„Dunărea de Jos" University of Galaţi
Doctoral School of Fundamental and Engineering Sciences

PHD THESIS

-PhD Thesis Summary -

CONTRIBUTIONS REGARDING DIAGNOSIS OF WASTEWATER TREATMENT PROCESSES USING NEURAL NETWORKS

Scientific supervisor,
Prof. Sergiu CARAMAN, PhD

PhD student,
Eng. Mihaela MIRON

Seria I8: System Engineering No. 4
GALAŢI
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Chair:	Prof. Eugen RUSU, PhD
Scientific supervisor,	Prof. Sergiu CARAMAN, PhD
Members of jury:	Prof. Nicolae PARASCHIV, PhD
	Prof. Liviu MICLEA, PhD
	Prof. Laurențiu FRANGU, PhD

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Thesis – Table of contents

Thesis summary – Table of contents

Introduction

In the last century, the growing population and the evolving of the modern society on different segments, represents the principal cause of contaminating the environment and the water resources. Taking into consideration that the clean water supplies are reduced, it is important to take measures to protect and prevent the pollution from the water sources which affects negatively the environment and to assure living conditions and development for all living species. Nowadays, there is an increased awareness of the importance of preventing pollution and minimizing waste in activities like industrial, urban and agriculture, but also in the recycling process. Biotechnology has a major importance in dealing with these contemporary challenges, at this time being the best technology available to assure environment protection and durability. The technologies from the biotechnology are multiple, but one of the most common are the wastewater treatment processes from the industrial processes, people’s households etc.

The Wastewater treatment plants are designed to reduce the amount of organic matter and suspended solids from water by using appropriate treatments in order to purify water before it is discharged into any emissary (sea, rivers, lakes etc.). These processes are inherently dynamic due to high variations of the wastewater admission flow, concentration and its composition. Because of this, mathematical models and computer simulations are essentials to model, predict and control these complex processes. The operation of wastewater treatment processes is very complex. In some plants low performances, high costs and environment degradation were caused by operational problems. Improving performance of the wastewater treatment plants depends mainly on the detection, isolation and identification defects (FDI - Fault Detection and Isolation) in order to increase safety and reliability of the equipment. Therefore, several approaches referring to diagnosis in the wastewater treatment processes were proposed: approaches based on heuristic knowledge like artificial intelligence (neural networks), statistical analysis and approaches based on mathematical models.

In the research carried out within the present PhD thesis, the following research directions were considered: the first objective consists in modeling biotechnological processes, in particular, the wastewater treatment plants, using artificial intelligence techniques, like neural networks. It is intended to implement a neural model that predicts the outputs of a wastewater treatment plant in which the organic substrate is biologically removed. The advantage of the neural network, used as a model of the system, is that it learns directly from the experimental data without using an analytical model. In general, for network training it is necessary to use a very large and representative dataset for the operating domains in which the model will be used. The neural network which predicts the outputs can be used for purposes like regulation or diagnosis of the biotechnological system.

The second direction of research focuses on the diagnosis of faults in biotechnological processes. Since the diagnosis involves two steps, like detection and isolation of faults, the propose is to implement techniques for detecting and recognizing faults using neural networks in an active sludge treatment process. In case of detection, two situations will be analyzed: 1. the process outputs are considered measurable and 2. some of the process outputs are not directly measurable via dedicated sensors. In case if some process outputs are not measurable, it can be used state and parameter estimators such as observers, but the main disadvantage of this method remains the problem of determining an accurate mathematical model of the process as good as possible. In order to recognize faults, it will be designed a neural network which works as a classifier. The performance of the detection algorithm and of the recognition method will be tested in the case of net faults and partial faults of specific actuators or transducers used in the wastewater treatment processes.

The structure of the PhD thesis includes: an introduction, four chapters and conclusions. In the ***introduction*** the main research directions proposed and the motivation that underpinned the approach of the study topic in this PhD thesis are presented.

Chapter 1 presents an overview which consists in the state of the art regarding detection and diagnosis of faults in wastewater treatment processes. Arguments are presented on the importance of fault diagnosis, the main types of faults, various fault detection methods and a number of isolation techniques are analyzed. Also, here are mentioned and analyzed some recent results from the field of fault detection and isolation in biotechnological processes, with applications especially on the wastewater treatment plants.

In ***Chapter 2***, some general aspects of the neural networks (architectures, activation functions, learning rules etc.) are mentioned, highlighting their domain of applicability. The main functionalities of the biotechnological systems, in particular, of the wastewater treatment plants with activated sludge, are also presented. The wastewater treatment plant from "Dunărea de Jos" University of Galati laboratory, with the monitoring and control equipment, is presented. A real fault is described, appeared in an experiment conducted at the mentioned treatment plant, in which the air flow transducer malfunctioned, along with the observed symptoms. In the last part, the emphasis is on contributions that consist in modeling a wastewater treatment plant (where biological substrate is biologically removed) using neural networks. The simulation and the validation results of the neural model shows that the biotechnological process can be successfully modeled through a feedforward neural network. The modeling error obtained is more than acceptable for the normal operating state of the process.

Chapter 3 presents the contributions referring to the detection of faults in the wastewater treatment plants. Two model-based fault detection methods are proposed for a wastewater treatment process with activated sludge. In the first situation, when the process outputs are considered measurable, detection is performed using the neuronal model of the analyzed process, obtained in Chapter 2. In the second situation, when some process outputs are not measurable, a detection method based on the analytical model of the process is proposed using an extended Kalman filter. The conditions that are considered in designing the both methods are: the response speed of the alarm signal in the presence of the fault, the sensitivity to the fault (detection of partial faults that have reduced effects on the process), the robustness (operations in the presence of noise, external disturbances and modeling errors) and the low number of false alarms. In both situations, the performance of the methods is tested by simulating the net and partial faults of the actuators and transducers which can occur in the wastewater treatment plants. An important contribution in this chapter is the investigation of two methods for choosing the main parameters of the fault detections method (sensitivity threshold, ε, and residue calculation horizon, N). The first method consists of a theoretical analysis in which three hypotheses are considered, as follows: Ip. 1 - there are no modeling errors ($er(k) = 0$, meaning that the model reproduces very well the evolution of the supervised process), if there is a fault, it is assumed that the deviation produced by it has reached steady state in a very short time (several sampling periods) the decision must be taken quickly, only on the value of the current sample, so $N=1$, which is equivalent of saying that the residual was determined for the current sample only; Ip. 2 - there are no modeling errors (meaning that the model faithfully reproduces the evolution of the supervised process), the deviation produced by the faults evolves slowly, with known growth time and the decision can be made on the basis of several successive samples, the residual is calculated on the time horizon $N>1$; Ip. 3 - there is a modeling error with a known density of probability, the deviation caused by the fault evolves slowly, with known growth time, the modeling error varies more slowly than the deviation produced by the fault, and the decision can be made on several successive samples ($N>1$). The second method consists of the heuristic determination of the parameters ε and N. It has been concluded that the theoretical analysis of choosing the two parameters of the detection method is confirmed by the results obtained by heuristic techniques in section 3.2.

In ***Chapter 4*** a neural classification network is designed to recognize net faults and partial faults that can occur in a wastewater treatment process. The experimental data set is large enough and contains representative data for all the faults analyzed. Following the training, validation and testing of the neural network, it is concluded that it is obtained good recognition rates for all type of defects analyzed.

In the final chapter, called final ***conclusions***, the original contributions of the thesis are mentioned and the following research directions are established.

Chapter 1

State of art regarding detection and diagnosis of faults in biotechnological processes

1.1 Generalities regarding biotechnological processes

Biotechnology is the science that studies “living” processes which contain microorganisms, cells or cellular components in order to develop new technologies and products to significantly improve people's lives and make a significant contribution in protecting the environment.

Related to environmental protection, the wastewater treatment processes, which are essencially biotechnological processes, have innovative technologies that reduce energy consumption and wastewater in order to protect and regenerate the environment, and so the industrial processes become more "clean" and more efficient.

Regarding the wastewater treatment processes, they have the role of eliminating or reducing the amount of chemical or organic waste from the wastewaters. Wastewater treatment can be achieved through several types of treatment: mechanical, biological and chemical. Numerous researchers are focusing on the development of new wastewater treatment technologies, as well as increasing the efficiency, safety and maintenance of existing technologies through detection and diagnosis techniques, especially applied in the biological stage. Thus, nowadays, the detection and diagnosis of faults in wastewater treatment plants has become a challenge due to the complexity of these systems. Cells, contained by populations of living microorganisms, develop unpredictably, may undergo mutations that may affect their development, and in particular growth, transport and propagation dynamics that are difficult to understand, non-linear, and time-varying. Last but not least, these processes are affected by measurement and process noise, as well as parametric and model uncertainties that create major difficulties in mathematical modeling and control, including diagnostic issues. The lack of dedicated sensors that can provide accurate real-time information, the low reliability of existing ones and, in particular, prohibitive costs for their use in industrial applications contribute to the above-mentioned difficulties in systemic treatment of such processes. Generally, measurements in bioprocesses are done through laboratory analyzes performed off-line, which creates a major handicap in implementing the automatic control laws. Thus, problems with the on-line measurement of the concentrations of interest variables in bioprocesses have been attempted to be overcome by designing and using state and parameter observers, which are a viable alternative for measuring the main variables in bioprocesses. The main disadvantage of this method is obtaining a mathematical model of the process.

The literature from this domain recommends a number of models of wastewater treatment processes. The best known are the mathematical models developed by a team led by Professor Henze within the IWA (International Water Association). This include the ASM1 ("Activated Sludge Model 1") [1] designed to remove residues containing organic carbon and nitrogen. A second mathematical model developed within IWA is ASM2, which additionally performs phosphor removal [2]. In ASM2, the unresolved part was denitrification of PAO (phosphorus accumulation organisms). This has led to the need to extend the ASM2 to the ASM2d version. The model is an extension of the two ASM2 and ASM1 models, and uses the concepts included in these mathematical models. ASM2d includes two additional processes that take into account that phosphorus accumulation organisms can use biological products stored inside cells for denitrification. As ASM2 implies that PAO will only increase in aerobic conditions, ASM2d also includes PAO denitrification [3]. ASM2d is an improved model of wastewater treatment processes, particularly with regard to the dynamics of nitrate and phosphate concentrations. The ASM3 model can estimate the oxygen consumption, sludge production, nitrification and denitrification of active sludge systems.

Further, this chapter presents a review which consists in a state of art regarding detection and diagnosis of faults in wastewater treatment processes. Arguments on the importance of fault diagnosis, the main types of faults, various fault detection methods and a number of isolation techniques are presented. In the last part are mentioned some recent results from the field of fault detection and isolation in the biotechnological processes, with particular application on the wastewater treatment plants. The last section is reserved for the conclusions.

1.2 The importance of fault detection and diagnosis in biotechnological processes

Fault diagnosis is an important issue in the control of biotechnological processes and continues to be an active field of research in modern automation.

In the case of bioprocesses, fault diagnostics techniques can be used to improve the efficiency, maintenance, and reliability of these processes. Early detection of a fault can help avoid collapse of a whole system or eventual catastrophe by corrective action, depending on the severity of the source that caused the fault. Steps to be followed in the diagnosis of defects are: 1. determining the presence of a fault and 2. determining the type and magnitude of the fault [4]. These steps are applied depending on the plant, equipment and technologies used.

According to the IFAC SAFE - PROCESS technical committee [5] and [6], “a fault is an unpermitted deviation of at least one characteristic property or system parameter from normal, acceptable, normal system conditions”. Faults can occur in some subsystems, for example sensors and actuators.

In general, diagnostic methods use the concept of redundancy, which can be of two types [7] (Figure 1.1): hardware redundancy and software redundancy.

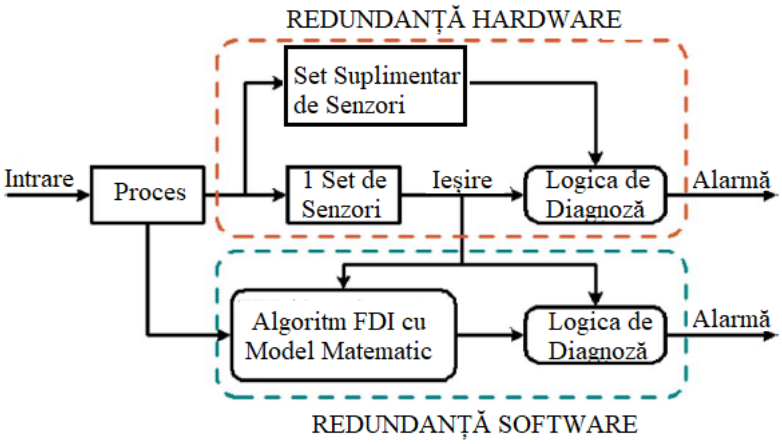

Fig. 1.1 - Hardware and Software Redundancy (Analytical) Applied for Fault Detection and Isolation (FDI) [7]

Hardware redundancy refers to the ability to compare duplicate signals generated by various hardware sources, such as the result of measurements of the same signal obtained from two or more sensors. The techniques used in this approach are: signal processing methods (e.g. Wavelet transform), boundary testing (measurements compared to various thresholds indicating the presence of an anomaly), use of special sensing sensors (designed to measure only certain parameters), parallel sensors for measuring the same parameter or use of expert systems (based on rules such as "IF THAT ..." for an abnormality).

Software redundancy (analytical) uses a mathematical model of the system along with other estimation techniques [8], [9]. In general, this approach does not require additional hardware resources and is usually more cost effective compared to hardware redundancy. On the other hand, analytical redundancy is more difficult to implement because it has to provide a degree of robustness in the presence of noise, disturbances or approximation errors introduced by the mathematical model. If these conditions are not taken into account, false alarms may occur in the presence of input variations or noise. By comparing the estimated values of the analytical model with the measurements obtained from the sensors, it can be detected and isolated faults that occur in the process. The goal is to observe the difference between the model and the faulty real system. The difference between the actual measured output of the process and the estimated output of the analytical model is called residual. The value of the residue is compared to a threshold that can be fixed or variable (e.g., adaptive threshold), which determines whether or not a fault occurs in the process.

In Fig. 1.2 it can be observed that analytical redundancy is also divided into diagnosis methods using quantitative and qualitative models [4], [10] and [11]. All these diagnosis methods use parameter estimators, status observers, artificial intelligence techniques (neural networks, evolutionary algorithms, etc.), hybrid methods (neuro-fuzzy models), parity equations, or statistical classifiers to detect and isolate discrepancies between the observed behavior of the process and the output predicted by the model. In addition, diagnosis methods based on qualitative models (fuzzy logic, graphs, trees, search methods, expert systems) use quality relationships between inputs and outputs of the process. These relationships provide declarative information about the state of the process parameters (generally the variation of the parameter values). The motivation for the use of these qualitative models is reinforced by the fact that not all processes and faults can be described by analytical models, and knowledge can easily be incorporated into diagnosis schemes [13], [14] and [15].

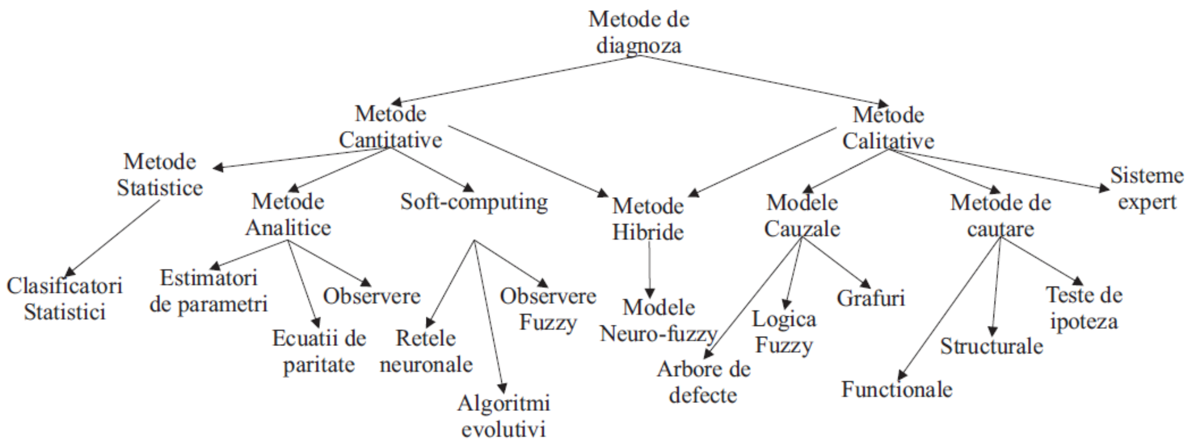

Fig. 1.2 – Model based diagnosis methods [12]

Chapter 2

Modeling biotechnological processes using neural networks

Biotechnological processes are complex systems, strongly non-linear, and influenced by parametric and model uncertainties (hidden dynamics - unmodelled). These processes contain living microorganisms that can have mutations affecting in particular the growth, transport and propagation dynamics that are difficult to understand, non-linear and time-varying. There are few sensors that can provide accurate, real-time information about the development of a cell culture. In general, concentrations of biological variables can only be determined by laboratory analyzes performed off-line, which creates a major handicap in the mathematical modeling of these processes, the implementation of control laws or diagnostic techniques. In this way, it is important to have a precise model as possible to best approximate the behavior of the biotechnological process and to generate the residual sets subsequently to be evaluated for fault diagnosis. In the category of bioprocesses are included the wastewater treatment processes, which will be the subject of developing some diagnostic methods in this research work.

