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NEURAL MODELING BY DEEP LEARNING, PREDICTING THE OPERATION OF AN ECCENTRIC INJECTION PUMPS USED IN NATURAL GAS ODORIZATION

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Abstract: *The paper presents a predictive modeling in the operation of an odorizing pump operated with an eccentric mechanism, using a field of artificial intelligence (AI) called Deep Learning according to the parameters of flow and pressure in a piping system. natural gas transportation; odorization is necessary because natural gas is odorless, and in case of a leak in the transmission or distribution system for natural gas and if this oil spill is not detected, monitored, there is a danger of explosion, the worst danger being in urban areas.*
The operation of this pump with the eccentric using a DC motor without brushes, this motor being constructively adapted for a potentially explosive environment - according to the Ex zoning explosion described in stas SR 60079-10: 2016 through which the variation of the odorant flow injected into the pipe is determined. Using an application from the MATLAB program, more precisely an additional package of this program, Simulink, through which simulations of dynamic systems can be performed using mathematical models in order to optimize them, we will analyze the predictive operation of the injection pump. The neural model, which is implemented in the Deep Learning Toolbox software, and through a non-linear programming will predict the operation of this odorant pump used in the system of natural gas transmission pipelines. The controller, used in Simulink, will then model the control input that will optimize the operating performance of the eccentric injection pump in a defined time range.
Key words: *Artificial intelligence (AI), predictability, deep learning, Matlab, Simulink, artificial neural networks (NNA), odorization of natural gas, odorless, explosions, potentially explosive environment, pump with eccentric mechanism.*

1. NOTIONS OF ARTIFICIAL NEURAL NETWORKS AND DEEP LEARNING

The use of computer technology has contributed substantially to solving as accurately and quickly as possible the problems that humans face both in the activities they perform and in their habitat. Thus, the computer system and the variety of programs used by it have created, determined, the emergence of a new science "Artificial Intelligence" (AI), which through concepts of reasoning, deduction, induction, analogy applied in a field of the surrounding world can understand systems with specific human capabilities. Thus, by using AI, logical architectures can be created that behave perhaps similarly to human intelligence, [1].

According to scientists there are two somewhat different approaches to AI, the first, traditionally called symbolic AI, is characterized by a high level of abstraction and a macroscopic look and is called strong AI, the other approach is to a lower level, representing microscopic biological models, but also models inspired by psychology or genetics, this approach in AI is called weak artificial intelligence (weak AI), [2].

It is important to point out, from the beginning of this article, that artificial intelligence (AI) research has shown that this notion involves more than the ability to reason. Based on this observation, it has been shown over time that a well-composed software can simulate intelligent behavior only when it contains, in its algorithmic structure, a necessary and sufficient amount of knowledge to result in systems that learn new logical notions, which they can reason and deduce useful concepts in a field of the surrounding world. Thus, through the use of information processing algorithms, with multiple applications in technology, machine learning is a rather challenging field of the concept of artificial intelligence.

In other words, neural networks (NRs) should be shown to consist of a large number of simple and identical processing elements; these functional entities are similar to neurons in the human brain, and functionally they can be considered as a set of elements of nonlinear processing, which operate in parallel and which are connected to each other in structures resembling biological neural networks, [1]. Neural networks are also considered as a support hardware neural computation. Thus, a neural network is equivalent to one computer has as fundamental characteristic of the acquisition of knowledge, previous experience, and make it available for future use, [3].

Basically, the neural network works the same way as the human brain, but in a pragmatic way:

• Through the neural network knowledge is assimilated in a learning process;

• All knowledge is stored not in the processing units (neurons), but in the inter-neural connections;

• Neural networks can create their own organization or representation of the information received during learning, acquiring new knowledge

• Failure of a certain number of nodes or connections does not generally affect the behavior and performance of the network. High degree of robustness and fault tolerance, [1], [4].

Regarding the deep neural networks, with several hidden layers, it should be mentioned that through their different applications they are used in different fields of activity: psychology, education, technique, as well as neuroscience. However, applications through successful deep neural networks remain an extremely practiced art, full of many heuristics, rather than an exact science, [5]. This raises interesting challenges and opportunities for the theoretical sciences in creating a mature theory of deep neural networks, strong enough to guide a wide range of design options in engineering through deep learning. Thus, it can be said that we are not far from such a mature theory, and through a series of recently published works, at the intersection of statistical mechanics and deep learning, we were given theoretical information about how deep networks learn and calculate, sometimes describing new and improved methods for deep learning, [6].

