Application of Neural-Fuzzy System in Prediction of Methane Hazard

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Abstract. In the paper there are presented possibilities of use of artificial intelligence to build predictive models based on the measurement data. Fundamental problems concerning fuzzy logic, neural network and ANFIS system were discussed. This system connects capability of representation and processing of fuzzy logic and capability of learning of neutral networks. The ANFIS interface has been characterized relating to training a fuzzy model of Sugeno type. An example of using its interface to predicting of methane hazard in the region of mined longwall was presented. Predictive model based on the real methane measurement data from this longwall was developed.

Keywords: Neuro-fuzzy systems · ANFIS interface · Prediction of methane-bearing capacity in a mine

1 Introduction

The artificial intelligence is an area of problems based on features specified for human intelligence. The algorithm mimics more or less these features; it is able to learn (by creating rules of reasoning) and next to act (generalization of knowledge, data classification and decision making). The fundamental problem of creating a model of an investigated phenomenon is its generation based on numeric data. One of the techniques of creation of a reasoning system is the ANFIS network [4] which is an adaptive system characterized by functionality of neural networks and fuzzy reasoning. The effective functioning of this algorithm allows us to determine the parameters of the model including an organization of its structure. The network just learned on the basis of historical data is able to predict future values.

Methane hazard is a very important issue with regard to safety in the Polish coal mines. This hazard consists in releasing methane from coal and rock deposits [1, 12]. Affecting the balance in strata caused by mining operations is the reason for methane releasing. A user's guide issued by the Central Mining Institute (GIG) describes the principles of longwall working under conditions of methane hazard. A value describing a working face area is its methane bearing capacity. This value is calculated on the basis of the averaged values of the measured methane concentrations and the air flow

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velocities (air flow volume streams). To characterize methane bearing capacity at the working face area the following concepts are defined:

– ventilation methane bearing capacity;
– absolute methane bearing capacity;
– criterial methane bearing capacity.

A value of the criterial methane bearing capacity may be a necessary condition for use of methane drainage or other methods to reduce methane emission into workings (e.g., air ducts) in case when the calculated value of the criterial methane bearing capacity is lower than the forecasted or the real one occurring during mining works at the working face area.

A subject matter of prediction of the methane hazard was discussed among others in [7–9]. With regard to method of data collecting being necessary for hazard assessment made by mining services (averaging the measuring results), the detailed data processing is characterized by a long delay. A current assessment of methane hazard concluded on the basis of analysis of a course of absolute methane-bearing capacity with reference to criterial methane-bearing capacity will allow us to control much better the ventilation parameters [11]. Thanks to use of Fuzzy Logic Toolbox library and ANFIS interface it is feasible to create a neuro-fuzzy network to be applied for prediction of value of methane-bearing capacity calculated on the basis of the parameters measured during mining operations carried out at a working face area.

2 Neuro-fuzzy Networks

2.1 Fuzzy Models

Fuzzy reasoning is generally used there where it is difficult to describe the investigated phenomenon by means of a mathematic model. A process of fuzzy reasoning is divided into three stages [11]. The first stage is fuzzifying which consists in computing a membership degree of input values to fuzzy sets. The second stage is an inference which is responsible for computing a resulting membership function on the basis of input values. The calculations are made with use of inference mechanism and base of rules. The third stage is a transformation of the resulting membership function into numeric value in the process of de-fuzzifying.

The most frequently used fuzzy models are:

1. Rule-based Mamdani-type fuzzy modelling defined so [10]:

$$R = \left\{ IF\ x_n = A_n,\ THEN\ y = B \right\}$$

   where: x_n – input linguistic variables; y – output linguistic variable; A_n, B – linguistic values.
2. Takagi–Sugeno (Sugeno) model – a connection of a model based on linguistic description with polynomial functions. The model includes a base of knowledge with the rules described as follows [10]:

$$R = \{IF\ x_n = A_n,\ THEN\ y = f(x_n)\}$$

where: x-$_n$ – input linguistic variables; A_n – premise value, $y = f(x_n)$ – function in conclusion of “i-rule”.

The fundamental difference between the Mamdani and Sugeno models consists in use of a function in rule conclusion (in Sugeno model). This improves considerably a computing performance of the system due to lower load for assessment of the output value of the system.

2.2 Neuro-fuzzy Systems

The artificial neural network is a system which operates on the basis of a human intelligence. Its aim is a modelling an input/output relationship [10]. The network consists of neurons which create the consecutive network layers. The output signals of the individual neurons are transferred to the neuron inputs of the next layer. The knowledge is recorded by means of the weights of each connection between the individual neurons. The weights are modified on the basis of examples in the learning process. The learned structure can associate the obtained knowledge and use it for replies to the states unprecedented before.

