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APPLICATION OF INTELLIGENT OPTIMIZATION TOOLS IN DETERMINATION AND CONTROL OF DOSING OF FLOCCULENT IN WATER TREATMENT

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Abstract: This research presents an application of some intelligent tools–optimization methods in automated technological systems and processes. Case study is an existing drinking water treatment system. An important segment in the water treatment processes is determination and control of the amount of flocculation dosing. The choice of optimal dosing has a crucial role in the water treatment process both from the aspect of health safety through the consolidation of the coagulated particles and their separation from the water to a satisfactory level after the phase treatment, also from the aspect of economy, overdose–increased costs, and insufficient dosing–disorders the water treatment process. The amount of dosing determined manually through the JAR test. JAR test is a laboratory procedure that simulates a water treatment plant's coagulation/flocculation units with differing chemical doses, mix speeds, and settling times to estimate the minimum or ideal coagulant dose required to achieve certain water quality goals. The second option is using the experience of the operator. But in many cases when we use the two above mentioned options the determination is reactive and delayed. Also a problem that occurs when we determine the optimal amount of dosing flocculent is the nonlinear dependence that exists between some of the variables such as the turbidity of the raw water and the amount of dosing, and the most important of all is the dynamic characteristics of the process. In this paper models for the calculation of dosing, i.e. a program that can be used an additional module in the flocculent dosing system in the case study water treatment capacity is presented. In order to create such models, tools such as linear regression, the hybrid tool of Adaptive neuro fuzzy inference system–ANFIS, as well as the experiential knowledge from operators obtained through verbally qualitative gradation of the values of the observed historical records–measurements derived from the appropriate sensors for turbidity and flow of raw water as input variables, and presented network in subgroups and the amount of dosing of the flocculent as an output variable, are used. The purpose of this combination of the above methods is to set a linear dependence between the mentioned variables.
Keywords: optimal dosing, ANFIS, artificial neural networks, fuzzy logic systems, linear regression

1. INTRODUCTION

During the processing of drinking water it is necessary to meet two important conditions, such as achieving the required quality in terms of health safety of drinking water and reducing processing costs. This contributes in finding solutions for improvement the water treatment process by automating it or improving the performance of an already automated processing system, by applying some optimization methods. Animportant part of the water treatment process is the step of flocculation in which the coagulated solid particulate matter is enriched, facilitating their deposition in the sedimentation step, thereby effectively purifying the step filtering. With the optimal dosing of the flocculent, two important goals are achieved: the efficiency of the step flocculation that has a crucial role in the treatment of water, and thus the complete treatment phase, and the second goal is reducing the processing costs. Overdose increases costs, while the water treatment process disrupts with insufficient dosing. In general, the determination of the amount of dosing in the processing facilities is carried out by operators on the basis of acquired experience or through the JAR test. The JAR test manually simulates the steps of coagulation, flocculation and sedimentation in laboratory conditions, but such determination in many cases is reactive i.e. is delayed because it refers to the current qualitative parameters (variables) of the raw water. In order to avoid such reactive behavior and also to stabilize the water treatment process, a program is needed to determine the optimal amount of dosing based on some of the parameters of the raw water. In the automated technological systems and processes, as it is in our case, for monitoring and control of the process, measuring instruments (transmitters) are used to measurethe technological parameters (variables).The data of some of these measuring instruments (transmitters), in addition to monitoring the process, can are used as input variables to calculate the optimal amount of anionic flocculent dosing.

