

Modeling and Managing The Biological Treatment Process Through The Use of Neural Networks

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Abstract— Neural networks, characterized by parallelism and learning capacity, represent a prime solution for the development of robust and adaptive regulators, especially in situations in which the dynamics of the process is non linear, complex or unknown. In this paper, the authors propose the implementation of modeling and management techniques of the biological wastewater treatment process, utilizing neural networks, elaborating a series of schemes such as: Control methods based on neural networks, Principle scheme of a neural optimizer etc.

Keywords— neural network, biological neuron, sinapse

I. INTRODUCTION

An artificial neural network is a software and/or hardware distributed system of parallel processing of information, with certain common performance with a biological neural network, comprised of a finite number of non linear processing elements, called artificial neurons, which are interconnected in compliance with a given typology and boasting the capacity to quantitatively modify the values assigned to the connections and self processing parameters [1].

The success of neural networks in management applications is based on their possibilities to face three major issues in regard to automated management: complexity, non linearity, uncertainty.

II. BIOLOGICAL PRINCIPLES WHICH FORM THE BASIS OF ARTIFICIAL NEURAL NETWORK DEVELOPMENT

Most research, in the field of artificial neural networks, have been inspired and influenced by existing knowledge of the biological nervous system. The human brain is a complex system, capable of thought, remembrance and problem solving.

The fundamental cellular unit of the human brain's nervous system is the **neuron**. One biological neuron (**fig. 1.**) is a cell that receives electronic stimuli from multiple sources (sensors) and responds through the generation of electrical impulses that will be transmitted to other neurons or effecting cells (muscles or glands) [2].

The neuron is composed of a nucleus, the cell's body, numerous links that produce connections from and towards other neurons through **synapses** and an **axon** trunk which transport a potential output action to another neuron through terminal links and synapses.

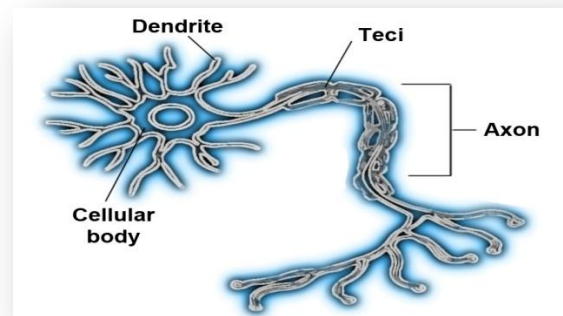


Fig. 1. Structure of the human biological neuron

The analysis of the biological neuron suggests a series of characteristics that are susceptible to takeover by an artificial neuron model:

- the neuron is a processing element which receives multiple signals;
- signals corresponding to input stimuli can be modified through the association of a variable percentage to the receiving synapse;
- the neuron sums up the pondered input signals;
- the neuron outputs a single signal;
- the output signal of one neuron can be transmitted to multiple neurons;
- data processing is local;
- the corresponding memory is distributed; long term memory resides within the synapses of the neurons; short term memory corresponds to the signals transmitted by neurons;
- the durability of a synapse can be modified by experience;
- biologic neurotransmitters can be exciters or inhibitors.

A biological system is tolerant towards defects, in the sense that it can support the defection of the system itself. During its lifespan, a considerable quantity of neurons in the human brain dies off and is replaced. Despite constant loss of neurons, "man continues to learn", due to the fact that other neurons "train" themselves to overtake the functions of the neurons that cease their activity. Similarly, artificial neural networks must be insensible to small scale damage and be able to retrain themselves in the case of significant damage over the system as a whole.

Neural networks are information processing systems, composed of simple processing units, which are interconnected. The weights of the links between the units are the memory units for the information that has been learned by the network. The network learns through the adjustment of these weights, according to a learning algorithm or learning rule [3].

Each unit or neuron can be thought of as a processor, operating independently from the other units in the network. The model of an artificial neuron is presented in **fig.2**.

The artificial neuron or processing element can be considered as having two components: a comparator (which creates the sum of the inputs) and a non linear function, defined through a static characteristic.

