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POSSIBLE APPLICATION OF NEURAL NETWORKS IN CONCRETE PRODUCTION

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МОЖЛИВІСТЬ ЗАСТОСУВАННЯ НЕЙРОННИХ МЕРЕЖ У ВИРОБНИЦТВІ БЕТОНУ

This paper present overview of possible application of neural networks in concrete production. Describe potential usage of recycled materials such as fly ash and limestone powder in order to develop more sustainable pattern of resource use.

Keywords: *neural networks; emissions; manufacturing processes; concrete; strength; sustainability; resource use; cleaner production.*

У цій статті розглядається можливість застосування нейронних мереж у процесі виробництві бетону. Розглядаються перспективи використання відновлювальних матеріалів таких як летючий попіл та подрібнений вапняк з точки зору розробки більш надійної моделі використання ресурсів.

Ключові слова: *нейронні мережі; викиди; процес виробництва бетону; міцність; стійкість;використання ресурсів; екологічно чисте виробництво.*

В этой статье рассматривается возможность применения нейронных сетей в процессе производстве бетона. Рассматриваются перспективы использования возобновляемых материалов таких как летучий пепел и измельченный известняк, с точки зрения разработки более надежной модели использования ресурсов.

Ключевые слова: *нейронные сети; выбросы; процесс производства бетона; прочность; устойчивость; использованиее ресурсов; экологически чистое производство.*

Introduction. Concrete production is an important part of infrastructure development. This construction material is easy to use, it allows to make different shapes and provides strong durability. But from other side, construction and demolition activities are responsible for around 860 million tons of waste generated in 2010 on the EU territory [1].

Public become more and more concern about global warming and concrete contribution to it, due to variety of awareness rising events. As result, there were done many researches in order to eliminate ecological impact from concrete production and also provide strong durability to the concrete aggregates. The use of combined cements or supplementary cementitious materials can be a good alternative to basic cement mix and decrease permeability of concrete. As result, concrete will be more resistant to climate conditions. Consequently, the blending of Portland cement with composite cementitious materials, such as pulverized fuel ash (PFA) and silica fume (SF), has become an increasingly conventional practice in the construction of structures exposed to harsh environments such as offshore structures, highway bridges, tunnels, sewage pipes and structures for wastes containing toxic chemicals and radioactive elements [2].

As far as number of ingredients has a tendency to increase, it is difficult to predict properties of such concrete aggregates by using statistical empirical relationship. Neural network can be used as alternative approach for data evaluation. Such approach aloud to work with variation in data sets and model non-linear systems. In the past, various fruitful attempts have been made to forecast properties of concrete using artificial neural network (ANN) [3].

NN model was made in MATLAB environment. ANN consist of input layer, output layer and one hidden layer of nonlinear processing elements.

The purpose and objectives. Basic raw material composition of clinker, which is the primary component of Portland cement can be seen at table 1. Limestone, shells and chalk (lime) have majority with respect to other components, such as sand, fly ash or clay (silica/alumina).

Table 1

Raw material composition of clinker, the primary component of Portland cement [4]

Raw materials	Sources	Mass percent
Lime	Limestone, shells, chalk	60-67
Silica	Sand, fly ash	17-25
Alumina	Clay, shale, fly ash	2-8
Iron oxide	Iron ore	0-6

Around 50 percent of the CO_2 emissions released during manufacturing of the cement (orapproximately 540 kg of CO_2per ton of clinker) is from calcination in which limestone ($CaCO_2$)is transformed into lime (*CaO*) [5]. Following reaction can be described as:

$$CaCO_3 \rightarrow CaO + CO_2 \tag{1}$$

Another part of CO_2, emitted during manufacturing, is the result of fuel use in calcination process. Kilns need to be heated up to 1400-1500 ℃ in order to enable process of calcination.

So, data regarding strength of concrete with respect to percent relation of pulverized fuel ash, silica fume and Portland cement mix were collected in order to create data set for ANN. Least Squares Solution(LSS) were used for numerical optimization. “*Least Square problems have often their origin in fitting models to observations. In its simplest form, we know this from the problem of fitting a regression line, y = ax+b, through a set of data points {x_i, y_i }; i = 1; N. When N > 2, it is in general impossible to put the line through all points, but we try to determine an optimal line, for example by determining the pair a^*, b^*which minimizes the objective function*”[6]

$$f(a,b) = \sum_{i=1}^{N}(ax_i + b - y_i)^2 \tag{2}$$

For this specific case MATLAB going to perform last squares solution 2nd order because it was determined that 2nd order is the most suitable for such data set.

For this specific case, architecture of ANN will have "input" with 5 clusters: total cementitious materials, percentages of cement, pulverized fuel ash, silica fume and water-binder ratio; "hidden layer" with 100 neurons and "output layer" fig. 1.

