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

In a previous article [1], a method for the calibration of activated sludge model No. 1 (ASM1) based on genetic algorithms is proposed. For the needs of calibration, use was made of 153 objective functions. For some objective functions, the results obtained differ from expected values. In this article, additional analyses are presented to explain the inconsistencies in the results. Both the methods presented are based on a series of simulations. The first series allows us to obtain the objective function sensitivity to the parameters in the proximity of expected values. The second one shows the relationships between model parameters versus the objective function value. It was found that with 18 objective functions, it is possible to obtain reliable results of calibration for the model of the system investigated.

SYMBOLS

Model parameters

- b_H – decay rate for heterotrophs, 1/d,
- $\hat{\mu}_A$ – 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,

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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,
V_{max}	– maximal value of a parameter,
V_{min}	– minimal value of a parameter,
W_{max}	– maximal value of pollutant concentration in an activated sludge tank,
W_{min}	– minimal value of pollutant concentration in an activated sludge tank,
ΔW	– variability of pollutant concentration,
ρ	– process rate.

1. INTRODUCTION

In a previous article [1], the method for the calibration of activated sludge model No. 1 (ASM1) using genetic algorithms is proposed. The system investigated consists of one completely mixed aerobic tank and a secondary settler. Preliminary analyses enable the assumption that, based on the steady state, it is possible to estimate simultaneously the parameters $\hat{\mu}_H$, $\hat{\mu}_A$ and b_H .

Sensitivity analysis is a powerful tool for selecting data that might be useful for parameter estimation. The calibration results prove clearly that the parameter values obtained with different objective functions differ from one another. Thus we can conclude that the sensitivity analysis is not sufficient for obtaining a real model identifiability. Additional researches were done to find simple methods allowing the exclusion of objective functions that do not contain enough information for performing successful calibration. The results of these researches are presented below.

2. SCOPE AND METHODS

2.1. ANALYSIS OF PARTIAL DERIVATIVES

As the calibration was carried out for a virtual WWTP, it was possible (though for a real WWTP such a possibility does not exist) to perform analyses with the aim of evaluating the applied calibration method itself, as well as the results of calibration obtained for the ASM1 model. The convergence of the algorithm was analysed for each parameter of the model in the proximity of the expected value. This analysis was aimed at determining (for each of the parameters separately) which objective functions offered the potentiality for convergence to a point. The results obtained with this method differ from those achieved by sensitivity analysis, because they describe only the changes that occur in the immediate proximity of the expected value of the relevant parameter and not within the entire range of search. Computations were carried out for the following intervals: $4 < \hat{\mu}_H < 8$, $0.4 < b_H < 0.8$ and $0.8 < \hat{\mu}_A < 1.2$. The method used is exemplified below by the parameter $\hat{\mu}_H$.

Table 1

Local unit slopes for parameter $\hat{\mu}_H$

$\delta\hat{\mu}_H$		OG								
		1	2	3	4	5	6	7	8	9
NG	1	0.00	0.00	0.02	0.21	0.22	0.23	0.22	0.22	0.23
	2	0.00	0.00	0.02	0.22	0.22	0.23	0.22	0.22	0.23
	3	0.00	0.00	0.02	0.22	0.22	0.23	0.22	0.22	0.23
	4	0.00	0.00	0.02	0.22	0.22	0.23	0.22	0.22	0.23
	5	0.01	0.01	0.02	0.22	0.22	0.23	0.22	0.22	0.23
	6	0.00	0.00	0.02	0.22	0.22	0.23	0.22	0.22	0.23
	7	0.00	0.00	0.02	0.22	0.22	0.23	0.22	0.22	0.23
	8	0.00	0.00	0.02	0.22	0.22	0.23	0.22	0.22	0.23
	9	0.00	0.00	0.02	0.22	0.22	0.23	0.22	0.22	0.23
	10	0.01	0.01	0.02	0.22	0.22	0.23	0.22	0.22	0.23
	11	0.00	0.00	0.02	0.21	0.21	0.23	0.22	0.22	0.23
	12	0.00	0.00	0.02	0.22	0.22	0.23	0.22	0.22	0.23
	13	0.00	0.00	0.02	0.22	0.22	0.23	0.22	0.22	0.23
	14	0.01	0.01	0.02	0.22	0.22	0.23	0.22	0.22	0.23
	15	0.00	0.00	0.02	0.21	0.21	0.23	0.22	0.22	0.23
	16	0.00	0.00	0.02	0.21	0.21	0.23	0.22	0.22	0.23
	17	0.00	0.00	0.02	0.22	0.22	0.23	0.22	0.22	0.23