The operation of a neural network can be divided into a stage of learning and a normal operation. In the first stage the network defines the parameters necessary for its functioning according to requirements. In the normal stage the network solves the tasks on the basis of the knowledge obtained before.

The neuro-fuzzy systems are created by connection of artificial neural networks and fuzzy systems. The fuzzy model transforms into a neuro-fuzzy network. The weights of the network correspond with parameters of a membership function in premises and coefficients of polynomials in conclusions of rules of a fuzzy model. The first or zero degree polynomials are the most frequently polynomials used in rule conclusions (Sugeno model).

2.3 Creation of a Fuzzy System on the Basis of Numeric Data

In order to create a model representing a selected question it is first of all important to obtain knowledge required to organize a structure of a model. In fuzzy systems there are used two methods of obtaining knowledge. The first one is to obtain knowledge from an expert. A structure and parameters are determined arbitrarily on the basis of the expert’s knowledge. This approach may dubious due to difficulties referred to precise determination of parameters in case of a complicated representation. Therefore the frequently used solution is a creation of an initial model which is next precisely trained on the basis of the measuring data [10]. The second method is automatic getting data on the basis of numeric data. The effective running such algorithm allows us to determine the parameters of the system including the organization of its structure. It is also possible to connect this method with the expert’s knowledge. In this case a part of knowledge will be obtained from the expert and the next part from automatic selection of rules.

To create a fuzzy system it is necessary to aim at maximal simplification of a structure and base of rules. A complicated and extended base may not give satisfactory results at all. The training of this model may be difficult or simply impossible.

Clustering of measuring data consists in partition of a set of elements into subsets. Among fuzzy clustering methods one may distinguish: c-means Gustafson-Kessel method, a subtractive method and a clonal selection method [2]. The clustering methods can be used in the absence of a base of rules designed for creation of an initial model on the basis of a set of numeric data.

The final stage of selection of parameters of a fuzzy model can be its transformation into an equivalent multi-layer neural network. Such a network can be additionally subjected to the process of learning on the basis of a learning data set.

3 ANFIS

The ANFIS system is the abbreviation of the adaptive-network-based fuzzy inference system according to the Takagi–Sugeno model [6]. The system is equivalent to a neural network with four hidden layers.

The ANFIS network consists of the following layers [5, 10]:

1. input layer – distribution of the input signals; no calculations;
2. first hidden layer – calculating degrees of compliance of input values in premises of conditional rules;
3. second hidden layer – determination of a level of activation of every conditional rule for previously calculated values of degrees of compliance;
4. third hidden layer – calculating a standardized level of activation of every conditional rule;
5. fourth hidden layer – determining products of rule conclusions and standardized levels of activation of the rules;
6. output layer – determining the output value of the ANFIS network on the basis of the sum of the weighted signals from the previous layer.

The training of the ANFIS network consists in modification of parameters in order to obtain a set of conditional fuzzy rules. At the beginning of the process there are defined membership functions of fuzzy sets in premises of rules. The input data space is divided with use of a uniform grid distribution [10]. The disadvantage of this solution is a dependence of a number of rules on the space dimensions; this makes use of applications with many inputs difficult. After dividing the space there are obtained the initial values of parameters in rule premises.

A hybrid training method for a network consists in selection of values of parameters by means of various methods. In forward pass the algorithm determines the values of conclusion parameters by means of a recursive least-squares method. While in backward pass the error signals propagate backwards and the parameters of premises are selected by a modified gradient method [5].

The Fuzzy Logic Toolbox library [3] (a component of the MATLAB packet of MathWorks, Inc. Company) allows a generation of the ANFIS network. For that purpose it is used a graphic interface ANFIS Editor which makes a training process for artificial neural networks with regard to training of fuzzy models. Running the ANFIS algorithm consists in transformation of the Sugeno fuzzy model into a neuro-fuzzy network. The obtained this way structure consists of six layers. The weights of the network correspond to parameters of a membership functions in premises and coefficients of functions in conclusions of rules of a fuzzy model.

Creation of a model of the ANFIS network in the MATLAB environment requires the definition of an initial structure of the model. As the initial model subjected later to a process of learning it is the most often used the loaded Sugeno structure, i.e., the model created on the basis of partition of the input data space (grid partition) or use of subtractive clustering as well as fuzzy c-means [3].

A training of the structure begins with loading the learning, checking and testing data. After the data have been loaded the process of learning starts. The interface makes possible to determine a method of optimization (hybrid method, backward error propagation), number of periods, and tolerance error to define conditions to stop running the algorithm. After all parameters have been defined the process of training the network begins. In order to check learning efficiency it is necessary to load the testing data and to start the testing procedure.

