BULETINUL INSTITUTULUI POLITEHNIC DIN IAŞI
Publicat de
Universitatea Tehnică „Gheorghe Asachi" din Iaşi
Tomul LIV (LVIII), Fasc. 3, 2011
Secţia
CONSTRUCŢII. ARHITECTURĂ

DESIGN OF AIRPORT RIGID RUNWAY STRUCTURES WITH NEURAL NETWORKS

BY

GABRIELA COVATARIU*, H. ZAROJANU, I. CIONGRADI and MIHAI BUDESCU

"Gheorghe Asachi" Technical University of Iaşi,
Faculty of Civil Engineering and Building Services

Received: August 1, 2011
Accepted for publication: September 20, 2011

Abstract. Computing with neural networks ranges between engineering and artificial intelligence. It uses classical engineering mathematical techniques and heuristic methods specific for Artificial Intelligence. This paperwork illustrates the way of using neural networks for improving the computing method by increasing the accuracy in design the concrete slabs from airport infrastructure. The results obtained using the models developed with the method of finite element were used for creating neural networks (one for each type of landing gear), simulating the function $H=f(P,K,\sigma_t)$ to design the new 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; nomograms; runway structure design.

1. Introduction

The Artificial Intelligence using genetic algorithms, neural networks and fuzzy systems, provides intelligence simulation techniques in decision

*Corresponding author: *e-mail*: covagab@ce.tuiasi.ro

making, evolution and "training" the computer. Designing, planning and management can be improved using intelligent methods.

The computation with neural networks is considered between engineering and Artificial Intelligence. It uses classical engineering mathematical techniques as well as heuristic methods specific to Artificial Intelligence.

Some of the most important characteristics of neural networks, by which the other traditional computing systems are differentiated, are

a) Training based on examples (from experiments).
b) Associative distributed memory.
c) Tolerance to errors.
d) Recognition of models.
e) Synthesis capacity.

The neural networks represent a computing alternative that proved to be useful in approximation of functions, recognition of models and their classification, signal processing, identification and control of systems, prognosis of dynamic systems, clustering (grouping of models according to similarities).

Generalizations may be obtained ranging from small structures (testable, measurable, and verifiable) to large structures (difficult to test and quantify). Neural networks can reduce the time of analysis or designing process and can lead to its optimization.

2. Artificial Neural Networks

A neuron is an entire informational process that is fundamental for the operations of neural networks. In Fig. 1 it is presented the block diagram of an

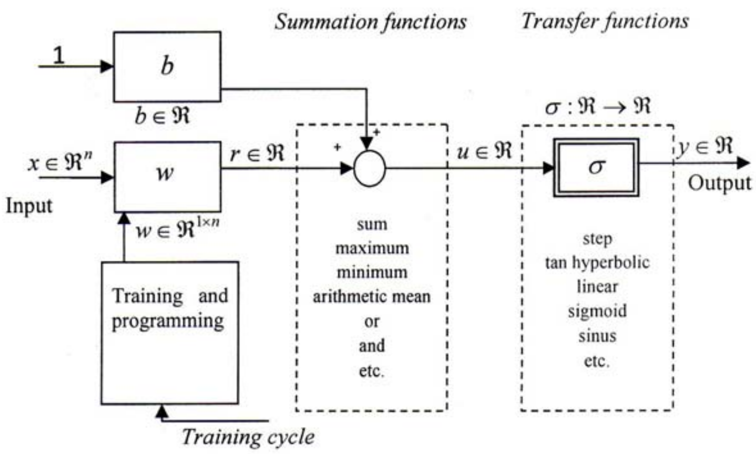

Fig. 1 – Model of an artificial neuron (block diagram)
(Matcovschi & Păstrăvanu, 2008).

artificial neuron with n inputs, noted $x_1, \ldots, x_n$, and one output, noted y. On this diagram, three basic elements of the neuron model (Haykin, 1999) may be identified

a) Synaptic weight.
b) Input operator.
c) Activation function (transfer)

with

$$u = \sum_{i=0}^{n} w_i x_i = \sum_{i=1}^{n} w_i x_i + b\,, \tag{1}$$

where: x_i is the *input signal* through connection i; w_i – the *synaptic weight* of the input signal, i; b – the *threshold value* or *bias*; and

$$y = \sigma(u)\,, \tag{2}$$

with σ – the *activation function.*

Thus

$$y = \sigma\left(\sum_{i=1}^{n} w_i x_i + b\right). \tag{3}$$

The transfer $y = f(x)$ is weighted by the synaptic weights w, ($w \in \mathbb{R}^{1\times n}$) and movement (bias) b ($b \in \mathbb{R}$).