The interval of the values for the parameter $\hat{\mu}_H$ under analysis (4.0–8.0 d⁻¹) was divided into 20 sections, and simulations of the steady state (21 altogether) were carried out on their edges. Based on the results obtained, calculations were performed at

each point to determine the value for any of the 153 objective functions (the moduli responsible for the nondifferentiability of the points were omitted in the notation). Then, using the least squares method, the second-order polynomial equations were fitted to the $\hat{\mu}_H$ -dependent value of each objective function. With the fitted polynomials, the partial derivatives of the objective functions were calculated for the expected value of the parameter ($\hat{\mu}_H = 6.0 \text{ d}^{-1}$). The calculated values were scaled via multiplication by the width of the search interval ($W_{\max} - W_{\min} = 13.0 - 3.0 = 10 \text{ d}^{-1}$) and division by 1024 (2^{10}), i.e., by the number of segments into which the interval is divided by the algorithm during operation.

Table 2

Local unit slopes for parameter b_H

δb_H	OG									
	1	2	3	4	5	6	7	8	9	
NG	1	0.09	0.09	0.10	0.24	0.25	0.26	0.25	0.25	0.26
	2	0.10	0.10	0.11	0.26	0.26	0.27	0.27	0.27	0.28
	3	0.10	0.11	0.12	0.26	0.26	0.28	0.27	0.27	0.28
	4	0.10	0.11	0.12	0.26	0.27	0.28	0.27	0.27	0.28
	5	0.11	0.11	0.12	0.27	0.27	0.28	0.28	0.28	0.29
	6	0.10	0.10	0.11	0.26	0.26	0.27	0.27	0.27	0.28
	7	0.10	0.11	0.12	0.26	0.26	0.27	0.27	0.27	0.28
	8	0.10	0.11	0.12	0.26	0.26	0.27	0.27	0.27	0.28
	9	0.11	0.11	0.12	0.27	0.27	0.28	0.27	0.28	0.29
	10	0.11	0.12	0.13	0.27	0.27	0.28	0.28	0.28	0.29
	11	0.12	0.12	0.13	0.28	0.28	0.29	0.29	0.29	0.30
	12	0.13	0.13	0.14	0.29	0.29	0.30	0.29	0.29	0.30
	13	0.19	0.19	0.20	0.34	0.35	0.36	0.35	0.35	0.36
	14	0.19	0.19	0.20	0.35	0.35	0.36	0.36	0.36	0.37
	15	0.04	0.05	0.06	0.20	0.20	0.22	0.21	0.21	0.22
	16	0.04	0.05	0.06	0.20	0.20	0.22	0.21	0.21	0.22
	17	0.05	0.05	0.06	0.21	0.21	0.22	0.22	0.22	0.23

In this way, each objective function and each calibrated parameter obtained a value named local unit slope (δ) which expressed the decrease in the objective function while approaching the expected parameter value by the least possible step. The higher the δ value of the objective function, the greater the differences in the objective function values between the closest sets of the model parameters (\mathbf{P}), and consequently the greater the selection pressure which produces convergence. The calculated values of the decrease in the objective functions (δ) for the parameters under calibration are gathered in tables 1 to 3. Values higher than 0.10 are printed in bold in order to underline their practical importance for the convergence of the algorithm.

