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Artificial neural network modeling ginger rhizome extracted using rapid expansion Super-Critical Solution (RESS) Method

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Abstract—In this study, a feed-forward multilayer back propagation with Levenberg-Marquardt training algorithm Artificial Neural Network (ANN) was developed to predict the particle size from the extraction of ginger rhizome using super-critical carbon dioxide in Rapid Expansion Super-critical Solution (RESS). Solid oil particle formation analysis is carried out using Scanning Electron Microscopy (SEM) and Image processing and analysis software, ImageJ. The ANN model accounts for extraction temperature (40, 45, 50, 55, 60, 65, and 70°C) and pressure (3000, 4000, 5000, 6000, and 7000psi) the size of the particle. A two-layer ANN with two input variables (extraction temperature and pressure) and one output (particle size) with 35 experimental data was used for the modeling purpose. Different networks were trained and tested by changing the number of neurons in the hidden layer. Using validation data set, the network having the highest (nearest to the value of one) regression coefficient (R) of 0.99721 and the lowest (nearest to the value of zero) Mean Square Error (MSE) of 0.00031 was selected as an optimum ANN model. The suitable ANN model is found to be one hidden layer with seven hidden neurons.

I. INTRODUCTION

Ginger (Zingiberofficinale, Rosc.) is a herb plant belonging to the Zingiberceae family. Ginger is widely used in pharmaceuticals, cosmetics and as flavouring agents in food and beverage industry [1]. Ginger is known to contain large number of antioxidants that can provide additional defence against oxidation [2] and is a natural dietary

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component, which has antioxidant and anticarcinogenic properties [3].

Over the past few years, demand for super-critical fluid extraction process for particle formation in industry has rapidly increased [4]. To date, there is a growing interest in studies on natural product to direct solid oil particle formation in the pharmaceuticals industries [5]. Development of solid oil particle will increase the efficiency of drug delivery, reduce drug dosage and improve bioavailability of the drug [6]. Rapid Expansion Of Super-Critical Solutions (RESS) is a new and promising technology to produce small particles and is suitable to be used for thermally degradable pharmaceutical compounds [7]. Recently, RESS method has been used by researchers to produce fine particles for pharmaceutical drug substances [8]. RESS was successfully employed to produce small-sized contaminant-free particles of heat sensitive materials such as aspirin and carbamazepine [9], [10].

Super-critical fluid can be referred to as a substance whose operating conditions are above its critical temperature and critical pressure, where properties of the substance are particularly the mix of gas-like and liquid-like properties and it does not condense to form liquid or gas [11]. Common compound which is used as super-critical fluid is carbon dioxide (CO_2) due to its environment-friendly properties, nontoxic and non-flammable nature, easy to recycle, inexpensive, easy availability, low critical temperature (31.05°C) and moderate critical pressure (7.38 Mpa), and easeo fremoval from extraction product.

To date, there is no reported data on particle size of solid oil particle from ginger powder using RESS technology. An understanding of the complex phenomena happening in the RESS process has not yet been reached.There are a lot of variables that can affect the RESS process such as the temperature and pressure in the pre-expansion and post-expansion chamber, the nozzle diameter and geometry, and the solute concentration [12]. Determination of particle size is one of the critical parameters. Additionally, experimental studies on the solid oil particle formation from ginger rhizome using RESS technology over the entire range of temperature and pressure need a very expensive and time consuming experimental procedure [13]. Hence, Artificial Neural Network (ANN), was recommended to predict particle size within the specified operating conditions.

In this work, focus has been placed on application of Artificial Neural Network (ANN) for ginger solid oil particle size prediction.

II. ARTIFICIAL NEURAL NETWORK (ANN)

ANN model is the best technique for solving complex engineering problems. The basic advantage of ANN is that it does not need any mathematical model since an ANN learns from examples and recognizes patterns in a series of input and output data without any prior assumptions about their nature and interrelations [14]. Since thelast two decades ANN models have been used in different fields of engineering with a basic objective of achieving human-like performance since it is a powerful tool to identify complex relationship between input and output data [15].

The first significant paper on neural network model that inspired many other researchers in the neural network development was proposed in 1943 by McCulloch and Pits, where the developed model had two inputs and a single output [16]. McCulloch and Pitts noted that a neuron would not be activated if only one of the inputs was active. In 1949 [17] formed the basis of 'Hebbian learning' which is now considered as an important part of ANN theory and in 1958, John von Neumann proposed the modern brain performance of neural network using digital computer for further investigation of ANN performance. In 1957, Frank Rosenblatt created a neuron model in hardware [16].

Similar to the neurons found in the brain, ANN is composed of two or more artificial neurons. ANN is a biologically inspired human brain working situations and potentially fulfills the vision of scientists to develop machines that can think like human beings [18]. ANN is a computer program that mimics the way human brain processes information [19]. An ANN consists of processing elements, connections between them, training and learning algorithms and recall algorithms [20].

The information coming into the body of an artificial neuron is called input that is weighed by multiplying each input with weights [21]. An input function calculates the summation of net input signals to neuron coming from all its inputs and passing through a transfer function to produce an output. The activation signal function calculates the activation level of the neuron as a function of its summation input signal and of its previous state [20]. An output signal is considered equal to the output of a neuron to its activation level [22].

