Neural modelling of *CBR* values for compacted fly ash

Modelage neuronique du valeur *CBR* pour les cendres volantes compactes

K. Zabielska-Adamska
M. J. Sulewska
Bialystok Technical University, Poland

ABSTRACT

The aim of the paper was to study a prediction model of California Bearing Ratio values on the basis of other geotechnical parameters of fly ash. Reliable statistical correlations were not obtained. Next tests were conducted with the use of the MPL type (Multi-Layer Perception) artificial neural networks. The topology of the best ANNs model is denoted by 8-5-1. It was determined that the most significant variables were dry density and w/w_{opt}, which confirmed that fly ash optimum water content and moisture content at compaction were the dominant parameters in *CBR* estimation. Dry density was the dominant parameter at comparison of different fly ash shipments, compacted by various methods.

RÉSUMÉ

Le but de cet article est la détermination d'un modèle prédicteur pour la valeur *CBR*, en vertu d'autres parametrès géotechniques pour les cendres volantes. On n'a pas trouvé des dependances statistiquement fidèles. On a les obtenu en cas d'usage des réseaux de neurones artificiels de type MPL (Multi-Layer Perceptron). On s'est révélé que le meilleur est le réseau 8-5-1. Les plus signifiantes variables était masse volumique de sol sec et w/w_{opt}, quoi confirme qu'une humidité optimale des cendres volantes et une humidité en train de compactage était des paramètres dominantes en évaluation de la valeur *CBR*. Masse volumique de sol sec était le paramètre dominant en comparisation des divers cendres volantes, compactes en usage des méthodes différentes.

Keywords : *CBR* value, compacted fly ash, artificial neural networks

1 INTRODUCTION

California Bearing Ratio, *CBR*, is the percentage ratio of unit load, p, which has to be applied so that a standardized piston may be pressed in a soil sample to a definite depth with a speed of 1.25 mm/min and standard load, corresponding to unit load, p_s, necessary to press the piston at the same speed into the same depth of a standard compacted crushed rock.

$$CBR = \frac{p}{p_s} \cdot 100\% \qquad (1)$$

The author's study of *CBR* of fly ash compacted with a definite amount of energy shows that the dominant feature when evaluating *CBR* is moisture content while compacting both for a saturated sample and the ones studied directly after compaction (Zabielska-Adamska 2004 & 2006), which was also stated for cohesive soils by Turnbull and Foster (1956). What is interesting to note is the effect of compaction energy on *CBR* value of the samples of the same moisture content but compacted with the use of different energies. The change in compaction energy of ash compacted at a given moisture content which, depending on the energy applied can be on dry or wet side of the optimum, causes a considerable diversification of *CBR* values.

The fly ash samples compacted at moisture contents equalled w=w_{opt}+5% by Standard (SP) and Modified Proctor (MP) methods are characterized by the lowest *CBR* values. A considerable drop in *CBR* value related to moisture at compaction (compaction moisture) is particularly noted for the samples compacted by a higher energy. High moisture results in the loss of contact among fly ash grains. The highest *CBR* values are noted at moisture contents bigger than or equal to optimum content when the capillary forces within a sample hinder grain movement and strengthen the sample.

Fly ash compaction by various energies, which causes dry density, ρ_d, to be highly diversified, results in *CBR* value becoming dependant on value ρ_d.

2 TEST RESULTS SUBMITTED TO ANALYSIS

Fly ash *CBR* tests were conducted on the basis of three different shipments of fly ash from hard coal burning in Bialystok Thermal-Electric Power Station stored at a dry storage yard. All the fly ash shipments corresponded in graining to sandy silt but

Tab. 1. Geotechnical parameters of tested fly ash shipments: I, II i III.

