InterCriteria Analysis of Control Parameters Relations in Artificial Bee Colony Algorithm

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Abstract: - InterCriteria analysis (ICrA) has been applied here to examine the influence of three main artificial bee colony (ABC) algorithm's control parameters, namely number of population, maximum cycle number and limit, during the model parameter identification of *Saccharomyces cerevisiae* fed-batch fermentation process. The relations and dependences between ABC parameters, on the one hand, and convergence time, model accuracy and model parameters on the other hand, have been outlined. Some valuable conclusions, about derived interactions are reported, expected to be very useful especially in the case of fermentation process modelling.

Key-Words: - Artificial bee colony algorithm, Control parameters, InterCriteria analysis, Parameter identification.

1 Introduction

Fermentation processes (FP), as a part of biotechnological ones, have been widely applied in pharmaceutical, food and beverages industries. But FP combine the dynamics of biological and non-biological processes, thus their modeling and future high-quality control become rather difficult to be solved task. In the most cases, conventional optimization techniques, applied to parameter identification of FP complex models could not find the satisfied solution. Thus, different metaheuristic methods have been developed and tested for the considered problem. Recently, the effectiveness and efficiency of nature-inspired methods, such as genetic algorithms (GA), ant colony optimization (ACO), firefly algorithm (FA), cuckoo search (CS), etc. receive more and more attention [1-4]. These stochastic approaches have been used for solving wide range of optimization problems, among them FP modelling and control [5-9]. Although many different global optimization methods have been developed, their efficiency is always determined by the problem specifics. So, the challenge for finding new or improving the existing modelling approaches strongly guides the researchers work.

The artificial bee colony (ABC) algorithm, proposed by Karaboga [10] in 2005 is another promising contemporary population-based approach. Up to now, the efficiency of ABC algorithm has been demonstrated for many optimization problems [11-14], among them parameter identification of *S. cerevisiae* fed-batch fermentation process model [9]. Typically, metaheuristic methods require fine-tuning of large number of parameters, depending on the specifics problem solving. While, ABC algorithm requires a few control parameters to be tuned, among them number of population, maximum cycle number and limit.

Recently developed InterCriteria analysis (ICrA) [15] that gives the possibility some criteria reflecting the behavior of considered objects to be compared is applied here in the field of ABC control parameters influence investigation. First promising application of ICrA for genetic algorithms parameters impact examination is presented in [16], where the domination of two of the main GA parameters, namely crossover and mutation rates during the model parameter identification of *S. cerevisiae* and *E. coli* fermentation processes have been examined.

Here, the apparatuses of index matrices (IM) and intuitionistic fuzzy sets (IFS), which are the core of ICrA have been used to establish the relations and dependences between number of population, maximum cycle number and limit from one hand and model parameters, optimization function value and convergence time, from the other hand, when ABC algorithm have been applied to parameter identification of *S. cerevisiae* fed-batch fermentation process model.

2 Problem Formulation

The dynamics of biomass, substrate and ethanol concentrations in *S. cerevisiae* fed-batch fermentation process model are presented by following system of non-linear differential equations [7]:

$$\frac{dX}{dt} = \left(\mu_{2S} \frac{S}{S + k_S} + \mu_{2E} \frac{E}{E + k_E} \right) X - \frac{F}{V} X \tag{1}$$

$$\frac{dS}{dt} = -\frac{\mu_{2S}}{Y_{SX}} \frac{S}{S + k_S} X + \frac{F}{V}\left(S_{\text{in}} - S\right) \tag{2}$$

$$\frac{dE}{dt} = -\frac{\mu_{2E}}{Y_{EX}} \frac{E}{E + k_E} X - \frac{F}{V} E \tag{3}$$

$$\frac{dV}{dt} = F \quad , \tag{4}$$

where: X, S and E are respectively the concentrations of biomass, [g/l], substrate (glucose), [g/l], and ethanol, [g/l]; F – feeding rate, [l/h]; V – volume of bioreactor, [l]; S_{in} – initial substrate concentration in the feeding solution, [g/l]; μ_{2S}, μ_{2E} – maximum growth rates of substrate and ethanol, [1/h]; k_S, k_E – saturation constants of substrate and ethanol, [g/l]; Y_{SX}, Y_{EX} – yield coefficients, [g/g]. All model parameters fulfil the non-zero division requirement. Also, all model functions in the Eqs. (1)-(4) are continuous and differentiable. Detailed description of the process conditions and experimental data could be found in [7].

