Application of an artificial neural network to the prediction of firedamp emissions in coal mines

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Application of an Artificial Neural Network to the Prediction of Firedamp Emissions in Coal Mines

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ABSTRACT

Coal extraction at great depths and high output faces lead to more and more elevated and irregular firedamp emissions. To respect safety conditions, coal production must be programmed to limit methane emissions in airways.

In this context, the prediction of firedamp emissions is an interesting tool to optimize safety and production.

But mathematical modelling of firedamp desorption and gas circulation physical processes involve non-linear physical laws and a high number of hardly accessible parameters.

So artificial neural networks have been developed to model firedamp emissions : artificial neural networks as universal approximators are able to learn from examples and generalize in unknown situations.

Artificial neural networks need a large amount of data sufficiently representative to learn the physical processes. Data relative to mining ventilation, such as methane concentration and air velocity in airways, are monitored and can be used to model firedamp emissions.

The model based on artificial neural networks has been calibrated and validated using data from coal faces recently exploited in Lorraine Coalfield (East of France). The model reliability has been appreciated on the results of *a posteriori* forecasts.

The model is used to forecast methane concentration values in airways as a function of coal production.

1. INTRODUCTION

French colliery operations are now characterised by a considerable degree of mechanisation and high output faces. Also the increasing depths at which coal is extracted is bringing about a change in the characteristics of firedamp emissions : their levels are relatively high, with wide variations.

In this situation, mining operations must be continued with great care in order to optimise safety. The presence of high levels of firedamp in the air may restrict or interfere with output. The operator must therefore adapt production in order to ensure that the regulatory limits are not exceeded.

The ability to predict firedamp emissions can then be seen as a particularly attractive way of satisfying the safety requirements, as well as productivity goals, by making it possible to select production faces over time in the most appropriate way.

Methods for predicting firedamp emissions have already been developed in the past. However the early models used could do no more than predict average releases [JEGER, 1980], did not incorporate the effects of time and the rate of face advance, and could therefore not be used for monitoring fluctuations in emissions.

Later developments were based upon the routine statistical techniques of simple or multiple linear regression [POKRYSZKA Z., TAUZIEDE C., 1994 ; COUILLET J.-C., POKRYSZKA Z., 1996]. Although these models do take into account the dynamics of firedamp emissions and the local specific features of the working area as regards firedamp, they can unfortunately provide predictions only on a weekly basis.

In fact for predictions over a shorter period – a day or a shift – the problem is more complex, essentially owing to the nonlinearity of firedamp desorption and transport. And of course it is precisely this knowledge of the emission, at least on a daily basis, that would make it possible to programme the work more effectively.

In the same time, an higher performance modelling method has been identified as a particularly novel technique, that of artificial neural networks. A study was then carried out with a view to apply this technique to predict firedamp emissions at a longwall face.

This presentation of the research includes :

– a description of the principles underlying the technique of artificial neural networks ;

– a presentation of the major developments to optimise the prediction method ;

– and a practical application to a particular case.

2. BACKGROUND AND MAJOR ISSUES

2.1. POTENTIAL OF THE TECHNIQUE

The artificial neural network technique is a modelling tool that has already proved its worth in a number of fields (banking, military applications, meteorology, and so on) in dealing with problems as diverse as those concerning the prediction, classification or even the processing of the signal.

The advantages of this technique are its ability to reflect nonlinear relationships, to learn from examples, and also to describe the physical phenomenon to be modelled on the basis of a sample of data. Accordingly physical knowledge of the problem – usually expressed in terms of mathematical equations – is not essential for it to be modelled.

This also means that the technique shows considerable resistance to any perturbation of the basic data (for example, data that are partially erroneous or biased) and an ability to adapt to possible changes in the physical phenomenon.

On the other hand, the neural system must nonetheless satisfy certain requirements : among other things, there must be an adequate quantity of data relating to the physical phenomenon.

2.2. NEURAL NETWORKS AND FIREDAMP EMISSIONS

The mechanisms that govern firedamp desorption and gas circulation in the strata are such that it is complicated or even impossible to describe firedamp emissions in mines completely by means of a physical equation.

On the other hand, measurements relating to the coal extraction process and to the composition of the atmosphere are made frequently and regularly in existing mines. These measurements constitute a valuable database as to the history of the extraction zones and can be used to improve understanding of the phenomenon.

On this basis the technique of artificial neural networks proves to be a suitable tool for modelling firedamp emissions. Some foreign research [DIXON et al., 1995] on this topic, and feasibility studies on a number of French coalfaces have in fact confirmed this potential.