No. of shipment	D_{50}	ρ_s	$C_U = \frac{D_{60}}{D_{10}}$	$C_C = \frac{D_{30}^2}{D_{10} \cdot D_{60}}$	Compactibility parameters: Standard Proctor method		Compactibility parameters: Modified Proctor method	
					w_{opt}	$\rho_{d\,max}$	w_{opt}	$\rho_{d\,max}$
	[mm]	[Mg/m^3]	[-]	[-]	[%]	[Mg/m^3]	[%]	[Mg/m^3]
I	0.08	2.28	6.00	0.80	39.0	1.120	33.0	1.202
II	0.04	2.08	2.19	1.13	48.0	0.933	39.0	1.040
III	0.07	2.15	3.40	1.69	50.0	0.950	42.0	1.036

D_n – effective size is the grain size corresponding to n% of the passing by weight (mm)

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they featured different effective particle size, D_{50}, and coefficients of uniformity and curvature, C_U and C_C, values of solid particle density, ρ_s, as well as compactibility parameters – optimum water content and maximum dry density, w_{opt} and $\rho_{d\,max}$, which is shown in Tab. 1.

Considerable differences between shipment I (the most advantageous graining) physical parameter values and those of shipments II and III.

Laboratory *CBR* tests were conducted on unsaturated samples and ones saturated (SAT) in water for 4 days. The tested samples were compacted by two methods: the Standard Proctor and the Modified Proctor at moistures within the range of w_{opt}±5% for each compaction method. All the samples subjected to penetration were loaded with ASTM 1883-73 recommended load of 2.44 kPa.

Figures 1 and 2 show a noticeable effect of the tested fly ash moisture content and dry density on *CBR* value when different shipments of fly ash compacted by both methods are compared. Generally *CBR* decreases as compaction moisture content increases and solid particle density drops. *CBR* values are twice as big in the event of shipment I compared to II and III shipments. *CBR* value decrease is influenced by the tested fly ash graining and the optimum water content value defined for each fly ash shipment. Shipment II featuring the finest graining of the worst graining indexes and reaching the lowest solid particle density produces the lowest *CBR* values.

The result indicated that fly ash shipment type (i.e. grain-size distribution) had a statistically significant effect on average of *CBR* as depicted in Fig. 3.

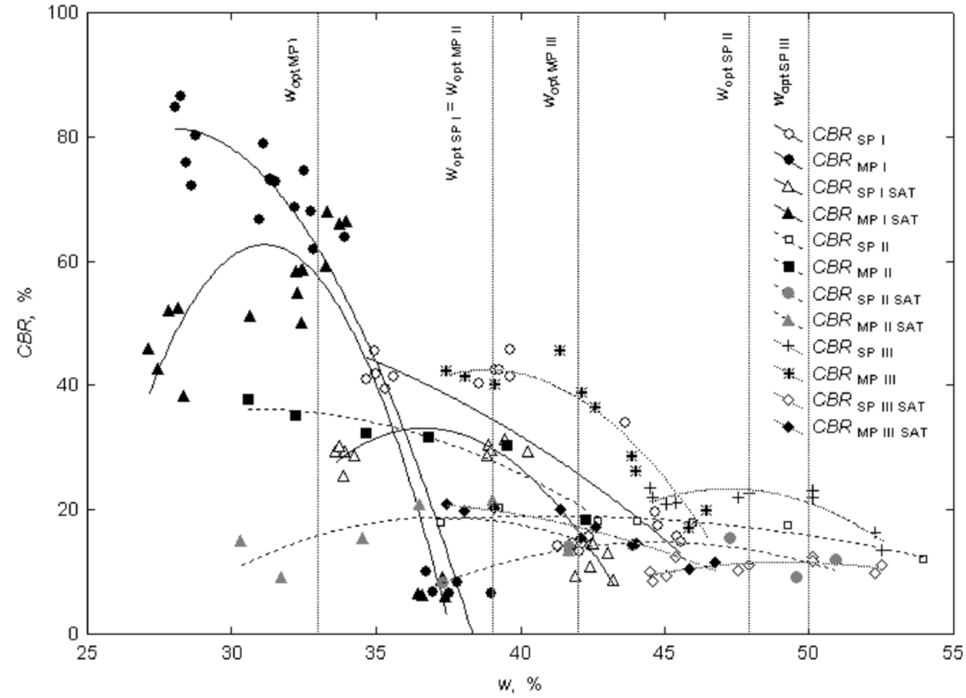

Fig. 1. *CBR* test results obtained for three different fly ash shipments in dependence to moisture content at compaction.