Altogether six model parameters have been identified for the considered model Eqs. (1)-(4). The vector of parameters is presented as follows: $p = [\mu_{2S}, \mu_{2E}, k_S, k_E, Y_{SX}, Y_{EX}]$.

Aiming the best fit to a data set, mean square deviation between model output and experimental data for biomass, substrate and ethanol has been used as an optimization criterion:

$$J = \sum \left(Y - Y^* \right)^2 \rightarrow min \quad , \tag{5}$$

where Y are the experimental data and Y^* are model predicted data, $Y = [X; S; E]$.

3 Artificial Bee Colony Optimization Algorithm

In 2005 Karaboga developed the artificial bee colony algorithm for numerical optimization problems [10], inspired by the intelligent foraging honey bees behavior.

Three groups of artificial bees, namely employed bees, onlookers and scouts guide the ABC algorithm’s work. A colony of ABC consists of employed bees and onlookers. For each food source, there is only one employed bee, i.e. the number of employed bees is equal to the number of food sources. The employed bee becomes a scout, when its food source is exhausted and abandoned. While employed and onlooker bees carry out the exploitation process in the search space, the scouts control the exploration process.

ABC algorithm search consists of three main steps [17] repeated until a predetermined number of cycles, called maximum cycle number, or a termination criterion is satisfied. Firstly, the ABC algorithm sends the employed bees onto their food sources and evaluates their nectar amounts. On the next stage, a selection of food source regions by the onlooker bees is proceeded, based on evaluation of the food sources nectar amount. Finally, the ABC algorithm determines the scout bees and sends them randomly onto possible new food sources. In ABC algorithm, a food source represents a possible solution of the optimization problem, while the nectar amount of a food source corresponds to the quality of the solution.

The ABC generates a randomly distributed initial population of SN solutions (food sources). In order to produce a candidate food position from the old one in the memory, the ABC uses the following equation [17]:

$$\upsilon_{i,j} = x_{i,j} + \phi_{i,j}\left(x_{i,j} - x_{k,j}\right) \quad , \tag{6}$$

where k = 1, 2, …, SN and j = 1, 2, …, D are randomly chosen indexes and D is the number of parameters of the problem to be optimized. Although k is determined randomly, it has to be different from i. $\phi_{i,j}$ is a random number between [–1, 1], which controls the production of neighbor food sources around $x_{i,j}$ and visually represents the comparison of two food positions by a bee.

The onlooker bee chooses a food source depending on the probability value associated with that food source, p_i, calculated by the following expression [17]:

$$p_i = f_i \Big/ \sum_{n=1}^{SN} f_n \tag{7}$$

where f_i is the fitness value of the solution i, which is proportional to the nectar amount of the food source in the position i, and SN is the number of food sources, which is equal to the number of employed bees or onlooker bees, i.e. the *SN* equals to the half of the colony size.

The food source which nectar is abandoned by the bees is replaced with a new food source by the scouts. In ABC, this is simulated by producing a position randomly and replacing it with the abandoned one. Further, if a position cannot be improved through a predetermined number of trials, then that food source is abandoned. The number of trials for releasing a food source is equal to the value of "*limit*", one of the important ABC algorithm control parameters.

4 InterCriteria Analysis Approach

InterCriteria analysis approach, given in details in [15] is a contemporary technique for multi-criteria decision making. ICrA implements two fundamental concepts, namely the apparatuses of index matrices and intuitionistic fuzzy sets in order to detect possible correlations between pairs of involved criteria and provides on this basis an additional information for the investigated objects.

For the purposes of ICrA application, the initial IM index set consists of the criteria (for rows) and objects (for columns) with the IM elements assumed to be real numbers. Further, an IM with index sets consisting of the criteria (for rows and for columns) with intuitionistic fuzzy pair (IFP) elements determining the degrees of correspondence between the respective criteria is constructed. The IFP elements, denoted as (μ and υ) might be interpreted respectively as degrees of "validity" and "non-validity"; "agreement" and "disagreement"; "correctness" and "non-correctness", etc. For the most of the obtained pairs the sum $\mu + \upsilon = 1$, but in some cases, there might be pairs for which this sum is less than one. The difference is considered as a degree of "uncertainty": $\pi = 1 - \mu - \upsilon$.