III. MATERIALS AND METHOD

A. Materials

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The Zingiberofficinale, Rosc. rhizome used in this study was purchased from local market. Fresh ginger rhizomes were washed thoroughly with tap water to remove the dirt. The skin of the ginger rhizome was peeled and then it was cut into cross-sectional slices 2 to 3 mm thick. An amount of 500 g ginger slices was weighed and oven dried in an oven model Memmert UFE 500 to remove moisture content until it remains in the sample at 10 to 12% [1]. Dried ginger sample then was ground using mechanical grinder Retsch model SM100 for 3 minutes through a plate having 1 mm pore size to obtain the ginger powder. The sample was then stored in the refrigerator at -4°C for further use.

B. Rapid Expansion Super-Critical Carbon Dioxide (RESS)

The studies were based on ginger solid oil particles extracted from the ground ginger sample at operating temperatures of 40, 45, 50, 55, 60, 65 and 70ºC, and pressures of 3000, 4000, 5000, 6000 and 7000psi for 40 minutes of extraction time [23]. Values for operating temperature and pressure for extraction of ginger rhizome were selected based on the average of the operating conditions of several other literatures that utilized RESS-CO_2 from previous researches done by many other researchers in particle formation using RESS method [24], [26]-[10], [27], [28] and [29]. RESS equipment in this study was modified from Super-critical Fluid Technologies Model SFT-100 equipment. Each run will be conducted using 8 g sample of ground ginger based on the observation of the maximum mass of ground ginger that can be loaded and fitted in 25 mL of the extraction vessel. If the mass of the sample is higher than 8 g, it will cause some loose fitting at the top of the extraction vessel seal that will cause fault or leaking of CO_2 when the extraction process would be in progress.

Extraction pressure and temperature were set at the desired values, and ginger sample was inserted in a cotton bag before putting in the extraction vessel. The seal on the top of the extraction vessel was sealed tightly before closing the top cover. Dynamic valve was opened and restrictor valve was closed during the extraction time. Glass vial was inserted in the expansion chamber. When extraction temperature achieved the desired value, CO_2 pump was run to feed high pressure liquid CO_2 (99 % purity provided by MOX Linde Gases SdnBhd) continuously in the extraction vessel at fixed solvent flowrate of 24 mL/min. Basically, liquid CO_2 will be converted to a super-critical condition when it would bepumped into the extraction vessel (heated zone). To achieve the desired pressure set point, CO_2 pump will be continuously actuated.

After 40 minutes of extraction, the restrictor valve was quickly opened to depressurize the super-critical solution for separation of solute from the solvent through the expansion noozle with external diameter of 2.0 mm and distance of 80 mm from the nozzle to the collection bottle. Depressurized CO_2 at the ambient pressure will convert into gaseous form and would be purged into the ambient. Extraction product will be collected in collection vials. To determine the extraction yield, weight of the collection vials will be measured before and after RESS process. The extraction product was weighed using the analytical balance model Mettler Toledo AB204-S. The procedure of extraction process was repeated in triplicate under desired operating conditions and the data were given as the average values.

C. Characterization Method and Instruments

Scanning Electron Microscopy (SEM)

Analysis on particle size was carried out using Scanning Electron Microscopy (SEM), model TM3000 Tabletop Microscope, brand Hitachi. For the analysis, samples were applied on double sticky carbon tape located on top of circular aluminium stub [30]. SEM images from different regions of the stub were captured.

ImageJ Analysis (ImageJ)

Image processing and analysis software, ImageJ was used to perform particle size analysis [10]. 100 particles selected randomly from SEM image were used to calculate average solid oil particle size of the ground ginger obtained from RESS process [26].

D. Data Set

A set of input data with 35 samples was used as input matrix (35 x 2) with corresponding values of particle size obtained from RESS experiment used as target matrix (35 x 1) in the developed ANN model. There is no unique method for determining the size of the data to the appropriate network training [31]. In this study, input data were divided randomly into three data sets which were 70 % for training (25 samples), 15 % for validation (5 samples) and 15% for training (5 samples) [32]. The training data was applied to compute the network parameters while the validation data was applied to ensure robustness of the network parameters and the

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testing stage was used to control error; when it increased, the training stopped.

Inputs and output data are normalized in the range of 0–1 for the reduction of network error and higher homogeneous results [33], [20] by using equation (1):

Xnorm= (Xreal - Xmin)/(Xmax–Xmin) Equation (1)

Where:Xnorm = is a normalized value, Xreal = is a real value, Xmin = the minimum values for the variable X, Xmax = the maximum values for the variable X [34], in his study on modeling of soil particle diameters normalized input and output data between 0 and 1 using the same equation as shown above [34]. Table 1 shows the experimental data and normalization experimental data which were used in this ANN model.

E. Artificial Neural Network for Prediction of Particle Size

Modeling for particle size prediction of solid oil particles from ginger rhizome in RESS process was done using MATLAB software (version 7.9.0.(R2009b)) neural network toolbox. In this study, feed forward back-propagation neural network was applied since it is the most commonly applied ANN layout [18]-[31]. Feed-forward back-propagation neural network developed by Rumehart and McClelland in 1986 is the most widely applied ANN layout [19]-[25]-[18] and [35]. Extraction temperature and extraction pressure were designated as input data, while particle size data from ImageJ analysis was established as output data for further use and was subjected to ANN modeling for training, testing and validation.

