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**CALIBRATION OF THE ACTIVATED SLUDGE MODEL
WITH GENETIC ALGORITHMS.
PART I. CALIBRATION RESULTS**

A method for the calibration of activated sludge model No. 1 (ASM1) using genetic algorithms is proposed. The model to be calibrated was a virtual wastewater treatment plant (WWTP) which consisted of a complete-mix aerobic tank and a secondary settler. Preliminary analyses enabled the assumption that, based on a steady state, it is possible to simultaneously estimate the parameters $\hat{\mu}_H$, $\hat{\mu}_A$ and b_H . For the needs of calibration, use was made of 153 objective functions. Inconsistencies in the results obtained with different objective functions are explained in the part II of this article [15].

SYMBOLS

Model parameters

- b_A – decay rate for autotrophs, 1/d,
- b_H – decay rate for heterotrophs, 1/d,
- f_{CB} – COD to TSS ratio for biomass, g COD/g TSS,
- f_{CZ} – COD to TSS ratio for particulate COD, g COD/g TSS,
- f_P – fraction of inert COD generated in biomass decay, g COD/g COD,
- i_{XB} – mass of nitrogen per mass of COD in biomass, g N/g COD,
- k_a – ammonification rate constant, m³/g COD/d,
- K_{alk_A} – alkalinity half-saturation coefficient for autotrophs, mole HCO₃⁻/m³,
- K_{alk_H} – alkalinity half-saturation coefficient for heterotrophs, mole HCO₃⁻/m³,
- k_h – hydrolysis rate constant, g COD/g COD/d,
- K_{NA} – ammonia half-saturation coefficient for autotrophs, g N/m³,
- K_{NH} – ammonia half-saturation coefficient for heterotrophs, g N/m³,
- K_{OA} – oxygen half-saturation coefficient for autotrophs, g O₂/m³,
- K_{OH} – oxygen half-saturation coefficient for heterotrophs, g O₂/m³,
- K_S – substrate half-saturation coefficient for heterotrophs, g COD/m³,
- k_X – half-saturation coefficient for hydrolysis, g COD/g COD,

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- Y_A – growth yield coefficient for autotrophs, g COD/g N,
 Y_H – growth yield coefficient for heterotrophs, g COD/g COD,
 η_s – correction factor for anoxic growth of heterotrophs,
 $\hat{\mu}_A$ – maximum specific growth rate for autotrophs, 1/d,
 $\hat{\mu}_H$ – maximum specific growth rate for heterotrophs, 1/d.

Pollutant fractions

- BOD_{5S} – 5-day biochemical oxygen demand of soluble compounds,
 COD – chemical oxygen demand,
 COD_P – chemical oxygen demand of particulate compounds,
 COD_S – chemical oxygen demand of soluble compounds,
 S_{alk} – alkalinity,
 S_{nd} – soluble organic nutrient,
 S_{NH} – ammonium,
 S_{NO} – nitrate nitrogen,
 S_I – soluble inert organic matter,
 S_O – oxygen,
 S_S – readily biodegradable substrate,
 TKN – total Kjeldahl nitrogen,
 N_{org} – organic nitrogen,
 TKN_S – soluble Kjeldahl nitrogen,
 N_{tot} – total nitrogen,
 TKN_P – particulate Kjeldahl nitrogen,
 X_{BA} – autotrophic biomass,
 X_{BH} – heterotrophic biomass,
 X_I – particulate inert organic matter,
 X_{ND} – slowly biodegradable organic nutrient,
 X_S – slowly biodegradable substrate,
 X_{min} – mineral particulate fraction.

Other symbols

- F_O – objective function,
 NG – group of nitrogenous pollutants,
 OG – group of organic and alkaline pollutants,
 \mathbf{P} – set of values for the parameters,
 Q_{in} – influent flow rate,
 Q_{out} – effluent flow rate,
 Q_{rec} – return sludge flow rate,
 Q_{ws} – waste sludge flow rate,
 V_{max} – maximal value of the parameter,
 V_{min} – minimal value of the parameter,
 W_{max} – maximal value of pollutant concentration in the activated sludge tank,
 W_{min} – minimal value of pollutant concentration in the activated sludge tank,
 ΔW – variability of pollutant concentration,
 ρ – process rate.

1. INTRODUCTION

Modelling has become an increasingly frequent method for predicting the behaviour of wastewater treatment plants (WWTPs) – not only those under design, but also the existing ones. The past few years have witnessed an enhanced development of computer techniques, so more and more physical models have been replaced with mathematical ones. Thus, the experiments on physical models have been substituted for simulations that are based on mathematical models. There are many different uses where simulation is applicable, e.g., computer-aided process designing, analysis of the behaviour of a given WWTP under varying loading conditions, finding the optimal configuration for the unit processes, or the development of control strategies enabling a more efficient operation, a higher performance and lower plant operating costs.

Although mathematical models have the inherent advantage over physical ones as they are cheaper, their development requires profound knowledge of the theoretical principles of the process which is to be modelled. The more profound such a knowledge is, the higher the fidelity of the projection to real conditions can be achieved. It should be emphasised, however, that an increase in the sophistication of the model does not necessarily increase its accuracy to the same extent. This implies that we need to confine ourselves to a satisfactory approximation, since an ideal model is beyond the realm of possibility. Thus, on one hand, the model must include the major phenomena involved and, on the other hand, the equations should be solved within a reasonable time span so as to make the model applicable to engineering conditions.