5 Numerical Results and Discussion

The purpose of current investigation is the influence of three main ABC parameters, namely number of population (*NP*), maximum cycle number (*MCN*) and *limit* to be examined when ABC algorithm has been applied to parameter identification of *S. cerevisiae* fed-batch fermentation process model. Seven different values for each ABC parameters *NP*, *MCN* and *limit* are applied. According to [9, 17], the *NP* values have been chosen: *NP* = {6; 10; 20; 40; 60; 80; 100}, the *MCN* values are: *MCN* = {50; 100; 150; 200; 300; 400; 500}, while the *limit* is tried for: *limit* = {100; 300; 500; 700; 900, 1100, 1300}.

When *NP* was examined, the *MCN* and *limit* were set to 100. When *MCN* was investigated the *NP* was set to 20 and the *limit* was 100. *NP* and MCN were respectively 20 and 100, when the ABC control parameter *limit* has been studied. The number of model parameters were $D = 6$, while the number of food source was $SN = NP/2$.

Thirty independent runs of ABC algorithm have been performed for each value of *NP*, *MCN* and *limit*. Thus, the reliable averaged results for optimization criterion, convergence time and model parameters estimations have been obtained. After that three initial IMs have been constructed: $A_{1(NP)}$, $A_{2(MCN)}$ and $A_{3(limit)}$, respectively for ABC algorithm with different values of *NP*, *MCN* and *limit*. As it could be seen from presented below IMs $A_{1(NP)}$, $A_{2(MCN)}$ and $A_{3(limit)}$, the objective function value, convergence time and six model parameters are given with more digits after the decimal point in order to be distinguishable.

Based on the initial IMs $A_{1(NP)}$, $A_{2(MCN)}$ and $A_{3(limit)}$, ICrA algorithm calculates the IFP $\langle\mu, \upsilon\rangle$ and π – value for every two pairs of the considered criteria. The obtained results are grouped in Table 1 considering dependences between ABC control parameters, optimization criterion, convergence time and model parameters themselves.

The consonance or dissonance between altogether thirty-six pairs of criteria have been outlined, based on the scale, presented in [18].

In the beginning, the relations between ABC control parameters and *J*, *T* and six model parameters will be reviewed. As it could be seen from Table 1, there is a strong negative consonance between *J* and two of the investigated ABC control parameters, namely *NP* and *MCN*. The highest $\mu = 1$, e.g. strong positive consonance is observed for the pairs *NP* ↔ *T* and *MCN* ↔ *T*. Outlined relations have been expected, since incrementation of the *NP* and *MCN* led to slightly decrease of *J*, while *T* significantly increase. When the third ABC control parameter is considered, a weak negative consonance between *T* and *limit* is found, while the pair *J* ↔ *limit* is in dissonance. That means, ABC parameter *limit* influences the algorithm's convergence time much more than objective function value. Going further in details, the dependencies between ABC control parameters and model parameters estimations is thoroughly analyzed. The number of population strongly influences evaluation of model parameters μ_{2E}, k_E, Y_{SX}, Y_{EX}. The maximum cycle number impacts evaluation of μ_{2S} and again k_E, Y_{SX}, Y_{EX}, while the

Table 1. ICrA obtained relations.