Neural Networks (RNA) are artificial intelligence techniques that provide efficient predictive models for complex processes, and can also be applied in situations where insufficient process knowledge is available. The advantages of neural networks are that:

- it's not necessary to describe mathematically the phenomena involved in the process;

- is needed less time to build models versus traditional mathematical models;

- it have a very good prediction ability with a limited number of experiments [107] – [110].

It has been demonstrated by various applications that neural networks approximate very well if the training data set contains sufficient examples and the number of neurons in the hidden layer is sufficient. It should also be mentioned that neural models with feedforward architecture are most commonly used in recent biotechnological modeling studies [111], [112] and [113].

2.1 General aspects of neural networks

Over the years, it has been recorded numerous advances in the direction of developing intelligent systems using neural networks. Neural networks have been studied by researchers to solve problems in various scientific fields such as pattern recognition, prediction, optimization, associative memory, control, and so on. Although several algorithms that use neural networks are encountered in the literature, they are not flexible enough to operate outside their applicability domain.

Artificial neural networks are inspired by the model of biological neurons. The features that artificial neural networks are trying to imitate are:

- parallelism;
- distributed computation and representation;
- learning ability;
- improving performance;
- the ability to generalize;
- adaptability;
- the possibility to process information and make decisions;

- fault tolerance.

An artificial neural network is an information processing structure, formed by a number of interconnected nodes (neurons). Each connection is characterized by a numerical weight. Through weight it is retained the learned information by the network and by adjusting its weight value, the neural network is trained.

The main features of a neural network are:

- operation (the method of calculating the output depends on input);
- arhitecture (how neurons are interconnected);
- training (determining the parameters of the neural network).

2.3. Case study: Neural network modeling of a wastewater treatment process

The scientific approach of this PhD thesis consists in developing some diagnosis methods of the wastewater treatment processes. For this purpose, we started from a mathematical model of a pilot treatment plant designed in our university, within the project CEEX – MENER, Nr. 717/25.07.2006, Improvement of qualitative indicators for the biological treatment of wastewater in the food industry based on advanced management systems – APEPUR acronym [128], presented in Fig 2.22. The mathematical model is known in the literature as the Nejjari model. The pilot plant was designed for an influent flow rate of 1 liter / h and was designed so that the results obtained within the project could be extrapolated to a larger station. In the aerobic treatment phase of the wastewater, the bioreactor was designed to be able to retrieve loads in CBO_5 up to 1700 mg/l, to ratios of $CCO/CBO_5 \leq 2.2$ and CBO_5:N:P CBO_5:N:P ratios of 100:5:1, these parameters being associated with the heavily loaded waters of organic substances, mostly from the food industry.

2.3.2 Fault occured during an experiment conducted on the pilot wastewater treatment plant from “Dunărea de Jos” University of Galați

Further, it is presented a real fault occurred in the experiments conducted with the pilot plant from "Dunărea de Jos" University of Galați. The experiment was conducted over several days; some of the results relevant for this PhD thesis are being shown in Fig. 2.24 – 2.26. Thus, in Fig. 2.24 shows the evolution of the air flow, in Fig. 2.25 - the dissolved oxygen concentration, and in Fig. 2.26 - turbidity, measurement by which the biomass concentration is measured. In the above-mentioned figures it can be seen that the purification process had a normal evolution up to the 15700 sample, after which the measured air flow drops to zero, the dissolved oxygen concentration increases excessively and after 750 - 800 samples appears a substantial decrease of biomass concentration. The explanation is as follows: at the mentioned time, the air flow transducer has not provided the measured value (basically it has failed). The dissolved O_2 regulator has commanded maximum air valve opening, which resulted in a strong increase in the dissolved oxygen concentration, and, later, a decrease in the sludge concentration. Finally, it turned out that at the origin of the fault, was a failure of the flowmeter power supply. After its replacement, the process returned to a normal evolution.

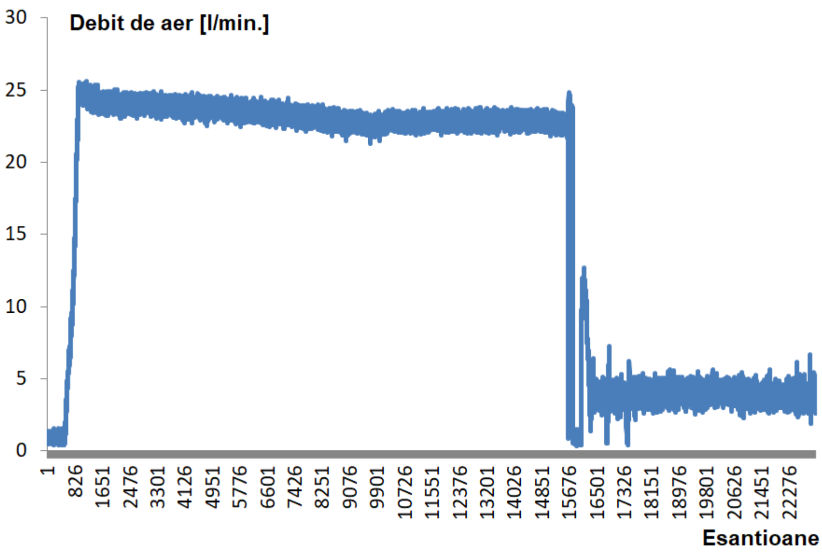

Fig. 2.24 – Evolution of the air flow

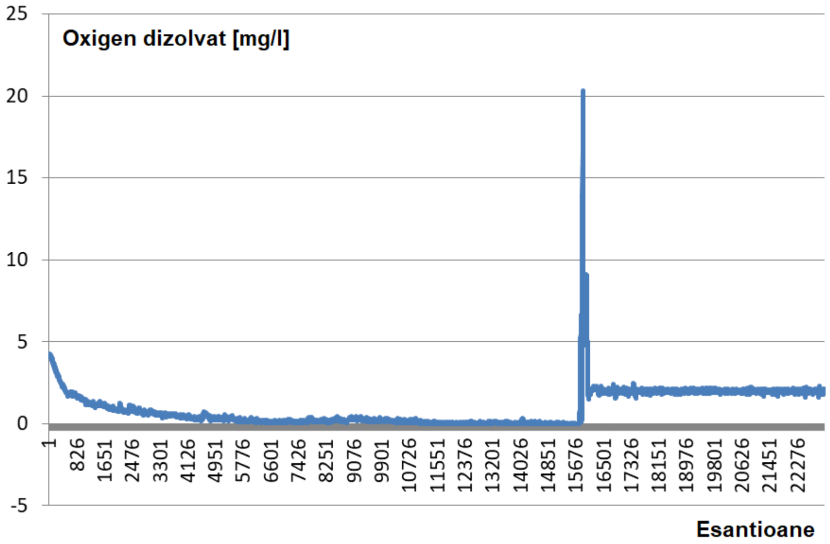

Fig. 2.25 – Evolution the dissolved oxygen concentration

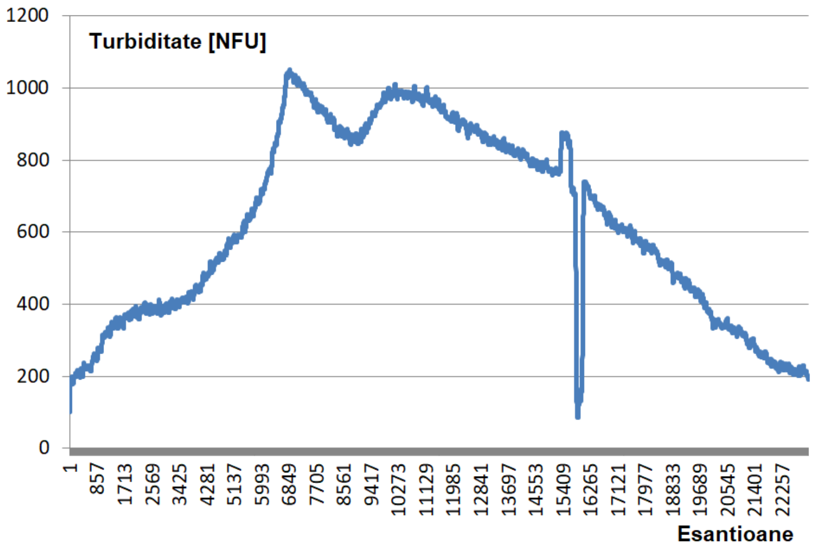

Fig. 2.26 – Evolution of turbidity

2.3.3 The mathematical model of the wastewater treatment process

In the case study analyzed in this section is considered a wastewater treatment plant where it is performed a biological removal of the organic substrate of the type presented in the previous section. The process model has four outputs: biomass, $X(t)$ [mg/l], organic substrate concentration, $S(t)$ [mg/l], dissolved oxygen concentration, $DO(t)$ [mg/l] and recirculated biomass concentration, $X_r(t)$ [mg/l]. The analyzed model is non-linear and has the command inputs: aeration speed, W $[m^3/h]$, dilution speed (D = the ratio beetwen the input flow of the aerated basin and its volume $[1/h]$) and the recirculation rate of the r sludge. In Fig. 2.27, F_{in} is the input influence flow that eneters in the aerated bioreactor, and F_{out} is the effluent flow.

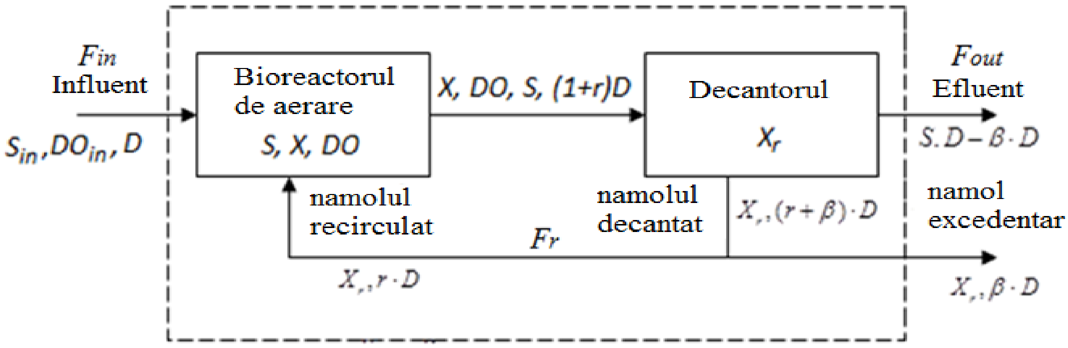

Fig. 2.27 – Systemic representation of the instalation that reduces the organic matter in wastewater treatment processes with active sludge [111]

The following hypotheses are considered for the mathematical model of the analyzed process [129]:

- The system regim, in which the bioreactor works, has $V = ct$ $(F_{in} = F_{out} = F)$;
- The recirculation flow of the active sludge is considered proportional to the process flow F: $F_r = r \cdot F$;
- the flow of the sludge in excess from the bioreactor is considered proportional to the inflow (F): $F_\beta = \beta \cdot F$;
- there is no substrate or dissolved oxygen in the recirculated flow of the active sludge;
- the output flow of the aerated bioreactor is considered equal to the sum between the input flow of the bioreactor and the recirculated flow of the active sludge.

Considering Fig. 2.27 and the 5 hypotheses formulated above, results the following differential equations which describe the mathematical model of the process:

$$\frac{dX}{dt} = \mu(t)X(t) - D(t)(1+r)X(t) + rD(t)X_r(t) \quad (2.15)$$

$$\frac{dS}{dt} = -\frac{\mu(t)}{Y}X(t) - D(t)(1+r)S(t) + D(t)S_{in} \quad (2.16)$$

$$\frac{dDO}{dt} = -\frac{(1-Y)\mu(t)X(t)}{Y} \cdot 10^3 - D(t)(1+r)DO(t) + 60\alpha W(t)\big(DO_{sat} - DO(t)\big) + D(t)DO_{in} \quad (2.17)$$

$$\frac{dX_r}{dt} = D_s(t)(1+r)X(t) - D_s(t)(\beta+r)X_r(t) - 0.5D_s(1+\beta)X_r(t) \quad (2.18)$$

$$\mu(t) = \mu_{max}\frac{S(t)}{K_s+S(t)} \cdot \frac{DO(t)}{K_{DO}+D\,O(t)} \quad (2.19)$$

$$D = \frac{F_{in}}{V}; D_s = \frac{D \cdot V}{V_s} \quad (2.20)$$

where $X(t)$ – biomass concentration, $S(t)$ – substrate concentration, $DO(t)$ – dissolved oxygen concentration, $X_r(t)$ – recirculated biomass concentration, $\mu(t)$ – the specific biomass growth rate, μ_{max} – the maximum specific speed of biomass growth, $D(t)$ – the dilution speed, $W(t)$ – the aeration speed, r – the recirculation speed, S_{in} – the influent concentration of the substrate, DO_{in} – concentration of the influent dissolved oxygen, DO_{sat} – the saturation value of the dissolved oxygen, Y – efficiency coefficient, K_s – saturation constant of the substrate, K_{DO} – saturation constant of the dissolved oxygen, α – transfer rate of the oxygen, β – excess sludge rate, F_{in} – influent flow, V – bioreactor volume, D_s – the dilution speed of sludge, V_s – sludge volume.

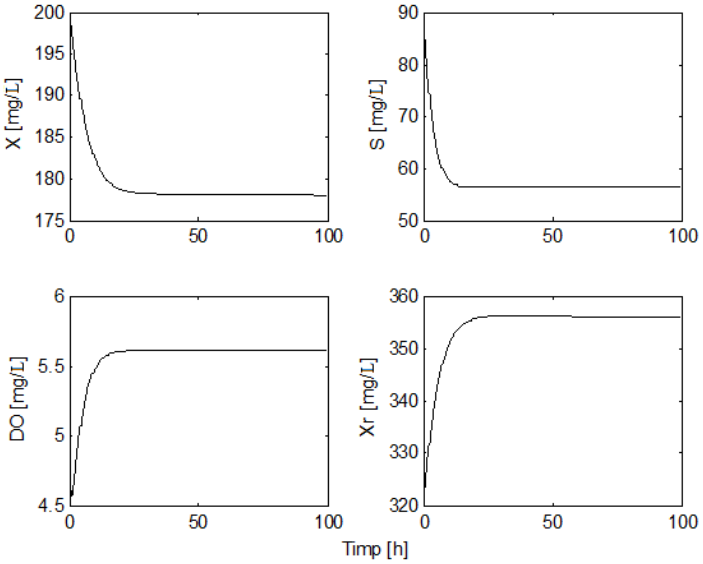

Fig. 2.28 – The simulation results of a wastewater treatment process in open loop [111]

Fig. 2.28, presents the results of simulating the mathematical model described by the equations (2.15) – (2.19) in open loop, during the transient response when it is applied a step on the $D(t)$ input.

The results of simulating the mathematical model were obtained by considering the following input parameters values:: μ_{max}= 0.11[h^{-1}], K_s = 0.18[g·L^{-1}], K_{DO} = 0.2 [g·L^{-1}], Y = 0.67, DO_{sat} = 8 [mg·L^{-1}], α = 0.0033 [L^{-1}], r = 1; β = 0.2, V = 35 [L], V_s = 6 [L], D = 0.025 [h^{-1}], W = 5 [L·min^{-1}], S_{in} = 0.8 [g·L^{-1}], DO_{in} = 2 [mg· L^{-1}] and initial conditions: $X(0)$ = 0.5 [mg· L^{-1}], $S(0)$ = 0.8 [mg· L^{-1}], $DO(0)$ = 2 [mg· L^{-1}], $X_r(0)$ = 0 [mg· L^{-1}].

