Experimental Process Identification for Industrial Water De-carbonization in Power Plants

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Abstract

Water Treatment Plant (or WTP) is the most important part of the Power Plant, because it produces vital-water it needs for steam production. Power Plants are the biggest air, ground and groundwater pollutants. Bad water quality directly impacts machine duration. Polluted water from Water Treatment Plant has a negative effect on people, flora and fauna, thus better waste management programs should be put in place to eliminate this problem.

In this paper we are going to present the de-carbonization process of raw water as a part of water treatment plant, within coal fired power plants. De-carbonizing water is a time consuming process. We are going to present an advanced method for process identification with big time delay. The results are compared and one of the most appropriate methods is selected as identification method for this process. Further research and possibilities in this area are going to be presented by the end of the paper.

Progress in identifying the process by which we work in this paper may serve as a new way to identify highly nonlinear processes. The used algorithm for identification of the process that is outlined in this paper can be applied, and it will be the basis for the creation of the software for the application of microcomputer techniques. Here we are applying the relevant software which can be applied in the form of programming packages for identification. This has to do with passive identification methods.

Key words: Nonlinear system identification, System with big time delay, Water Treatment Plant, Reactor, Dosing System, Flocculation, speed of sedimentation.

1. Introduction

To control a process, we need to have as much information about said process and understand it as best possible. This information will be needed and come in hand in identifying and creating a mathematical model.

Mathematical model can be determined in two different modes: the first one is using laws of physics (equations) to describe its dynamic behaviour, and the second one is to set process identification. For the second method we don't need mathematical and physical formulations of the process but it is based on experimental data.

Highly nonlinear and complex process of de-carbonization is simplified by excluding variables with small or negligible impact on output variable (such as water pH in reactor).

Experimental methods are used in order to identify the process, whereas, real data has been recorded within 40 days directly in one of two reactors (de-carbonators) in power plant Kosovo B (Prishtina, Kosovo)

A part of the real data used for the more important aspects of nonlinear system identification is the *selection of the correct time delay for each input variables and the choice of the number of regressors*, respectively the number of previous samples to each of the variables taken into account in the model system in a (given) moment.

Most common methods used for such identification are NFIR and NARX models. The model NARX (*Nonlinear Auto Regresive eXogenous*) fits best in the identification process, as it uses as regressors of the past imputes and outputs data. The model NARX seems structurally stable which structure allows simple application of neural networks for approximation of nonlinear functions of the process.

Among nonparametric methods, neural network is a new technique developed for the purpose of identification. Because of its properties, such as high adaptability, robustness and inherent ability to handle non-linear systems, this technique is widely used in mapping complex nonlinear functions, image processing, recognition and classification. Static mapping function can be determined without knowing any fundamental physics of the system, using the technique of neural network. However, the dynamic mapping function, including the dynamic model identification, is still a challenge in the neuronal network applications.

A number of techniques for neural networks are used for identification systems such as back-propagation (backward learning) neural network. In the presented record (document), the most used technique, "backpropagation" neural network is adapted to identify the model with dynamic structure.

We used neural network with direct connection (feedforward) with three hidden layers, transfer functions of the type "logsig", "radbas" and "purelin" (MATLAB®). We tried it under a given set (set) of input data and it shows good results, although the calculations are too slow and the output should be discretized to neural network function properly.

The results of the simulated output of the model using the method of neural network are compared with measured values of output.
The results of the simulation are obtained using only the MATLAB®.

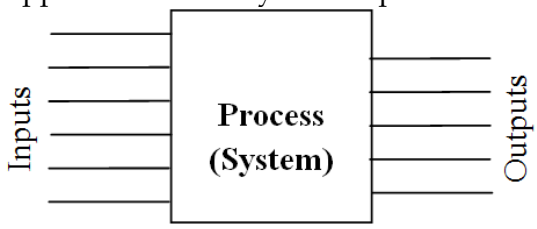
2. Important insights in identifying the processes

The purpose of identification is the benefit of the model which will be 'replacement' for the actual process. In addition, this model will be used to research options for managing system design (for control). Identification is the first process in the design of regulatory systems for any process.

If we want to control the process from the initial state and to push it towards the desired state, even if we do not possess any information, then we can do this by trying to change randomly selected quantities to manage (regulation of) the process. The likelihood of achieving any kind of control in this process is very small. The best way to achieve any kind of controlling effect is, for different changes in quantities, to have corresponding responses of the system, respectively the change in its output to be recorded. From the set of responses obtained it can be assessed which of the quantities of the process are leading towards the desired state. Therefore, this particular set of data will be chosen to control the process (Hametner, C and Jakubek, S, 2010).

Obviously, it would have been better if we knew the process when we do its identification, respectively know its mathematical description. This would be the ideal situation. However, full process recognition is not always necessary. For example, a computer can be used as a device in which a process goes on, even though you don't have any knowledge on how it works. Therefore, for the process we can make the collection and selection of all the best controls and responses of the system (process).

Figure 1: Structural appearance of the system or process



Source: Author's own calculation and design

Often, engineers don't fully identify a process. For this reason it is sufficient to determine the direction of the action of control output relevant to the variables of the process. As an example we can take the heating device in our rooms, for which we have no knowledge about differential equation for heating device (thermal process), but, by using the on/off switch control the temperature in the room will increase or decrease.

Identification of a process cannot be done by certain rules. This leads us to believe that certain methods do not apply to the identification of all processes. Certain methods can be applied to the identification of several types of processes, while others fail in giving results.

Therefore, to any process that needs identifying, is needed a certain approach which implies any of the known methods and their best possible combinations. Obviously, identification requires experienced staffs that work with it.

In the beginning of identification process we should know some of the characteristics of the process, which are:

- Processes can be linear or nonlinear. Therefore, identification methods depending on the linearity of the process are different.
- Processes may have non-stationary or stationary behaviour. Stationary processes are affected by the constant parameters of the system (process), while in the system with variable parameter (not stationary) identification process becomes more difficult. Most of the identification methods have been developed to identify processes with stationary behaviour, while active identification methods or on-line methods are used to identify non-stationary behaviour.
- The process can be continuous, discrete or combined.
- Process identification methods evolve and become tougher depending on the number of entries and outputs from the system.
- Process states may be deterministic (defined) or stochastic (random). Deterministic system is a system in which the future development of the system state cannot contain randomness. For this, deterministic process

will always generate the same output for a given input. Since the exact state of stochastic process cannot be defined, then it is determined by the probability.

