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NEURAL NETWORKS IN MINING SCIENCES – GENERAL OVERVIEW AND SOME REPRESENTATIVE EXAMPLES

SIECI NEURONOWE W NAUKACH GÓRNICZYCH – OGÓLNE OMÓWIENIE I KILKA REPREZENTATYWNYCH PRZYKŁADÓW

The many difficult problems that must now be addressed in mining sciences make us search for ever newer and more efficient computer tools that can be used to solve those problems. Among the numerous tools of this type, there are neural networks presented in this article – which, although not yet widely used in mining sciences, are certainly worth consideration. Neural networks are a technique which belongs to so called artificial intelligence, and originates from the attempts to model the structure and functioning of biological nervous systems. Initially constructed and tested exclusively out of scientific curiosity, as computer models of parts of the human brain, neural networks have become a surprisingly effective calculation tool in many areas: in technology, medicine, economics, and even social sciences. Unfortunately, they are relatively rarely used in mining sciences and mining technology. The article is intended to convince the readers that neural networks can be very useful also in mining sciences. It contains information how modern neural networks are built, how they operate and how one can use them. The preliminary discussion presented in this paper can help the reader gain an opinion whether this is a tool with handy properties, useful for him, and what it might come in useful for.

Of course, the brief introduction to neural networks contained in this paper will not be enough for the readers who get convinced by the arguments contained here, and want to use neural networks. They will still need a considerable portion of detailed knowledge so that they can begin to independently create and build such networks, and use them in practice. However, an interested reader who decides to try out the capabilities of neural networks will also find here links to references that will allow him to start exploration of neural networks fast, and then work with this handy tool efficiently. This will be easy, because there are currently quite a few ready-made computer programs, easily available, which allow their user to quickly and effortlessly create artificial neural networks, run them, train and use in practice.

The key issue is the question how to use these networks in mining sciences. The fact that this is possible and desirable is shown by convincing examples included in the second part of this study. From the very rich literature on the various applications of neural networks, we have selected several works that show how and what neural networks are used in the mining industry, and what has been achieved thanks to their use. The review of applications will continue in the next article, filed already for publication

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in the journal „Archives of Mining Sciences". Only studying these two articles will provide sufficient knowledge for initial guidance in the area of issues under consideration here.

Keywords: neural networks, applications in mining sciences, process modeling, systems modeling, machine learning, modeling of the oil mining process, forecasting of reservoir properties

Liczne i trudne problemy, jakie muszą być obecnie rozwiązywane w naukach górniczych, skłaniają do poszukiwanie i wypróbowywania wciąż nowszych i bardziej sprawnych narzędzi informatycznych, które mogą być wykorzystane do rozwiązywania tych problemów. Wśród narzędzi tego typu, które wprawdzie jeszcze powszechnie wykorzystywane nie są, z pewnością zasługują na uwagę, warto rozważyć przedstawiane w tym artykule sieci neuronowe. Sieć neuronowa, której schemat przedstawiony jest na rysunku 1, jest narzędziem tak zwanej sztucznej inteligencji, wywodzącym się z prób modelowania struktury i funkcji biologicznych systemów nerwowych. Początkowo budowane i badane wyłącznie z ciekawości naukowej, jako komputerowe modele fragmentów ludzkiego mózgu, sieci neuronowe nieoczekiwanie okazały się skutecznym narzędziem w wielu zastosowaniach: w technice, w medycynie, w ekonomii a nawet w naukach społecznych. Mogą one dostarczać pojedynczych rozwiązań (wartości oszacowań poszukiwanych parametrów, lub przesłanek do podjęcia określonych decyzji), bądź całych wektorów rozwiązań – jakkolwiek w tym drugim przypadku celowe jest rozważenie kwestii, czy zastosować jedną sieć o wielu wyjściach, czy kilka sieci mających pojedyncze wyjście (Rys. 2). Przy tworzeniu sieci neuronowych trzeba wybierać stopień złożoności jej struktury, co nie jest łatwe, ponieważ sieć o zbyt ubogiej strukturze (zwłaszcza dysponująca zbyt mała liczbą tak zwanych neuronów ukrytych) może nie podołać rozwiązaniu bardziej złożonego zadania, natomiast sieć mająca zbyt skomplikowaną i bogatą strukturę zawsze sprawia kłopoty podczas procesu uczenia.

