PREDICTION OF RAW MATERIAL BATCHES FOR THE PRODUCTION OF CLINKER BY MEANS OF ARTIFICIAL NEURAL NETWORKS - ANALYSIS OF BEHAVIOUR

Zuzana Kominkova Oplatkova, Roman Senkerik

Tomas Bata University in Zlin, Faculty of Applied Informatics
Nam T.G. Masaryka 5555, 760 01 Zlin, Czech Republic
{oplatkova, senkerik}@fai.utb.cz

KEYWORDS
chemical composition, cement, artificial neural networks.

ABSTRACT

This research deals with the analysis of the behaviour of artificial neural nets for prediction of raw material batches for the production of clinker. During the production several oxides that are present in raw materials in quarries have to be extracted for homogenization of the mixture suitable for clinker production. There is some delay between the measurement of the mixture and the material which is send from quarry. It is necessary to "send" precise chemical composition to ensure a good quality of clinker and resulting product - cement. Artificial neural networks (ANN) are suitable for such kind of time-independent prediction. The results show that not all oxides are necessary to use for the prediction of one oxide. The ANN were designed into several nets with one input similarly as pseudo neural networks are able to work. The results will be used for the purpose of further research of pseudo neural nets which currently serve only as classifiers.

INTRODUCTION

The paper deals with the analysis of behaviour of artificial neural networks during the data training for prediction of raw materials batches for the production of clinker. This analysis should help for further research of pseudo neural networks.

Pseudo neural networks were developed in 2013 and further tested (Kominkova Oplatkova et al. 2013a, 2013b, 2014). Pseudo neural networks (PNN) were inspired in artificial neural nets (ANN). There is synthesis of the model - structure - relation between inputs and outputs in both - pseudo neural networks and artificial neural nets. ANN uses structures of nodes with transfer functions like sigmoid and training algorithms like back propagation or Levenberg-Marquardt. On the contrary, pseudo neural net synthesizes the structure via evolutionary process of symbolic regression - there are no nodes and weights from the respective of ANN but there is a function dependent on inputs.

The first simulations with PNN were connected with the area of classification. The principle of pseudo neural network allows usage of only one output but it can be used multiple inputs. Therefore classification into several classes was done in the way either of continuous intervals in one output node or connection of several independent nets (symbolically designed models) gives the combinations of values in more output nodes.

As the process of pseudo neural networks is evolutionary driven some inputs were omitted in the final model. In some cases, it might serve as an advantage which reduces the complexity of the structure. And at the same time, the most important inputs connected with the problem are evolutionary selected.

Tasks like prediction need values from the history and also historical data of other features and most probably all of them are necessary. As these values are given to the input layer, it might happen that PNN would omit some inputs. For the purpose of the further research with pseudo neural nets, the analysis of behaviour of standard multilayered perceptron (feedforward artificial neural net) was studied in this paper.

As the dataset, data from the production of clinker was used. Researchers have explored some stages of the cement and clinker production with usage of ANN (Svinning et al. 2010, Stanisic et al. 2014, Topalov 2004) but they do not solve the prediction of the chemical composition of raw material.

Firstly, introduction into the clinker production is given, than a description of artificial neural network (ANN) follows. Afterwards, the proposed experiment with results is explained. Conclusion and future work overview finish the paper.

INTRODUCTION INTO CEMENT PRODUCTION

Cement is the most common structural binder. It is a powdered inorganic hydraulic binder, which contains mainly a finely ground clinker. It is possible to affect its properties by means of selection, composition of raw materials and technological process of cement production and thus it can be predetermined to the widest possible usage or the specific usage. Nowadays, factories check workflow production and associated operations regularly and everything is subject to the maintenance and development of a functioning quality management system.