Identification of processes is possible only if the measurements are performed during the transitional processes, because the process parameters cannot be set or estimated when the process is in a stationary state.

3. Structural model of the process

After the identification of the process (e.g. his model can tell that is linear with constant coefficients) we determine *structural model* (needed for engineers and 'not to physicists'!). The structural model is a mathematical model which describes the physical structure of the process, and thus describes the behaviour of the system. Functional model should have approximately equal responses to the real process towards certain incoming signals. Throughout the identification it is not necessary to know the real structure of the process.

In our further explanations we have used the so-called *passive identification*, respectively, *out of real time identification*.

4. Methods for processes identification

There are many methods for the identification of linear and nonlinear processes.

In this study, we have chosen the identification of the real system which is a nonlinear process, thus nonlinear identification will be applied. Different methods for the identification of nonlinear processes were applied in the engineering design for the regulation of processes. This study analyses one of the most used method for the identification of processes, which is *the neural network method*.

5. De-carbonization system - water reactor

This will be a brief description of the system installed in Kosovo B (KEK) designed to remove water carbonates.

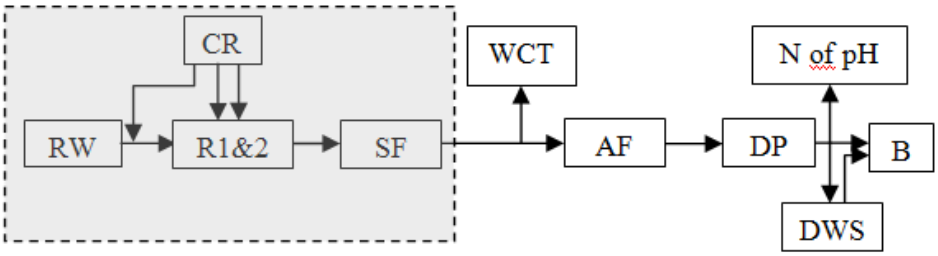
In nature it is difficult to find quality water which would respond to the technical requirements set by the industry. The water used for the needs of power plants 'Kosovo B' is surface water from the river, or from other sources of water. This water is called untreated water or raw water.

5.1 The technological procedure of chemical processing of raw water

The general functional scheme (Functional Description, Decarbonisation Plant, KEK-Kosovo B, Siemens, 2010) of the Water Treatment Plant (WTP) of real Power Plant (PP Kosovo B) is presented in figure 2. There are presented: raw water (RW) in which is added (dosed) ferrous sulphate by dosator of chemical reagents (CR) before the water reaches the reactor (R1 & R2). The first part of the overall process of WTP for the needs of power plants includes de-carbonization and flocculation processes of the raw water, as well as further mechanical filtration after chemical treatment of the water in reactor. Mechanical cleaning of water is made through sand filters (SF). The filtered water stored in decarbonisation tanks is now de-carbonized water (treated by Calcium hydroxide).

De-carbonized water is added to the cooling water, and a part of it goes through the coal active filter further to be treated for water de-mineralization production process. The de-mineralized water is used to produce turbine steam.

Figure 2: Functional block-scheme of Water Treatment System and his use: RW – Raw Water; R1&2 – Reactors 1 & 2; CD-Chemical Dosators; SF – Sand Filters; WCT – Water Cooling Tower; AF – Active Filter; DP-Demineralization Plant; N of pH – pH Neutralization process of waste water; B – Boiler of PP; DWS-De-mineralized Water Store

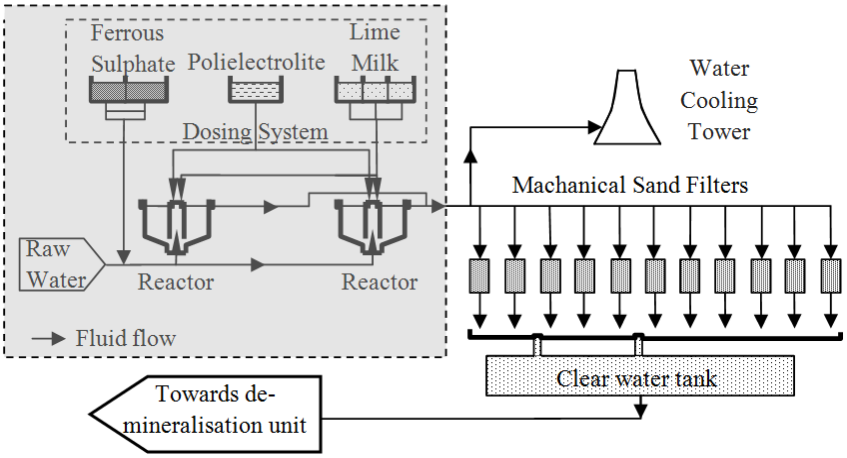


Source: Author's own calculation and design

The water treatment for Power Plants can be done chemically (*flocculation and coagulation*) and physically or by clearing (*stratification or sedimentation and filtration*). The chemical treatment of the water means adding various chemical reagents in the water, thus connecting different components in the water, respectively connecting in large flocks which can be easily sedimented or filtered.

5.2 Technical description of the function of water de-carbonization system

Figure 3: Simplified scheme of the reactors and dosages with enter flow pipes and exit flow pipes for fluid (water) with mechanical sand filters (Source: PP Kosovo B).

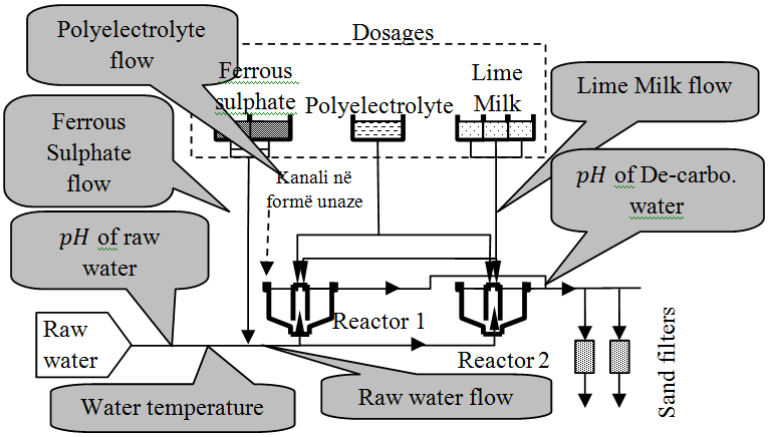


Source: Author's own calculation and design

In figure 3 we have a simple scheme of the reactor, and flows dosage and drive fluid leaks (water) to / from the reactor. Moreover, in the figure one can see functional part of the WTP (sand filters, etc.), and some other parts of Power Plant (Water Cooling Tower, etc.) where the chemically treated water from reactor is used.

