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ANALYSIS OF LABOUR EFFICIENCY SUPPORTED BY THE ENSEMBLES OF NEURAL NETWORKS ON THE EXAMPLE OF STEEL REINFORCEMENT WORKS

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This study presents an artificial intelligence technique based on ensemble of artificial neural networks for the purposes of analysis and prediction of labour productivity. The study focuses on the development of model that combines several artificial neural networks on the basis of real-life data collected on a construction site for steel reinforcement works. The data includes conditions, characteristics, features of steel reinforcement works and related efficiencies of workers assigned to particular tasks recorded on site. The proposed ensemble based model combines five supervised learning models — five different multilayer perceptron networks, which contribution in the prediction is weighted due to the application of generalised averaging approach. Testing results show that the proposed ensemble based model achieves the satisfactory evaluation criteria for coefficient of correlation (0.989), root-mean-squared error (2.548), mean absolute percentage error (4.65%) and maximum absolute percentage error (8.98%).

Keywords: labour efficiency, ensembles of neural networks, prediction, steel reinforcement works

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1. INTRODUCTION

Although the picture is constantly changing as the human's work on a construction site is either aided or replaced by variety of machines and tools, labour still remains the resource of very high importance for construction project and construction industry. Thus efficiency of labour has the essential impact on project duration or costs. (The efficiency of labour is understood here as an output of work measured in units of weight, length, surface or volume per man-hour.) To make the analysis of labour efficiency possible some effort in data collection is needed. Not only the measures of efficiency but also, to have the fuller view, some information on the conditions, features and characteristics of construction works must be recorded on a construction site. The effort may be counterbalanced by benefits. The results of analysis may be seen as a valuable source of knowledge useful for planning purposes, scheduling or cost estimation. On the other hand the results can be used for comparison either to those used in planning or to some production standards. Development of computer technologies and data sciences brought lots of possibilities in terms of data collection and storage, as well as broad family of mathematical tools that can be used for analysis of the collected data. The paper presents results of the research on the exploitation of neural networks ensembles for the analysis of labour efficiency for the exemplary construction works – namely steel reinforcing works. The analysis was carried out on the basis of data recorded by a contractor on a construction site including conditions, characteristics and features of steel reinforcement works and related efficiencies of workers assigned to particular tasks. The aim of the research was to examine the usability of data collected by a contractor and the proposed mathematical tool for analysis and prediction of labour efficiency. This paper is a continuation and extension of previous investigations, in which the author contributed, on duration of construction works [9], [14] and labour efficiency [15]. The content of this work includes concise state of the art review, presentation of data used for development of predictive model, brief discussion of theoretical background and assumptions for development of the ensemble based model, research results with discussion and summary. The training of all the neural networks was made with use of STATISTICA™ software suite.

2. STATE OF THE ART

Artificial neural networks belong to collection of data processing, mathematical tools useful in regression and classification problems. Neural networks' mode of action is inspired by patterns of learning and storing knowledge observed in nature. The theory and fundamentals of artificial neural networks are well established and presented in many comprehensive works - e.g. [1, 6, 12, 16, 19]. Main features of neural networks are:

ability of learning and storing the learnt knowledge for future use, ability of generalisation of the acquired knowledge. The mentioned advantages make the neural networks suitable tools for various engineering problems, also in terms of analyses of efficiency, productivity or technology of construction works. The exemplary, worth mentioning works cover the problems of: assessing the productivity of earthmoving machinery [17], estimation of formwork labour [3], estimation of construction technology acceptability [2], cost estimation of road tunnel construction [13], estimation of earthmoving, loading and unloading equipment capital cost [20] and predicting the maintenance cost of construction equipment [21]. Traditional approach of implementation neural networks in either classification or regression model relies on selection of a single network from a number of trained candidate networks. Such an action means discarding many trained networks which may offer comparable performance as the selected one. In contrast ensemble approach relies on the assumption that several trained networks are combined to become an ensemble members. The theory can be found again in the earlier cited works [1, 6], as well as in works dedicated to ensemble approach [10, 18]. The general expectation about employing ensemble of neural networks, instead of a single neural networks, as a core of a regression or classification model, is the improvement of model's performance, accuracy and error reduction [1, 5, 6, 10, 18]. Some exemplary applications of ensembles of neural networks for construction engineering are: prediction of tunnel boring machine performance [22], structural damage identification [4], prediction of heating energy consumption [7], cost estimation of buildings' floor structural frames [8], prediction of site overhead costs [11]. Models based on ensembles of neural networks offer certain capabilities and advantages, which can be achieved with reasonable computational effort.