4 Example of Creation and Training of Neuro-fuzzy Network with Use of the ANFIS Interface

This chapter presents an example of prediction of methane hazard with use of a neuro-fuzzy network. A set of numeric data has been obtained on the basis of the trials carried out at the working face area N-2 in “Pniówek” coal. This is a longwall with high methane-bearing capacity with active methane drainage operations. The longwall has been designed with “Y” type ventilation. The intake air has been ducted through the incline N-1 and next the main gate N-2. A part of the air from the incline N-1 has flowed through the main gate N-3 and then has connected with the return air from the longwall N-2. The return air has been exhausted from the longwall through the main gate N-3 and the raise N-3. The assumed criterial methane bearing capacity for the working face area was 12.76 m^3/min. To determine the criterial methane bearing capacity, it was assumed methane drainage efficiency at the level of 45%. As a result of calculations it was obtained a value of 23.2 m^3/min. A project of the longwall contained a notation that a value of criterial methane bearing capacity will be calculated every day on the basis of indications of sensors and quantity of the air will be regulated depending on the output and methane bearing capacity of the longwall. In case of differences among values of the forecasted and real methane bearing capacity, a ventilation service officer will take a decision to increase if needed a quantity of the air to be provided to the longwall and/ or to change a range of methane drainage works.

The numeric data set *METAN* was created on the basis of numeric data obtained as a result of the trials. The measurements were done in 14 days of a normal work of the longwall. The values of the criterial absolute methane-bearing capacity were calculated on the basis of the Instruction No. 17 (2004) developed by Central Mining Institute

(GIG) taking into account the parameters given in the project of the longwall. The methane-bearing capacity at the N-2 longwall area measured during the trials is shown in Fig. 1.

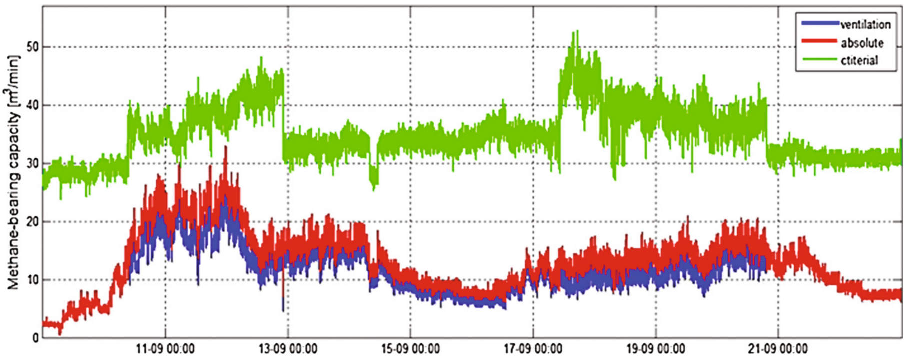

Fig. 1. Methane-bearing capacity at longwall N-2 area during trials

A task of the model is a prediction of methane hazard on the basis of estimation of the absolute methane-bearing capacity in relation to the criterial methane-bearing capacity. For test purpose it was defined a methane hazard rate which is a ratio of the absolute methane-bearing capacity to the criterial capacity. Depending on the value of the quotient it is determined a level of the hazard, where 0 means the highest level of safety, 1 – the real methane hazard which requires to take several steps in order to reduce methane content in the mine air. Figure 2 presents a methane hazard rate.

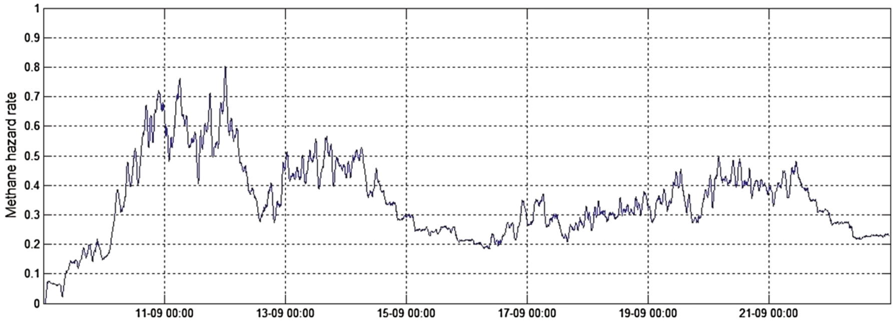

Fig. 2. Methane hazard rate during trials carried out at the working face area

The first stage of creation of a neuro-fuzzy model for prediction of methane hazard is a creation of the training and checking vectors of the time series. For purposes of tests there have been created the training vectors in the following form

$$w(t) = [\, x(t-60)\;\; x(t-40)\;\; x(t-20)\;\; x(t)\;\; x(t+20)\,] \tag{1}$$

where t – time of a current measurement, and t + Δ – times of measurements shifted by Δ [min].