Proceedings 29th European Conference on Modelling and Simulation ©ECMS Valeri M. Mladenov, Petia Georgieva, Grisha Spasov, Galidiya Petrova (Editors)
ISBN: 978-0-9932440-0-1 / ISBN: 978-0-9932440-1-8 (CD)

Cement production is very complicated, technically, time and energy consuming process, which comprises several stages:

1. Resource extraction. The crushed and milled material progresses through homogenization silos into stock silos. In this phase, regular analysis of chemical composition of mined rock are carried out. Based on analysis results, eg. the composition of raw materials or ground fineness can be adjusted.
2. Firing of clinker. The most important part of the cement production process. The raw powder passes through the heat exchanger, where the raw material is preheated and partial decarbonized, into the rotary kiln. During burning process artificial minerals are produced and by quenching they are stabilized and formed into Portland cement clinker. The most of the firing process is automatically controlled focusing on stability and little variability of resulting clinker parameters.
3. Grinding of clinker and storage. Clinker, together with other ingredients is ground to fine meal and then stored in silos. Relevant parameters are continuously checked. Testing is carried out on the modern equipment, such as a laser granulometer, automatic X-ray analyser and others.
4. Expedition. Cement is supplied either in bulk or packaged in paper bags. Prior to the shipment of cement is testing in accordance to technical standards.

Modern control systems and the computer technology used in the cement production should guarantee its stable properties. An important contribution to the optimization, uniformity and control of the entire cement production process is automatic service laboratory. It is used for automated sampling at regular intervals, analyses and results archiving with minimizing of the human factor influence on inspection and test procedures during the cement production. The paper deals with the part of cement production which is aimed on optimal regulation (prediction) of the dosage of each mineral resource for the correct composition of clinker.

PRODUCTION PROCESS

The main raw materials for the production of cement are limestone and sodalite. These materials are mined in quarries with the help of blasting or only dragline using heavy equipment (Fig. 1). Wheel loaders and trucks transport the raw material into a crushing. Large stones are crushed to the size of the road gravel.

Figure 1: Mining of the raw material in quarry and its crushing

The crushed material with the help of a belt conveyor is transported to a materials landfill. The raw material is stored in the prehomogenized silo (Fig. 2) and then homogenized.

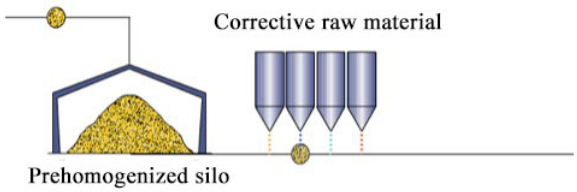

Figure 2: Homogenization of the raw material

Required mixture of crushed basic raw materials and correction of raw materials (silica sand, iron oxide correction) is prepared with the help of precision measuring equipment. Cylindrical or ball mills grind the raw material mixture to fine meal dry it at the same time. Then the meal is stored in silos and further homogenized (Fig. 3).

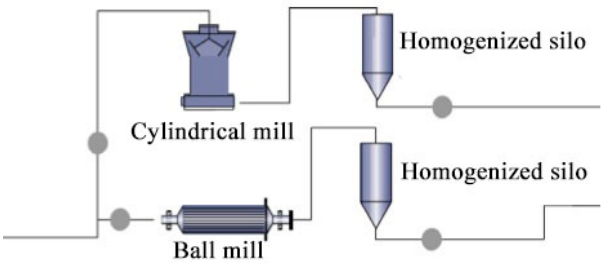

Figure 3: Milling and drying of the raw material

Firing of the raw materials needs temperatures about 1450 °C in an oven or in a rotary kiln with superior heat exchanger. These types of furnaces work in different techniques, while the main difference is the method of preparation and preheating the raw meal. The chemical reactions in a process known as sintering and subsequent quenching arises new product - Portland cement clinker (Fig. 4).

Clinker is the basic raw material for cement production. The production begins by grinding of input materials - limestone, marl, clay shale, silica sand, fluorspar and iron ore. Raw materials are batched onto the conveyor belt, which is continuously analysed and the chemical composition of aggregates monitored continuously throughout volume and time. Dosing of the individual

ingredients is specified in the recipe for production raw meal identifying their specific ratio at the inlet to the raw mill. Basic oxides characterize the resulting composition of the raw meal: SiO_2, Al_2O_3, Fe_2O_3, CaO, SO_3.