Recent years have brought about significant advances in the understanding of biological processes. It is now possible to construct reliable models suitable for representing the activated sludge process. Thus, the ASM1 model (published in 1987) [12] is based on the mass balance equations for particular fractions (state variables) and represents the removal of organic substances and the conversion of nitrogen compounds. There are many references in the literature which substantiate the engineering applications of the model [4], [8], [10]. The core of the model is built from equations describing the rates of the unit processes involved and quantifying their influence on the concentrations of particular wastewater and sludge components. Many kinetic and stoichiometric constants in the model equations depend more or less on the type of the wastewater to be treated and on the plant configuration. But if the model is to describe adequately the processes that occur in the WWTPs tested, its calibration is a prerequisite. The scope of calibration should be established for each case individually, according to the needs, desired accuracy and the available funds. As for the ASM1 model, these problems are still far from being fully understood and thus require further studies.

The objective of the study reported on in the present paper was to answer the question of whether or not it is possible to calibrate the ASM1 model with an optimising method based on genetic algorithms.

1.1. CALIBRATION METHODS

No consistent or effective method for the calibration of the ASM1 model has been developed so far. Many of the approaches involve respirometric tests [2]–[4], [6]–[7], [8], [13], [14] which consist in measuring the rate of biological oxygen consumption by the activated sludge under strictly defined conditions. The advantages of using the respirometric tests can be itemised as follows: they are based on the profound knowledge of the mechanisms governing the processes that are carried out in the wastewater treatment plant and they enable the composition of the influent wastewater to be partly determined. A major drawback concomitant with the use of the respirometric tests is a sophisticated calibration procedure.

NOWAK and coworkers [1] have attempted to estimate the parameters of activated sludge models making use of mass balances. They have obtained partial calibration of the ASM1 model by balancing all the mass transport pathways for carbon, nitrogen and phosphorus. The method applies to steady-state conditions and only allows the determination of those parameters that are responsible for the long-term behaviour of the system (Y_H , f_P , b_H and X_I). This explains why its application yields partial calibration alone and why the method itself should be regarded as a supporting one.

In the past decade, use has also been made of calibration based on human expertise [9]. In this method, an initial set of parameters is adopted on the basis of literature reports or on the investigators' own experience, and thereafter corrected according to the available knowledge of how each of the assumed parameters influences the process. Relevant simulations and corrections are carried out until a satisfactory prediction of the WWTP performance has been obtained with the model. If the relations governing the model are well known, calibration can be quite successful even with little effort.

1.2. CALIBRATION WITH GENETIC ALGORITHMS

In spite of their efficiency, the available methods of calibration have a number of inherent drawbacks. In some instances, there is a need to perform troublesome and time-consuming investigations; the methods enable partial calibration only and do not allow any automation of the calibrating procedure. It seems therefore advisable to develop such a method that would enable us:

- To use standard data made available by wastewater treatment plants.
- To include data from additional tests.
- To determine the extent of calibration, according to the type and amount of information about the process.
- To automate the calibrating procedure.

In principle, these are the optimising procedures defined as genetic algorithms (GA) that meet the criteria itemised above. The literature contains references to the

variety of uses where GAs can be applied [5], [11]. For many years GAs have been successfully used in numerous scientific disciplines not only for parameter estimation, but also for the development of adaptive control and system identification. Furthermore the literature includes references substantiating the efficiency of the GAs in troublesome applications, especially when the possibility of deriving an explicit function which depends on a defined number of parameters is lacking.

1.3. GENETIC ALGORITHMS

GAs are digital versions of evolution in the same sense as a dynamic model is a digital version of a wastewater treatment plant. In a general sense, GAs involve random (but not blindfold) choices which guide them during a strongly objective-oriented search for an optimal solution within a coded multidimensional space.

A major GA feature made use of in this study is the capability of carrying out optimisation based on only one objective function. Search is made either for the minimum or maximum of this function. Generally, the objective function defines the distance from the optimal solution. The objective function used in this study will be described in more detail later.

2. SCOPE AND METHODS

The method proposed for the GA-based calibration of the activated sludge model is a novel one, hence the need for exploring the potential it may offer to technological systems differing in complexity and process parameters. This paper presents the results of the first stage of the research on the calibration of the ASM1 model. They refer to the simplest configuration of the plant (single aerobic activated sludge tank) and the simplest (in terms of modelling) state of the system, i.e., the steady state.

There are two ways of assessing the quality of the model calibration carried out with a particular method for a given WWTP. The results of simulation can be compared with the data obtained from the WWTP. Yet, this offers no possibilities of a direct verification of the calibrated parameter values. Thus, there is no guarantee that the calibrated model will give adequate predictions under different operating conditions. Particular doubts may arise when the empirical data are corrupted with considerable noise, and this is typical of wastewater treatment processes. The results of calibration obtained by using a particular method can be compared with those obtained by other methods, but then we should approve the reliability of the verifying method. In this context, we abandoned any attempts to compare the GA method with other calibration routines, but we did not abandon the idea of verifying its quality. For this reason, in our present study, use is made of a virtual wastewater treatment plant, i.e., of

an object calibrated at assumed parameter values.