As a result of the implemented measurement systems for monitoring the process, some of the values of the variables observed in the operating sheets using the operator's experimental knowledge can be presented verbally in subgroups. In the past years some of the intelligent tools–methods such as Artificial Neural Network (ANN), Fuzzy Logic Systems, Linear Regression – have been used to model and optimize the complex process of water processing. On the basis of the ANN, a model for the removal of organic matter has been developed, in a recyclable water capacity in Edmonton, Canada. The results showed that this type of dosing control is feasible and contributes to savings in the water treatment process [1], [2], [3]. The ANN model is applied in the step of coagulation in a water treatment process that uses raw water from a river in France [4], [5]. Parameter data: permeability, conductivity, acidity, temperature, dissolved oxygen and UV absorption of raw water that were collected over one year are input variables, while the optimal amount of coagulant dosing as output parameter (variable). After the application of the results of such research in the control of the water treatment process, it contributed to the reduction of a significant amount of coagulants [4], [5]. A similar study was carried out in Morocco on a large water treatment system, in which temperature, acidity, conductivity, dissolved oxygen, turbidity were taken as input parameters (variables). To create a model, the samples were collected over four years [6]. In a Taiwanese water processing system for the purpose of creating a model using the Neural Network.as well as for creating a model using the Adaptive neuro fuzzy inference system(ANFIS) the following input parameters (variables) were used: temperature, acidity, cloudiness, color, while the output variable is the amount of dosing solution of polyaluminiumchlorite. The model created using ANFIS gave better results in terms of the model created using the ANN and was used as an application aid in determining the amount of dosing in the control of dosing systems by operators [7].In the JAR–tests and experiments of raw water, where iron–chlorite was applied as a coagulant, a phased logical feed–forward control system was used. The results were a decrease in water turbidity after sedimentation of less than 10 Nephelometric Turbidity *Units* (NTU) units, while the turbidity of the raw input water was 110 NTU units [8]. The possibility of application Fuzzy–Logic systems n water treatment where the incoming water quality varies steadily was based on the application of the feed–forward system in the treatment of raw water with a turbidity of up to 16 NTU units. The result was a decrease of turbidity to 0.1 NTU units after the treatment [9]. Two approaches are used to create an Adaptive neuro fuzzy inference system (ANFIS): the first approach is network–based, while the second approach is subtractive grouping. ANFIS is a multilayered feed–forward network in which the adaptive parameters of the learning (training) of the network are applied to achieve the optimal values. The main difference between these two approaches is in determining the optimal number of rules. Input parameters were temperature, acidity, conductivity, turbidity, UV absorption and dissolved oxygen, while the amount of dosing of aluminum sulphate as a coagulant was observed as an output variable. A total number of 725 samples were collected at the water treatment plant "Buduau" –Alger for the purpose of creating a model [10]. Several year tests were carried out with water from Nkdong River in Korea, applying a square model in determining the dependence between acidity and the amount of coagulant dosing as input parameters, while the turbidity and removal of dissolved organic matter as output parameters.With application of linear regression analysis were determined the coefficients [11]. Another example is using laboratory and operational data from the treatment of lake water in Finland, in order to use both methods: multiplication linear regression and neural network model with five neurons by selecting forward and decomposing backwards. The input qualitative parameters of the water were: index of permanganate, color, acidity, hardness, turbidity, conductivity and concentration of silicates. The flow, dosage of coagulant, acidity in coagulation and temperature were taken as the most important process variables. The aim was to predict the final water contamination as well as the residual aluminum concentration. The results confirmed that the two methods can be applied for this purpose [12, 13]. Concept for managing dosing in mechanical and chemical wastewater treatment was applied in Norway.By using operational data, was applied regression analysis to determine the dependence of the amount of coagulant dosing in terms of flow, temperature, acidity, conductivity, turbidity. The first result was reliable and contributed to the development of an on–line control tool in dosing called DOSCON. The application of this concept resulted in a reduction in coagulant consumption of up to 30%, compared to the flow–proportional control [14, 15].

The main goal of this research was to develop a program –model that can be a control unit, using a small number of input variables obtained from a small number of sensors in order to calculate and control the optimal amount of flocculent dosing by establishing a linear function dependence between the input variables and the amount of flocculation dosing as output variable. Here the turbidity and the flow of raw water are applied as input variables. For the preparation of this model, 240 samples or 720 records from the operating lists conducted over four years (2014,2015,2016,2017) were applied in order to cover different processing periods as well as different range of the values of the variables observed in the Water Treatment Plant "Ilovitsa", municipality of Bosilovo, Republic of Macedonia. Here the integration of the experiential knowledge of the operators is represented by the verbal qualitative degree of the observed variables, i.e. their division of groups, with intelligent tools such as linear regression and ANFIS which is a hybrid of the Artificial Neural Network and Fuzzy logic systems. The performance (validation) of the obtained models are compared by calculating the Mean Absolute Error –MAE.

