Fuzzy models of the biological-chemical processes in the west-water treatment plant

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In the work issues related to control of the electrical blowers installed in the waste water treatment plant (WWTP) are demonstrated. After a short introduction a description of a real treatment plant is presented. Then the main sewage drives are described. Next the commonly used control strategies for the biological-chemical process are presented. The model ASM1 of the biological chemical transformation used in the advanced MPC (model predictive control) strategy is introduced. Then the fuzzy system based on the TSK model is presented. The ability of the TSK fuzzy system to estimate the biological-chemical variables are demonstrated.

1. Introduction

Control processes in WWTP is a rapidly growing field of knowledge [1]-[4]. This follows the universality of using urban and industrial processes in wastewater treatment, striving for continuous reduction of maintenance costs as well as a complicated and non-linear model of the transformation of compounds in the treatment process. Optimal control strategy should be on one hand, easy to install on the other hand leads to a reduction of operating costs and prevent exceeding the limits on the outflow of sewage [1]-[5].

The electrical drives installed in the WWTP can be divided into a few group. To the first group a electrical blowers which are responsible for delivering the air (oxygen) to the bioreactor are included. Those drives are the main consumption elements in the WWTP [4]-[6]. In the typical WWTP they take approximately of 80%- 90% of the electrical consumed energy. The second group encompasses the pumps and mixers. The other drives are including in the third group (e.g. in the station of mechanical cleaning).

The design of the control strategy which saves the energy is quite a complicated process because it required knowledge from different fields (chemical, electrical and control engineering). Additionally, the process is nonlinear and depending on many hardly identified factors. Therefore, commonly-used strategies are not advanced and usually relying on keeping a constant dissolved oxygen level in bioreactor. The more advanced concepts such as MPC are still not used in practice but they are in intensive laboratory tests [6]-[7]. Its application can decrease the operational costs significantly. However, one of the main drawback of the MPC is a large computational burden which can be reduced by finding a faster model.

The main goal of the paper is to present the ability of the TSK fuzzy system to model the biological-chemical processes of a WWTP. The design model will be used in the advanced control structure (MPC) of the electrical blowers installed in a WWTP. The paper presents the a first part of the work connected to the research project: advanced monitoring and control of the electrical drives in the WWTP and its devoted to analysis of the ability of the different fuzzy system to model the biological-chemical transformation. Contrary to the papers [8]-[9] where the comparison of the properties between the Mamdani and TSK systems was presented, in the current work more deeply analysis concerned only TSK system is included.

The paper is organized as follows. After a short introduction a description of the plant used in the study is provided. Then the commonly-used strategies of the WWTP are briefly described. The advantages and drawbacks of the MPC are analyzed. Next the fuzzy models are introduced. The ability of the fuzzy system to model the biological-chemical transformation processes are presented. In conclusion some final remarks are given.

2. Description of the plant

In order to remove the nitrogen from the wastewater two biological processes nitrification and denitrification are used. In the nitrification process ammonium is oxidized to nitrate and then in the denitrification process nitrate is transformed to gas nitrogen. In order to ensure an adequate nitrification level in the aerobic environment the following factor must be fulfilled: namely the sufficient concentration of dissolved oxygen level in aerobic zone. However, aeration causes high energy costs and may unfavorably influence the denitrification rate in the anoxic compartments [4]. Different configurations of the WWTP can be used in practice. A diagram of the test plant is shown in Fig.1.

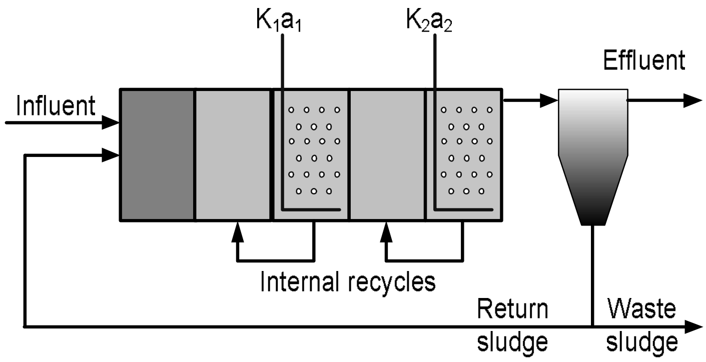


Fig. 1. The general scheme of the WWTP

It consists of the five zones. In the first zone (80 m3) the phosphorus is removed by special microorganisms. Then the plant has two series denitrification-nitrification (110 m3-210 m3) zones. The internal recycle circuits deliver nitrate to the denitrification zones. After those zones the waste water flows into secondary settlers (225 m3), in which sedimentation and clarification take place. Some of the waste water is clear after reaching the output of the plant. The sludge is turned back to the input of the plant or optimally to the waste-sludge tank. The daily inflow of the plant is approximately 850 m^3, which means that the tested plant is relatively small (countryside with the population of approximately 8 thousands citizens). In Fig. 2a the bioreactor of the WWTP is shown. The inner partitions which divide the zones are hidden by the wastewater.

