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Predicting CBR Values of Black Cotton Soil Stabilized with Cement and Waste Glass Admixture Using Regression Model

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Abstract: In highway constructions, sub-grade and sub-base soil stabilization has been used as one of the prime and major process for many years in order to improve the engineering properties of soil. The strength of theses layers is indicated by their California bearing ratio (CBR) value which is quite expensive and time consuming. In order to overcome this situation, this study presents a methodology for predicting soaked California Bearing Ration (CBR) value of Black Cotton Soil Stabilized with Cement and Waste Glass Admixture using Multiple Regression Analysis (MRA). Experimental test results such Atterberg limit (Liquid limit (LL), Plastic limit (PL) and Plasticity index (PI)), Compaction characteristics of two compactive efforts namely standard proctor (SP) and modified proctor (MP) (maximum dry density (MDD) and optimum moisture content (OMC)), CBR, Waste glass (WG) content and Cement content (Cm), obtained from a laboratory at Abubakar Tafawa Balewa University Bauchi, Nigeria, have been employed in developing multiple regression models. California Bearing Ration was taken as the dependent variables while Liquid limit, Plastic limit, maximum dry density, optimum moisture content, waste glass content and Cement content were taken as independent variables. The regression analysis calculated the error mean square (MS_E) for each possible model, and models with large MS_E were not selected for the best regression equations. The best models have a minimum value of MS_E occurring for the six-variable model (Cm, WG, LL, PL, OMC_{sp}, MDD_{sp}) and (C_m, WG, PL, LL, OMC_{mp}, MDD_{mp}) with a corresponding higher value of coefficient of multiple determination $R^2 = 0.98$ and 0.94. The performance evaluation of the fitted regression models indicates a strong correlation ($R^2 = 0.89$ - 0.98) between the mentioned variables, and the model equations developed from this work provided a very good prediction of the response, as the equations can be employed for making estimates of soaked CBR of other black cotton soils having similar geotechnical properties.

Keywords: Soil Stabilization, Black Cotton Soil, Waste Glass Admixture, Regression Models

1. Introduction

In order to improve the strength properties of Black cotton soil, several types of stabilized materials are used as base courses, sub-base courses, or treated sub-grade for highway pavements, [1]. These include cement stabilized or treated aggregate, soil cement, lime-cement fly-ash, and lime-stabilized materials. Typically, the CBR values of these materials is used for pavement design purpose.

Highway pavement is a relatively stable supper-imposed layers of materials, constructed over the natural soil for supporting and distributing wheel loads and providing durable wearing surface for transportation and economic development of a country, [2]. The flexible pavement is most favoured in almost all developing nations such as Nigeria. The Design and performance of flexible pavement mainly depends on the strength of the sub-grade material, the load from the pavement surface is ultimately transferred to sub-base and to the sub- grade, [3]. The California bearing ratio (CBR) test is an empirical method used in design of flexible pavement, it determines the thickness of the pavement, in other words, sub grade with lower CBR value will have relatively thicker pavement compared to the sub grade that has higher CBR value [3]. Hence, the suitability and stability of sub-grade material need to be evaluated before the construction of pavements.

Various researchers such as Satyanarayana & Pavani, Gregory & Cross, Vinod & Reena, Patel & Desai, and Yildrim & Gunaydin have developed models for estimating the CBR values on the basis of low cost, less time consumption and easiness to carry out such tests [4-8]. Some other researchers like Patel & Patel, Venkatasubramanian & Dhinakaran, Sabat, Alawi & Rajab and Talukdar also developed multiple liner regression analysis models *(MLRA)* for correlating the *CBR* with index properties of soil using soft computing systems like Artificial Neural Networks (ANN) and gene expression programming (GEP) [9-13].

Previous research by [14] has shown the potential of using cement stabilized Black cotton soil with Waste Glass (WG) admixture as a subgrade layer. This study, is aimed at using the application of multiple regression method for the estimation of soaked CBR by reliably correlating the soaked CBR value of cement stabilized Black cotton soil with Waste Glass (WG) admixture, using index properties like, Plasticity Characteristics (LL and PL), Compaction Characteristics (MDD and OMC), WG and cement content (Cm), so as to be able to take care of the effect of the stabilizer and the admixture in the regression.

