Fuzzy-APA: Employing Fuzzy and Neural Network Techniques in Data Analysis of Industrial Wastewaters Monitoring

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Abstract: - A fuzzy logic based system for wastewater quality monitoring with the purpose of attenuating the environmental impact of the heavy metals loaded wastewaters is presented in this work. The design and implementation of a supervisory system in LabVIEW for data acquisition, system operation and distributed equipment control is briefly described. Fuzzy logic techniques were used to integrate nine water quality variables into a single quality index of the industrial effluent (EQI) by applying specific rules. The fuzzy rules for diagnosis were developed in MATLAB and were translated and integrated in a virtual instrument, which acted as a fuzzy rule based system, using quantitative and qualitative information, to support the decisional process in case of disturbances of the water quality status due to the effluent discharge impact. Generated EQI was used to train the artificial neural network using Quickprop algorithm, which has efficiently dealt with complex patterns, and had a great ability to build up a neural system for prediction.

Key-Words: - Fuzzy logic, Fuzzy rules, Quickprop algorithm, Wastewater quality monitoring, Environmental indices

1 Introduction

Artificial Intelligence (AI) provides a variety of methods and techniques that can be applied with success in the environmental protection domain. Several systems based on AI have been reported in the literature, for air, water and soil quality monitoring, analysis, diagnosis, forecasting, planning and control (see e.g. references [1], [2], [3], [4]). Computational intelligence provides alternative methods to the traditional ones (i.e. non-AI based) and to the classical AI methods (i.e. those based on the symbolic paradigm). Fuzzy logic, neural networks (NN), and evolutionary computing can be applied in the area of environmental sciences and environmental management (see e.g. [5], [6], [7], [8], [9]).

The purpose of our research work was to develop a fuzzy logic based system for wastewater quality monitoring in order to attenuate the environmental impact of heavy metals loaded wastewaters. In this paper it is presented the current version of the Fuzzy-APA system, as well as some experimental results. The proposed fuzzy system provides information about the wastewater status through a unique effluent pollution indicator, named EQI. The water quality is characterized by fuzzy techniques applied to time series of parameters measured on-line by a complex wastewater monitoring system. A prediction module that uses an artificial neural network was included in the Fuzzy-APA system.

2 Computational Intelligence Applied to Environmental Problems

Environmental problems are characterized by a great degree of complexity, mainly due to the use of ecological data that can have different data structures and data formats (e.g. time series, spatial data), significant uncertainty due to incomplete data, inaccurate data, approximate estimations, incomparability of data (resulting from varying conditions of the observations and measurements). The solution to such problems is to use proper approaches, such as those provided by computational intelligence. In particular, fuzzy logic, neural networks, and evolutionary computing can tackle some types of environmental problems: environmental monitoring, analysis, prediction and control.

We present briefly some references to research work already done in the environmental domain, which uses computational intelligence.

Ecological modelling with fuzzy logic is tackled in [10], while in [11] it is discussed fuzzy data analysis in ecological research. In [5] it is presented an application of fuzzy mathematical methods to soil survey and land evaluation. An example of fuzzy classification used in wastewater treatment plants is shown in [7].

Some environmental applications that use neural networks are: ecosystem metabolism estimation [12], environmental quality forecasting [13] and analysis [14]. Feed-forward NN were applied to environmental air pollution forecasting in urban regions (see e.g. [6], [15], [16]). Moreover, various comparisons between different approaches were also presented in the literature (see e.g. [15] – a comparison between statistical and NN approaches applied to urban air quality forecasting, [8] – a comparison of NN model and qualitative models applied to environmental engineering, [9] – a comparison between fuzzy reasoning and NN methods applied to runoff discharge forecast, and [17] – a comparative study of the multi-period predictive ability of linear ARIMA models to nonlinear time delay NN models in water quality management applications). Combinations of the neuro-fuzzy and NN approaches are also reported in the literature (see e.g [18]).

Few of the systems presented in the literature are applying computational intelligence to water quality forecasting and analysis. In [19] it is presented a prototype fuzzy system, FuzzyApa, that we have developed for surface water pollution analysis. We have extended the functionality of the system to survey and control heavy metal loaded wastewater. A preliminary version of the resulted system was described in [20].

Next section presents the environmental problem of industrial wastewater treatment.

2.1 Industrial wastewaters treatment station

Stainless steel production processes generate significant quantities of wastewaters loaded with heavy metals. In the process, chromium is used for surface coating and its discharge into surface water poses serious environmental treats. Before leaving the plant, wastewaters need to be treated in the environmental protection installations.

One of the most important installations is the industrial water neutralization system (fig. 1), in which the pickling wastewaters discharged from the chemical and electrochemical etching lines of a stainless steel factory are treated by neutralization, cobbering sedimentation and filtration. The neutralization station is structured into three components as follows: acid wastewater neutralization system, dewatering system and chemical dosing system.