a) b)

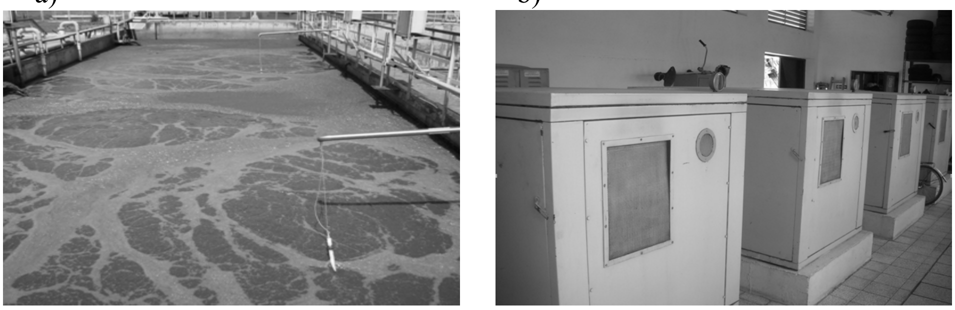


Fig. 2. A view of the bioreactor (a) and blowers station (b)

The tested plant has the following drives: a pump from the primary settlers to bioreactor (4.7kW), recirculation pumps (3x1.3kW) and a blowers station (4x18kW). As can be concluded from the presented data, the main consumption elements are the electrical blowers. Therefore, the strategy which can save energy is look for. In Fig. 2b view of the blowers station is shown. In order to minimize the noise the blowers have special housing.

In the literature a number of control structures for control processes used in the sewage treatment plant are presented [1]-[5]. The simplest control strategies are based on maintaining constant air flow to the zones of nitrification in the biological reactor. An advantage of this approach is its simplicity. Disadvantages of this strategy steam from the constant flow of air from the electrical blowers. Under conditions of low water flow the bioreactor is overaerated. Even a slow increase in the flow of pollution can bring about exceeding the limits in the outflow. Despite these drawbacks, this strategy is still in use in practice [1].

A more advanced control strategy commonly used for small wastewater treatment plants in Poland relies on the controlling of the dissolved oxygen level in bioreactor. It requires installation of oxygen sensors in the selected parts of the bioreactor. Usually the PI (in the case of the variable speed drive) or hysteresis (in the case of the direct switched motors without converter) controllers are applied.

Depending on the value of the control signal a number of the electrical blowers can be set on or off. This control strategy does not take into consideration the variation of the input of the bioreactor. The large values of the inflow can lead the dissolved oxygen level below the required value. On the contrary, smaller inflow of the ammonia can make the waste water overaerated which can disturb the denitrification process. This may result in unnecessary consumption of the energy by the blowers.

One of the most advanced control strategies for the WWTP is MPC. MPC is an optimization-based strategy requiring a solution to a mathematical optimization problem at each sampling time. The control objectives are directly expressed in a cost function. Despite the fact that optimization problems can be solved efficiently using off the- shelf solvers, the computational effort required for the implementation of the MPC algorithms on-line can be quite prohibitive for many real-time applications. This is particularly evident in systems with complicated nonlinear mathematical model. One of the ways which can ensure the real-time MPC application is the simplification of the mathematical model of the plant [7],[10].

