

Research Article

# Artificial Neural Network-CFD Model to Predict the Bio Production Rate of High Fructose Date Syrup

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## Abstract

Many parameters involved in the bioproduction of fructose from date. These parameters can have significant effects on the yield and quality of the bioproduction of the high fructose date syrup (HFDS); they can be determined by either empirical or numerical investigations for the selected configurations; however, they are expensive procedures. The problem becomes more difficult if the aim is the inverse determination of the operating production process. This paper presents a predictive hybrid model based on the artificial neural networks (ANNs) and finite element method (FEM) that can be used for both forward and inverse prediction. The former is able to determine the diffusion rate, the bioconversion rate and the Fructose % at varying of process parameters, namely the date variety, the speeds of agitation, the date/water ratio, the initial concentration of glucose, the inoculum volume of biomass and the induction time of bioconversion process. The optimal ANN model was found to be a network with two hidden layers and nine neurones in each hidden layer for forward prediction and eleven neurones in each hidden layers for inverse prediction. Prediction errors range between 4% and 5% for the whole data set, both for forward analysis and inverse process design. The results show very good agreement between the predicted and the desired values.

**Keywords:** HFDS, hybrid approach, ANN, FEM.

## 1. Introduction

Fructose is the sweetest naturally occurring sugar and is preferred by industrial since it is estimated to be twice as sweet as sucrose. Fructose is industrially commercialized as a high fructose syrup HFS from corn. Since the fructose is a natural component of date, the High fructose syrup can be produced from date instead of corn. This process is composed essentially by two steps: a) the diffusion of sugar from date pulp, b) the bioconversion of glucose to fructose.

Many parameters involved in the diffusion process of sugar from date such as variety of date, temperature, flow rate, agitation and process applied. In addition the performance of the bioconversion process can be affected by many others parameters such as initial concentration of glucose in date's syrup volume, period incubation and inoculum volume for the bioconversion rate of glucose. Consequently, the yield of fructose production from date depends on all these parameters. Several researchers have experimentally investigated these relationships (Gabsi, *et al*, 2013), (Trigui, *et al*, 2015).

However, empirical and numerical models are not suitable for both the prediction of fructose production and the inverse process design. On the other hand, around the 1990s, the development of the artificial intelligence based models supplied a new way for approaching the analysis of processes. The point of strength consisted in the possibility to model some input-output relations without a proper knowledge of the involved phenomena. This availability, of course, increases the analysis efficiency both in the process investigation and optimization.

Today a very interesting challenge derives from the coupling of different classes on analysis tools, generating the so called hybrid-models. Among them, the ones based on the use of the finite element method and the artificial neural networks seem to be one of the most promising for the effective analysis of process (Zuperl, *et al*, 2004), (Jawahir, *et al*, 2003), (Jawahir and Wang, 2007).

Numerical simulation, in fact, is intrinsically able to supply a large quantity of information related to the process, calculating several variables. If the designer can be confident of the prediction accuracy, simulation data can be properly related and generalized using a proper ANN, exalting the analysis capability of the FE method.

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In this paper, just this approach has been pursued. The objective of this research was, therefore, to use artificial neural network concepts for dynamic modeling of the high fructose date syrup(HFDS) production process both for forward predictions and inverse process design.