Hexavalent chromium is known for its negative impact on health and environment, and its extreme toxicity. It is used for the production of stainless steel, textile dyes, wood preservation, leather tanning, and as anti-corrosion and conversion coatings as well as a variety of niche uses. It causes allergic and asthmatic reactions, is carcinogenic and is 1000 times as toxic as trivalent chromium.

Chromium (VI) compounds are divided up in water hazard class 3, and are considered very toxic [21].

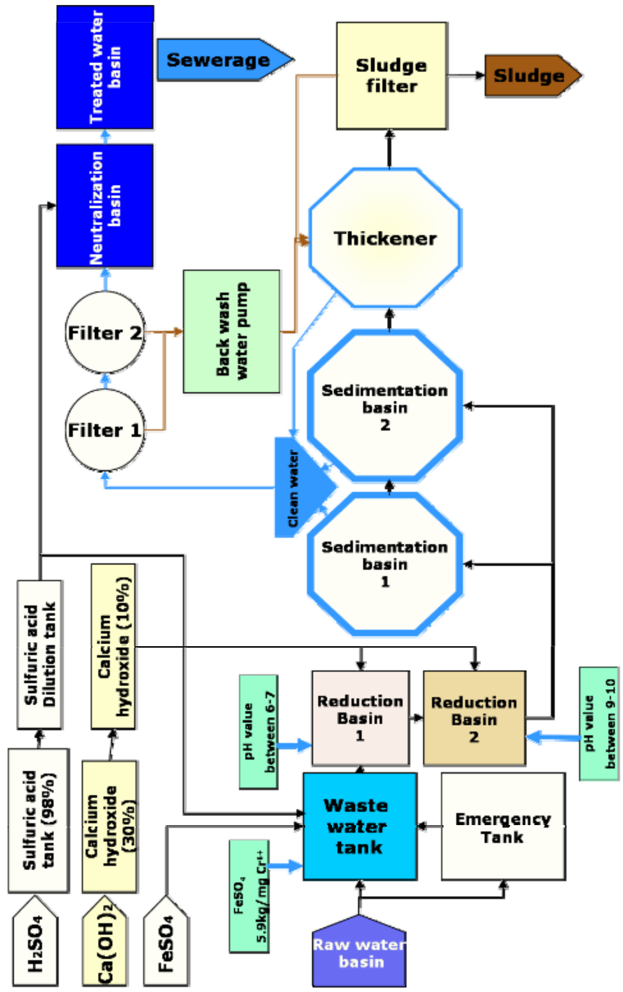


Figure 1 General structure of the wastewater neutralization system used to treat the effluent from a stainless steel factory considered in the present study.

Hexavalent chromium is transported into cells via the sulfate transport mechanisms, taking advantage of the sulfate and chromate similarity with respect to their structure and charge.

Trivalent chromium, which is the more common variety of chromium compounds, is not transported into cells.

Water containing hexavalent chromium is treated with a chemical reduction process. Ferrous sulfate ($FeSO_4$) is added to the wastewater and the pH is lowered to 3.0 or less using acid (typically sulfuric acid). A retention time is usually maintained, ensuring adequate mixing and reaction with the ferrous sulfate. This process converts chromium from the hexavalent form to the trivalent form. The trivalent form can be treated similar to other metals and the effluent from this process is treated with the other metals wastewater.

As metals enter the treatment process, they are in a stable, dissolved aqueous form and are unable to form solids.

The objective of metals treatment by hydroxide precipitation is then to adjust the pH (hydroxide ion concentration) of the water so that the metals will form insoluble precipitates.

Once the metals precipitate and form solids, they can then easily be removed, and the water, now with low metal concentrations, can be discharged in the sewerage. Metal precipitation is primarily dependent upon two factors: the concentration of the metals, and the water pH.

Heavy metals are usually present in wastewaters in diluted quantities and at neutral or acidic pH values (<4.0). Both of these factors are disadvantageous for metals removal.

However, when one adds calcium hydroxide to water, which contains dissolved metals, the metals react with hydroxide ions forming metal hydroxide solids.

In this way, calcium fluoride, iron hydroxide, nickel hydroxide and chromium hydroxide are insoluble in water and are separated as solid sludge.

The solids resulted in the sedimentation stage are denoted as sludge and periodically removed. This sludge is sent to the dewatering stage to remove excess water and leave only solids.

In the next sections we present our fuzzy logic based system, named Fuzzy-APA, the artificial neural network forecasting tool and the supervisory system designed to control and survey the treated water discharging process into sewerage, which afterwards discharges the effluent in WWTP, and finally into the natural surface water.