3. Mathematical model of the bioreactor

ASM1 model describes the transformation of organic compounds and nitrogen in the sewage treatment plant. Its original form was proposed in 1987 in [11]. It consisted of eight equations that describe the kinematics of change by manipulating the 13 state variables. ASM1 model was based on mass balance equations and stoichiometric relationships of kinematics. The currently used form consists of ten equations which describe the transformation of the fourteen variables. ASM1 model operates on the following state variables:

- S_S easily degradable organic compounds considered as dissolved,
- S_I dissolved organic compounds biologically nondegradable,
- S_{NH} – ammonium nitrogen, expressed as the sum of ammonia (NH_3) and ammonium (NH_4^+),
- S_{NO} nitrate nitrogen, expressed as an aggregate concentration of nitrates and nitrites,
- S_{ND} Dissolved organic nitrogen,
- S_O dissolved oxygen,
- S_{ALK} alkalinity,
- X_S slowly biodegradable organic compounds,
- X_I organic compounds in a suspension of biologically non degradable,
- X_{BH} heterotrophic bacteria, microorganisms, which in carry out the biodegradation in aerobic and anaerobic zones, as well as the hydrolysis and ammonification of X_S,
- X_{BA} autotrophic bacteria, microorganisms that carry out the process of nitrification - derive energy from oxidation of ammonia; this fraction express at the same time the microorganisms which oxidizing of nitrite and ammonia,

- X_P products of biomass death,
- X_{ND} organic nitrogen in the suspension, Organic nitrogen which is connected with the fraction X_S. Together with X_S hydrolyzes to dissolved organic nitrogen (S_{ND}),
- X_{MIN} – mineral slurry, a suspension, which is not included in the COD and do not undergo any treatment.

The transformations of the wastewater, taking into account the above-mentioned fractions, are described by ten kinematics equations and the stoichiometric and number coefficients. Due to the length of the model, it is not presented. The exact description can be found in [2]-[5].

4. Takagi-Sugeno fuzzy model

The TSK model was proposed in 1985 by Takagi and Sugeno and later in 1988 by Sugeno and Kang. Nodaways it is one of the most frequently applied fuzzy systems. It consists of several rules in the following form [12]:

R1:IF $x_1=A_{11}$ AND…AND $x_j=A_{1j}$ THEN $y=f(x_1, x_2\ldots x_j,x_0)$

Rn:IF $x_1=A_{n1}$ AND … AND $x_j=A_{nj}$ THEN $y=f(x_1, x_2\ldots x_j,x_0)$

where x_0 is a constant value.

An illustration of the TSK system computational scheme is presented in Fig. 3. After the fuzzyfication procedure of the two input values e_1 and e_2, the degree of the premises part of each rule is computed using the *min* operator as the t-norm. The consequent part of the rule is a function of the input variables. After its calculation the implication and aggregation methods are applied to the system. Then the output of the system is conducted by means of the singleton defuzzyfication strategy.

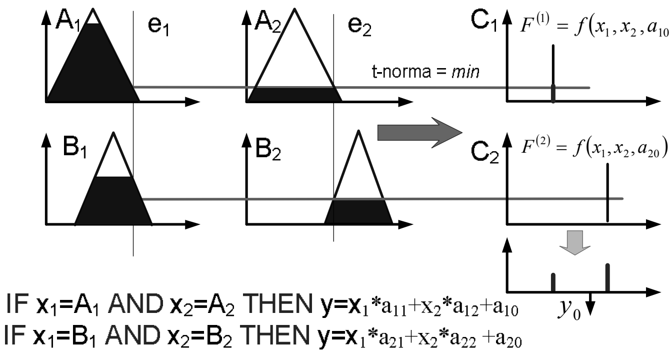


Fig. 3. Illustration of the TSK system computation scheme

The TSK model has the following advantages. First of all, it allows reducing the computational complexity of the whole system. This steams from the fact that the integration of the non-linear surface is replaced by the *sum* and *prod* operations (in defuzzyfication methodology). Furthermore, by suitable selection of the input membership functions it is possible to obtain the sectors in the control surface depending only on one rule, which simplifies optimization of the fuzzy system. Due to this reason the TSK model is often called a quasi-linear fuzzy model.

Fuzzy c-clustering method

Fuzzy clustering plays an important role in solving problems in the areas of fuzzy model identification. It have been widely applied in different engineering areas such as: information technology, electrical engineering, chemical engineering etc. A variety of fuzzy clustering methods have been proposed in the literature [13]-[16]. Most of them are based upon distance criteria. Contrary to the classical clustering method, in fuzzy clustering one sample can belong to more than one cluster. It means, that a specific certain datapoint that is located near to the center of a cluster has a bigger degree of belonging to that cluster than another datapoint located farther. One commonly used algorithm is the fuzzy c-means (FCM) algorithm. It uses reciprocal distance to compute fuzzy weights. Although more advanced methodologies have been proposed, fuzzy c-mean is still one of the most popular approaches.