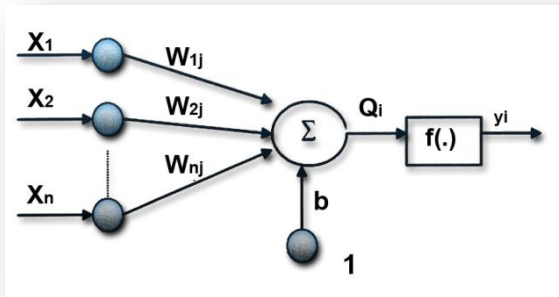


Fig. 2. Base model of an artificial neuron

The y_j output of neuron j from the network is calculated using the following relations:

$$\sigma_j = \sum_{i=1}^n w_{ij} x_i + b \quad (1)$$

$$y_i = f(\sigma_j) \quad (2)$$

Where: y_i – inputs; w_{ij} - link weight between node i and node j ;

b – polarization term (**bias**) of node j , represents the influence of a constant input (+1) and allows the modification of the core function activator;

$f(\cdot)$ – activation function of the network's nodes;
 y_j – output of neuron j .

III. STRUCTURES OF MANAGEMENT SYSTEMS WITH NEURAL NETWORKS

The problem of implementing neural networks in process management is that of determining the outputs of the regulator, represented by a neural network, outputs that become inputs of the process, thus the current state of the process being given [4]. Some of the advantages of neural regulators over conventional ones are:

- a neural regulator can use in an efficient way (in designing and execution of an action command) a far greater quantity of information from the sensors than classic regulators;
- the high processing capacity of a neural regulator allows it to respond rapidly to complex inputs, while the execution speed of complex algorithms in a classic regulator has severe limitations;
- the neural regulator allows the creation of a adequate management due to its ability to adapt and "learn". Control systems based on neural networks can be classified into two primary categories:
- **direct control** - the neural network implements in a direct fashion the regulator (the network is trained to work as a regulator, determining the control actions directly);
- **indirect control** - the regulator is not a neural network, but it is based on the neural network processing model (the neural network is trained to represent the opposite of the management process, calculating the necessary inputs into the process that create the desired outputs of the process).

In **fig. 3**, the main principles behind the control methods of neural networks are presented:

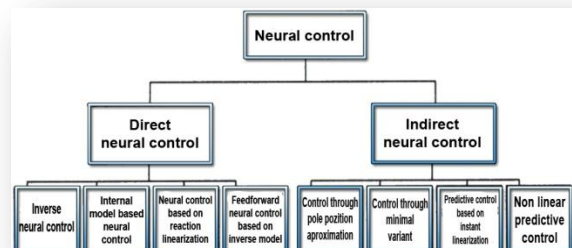


Fig. 3. Control methods based on neural networks

a. Direct neural control:

In the case of this control technique (**fig.4.**), the neural network that implements the regulator must operate like any other traditional regulator: given the error ϵ , the network must produce the control level u which in turn reduces the value of the error ϵ .

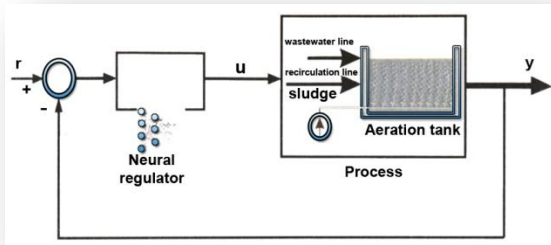


Fig. 4. Direct neural control

This method is applied when the neural regulator is to replace a traditional regulator, such as a PID regulator. The network will be trained initially with a set of data extracted from the operation of the PID regulator, and finally, the weights of the neural links will be fine tuned, both off-line and on-line with additional data [1].

The main management structures for direct control are as follows:

- direct inverse control;
- internal model control;
- feedback linearization;
- feed-forward control;
- optimal control.

b. Reverse neural control:

This control technique tries to find an inverse model of the process, through one of two possible methods: by inverting a neural network that models the process; training a neural network directly which has as inputs into the network, the outputs of the process and which produce as outputs of the network inputs in the process [1].

