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COMPARATION OF MATHEMATICAL MODELING AND ARTIFICIAL NEURAL NETWORKS TO PREDICT THE OUTPUT THE CAPACITY OF MATERIALS ON MODIFIED SAGO STRACH PNEUMATIC CONVEYING RING DRYER

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ABSTRACT

Modified starch can be obtained through the process of fermentation and UV light irradiation. To dry the modified starch, a pneumatic conveying ring dryer (PCRD) equipped with dewatering and stirring fermentors and irradiation with UVC lamps. One of the important factors in designing the dryer is to know the capacity of the dryer. PCRD dryer capacity can be known through mathematics and artificial neural network (ANN). The purpose of this research is to compare between mathematical models based on dimensional analysis and ANN to predict the output capacity of the material in PCRD type modified wet sago starch dryers. Mathematical models and ANNs are analyzed, tested and trained using experimental data obtained from PCRD performance testing. The comparison results between the mathematical models with ANN shows that the ANN model is the best for predicting material output capacity (Q_{ob}) on PCRD. Each input variable has a very valid influence on the material's output capacity.

Key words: material's output capacity, mathematical models, ANN, modified starch.

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1. INTRODUCTION

Modified starch can be produced through the fermentation process and UV irradiation. Modified starch has physical and chemical characteristics that are close to the characteristics of wheat flour (wheat). Therefore, modified starch can be used more broadly for various food product processing. It can even be used as a substitute for wheat in food products [1]. The modified starch drying process can use artificial or pneumatic type flash dryers, as developed by [2]. A dryer for wet sago starch of pneumatic conveying ring dryer type (PCRD) have developed for drying modified starches based sago and tuber [3-4]. The development was carried out by designing a feed system and predicting the time of material feeding based Artificial Neural Network (ANN). However, an analysis and modeling has not been carried out to predict the capacity of the material in the PCRD dryer. According to [2], material capacity is one of the factors that needs to be considered in the design process of flash or pneumatic type dryers.

To find out the material capacity of PCRD, a mathematical and non-mathematical model is needed, such as ANN. The model must be accurate so that it can predict the material output capacity. Until now, there has not been found any mathematical model and ANN that are used to predict the output capacity of the material in pneumatically modified sago starch drying. However, mathematical models for predicting the output capacity of materials in pneumatic type dryers have been developed for cassava flour drying [5]. The model was developed based on the material variables and the drying process that affects the output capacity of the material. It has not involved the influential variables that are based on physical variables or dimensions in pneumatic dryer construction.

Mathematical and ANN models that have been produced on wet sago starch dryers of PCRD type are prediction models of final moisture content of material [6-7], material modulus finenes [8], and material color difference [9], and drying efficiency [10]. In addition, an analysis of the temperature distribution and velocity of the air flow rate in the drying pipe on the PCRD using computational fluid dynamics (CFD) by [11] has been carried out. Other mathematical models for pneumatic type cassava starch dryers include the model of material finenes modulus [12], model of the final moisture content prediction [13] and the mathematical model for predicting the coefficient value of convection heat transfer [14]. In addition, mathematical models have been developed based on numerical analysis to design small-scale cassava starch dryers [15] and solid-gas flow models in pneumatic and flash drying [16]. Furthermore, mass and energy balance analysis has been carried out, as well as model optimization on the performance of pneumatic dryers [17].