Proces uczenia jest kluczem do wszystkich zastosowań sieci neuronowych. Kluczem do skutecznego nauczenia sieci rozwiązywania jakiejś klasy zadań jest posiadanie tak zwanego zbioru uczącego, to znaczy zbioru przykładowych zadań wraz z ich prawidłowymi rozwiązaniami (Rys. 4). Wprowadzając na wejście sieci dane stanowiące przesłanki do rozwiązania zadania i porównując odpowiedź sieci z prawidłową odpowiedzią zapisaną w zbiorze uczącym można na podstawie wykrytego błędu automatycznie korygować parametry sieci, co prowadzi zwykle do tego, że sieć po pewnym czasie sama nauczy się rozwiązywania rozważanej klasy zadań.

Dzięki korzystaniu z procesu uczenia (opartego na przykładach, a nie na regułach) sieć neuronowa może rozwiązywać zadania, dla których my (użytkownicy sieci) nie dysponujemy wiedzą, jak te zadania należy rozwiązywać (Rys. 6). Dzięki temu sieć neuronowa może służyć jako model dowolnego złożonego procesu, co pozwala na wykonywanie dla tego procesu wielu istotnych czynności (Rys. 7).

Niestety, mimo niewątpliwych zalet sieci neuronowych w naukach górniczych są one stosowane raczej rzadko. Prezentowany artykuł ma przekonać Czytelników, że sieci neuronowe mogą się okazać bardzo przydatne także w naukach górniczych. Artykuł stanowi również użyteczne wstępne wprowadzenie do wiedzy o sieciach neuronowych. Praca zawiera bowiem informacje o tym, jak są zbudowane nowoczesne sieci neuronowe, jak one działają i jak można ich używać. To wstępne omówienie przedstawione w artykule może pomóc w tym, by Czytelnik wyrobił sobie opinię, czym jest to narzędzie, jakie ma właściwości i w związku z tym do czego może mu się przydać.

Oczywiście skrótowe wprowadzenie do problematyki sieci neuronowych zawarte w prezentowanym artykule nie wystarczy tym Czytelnikom, którzy dadzą się przekonać i naprawdę będą chcieli użyć sieci neuronowych. Będą oni potrzebowali jeszcze sporej porcji szczegółowej wiedzy, żeby mogli zacząć samodzielnie tworzyć takie sieci i ich używać w praktyce. Jednak jeśli decyzja o wypróbowaniu możliwości sieci neuronowych będzie pozytywna, to zainteresowany Czytelnik będzie mógł w artykule znaleźć odnośniki do pozycji literatury, pozwalających szybko i sprawnie poznać technikę sieci neuronowych na poziomie wystarczającym do rozpoczęcia własnych prac z tym wygodnym narzędziem. Będzie to tym łatwiejsze, że obecnie dostępnych jest sporo gotowych programów komputerowych pozwalających szybko i bez wysiłku tworzyć sztuczne sieci neuronowe, uruchamiać je, uczyć i wykorzystywać praktycznie.

Oczywiście kluczową sprawą jest kwestia, jak tych sieci używać w naukach górniczych. O tym, że jest to możliwe i celowe przekonują jednak przykłady zawarte w drugiej części opracowania. Z przebogatej literatury, dotyczącej różnych zastosowań sieci neuronowych, wybrano kilkanaście prac, które pokazują, jak i do czego sieci neuronowych w górnictwie użyto i co zostało osiągnięte dzięki ich zastosowaniu. Ten

przegląd zastosowań będzie kontynuowany w następnym artykule, zgłoszonym już do publikacji w czasopiśmie „Archiwum Górnictwa" i dopiero przestudiowanie obydwu tych artykułów dostarczy wiedzy wystarczającej do wstępnej orientacji w obszarze rozważanej tu problematyki.

Słowa kluczowe: sieci neuronowe, zastosowania w naukach górniczych, modelowanie procesów, modelowanie systemów, uczenie maszyn, modelowanie procesu wydobycia ropy naftowej, przewidywanie właściwości zbiornikowych pokładów geologicznych

1. Introduction

Neural networks are currently widely used as a tool for intelligent computations. Because of these applications, neural networks (NN) are now known and used also by the people who are definitely not interested in neurocybernetics, and consider NN only as a computational tool for solving practical problems. For people who are not familiar with neural networks yet, but are planning their use in future, the book (Tadeusiewicz et al., 2014) can be recommended as a very friendly introduction with numerous practical exercises which can be performed by the reader on his own laptop using the many free programs attached to the book.

For people at least a little familiar with neural networks, a useful aid in reading this article should be the schema of a typical application of an NN presented in Fig. 1 in the most simplified and condensed form.

