Modeling of muskmelon seed oil extraction under supercritical carbon dioxide condition

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Abstract— From a secondary supercritical extraction data of muskmelon seed which was obtained from the work done by J. Prakash Maran and B. Priya, a suitable mathematical model was found for the oil yield extracted. The reason this study was done is to obtain a model for the process which will be able to predict oil yield of future experiments on supercritical carbon dioxide extraction of muskmelon seed oil. An application of Artificial Neural Network model was used where it was trained until desired output was obtained. A simple mathematical model was derived by applying the equation of straight line to the regression plot of the model. The regression value of the plot is 0.97. The average absolute deviation obtained for the comparison of actual and model oil yield is 2.63%. The actual oil yield and model values show good agreement with each other thus making the model obtained reliable to be used in the future.

Keywords— Artificial Neural Network, Modeling, Muskmelon seed oil, Supercritical fluid extraction

I. INTRODUCTION

Muskmelon (*Cucumis melo*) is a fruit under the melon species. It has been cultivated into many types such as honeydew, crenshaw, casaba as well as variety of cultivars namely cantaloupe, persian melon and christmas melon. The armenian cucumber is known as a type of muskmelon but it resembles mostly to cucumbers. This fruit has such an assortment in variation that it was even grown in a square shape (Ellis, 2004).

In character with other fruits, muskmelon has seeds. Typically, its seeds are thrown away after the fruit is being consumed. Muskmelon seeds are known to contain oil which is very beneficial to the human health. Therefore, muskmelon seeds have a potential to be a good substitute resource for vegetable oil production (Priya, 2014).

Supercritical carbon dioxide (SC-CO_2) as the solvent for extraction is accepting a big attention as a potential industrial solvent. This fluid possesses diffusivity and viscosity which are similar to a gas. While its density and solvent power are liquid-like. Through simple depressurization, SC-CO_2 easily separates from the extracted product (Fiori, Duba, & Luca, 2016).

Moreover, by tuning the operating conditions of process, thermodynamic properties of SC-CO_2 can be adjusted. This solvent is also commonly preferred over other solvents such as n-hexane due to its non-flammable and non-toxic properties (Sodeifian, Ghorbandoost, Sajadian, & Ardestani, 2015).

A mathematical model is commonly used to represent a set of data. In this case, a model for extraction process on its oil yield will be obtained. The uses of a model are for process optimization and scale up process. Furthermore, oil yield can be easily predicted by inserting parameters for different temperatures and pressures without having to conduct the experiment. Example of well-known mathematical models which are applied for vegetable materials are Sovova's broken and intact model (BICM) and shrinking-core model (SCM). Other method for mathematical modeling is by using Artificial Neural network (ANN) (Olivier Boutina, 2011).

For this particular research, ANN modeling will be used. ANNs are computational structures which has basic process units connected to each other namely the neurons. ANN has been widely used in function fitting and pattern recognition. Feed forward neural network was used which contains one input layer and a single or a few hidden layers as well as an output layer. Levenberg-Marquardt method was used to train this network where training an algorithm is done to achieve the best possible outputs from it. This method is more on the trial and error side. ANN does tasks which resembles to the human brain where it gains knowledge during learning and stores it inside the inner neuron (Tehlah, Kaewpradit, & Mujtaba, 2016).

The objective of this study is to obtain a mathematical model which fits the experimental data of muskmelon seed oil extraction using supercritical carbon dioxide as the solvent. The model then can be used to predict oil yield of future experiments on SC-CO_2 extraction of muskmelon seed oil.

II. METHODOLOGY

1. Artificial Neural Network modeling

The procedure for this research was separated into two parts. The first one was the selection for the most suitable number of neurons to be trained. For the second part, the oil yield was predicted by using the best neuron number. Note that before proceeding with training the networks using ANN, a secondary data was first obtained from previous research conducted. The application of ANN is applied through the usage of MATLAB software.