3. Presentation of the data for modelling

In the course of the research the author was able to use data collected on site by a contractor. The contractor shared the data under the restriction that his name as well as the details of the project will not be revealed. The data, including details about steel reinforcement works, needed ordering to make them exploitable for training and testing of neural networks. Table 1 presents types of data values collected on a construction site as well as the way they were ordered and divided into independent and dependent variables for the purposes of model development.

Table 1. General characteristics of collected data to be used in the course of analysis

Description	Original values	Ordered values used for the training and testing of neural networks	Symbols
Independent variables:			
day of week	name of the day	nominal values: Monday: M Tuesday, Wednesday, Thursday: TWT Friday, Saturday: FS	x_1 x_2 x_3
temperature	range of temperatures	nominal values: between -10^{0}C and +5^{0}C: LOW between +5^{0}C and +25^{0}C: AVERAGE	x_4 x_5
weather conditions	information whether any kind of fall or wind occurred during the day	nominal values: no rainfall, no snowfall, no wind: FAVORABLE rainfall or snowfall or wind: UNFAVORABLE	x_6 x_7
type of an element	name of the structural member to be reinforced	nominal values: WALL COLUMN SLAB	x_8 x_9 x_{10}
type of reinforcement	description whether the rebars were fully prepared on site or were prefabricated or the reinforcing mesh was used	nominal values: rebars cut and bent on site: RC&B prefabricated rebars: PR reinforcing mesh: RM	x_{11} x_{12} x_{13}
shape of the reinforced element	description of the elements' shape complexity	nominal values: SIMPLE MODERATE DIFFICULT	x_{14} x_{15} x_{16}
number of workers on a certain workday	total number of workers performing steel reinforcement works present on a certain day on a construction site	numerical values	x_{17}
number of workers assigned to an element	number of workers assigned to reinforcement works for particular element (structural member)	numerical values	x_{18}
Dependent variable:			
labour efficiency	quantity of processed steel in kilograms per hour	numerical values	y

The data presented in Table 1 become 18 independent variables (16 of the nominal type and 2 of the numerical type) and 1 dependent variable (of the numerical type). Overall number of data samples ($x_1, x_2, \ldots, x_{18}, y$) that were available for the purposes of training and testing of neural networks equalled 145. Important remark, that must be made here, is that the data was originally collected for the purposes of reporting of completed works quantities and controlling of labour costs. Some of the factors influencing the labour efficiency, that could potentially be taken into account, are omitted – compare e.g. [15]. Moreover the way of the data collection, in terms of the values recorded, seems to be too simple (e.g. temperature). That makes the limitation of the research. On the other hand the data reflect the real life conditions and, in the author's opinion, even the use *"as is"* makes the research interesting and justifiable.

Table 2 presents descriptive statistics for the dependent variable *y*. Values are presented in terms of maximum, average, minimum values and standard deviation of observed labour efficiency. The descriptive statistics are set together for all 145 observations and in the division regarding values of two dependant variables as a criteria – namely type of element to be reinforced and shape of the reinforced element (compare Table 1).

Table 2. Descriptive statistics for labour efficiency

	All observations	type of an element			shape of the reinforced element		
		wall	column	slab	simple	moderate	difficult
maximum	69.400	27.600	37.500	69.400	69.400	55.100	47.700
average	35.280	20.759	25.508	55.738	38.396	31.751	22.331
minimum	15.100	15.100	15.900	31.400	15.100	17.300	15.100
standard deviation	16.656	3.230	4.567	7.600	19.214	12.399	8.611

The maximum and average values confirm intuitive anticipations that higher values should be expected for slabs in terms of type of element and for simple shapes of elements to reinforced. On the other hand the differences in descriptive statistics between the efficiencies observed for different elements and varying in complexity of shape justify introduction to the model and analysis number of variables that may influence labour efficiency.

For the purposes of the supervised training and testing of neural networks, as well as assessment of their performance, the whole data set was divided training and testing subsets. The division ratio equalled 90%/10%. (The purpose of testing process is to examine neural networks ability to generalise knowledge, and to check the performance of network for the data that was not presented to trained networks - thus the testing subset did not take part in the training - compare e.g. [1, 6]). The testing subset was later referred to as T. The training subset was further divided into subsets used for learning and validating purposes, the division ratio equalled 70% / 30%. The random division of the training subset was repeated 5 times – so the 5 alternative folds of data were data available. The subsets used for learning purposes were later referred to as L. The validating subsets were later referred to as V. The whole training subset was later referred to as L&V.