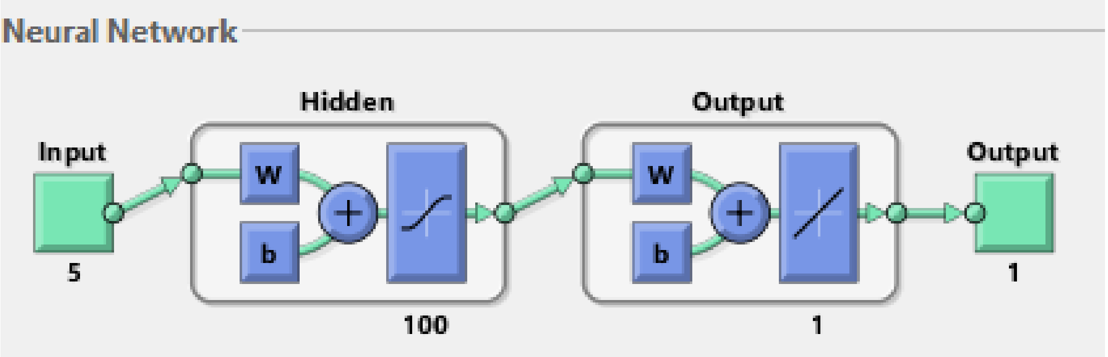


Fig. 1. Artificial Neural Network Architecture used in MATLAB

ANN will be trained with use of Levenberg–Marquardt Method. Tis method was named after Levenberg (1994) and Marquardt (1963) and it is a compromise between Newton's method and Gradient descent. According to the Levenberg–Marquardt method, the optimum adjustment Δw applied to the parameter vector **w**[7] is defined by:

$$\Delta w = [H + \lambda I]^{-1} g \tag{3}$$

Where: I – identity matrix of the same dimensions as H and λ is a regularizing, or loading, parameter that forces the sum matrix (H + λI) to be positive definite and safely well-conditioned throughout the computation [7].

The network is trained by minimizing the cost function [7] Eq. 4.

$$\varepsilon_{av}(w) = \frac{1}{2N}\sum_{i=1}^{N}[d(i) - F(x(i);w)]^2 \tag{4}$$

$$g(w) = \frac{\partial \varepsilon_{av}(w)}{\partial w} = -\frac{1}{N}\sum_{i=1}^{N}[d(i) - F(x(i);w)]\frac{\partial F(x(i);w)}{\partial w} \tag{5}$$

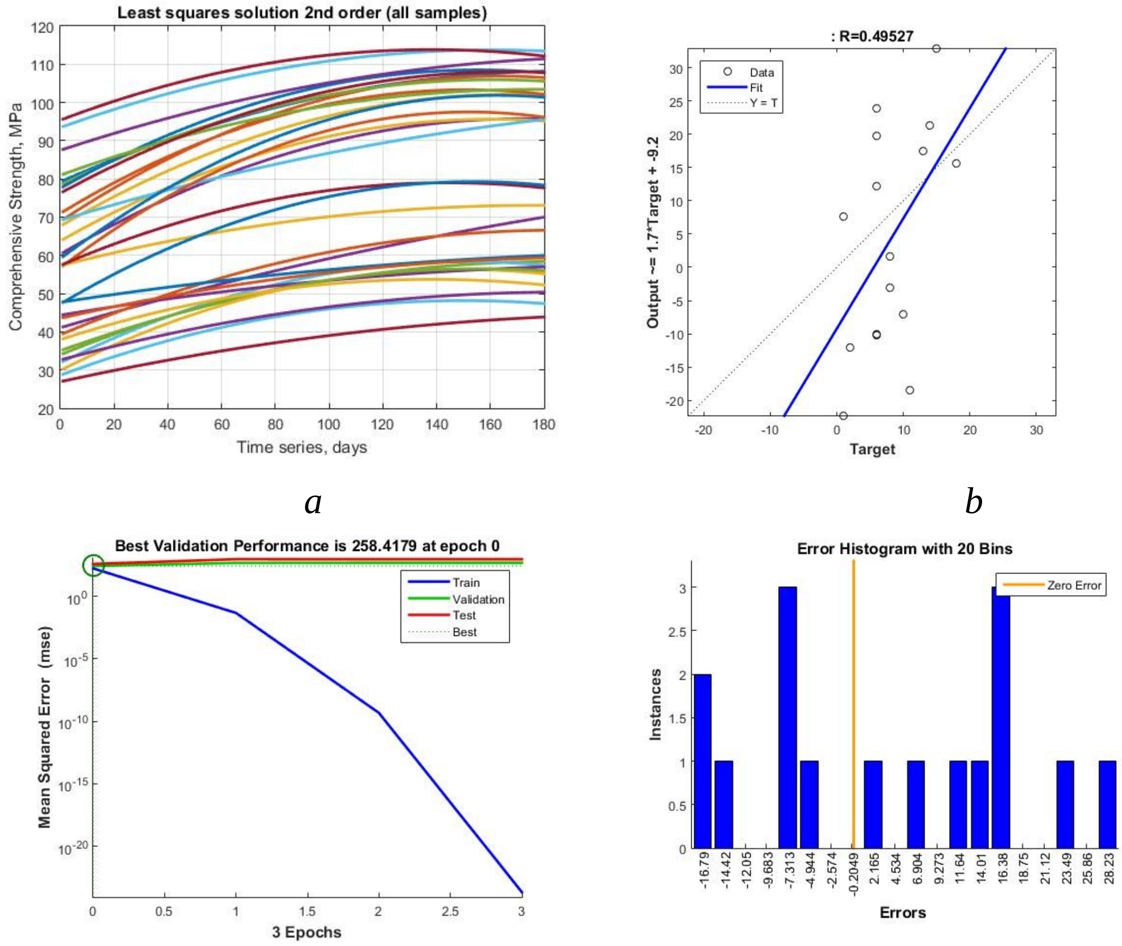
$$H(w) = \frac{\partial^2 \varepsilon_{av}(w)}{\partial w^2} = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{\partial F(x(i);w)}{\partial w}\right]\left[\frac{\partial F(x(i);w)}{\partial w}\right]^T - -\frac{1}{N}\sum_{i=1}^{N}[d(i)F(x(i);w)]\frac{\partial^2 F(X(i);w)}{\partial w^2} \tag{6}$$