**2. Methodology**

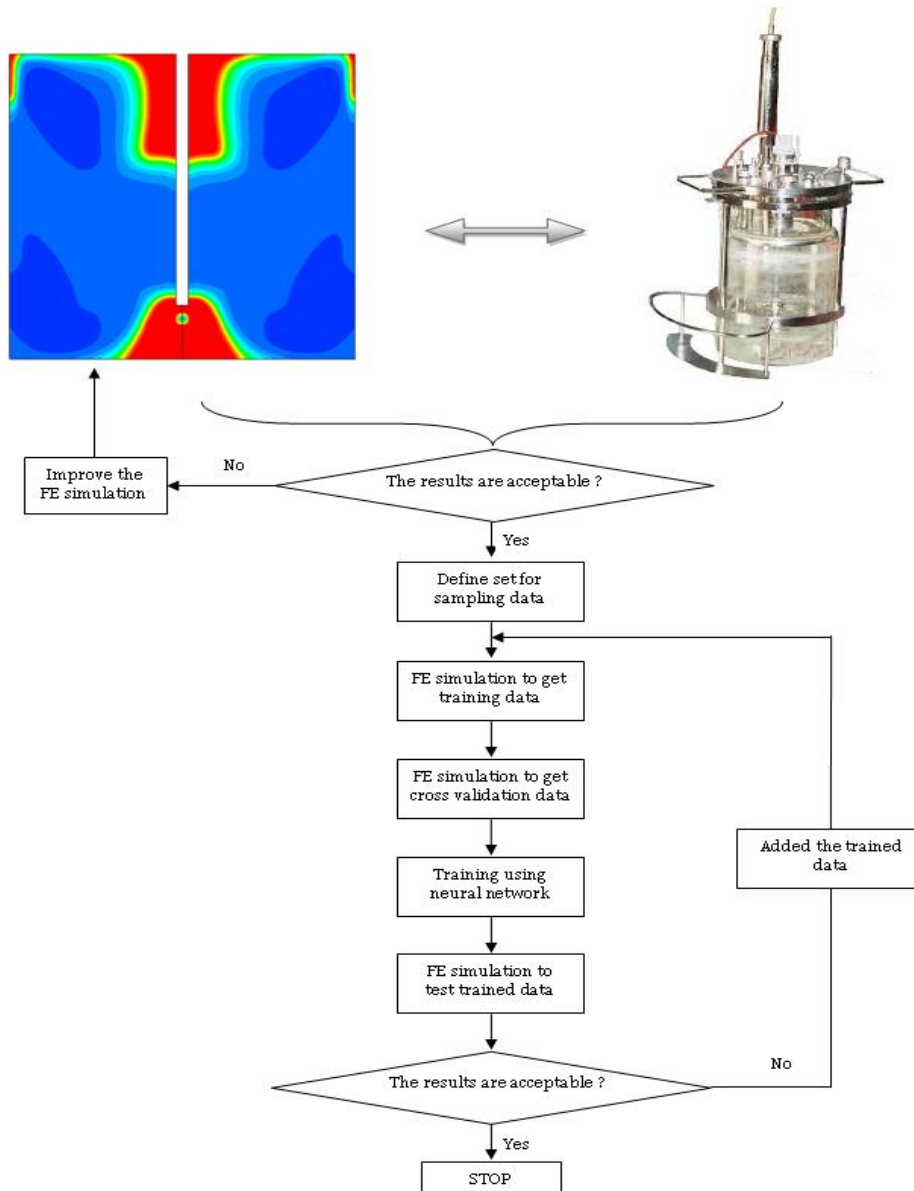
*2.1 ANN-FEM approach*

The main drawback of ANNs is the need of large data set for training and validation effort. Thus, in this study a FEM-ANN (finite element method-artificial neural network) hybrid technique is used to generate a reasonable data set which permits to avoid the expensive and time consuming experimental tests. The ANN training methodology proposed in this paper is sketched in Fig. 1.

*2.2 Data generation: numerical investigation*

Two consistent finite element (FE) models were previously developed and validated. The first one is developed to predict diffused date syrup yield and quality from sugar production process (Gabsi, et al, 2013). The extraction process of sugar from date viewed as transport through porous media since the date structure has diameter less than  $10^{-7}$  m pores. The two phases are counter current The Eulerian two-phase model was used to model sugar-water flow.

The second is developed to predict the bioconversion rate of glucose to fructose using *Escherichia coli K12* for sugar production from Date syrup (Trigui, et al, 2015). The kinetics of fructose formation was based on the Luedeking–Piret equations. These models use an Eulerian–Eulerian approach to calculate the date volume fraction transferred during time from date.