4. ASSUMPTIONS FOR DEVELOPMENT OF THE ENSEMBLE BASED MODEL

Let the variables presented in Table 1 be denoted as x_j (as independent variables and j=1, …, 18) and y (as dependent variable). Prediction model is expected to provide mapping function $x_j \rightarrow y$ implemented by neural networks. The use of neural networks for the investigated problem resulted in no need for assuming *a priori* analytical form of relationships between the model variables. Moreover it was possible to use nominal values of the variables in computations.

As this was mentioned before in classical approach the function is based on a single neural network. The disadvantage of such solution is that the generalisation performance of the chosen network is biased, to some extent, due to the selection of learning, validating and testing subsets, structure of the network, its parameters, and conditions of training process initialisation - compare [1]. In case of ensemble approach several neural networks are combined together. An alternative approach is to combine several trained neural networks and form an ensemble. Networks that become members of an ensemble may differ in their structures, parameters, and way of training. The main expectation about the ensembles of neural networks, which combine several trained neural networks, is the prediction error reduction, improved performance and accuracy when compared to networks acting in isolation [1, 5, 6]. There are different variants of ensembles – for this research the use of generalised ensemble averaging approach was assumed.

Formal notation of prediction, implemented by several neural networks using the generalised ensemble averaging approach, is given by the equation (1.1) with regards to the constraint (1.2) – compare [1, 6]:

$$\hat{y} = \sum_{k=1}^{K} \alpha_k f_k(x_j) = \sum_{k=1}^{K} \alpha_k \hat{y}_k \tag{1.1}$$

$$\sum \alpha_k = 1 \tag{1.2}$$

where:

$\hat{y}$ – prediction of y made by of the ensemble of neural networks, $\hat{y}_k$ – prediction of y made by the k-th member network, f_k – mapping function implemented by k-th member network, α_k – weight of k-th member network.

To find the weights α_k correlation matrix C of prediction errors must be computed [1]. Elements of the matrix C were found with the use of finite sample approximation – equation (1.3). Finally the weights were computed with the equation (1.4).

$$c_{kl} \cong \frac{1}{N} \sum_p \left(\hat{y}_k^p - y^p\right)\left(\hat{y}_l^p - y^p\right) \tag{1.3}$$

(1.4) $$\alpha_k = \frac{\sum_{l=1}^{K}(C^{-1})_{kl}}{\sum_{h=1}^{K}\sum_{l=1}^{K}(C^{-1})_{hl}}$$

where:

c_{kl} – element of matrix C, p – index of sample, N – cardinality of a set of samples, h, k and l – indexes of the member networks used in (1.3) and (1.4) for clarity.

In correspondence to the division of training subset into the alternative folds, it was assumed that the ensemble consists of five multilayer perceptron neural networks with one hidden layer. Each of the five networks was selected for one of the folds. In terms of the structures networks number of neurons in input layer equalled 18 (following the number of independent variables as presented in Table 1). Number of the neurons varied between 3 and 12 neurons. Activation functions that were taken into account included: sigmoid, hyperbolic tangent, exponential and linear. Broyden-Fletcher-Goldfarb-Shanno algorithm was used in the course of training of neural networks. The ensemble was formed after the selection of the neural networks that became the members of the ensemble. Measures of investigated networks' performances taken into for the selection purposes were as follows:

- Pearson's correlation coefficient R between the real life values and predicted values of the dependant variable – equation (1.5),
- measures of errors computed for the training and testing subsets to reflect the differences between the real life values and predicted values of the dependant variable:
  - half of the mean squared error, ½*MSE* – equation (1.6),
  - root mean square error, *RMSE* – equation (1.7),
  - mean absolute percentage error, *MAPE* – equation (1.8),
  - percentage errors, PE^p – equation (1.9),
  - absolute percentage errors, APE^p – equation (1.10),
  - maximum of the absolute percentage errors, APE^{max} – equation (1.11).

(1.5) $$R = \frac{cov(y,\hat{y})}{\sigma_y \sigma_{\hat{y}}}$$

where: $cov(y,\hat{y})$ – covariance between y and $\hat{y}$, σ_y – standard deviation for y, $\sigma_{\hat{y}}$ – standard deviation for $\hat{y}$.