The virtual WWTP was implemented in the simulation programme and its steady state was simulated. The results of such a simulation were formally regarded as experimental data coming from a digital experiment being equivalent to an ideal physical experiment which is impossible to perform. The concentrations of the mixed stream dissolved and particulate constituents provided basic information which was used for the calibration of the virtual WWTP model. Owing to the adoption of the virtual wastewater treatment plant as the object of calibration, it was possible to define the quality of calibration via direct comparisons of the model parameter values assumed for the purpose of simulation with those obtained as a result of calibration. The use of a virtual wastewater treatment plant instead of a real one for testing the quality of the calibration method allows a number of additional analyses to be carried out, thus enabling a more comprehensive interpretation of the results obtained.

2.1. DESCRIPTION OF THE CALIBRATION METHOD

Figure 1 depicts the scheme of the method applied. Any data being essential for the calibration procedure has been collected from the investigated virtual WWTP. In that particular case, this is the composition of the mixed stream in the aeration tank. It is included in the objective function on which the calibration is based. In the optimisation procedure, the GA generates the sets of values for the parameters (P) that are to

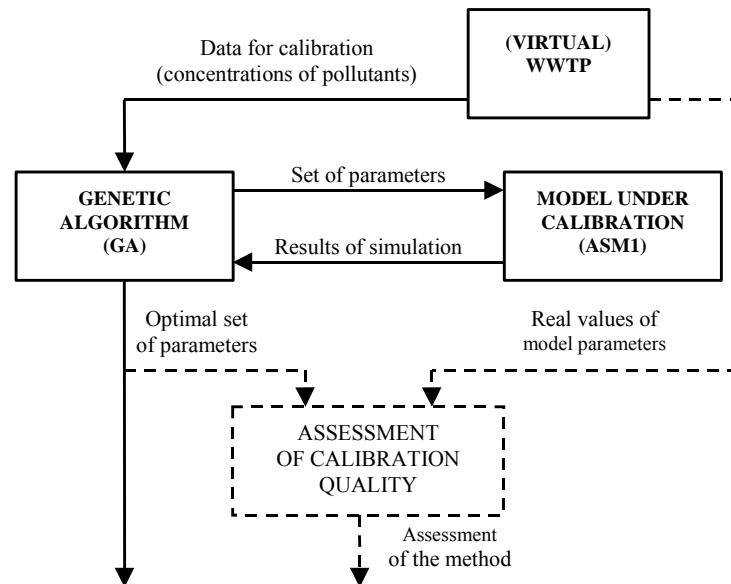


Fig. 1. Data flow diagram for the calibration method applied

be calibrated, and thereafter performs simulations of the state of the process, using the model which is subject to calibration. The results of simulation, expressed as the concentration of pollutants, are compared with the experimental results (coming from the object under investigation – in this case from the virtual WWTP), and the objective function is used to assess the quality of the choice of the parameter values. The process of generating the sets of parameter values is repeated until one of the conditions for completing the calibration procedure has been fulfilled. In the scheme applied, these have been either checking 1200 sets of parameter values or arriving at a objective function value lower than 1%. After the calibration has been completed, the best set of the parameter values is derived and regarded as the result of calibration. The application of a virtual WWTP (instead of a real one) made it possible to verify the reliability of the method by comparing the real values of the model parameters (used for data generation) with those obtained as the result of calibration. The verification-related elements of the method are shown in figure 1 (dashed line).

2.2. CHARACTERISATION OF THE VIRTUAL WWTP

The model under calibration was that of a virtual WWTP which consisted of a complete-mix aerobic tank and a secondary settler. The flow diagram is shown in figure 2. Table 1 summarises some major operational parameters, while the influent composition is detailed in table 2.

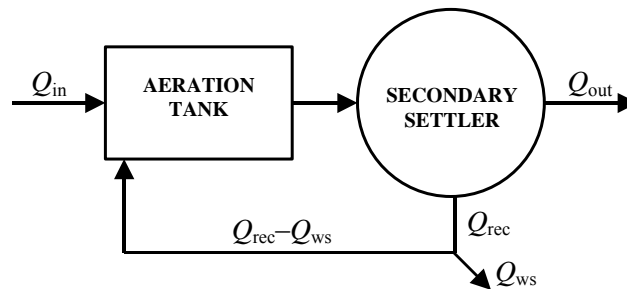


Fig. 2. Flow diagram for virtual WWTP

The study reported on in the present paper is focused on the method of model calibration making use of the steady-state data of the process. Although a steady state is not attainable in real WWTPs, the mean state of the process (when described by measured data averaged over an appropriately long, representative time span) can be regarded as a very good approximation. Having a model calibrated for the steady state,

we can perform some analyses of the dynamic behaviour of the object.