2. MATERIALS AND METHODOLOGY

— Process of water treatment

WTP "Ilovitsa" is equipped with water treatment capacity of 3840 m3 / day or maximum processing regime of 44 l / s. The water treatment process is completely automated and is managed through the PLC S7–300 product of the company Siemens. The process takes place through the following three phases: pre–treatment treatment, disinfection and storage (Figure 1). In the pre–treatment phase, the following steps are performed: ozonation and aeration, which oxidize some metals from water such as manganese and iron, and remove the unpleasant smell from the water. In the treatment phase the following steps are performed: coagulation, flocculation, sedimentation, and filtering. In coagulation step, the process of de–structuring of solid particles in the water through the dosing of coagulants is the most often done with a solution of aluminum sulphate, while in flocculation step in the coagulated water is dosed an anionic flocculent in order to enlarge the solid particles in floccules and their deposition in the sedimentation step to a satisfactory level, and thereby obtaining effective water purification to a safe level from the suspended solids, as well as other soluble substances after filtration. A final phase is disinfection and storage. Disinfection of water is done by dosing a solution of sodium hypochlorite. The storage of processed water is in flow reservoirs with a capacity of 600 m3. For the control of the process it is necessary to monitor (record), i.e.to measure the parameters (variables). The way of monitoring (recording) of the parameters (variables) is defined through its own monitoring system. The measurement of some of the parameters is realized in real time with built–in gauges–sensors, while for the some of the parameters (variables) measurements are performed manually with mobile gauges, comparators, which is shown in Table 1.

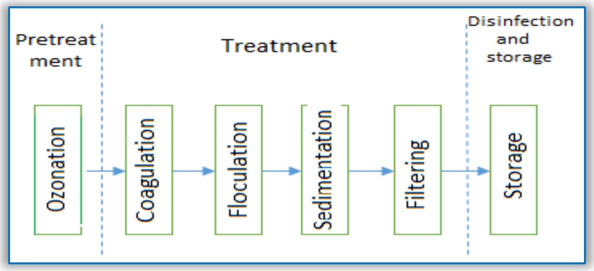

Figure 1: Phases of water treatment

Table 1: Integrated process– gauges (sensors) in WTP "Ilovitsa"

Type of gauge (sensor)	Parameters (variable)	Processing phase (step)	Direct application	Indirect application	Real–time measurement (on–line)
E+H Promag 50	Flow	treatment (coagulation, flocculation)	Control of proportional dosing of the anionic flocculant, aluminum sulfate (open circuit)	Calculation of the required amount of dosing of the anionic flocculant, aluminum sulphate, sodium hydroxide / recording the data	Yes
E+H Promag 50	Flow	Treatment (Filtering)	Control of proportional dosing of NaOCl (open circuit)	recording the data	Yes
E+H Liquisys CCM 253	pH (Acidity)	Treatment (Sedimentation)	Adjusting the pH (acidity) by dosing solutions of NaOH, or HCl	recording the data	Yes
E+H Liquisys CCM 253	pH (Acidity)	Disinfection and Storage (Chlorination)	Adjusting the pH (acidity) by dosing solutions of NaOH, or HCl	recording the data	Yes
E+ H Deltabar PMD75	Pressure	Treatment (Filtering)	Turn on the reverse washing of one of the sand filters	recording the data	Yes
E+H Prosonic FMU 40	Level	Treatment (sedimentation)	Regulation of the accumulation basin	recording the data	Yes
E+H Prosonic FMU 40	Level	Treatment (sedimentation)	Switching on the recycling pump	recording the data	Yes
E+H Prosonic FMU 40	Level	Disinfection and Storage	Regulation of the water filling of one of the basins for clean water	recording the data	Yes
E+H Prosonic FMU 40	Level	Disinfection and Storage	Regulation of the water filling of one of the basins for clean water	recording the data	Yes
HACH sc 100	Turbidity	Treatment (coagulation, flocculation)	/	Calculation of the required amount of dosing of the anionic flocculant / recording the data	Yes
HACH sc 100	Turbidity	Disinfection and Storage	/	recording the data	Yes


Figure 2. Flow meter, type: E + H Promag 50


Figure 3. Turbidity meter type: HACH SC 100


Figure 4. Dosing pump type: Prominent

For the coagulation process, an important parameter is electro–conductivity, which determines the degree of ionized particles, as well as the amount of soluble particles. In order to determine the amount of dosing of a flocculent solution to form floccules besides measuring the flow of raw water, an important parameter (variable) is the turbidity of raw water. By measuring water turbidity in sedimentation, the level of flocculation is determined. The success of the filtering step and the phase treatment is determined by measuring the water's turbidity after filtering. For the determination of the required quantity of sodium hypochlorite solution for the disinfection of the treated water, the parameter residual quantity of sodium hypochlorite in the water is measured. To maintain neutral acidity, the pH of the water is measured after sedimentation, and after filtering. To maintain the required level of processed water in the flow reservoirs the measured parameter (variable) is the water level. During the running of the water treatment process, the values of these parameters (variables) are recorded in the operating lists by the operators.