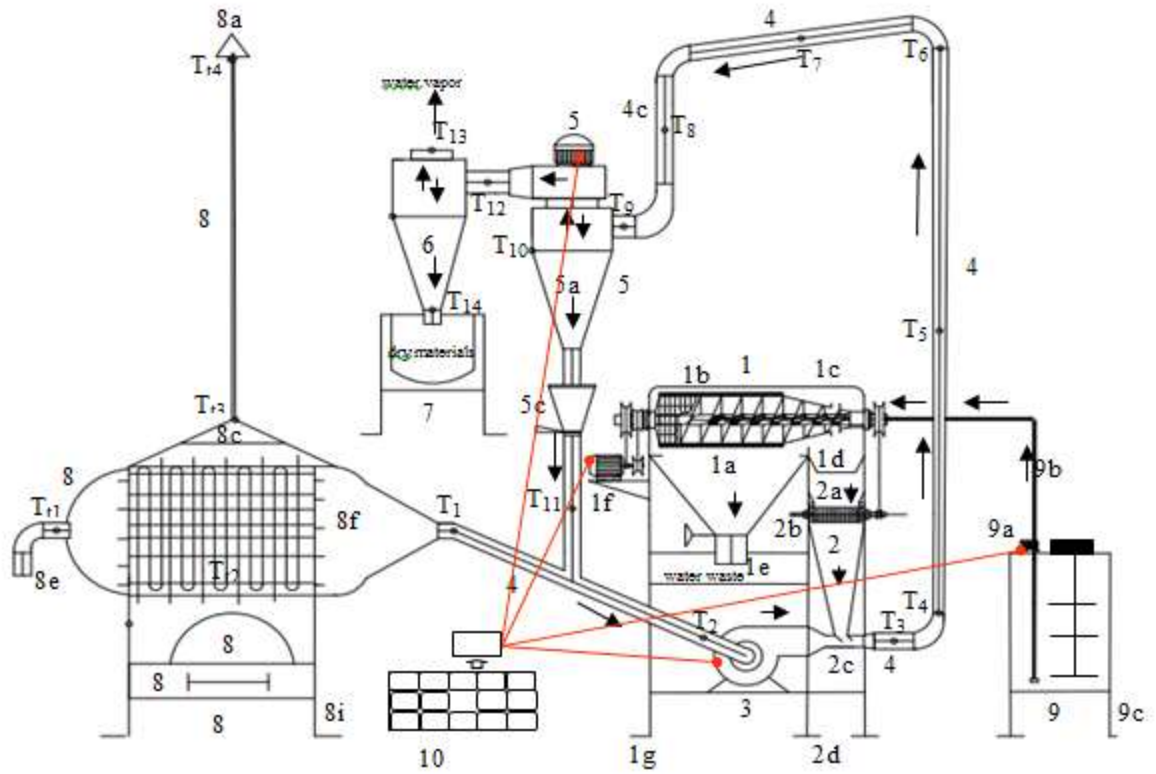
To predict material output capacity on PCRD, it is necessary to do modeling by comparing mathematical models with ANN, so that an accurate material output capacity prediction model is obtained. In addition, the comparison of these models can be used to find out the best prediction model based on the input variables that affect PCRD.

Some other research results that have compared the mathematical model with ANN in the drying process include a model to predict the kinetics of mushroom drying in a vacuum microwave dryer [18], the kinetics model of osmotically dehydrated and fresh figs under open sun drying [19], drying apple slices model preated with high intensity ultrasound [20], models to predict drying terebinth fruit under fluidized bed drying [21], prediction models of paddy drying kinetics [22], models to predict the process and product indices in deep bed drying of rough rice [23] and thin layer drying kinetics of sesame seeds [24]. The purpose of this research is to compare the mathematical models based on dimensional analysis with ANN to predict the output capacity of the material in the PCRD type modified wet sago starch dryer.

2. MATERIALS & EXPERIMENTAL PROCEDURES

2.1. Materials

The material used in this research was modified wet sago starch from the center of the processing of sago and tubers of Kharisma and SagUmbi located in Masni District, Manokwari, West Papua, Indonesia. Modified wet sago starch was obtained by fermentation accompanied by stirring and UV irradiation using UVC lamps. Modified wet sago starch varies in water content to 21, 31 and 41% wet basis (wb). Variations in the initial moisture content of the modified sago starch were carried out by reducing the water content of the material using a 20 ton capacity manual hydraulic press (Design of the Department of Agriculture and Biosystems Engenering, University of Papua).



Annotation:

1)Dewatering centrifuge: 1a. rotary cyilinder, 1b. screw fins, 1c. chasing, 1d. solid outlets, 1e. liquid outlet, 1f. driving motor, 1g. frame, 2) feeder: 2.a. hopper, 2b. feeder cylinder, 2c. ventury pipe, 2d. frame, 3) blower disintegrator, 4) recirculation pipe: 4a. vertical upriser, 4b. u-bend, 4c. vertical downcomer, 4d. horizontal, 5) manifold: 5a. recirculation cyclone, 5b. blower, 5c. recirculation regulator, 6) material output cyclone, 7) dry material reservoir, 8) furnace and Heat exchanger: 8a. chimney cover, 8b. chimney pipe, 8c. furnace cover, 8d. heat cover, 8e. intake air pipe, 8f. hot air chamber, 8g. combustion chamber, 8h. ash room, 8i. frame, 9) UV-stirred reactor: 9a. slurry pumps and stirrers, 9b. slurry flow pipe, 9c. frame, 10) Solar panel, and T = measurement point for temperature and air velocity

