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Keynote speaker **Vicki Barwick** Eurachem Chair; Head of Commercial Training, National Measurement Laboratory, United Kingdom **Ensuring the quality of analytical measurements – current support and future challenges**	184	189

Scientific Session: **Data Analytics, artificial intelligence techniques and machine learning for testing, diagnostics and inspection** *Chairperson:* **Prof. Lorenzo Ciani** Scientific secretary of the IMEKO TC10 on Testing, Diagnostics & Inspection University of Florence, Florence, Italy, School of Engineering, DINFO - Department of Information Engineering			
Makarewicz, G.; Bilski, P.	Diagnostics of the RIAA Equalizer in a Turntable Using Artificial Neural Network	190	195
Gaspari, A.; Natale, E.; D'Emilia, G.	Effect of Measurement Uncertainty on Artificial Vision Methods, for Quality Control on Composite Components	196	201
Bölkény, I.	AI Based Detection of Gas Hydrate Formation	202	207
Muravyov, S.; Khudonogova, L.; Ho Minh, D.	Precise Measurand Value Estimating by Interval Fusion with Preference Aggregation: Heteroscedasticity Case	208	213
Połok, B.; Bilski, P.	Diagnostics of the Ratchet Mechanism Using the Acoustic Analysis	214	219
Vasilijević, A.; Kapetanović, N; Mišković N.	Inspection of Submerged Structures	220	224

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AI Based Detection of Gas Hydrate Formation

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Abstract **– In the production process of natural gas one of the major problems is the formation of hydrate crystals creating hydrate plugs in the pipeline. The hydrate plugs increase production losses, because the removal of the plugs is a high cost, time consuming procedure. One of the solutions used to prevent hydrate formation is the injection of modern compositions to the gas flow, helping to dehydrate the gas. Dehydratation obviously means that the size of hydrate crystals does not increase. The substances used in low concentrations, have to be locally injected at the gas well sites. Inhibitor dosing depends on the amount of gas hydrate present. In the article two Artificial Neural Network (ANN)-based predictive detection solutions are presented. In both cases the goal is to predict hydrate formation. Data used come from two solutions. In the first one measurements were performed by a self-developed and -produced equipment (in this case, differential pressure was used as input). In the second solution data are used from the measurement system of a motorised chemical-injector device (pressure, temperature, quantity and type of inhibitor were used as inputs). Both systems are presented in the article.**

Keywords – Gas hydrate, Neural network, Hydrate detection, Injection System, Modelling Equipment.

I. INTRODUCTION

Natural gas hydrates are crystalline solids composed of water (host) and gas (guest). The guest molecules are trapped inside ice cavities, which are composed of hydrogen-bonded water molecules. Typical natural gas molecules include methane, ethane, propane and carbon dioxide. Hydrate particles can form ice-like hydrate-plugs that completely block the pipeline and can be up to several meters long. The number of hydrate molecules can increase to a level where the molecular agglomeration process begins, which can cause of plug formation in a given section of the pipeline. In worst cases the hydrate plugs result production outages [1, 2].

In the mid-1930s Hammerschmidt found out that natural gas hydrates can block gas transmission, especially at low temperatures. This discovery was pivotal and shortly thereafter led to the regulation of the water content in natural gas pipelines. The detection of hydrates in pipelines is a milestone marking the importance of hydrates to industry [3].

Gas wells are the cores of developing serious hydrate problems, because of the water content of the production. The cold zones of the ground can shift the temperature of the pipe and its contents into the hydrate-formation region. Hydrates start forming layers of water on the pipe walls. Crystallization can result in the formation of tens or hundreds of meters long plugs of hydrate [1, 4].