Table 3

Local unit slopes for parameter $\hat{\mu}_A$

$\delta\hat{\mu}_A$		OG								
		1	2	3	4	5	6	7	8	9
NG	1	0.01	0.01	0.01	0.01	0.01	0.01	0.05	0.06	0.06
	2	0.01	0.01	0.01	0.01	0.01	0.01	0.06	0.06	0.06
	3	0.02	0.02	0.02	0.03	0.03	0.03	0.07	0.07	0.07
	4	0.27	0.27	0.27	0.27	0.27	0.27	0.32	0.32	0.32
	5	0.28	0.28	0.28	0.29	0.29	0.29	0.33	0.33	0.33
	6	0.01	0.01	0.01	0.02	0.02	0.02	0.06	0.06	0.06
	7	0.03	0.03	0.03	0.03	0.03	0.03	0.07	0.07	0.07
	8	0.01	0.01	0.01	0.01	0.01	0.01	0.06	0.06	0.06
	9	0.02	0.02	0.02	0.03	0.03	0.03	0.07	0.07	0.07
	10	0.28	0.28	0.28	0.29	0.29	0.29	0.33	0.33	0.33
	11	0.11	0.11	0.11	0.12	0.12	0.12	0.16	0.16	0.16
	12	0.13	0.13	0.13	0.13	0.13	0.13	0.17	0.17	0.17
	13	0.12	0.12	0.12	0.12	0.12	0.12	0.17	0.17	0.17
	14	0.13	0.13	0.13	0.14	0.14	0.14	0.18	0.18	0.18
	15	0.26	0.26	0.26	0.27	0.27	0.27	0.31	0.31	0.31
	16	0.02	0.02	0.02	0.02	0.02	0.02	0.06	0.06	0.07
	17	0.28	0.28	0.28	0.28	0.28	0.28	0.32	0.32	0.32

2.2. TWO-DIMENSIONAL ANALYSIS

It has been observed that the change in the value of one ASM1 model parameter brings about a change in the values of several state variables which implies that the steady-state values of some pollutant concentrations depend on more than one parameter of the model under calibration. This leads to the formation of a line for identical concentration values of the relevant pollutant in the set of the parameters on which the pollutant depends. In the case considered here, none of the pollutants depend on all three parameters under estimation ($\hat{\mu}_H$, b_H and $\hat{\mu}_A$), so a two-dimensional analysis will suffice. From the data in table 6 (compare p. 43) it can be inferred that none of the pollutants depend on the parameters $\hat{\mu}_H$ and $\hat{\mu}_A$ at the same time. That is why we confined our analysis to two sets of relations, $Z = f(\hat{\mu}_H, b_H)$ and $Z = f(b_H, \hat{\mu}_A)$, where the equipotential lines for particular pollutants were substituted for the plots of the objective function values (the Z -axis) related to two parameters simultaneously (the X - and Y -axes).

If the value of a pollutant concentration depends on one of the two analysed parameters only, the objective function (based on that parameter alone) does not have a peak minimum; the minimum extends along the whole line parallel to the axis of the parameter on which the value of the objective function depends. If the value of a pol-

lutant depends on two parameters, the objective function does not have a peak minimum, either; the minimum takes the form of a line. This may be an arbitrary line, and its shape depends on the type of the relationship between the parameters and the pollutant concentration. In neither of the two cases can a correct estimation be performed for two parameters at the same time.

A necessary condition for a simultaneous estimation of both the parameters is the use of two pollutants differing in their relations to the parameters under analysis. The best solution to this problem is the application of such pollutants whose concentration depends on different parameters (each pollutant depending on one parameter). An approach like this enables an independent calibration of each parameter separately. If the object under calibration involves sophisticated relations, practically any of the parameters exerts a certain effect on each of the pollutants, so the choice of the appropriate pair (even if possible to make) noticeably limits the number of the pollutants that could be used. This limitation becomes troublesome when estimation is carried out simultaneously for a greater number of parameters.

Another method consists in using pollutants which are in different relations to the pair of the parameters analysed. This raises notably the number of pollutants that can be used, thus facilitating calibration. The differences between the types of interrelations must be sufficiently significant so that the decrease of the objective function toward the minimum would be sufficient for the algorithm applied and reliable in terms of measuring accuracy. The incorporation of further pollutants into the objective function improves convergence only if they show a relation different from that of the pollutants already used (or if they strengthen the relation of one of them).

Furthermore it should be mentioned that during estimating more than two parameters there may be established relations which manifest themselves only in some sets of the parameters. And this can lead to the shift of the results also in those sets of parameters where the objective function converges to the point. It is therefore essential to identify the objective functions that do not converge to the point and exclude them as incorrect ones.