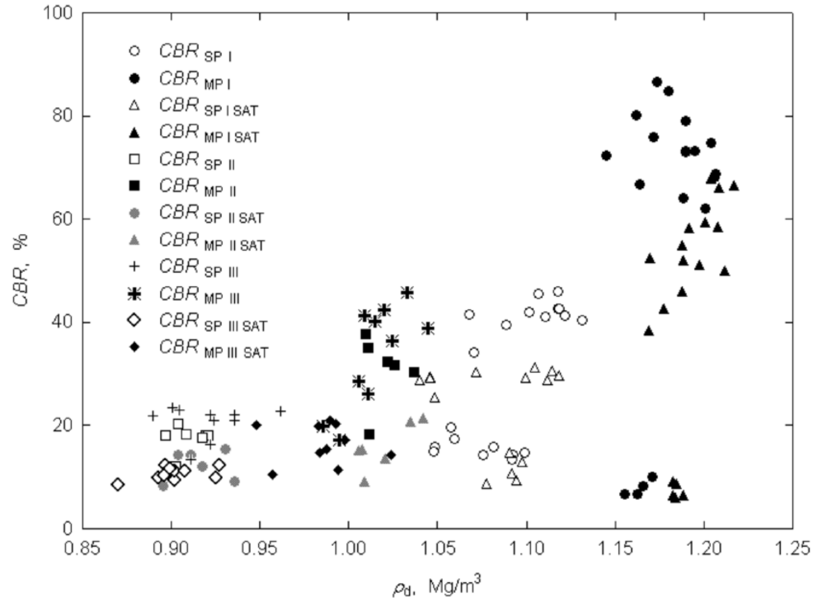

Fig. 2. *CBR* test results obtained for three different fly ash shipments in dependence to sample dry density.

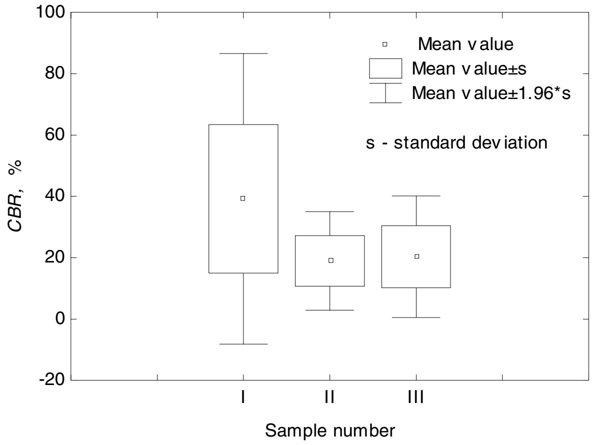

Fig. 3. Average values of *CBR* for different fly ash shipments I – III: I – D_{50}=0.08 mm, II – D_{50}=0.04 mm, III – D_{50}=0.07 mm.

What can be concluded is that the higher the fly ash from dry storage yards *CBRs* are, the coarser their graining is. $CBR = f(w)$ dependencies determined for each of the tested shipments are characterized by similar shapes, they all can be described by means of trinomial square curves reaching their maximum values at abscissa values similarly located relative to optimum moisture content values for each of the samples. The samples tested without saturating reach the highest *CBR* values at w=w_{opt}–5% moisture contents, and the saturated ones – at $w \le w_{opt}$. This finding justifies accepting values $(w–w_{opt})$ and w/w_{opt} as parameters influencing *CBR* value. Parameters $\rho/\rho_{d\ max}$ and $(\rho–\rho_{d\ max})$ were introduced in the same way.

3 STATISTICAL ANALYSIS

The conclusion that *CBR* values depend to some extent on fly ash graining, compaction method, saturation and compactibility parameters is drawn on the basis of Pearson's linear correlation matrix.

However, statistically good simple correlations between *CBR* and the analyzed particular geotechnical parameters were not obtained, the best of the obtained linear correlations $CBR = f(w)$ being determined at determination coefficient R^2=0.476; multiple linear regression models – R^2=0.468–0.747 (Sulewska & Zabielska-Adamska 2006).

