# ABC Algorithm based Fuzzy Modeling of Optical Glucose Detection

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***Abstract*—This paper presents a modeling approach based on the use of fuzzy reasoning mechanism to define a measured data set obtained from an optical sensing circuit. For this purpose, we implemented a simple but effective an *in vitro* optical sensor to measure glucose content of an aqueous solution. Measured data contain analog voltages representing the absorbance values of three wavelengths measured from an RGB LED in different glucose concentrations. To achieve a desired model performance, the parameters of the fuzzy models are optimized by using the artificial bee colony (ABC) algorithm. The modeling results presented in this paper indicate that the fuzzy model optimized by the algorithm provide a successful modeling performance having the minimum mean squared error (MSE) of 0.0013 which are in clearly good agreement with the measurements.**

***Index Terms*—fuzzy systems, heuristic algorithms, evolutionary computation, optical sensors, computational modeling.**

## I. INTRODUCTION

Modeling of measurement results in biological and/or chemical optical sensor systems has been a challenge for years. Main reason of that is to produce weak and highly nonlinear responses of biological and chemical species against optical sensing signals. Glucose which is one of the major research subjects in health and food industry is a simple sugar. It can be produced in mostly plants with the aid of photosynthesis and/or obtained by hydrolysis of milk, cane sugar, sugar beet, cellulose, cornstarch etc. Glucose is also called monosaccharide and found abundantly in foods; therefore, it is one of main energy sources for animals and humans because the energy emerges after an oxidation reaction.

Detection of glucose levels is of interest to especially food industry, health and nutrition. In food industry, this has been very important challenge for years in determination of energy content and nutrition facts of the foods [1] and determination of the plant origin contents in the foods of animal origin [2]. Another important subject with the glucose detection is to identify blood glucose levels in diabetic patients [3]. It is very important to keep the blood glucose concentrations in normal levels for humans suffered from diabetes disease [4].

In past two decades, researchers developed several methods for measurement of glucose both in vivo [5-11] and *in vitro* [12]. Stuart et al. used surface-enhanced Raman scattering in animals [5] for in vivo glucose measurements and they reported relatively low errors. Chen et al. [6] proposed an in vivo glucose monitoring system by using a microporous membrane prepared by nano material layers. Mohammadi et al. developed a NIR sensor made on a chip for continuous measurement of blood glucose [7]. The sensor contains a multi emitter LED to take the advantage of multi spectral interactions with the target analyte.

In recent years, sensor development efforts for the detection of the glucose in a dynamic medium like human body tends to use of optical methods to improve the selectivity and to compensate other effects that can cause misreading of the glucose concentration [14-16]. In many applications, the sensor outputs can need error correction and linearization algorithms in such highly dynamical media [17]. To overcome these difficulties, artificial intelligence based modeling approaches can provide fast and efficient solutions. In the modeling of complex or nonlinear systems, many impressive results can be obtained by using fuzzy logic based different model structures [18-34]. On the other hand, because the performance of the model is directly affected by the model's parameters, determining an appropriate optimization algorithm is one of the most important stages of the modeling procedure. Artificial bee colony (ABC) algorithm is an efficient population based optimization method which can be successfully used to determine the optimum parameters of the fuzzy models [21, 22, 35-39].

The main motivation for fuzzy modeling is that it presents an impressive modeling performance to successfully define the complex and/or nonlinear systems. Because many real world systems are inherently nonlinear, the use of the classical linear mathematical models is not sufficient in the modeling of complicated or ill-defined processes. On the other hand, the proposition of an efficient precise mathematical or non-fuzzy model which gives the satisfying results requires a considerable effort and time for users if not possible. A fuzzy logic based model prevents this difficulty, and it can provide the necessary connection between the system input and output data set.

In this work, we implemented a simple but effective an *in vitro* optical sensor to measure glucose content of an aqueous solution. The solution was prepared in different glucose concentrations and we added the Benedict's reagent in order to obtain color change in the solution. Then, we measured absorbance of three wavelengths from an RGB LED for elimination of environmental effects such as light

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and temperature fluctuations in the medium and EMI effects. Because of the fact that the sensor produces three voltage outputs, two fuzzy model structures were proposed for correct estimation of the glucose measurements acquiring from the voltage readings. The parameters of the fuzzy models were obtained by using the ABC algorithm. The results of the optimized fuzzy models were compared with each other and with the measurement results.

The rest of the paper is organized as follows. The next section presents the basic properties of the ABC algorithm briefly. Experimental study and the fuzzy models are presented in Section 3. Section 4 discusses the results of the fuzzy models optimized by the ABC algorithm. Finally, Section 5 presents the concluding remarks.

## II. Artificial Bee Colony (ABC) Algorithm

The main principle in the artificial bee colony (ABC) algorithm presented by Karaboga is to simulate the behavior of bees foraging [35-38]. In order to obtain the new possible solutions by the algorithm, the bee colony consists of three kinds of bees, namely, employed, onlooker and scout bees. The number of employed bees is equal to the number of food sources that represent the possible solutions in the search space. Each solution is defined by a set of optimization parameters. The nectar amount of the food sources shows the quality of the solutions which is called as the "fitness value". Employed bees explore the new food sources, and transfer the position information of these sources to the onlooker bees. Each onlooker bee selects a source depending on the quality of the solutions. The task of the scout bees is to randomly determine a new food sources in case of the abandonment of a food source.