Multiple techniques exist to prevent the formation of hydrates. In the gas industry one of the most popular solutions is the use of thermodynamic inhibitors (THI) for a prolonged time. The injection of THI shifts the hydrate curve to a region where the conditions are not adequate for stable hydrate formation [2]. These compounds (methanol, ethylene glycol) have to be injected in high volume to the gas to be effective against hydrate formation. This is not a modern solution, because it has several disadvantages like cost of additional pipelines necessary to lead to the gas wells [5], the cost of methanol regeneration, which also contaminates the environment.

One of the newer alternatives is the injection of low-dosage hydrate inhibitors such as kinetic hydrate inhibitors (KHI) which can prevent the growth of hydrate molecules [6]. Antiagglomerants (AA) also belong to this group, they allow for the formation of gas hydrates but keep the hydrate crystals small and dispersed [7]. These modern, low-dosage inhibitors enable the usage of locally installed injection systems in the field, at the site of gas wells [8].

As can be seen, hydrate detection is key to administering the appropriate amount of inhibitor.

A. Objective and Methodology

The paper compares two approaches. In the first one, the formation of gas hydrate was studied in laboratory conditions. The gas hydrate formation can be determined from the pressure curve. Using the measurement results, a single ANN-based solution was created where the input is the differential pressure. In the second project, test measurements were performed with a field hydrate dosing and monitoring system. Using the measurement results, a multi-input ANN-based solution was developed, where the inputs are *pressure, temperature, quantity and quality of inhibitor* as these also influence hydrate formation.

In the first method measurements were performed by a self-developed and produced equipment. Modelling the equipment is suitable for the simulation of the gas flow in the pipeline. Its conditions are as follows: temperature is in the range of -20…+30 °C, and typical gas pipeline pressure is in 1-10 nl/min flow rate range. During the measurements different inhibitor materials and gases from all over Hungary were used, and the values of *differential pressure, inlet pressure, the gas temperature and the flow rate* of the pipeline were recorded, but only differential pressure was used to teach neural networks.

In the second approach data are used from the measurement system of a motorised chemicals-injector device, placed in the area of a well. This model was installed to test the equipment at the site of the SCADA Ltd, near Hajdúszoboszló in Hungary. The following parameters were monitored there: well siphon pressure, drill pipe pressure, injection pipe pressure, well pipe pressure, well pipe temperature, soil temperature, temperature of chemicals, controller temperature, inverter temperature, chemical tank liquid level, inverter current, voltage and frequency. Only well *pipe pressure (pressure), well pipe temperature (temperature) and inverter frequency (quantity of inhibitor) were used* to teach neural networks.

After the successful test of the technology model, the equipment was transported to a real gas well in Szeghalom (Hungary). In the research data generated through 29 test weeks were used. The gas well was monitored online (one sample per minute) in the 29-week testing period, during which several hydrate plugs formed due to the weather conditions.

The most important parameters of both approaches (equipment, inputs, outputs, ANN) are in Figure 1 and 2.

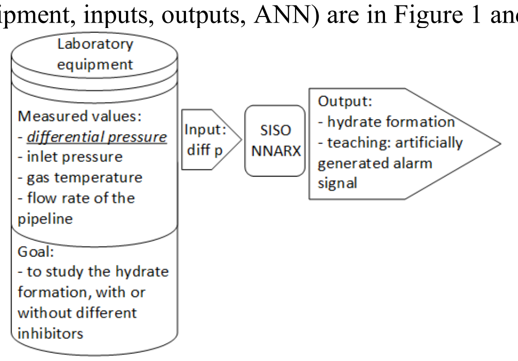

Fig. 1. The two compared project – first approach

The goal was to develop an accurate, stable and reliable ANN-based structure. Several architectures have been studied. Finally, the Neural Network Auto-Regressive X (NNARX) model with exogenous input is presented. [9].