— **Presentation of experiential knowledge**

The purpose of finding a solution through experiential knowledge is to link the set of values to the input variables with the set of values of the output variables [16]. Historically observed samples of input–output variables are implicitly "hidden" knowledge and can be represented as a vector (x_i, y_i), i = 1, 2, ... ,p.

In processing technological systems, knowledge by experienced operators can be used in determining "if–then" rules of processing through verbally qualitative definition of subgroups, and to define the set of values of the each of the input variables. From the chosen number of subgroups, directly depends the number of selected "if–then" rules (Figure 5). In our case, the verbal qualitatively definition (separation) of the set of values for the two variables (flow and turbidity) is expressed by four degrees, respectively:

small(A_1),medium–small(A_2), medium(A_3), big (A_4), for flow (x_1)

and

low (B_1), medium–low (B_2), medium (B_3), high (B_4), for turbidity (x_2).

The optimal connection of input–output variables through which calculations can be performed could be represented by a particular algorithm–program or heuristic. In our case, it is through an algorithm– program composed of "if–then" rules while the calculations are performed with the regression formula given in equation (1) for each rule, respectively, or:

If x_1 is in A_i and x_2 is in B_j then

$$y = x_1 * B_1(ij) + x_2 * B_2(ij) + B_0(ij) \quad (1)$$

i = 1, ... ,m j = 1, ... , n where: A_i–subset (group), B_j–subset (group), x_1, x_2– input variables, y–output variable, B_0, B_1, B_2 – coefficients

The division of the set of values of the input variables of subgroups is obtained through a network division that can be uniform and no uniform. A fuzzy no uniform network division is applied for the adaptability adaptation and the establishment of a functional connection between the variables. Such adaptability is obtained by applying some methods or training (learning) algorithms. When creating a no uniform network partition, the number of input variables, the number of groups (subsets) of the values of each variable is initially initialized, and then, through the application of training (learning)methods "fine tuning" is performed and optimization of parameters that define the fuzzy membership functions [17]. Obtaining the optimized parameters of each of the membership functions was done using an intelligent ANFIS tool that is a hybrid of fuzzy logic systems and the artificial neural network. The boundaries of each group in our case are obtained as a cross section between the membership functions, Figure 5.The selection of the number of samples (pairs) for each rule is done by using the algorithm developed in the programming language C, while determining the linear coefficients for each rule is realized by applying a linear regression. Integration of these intelligent tools is shown in Figure 7 and in Figure 8.

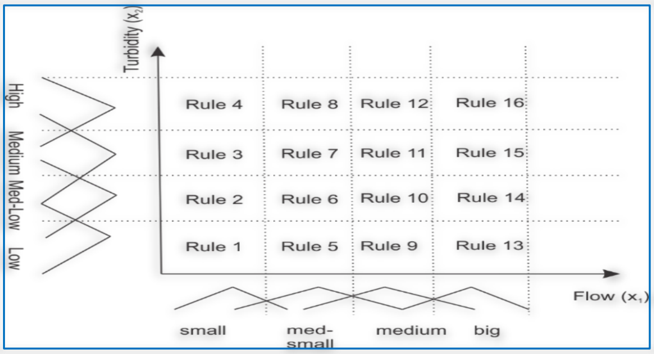

Figure 5. Division of groups

— **Data preparation**

Because the input variables, such as the flow of raw water and the turbidity of the raw water and the dosing of flocculent solution as an output variable (Table 2), have a direct impact of the turbidity of the water after filtering. That is, any change in any of the mentioned variables implies a change in quality of processed water in real time. Due to the upgraded concept of water treatment (rapid treatment, i.e. filtering under pressure), the example in our case does not require a time shifting. The established functional dependency between the input–output variables, is represented by the regression formula:

$$y = x_1 * B_1 + x_2 * B_2 + B_0 \quad (2)$$

where: y – amount of dosing of flocculent solution, x_1– flow of raw water, x_2 – turbidity of raw water, B0, B1, B2–coefficients