(1.6) $$1/_2\, MSE = 1/_2 \left(\frac{1}{M}\sum_p (y^p - \hat{y}^p)^2\right)$$

(1.7) $$RMSE = \sqrt{\frac{1}{M}\sum_p (y^p - \hat{y}^p)^2}$$

(1.8) $$\mathrm{MAPE} = \frac{1}{M}\sum_p \left|\frac{y^p - \hat{y}^p}{y^p}\right|$$

(1.9) $$PE^p = \frac{y^p - \hat{y}^p}{y^p} \cdot 100\%$$

(1.10) $$APE^p = \left|\frac{y^p - \hat{y}^p}{y^p}\right| \cdot 100\%$$

(1.11) $$APE^{max} = max_p \left|\frac{y^p - \hat{y}^p}{y^p}\right| \cdot 100\%$$

where:

p – index of a sample, M – cardinality of L, V or T subsets, in (1.9) *maximum* computed for p belonging to either L, V or T subsets.

5. RESULTS AND DISCUSSION

For each of the five folds of data, differing in composition of L and V subsets, training of number of neural networks was carried out. For each of the folds over 50 neural networks varying in: number of neurons in the hidden layer, employed activation functions and initial conditions for the BFGS algorithm, were trained and assessed in terms of their performance. To be selected the member of the developed ensemble neural networks had to meet two prerequisites: $R > 0.980$ and similar values of $½MSE$ for L, V and T subsets. Among the networks that fulfilled the two conditions final choice relied on smallest $½MSE$ error for T subset.

Table 3 presents 5 networks selected to be the members of the ensemble. The table includes characteristics of the networks in terms of their structure, activation function in hidden and output layer, training algorithm and number of training epochs. Table 3 presents also the correlation coefficients R and $½MSE$ errors, for training and testing subsets, computed for the five neural networks selected acting in isolation . Table 4 presents $RMSE$, $MAPE$ and APE^{max} errors for the five selected networks in the same manner.

Table 3. Characteristics, correlations and ½*MSE* errors of the neural networks selected to be the members of the ensemble

ANN	Network structure	Activation functions HL / OL	Number of training epochs	*R*				½*MSE*			
				L	V	L&V	T	L	V	L&V	T
1	18-5-1	tanh / lin	19	0.983	0.985	0.983	0.985	4.628	4.406	4.555	4.485
2	18-10-1	exp / exp	58	0.985	0.985	0.984	0.985	4.181	4.890	4.414	4.460
3	18-5-1	tanh / tanh	22	0.984	0.983	0.983	0.987	4.435	4.818	4.561	4.338
4	18-5-1	exp / lin	12	0.983	0.983	0.983	0.986	4.817	4.402	4.680	4.220
5	18-9-1	tanh / lin	19	0.983	0.984	0.983	0.986	4.711	4.638	4.687	4.643

Table 4. *RMSE*, *MAPE* and APE^{max} prediction errors of the neural networks selected to be the members of the ensemble

ANN	*RMSE*				*MAPE* [%]				APE^{max} [%]			
	L	V	L&V	T	L	V	L&V	T	L	V	L&V	T
1	3.042	2.968	3.018	2.995	7.11	7.15	7.12	5.42	42.14	22.63	42.14	10.96
2	2.892	3.127	2.971	2.987	7.40	6.58	7.13	4.78	38.81	16.03	38.81	11.80
3	2.978	3.104	3.020	2.946	6.59	7.79	6.99	5.58	40.92	25.72	40.92	12.05
4	3.104	2.967	3.060	2.905	7.34	7.31	7.33	5.76	39.16	25.99	39.16	13.19
5	3.070	3.046	3.062	3.047	7.19	7.25	7.21	5.06	39.75	21.63	39.75	12.58

In terms of the values *R*, ½*MSE* and *RMSE* error measures presented in Table 3 and Table 4 all the member networks are of the comparable quality.