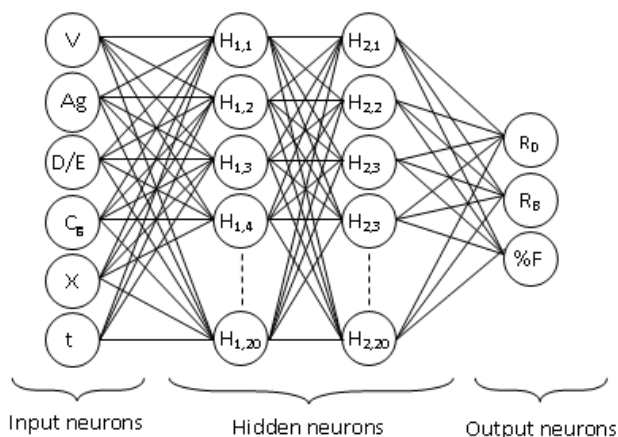


**Fig.1** Organisation chart of the proposed approach

### 2.3 ANN model framework

#### Forward prediction

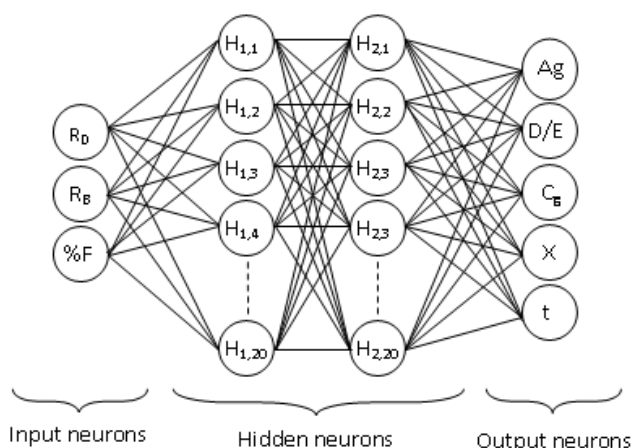
To predict the diffusion rate ( $R_D$ ), the bioconversion rate ( $R_B$ ) and the Fructose %, The ANN was trained at varying of process parameters, namely the date variety ( $V$ ), the speeds of agitation ( $Ag$ ), the date/water ratio ( $D/E$ ), the initial concentration of glucose ( $C_G$ ), the inoculum volume of biomass ( $X$ ) and the induction time of bioconversion process ( $t$ ) (Fig.2).



**Fig.2** Structure of the utilized neural network for forward prediction

#### Inverse prediction

Neural network was also utilized for performing the very interesting phase of the inverse process design. The input data set consisted of three neurons: Diffusion rate, bioconversion rate and % of fructose. The output data set contained five neurons representing the speeds of agitation, the date/water ratio, the initial concentration of glucose, the induction time of bioconversion process and the inoculum volume of biomass (Fig.3).



**Fig.3** Structure of the utilized neural network for inverse process design

#### 2.3.1 Neural network selection

An artificial neural network (ANN) is a computational structure inspired by biological neural systems (Neurosolutions, 2006). Among the many neural network models proposed, the NeuroSolutions commercial software was used to develop the ANN model and more specifically, the multilayer perceptrons networks (MLPs) was selected. MLPs are layered feedforward networks typically trained with static backpropagation. These networks have found their way into countless applications requiring static pattern classification. Their main advantage is that they are easy to use, and that they can approximate any input/output map (Neurosolutions, 2006).

To select the number of hidden layers and the number of processing elements (neurons) in the hidden layers, a trial and error procedure is conducted to reach the required behaviour. In the present study, the ranges of settings for the main configuration parameters are shown in Table 1. The optimal configuration was found using 1 and 2 hidden layers, with a range of 1 to 20 neurons in each hidden layers, and 1000-10000 learning runs.

**Table 1** Main configuration parameters and their levels of neural networks models

Factors	Levels
Learning rule	Momentum
Transfer	TanH Sigmoid
Number of hidden layer	1 and 2
Number of neurons	2to20
Learning runs	1000 to 10000

#### 2.3.2 Training

Once the ANN architecture was defined, the training was initiated and repeated several times to get the best performance (Ochoa-Martinez and Ayala-Aponte, 2006). Training of neural network models requires a lot of data. A central composite unblocked full design method was used in this study to construct the data for training ANN while central composite unblocked half design was used for cross validation of trained ANN models and a Box-Behnken unblocked design was used for testing of trained ANN models. The training, cross validating and testing of the model used 90, 53, and 54 data points, respectively. Cross validation is highly recommended to stop network training because it monitors the error using an independent set of data and stops the training when this error begins to increase. This is considered to be the point of best generalization.

The model weights are frozen once the network is trained and the testing set is fed into the network to compare its output with the desired output (Neurosolutions, 2006). The error minimization process is achieved using the momentum rule, which is an improvement as compare to the straight gradient

descent since a memory term (the past increment to the weight) is used to speed up the process and stabilize convergence.

### 2.4 Selection of Optimal Configuration

For each specified problem, the following neural network parameters must be optimized: number of hidden layers, number of neurons in each hidden layer, and number of learning runs. The optimum configuration was decided based on minimizing the difference between the neural network and the desired outputs.

The performance of the various ANN configurations were compared using: the mean squared error (*MSE*) and the % Error; the Akaike information criterion (*AIC*) which measures the trade-off between training performance and network size, and; the *MDL* criterion (minimum description length) which is similar to the *AIC* in that it tries to combine the model's error with the number of degrees of freedom to determine the level of generalization? The goal is to minimize respectively the *ACI* and *MDL* terms to produce a network with the best generalization. The coefficient of determination,  $R^2$ , of the linear regression line between the values predicted by the neural network model and the desired output was also used as a measure of performance. The *MSE*, *AIC*, *MDL* and  $R^2$  equations used to compare the performance of various ANN configurations are:

$$MSE = \frac{1}{n} \sum_{i=1}^n (C_D - C_P)^2 \tag{1}$$

$$AIC(k) = n \log(MSE) + 2k \tag{2}$$

$$MDL(k) = n \log(MSE) + 0.5k \log(n) \tag{3}$$

$$R^2 = \frac{RSS}{TSS} \tag{4}$$

where  $n$  is the number of exemplars of the training set,  $C_D$  and  $C_P$  are the desired and predicted values of sugar concentration, respectively and  $k$  is the number of network weights. The coefficients *RSS* and *TSS* represent the regression sum of squares and the total sum of squares, and are defined respectively as:

$$RSS = \sum_{i=1}^n (f_i - \bar{f})^2 \tag{5}$$

$$TSS = \sum_{i=1}^n (Y_i - \bar{Y})^2 \tag{6}$$

where  $\bar{f}$  and  $\bar{Y}$  are the means of the observed data ( $Y_i$ ) and predicted values ( $f_i$ ) respectively.