An artificial neural network, briefly called *neural network*, represents a group of artificial neurons linked by connections associated with intensity and a circulation direction of information. The use of artificial neurons as basic elements of a network was performed for the first time by F. Rosenblatt (1957).

The architecture of a neural network refers to the way in which the functional units are placed (topology) and interconnected (connectivity).

The way in which the neurons of a network are structured is directly related to the training algorithm (learning).

3. Transportation Issues Solved with Neural Networks

In 1994 Meier and Rix introduced the computation methodology with neural networks for designing the road pavement adding a real time analysis and a high accuracy.

In 1995 Williams and Gucunski used a backpropagation neural network (NN) for reversing the results of the evaluation test of the elasticity modulus and the thickness of the soil layer and asphaltic pavement in the Seismic Spectral Analysis of Surface Waves.

Two issues have been addressed

a) Structural computation – road structure thickness with an improved accuracy (Saltan, 2002), estimation of elasticity modulus of component layers (Gopalakrishnan, 2008; Lee *et al*., 1998; Ceylan *et al*., 2008), monitoring the maintenance and repair activities of damaged road structures (Alsugair, 1998), analysis of road infrastructure based on non-destructive tests with deflectometer (FWD) (Goktepe, 2006).

b) Traffic management – detecting the traffic incidents on the highways (urban or interurban) for improving the transport system and the prognosis of road traffic for the management of traffic jams (Karim & Adeli, 2002, 2003; Jiang & Adeli, 2005), designing an advanced system of decisional support for the effective management of traffic in working areas (Jiang & Adeli, 2004), designing a model for prognosis of payment-risk on the asphalting process (payment adapted to the various levels of quality and possibility of identifying the responsible factors for payment adjustment (Manik *et al*., 2008).

4. Case Study on the Rigid Runway Structure Design

The evolution of air traffic (intensity, types of aircrafts) requires the design with a high confidence level for airport infrastructure, because the strengthening due to a design error as slab thickness underestimation goes to the interruption of service for a number of runways/airfields.

The airport road structures are mainly designed as rigid slabs.

The design criterion of airport rigid structures is represented by the allowable flexural tensile stress of the cement concrete (σ_{t_adm}). Generally, the design of concrete slabs for airport runways is carried out based on nomograms drawn up for various types of landing gears and load cases. From these diagrams the concrete slab thickness results from the maximum stress in the slab, the load case and the soil reaction coefficient (K) at the footing level.

4.1 . Computing Parameters. Computing Hypothesis

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.

The airfield strips are sectioned in slabs to provide contraction – bending and expansion joints.

The study regarding the influence of loading positions leads to the conclusion that loading at the midpoint of the length is the most disadvantageous one if the uniform resting condition of the slab is fulfilled.

The hypothesis of the structure working as an isolated slab is explained as in time of service the friction between the contact surfaces at the contraction – bending joints decreases due to the wear of the two slabs under the traffic action as well as under thermal cycles.

The FE model prevents over-dimensioning, the values of σ_t (flexural tensile stress due to traffic loading) being smaller than those resulted by Westergaard-Ioannides formulas.

The influence of K value on the σ_t value explains the necessity of foundation layers with a relatively high bearing capacity, providing also the uniform resting conditions of the slabs.

The following parameters were taken into account when creating the nomograms, based on the conclusions of the previously carried out studies:

a) Dynamic elasticity modulus of concrete: E = 30,000 MPa.

b) Poisson's coefficient: ν = 0.15.

c) Concrete grade: B_cR 5.0.

d) Plane dimensions of the slab: $L \times l = 7.00 \times 5.00$ m.

The landing gears are standard represented by the four categories namely, simple, dual, boogie and tandem gear (Zarojanu *et al*., 2009).