3. GENERAL FUNCTIONING OF ARTIFICIAL NEURAL NETWORKS

The first developments of artificial neural networks date from 1943 when a simplified mathematical model of the biological neuron was worked out [McCULLOTH W.S., PITTS W.A., 1943]. The first artificial networks were used in the 1960s, but then it was not until 1982 that the technique saw a resurgence of interest [HOPFIELD, 1982].

3.1. PROCESSING ELEMENT

The processing element reproduces the operation of the biological neuron in a simplified manner. Each neuron has a number of inputs, denoted e_i, from which an output denoted S is calculated.

In concrete terms, each input is weighted by a synaptic weighting factor denoted p_i whereupon an activation function then works out the weighted sum of these inputs : $\left(\sum_{i=1}^{n} p_i \cdot e_i\right)$

Finally, a nonlinear transfer function φ (a sigma function for example) calculates the output S as a function of the value of the activation function, or $S = \varphi\left(\sum_{i=1}^{n} p_i \cdot e_i\right)$.

3.2. NEURAL NETWORKS

To form a network, the neurons are connected to one another. In a conventional structure, the neurons are arranged in a series of layers in which there is respectively : an input layer, then one or more hidden layers and then an output layer. All the neurons in a given layer, except those in the last layer, are then connected to each neuron in the next layer (figure 1).

The input variables of the model are fed to the neurons in the input layer and the neurons in the output layer then provide certain values.

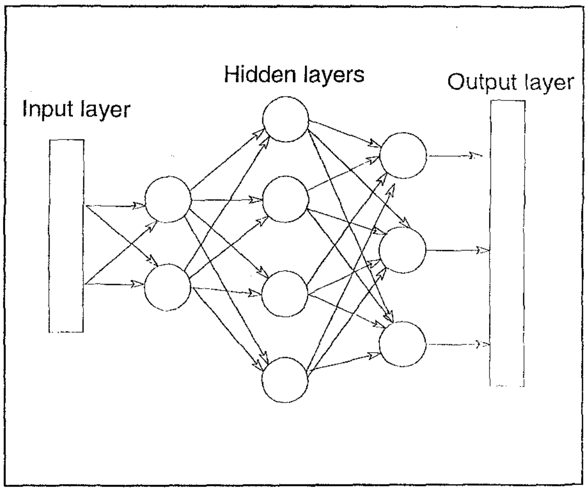

Figure 1 : neural network

3.3. LEARNING ABILITY

The modelling of the physical phenomenon by the neural network begins with a learning phase. Input vectors are presented a certain number of times to the network which then adjusts the weighting of each neuron in such a way that the calculated outputs are as close as possible to those required.

If the network is to perform well in the learning phase, it must also respond correctly when vectors it has never encountered before are presented. To check this fact, new vectors are introduced to the network. A result of good quality will then validate satisfactory learning by the network.

In this way the neural network expresses its ability to generalise : from a sample of the population, it can deduce the rule governing the entire population.

4. MODELLING FIREDAMP EMISSIONS

4.1. METHODOLOGY

Developing an artificial neural network is based primarily on determining :

- the model ;
- a neural structure adapted to the model defined and hence related to the architecture of the network. What has to be defined is the arrangement of neurons, the connections between the processing elements, the transfer function and the initial weighting factors.

The mechanism of firedamp emission involves a number of parameters such as the geological structure around the seam being worked, the gas concentration in the coal seams and rock strata, the CH_4 adsorption isotherm of the coal seams, the extent of degassing of the strata, the nature of the surrounding rocks, the permeability of the whole structure, and so on.

A great deal of research has shown that in steady-state firedamp releases, the quantity of firedamp released into a particular working area depends closely on the rate of coal extraction [BRUYET, 1967 ; BOROWSKI, 1969 ; KAFFANKE, 1980].

The approach using artificial neural networks also shows that it is preferable to make use of those variables that characterise the physical phenomenon being studied in the most basic form possible.

Accordingly the model was developed so as to relate the firedamp emissions to the face output, on the basis of the following three variables :

- the CH_4 concentration in the air return [%] and the air flow in the face airway [m^3/s], expressing the firedamp emission ;
- the distance travelled by the shearer during cutting at the face (m), reflecting the face extraction rate.

The neural network was therefore constructed using the following input and output variables, using :

- as output variable :
  - the mean methane concentration at a period located more or less far in the future
- as input variables :
  - the mean methane concentrations at periods in the past ;
  - the mean air flows at the past points and the predicted values at the future periods ;
  - the distances travelled by the shearer in the cutting phase at the passed periods and the predicted values at the future periods.

