation and lead to lower correlation coefficients [13]. Therefore, it is expected that bivariate correlations of the height variable will be somewhat lower, since its variability is approximately four times smaller than the variability of other variables
- All variables but age show normal distributions (tested by Kolmogorov-Smirnov, Shapiro-Wilk and Chi-square tests), which suggests possible distortion of correlational coefficients only for the age-variable. Nevertheless, the consequences of this distortion are confined only to correlation of age with other variables, but mostly with *BMI* and *m*, which show the opposite distribution asymmetry in relation to age distribution [13].

Table 2 shows that the variables of mass *m* and height *h* (expressed by the amount of the coefficient of variation *CV*) behave similarly for different groups of respondents, regardless of their sex, age and occupation. The variable *h* is very homogeneous across all subjects (*CV* is in the range from 2.97 to 3.66), while *m* has a significantly greater variability (in relation to height *h*) as indicated by the amount of the coefficient of variability *CV* (*CV* is in the range of 15.4 to 21.15). These findings on high height homogeneity across different samples will be discussed later in the paper.

Table 2 – Analysis of the variability of m and h for subjects of different ages, different sex and different occupations [6, 14, 15]

	Male engine drivers from Croatia		Male students of the Zagreb University up to age 29		Female students of the Zagreb University up to age 29		Female tram drivers in Zagreb	
	n = 50		*n* = 62		*n* = 68		*n* = 36	
	age 29 to 53		age 20 to 28		age 20 to 28		age 30 to 55	
	m	*h*	*m*	*h*	*m*	*h*	*m*	*h*
	[kg]	[cm]	[kg]	[cm]	[kg]	[cm]	[kg]	[cm]
M	94.5	180.4	86.2	181.60	61.8	168.3	74.2	166.6
sd	14.6	6.2	15.1	6.3	10.4	6.2	15.7	4.9
CV [%]	15.40	3.41	17.51	3.47	16.79	3.66	21.15	2.97

Table 3 shows the integrated Pearson-Spearman correlation matrix of all variables that are candidates for lumbar moment predictors: mass, height, age and *BMI*. The Pearson correlations are shown above the main diagonal of the matrix, while the Spearman correlations are presented below the diagonal. This comparative presentation of correlation coefficients (Pearson vs Spearman) among predictor candidates is useful to quickly check whether the dependence between any *x* and *y* variable is linear: since Spearman's *Rho* is more appropriate than Pearson's *r* for non-linear relations/dependences in all non-linear relations, Spearman's *Rho* should have larger values then Pearson's *r* [16]. Comparison of Pearson's *r* and Spearman's *Rho* (or *r*$_s$) for any 10 relations in the correlation matrix suggests that every *Rho* is smaller than the related *r*, which means that all relationships between the predictors variables candidates are linear. Therefore, the linear relationship presumption for regression calculation has been completely obeyed.

Since the predictors selection in multiple regression demands (i) the highest correlation between predictor and criterion variable and (ii) the lowest correlation between the two possible predictors, the above-mentioned correlation matrix suggests the following:

- the best lumbar moment predictor is mass, the worst predictor is age, so the second predictor should be selected among height and *BMI*
- a better choice for second prediction is height since *BMI* almost completely correlates with the mass-predictor ($r = 0.904$) and it will not contribute separately to the prediction of M_{ly} (which is not the case for the height-variable that shares less than 30% of variance with mass).

Table 3 – Comparative correlation matrix (Pearson vs Spearman) for mass, height, age and BMI variables based on 50 respondents

		M_{ly}	Age	m	h	BMI
M_{ly}	Pearson/Spearman correlation	1	0.272	0.930**	0.666**	0.764**
	Sig. (2-tailed)		0.056	< 0.01	< 0.01	< 0.01
Age	Pearson/Spearman correlation	0.132	1	0.308*	0.115	0.316*
	Sig. (2-tailed)	0.361		0.03	0.428	0.026
m	Pearson/Spearman correlation	0.903**	0.172	1	0.546**	0.904**
	Sig. (2-tailed)	< 0.01	0.232		< 0.01	< 0.01
h	Pearson/Spearman correlation	.634**	0.047	0.510**	1	0.14
	Sig. (2-tailed)	< 0.01	0.745	< 0.01		0.333
BMI	Pearson/Spearman correlation	0.713**	0.244	0.884**	0.12	1
	Sig. (2-tailed)	< 0.01	0.088	< 0.01	0.406	