In the case of multilayer neural networks, learning algorithms face two kinds of problems:

• specifying the desired output path of the neural network;

• the need to define a method of communicating information on errors that may occur to all connections.

Both problems can be avoided by a deep learning algorithm.

Thus, we can quantify this goal by imagining a communication in which each vector of raw sensory inputs is communicated to a receptor with neural structure which in turn by responses (iterations) selects important output sizes and then sending the difference between input and output size, purpose learning is to minimize input size information, [7].

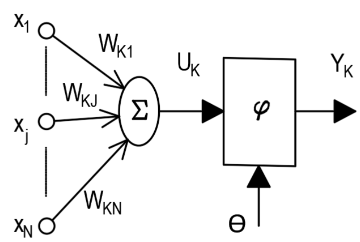

Fig. 1. The artificial neuron (NA), [3].

By presenting the model of artificial neuron, considered as an elementary processor (node), the main component parts are described, as well as the logical operation of a biological neuron. Model NA presented in figure 1. was composed by McCulloch-Pills in 1943 is the most widespread and used as a way to analyze the functioning of a neuron, [3].

As component parts, NA includes a number of inputs, specifying that each of them is characterized by its own synaptic weight. Thus, the signal x_j at the input of the synapse "j" is connected to the neuron "k" by multiplication with the weight W_{kj} (fig. 1) Another component shown in the figure is the adder for summing the weighted inputs, and the result of the summation is called net input u_k:

$$u_k = \sum_{j=1}^{N} W_{kj} \cdot X_J \quad (1)$$

To limit the amplitude of the output signal of the neuron it is provided with an activation function, φ,[3]:

$$y_k = \varphi(u_k - \theta_k) = \varphi(u_k + b_k) \quad (2)$$

where: θ_k represents the value of the trigger threshold of the neuron.

In some situations, the net input is increased by the term b_k called the scale shift factor (bias), and the scale shift is the negative of the activation threshold,[3].

Activation potential:

$$v_k = u_k - \theta_k \quad (3)$$

It should be noted that the type of activation function is generally a nonlinear function, the present paper does not propose an approach to this NNA classification and / or presentation in more detail, as we will present an RN application using the MATLAB environment to perform a running prediction (MPC) of an injection pump with eccentric mechanism. About the skills needed to solve a problem through Deep Learning, it should be noted that this application of AI uses a technique called deep neural network, which improves both the prediction in operation and the amplification of the smallest models resulting from existing data. These networks have multiple layers of "computational nodes" that work together to analyze and process existing data and, respectively, to obtain the final result in the form of a prediction, [2].

Basically, this technique tries to replicate, up to a point, the way the brain works. These nodes are neurons, and their connection to each other is compared to the neural interconnection in the brain. The one who can be called the founder of this concept of deep learning in the literature is considered Geoffrey Hinton, who in 1986 published a paper with two other colleagues, David Rumelhart and Ronald Williams, in which he describes a technique called " backpropagation ", [7].

2. NATURAL GAS ODORING, FROM TRANSPORT NETWORKS, USING AN ECCENTRIC MECHANISM PUMP

In order to odorize natural gas, hydrocarbons are used, considered by the literature, almost odorless or smelly, this situation highlights the obligation of technical and organizational measures, by distribution companies, to prevent explosions in case of accidental emissions of on the itinerary of the pipeline networks in the urban landscape and not only. Thus, by odorizing the natural gas, one can notice the lack of tightness of the tubular material or any corrosion, crack or damage, through which the distribution to consumers is made. Basically, this addition of odorant, in well-established quantities, in the volumes of gases transported, distributed through pipes, reduces the risk of explosion, thus eliminating the danger of loss of life, but also the destruction of buildings, buildings and environmental damage. Any such event creates beyond the above and a discontinuity, interruption in the supply of hydrocarbons to consumers and hence large financial losses or even bankruptcy of some natural gas distribution companies, [8].

Odorizing substances that meet the conditions of odorants are organic combinations with sulfur, called thiols (mercaptans) and thioethers. It should be noted that thiols have the highest odorizing capacity.

