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NEURAL NETWORKS USED IN DESIGN OF REINFORCED LAYER FOR EXISTING SLABS FOR AIRPORT RIGID RUNWAY STRUCTURES

BY

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Abstract. In this paper a method of using neural networks for improving the computing method by increasing the accuracy in design of the reinforced concrete slabs from airport infrastructure is presented. The obtained results after the models developed with the method of finite element were used in order to create a neural networks simulating the function $H_R=f(H_e , c_{ss} , K,\sigma_{\mathrm{adm}})$, for dual type of landing gear, for each loading, reaction modulus considered, to design the reinforced layer for existing cement concrete slabs. The use of neural networks for the interpolations of functions to dimension the slabs proved an increase of result accuracy compared to the reading of nomograms, previously carried out, as well as the possibility of computing the variable concrete slab thickness, other than the one considered for the nomograms.

Key words: neural networks; airport reinforced slabs; nomograms; runway structural design.

1. Introduction

The evolution of air traffic (intensity, types of aircraft) requires dimensioning of airport surfaces, with a high level of confidence. This airports

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need to direct service to as many zones (cities) and requires increasing number of airbases, and for the existing ones, increase the track lengths and specifications.

Necessity of reinforcing rigid structure airport roads determined by adaptation to new aircrafts types, with masses higher than those for which it has been sized and/or determined by decreasing bearing capacity, resulting from technical expertise, expressed through the technical condition.

Reinforcement with cement concrete is designed to ensure the bearing capacity of rigid road structures necessary for prospective air traffic.

This paper continues the studies from other two articles (Zarojanu *et al*., 2009; Covatariu *et al*., 2011) previous published.

2. Neural Networks Computation

Instead of all the progress in mathematics and computers evolution, some problems can't be mathematically modelled or their implementation involve inadmissible computing period. In this way, problems can be classified in two types:

a) “ill-posed” problems – where it doesn't know an algorithm, yet, to find a result, or necessary working period of one of this algorithm is inadmissible;

b) “well-posed” problems – can be associated with a formal model which can develop a solving method with algorithmic character, with acceptable times of execution.

Intelligent computing is a domain of Artificial Intelligence which handled development of solving problems of "ill-posed" problems. Neural computing, like part of intelligent computing, can solve associated problems (classification, approximation, prediction, etc.).

Neural networks are inspired from biology, certain, but there are big differences between artificial neural networks and the natural ones. Its allow solving of some complicate problems, with no sequential algorithm but posses some examples of solutions. Learning from this examples (training stage), network will be able to solve similar cases (work stage).

Its can represent any computable function, but they can learn any of this function from examples.

Structural analysis programs used in solving design are often expensive. Obtaining optimal solutions usually requires much iteration using analysis and optimization programs. These processes have become prohibitive, resulting in increased working time required for computer troubleshooting. A promising technique is to simulate a structural analysis program (expensive and slow) with an inexpensive and expeditive neural network. A neural network can reduce time and can lead to the optimisation of the design process or analysis.

Generally, in Civil Engineering domain, studies have combined laboratory tests with classical methods of analysis (numerical calculation, finite element programs, etc.) with the simulation of processes with neural networks.

3. Reinforcing of Airport Rigid Runway Structures

The airport road structures are designed usually as rigid slabs.

Methods used to reinforcing's dimensioning with cement concrete of existing road airport rigid structure present criterion for sizing, hypothesis and computing parameters similar methods of dimensioning the new rigid road airport structures.

Nowadays, the direction of reinforcing's redimensioning existing road airport rigid structures consist in solving with finite element method.

The reinforced runway structure has, usually, several elements, like: subsoil; improved soil (stabilized, compacted); old layer; separating layer (maximum 5 cm) (optional); new layer (min. 15 cm).

For reinforcing existing concrete runway structures it can be used two variants:

a) reinforcing with mixture and asphaltic rock layer/layers;

b) reinforcing with cement concrete slabs.