By taking into account the fact that the previously mentioned reduced variability of the height-variable suggests its correlations might be only higher with the approaching variability level of other variables, the obeyed distribution normality and linear relationship lead to conclusion that the optimal candidates for the two-predictors multiple regression prediction of $M_{ly}(x_1, x_2)$ are mass and height.

4. CALCULATION OF THE INDIVIDUAL LUMBAR MOMENT VALUE

This chapter is taken in abbreviated form from the previous paper [6], with the aim of briefly explaining how the amount of lumbar moment for each individual male engine driver can be calculated in sagittal plane, according to *Figure 1*, in the least favourable hypothetical static equilibrium working position, with both arms horizontally extended in the zone of maximal reach.

Knowing the height and mass of the human body, by using the Donskij-Zacijorskij method [17] and multiple regression *Equation 7*, it is possible to calculate the amounts of single segmental masses mi for hands, forearms and upper arms in the respondents, i.e. engine drivers.

$$m_i = B_0 + B_1 \cdot m + B_2 \cdot h \tag{7}$$

The positions of mass centres m_i were calculated according to *Table 4*, measured from the upper border of the body segments [18].

Body segment gravities F_{gzi} parallel to the z axis (hand gravity F_{gs}, forearm gravity F_{gp}, upper gravity Fgn and torso gravity F_{gt}) have been calculated according to *Equation 8*, and the amounts of lumbar moments M_{ly} according to *Equation 9* have been obtained by the reduction of all F_{gzi} from segmental masses m_i into the origin of the xz coordinate system (*Figure 1*).

$$F_{gzi} = m_i \cdot 9.81 \tag{8}$$

$$M_{ly} = \sum_{i=1}^{n} F_{gzi} \cdot x_i \tag{9}$$

Table 4 – Mass centres in the percentage of the function of the body segment length [18]

Body segment	Distance [%]*
Head and neck	50.02
Upper torso	50.66
Middle torso	45.02
Lower torso	59.59
Hand	36.91
Thigh	45.49
Lower leg	40.49
Foot	44.14
Upper arm	44.98
Forearm	42.74

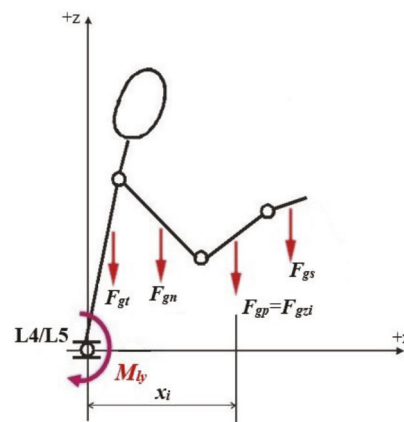**measured from the upper border of the segment*

Figure 1 – Two-dimensional stick model of the respondent in sagittal plane [19]

In compliance with the considerations of Mairiaux et al. [10] or Muftić et al. [20], the origin of the zx coordinate system represents also the point of reduction L4/L5 of the lumbar moment to the level between the fourth (penultimate) and fifth (last) lumbar vertebra in the mobile part of the spine viewed from above downwards.

For the purposes of the calculation explained in this chapter, it is important to note that the following static measured anthropometric measures were used as input variables: height, mass and anthropometric measures based on length (hand, forearm, upper arm). Segmental masses m_i for the hands, forearms and upper arms were calculated using the multiple regression by using only the height and mass as predictors (*Equation 7*). The amount of lumbar moment calculated in this way will be mentioned several times in the following chapters under the name "calculated lumbar moment M_{ly} based on the measured anthropometric measures".