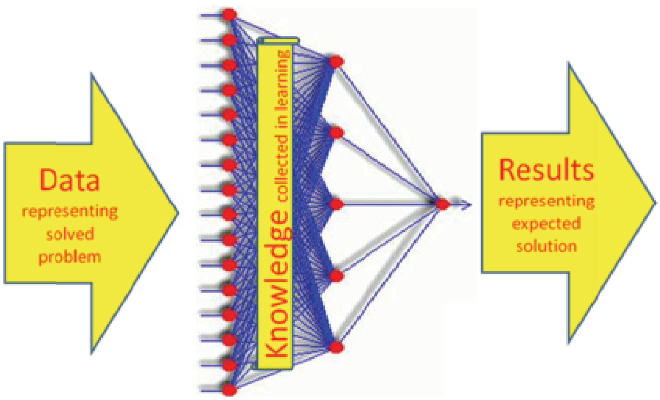

Fig. 1. Typical view of a neural network application

The most important element in Fig. 1 is the **knowledge** collected in the neural network in the form of values of parameter tuning during the learning process. Thanks to this learning methodology used for neural network adaptation to solving particular practical problems, an NN can be used in many applications, even those for which the neural network user himself cannot propose (or even imagine!) a method of problem solving.

The neural network presented in Fig. 1 has – as usual – a lot of input data representing the problem being solved, and one output. Very often such a schema is enough, but sometimes the problem under consideration needs more outputs. In such cases, networks with many outputs can be used, but a more recommended approach is to use some separate networks with the same inputs and a single output value from every network. This problem is discussed in Fig. 2, where the reader can find all necessary justifications.

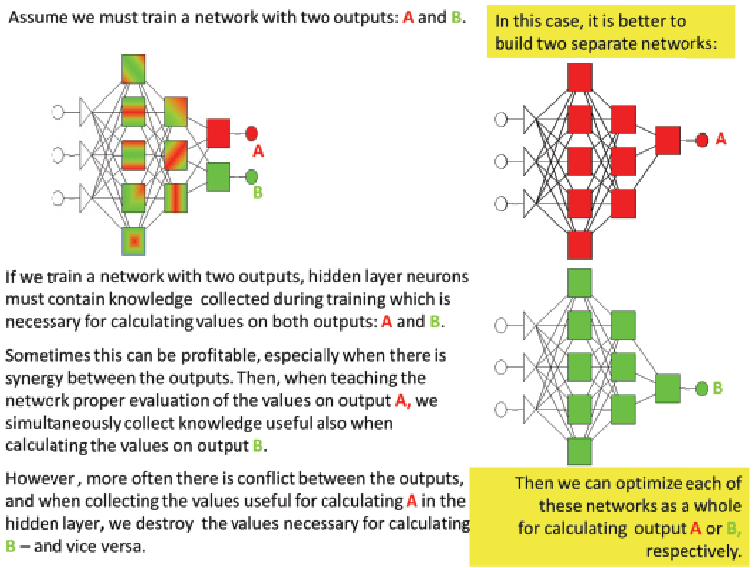

Fig. 2. Discussion of the problem of one versus more outputs

For every well-defined problem, the number of input data items and the number of desired output results are predetermined. The user of a neural network must select in fact one parameter only: the number of hidden neurons. Selection of the proper number is important because of the arguments shown in Fig. 3. In a typical situation, this selection is accomplished using a simple empirical method: the researcher builds some bigger and smaller networks and tests their efficiency, selecting for permanent use the best one. Sometimes special programs can be helpful, which recommend the neural network structure by generating many networks with different structures and finding automatically the best one.

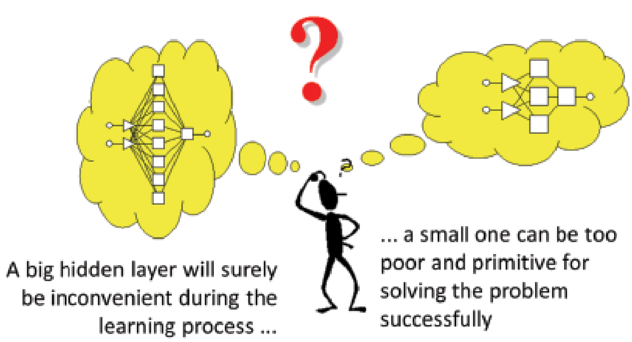

Fig. 3. Selection of the proper number of hidden neurons is difficult

The most important part of problem solving with neural networks use is the neural network learning, or training process. It is very important and comfortable for the user, who instead of elaborating and programming an algorithmic solution to the considered problem – can start the network training process, and then the solution can be found automatically. The key point in the network training process is a collection of correctly solved examples, named the learning set. It can be represented by a table with rows representing particular examples, and two sets of columns, representing: the first set – the input data for the considered problem, and the second – the desired output. An example of such a table is shown in Fig. 4.