2. Methodology

However, to conduct a CBR test, representative soil sample has to be collected from the selected location, from which a remoulded specimen has to be prepared at predetermined optimum moisture content (OMC) and maximum dry density (MDD) with standard or modified proctor compaction energy as the case may be, for the test to be conducted. To obtain the soaked CBR value of a soil sample, it takes at least 48 hours making CBR test expensive, time consuming and laborious [2]. As a result, only a limited number of CBR tests could be performed per kilometer length of a proposed road to be constructed. Similarly, in a situation where stabilization is required, such limited number of CBR test results may not generally reveal the variation in the CBR values over the length of the road that need stabilizing to enable rational, economic and safe construction [2]. This could be avoided only if a large number of soil sample are taken along the length of the road. But such a procedure will increase project cost and time. To overcome this problem a simple and less time-consuming approach is necessary, this can be done by correlating soaked CBR value with easily determining soil parameters.

Twenty (20) disturbed soil samples stabilized with the required Ordinary Portland cement (OPC) with WG blend at OMC were prepared. The prepared soil/OPC/WG blend samples were tested for soaked CBR value, OMC, MDD, LL, PL, and PI. These tests were performed in accordance with BS 1377 [15] for natural soil and BS 1924 [16] for the stabilized soil, using the standard proctor (SP) and modified proctor (MP) compactive efforts.

MINITAB 16.1, statistical software was used to develop the regression models for the data. The CBR was used as the dependent variables, while MDD, WG, Cm, LL and PL were used as independent variables.

The general multiple linear regression model is given equation 1, and the fitted equation is presented in equation 2.

$$Y = \beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k + e \tag{1}$$

The fitted equation:

$$\hat{Y} = b_0 + b_1 x_1 + \cdots + b_k x_k \tag{2}$$

Where: Y = response, X_k = k^{th} predictor,

β_k = k^{th} population regression coefficient, e = error term, b_k = estimate of k^{th} population regression coefficient, $\hat{Y}$= fitted response

3. Results and Discussion

The result of the laboratory prepared soil/OPC/WG blend samples are shown in Table 1. The results based on the geotechnical parameters were used to develop regression models using multiple linear regression analysis (MLRA). The ranges of soil/OPC/WG blend properties studied in this investigation were: WG = 0 - 20%, Cm = 2 - 8%, LL = 47.1-59.8%, PL = 31 – 36.3 %, MDD = 1.47 – 1.63 and 1.55 - 1.76 Mg/m^3 for SP and MP, OMC = 19.8 – 25.4 and 17.6 – 23 % for SP and MP with corresponding soaked CBR values = 9.1 - 20.4 and 16 - 29.3 % for SP and MP compactive effort, as shown in Table 1. The entire range of parameters are selected for the regression analysis to predict the soaked CBR value.

For a reliable prediction model, the model should possess a high value of R^2 and have a low value of MS_E [17] The regression analysis calculated the error mean square (MS_E) for each possible model, and models with large MS_E were not selected for the best regression equations in order to obtain a reliable model. The MS_E is a measure of the units of the response variable and represents the standard distance values that fall from the fitted values. Therefore, the lower the MS_E the better the model predicts the response and the Coefficient of multiple determination (R^2) describes the amount of variation in the observed response values by the predictor(s). The higher the value of R^2, the better the model fits the data. By and large, only models with small values of MS_E were examined in detail. Tables 2 and 3, gives the list of all possible regressions for the 20 observations listed in Table 1.