3. RESULTS

3.1. ANALYSIS OF PARTIAL DERIVATIVES

3.1.1. MAXIMUM SPECIFIC GROWTH RATE OF HETEROTROPHIC BIOMASS

Sensitivity analysis has shown that the parameter $\hat{\mu}_H$ affects the concentration of readily biodegradable organic compounds (BOD_{5S}) alone. This finding is also substantiated by the data in table 1, i.e., by the high $\delta\hat{\mu}_H$ values obtained only for

BOD_{5S} containing objective functions (OG_4–9). Further, though very small, an increase in the $\delta\hat{\mu}_H$ value produces COD in each form considered in this study. We should, however, keep in mind that the fraction COD_S multiplies information on the readily biodegradable compounds expressed as BOD_{5S}. Comparing the derivatives for the objective functions with and without the alkalinity term, i.e., (OG_7–9) and (OG_4–6), respectively, we can see that the lack of the alkalinity term is without any effect on the quality of the estimation of $\hat{\mu}_H$. If the parameter $\hat{\mu}_H$ is taken into account, the choice of the nitrogenous group for the objective function (or the lack of the nitrogenous group) is of no significance as the values of $\delta\hat{\mu}_H$ given in table 1 are practically the same.

3.1.2. DECAY RATE CONSTANT FOR HETEROTROPHIC BIOMASS

Sensitivity analysis has shown that in the group of organic pollutants the change in the parameter b_H influences primarily the fractions expressed as BOD_{5S}. A similar conclusion can be drawn from the analysis of δb_H whose highest values were obtained for the objective functions incorporating BOD_{5S} (OG_1–3). As in the case of the parameter $\hat{\mu}_H$, the inclusion of different COD fractions and alkalinity into the objective functions did not account for any improvement (e.g., the values of the derivatives δb_H for OG_4 and OG_9 were not significantly different even though OG_9 contains COD divided into fractions and alkalinity).

Of the nitrogen compounds group, the lowest δb_H values were obtained for the objective functions with no information about organic nitrogen (NG_15–17), which implies a comparatively small influence of ammonia nitrogen and nitrates on calibration. Of the other sets of nitrogen compounds, the highest values of δb_H were achieved for the objective functions that contained TKN in soluble and suspended form (NG_14 and NG_14), the soluble fraction playing a more important role (NG_13 compared to NG_8). Because of the low ammonia concentration, high δb_H values were also obtained for organic nitrogen (NG_2). The values of δb_H were slightly lower when total nitrogen was included (NG_1). This should be attributed to the high concentration of nitrates, which is (to a slight extent) associated with the decay rate for the heterotrophic biomass.

3.1.3. MAXIMUM SPECIFIC GROWTH RATE FOR AUTOTROPHIC BIOMASS

Of the group of organic pollutants and alkalinity (OG), only the latter exerted an influence on the $\delta\hat{\mu}_A$ value (OG_7–9 compared to OG_4–6). This should be attributed to a close relation between the stoichiometric amount of nitrified ammonia and the consumption of alkalinity.

The concentrations of nitrogen compounds are more closely related to the parameter $\hat{\mu}_A$ compared to organic fractions. This difference is particularly distinct with ammonia nitrogen; its inclusion into the objective function remarkably increases the slope of $\delta\hat{\mu}_A$ (NG_2 and 9 compared to NG_4 and 10). Since ammonia nitrogen accounts for over 40% of TKN_S , it can be substituted for the latter. Such substitution, however, results in the decrease in the $\delta\hat{\mu}_A$ value (because of the poor influence of soluble organic nitrogen). Although nitrates are the products of nitrification, they have practically no effect on the value of $\delta\hat{\mu}_A$ (NG_4 compared to NG_5). Organic nitrogen slightly changes the slopes of the error curves, irrespective of whether it is incorporated separately (NG_16 compared to NG_3) or as part of TKN (NG_7) or TKN_P (NG_9). That is why the incorporation of organic compounds into the objective function does not significantly affect the $\delta\hat{\mu}_A$ value.