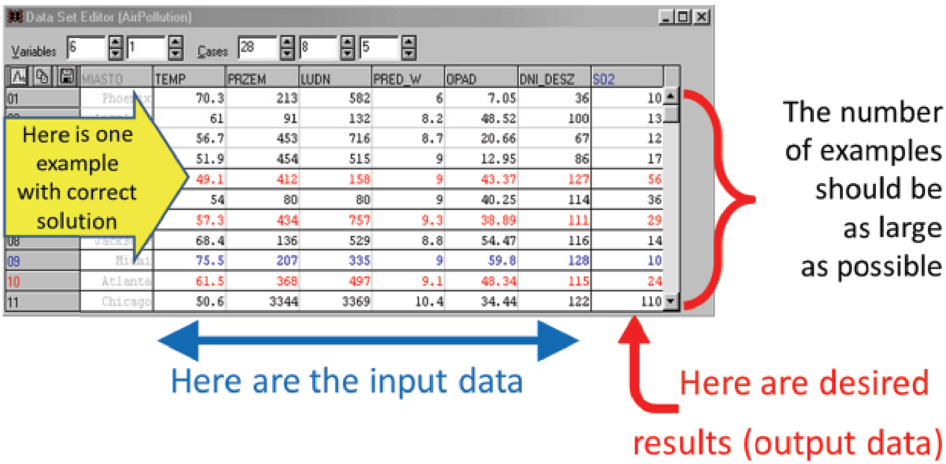

Fig. 4. Example learning set for a neural network

The training process consists of three steps: First, the input data from a selected example belonging to the learning set are sent to the network input. All neurons in the network work together using the current values of parameters (representing the network knowledge), and the final result, given as the network answer, is calculated. The next step is comparison of the network answer and the true answer (desired result) taken from the learning set for the considered example, and calculation of the error measure. This measure, calculated on the network output, must be then distributed among all neurons inside the network; therefore, the most popular method of neural network learning is named *backpropagation*. The third step is correction of parameters for all neurons in the whole network. The method of carrying out this correction is based on calculating the gradient of the network error. As a result of such corrections, the network knowledge represented by the mentioned parameters changes.

The sequence of operations presented above must be repeated many times for all examples contained in the learning set, because the increase in network knowledge is rather slow. But the results are impressive!

At the end of this introduction, let us try to answer the question: When does it pay to use neural networks?

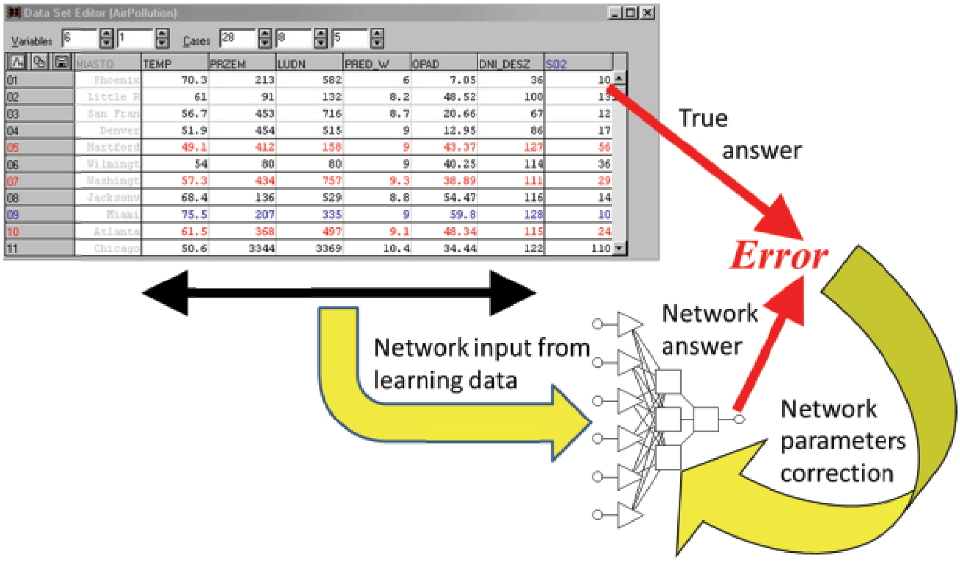

Fig. 5. General schema of the learning process

To answer this question, we introduce a kind of general classification of problems solved by means of computers (Fig. 6). The problem complexity level is represented by the abscissa coordinate. This axis is not scaled, because the exact measure of problem complexity can be a non-trivial problem in itself. However, there are surely easier problems (located in left part of the proposed coordinate system) and more complicated ones (located in its right part). The ordinate is connected with a more strange property of the problems being solved. This is the lack of prior knowledge about the rules governing the problem under consideration. The lower part