The reinforcement with concrete of an existing airport rigid structures, is taking into account of the structural degradation (technique), in two manners:

1º partially adherent slabs, when concrete reinforcement tile is moulded directly onto the existing concrete slab, whose state of disrepair allows working with tile to reinforce (Fig. 1);

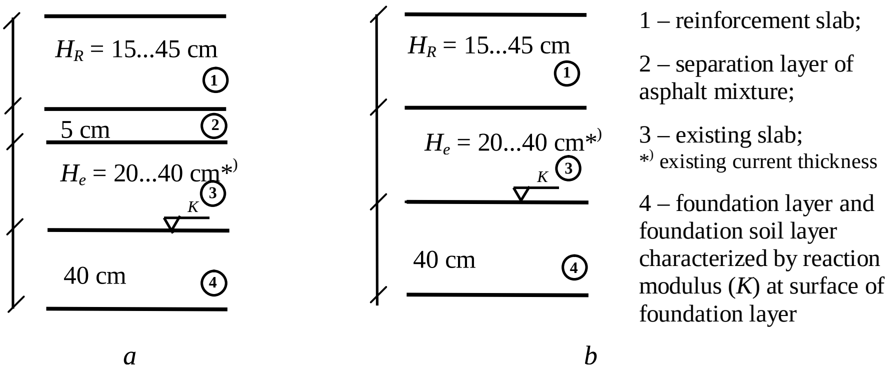


Fig. 1 – Calculation scheme for reinforced rigid road structures: *a* – non-adherent plates; *b* – partial adherent plates.

2º non-adherent slabs, when between cement concrete slab to reinforce and existing concrete slab will be interposed a layer of separation, because the state of degradation of the existing slab does not permit working with tile reinforcement (Fig. 1). The separation layer is made of mixture and asphaltic rock and has, generally, average thickness of 5 cm.

In this study was taking into consideration the following values:

1° Hypothesis of non-adherent plates (NA) – loads, P = 27.5; 35; 42.5 tf, thickness of the reinforcing slab, H_R = 15; 20; 25; 30; 35; 40; 45 cm, thickness of the existing slab, H_e = 25; 30; 35; 40 cm, coefficient of structural state, c_{ss} = 0.35; 0.75.

2° Hypothesis of partial adherent plates (PA) – loads, P = 27.5; 35; 42.5 tf, thickness of the reinforcing slab, H_R = 15; 20; 25; 30; 35; 40; 45 cm, thickness of the existing slab, H_e = 25; 30; 35; 40 cm, coefficient of structural state, c_{ss} = 0.75; 1.00.

For reaction's modulus at the surface of foundation soil are considered values K = 15, 30, 70, 100, 150 kN/m^3. Loads, P, represent normal loads transmitted through the dual landing gear.

The analysis of computing parameters was carried out by various simulations of cement concrete slab behaviour. The simulations were performed on models made with Finite Elements (FE), in variable composition of the airport structures (Zarojanu *et al*., 2000).

4. Solving Problem of Dimensioning of Reinforced Layer for Existing Slabs

3.1. Structure of Neural Network

It was created a feedforward backpropagation network with 4 neurons on input layer and 1 neuron on output layer, and for hidden layer have tried many variations in the number of neurons to a small enough amount of the error.

There has been created a pattern for each value of the load on the landing gear and every type of slabs (adherent or partial adherent) (Table 1).

The obtained data by FE modelling was grouped by values sets and has been complied in order to create neural networks (280 sets for each combination: slab type and load value used for the reinforcement solution). From the data sets available, 60% were used for training, 20% for validation and 20% for the network's testing.

Inputs for neural networks were considered: existing slab thickness (H_e), coefficient of the structural state (c_{ss}), reaction modulus (K), the limit bending tensile stress (σ_{adm}) and the output is thickness of reinforced slab (H_R).

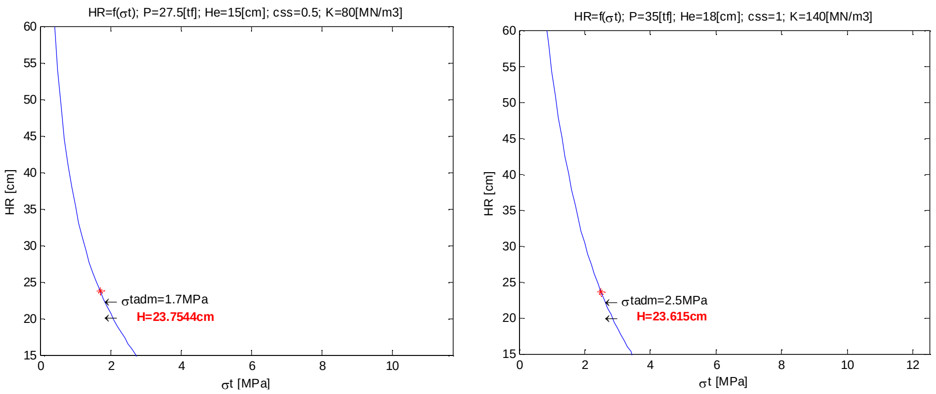
Table 1
Structures and Performances of Realized Neural Networks