4 APPLICATION OF NEURAL NETWORKS

Due to the difficulties in developing a reliable *CBR* variable regression model, an attempt was made to apply Artificial Neural Networks. Artificial Neural Network (ANN) of MPL (Multi- Layer Perceptron) type with one hidden layer was used for the analysis. *STATISTICA Neural Networks* software was used for ANNs simulation.

A set of power P=140 cases was randomly divided into the subsets: the learning subset (of subset power L=70), the validating subset (V=35) and the testing subset (T=35). A maximum of 9 variables x_i were assumed to be the components of the input vector and *CBR* value was the output vector. In the ANN model the following variables and parameters are used in the input vector:

$$\mathbf{x} = \{x_1, x_2, x_3, ..., x_9\} \tag{2}$$

where x_1 is fly ash graining describing by D_{50}, x_2 is numerical code meaning the sample preparation (saturated or without saturation), x_3 is numerical code meaning the compaction method (Standard Proctor or Modified Proctor), x_4 is moisture content at compaction, w, x_5 is dry density of fly ash, ρ_d, x_6 is ratio of w and w_{opt}, x_7 is difference of w and w_{opt}, x_8 is ratio of ρ_d and $\rho_{d\max}$, and x_9 is difference of ρ_d and $\rho_{d\max}$. It was decided that variable $(w–w_{opt})$, which was omitted in the analysis of network sensitivity to the absence of particular variables, should not be taken into consideration.

After numerous simulations the presented in Fig. 4 neural network of 8-5-1 architecture (8 input variables, 5 neurons in the hidden layer and 1 output) was accepted. Variables ρ_d and w/w_{opt} proved to be the most significant ones. Variable metric method (Bishop 1995), called Quasi Newton QN method in *STATISTICA* (Lula & Tadeusiewicz 2001) proved to be the best learning method. The accuracy of the network predictions was quantified by the lowest value of root of the mean squared error difference, *RMSE*, between the measured y_i and predicted values $\hat{y}_i$, the highest value of determination coefficient, R^2, as well as the lowest mean absolute error, *MAE*, independently for *L*, *V*, and *T* sets. The values of neural network error measures are shown in Table 2.

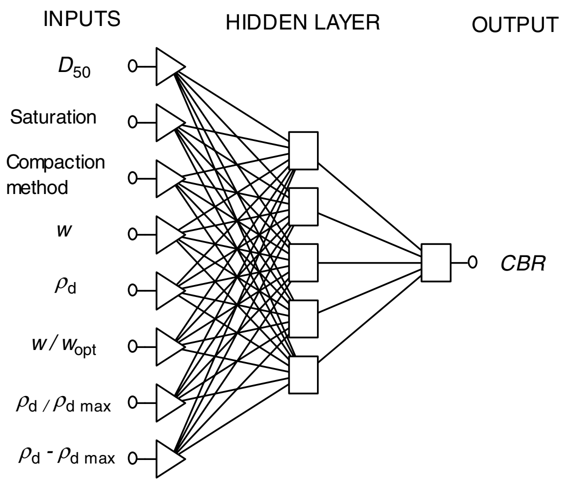

Fig. 4. Diagram of the best ANN of architecture 8-5-1.

The neural network obtained has a high prediction quality. Correlation coefficient, *R*, between the actual values of *CBR* and the predicted ones amounts to 0.973 in the validating set, and 0.949 in the testing set. Figure 5 shows the comparison of the actual *CBR* values obtained with ANN 8-5-1 predicted ones in a set of all data, along with 25% relative error, *RE*, areas.

Tab. 2. Accuracy of network prediction for ANN 8-5-1 with 183 epoch number

Root of the mean squared error difference *RMSE* $RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$		
L	V	T
0.059	0.073	0.084
Mean absolute error *MAE* $MAE = \frac{\sum_{i=1}^{N}\lvert\hat{y}_i - y_i\rvert}{N}$		
L	V	T
3.46	4.40	4.92
Determination coefficient R^2		
L	V	T
0.945	0.947	0.901

y_i – actual value of output data, $\hat{y}_i$ – predicted value of output date;
N – number of set L or V.