3.1.4. SUMMARY OF PARTIAL DERIVATIVES ANALYSIS

As three parameters ($\hat{\mu}_H$, b_H and $\hat{\mu}_A$) are to be calibrated simultaneously, it is necessary to perform estimation with objective functions of large local unit slopes for all the parameters. Although small slopes may cause convergence in the desired direction, the final result is in fact a random one. It is therefore necessary to exclude the objective functions based on OG_1,2 and 3 (low values of $\delta\hat{\mu}_H$), as well as on NG_1, 2, 3, 6, 7, 8, 9 and 16 (low values of $\delta\hat{\mu}_A$). Such an approach automatically excludes the objective functions with low δb_H values (e.g., *Fo1* belonging to OG_1). In this way, a total of 99 objective functions have been excluded.

Summing up, at that stage it is possible to establish which pollutants are significant in terms of the calibration of particular parameters. An estimation of the maximum specific growth rate for heterotrophic biomass is feasible only if the objective function includes information about BOD_{5S} (all the functions that have not been excluded incorporate the BOD_{5S} term). The same holds for the estimation of the decay rate for the heterotrophic biomass. Of the group of nitrogen compounds, TKN_S (NG_11–14) is most useful. The maximum specific growth rate for autotrophic biomass depends primarily on the concentration of ammonia nitrogen (NG_4, 5, 10, 15 and 17), as well as on TKN_S (NG_11–14).

Each of the not excluded 54 objective functions has at least one component required for the calibration of any parameter. However, not all of these functions enable a successful calibration of the three parameters under analysis. This is so because the parameters are interrelated but these relations do not appear during one-dimensional analysis. For these reasons, use will be made of two-dimensional analysis in order to exclude further objective functions which may lead to erroneous results.

3.2. TWO-DIMENSIONAL ANALYSIS

3.2.1. RELATIONS BETWEEN $\hat{\mu}_H$ AND b_H

The objective functions that have not been rejected during analysis of partial derivatives include the term BOD_{5S} , whose value depends on the parameters $\hat{\mu}_H$ and b_H . The plot corresponding to the value $BOD_{5S} = 2.24 \text{ g COD/m}^3$ in the set of these parameters is a straight line expressed by $b_H = 0.133\hat{\mu}_H - 0.177$. This is a very crucial relation, so all the objective functions converge to this line (unless there are some relations in the $b_H - \hat{\mu}_A$ system).

Not all of the objective functions, however, include pollutants which attenuate this relationship. Such are the functions that do not contain information about organic nitrogen; what they include is the information about mineral nitrogen fractions alone (NG_15 and 17). Although ammonia nitrogen concentration depends only on the parameter b_H , this dependence is not strong enough to make the objective function peak in the proximity of the expected value of the parameters $\hat{\mu}_H$ and b_H . The plot for Fo_{66} given in figure 1 shows a valley to which the algorithm is convergent. For the purpose of comparison, figure 2 presents a similar plot for Fo_{64} , which displays a distinct point minimum (because the objective function contains the fractions TKN_s and TKN_x).