3 Fuzzy Logic System Structure

Industrial sewage, treated to leave the industrial plant was monitored through 9 parameters according to the Water Management Authorization: pH, suspended solids, fixed residue, Chemical Oxygen Demand (COD-potassium dichromate), total chromium, hexavalent chromium (Cr^{6+}), calcium (Ca^{2+}), nitrates ($NO3^{-}$), and fluoride (F^{-}).

The objective of developing the fuzzy logic supervisory system was to obtain an integrated indicator of the effluent status after wastewater treatment. Defining an input space into output space and the primary mechanism by using *If-Then* (*facts – state* /*action*) rules has solved such requirement. All defined rules were evaluated in parallel in a random order. These rules were useful because they have made references to variables and the adjectives that described those variables.

Fuzzy inference permitted the reading of the input vector values and based on the set of rules, allocated the values of vector output.

Membership functions, as specific curves, defined how each entry point in space belonged to a degree of membership in the range 0 and 1.

The forms of the membership function used in the Fuzzy-APA system were selected to meet the computational efficiency and memory savings requirements. From this point of view, the triangular and trapezoidal membership functions fitted to the intended purpose.

The structure of the production rules was developed using Fuzzy Logic Toolbox module of MATLAB (fig.2). The rules were structured by level of effluent pollutants concentration (low, normal, high) taking into account the maximum limit values from the European and national standards (e.g. Directive 98/83/EC on quality of water for human consumption, Directive 91/271/EC on urban wastewater treatment, [22] etc).

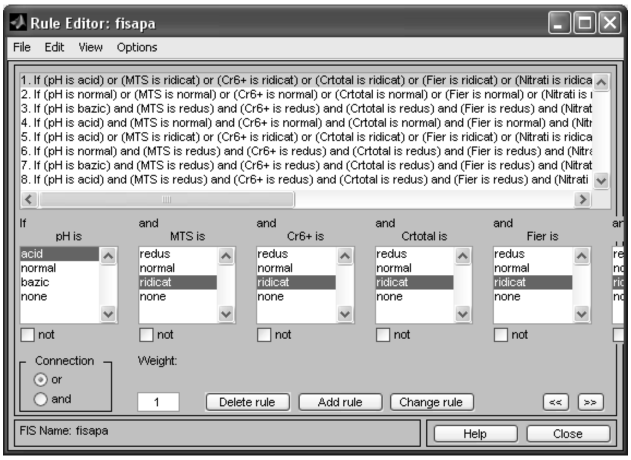
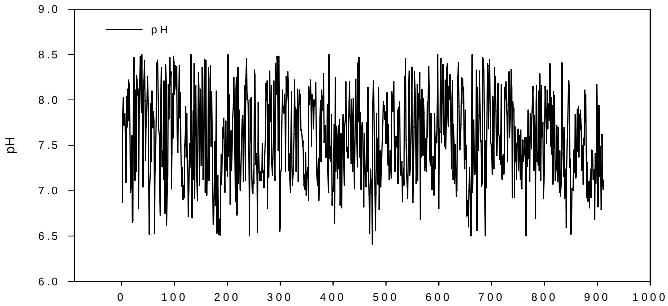


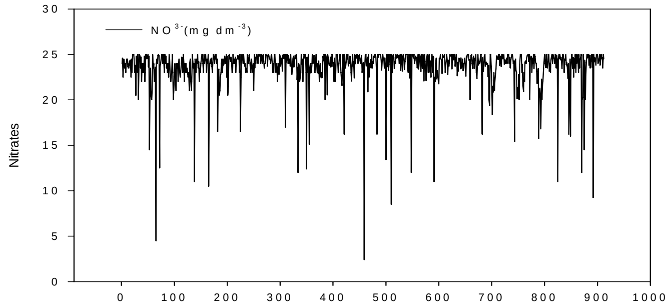
Figure 2 MATLAB Rule editor showing the production rules structure used in FuzzyAPA

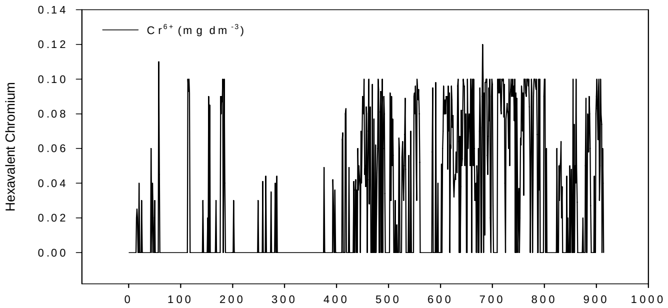
Because it is a more compact and computationally efficient representation than a Mamdani system, the Sugeno system lends itself to the use of adaptive techniques for constructing fuzzy models [23]. These adaptive techniques were used to customize the membership functions so that the fuzzy system best modeled the effluent collected data for different intervals of time.