The best neuron number was to be selected by training number of neurons from 1 to 25. Secondary data was inputted from an excel file to the command window through copy paste option. Target and input were defined in the command window. Function fitting design tool was called by inputting "nftool" in the command window. Training, validation and testing were selected to be 70%, 15% and 15% respectively. Number of hidden neurons was inputted to be 1. Levenberg-Marquardt was selected as the network to be trained. The network was retrained until all of the regression values reached over 0.80.

When the best neuron number has been found, multiple trainings on the network using the specific neuron number was done. Training was stopped when regression values were above 0.95 and mean square error values were acceptable. The output of the yield was then displayed in the command window.

From the regression plot, equation of straight line was used to produce a simple mathematical model for this study.

2. Finding the most suitable number of neuron to be trained

In the effort to find the best model representing the oil yield extracted for SFE secondary data for the muskmelon seeds, training of the Artificial Neural Network was done. Further discussion on the outcome of the research are presented below.

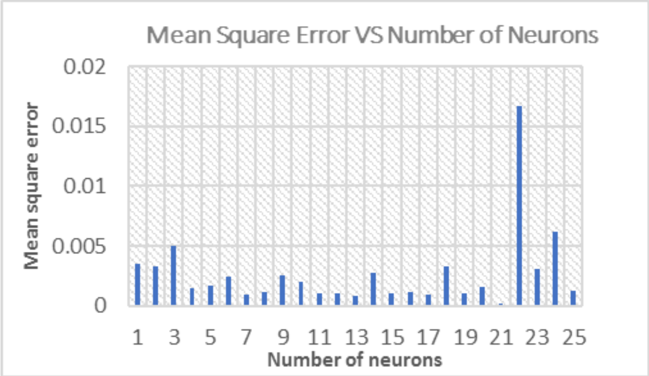

Fig 1: Bar chart of MSE VS number of neurons

It can be seen from figure 1, effect of neuron number was investigated for this network. The neuron number was trained from 1 to 25. Different number of neurons were trained and tested to find the most suitable number to be used for the secondary data. Figure 1 depicts number of neurons trained with their respective MSE values. It can clearly be seen that 21 neuron number has the lowest MSE value and was chosen as the best neuron number to be used for this research.

III. RESULTS AND DISCUSSION

1. Regression plot and error histogram of network

Figure 2 shows the regression plot of the network. They present the relationship between the target and output. Network with 21 neuron number was trained until the R values for all four graphs namely training, validation, test and all reach over 0.95. Regression values are nearly equal to 1 which are very desirable, which measures that the data are very close to the fitted regression line. From the 'All' regression plot, a model is obtained by applying the straight line equation, y=mx+c. The model obtained is shown below.

y = 0.7006x + 0.075

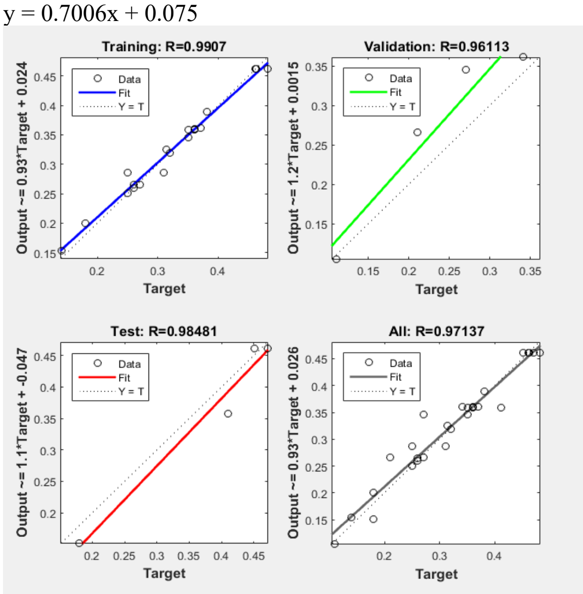

Fig 2: Regression graphs for the trained model with 21 neuron number

As for figure 3, it depicts the error histogram of the trained network. It visualizes the errors between target and predicted values. It can be seen that training values give the smallest errors as compared to testing and validation values, which tallies with the regression values presented in figure 2.