2.3.4 Neural network modeling of a wastewater treatment process

Neural networks are a powerful tool for predicting, controlling and modeling processes and, in particular, for biological wastewater treatment processes [130, 131]. The main objective of this chapter is to develop a neural model that can be used to diagnose a biological wastewater treatment process in which organic carbon residue is removed.

In Fig. 2.33 is presented the structure of the neural network designed with Matlab. It can be observed 8 input variables (the inputs D, W, r, S_{in} and the outputs delayed with one sample step, X, S, DO, X_r). The dissolved oxygen concentration from the influent is considered constant ($DO_{in} = ct$). Also, 4 neurons in the hidden layer are sufficient, taking into account the training performance and network generalization ability (tested during the validation step).

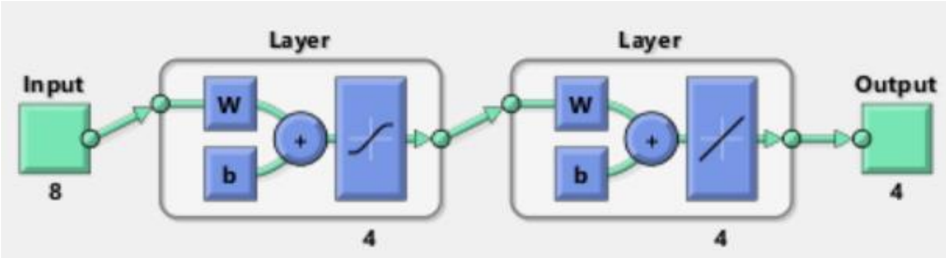

Fig. 2.33 – Structure of artificial neural network for approximating the non-linear model of the wastewater treatment process

For training, the learning algorithm Levenberg-Marquardt (trainlm - neural transfer function in Matlab) was used, also known as the "damped least-squares method" [135]. This method, according to [133], is much more effective for nonlinear systems even if it consumes more computer memory. The final step validates the neural network using independent data sets obtained by simulating the process model with representative data inputs.

2.3.5 Neural network training results

For training, two sets of data were prepared. The input data sets is a $P\,[8x10000]$ array, which contains the current values of the outputs (X, S, DO, X_r), of the command variables (D, W, r) and of disturbance S_{in}. The “target” data set is a $T\ [4x10000]$ array which contains the outputs values, forward with a sampling step, compard with those from P array.

The Matlab commands used in designing the modeling algorithm using the artificial neural networks are: *newff*, *train* and *sim*.

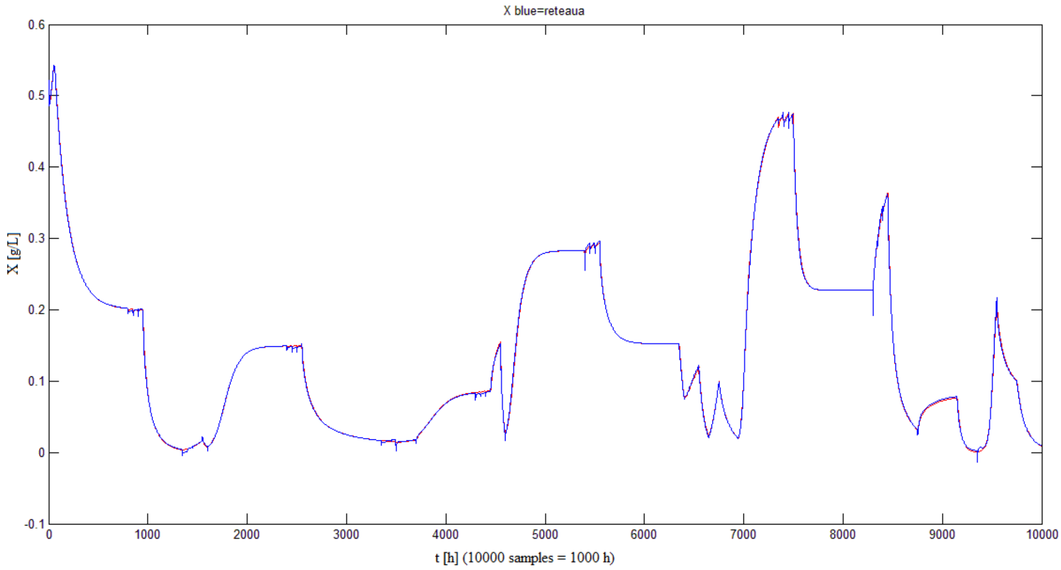

Fig. 2.36 – Biomass concentration, X (red – the output obtained from analytical model simulation and blue – the output obtained from neural network approximation)

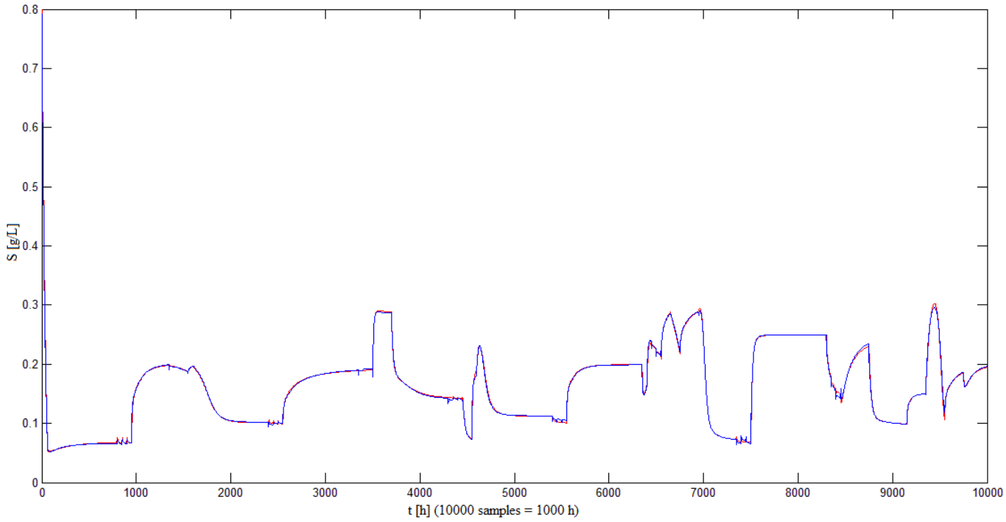

Fig. 2.37 – Organic substrate concentration, S (red – the output obtained by simulating the analytical model and blue – the output obtained from the approximation obtained with neural network)

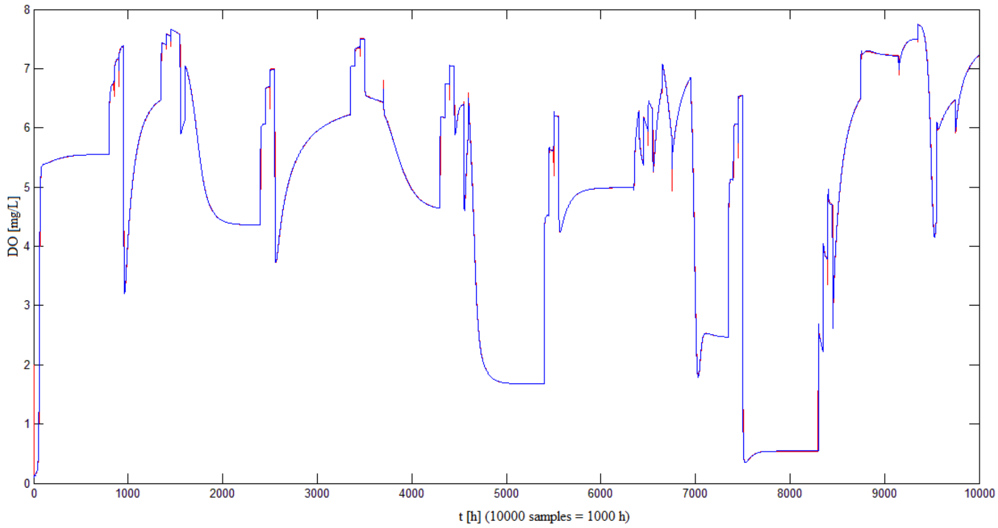

Fig. 2.38 – Dissolved oxygen concentration, DO (red – the output obtained from analytical model simulation and blue – the output obtained from neural network approximation)

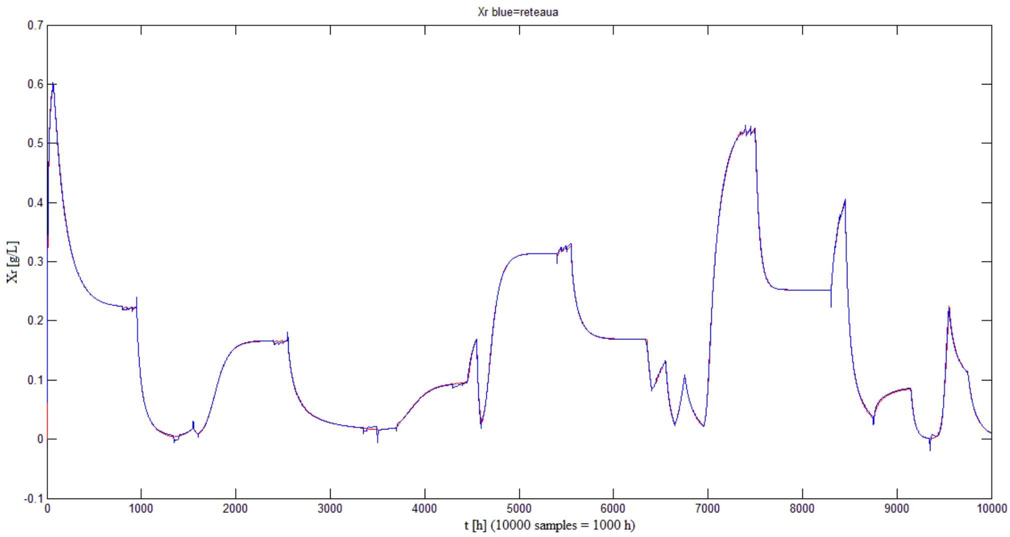

Fig. 2.39 – Recirculated biomass concentration, X_r (red – the output obtained from analytical model simulation and blue – the output obtained from neural network approximation)

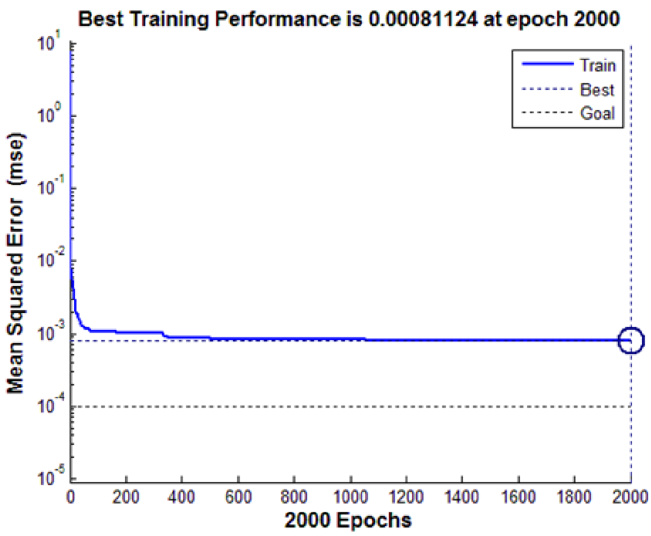

Fig. 2.40 – The mean square error obtained by training the neural network

2.3.6 The neural network validation results

For the validation step, a distinct data set was used. The validation results are presented in Fig. 2.43 – 2.46. They indicate a good generalization ability of the neural network because its outputs closely follow the outputs of the original model.

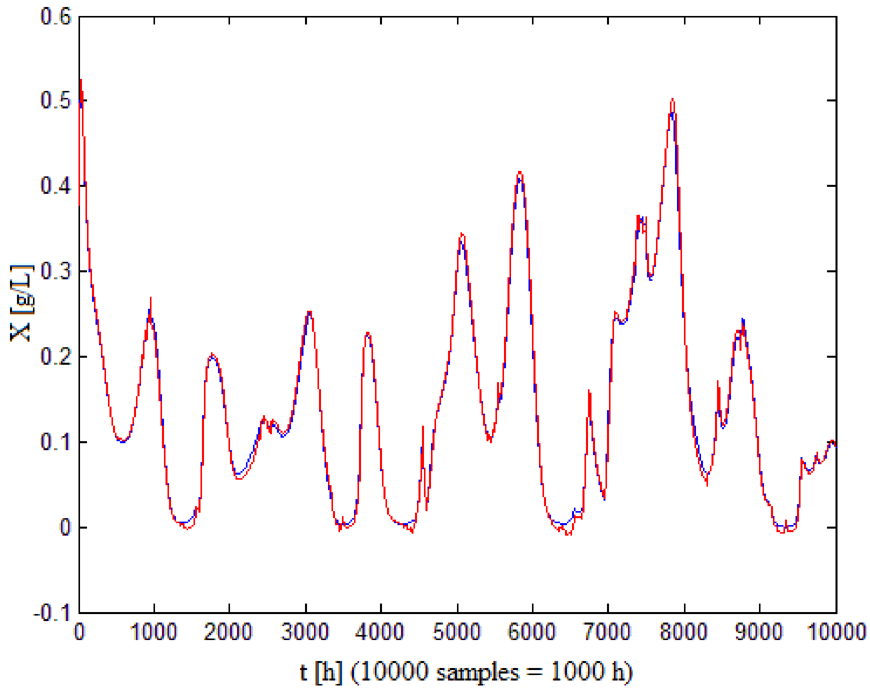

Fig. 2.43 - Validation result for biomass concentration, X (blue – result from analytical model simulation, red – result from neural network approximation) [111]

Modeling errors are not relevant to the process because they are near of *0* value (the "bioreactor" washout state), which should not occur during normal operation. The deviation of the network in this area is caused by the lack of sufficient training data in that interval.

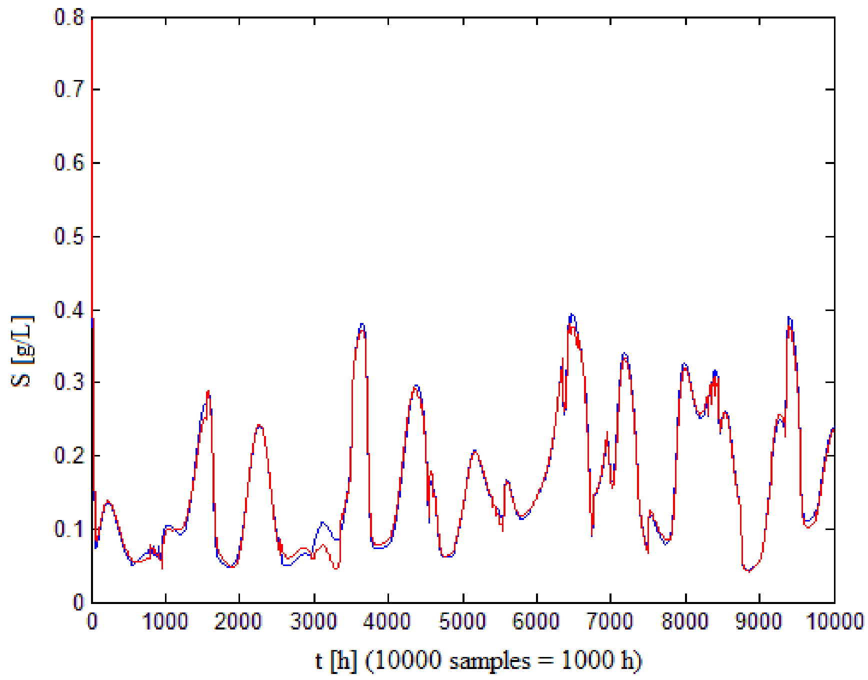

Fig. 2.44 - Validation result for substrate concentration, S (blue – result from analytical model simulation, red – result from neural network approximation) [111]