The predicted output data from ANN was optimized by referring to the Mean Square Error (MSE) value and regression value (R) gained from developed models when comparison was performed between predicted and experimental value. Trial and error method was applied in the network optimization process until the model showed the lowest value for MSE or nearest to zero would be better and R value nearest to 1 for testing, validation and training data set, in order to determine the suitable number of neurons and hidden layer required for the ANN architecture are all the major concerns of this study.

Figure 1 shows ANN schematic diagram representing ANN model with one hidden layer, with seven hidden neurons and one output layer with one neuron used in this modeling study for particle size prediction. X1 and X2 represent two input parameters applied in this research as temperature and pressure that previously were applied in the laboratory work. "D" represents the target output which is particle size (μm) computed from experimental work (ImageJ analysis). "E" is the cycle error. "O" represents the predicted particle size (μm) computed from network. "Wh" represents the weight connection in the hidden layerand "Wo" is the weight connection in the output layer, "b" is bias. f(hn) is transfer function for each neuron in hidden layer. In this case we used tansig and f(y) as transfer functions in output layer, where pure linear was chosen.

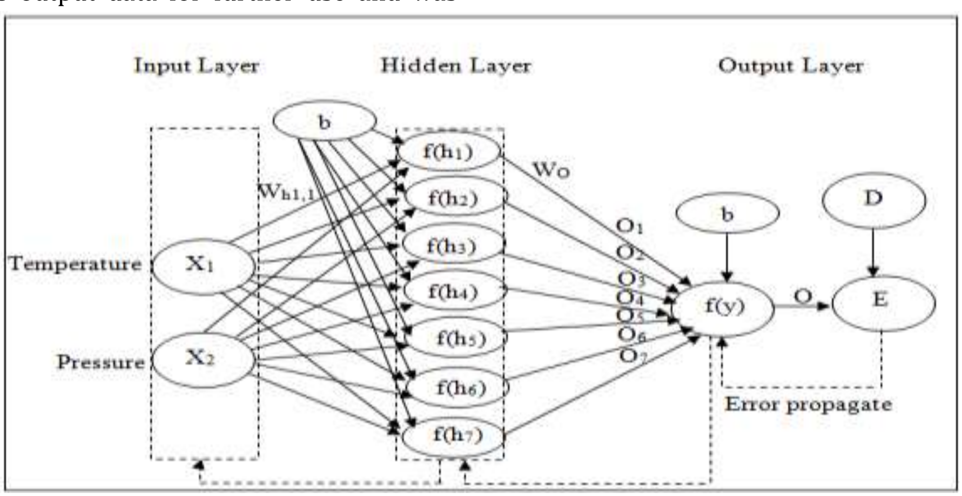

Fig. 1. Schematic diagram for multilayer feed forward back propagation ANN for solid oil ginger rhizome particle size prediction.

Feed-forward back-propagation neural network developed by Rumehart and McClelland in 1986 is the most widely applied ANN layout [19]-[25]-[18] and [35]. The back-propagation algorithm is the most popular supervised learning method because weights are adapted to minimize the error between the desired outputs and

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those calculated by the network. [36] have reported in their paper from the survey about 80% of neural network application applied back-propagation learning algorithm since it's considered to be most reliable and most applicable [36]. Hence, feed-forward back-propagation neural network was discussed in this study.

Multi-layer feed-forward back-propagation neural network means that the artificial neurons are organized in

TABLE 1
ORIGINAL AND NORMALIZATION DATA OF PARTICLE SIZE

	Original Data			Normalization Data		
No.	Extraction Pressure (psi)	Extraction Temperature (°C)	Particle Size (μm)	Extraction Pressure (psi)	Extraction Temperature (°C)	Particle Size (μm)
Training set						
1	3000	40	4.15	0.00	0.00	0.37
2	4000	40	5.01	0.25	0.00	0.53
3	5000	40	2.22	0.5	0.00	0.00
4	6000	40	3.03	0.75	0.00	0.15
5	7000	40	3.46	1.00	0.00	0.24
6	3000	45	4.21	0.00	0.17	0.38
7	4000	45	5.95	0.25	0.17	0.71
8	5000	45	3.71	0.5	0.17	0.28
9	6000	45	3.64	0.75	0.17	0.27
10	7000	45	3.74	1.00	0.17	0.29
11	3000	50	4.50	0.00	0.33	0.44
12	4000	50	6.56	0.25	0.33	0.83
13	5000	50	5.33	0.50	0.33	0.59
14	6000	50	3.77	0.75	0.33	0.30
15	7000	50	4.45	1.00	0.33	0.43
16	3000	55	5.18	0.00	0.50	0.56
17	4000	55	7.46	0.25	0.50	1.00
18	5000	55	6.07	0.50	0.50	0.73
19	6000	55	3.59	0.75	0.50	0.26
20	7000	55	3.74	1.00	0.50	0.29
21	3000	60	2.99	0.00	0.67	0.15
22	4000	60	6.59	0.25	0.67	0.83
23	5000	60	4.89	0.50	0.67	0.51
24	6000	60	3.28	0.75	0.67	0.20
25	7000	60	3.44	1.00	0.67	0.23
Validation Set						
26	3000	65	2.62	0.00	0.83	0.08
27	4000	65	6.1	0.25	0.83	0.74
28	5000	65	3.9	0.50	0.83	0.32
29	6000	65	2.91	0.75	0.83	0.13
30	7000	65	2.74	1.00	0.83	0.10
Test Set						
31	3000	70	2.62	0.00	1.00	0.08
32	4000	70	5.2	0.25	1.00	0.57
33	5000	70	2.86	0.50	1.00	0.12
34	6000	70	2.63	0.75	1.00	0.08
35	7000	70	2.75	1.00	1.00	0.10