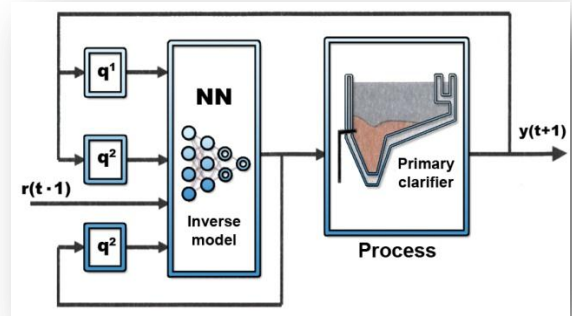


Fig.5. Inverse neural control

In the first case, having a neural network that represents the direct control method of the process, the problem is finding those inputs into the network the produce the desired outputs. In the second case, the neural network is trained using as inputs into the network the previous, current and future outputs of the process.

The base principle of inverse neural control, (**fig. 5.**), that is also called inverse direct control is presented in the following.

Admitting that the process can be described through the relation:

$$y(t+1) = g[y(t), \dots, y(t-n+1), u(t), \dots, u(t-m)] \quad (3)$$

Then the neural network is trained as being inverse towards the process, meaning:

$$\hat{u}(t) = g^{-1}[y(t+1), y(t), \dots, y(t-n+1), u(t), \dots, u(t-m)] \quad (4)$$

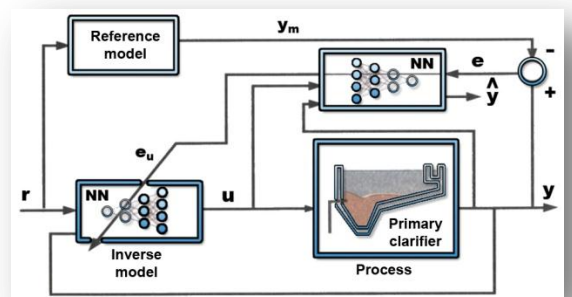


Fig. 6. Specialized training

Determining the inverse model can be achieved through two learning methods:

- learning generalized off-line method also known as general training;
- specialized learning on-line method also known as specialized training.

The inputs of the management system with internal model are reference r and the output (measured) of process $y(t)$.

The control method based on the model predicts the future outputs of the process, based on a model of the process, and then it minimizes the error between the model and the process. A classic management structure with internal model (fig. 7) presumes a certain parameterization of the regulator [4].

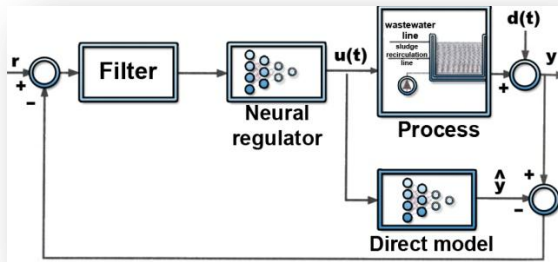


Fig. 7. Internal model control

The advantages of utilizing such a management structure are:

- if the process' model is a perfect representation of the process, the reaction signal will contain only the perturbation effect at the process' output and will not be affected by the action of command $u(t)$. This way, the effect of the command from the process' output is eliminated, and the system will operate effectively in an open loop, the problems associated to negative reaction being removed [5];
- the (immeasurable) perturbation effect can be compensated by modifying the regulator reference accordingly;
- if the model does not exactly represent the process, the reaction signal will contain both the (immeasurable) perturbations' influence and the effect of the modeling error $e(y) = y(t) - \hat{y}(t)$. This error will represent a real reaction signal that can generate stability issues, forcing the modification of the ideal regulator in order of obtaining robust performances.

IV. MODELING AND MANAGEMENT OF THE BIOLOGICAL WASTEWATER TREATMENT THROUGH NEURAL NETWORKS

In order to optimize the biological treatment process, a feed forward artificial neural network is proposed, trained through the method of back propagation using the supervised learning mechanism [2].

The neural optimizer works at a superior hierarchic level compared to automated adjustment, as shown in (fig. 8).

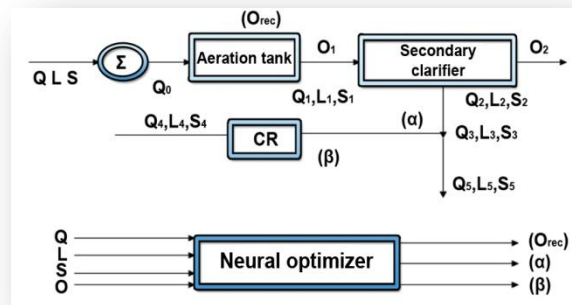


Fig. 8. Principle scheme of the neural optimizer

According to this scheme, the neural network receives at the input the four parameters that characterize the wastewater that enters the biological treatment installation. These parameters are: the flow (debit) - Q , organic charge concentration - L , active sludge concentration - S and oxygen concentration - O . These parameters generally have a random variation during long time spans, which is why they are measured with dedicated transducers and are applied to the neural network as input values.

