

Artificial Neural Network Models for Predicting the Energy Consumption of the Process of Crystallization Syrup in Konya Sugar Factory

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Abstract: In this study, a model has been developed from the sugar production process stages in Konya Sugar Factory using artificial neural networks to estimate the energy consumption of the process of crystallization syrup. Model developing specific enthalpy, mass and pressure as input layer parameters and consumption energy as output layer was used. 124 different data are taken from Konya Sugar Factory during January 2016. Feed-forward backpropagation algorithm was used in the training phase of the network. Learning function LEARNGDM and the number of hidden layer kept constant as 2 and transfer functions are modified. To find the most optimal model, 27 artificial neural networks with different architectures have been tested. 2-5-1 network architecture was determined as the best suitable network architecture and transfer function is determined logsig function as the optimal transfer function. Optimum results of the model taken in the coefficient of determination was found $R = 0.98$ neural network training, testing and validate was also found to be $R = 0.98$, the performance of the network for not shown data to network was found $R=0.99$.

Keywords: Artificial Neural Network, Modelling, Energy Consumption, Process Of Crystallization Syrup.

1. Introduction

Nowadays, as a result of technological development and growth in world population energy requirement keeps increasing. In contrast, in the future, classic energy reserves used in the world will not meet the requirements and they will be so expensive to afford. Because of that, the need of using energy sources more efficiently and improving alternative types of energy arises.

During the second half of 20th century, research on alternative energy sources and studies about the efficient use of existing energy resources increased intensively. An enormous increase in studies, conducted by scientists, engineers, and researchers, concerning environmental pollution and especially, aiming energy saving or recovery of lost energy, was observed in recent years. Studies [1-5] related to energy estimation are important for the developing countries such as Turkey. Because, energy consumption resulting from the use of energy in industrial fields can be minimized through energy modelling method. This is expected to contribute to national economy. On the other hand, sugar production in the world is in the most important position in the food sector. Sugar factories use energy in large quantities. Due to the large amount of steam energy used in sugar production processes, the need for energy is high. The contribution of energy analyses in food processing to operating profitability is huge. In the food sector, energy consumption is very high due to the high use of energy in the production process. For the profitability of the enterprises; It is very important to obtain maximum energy savings and to estimate the energy to be consumed [6]. In the literature, energy consumption is estimated for different areas [7-10].

Similarly, energy and exergy analyses were conducted for different sugar factories [11-13]. However, no studies have been done to predict the energy consumption required for sugar production in sugar factories. This study is the estimation of the energy consumed during the process of crystallization syrup, which is one of the stages of sugar production, by using artificial neural networks.

2. Material and Methods

2.1. Artificial Neural Network

Artificial neural networks, developed inspired by human brain, are parallel and distributed information processing structures that are connected each other by means of weighted connections and are made up of processing elements each having own memory. In other words, artificial neural networks are computer programs imitating biological neural networks [14].

As it is shown in (Figure 1), there are basically three layers in an artificial neural network —namely, input layer, where interconnected nerve cells are situated, output layer, and hidden layer.

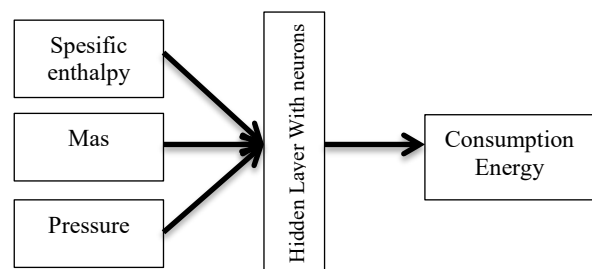


Figure 1. Schematic diagram of the three layers ANN model with three input and one output layer.

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Artificial neural networks learn a particular problem by being trained directly through existing examples. Training procedure consists of giving input and output data to the neural network. After finishing training procedure of the network, it is stimulated by unfamiliar real data in order to test the training performance. The network generates output for the unfamiliar data using connection weights determined during the training [15]. The network has algorithms and transfer functions that are used during the training. The network may produce different results based on different algorithms and functions. The most optimized result is found by trial and error method.

2.2. Data Collection

Artificial neural networks with different architecture were developed to simulate the consumption of energy during the crystallization period of syrup in Konya Sugar Factory. Konya Sugar Factory accounts for 25% of the total production of beet sugar in Turkey. Mass, specific enthalpy, pressure and consumption energy data used in the model, are obtained through making measurements for a year. From these measurements, 124 data set are randomly chosen to improve. This period is thought to be satisfactory for the models that will be developed. The ranges of different operating parameters are given in (Table 1).

Table 1. The ranges of data set and their statistic

Parameters	Data Statistic		
	Ranges	Mean ± S.D.	Unit
Input Layer			
ass	31.15 - 36.70	34.29 ± 1.57	m
S. Enthalpy	215.10 - 219.31	217.31 ± 1.24	h
Pressure	65.70 - 70.00	67.41 ± 1.40	P
Output Layer			
Energy	6705.00 - 8029.26	7447.17 ± 353.99	E

In order to avoid numerical overflows and increase prediction accuracy, all the obtained data for ANN architecture were normalized between 0 and 1 [16]. The most commonly applied is the normalization expression as follows:

$$X_{normal} = \frac{X_i - X_{min}}{X_{max} - X_{min}} \quad (1)$$

where X_i is original data, X_{min} and X_{max} are minimum and maximum experimental data, respectively.