As an important observation, we emphasize that normal thiols, due to their acyclic structure, have a low chemical stability which leads, in the case of steel pipes, to a reaction of the odorant with iron oxide - as a catalyst -, which results in oxidation mercaptan and the odorizing effect diminishes, [9].

In accordance with those presented, an odorant must meet the following conditions:

• have a strong unpleasant and distinct odor so as not to be confused with other common odors;

• have a low limit of olfactory perceptibility, and be perceptible at the lowest possible concentration in the gas;

• to present a good chemical and thermal stability during storage and odorization in order not to react with the gas components and not to deposit on the transport pipe;

• to present a high volatility in order not to condense neither at low temperatures nor at high pressures, to be able to be used at temperatures of minimum -5˚C;

• show a variation of the boiling point in a narrow temperature range and the evaporation is complete;

• be non-corrosive;

• to burn completely with gas without emissions of toxic substances;

• to be as little adsorbed as possible by pipes, installations or soil;

• not to emboss the sealing materials of the pipes and fittings on the distribution network;

• be available on an industrial scale and not be expensive, [10].

The required quantity of odorant, which must be dosed in a volume of gas, must have the effect of reaching the limit of odor perception, this being the necessary condition to avoid the danger of explosion before mixing the gas with air, in a given volume, to reach the lower explosion limit, [11]. Based on these conditions, the calculation of the minimum concentration of the odorant is based on the constant "K" which represents the value of the concentration of the odorant in the air to reach the stage of odor perception. The values of this constant are different depending on the type of odorant used.

Table 1

K constant values for the most common odorizing agents, [8]

No crt	Odorizing agent	Value K, g agent /m³ N air
1.	Tetrahydrothiophene (THT)	0,009
2.	Tertiarybutylmercaptan (TBM)	0,008
3.	Ethylmercaptan (EM)	0,008

Because the present paper aims at the neural modeling, by automatic learning, of an injection pump with eccentric mechanism we will not insist on the use of odorants in the process of distributing natural gas to consumers, but we will refer to some reference parameters on which we will use in the IA application, using the MATLAB, [12].

The calculation of the quantity of air freshener taken by 1 kg of natural gas is determined with the relation:

$$x = \frac{M_v}{M_g} \cdot \frac{\rho P_{sat}}{P - \rho P_{sat}} \qquad (3)$$

Where:

x = kg steam / kg dry gas;

M_g, M_v = molar masses of gas and vapor;

ρ = relative humidity of the gas;

P = total vapor and gas mixture pressure, in mm Hg (Kgf / cm^2) or (N / m^2);

P_{sat}= saturated vapor pressure at P and t (Kgf / cm^2) or (N / m^2), [8].

Thus, the calculation is made considering ethyl mercaptan (CH3-CH2-SH) as an odorant, using the relation 3 respecting the following conditions:

ρ = 1, when natural gas is saturated;

P_{sat} will be taken at a temperature of 20º C,

P_{sat} = 440 (mm Hg);

P, the total pressure will be considered 1.5 (bar), and in (mm Hg) is, P = 1140 (mm Hg);

Molar mass for ethyl mercaptan, M_v = 62,13 Kg/Kmol;

Molar mass of natural gas, M_g= 16 (kg/ Kmo)

Replacing in the relationship (2.1):

$$x = \frac{62{,}13}{16} \cdot \frac{1 \cdot 440}{1140 - 1 \cdot 440} = 2{,}44 \frac{Kgf}{kg} \text{ dry gas} \qquad (4)$$

Then, determine the amount of ethylmercaptan that takes 1 m^3 of natural gas, thus, knowing that the density of natural gas is ≈0.71 (kg / m^3) you can get 16 (kg) of natural gas that occupies a volume of 22.4 (m^3), and from here and using the result of the relation (4) it results that 1 m^3 of natural gas can take 1.74 kg of ethylmercaptan.

In order to achieve the required odorant concentration required, according to Table 1, it follows that 1.74 (kg0 of ethylmercaptan can provide odorization at a volume of 217 500 (m^3) of natural gas delivered.

We will use this data to create a predictive simulation in the operation of an injection pump, with eccentric mechanism, for the odorant, the aim being to create an industrial application, more precisely in the transport and distribution of natural gas, using artificial intelligence. The prediction is based on the analysis of a history of the periods of variation of natural gas flows in the process of delivery to consumers, [13].