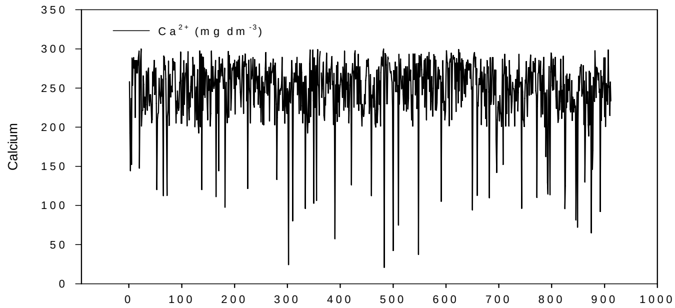
Each time series recorded during one year of monitoring is presented in figure 3. These parameters were used as inputs in the fuzzy logic system without pre-processing techniques.

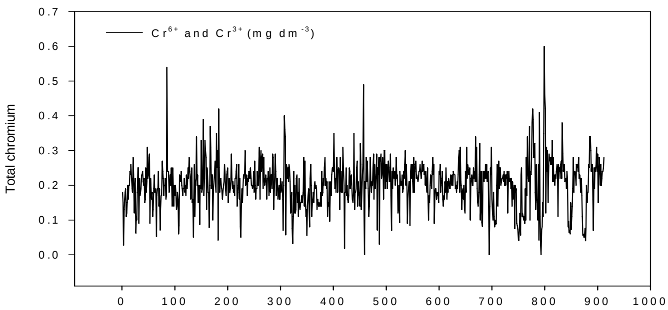
The main objective of the control system was to ensure the absence of hexavalent chromium (due to its high toxicity), and low concentrations of nitrates, total suspended solids and COD in the plant effluent, actuating in the output variables of the fuzzy control system.

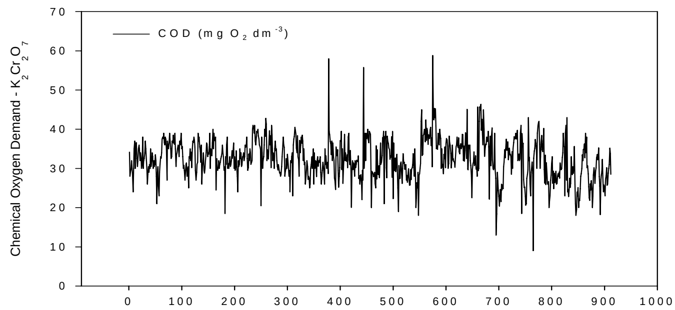


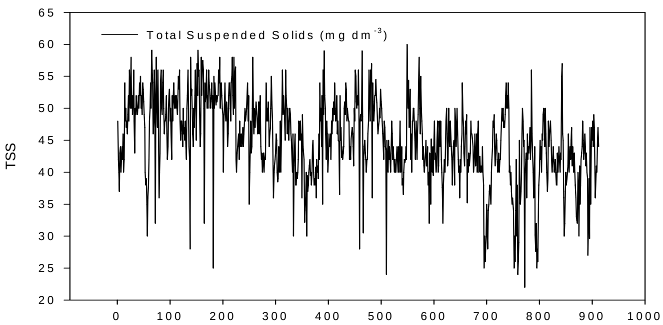


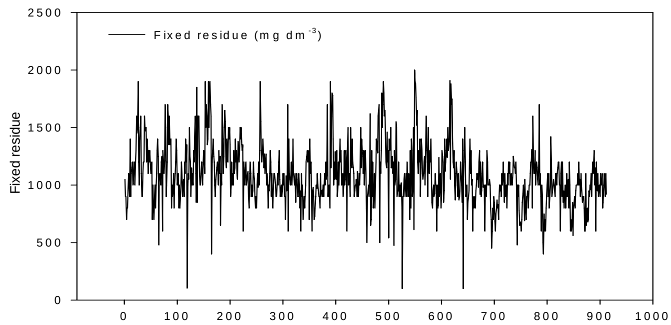


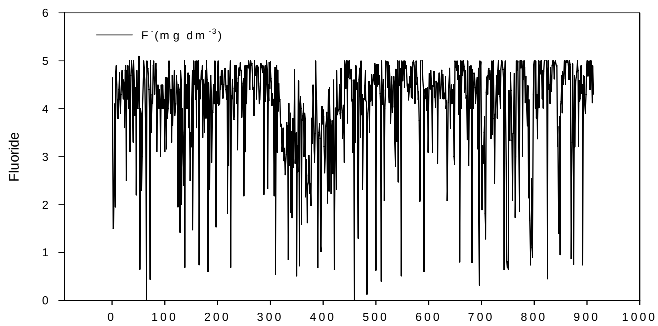












Variable	pH	Cr^{6+}	Total Cr	TSS	F-	NO^{3-}	Ca^{2+}	COD -$K_2Cr_2O_7$	Residue
Limit Value	6.5 - 8.5	0.1	1.0	35.0	5	25.0	300	70	2000

Figure 3 Monitored pollutant time series during one year: pH, hexavalent chromium, total chromium, Total Suspended Solids, fluoride compounds, nitrates, calcium, chemical oxygen demand and fixed residues, used as inputs in the fuzzy logic system.