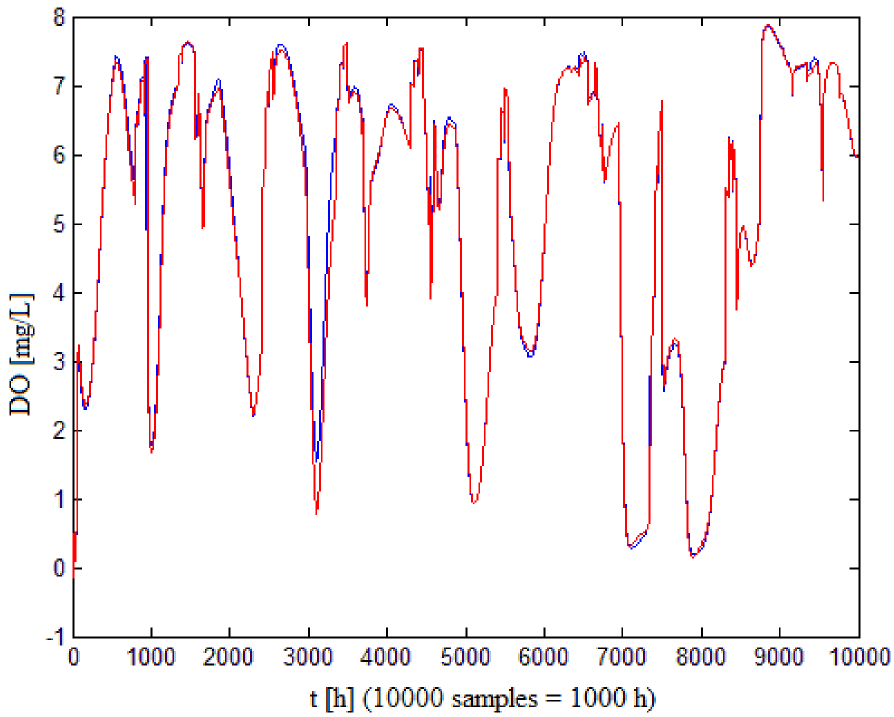

Fig. 2.45 - Validation result for dissolved oxygen concentration, DO (blue – result from analytical model simulation, red – result from neural network approximation) [111]

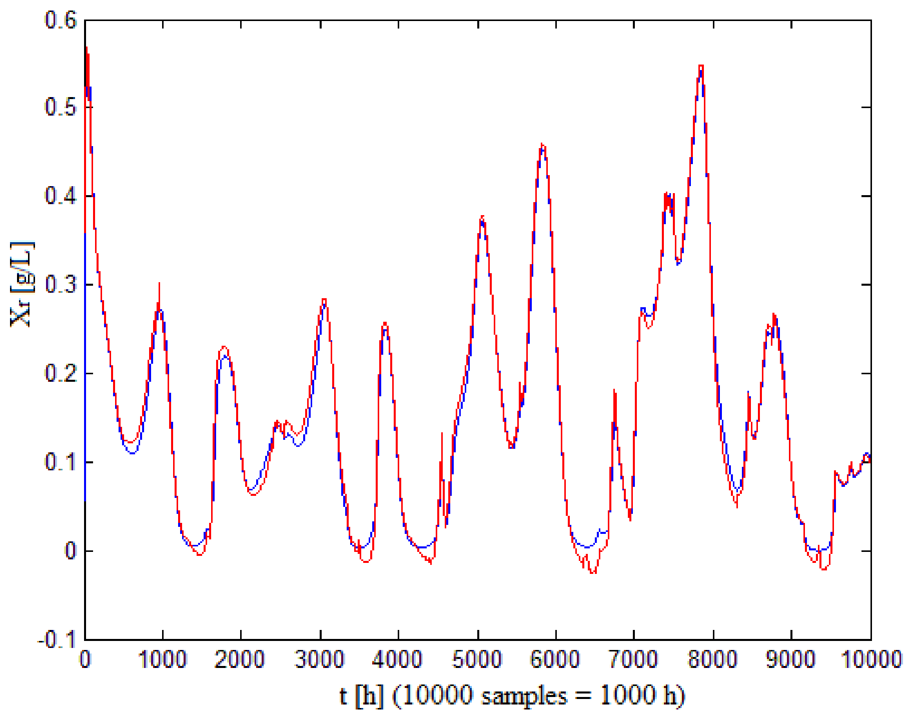

Fig. 2.46 - Validation result for recirculated biomass concentration, X_r (blue – result from analytical model simulation, red – result from neural network approximation) [111]

Chapter 3

Contributions regarding fault detection in the biotechnological processes

3.1 Common problems in fault detection

In our days, fault detection in wastewater treatment plants has become a challenge for specialists due to the complexity of these processes. In this context, many researchers have contributed to the development of various methods of detecting defects, but also to improving existing ones [136], [137], [138], [139], [140] și [141].

Data-based models such as neural networks or fuzzy techniques provide a powerful and fast computational tool for dealing with detection problems. Fault detection signal processing techniques can be used to observe changes in signals either directly from measurements or from residuals resulting from other fault detection techniques [147].

Wastewater treatment processes are very complex systems that can be affected by various disturbances and noises during normal operation, being susceptible to the appearance of various faults that compromise their normal operation. Faults that may affect the operation of a WWTP (Wastewater Treatment Process) may be: mechanical / electrical (equipment faults due to mechanical or electrical problems) of physico-chemical nature (pH, dissolved oxygen or other unknown chemical), biological (biomass was affected – e.g. through contamination) or operational (due to lack of trained personnel).

3.2 Fault detection method for a wastewater treatment process based on a neural model

In this section, a fault detection method based on the neural model of a wastewater treatment process described in Chapter 2 is proposed. In essence, each measurable output is monitored by an automaton that has to decide whether a fault has occurred. For this purpose, a model of the supervised process is used, in this case a neural model supposed to provide the same evolution of the outputs, as well as the outputs from the process, if the same values of the inputs are applied (aspects regarding the fact that not all input states are measurable are not discussed here).

3.2.1 Defining the conditions for choosing parameters of the fault detection algorithm

The automaton algorithm's decision parameters are: the decision threshold value and the number of samples on which the residual is calculated, respectively ε and N. In the following, the probabilities and the delay of the decision are calculated so that based on them, to be chosen an effective objective function. The objective function and the parameter selection procedure (ε and N) are based on the statistical decision theory.

So, it is realized a theoretical analysis in which three hypotheses are considered, as follows: Ip. 1 - there are no modeling errors ($er(k) = 0$, meaning that the model reproduces very well the evolution of the supervised process), if there is a fault, it is assumed that the deviation produced by it has reached steady state in a very short time (several sampling periods) the decision must be taken quickly, only on the value of the current sample, so $N=1$, which is equivalent of saying that the residual was determined for the current sample only; Ip. 2 - there are no modeling errors (meaning that the model faithfully reproduces the evolution of the supervised process), the deviation produced by the faults evolves slowly, with known growth time and the decision can be made on the basis of several successive samples, the residual is calculated on the time horizon $N>1$; Ip. 3 - there is a modeling error with a known density of probability, the deviation caused by the fault evolves slowly, with known growth time, the modeling error varies more slowly than the deviation produced by the fault, and the decision can be made on several successive samples (*N>1*).

<u>Comment on choosing the residual function used in the decision algorithm</u>

Reffering to the definition of the residual function, used for fault detection, in this section I have studied three versions, which are presented in (3.24), (3.25), (3.26).

$$R_1(k) = \frac{1}{N} \sum_{i=k-N+1}^{k} ab(i) \tag{3.24}$$

$$R_2(k) = \frac{1}{N} \sum_{i=k-N+1}^{k} | ab(i) | \tag{3.25}$$

$$R_3(k) = \frac{1}{N} \sum_{i=k-N+1}^{k} (ab(i))^2 \tag{3.26}$$

Fig. 3.12 contains three graphs for these three solutions, calculated on N = 20 samples, to show the difference between the three versions. This is the reson, for which, if the expected deviations and modeling errors are high compared to the noise level, the three versions of the residual will produce similar results, so **it can be said that they are equivalent**. If, on the contrary, the expected deviation is low compared to the noise level, the most advantageous residual is R_1.

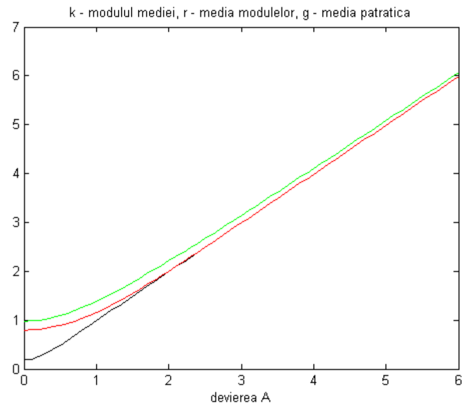

Fig. 3.12 – The variation of the three residual, with the *A* deviation value

Further, taking into account the above analysis, **the 3th version of obtaining the residual for the biological wastewater treatment process was chosen,** where the residuals is calculated as average of the deviations squares.

3.2.2 Fault detection scheme using a neural network

In this chapter it is recommended to apply the method of detecting faults based on the residuals determination. To test the fault detection system, various faults are simulated using the analytical model of the process. The following are considered possible:

1. net faults of filed equipments from the process (actuators and transducers);
2. partial faults of the equipments mentioned at the step 1;
3. faults which appears during unfavorable conditions of the micro-organism (e.g.: toxic shock or contamination), which lead the sludge to an unviable state;

The general fault detection scheme is shown in the below figure:

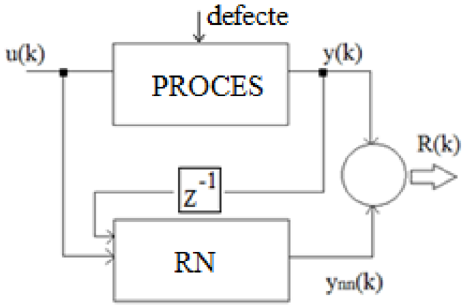

Fig. 3.13 – The general scheme of fault detection method

3.2.3 Validation of the fault detection method based on a neural network using numerical simulations

In this section it is presented a series of numerical simulations to analyze the effect of N și ε parameters on the performance of the method (undetected faults or false alarms) and the detection speed (the alarm duration in the presence of a fault). It should be mentioned that **the sampling period was chosen as follows: $\boldsymbol{T_e = 6\,min}$**, the process being very slow.

1. **<u>Presence of net faults at the field equipment</u>**

a) Fault of the recirculation pump

For simulating a net fault of the recirculation pump it is considered that the value of the parameter $r = 0$ on the interval $N_f \in [4300, 5400]$). In the Fig. 3.15 it can be observed the deviations on each output of the process at the time when fault occurs.

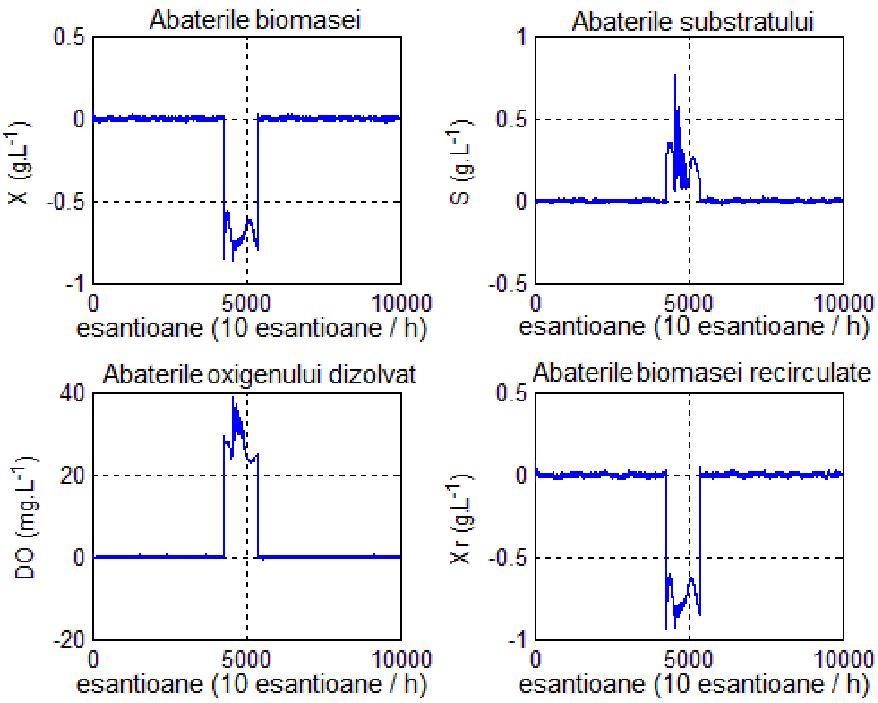

Fig. 3.15 – The output deviations X, S, X_r, DO due to failure of the recirculation pump ($r = 0$) on the interval $[4300, 5400]$ samples

Next, the residual for each process output are obtained for the following values of N [samples]: $N = 10,\ N = 20,\ N = 40,\ N = 80$. Fig. 3.17 shows the value of the residual when N = 20.

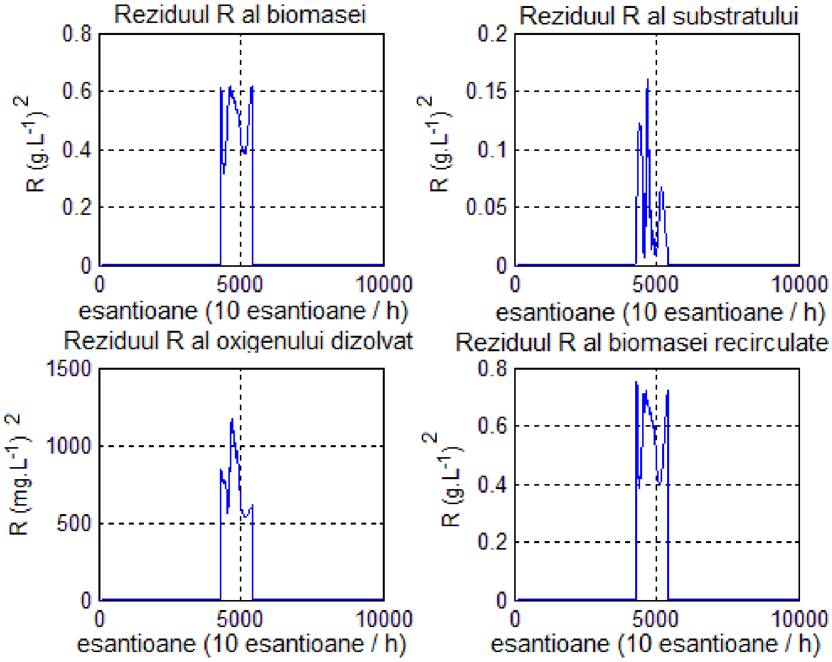

Fig. 3.17 – The residual, R, obtained in the case of recirculation pump failure when $N = 20$

b) Net fault of the biomass concentration transducer

A net fault of the biomass transducer can be simulated by the fact that the measured biomass of the process $X = 0$ (the treatment plant is in the "washout" state. In Fig. 3.20 are presented the deviations obtained by simulating this type of fault, which occured in the process for a certain period of time, namely, between 4300 and 5400 samples.