The next step was a creation of an initial structure of a model on the basis of a grid partition of a numeric data set. A default number of bell membership functions (curves) of inputs of the model is 2, while at the outputs there are generated linear functions. The fuzzy model created in such a way was subjected to training with use of the ANFIS algorithm. The model has been transformed into a neuro-fuzzy network shown in Fig. 3.

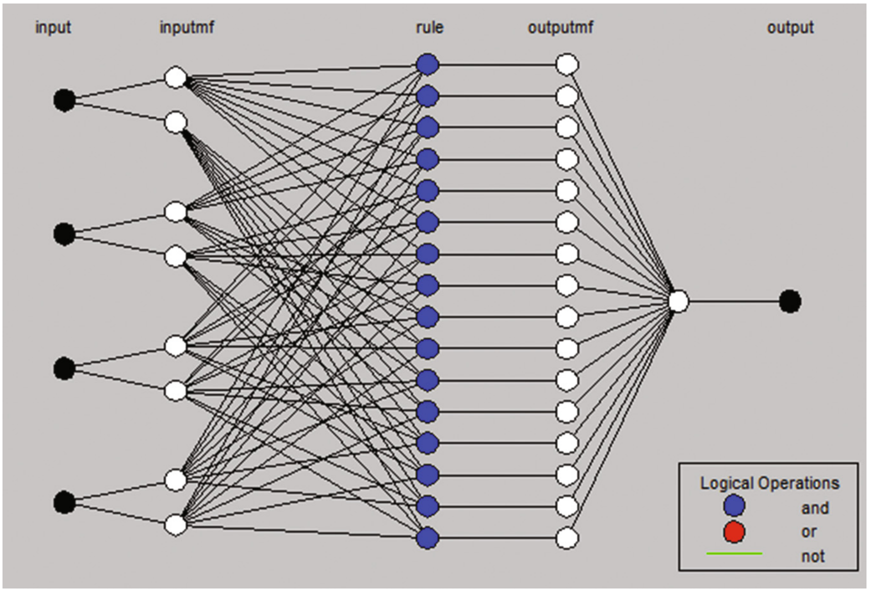

Fig. 3. Structure of a neuro-fuzzy network

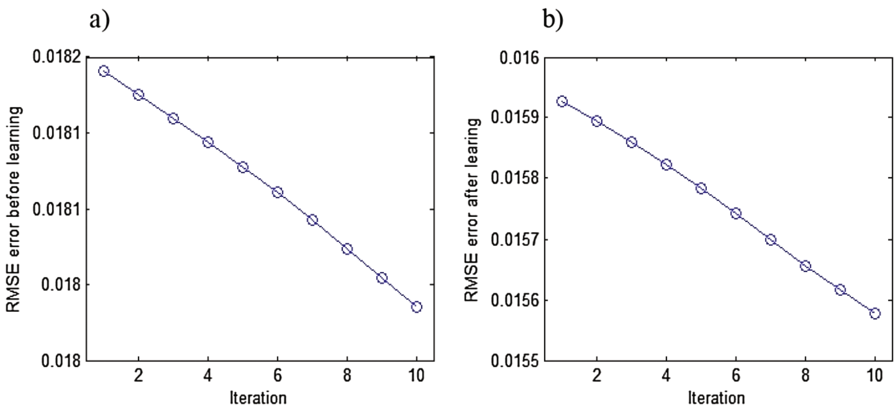

Fig. 4. Error of neuro-fuzzy network learning: (a) before learning; (b) after learning

In the training process of the network it has been used a hybrid method which is combination of the least-squares method and the backward error propagation method. Figure 4 shows the learning error of the network for further iterations of the training.

Figure 5 shows an exemplary inference of a neuro-fuzzy network. The way of inference for the created network is as follows. In the first place the outputs of the model are fuzzified by calculation of membership functions. The values are connected by means of a product creating this way levels of activation of every rule. The functions in conclusions of fuzzy rules are determined also on the basis of measurements. The final output value of the model is a weighted average of all elements of a rule base of the model. The weights are the levels of activation and the elements are the functions in rule conclusions.