The developments then involve characterising these variables with regard to the physical phenomenon of firedamp emissions. For this purpose, several configurations were prepared and tested using data representative of the problem raised.

Ultimately a synthesis of these experiments should result in the definition of the best possible prediction model.

4.2. EXPERIMENTS

The experiments can be illustrated using the results obtained for the "Irma Nord" face 1140/1250 at the Reumaux mine. This face is undercut and the goaf is caved. The panel length is 1680 m for an average opening of 3.6 m. The ventilation follows a U pattern with an airflow of between 38 and 50 m^3/s. The face is worked on a 3 x 8-hour shift basis from Monday to Friday.

The changes in the different characteristic variables (CH_4 concentration, airflow and output) during working of the face is shown on figure 2 using a time interval of 8 hours.

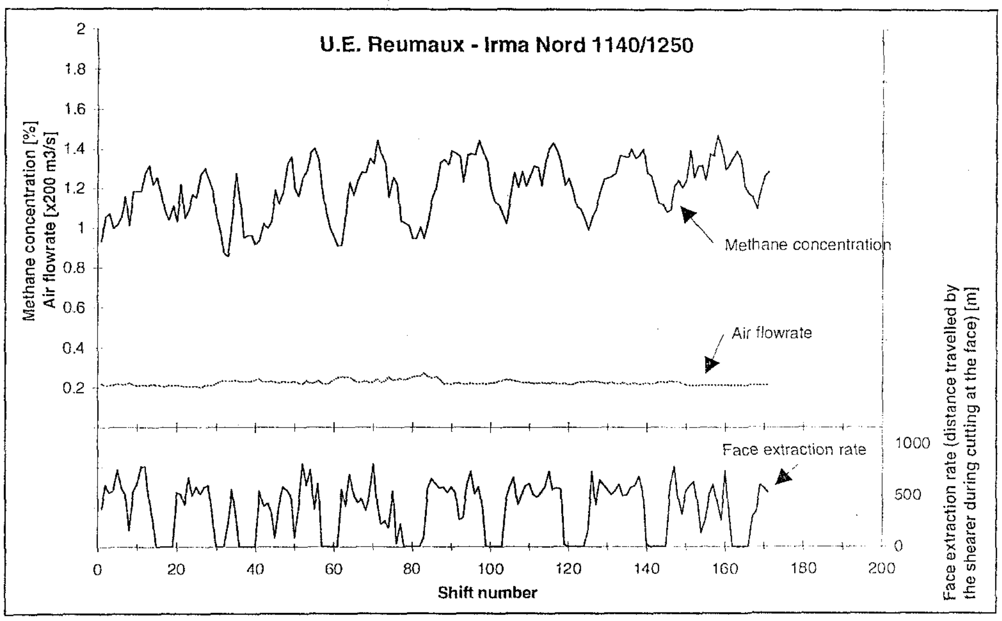

Figure 2: Changes in characteristic variables for the Irma Nord face 1140/1250 at the Reumaux colliery

Several models were developed and applied using data from the face studied.

The calculations showed first of all how important it was to have representative calibration data. The calibration database must be sufficiently extensive so as faithfully to represent the output at the face. Similarly, the results were mostly much better when the model was calibrated over the period as close as possible to the prediction period.

The experiments also demonstrated the need to construct the network carefully : a badly constructed network will in fact never be able to provide useful predictions, however relevant the variables.

Ultimately, an optimal configuration was devised, capable in particular of learning how to model unstable firedamp emissions (changes to the volume of influence, in the output rate, and so on).

The results given in figures 3 and 4 are from an optimal configuration of the neural network. These are *a posteriori* predictions, for which the values of CH_4 concentrations calculated by the model are compared with those actually measured at the face.