Table 1. *Laboratory test results of prepared soil/OPC/WG blend samples.*

S/n.	Replacement proportion by dry weight of soil (%)			Index properties (%)			MDD (Mg/m³)		OMC (%)		Soaked CBR (%)	
	SOIL	OPC	WG	LL	PL	PI	SP	MP	SP	MP	SP	MP
1	98	2	0	59.8	31	28.8	1.47	1.55	25.4	23	9.1	16
2	96	4	0	57	32.3	24.7	1.53	1.57	24.1	22.2	12	20
3	94	6	0	53	33.6	19.4	1.59	1.64	23.7	21.1	13	21.7
4	92	8	0	49.9	35.1	14.8	1.61	1.66	21.9	20	16	25
5	93	2	5	55.5	31.4	24.1	1.53	1.66	24.7	20.6	9	16.7
6	88	2	10	53.3	32.3	21	1.57	1.68	23.1	19.5	9.6	18
7	83	2	15	52.3	32.8	19.5	1.59	1.68	21.8	19.5	10.8	19
8	78	2	20	51.4	33.1	18.3	1.62	1.69	20.2	18.9	12.5	20.1
9	91	4	5	54.3	33.2	21.1	1.57	1.69	23.7	20	12.4	.9
10	86	4	10	52.7	34.1	18.6	1.58	1.69	22.9	19.2	12.8	21.4
11	81	4	15	52	34.9	17.7	1.59	1.71	21.7	19.3	14.3	.1
12	76	4	20	51.6	35.7	15.9	1.62	1.72	20.1	18.7	14.7	23.7
13	89	6	5	50.3	33.8	16.5	1.60	1.71	22.8	19	14	22.8
14	84	6	10	48.9	34.8	14.1	1.61	1.71	22.1	18.9	15.1	23
15	79	6	15	49.3	35.1	14.2	1.60	1.72	21.1	18.1	15.1	23
16	74	6	20	48.7	35.9	12.8	1.62	1.73	19.8	18.1	15.5	25.1
17	87	8	5	49.2	34.6	14.6	1.61	1.73	21.4	18.5	17.1	26
18	82	8	10	48.2	35.2	13	1.62	1.73	20.6	18.3	7.9	26.8
19	77	8	15	48.3	35.9	12.4	1.61	1.75	20.9	17.9	18.7	27
20	72	8	20	47.1	36.3	10.8	1.63	1.76	19.8	17.6	.4	29.3

Table 2. *Regression variables for Standard Proctor compactive effort.*

S/n	No. of variables in model	Variables in model	$SS_R(p)$	$SS_E(p)$	$MS_E(p)$	R^2
1	3	Cm, WG, LL	110.870	72.860	4.554	0.63
2	3	Cm, WG, PL	140.426	43.303	2.706	0.76
3	3	Cm, WG, OMCsp	163.274	20.455	1.131	0.89
4	3	Cm, WG, MDDsp	110.552	73.177	4.574	0.60
5	4	Cm, WG, LL, PL	162.265	21.465	1.431	0.88
6	4	Cm, WG, LL, OMCsp	160.852	22.878	1.525	0.86
7	4	Cm, WG, LL, MDDsp	121.934	61.795	4.120	0.66
8	5	Cm, WG, LL, PL, OMCsp	171.916	11.813	0.844	0.94
9	5	Cm, WG, LL, PL, MDDsp	162.345	21.385	1.527	0.88
10	6	Cm, WG, LL, PL, OMCsp, MDDsp	180.149	3.580	0.275	0.98

Table 3. *Regression variables for Modified Proctor compactive effort.*

S/n	No.of variables in model	Variables in model	$SS_R(p)$	$SS_E(p)$	$MS_E(p)$	R^2
1	3	Cm, WG, LL	154.374	82.968	5.186	0.65
2	3	Cm, WG, PL	183.028	54.314	3.395	0.77
3	3	Cm, WG, OMCmp	156.166	81.176	5.073	0.66
4	3	Cm, WG, MDDmp	130.801	106.541	6.659	0.55
5	4	Cm, WG, LL, PL	209.539	27.803	1.854	0.88
6	4	Cm, WG, LL, OMCmp	166.331	71.011	4.734	0.70
7	4	Cm, WG, LL, MDDmp	162.019	75.323	5.022	0.68
8	5	Cm, WG, LL, PL, OMCmp	210.634	26.708	1.908	0.89
9	5	Cm, WG, LL, PL, MDDmp	211.331	26.011	1.858	0.89
10	6	Cm, WG, PL, LL, OMCmp, MDDmp	223.582	13.760	1.058	0.94

Where: SS_R = regression sum of squares; SS_E = error sum of squares; SS_T = total sum of squares; MS_R = regression mean square; MS_E = error mean square

In terms of R^2 improvement, there is an average gain in going from a three-variable model to a six-variable model, with the several models having good values of MS_E. The best models have a minimum value of MS_E occurring for the six-variable model (Cm, WG, LL, PL, OMC_{sp}, MDD_{sp}) and (C_m, WG, PL, LL, OMC_{mp}, MDD_{mp}) with a corresponding higher value of coefficient of multiple determination for both SP and MP compactive efforts i.e 0.98 and 0.94. Even though, other models have small values of MS_E, those with high values of R^2 were also considered for validation. Such other models include; (Cm, WG, LL, PL, OMCsp), (Cm, WG, LL, PL, OMCmp), (Cm, WG, LL, PL, MDDmp) and (C_m, WG, OMC_{sp}). According to [18], the closer the R^2 value is to unity and the smaller the standard deviation, the better the model in predicting the response variable. Also, [19] noticed that large R^2 (near unity) are considered good in model development. The equations obtained from the regression of the above models are presented in Table 4.