The fuzzy rules algorithm has performed the following steps:

- scalar representation of the system input – 9 variables (pH, hexavalent chromium, TSS, etc.) were transformed into membership functions through the fuzzyfying functions;
- transferration of this information to the inference engine;
- transformation of the membership functions values into output by defuzzyfication of the scalar value, representing the output indicator that evaluated the effluent quality status (0 – low quality; 1 – good quality).

The fuzzy inference system (FIS) has provided reliable information on the quality parameters of the effluent by integrating multiple variables into a single synthetic indicator – Effluent Quality Index (EQI) – 958 values, which allowed the user to accurately assess the pollution status (1 as "ideal" – 0 as “polluted”).

Table 1 depicts the descriptive statistics of the effluent quality index generated by the FIS structure using statistical parameters - average, standard deviation, standard error, minimum, maximum and coefficient of variation (C.V.).

EQI varied between 0.18 (lowest value) and 0.5 (maximum value), suggesting the existence of relatively significant levels of contaminants. The annual average of the EQI was 0.342.

Table 1 Descriptive statistics of the effluent quality index (EQI) – average, standard deviation, standard error, minimum, maximum and coefficient of variation (C.V.)

Month	Average	Std. dev.	Std. err.	Min.	Max.	C.V. %
January	0.323	0.042	0.004	0.26	0.48	12.87
February	0.319	0.048	0.005	0.25	0.50	15.20
March	0.317	0.032	0.003	0.26	0.50	10.10
April	0.348	0.038	0.004	0.28	0.48	11.06
May	0.337	0.036	0.004	0.27	0.50	10.74
June	0.337	0.041	0.004	0.18	0.50	12.14
July	0.347	0.032	0.003	0.27	0.45	9.16
August	0.346	0.024	0.004	0.29	0.41	7.02
September	0.380	0.061	0.007	0.29	0.50	15.98
October	0.367	0.049	0.005	0.28	0.50	13.28
November	0.377	0.044	0.006	0.28	0.50	11.72
December	0.334	0.045	0.006	0.27	0.48	13.50
Annual	**0.342**	**0.046**	**0.001**	**0.18**	**0.50**	**13.52**

The coefficient of variation for the generated EQI during one year of monitoring was relatively constant (13.52%). The advantage of the C.V. is that it is without unit. This makes possible the comparison of C.V.s to each other in ways that other measures, like standard deviations or root mean squared residuals, cannot be.

The monthly variable with the smaller C.V. (February) was less dispersed than the variable with the larger C.V. (October). EQI time series showed characters of homogeneity, which means stability across time as opposed to a trend and stability of local fluctuations over time.

ANOVA presented an F-ratio of 19.50, p-value of the F-test was less than 0.05, and there was a statistically significant difference between the means of the 12 variables at the 95.0% confidence level. Multiple sample comparison of the monthly means using Tukey HSD test showed statistically significant differences at the 99.9% confidence level amongst 25 pairs of means ($p<0.001$).

It can be summarized that EQI results shown that the effluent pollutants load was relatively high even if the standard limit value exceedances for individual pollutant concentrations did not have a higher frequency over the sampling interval. This cumulative effect of the nine variables had the same pattern when considering the yearly interval.

Figure 4 presents EQI fluctuations during one year of surveying, which as compared to the unit (representing the ideal) showed a general low quality of the effluent that left the neutralization station.

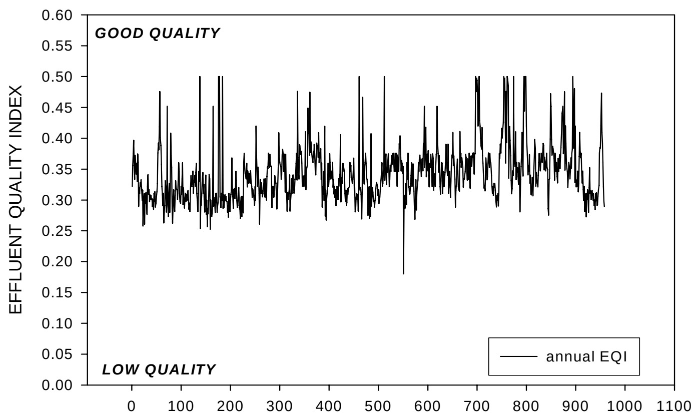


Figure 4 Annual evolution of the Effluent Quality Index – cumulated output of the fuzzy logic system (958 fuzzyfied synthetic values)

Figure 5 shows the resulted output after introducing the acquisitioned data for each month between January and December as inputs in FIS. Even in the absence of chromium in the effluent, the negative effects of other parameters (e.g. TSS, COD) showed their influence.