The idea of FCM is using the weights that minimize sum of distances d_{ik} between the k_{th} sample and the i_{th} cluster center v_i, i.e., the total mean-square error function defined as:

$$J(U,V)=\sum_{i=1}^{C}\sum_{k=1}^{N}(u_{ik})^m d_{ik}^2 \tag{1}$$

where

$$d_{ik}^2=\|x_k-v_i\|^2=(x_k-v_i)^T\mathbf{A}(x_k-v_i) \tag{2}$$

$$v_i=\sum_{k=1}^{N}(u_{ik})^m x_k \Big/ \sum_{k=1}^{N}(u_{ik})^m \tag{3}$$

The **A** matrix ($M \times M$) in (?) is set to the identity matrix **I** in most cases**.** The degree of membership of the k_{th} datapoint to the i_{th} cluster has a fuzzy value (in the range between 0 and 1). The bigger membership value means higher degree of membership to specific cluster. The sum of membership values of the k_{th} datapoint for each of the clusters should satisfy the following equation:

$$\sum_{i=1}^{C}u_{ik}=1, \qquad \forall k, \qquad 0\le u_{ik}\le 1 \tag{4}$$

m is a fuzziness coefficient which could has a range between 1 and infinity. Setting the coefficient m=1 means that the membership function of each datapoint could have only one of the two values: zero or one. It means that instead of fuzzy the hard clustering methodology is implemented. When m goes to infinity, the result of minimization leads to $u_{ik}=1/C$ for all of the datapoints and cluster centers. That means all of the datapoints have equal membership values.

To start of the algorithm the following parameters should be specify: cluster number C, fuzziness coefficient m and membership matrix U. The center of the cluster are determined with the help of the (3). Next membership values are calculated by:

$$u_{ik} = 1 \Big/ \sum_{j=1}^{C} \left(\frac{d_{ik}}{d_{jk}} \right)^{2(m-1)} \tag{5}$$

Iterative calculations based on above presented equation 2, 3, and 5 are performed.. The stop criterion usually is defined as the minimal value of the objective function J or the set number of the iteration.

5. Results

Training data have been generated in an analytical model separately in two temperatures: 20 and 10 degrees Celsius (because behavior of the bioreactor depends on the temperature). The total duration of one simulation has been set to 40 days. To the learning procedure only every 50-th sample has been selected. During the learning the fuzzy c-means clustering method has been applied. In this work the results related to the transformation processes in a one nitrification zone are considered. They can be easy extended to the other zones.

The input vector of the fuzzy system consists of the following element: the state vector of the nitrification zone in the previous sample (*k-1*), the state vector of the inflow to the nitrification zone in the current sample (*k*), the volume of the inflow over the volume of the nitrification zone in the current sample (*k*). The output vector consist of the state vector of the nitrification zone in the current sample (*k*).

From the output vectors the state S_0 has been eliminated. The dissolved oxygen is not used in the output vector due to the two reasons. First of all the level of the S_0 can be easy regulated so it can be treated as a control variable. Secondly the regulation time of this variable is very short – in the range of a few minutes compared to the sampling time of the fuzzy model which is approximately one hour. Also X_{ND} has been eliminated form the input and output vector because in the nitrification zone its value is very close to zero.

In order to check the learning ability of the TSK fuzzy system the test data have been generated in different conditions. First of all they were obtained in the temperature of 15 degrees Celsius. Also the amplitude of the inflow and its component has been changed. The inflow of the bioreactor used in the testing data is shown in the Fig. 3. The variation of the input of the plant due to the different days (week days and weekend), part of the day (day and night) are clearly visible in its transient. Additionally some bigger disturbances connected with the raining period and two storms are evident in the picture. During the weekdays the inflow varies from the 550 to over 1500 m^3. Contrary to the weekdays, at the weekend the maximal inflow is reduces to1200 m^3. During the raining day the value of the wastewater delivered to the sewage treatment plant increased to 2500m^3. The storm events add to the system short disturbances with the inflow on the boundary of 3000 m^3.