Table 4. *Best equations obtained from the regression models.*

Equation No.	Variables in model	Model equation	$MS_E(p)$	R^2
1	Cm, WG, OMCsp	CBRsp = 59.5 + 0.239 Cm - 0.187 WG - 2.03 OMCsp	1.131	0.89
2	Cm, WG, LL, PL, OMCsp	CBRsp = 0.7 - 0.356 Cm - 0.189 WG - 0.088 LL + 1.37 PL - 1.13 OMCsp	0.844	0.94
3	Cm, WG, LL, PL, OMCsp, MDDsp	CBRsp = 108 - 0.464 Cm - 0.240 WG - 0.607 LL + 1.31 PL - 1.47 OMCsp - 44.4 MDDsp	0.275	0.98
4	Cm, WG, LL, PL, OMCmp	CBRmp = - 15.1 - 0.663 Cm - 0.270 WG - 0.411 LL + 2.20 PL - 0.517 OMCmp	1.908	0.89
5	Cm, WG, LL, PL, MDDmp	CBRmp = 19.5 - 0.836 Cm - 0.178 WG - 0.759 LL + 2.33 PL - 18.5 MDDmp	1.858	0.89
6	Cm, WG, PL, LL, OMCmp, MDDmp	CBRmp = 151 - 1.05 Cm - 0.152 WG + 2.32 PL - 0.935 LL - 1.66 OMCmp - 71.6 MDDmp	1.058	0.94

The model validation assessment determines the degree to which a model is an accurate representation of the experimental data.

In validating the models, predicted values were computed using the best model equations i.e Eqn. 1-6 and plotted against number of samples, similarly, experimental data were also plotted against number of samples and comparison is made as presented in figures 1-6. It could be observed from the figures that the experimental values are close to the predicted values, which is evident from the plot which showed the same trend as could be seen from the values of the R^2 trends.