Please note that the properties of the equations must not be locked

## 3. Results and discussions

### 3.1 Artificial Neural Network Performance for forward prediction

The ANN model was tested and developed to predict the diffusion rate, the bioconversion rate and the % of Fructose as a function date varieties, the speeds of agitation, the date/water ratio, the initial

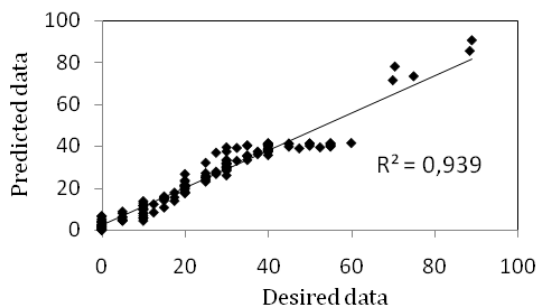
**Table 2** Performances of various ANN configurations once trained with the data set, for the neural network for forward prediction

Run	Hidden layer (HL)	Processing elements (PEs) in each HL	Transfer	MSE	R <sup>2</sup>	% error	AIC	MDL
1	1	2	TanH	0.4539	0.0183	66.4344	65.4655	49.5145
2	1	3	TanH	0.3044	0.3822	50.5309	7.0783	0.0302
3	1	4	TanH	0.9117	0.1302	138.9401	107.5978	87.1954
4	1	5	TanH	0.8973	0.2157	137.9937	59.1840	47.6845
5	1	6	TanH	0.9117	0.0166	138.9382	95.5969	77.4202
6	1	7	TanH	0.8784	0.0754	136.6238	34.6295	27.5814
7	1	8	TanH	0.4330	0.3717	61.6344	76.2441	58.0675
8	1	9	TanH	0.8196	0.1041	130.7882	140.8289	113.7491
9	1	10	TanH	0.5273	0.3248	65.7626	81.1839	63.0072
10	1	11	TanH	1.0540	0.0676	97.7968	255.3675	208.2567
11	1	12	TanH	0.9113	0.5538	138.9134	83.5865	67.6650
12	1	13	TanH	0.6384	0.0377	113.2734	170.3315	136.5749
13	1	14	TanH	1.0655	0.1120	94.3371	39.6509	32.6028
14	1	15	TanH	0.4450	0.0592	51.7342	16.9490	9.9009
15	1	16	TanH	0.2583	0.0161	62.4845	2.8117	-4.2363
16	1	17	TanH	0.8075	0.0949	131.5248	20.4422	15.6198
17	1	18	TanH	0.8119	0.1327	96.8781	272.5831	221.0208
18	1	19	TanH	0.8946	0.2942	137.8106	107.1052	86.7029
19	1	20	TanH	0.3375	0.3793	53.0577	9.7656	2.7175
20	1	2	Sigmoid	0.0345	0.3340	56.6144	202.4864	148.6984