3. NEURAL MODELING, BY DEEP LEARNING, FOR THE PREDICTION IN OPERATION OF AN ECCENTRIC INJECTION PUMP USED TO SMELL NATURAL GAS

Using in an application way the Deep Learning Toolbox software from Math Works, we will define a predictive controller model, through a neural network, in order to perform an analysis in operation, for a defined period of time, for a pump with mechanism eccentric, to predictively perform the injection of odorant into a natural gas transmission pipeline. Basically, this application uses a neural network model with nonlinear processing units, in order to anticipate the optimal operation of the odorant injection pump, fig. 2.

The controller then manages the control input that will optimize the performance of the installation in a specified future time horizon.

The first step in predictive model control is to determine the neural network model and identify the system. Next, the installation model is used by neural network NN predictive controller applied from Simulink library, and the errors resulting from both the defined neural network and the injection equipment (pump) represent the set of information with which to anticipate, optimize operation in a horizon definite time.

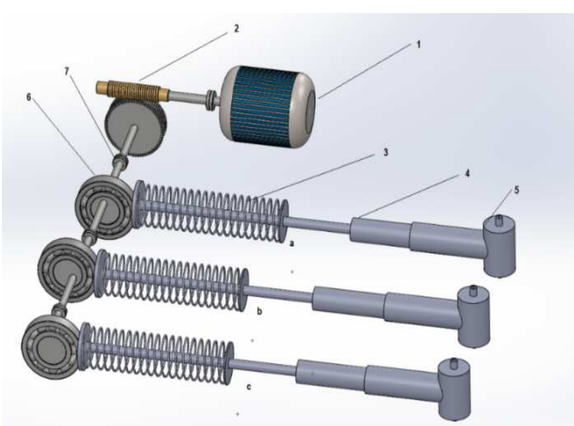

Fig. 2. Odor pump with eccentric mechanisms, [10].

1-brushless DC electric motor; 2- worm-wheel worm reducer; 3-helical spring and plates mounted rigidly in the same plane; 4-pump piston; 5- odor pump (shaft with eccentric mechanism drives three odor pumps to which different piston diameters can be adapted to ensure three distinct odorant flows; 6- eccentric mechanism (using ball bearings); 7-couplings.

By schematically describing the process of identifying the system we have compiled, we will be able to compile a model for optimizing the operation process. How to use the predictive control block for the odorization installation will be visualized, analyzed and simulated by the model that is implemented in the Simulink®. [12].

The main stage of organizing predictive control through deep learning is the formation of a neural network that represents the dynamics of the future operation of the odor system. Regarding the prediction error between the parametric quantities at the outlet of the odorant injection pump and the outlet of the neural network NN, it is considered as input quantities of the neural network, this schematic operation is shown in figure 3.

Using statistical data, recorded from a previous time, when the injection pump for odorant operated to provide the required amounts of odorant (concentrations of ethyl mercaptan), depending on the flow of natural gas delivered to consumers, we can anticipate its operation. Thus, through the formation algorithms used in the superficial multilayer neural networks, as well as in the backpropagation formation in the NN, it will be possible to predict the operation of the odorizing installation.

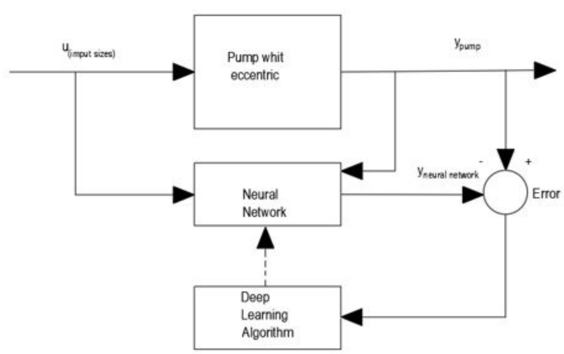

Fig. 3. Model of the predictive control process for NN

The type adopted by the neural network NN explains the behavior of the odorant injection pump within a specified time horizon. The predictions are made by a numerical optimization software in order to determine the control signal on the considered horizon.
Operating performance is described by the equation, [12]:

$$J = \sum_{J=N_1}^{N_2} (y_r(t+j) - y_{rn}(t+j))^2 +$$
$$+\rho \sum_{j}^{N_u} (u'(t+j-1) - u'(t+j-2))^2 \quad (4)$$

Where:
-N_1, N_2 and Nu are the horizons over which the tracking error and control increases are evaluated;
- u ′ is the tentative control signal;
- y_r is the expected response;
- y_{rn} is the answer of the neural model;
- ρ the contribution that the sum of the squares of the control increments has on the performance index.