Table 1

Operational parameters of virtual WWTP

Parameter	Unit	Value
Activated sludge tank		
Volume	m ³	1550
Dissolved oxygen concentration	g O ₂ /m ³	2.0
Sludge age	d	8
Temperature	°C	15
Secondary settler		
Surface area	m ²	170
Average total depth	m	4.00
Depth of feed point	m	2.00
Depth of disturbance area	m	0.30
Sludge volume index	cm ³ /g	150
Recycle rate	m ³ /d	1000

Table 2

Influent composition

Component	Unit	Value
Q_{in}	m ³ /d	2200
COD	g O ₂ /m ³	400.0
S_S	g COD/m ³	80.0
S_I	g COD/m ³	48.0
X_S	g COD/m ³	232.0
X_I	g COD/m ³	40.0
TKN	g N/m ³	50.0
S_{NH}	g N/m ³	34.5
S_{ND}	g N/m ³	3.0
X_{ND}	g N/m ³	12.5
S_{NO}	g N/m ³	0.0
X_{min}	g /m ³	66
S_{alk}	mole HCO ₃ ⁻ / m ³	6

For the purpose of calibration, we used the values of the pollutant concentrations in the activated sludge tank, not in the treated wastewater. The latter is affected by the suspended solids in the effluent from the secondary settler whose model was deliberately excluded (at this stage of the study) from our considerations. According to the assumption that biochemical transformations in the secondary settling tank

are negligible, the pollutant concentrations in filtered samples from the aeration tank are the same as those in the treated wastewater. And so are the proportions of particulate fractions in the activated sludge and in the suspended solids of the treated wastewater. Thus, if the concentration of effluent suspended solids is known, we can unequivocally characterise the treated wastewater. Considering the accuracy of analytical methods, it is also advisable to characterise the content of suspended solids in the sludge in those samples where its concentration is high, i.e., in the mixed stream.

Table 3

Results of steady state simulation of virtual WWTP

Pollutant fraction	Unit	Sludge tank	Recirculate	Effluent
S_{NH}	g N/m^3	1.41	1.40	1.40
S_{NO}	g N/m^3	31.8	31.8	31.8
S_{alk}	$\text{mole HCO}_3^-/\text{m}^3$	1.36	1.36	1.36
COD_S	g COD/m^3	51.4	51.4	51.4
COD_P	g COD/m^3	1818	5696	7.04
COD	g COD/m^3	1870	5748	58.4
BOD_{5S}	g COD/m^3	2.24	2.24	2.24
TKN_S	g N/m^3	3.54	3.54	3.54
TKN_P	g N/m^3	109	342	0.42
TKN	g N/m^3	113	346	3.96
N_{org}	g N/m^3	111	344	2.56
N_{tot}	g N/m^3	145	378	35.8

Table 3 presents some selected results from the steady-state simulation of the virtual WWTP. Formally, they are regarded as empirical data (from a simulation experiment) for the calibration of the WWTP model. Such data set provides a comparatively accurate description of the composition of both the wastewater and the activated sludge and can be collected at a real WWTP. For the purpose of calibration, various sets of pollutant fractions were selected, and on this basis different objective functions were generated.

2.3. OBJECTIVE FUNCTION

In itself, it is a problem to make the right choice of the objective function that will be used in the calibration procedure. The point is to decide which of the empirical data should be included in the objective function in order to make the calibration procedure

effective. And this is what our present study concentrated on. It was assumed that the objective function is a weighed sum of the errors of model predictions for the pollutants chosen. The function can be described in terms of the general formula

$$F_O = \sum_i w_i \cdot f(X_i^p, X_i^e), \quad (1)$$

where F_O stands for the value of the objective function; X_i^p is the value of the i th component (e.g., ammonia nitrogen or alkalinity) predicted by the model for the given set of the values of the model parameters (\mathbf{P}) at an iteration point of the optimisation algorithm; X_i^e denotes the empirical value of the i th component; f indicates the error function for the i th component, and w_i is the weight of the i th component.

A major advantage of the objective function represented by relation (1) is the potentiality of controlling the significance of each of the constituents. Another benefit is the possibility of calculating the values of the partial derivatives of each of the calibrated parameters of the model, both for the whole objective function and for its particular elements. The derivatives are of utility when analysing the results of the calibration.

Another problem is the determination of the function f which is to describe the error in the predictions. In our study, we adopted the following general formula:

$$f(X_i^p, X_i^e) = w_i \cdot \frac{|X_i^e - X_i^p|}{X_i^e} \cdot 100\%. \quad (2)$$

This formula automatically equalises the order of magnitude of the errors for all the components of the objective function (in some instances differing as much as 1000fold, e.g., COD and S_{NH}) and provides a constant convergence even for solutions arbitrarily close to the optimal ones. A drawback of this function is the potential existence of non-differentiability points even if the estimated parameters and the calibrated model are continuous. This feature is, however, of no importance to the GA.

2.4. SCOPE OF CALIBRATION

The ASM1 model quantifies the activated sludge process in terms of the mass balance equations for defined fractions of pollutants. These mass balance equations incorporate kinetic and stoichiometric parameters which characterise the process rates and stoichiometric proportions of particular fractions. In order to perform calibration, it is necessary to fit the values of six basic kinetic parameters ($\hat{\mu}_H$, K_S , η_g , b_H , $\hat{\mu}_A$ and K_{NA}), as they depend to a great extent on the characteristics of the wastewater and on the configuration of the activated sludge tanks. The values of these parameters

adopted for the virtual WWTP (the underlined ones) as well as those of the other parameters incorporated in ASM1 are presented in table 4.