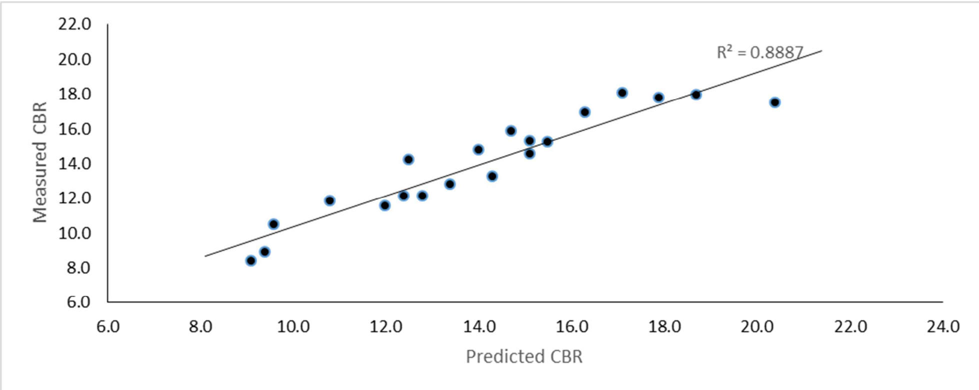

Figure 1. *Validation plot of CBRsp = 59.5 + 0.239 Cm - 0.187 WG - 2.03 OMCsp.*

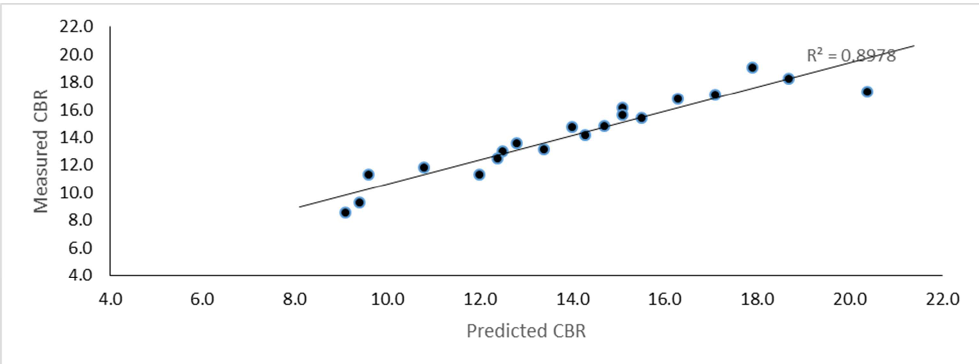

Figure 2. *Validation plot of CBRsp = 0.7 - 0.356 Cm - 0.189 WG - 0.088 LL + 1.37 PL - 1.13 OMCsp.*

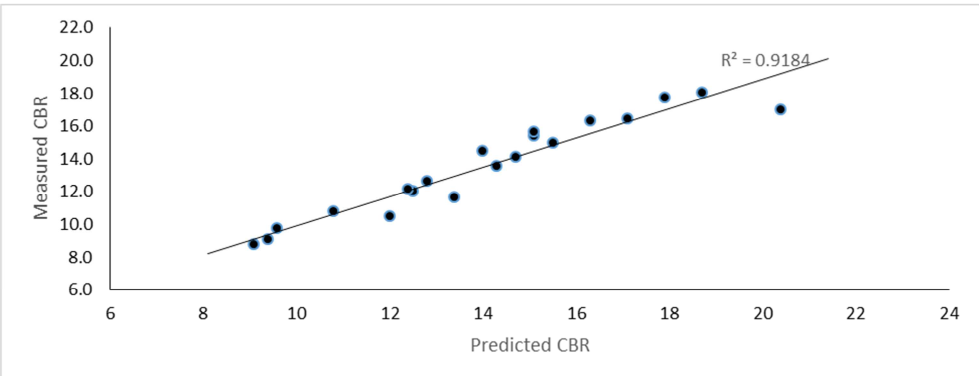

Figure 3. *Validation plot of CBRsp = 108 - 0.464 Cm - 0.240 WG - 0.607 LL + 1.31 PL - 1.47 OMCsp - 44.4 MDDsp.*

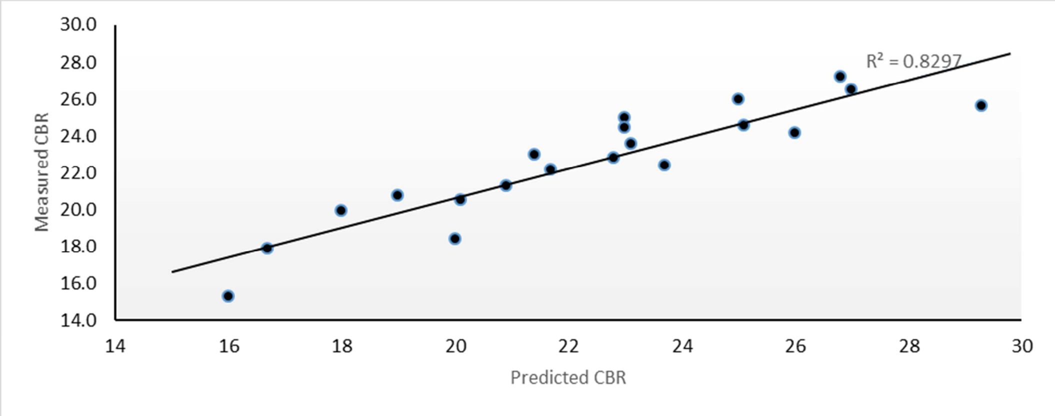

Figure 4. *Validation plot of CBRmp = - 15.1 - 0.663 Cm - 0.270 WG - 0.411 LL + 2.20 PL - 0.517 OMCmp.*