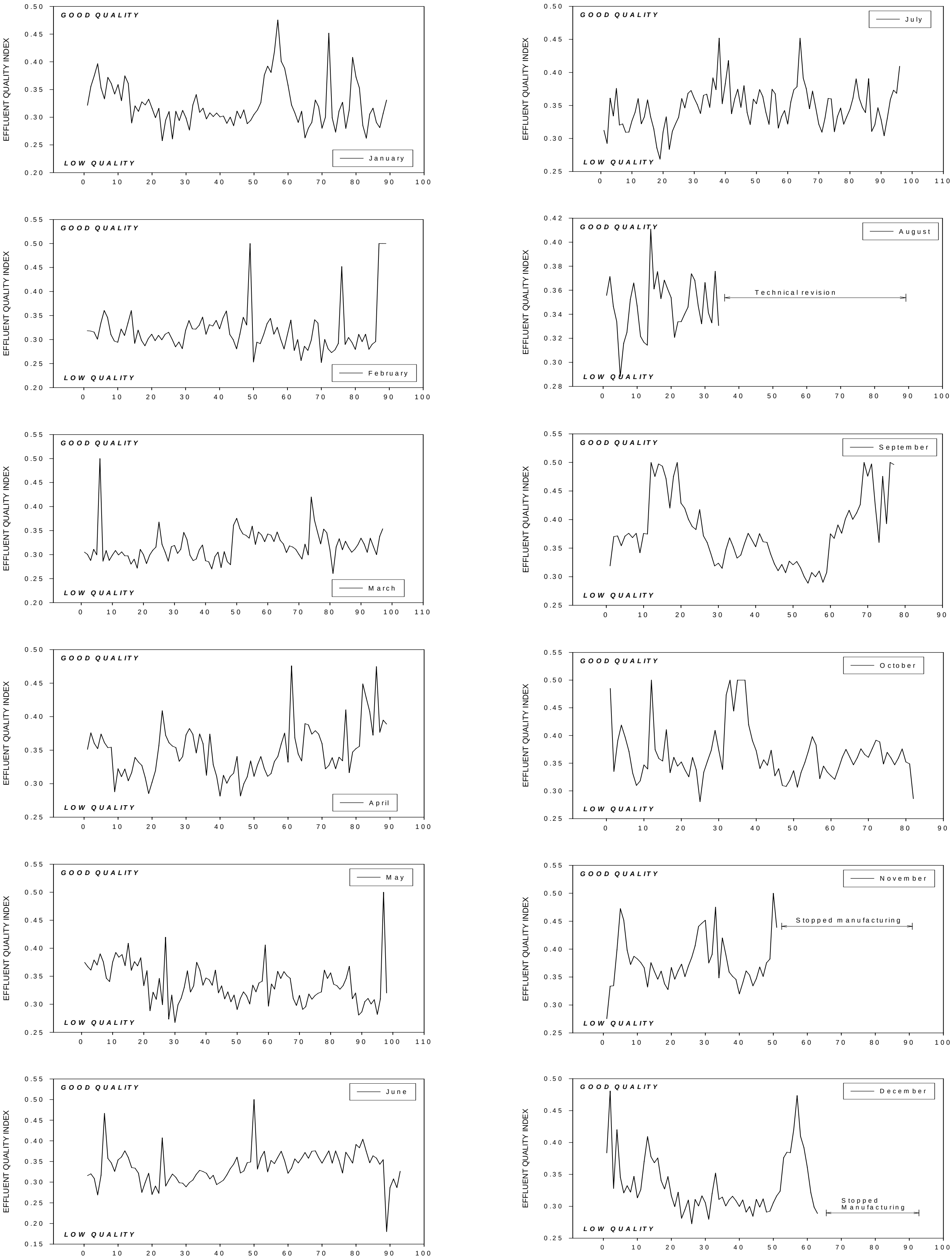


Figure 5 Effluent Quality Index for each month between January and December – outputs generated by the fuzzy logic system

The construction and testing of the fuzzy logic system was performed in MATLAB Fuzzy Logic Toolbox due to its versatility in developing FIS structures.

4 Effluent quality modeling using artificial neural network

The environmental pollution forecasting is one of the critical problems to be addressed improving real time accurate predicted values.

Based on the recorded time series with pollutants' concentrations in a certain interval of time, a forecasting system must provide reliable information on the near future evolution of those pollutants concentrations. In this context, one of the computational instruments that provide efficient forecasting is the artificial neural network with different algorithms and structures.