Table 4

Values of ASM1 parameters adopted for the virtual WWTP

Parameter	Unit	Value
b_A	1/d	0.15
b_H	1/d	0.62
f_{CB}	g COD/g TSS	1.48
f_{CZ}	g COD/g TSS	1.50
f_P	g COD/g COD	0.08
i_{XB}	g N/g COD	0.086
K_a	m ³ /g COD/d	0.03
K_{alk_a}	mole HCO ₃ ⁻ /m ³	0.5
K_{alk_h}	mole HCO ₃ ⁻ /m ³	0.1
K_h	g COD/g COD/d	3.0
K_{NA}	g N/m ³	1.0
K_{NH}	g N/m ³	0.05
K_{OA}	g O ₂ /m ³	0.5
K_{OH}	g O ₂ /m ³	0.2
K_S	g COD/m ³	20
k_X	g COD/g COD	0.1
Y_A	g COD/g N	0.24
Y_H	g COD/g COD	0.67
η_g	–	0.80
$\hat{\mu}_A$	1/d	1.0
$\hat{\mu}_H$	1/d	6.0

The system under analysis consists of a single tank operating at a dissolved oxygen concentration of 2.0 g O₂/m³. This means that of the four processes of heterotrophic biomass growth described by the model only aerobic process may occur. It is therefore infeasible to determine the value of the correction factor (η_g) for an anoxic growth of heterotrophic biomass.

The steady state of the system is fully defined by a single set of values of state variables. This information, however, is insufficient for a simultaneous determination of the values for the model parameters included in one kinetic equation. In our study, we had to deal with such a situation twice: in the case of the equation describing the kinetics of heterotrophic biomass growth (limited by organic compounds) and in the case of the equation defining the kinetics of autotrophic biomass growth (limited by ammonia nitrogen).

Calibration itself is aimed at achieving the conformity of empirical concentrations with those predicted by the model. However, during a calibration experiment with

constant process rates (and this is so when calibration involves the results of the steady state), estimations are carried out for the process rates ρ rather than for the model parameters themselves. The rates are the functions of the sought values for the model parameters and pollutant concentrations. The requisite for attaining such a conformity is, in fact, a correct identification of the process rates. In contrast to kinetic tests, where concentration variations with time are analysed, during calibration based on the steady-state data all the available information is included in the point value of the vector of state variables.

If the process rate is a function of more than one of the estimated parameters, we cannot identify them separately, using the point image of the process. With the ASM1 model, this holds for the rate of heterotrophic biomass growth (which is a function of the concentration of the fraction S_S and of the parameters $\hat{\mu}_H$ and K_S ; hence, $\rho_H = \hat{\mu}_H \cdot S_S / (S_S + K_S)$) and for the autotrophic biomass growth (which is a function of the fraction S_{NH} and of the parameters $\hat{\mu}_A$ and K_{NA} ; hence, $\rho_H = \hat{\mu}_A \cdot S_{NH} / (S_{NH} + K_{NA})$). It is therefore possible to fit more than one (in fact, an arbitrary) number of the pairs of the $\hat{\mu}_H$ and K_S values to the given set value of ρ_H . The same applies to the pair $\hat{\mu}_A$ and K_{NA} . In such instance, it is essential to establish the value of one of the two parameters (e.g., K_S) in separate tests or take it from the literature, and to estimate the other parameter value.

Table 5

Ranges of estimated parameters

Parameter	Unit	V_{\min}	V_{\max}
$\hat{\mu}_H$	1/d	3	13
b_H	1/d	0.4	1.5
$\hat{\mu}_A$	1/d	0.5	1.5

With this in mind, it has been anticipated that simultaneous estimation should be carried out for the following parameters: $\hat{\mu}_H$, $\hat{\mu}_A$ and b_H . Table 5 shows the ranges of the parameters sought, taken from the literature [8], [10], [12]. It was assumed that each parameter will be coded with a 10-bit codon dividing the interval of search for each parameter into 1023 segments. The total number of points in the searched space of the parameters amounts to $2^{30} = 1\,073\,741\,842 \approx 10^9$ and is far too high to enable a complete search.

3. RESULTS

3.1. SENSITIVITY ANALYSIS

In order to examine the model sensitivity to the variations in particular parameters, a number of steady state simulations were carried out, where the value of each parameter was varied sequentially within the range adopted for calibration. Of the simulation results, the minimum (W_{\min}) and the maximum (W_{\max}) values of the concentrations in the activated sludge tank were chosen for variability calculations (ΔW in g/m^3 and in per cent). The results are shown in table 6, where variabilities greater than 50% are printed in bold, and values higher than 10% are underlined. The accuracy with which the results are presented is greater than the accuracy that can be attained in laboratory analyses. We decided, however, to adopt this level of accuracy, as our study has the nature of theoretical analysis.