The design load is the load on the main landing gear depending on the mass during takeoff of the reference aircraft (contractual/general dimensioning method) or the masses at takeoff/landing of all the aircrafts in service on the aerodrome (optimized dimensioning method).

The reference/critical aircrafts are represented by the aircraft that requires the largest slab thickness. The computing hypotheses for this study are (Sci. Contract..., an???)

a) the loading position of the slab is the one for which the marks are tangent to the length of the slab with values from Table 1;

b) the loadings are transmitted by landing gears as rectangular marks;

c) the reaction modulus value (K) at the top of the foundation layer is obtained depending on the value of K_0 (at the level of the foundation soil), the thickness (H) and the foundation layer composition; the K values are considered as being: 15; 30; 50; 70; 100; 150 MN/m^3;

d) the thickness of concrete slab varies between 15 to 55 cm with a tolerance of 5 cm.

Table 1
The Variation Domain of Loading on the Landing Gears

Loading on the main landing gear, P, [kN]	
Simple	50 / 100 / 200 / 300 / 400
Dual	75 / 175 / 275 / 350 / 425
Boogie	600 / 750 / 900 / 1,050
Tandem	250 / 300 / 377

The values of the flexural tensile stress in the concrete slab (σ_t) are computed using FE models.

For the analysis of 3-D stresses and deformations in the runway system – infrastructure, the package with FE ALGOR (developed by Algor Inc., Pittsburg USA) were used including a series of linear-elastic mathematical models.

The system is made of two sub-systems: infrastructure (foundation soil + foundation) and concrete slabs. The system presents geometrical and mechanical symmetry as well as symmetry of loads and develops in particular models for each type of landing gear (simple, dual, boogie, tandem) and for each loading class.

A class is composed of models with various thicknesses for the runway slab, with the value set of the reaction modulus and another value set of E modulus of slab elasticity.

The nomograms $\sigma_t = f(P, K, H)$; $H = f(\sigma_t, P, K)$. are drawn for each of the values considered in the computation, K = 15, 30, 50, 70, 100, 150 MN/m^3, and standard P-values corresponding to each landing gear (Designing Norms..., 1999).

For values intermediary to those used in simulations, interpolation was adopted using correlations of fourth degree polynomial functions

$$y = a_0 + a_1x + a_2x^2 + a_3x^3 + a_4x^4,$$

$\sigma_t = f(P)$, H, K – constant values; $\sigma_t = f(H)$, P, K – constant values; $\sigma_t = f(K)$, P, H – constant values. The interpolations allow the variation of a single parameter (P, H or K).

4.2. Data Interpolation with Neural Networks

The objective of the next step in this study is to create simulation models of variation of some non-linear functions aiming at their interpolation for values not included in the previous calculation but related to real cases.

The solution consists in an approximation algorithm of non-linear functions. For solving the approximation problems, it is generally used a feed forward back propagation static NN (multi-layer perceptron) with supervized training.

a) *Neural Networks Parameters*

It is developed a correspondence of data (the previously studied parameters) calculated in the simulation with the FE of the function $H = f(P, K, \sigma_t)$. The following input parameters of the neural networks are used:

P – load value transmitted by the specified landing gear;

K – reaction modulus (coefficient of soil reaction);

σ_t - flexural tensile stress in the cement concrete slab.

The output of the neural network is H – thickness of airport cement concrete slab.

b) *Creating and Using Neural Networks*

NN have been designed with the MATLAB program package together with the library Neural Networks Toolbox created by MathWorks.

A feed forward back propagation networks is carried out with three neurons on the input layer and one neuron on the output layer of the network (Fig. 2). Many variants of neural networks were made, where the number of neurons on the hidden layer varied. It was created a model for each type of landing gear and various options for NN were tested (Table 2).

Thus, data sets such as 270 sets for simple type landing gear, 270 sets for dual, 164 sets for tandem and 432 sets for boogie type landing gear were considered necessary for creating the NN. From the available sets of data, 60% were used for network training, 20% for validation and 20% for network testing.

The Levenberg-Marquardt algorithm was selected as the network training algorithm. This proved to carry out the lowest variations of computed values compared to the target values of the network (under 1.5% considered as acceptable).