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layers, and send their signals forward to produce solution and then the errors are propagated backwards through the hidden layer towards the input layer to modify the weight [37]. It consists of an input layer, one or more hidden layer and one output layer [38]. Input layer receives experimental information and experimental parameter, and then sends weight values to hidden layer and later the output layer produces the calculated value of the independent variable. Hidden layer is between input layer and output layer. In the hidden layer, input such as pressure and temperature was multiplied by weights, then the output is calculated at the output node using transfer activation function [38]. Then the output from hidden layer was sent to final layer which is the output layer that comprises of a prediction of the target output of the model [39].

The size of the hidden layer is one of the most important considerations when solving actual problems using multi-layer feed forward networks [40]. In this study, a number of hidden layers was selected as one. The selection of the number of hidden layers was done based on study on prediction of particle size done by [14]-[15] and [41]. [42] also used one hidden layer in their study for prediction of solid solubility in super-critical CO_2. [43] used one hidden layer in their research on prediction of oil yield using super-critical fluid extraction method. [31]-[37] and [44] found out that one hidden layer is commonly applied and adequate to provide an accurate prediction of the performance of many processes.

Training algorithm was optimized by observing the ideal number of hidden neurons in the hidden layer in the developed ANN model. There is no unique method for determining the optimal number of hidden neurons [31]. The growing neural networks technique was used in this work, where training starts with a small number of hidden neurons and subject to the error calculated, the number of the hidden neurons may increase during the training procedure [20]. So, the selection of the number of hidden neurons was achieved by trial and error method in agreement by obtaining error function results with respect to the training data set, for MSE is nearest to [45], [46], [47], [48]-[14]. This is the most common approach for selecting the optimal number of the hidden neurons [37] and [44]. In this study, the number of hidden neurons varied from 2 to 15. After finalizing number of hidden layers and number of hidden neurons, ANN is ready for training.

Activation functions are used in ANN to produce continuous values rather than discrete ones [49]. In this work, the activation functions assigned to hidden layer neurons are sigmoid functions (TANSIG) and the linear activation function (PURELIN) is used for the output layer neurons, since it is the most commonly used one according to [48]. [15] used the same activation function in their study for modeling of Zinc Oxide Nanoparticles.

Application of ANN in prediction of particle size has been done and reported successfully by large numbers of researchers. [13] had synthesized silver nanoparticles (Ag-NPs) using green method and developed back propagation ANN model for the prediction of particle size of Ag-NPs based on experimental data. [13] had done biosynthesis of silver nanoparticles (Ag-NPs) from silver nitrate aqueous solution using water extract from Curcuma longa (C. longa) tuber powder using Levenberg–Marquardt (LM) back-propagation neural network model.

IV. RESULTS AND DISCUSSION

In this study, a multi-layer feed-forward back propagation neural network was used. Extraction temperature and extraction pressure were set as input data and particle size from SEM and ImageJ analysis was set as output or target data. Before use as input and output data in ANN model, all the data were normalized. A set of input data with 35 samples was used as the input matrix (35 x 2) with corresponding values of particle size obtained from RESS experiment used as target matrix (35 x 1) in the developed ANN model. Data was randomly divided into 3 main sets which were training (25 samples), validation (5 samples) and test set (5 samples) for 70%, 15% and 15% respectively. Table 1 shows the experimental data and normalization experimental data which were used in this ANN model. The training data were applied to compute the network parameters, the validation data was applied to ensure robustness of the network parameters and the testing stage was used to control error; when it increased, the training stopped. Figure 2 shows a graph of the MSE against the number of hidden neuron units to choose the optimal topology decision for the network. As shown in Figure 2, the decision to use 7 hidden neuron units in hidden layer was taken based on the minimum value of MSE for training data set, 0.00031. If too many hidden neurons were used, it will lead to over-fitting [16]. On the same lines, it will cause the ANN model to be insufficiently flexible to represent the experimental signal [50]. As mentioned by [16] in Handbook of Neural Network Signal Processing, it is difficult to determine the optimal amount of training.

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During the training and testing process, the training error decreases until over-fitting phenomenon occurs, till the time when the error starts increasing again [51], [37]-[47] and [52]. In this study, to prevent over-fitting, the training step was stopped when error value on the validation data set was increased.