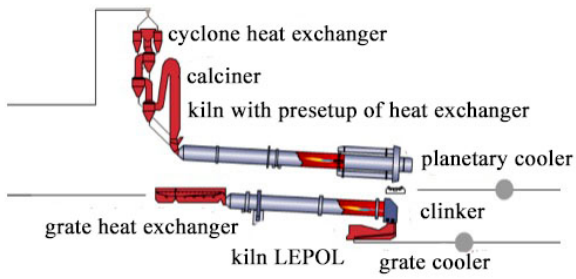

Figure 4: Milling and drying of the raw material

The raw meal must have precise composition, which can be influenced still by adding correcting additives. The resulting composition of the mixture is usually counted with some delay with respect to raw material in the quarry. The subsequent correction of individual raw material weights is based on the values actually measured by analysers. The time shift between the input of raw materials for processing and the real composition of the raw meal measured by laboratory unit is up to 30 minutes. This significant time shift causes that the change in the chemical composition of raw materials is detected late and subsequent material cost demanding modifications of the raw meal is necessary.
Therefore a need of prediction of the chemical composition arises to improve the direct batches of raw materials in quarry. As a prediction tool artificial neural networks were selected in this case and will be further studied for pseudo neural network usage.

ARTIFICIAL NEURAL NETWORKS

Artificial neural networks are inspired in the biological neural nets and are used for complex and difficult tasks (Hertz et al., 1991), (Wasserman, 1980), (Gurney, 1997), (Fausset, 2003), (Volna et al., 2013). The neurons in human brain uses a chemical reactions inside for transfer of the signal. The body - soma - has up to 10^4 dendrites (inputs) and one axon (output). The synaptic connection (weights) between neurons is made by transfer of signal from the active axon onto passive dendrites of another neuron. The importance of dendrites in the process inside soma can be visualized as a weighted sum of the input signals. When a bias of inner potential is reached the signal is then transferred into the axon and to other neurons.
The artificial neural networks adapted from the biological nets some terminology and some (given above in brackets) was given in more technical way.
ANNs are capable of generalization and hence tasks like classification is natural for them. Some other possibilities are in pattern recognition, control, filtering of signals and also data approximation, prediction and others.
There are several kinds of ANN. Basic division is into supervised and unsupervised training algorithm. Supervised ANN has to have input and also required output. The error on the output between actual value obtain from the training process and the required one control the adjusting weights (training).
The neural network works so that suitable inputs in numbers have to be given on the input vector. These inputs are multiplied by weights which are adjusted during the training. In the neuron the sum of inputs multiplied by weights are transferred through mathematical function like sigmoid, linear, hyperbolic tangent etc. Therefore ANN can be used for data approximation and prediction (Hertz et al., 1991) – a model on measured data, relation between input and required (measured data) output.
These single neuron units (Fig. 5) are connected to different structures to obtain different structures of ANN (e.g. Fig. 6 and Fig. 7), where $\sum \delta = TF[\sum (w_i x_i + b w_b)]$ and $\sum = TF[\sum (w_i x_i + b w_b)]$; TF is a transfer function like logistic sigmoid or hyperbolic tangent.

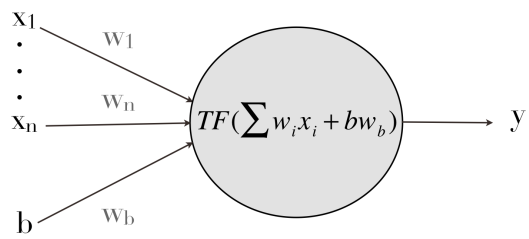

Figure 5: Neuron model, where TF (transfer function like sigmoid), x_1 - x_n (inputs to neural network), b – bias (usually equal to 1), w_1 – w_n, w_b – weights, y – output