Table 6

Variabilities of pollutant fractions

Pollutant fraction	Parameter											
	$\hat{\mu}_H$				b_H				$\hat{\mu}_A$			
	W_{\min}	W_{\max}	ΔW		W_{\min}	W_{\max}	ΔW		W_{\min}	W_{\max}	ΔW	
	g/m^3	g/m^3	g/m^3	.	g/m^3	g/m^3	g/m^3	.	g/m^3	g/m^3	g/m^3	.
S_{NH}	1.58	1.59	0.01	0.9	1.56	1.59	0.03	2.0	0.72	36.4	35.6	98.0
S_{NO}	31.6	31.8	0.27	0.9	31.1	31.8	0.67	2.1	0.28	32.6	32.4	99.1
S_{alk}	1.38	1.39	0.02	1.3	1.38	1.42	0.05	3.2	1.26	6.11	4.86	79.5
COD_S	49.4	56.2	6.74	<u>12.0</u>	50.3	56.8	6.44	<u>11.3</u>	51.2	51.4	0.21	0.4
COD_P	1798	1824	26.2	1.4	1538	2008	470	<u>23.4</u>	1777	1837	60.2	3.3
COD	1854	1874	19.5	1.0	1594	2058	464	<u>22.5</u>	1828	1888	60.1	3.2
BOD_{5S}	0.95	5.39	4.45	82.5	1.54	5.79	4.25	73.3	2.12	2.26	0.14	6.0
TKN_S	3.71	3.74	0.03	0.8	3.07	6.02	2.94	<u>48.9</u>	2.89	38.5	35.6	92.5
TKN_P	108	110	2.12	1.9	82.1	127	44.7	<u>35.3</u>	106	111	4.81	4.3
TKN	111	113	2.09	1.8	88.1	130	41.8	<u>32.2</u>	109	145	36.1	<u>25.0</u>
N_{org}	110	112	2.10	1.9	86.6	128	41.8	<u>32.6</u>	108	113	4.76	4.2
N_{tot}	143	145	1.82	1.3	119	161	41.7	<u>25.9</u>	141	146	4.59	3.1

As may be inferred from the results obtained, the change in the maximum specific growth rate $\hat{\mu}_H$ for heterotrophic biomass manifests itself in the variations of BOD_{5S} alone. This is so because, in the system under study, easily biodegradable organic compounds (S_S) are practically the only factor that limits the growth rate of heterotrophic biomass. The deficiency of easily available organic matter accounts for the decrease in the biomass growth rate even to the level of several per cent of the value observed when there are no limitations. The rise in the $\hat{\mu}_H$ value accelerates the

growth process, thus enhancing the reduction in organic matter content (S_S), which in turn increases the limitation to biomass growth. Variations in the $\hat{\mu}_H$ value are complementary to those in the S_S value. As a result, the $\hat{\mu}_H \cdot S_S$ to $S_S + K_S$ ratio does not change and hence the growth rate of heterotrophic biomass remains practically constant. The conclusion is that to perform the calibration of the parameter $\hat{\mu}_H$ we need to include the BOD_{5S} term into the objective function. However, the narrow range of variations in absolute units observed with BOD_{5S} implies the need of measurements with a resolution lower than $1 \text{ g O}_2/\text{m}^3$.

The change in the decay rate (b_H) in a heterotrophic biomass produces the changes in the concentrations of all pollutant fractions and consequently affects the rates of other processes. When the value of the constant b_H increases, this is concomitant with a decrease in the concentration of heterotrophic biomass (X_{BH}), as well as with an increase in the concentrations of non-biodegradable (X_P) and biodegradable (X_S) decay products. The rise in X_S and the fall in X_{BH} bring about an increase in the X_S to X_{BH} ratio (from 0.05 to 0.37 at the rise in b_H from 0.4 to 1.5) and consequently a decrease in the extent of hydrolysis limitation owing to the availability of X_S (the Monod factor in the expression representing the hydrolysis rate increases from 0.33 to 0.78). A decrease in the value of X_{BH} and an increase in the availability of the substrate slightly accelerate the rate of hydrolysis of slowly biodegradable organic matter (X_S) and slowly biodegradable organic nitrogen (X_{ND}). As a result, the concentrations of the hydrolysis products (S_S and S_{ND}) are raised. An increase in soluble organic nitrogen concentration S_{ND} is proportionally greater than a decrease in heterotrophic biomass concentration, and this accounts for the rise in the rate of ammonification. When the concentration of readily biodegradable organic compounds (S_S) rises, the limitation to heterotrophic biomass growth decreases (the Monod factor increases from 0.10 to 0.30). Despite the drop in concentration, the growth rate of heterotrophic biomass increases, partly compensating for the rise in the rate of decay. Thus the loop of changes and interactions closes. Ammonia nitrogen concentration remains unchanged, and so does the nitrification rate. The same holds for autotrophs and nitrates. Summing up, variations in the value of b_H primarily affect the soluble and particulate fractions of organic substances and organic nitrogen.

Any change in a maximum specific growth rate of autotrophic biomass $\hat{\mu}_A$ produces considerable changes in alkalinity as well as in the concentrations of nitrogen compounds – notably ammonia nitrogen and nitrates. The highest concentrations of ammonia nitrogen (together with the lowest concentrations of nitrates) correspond to extremely low values of the constant $\hat{\mu}_A$. Then, an effective growth rate of autotrophic biomass is below the required minimum resulting from the time of residence of the bacteria in the system at a given sludge age. With $\hat{\mu}_A$ values greater than 0.7 d^{-1} , the autotrophic biomass acquires an appropriately long time of residence in the system and its growth is limited by ammonia nitrogen. By analogy to what has been said

COD	X			X			X		
BOD _{5S}				X	X	X	X	X	X
S _{alk}							X	X	X

pollutants (S_{NH} , S_{NO} , TKN_S , TKN_P , N_{org} , N_{tot}), the other one with organic pollutants and alkalinity (COD_S, COD_P, COD, BOD_{5S}, S_{alk}). The elements of each group were combined in different ways to form the sets of parameters containing elements of one group only. In this way, 9 sets belonging to the group of organic compounds and alkalinity (OG_1 to OG_9) and 17 sets of indicators belonging to the group of nitrogenous pollutants (NG_01 to NG_17) were established. Combining, one by one, a set of the group NG with a set of the group OG, $9 \times 17 = 153$ objective functions were constructed in the form given by relations (1) and (2). The components of particular sets of parameters and objective functions, along with the adopted numeration, are shown in table 7. Thus, objective function F_{o60} includes COD, BOD_{5S}, S_{NO} and TKN_P. The rows contain sequential NGs, while OGs are gathered in the columns (X denoting the components of the objective functions). In the objective functions, each pollution constituent was assigned the same weight (w_i), which equals 1.