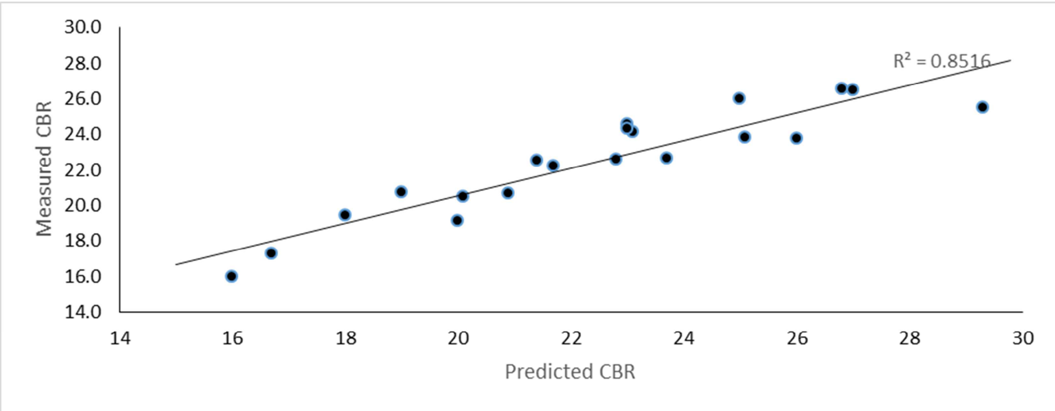

Figure 5. *Validation plot of CBRmp = 19.5 - 0.836 Cm - 0.178 WG - 0.759 LL + 2.33 PL - 18.5 MDDmp.*

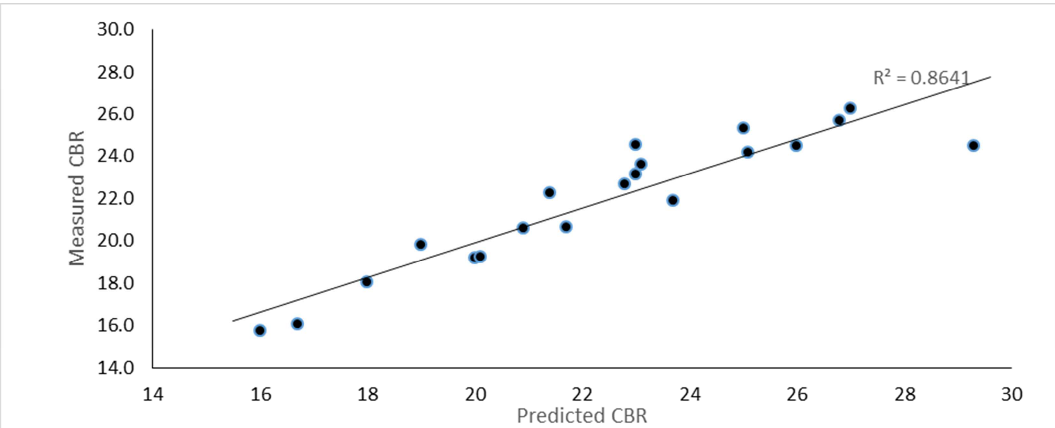

Figure 6. *Validation plot of CBRmp = 151 - 1.05 Cm - 0.152 WG + 2.32 PL - 0.935 LL - 1.66 OMCmp - 71.6 MDDmp.*

4. Conclusion

Regression analysis correlating soaked CBR value with easily determined soil parameters was carried out on twenty (20) disturbed soil samples stabilized with (2-8%) Ordinary Portland cement (OPC) and (5-20%) WG blend at OMC. The CBR was used as the dependent variables, while MDD, WG, Cm, LL and PL were used as independent variables and it was found that these independent variables for both compactive efforts and the prediction models of the soaked CBR is fairly close to the corresponding actual results. Regression analysis estimation of these variable indicated strong correlations (R^2 = 0.98 and 0.94) for SP and MP respectively. It was shown that the correlation equations obtained as a result of regression analysis were in agreement with the test results and the model equations developed from this work provided a very good prediction of the response, as the equations can be employed for making estimates of soaked CBR of other black cotton soils having similar geotechnical properties. The equations are:

CBRsp = 108 - 0.464 Cm - 0.240 WG - 0.607 LL + 1.31 PL - 1.47 OMCsp - 44.4 MDDsp (R^2 = 0.98)

CBRmp = 151 - 1.05 Cm - 0.152 WG + 2.32 PL - 0.935 LL - 1.66 OMCmp - 71.6 MDDmp (R^2 = 0.94)

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