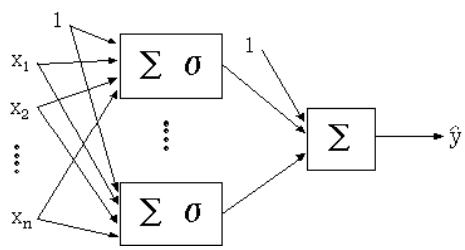

Figure 6: ANN models with one hidden layer

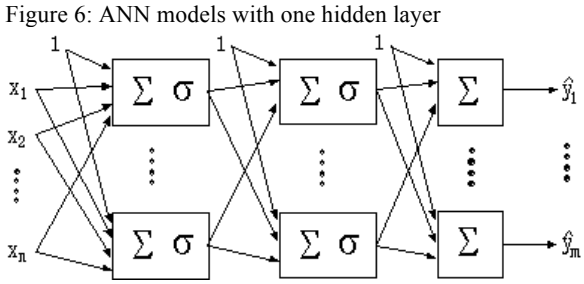

Figure 7: ANN models with two hidden layers and more outputs

ANN needs a suitable training set of known solutions to be learned on them. It is known that the training set is the core of the success of the training quality.
The ANN structure influences the process too. There is no "cookbook" how to set up the number of layers and nodes in layers. There are optimization techniques, which help with the structure, connections and node number, like evolutionary computation (Fekiac, 2011) or pseudo neural networks (Kominkova Oplatkova et al. 2013 - 2014) allow to produce a relation between input and output without setting of above mentioned parameters. PNN do not have the structure similar to ANN.
The example of relation between inputs and output can be shown as a mathematical form (1). It represents the case of only one neuron and logistic sigmoid function as a transfer function.

$$y = \frac{1}{1 + e^{-(x_1 w_1 + x_2 w_2)}}, \qquad (1)$$

where y – output
x_1, x_2 – inputs
w_1, w_2 – weights.

For ANN, it is usually recommended to use maximally 2 hidden layers according to Kolmogorov theorem (Kurkova, 1992) and also the higher number increases the computational time. The number of nodes in each layer can be set up on the basis of heuristic or an adaptive way. For the purpose of this paper we have used an adaptive way and make comparisons between different numbers of nodes.
There are several training algorithms for feedforward neural nets: the most known is back propagation, based on Levenberg-Marquardt algorithm, Gauss-Newton method and others.

PROBLEM DESIGN

As described above, there are some basic oxide which are necessary for the clinker production and appear in the raw material meal which is homogenized in the silo. In quarry, the raw material contains also other oxide which are measured by the laboratory equipment. For the further processing only 5 oxides - SiO_2, Al_2O_3, Fe_2O_3, CaO, SO_3 have been used. The reported values mean percentage (%) of the element representation in the measured sample. Authors had a 4688 real data available for modeling and testing.
In the long term (4688 records, fig. 8) can be visible an oscillation of oxides values around an average value, but actually measured data can differ from this average value significantly as can be seen from the selection of data for one day (fig. 9). The question is whether the significant oscillation is caused by a significant change in the composition of raw material input, long delays between data evaluation and automatic modification of quantity of raw material into the preparation of a mixture or only inadequate operator intervention causing the same. In any case, the data is not time-dependent. Instead of the ARX training for predictive ANN standard form of feed forward ANN is used.

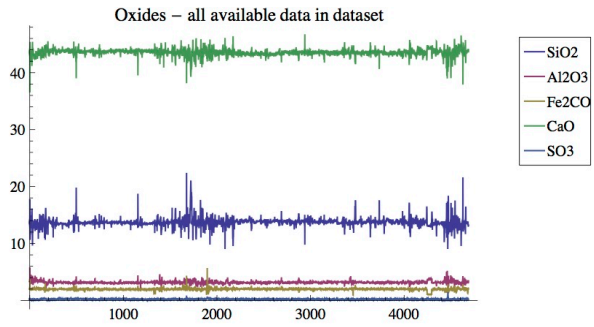

Figure 8: Measured values of oxides (% representation) in whole dataset

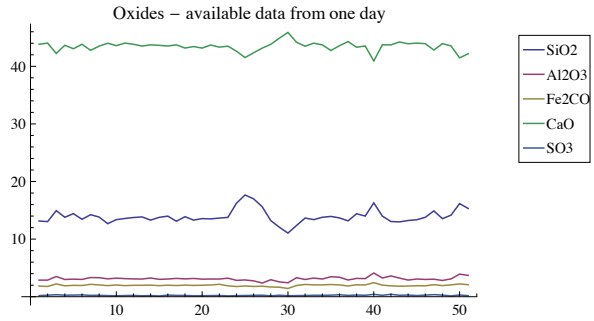

Figure 9: Measured values of oxides (% representation) in one day - 30 minutes measured points

For further simulations, the dataset was divided into two parts - training data (2494) and testing data (2189). It seems that 5 patterns are missing. As the paper deals with the prediction some values are taken from history, in this case 5 previous values (Zufan Tichy 2010).