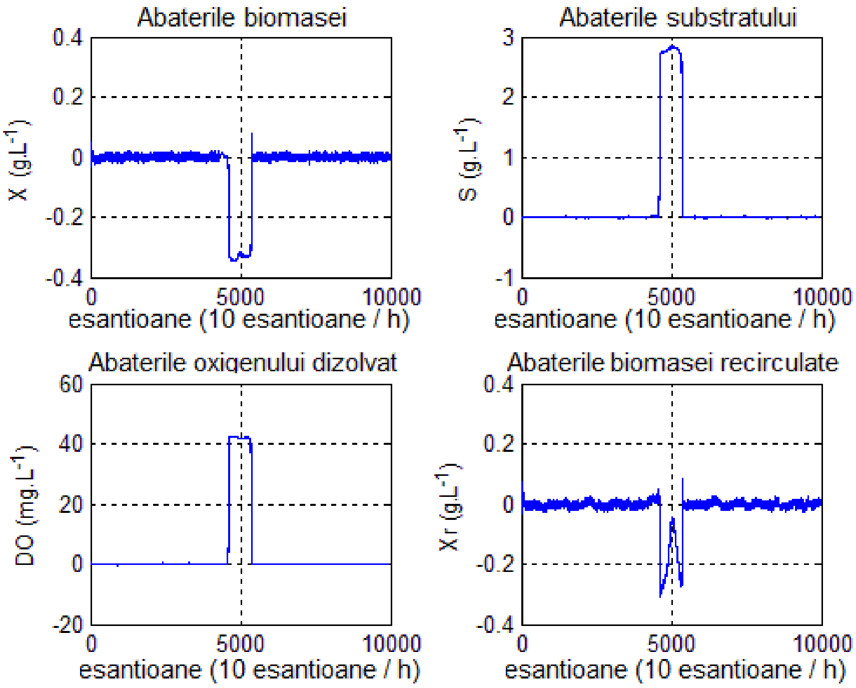

Fig. 3.20 - The output deviations X, S, X_r, DO due to failure of the biomass transducer ($X = 0$) on the interval $[4300, 5400]$ samples

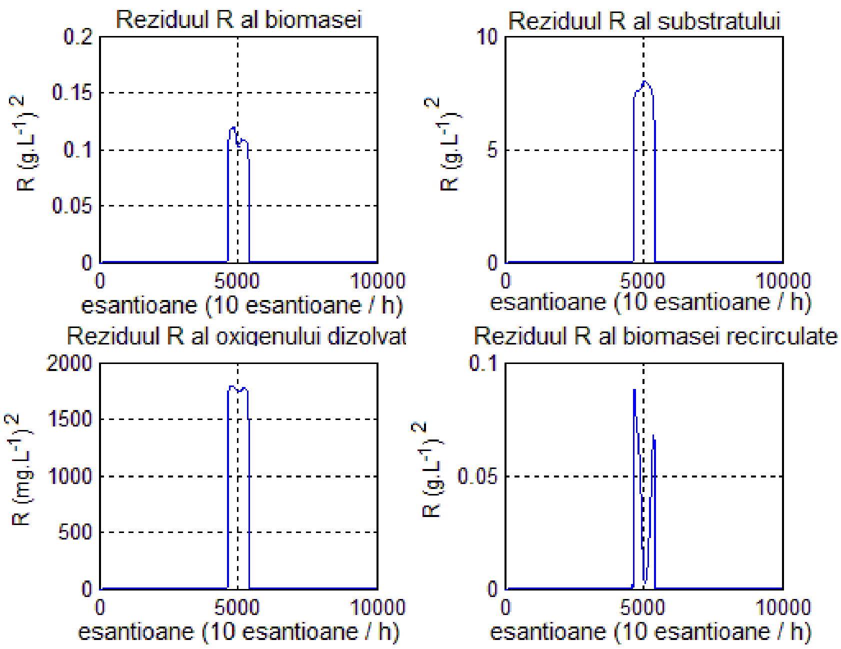

Fig. 3.22 - The residual, R, obtained in the case of biomass transducer failure when $N = 20$

The residual is also performed for other values of N [samples]: $N = 10$, $N = 40$, $N = 80$.

2. The presence of partial faults (25%) of field equipment

a) Partial fault of the supplying pump failure with influent (25% of the total capacity)

Further, it is analyzed a partial fault of the supplying pump when it operates at 25% of the total capacity on the interval $N_f \in [4300, 5400]$). In Fig. 3.25 are obtained the deviations produce by the operation of the 25% capacity of this equipment.

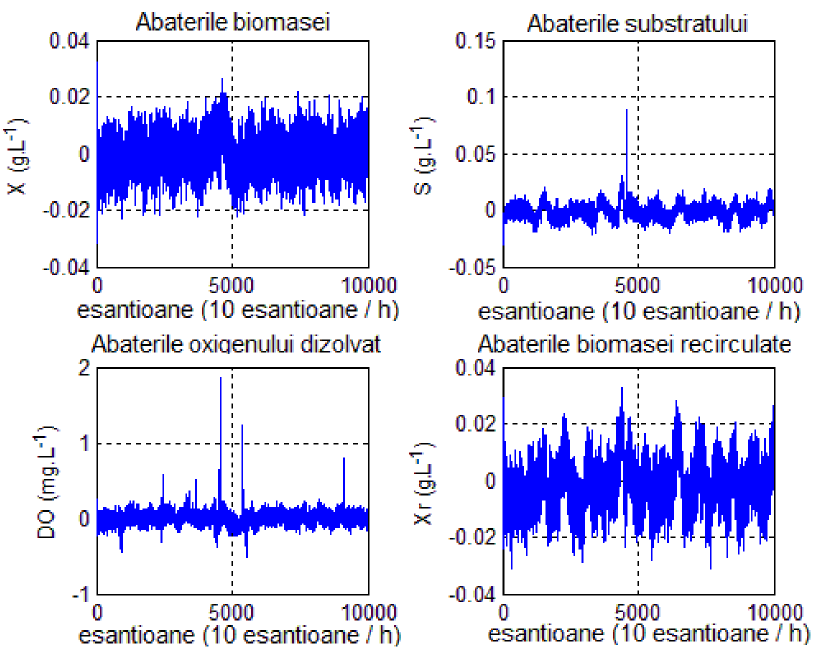

Fig. 3.25 - The output deviations X, S, X_r, DO due to partial failure of the supplying (operating at 25% of the total capacity) on the interval $[4300, 5400]$ samples

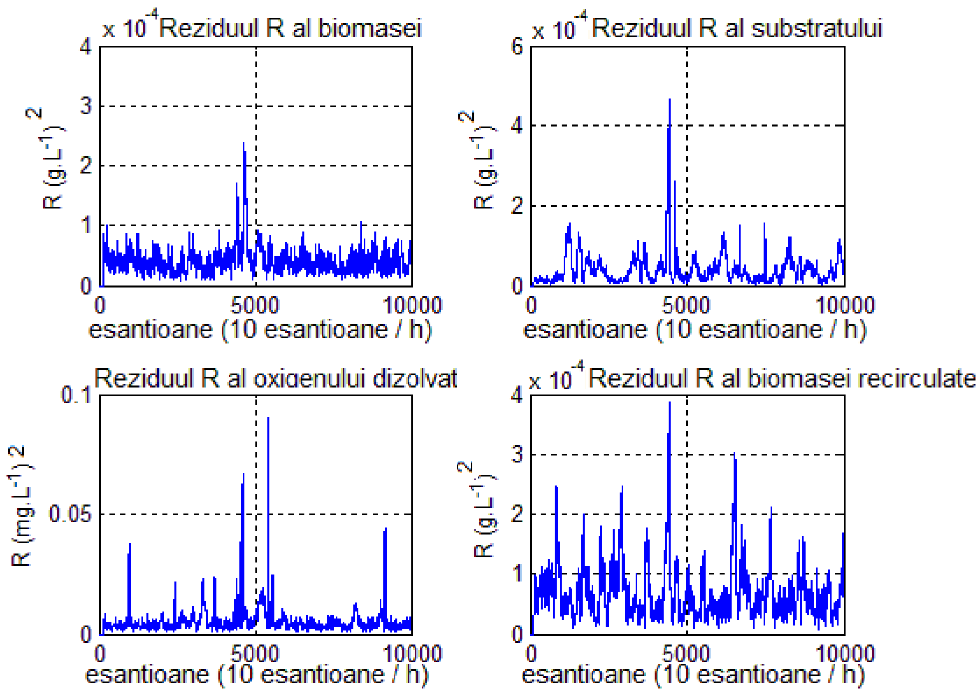

Fig. 3.27 - The residual, R, obtained in the case of partial supplying pump failure (operating at 25%of the capacity) when $N = 20$

Further, it is obtained the residual for other values of N [samples]: $N = 10$, $N = 40$, $N = 80$.

3. The presence of a fault due to a toxic shock suffered by the culture of the micro-organisms

The fault due to a toxic shock suffered by the micro-organism culture was simulated by halving the biomass growth rate, μ_{max}, on the interval $N_f \in [4300, 5400]$).

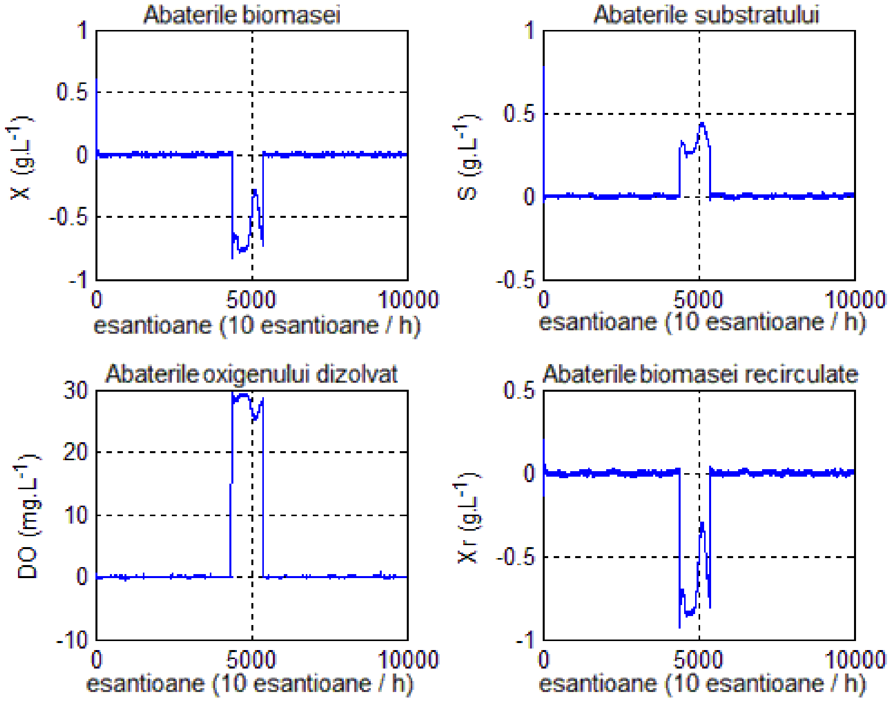

Fig. 3.30 - The output deviations X, S, X_r, DO due to the toxicity fault ($\mu_{max}/2$ on the interval $[4300, 5400]$ samples)

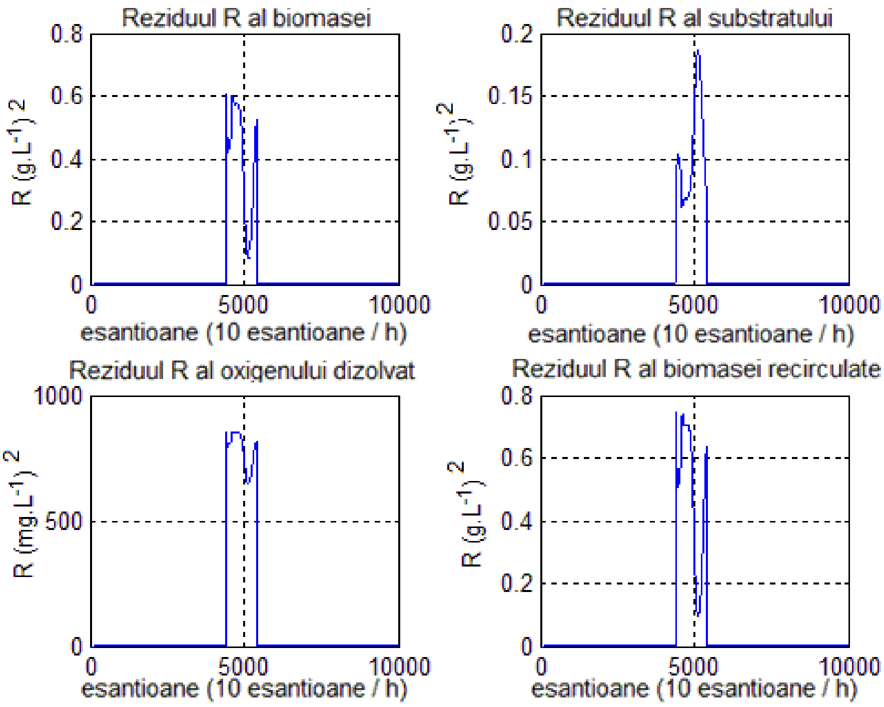

Fig. 3.32 - The residual, R, obtained in the case of toxicity fault when $N = 20$

In all cases of previously analyzed faults, the value $N = 20$ is chosen for the parameter *N*, which corresponds to the criterias analysis of choosing the parameters of the detection method discussed in section 3.2.1.

The sensibility threshould, ε, is set for each output: $\varepsilon_X = 2.2 \cdot 10^{-4}$, $\varepsilon_S = 2.6 \cdot 10^{-4}$, $\varepsilon_{DO} = 0.05$, $\varepsilon_{X_r} = 4 \cdot 10^{-4}$.

a). Detection for the net fault of the recirculation pump

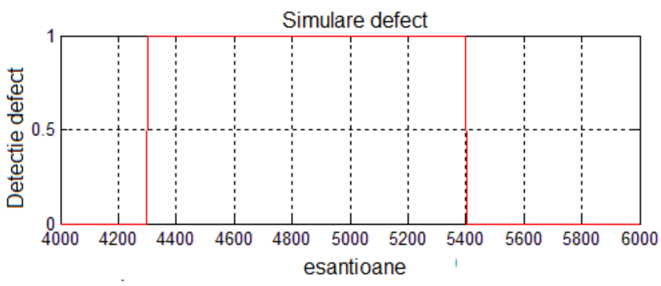

Fig. 3.35 – Fault simulated on the interval $[4300, 5400]$ samples

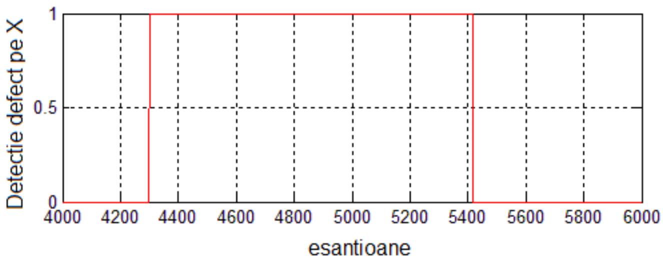

Fig. 3.36 - Alarm generation for the X output, in the case of recirculation pump failure (fault detection on the $[4300, 5419]$ samples)

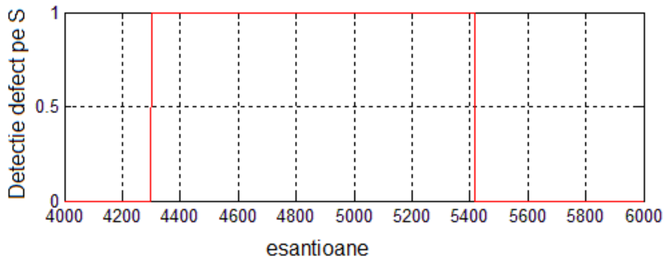

Fig. 3.37 – Alarm generation for the output S, in the case of recirculation pump failure (fault detection on the $[4300, 5419]$ samples)

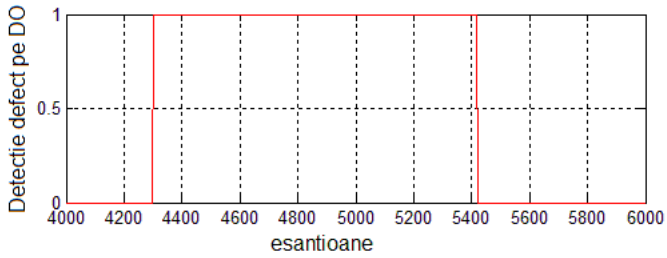

Fig. 3.38 – Alarm generation for the output DO, in the case of recirculation pump failure (fault detection on the$[4300, 5420]$ samples)

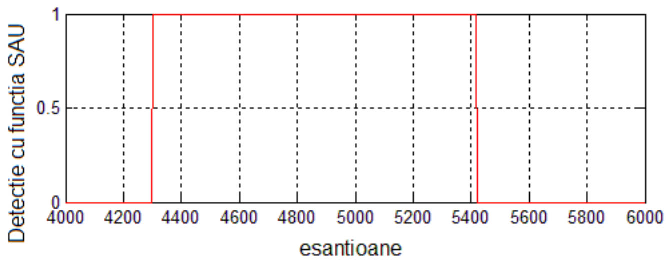

Fig. 3.39 – Alarm generation for the output X_r, in the case of of recirculation pump failure (fault detection on the$[4300, 5419]$ samples)

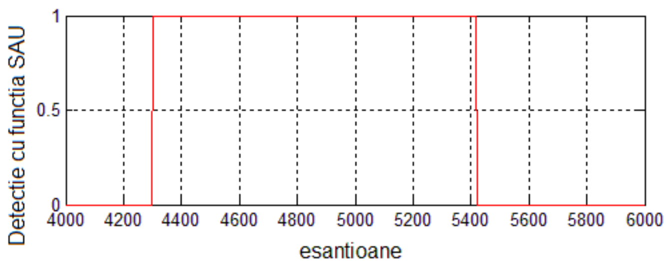

Fig. 3.40 – Alarm generation of the OR function in the case of of recirculation pump failure (fault detection on the$[4300, 5420]$ samples, after $\sim 0h$, instantaneous detection of the fault)

Detection is performed for all types of faults previously analyzed. In the performed simulations it was possible to correctly detect each fault that occurred in the process with a delay of no more than $12h$. The best result of the detection algorithm was obtained in the case of a failure of the recirculation pump, the detection of the fault being practically instantaneous.