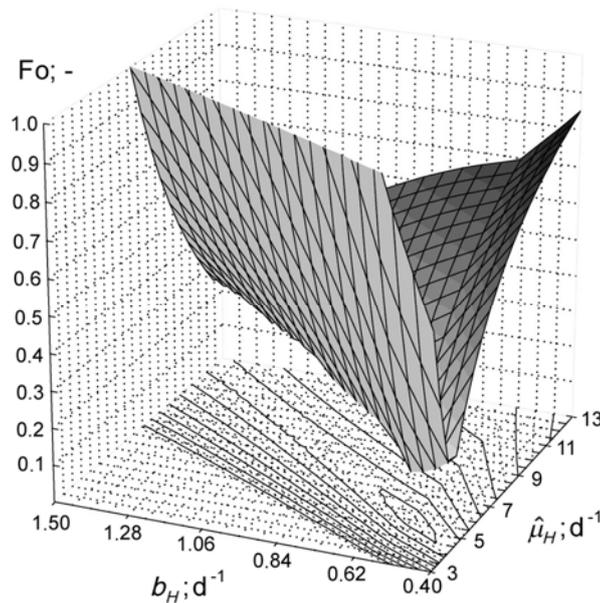


Fig. 1. Plot of Fo_{66} in the $\hat{\mu}_H - b_H$ system

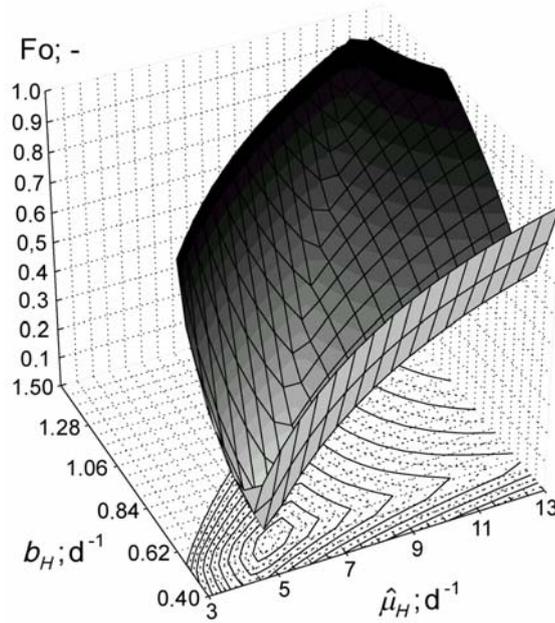
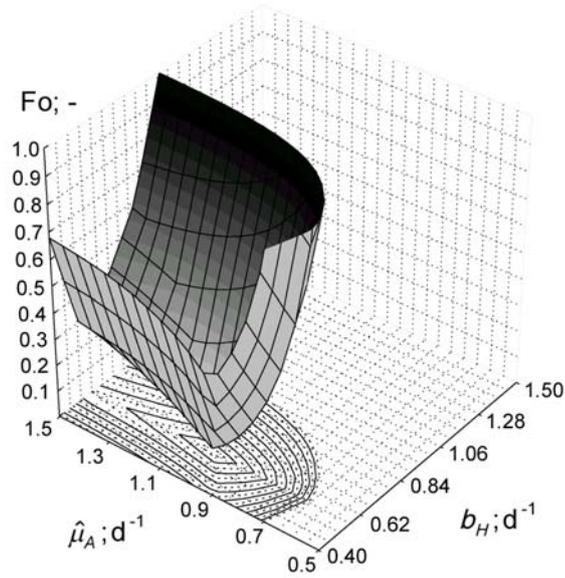
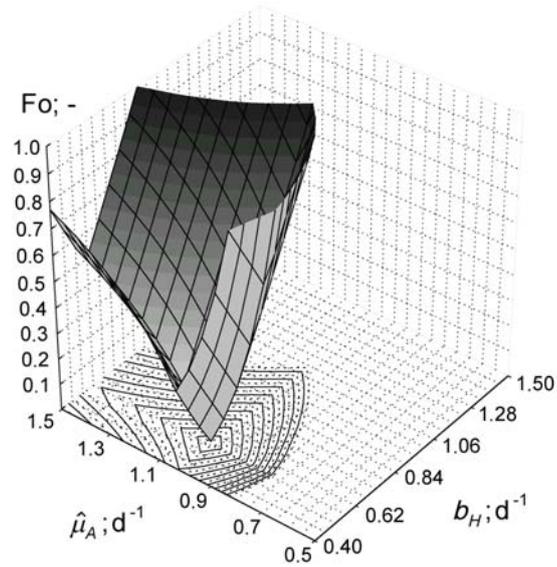