RESULTS

The feedforward artificial net with one hidden layer and different numbers inside together with Levenberg - Marquardt algorithm was used in this paper. The main aim was to analyze what inputs are important for making the models. If all 5 oxides are necessary or only one or two oxides and how many historical values are suitable to use for a reasonable prediction.
The 5 historical values of each oxide was used as a input vector to the ANN, i.e. if 2 oxides were used the input vector had 10 values, in the case of all 5 oxides the input vector contains 25 values. The net was designed for only one output connected with predicted oxide, similarly as it will be done with pseudo neural networks.
It was found out that not all oxides are necessary to use. The prediction model was similar within 2 oxides (of whatever combination) as within the 5 oxides. The following figures (Fig. 10 and Fig. 11) depict differences between measured and predicted value for

first 50 values of the dataset. A line above or under the actual measured value depicts the difference predicted by ANN. It can be visible that the model which uses only 2 oxide had similar errors as the 5 oxide model. The difference between actual and modeled values can be visible in fig. 12 - fig. 17. Fig. 12, 14 and 16 depict model on the known data from the training set, the last one for 2 and 5 oxide models at the same time. Fig. 13, 15 and 17 show the same but for the unknown data - testing data. Also it can be visible that the ANN is able to cover a huge jump from the average value.

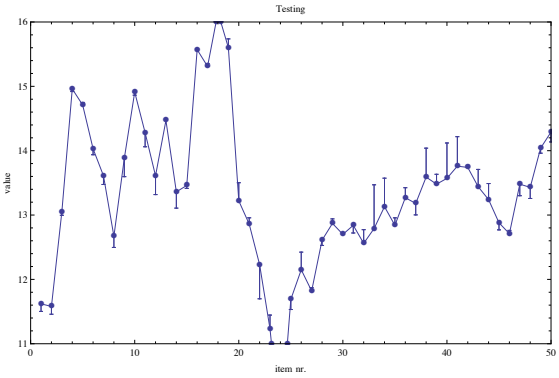

Figure 10: Difference chart of first 50 values for 2 oxide model for SiO_2 prediction

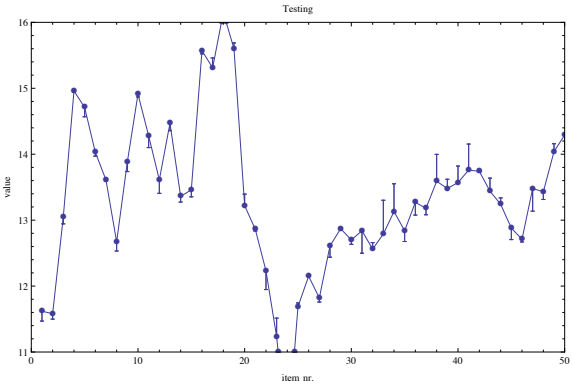

Figure 11: Difference chart of first 50 values for 5 oxide model for SiO_2 prediction

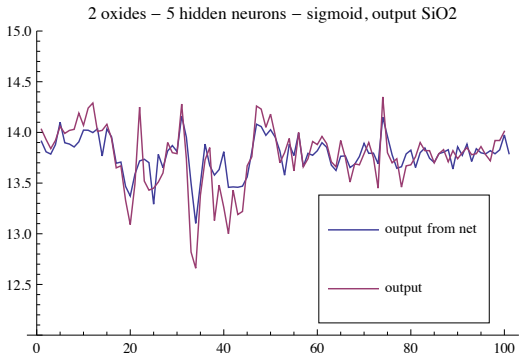

Figure 12: Actual and predicted output for first 50 values for 2 oxide model for SiO_2 prediction