According to the values of these vectors at the output of the neural network, the according command vectors are obtained, that have as components the values α , β și O_{ref} which are applied to the base level regulators.

The optimal correlation between the input and output vectors is established in the simulation phase of the biological treatment system, this operation being conducted prior to optimization. The training data of the network is presented in spreadsheet format. Though only certain, more widespread in practice, situations can be tabulated, any real situation that is recorded by the transducers will be interpolated by the neural network which will provide at the output a corresponding command vector.

The design and supervised training program of the neural network has been developed in Matlab. The training required 1176 cycles to reach an error margin of 0,001.



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For the training process, the back propagation algorithm has been used, implemented through the train box Matlab function. After the training process, the optimum weights of the network are retained in the W_1 , b_1 , W_2 , b_2 vectors [1].

With the obtained data, the simulation of the network's functionality is made possible in different practical situations, using the Matlab simuff function. The neural network, once trained, can be utilized within the management system of the biological treatment process. A variation matrix is constructed that will be controlled within the process [6].

The neural system, through adequate transducers, effectively controls in a continuous fashion the variation of parameters and searches for the values within the given matrix. It will interpolate the adjustment level and send the corresponding command in order to maintain the system at optimum operational levels.

V. CONCLUSIONS

After conducting the case study at the Oradea Wastewater Treatment Plant, Oradea, Bihor, Romania, identifying the origin and quantity of the residual and processed sludge, the authors of this paper have reached the following conclusions:

Neural networks, characterized by parallelism and learning capacity, represent an ideal solution toward upgrading adaptive and robust regulators, especially in situations in which the dynamic of the process is non linear, complex or unknown. Most of the research, in the field of artificial neural networks have been inspired and influenced by available knowledge of the biological nervous system. The human brain is a complex system, capable of thought, of memory and problem solving.

To achieve the optimization of biological treatment, an artificial neural network of feed forward type, trained through the back propagation method and utilizing the supervised learning mechanism (using the Matlab software) is proposed.

With the obtained data, the simulation of the operation of the network in different practical situations is possible, using the simuff Matlab function. The neural network, once trained, can be used within the management system of the biological wastewater treatment process. A value variation matrix is constructed that will be controlled within the process.

REFERENCES

- [1] G. L. Ionescu, Gh. C. Ionescu, Aura Sâmbeteanu, Tehnologii moderne pentru epurarea apelor uzate (Modern technologies for wastewater treatment), Editura MatrixRom – București, 2013.
- [2] E. Gligor, Contribuții la optimizarea energetică a instalațiilor și echipamentelor din cadrul stațiilor de epurare a apelor uzate (Contributions to energy optimization of facilities and equipment in the wastewater treatment plants, PhD. Thesis Oradea, 2011).
- [3] Diana Robescu, Modelarea proceselor biologice de epurare a apelor uzate (Modeling biological wastewater processes), Editura Politehnica Press București, 2009.
- [4] Diana, Robescu, S. Iliescu, D. Robescu ș.a., Controlul automat al proceselor de epurare a apelor uzate (Automatic control of wastewater treatment processes), Editura Tehnică București, 2008.
- [5] Gheorghe I. Gheorghe, N. Băran, O. Donțu, D. Besnea, G.L. Ionescu – Electromechanical system for the displacement of fine bubble generators that oxygenate stationary waters – 5th International Conference on Innovations, Recent Trends and Challenges in Mechatronics, Mechanical Engineering and New High-Tech Products Development – MECAHITECH'13 Bucharest, Romania September 12th-13th, 2013.
- [6] G.L. Ionescu, Paolo Bertola, O. Donțu – Solutions for qualitative and quantitative rainwater management – CIEM 2013 (Conferința Internațională de Energie și Mediu), 7-8 noiembrie 2013 București.