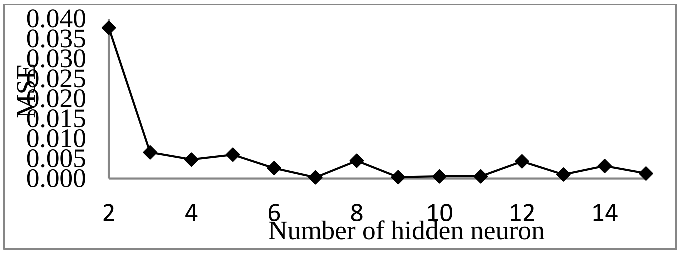

Fig. 2. Variation number of hidden neuron units.

TABLE 2
CHARACTERISTICS OF THE DEVELOPED ANN MODEL

Characteristic	Commentary
Algorithm	Feed forward back propagation
Minimized error function	MSE
Training algorithm	Levenberg-Marquardt
Learning type	Supervised
Hidden layer	Hyperbolic tangent transfer function
Output layer	Pure linear transfer function
Number of neuron in input layer	2
Number of hidden layer	1
Number of neuron in hidden layer	7
Number of neuron in output layer	1

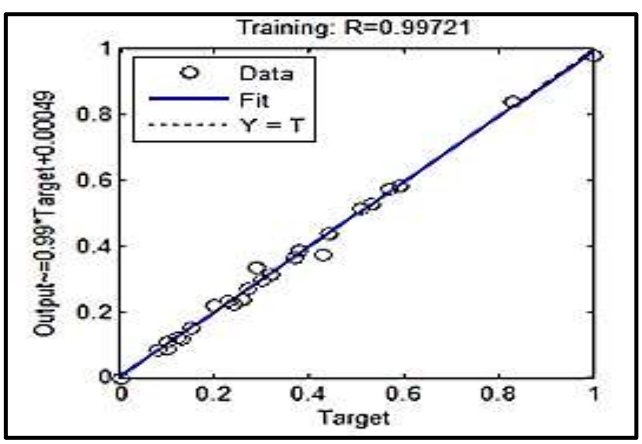

Fig. 3. Scatter regression plot of actual and ANN model.

Table 2 shows characteristics of the developed model in this study.Predicted Particle Size Value for Training Data Set is also given.Figure 3 shows the scatter regression (R) plots for the actual value from experimental data and predicted values for particle size from developed ANN model for the training data set. The solid linear line represents the best fit between the network output (predicted particle size from ANN model) and target output (particle size from experimental work). The best correlation coefficient of 0.99721 between the ANN model's predicted value and the experimental value data obtained showed a good correlation for the prediction with MSE value of 0.00031. [13] in their study used ANN model for prediction diameter of silver nanoparticles biosynthesized in curcuma longa extract.They got MSE value of 0.0155 and R value of 0.9996 [14]. And in a study conducted by Shabanzadeh, et al. (2013) on prediction of silver nanoparticles using green method, they found the R value for training set as 0.98398 [13]. It is proven that the value of MSE and R in this can be reflected as an exact value for the prediction of particle size.

According to [43], R value greater than 0.9 indicates a very satisfactory model performance, while R value in the range of 0.8-0.9 signifies a good performance and value less than 0.8 indicates unsatisfactory model performance [43]. The closer the R value is to 1, the better the model fits to the actual data [18]. In this study, minimum value of MSE and the maximum of R were considered as the best neural network model. So the structure of the utilized NN has been configured with 2 input neurons, 7 hidden neurons in 1 hidden layer and one output neuron. Figure 4 shows a comparison of the particle size between experimental values and predicted values from developed ANN model for training set. The developed ANN has the best correlation with the experimental results as displayed in Figure 5 where R2 value is 0.9499.

The performance of the optimal ANN is certified by using validation data test, where another new data set consists of 5 data points which have not been used during the training process. Figure 6 shows scatter plot for actual values and predicted values for particle size from validation data set. After analysing the data using ANN, R value for validation data set is 0.97449. This value demonstrates that the model has satisfactory predictive ability and good quality. Shabanzadeh, [13] and [14] in their study for prediction of silver nanoparticles found R value for validation data set as 0.97788 and 0.9920. As shown in Figure 7, the best validation performance is 0.013672 at epoch 11.

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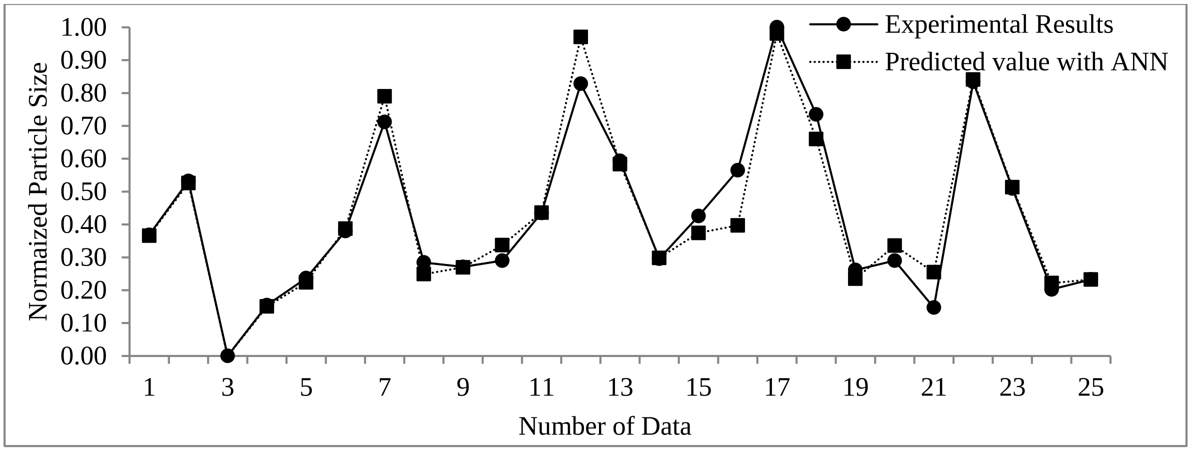