5. RESULTS

Since we proposed mass and height as the best predictors for lumbar moment M_{ly}, based on the data of the actual research, the next task was to calculate the regression equation for predicting $M_{ly}(m,h)$ with m and h in *Equation 10*:

$$M_{ly}(m,h) = b_0 + b_1 \cdot x_1 + b_2 \cdot x_2 = b_0 + b_1 \cdot m + b_2 \cdot h \tag{10}$$

Coefficients b_0, b_1 and b_2 are calculated in the next *Equations 11–13*:

$$b_0 = M(M_{ly}) - b_1 \cdot M(m) - b_2 \cdot M(h) \tag{11}$$

$$b_1 = \beta_1 \cdot \frac{sd(M_{ly})}{sd(m)} \tag{12}$$

$$b_2 = \beta_2 \cdot \frac{sd(M_{ly})}{sd(h)} \tag{13}$$

whereby standardised coefficients β_1 and β_2 are fully determined by the correlation matrix shown in *Table 3* and calculated in *Equations 14 and 15* taking into account that $y = M_{ly}$, $x_1 = m$, and $x_2 = h$.

$$\beta_1 = \frac{r_{x_1 y} - r_{x_2 y} \cdot r_{x_1 x_2}}{1 - r_{x_1 x_2}^2} \tag{14}$$

$$\beta_2 = \frac{r_{x_2 y} - r_{x_1 y} \cdot r_{x_1 x_2}}{1 - r_{x_1 x_2}^2} \tag{15}$$

Applying the above formulas on the related values from *Table 2* and *Table 3* gives the target multiple regression for predicting $M_{ly}(m,h)$ with m and h (*Equation 16*):

$$M_{ly}(m,h) = -20.782 + 0.218 \cdot m + 0.144 \cdot h \tag{16}$$

Coefficients b_0, b_1 and b_2 obtained on the sample of 50 engine drivers are statistically significant (the related t-statistics and p-values are t(b_0) = -3.669 with p = 0.01, t(b_1) = 14.781 with p < 0.01, t(b_2) = 4.124 with p < 0.01) and their real values in the whole engine drivers' population lie in the next intervals, with a 95% probability:

b_0*: [-32.169, -9.395]

b_1*: [0.188, 0.248]

b_2*: [0.074, 0.214]

Multiple regression *Equation 16* predicts lumbar moment $M_{ly}(m,h)$ surprisingly well, which is obvious from statistically significant multiple correlation coefficient R calculated in *Equation 17* (Pearson correlation between calculated values of M_{ly} based on measured anthropometric measures and predicted values of $M_{ly}(m,h)$ calculated in *Equation 16*: $R = 0.949$, F = 215.002, $df_1 = 2$, $df_2 = 47$, p<0.001.

Multiple correlation coefficient R is calculated in *Equation 17*:

$$R = \sqrt{\beta_1 \cdot r_{x_1 y} + \beta_2 \cdot r_{x_2 y}} \tag{17}$$

Such high prediction has small standard error $s_{y.x_1 x_2} = 1.26$ and sends an important message: 91% of lumbar moment variance can be explained by optimal linear combination of mass and height. Visual illustration of that prediction gives us *Figure 2*.

Separate contribution of both predictors to such a good prediction has been analysed through standardised regression coefficients β_1 and β_2, i.e. β_m and β_h, respectively. Values of these coefficients ($\beta_m = 0.808$ and $\beta_h = 0.225$) clearly demonstrate that the mass contribution to M_{ly} prediction is almost four times greater than the height contribution. This finding is not surprising when we take into account the values of the related Pearson correlations from *Table 3* ($r[M_{ly},m] = 0.93$) and ($r[M_{ly},h] = 0.666$), but the M_{ly}-m correlation itself and the related "prediction power" of mass is surprising.