The main steps of the ABC algorithm can be given as the following:

1. *Generate randomly the initial population ($x_i$)*
2. *Evaluate the population*
3. *Repeat the following steps until the stopping criterion is met*
4. *For each employed bee*
   *(i) produce new solution ($v_i$), (ii) calculate the fitness value, (iii) apply the selection process*
5. *Send the onlooker bees to the food sources and select a solution depending on nectar amounts*
6. *Send the scouts for searching new food sources*
7. *Keep the best solution achieved so far*
8. *If stopping criterion is not met, go back to step 4.*

The procedure of the algorithm begins by randomly producing (SN×D)-dimensional an initial population, where SN is the population size and D is the number of optimization parameters. The $i^{th}$ solution in the population is defined by a solution vector shown as $x_i=[x_{i1}, x_{i2}, \ldots, x_{iD}]$, i=1, 2, …., SN. In general, in order to obtain an initial population, a definition given as the following is used:

$$x_{ij} = x_j^{\min} + rand(0,1).(x_j^{\max} - x_j^{\min}) \quad (1)$$

where $x_j^{\min}$ and $x_j^{\max}$ are the lower and upper bounds of the $j^{th}$ parameters of the solution $i$, respectively. The new neighboring solution $x_{new,j}$ for $i^{th}$ solution in the population is calculated by using a definition as given in the following equation:

$$x_{new,j} = x_{i,j} + rand(-1,1).(x_{i,j} - x_{k,j}) \quad (2)$$

where k ∈ {1, 2, …, SN} with k≠i and j ∈ {1, 2, …, D} are randomly chosen values. By using this description, new food sources which represent the new possible solutions can be found in the near of $x_{i,j}$ source.

In ABC, there are also three critical control parameters that directly affect the performance of the algorithm such as colony size, limit, and maximum cycle. When reaching a predetermined limit value, the current solution can not improve anymore. Hence, the related food source is abandoned by the algorithm, and new possible sources are searched by the scout bees. These control parameters are generally determined by the trial-and-error method or by using the user's experience. In this paper, different values of the colony size such as 30 and 40 are tested. ABC algorithm is run for the maximum cycles of 1000 and 2000. As the limit value, description of [(colony size÷2) × number of the parameters] is employed.

## III. Experimental Study and Fuzzy Rule Base Models used in This Study

The principle scheme of the experimental setup is shown in Figure 1a [40]. Optical signals of the sensor are generated by an RGB LED for absorbance measurements. Red, green and blue terminals of the diode are successively triggered and output voltages on LDR (Light Dependent Resistor) are read after individual optical pulse. Some wavelengths of the optical signal are attenuated by the absorbance of the glucose solution with Benedict's reagent while the light passes through the solution, because the color of the solution changes from blue to reddish with the glucose concentration after a particular oxidation reaction (see Figure 1b). It is obvious that RGB responses on the LDR can be affected by the surrounding medium light since the sensor works in visible region. So, for each measurement, we used a black box as screen covering the sensing area to block environmental light. At the end of the process, the control circuit transfers the data converted from analog to digital for monitor readouts.

Regarding this process, we can say that the sensor acts as a discrete wavelength spectrophotometer working in visible region. This simple and effective idea makes uncomplicated the optical part of the design, too. On the other hand, it requires additional computing efforts in order to reduce error/misreading and to improve measurement results. An effective way to overcome this difficulty is to use a model structure that can provide fast and accurate results for additional values of the measurements. Fuzzy logic based models can present the efficient solution alternatives in estimation and definition of complex data sets for many engineering systems.

In this study, two types of fuzzy model structure were selected for the modeling of the glucose concentration; Takagi-Sugeno (TS) type fuzzy inference mechanism [21, 28, 31] and fuzzy rule structure presented by Bagis in [20]. The main difference of these fuzzy models is in the consequent sections. In the TS model, the consequent section has a linear combination of the input variables. However, in the reasoning procedure of the other model, the output values defined by the singleton values are multiplied by the weighted membership functions of the input variables.

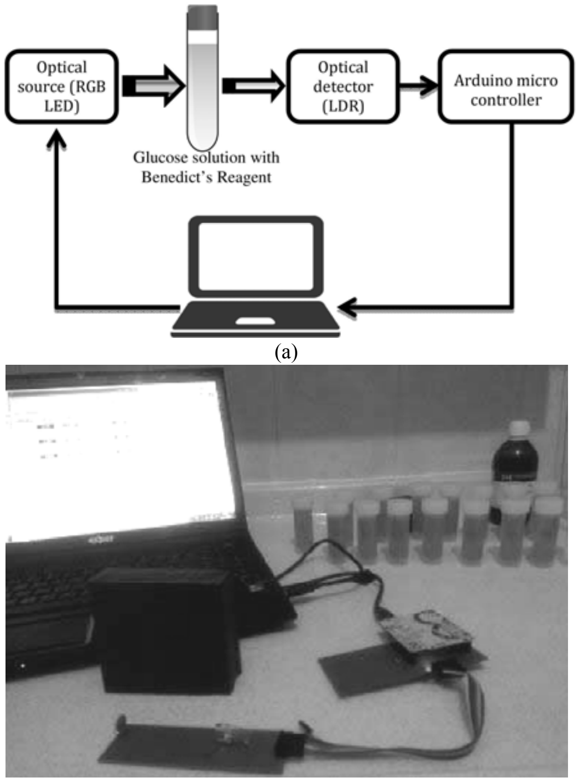


Figure 1. (a) Schematic and (b) picture of proposed experimental setup for measurement of in vitro glucose concentration [40]