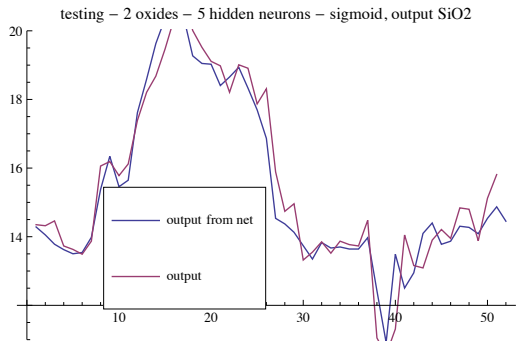

Figure 13: Actual and predicted output for 50 values from testing set (the one which ANN has not used for training) 2 oxide model for SiO_2 prediction

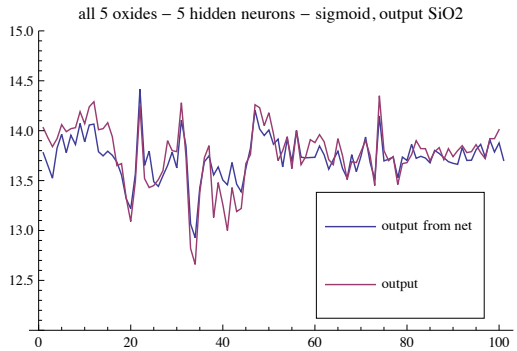

Figure 14: Actual and predicted output for first 50 values for all 5 oxide model for SiO_2 prediction

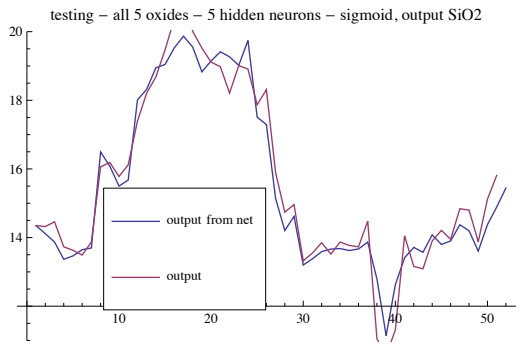

Figure 15: Actual and predicted output for 50 values from testing set (the one which ANN has not used for training) - all 5 oxide model for SiO_2 prediction

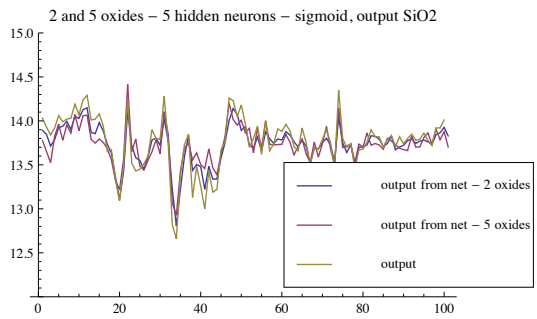

Figure 16: Actual and predicted output for first 50 for both - 2 and 5 oxide models for SiO_2 prediction

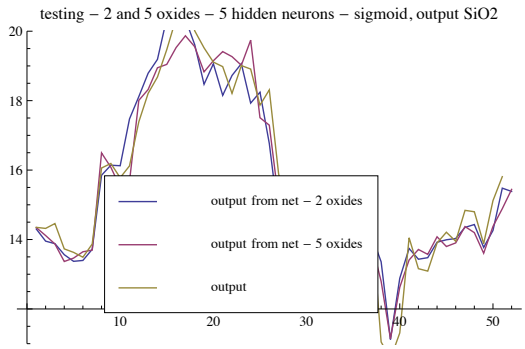

Figure 17: Actual and predicted output for 50 values from testing set (the one which ANN has not used for training) for both - 2 and 5 oxide models for SiO_2 prediction

CONCLUSION

This paper deals with an analysis of behaviour of prediction by means of ANN for the chemical composition of raw material for a clinker production. The results showed that it is possible to predict raw material batches to ensure a suitable mixture composition for the homogenization. The results show that not all oxides are necessary as input values. The results will be used for further research with pseudo neural networks which are currently used only for classification. Future plans will be focused on further tests and design of pseudo neural nets suitable for prediction and will be compared with classical neural nets.