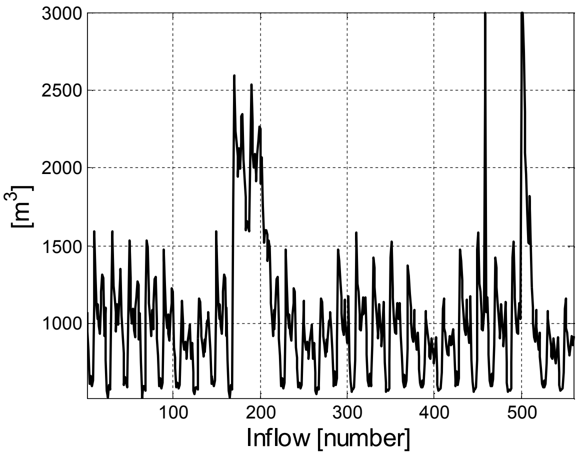


Fig. 4. The inflow of the WWTP

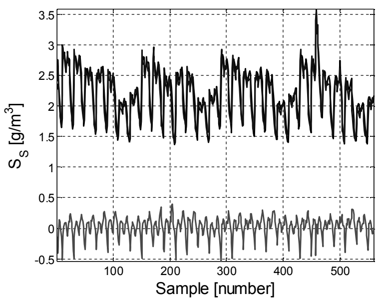
First the TSK fuzzy system with two clusters has been investigated. After the learning procedure the fuzzy TSK model of the transformation processes has been obtained. Then the system has been examined using testing data. The transients of the real and estimated state variables as well as their estimation errors are presented in Fig. 5.

As can be concluded from the transients presented in Fig. 5 the fuzzy TSK model based on the two cluster has very good generalization ability. In the most of the state the estimation error are very small. Only in the transients of S_{NH} and S_{ND} the estimation errors reach bigger value. Then the percentage estimation error for all variables has been calculated. There are presented in Table 1.

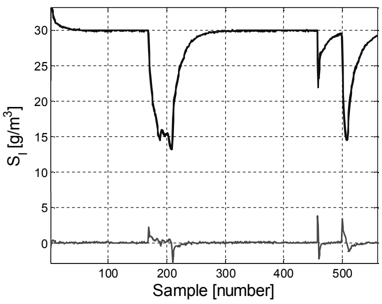
The generalization ability of the fuzzy system can be improved by increasing the number of clusters. Unfortunately, on the other hand this will also boost the computational complexity of the obtained model. In the presented study the number of the fuzzy clusters has been increased while the estimation error has been reduced. The optimal number of clusters has been set to 290. The estimation error of such system are presented in Table 2.

As can be concluded from the data presented in Tab. 1 and Tab. 2, the system with the much bigger number of clusters (290) has very similar performance as the simple one. The percentage errors are almost the some for those two system. It means that the TSK system with only two clusters can successfully represent the biological-chemical processes in the bioreactor (contrary to the Mamdani system [8]). The small number of clusters means also simplicity of the future of the real-time implementation of the obtained fuzzy system.

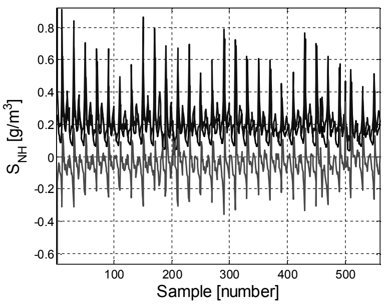
a)


S_S [g/m^3]
Sample [number]

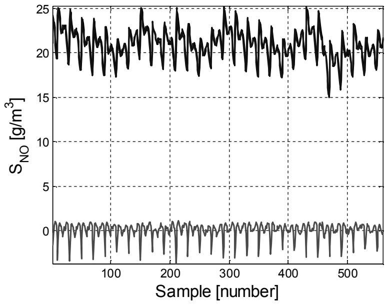
b)


S_I [g/m^3]
Sample [number]

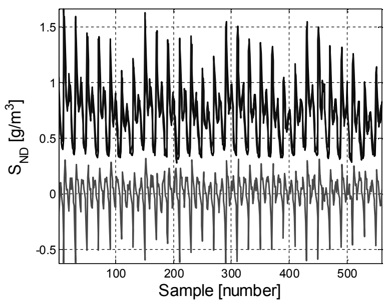
c)


S_NH [g/m^3]
Sample [number]

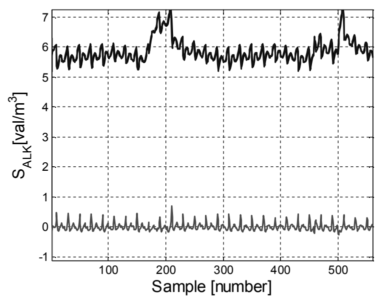
d)


S_NO [g/m^3]
Sample [number]