To test the prediction of the lumbar moment $M_{ly}(m)$ only with mass, we performed a single linear regression procedure with the model $M_{ly} = b_0 + b_1 \cdot m$. The related calculus gave us the next regression (*Equation 18*):

$$M_{ly}(m) = 2.0662 + 0.2513 \cdot x = 2.0662 + 0.2513 \cdot m \tag{18}$$

From two regression coefficients ($b_0 = 2.0662$ and $b_1 = 0.2513$), only b_1 is statistically significant (the related t-statistics and p-values are t(b_0) = 1.513 with p = 0.137 and t(b_1) = 17.598 with p < 0.01), which means that b_0 equals zero in the related engine driver population, while b_1 lies in the next 95% confidence interval: b_1*: [0.223, 0.280].

The standard error of single regression prediction is small $s_{y.x} = 1.46$ and does not differ much from the multiple regression prediction standard error ($s_{y.x_1 x_2} = 1.26$). This finding is expected from comparison of

Table 5 – Comparative representation of several lumbar moment calculation models and the related proposed predictors of the analysed Croatian engine drivers sample

| Resp. No.	BMI	m [kg]	h [cm]	Age [years]	M_{ly} [Nm]	$M_{ly}(m)$ [Nm]	$M_{ly}(m,h)$ [Nm]	$M_{ly}(BMI)$ [Nm]	Resp. No.	BMI	m [kg]	h [cm]	Age [years]	M_{ly} [Nm]	$M_{ly}(m)$ [Nm]	$M_{ly}(m,h)$ [Nm]	$M_{ly}(BMI)$ [Nm]
1	28.4	94	182	40	27.46	25.69	25.92	25.31	71	26.2	85	180	50	22.19	26.44	23.67	23.62
2	31.8	94	172	52	23.75	24.68	24.48	27.97	72	30.6	97	178	51	27.35	28.45	26.00	27.06
3	24.9	90	190	51	23.54	20.91	26.20	22.60	73	29.1	105	190	38	30.78	21.17	29.47	25.86
7	24.5	75	175	46	21.66	28.45	20.77	22.26	75	26.0	76	171	42	21.10	32.72	20.41	23.43
8	30.0	105	187	42	30.43	26.44	29.04	26.60	76	35.6	122	185	49	32.14	31.72	32.45	31.01
13	27.7	97	187	46	26.65	27.95	27.29	24.81	77	33.4	118	188	50	31.34	30.97	32.01	29.24
15	29.1	103	188	37	28.58	24.68	28.74	25.91	207	30.6	115	194	53	32.47	26.44	32.22	27.02
16	26.3	90	185	38	25.08	25.19	25.48	23.67	208	29.0	97	183	46	25.23	18.15	26.72	25.77
17	27.5	92	183	51	28.00	24.18	25.63	24.60	85	23.5	64	165	37	16.36	26.19	16.93	21.49
18	25.7	88	185	35	25.46	25.69	25.04	23.22	100	30.3	96	178	46	25.70	23.43	25.78	26.81
19	29.0	94	180	36	24.61	28.45	25.63	25.80	101	28.1	85	174	28	22.23	23.43	22.80	25.07
21	31.7	105	182	44	27.85	27.20	28.32	27.91	102	24.6	85	186	48	25.05	25.44	24.53	22.32
22	29.2	100	185	39	26.45	27.20	27.66	25.97	103	27.8	93	183	47	27.04	19.66	25.84	24.83
27	27.7	100	190	46	28.48	26.69	28.38	24.78	104	22.9	70	175	28	18.74	22.67	19.68	20.97
28	29.9	98	181	37	26.84	29.21	26.65	26.51	105	27.1	82	174	48	22.05	36.75	22.15	24.29
35	34.1	108	178	47	29.32	28.45	28.39	29.79	106	41.7	138	182	52	35.19	25.44	35.51	35.73
41	32.4	105	180	45	29.54	28.20	28.03	28.47	107	29.4	93	178	48	26.83	28.45	25.12	26.07
53	33.6	104	176	50	25.94	25.44	27.23	29.38	108	28.5	105	192	45	30.94	20.16	29.76	25.39
57	30.4	93	175	49	24.92	30.97	24.69	26.87	109	24.3	72	172	48	20.46	24.68	19.68	22.14
62	34.0	115	184	48	26.51	18.40	30.78	29.69	110	27.8	90	180	52	25.27	28.96	24.76	24.84
63	20.5	65	178	50	17.97	28.20	19.02	19.14	111	34.9	107	175	50	28.78	23.18	27.74	30.46
65	32.8	104	178	48	27.82	19.66	27.52	28.80	112	27.4	84	175	46	22.32	27.45	22.73	24.56
66	23.7	70	172	37	18.42	24.68	19.25	21.61	113	32.2	101	177	44	28.42	24.68	26.72	28.34
67	28.7	90	177	51	22.46	22.67	24.33	25.58	114	27.8	90	180	36	26.03	26.19	24.76	24.84
70	24.8	82	182	51	24.32	23.43	23.30	22.46	115	32.1	96	173	45	25.01	25.82	25.06	28.21
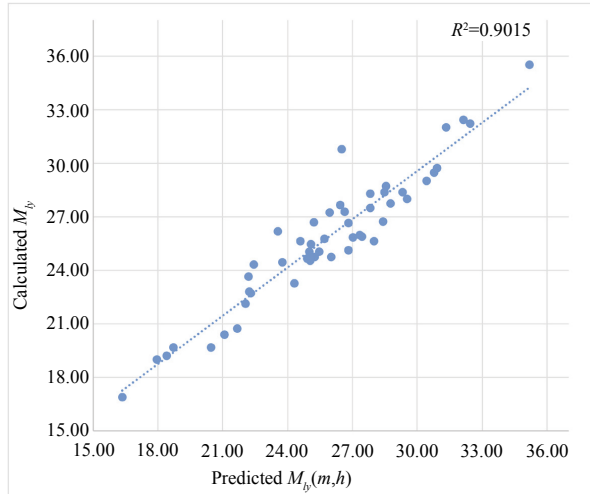
Figure 2 – Relationship between the calculated values of lumbar moment M_{ly} based on measured anthropometric measures and the ones predicted by mass and height through multiple regression $M_{ly}(h,m)$