Some of our previous works have shown that batch training Quickprop algorithm performed well in short term environmental forecasting as compared to other classical ANN algorithms, based on a detailed analysis of the effects that different parameters of the feed-forward neural network have on the accuracy of the forecasted environmental data [14], [15].

QuickProp is a batch training algorithm introduced by Fahlman [24], which considers the information about the second order derivative of the performance error function.

Exactly the same data generated by the FIS structure were used as input to train the ANN. No pre-processing was applied, having no influence on the predictive ability of the model.

Best fitting results were obtained using QuickProp algorithm with 6 units in the input layer, 4 neurons in the hidden layer and one output neuron. The output represented one EQI ahead forecasted value.

Mean square error (MSE) evaluated the residual between observed and forecasted EQI. This indicator assumes that larger forecast errors are of greater importance than smaller ones. MSE on train data was 0.01213 and on test data was 0.01468. MSE equal to zero denotes perfect fit.

The plots of the observed and simulated pollutants in figure are difficult to distinguish since the measured and simulated data are close (fig. 6). Consequently, the model performances were assessed using several criteria as follows: *Correlation coefficient* (CC) that indicated the strength of relationships between observed and estimated EQI, *Mean absolute error* (MAE), a weighted average of the absolute errors, and *R-squared value*.

Figure 7 shows the observed EQI versus Quickprop predicted series. The correlation coefficient was 0.637, indicating a moderately strong relationship between the variables. R-squared (40.61%) explained the variability in ANN model.

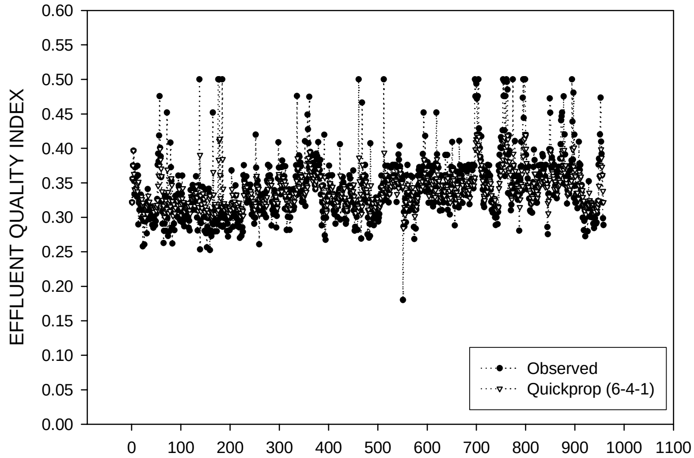


Figure 6 Effluent Quality Index modeling using the batch training Quickprop algorithm – 958 fuzzyfied synthetic values were used to train the artificial neural network

The standard error of the estimate showed that the standard deviation of the residuals was 0.018. Mean absolute error was 0.013, representing the average value of the residuals.

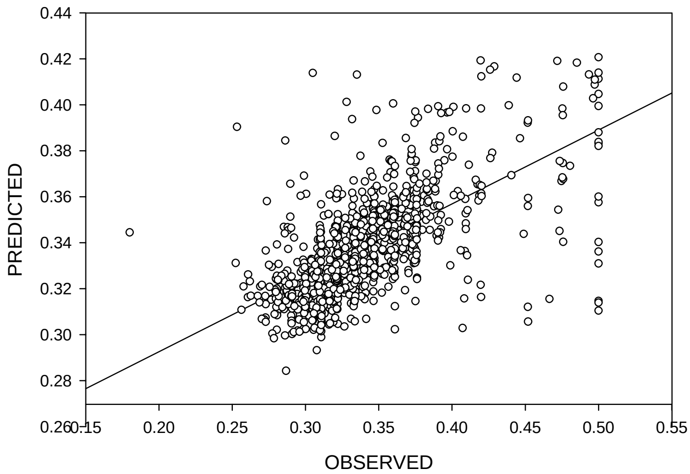


Figure 7 Observed EQI versus predicted Quickprop series – CC =0.637, R^2 = 40.61%

We have observed that the structure of ANN model using Quickprop algorithm has efficiently dealt with complex input–output patterns, and had a great ability to learn and build up a neural system for prediction of the synthetic indicator of the effluent quality.

5 Effluent quality supervisory system

In order to obtain a supervisory system, the optimized and tested FIS structure from MATLAB was translated into National Instruments LabView Vi (virtual instrument) [25] using the dedicated functions of the PID module that contains fuzzy logic capabilities.