21	1	3	<i>Sigmoid</i>	0.0325	0.2587	53.2451	20.9261	0.5230
22	1	4	<i>Sigmoid</i>	0.0424	0.1680	60.3758	87.8848	56.3539
23	1	5	<i>Sigmoid</i>	0.0338	0.3562	56.1826	213.9785	157.9648
24	1	6	<i>Sigmoid</i>	0.0643	0.0559	74.3943	170.6840	125.7990
25	1	7	<i>Sigmoid</i>	0.0343	0.2470	54.2966	166.2875	119.1766
26	1	8	<i>Sigmoid</i>	0.0400	0.1930	59.2321	218.2849	162.2712
27	1	9	<i>Sigmoid</i>	0.0361	0.2840	55.6015	215.6516	159.6370
28	1	10	<i>Sigmoid</i>	0.0303	0.3229	52.4751	199.0788	145.2908
29	1	11	<i>Sigmoid</i>	0.0357	0.2963	55.5978	203.3687	149.5807
30	1	12	<i>Sigmoid</i>	0.0749	0.0508	79.6115	210.6176	159.0553
31	1	13	<i>Sigmoid</i>	0.0334	0.2910	53.9959	-38.3058	-47.5796
32	1	14	<i>Sigmoid</i>	0.0382	0.2754	57.9884	205.1133	151.3253
33	1	15	<i>Sigmoid</i>	0.0518	0.1688	66.3100	-50.9543	-55.7766
34	1	16	<i>Sigmoid</i>	0.0373	0.2125	57.3789	216.5135	160.4998
35	1	17	<i>Sigmoid</i>	0.0401	0.2554	59.0692	206.3828	152.5948
36	1	18	<i>Sigmoid</i>	0.0302	0.3496	53.1685	163.0167	115.9058
37	1	19	<i>Sigmoid</i>	0.0684	0.1041	76.3153	28.2651	10.0884
38	1	20	<i>Sigmoid</i>	0.0357	0.3216	56.6196	203.3183	149.5303
39	2	2	<i>TanH</i>	1.0093	0.5217	445.7711	222.1198	142.4744
40	2	3	<i>TanH</i>	1.0148	0.7614	447.4610	398.1913	255.4038
41	2	4	<i>TanH</i>	1.0258	0.4041	458.7958	158.3321	101.6476
42	2	5	<i>TanH</i>	1.7795	0.4876	83.5621	238.0345	117.8702
43	2	6	<i>TanH</i>	1.0248	0.4138	473.0001	334.5456	214.7189
44	2	7	<i>TanH</i>	2.0530	0.0027	89.1945	611.0352	299.8405
45	2	8	<i>TanH</i>	0.9665	0.7210	440.1591	749.5576	480.4857
46	2	9	<b>TanH</b>	<b>0.0672</b>	<b>0.9748</b>	<b>4.53917</b>	<b>219.5665</b>	<b>140.6388</b>
47	2	10	<i>TanH</i>	0.9614	0.1229	426.2375	341.4881	218.7912
48	2	11	<i>TanH</i>	1.8872	0.4744	85.6787	166.4458	83.2551
49	2	12	<i>TanH</i>	0.8591	0.8356	368.8230	348.0260	222.4600
50	2	13	<i>TanH</i>	1.0055	0.0000	419.1090	162.0716	103.9580
51	2	14	<i>TanH</i>	2.0689	0.0632	89.5962	869.0890	425.4056
52	2	15	<i>TanH</i>	0.8161	0.8945	401.2004	69.3570	43.5270
53	2	16	<i>TanH</i>	1.1229	0.8497	482.4704	316.9567	202.8701
54	2	17	<i>TanH</i>	0.4157	0.2001	57.0064	367.1814	294.8458
55	2	18	<i>TanH</i>	0.2313	0.1919	46.5985	1077.9436	870.9526
56	2	19	<i>TanH</i>	0.2326	0.1080	52.4751	680.0896	546.9179
57	2	20	<i>TanH</i>	0.3346	0.0595	72.7641	63.5405	46.4767
58	2	2	<i>Sigmoid</i>	0.0344	0.0950	56.5361	-33.5735	-43.5890
59	2	3	<i>Sigmoid</i>	0.0420	0.3732	60.7329	871.6380	694.6940
60	2	4	<i>Sigmoid</i>	0.0405	0.4812	60.1827	822.6530	654.6120
61	2	5	<i>Sigmoid</i>	0.0286	0.1488	52.2650	93.6444	59.1459
62	2	6	<i>Sigmoid</i>	0.3615	0.1945	261.6776	184.7752	113.7402
63	2	7	<i>Sigmoid</i>	0.0433	0.6624	62.8340	992.3807	793.1790
64	2	8	<i>Sigmoid</i>	0.0360	0.1142	57.6209	51.5795	25.9838
65	2	9	<i>Sigmoid</i>	0.0414	0.3788	61.5037	507.2391	397.8084
66	2	10	<i>Sigmoid</i>	0.0405	0.0313	60.4691	-65.3461	-68.6847
67	2	11	<i>Sigmoid</i>	0.0292	0.1302	52.6156	154.2056	108.5785
68	2	12	<i>Sigmoid</i>	0.0262	0.4465	46.2511	-76.6774	-80.0160
69	2	13	<i>Sigmoid</i>	0.0337	0.1467	55.6512	55.9243	29.2157
70	2	14	<i>Sigmoid</i>	0.0262	0.3528	46.3431	-76.6660	-80.0051
71	2	15	<i>Sigmoid</i>	0.0277	0.0927	51.6435	-75.1732	-78.5118
72	2	16	<i>Sigmoid</i>	0.0382	0.4048	59.8174	365.1768	281.7127
73	2	17	<i>Sigmoid</i>	0.0366	0.1187	57.8674	176.0430	127.4484
74	2	18	<i>Sigmoid</i>	0.0430	0.2659	61.0419	740.2470	587.7860
75	2	19	<i>Sigmoid</i>	0.0409	0.4721	60.7450	910.9210	726.5580
76	2	20	<i>Sigmoid</i>	0.0401	0.4041	59.5825	1098.4153	879.1829

concentration of glucose, the induction time of bioconversion process and the inoculum volume of biomass. The performance of ANN configuration was evaluated several times using the data set and the various configurations (Table 2). The ANN configuration that minimized the MSE value and the % Error, and that optimized  $R^2$ , were considered to be optimal. The verification of the ANN model performance is illustrated in Figure 4. The best ANN

configuration used two hidden layers, with nine neurones in each hidden layer. The MSE and % Error for this optimal configuration were 0.067 and 4.54%, respectively. The coefficient of determination was also very good ( $R^2=0.97$ ), as a result of the small prediction error. The results showed very good agreement between the predicted and the desired values of the yield fructose production ( $R^2 > 0.9$ ) as presented in figure 4.