$$H(w) \approx \frac{1}{N}\sum_{i=1}^{N}\left[\frac{\partial F(x(i);w)}{\partial w}\right]\left[\frac{\partial F(x(i);w)}{\partial w}\right]^T \tag{7}$$

Eq. 5 and Eq. 6 represent adjustment of Δw. In order to mitigate difficulties of Eq. 5 and Eq. 6 it is recommended to ignore the second term on the right-hand side of Eq. 5 thereby approximating the Hessian simply as Eq. 7 [7].

Also, additional function, which enable data input from user, was added in programming code. It was made in order to provide further investigation in planning of cement mix ingredients for manufacturing or domestic use. Therefore, person need to provide data set regarding ingredients that potentially would be used, such as: TCM – total cementitious materials [kg/m^3], Cement $[\%]$, PFA – pulverized fuel ash $[\%]$, SF – silica fume $[\%]$ andw/b ratio – water-binder ratio. Calculation output will be prediction of “expected weeks to wait” in order to create concrete with proper durability.

Research results. Neural Network supervised training went well and NN is performing prediction of the concrete strength. If we consider 90 MPa as threshold value for compressive strength of ready concrete unit – following data going to be achieved fig. 2, *a*-*d*.

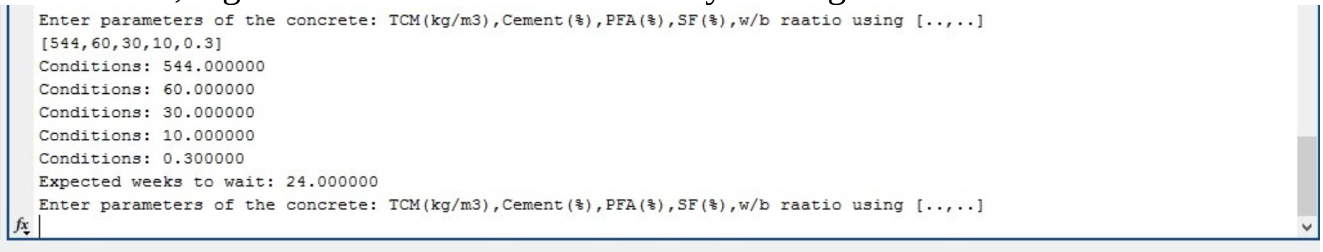


a *b*

c *d*

Fig. 2. Data of performing prediction of the concrete strength:
a – Last Squares Solution 2nd order for all samples; *b* – Regression; *c* – Best Validation Performance; *d* – Error Histogram;

Further action will be to perform prediction of weeks' amount for specific cement mix, ingredients of which determined by user fig. 3.



```
Enter parameters of the concrete: TCM(kg/m3),Cement(%),PFA(%),SF(%),w/b raatio using [..,..]
[544,60,30,10,0.3]
Conditions: 544.000000
Conditions: 60.000000
Conditions: 30.000000
Conditions: 10.000000
Conditions: 0.300000
Expected weeks to wait: 24.000000
Enter parameters of the concrete: TCM(kg/m3),Cement(%),PFA(%),SF(%),w/b raatio using [..,..]
fx
```

Fig. 3. Demonstration of prediction performance

As can be seen from fig. 3 in order to create concrete unit from 60% of Portland cement, 30% of PFA and 10% of SF we need 24 weeks in order to reach strength of 90 MPa.

Conclusions

As can be seen from gained results – it is possible to investigate in concrete ecological performance with artificial neural network. Potential reduction in CO_2 emissions is important factor for the environment and human health. By enabling procedure of strength prediction for customized cement mixes, it is possible to implement pattern of sustainable resource use at manufacturing companies and at domestic usage of concrete.

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