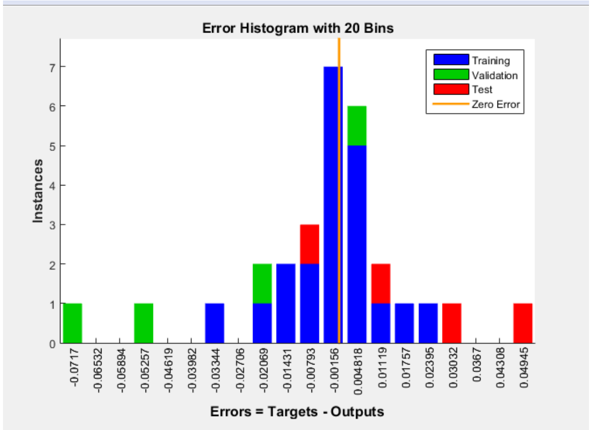

Fig 3: Error histogram for the trained model with 21 neuron number

2. Model adequacy

Table 4.1 presents the predicted oil yield values by the network. The actual oil yield and the predicted oil yield values were compared and calculation on errors were made. The average absolute deviation was calculated using the equation below and 2.63% was obtained.

$$\text{AAD } (\%) = \frac{1}{n}\sum_{i=1}^{n} \left| \frac{yexp - ycalc}{yexp} \right| \times 100$$

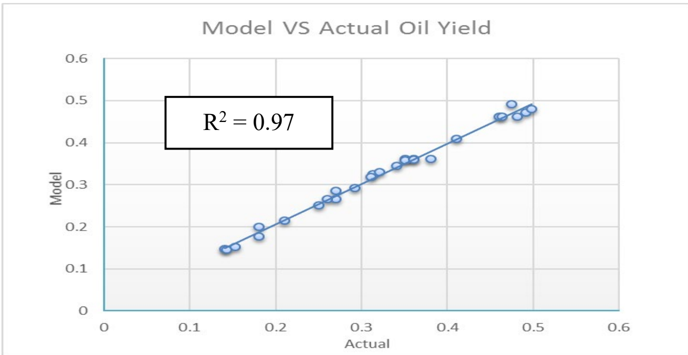

Fig 4: A plot of model against actual oil yield data

From the tabulated result in table 1, a plot of model against actual oil yield data was done and is depicted through figure 4. It is very crucial to ensure that the model gives an adequate approximation to the actual values. Diagnostic plot of model versus actual aids in the evaluation of model stability as well as enabling to analyze the correlation between model and actual values. It can be seen that the data points on figure 4 are decently near to the straight line. This of course shows that actual data from the secondary data as well as the predicted values given by the model have reasonable agreements with each other.

From figure 4, it is safe to say that the simple model applied to fit the extraction of oil yield for this research is sufficient whereby ANN model was trained and applied.

3. Effect of parameters

Moving on to the effect of parameters towards the oil extraction. Discussion on effect of pressure, time and temperature were done.

3.1 Effect of pressure on oil yield

Pressure is known to be one of the crucial parameters in oil extraction using SFE technique. As depicted in figure 5, increase in pressure leads to an increase in oil yield. Pressure increment leads to increase in fluid density, thus making distance between molecules closer. This happens due to the breaking effect because of the higher pressure. This will then strengthen the interactions between matrix and fluid making oil extraction more efficient.

Pressure increase from 30 to 40 MPa shows a drastic increment in oil yield as compared to from 40 to 50 MPa which shows lesser increment gap. This is due to in nature all seeds have their own limits on how much they are able to sustain the pressure. Beyond certain pressure, increasing the pressure will decrease the oil extraction.