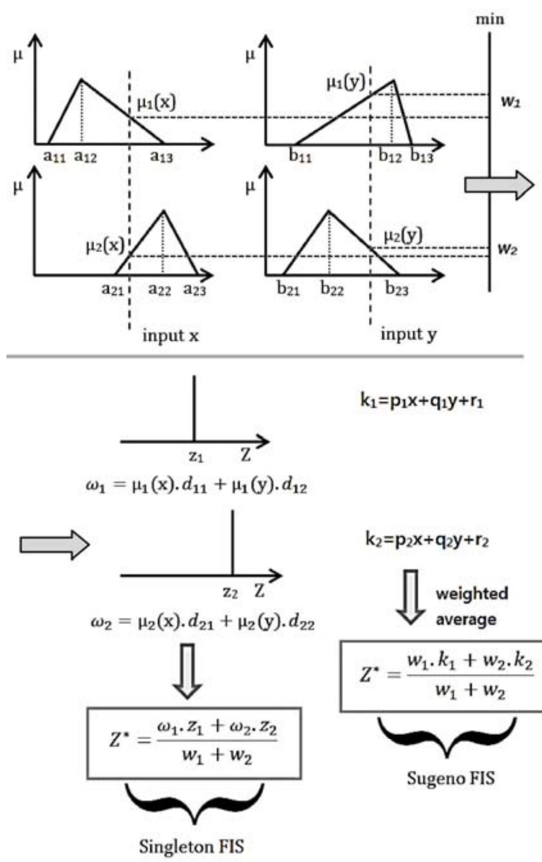


Figure 2. Sugeno and Singleton type fuzzy inference mechanisms

Figure 2 shows the TS and the other fuzzy inference system (FIS) called as singleton model for two rules. From the fuzzy model structures given in Figure 2, triangular type membership functions characterized by three numerical values are used for defining the input variables. In order to define a rule in the TS and singleton model, 9 numerical parameters are used by the model having 2 inputs and 1 output. When the system has 3 inputs and 1 output, the number of parameters needed by the fuzzy models for one rule is 13 as shown in Table I. In the case of 3 rules, the number of parameters to be optimized is 39.

TABLE I. PARAMETER MATRIX FOR DEFINING THE MEMBERSHIP FUNCTIONS AND RULES IN A MODEL WITH 3 INPUTS AND 1 OUTPUT

| *fuzzy model* | *input 1 (x)* | *input 2 (y)* | *input 3 (t)* |
|---|---|---|---|
| **Singleton** | $a_{11}$ $a_{12}$ $a_{13}$<br>$a_{21}$ $a_{22}$ $a_{23}$ | $b_{11}$ $b_{12}$ $b_{13}$<br>$b_{21}$ $b_{22}$ $b_{23}$ | $c_{11}$ $c_{12}$ $c_{13}$<br>$c_{21}$ $c_{22}$ $c_{23}$ |
| **TS** | $a_{11}$ $a_{12}$ $a_{13}$<br>$a_{21}$ $a_{22}$ $a_{23}$ | $b_{11}$ $b_{12}$ $b_{13}$<br>$b_{21}$ $b_{22}$ $b_{23}$ | $c_{11}$ $c_{12}$ $c_{13}$<br>$c_{21}$ $c_{22}$ $c_{23}$ |
| *fuzzy model* | *Output (Z)* | *adjustment parameters* | *rule numbers* |
| **Singleton** | $z_1$<br>$z_2$ | $d_{11}$ $d_{12}$ $d_{13}$<br>$d_{21}$ $d_{22}$ $d_{23}$ | → rule 1<br>→ rule 2 |
| **TS** | $k_1=p_1x+q_1y+r_1t+s_1$<br>$k_2=p_2x+q_2y+r_2t+s_2$ | --<br>-- | → rule 1<br>→ rule 2 |

In a fuzzy modelling application, the fuzzy model structure involves the following choices [20]:

***(a) input and output variables***: The essential of this problem is to estimate the glucose concentration ratio (%) of aqueous solutions having different concentrations by using a measured data set. For this aim, three input variables which contain the voltage values created on a photo resistor (LDR) by red, green and blue wavelengths (R, G, B) are used for the modelling. Thus, the fuzzy model structures used in this study are identified as 3 inputs and 1 output as given in Figure 3. The measured data set is also given in Table II. In order not to need for a calibration process, we obtained the sensor readouts in arbitrary units by using induced voltages on LDR.

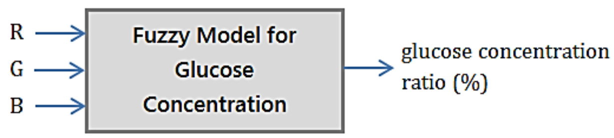


Figure 3. Fuzzy model used for glucose concentration

***(b) number and type of membership functions for each variable:*** The input variables R, G and B are defined by triangular type membership functions. For output variable glucose concentration, in the model structures of singleton and Sugeno, singleton and linear equation type functions are used respectively (Figure 2).