Several independent data sets were needed for training networks. Previously selected raw data were scaled and normalized. The resulting data were used to generate three training, validation and test datasets for the networks

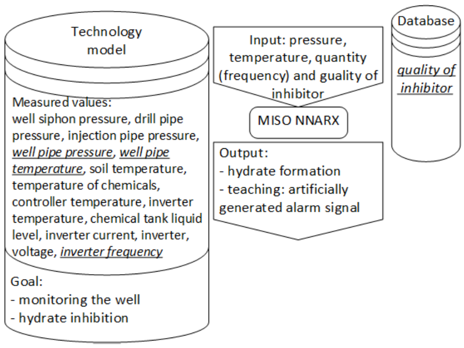

Fig. 2. The two compared project – second approach

B. Results

Final versions of ANN-based predictive detection solutions were selected after the extended comparison processes. For both approaches NNARX was used. In both cases several networks were trained using different datasets. For the first neural network based predictive detection solution twelve, while for the second five networks were compared and the best one is selected. In both cases a relatively small and simple networks resulted the best performance. Finally, two predictive solutions were compared.

II. RELATED RESULTS IN THE LITERATURE

Even though the injection of methanol into natural gas is not advised due to environmental concerns, such experiments can be found in the scientific literature. For example, in [10] French and English researchers reported that methanol was injected into the pipeline, in an environmentally not-so-friendly manner to prevent the formation of hydrates for gas extraction in the North Sea. The Karl Fischer method was used for injection. It is not the most appropriate approach, because it doesn't take salt content into account. As a result, new method was developed, by which the electrical conductivity and the sound propagation velocity can be measured in addition to the temperature and the pressure. Using these four parameters and the devised method, the methanol injection can be kept at an optimum. The paper published in 2013 in [11] also deals with optimising the methanol injection for the inhibition of hydrate formation in industrial processes. Authors stress the importance of the vapour state methanol, because it doesn't participate in the hydrate formation inhibition. To determine the quantity of inhibitor, two methods were introduced. The first one is a mathematical correlation from real data sets, the second one is based on ANN.

The problem of the accurate assessment of hydrate formation is discussed in [12]. Authors use the Katz gas-gravity method with the Ghiasi correlation [13]. The same model was used with the imperialist competitive algorithm [14]. The ANN was used to determine a kinetic model for the prediction of methane gas hydrate formation. The authors tried to determine the correct number of hidden neurons and layers. The ANN-based model takes the temperature and pressure as the inputs and the output is the hydrate growth speed. In [15] comparison was made between two methods for the inhibition of gas hydrate development. Both use ANN, in the second it is optimised with the imperialist competitive algorithm [16]. The outcome met expectations and proved that the normal neural network provides better results than the optimised one [16], [17].

III. DESCRIPTION OF THE PROPOSED METHOD

In this section, two systems providing the measurement data are presented. Also, predictive hydrate detection methods are introduced.

A. *Hydrate Forming Test Equipment*

In the first analysis measurements have been performed by a hydrate forming test machine developed for MOL plc. by the Department of Research Instrumentation and Informatics at the Research Institute of Applied Earth Sciences. Development of the control system was carried out by the author. (Fig. 3).

Fig. 3. Hydrate Forming Test Equipment

The modelling equipment is suitable for simulation of gas pipeline flow. The equipment creates field conditions within (-20 … 30) °C temperature range, and original gas pipeline pressure range, which is typically 60 bars. The flow rate value can be set in accordance to modelling principles, between 1-10 nl/min. The hydrate forms inside of a capillary cell which is placed in a thermostat. Fig. 4. shows the P&I (Piping and Instrumentation) Diagram of the equipment, where PT is the Pressure Transmitter, TT is Temperature Transmitter, FT is Flow Transmitter, GT is Gas Tank, PG is Pressure Gauge, TC is Temperature Control, TE is Temperature Element, VA is Valve, SP is Pressure Generator unit, DC and DR are separator cells.

Natural gas and interfacial water from a Szeghalom gas well (Hungary, near to Füzesgyarmat) were used in tests. Different inhibitor mixtures were also added.