Comparing the model and actual plots, a reasonable agreement of the model and actual oil yield are obtained. This can be seen for all pressure plots as shown in figure 5. It can also be seen that at constant temperature of 40ºC, highest oil yield obtained is at the pressure of 50 MPa, with approximately 36% oil yield extracted.

Figure 6 presents the oil extraction plots at constant temperature of 50ºC. As compared to figure 5 which only give the highest oil yield of 36%, figure 6 gives a higher oil yield with the value of 42% at 50 MPa. This is due to the effect of higher temperature gives higher oil yield as discussed previously.

Higher pressure gives higher oil yield as well in figure 6, it is the same as in figure 5. High pressure is known to compress the seeds and extractable components will be easily dissolved in supercritical carbon dioxide. This makes mass transfer between the solid matrix and solvent fluid much more efficient.

Pressure increase from 30 to 40 MPa shows a more drastic increment in oil yield as compared to from 40 to 50 MPa, which is the same as in figure 5. The model and actual plots of the figure also show a decent agreement with each other.

Moving on another plot which is at constant temperature of 60ºC, highest oil yield of 49% is obtained. Pressure increase from 30 to 40 MPa shows a drastic increment in oil yield just as depicted in both figure 5 and 6. However, it can be seen in figure 7 that pressure increment from 40 to 50 MPa shows a very close oil extraction yield values as the plot almost overlaps each other. This shows that at 60ºC, further increase of pressure starting from 40 MPa will not give significant increment towards the oil yield at this temperature. This thus shows the optimum pressure at this temperature lies in between 40 to 50 MPa, nothing more than this pressure range.

It can also be seen through this figure that model and actual plots of oil yield show a good agreement with each other just as figure 5 and 6 depicts in the case of constant temperature.

It can be concluded from figure 5, 6 and 7 that higher pressure gives higher oil yield. This observation is linked to the increase in solute-solvent interactions with higher compressed carbon dioxide. These results tallies with other supercritical carbon dioxide extraction of sunflower oil and grape seed oil which were studied by Olivier Boutin and Natacha Rombaut respectively.

3.2 Effect of extraction time on oil yield

Discussing on the effect of time towards increase in pressure at constant temperature, all three figures 5, 6 and 7 show dramatic oil extraction increment from 0 minute to the 60th minute. This is due to during the first 60 minutes, bigger amount of extractable components exist in the surface of the seeds which allow SC-CO_2 to easily extract the oil. However, after the 60th minute, oil extraction increases slower. This is because, most of the oil which is still held by the seeds are within the deeper inner cell. This requires SC-CO_2 to diffuse deeply into the cell extracting the leftover oil. Which of course result in smaller change of oil extraction as compared to the first 60 minutes.

At higher pressure and temperature as shown in figure 7, increase in time shows an almost constant value of oil extracted, this is due to at a certain pressure and temperature and with the increase of time, very little or no change of oil yield occur. Similar behaviour has been shown for extraction of oil from Pistacia Khinjuk, a study done by G. Sodeifan.

The effect of extraction time discussed above applies for increase in temperature at constant pressure as well, as the pattern of the graphs as shown in figure 8, 9 and 10 are similar to as of the graphs at constant temperature shown in figure 5, 6 and 7.

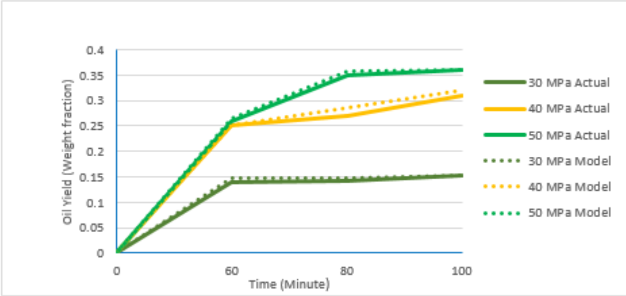

Fig 5: Plot of oil yield of actual and predicted values against time at constant temperature 40ºC