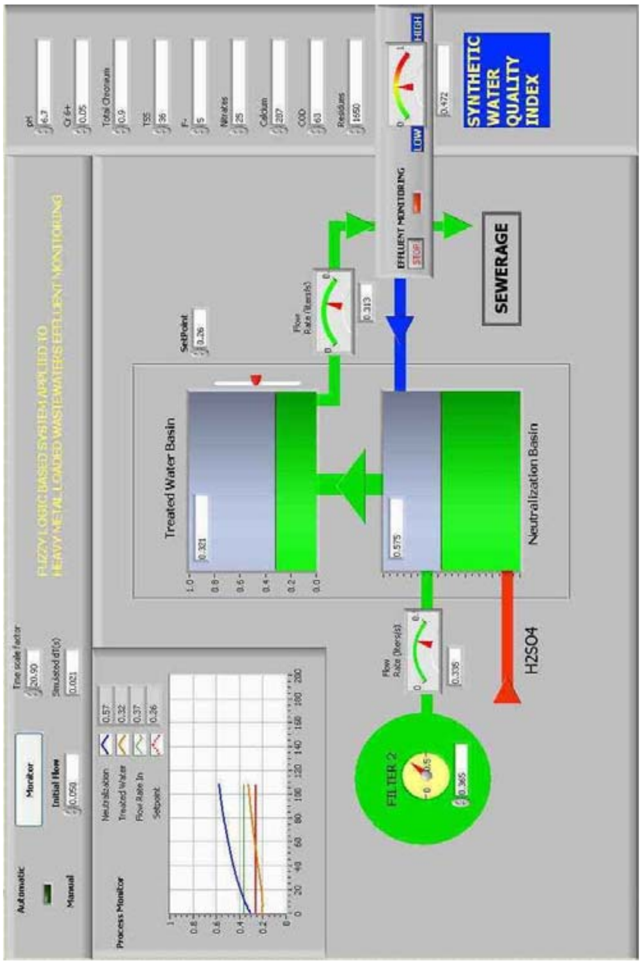


Figure 8 Graphical User Interface (Vi) – visualizing and controlling the discharge of treated effluent into industrial sewerage based on the synthetic effluent quality index (0-1; 0 – low quality; 1 – maximum quality).

The graphical user interface (fig. 8) of the LabView virtual instrument (Vi) was associated to the technological installation providing control of the discharge of industrial treated water into the sewerage based on the synthetic effluent quality index (0-1; 0 – bad; 1 – very good). The main advantages of the Vi supervisory system are as follows:

- display of the synoptic schemes associated to the neutralization station;
- display of the events and alarms when exceedance of limit values occurs;
- processing the information for the optimum functioning of components and of the overall system, according to the implemented fuzzy algorithms;
- display of variables measured or modeled by the fuzzy algorithm;
- periodical recording of the measurements and their vizualization in various forms (graphs, tables, file);
- reports on current status and historical events.

Figure 8 highlights a screen capture of the Virtual Instrument showing the real-time installation control (flow rates, basin levels, various setpoints etc.), but most important, the evolution of each of the nine parameters that characterize the effluent pollutant load.

Furthermore, depending on the EQI provided by the integrated fuzzy inference system, the effluent can be redirected to the neutralization basin. This is the case when the effluent pollutant load does not meet the established EQI, for discharging in the sewerage.

6 Conclusion

The proposed method should provide an improvement over the traditionally modelling techniques used in water quality analysis [26], and in industrial wastewater analysis.

Fuzzy logic can bring potential benefits even in areas where traditional control engineering already offers versatile solutions.

The concepts underlying fuzzy technology are successfully used in water quality modeling, allowing an alternative approach in solving specific environmental problems when the objectives or constraints are not precisely defined, and necessary information is missing, sporadic or discontinuous.

The presented method facilitates the characterization of the effluent pollutant load resulted from a stainless steel factory using fuzzy techniques for parameters time series processing.

The EQI synthetic indicator allows the user to make a quick interpretation of the analyzed water status.

The inclusion of a prediction module based on neural networks has improved the efficiency of the whole Fuzzy-APA system due to the flexibility and ability of neural networks to model nonlinear relationships. The combination of fuzzy logic with artificial neural networks provides a better model for industrial wastewater quality analysis.

For policy makers, the proposed system of effluent quality monitoring facilitates the following goals: water quality planning, water quality monitoring, level of compliance verification of the collected data with the environmental standards, and application of prevention, remediation and control measures to meet the planned objectives of water quality.

FUTURE WORK

We have identified some directions of future research.

The first direction of research will extend the investigation to the long term forecasting, taking into account some other factors that influence the variation of the pollutants concentration level (e.g. industrial influent characteristics, manufacturing process).

The second research direction will be oriented towards the implementation of some evolutionary algorithms to automate the design of the artificial neural network topology. Also, we shall study the applicability of genetic algorithms to the industrial wastewater quality assessment.

Finally, we will focus our attention to test the adequacy of a time delay neural network implementation selecting the structure according to the best forecasting properties.

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