Type of landing gear	Type of slabs	NN topology / activation functions	Algorithm training / learning	No. of training epochs	The mean square error MSE	Normalised MSE	*R* correlation coefficient
Dual P = 27.5	NA	5-20-1 logsig - logsig - purelin	LM / GDM	239	6.591237e -004	6.568818 e-006	1.00000
	PA	5-25-1 logsig - tansig - purelin	LM / GD	201	4.093877e -004	3.835786 e-006	1.00000
Dual P = 35	NA	5-25-1 logsig - tansig - purelin	LM / GD	179	4.599394e -004	4.509387 e-006	1.00000
	PA	5-20-1 tansig - logsig - purelin	LM / GD	126	2.246167e -004	2.187248 e-006	1.00000
Dual P = 42.5	NA	5-20-1 logsig - tansig - purelin	LM / GD	300	3.067685e -004	2.717876 e-006	1.00000
	PA	5-20-1 tansig - logsig - purelin	LM / GDM	123	1.206526e -003	1.176675 e-005	0.99999

LM – Levenberg-Marquardt algorithm; GD – gradient descent method; GDM – gradient descent method with moment.

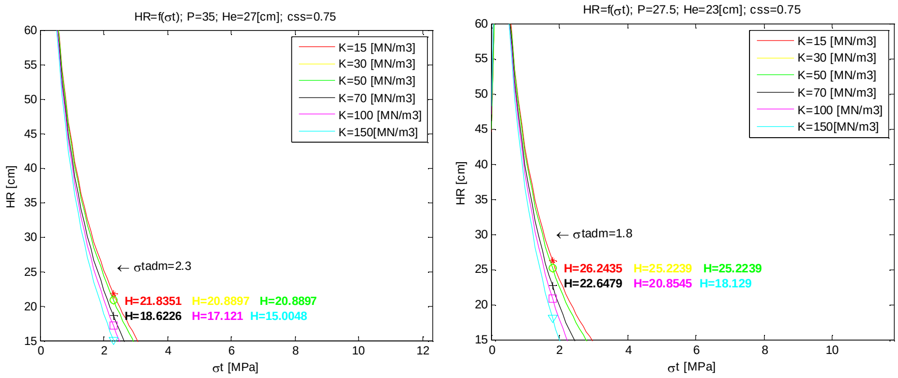
Figs. 2,...,4 shows the resulted graph values computed for reinforcing slab thickness in both hypothesis (adherent or partial adherent slabs) and various of input variables.

The Figs. 5 and 6 illustrate different versions of the dimensional diagrams based on the values obtained with neural network.



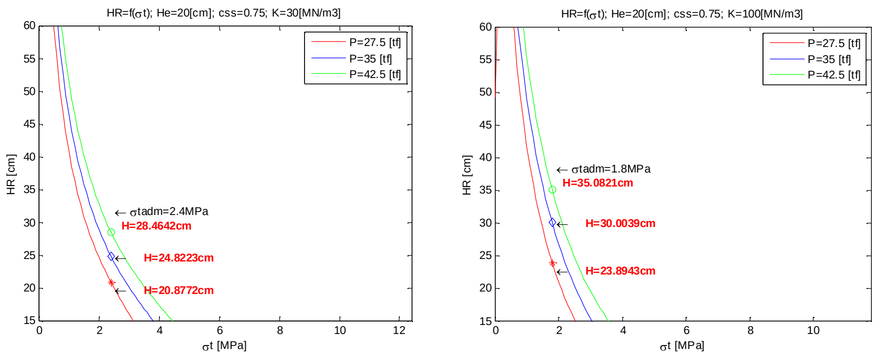
a *b*

Fig. 2 – Computing of thickness of reinforced slab for dual landing gear type:
a – non-adherent hypothesis; *b* – partial adherent hypothesis.