***(c) rule base:*** The number of the rules in a fuzzy model are generally obtained by depending on the user's preference or experience. A sample rule in the singleton type rule base has a general form expressed by

*If **input x** is* $A_1^i(x_1)$ *and **input y** is* $B_1^i(y_1)$ *and*
***input t** is* $C_1^i(t_1)$ *then **output Z** is* $z_1$ (3)

where x, y, t are the input variables, A, B, C are the fuzzy linguistic values. The value of $A_1^i$ for input $x_1$ can be defined as follows:

$$A_1^i = \max(\min[(\mathbf{x_1}-a_{11}) / (a_{12}-a_{11}) , (a_{13}-\mathbf{x_1}) / (a_{13}-a_{12})], 0) \quad (4)$$

In Equation (4), $a_{11}$, $a_{12}$ and $a_{13}$ are the main parameters of a triangular membership function as given in Table I. The values of $B_1^i$ and $C_1^i$ can be similarly calculated as in Equation (4). In the reasoning stage, these membership values for each input are multiplied by the adjustment parameters described as "d" term in Table I and Figure 2.

TABLE II. THE MEASURED VOLTAGE VALUES FOR DIFFERENT GLUCOSE CONCENTRATIONS

| Glucose Concentration (%) | Red (R) (volts) | Green (G) (volts) | Blue (B) (volts) |
|---|---|---|---|
| 0.10 | 0.39 | 0.89 | 1.01 |
| 0.20 | 0.48 | 1.13 | 1.47 |
| 0.30 | 0.46 | 1.23 | 1.49 |
| 0.50 | 0.54 | 1.53 | 2.08 |
| 0.65 | 0.55 | 1.60 | 2.23 |
| 0.80 | 0.54 | 1.58 | 2.12 |
| 0.90 | 0.63 | 1.92 | 2.59 |
| 1.00 | 0.57 | 1.69 | 2.26 |
| 1.25 | 0.64 | 2.02 | 2.72 |
| 1.50 | 0.65 | 1.92 | 2.57 |
| 1.75 | 0.61 | 1.85 | 2.56 |
| 2.00 | 0.61 | 1.95 | 2.70 |
| 2.25 | 0.61 | 1.89 | 2.59 |
| 2.50 | 0.60 | 1.78 | 2.45 |
| 5.00 | 0.75 | 2.31 | 3.03 |

As mentioned earlier, because the fuzzy models used in this work have 3 inputs and 1 output, the number of the parameters optimized by the ABC algorithm for a rule is 13. To improve the algorithm and model efficiency, normalization intervals for the variables of inputs (R, G, B) and output (glucose concentration ratio) are selected in order of [0.25, 0.85], [0.75, 2.45], [0.85, 3.25], and [0.05, 5.5], respectively as input data coding.

Because there is no systematic and efficient procedure for choosing the most appropriate rule number, different rule numbers such as 2, 3, 4 and 5 are used for fuzzy models in this study.

***(d) inference mechanism:*** In this paper, two fuzzy reasoning mechanisms are tested in the modeling of a glucose concentration process given in the literature. These are singleton and Sugeno type inference mechanisms which are shown in Figure 2 as notation of Z*. In here, $\mu_1(x)$ and $\mu_1(y)$ are the membership values for x and y inputs, respectively.

To evaluate the performance of the fuzzy models, MSE performance criterion is used in this study [20, 24, 25]. The MSE is calculated from N data point as

$$MSE = \frac{1}{N}\sum_{k=1}^{N}(O_k^d - O_k)^2 \quad (5)$$

where $O_k^d$ (k=1,……,$N$) are actual (real) output values obtained by the experimental setup (Figure 1), and $O_k$ (k=1,……,$N$) are the model outputs obtained by the fuzzy models proposed in this work. Note that $O_k^d$ and $O_k$ are percentage concentrations of the glucose provided by the measurement procedure and the fuzzy models, respectively.

***(e) optimization method:*** The parameters of the fuzzy models are optimized by using the ABC algorithm. In the solution of the modeling problem, ABC algorithm based fuzzy models with different number of rules such as 2, 3, 4, and 5 are tried for different maximum cycles as 1000 and 2000. The size of maximum cycles is also *ending criterion* of the algorithm. Optimization procedure is repeated for colony sizes of 30 and 40. The number of the parameters optimized for the rules of 2, 3, 4 and 5 are 26, 39, 52 and 65, respectively. Thus, according to definition of [(colony size÷2) × number of the parameters], the values of the limit parameters in the studies for colony size of 30 are used as 390, 585, 780 and 975, respectively again. When the colony size is 40, these values are obtained as 520, 780, 1040 and 1300, respectively.

In the first step of the algorithm, a fuzzy model parameter set which has the number of solution elements of (rule number × 13) is randomly produced in a predetermined search interval selected as [0-1]. The output of the fuzzy model is obtained by using the experimental inputs. The MSE values are calculated by the differences between the actual and model outputs. A new population is composed by operating the procedures of the ABC algorithm. Until the parameter set having minimum MSE value is obtained, this searching is continued (the detailed information about the algorithm can be obtained by the link of *http://mf.erciyes.edu.tr/abc/*).