Relations	***NP μ***	***MCN μ***	***limit μ***
NP/MCN/limit ↔ J	0.00	0.00	0.52
NP/MCN/limit ↔ T	1.00	1.00	0.19
NP/MCN/limit ↔ μ_{2S}	0.38	0.76	0.33
NP/MCN/limit ↔ μ_{2E}	0.86	0.67	0.43
NP/MCN/limit ↔ k_S	0.62	0.52	0.38
NP/MCN/limit ↔ k_E	0.81	0.95	0.71
NP/MCN/limit ↔ Y_{SX}	0.14	0.00	0.76
NP/MCN/limit ↔ Y_{EX}	0.90	0.95	0.38
J ↔ T	0.00	0.00	0.52
J ↔ μ_{2S}	0.62	0.24	0.71
J ↔ μ_{2E}	0.14	0.33	0.23
J ↔ k_S	0.38	0.48	0.67
J ↔ k_E	0.19	0.05	0.43
J ↔ Y_{SX}	0.86	1.00	0.57
J ↔ Y_{EX}	0.10	0.05	0.19
T ↔ μ_{2S}	0.38	0.76	0.62
T ↔ μ_{2E}	0.86	0.67	0.52
T ↔ k_S	0.62	0.52	0.57
T ↔ k_E	0.81	0.95	0.24
T ↔ Y_{SX}	0.14	0.00	0.29
T ↔ Y_{EX}	0.90	0.95	0.57
μ_{2S} ↔ μ_{2E}	0.33	0.43	0.43
μ_{2S} ↔ k_S	0.57	0.48	0.95
μ_{2S} ↔ k_E	0.38	0.81	0.24
μ_{2S} ↔ Y_{SX}	0.57	0.24	0.38
μ_{2S} ↔ Y_{EX}	0.38	0.71	0.38
μ_{2E} ↔ k_S	0.57	0.76	0.48
μ_{2E} ↔ k_E	0.67	0.62	0.43
μ_{2E} ↔ Y_{SX}	0.10	0.33	0.29
μ_{2E} ↔ Y_{EX}	0.95	0.71	0.95
k_S ↔ k_E	0.52	0.57	0.29
k_S ↔ Y_{SX}	0.43	0.48	0.33
k_S ↔ Y_{EX}	0.62	0.57	0.43
k_E ↔ Y_{SX}	0.24	0.05	0.86
k_E ↔ Y_{EX}	0.71	0.90	0.48
Y_{SX} ↔ Y_{EX}	0.14	0.05	0.33

IM $A_{1(NP)}$:

$A_{1(NP)}=$		$ABC_{NP=6}$	$ABC_{NP=10}$	$ABC_{NP=20}$	$ABC_{NP=40}$	$ABC_{NP=60}$	$ABC_{NP=80}$	$ABC_{NP=100}$
	J	0.025173	0.021736	0.021715	0.021707	0.021697	0.021694	0.021689
	T	61.90104	106.1604	216.6998	439.7299	649.1228	911.2759	1086.414
	NP	6	10	20	40	60	80	100
	μ_{2S}	0.948904	0.954823	0.945564	0.938493	0.940957	0.926043	0.957871
	μ_{2E}	0.113095	0.126293	0.137450	0.135964	0.139329	0.142743	0.139229
	k_S	0.129986	0.134408	0.136143	0.131857	0.131514	0.132636	0.135171
	k_E	0.759914	0.797942	0.799136	0.800000	0.799900	0.799750	0.799971
	Y_{SX}	0.533239	0.497154	0.491245	0.492779	0.481802	0.485644	0.484526
	Y_{EX}	1.620505	1.677231	1.869908	1.840507	1.989484	2.001172	1.993990

IM $A_{2(MCN)}$:

		$ABC_{MCN=50}$	$ABC_{MCN=100}$	$ABC_{MCN=150}$	$ABC_{MCN=200}$	$ABC_{MCN=300}$	$ABC_{MCN=400}$	$ABC_{MCN=500}$
	J	0.021814	0.021715	0.021699	0.021696	0.021687	0.021686	0.021684
	T	105.7474	216.6998	315.025	437.9018	650.779	862.2869	1089.75
	NP	50	100	150	200	300	400	500
	μ_{2S}	0.944137	0.945564	0.942713	0.936686	0.953936	0.956464	0.956471
$A_{2(MCN)}=$	μ_{2E}	0.119657	0.137450	0.140392	0.144986	0.138193	0.144186	0.138136
	k_S	0.129645	0.136143	0.136617	0.134557	0.132393	0.136950	0.129957
	k_E	0.789433	0.799136	0.799939	0.799293	0.799950	0.799957	0.799986
	Y_{SX}	0.497274	0.491245	0.489966	0.487548	0.485449	0.485311	0.483534
	Y_{EX}	1.575970	1.869908	1.912111	2.007543	1.982385	2.030751	2.034825