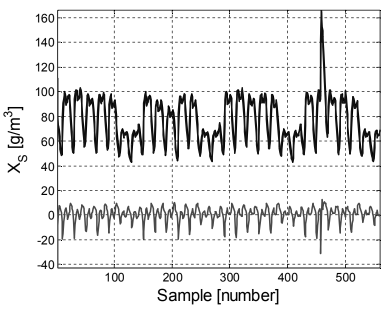
e)


S_ND [g/m^3]
Sample [number]

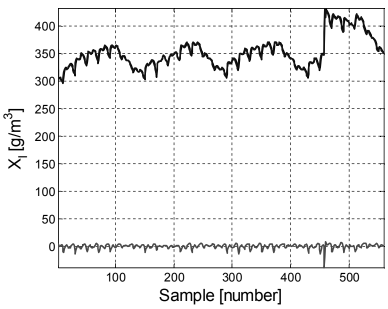
f)


S_ALK [val/m^3]
Sample [number]

g)


X_S [g/m^3]
Sample [number]

h)


X_I [g/m^3]
Sample [number]

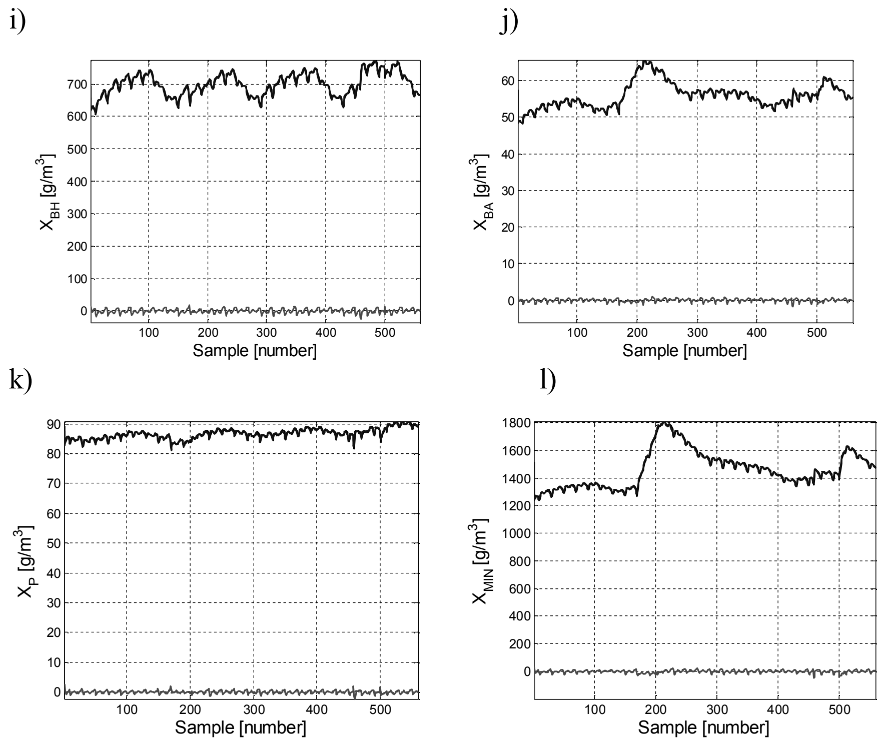


Fig. 5. Real and modeled by fuzzy system transients as well as an modeled error of the state variables in the case TSK model with 2 clusters and testing data

Table 1. Estimation errors for the TSK system with number of the cluster 2

Number of the cluster	Number of the variable											
	1	2	3	4	5	7	8	9	10	11	12	14
2	5,67	0,67	42,74	2,95	16,46	1,61	6,05	0,83	0,74	0,60	0,46	0,58

Table 2. Estimation errors for the TSK system with number of the cluster 290

Number of the cluster	Number of the variable											
	1	2	3	4	5	7	8	9	10	11	12	14
290	5,66	0,63	42,10	2,95	16,43	1,59	5,95	0,82	0,74	0,59	0,46	0,56

6. Conclusions

In the paper issues connected with fuzzy modeling of the chemical-biological processes for the MPC control strategy of the electrical blowers are presented. From the presented analyses and results the following remarks can be formulated:
− In order to save the energy consumed by the electrical blowers an advanced strategy should be applied. The main drawback of the real time realization of the MPC is its computational complexity, which can be decreased by suitable selection of the applied model.

The TSK system has a very good generalization ability. The obtained model based on the TSK system has small modeling errors of all state variables. Due to its simplicity the TSK model can be successfully applied in the real-time MPC control structure of the WWTP.

The next investigation will concern the real time implementation of different control strategies (including MPC) in a real WWTP plant.

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