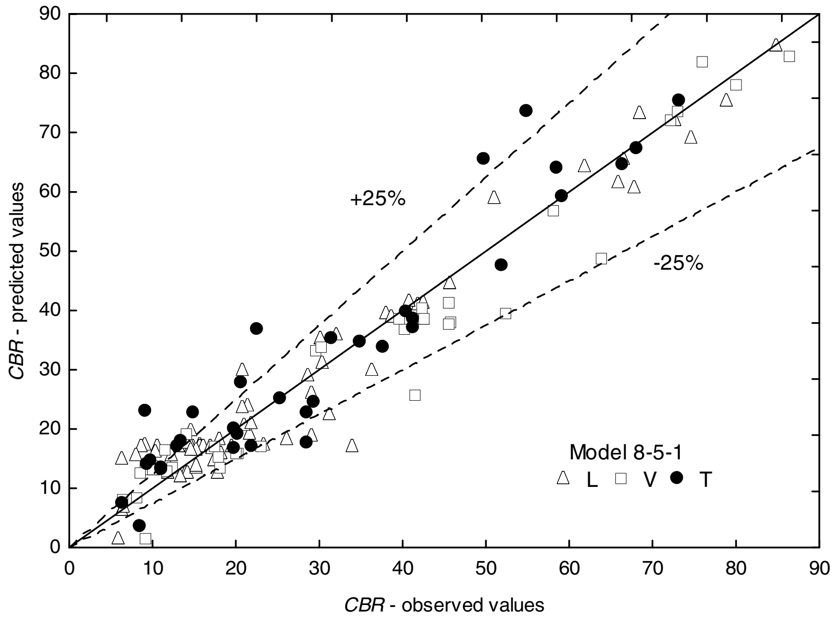

Fig. 5. *CBR* values obtained from tests and calculated by ANN 8-5-1 in all data set, along with 25% relative error, *RE*, areas.

$$RE = \left| \frac{\hat{y}_i - y_i}{\hat{y}_i} \right| \cdot 100\% \tag{3}$$

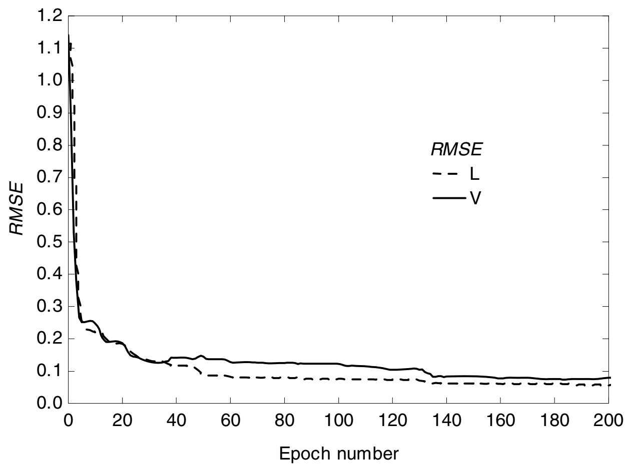

Fig. 6. Variation of *RMSE* with iteration for learning and validation stages for ANN 8-5-1.

The progress of the training process was monitored by observing the RMSE during iteration of the learning process. Figure 6 represents the variation of error measure during training. Besides, performance of the network during training was also evaluated using the validation patterns as shown in Fig. 6.

5 CONCLUSIONS

The aim of the study was to develop a prediction model of *CBR* values on the basis of other geotechnical parameters. No reliable simple correlations between the analyzed parameters were obtained, which resulted in an attempt to apply Artificial Neural Networks (ANNs). The neural network of 8-5-1 topology proved to be the best.

Variables ρ_d and w/w_{opt} were found to be the most significant ones, which confirmed that optimum water content and moisture content at compaction are the dominant parameters when evaluating California Bearing Ratio. Dry density, as another significant parameter, should be considered as dominant when comparing *CBR* values for different fly ash shipments compacted with the use of different energies.

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