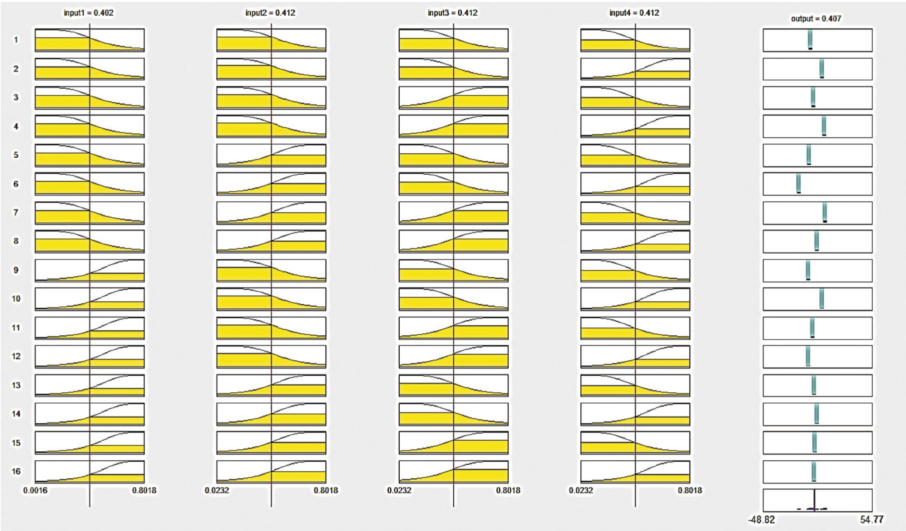

Fig. 5. Exemplary inference of the trained network

Figure 6 shows a prediction of a level of methane hazard at a working face area; Fig. 7 presents a prediction error. The trained neural network represents well a real time course; the average prediction error is 0.0114, and the maximum error is 0.0845.

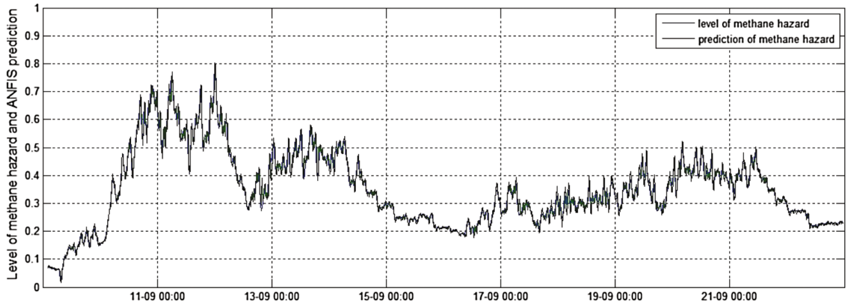

Fig. 6. Prediction of the neuro-fuzzy network

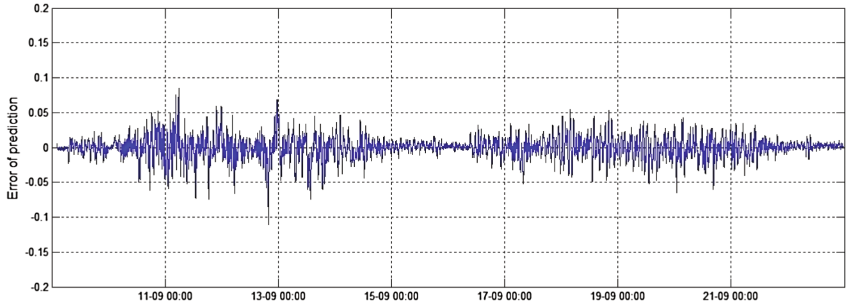

Fig. 7. Error of prediction

5 Summary

The paper presents the ANFIS interface in relations to use for creation and training of neuro-fuzzy models. A process of creation of the models is complex and depends on many factors such as selection of a method of input/output data space partition, a type of a fuzzy model and its parameters and also on numeric data themselves. A use of artificial intelligence methods gives great opportunities for creation of models representing the investigated phenomena on the basis of numeric data. It is possible to describe very complex phenomena. A description of them by mathematic functions would be difficult.

The paper shows an example of application of the ANFIS interface designed for prediction of methane hazard at a working face area during winning operations. With regard to method of data collecting being necessary for hazard assessment made by mining services, the detailed data processing is characterized by a long delay. It has been shown in the paper that a current assessment of methane hazard concluded on the basis of analysis of a course of absolute methane-bearing capacity with reference to criterial methane-bearing capacity may allow us to control much better the ventilation parameters in particular in situations of dynamic changes and when the limit values are exceeded.

A problem of safety in mining is a key issue. A prediction with use of a neuro-fuzzy network allows us to control on-line a level of methane hazard and to take appropriate action in case of occurring dangerous situations. Therefore these methods can usefully complement the conventional methods of acquiring knowledge.

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