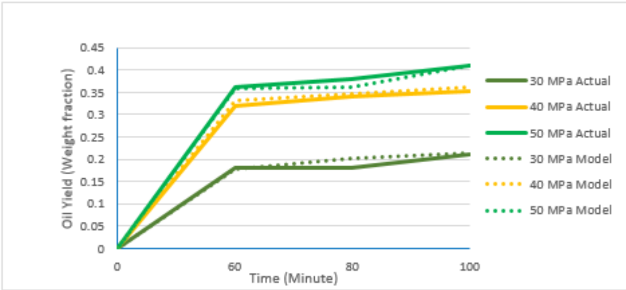

Fig 6: Plot of oil yield of actual and predicted values against time at constant temperature 50ºC

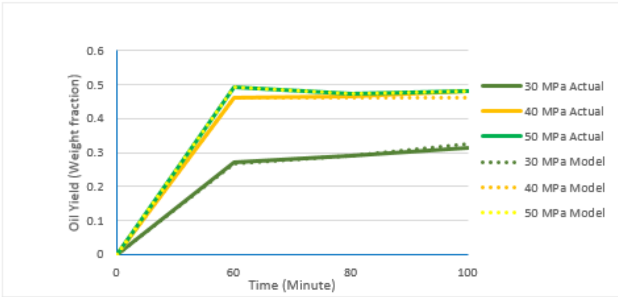

Fig 7: Plot of oil yield of actual and predicted values against time at constant temperature 60ºC

3.3 Effect of temperature on oil yield

Onto the effect of temperature, figure 8 presents oil yield extraction trend at constant pressure of 30 MPa, with pressure increment from 40ºC to 60ºC. It can be clearly seen that increase in temperature leads to increment of oil yield. It is known that with the increase of temperature, extraction efficiency is optimized. This is linked to the increased vapor pressures and higher thermal desorption of oil from the seed. Comparing the model and actual plots, a reasonable agreement of the model and actual oil yield are obtained. This can be seen for all temperature plots as shown in figure 8. It can be seen that at constant pressure of 30 MPa, highest oil yield obtained is at the temperature of 60ºC, with approximately 32% oil yield extracted. Figure 9 presents the oil extraction plots at constant pressure of 40 MPa. As compared to figure 8 which only give the highest oil yield of 32%, figure 9 gives a higher oil yield with the value of 48% at 60ºC. This is due to the effect of higher pressure gives higher oil yield. Higher temperature gives higher oil yield as well in figure 9, it is the same as in figure 8. This experimental observation can be associated with components which have high molecular weight such as oils could be extracted efficiently under the combination of high carbon dioxide temperatures and pressures.

The model and actual plots of the figure also show a decent agreement with each other.

Moving on to the final plot which is at constant pressure of 50 MPa, highest oil yield of 49% is obtained. It can also be seen through this figure that model and actual plots of oil yield show a good agreement with each other just as figure 8 and 9 depicts in the case of constant pressure.

It can be concluded from figure 8, 9 and 10 that higher temperature gives higher oil yield. This observation is linked to the increase in solute-solvent interactions with higher thermal activity of carbon dioxide. These results agree with other supercritical carbon dioxide extraction of sunflower oil and grape seed oil which were studied by Olivier Boutin and Natacha Rombaut respectively.

A mathematical model was successfully obtained which represents the oil yield extracted for SFE of the muskmelon seeds through the application of Artificial Neural Network.