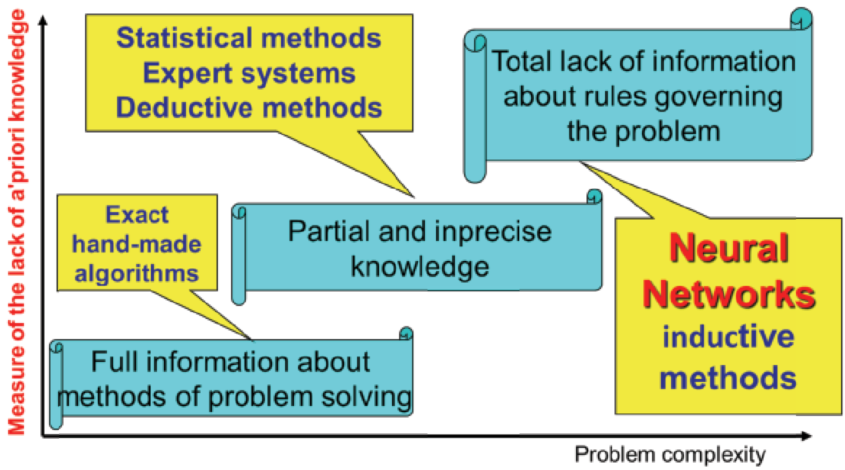

Fig. 6. Classification of problems solved by means of different computer methods

of the presented coordinate system is the location of problems, for which all rules are known. We know how the problem is formulated, and we can describe the precise method of its solving. The upper part is the location of problems, for which we cannot obtain any rules or any methods of problem solving. An example can be the forecasting problem. We believe that the future is determined by the present situation and the past – but nobody can give an exact formula for calculating this determined future.

Let us consider three types of problems, indicated in Fig. 6.

The left lower corner of the coordinate system shown in this figure belongs to easy problems, with limited complexity and full information about the methods that can be used for their solving. For such problems, exact hand-made algorithms can be used.

The central part of the chart is reserved for problems whose complexity is moderate and for which we do not have exact information about the exact rules governing the given problem, but we can use statistical methods or apply expert systems.

The last part of the chart belongs to really difficult problems with total lack of information about rules governing the problem. And the optimal methods for solving these problems are neural networks.

This result can be achieved, because neural networks (NN) are very effective modelling tools. Instead of searching for an algorithmic or statistical solution to the considered problem – we can build an NN **model**, train it using example data, and then use it for solving the said problem.

This approach can be used both for regression problems, when one or more variables (which we need) are dependent on several independent variables (which we know). Such an approach can be also used for solving classification problems, when one or more decisions (which we need) depends on several independent variables (which we know). All these results can be achieved because NN is a tool capable of modelling extremely complex functions. In particular, NNs can be non-linear, and the nonlinearity of NN models can be of an arbitrary form. Traditional methods for fitting nonlinear models suffer from the need to give an a priori, explicit definition of the form of model's non-linearity (e.g. polynomial, harmonic, exponential or logistic function), and the approximation methods can only fit the optimal parameters to the function form given by the user. On the other hand, NNs can model an arbitrary form of non-linearity during the learning process. Moreover, the optimal form of non-linearity is developed by an automatic machine learning process, without any interaction from the user. Neural networks also control the dimensionality problem, which hampers attempts to model non-linear functions with large numbers of variables. As a result, NNs are able to find an optimal set of variables, and attribute them with the proper parameters.

These properties of NNs make them an ideal tool for many purposes (Fig. 7). In this paper we try to compile a survey of NNs applications in mining sciences. We hope it will be useful for many researchers and practitioners who are searching for solutions to numerous problems related to mining sciences.