There are two reactors at PP Kosovo B, and for each reactor exists a system for dosing flocculent (ferrous sulphate), a system for dosing milk lime, and a system for dosing polyelectrolyte. Whereas, common for both reactors are 11 mechanical water filters for the de-carbonized water. The filtered water after filtration is stored in two tanks, which through pumps it is sent to the last consumer: water cooling tower and water de-mineralization system. Figure 4 includes the most important variables of de-carbonization system.

Figure 4: Most important variables of de-carbonization system



Source: Author's own calculation and design

5.2.1 Technical characteristics of water de-carbonization plant

The data listed below are taken from de-carbonization system (or reactor) from the concrete plant (Functional Description, De-carbonization Plant, KEK-Kosovo B, Siemens, 2010), from the PP Kosovo B. The device is composed of:

- 2 reactors (de-carbonizations) with a capacity of $1750\text{m}^3/\text{h}$, and the diameter of $\phi 29\text{m}$.
- 11 mechanical sand filters
- 1 lime dosing system $(1{,}5 - 3{,}5)\,m^3/h$
- 1 ferrous sulphate dosing system $\frac{(150-350)\text{l}}{\text{h}}$
- 1 polyelectrolyte dosing system
- Measuring devices (instruments) (for example: pH of raw water $(8{,}3 - 8{,}7)$, pH of water in reactor $(9{,}5 - 11)$.

5.2.2 The function of reactor

Raw water in reactors comes from rivers through channels by free fall. Each of the reactors can operate independently and they are the types that quickly do the sedimentation which in the reactor is found in a form of flotation. The sludge in reactor is in a form of floatation particles. Water enters in the centre of reactor (see fig.4), from the bottom of his eccentric cylinder separated with the concrete wall from the rest of the reactor. The way how water flows (among reactor) causes turbulence, and rotation of stratification (sediment) located at the bottom of the reactor. The cleaned water flows at the top of the reactor, respectively water flows just below the water level in the ring canal water collector located at the top of the reactor.

Adding lime milk into reactor softens the water's hardness, while the suspended matters in the water are removed by adding (injecting) flocculent and polyelectrolyte. Flocculent is added to the water flow pipe in amounts that depend on the amount of water flow in the reactor. Lime milk is added inside the reactor due to de-carbonization process, depending on the amount of flow and the pH value of the raw water. After the reaction of the two chemical reagents in the reactor, polyelectrolyte is added in the area where there is no turbulence due to the creations of larger flocs, and due to their better sedimentation at the bottom of the reactor. Sludge (sediment) created at bottom of the reactor has to be removed by pushing it in the centre of the reactor, and then it is removed with special pumps.

After this procedure is done, the water in the surface of the reactor looks clean. Major (mechanical) waste particles remaining need to be removed from the water in the reactor, and should be sent to the sand filters (11 sand filters). In the sand filters the water flows by free fall, and after passing the filters it is collected in water tanks of de-carbonized water.

5.2.3 Dosage of chemical reagents

In every entry (input) of each reactor there is a measurement device installed, which measures the flow of the amount of raw water that give electric impulses. These impulses then make activation of equipment for dosage of chemical reagents into the reactor. Dosage time has to be adjusted in advance.

The quality of de-carbonized water can be checked at any time if there is a dosage schedule. After analyzing the water quality and coming into a conclusion that its quality has changed, the dosage level of chemical reagents can be revised if the duration of dosing is changed. The quality of de-carbonized water can be controlled by a pH-meter. All dosages are shown in fig.4.

5.2.4 Cleaning by flocculation

Suspended materials (floating) in the raw water which is taken from the river are removed by various methods. Removal of suspended materials from raw water is possible by *flocculation, coagulation, and sedimentation* process. The combination of these three processes is called *conventional cleaning*.

Very small suspended particles in surface of the water evict within each other because their surfaces are charged with negative electricity. Such particles have static electricity, thus they spread in the water by eviction. In order for them to be separated from the water they are treated with chemical process called flocculation (connection of small particles in larger particles suitable for filtration). Suitable formed flocks should have size (from 0.5 to 0.6) mm (Auger, G., 2004).

5.2.5 Sedimentation process

At the moment of connection of the suspended particles in the reactor, they are settled in larger groups at the bottom of the reactor. This sediment would be called cohesive sediment, because the formed flocs are linked by cohesive forces. Sometime these flocs are linked into larger groups, and during their fall to the bottom of the reactor they can be broken or destroyed.

The turbulence intensity is highly important during the flock's behaviour process in the reactor. Keeping the group of particles united depends mainly on the frequency and the speed of particle clashes, during which the number of grouped particles increases or decreases. These phenomena are highly dependent on the intensity of turbulence in the reactor, respectively from the velocity of fluctuations, from the rate of flow, and the gravity (Maggi, F. 2005a).

One of the most useful parameters for evaluating the characteristics of sedimentation is the speed of sedimentation. This speed presents the capacity of water purification.

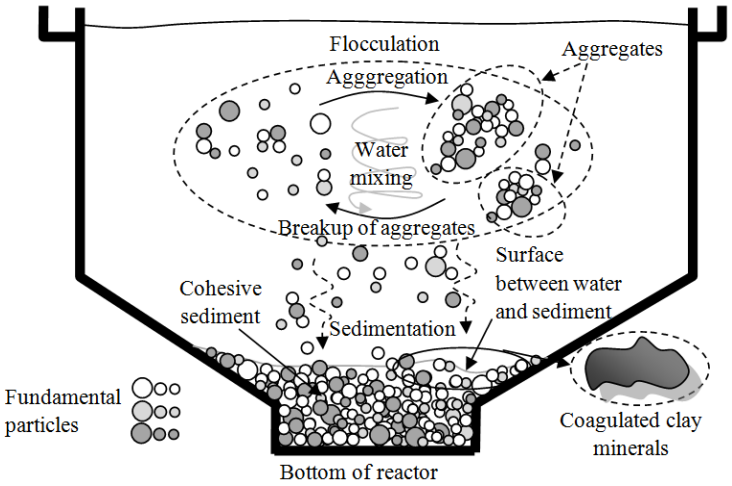
6. Structure of flocs and the meaning of the distribution of dimensions of the flocs

In the sedimentation processes, dimensions and morphology of the formation of particle aggregates is an important process (See fig.5). Flocs populations with different characteristics are formed by aggregation of particles comprising various entities of individual particles.