2.3. Network Properties

After the completion of statistical operations step, artificial neural network architectures were created using MATLAB software. In MATLAB software nntools is very suitable for import data, networking, usage, and export data. In this study, feed-forward backpropagation algorithm was used. “tansig”, “purelin” and “logsig” were tested as transfer function for hidden layer and “tansig” function was used as the output layer transfer function. The algorithms of transfer functions used are given in (Table 2).

Moreover, mass, specific enthalpy, pressure data were used as input while energy is referred as output. There are randomly chosen 124 data in our data set which are obtained for a year. 78 data were used for network training, while 46 data were used for simulation of the system. In architectures, which are made for training, the transfer function was kept

constant as TrainLM, learning function as LEARNGDM, the number of hidden layer as 2. Number of neurons and transfer functions are changed.

Table 2. Transfer functions used in algorithms

Transfer function	Algorithm
Tansig	$\text{tansig}(n) = 2/(1 + \exp(-2n)) - 1$
Purelin	$\text{purelin}(n) = n$, for all n
Logsig	$\text{logsig}(n) = 1/(1 + \exp(-n))$

2.4. Model Validation

The performances of the developed ANN architecture in the present study were evaluated through two different statistical criteria that were previously used in numerous studies [17-21]. These criteria are mean squared error (MSE-eq. 2) which measures the network’s performance and correlation coefficient (R). The formula for the calculation of MSE is:

$$\text{MSE} = \frac{1}{n} \sum_1^n (Y_{exp,i} - Y_{prd,i})^2 \quad (2)$$

where $Y_{prd,i}$ is the estimated data of ANN model, $Y_{exp,i}$ is the batch study data.

Then, measurements can be done mainly for cross-checking the response of the model with respect to the actual system response. If the agreement between the simulated and measured variables starts to fail, the model can be trained using the more recent data. Therefore, ANN can adapt to changes in the system. This, in turn, makes them useful tools in developing expert systems for the more efficient operation of prediction consumption energy in sugar factory [22].

3. Results and Discussion

Obtained data from Konya Sugar factory set at different transfer function and number of neurons were used to train, test and validation the artificial neural network architectures. In order to evaluate the ANN modelling ability, obtained data were compared to the predicted data. The correlation coefficient and the mean squared error (MSE) were used to assess model predictability. Different algorithms, transfer functions and number of neurons have been tested are given in (Table 2). Also table 3 shows that the consumption of energy predicted by the ANN for data points used for training, validating, and testing. The correlation coefficients of training, testing and validation for the optimal model are shown in (Figure 2).

The optimum and most reliable model (with the highest R and the lowest MSE) was found based on the test results. (Figure 2) shows the results. It is observed that the output tracks the targets very well for training (R-value = 0,99769), validation (R-value 0,99861), and testing (R-value = 0,99866). These values can be equivalent to a total response of R-value = 0,99797. In this case, the network response is satisfactory, and simulation can be used for entering new inputs. The simulation results of consumption energy are presented in (Figure 3) by plotting the obtained real data and predicted output.

Table 3. Developed ANN models

Number of Arc.	Number of Neurons	Transfer Function	Training R	Validation R	Test R	MSE	Simulated R
1	1	TANSIG	0,99212	0,99528	0,99866	0,00374	R = 0,9875
2	1	LOGSIG	0,99224	0,9969	0,99759	0,03531	R = 0,9871
3	1	PURELIN	0,99598	0,99634	0,9836	0,00326	R = 0,9866
4	2	TANSIG	0,99569	0,98993	0,97747	0,00231	R = 0,9847
5	2	LOGSIG	0,99105	0,99257	0,96935	0,00812	R = 0,9764
6	3	TANSIG	0,99524	0,9816	0,99495	0,00226	R = 0,9846
7	3	PURELIN	0,98957	0,99751	0,99506	0,00334	R = 0,9867
8	4	TANSIG	0,9963	0,99614	0,99048	0,00051	R = 0,9903
9	4	LOGSIG	0,99653	0,99698	0,99988	0,00232	R = 0,9945
10	5	TANSIG	0,99539	0,99642	0,99163	0,00433	R = 0,9886
11	5	PURELIN	0,99283	0,9934	0,99679	0,00054	R = 0,9871
12	6	TANSIG	0,99839	0,99927	0,99315	0,00073	R = 0,9955
13	7	TANSIG	0,54575	0,8809	0,46918	0,00596	R = 0,3552
14	7	LOGSIG	-0,5661	-0,0952	-0,357	0,00994	R = 0,2303
15	8	TANSIG	0,99039	0,98906	0,99428	0,00053	R = 0,9811
16	8	LOGSIG	0,67451	0,68932	0,92341	0,00063	R = 0,4989
17	9	LOGSIG	0,99769	0,99861	0,99866	0,00011	R = 0,9959
18	10	TANSIG	-0,0304	0,39547	0	0,00044	R = 0,0084
19	10	PURELIN	0,99511	0,99644	0,97771	0,00084	R = 0,9857
20	11	TANSIG	0,99589	0,99511	0,97932	0,00015	R = 0,9863
21	11	LOGSIG	0,9205	0,88271	0,84797	0,00067	R = 0,8348
22	6	PURELIN	0,91972	0,9391	0,92675	0,00017	R = 0,8467
23	9	PURELIN	0,90307	0,93853	0,92941	0,00096	R = 0,8226
24	4	PURELIN	0,92567	0,93197	0,9222	0,00085	R = 0,8572
25	9	TANSIG	-0,0623	-0,35455	-0,3835	0,00813	R = 0,0169