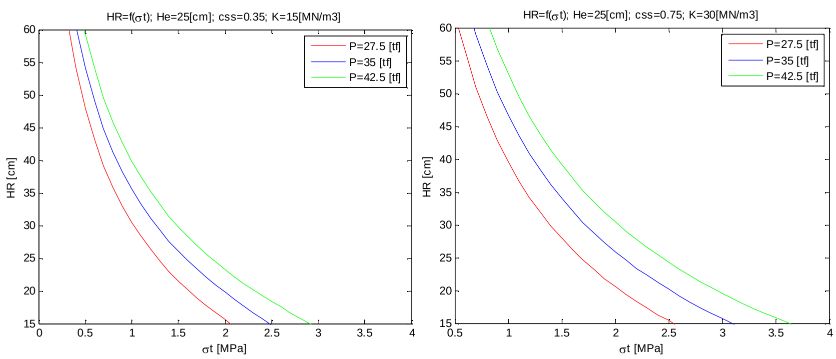
a *b*

Fig. 3 – Computing of thickness of reinforced slab for dual landing gear type: *a* – non-adherent hypothesis; *b* – partial adherent hypothesis.



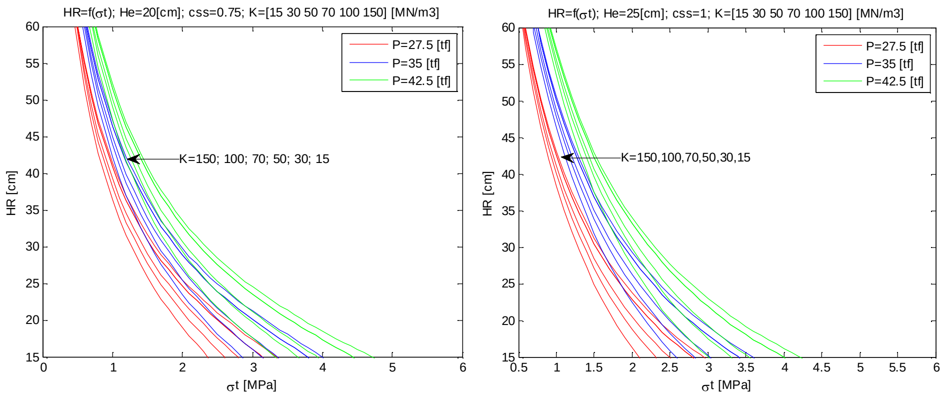
a *b*

Fig. 4 – Computing of thickness of reinforced slab for dual landing gear type: *a* – non-adherent hypothesis; *b* – partial adherent hypothesis.



a *b*

Fig. 5 – Dimensional diagrams of reinforced slab for dual landing gear type: *a* – non-adherent hypothesis; *b* – partial adherent hypothesis.



a *b*

Fig. 6 – Dimensional diagrams of reinforced slab for dual landing gear type: *a* – non-adherent hypothesis; *b* – partial adherent hypothesis.

Checks have been carried out between the interpolated values from norms and the values calculated with neural networks (Table 2).

Table 2

Comparison of Obtained Values from Reading the Nomograms vs. Neural Networks

P tf	K kN/ m^3	H_e cm	Degra-dation coeff.	σ_{adm} MPa	H, [cm] Reading diagrams	NN Computing	Rounded values	Difference H (D-RN)	Difference H %
Dual – non-adherent slabs									
27.5	80	15	0.50	1.70	*	23.7544	23.8		
27.5	30	30	0.35	1.61	15.0	15.0382	15.1	–0.1	–0.007
27.5	90	28	0.75	1.60	*	21.3512	21.4		
27.5	150	40	0.35	0.49	35.0	35.1855	35.2	–0.2	–0.006
27.5	70	33	0.75	0.65	*	45.0796	45.1		
27.5	100	21	0.75	1.20	*	32.7579	32.8		
27.5	110	25	0.35	0.85	*	29.0478	29.1		
35	140	18	0.75	2.50	*	19.8016	19.9		
35	150	35	0.35	0.92	25.0	25.1425	25.2	–0.2	–0.008
35	50	21	0.35	2.55	*	13.9989	14.0		
35	70	30	0.75	2.00	20.0	19.9895	20.0	0.0	0.000
42.5	90	36	0.35	1.35	*	20.5926	20.6		
42.5	100	25	0.35	0.85	40.0	39.8047	39.9	0.1	0.003
42.5	35	42	0.75	1.70	*	20.8116	20.9		
42.5	15	30	0.75	2.17	25	24.9810	25.0	0.0	0.000
42.5	50	28	0.35	1.85	*	20.1158	20.2		
42.5	75	34	0.35	1.45	*	20.8225	20.9		