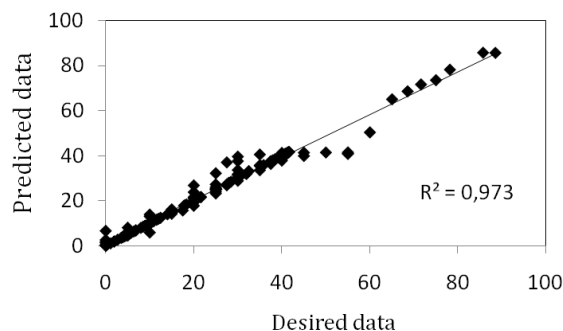
**Fig.4** Correlation of desired versus neural network values after testing the data set.

The second best ANN model was obtained with the network having two hidden layers, and fifteen neurons in each layer. This ANN model also demonstrated a good agreement between the predicted and the desired values ( $R^2 = 0.89$ ) but the MSE was larger as compared to the previously selected model ( $0.81 > 0.067$ ), and in addition the AIC and MDL were also larger.

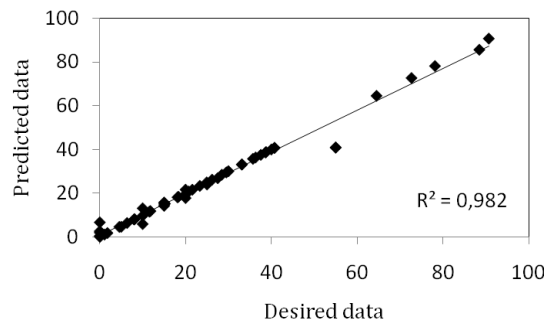
**3.2 Artificial Neural Network Performance for inverse prediction**

It may be observed from Table 3 that the 48<sup>th</sup> configuration results in the minimum MSE error (0.0091) and at a lower % of error (4.76). The coefficient of determination was also very good ( $R^2=0.98$ ). It may also be observed from Table 3 that configurations 3<sup>th</sup> and 12<sup>th</sup> showed a good coefficient of determination but at the MSE error and the % of error are very high. Hence, 48<sup>th</sup> configuration is selected as the optimal ANN topology. As discussed earlier the network model with two hidden layers and eleven neurons in each hidden layer resulted in the best prediction.

The performance of the ANN model for the training and validation data set is presented in Figs. 5 and 6, respectively. The comparison of the model prediction with the experimental values is shown in these figures. The correlation coefficient associated with Fig. 5 is 0.97 and that is for Fig. 6 is 0.98. It may be noted that the correlation coefficient for the validation set (in Fig. 6) is more than that for the training set. This shows a better performance of the present ANN model for the validation data set.



**Fig.5** Correlation of desired versus neural network values after training the data set.



**Fig.6** Correlation of desired versus neural network values after validation the data set

**Table 3** Performances of various ANN configurations once trained with the data set, for the neural network for inverse process design

Run	Hidden layer (Hl)	Processing elements (PEs) in each Hl	Transfer	MSE	R <sup>2</sup>	% error	AIC	MDL
1	1	2	TanH	0.2889	0.8407	54.8118	1136.6080	1065.5650
2	1	3	TanH	0.0455	0.7928	19.8850	1787.1192	1344.7330
3	1	4	TanH	0.2929	0.8808	57.4506	1277.2080	1197.8070
4	1	5	TanH	0.2522	0.7796	49.9781	1762.7709	1653.9970
5	1	6	TanH	0.2114	0.7976	38.4253	1425.1800	1336.1080
6	1	7	TanH	0.3055	0.7266	56.0967	1395.0130	1308.6870
7	1	8	TanH	0.2336	0.7869	36.5886	777.4840	727.3366
8	1	9	TanH	0.2064	0.8138	36.0879	1396.1630	1308.7630
9	1	10	TanH	0.2010	0.8286	39.7495	1861.0230	1745.8020
10	1	11	TanH	0.3341	0.7375	39.8830	1548.8647	1453.5836
11	1	12	TanH	0.4495	0.6911	74.5392	789.6204	740.4276
12	1	13	TanH	0.2472	0.8931	49.0592	1117.9085	1047.5819
13	1	14	TanH	0.1914	0.7052	37.3667	810.9028	758.2475
14	1	15	TanH	0.3684	0.8212	67.3480	263.0710	244.8028
15	1	16	TanH	0.3646	0.8343	63.2199	1206.6226	1131.9976
16	1	17	TanH	0.3347	0.5092	49.6625	1222.9433	1147.1243
17	1	18	TanH	0.5239	0.5835	78.6293	870.2051	816.5945
18	1	19	TanH	0.1797	0.8245	41.6323	1680.2008	1575.4871