The main purpose of the ABC algorithm is to obtain the best model performance as soon as possible by using the minimum rules. This paper presents the best results of these studies which were repeated 30 times for each of the different conditions. In the simulations, the Matlab® programming package and Intel Pentium 2800MHz computers are used.

## IV. RESULTS OF THE FUZZY MODELS

The minimum MSE values for TS and singleton type fuzzy models having different rule numbers are presented in Table III.

TABLE III. MINIMUM MSE VALUES FOR DIFFERENT FUZZY MODELS WITH DIFFERENT RULE NUMBERS

| Rules | Fuzzy Model | ABC | | | |
|---|---|---|---|---|---|
| | | Colony Size=30 | | Colony Size=40 | |
| | | Maximum Cycle | | Maximum Cycle | |
| | | 1000 | 2000 | 1000 | 2000 |
| 2 | **Sugeno** | 0.0722 | 0.0672 | 0.0740 | 0.0646 |
| | **Singleton** | 0.0079 | 0.0103 | 0.0103 | 0.0084 |
| 3 | **Sugeno** | 0.0365 | 0.0171 | 0.0207 | 0.0157 |
| | **Singleton** | 0.0064 | **0.0013** | 0.0054 | 0.0030 |
| 4 | **Sugeno** | 0.0418 | 0.0311 | 0.0210 | 0.0211 |
| | **Singleton** | 0.0026 | 0.0030 | 0.0037 | 0.0017 |
| 5 | **Sugeno** | 0.0261 | 0.0110 | 0.0190 | **0.0108** |
| | **Singleton** | 0.0048 | 0.0015 | 0.0039 | **0.0016** |

It can be seen from Table III, singleton type models have obvious performance superiority compared to the TS type models. Minimum MSE value is obtained from 3-rules singleton model as 0.0013 in colony size of 30. Another remarkable minimum MSE value closest to that value is presented again by a singleton model with 5 rules as 0.0016, when the colony size is 40. On the other hand, the error value of the 5-rules Sugeno model is 0.0108 for colony size of 40. After 30 runs of the ABC algorithm, the standard deviation values for the singleton models presenting the best

MSE values of 0.0013 and 0.0016 in colony sizes of 30 and 40 are noted as 0.0045 and 0.0029, respectively (the program source code for the singleton model can be obtained from the link of *https://yadi.sk/i/Zo_uzgKktDjHG* or corresponding author via electronic mail).

These results clearly demonstrate the effectiveness of the ABC algorithm and the power of the singleton type fuzzy models. Figure 4 graphically compares the outputs of the best TS and singleton fuzzy models. A detailed list of the results including the error values for each calculation of the fuzzy models as percentage is given in Table IV. The convergence rates of the algorithm for 3 and 5 rules singleton fuzzy models are given in Figure 5 as cycle-MSE variation. This figure clearly shows that the most striking reduction in the MSE occurs in the first 100 cycles. Thus, to improve the model performance, algorithm can provide a fast convergence in a short time.

The normalized rule parameters of the best fuzzy model with minimum MSE value of 0.0013 are also given in Table V. Because the type of best model is a singleton structure with three rules, the number of the parameters optimized for three inputs and one output is 39.