Fig. 4. Comparison of the particle size between experimental and predicted values from developed ANN model for training set.

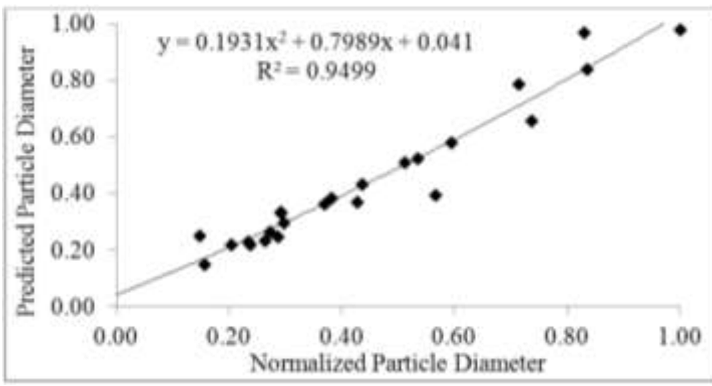

Fig. 5. Correlation coefficient between normalized and predicted particle size for training set.

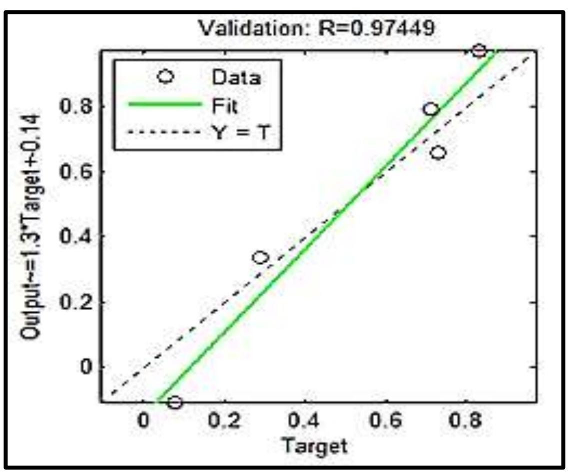

Fig. 6. Scatter regression plot of actual and ANNmodel predicted particle size value for validation data set.

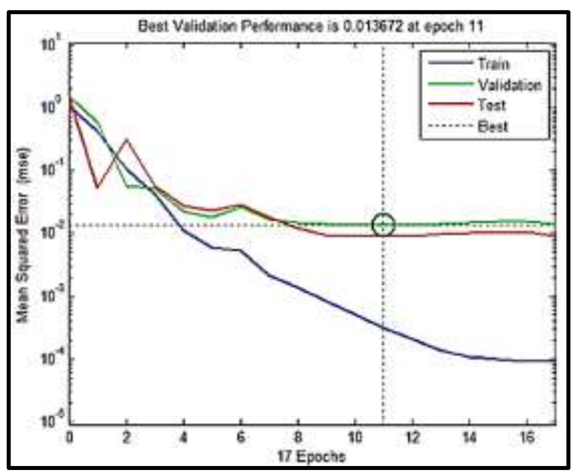

Fig. 7. Best validation perfomance.

Then, for testing fitness of developed ANN model, the scatter plot of experimental data versus the predicted particle size data is presented in Figure 8. The testing data set shows that the results obtained from the developed ANN model are acceptable since the R value is 0.94767. Figure 9 shows comparison of the particle size from

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experimental and predicted values from developed ANN model for testing data set, and Figure 10 represents the correlation coefficient with the experimental results where R2 value is 0.9967.

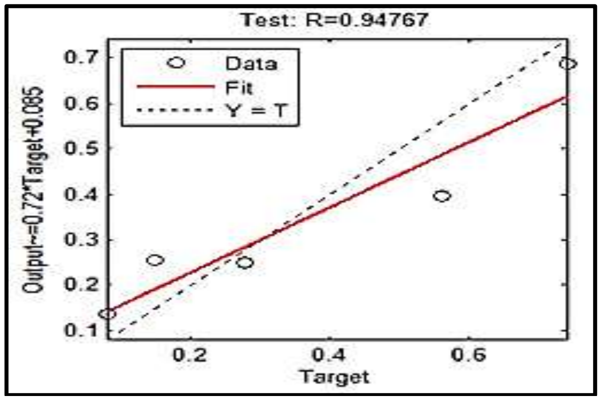

Fig. 8. Scatter regression plot of actual and ANN model predicted particle size value for testing data set.