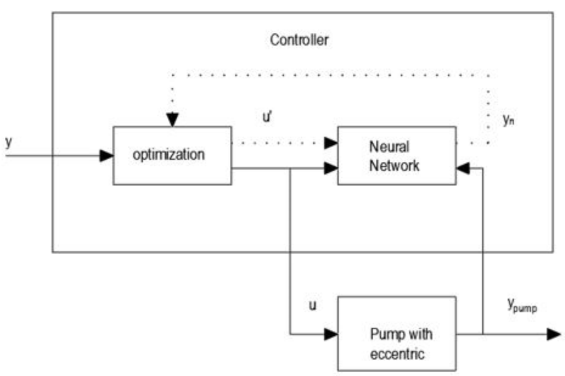

Fig. 4. Predictive control of the injection pump

3.1. Applying a predictive controller model using Matlab Deep Learning Toolbox software in order to predict pump operation.

The objective of the predictive controller is to maintain the product concentration by adjusting the flow rate Q_1 (t). The level of the tank h(t) is not considered to be monitored by this simulation, as these quantities are considered to exist.

Thus, in order to organize the simulation we will consider a natural gas flow, delivered to consumers, of 67708 (m^3/ h), thus registering a delivered gas flow Q_2 = 3250000 (m^3 / 48h); the concentration of ethylmercaptan C_2 = 0.000008 (kg/m^3) and respectively C_1 = 26 (kg) / 3250000 (m^3).

$$\frac{dh(t)}{dt} = Q_1(t) + Q_2(t) - 0{,}2\sqrt{h(t)} \quad (5)$$

$$\frac{dC(t)}{dt} = \left(C_1 - C(t)\right)\frac{Q_1(t)}{h(t)} +$$
$$+(C_2 - C(t)\frac{Q_2}{h(t)} - \frac{k_1 C(t)}{(1 + k_2 C(t))^2} \quad (6)$$

where h (t) is the level of the odorant, C (t) is the concentration of odorant at the outlet of the injector head of the pump, Q_1 (t) is the flow rate considered at the concentration C_1, and Q_2 (t) is the reference flow, subunit, necessary to ensure the minimum concentration C_2, and to simplify the modeling Q_2 (t) equal to 0,1 (m^3 / h) will be adopted. Input concentrations are set at C1 = 26 (kg) and C_2 = 0.008 · 10-3 (kg). As for the associated constants in the Simulink model, they will be adopted for the odorant consumption rate: k_1 = 1 and k_2 = 1.