Elements of matrix *C* were calculated according to equation (1.3) with the use of finite sample of prediction errors obtained for training subsets for each of the member networks. Weights α_k were calculated with the use of equation (1.4) after computation of the inversion matrix C^{-1}. Matrix C^{-1} as well as weights α_k are presented below.

$$C^{-1} = \begin{bmatrix} 0.316 & -0.148 & -0.042 & -0.076 & 0.002 \\ -0.148 & 0.511 & -0.144 & -0.100 & -0.114 \\ -0.042 & -0.144 & 0.375 & -0.094 & -0.062 \\ -0.076 & -0.100 & -0.094 & 0.422 & -0.139 \\ 0.002 & -0.114 & -0.062 & -0.139 & 0.347 \end{bmatrix}$$

$$\alpha_1 = 0.3778 \quad \alpha_2 = 0.0348 \quad \alpha_3 = 0.2389 \quad \alpha_4 = 0.0928 \quad \alpha_5 = 0.2557$$

The weights α_k along with the networks presented in Table 3, values of independent variables x_j and equation (1.1) allowed for the computations of predictions of labour efficiencies $\hat{y}$ as well as performance and error measures for the developed ensemble of neural networks. Table 5 presents correlation coefficients R, as well as the error measures for training and testing subsets computed for the ensemble of neural networks.

Table 5. The correlations, ½*MSE, RMSE*, *MAPE* and APE^{max} errors of the ensemble of neural networks

ANN	*R*		½ *MSE*		*RMSE*		*MAPE* [%]		APE^{max} [%]	
	L&V	T	L&V	T	L&V	T	L&V	T	L&V	T
ENS	0.984	0.989	4.302	3.245	2.933	2.548	6.87	4.65	31.17	8.98

Comparison of errors measures between the member networks acting in isolation (Table 3 and Table 4) and the ensemble (Table 5) demonstrates the expected reduction of errors in favour of the ensemble. The reduction is especially significant for *MAPE* and APE^{max}.

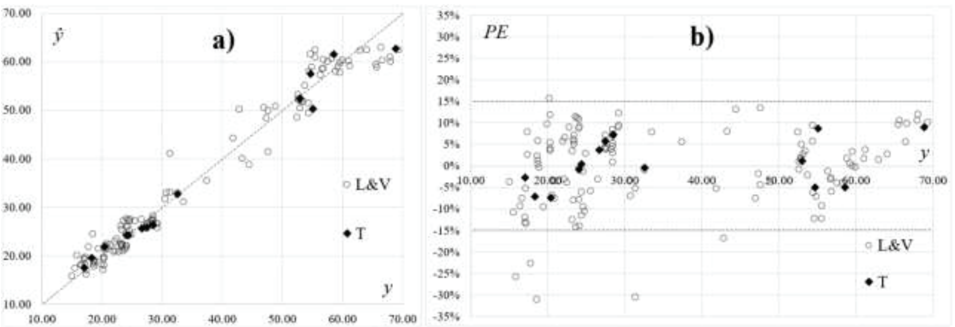

Fig. 1. Scatter plots: a) the real life values y and values $\hat{y}$ predicted by the ensemble, b) the real life values y and corresponding *PE* prediction errors.

Figure 1 a) presents scatter plot of labour efficiencies for steel reinforcing works as real life values y and values predicted by the proposed ensemble of neural networks $\hat{y}$. One can see that the distribution of the points along the line of the perfect fit $y = \hat{y}$ is satisfactory for both L&V and T subsets. Figure 1 b) presents scatter plot of real life values y and corresponding *PE* prediction errors. Most of the errors for L&V subset are located in the range < –15%; 15%>. Only a few points are outside this range. For the subset T the situation is even better as all of the errors are located in the range < –10%; 10%>.

Table 6 presents descriptive statistics computed for APE errors of labour efficiency predictions. Moreover, percentage shares of APE prediction errors that are less than or equal to 5%, 10% and 15%, respectively, are given in the table. The values are set together for predictions made on the basis of all data samples, belonging to either L&V or T subsets. The values are presented for all observations and in the division into types of elements and shapes of the reinforced elements.

Table 6. Descriptive statistics for *APE* errors of labour efficiency predictions made by the ensemble based model

	All observations	type of an element			shape of the reinforced element		
		wall	column	slab	simple	moderate	difficult
maximum	31.17%	23.23%	31.17%	30.39%	13.68%	31.17%	30.39%
average	6.66%	7.22%	6.76%	6.13%	5.83%	6.28%	8.39%
minimum	0.04%	0.86%	0.05%	0.04%	0.04%	0.05%	0.86%
standard deviation	5.22%	4.63%	5.62%	5.30%	3.97%	5.13%	6.35%
percentage share of APE $\leq$ 5%	43.45%	39.02%	41.18%	49.06%	45.24%	47.06%	34.29%
percentage share of APE $\leq$ 10%	80.00%	78.05%	80.39%	81.13%	80.95%	85.29%	68.57%
percentage share of APE $\leq$ 15%	95.86%	95.12%	96.08%	96.23%	100.00%	85.29%	91.43%

Data given in the Table 6 can be discussed briefly in terms of performance of the developed model. The values presented for all observations correspond with results in table 5, Figure 1 and comments that follow the table and the figure. Distribution of APE errors for the type of an element as a criteria suggests that, in terms of performance, the model works best for slabs, in the second place for columns and in the third place for walls. Distribution of APE errors for the shape of the reinforced element as a criteria suggests that the model works best for simple shape. In the range <0%-10%> share of the APE errors indicates better performance for shapes of moderate complexity. On the other hand in the range <0%-15%> share of the APE errors superiority of performance for simple shapes should be recognized.