the explained M_{ly} variance by single prediction ($r^2 = 0.865$) and by multiple prediction ($R^2 = 0.901$), and requires discussion on multiple regression usefulness, when compared to single regression prediction.

To evaluate the contribution of the two regression models in the actual research (based on mass and height, and based only on mass) in relation to the previous one (based on *BMI*), we created *Tables 5 and 6.*

Table 5 shows a comparison of analytically calculated value of lumbar moment based on the measurement of static anthropometric measures [6] with the three above-analysed regression predictions for lumbar moment given by three different regression *Equations 1, 16,* and *18.*

The column titled M_{ly} presents the individually calculated values of the lumbar moment for each individual engine driver as described briefly in Chapter 3 [6]. The column titled $M_{ly}(BMI)$ represents the prediction of the lumbar moment by using single linear regression *Equation 1*, with the variable BMI as predictor [6]. The column titled $M_{ly}(m)$ represents the prediction of the lumbar moment by using the single linear regression *Equation 18*, with the variable m as predictor. The column titled $M_{ly}(m,h)$ represents the prediction of the lumbar moment by using the multiple linear regression *Equation 16*, with variables *m* and *h* as predictors.

For the lumbar moment values predicted in the regression *Equations 1, 16, 18* in relation to the calculated lumbar moment M_{ly} based on the measurement of static anthropometric measures [6], the mean percentage value of relative error E_{RM} (shown in *Table 6*) was calculated based on the entire sample of 50 engine drivers (*Equation 19*).

$$E_{RM} = \frac{\sum_{i=1}^{50}\left|\frac{\Delta M}{M_{ly}} \cdot 100\right|}{n} \tag{19}$$

In accordance with the results shown in *Table 6*, for this sample, the lowest mean percentage value of the relative error E_{RM} is for the lumbar moment value $M_{ly}(m,h)$ predicted by the multiple regression *Equation 16*, using the variables *h* and *m* as predictors. It should be emphasised that, when compared, the multiple regression model

Table 6 – Calculation parameters of the mean percentage value of the relative error