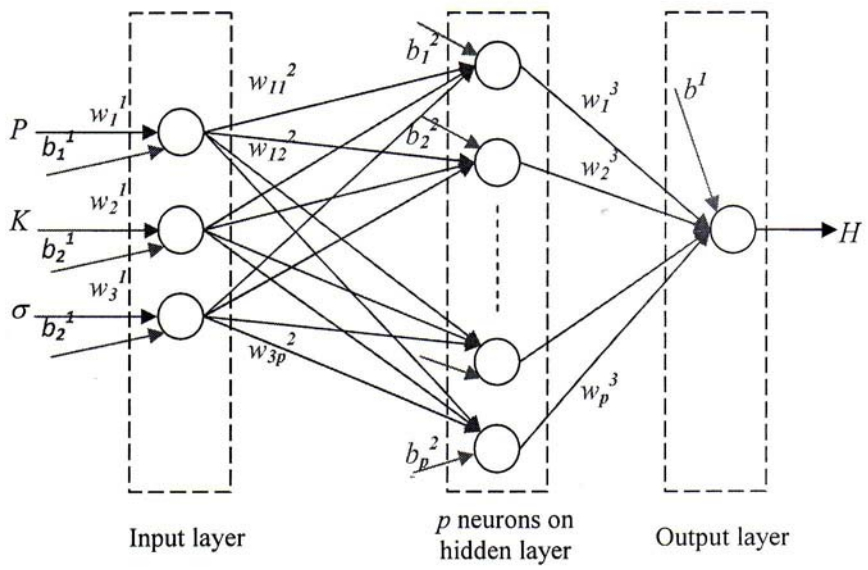

Fig. 2 – Topology of feed forward back propagation networks used for dimensioning new road structures.

After training (Fig. 3), validation and testing of neural networks as the effective usage of networks was carried out.

Table 2
Structures and Performances of Neural Networks

Landing gear type	Network config. / activation functions	Learning / training algorithm	No. training epochs	Mean squared error MSE	Normalized MSE	*R* correlation coefficient
Simple	3-10-1 logsig - tansig - purelin	LM / GD	91	2.961314 e-002	3.343025 e-003	0.99833
Dual	3-20-1 tansig - tansig - purelin	LM / GDM	47	7.251054 e-002	4.251819 e-004	0.99979
Bogie	3-20-1 tansig - tansig - purelin	LM / GD	145	5.862828 e-002	3.738345 e-004	0.99981
Tandem	3-10-1 logsig - tansig - purelin	LM / GDM	42	1.521579 e-001	8.421127 e-004	0.99958

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

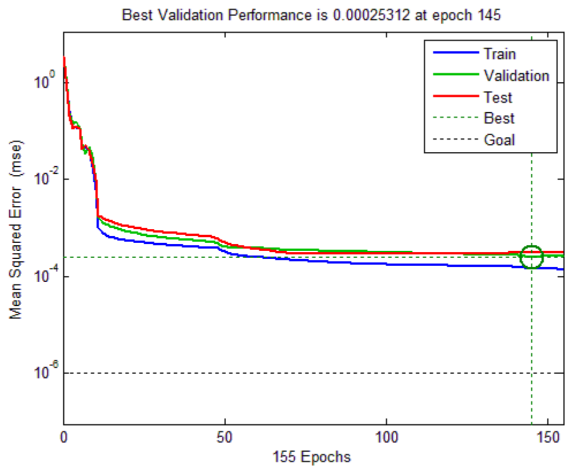

Fig. 3 – Training-validation-testing evolution (cross-validation) for boogie type landing gear.

The network training was carried out with standard values for P – loading transmitted by the specified landing gear, K – reaction modulus at the top of the foundation layer. The value of H – slab thickness, for various values of P, K and σ_t (flexural tensile stress) (Figs. 4,...,6) are provided accurately due to the appro-ximation function using the NN.