3.3. RESULTS OF CALIBRATION

The results of calibration are presented in table 8, which shows the minimum values of the objective functions and relevant estimated values of the ASM1 model parameters. We can tell at a glance that the quality of calibration differs from one form of the objective function to another. In every instance, the calibration process yielded points which corresponded with objective function values lower than 3%. With each

Table 8

Results of calibration

F_o	F_o	$\hat{\mu}_H$	b_H	$\hat{\mu}_A$	F_o	F_o	$\hat{\mu}_H$	b_H	$\hat{\mu}_A$	F_o	F_o	$\hat{\mu}_H$	b_H	$\hat{\mu}_A$
No.	%	1/d	1/d	1/d	No.	%	1/d	1/d	1/d	No.	%	1/d	1/d	1/d
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0.3	7.41	0.623	0.542	52	0.5	5.99	0.619	1.005	103	0.6	5.94	0.613	1.061
2	0.5	12.23	0.653	0.654	53	0.9	5.62	0.568	1.447	104	0.5	5.94	0.613	1.064
3	0.8	6.85	0.611	1.117	54	1.0	6.05	0.627	1.043	105	0.7	5.99	0.617	1.059
4	0.9	8.48	0.622	1.055	55	0.5	5.93	0.611	1.052	106	0.8	6.01	0.620	1.052
5	1.0	10.05	0.613	1.051	56	0.7	5.98	0.615	1.051	107	1.0	5.94	0.612	1.054
6	0.3	8.42	0.628	0.975	57	1.0	5.86	0.605	1.097	108	0.8	5.87	0.601	1.063
7	1.0	4.81	0.619	1.022	58	0.9	5.94	0.612	1.077	109	0.8	5.90	0.607	1.050
8	0.4	5.72	0.577	1.430	59	0.9	5.88	0.598	1.217	110	0.8	5.95	0.610	1.061
9	0.3	4.38	0.605	1.049	60	0.8	5.91	0.611	1.065	111	0.7	5.95	0.615	1.063
10	0.6	4.48	0.604	1.052	61	0.9	5.99	0.617	1.051	112	0.8	5.94	0.613	1.053

11	0.9	12.81	0.631	1.069	62	0.9	6.02	0.619	1.055	113	0.9	6.01	0.624	1.057
12	0.7	11.04	0.610	1.044	63	1.6	6.18	0.651	1.072	114	0.9	5.91	0.609	1.043
13	1.0	8.52	0.615	1.057	64	0.9	5.96	0.614	1.042	115	1.0	5.97	0.615	1.047
14	0.2	6.48	0.616	1.052	65	0.4	5.97	0.615	1.049	116	1.0	5.99	0.618	1.056
15	0.3	7.65	0.616	1.051	66	0.9	6.04	0.626	1.050	117	0.9	6.02	0.623	1.053
16	0.4	3.64	0.610	1.005	67	1.0	5.85	0.600	1.023	118	0.9	5.85	0.598	1.068
17	0.8	7.06	0.605	1.054	68	0.3	5.96	0.615	1.051	119	0.8	5.92	0.612	1.051