Predicted lumbar moment label	$M_{ly}(m)$	$M_{ly}(m,h)$	$M_{ly}(BMI)$
Variable(s) used as predictors	*m*	*m, h*	*BMI*
Regression equation for the calculating of predicted lumbar moment	*Equation 18*	*Equation 16*	*Equation 1*
Equation for the lumbar moment deviation ΔM	$\Delta M = M_{ly}(m) - M_{ly}$	$\Delta M = M_{ly}(m,h) - M_{ly}$	$\Delta M = M_{ly}(BMI) - M_{ly}$
Calculated value of E_{RM} (%)	4.6	3.8	8.3

$M_{ly}(m,h)$ in relation to the single regression model $M_{ly}(m)$ has only 0.8% lower mean percentage relative error E_{RM}. In addition, to predict the value of the lumbar moment M_{ly}, it is necessary to measure an additional anthropometric measure, body height h.

6. DISCUSSION

The engineer's goals met good statistical presumptions in the measured sample of engine drivers and produced some interesting scientific findings in the field of anthropometry.

First, all anthropometric measures obeyed most of the statistical presumptions for linear regression calculation (interval or ratio measurement scale, linear relationship between measures, distribution normality and appropriate variability) and that enabled a valid interpretation of the obtained regression models. Only the height variable had quite a reduced variability (compared to the other anthropometric variables) and we might speculate on an even better model if that variability were higher. Nevertheless, data in *Table 2* clearly state that the height variability is consistently several times lower than the mass variability across four various samples defined by sex and profession [6, 14, 15] and this feature seems not to be a local phenomenon [21, 22].

Correlation matrix data (*Table 3*) mostly corroborate findings expected on calculation formulas, but also reveal two findings that were not so expected. The first one is non-significant correlation between h and *BMI* (despite the functional dependence of *BMI* on h) that might be explained by two arguments:

Argument (1): inverse quadratic dependence of *BMI* on h with simultaneous linear dependence on m (which is linearly dependent on h), which are two antagonistic relations that produce dependence annihilation.

Argument (2): the fact that Pearson's correlation detects only linear dependence, which is not present in the *BMI-h* relation.

Nevertheless, since Spearman's *Rho* did not detect a non-linear *BMI-h* correlation, it seems that the first argument gives a reasonable explanation.

Second relevant correlational finding is a surprisingly high M_{ly}-m correlation ($r = 0.93$), which requires further measurements on different samples, since it sends one important message: in order to determine lumbar moment with a decent precision level, you need only the weight scale.

A high M_{ly}-m correlation does not leave much space to any other anthropometric measure to contribute to the prediction in the multiple regression equation. That is why the mass-variable m predicted $M_{ly}(m)$ independently several times more than the height-variable ($\beta_m = 3.59 \cdot \beta_h$), which leads to one logical question despite the high and significant multiple correlation ($R = 0.949$) and despite significant regression coefficients: why should we not predict M_{ly} with a single linear regression by using the mass as the only predictor?

The additionally conducted single regression model for $M_{ly}(m)$ shown in *Equation 18* gave a slightly weaker $M_{ly}(m)$ prediction than the target multiple regression model $M_{ly}(m,h)$, shown in *Equation 16*. Namely, the multiple regression model (*Equation 16*) explained only 3.6% more M_{ly} variance than the single regression model (*Equation 18*), thereby having only 0.2 lower standard error of prediction and only 0.8% lower mean percentage value of the relative error. The final decision on the choice between the two regression models will have to wait until they are tested on more different subject samples (different ages, bigger samples, more representative for the regular population), but will also depend on the measurement purpose and conditions.

7. CONCLUSION

These studies point to the fact that mass is the most important predictor of increased physical load on the driver in obese and overweight drivers in the least favourable hypothetical static equilibrium of the driver's working position (evaluated by predicting the lumbar moment $M_{ly}(m)$), if frequently used commands served by hands are placed in maximum arm reach.