Fig. 2. Plot of Fo_4 in the $\hat{\mu}_H$ - b_H system

3.2.2. RELATIONS BETWEEN b_H AND $\hat{\mu}_A$

Only one pollutant depends greatly on the parameters b_H and $\hat{\mu}_A$. This is TKN_S , which includes ammonia nitrogen ($\hat{\mu}_A$ -dependent S_{NH}) and dissolved organic nitrogen (b_H -dependent S_{ND}). The line depicting the concentration of $TKN_S = 3.54 \text{ g N/m}^3$ in the set of these parameters can be described by the parabola expressed by the equation $\hat{\mu}_A = 2.4829 b_H^2 - 1.8719 b_H + 1.2581$. The convergence of the algorithm to this curve should be attenuated by other parameters. And these are the components of OG that attenuate the relation and point the function in the neighbourhood of the minimum. The pointing, however, is insufficient and the points are slightly scattered on the parabola. Finally, the objective function based on TKN_S alone (NG_11) cannot be considered as convergent to the point. The incorporation of nitrates and/or TKN_P into the objective function slightly changes the relations between the parameters and slightly improves their convergence. However, all those changes are insufficiently distinct to be regarded as satisfactory. That is why we have to exclude the objective functions based on NG_12, 13 and 14. Figure 3 shows a plot that reveals the relationship between b_H and $\hat{\mu}_A$, and this relation should be attributed to the TKN_S (Fo_{64}).

Fig. 3. Plot of Fo_{64} in the $b_H-\hat{\mu}_A$ systemFig. 4. Plot of Fo_{66} in the $b_H-\hat{\mu}_A$ system

All other objective functions are based on ammonia nitrogen, so they account for a strong convergence to the point. The inclusion of nitrates and/or organic nitrogen

into the objective function had no influence on the estimation, similarly to what we observed with the objective functions based on TKN_S . An example of an objective function providing convergence to the point in the $b_H-\hat{\mu}_A$ system is shown in figure 4 (*Fo_66*).

3.2.3. SUMMARY OF TWO-DIMENSIONAL ANALYSIS

The considerations presented in the foregoing sections enable us to exclude some of the objective functions as potentially ineffective. It is interesting to note that not all of the excluded functions lead to results which are far from being correct. This is so for two reasons. One of these is that the strongest convergence was always toward the lines, although for some of them there was also a vector of the decrease in the objective function toward the point. Although this decrease was several times lower compared to that toward the lines, in some instances it proved to be sufficient. The other reason explaining why these functions reached the exact point relies on the principle of algorithm operation. The algorithm starts with randomly selected points and randomly selects further points. Thus, it may happen that the algorithm will start from a closer point and reach a closer point.

Considering the relations that occur in the $\hat{\mu}_H-b_H$ systems, the objective functions based on NG_15 and 17 should be regarded as erroneous. If we consider the relations occurring in the $b_H-\hat{\mu}_A$ set, we should reject the objective functions based on NG_11–14. The remaining objective functions based on NG_04, 05 and 10 lead to correct results. What should be emphasised here is the necessity of identifying the relations in those sets of parameter pairs where they occur. This has been exemplified by the functions *Fo_64* and *Fo_66* plotted in figures 1 to 4. Each of the two functions converges to the point in one set and to the line in another set.

4. SUMMARY

After having removed all objective functions that were likely to yield non-optimal results (for the reasons already mentioned), we obtain a real image of how efficiently the method works. Calibrations based on the remaining 18 functions have practically led to the same results. The values of the parameters $\hat{\mu}_H$ and b_H have been found with a maximal error lower than 1.9% and 2.5%, respectively. In every instance, the estimation of the parameter $\hat{\mu}_A$ has led to the proximity of the value of 1.05 d^{-1} with an error smaller than 0.4%. Although this is not the expected value, it produces a stronger convergence than the true value of 1.00 d^{-1} adopted for the virtual WWTP. The underlying cause is the difference in the influent wastewater composition between the model used for data generation and the calibrated model. The raw wastewater stream entering the virtual WWTP carried autotrophic biomass in an

amount of 0.5 g COD/m³; in the wastewater stream fed to the calibrated model autotrophs were absent. The same holds for the presence and absence of heterotrophic microorganisms. However, considering a faster growth rate and a greater limitation of growth observed with heterotrophs, their role appears to be negligibly small.

On the basis of the analyses presented in this paper, it has been possible to establish a minimal set of pollutants enabling a reliable calibration of the model. The set contains BOD_{5S}, S_{NH} and N_{org} or TKN_P. It is also possible to additionally include COD (in any form), S_{alk} and S_{NO}. The inclusion of them slightly improves convergence, but the reasons for including them (as well as the remaining pollutants which do not account for convergence in the sets tested) are different. If the number of the included pollutants increases, this will improve the balance of the model fractions and enable a reduction in the influence of the measuring errors by averaging the results. If the set of basic data being used for calibration is insufficiently accurate, the algorithm will find the point of a low objective function value. However, the parameter values obtained will differ from the real ones. But if calibration is carried out with a larger set of data (which also promotes errors), the algorithm will find the point of a higher objective function value, but the parameter values obtained will be closer to the real ones.