The obtained results show that the proposed model, based on the ensemble of neural networks and generalised averaging approach, is capable of prediction of labour efficiency for steel reinforcement works with a tolerable accuracy. One must not forget that the modelling was carried out on the basis of data which collection was not targeted directly for such analysis. However the results, even if obtained for the *as is* data, are promising. For now the model can be used for prediction of efficiency for a certain type of steel reinforcement work with the use of basic information, with the restriction of accuracy. In further research both the scope of factors influencing efficiency and the way the values of data is recorded may bring improvements in models performance and efficiency.

6. CONLUSIONS

The paper presents research results on development of model based on the generalised averaging ensemble approach, combining five different multilayer perceptron neural networks, capable of prediction labour efficiency for steel reinforcement works with a tolerable accuracy. Employing ensemble of neural networks to be the core of the model instead of single neural network resulted in improvement of model's performance and reduction of prediction's errors. Obtained measures of performance and errors for the proposed ensemble equalled: in terms of R 0.984 for L&V subset and 0.989 for T subset, in terms of $RMSE$ 2.933 for L&V subset and 2.548 for T subset, in terms of $MAPE$ 6.87% for L&V subset and 4.65% for T subset.

Taking into account type of an element (structural member) to be reinforced the model provides slightly better predictions for slabs than for walls and columns, though the performance of the model is comparable for all of the elements considered in the course of the research. Taking into account complexity of shape of the element to be reinforced the model's performance is better in case of simple or moderate shape than for difficult shape.

Limitation of the model results from the fact that the data used in the course of training of member networks was not directly targeted for such use. On the other hand the modelling was carried out on the basis of real life data including conditions, characteristics, features of steel reinforcement works and related labour efficiencies recorded on site. Improvement in the proposed model's performance can be achieved by collection of data targeted for efficiency analysis and use of such data for the training of neural networks.

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LIST OF FIGURES AND TABLES:

ANALIZA WYDJANOŚCI PRACY WSPOMAGANA ZESPOŁEM SIECI NEURONOWYCH NA PRZYKŁADZIE ROBÓT ZBROJARSKICH

Słowa kluczowe: wydajność pracy, zesoły sieci neuronowych, predykcja, roboty zbrojarskie

STRESZCZENIE:

Wydajność pracy ma kluczowy wpływ na czas realizacji i koszty przedsięwzięć budowlanych. W publikacji przedstawiono wyniki prac badawczych nad wykorzystaniem zespołów sztucznych sieci neuronowych w analizie i predykcji wydajności pracy na przykładzie robot zbrojarskich. Analiza została przeprowadzona w oparciu dane zbierane przez wykonawcę w trakcie realizacji robót. Celem pracy badawczej była ocena przydatności danych zebranych przez wykonawcę robot oraz proponowanego narzędzia matematycznego do analizy i predykcji wydajności pracy.