Another important conclusion is that we could calculate lumbar moment of Croatian engine drivers with significantly high precision by simply measuring mass and height of the drivers. That means that we could

get the lumbar moment value along the way, together with body mass index, which has its practical implications in applied research. Nevertheless, the question why the lumbar moment is so highly determined by the overall body mass (i.e. why one physical quantity defined by partial body masses and dimensions can be highly reduced to the overall body mass) still remains open as a fundamental research question and it will require more measurements and modelling.

The authors' two recommendations for possible further research are as follows. It would be preferable to repeat this research on another sample from the same population of male engine drivers. From the point of view of the authors, it would also be interesting to repeat this research on drivers of different sexes (e.g. female ZET tram drivers in Zagreb, since there are currently only nine female engine drivers in the whole of Croatia).

REFERENCES

[1]   Václav L, Vojtěch N. Role of railway transport in Green Deal 2050 challenge – Situation in the Czech Republic. *Promet – Traffic&Transportation*. 2022;34(5):801-812. DOI: 10.7307/ptt.v34i5.4117.

[2]   European Commission. *The European Green Deal*. Brussels: European Commission; 2019. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52019DC0640&qid=1702131042750 [Accessed 4th December 2023].

[3]   European Commission. *Mobility and transport: ECTS levels and modes*. Brussels: European Comission; 2019. https://transport.ec.europa.eu/transport-modes/rail/ertms/what-ertms-and-how-does-it-work/etcs-levels-and-modes_en [Accessed 4th December 2023].

[4]   Fuller R. Towards a general theory of driver behaviour. *Accident Analysis and Prevention*. 2005;37(3):461-472. DOI: 10.1016/j.aap.2004.11.003.

[5]   Wilson JR, Norris BJ. Rail human factors: Past, present and future. *Applied Ergonomics*. 2005;35:649-660. DOI: 10.1016/j.apergo.2005.07.001.

[6]   Sumpor D, Taboršak D, Jurum-Kipke J. Anthropometric measures important for control panel design in locomotive or railcar. *Technical Gazette*. 2015,22(1):1-10. DOI: 10.17559/tv-20140206135045.

[7]   Mikulčić M, Modrić M, Sumpor D. Application possibility of engine drivers' body segments ratios in designing the cab' working environment in Croatia. *Proceedings of the 26th International DAAAM Symposium, 18-25 Oct. 2015, Zadar, Croatia*. 2016. p. 842-848. DOI: 10.2507/26th.daaam.proceedings.117.

[8]   Ostan I, Poljšak B, Podovšovnik AE. Motivations for healthy lifestyle in railroad employees. *Promet – Traffic&Transportation*. 2012;24(1):45-52. DOI: 10.7307/ptt.v24i1.267.

[9]   Jianhua L, Qiaomeng P, Ming C. Influence of body mass index on comfort and parametric optimization design of seat. *Technical Gazette*. 2022;29(4):1262-1269. DOI: 10.17559/tv-20210306023605.

[10]   Mairiaux PH, Davis DR, Stubbs DA, Baty D. Relation between intra-abdominal pressure and lumbar moments when lifting weights in erect posture. *Ergonomics*. 1984;27(8):883-894. DOI: 10.1080/00140138408963562.

[11]   Sumpor D. *Laboratory equipment cataloque of laboratory for applied ergonomics in traffic and transport*. University of Zagreb, Faculty of Transport and Traffic Sciences; 2013. https://www.fpz.unizg.hr/hr/o-fakultetu/laboratoriji-fakulteta [Acccessed 4th December 2023].

[12]   Brlobašić ŠB, Petrak, S. Application and advantage of 3D body scanning in the ergonomic design of a sitting workplace. In: Salopek Čubrić, Ivana, et al. (eds.) *Proceedings of the 9th International Ergonomics Conference - ERGONOMICS 2022, volume 701*. Springer Nature Switzerland AG; 2023. p. 37-44. DOI: 10.1007/978-3-031-33986-8_5.

[13]   Gudgeon AC, Howell DC. *Statistical Methods for Psychology*. Burlington, SAD: Wadsworth, Cengage Learning; 2010.