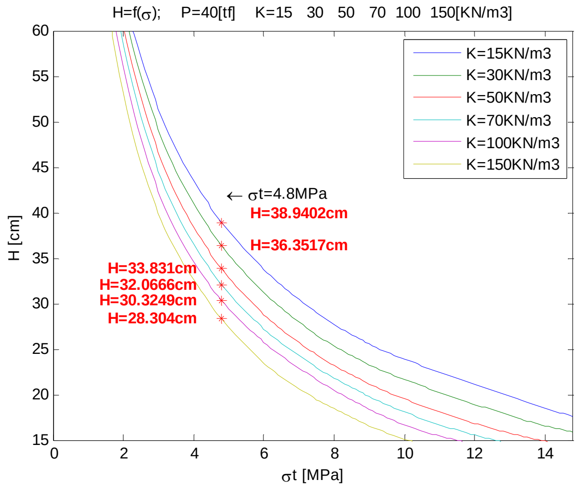

Fig. 4 – Nomogram for the dual type of landing gear.

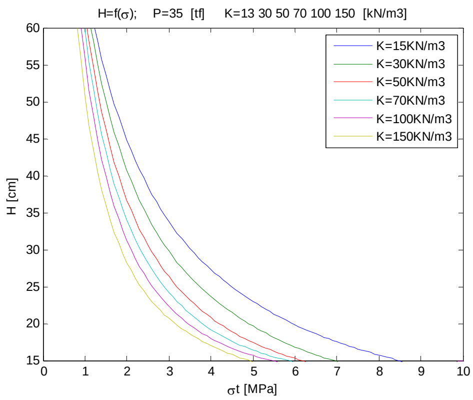

Fig. 5 – Nomogram for the boogie type of landing gear.

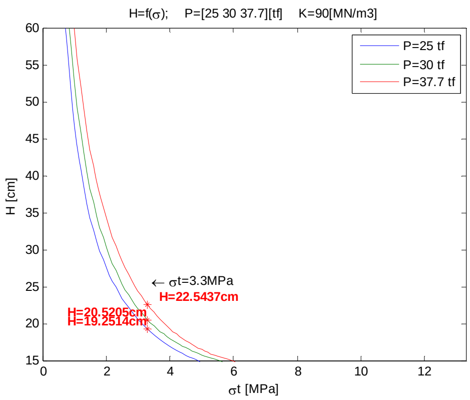

Fig. 6 – Nomogram for the tandem type of landing gear.

5. Conclusions

From the studies carried out in the last two decades there is a strong focus on using neural networks in design works for civil engineering and their utility was demonstrated also on the construction site.

Neural networks do not replace the classical calculation methods, but are complementary to them.

They come with a good modelling in fields where classical simulations (finite elements, finite differences, etc.) would require large resources of computation.

Table 3

Comparison of Values Obtained from Nomograms versus Approximations of Neural Networks

P, [tf]	K kN/m^3	σ_t MPa	H, [cm]			H differences	H differences
			Diagram reading	NN computation	Rounding	$D–RN$	%
Simple							
5	15	2.20	23.0	23.4881	23.5	–0.50	–2.128
5	20	3.15	*	18.4434	18.5		
5	30	1.60	25.0	26.6778	26.7	–1.70	–6.367
5	40	5.00	*	12.2603	12.3		
5	70	1.70	23.9	23.5841	23.6	0.30	1.271
5	100	3.00	≅15*	15.8974	15.9		
5	110	2.30	*	18.7352	18.7		
5	120	2.90	*	15.9989	16.0		
5	140	2.00	*	20.0359	20.1		
5	150	2.70	≅*	20.8070	20.9		
20	35	4.15	*	28.8413	28.9		
20	50	2.75	35.8	35.9042	36.0	–0.20	–0.555
20	90	3.60	*	27.8283	27.9		
20	100	3.90	26.0	25.9214	26.0	0.00	0.000
20	130	2.30	*	35.6739	35.7		
20	150	4.20	23.4	22.7961	22.8	0.60	2.632
25	75	5.20	*	24.5454	24.8		
35	120	2.10	*	49.4827	49.5		
40	50	2.20	>55.0*	56.8907	56.9		
40	55	4.60	*	33.5098	33.6		
40	70	5.20	30	29.3753	29.4	0.60	2.041
40	85	3.10	*	42.0378	42.1		
40	100	4.40	31.7	30.9314	31.0	0.70	2.258
40	115	5.30	*	26.1192	26.2		
40	130	2.75	*	42.7305	42.8		
40	150	2.50	45.5	44.6204	44.7	0.80	1.790
Dual							
7.5	15	3.10	≅*	20.4577	20.5		
7.5	25	1.80	*	27.2955	27.3		
7.5	30	4.00	≅*	15.6018	15.7		
7.5	100	3.80	≅*	14.7081	14.8		
7.5	125	2.30	*	18.6197	18.7		
7.5	150	1.65	22.0	22.9211	23.0	–1.00	–4.348
17.5	150	3.80	19.8	19.4017	19.5	0.30	1.538
25	75	1.60	*	50.102	50.2		
35	90	4.20	*	31.4836	31.5		
42.5	30	2.70	53.6	53.9343	54.0	–0.40	–0.741
42.5	90	3.55	*	39.1873	39.2		
42.5	130	4.45	*	31.5638	31.6		