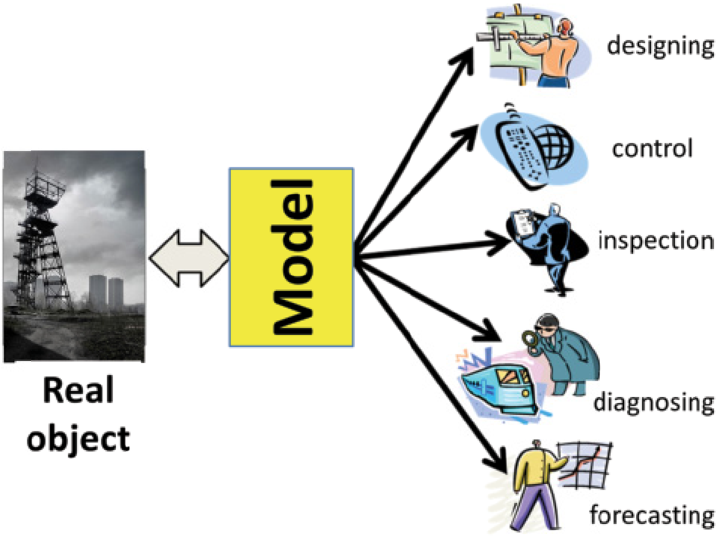

Fig. 7. Example applications of models build with neural networks

2. Example applications

2.1. Neural modeling of the oil mining process and reservoir properties

The most important applications of neural networks in mining sciences are those that describe neural modeling of the mining process, and can serve as a tool for decision making processes. Most models, similar to that presented in Fig. 1, are related to oil or gas mining, because drilling and oil pumping are relatively less complicated than exploitation of solid minerals. A typical example can be the paper (Wonseok-Lee et al., 2014), in which a technical screening guide system was developed using a neural network (NN) to assist in the selection of production methods, such as drilling, completion, and stimulation in a coalbed methane (CBM) reservoir. The NN used field data obtained from various CBM projects. To develop the system, a field database (similar to that presented in Fig. 4) was prepared, and a neural model was constructed. Based on the literature, the factors and ranges affecting the decision on CBM production methods were determined. The optimum system architecture was designed by conducting a sensitivity analysis with a training algorithm and a proper number of hidden neurons (see Fig. 3). The results obtained from the NN evaluation model indicated that the test was successful, yielding the correlation coefficient of 0.99. The system was also utilized to evaluate a field application in the North American basin, and positive results were obtained. They confirmed that the technical screening guide system can be successful in predicting a proper CBM production method.

Neural networks can be also used to predict physical properties of reservoir fluids. This is necessary for reservoir performance optimization, field development, and modeling of the numerous enhanced oil recovery processes. The widely used methods of statistical prediction work well, except for heavy oil. Therefore, the paper (Torabi et al., 2014) investigated an application of neural networks for prediction of viscosity, the formation volume factor, and the bubble point pressure of heavy oil. The results were very promising, and good agreement between the results of neural modeling and the experimental values was observed.

It is known that reservoir permeability (ability of porous rock to transmit fluids) is necessary for reservoir management and development. Neural networks, as shown in the paper (Ghiasi-Freez, 2012), can be used for integrating petrographic data and conventional logs, and can predict permeability. Petrographic image analysis was employed to measure optical porosity, pore types, pore morphologies, mineralogy, amount of cement, and type of texture. The available conventional log measurements included bulk density, neutron porosity, and natural gamma ray. Permeability was predicted using a neural network alone, and arranged in a committee intelligent system (CMIS). The results showed that CMIS performed better than NN models acting alone. The newest results in the same area can be found in the paper (Silva et al., 2015). This paper demonstrates petrographic classification of carbonate-siliciclastic rocks using a neural network. Elastic, mineralogical, and textural information from the well data was used as the network input, and the desired output was petrographic classification. The method was tested by means of well data sets for locations in the South Provence Basin, in the southwest of France. The testing accuracy suggests that neural networks offer an auxiliary tool for petrographic class identification.

Other research, also related to oil and gas permeability prediction, was described in the earlier papers (Fegh, 2013) and (Olatunji, 2013). The neural networks used and the results achieved were similar as in the later papers cited above. Therefore, they are not discussed here in detail, but the empirical results from simulation show a promising prospect for neural networks in the field of reservoir engineering, including in particular oil and gas exploration.

An analogous problem related to stripping gas rate during glycol dehydration is considered in the paper (Ghiasi et al., 2015). In that paper, a neural network is used for prediction of the optimum stripping gas flow rate in natural gas dehydration systems. Based on statistical analysis, an excellent match is noticed between the values obtained from the neural network as a predictive tool and the real data, so that the average absolute relative deviation percent is determined to be lower than 0.01%.

Similar research for air permeability prediction using neural networks (named a soft computing method) is reported in the paper (Nooruddin et al., 2014). The inputs to the models are air porosity, grain density, and Thomeer parameters obtained using mercury injection capillary pressure profiles. The target variable is corrected air permeability. A comparative study of some calculation methods showed that a neural network is the best model for such problems.