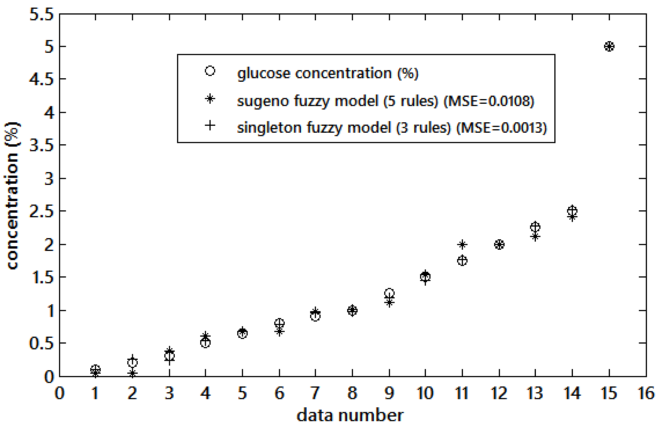


Figure 4. The outputs of fuzzy models and measured concentration ratio

TABLE IV. A DETAILED COMPARISON OF THE FUZZY MODEL RESULTS

| G.C. (%) | ABC Based Fuzzy Models | | | | | |
|---|---|---|---|---|---|---|
| | Sugeno (5 rules) | Error (%) | Singleton (3 rules) | Error (%) | Singleton (5 rules) | Error (%) |
| 0.1000 | 0.0500 | 50.00 | 0.0911 | 8.90 | 0.0958 | 4.20 |
| 0.2000 | 0.0500 | 75.00 | 0.2580 | 29.00 | 0.2065 | 3.25 |
| 0.3000 | 0.3814 | 27.13 | 0.2332 | 22.27 | 0.2990 | 0.33 |
| 0.5000 | 0.6067 | 21.34 | 0.5345 | 6.90 | 0.4931 | 1.38 |
| 0.6500 | 0.6702 | 3.11 | 0.6692 | 2.95 | 0.6806 | 4.71 |
| 0.8000 | 0.6699 | 16.26 | 0.7874 | 1.58 | 0.7981 | 0.24 |
| 0.9000 | 0.9681 | 7.57 | 0.9608 | 6.76 | 0.9893 | 9.92 |
| 1.0000 | 1.0022 | 0.22 | 0.9806 | 1.94 | 0.9972 | 0.28 |
| 1.2500 | 1.1160 | 10.72 | 1.1926 | 4.59 | 1.2899 | 3.19 |
| 1.5000 | 1.5331 | 2.21 | 1.4554 | 2.97 | 1.4032 | 6.45 |
| 1.7500 | 1.9862 | 13.49 | 1.7585 | 0.49 | 1.7729 | 1.31 |
| 2.0000 | 1.9931 | 0.35 | 2.0014 | 0.07 | 1.9733 | 1.34 |
| 2.2500 | 2.1233 | 5.63 | 2.2720 | 0.98 | 2.2562 | 0.28 |
| 2.5000 | 2.4225 | 3.10 | 2.5161 | 0.64 | 2.5134 | 0.54 |
| 5.0000 | 4.9985 | 0.03 | 5.0038 | 0.08 | 4.9493 | 1.01 |
| **MSE** | **0.0108** | -- | **0.0013** | -- | **0.0016** | -- |

G.C.: Glucose Concentration

The simulation results demonstrate that there is a good agreement between the singleton type fuzzy models and the outputs. Although the errors between the target concentrations and calculated results are not zero, these indicate a comparable model performance. Moreover, a modeling procedure based on the use of the ABC algorithm can allow us to design more accurate fuzzy models for highly nonlinear or complex data sets. One important advantage of the method presented in this study is that an efficient modeling performance can be achieved by fewer rules optimized by the ABC algorithm.

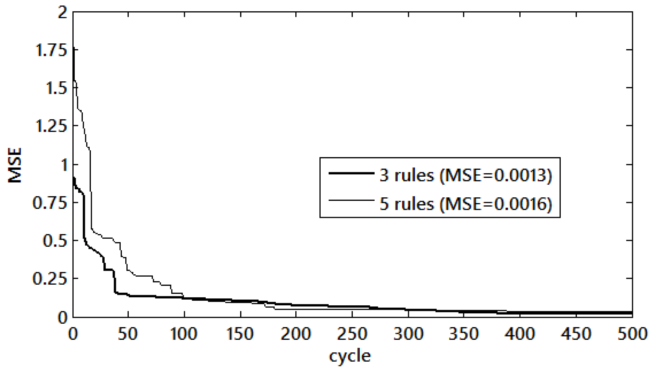


Figure 5. Cycle-MSE variation of the singleton fuzzy models with minimum error for first 500 cycles (MSE values are calculated in terms of percentage concentrations)

TABLE V. NORMALIZED RULE PARAMETERS FOR SINGLETON TYPE BEST FUZZY MODEL WITH 3 RULES

| *input 1 (x)* | *input 2 (y)* | *input 3 (t)* |
|---|---|---|
| 0.3969 0.4114 0.8581 | 0.4835 0.5805 0.6103 | 0.5101 0.6459 0.7107 |
| 0.3611 0.4393 0.4759 | 0.6882 0.7209 0.9142 | 0.0963 0.5295 0.8539 |
| 0.6090 0.6274 0.6816 | 0.0000 0.4316 0.6546 | 0.5378 0.5738 0.6394 |
| ***Output (Z)*** | ***adjustment parameters*** | ***Rules*** |
| 0.9090 | 0.0453 0.0719 0.2877 | → Rule 1 |
| 0.2314 | 0.0000 0.1221 0.1871 | → Rule 2 |
| 0.0075 | 0.1525 0.8527 1.0000 | → Rule 3 |

## V. CONCLUSION

This paper presents the results of a study about the fuzzy logic based modeling of the glucose values obtained from the measured voltages for a given concentration. The experimental data set employed in the modeling procedure is provided by an optical sensor that acts as a discrete wavelength spectrophotometer working in visible region for the measurement of *in vitro* glucose concentration in an aqueous solution. The sensor uses an RGB LED as the source and produces corresponding voltages on the LDR related with the absorbance. The parameters of the fuzzy models proposed are optimized by the ABC algorithm. Simulation studies demonstrate that the computational requirements can be significantly eliminated by using the ABC algorithm based fuzzy logic models. Moreover, these impressive and motivating results encourage us to design of the robust optical measurement systems.

## REFERENCES

[1] G.A. Bray, "Energy and fructose from beverages sweetened with sugar or high-fructose corn syrup pose a health risk for some people", Advances in Nutrition: An International Review Journal, 4(2), pp.220-225, 2013. doi: 10.3945/an.112.002816

[2] L.D. Mello, L.T. Kubota, "Review of the use of biosensors as analytical tools in the food and drink industries", Food Chemistry, 77(2), pp.237-256, 2002. doi: 10.1016/S0308-8146(02)00104-8

[3] S.F. Clarke, J.R. Foster, "A history of blood glucose meters and their role in self-monitoring of diabetes mellitus", British Journal of

Biomedical Science, 69(2), pp.83-93, 2012. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/22872934

[4] A. Arnoldi (Ed.). "Functional Foods, Cardiovascular Disease and Diabetes", pp.19-55, Elsevier, 2004.