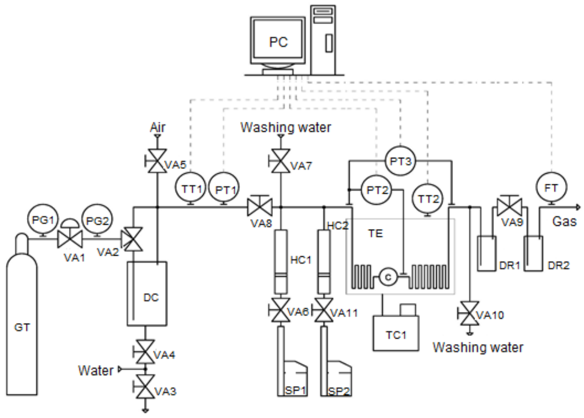

Fig. 4. P&I Diagram

Gas hydrate formation time was examined under gas well conditions (p, dp, T, Q), with or without the addition of different inhibitors. The following parameters were recorded: pressure, differential pressure, temperature and flow rate [18].

B. *Control and Chemical Dosing Equipment*

The well area control and the chemical injector equipment was installed on the Szeghalom-29 well in Füzesgyarmat (Fig. 5).

Fig. 5. Control and Chemical Dosing Equipment

The injection system is optimized mainly for Hungarian gas wells. Thus, the temperature requirement of the system was in the (-40°C … 60°C) range. The system must be capable of working in EX (EXplosive atmosphere) environment with high efficiency. The power source of the actuator is solar energy to reach the almost zero emission of the system [18]. Fig. 6. shows the P&I Diagram of the equipment, where PT is Pressure Transmitter, TT is Temperature Transmitter, LT is Level Transmitter and PI is Pressure Indicator.

The following parameters were recorded on a minute basis: well siphon pressure, drill pipe pressure, injection pipe pressure, well pipe pressure, well pipe temperature, soil temperature, temperature of chemicals, controller temperature, inverter temperature, chemical tank liquid level, inverter current, voltage and frequency [18]. *The output of the system is the inverter frequency. The frequency is proportional to the amount of administered inhibitor.*

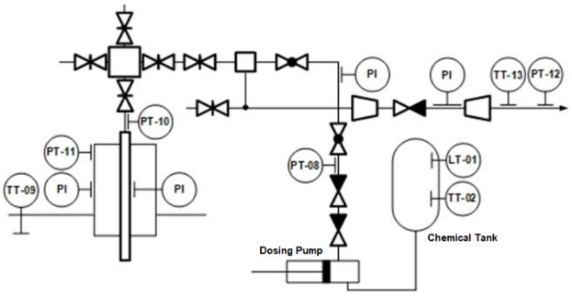

Fig. 6. P&I Diagram

C. Neural Network

For the identification the NNARX was used. [9]. This network creates a nonlinear model using its inputs. The applied regression machine complies with the following relation:

$$y_{est} = f\big[x(t-1), x(t-2), \dots, x(t-n_i), y_{req}(t-1), \dots, y_{req}(t-n_{ro})\big], \quad (1)$$

where $y_{est}(t)$ is the network output at the t^{th} time istant; *x(t-1)* is the used input of the network at *t-1*st time instant; $y_{req}(t-1)$ is the required output from the network at *t-1*st time instant; n_i is the size of used tapped delay line of the inputs; and n_{ro} is the size of used tapped delay line of the required outputs.

During the model selection, size of the regressor and the number of hidden neurons in hidden layers were changed. Based on the previous practical experience, the number of regressors was 1 or 2, while the number of hidden neurons was between 10 and 12.

The selected raw data has been preprocessed using the SciLab software. According to [19], preprocessing can consist in a simple transformation or a complex operation. The raw data were first filtered by a low-pass filter, then normalized. When normalizing the input data, the minimum and maximum values of each component are selected to cover the set of values and the interpretation range of the neural networks. This interval is typically [0; 1] and [-1; 1]. In the presented case, the [0; 1] interval was selected for normalization.