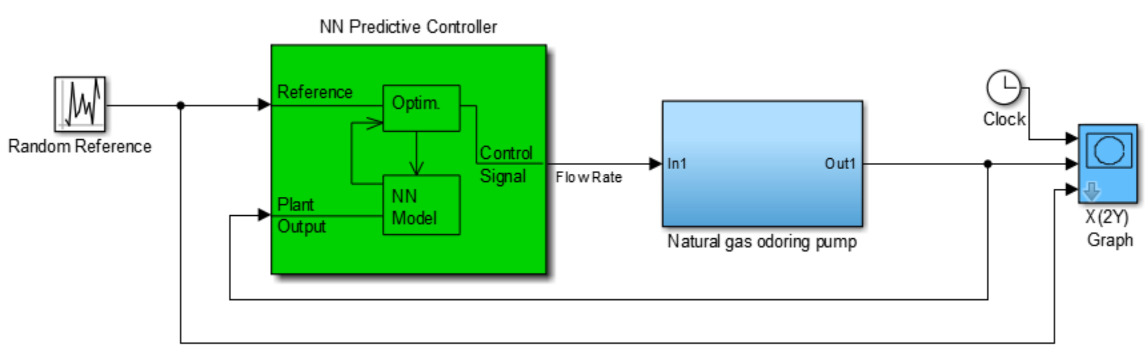

Fig. 5. Simulink model for neural control of odor pump operation

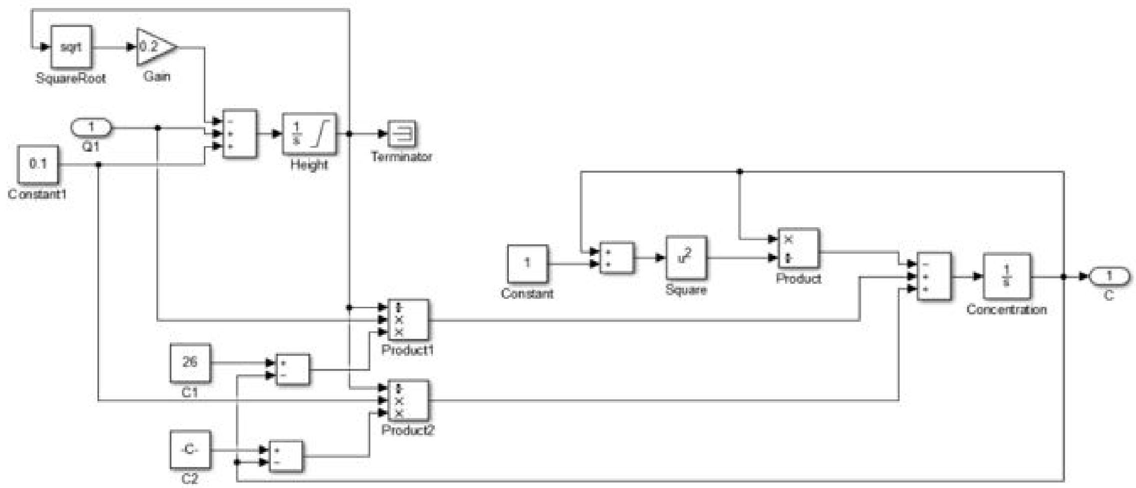

Fig. 6. Simulink model for neural control of odor pump operation

Through the graph presented with brown line in fig 10 this is the reference built on the information scheduled for a time horizon in the future, and through the blue line is marked the predictive operation of the pump. So, depending on the time, the output sizes of the pump operation try to copy the predicted model in a random form, and by modifying the optimization algorithm this process can be done faster or slower, the controller model was selected from the Simulink Matlab library.

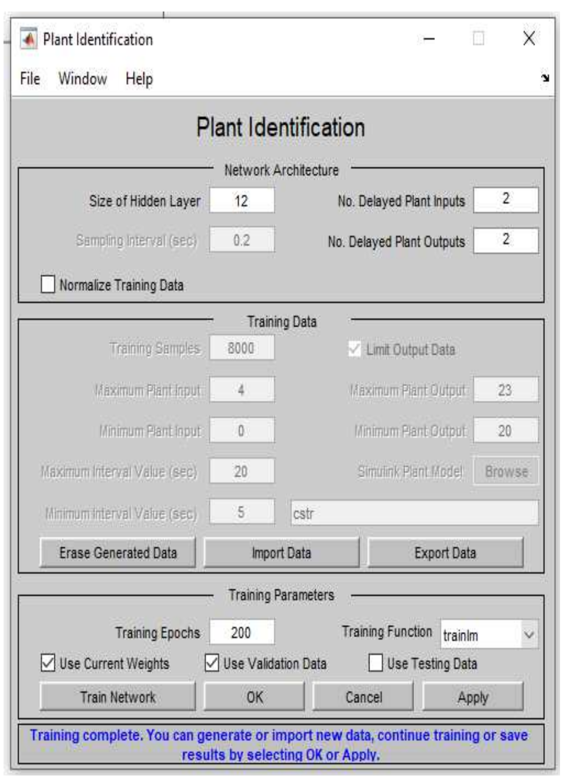

Fig. 7. Setting the parameters necessary for the predictive neural simulation of the odor pump.