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
18	0.3	11.94	0.601	1.215	69	0.7	5.68	0.570	1.427	120	0.9	5.92	0.609	1.048
19	0.2	9.90	0.629	0.970	70	0.7	6.07	0.643	0.727	121	0.8	5.96	0.614	1.049
20	0.6	4.42	0.603	1.040	71	0.9	6.01	0.623	0.988	122	0.8	6.00	0.620	1.052
21	0.5	7.53	0.624	1.052	72	0.9	5.97	0.613	1.053	123	0.7	5.94	0.613	1.052
22	0.9	11.91	0.620	1.053	73	1.0	5.95	0.616	1.050	124	0.9	5.94	0.612	1.053
23	0.1	3.51	0.599	1.005	74	0.7	5.82	0.596	1.174	125	0.9	5.85	0.600	1.087
24	0.3	3.73	0.603	1.003	75	0.6	5.94	0.613	1.058	126	0.9	5.94	0.613	1.053
25	0.3	8.07	0.617	0.526	76	0.4	5.84	0.595	1.255	127	0.9	5.98	0.614	1.053
26	0.9	11.77	0.615	1.154	77	0.9	6.02	0.620	1.028	128	1.0	5.99	0.619	1.058
27	0.9	6.56	0.609	1.053	78	1.0	5.99	0.619	1.054	129	1.2	6.04	0.627	1.053
28	1.0	3.16	0.583	1.033	79	2.8	6.45	0.676	1.096	130	0.8	6.04	0.624	1.060
29	0.4	12.87	0.630	1.062	80	0.9	6.03	0.623	1.060	131	0.9	6.03	0.624	1.055
30	0.4	6.42	0.612	1.049	81	0.8	5.97	0.612	1.046	132	0.9	5.96	0.614	1.055
31	1.0	11.22	0.630	1.066	82	0.4	5.95	0.614	1.051	133	0.9	5.99	0.617	1.052
32	0.8	3.97	0.590	1.056	83	0.9	5.81	0.596	1.051	134	1.1	5.80	0.597	1.052
33	0.1	11.47	0.616	1.074	84	1.0	5.91	0.604	1.044	135	0.7	6.01	0.620	1.058
34	1.0	4.11	0.587	1.054	85	0.4	5.99	0.618	1.052	136	1.2	6.25	0.651	1.053
35	0.6	5.87	0.631	0.850	86	0.9	5.80	0.595	1.211	137	0.8	5.86	0.603	1.055
36	0.4	6.10	0.653	0.689	87	0.7	6.16	0.655	0.684	138	0.9	5.96	0.617	1.051
37	0.5	6.13	0.615	1.043	88	0.7	6.01	0.620	1.037	139	0.9	5.89	0.607	1.062
38	0.9	5.57	0.616	1.053	89	0.9	5.88	0.604	1.052	140	1.0	6.01	0.618	1.052
39	0.9	6.08	0.614	1.054	90	0.8	5.98	0.617	1.049	141	0.8	6.00	0.619	1.052
40	0.8	5.87	0.565	1.412	91	0.8	5.80	0.589	1.261	142	0.8	5.85	0.601	1.073
41	0.6	6.06	0.604	1.067	92	1.5	5.71	0.576	1.296	143	0.9	5.95	0.611	1.059
42	0.4	6.28	0.625	0.951	93	0.9	6.03	0.634	0.845	144	0.8	5.92	0.611	1.073
43	0.9	6.48	0.614	1.061	94	2.1	5.60	0.567	1.439	145	1.0	5.92	0.609	1.050
44	0.9	5.63	0.615	1.052	95	0.9	5.97	0.617	1.053	146	0.9	5.99	0.619	1.052
45	0.7	5.85	0.608	1.040	96	2.5	6.36	0.670	1.118	147	0.9	5.97	0.615	1.055
46	0.7	6.18	0.617	1.053	97	0.8	5.94	0.612	1.054	148	0.9	6.03	0.624	1.056
47	0.8	6.22	0.617	1.055	98	0.7	6.00	0.619	1.055	149	1.0	5.95	0.612	1.049
48	0.7	5.78	0.614	1.044	99	0.7	5.93	0.611	1.044	150	0.8	5.94	0.614	1.049
49	0.7	6.33	0.609	1.052	100	0.8	5.94	0.613	1.055	151	0.8	5.97	0.614	1.053
50	0.5	6.14	0.617	1.031	101	1.1	5.46	0.557	1.014	152	0.8	5.83	0.596	1.071
51	1.0	5.87	0.611	1.048	102	1.3	5.60	0.563	1.051	153	0.9	5.93	0.610	1.054

component being the part of the objective function, the error obtained fell below 1%. The results were subject to further analysis [15] in order to ascertain what made the calibration fail in the case of some objective functions and to exclude them.

4. CONCLUSIONS

A GA-based method for estimating the parameters of the ASM1 model is presented. The method makes use of objective functions which include pollution parameters measured in standard procedures. The verification of the method involves simulations of the steady state of the process. The results discussed in this paper refer to the steady state of a system with a single aerobic activated sludge tank. Research on more sophisticated systems (not described here) also substantiates the reliability of the method proposed.

As may be inferred from the analysis of the model equations, the calibration of the model, on the basis of data sets characterising the steady state of a single aerobic reactor system, is feasible only with the following three kinetic parameters: $\hat{\mu}_H$, b_H and $\hat{\mu}_A$. The sets of pollutants susceptible to the values of particular parameters of the model are identified. As a result, a set of 153 objective functions differing in the pollutants that have been included is proposed. Our experiments have revealed that the sets of the estimated parameter values differ from one another.

It seems thus that the sensitivity analysis performed in order to select the data used in objective functions is not sufficient for obtaining the real model identifiability. In our next article [15], we propose two original methods: one- and two-dimensional analyses that explain the reasons for the inconsistencies obtained.

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KALIBRACJA MODELU OSADU CZYNNEGO
ZA POMOCĄ ALGORYTMÓW GENETYCZNYCH.
CZĘŚĆ I. WYNIKI KALIBRACJI

Przedstawiono metodę kalibracji modelu osadu czynnego nr 1 (ASM1) za pomocą algorytmów genetycznych. Kalibracji podlegała wirtualna oczyszczalnia ścieków składająca się z tlenowej komory o pełnym wymieszaniu oraz z osadnika wtórnego. Analizy wstępne wykazały, że znając stan miarodajny, można przeprowadzić jednoczesną kalibrację trzech parametrów: $\hat{\mu}_H$, $\hat{\mu}_A$ i b_H . Podczas kalibracji wykorzystano 153 różne funkcje celu. Niespójności w uzyskanych wynikach wyjaśniono w następnym artykule [15].