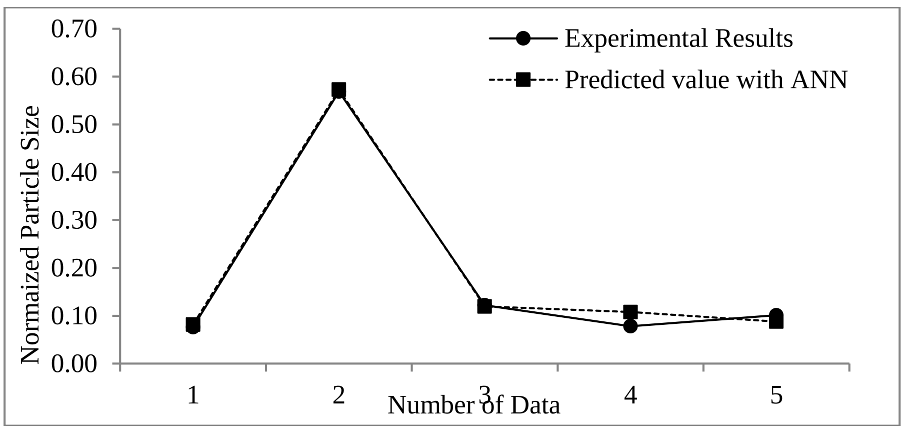

Fig. 9. Comparison of the particle size from experimental and predicted values from developed ANN model for testing data set.

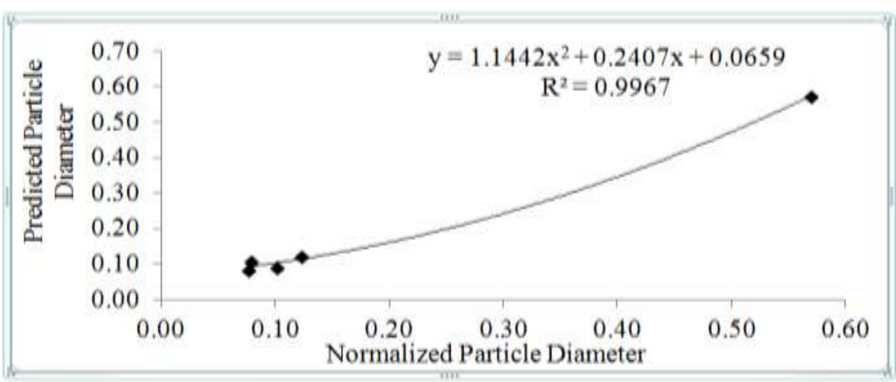

Fig. 10. Correlation coefficient between normalized and predicted particle size from testing data set.

Figure 11 shows scatter regression plot of actual and ANN model predicted particle size values for all 35 data points used in this study, where the R value found in this model is 0.97477, that can be considered as a very satisfactory model performance. Table 3 represents summary for MSE and R value for training, validation and testing data sets that were found in this study.

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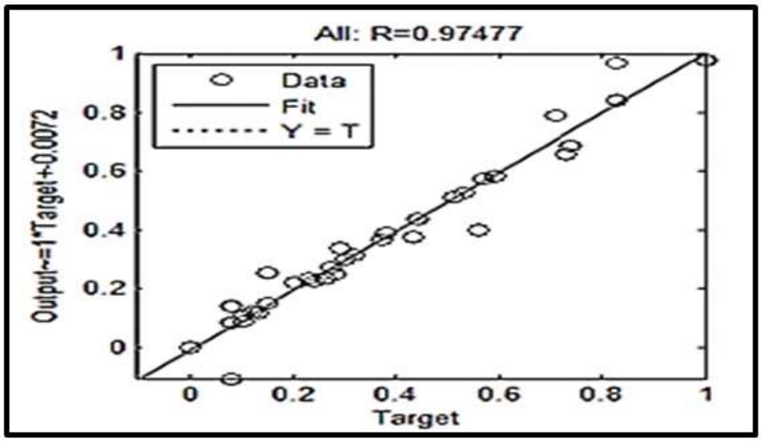

Fig. 11. Scatter regression plot of actual and ANN model predicted particle size values for all data sets.

TABLE 3
THE MEAN SQUARE ERROR (MSE) AND REGRESSION (R) VALUES FOR THE TRAINING, VALIDATION AND TESTING

	MSE Value	R-Value
Training	0.00031	0.99721
Validation	0.01367	0.97449
Test	0.00892	0.94767

Table 4 shows the actual particle size in µm for experimental data of the entire experimental work, the predicted particle size of the developed ANN model, the error between particle sizes of the experimental data and the developed ANN model, an estimation of particle size using Response Surface (RS) tool in MATLAB using pure quadratic model and an estimation of particle size using equation from EXCEL. For the prediction of pure quadratic model, Equation (2) was developed and the constant values were found from the prediction plot of RS tool in MATLAB:

y=B0+B1X1+B2X2+B3X12+B4X22 Equation (2)

Where: value of B0, B1, B2, B3 , B4 is 0.309958, 1.053659, 0.427265, -1.17452 and -0.68898, respectively; X1 = Temperature (°C) and X2 = Pressure (Psi)