* values that cannot be read on diagrams

The artificial neural network offers a very good solving of direct mapping of non-linear problems containing many independent variables, a class of problems common to engineering.

This approach offers solutions with a higher accuracy than the alternative modelling techniques and need less requirements for modelling, from the point of view of knowing the form of the function to be represented.

By approaching the problem using neural networks, the following benefits have been obtained (Table 3):

a) improvement of the design methodology of airport rigid structures, increasing the accuracy of the *H* thickness of the concrete slab;

b) increase of the confidence level of the results compared to the reading of nomograms, limited to a reduced number of values of calculation parameters;

c) possibility of introducing values of calculation parameters for larger domains of variation in order to elaborate the official design method.

REFERENCES

Demuth H., Beale M., *Neural Networks Toolbox – for Use with MATLAB.*

Matcovschi M., Păstrăvanu O., *Applications of Neural Networks in Automatics* (in Romanian). Ed. Politehnium, Iaşi, 2008.

Zarojanu H., Roşca O.V., Ciongradi I., Budescu M., *Finite Element Modeling of the Reinforced Airport Slabs*. Proc. of the 5th Internat. Conf. on Boundary and Finite Element, Section 4, Oradea, 2000.

Zarojanu H., Ciongradi I.P., Budescu M., Roşca O.V., Covatariu G., *The Dimensioning of the Rigid Runway Structures*. Intersections/Intersecţii, **6**, *4* (2009), www.intersections.ro.

* * * *Designing Norm for Airport Rigid Road*. NP 034-99.

* * * *Designing Norm of Cement Concrete Reinforcement of Airport Rigid Road Structures* NP 038-99

* * * *Determination of Admissible Loading for the Airport Rigid Road System at Oradea Airport*. Technical Univ. "Gh. Asachi" of Iaşi, Fac. of Constr. a. Archit., Sci. Res. Contr. no.*11430/283*

* * * *Methodology of Drawing Up the Dimensioning Diagrams of Road System for Airport Strips*. Sci. Res. Contr. *C 1825*, Techn. Univ. "Gh. Asachi" of Iaşi.

DIMENSIONAREA STRUCTURILOR RUTIERE RIGIDE AEROPORTUARE CU AJUTORUL REŢELELOR NEURONALE

(Rezumat)

Calculul cu reţele neuronale se situează între inginerie şi Inteligenţă Artificială. Foloseşte tehnici matematice inginereşti clasice, dar şi metode euristice specifice Inteligenţei Artificiale. Lucrarea ilustrează modul de utilizare a reţelelor neuronale pentru îmbunătățirea metodei de calcul prin sporirea preciziei în dimensionarea dalelor din beton din infrastructura aeroportuară. Rezultatele obținute după simulările modelelor create cu metoda elementului finit au fost utilizate pentru realizarea unor rețele neuronale (câte una pentru fiecare aterizor tip), care simulează funcția $H = f(P, K, \sigma_t)$ în cazul dimensionării dalelor din beton de ciment noi. Utilizarea rețelelor neuronale pentru interpolările funcțiilor folosite pentru dimensionarea dalelor a demonstrat o creştere a preciziei rezultatelor față de citirea diagramelor de dimensionare, realizate anterior, cât şi posibilitatea calculării grosimii dalei de beton pentru alte valori ale variabilelor decât cele luate în considerare de simulările efectuate.