Dane wykorzystane w analizie obejmowały 18 zmiennych niezależnych (16 zmiennych typu nominalnego i 2 zmienne typu numerycznego) oraz 1 zmienną zależną (typu numerycznego). Zmienne niezależne x_j obejmowały informacje dotyczące warunków, specyfiki i charakterystyk robót zbrojarskich. Zmienne niezależne wnosiły do modelu następujące informacje: dzień tygodnia - x_1, x_2, x_3; zakres temperatur występujących w ciągu dnia roboczego – x_4, x_5; warunki pogodowe – x_6, x_7; rodzaj zbrojonego elementu konstrukcyjnego – x_8, x_9, x_{10}; informację czy pręty zbrojeniowe były przygotowywane na placu budowy, prefabrykowane czy też do zbrojenia używano siatek zbrojeniowych - x_{11}, x_{12}, x_{13}; informację o stopniu skomplikowania kształtu zbrojonego elementu - x_{14}, x_{15}, x_{16}; całkowitą liczbę zbrojarzy obecnych i wykonujących pracę w danym dniu na budowie - x_{17}; liczbę robotników przydzielonych do zbrojenia poszczególnych elementów konstrukcyjnych w danym dniu - x_{18}. Zmienna zależna y wnosiła do modelu informację o wydajności pracy, jej obserwowane wartości stanowiły jednocześnie oczekiwane odpowiedzi modelu w zakresie predykcji wydajności pracy robotników przypisanych do poszczególnych zadań. Całkowita liczba próbek obserwacji obejmujących zmienne (x_1, x_2, …, x_{18}, y) jaka była dostępna dla potrzeb trenowania i testowania sieci neuronowych wynosiła 145. Dla potrzeb nadzorowanego trenowania i testowania sieci neuronowych, jak również dla oceny jakości ich działania, cały zbiór danych został podzielonych na podzbiory treningowe i testowe w stosunku odpowiednio 90% / 10%. Dalszy podział dotyczył podzbioru treningowego, który pięciokrotnie, losowo podzielono na podzbiory wykorzystane w uczeniu i walidacji sieci neuronowych – w konsekwencji dostępne było pięć zestawów danych treningowych. Proponowane podejście opiera się na założeniu, że kombinacja kilku wytrenowanych sieci neuronowych, z których formowany jest zespół skutkuje lepszą jakością działania i predykcji niż model oparty o jedną sieć neuronową. W przypadku niniejszych badań wykorzystano podejście oparte o *generalised ensemble averaging* (uśrednianie odpowiedzi sieci neuronowych należących do zespołu z uwzględnieniem wagi obliczonej dla każdej sieci). W związku z założeniem o podziale danych treningowych na pięć zestawów, założono że zespół sieci będzie składał się z pięciu sieci neuronowych typu *multilayer perceptron* (MLP) z jedną warstwą ukrytą. Każda z pięciu sieci neuronowych mających należeć do zespołu była wybrana spośród kilkudziesięciu sieci trenowanych z wykorzystaniem jednego zestawu treningowego danych. Jeżeli chodzi o strukturę sieci liczba neuronów w warstwie wejściowej wynosiła 18, a liczba neuronów w warstwie ukrytej wahała się od 3 do 12. Funkcje aktywacji jakie były brane pod uwagę to: sigmoidalna (SGM), tangens hiperboliczny (TANH), wykładnicza (EXP) i liniowa (LIN). W trenowaniu sieci wykorzystano algorytm Broyden-Fletcher-Goldfarb-Shanno (BFGS). Dla każdego z zestawów danych treningowych, różniących się podziałami danych na dane uczące i walidacyjne, wytrenowano i przeanalizowano działanie wielu sieci neuronowych. Ostatecznie zespół został sformowany po wyborze pięciu sieci neuronowych, które stały się członkami zespołu:

ANN 1 – struktura sieci: 18-5-1, funkcje aktywacji, odpowiednio dla warstwy ukrytej i warstwy wyjściowej: TANH i LIN,

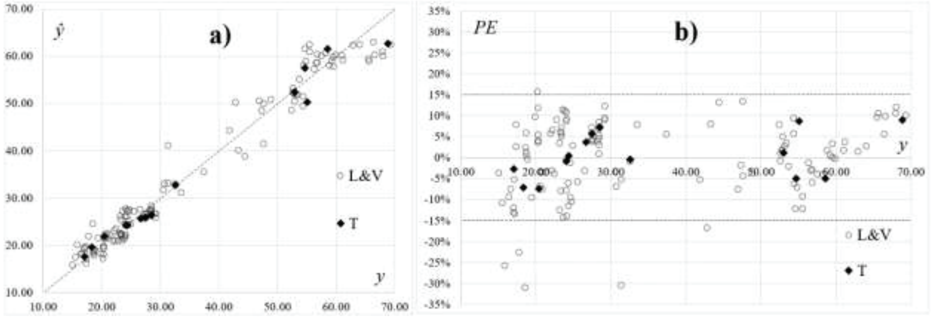
ANN 2 – struktura sieci: 18-10-1, funkcje aktywacji, odpowiednio dla warstwy ukrytej i warstwy wyjściowej: EXP i EXP,

ANN 3 – struktura sieci: 18-5-1, funkcje aktywacji, odpowiednio dla warstwy ukrytej i warstwy wyjściowej: TANH i TANH,

ANN 4 – struktura sieci: 18-5-1, funkcje aktywacji, odpowiednio dla warstwy ukrytej i warstwy wyjściowej: EXP i LIN,

ANN 5 – struktura sieci: 18-9-1, funkcje aktywacji, odpowiednio dla warstwy ukrytej i warstwy wyjściowej: TANH i LIN.