Characteristics of these populations (flocs) are the quantities like the distributions (or expansion) of their dimension[1]. However, the mechanism by which the regulation of the form of flocs dimension distribution is done is still unknown.

[1]Under the dimension we understand their geometrical size.

Figure 5: Presentation of the cycle of creating cohesive sediment and their behaviour during the aggregation and destruction (breakup)



Source: Maggi, F. 2005 b

However, it is concluded that the generation of flocs is followed by the appearance of more complex geometrical characteristics. Therefore, no floc is similar to another, even though the particles that form it can look alike. So particles have the characteristic of self-similarity[2], while flocs do not! So, generation of the flocs is the result of stochastic processes of aggregation, and destruction of elementary particles and aggregates of higher orders.

Therefore, their structure can be described using geometry and size (geometric) between certain defined characteristic parameters. With this we can conclude that the process of flocculation is the primary mechanism which controls the sediment transport mode at the bottom of the reactor. The speed of sedimentation is controlled by the form of aggregated flocs. Two parameters that influence the flocculation degree are the number of substances suspended in water, and the flow of the suspension with turbulence (Maggi, F. 2005b; Bigss, C.A., 2000).

There are three mechanisms known as the cause of flocs aggregation, and they include: brawn velocity, fluid flow, and differential sedimentation.

7. Identification of de-carbonization process (reactor)

Modern systems of automatic regulation in the industry are facing demands due to the implementation of static and dynamic behaviour of them. However, we were unable to provide sufficient information to identify the process of the

[2] Particles resemble one another.

reactor. The reason why we were unable to give such explanations is due to the fact that flocculation process is not sufficiently described mathematically, and the process is not known either.

The mathematical approach for modelling of the processes in reactor for decarbonization is impossible with this level of knowledge of process phenomena in the reactor. Hence, we chose *experimental method* as a way to describe the process identification.

Since the chemical processes which take place in the reactor are complex, respectively their behavioural characteristics are very nonlinear; their models cannot be easily approximated by linear models. They can only be approximated with nonlinear models, thus the applied methods belong to nonlinear identification methods.

7.1 The principle of structural identification

From the technological point of view, it is important first to do the structural identification of the process. From this structure the dependencies between input and output variables, under process disturbances, can be defined. Afterwards the selection of the model is done, and at the end we make the parametric identification.

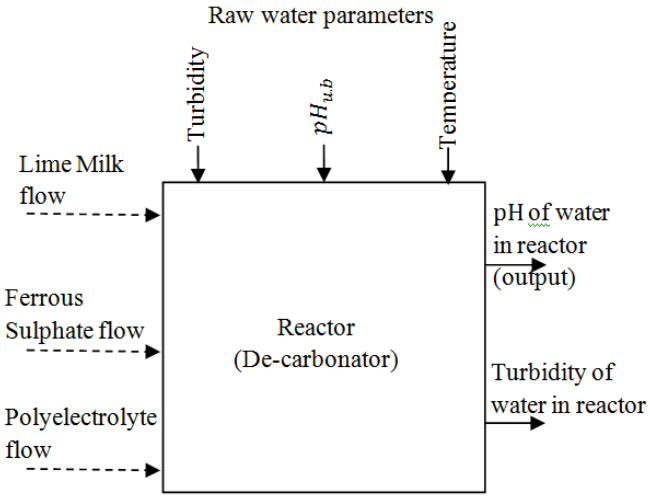
After the structural identification we will present an advanced method for identification, and as such the results of parametric identification will be presented for each model. The results obtained are compared with real data, and as such the model that will be chosen will be mostly compatible with the data from the real process. Furthermore, the experimental results of identification will be presented using data, and the parameter evaluation of the transmission function of the process will be done.

During structural identification we chose the structure which will replace the real object, based on theoretical knowledge, on technical data of the system, on the recorded data from the real system, and on experience. So, for structural identification of the process (system), a priori information is important.

Based on scientific data and other knowledge on the chemical process of flocculation it can be concluded that the reactor may appear as multivariable system. Therefore, the input variables are the flow for dosing of lime milk, the flow of ferrous sulphate, and the flow of raw water, whereas the output variable is the pH of the water in the reactor. Finally, it can be concluded that the water purification process affects several variables. As direct participants in the chemical treatment of water we have lime milk flow, ferrous sulphate flow, and polyelectrolyte flow (Fig.4). Floc capture and settling through these chemical reagents depends on their weight and density, as well as the raw water temperature (Maggi, F.2005a; Stone, M. and Krishnapan, B. G., 2003; Francisko, A. et al., 1994).

Based on what is said above and based on the fig.4 where we have identified the variables of the system, we have presented the structural scheme in fig.6.

Figure 6: Variables and structural scheme of reactor.



Source: Author's own calculation and design

De-carbonization of the raw water is a process which is done by removing the carbonate salt of calcium and magnesium by adding the milk lime in the reactor. Water alkality is decreased by de-carbonization, which directly affects the reduction of pH in water, helps the flocculation process, and reduces the water turbidity.

Based on what was said and figure 6, some of the variables (parameters) of the reactor are designed, respectively they are predefined, as natural parameters for raw water, and it is supposed that *they will not change*.