3.3 Fault detection using extended Kalman filter for a wastewater treatment plant

In this section it is proposed, versus the neural network detection method, when all outputs of the process were considered measurable, a method for detecting faults based on the analytical mathematical model of the treatment process, plus a Kalman filter to determine non-measurable state variables.

In Fig. 3.59 shows the estimation results of the process states using the extended Kalman filter.

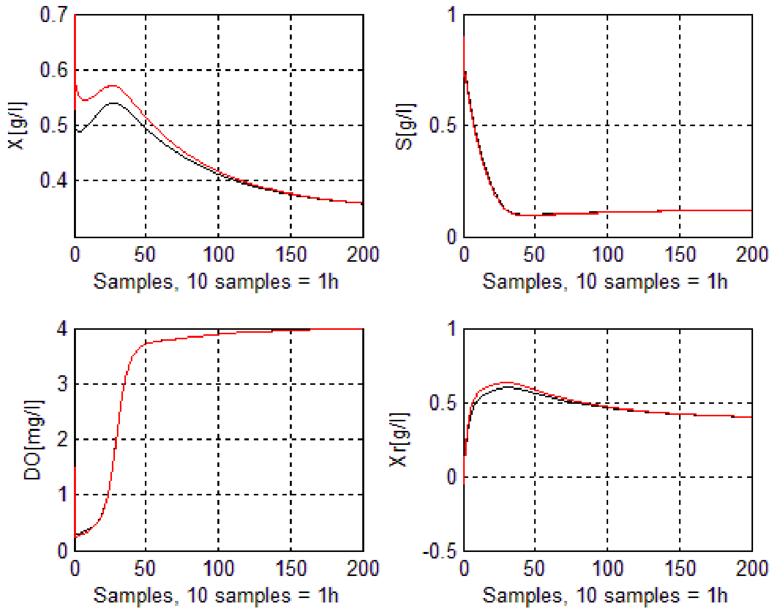

Fig. 3.59 – The states estimation using the extended Kalman filter (red – the output of the process, black – their estimation)

3.3.3 The fault detection scheme using the extended Kalman filter

Fig. 3.60 shows the fault detection scheme used for residuals generation. The input DO_{in} is considered constant.

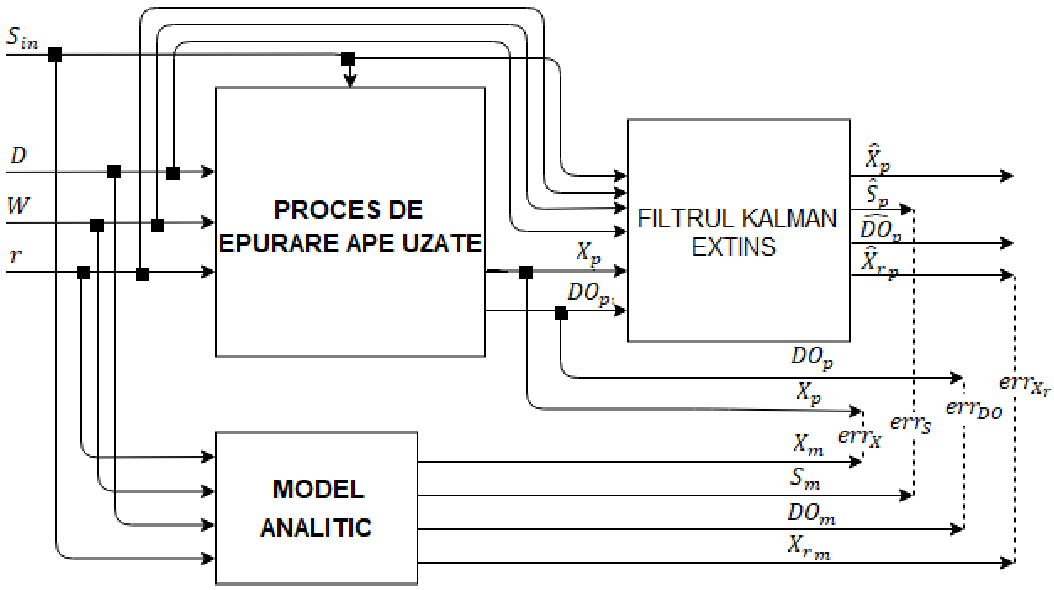

Fig. 3.60 – The fault detection scheme using the extended Kalman filter

3.3.5 Validation of the fault detection method based on the extended Kalman filter using numerical simulations

At this stage, some types of simulated faults are resumed in section 3.2.3 and the proposed new detection method is tested in the case when a Kalman filter is used.

1. <u>**Presence of net faults at the field equipment**</u>

a) Net fault of the recirculation pump

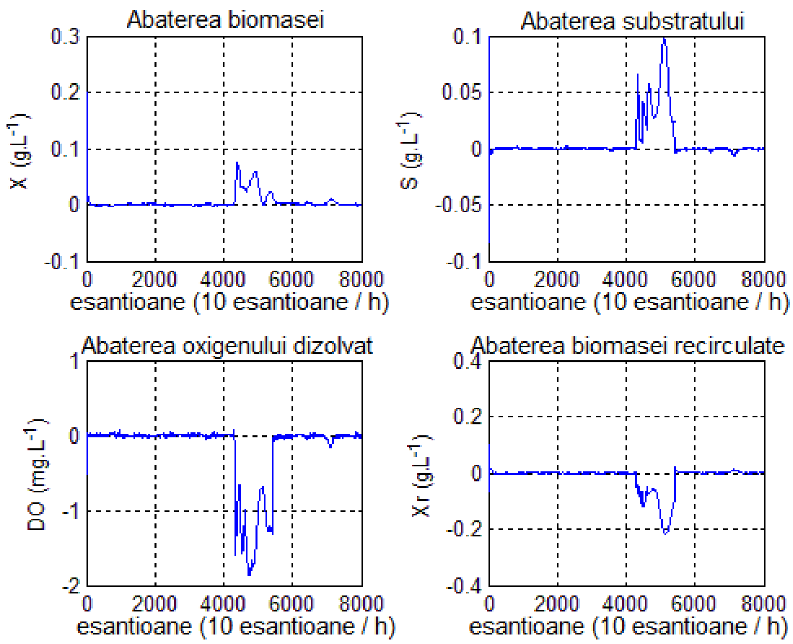

Fig. 3.62 - The output deviations X, S, X_r, DO due to failure of the recirculation pump ($r = 0$) on the interval $[4300, 5400]$ samples

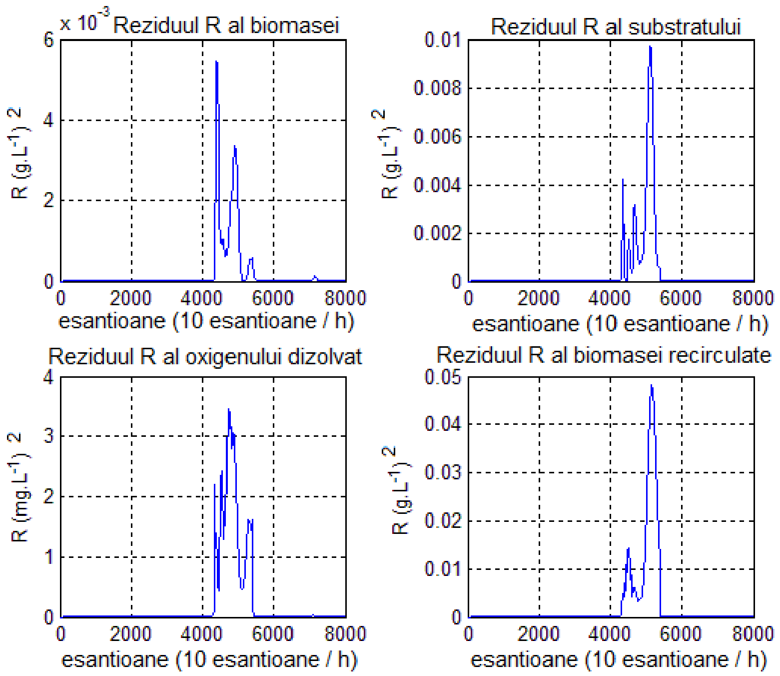

Fig. 3.63 - The residual, R, obtained in the case of recirculation pump failure when $N = 10$

The same procedure for calculating the residue is also performed for N = 20, N = 40.

b) Net fault of the biomass concentration transducer

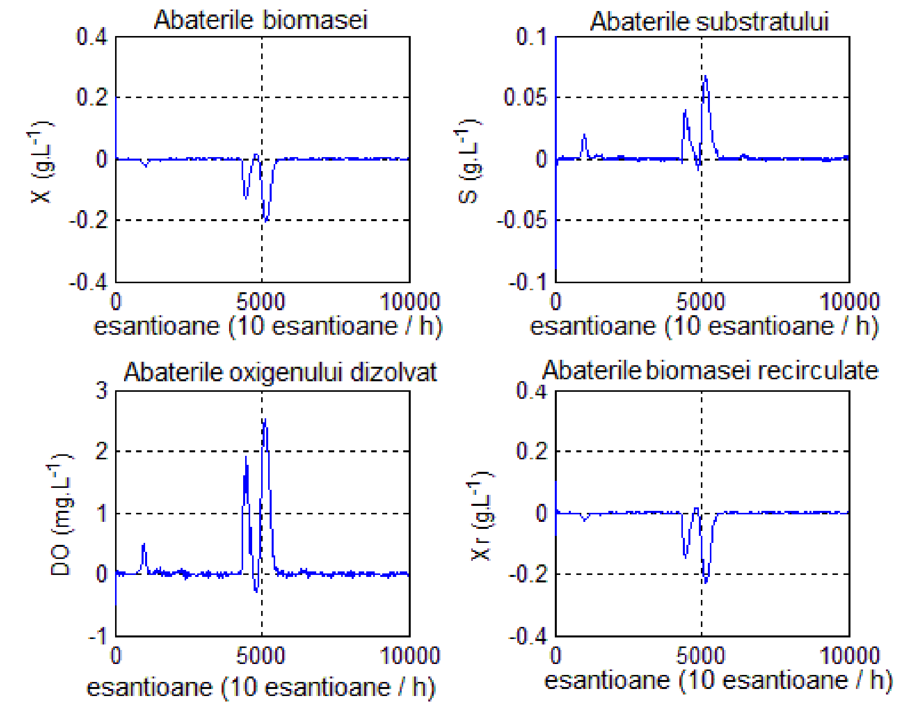

Fig. 3.66 - The output deviations X, S, X_r, DO due to failure of the biomass transducer ($X = 0$) on the interval $[4300, 5400]$ samples

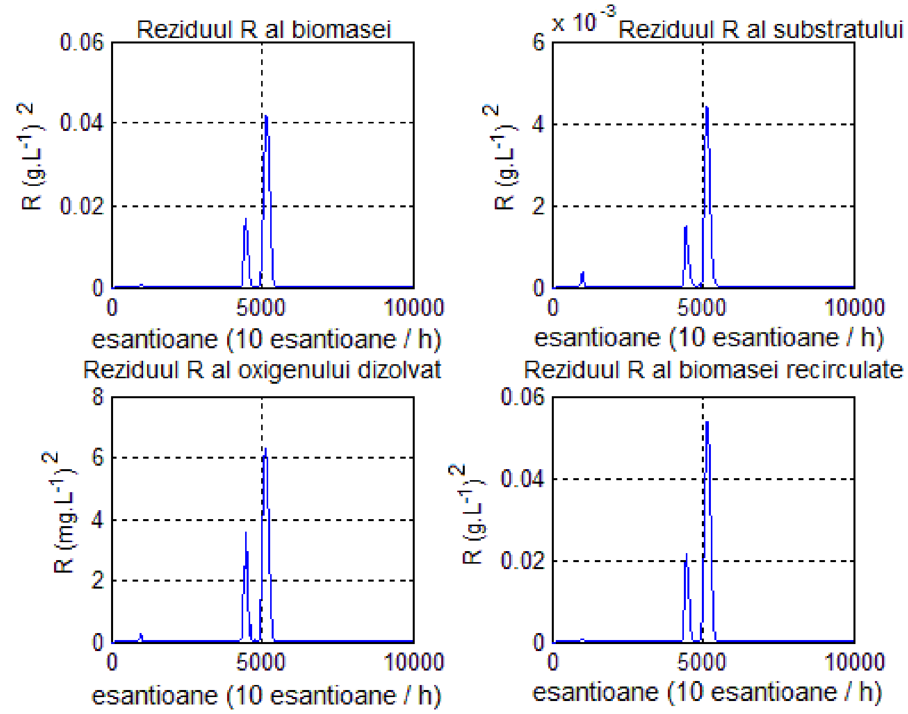

Fig. 3.67 - The residual, R, obtained in the case of biomass transducer failure when $N = 10$

The residual is also obtained in the case of $N = 20, N = 40$.

2. The presence of partial faults (25%) of field equipment

a) Partial fault of the supplying pump failure with influent (25% of the total capacity)

It is considered the case when the supplying pump operates at a maximum capacity of 25% of total capacity over the period $N_t \in [4300, 5400]$. In Fig. 3.70 it is obtained the outputs deviations X, S, DO, X_r.

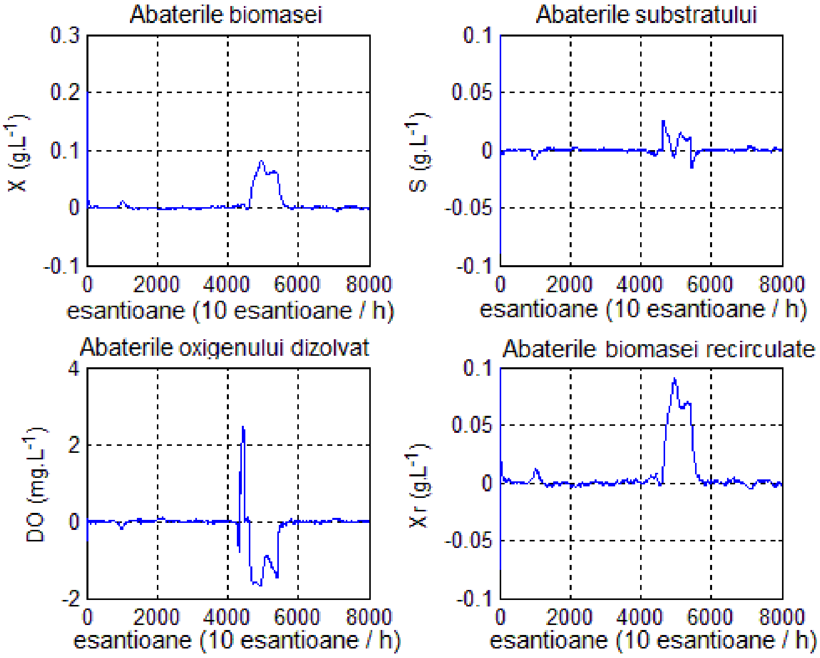

Fig. 3.70 - The output deviations X, S, X_r, DO due to partial failure of the supplying (operating at 25% of the total capacity) on the interval $[4300, 5400]$ samples

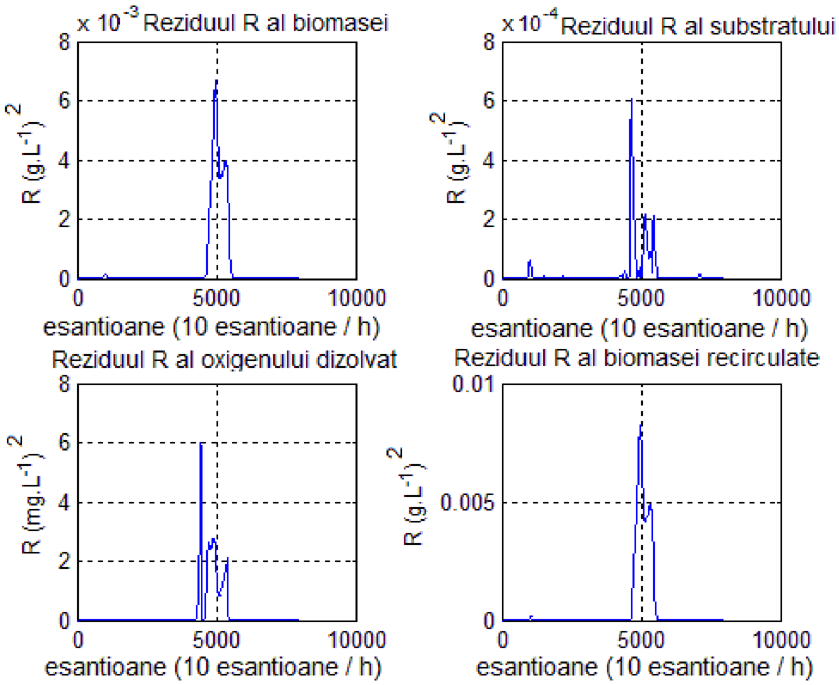

Fig. 3.71 - The residual, R, obtained in the case of partial supplying pump failure (operating at 25% of the total capacity) when $N = 10$

Based on the results of the simulations obtained in all the above-mentioned faults (detection method using the Kalman filter), it is recommended to choose the following values for the parameters of the detection method:

a) $N = 10$ samples;

b) The sensibility thresould, ε, for each output is given by the following values: $\varepsilon_X = 0.5 \cdot 10^{-3}$, $\varepsilon_S = 0.2 \cdot 10^{-3}$, $\varepsilon_{DO} = 0.2$, $\varepsilon_{X_r} = 3 \cdot 10^{-3}$.