2.2. Identification of hydrocarbons layers

The next interesting neural network application – for identification of hydrocarbons layers on the basis of well log interpretation – is described in the paper (Dali Guo et al., 2014). As well log interpretation is one of the prime sources of information for deep lithology in drilling research, such an application of a neural model is especially interesting. The input selected for the network were parameters reflecting lithological, petrophysical and electrical responses, which are strongly related to reservoir fluids. The expected network output was identification of the fluids (water layers and oil or oil/water layers). Experiments conducted on well log data from the Eastern Junggar Basin (Permian Wutonggou Formation) showed the system's accuracy and effectiveness.

A very similar study of neural network use for interpretation and classification of well log data in terms of lithology is given in the paper (Konate' et al., 2015). The cited paper explored the application of a special type of neural network, so-called self-organizing map (SOM), for the classification of metamorphic rocks from Chinese Continental Scientific Drilling Main Hole log data. In the mentioned work, the total of 33 326 data points were taken into account, derived from resistivity, P-wave velocity, bulk density, photoelectric absorption capture cross section, gamma ray, potassium content and neutron logs. Such data were introduced as an input data to the neural network, which had to classify lithology in five categories: orthogneiss, paragneiss, eclogite, amphibolite and ultramafic rocks. The results showed that a neural network, also of the SOM type, could serve as helpful technology in drilling research. Similar results were reported in the paper (Aliouane et al., 2013). In that paper, SOM-type neural networks were used for lithofacies classification based on well log data. The authors tested five datasets used as inputs to the neural network, namely:

1. five raw parameters from well logs (hereafter referred to as data set 1), including: gamma ray, density, neutron porosity, photoelectric absorption coefficient and sonic well logs;
2. estimated Holder exponents, obtained using a continuous wavelet transform on data set 1;
3. data set 1 and three radioactive elements concentrations;
4. estimated Holder exponents of data set 1 and Holder exponents of radioactive elements concentrations;
5. estimated Holder exponents of data set 1 and the three logs of radioactive elements concentrations.

Research was based on two boreholes located in the Algerian Sahara, and showed that the best input to the network, giving the best lithofacies classification, was data set 5 above. A more general discussion of similar problems (mineral potential studies) can be found in the paper (Torppa & Nykanen, 2013). In that research, data from the Savukoski area in northern Finland was used. The size of the study area was 35 km × 35 km, and the data set comprised aeromagnetic and aeroelectromagnetic data, and till geochemistry. The usefulness of a SOM type neural network in such an application was proven once more, and such systems can be used as a robust tool in well test analysis.

Analogous considerations of a neural network application for mineral potential mapping were shown in the paper (Lee & Hyun Joo Oh, 2011). In that paper, gold-silver potential maps were generated by means of neural networks for the Taebaeksan mineral district, Korea. The neural model productivity for various training sets was assessed, and the estimate predictive accuracy of the potential maps was calculated, showing very good results.

Correspondingly, well logging while drilling can be aided by means of neural networks. The acoustic telemetry technology for well logging while drilling uses the elastic wave propagating along the drill string as a carrier to transmit downhole measurement data up to the ground. However, the acoustic signals used are polluted by the acoustic noises produced by drilling rigs and mud circulation, as well as attenuated during the propagation process. For proper interpretation of the noisy surface telemetry signal, neural networks can be used. This application is described in the paper (Wei-Zhang et al., 2014). In fact, in the cited paper, an efficient wavelet neural network classifier trained by an improved particle swarm optimizer algorithm was used, but the central point of that system was the neural network. Experiments showed that the system proposed by the authors can be used for an intelligent mapping between the original downhole data and the noisy surface data. The considered method was proven to have a good effect through practical application.

2.3. Evaluation of hydrocarbon reservoir characteristics

Not only permeability estimation, but also other features characterizing hydrocarbon reservoirs, such as fracture evaluation and formation anisotropy identification, have been predicted using neural networks. An example of such work can be the paper (Asoodeh et al., 2015). In that article, various types of neural networks, including a generalized regression neural network, a radial basis neural network, and a feed-forward backpropagation neural network, are used to predict Stoneley wave velocity (Vst) from conventional well log data. The proposed methodology was applied to the Asmari formation, which is the major carbonate reservoir rock of the Iranian southern oil field. A group of 1,640 data points was used to establish the neural network model, and a group of 800 data points was employed to assess the reliability of the constructed model. The results showed that neural networks can significantly improve the accuracy of the final prediction of Stoneley wave velocity.

A very similar problem of well logging evaluation in a volcaniclastic rock reservoir was considered in the paper (Wei Zheng & Xiuwen Mo, 2014). The authors complained that at present the accuracy of lithological discrimination of such rock reservoirs is very low because of their complex mineral composition and special lithology. In this situation, a neural network was applied to recognize lithology using the logging data of a volcaniclastic reservoir in the H basin, based on the layer-wise method of logging curves, which combines the intra-layer difference method with the clustering analysis method. The results of the considered application showed that the recognized lithology results were in good agreement with the result of core description. The coincidence rate of accuracy was more than 80%.