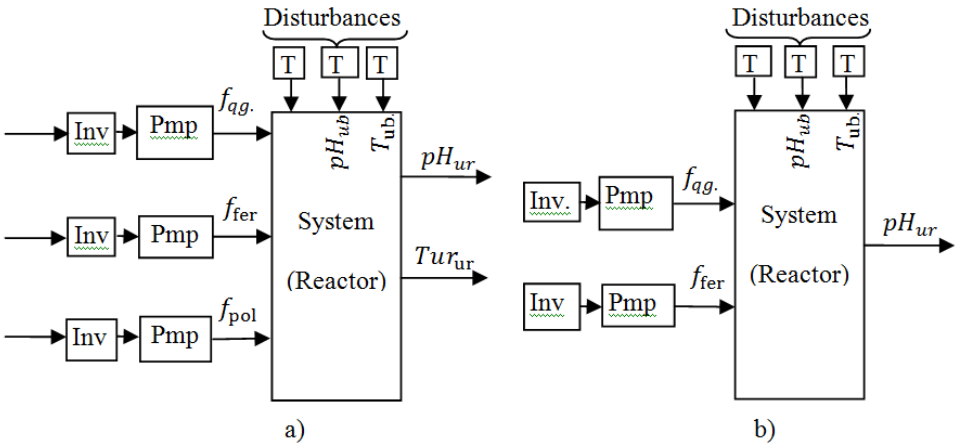
Some of raw water parameters do not change as often, thus their impact is not well expressed on the output variables. For this reason, these variables will be treated as *disturbance variables*.

Variables of dosing chemical reagents have great influence on the output variables. If the variable of lime milk flow changes, then this change will strongly be reflected in the pH of the water in the reactor. Moreover, ferrous sulphate and polyelectrolyte influence changes in the reactor's water.

Ferrous sulphate highly impacts the flocculation process. With ferrous sulphate chemical reaction, only a small part of the particles is not stratified, so the effect of polyelectrolyte in creating flocs remains very negligible, respectively its impact on the process variable output reactor is negligible.

In addition, the raw water turbidity does not change so often, so this variable cannot be considered further in the process. The water temperature of the raw water does not change either, no matter the season. Therefore, this variable *can be removed from the process disturbances*.

Figure 7: a) Structural scheme of reactor; b) Reduced structural scheme of reactor.



Source: Author's own calculation and design

The structure shown in Fig.6 can be detailed by the process variables. They will have short symbols. Thus, based on the structural scheme of reactor fig.7.a, the predefined signs for process parameters will be: f_{lm} - lime milk flow, f_{fer} – ferrous sulphate flow, f_{pol} - polyelectrolyte flow, Tur_{rw} – turbidity of raw water, pH_{rw} - pH of raw water, T_{rw} – raw water temperaturet, pH_{wr} - pH of water in reactor dhe Tur_{wr} – turbidity of the water in reactor. Block T presents the transmiter (measuring transducer) of any of the disturbance variables of the process. While, block presented with symbol INV shows inverter through which flows signals control the pumps of lime milk, ferrous sulphate, and polyelectrolyte. Moreover, Pmp is a symbol for the pump.

The structural scheme presented in fig.7.a, which takes in consideration all variables of the process now is reduced in scheme in fig.7.b where only the most important (dominant variables) of the process in the reactor are taken into consideration. The structural model shown in fig.7.b is the final simplest structural model of the process in the reactor. This reduction was made based on the idea that sometimes, the complex processes for mathematical analysis, can be reduced *by reducing the number of variables with the smallest impact* on those with the greatest influence on the process. With such approximation

approach, analyses are simplified *without losing the reliability of models* of the systems that give a very rough description of the real system.

Finally, based of what was said above, the structural model of the reactor process consists of two entrances: one disturbance and one output.

7.2 Parametric identification of the process

One of the best ways to do the identification on a complex nonlinear process is by presenting the parametric identification of the nonlinear system. The same regressors (means: 'to go back' or 'move backward') used for linear models should be used for nonlinear ones too (NFIR, NARX, NARMAX, NBJ).

While the structure of the linear model is completely determined by the choice of regressors, nonlinear model structure depends on the selected regressor, and the type of nonlinear function (*Matlab for Microsoft Windows"-User's Guide. The Math Works inc, USA, 2009*).

7.3 Nonlinear identification methods

Real data were used for the identification of the process of water reactor, respectively experimental (measured) data are taken (for 40 days) directly from de-carbonization plant (reactor) process itself. These data (signals) are followed by noise due to measurement instruments, thus their processing by conventional methods would yield erroneous results. In contrary, additional equipment (filters, etc.) have to be installed.

To use these data for identification, advanced methods which are tools in MATLAB® programming package should be implemented (*Bina, et al., 2012*).

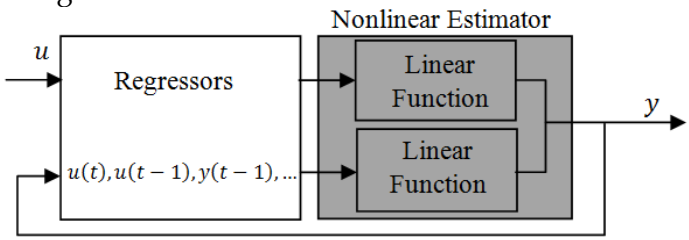
Nowadays, based on experimental data and the computers speed, and sophisticated programs, new methods for identification, such as *neural networks method*, are being used.

Two models which are predominantly used for identification of nonlinear systems are: nonlinear ARX and Hammerstein-Wiener model. Nonlinear ARX model, respectively NARX (see fig.8) relies on linear ARX structure which implies that the output y (t) is prescribed as a sum of weights of past values of outputs, and also current and past values of inputs. However, when dealing with chemical processes which tend to be more nonlinear, it is preferable to use NARX model. NARX model diagram is shown in fig. 8 (*L. Bina, and al. 2012)*

MATLAB ® System Identification Toolbox provides six methods for identification by NARX model (Matlab for Microsoft Windows"-User's Guide. The Math Works inc, USA, 2009).

To be able to prove that the model that we have identified is correct, it is necessary *to validate the model*. For this purpose *we use the set of data that were not used during the identification of the model*, which deal with the same system (reactor) in the same working regime.

Figure 8: Block-diagram of model NARX



Source: from *MATLAB® Tutorial*

Let us invoke on measured data of inputs and outputs of the reactor. One of the more important aspects of nonlinear system identification is the *selection of the correct time delay for each input variables and the choice of the number of regressors*, respectively the number of previous samples to each of the variables taken into account in the model system in a (given) moment.