The number of samples (pairs) of the input–output variables in one observation and for a given criterion (in our case the value of the turbidity of water after filtering to be less than 0,100 Nephelometric Turbidity *Units* (NTU) depends on the hydraulic retention, i.e the total volume of the treatment phase and the given regime of processing or:

$$NS= TV/ PR$$

where: NS– number of samples (pairs) in one observation, TV– total volume of phase treatment, PR– processing regime

The total volume of the phase treatment is composed of the following volumes: basin of coagulation, flocculation, sedimentation, and filtering volume Table (3).

Table 2. Observed values of samples

	flow of raw water	Turbidity of raw water	Dosage of the flocculent	
	m3/h	NTU	Str./min	l/h*
max	160,400	98,717	108	129,6
aver.	82,686	52,467	42	50,4
min	28,971	5,753	13	15,6

* idealized (calculated) values

Table 3. Total volume of phase treatment

Coagulation and flocculation	129,4 m^3
Sedimentation	121,4 m^3
Filter volume	26,7 m^3
Total	277,5 m^3

In our case, due to unification, the values of the variables are represented with the same measuring unit, the value of the current analog signal in milliamps (mA) from the process gauges and to the analogue dosing pump. The inverse obtaining of these idealized values is made by applying the proportional functional relation [18]:

$$S = C + mc \tag{3}$$

where: S – calculated (idealized) value (mA), C – constant value (4 mA), m – constant value of sensibility, c – read value (record)

— **ANFIS (Adaptable Neuro–Fuzzy Inference System)**

One of the first hybrid neuro–fuzzy systems for function approximation was ANFIS model developed by Jang in 1993. It represents Sugeno type fuzzy system in a special five– layer feedforward network architecture [19]. ANFIS implements rules of the,"if –then" form for given set of input–output values [19]. ANFIS as an intelligent tool has the ability to apply optimization in water treatment systems using observed and historical records in the operational lists of the values of variables such as input–output samples [20]. The general structure of ANFIS combines reasoning fuzzy system with the multilayer feed–forward neural network. "If–then rules" are obtained as a combination of the number of membership functions for each input variable respectively. Generally, ANFIS is a five–layer feed–forward neural network. In our case, the architecture of ANFIS is a Sugeno fuzzy model of zero order. The network consists of two inputs (x_1, x_2) and one output f (x_1, x_2). Each of the input variables is represented by four membership functions, while the output variable is a constant value. The general architecture of the ANFIS structure with two input variables and two membership functions is presented in Figure (6). In our case, we have two input variables and four membership function that generate sixteen "if–then" rules and they are represented as:

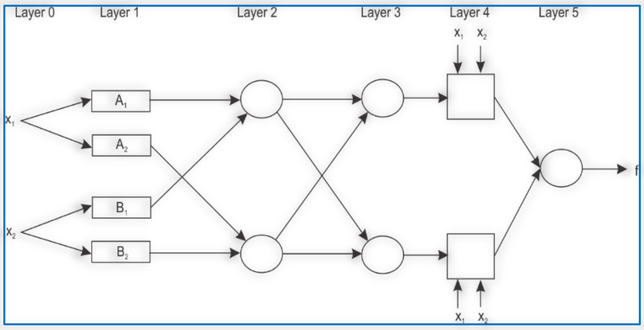

Figure 6. Structure of ANFIS

If x_1 is in A_1 and x_2 is in B_1 then f (x_1, x_2)–1
If x_1 is in A_1 and $x_2$is in B_2 then f (x_1, x_2)–2
If x_1 is in A_1 and $x_2$is in B_3 then f (x_1, x_2)–3
If x_1 is in A_1 and $x_2$is in B_4 then f (x_1, x_2)–4
If x_1 is in A_2 and $x_2$is in B_1 then f (x_1, x_2)–5
If x_1 is in A_2 and $x_2$is in B_2 then f (x_1, x_2)–6
If x_1 is in A_2 and $x_2$is in B_3 then f (x_1, x_2)–7
If x_1 is in A_2 and $x_2$is in B_4 then f (x_1, x_2)–8
If x_1 is in A_3 and $x_2$is in B_1 then f (x_1, x_2)–9
If x_1 is in A_3 and $x_2$is in B_2 then f (x_1, x_2)–10
If x_1 is in A_3 and $x_2$is in B_3 then f (x_1, x_2)–11
If x_1 is in A_3 and $x_2$is in B_4 then f (x_1, x_2)–12
If x_1 is in A_4 and $x_2$is in B_1 then f (x_1, x_2)–13
If x_1 is in A_4 and $x_2$is in B_2 then f (x_1, x_2)–14
If x_1 is in A_4 and $x_2$is in B_3 then f (x_1, x_2)–15
If x_1 is in A_4 and $x_2$is in B_4 then f (x_1, x_2)–16

A_1, A_2, A_3, A_4, and B_1, B_2, B_3, and B_4 are membership functions of the input variables x_1 and x_2 respectively, while f(x_1, x_2) represents a constant output value.

The parameters that are optimized, using the ANFIS tool that define the triangular membership functions of the input variables, actually represent "previous" parameters and they are in the field of interest of this research, while the output constant values are called "consequential" parameters. A mixture of backpropagation and least squares estimation (LSE) is used for the learning of ANFIS [19] . To obtain the optimized parameters a fuzzy logic toolbox from the MATLAB program package is applied. When we define the fuzzy approximation system, a grid partition of the sets of the values of the input variables is applied.

— Regression analysis

Regression analysis is a statistical method for determining the dependence of variables. The purpose of such determination of the dependence between the variables is to determine the connection and extent of such a connection. Dependence between variables can be functional (deterministic) which is a field of interest in our research and statistical (stochastic).

≡ Functional or deterministic dependence is constant and is represented analytically by formula.

$$y = f(x) \tag{4}$$

≡ Statistical or stochastic dependence is represented by the relation

$$y = f(x) + e \tag{5}$$

where: f (x) is a function (deterministic) component, and e–stochastic variable

In our case for determining linear coefficients, a linear regression of multiple variables will be applied. The general form of the linear regression of multiple variables is represented as:

$$y = f(x_1, x_2, x_3, ..., x_i..., x) + e \tag{6}$$

In the specified relation y is a dependent variable, x_1, x_2, x_3, ...x_k are independent variables. The variable is a deviation from the function dependence.

The linear dependence between the variables y and x_1, x_2, ...x_k is represented as:

$$y = B_0 + B_1x_1 + B_2x_2 + ... + B_jx_j + ...+ B_kx_k + e \tag{7}$$

In the given equation y is a dependent variable, x_1, x_2, ...x_k are independent variables and B_0, B_1, B_2, B_3, ..., B_k are unknown linear coefficients.

The linear regression set between the variable y and the selected independent variables, determined on the basis of n samples (measurements) can be written as a system in the form of n relations.

The determination of coefficients can be performed using the least squares method and matrix approach. In this research the linear coefficients are obtained by Linear Regression in Excel program package.

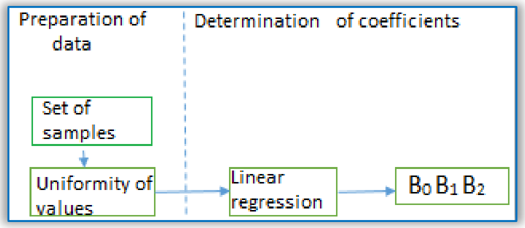

Figure 7. Obtaining coefficients with a regression model

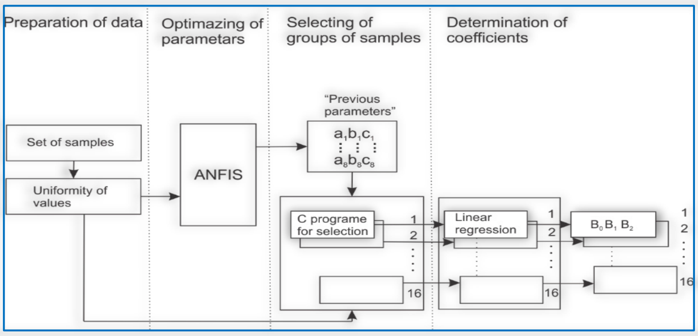

Figure 8. Obtaining coefficients with ANFIS – regression model

3. RESULTS

The validation is done by determining the performance, expressed through the statistical measurement of the mean absolute error (MAE), using 240 samples. The results showed better performance of the ANFIS regression model compared to the model obtained with general regression, i.e. the values obtained were closer to the observed sample values. This is given in Table 4.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_{oi} - y_{ci}| \tag{8}$$

where: MAE – Mean Absolute Error, y_o – observed values and y_c – calculated values, i=1,.........,n

The results of the calculations of the two models of the ANFIS–regression model and the regression model, as well as the observed values are shown in Figures, 9, 10 and 11.