Another paper describing the use of neural networks for reservoir characterization refers to the process of quantitative assignment of reservoir properties by a network using all available field data. This research was described in the paper (Baijie-Wang et al., 2013). The paper uses fuzzy ranking (FR) and a neural network in the multilayer perceptron (MLP) form for reservoir characterization. FR can automatically identify a minimum subset of well log data as neural inputs, and the MLP is trained to learn the complex correlations from the selected well log data to a target reservoir property. FR guarantees the selection of the optimal subset of representative data from the whole well log data set for the characterization of a specific reservoir property, which implicitly improves the modeling and predication accuracy of the MLP. Three separate petroleum wells from southwestern Alberta, Canada, were used in the presented case study of reservoir porosity characterization. Experiments demonstrated that a neural network based method can generate reliable results.

The next problem of hydrocarbon reservoirs characterization solved by means of neural networks is predicting of the Bottom-Hole Flowing Pressure (BHFP) on an initially undersaturated reservoir. Typically, GHFP is calculated by means of a numerical reservoir model, but its use is connected with high computational costs and long processing time, because a reservoir model contains a large number of grids in its geological structure. Very good results were also reported in the paper (Li Yang et al., 2012), where the problem of oil-gas reservoir protection was solved by means of a neural network and a multi-expert system.

Another neural network application related to hydrocarbon reservoirs was described in the paper (Morshedi et al., 2014). A neural network was used there for modeling the increase in oil recovery caused by bacteria injection into an oil reservoir. The input data for the network were the reservoir temperature and the amount of water injected into the reservoir for enhancing oil recovery. Comparing experimental and simulation results, the authors showed that the neural networks had modeled this system properly, and that they could develop a proper model for the oil recovery factor in various conditions. A similar problem of neural network use for predictive modeling of chemical flooding in petroleum reservoirs was considered in the paper (Ahmadi, 2015). The considered problem is important both from the economical (net present value, NPV) and the technical point of view (recovery factor, RF). Thus, the proposed neural network model can be considered an effective tool for predicting the efficiency of chemical flooding in an oil reservoir when the required experimental data are not available or accessible.

A study demonstrating a great potential for the application of neural networks in petroleum reservoir characterization was also given in the paper (Jiuyong Li, 2013). The performance of the neural network model was evaluated using standard decision rules, and compared with those of a neural networks ensemble with the conventional Bootstrap Aggregation method and Random Forest. The results showed that the neural method outperformed the others with the highest correlation coefficient and the least errors. The achieved results were very good.

Moreover, general properties of oil and gas formation and behavior can be also predicted by neural network models. For example, the paper (Ghavipour et al., 2013) discussed an application of a neural network for hydrate formation prediction. In order to achieve an appropriate understanding of the gas hydrate behavior during formation and destabilization, series of laboratory experiments with six different gas mixtures were carried out, and more than 130 hydrate equilibrium points in the pressure range of about 450-3000 psia were recorded. Various methods of hydrate formation prediction were discussed, and finally the neural networks method was used. Authors ensure that the neural network method is a reliable technique for accurate prediction of hydrate formation conditions for generalized gas systems, and can be used in future automatic inhibitor dosing devices.

3. Conclusion

The selected papers presented above show that neural networks can be a very useful tool for solving many scientific and practical problems related to the mining industry. After searching for the examples discussed above we can assure that, despite their indisputable usefulness, neural networks are applied to mining problems only rarely. Taking into account the contents of databases with information about various applications of neural networks, we can roughly estimate that about 30% papers are related to pattern recognition, 20% are connected to signal and image processing, also 20% – to various engineering problems (excluding the problems related to mining engineering, counted separately), 20% papers serve medicine, biology and agriculture, and about 10% are dedicated to economic (financial) forecasting. In the above count, papers related to mining applications of neural networks can be estimated to account for 0.1% or less.

On the other hand, we can also estimate that among the papers discussing various scientific and practical problems related to the mining industry, less than 0.1% are papers where artificial neural networks are used.

However, the discussion presented in this paper shows that neural networks can be a useful tool for solving various mining-related problems, and the results achieved by means of this tool can be better than those obtained using other methods.

Therefore, the main conclusion of this paper is that neural networks should be used more often for solving problems originating from the mining industry and geological sciences. The examples shown in this paper are only a small sample of the relevant papers, but we hope they can be an inspiration for other researchers to take up similar issues in their future work.

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