These values are presented by three matrices N_a, N_b and N_k. N_a is composed of the elements which make up the number of regressors for each output variable, N_b has the same use for the input variables, and N_k contains the time delays of inputs. In our case we chose:

$$N_a = [10]$$
$$N_b = [3; 2; 15]$$
$$N_k = [4; 14; 5]$$

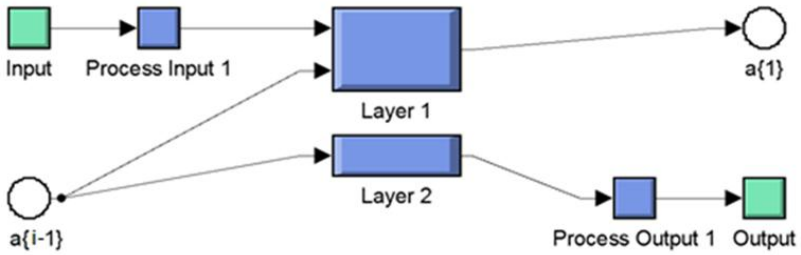
Finding the time delay is relatively intuitive process, because MATLAB ®, provides a useful tool for determining the time needed to change the input data to reflect on the change of the output data. However, vectors N_a and N_b are defined with the help of the trial and error method. Initial values mostly come intuitively, depending on how well we know the nature of the process. In this case during iteration for determining the optimal value of coefficients we used the wavelet networks method, because this method was more rapid in comparison with the method of binary trees (*L. Bina, and al.2012*).

7.4 Test for clarification of training progress

To have an adequate adjusted system, a detailed procedure for network performance which is used as approximates needs to be issued. In the following is presented a neural network structure which is used for approximation of the reactor function in WTP. The processed data are entered in neural network with bi-layer, during which besides active data (measuring the senders a{i}, we add the data from previous measurement (a{i-1}).

With the help of the set of such data, which is a subset of all the data that we possess, *we trained neural networks*. Used structure of the neural network is presented in fig. 9.

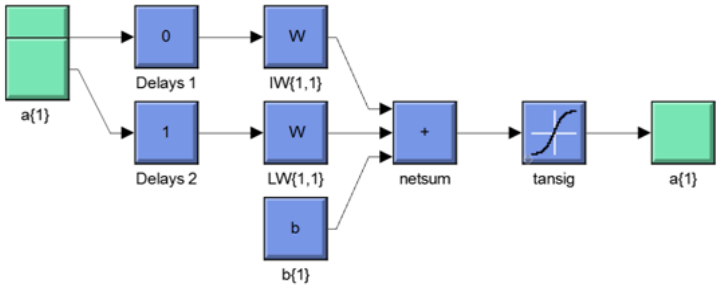
Figure 9: Structure of neural network.



(Source: use of $MATLAB^{®}$ tools, Author's own calculation and design)

The structure of the inner first layer of neural network is shown in figure 10.

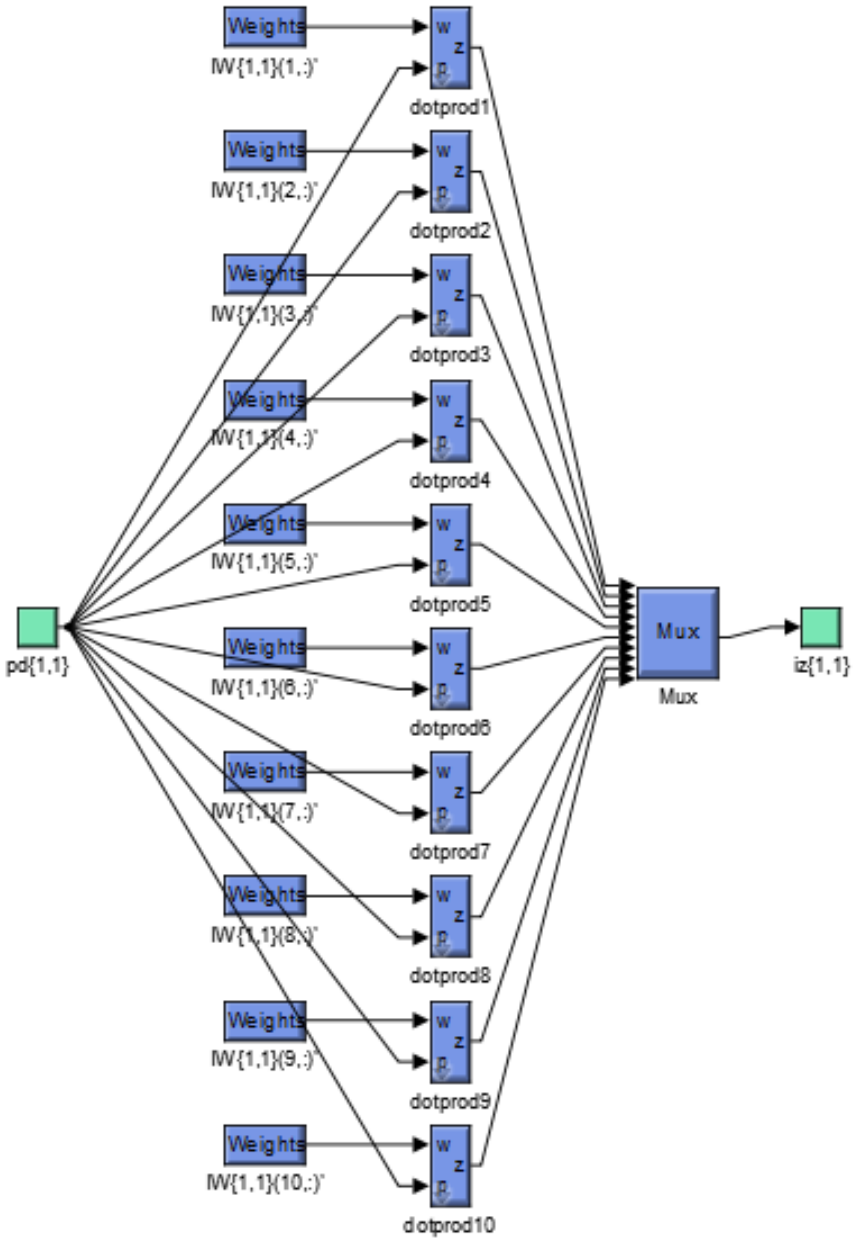
Figure 10: First layer of the neural network



(Source: use of $MATLAB^{®}$ tools, Author's own calculation and design)