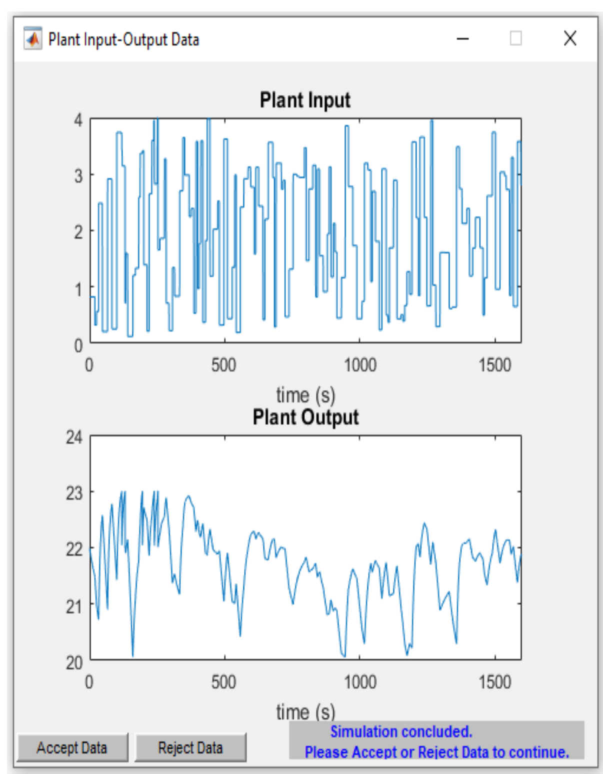

Fig. 8. Graphical, comparative model of the simulation of the input and output parameters of the injection pump

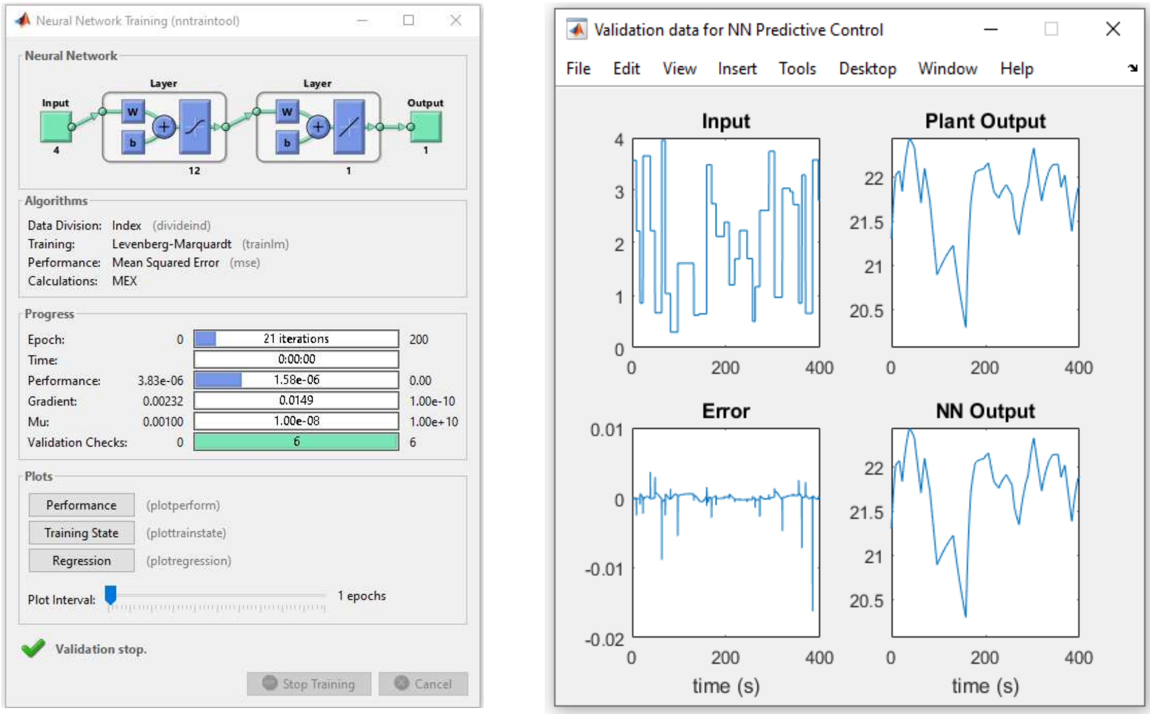

Fig. 9. Simulink model for neural control and graphical result of odor pump operation

With the help of the simulation process through the predictive controller and the NN neural network, it was possible to analyze the operation, for a defined future, of the odor pump, by a parametric setting performed either by choosing a number of layers in the NN network and iterations, or by modifications of the defined input / output sizes, the windows in fig. 7., can be obtained better operating results.