For the efficiency study of particle size using EXCEL, Equation (3) was applied. This equation was found from the plot of actual data versus predicted data. The R2 value obtained from this relationship is 0.9625 as shown in Figure 12. Therefore it can be proven that, the actual and predicted data from developed ANN modelarein good agreement.

y = 0.031x2 + 0.6916x + 0.7005 Equation (3)

where x= actual particle size (µm)

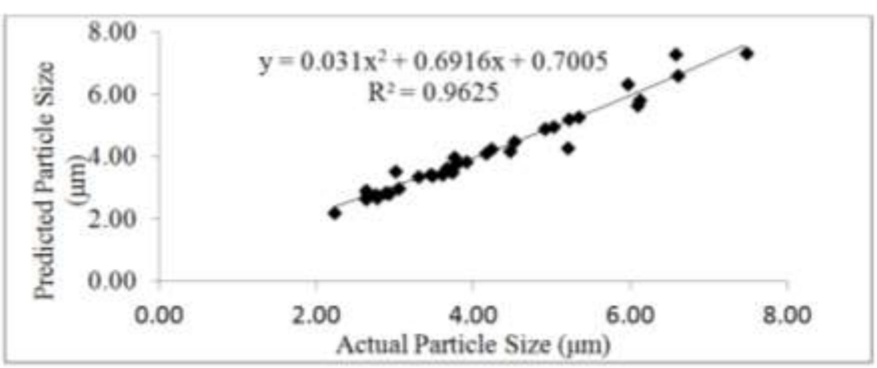

Fig. 12. Relationship between actual particle size from experimental data and ANN developed predicted data.

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TABLE 4
THE ESTIMATED RESULTS OBTAINED BY PROPOSED ANN MODEL AND DATA FITTING

No.	Pressure (psi)	Temperature (°C)	Particle Size (μm)		Error	Estimation of Particle Size (μm)	
			Experimental Data	Predicted ANN model		Pure Quadratic in MATLAB	Equation in Excel
1	3000	40	4.15	4.14	0.01	3.84	4.10
2	4000	40	5.01	4.98	0.03	4.18	4.94
3	5000	40	2.22	2.22	0.00	4.06	2.39
4	6000	40	3.03	3.01	0.02	3.49	3.08
5	7000	40	3.46	3.39	0.07	2.47	3.46
6	3000	45	4.21	4.25	-0.04	4.60	4.16
7	4000	45	5.95	6.36	-0.41	4.94	5.91
8	5000	45	3.71	3.52	0.19	4.82	3.69
9	6000	45	3.64	3.63	0.01	4.25	3.63
10	7000	45	3.74	3.99	-0.25	3.23	3.72
11	3000	50	4.50	4.50	0.00	5.00	4.44
12	4000	50	6.56	7.30	-0.74	5.33	6.57
13	5000	50	5.33	5.28	0.05	5.21	5.27
14	6000	50	3.77	3.78	-0.01	4.64	3.75
15	7000	50	4.45	4.18	0.27	3.62	4.39
16	3000	55	5.18	4.30	0.88	5.07	5.11
17	4000	55	7.46	7.36	0.10	5.40	7.59
18	5000	55	6.07	5.68	0.39	5.28	6.04
19	6000	55	3.59	3.45	0.14	4.71	3.58
20	7000	55	3.74	3.98	-0.24	3.69	3.72
21	3000	60	2.99	3.55	-0.56	4.78	3.05
22	4000	60	6.59	6.63	-0.04	5.11	6.60
23	5000	60	4.89	4.91	-0.02	5.00	4.82
24	6000	60	3.28	3.38	-0.10	4.43	3.30
25	7000	60	3.44	3.44	0.00	3.41	3.45
26	3000	65	2.62	2.94	-0.32	4.19	2.73
27	4000	65	6.1	5.82	0.28	4.52	6.07
28	5000	65	3.9	3.87	0.03	4.40	3.87
29	6000	65	2.91	2.83	0.08	3.84	2.98
30	7000	65	2.74	2.79	-0.05	2.82	2.83
31	3000	70	2.62	2.65	-0.03	3.21	2.73
32	4000	70	5.2	5.22	-0.02	3.54	5.14
33	5000	70	2.86	2.85	0.01	3.43	2.93
34	6000	70	2.63	2.79	-0.16	2.86	2.73
35	7000	70	2.75	2.68	0.07	2.60	2.84

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For the efficiency study of particle size using EXCEL, Equation (3) was applied. This equation was found from the plot of actual data versus predicted data. The R2 value obtained from this relationship is 0.9625 as shown in Figure 12. Therefore it can be proven that, the actual and predicted data from developed ANN modelarein good agreement.

$y = 0.031x2 + 0.6916x + 0.7005$ Equation (3)

where x= actual particle size (μm)

V. CONCLUSION

In this research, an ANN model for prediction of particle size from extraction of ginger rhizome powder using RESS method was presented. The model accounts for the effects of extraction temperature and pressure on the particle size. Based on the results obtained, it can be concluded that the feed-forward back propagation Levenberg–Marquardt model with one hidden layer and 7 hidden neurons is a good training and shows a good performance in predicting experimental data. Hence, it can be concluded that the ANN model is a useful tool for saving time and cost for predicting the particle size.

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