[14]   Sumpor D, Mikulčić M, Modrić M. Female students' body segments ratios. In: Sušić A, et al. (eds.) *Book of Proceedings of the 6th International Ergonomics Conference „Ergonomics 2016 – Focus on synergy"*. Croatian Ergonomics Society; 2016. p. 323-330. DOI: 10.7307/ptt.v28i5.2294.

[15]   Ozbec-Ban M, Zečević-Tadić R, Sumpor D. Static anthropological measures of female tram drivers in Zagreb important for tram control panel design. In: Mijović B, et al. (eds.) *Proceedings of 5th International Ergonomics Conference „Ergonomics 2013"*. Croatian Ergonomics Society; 2013. p. 37-44.

[16]   Kornbrot D. Spearman's Rho. In: Everitt BS, Howell DC. (eds.) *Encyclopedia of statistics in behavioral science*. Chichester, UK: John Wiley & Sons Ltd; 2005. p. 1887-1888.

[17] Donskij DD, Zacijorskij VM. *Biomehanika*. Moskva, SSSR: Izdavateljstvo Fizkultura i sport; 1979.

[18] Milčić D, Muftić O, Ljubišić M. Metoda utvrđivanja promjene trbušnog tlaka za čučanj i povratak u početni položaj. *Safety – Journal for the Safety in the Work Organisation and Living Environment.* 1999;41(1):1-12.

[19] Jurum-Kipke J, Baksa S, Sumpor D. Implementation of ergonomic judgement of the passenger workload in virtual aircraft cabin space. Invited lecture. In: Ivaković, Č. (ed) *Proceedings of International Scientific Conference "Science and Traffic Development - ZIRP 07".* University of Zagreb, Faculty of Transport and Traffic Sciences; 2007.

[20] Muftić O, Milčić D. *Ergonomija u sigurnosti.* Zagreb, Croatia: Iproz; 1999.

[21] Muscella A, Stefàno E, Di Maglie A, Marsigliante S. Referees physical performance over a soccer season. *Sport Sciences for Health.* 2020;16(4):765-773. DOI: 10.1007/s11332-020-00655-1.

[22] Passariello CL et al. The Mediterranean athlete's nutrition: Are protein supplements necessary? *Nutrients.* 2020;12(12):3681. DOI: 10.3390/nu12123681.

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Procjena lumbalnog momenta strojovođa u statičkom sjedećem radnom položaju korištenjem višestruke linearne regresije

Sažetak

U radu je prikazan jednostavniji i precizniji model predviđanja lumbalnog momenta temeljen na jednostrukoj ili višestrukoj linearnoj regresiji, koja sadrži najviše dva prediktora. Indeks tjelesne mase (*ITM*) kao prediktor sadrži dvije najvažnije statičke antropometrijske mjere, visinu i masu, čija odvojena uloga u predviđanju lumbalnog momenta, kao i njihovi među-sobni odnosi, nisu dovoljno istraženi. U ovom istraživanju masa, visina, dob i *ITM* anali-zirani su kao prediktori lumbalnog momenta, na uzorku od 50 strojovođa muškog spola iz Republike Hrvatske. Uspoređivana su dva modela predviđanja: (1) višestrukom linearnom regresijom s masom i visinom kao prediktorima; (2) jednostrukom linearnom regresijom s masom kao jedinim prediktorom. Rezultati su potvrdili višestruki regresijski model kao najbolji (R^2 = 0,9015 sa standardnom pogreškom predviđanja 1,26), s masom kao najboljim prediktorom. Iznenađujuće, jednostruki regresijski model s masom kao prediktorom obja-snio je samo 3,6 % varijance lumbalnog momenta manje od modela višestruke regresije, s pripadnom standardnom pogreškom predviđanja 1,46 (srednja postotna vrijednost relativne pogreške bila je samo 0,8 % veća nego kod višestrukog regresijskog modela). Dobiveni re-zultati sugeriraju visok predikcijski potencijal mase i visine koji treba provjeriti na različitim uzorcima ispitanika.

Ključne riječi

lumbalni moment; strojovođa; statička sjedeća pozicija; višestruka linearna regresija; prediktori.