Further, the detection is performed for all types of analyzed faults. For example, the detection result will only be shown for the net fault of the recirculation pump. This is the case where the best detection result is obtained, i.e. after approximately $0.7h$.

a).Net fault detection of the recirculation pump

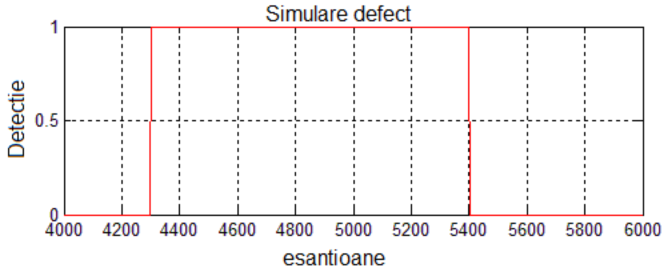

Fig. 3.74 - Fault simulated on the interval $[4300, 5400]$ samples

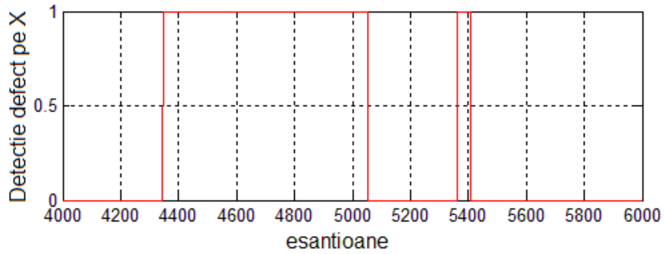

Fig. 3.75 - Alarm generation for the X output, in the case of recirculation pump failure (fault detection on the intervals $[4345, 5047]$, $[5366, 5406]$ samples)

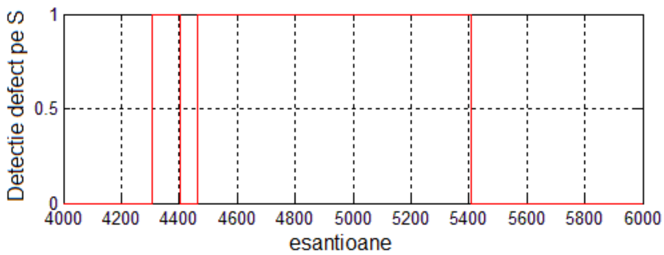

Fig. 3.76 - Alarm generation for the S output, in the case of recirculation pump failure (fault detection on the intervals $[4307,4402]$, $[4461,5410]$ samples)

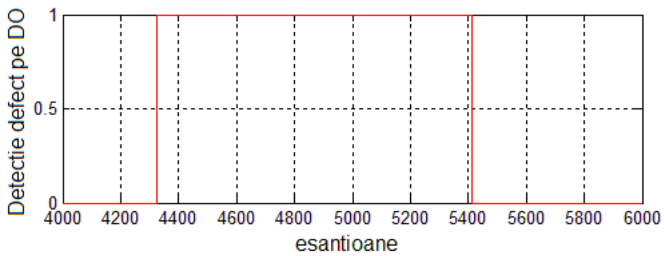

Fig. 3.77 - Alarm generation for the S output, in the case of recirculation pump failure (fault detection on the intervals $[4324, 5414]$ samples)

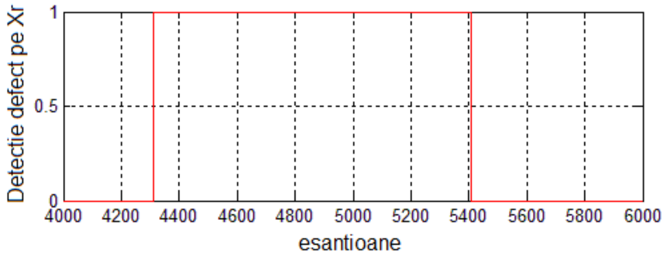

Fig. 3.78 - Alarm generation for the X_r output, in the case of recirculation pump failure (fault detection on the intervals $[4312, 5409]$ samples)

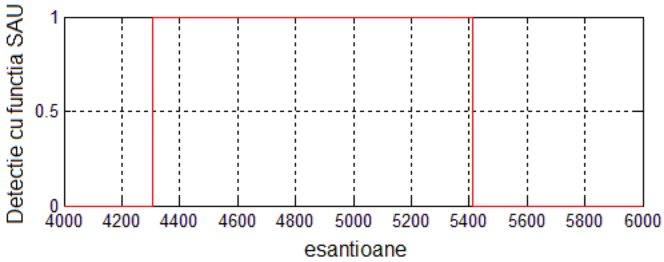

Fig. 3.79 – Alarm generation using OR function in the case of recirculation pump failure (fault detection on the intervals $[4307, 5414]$ samples, after $\sim 0.7h$)

Chapter 4

Fault isolation using neural networks

4.1 Common problems in fault isolation

Fault isolation is an important step in designing the Fault Detection and Isolation (FDI) systems. Isolation is referring to define the type of fault, to determine the location where the fault occured and the moment of its detection in the analyzed process. Thus, the faulty components need to be replaced or "isolated" as soon as possible, to avoid propagation of the fault through the entire biotechnological process. However, the classical diagnosis methods used in wastewater treatment plants have not proved to be very effective to control the operation and internal dynamics of processes. Therefore, it is not surprising that there is an increase in the number of papers in which various advanced techniques reffering to fault isolation are presented.

These can be divided into three main categories: knowledge-based methods, methods based on analytical models and pattern recognition methods. Each of them represents a combination of a certain type of a priori knowledge and presents various advantages and limitations for a particular application or a particular process [152], [153].

Patern recognition methods can be statistical [154], [155] (parametric or nonparametric classifiers) or deterministical (neural classification networks). They use information about the history of the processes and their main advantage is its real-time performance, the ability of knowledge acquisiton, and their applicability in a wide variety of systems. On the other hand, they present limitations regarding generalization capacity outside the training domain and encounter difficulties in the case of multiple faults detection.

One of these methodologies, namely, the one that uses artificial neural networks, has demonstrated its capabilities in modeling, controlling and diagnosing complex systems by processing incomplete or uncertain data [111], [134], [157] - [160]. However, less attention has been paid to their application in the scope of detection, isolation and surveillance of faults in biotechnological systems.

4.2 Artificial neural network method for fault recognition in a wastewater treatment process

This section describes a neural network recognition method to classify faults that may occur in a wastewater treatment plant. The wastewater treatment process is detailed in section 2.3.3 of Chapter 2. According to [161], wastewater treatment is a complex process in which sensors and equipments operate in harsh conditions, and often there are quite a lot of delays of the variables response to disturbances. It should be noted that fault isolation was made only for faults of field equipment (transducers and actuators, net and partial faults), and not for faults related to the nature of the treatment process (very complex biotechnological process), as shown in Chapter 3 - faults due to a toxic shock in microorganisms culture.

4.2.1 The fault diagnosis scheme

As shown in the diagnosis scheme (Figure 4.1) of the faults proposed in this section, artificial neural network inputs for pattern recognition of faults are: input variables (D, W, r, b, S_{in}), output variables (X, S, DO, X_r) and their history over the last 10 samples. At the output, the recognition result of each fault is obtained.

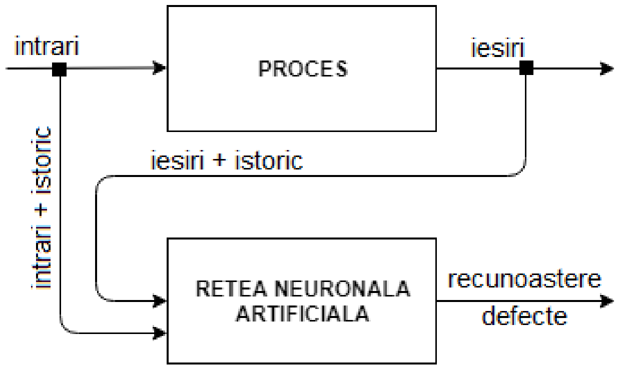

Fig. 4.1 – Fault diagnosis scheme

4.2.2 Designing the neural network for fault recognition

To isolate faults, an artificial feedforward neural network is designed as a classifier. The designing stages of the artificial neural network for fault recognition are similar with those presented in Section 2.3.4, Chapter 2.

The activation function is sigmoid (logsig) for the hidden layer and the output layer (with output values of 0 and 1). For training the network, a backpropagation training algorithm based on a conjugate gradient-based minimization method (the Matlab-trainscg function), also known as the "Scaled conjugate gradient backpropagation", is used. The performance function chosen for the training process is the mean square error (MSE).

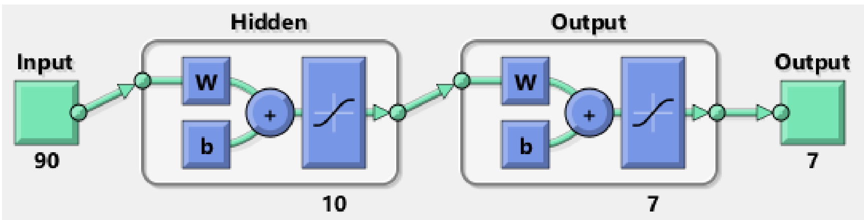

Fig. 4.2 - Artificial Neural Network Structure for Recognising faults in the Wastewater Treatment Process

To train the neural network, the input data set is a P array of dimensions 90 x 10889. Each column is an example containing 90 values: input variables (D, W, r, b, S_{in}), output variables (X, S, DO, X_r) and their history over the last 10 samples. For training, a total of 7623 examples are considered, i.e. 70% of the total number of examples in the input data set. The data is obtained by numerical simulation of the analytical model.

The output data set is a T array of dimensions 7 x 10889 (7 distinct classes). Each column is a 7 element column vector that contains values of 0 and 1, as follows:

$[1\ 0\ 0\ 0\ 0\ 0\ 0]^T$ - The vector belongs to class 1 (normal operation);

$[0\ 1\ 0\ 0\ 0\ 0\ 0]^T$ - The vector belongs to class 2 (fault of the recirculation pump);

$[0\ 0\ 1\ 0\ 0\ 0\ 0]^T$ - The vector belongs to class 3 (fault of the supplying pump);

$[0\ 0\ 0\ 1\ 0\ 0\ 0]^T$ - The vector belongs to class 4 (fault of the excess sludge pump);

$[0\ 0\ 0\ 0\ 1\ 0\ 0]^T$ - The vector belongs to class 5 (fault of the biomass transducer);

$[0\ 0\ 0\ 0\ 0\ 1\ 0]^T$ - The vector belongs to class 6 (fault of dissolved oxygen transducer);

$[0\ 0\ 0\ 0\ 0\ 0\ 1]^T$ - The vector belongs to class 7 (partial fault of the supplying pump).

Table 4.1 – Distribution by classes of the number of examples in the training, validation and testing data set

Data sets	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Total
Input set	4289	1091	1100	1100	1100	1100	1109	10889 (100%)
Training	3019	753	760	763	771	779	778	7623 (70%)
Validation	637	165	170	163	161	154	183	1633 (15%)
Testing	633	173	170	174	168	167	148	1633 (15%)

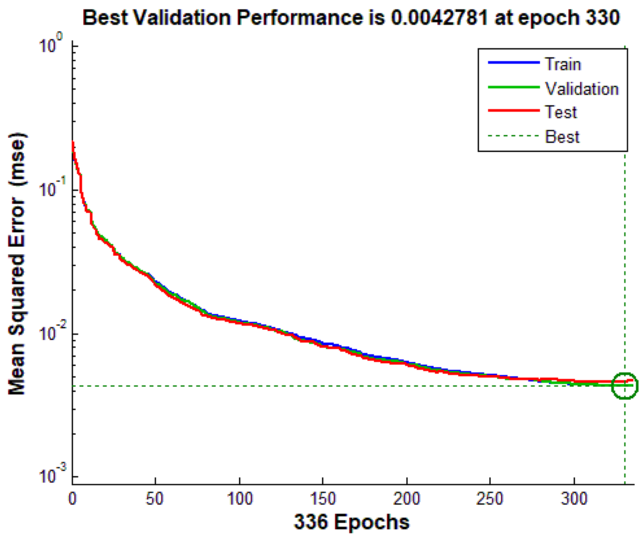

Fig. 4.4 - Evolution of MSE error during training

4.2.3 The results of training, testing and validation of the neural network

After training the neural network, the confusion matrix presented in Fig. 4.5, is obtained:

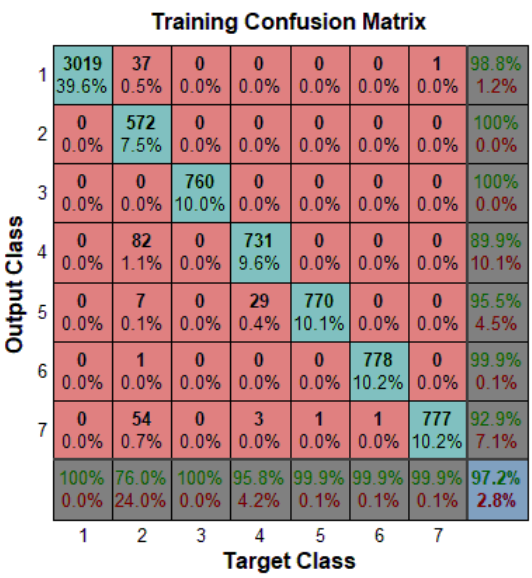

Fig. 4.5 – The confusion matrix for training the neural network

The percentage of correct recognition for the 7 classes is 97.2% and the incorrect recognition rate is 2.8%.

Table 4.2 - Recognition percentages for neural network training

Clas	Nr. of examples	TP [%]	FP [%]	TN [%]	FN [%]
1	3019	98.75	1.25	100	0
2	753	100	0	97.43	2.57
3	760	100	0	100	0
4	763	89.91	10.09	99.53	0.47
5	771	95.53	4.47	99.98	0.02
6	779	99.87	0.13	99.98	0.02
7	778	92.94	7.06	99.98	0.02

Table 4.2 shows that were obtained best recognition rates for Class 3 and Class 6 with very good recognition rates true (class 3: $TP = 100\%$, $TN = 100\%$; class 6: $TP = 99.87\%$, $TN = 99.98\%$) and low values for false recognition rates (class 3: $FP = 0.13\%$, $FN = 0.02\%$; class 6: $FP = 0\%, FN = 0.05\%$).

Validation of the neural network - the confusion matrix in Fig. 4.6:

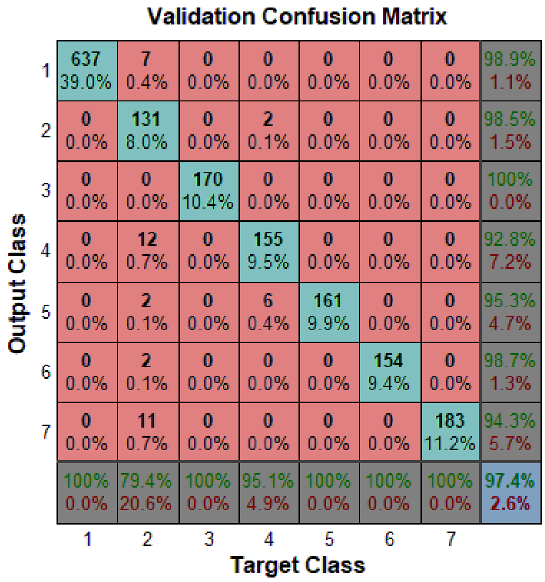

Fig. 4.6 – The confusion matrix for the neural network validation data set

The correct recognition percentage of the all 7 classes is 97.4% and the incorrect recognition percentage is 2.6%.