* values which cannot be read from diagrams

Table 2
(*Continuation*)

P tf	K KN/m^3	H_e cm	Degra-dation coeff.	σ_{adm} MPa	H, [cm] Reading diagrams	NN Computing	Rounded values	Difference H (D-RN)	Difference H %
Dual – dale partial adherent									
27.5	80	15	0.50	1.70	*	28.1104	28.2		
27.5	30	30	0.75	2.04	15.0	14.9868	15.0	0.0	0.000
27.5	90	28	1.00	1.60	*	22.5575	22.6		
27.5	150	40	1.00	1.09	20.0	19.8841	19.9	0.1	0.005
27.5	70	33	0.75	0.65	*	44.0724	44.1		
27.5	100	21	1.00	2.20	*	20.4655	20.5		
35	120	35	0.75	1.45	*	20.1540	20.2		
35	140	18	1.00	2.50	*	24.6329	24.7		
35	150	35	0.75	0.80	40.0	40.0814	40.1	–0.1	–0.003
35	35	37	1.00	1.65	*	22.3615	22.4		
35	50	21	0.75	2.55	*	22.9916	23.0		
35	70	30	1.00	1.75	25.0	24.9280	25.0	0.0	0.000
42.5	90	36	0.75	1.35	*	28.2285	28.3		
42.5	100	25	0.75	1.16	45.0	44.8105	44.9	0.1	0.003
42.5	35	42	1.00	1.70	*	44.0999	44.1		
42.5	15	30	1.00	2.75	20.0	20.0364	20.1	–0.1	0.005
42.5	50	28	0.75	1.85	*	28.4232	28.5		
42.5	75	34	0.75	1.45	*	28.6615	28.7		

* values which cannot be read from diagrams

It has to be mentioned that the nomograms from norm NP038-99 are obtained for the unique value of cement concrete $E = 30{,}000$ MPa adjusted by c_{ss}.

In Figs. 5 and 6 load's values, P, can be obtained from values interpolated from diagrams.

5. Conclusions

Proposed methodology can improve results through: a) increasing of confidence level of results beside to reading the nomograms from norms, which have a limited number of values from computing parameters; b) possibility to introduce larger variation domains for computing parameters in order to elaborate an official method for dimension; c) reinforcement's thickness for wide ranges of the values of parameters (the existing concrete class, σ_t, the existing slab thickness, H_e, coefficient of structural state – technical state – c_{ss} and the reaction modulus, K, value at la track bed level (the foundation soil or the upper level of the foundation).

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UTILIZAREA REȚELELOR NEURONALE ÎN PROIECTAREA STRATULUI DE RANFORSARE PENTRU DALELE EXISTENTE ALE STRUCTURILOR RUTIERE RIGIDE AEROPORTUARE

(Rezumat)

Este prezentată o metodă de utilizare a rețelelor neuronale pentru îmbunătățirea metodei de calcul prin mărirea acurateței în proiectarea dalelor ranforsate din beton pentru infrastructurile aeroportuare. Rezultatele obținute, după dezvoltarea prin metoda elementului finit, au fost folosite pentru crearea rețelelor neuronale ce simulează funcția $H_R=f\ (H_e,\ c_{ss},\ K, \sigma_{\mathrm{adm}})$, pentru aterizorul de tip dual, pentru fiecare încărcare, modul de reație considerate, pentru proiectarea stratului de ranforsare pentru dale din beton existente. Utilizarea rețelelor neuronale pentru interpolarea funcțiilor în dimensionarea dalelor au demonstrate o îmbunătățire a acurateții rezultatelor comparative cu citirea nomogramelor, realizate anterior, de asemenea, posibilitatea calculării grosimilor dalei de beton altele decât cele ce pot fi obținute din nomograme.