Wagi α_k dla każdej sieci zakwalifikowanej do zespołu zostały obliczone zgodnie z założeniami podejścia *generalised ensemble averaging*: α_1 = 0.3778, α_2 = 0.0348, α_3 = 0.2389, α_4 = 0.0928, α_5 = 0.2557. Wagi α_k, sieci należące do zespołu oraz wartości zmiennych niezależnych i zależnych umożliwiły predykcję wartości wydajności pracy w robotach zbrojarskich $\hat{y}$ jak również obliczenia miar jakości działania oraz błędów zaproponowanego modelu opartego o zespół sieci neuronowych. Porównanie miar błędów pomiędzy pojedynczymi sieci działającymi oddzielnie oraz zespołu sieci wykazało redukcję błędów na korzyść zespołu. Redukcja błędu jest szczególnie widoczna w przypadków średniego bezwzględnego błędu procentowego (*MAPE*) i maksymalnego bezwzględnego błędu procentowego (APE^{max}).



Rys. 1. Wykresy punktowe: a) wartości rzeczywiste y i wartości $\hat{y}$ jako wynik predykcji zespołu sieci, b) wartości rzeczywiste y i odpowiadające im błędy predykcji *PE*

Analiza wykresu punktowego (Rys. 1a) wydajności pracy dla robót zbrojarskich jako wartości obserwowanych w rzeczywistości y oraz wartości predykcji modelu opartego o zespół sztucznych sieci neuronowych $\hat{y}$ pozwala stwierdzić, że rozkład punktów wzdłuż linii idealnego dopasowania $y = \hat{y}$ jest zadowalający zarówno dla danych treningowych jak i danych testowych. Porównanie wydajności pracy dla robót zbrojarskich jako wartości obserwowanych w rzeczywistości y oraz odpowiadających im błędów procentowych predykcji (*PE*) (Rys. 1b) pokazuje że większość błędów dla danych trenujących mieści się w przedziale < –15%; 15%>. Tylko kilka punktów jest położonych poza tym przedziałem. W przypadku danych testowych sytuacja jest nawet lepsza ponieważ wszystkie błędy mieszczą się w przedziale < –10%; 10%>. Rozkład błędów *APE* z uwzględnieniem jako kryterium podziału typu zbrojonego elementu konstrukcyjnego pozwala stwierdzić, że jakość działania modelu jest najlepsza w przypadku płyt stropowych, w drugiej kolejności dla słupów, w trzeciej kolejności dla ścian. Rozkład błędów *APE* z uwzględnieniem skomplikowania kształtu zbrojonego elementu jako kryterium podziału pozwala stwierdzić, że jakość działania modelu jest najlepsza dla elementów o prostym kształcie. Rozważając pozostałe wartości dla tej samej zmiennej jako kryterium: w przedziale <0%-10%> udział błędów *APE* wskazuje na lepszą jakość działania dla elementów o średnio skomplikowanym kształcie; z drugiej strony w przedziale <0%-15%> ze względu udział błędów *APE* można wskazać lepszą jakość działania dla kształtów skomplikowanych.

Uzyskane wyniki, pozwalają skonstatować, że zaproponowany model oparty o zespół sztucznych sieci neuronowych opracowany z wykorzystaniem podejścia *generalised ensemble averaging*, umożliwia predykcję wydajności pracy dla robót zbrojarskich z akceptowalną dokładnością. Dla modelu uzyskano następujące miary jakości działania i błędów: współczynnik korelacji Pearsona pomiędzy wydajnością pracy obserwowaną w rzeczywistości i predykcją modelu: R = 0.984 dla danych treningowych i R = 0.989 dla danych testowych, pierwiastek błędu średniokwadratowego: *RMSE* = 2.933 dla danych treningowych i *RMSE* = 2.548 dla danych testowych, średni bezwzględny błąd procentowy: *MAPE* = 6.87% dla danych treningowych i *MAPE* = 4.65% dla danych testowych.

Poprawa jakości działania modelu i jakości predykcji może być osiągnięta poprzez wykorzystanie w modelowaniu i trenowaniu sieci neuronowych danych zbieranych dla potrzeb analiz wydajności pracy.

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