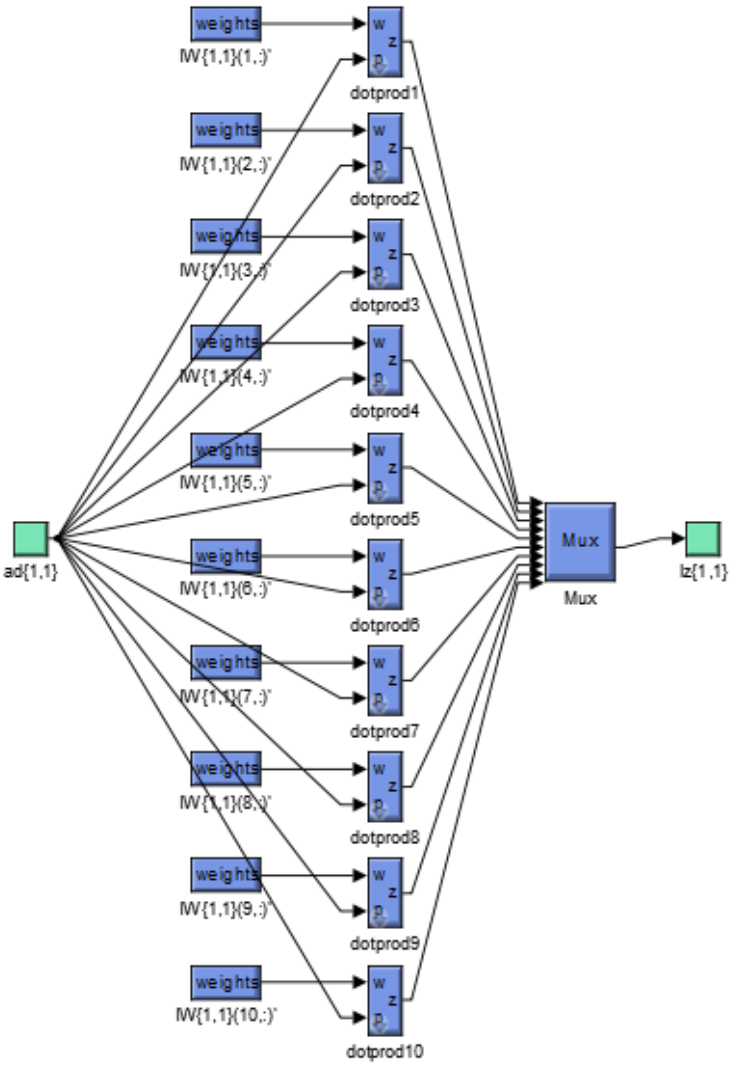
The substructure of the two hidden layers from the first layer of neutral network is presented in figure 11.

Figure 11: Substructure of the first layer of neural network.



Source: use of *MATLAB*® tools, Author's own design

Figure 12: Substructure of the second layer of neural network.



Source: use of *MATLAB*® tools, Author's own calculation and design

After training the network with a set of input data, we obtain coefficients of weights which are adjusted to the same lodge in Table 1 for the first inner matrix of weights factors, while in Table 2, for the second inner matrix.

Table 1: Factors of weights of input matrix – IW

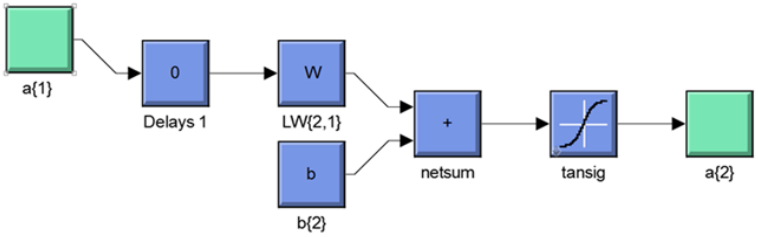
IW(i)	IW(i-1)	IW(i-2)	IW(i-3)	IW(i-4)	IW(i-5)	IW(i-6)	IW(i-7)	IW(i-8)	IW(i-9)
-0.21704	1.690075	-0.32554	-1.49028	-0.57875	-2.51514	0.950906	1.750971	-3.16151	-4.07405
-1.06028	-0.31585	0.287856	0.449262	0.171317	0.740861	-3.75249	-0.10866	-2.85596	0.193252
0.315436	-1.00786	0.91685	-0.54059	-1.17777	0.479314	0.268904	-1.84006	-1.05608	2.897658
-0.1598	0.031835	-0.12294	0.076754	0.309286	-1.02966	-1.44318	0.198126	1.200826	1.105681
-0.09097	-0.93171	1.307002	-1.19486	-1.36925	-2.13917	-0.24355	1.054109	-0.73704	-1.94561

Table 2: Factors of weights of output matrix – LW

LW(i)	LW(i-1)	LW(i-2)	LW(i-3)	LW(i-4)	LW(i-5)	LW(i-6)	LW(i-7)	LW(i-8)	LW(i-9)
0.41212	-0.60041	0.400831	0.102785	-0.05588	0.586024	0.264284	-0.38273	0.220994	-0.25824
-0.02891	0.235907	0.293436	0.025231	0.383128	-0.1561	-0.67844	0.573031	0.464953	0.661871
-0.68267	-0.25823	0.477614	-0.13027	-0.0301	0.533076	-0.13812	0.010065	0.605071	0.651581
0.463527	-0.00024	0.118823	0.366123	0.604223	0.573392	0.463632	-0.57799	0.55743	-0.62065
0.301401	0.715632	0.174775	-0.65602	0.453484	0.097057	0.396214	-0.50855	-0.0858	-0.02208
0.219129	0.500073	0.136175	0.765174	0.509046	0.451148	0.798711	0.020436	0.371863	-0.29192
0.105393	-0.01586	0.342958	-0.09119	-0.71768	0.085524	0.428439	0.568717	0.382349	-0.47079
0.346644	0.389278	0.499008	-0.024	-0.05723	0.533598	0.259992	-0.38038	0.373064	-0.6654
0.635183	0.354484	0.620668	-0.2821	-0.35461	0.581362	-0.02555	-0.04582	-0.06168	0.163239
-0.26263	-0.51781	-0.66188	-0.52191	-0.22345	-0.18585	-0.7967	-0.1891	0.647283	0.449484

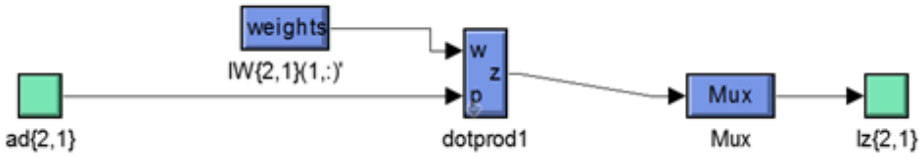
The structure of the second inner layer of the neutral network is presented in figure 12. Substructure of hidden layer from the second layer of neural network is presented in fig.13.