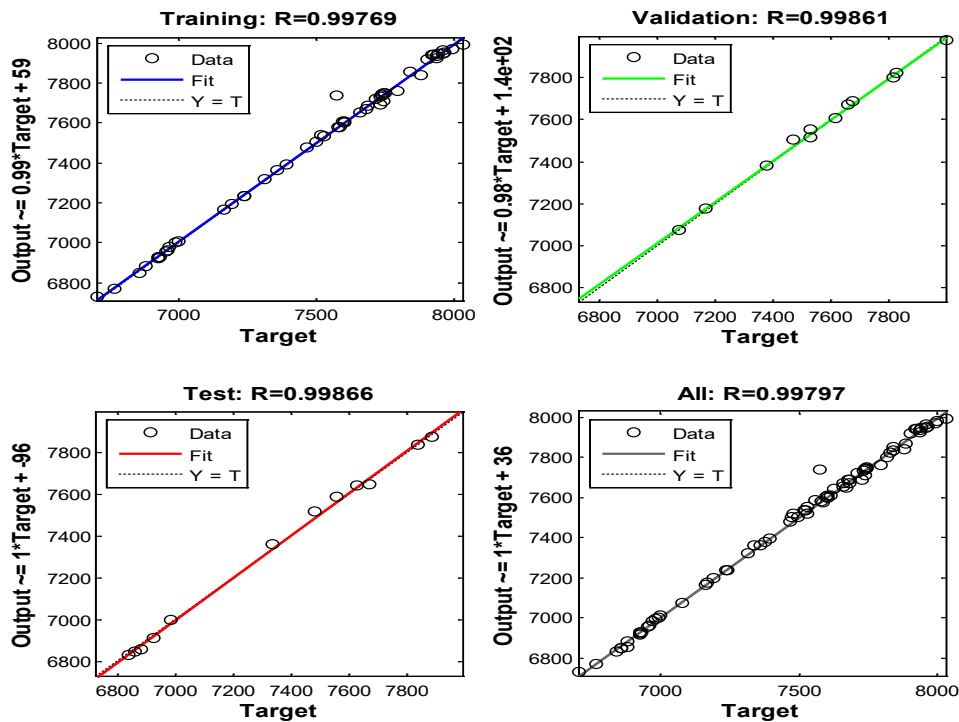


Figure 2. The optimal network regression

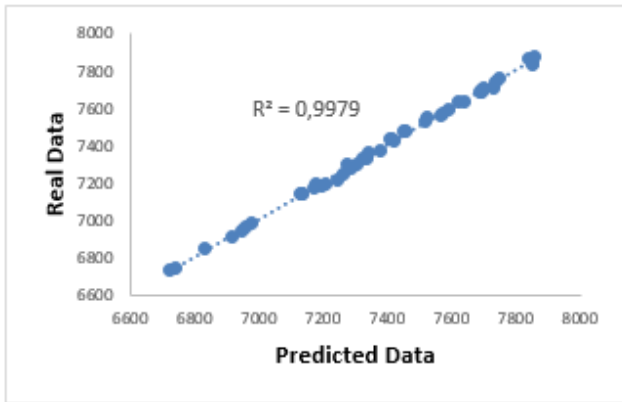


Figure 3. Simulation Result

4. Conclusion

In architectures for prediction to consumption energy, the transfer function was kept constant as TrainLM, learning function as LEARNGDM, the number of hidden layers as 2, while the number of layers, number of neurons and transfer functions are not changed.

The best optimized results are obtained in the model with layer number 1, neuron number 2 and the transfer function LOGSIG.

The results of this study indicated high correlation coefficient (R-value) between the obtained real data and predicted output is 0.9979. Therefore, the model developed in this work has an acceptable generalization capability and accuracy. As a result, the neural network modelling could effectively simulate and predict the performance of energy consumption in Konya Sugar Factory. It is concluded that, ANN provides an effective analysing and diagnosing tool to understand and simulate the non-linear behaviour of the sugar factory, and is used as a valuable performance assessment tool for sugar factory operators and decision makers. Moreover, results obtained from developed ANN model indicated that it is also possible to determine consumption energy percentages very close to, even same, experimental results without performing high-cost experiments.

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