ACKNOWLEDGEMENT

This work was supported by Grant Agency of the Czech Republic - GACR P103/15/06700S, further by financial support of research project NPU I No. MSMT-7778/2014 by the Ministry of Education of the Czech Republic and also by the European Regional Development Fund under the Project CEBIA-Tech No. CZ.1.05/2.1.00/03.0089.

REFERENCES

Fausett L. V.: Fundamentals of Neural Networks: Architectures, Algorithms and Applications, Prentice Hall, 1993, ISBN: 9780133341867

Fekiac J., Zelinka I., Burguillo J. C.: A review of methods for encoding neural network topologies in evolutionary computation, ECMS 2011, Krakow, Poland, ISBN: 978-0-9564944-3-6

Gurney K.: An Introduction to Neural Networks, CRC Press, 1997, ISBN: 1857285034

Hertz J., Kogh A. and Palmer R. G.: Introduction to the Theory of Neural Computation, Addison – Wesley 1991

Kominkova Oplatkova Z., Senkerik R. (2013 a): Evolutionary Synthesis of Complex Structures - Pseudo Neural Networks for the Task of Iris Dataset Classification. In Nostradamus 2013: Prediction, Modeling and Analysis of Complex Systems. Heidelberg : Springer-Verlag Berlin, 2013, p. 211-220. ISSN 2194-5357. ISBN 978-3-319-00541-6.

Kominkova Oplatkova Z., Senkerik R., Jasek R. (2013b): Comparison Between Artificial Neural Net and Pseudo Neural Net Classification in Iris Dataset Case. In MENDEL 2013 19th International Conference on Soft Computing. Brno, Czech Republic, 2013, p. 239-244. ISSN 1803-3814. ISBN 978-80-214-4755-4.

Kominkova Oplatkova Z., Senkerik R.: Lenses Classification by means of Pseudo Neural Networks – Two Approaches. In MENDEL 2014 - 20th International conference on soft Computing. Brno, Czech Republic, 2014, p. 397-401. ISSN 1803-3814. ISBN 978-80-214-4984-8.

Kurkova V.: Kolmogorov's theorem and multilayer neural networks, Neural Networks, Volume 5 Issue 3, 1992, p. 501-506

Stanisic D, et al. Soft sensor for real-time cement fineness estimation. ISA Transactions (2014), http://dx.doi.org/10.1016/j.isatra.2014.09.019

Svinning K., Høskuldsson A., Justnes H.: Prediction of potential compressive strength of Portland clinker from its mineralogy, Cement and Concrete Composites, Volume 32, Issue 4, April 2010, Pages 300-311, ISSN 0958-9465, http://dx.doi.org/10.1016/j.cemconcomp.2009.12.004.

Topalov A. V., Kaynak O.: Neural network modeling and control of cement mills using a variable structure systems theory based on-line learning mechanism, Journal of Process Control 14, 2004, p. 581 - 589

Volna, E. Kotyrba, M. and Jarusek, R. 2013 "Multiclassifier based on Elliott wave's recognition" Computers and Mathematics with Applications 66 (2013) ISSN: 0898-1221.DOI information: 10.1016/j.camwa.2013.01.012.

Wasserman P. D.: Neural Computing: Theory and Practice, Coriolis Group, 1980, ISBN: 0442207433

Zufan Tichy R.: The regulation of the dose raw materials for the manufacture clinker - main component of the cement, diploma thesis, Tomas Bata University in Zlin, 2010

AUTHOR BIOGRAPHIES

ZUZANA KOMINKOVA OPLATKOVA is an associate professor at Tomas Bata University in Zlin. Her research interests include artificial intelligence, soft computing, evolutionary techniques, symbolic regression, neural networks. She is an author of around 100 papers in journals, book chapters and conference proceedings. Her e-mail address is: oplatkova@fai.utb.cz

ROMAN SENKERIK is an associate professor at Tomas Bata University in Zlin. His research interests include artificial intelligence, soft computing, evolutionary techniques, theory of deterministic chaos. He is an author of more than 100 papers in journals, book chapters and conference proceedings. His email address is: senkerik@fai.utb.cz