19	1	20	<i>TanH</i>	0.4132	0.7429	69.6421	1024.0022	960.6009
20	1	2	<i>Sigmoid</i>	0.1316	0.7998	35.5512	2478.8000	2325.6090
21	1	3	<i>Sigmoid</i>	0.1598	0.7807	39.3206	1177.1550	1102.1726
22	1	4	<i>Sigmoid</i>	0.0790	0.8129	27.1539	2370.8810	2222.8250
23	1	5	<i>Sigmoid</i>	0.1293	0.7838	35.2064	2034.0530	1907.3690
24	1	6	<i>Sigmoid</i>	0.1532	0.7866	38.5889	1563.3430	1465.1960
25	1	7	<i>Sigmoid</i>	0.1641	0.2868	52.3008	894.3076	836.2792
26	1	8	<i>Sigmoid</i>	0.1260	0.8048	34.6267	1624.9490	1522.6230
27	1	9	<i>Sigmoid</i>	0.1008	0.8019	30.8955	2153.3470	2018.9036
28	1	10	<i>Sigmoid</i>	0.1680	0.7785	41.8508	1153.4280	1079.9970
29	1	11	<i>Sigmoid</i>	0.3341	0.7375	39.8830	1548.8647	1453.5836
30	1	12	<i>Sigmoid</i>	0.0412	0.8270	23.7250	1852.9468	1734.1439
31	1	13	<i>Sigmoid</i>	0.0425	0.8378	23.4994	1744.2420	1632.0061
32	1	14	<i>Sigmoid</i>	0.4009	0.8361	23.2392	2279.6940	2135.3402
33	1	15	<i>Sigmoid</i>	0.0403	0.8283	23.4179	1785.8599	1670.9972
34	1	16	<i>Sigmoid</i>	0.0399	0.8358	22.9159	2321.5402	2174.6783
35	1	17	<i>Sigmoid</i>	0.0434	0.8327	23.6121	1261.1178	1177.7766
36	1	18	<i>Sigmoid</i>	0.4613	0.6916	73.7595	936.7307	878.8210
37	1	19	<i>Sigmoid</i>	0.0394	0.8256	23.7736	1702.9573	1592.9899
38	1	20	<i>Sigmoid</i>	0.0398	0.8274	23.3157	1829.4658	1711.9763
39	2	2	<i>TanH</i>	0.4823	0.8457	59.7180	743.9789	442.7830
40	2	3	<i>TanH</i>	0.3416	0.7786	47.0149	1409.8240	1322.9010
41	2	4	<i>TanH</i>	0.1647	0.8625	30.0491	740.4490	691.6145
42	2	5	<i>TanH</i>	0.2023	0.7946	30.7097	2401.2860	2253.8270
43	2	6	<i>TanH</i>	0.2222	0.8778	48.8928	1529.3310	1434.1700
44	2	7	<i>TanH</i>	0.2698	0.8703	51.9633	3029.6670	2845.4330
45	2	8	<i>TanH</i>	0.4467	0.8172	74.3730	2315.3510	2175.0560
46	2	9	<i>TanH</i>	0.3552	0.6742	59.7478	2363.4920	2219.7350
47	2	10	<i>TanH</i>	0.5640	0.7914	43.2075	2175.3800	2044.0402
48	2	11	<b>TanH</b>	<b>0.0091</b>	<b>0.9818</b>	<b>4.7631</b>	<b>511.1988</b>	<b>387.3811</b>
49	2	12	<i>TanH</i>	0.3100	0.8787	58.7851	2505.6400	2353.0460
50	2	13	<i>TanH</i>	0.1666	0.2544	53.0024	2566.9617	2409.1150
51	2	14	<i>TanH</i>	0.2665	0.8551	53.0772	1831.1386	1718.4250
52	2	15	<i>TanH</i>	0.1499	0.8998	30.1768	1190.4224	1060.7540
53	2	16	<i>TanH</i>	0.2545	0.8632	24.0301	1513.1681	1419.3197
54	2	17	<i>TanH</i>	0.2798	0.8055	55.1306	2355.2388	2211.3619
55	2	18	<i>TanH</i>	0.2099	0.8431	26.0187	1858.8730	1742.8911
56	2	19	<i>TanH</i>	0.2004	0.7939	37.7379	294.8930	273.1629
57	2	20	<i>TanH</i>	0.1411	0.8524	31.6572	2241.7832	2102.9211
58	2	2	<i>Sigmoid</i>	0.1648	0.0019	53.8596	2710.4830	2544.0400
59	2	3	<i>Sigmoid</i>	0.1658	0.3630	53.3267	3022.7410	2837.6720
60	2	4	<i>Sigmoid</i>	0.1652	0.0007	53.7851	2968.5810	2786.7350
61	2	5	<i>Sigmoid</i>	0.1659	0.5342	53.5458	1492.7810	1399.0520
62	2	6	<i>Sigmoid</i>	0.1661	0.7889	53.8500	3292.8300	3091.6410
63	2	7	<i>Sigmoid</i>	0.1647	0.6871	53.3908	3084.4640	2895.6930
64	2	8	<i>Sigmoid</i>	0.1668	0.5454	53.2804	3530.9930	3315.5950
65	2	9	<i>Sigmoid</i>	0.1644	0.8894	51.6924	1794.3860	1682.6280
66	2	10	<i>Sigmoid</i>	0.0524	0.5580	48.5889	2768.0807	2092.0803
67	2	11	<i>Sigmoid</i>	0.1651	0.0813	53.9171	1528.5386	1432.6604
68	2	12	<i>Sigmoid</i>	0.1661	0.8121	52.0491	3028.8286	2843.4004
69	2	13	<i>Sigmoid</i>	0.1645	0.8715	25.6597	2132.3968	2000.4599
70	2	14	<i>Sigmoid</i>	0.1666	0.3860	53.3561	2222.9400	2085.6325
71	2	15	<i>Sigmoid</i>	0.1662	0.0233	53.4785	3048.8406	2862.2185
72	2	16	<i>Sigmoid</i>	0.1668	0.8807	52.9837	2684.9920	2520.1006
73	2	17	<i>Sigmoid</i>	0.1654	0.7740	53.1112	2740.6424	2572.4078
74	2	18	<i>Sigmoid</i>	0.1666	0.8213	52.4615	3592.9569	3373.8580
75	2	19	<i>Sigmoid</i>	0.0341	0.8793	24.4542	56.6883	44.6289
76	2	20	<i>Sigmoid</i>	0.1667	0.0597	53.4685	1850.9662	1735.8646