[5] D.A. Stuart, J.M. Yuen, N. Shah, O. Lyandres, C.R. Yonzon, M.R. Glucksberg, J.T. Walsh, R.P. Van Duyne, "In Vivo Glucose Measurement by Surface-Enhanced Raman Spectroscopy", Analytical Chemistry, 78(20), pp.7211-7215, 2006. doi: 10.1021/ac061238u

[6] D. Chen, C. Wang, W. Chen, Y. Chen, J.X. Zhang, "PVDF-Nafion Nanomembranes Coated Microneedles for in Vivo Transcutaneous Implantable Glucose Sensing", Biosensors and Bioelectronics, 74, pp. 1047-1052, 2015. doi: 10.1016/ j.bios.2015.07.036

[7] L.B. Mohammadi, T. Klotzbuecher, S. Sigloch, K. Welzel, M. Goeddel, T.R. Pieber, L. Schaupp, L., "Clinical Performance of A Low Cost Near Infrared Sensor for Continuous Glucose Monitoring Applied with Subcutaneous Microdialysis", Biomedical Microdevices, 17(4), pp.1-10, 2015. doi: 10.1007/s10544-015-9983-4

[8] D. Li, Y. Sun, S. Yu, C. Sun, H. Yu, K. Xu, "A Single-Loop Fiber Attenuated Total Reflection Sensor Enhanced by Silver Nanoparticles for Continuous Glucose Monitoring". Sensors and Actuators B: Chemical, 220, pp.1033-1042, 2015. doi: 10.1016/j.snb.2015.06.028

[9] P.U. Abel, T. von Woedtke, "Biosensors for In Vivo Glucose Measurement: Can We Cross The Experimental Stage", Biosensors and Bioelectronics, 17(11), pp. 1059-1070, 2002. doi: 10.1016/S0956-5663(02)00099-4

[10] G.S. Wilson, R. Gifford, "Biosensors for Real-Time In Vivo Measurements", Biosensors and Bioelectronics, 20(12), pp. 2388-2403, 2005. doi: 10.1016/j.bios.2004.12.003

[11] H.E. Koschwanez, W.M. Reichert, "In Vitro, In Vivo and Post Explantation Testing of Glucose-Detecting Biosensors: Current Methods and Recommendations", Biomaterials, 28(25), pp.3687-3703, 2007. doi: 10.1016/j.biomaterials. 2007.03.034

[12] S. Yu, D. Li, H. Chong, C. Sun, H. Yu, K. Xu, "In Vitro Glucose Measurement Using Tunable Mid-Infrared Laser Spectroscopy Combined with Fiber-Optic Sensor", Biomedical Optics Express, 5(1), pp.275-286, 2014. doi: 10.1364/ BOE.5.000275

[13] J.C. Pickup, F. Hussain, N.D. Evans, N. Sachedina, "In Vivo Glucose Monitoring: The Clinical Reality and The Promise", Biosensors and Bioelectronics, 20(10), pp. 1897-1902, 2005. doi: 10.1016/j.bios.2004.08.016

[14] D. Li, J. Wu, P. Wu, Y. Lin, Y. Sun, R. Zhu, J. Yang, K. Xu, "Affinity based Glucose Measurement using Fiber Optic Surface Plasmon Resonance Sensor with Surface Modification by Borate Polymer", Sensors and Actuators B: Chemical, 213, pp. 295-304, 2015. doi: 10.1016/j.snb.2015.02.039

[15] S. Singh, B.D. Gupta, "Fabrication and Characterization of A Surface Plasmon Resonance based Fiber Optic Sensor using Gel Entrapment Technique for The Detection of Low Glucose Concentration", Sensors and Actuators B: Chemical, 177, pp.589-595, 2013. doi: 10.1016/j.snb.2012.11.094

[16] B. Nacht, C. Larndorfer, S. Sax, S.M. Borisov, M. Hajnsek, F. Sinner, E.J.W. List-Kratochvil, I. Klimant, "Integrated Catheter System for Continuous Glucose Measurement and Simultaneous Insulin Infusion", Biosensors and Bioelectronics, 64, pp.102-110, 2015. doi: 10.1016/j.bios.2014.08.012

[17] P. Squara, M. Imhoff, M. Cecconi, "Review Article: Metrology in Medicine: From Measurements to Decision, with Specific Reference to Anesthesia and Intensive Care", Anesthesia and Analgesia, 120(1), pp.66-75, 2015. doi: 10.1213/ANE.0000000000000477

[18] T.J. Ross, "Fuzzy Logic with Engineering Applications", pp.476-536, McGrawHill, 1995.

[19] H.T. Nguyen, M. Sugeno, "Fuzzy Systems: Modeling and Control", pp.63-90, Kluwer Academic Publishers, 1998.

[20] A.Bagis, "Fuzzy Rule Base Design using Tabu Search Algorithm for Nonlinear System Modeling", ISA Transactions, 47(1), pp.32–44, 2008. doi: 10.1016/j.isatra. 2007.09.001

[21] A. Bagis, M. Konar, "Comparison of Sugeno and Mamdani Fuzzy Models Optimized by Artificial Bee Colony Algorithm for Nonlinear System Modelling", Transactions of the Institute of Measurement and Control,38(5), pp.579-592, 2016. doi: 10.1177/0142331215591239

[22] M.Konar, A. Bagis, "Performance Comparison of Particle Optimization, Differential Evolution and Artificial Bee Colony Algorithms for Fuzzy Modelling of Nonlinear Systems (Accepted for publication)", Elektronika IR Elektrotechnika, 2016, to be published.