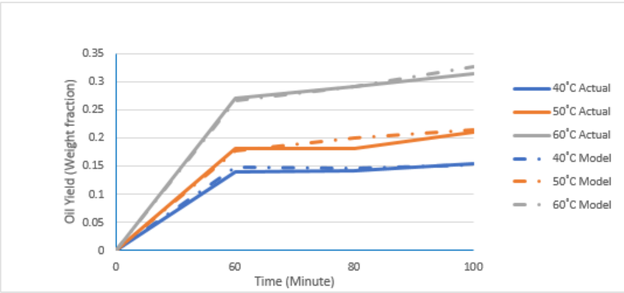

Fig 8: Plot of oil yield of actual and predicted values against time at constant pressure 30 MPa

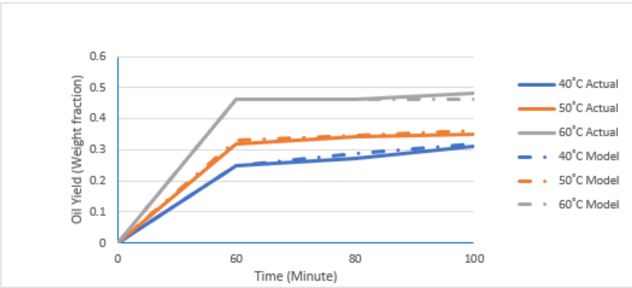

Fig 9: Plot of oil yield of actual and predicted values against time at constant pressure 40 MPa

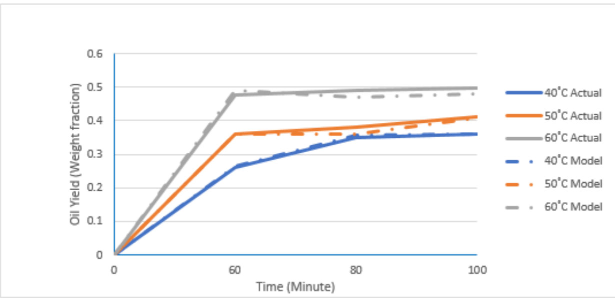

Fig 10: Plot of oil yield of actual and predicted values against time at constant pressure 50 MPa

Table 1: Data parameters of the experiment with actual and predicted oil yield

Pressure (MPa)	Temp.	Time (Min)	Actual oil yield (Wt fraction)	Predicted oil yield (Wt fraction)	Error (%)
30	40	60	0.1403	0.1478	5.35
30	40	80	0.1423	0.1464	2.88
30	40	100	0.1532	0.1526	0.39
30	50	60	0.1804	0.1778	1.44
30	50	80	0.1804	0.2005	11.14
30	50	100	0.2104	0.2154	2.38
30	60	60	0.2705	0.2658	1.74
30	60	80	0.2922	0.2922	0
30	60	100	0.3137	0.3259	3.89
40	40	60	0.2505	0.2505	0
40	40	80	0.2705	0.2865	5.91
40	40	100	0.3106	0.3192	2.77
40	50	60	0.3206	0.3304	3.06
40	50	80	0.3407	0.3454	1.38
40	50	100	0.351	0.361	2.85
40	60	60	0.4609	0.4618	0.2
40	60	80	0.4634	0.4618	0.35
40	60	100	0.481	0.4618	3.99
50	40	60	0.2605	0.2652	1.8
50	40	80	0.3507	0.3582	2.14
50	40	100	0.3607	0.3607	0
50	50	60	0.3607	0.3591	0.44
50	50	80	0.3809	0.3607	5.3
50	50	100	0.4108	0.4094	0.34
50	60	60	0.4754	0.4916	3.41
50	60	80	0.4914	0.4712	4.11
50	60	100	0.4986	0.4794	3.85

IV. CONCLUSION

Secondary data of muskmelon seed oil which was extracted by SFE was used and a simple mathematical model was developed from the data. By applying ANN model, neuron number of 21 was trained until regression value of 0.97 was obtained. The oil yield was modeled as a function of independent variables namely the pressure, temperature and extraction time.

On the mathematical modeling, the results which were obtained are encouraging. However, it is not a perfect model as it is only a predictive tool. It still of course can be used for future oil yield prediction on future experiments of SC-CO_2 extraction of muskmelon seed oil. The model gives an average absolute deviation of 2.63%, which is fairly sufficient to be used.

For this study, it is also found that increase in parameters such as pressure, time and temperature lead to increment of the oil yield.

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