## Conclusions

The objective of this study was to develop a hybrid FEM-ANN robust approach that can be used for prediction of the diffusion rate, the bioconversion rate and the Fructose % for different combinations of the date varieties, the speeds of agitation, the date/water

ratio, the initial concentration of glucose, the inoculum volume of biomass and the induction time of bioconversion process and for inverse design of processing conditions.

Finally, it is possible to state that:

– A consistent well performed numerical simulation can supply a good prediction of the yield of the

fructose production process from date as a function of the main material and process parameters.

– The neural networks can generalize these results in order to have a quick prediction.

– In the inverse strategy, for a given yield of the fructose production process, the technique supplies the possible process parameters compatible with this yield. What is more, a proper optimization process is able to supply the best result taking into account a defined goal function.

This gives reasonable hope that these hybrids ANN- FEM approaches can be coupled with genetic algorithm for determining optimal conditions for fructose production process.

## References

- C.I.Ochoa-Martinez, A.A.Ayala-Aponte, (2006). Prediction of mass transfer kinetics during osmotic dehydration of apples using neural networks. *Lebensmittel-Wissenschaft und -Technologie*, 40, 638-645.
- I.S.Jawahir,A.K.Balaji, K.E.Rouch, J.R.Baker, (2003).Towards integration of hybrid models for optimized machining performance in intelligent manufacturing systems. *Journal of Materials Processing Technology*, 139, 488-498.
- I.S.Jawahir, X.Wang, (2007).Development of hybrid predictive models and optimization techniques for machining operations. *Journal of Materials Processing Technology*, 185, 46-59.
- K.Gabsi, M.Trigui ,A.N.Helal, S.Barrington, A.R.Taherian, (2013). CFD modeling to predict diffused date syrup yield and quality from sugar production process. *Journal of Food Engineering*, 118, 205-212.
- M.Trigui, K.Gabsi, W.Zneti, S.Barrington, A.N.Helal, (2015). Finite Element Model to Predict the Bioconversion Rate of Glucose to Fructose using *Escherichia coli* K12 for Sugar Production from Date. *International Journal of Food Engineering*, 11, 105-113.
- Neurosolutions, (2006).The neural network simulation environment. *Getting started manual v. 5.0*. NeuroDimension Inc., FL USA.
- U.Zuperl, F.Cus, B.Mursec, T.Ploj, (2004).A hybrid analytical-neural network approach to the determination of optimal cutting conditions. *Journal of Materials Processing Technology*, 157-158, 82-90.