[23] H. Du, N. Zhang, "Application of Evolving Takagi–Sugeno Fuzzy Model to Nonlinear System Identification", Applied Soft Computing, vol.8, pp.676–686, 2008. doi: 10.1016/j.asoc.2007.05.006

[24] A. Evsukoff, A.C.S. Branco, S. Galichet, "Structure Identification and Parameter Optimization for Non-Linear Fuzzy Modeling", Fuzzy Sets and Systems, vol.132, pp.173–188, 2002. doi: 10.1016/S0165-0114(02)00111-2

[25] W.A. Farag, V.H. Quintana, G.L. Torres, "A Genetic based Neuro-Fuzzy Approach for Modeling and Control of Dynamical Systems", IEEE Trans. Neural Netw., 9(5), pp.756–767, 1998. doi: 10.1109/72.712150

[26] K. Guney, N. Sarikaya, "Comparison of Mamdani and Sugeno Fuzzy Inference System Models for Resonant Frequency Calculation of Rectangular Microstrip Antennas", Progress In Electromagnetics Research B, vol.12, pp.81–104, 2009. doi: 10.2528/PIERB08121302

[27] S-J. Kang, C-H. Woo, H-S. Hwang, K.B. Woo, "Evolutionary Design of Fuzzy Rule Base for Nonlinear Systems Modeling and Control", IEEE Transactions on Fuzzy Systems, (8)1, pp.37-45, 2000. doi: 10.1109/91.824766

[28] T. Takagi, M. Sugeno, "Fuzzy Identification of Systems and Its Applications to Modeling and Control", IEEE Transactions on Systems, Man, and Cybernetics, vol.15, pp.116-132, 1985. doi: 10.1109/TSMC.1985.6313399

[29] R.M. Tong, "The Evaluation of Fuzzy Models Derived from Experimental Data", Fuzzy Sets and Systems, vol.4, pp.1–12, 1980. doi: 10.1016/0165-0114(80)90059-7

[30] L. Wang, R. Langari, "Complex Systems Modeling via Fuzzy Logic", IEEE Trans. Syst. Man Cybern-Part B: Cybern, 26(1), pp.100–106, 1996. doi: 10.1109/3477.484441

[31] J.R. Jang , C. Sun, E. Mizutani, "Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence", pp.333-368, Prentice-Hall, Inc., 1997.

[32] F. Kulic, D. Matic, B. Dumnic, V. Vasic, "Optimal Fuzzy Controller Tuned by TV-PSO for Induction Motor Speed Control", Advances in Electrical and Computer Engineering, 11(1), pp.49-54, 2011. doi: 10.4316/AECE.2011.01008

[33] R.E. Precup, R.C. David, E.M. Petriu, S. Preitl, M.B. Radac, "Fuzzy Logic based Adaptive Gravitational Search Algorithm for Optimal Tuning of Fuzzy-Controlled Servo Systems", IET Control Theory Appl., 7(1), pp.99-107, 2013. doi: 10.1049/iet-cta.2012.0343

[34] M.J. Gacto, M. Galende, R. Alcala, F. Herrera, "METSK-HDe: A Multiobjective Evolutionary Algorithm to Learn Accurate TSK-Fuzzy Systems in High-Dimensional and Large-Scale Regression Problems, Information Sciences, 276, pp. 63-79, 2014. doi: 10.1016/j.ins.2014.02.047

[35] D. Karaboga, "An idea based on honey bee swarm for numerical optimization", Technical Report-TR06, Erciyes University, Engineering Faculty, Computer Engineering Department, 2005.

[36] D. Karaboga, B. Akay, "A Powerful and Efficient Algorithm for Numerical Function Optimization: Artificial Bee Colony (ABC) Algorithm", Journal of Global Optimization, vol.39, pp.459-471, 2007. doi: 10.1007/s10898-007-9149-x

[37] D. Karaboga, B. Akay, "A Comparative Study of Artificial Bee Colony Algorithm", Applied Mathematics and Computation, vol.214, pp.108-132, 2009. doi: 10.1016/ j.amc.2009.03.090

[38] D. Karaboğa, C. Öztürk, "A Novel Clustering Approach: Artificial Bee Colony (ABC) Algorithm", Applied Soft Computing, 11(1), pp.652–657, 2011. doi: 10.1016/ j.asoc.2009.12.025

[39] A. Kulanthaisamy, R. Vairamani, N.K. Karunamurthi, C. Koodalsamy, "A Multi-Objective PMU Placement Method Considering Observability and Measurement Redundancy using ABC Algorithm", Advances in Electrical and Computer Engineering, 14(2), pp.117-128, 2014. doi: 10.4316/AECE.2014.02020

[40] T.E. Tabaru, Ö.G. Saracoglu, E. Aslan, "Optical absorbance measurement of glucose in aqueous solution by using an RGB based simple spectrophotometer", Cankaya University 7th Engineering and Technology Symposium, May 15-16, 2014, pp. 219-223, Ankara, Turkey (in Turkish).