Three datasets were generated for the detection systems. The training set was needed to configure weights of the network. One of the most important parameter during the training process is the stopping criterion. If the training process stops too early, the network is not able to learn the data and gives poor estimation when an unknown dataset is used. To optimize the network the validation set is used. When Mean Squared Error (MSE) is the lowest, it is best to stop the training process of the network. The third, test dataset is independent from the training and validation sets. It is used to compare results for different networks.

Neural networks were trained using the generated datasets. To avoid overfitting, the training process was stopped at the minimum MSE value. The Levenberg-Marquard algorithm was used to optimize the ANN in Matlab.

D. Single Inputs Neural Network Based Detection

Large number of measurements was performed with the previously detailed hydrate forming test equipment using different inhibitor materials and gases from Szeghalom gas well. From this huge database 50 pieces were selected and used for the investigation. During measurements mainly values of differential pressure, inlet pressure and temperature of gas were saved for later investigation.

After the appearance of gas hydrate molecules in gas flow the pressure in pipe section was increasing because the agglomerated hydrate reduces the cross section area of the pipeline. Therefore fast gas hydrates detection is very important.

From practical perspective, the differential pressure gives the most valuable information about the processes in the tube. Thus this parameter was used as the input value of the alarm system.

As previously stated, three independent datasets have been created. In Table 1. the number of performed measurements and the number of datapoints included in the different datasets are shown. The scaled, normalized differential pressure value was used in datasets as input.

Table 1. Main Parameters of the datasets

Dataset	Number of performed measurements [pcs]	Number of data points [pcs]
Training dataset	26	2576
Validation dataset	10	1077
Test dataset	10	1698

The required output was an artificially generated alarm signal, which was created from the differential pressure values. The signal corresponds to the 75 percent of the maximum value (see Fig 7.)

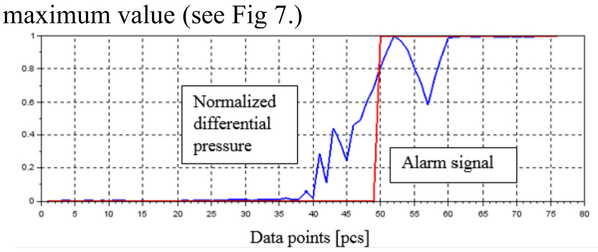

Fig. 7. Alarm signal (75%)

Until the actual differential pressure value is under the limit, the alarm signal is also zero. When it reaches the limit, the signal changes to one.

The single input NARX network is seen in Fig. 8, with the used regressor and the mapping function. In Fig 5. *y(t)* is the network output at the t^{th} time instant; *y(t-1..2)* is the network output at *t-1*st..*2*nd time instant; *x(t)* is the network inputs at the t^{th} time instant; $x(t-1..2)$ is the network input at t-$1^{st}..2^{nd}$ time instant; TDL is the tapped delay line, b is neuron bias, W is the weight matrix.

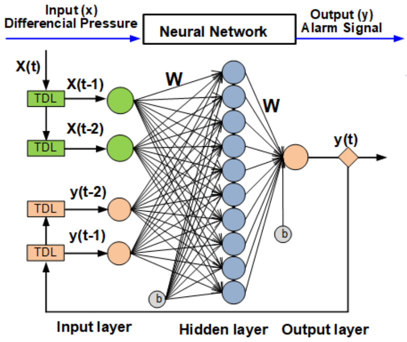

Fig. 8. Single Neural Network

E. Multi Input Neural Network Based Detection

The previously detailed control and chemical injection system has been operated in test mode for 29 weeks under continuous monitoring. Several parameters were monitored, but only three of them (well pipe pressure, well pipe temperature, quantity of inhibitor – inverter frequency) influenced the formation of hydration. The fourth parameter is the type of the applied inhibitor, which was recorded when the inhibitor was placed in the container. Demonstration of the effectiveness of each chemical in inhibiting hydration was performed with the previously described equipment. Depending on the inhibition ability of the inhibitors, they were graded on a scale of 4 to 1.