Table 4. Determination the performance of the models

Model	MAE
ANFIS regression	0,063
Regression	0,343

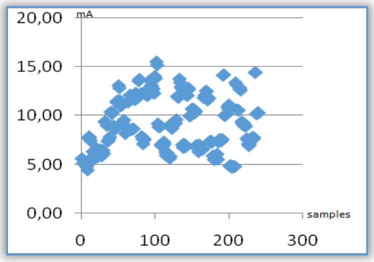

Figure 9. Calculated values of the analog signal for the dosing pump (mA), regression model

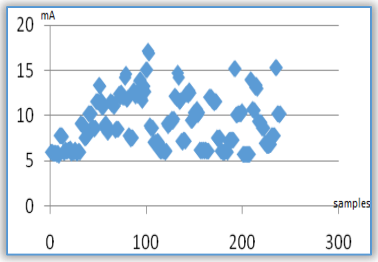

Figure 10. Calculated values of the analog signal for the dosing pump (mA), ANFIS– regression model

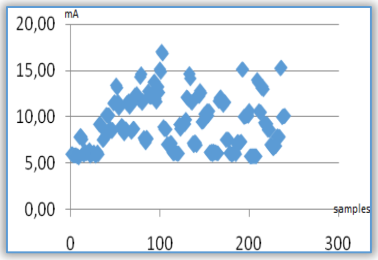

Figure 11. Observed (idealized) values of the analog signal for the dosing pump (mA)

4. CONCEPT AND GRAPHIC PRESENTATION

The main goal of this research was to establish a functional dependence between the input variables of the raw water and the flocculent dosing. The concept of implementing a dosing calculation program as a control unit in the dosing system is presented in Figure 12.

In our case, the measurements of the flow and turbidity for raw water are taken as input in control unit of the dosing system Figure 13. Using the LabVIEW software package graphically is represented with block diagrams in Figure 14 and Figure15.

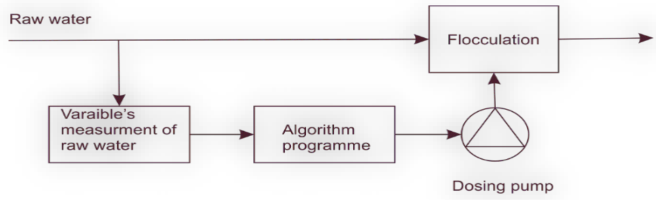

Figure 12. Dosage control based on measurements of input variables

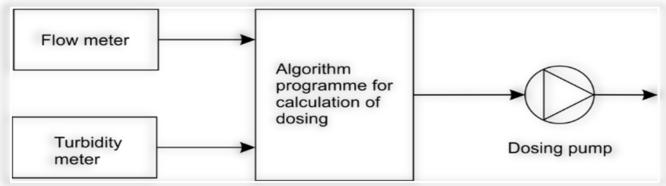

Figure 13. Flocculation dosing system

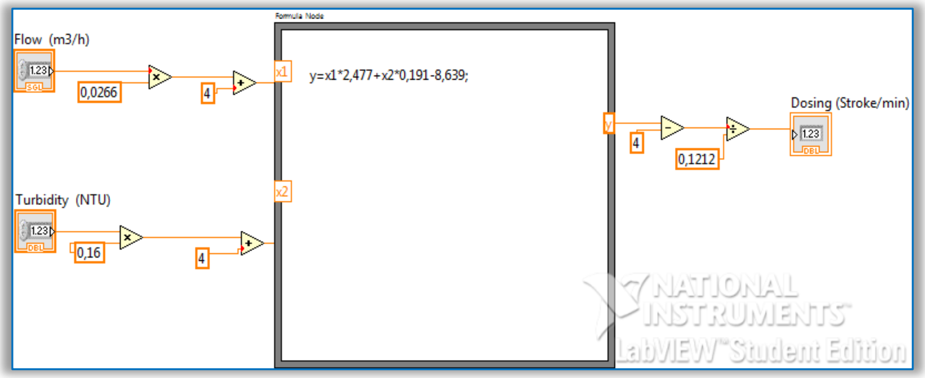

Figure 14. Block diagram for dosing system (regression model)