Table 4.3 - Recognition percentages for neural network validation

Class	Nr. of examples	TP [%]	FP [%]	TN [%]	FN [%]
1	637	98.91	1.09	100	0
2	165	98.49	1.51	97.73	2.27
3	170	100	0	100	0
4	163	92.81	7.19	99.45	0.55
5	161	95.26	4.74	100	0
6	154	98.71	1.29	100	0
7	183	94.32	5.68	100	0

Table 4.3 shows that the best recognition rates for Class 1 and Class 3 were obtained.

Testing the neural network - the confusion matrix in Fig. 4.7:

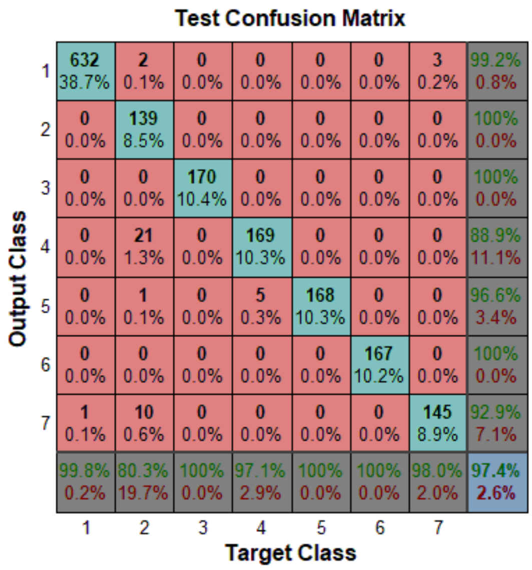

Fig. 4.7 – The confusion matrix for the neural network test data set

Table 4.4 shows that the best recognition rates for Class 3 and Class 6 were obtained.

Table 4.4 - Recognition percentages for neural network testing

Class	Nr. of examples	TP [%]	FP [%]	TN [%]	FN [%]
1	633	99.21	0.79	99.89	0.01
2	173	100	0	97.72	2.28
3	170	100	0	100	0
4	174	88.94	11.06	99.65	0.35
5	168	96.55	3.45	100	0
6	167	100	0	100	0
7	148	92.94	7.06	99.79	0.21

Overall analysis across the entire input data set:

The confusion matrix from Fig. 4.8 shows that the neural network correctly classifies data in 7 classes, in proportion of 97.2%.

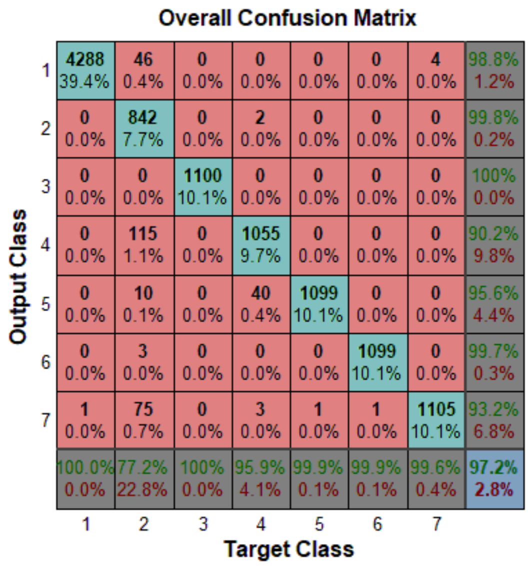

Fig. 4.8 – The confusion matrix for the entire input data set

Analysis based on ROC curves ("Receiver Operating Characteristic")

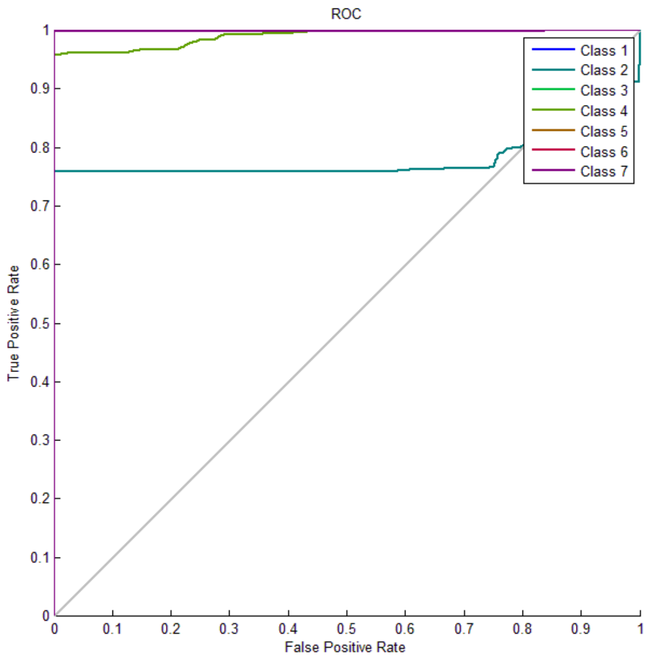

Fig. 4.9 - The ROC curve for the set of 7623 training data

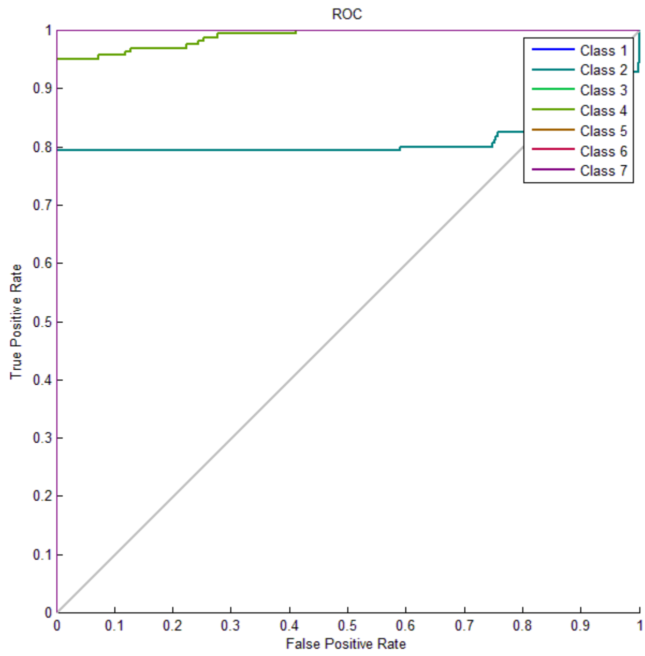

Fig. 4.10 - The ROC curve for the set of 1633 validation data

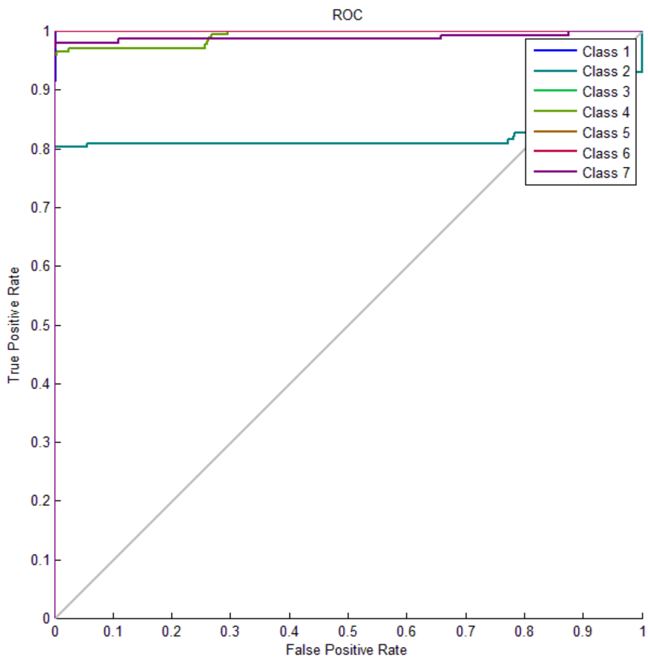

Fig. 4.11 - The ROC curve for the set of 1633 test data

From the ROC curves it appears that the lowest recognition rate is recorded for Class 2 and Class 4. Otherwise, it is noted that for the other classes very good recognition accuracy is obtained, especially for Classes 1, 3 and 6.

Conclusions

With the increasing pollution and the development of modern society in recent years, the use of biotechnological processes has become vital for sustainability and environmental protection. In nowdays, preventing pollution, minimizing waste in industrial, urban and agricultural activities, and encouraging recycling, have become a priority. Technologies used in the field of biotechnology are many but some of the most common are wastewater treatment processes which have a determining role in reducing the amounts of organic and solid matter suspended in water by appropriate treatments to purify water before be discharged into any emissary (seas, rivers, lakes, etc.).

Therefore, in addition to the monitoring and control methods, fault diagnosis has become increasingly important in order to achieve robust and efficient operation in terms of resource use of wastewater treatment plants. Wastewater treatment processes are very complex systems that can be affected by various disturbances and noises during normal operation, and are susceptible to the appearance of various faults that may compromise their correct operation. Faults that can occur in a wastewater treatment plant are: mechanical / electrical (faults in equipment due to mechanical or electrical problems), chemical (pH, dissolved oxygen or other unknown chemicals), biological (biomass was affected – e.g. contaminated) or operational (due to lack of trained personnel). The correct operation of sensors and actuators is important for the efficient control of these processes in terms of treatment performance and use of energy resources. Robust and powerful operation requires automated control that in turn requires reliable and accurate operation of sensors that transmit accurate process information. If the automation system uses transducers or defective components, it quickly leads to resource loss (raw material and energy) or process deviation until it goes out of operation.

In this PhD thesis, it is proposed, first of all, a modeling method using neural networks for a wastewater treatment process with activated sludge. The neural model is useful for prediction of process outputs. The advantage of using this method is that, in order to obtain a very good prediction capacity, no prior knowledge is needed on the mathematical model of the process, but only the data recorded in the process is used. The downside is that the amount of data required is very high. They must characterize the process in all the operating modes in which the model will be exploited.

Also, two model-based fault detection methods have been implemented for a wastewater treatment process with active sludge. Two situations are analyzed: 1. process outputs are considered measurable; and 2. some of the process outputs are unmeasurable. The first method uses a neural network as a model for prediction of process outputs under normal operating conditions. Detection is based on residuals, calculated as the mean squares of the deviations between the outputs of the process and those of the neural network. The second detection method uses an extended Kalman filter to estimate non-measurable outputs. Depending on the residuals values, it is determined whether a fault has occurred in the process. For each method, specific recommendations are made on how to configure the detection methods parameters in order to reduce the number of false alarms, improve detection time, and work even if the process is severely affected by noise. The choice of detection parameters (defect sensitivity threshold and residual horizon) was achieved by two approaches: a theoretical one, based on the theory of statistical decision, three hypotheses being analyzed, and the second, based on heuristic methods. Validation of detection methods was performed by numerical simulations, analyzing different types of net and partial faults of the actuators or transducers, including faults due to metabolically or biochemically unfavorable evolutions for the treatment process. In the simulations made it was possible to correctly detect each fault that appeared in the process, obtaining very good results compared to other studies.

On the fault isolation side, an algorithm has been developed to recognize faults that can occur in a wastewater treatment process using a neural network as a classifier. The first step was to collect data through numerical simulations to build the data sets needed to train, test, and validate the recognition algorithm. A large enough experimental dataset was required to contain representative data for all cases of faults analyzed, so that the neural network had a very good recognition rate. To isolate the faults, it has been found that it is sufficient to design a feedforward artificial neural network. From the obtained results, the neural network has a correct classification, 97.2% for all cases considered.

Original contributions of the PhD thesis

The following contributions were made in the PhD thesis:

1. Determining a feedforward neural model that approximates the operation of a wastewater treatement process.
2. Analysis of a biological wastewater treatment plant and possible hardware faults characteristic for wastewater treatment processes.
3. Conducting a theoretical analysis regarding the selection of the parameters of the detection algorithms (sensitivity threshold, ε, and the residue calculation horizon, N), analysis based on the statistical decision theory.
4. Implementation of a fault detection method in a wastewater treatment plant using a neural network as a model for predicting process outputs under normal (no fault) operating conditions. In this case, it is considered that all process outputs are measurable. Residues are generated on the basis of the comparison between measured outputs and predictor outputs. The procedure for choosing the parameters of the detection automaton aims to maximize performance (high sensitivity to fault, low detection time, avoiding false alarms).
5. Validation of the neural network detection method by numerical simulations for different types of net and partial faults of the actuators or transducers as well as for a fault due to the evolution of the treatment process from the point of view of sludge metabolism from the treatment station.
6. Implementation of a fault detection algorithm with extended Kalman filter applied to a wastewater treatment plant. It is assumed that only two output states (biomass and dissolved oxygen concentration) are measurable, the other two being estimated using the extended Kalman filter. The residual generation principle is used to detect process faults.
7. Heuristic determination of the detection algorithm parameters in order to obtain good detection results.
8. Validation of the detection method using extended Kalman filter, by numerical simulations, for various cases of net and partial faults that may occur in the studied process.
9. Establishing an algorithm for the recognition (isolation) of the net and partial faults of the actuators and the transducers in a wastewater treatment process using neural classification networks.
10. Parameter configuration, training, testing and validation of the neural network as a classifier, so as to obtain very good fault recognition performance for all considered faults (net and partial).
11. Analysing the performances of a fault classifier in the particular case of the wastewater treatment plant for the removal of organic substances based on confusion matrices.

Future research directions

Taking into account the results obtained within this PhD thesis, the research can be extended in the following directions:

- Improve the prediction error of the neural model which describes the operation of a wastewater treatment plant.

- Expanding the detection method with extended Kalman filter and the neural network detection method for other types of defects.
- Improving the results obtained with the neural network fault recognition method in a wastewater treatment plant by increasing the training data set and thus extending the scope of applicability.
- Resuming the researches from the the PhD thesis for more complex treatment processes that remove nitrogen and its compounds, as well as phosphorus in wastewater.
- Application of detection and recognition methods in other biotechnological processes.

Dissemination of results

The results of the research from the PhD studies were presented in the following published articles:

1. **Mihaela Miron**, Laurentiu Frangu, George Ifrim, Sergiu Caraman, “Modeling of a Wastewater Treatment Process Using Neural Networks”, 20th International Conference on System Theory, Control and Computing - ICSTCC 2016, October 13-15 2016, Sinaia, Romania, pp. 210 – 215, **ISI Proceedings - IEEE**;
2. **Mihaela Miron**, Laurenţiu Frangu, Sergiu Caraman, „Actuator fault detection using extended Kalman filter for a wastewater treatment process”, 21st International Conference on System Theory, Control and Computing, October 19 - 21, 2017, Sinaia, Romania, pp. 583-588, **ISI Proceedings - IEEE**;
3. **Mihaela Miron**, Laurentiu Frangu, Sergiu Caraman, "Fault detection method for a wastewater treatment process based on a neural model," *2017 5th International Symposium on Electrical and Electronics Engineering (ISEEE)*, October 20 – 22, 2017, Galati, Romania, pp. 1-6, Galati Romania, **BDI – IEEE**.
4. Laurentiu Baicu, Sergiu Caraman, Laurentiu Frangu, **Mihaela Miron**, “Measurement of the biomass concentration from a bioprocess by image processing techniques*”*, The 5th International Symposium On Electrical And Electronics Engineering (ISEEE), October 20 – 22, 2017, Galati Romania, **BDI – IEEE**.
5. **Mihaela Miron**, Laurenţiu Frangu, Sergiu Caraman, “Artificial neural network approach for fault recognition in a wastewater treatment process”, 22^{nd} International Conference on System Theory, Control and Computing, October 10 - 12, 2018, Sinaia, Romania, **ISI Proceedings – IEEE,** accepted paper.
6. Laurențiu Luca, Marian Barbu, George Ifrim, Emil Ceanga, **Mihaela Miron**, Sergiu Caraman, “Fuzzy control of a microalgae process in photobioreactors”, 22^{nd} International Conference on System Theory, Control and Computing, October 10 - 12, 2018, Sinaia, Romania, **ISI Proceedings – IEEE,** accepted paper.

All of these works are indexed by ISI Proceedings and IEEE-Xplore.

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