IM $A_{3(limit)}$:

		$ABC_{limit=100}$	$ABC_{limit=300}$	$ABC_{limit=500}$	$ABC_{limit=700}$	$ABC_{limit=900}$	$ABC_{limit=1100}$	$ABC_{limit=1300}$
	J	0.021717	0.021717	0.021716	0.021708	0.021707	0.021719	0.021726
	T	220.0922	219.3375	210.9094	210.45	210.7125	210.4578	210.6969
	NP	100	300	500	700	900	1100	1300
	μ_{2S}	0.961676	0.961676	0.936419	0.937877	0.934460	0.958684	0.942150
$A_{3(limit)}=$	μ_{2E}	0.132248	0.132248	0.129674	0.133797	0.136760	0.124977	0.130645
	k_S	0.138892	0.138892	0.130185	0.133423	0.131680	0.135478	0.133490
	k_E	0.799002	0.799002	0.799839	0.799785	0.799839	0.800000	0.799726
	Y_{SX}	0.492868	0.492868	0.497714	0.493321	0.494236	0.501409	0.496586
	Y_{EX}	1.787458	1.787458	1.762906	1.802549	1.860836	1.668798	1.737299

limit controls evaluation of only one model parameter, namely Y_{SX}.

When looking at J and T relations, a clear $J \leftrightarrow T$ connection in strong negative consonance is observed, at *NP* and *MCN*. The other coincidences for *NP* and *MCN* parameters are respectively for $J \leftrightarrow \mu_{2E}/\mu_{2S}$, $J \leftrightarrow k_E$, $J \leftrightarrow Y_{EX}$ and $T \leftrightarrow Y_{SX}$ pairs, which are in negative consonance, while $J \leftrightarrow Y_{SX}$, $T \leftrightarrow \mu_{2E}/\mu_{2S}$, $T \leftrightarrow k_E$ and $T \leftrightarrow Y_{EX}$ pairs show positive consonance. When ABC parameter *limit* is investigated, a negative consonance has been observed for $J \leftrightarrow \mu_{2E}$, $J \leftrightarrow Y_{EX}$ and $T \leftrightarrow k_E$. The stochastic nature of ABC algorithm is a prerequisite for the observed different relations.

In the last group of examined correlations, between model parameters themselves, positive consonance is obtained for one ($\mu_{2E} \leftrightarrow Y_{EX}$), two ($\mu_{2S} \leftrightarrow k_E$, $k_E \leftrightarrow Y_{EX}$) or three ($\mu_{2S} \leftrightarrow k_S$, $\mu_{2E} \leftrightarrow Y_{EX}$, $k_E \leftrightarrow Y_{SX}$) criteria pairs, respectively at *NP*, *MCN* and *limit*. While negative consonance appears for $\mu_{2E} \leftrightarrow Y_{SX}$, $k_E \leftrightarrow Y_{SX}$, $Y_{SX} \leftrightarrow Y_{EX}$ at *NP*; $\mu_{2S} \leftrightarrow Y_{SX}$, $k_E \leftrightarrow Y_{SX}$, $Y_{SX} \leftrightarrow Y_{EX}$ at *MCN* and $\mu_{2S} \leftrightarrow k_E$ at *limit*. For the rest of the criteria pairs the dissonance is observed. The established results are caused by the physical meaning of FP models parameters, as well as by the strong non-linearity of FP model structure.

As a conclusion, it worth to be noted, that ABC control parameters *NP* and *MCN* influence more than *limit* the objective function value, convergence time and estimations of FP model parameters, when ABC algorithm has been applied to parameter identification of *S. cerevisiae* fed-batch FP model.

6 Conclusion

In this paper, powerful ICrA has been used to examine the influence of three main ABC control parameters, when ABC algorithm has been applied to parameter identification of *S. cerevisiae* fed-batch fermentation process model. The relations and dependencies between *NP*, *MCN* and *limit* from one hand and convergence time, objective function value and six model parameters from the other hand, have been established. Obtained additional knowledge could be used for the improvement of the ABC algorithm performance, as well as for further identification procedures of FP models.

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