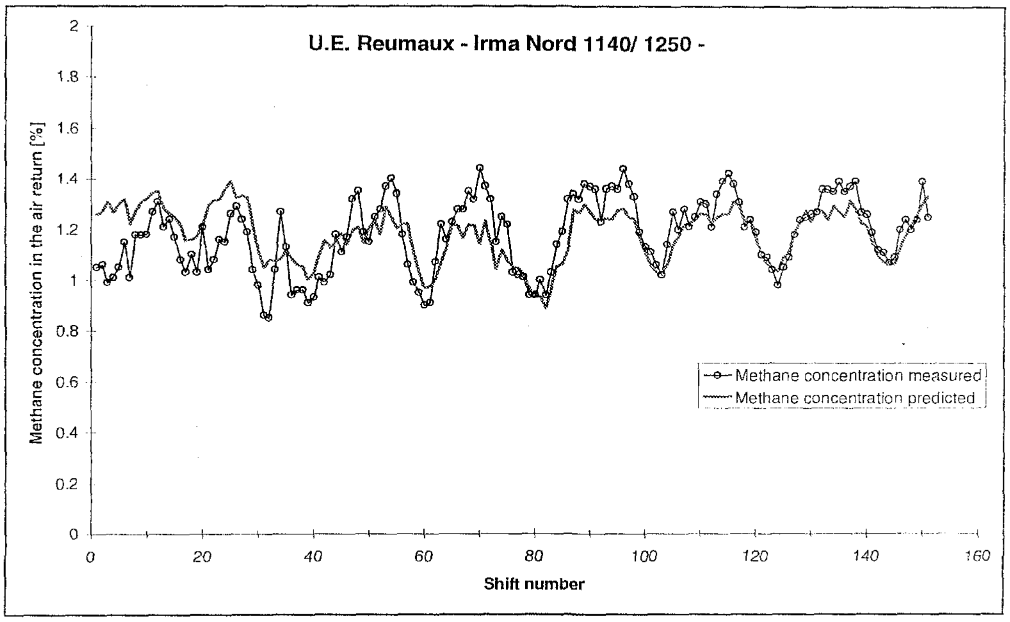

Figure 3 : Prediction of firedamp emissions (learning set)

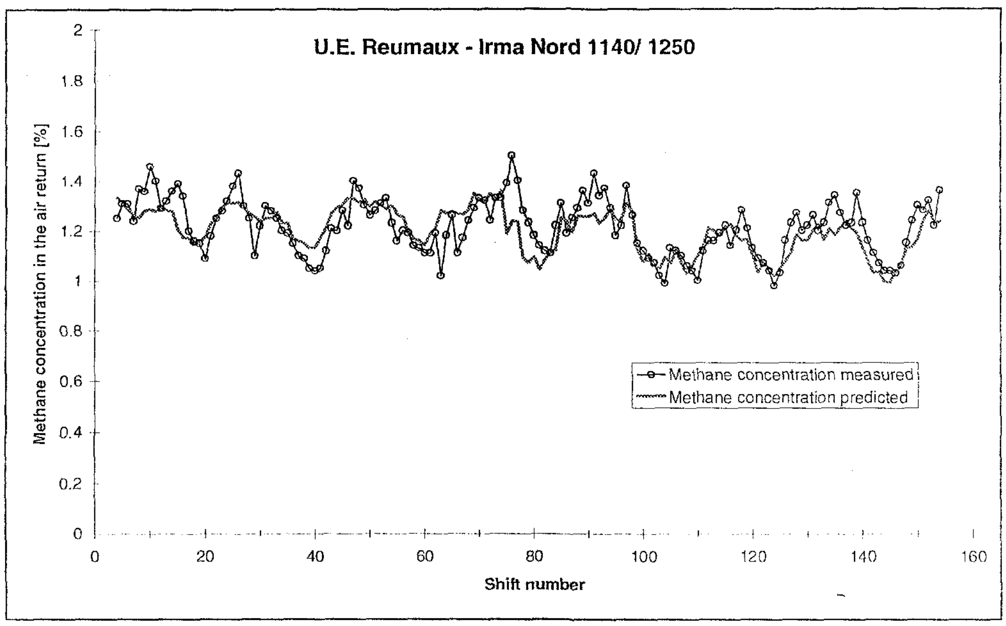

Figure 4 : Prediction of firedamp emissions (test set)

Quite apart from the overall shape of the above curves, the performance of the prediction can be evaluated using the coefficient of correlation between the predicted and measured values. For the calculations done for the Irma Nord face 1140/1250, this coefficient is sufficiently close to 1 for the results to be regarded as satisfactory. Its value is 0,69 for the test as a whole.

5. CONCLUSION

Application of the technique of artificial neural networks to predicting firedamp emissions at a coalface has clearly demonstrated the potential of this approach.

The model was developed with the aim of predicting values of methane concentration in the air return. These predictions are based on the past values of the methane concentration and on the past and future values of the other variables involved in the phenomenon considered (airflow at the face and face output).

The experiments clearly demonstrated the importance of the configuration of the neural network to the quality of the results. In fact the main difficulties arise in modelling unstable regimes of firedamp emissions (changes in the volume of influence, face output, and so on).

However the selected configuration learns these difficulties better than others. For modelling to be successful, the learning data must be representative. The results also show that the performance of the prediction is conditioned by an appropriate model of the neural network.

The model devised gives entirely satisfactory results and can be used to monitor ongoing faces in such a way as to permit improved programming of future production.

6. REFERENCES

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