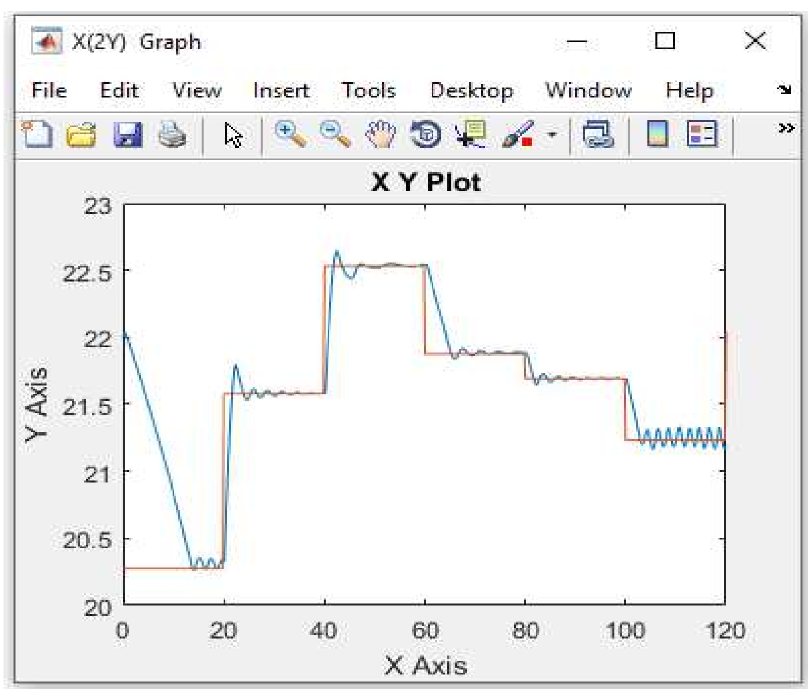

Fig. 10. Graphic model resulting from iterations

4. CONCLUSIONS

By using the Matlab predictive controller and the Deep Learning Toolbox software, which uses a neural network model as an algorithm, the optimal operation of the eccentric odor pump can be predicted, ensuring efficient operation.

With the deep learning application, you can create programs capable of generalizing a behavior of an equipment, installation, mechanism, based on the information provided and / or operating history in order to automate this operation.

The purpose of using this application is to eliminate both operating syncopes and a controlled and economical power consumption for electric drive equipment (e.g. electric motors).

The use of artificial intelligence for the operational control of the odor pump, is an advantage for a good operation over time of this installation and, last but not least, the possibility of selective signaling, from an olfactory point of view, of accidental emissions of natural gas. could cause explosions, dangerous incidents, fires; the possibility of performing a predictive maintenance that eliminates the failure of the equipment, mechanisms, due to overloads, fatigue occurred in an uncontrolled operation of the equipment.

Possibility to automate the operation of the injection pump for odorant, as well as its monitoring through SCADA (Supervisory Control and Data Acquisition); permanent control of the dosage of odorant corresponding to the requirements of transport and delivery of gases to consumers.

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Modelarea neuronală, prin învațare profundă, pentru predicția în funcționare a unei pompe de injecție cu excentric utilizată la odorizarea gazelor natural

Rezumat: Lucrarea de față prezintă o modelare predicțională în funcționarea unei pompe de odorizat actionata cu un mecanism cu excentric, utilizând un domeniu din IA numit învățarea profundă (*Deep Learning*) în funcție de parametrii debit și presiune dintr-un sistem de conducte de transport pentru gaze naturale; odorizarea este necesară deoarece gazele naturale sunt inodore, iar în cazul unei neetanșeități în sistemul de transport sau de distribuție pentru gazele naturale și dacă această scurgere de hidrocarburi nu este sesizată, monitorizată, există pericolul de explozie, cel mai grav pericol fiind în spațiul urban.

Utilizând o aplicație din cadrul programului MATLAB, mai precis un pachet adițional a acestui program, Simulink, prin care se pot realiza simulări ale sistemelor dinamice folosind modele matematice în vederea optimizării lor, vom analiza funcționarea predicțională a pompei de injecție. Modelul neuronal, care este implementat în software-ul Deep Learning Toolbox, și printr-o programare neliniară se va predicționa funcționarea acestei pompe de odorant folosită în sistemul unor conducte de transport pentru gaze naturale. Controlerul, utilizat în Simulink, va modela apoi intrarea de control care va optimiza performanța în funcționare a pompei de injecție cu excentric într-un domeniu temporal definit.

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