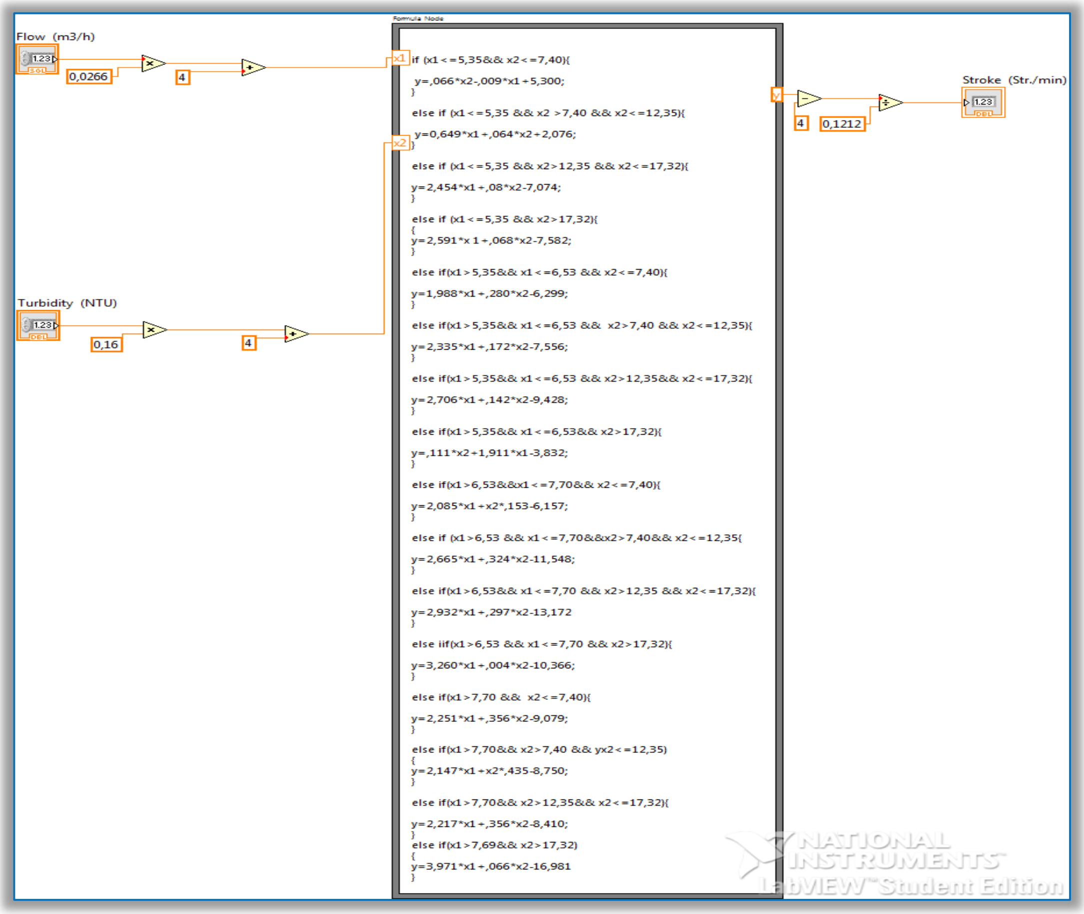

Figure 15. Blok diagram (ANFIS regression model)

5. CONCLUSION

In this this paper is presented a program for dosing of a flocculent in the real system for water treatment from the municipality of Bosilovo – Republic of Macedonia, using intelligent tools such as linear regression, hybrid tool ANFIS and programming language C. Two models of dosing program were developed. First model is obtained with the integration of ANFIS and linear regression, while the second model is obtained with regression only. The statistical indication, mean absolute error, (MAE) was used, in order to determine and validate the two models; it was shown that the ANFIS – regression model gives better results.

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