5. CONCLUSIONS

An original one- and two-dimensional method for analysing the results of simulation-based experiments has been proposed. One-dimensional analysis has shown that one of the reasons why objective function sets are inconsistent is the poor sensitivity of some of the pollutants to the changes in the values of the model parameters in the proximity of the minimum of the objective functions, despite their high sensitivity to a wider range of variations in these parameters determined earlier. Two-dimensional analysis has revealed that, in some instances, the character of the relations between the parameters of the model and the pollutants is responsible for the disadvantageous shape of the objective function surface in the neighbourhood of the minimum, which may be the reason why the algorithm does not converge to the point.

Finally, it has been found that with 18 objective functions it is possible to obtain reliable results of calibration for the model of the system investigated. The pollutants incorporated into these functions are listed in table 4. Each of the 18 objective functions includes BOD_{5S} and S_{NH}, as well as N_{org} or TKN_P. The pollutants form the basic set of experimental data which enables a reliable calibration of the ASM1 model. The remaining pollutants support the convergence of the algorithm to the point. According to the available set of experimental data, we can choose one of the objective functions proposed.

Table 4

Pollutants incorporated in the objective functions leading to reliable results of calibration

F_o no.	Pollutant fractions
55	COD, BOD _{5S} , S_{NH} , N_{org}
56	COD, BOD _{5S} , S_{NH} , S_{NO}
61	COD, BOD _{5S} , S_{NH} , S_{NO} , TKN _P
72	COD _P , BOD _{5S} , S_{NH} , N_{org}
73	COD _P , BOD _{5S} , S_{NH} , S_{NO}
78	COD _P , BOD _{5S} , S_{NH} , S_{NO} , TKN _P
89	COD _S , COD _P , BOD _{5S} , S_{NH} , N_{org}
90	COD _S , COD _P , BOD _{5S} , S_{NH} , S_{NO}
95	COD _S , COD _P , BOD _{5S} , S_{NH} , S_{NO} , TKN _P
106	COD, BOD _{5S} , S_{alk} , S_{NH} , N_{org}
107	COD, BOD _{5S} , S_{alk} , S_{NH} , S_{NO}
112	COD, BOD _{5S} , S_{alk} , S_{NH} , S_{NO} , TKN _P
123	COD _P , BOD _{5S} , S_{alk} , S_{NH} , N_{org}
124	COD _P , BOD _{5S} , S_{alk} , S_{NH} , S_{NO}
129	COD _P , BOD _{5S} , S_{alk} , S_{NH} , S_{NO} , TKN _P
140	COD _S , COD _P , BOD _{5S} , S_{alk} , S_{NH} , N_{org}
141	COD _S , COD _P , BOD _{5S} , S_{alk} , S_{NH} , S_{NO}
146	COD _S , COD _P , BOD _{5S} , S_{alk} , S_{NH} , S_{NO} , TKN _P

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KALIBRACJA MODELU OSADU CZYNNEGO
ZA POMOCĄ ALGORYTMÓW GENETYCZNYCH.
CZĘŚĆ II. ANALIZA WYNIKÓW

W poprzednim artykule opisano metodę kalibracji modelu osadu czynnego nr 1 (ASM1) za pomocą algorytmów genetycznych. Do kalibracji wykorzystano 153 różne funkcje celu. Wyniki uzyskane dla niektórych z nich odbiegają od wartości poprawnych. W tym artykule przedstawiono dwie dodatkowe analizy, za pomocą których można wyjaśnić niespójność wyników kalibracji. Opisane metody opierają się na przeprowadzeniu serii symulacji. Pierwsza z nich umożliwia obliczenie wrażliwości funkcji celu na poszczególne parametry w otoczeniu ich oczekiwanej wartości. Druga metoda pokazuje zależności między parametrami modelu w odniesieniu do wartości funkcji celu. Przeprowadzone analizy wykazały, że za pomocą 18 funkcji celu można uzyskać wiarygodne wyniki kalibracji badanego układu.