As previously mentioned, three independent datasets have been created: training-, validation- and test datasets. The main parameters of datasets are shown in the Table 2.

Table 2. Main Parameters of the datasets

Dataset	Number of performed measurements [pcs]	Number of data points [pcs]
Training dataset	22	2178
Validation dataset	12	1068
Test dataset	10	1080

The neural network has four inputs and one output, the four inputs are the four parameters listed above, and the output is an alarm signal.

IV. RESULTS AND DISCUSSIONS

Performance of the network is adequate if the required output (blue graph in Fig. 9) and the regular output (red graph on Fig. 9) match each other. MSE gives no satisfactory information about the performance, therefore, the number of edges in the sample sets were determined by rising edge (RE) method and then they were compared. If the edges matched each other it can be said that the alarm was at the proper time moment. A percentage value can be calculated (RE%) from the ratio of number of alarms occurred at proper time and number of total alarms [20].

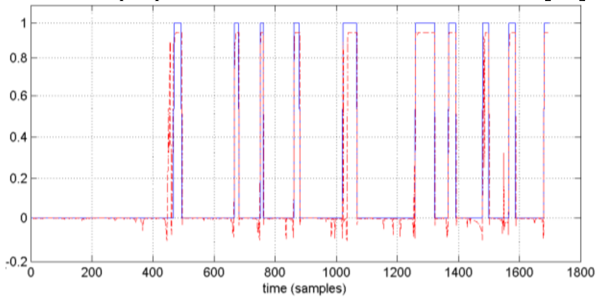

Fig. 9. Outputs match using test set

There are several methods, which can be used to find edges in one dimension. In this research the Canny edge detection method resulted the best calculation, in which the first Gaussian derivative is used to approximate the optimal finite length filter [21].

Results of both networks were compared, using the relative error of detected rising edges in the simulated output of the network and the required alarm signal. The comparison of the single input networks is summarized in Table 3.

Table 3. Results of Single Input Network

Regressor	Hidden neurons [pcs]	Training RE [%]	Validation RE [%]	Test RE [%]
$n_i = 1$; $n_{ro} = 1$	**10**	**96.2**	**100.0**	**90.0**
	12	96.0	100.0	90.0
$n_i = 1$; $n_{ro} = 2$	10	73.1	70.0	70.0
	12	73.1	80.0	90.0
$n_i = 2$; $n_{ro} = 2$	10	73.1	90.0	70.0
	12	69.2	50.0	60.0

The table shows that the network detected possible hydrate formation with more than 90% results. The best performance was provided by the smallest network. The comparison of the multi input networks can be found in Table 4. The table shows that the network recognized the possible hydrate formation with more than 92% results.

Table 4. Results of Multi Input Network

Regressor	H.neurons [pcs]	Training RE [%]	Validation RE [%]	Test RE [%]
$n_i = 1$; $n_{ro} = 1$	10	72.2	80.0	90.0
	12	95.2	90.0	90.0
$n_i = 1$; $n_{ro} = 2$	**10**	**99.8**	**100.0**	**92.2**
	12	95.2	100.0	91.2
$n_i = 2$; $n_{ro} = 2$	10	82.4	91.4	81.2
	12	81.2	90.7	80.2

V. CONCLUSIONS

There is no publication so far in scientific literature, which gives solution for hydrate formation prediction for industry exclusively from either the differential pressure or the inhibitor's quality and injected quantity.

The most effective results of the two presented projects are shown in Tables 3 and 4 in bold. For single input neural network, the smallest network provided the highest reliability in edge detection. In case of multi input neural network a larger regressor was the best. Both networks performed well, difference between the two results is not significant. Further studies are needed to assess which of the two methods is better.

VI. ACKNOWLEDGMENTS

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