Figure 13: Substructure of two hidden layers of the second layer of the neural network



(Source: use of $MATLAB^{®}$ tools, Author's own calculation and design)

Figure 14: The second layer of the neural network



Source: use of $MATLAB^{®}$ tools, Author's own calculation and design

After training of network through set of inputs data, we obtain the coefficients of weights adjusted to them, which are shown in Table 4 for the second inner matrix of factors of weights.

Table 3: Factors of weights for matrix outputs LW

LW
-2.01899
-1.66745
-3.56678
3.91828
-4.558
-1.30147
0.508283
-1.0455
-0.36689
-4.29332

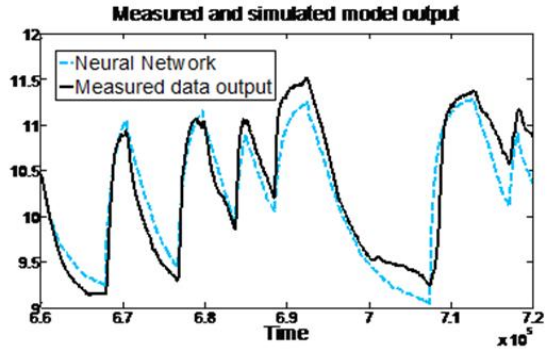
Source: use of $MATLAB^{®}$ tools, Author's own calculation and design

In this case, it is important that we are focused to the simulated data which have to carefully follow the measured data. What we need to achieve is full compliance (for a whole generation of data recorded for 40 days) of more than 35%, taking care about the dynamics of the process and successfully redirect all pics and trends of measured data. Also, we couldn't ignore the number (the quantities) of the non-compliances in working data (sensor defect, change the dynamics of the system, etc.). In order to simplify calculations and to improve the overall performance of estimator, the set of output values are approximated with precision of 0.25.

8. Results

The above reviews are using feedforward neural networks with three hidden layers, the functions for transfer of type 'logsig', 'radbas' and 'purelin, and unknown inputs and outputs data. This is proved by the set provided input data, and this gave good results even though the calculations were done very slowly and the output data were discretized in order to have right functioning (work) of neural network. The results of the simulation output data of the system (reactor) obtained by the method of neural network, is shown in fig.14.

Figure 15: Simulation output data using the method of neural network (64.69% fitting)



Source: use of $MATLAB^{®}$ tools, Author's own calculation and design

There have been five models defined for the reactor system, and they include: nlarx1, nlarx2, nlarx3, nlarx4, nlarx5 (MATLAB®). For each model the transfer functions between each input and output variable can be written separately; between lime milk and pH of water in the reactor; between ferrous sulphate and pH of the water in the reactor, between pH of raw water and pH of water in reactor. For this purpose we have to call the orders (MATLAB®).

1. For first model nlarx1
   >> tf1=linearize(nlarx1,[2.5,230, 8.5],10.25*ones(51,1))
2. For second model nlarx2
   >> tf2=linearize(nlarx2,[2.6,300, 8.5],10.25*ones(51,1))
3. For third model nlarx3
   >> tf3=linearize(nlarx3,[1.7,200, 8.5],10.25*ones(51,1))
4. For fourth model nlarx4
   >> tf4=linearize(nlarx4,[1.5,150, 8.3],10.25*ones(51,1))
5. For fifth model nlarx5
   >> tf5=linearize(nlarx5,[3.5,350, 8.7],10.25*ones(8,1)).

9. Conclusion

In the paper is presented the modelling process, process identification, which takes place in the water de-carbonization reactor in WTP, through recognition of chemical-physical phenomena that occur there. For this reason we explained some basic notions and we have described the phenomena associated with the behaviour of flocculation processes. It explains some basic notions and is describing phenomena that occur there. This is done to gain the basic idea of creating flocs as one of the dominant processes in the reactor. The paper addresses the topic interesting-Experimental Identification for Industrial

Process Water De-carbonization in Power Plants, and the paper present an aspect of good treatment, represents a basic research, while these methods may be upgraded.

List of References

Allgöwer, F. and Zheng, A. (Eds.). (2000). *Nonlinear model predictive control, progress in systems and control theory*. Vol. 26. Basel, Boston, Berlin: Birkhauser Verlag.

Auger G. (2004). The settling column and application to observe flocculation process. MSc-Thesis. Delft University of Technology, Delft.

Biggs, C.A. (2000). Activated sludge flocculation: Investigating the effect of shear rate and cation concentration on flocculation dynamics. Ph.D thesis, University of Queensland, Australia.

Bina, L., Davidovikj, D, Stojanovski G., Stankovski, M. (2012a). Advanced Identification Methods for Industrial Processes with Big Time Delays. JMEA, USA, Volume 2, pp.203-207.

Camacho, E. F. and Bordons, C. (2004). *Model predictive control*. London, Springer.

Functional Description, Decarbonization Plant, KEK-Kosovo B, Siemens, 2010.

Francisco V., Manuel P., and Carles S., (1994). A New Procedure for Water Decarbonation Process Control, Manuel Adroer, , Universitat Autonoma de Barcelona, 08193 Bellaterra, Spain.

Hametner, C. and Jakubek, S. (2010). Nonlinear System Identification through Local Model. InTech.

Maciejowski, J.M. (2002). *Predictive control with constraints*. Englewood Cliffs, NJ: Prentice Hall.

Maggi, F. (2005a). Survey of the numerical characterization of 2-D clusters

Maggi, F. (2005b). Flocculation dynamics of cohesive sediment. Doctoral thesis.

"Matlab for Microsoft Windows"-User's Guide. The Math Works inc, USA, 2009.

Stone M. and Krishnappan B.G. (2003). Floc morphology and size distributions of cohesive sediment in steady flow. Water Research 37, 2739-2747.