Figure 1 The skematis of pneumatic conveying ring dryer

Modified wet sago starch samples were weighed as much as 5 kg, and then compressed to reach a moisture content of 21, 31, and 41% wb. The number of repetitions of each variation of water content as much as 3 times. Modified wet sago starch water content was measured using a MA 50 R RADWAG moisture analyzer. Modified wet sago starch which has been compressed, then weighed as much as 1 kg, is fed to a mini-scale PCRD dryer unit that has been equipped with a feeder, dewatering and horizontal fermentor system with UVC lamps. The PCRD prototype scheme can be seen in figure 1. Each input variable carries out 3 times variation and 3 times repetition. The input variables used are described in the mathematical model and ANN used.

Other supporting tools used in this research include a 10 channel thermometer (LUTRON) and thermocouple type K (-199.9-1370^{o}C) to measure material temperature, outside air and drying air, digital hygrometer meter (KRISBOW-KW06-291) to measure humidity air, air flow meter (KRISBOW) to measure air flow velocity, and analytical balance (HWH-max 600 g) to weigh modified sago starch samples, and analog scales (KRISBOW-max. 200 kg) to measure modified wet sago starch.

2.2. Methods

2.2.1. Mathematical Model

Material output capacity is the ratio between the mass of dry material coming out of the output cyclone on the PCRD compared to the time required for the material leaving the output cyclone. Variables that are suspected to influence the material output capacity (Q_{ob}) in PCRD are the material input moisture content (M_{ib}), material density (γ_{ib}), material input temperature (T_{ib}), PCRD drying pipe diameter (D_p), PCRD drying pipe length (L_p), diameter of cyclone cylinder recirculation of PCRD material (D_{scrb}), pipe length of upper outlet on PCRD material recirculation cyclone (L_{Acrb}), height of PCRD material recirculation cyclone cylinder (L_{scrb}), pipe diameter of upper outlet on PCRD material recirculation cyclone (D_{Acrb}), material input capacity (Q_{ib}), PCRD dryer air speed (v_u), blower air velocity of PCRD material recirculation cyclone (v_{ucrb}), PCRD dryer air temperature (T_{u3}), and gravity acceleration (g).

To determine the effect of these variables on Q_{ob} on PCRD, a mathematical model was developed using dimensional analysis. Dimensional analysis is used in the development of mathematical models because it has several advantages that are easy to use and without involving complex analysis. The mathematical model produced from the analysis of relationship dimensional that affect the output capacity of materials in PCRD are expressed in the form of mathematical equations, as in Equation 1.

The mathematical model produced in Equation 1 was then analyzed using 81 experimental data obtained from the drying results of a modified wet sago starch sample using the PCRD prototype (fig. 1). Data were analyzed using regression analysis to compare Q_{ob} predictions (pred) with Q_{ob} experiments (exp). Then the effect of each input variable on Q_{ob} is analyzed.

$$Q_{ob} = 0{,}004(Q_{ib})(M_{ib})^{-0{,}579}\left(\frac{\gamma_{ib}^{\ 2} D_p^{\ 5} g}{Q_{ib}^{\ 2}}\right)^{0{,}223}\left(\frac{T_{ib}}{T_{u3}}\right)^{-0{,}773}\left(\frac{D_p}{L_p}\right)^{0{,}471}$$

$$\left(\frac{L_{scrb}}{D_{scrb}}\right)^{-0{,}305}\left(\frac{D_{Acrb}}{D_{scrb}}\right)^{-0{,}467}\left(\frac{L_{Acrb}}{D_{scrb}}\right)^{-0{,}377}\left(\frac{v_{ucrb}^{\ 2}}{gD_p}\right)^{0{,}485}\left(\frac{gD_p}{v_u^{\ 2}}\right)^{-0{,}143}$$

(1)

where:

Qob is the material output capacity (kg/s), M_{ib} is the material input moisture content (%wb), γ_{ib} is material density (kg/m^3), T_{ib} is material input temperature (^oC), D_p is PCRD drying pipe diameter (m), L_p is PCRD drying pipe length (m), D_{scrb} is diameter of cyclone cylinder recirculation of PCRD material (m), L_{Acrb} pipe length of upper outlet on PCRD material recirculation cyclone (m), L_{scrb} is height of PCRD material recirculation cyclone cylinder (m), D_{Acrb} pipe diameter of upper outlet on PCRD material recirculation cyclone (m), Q_{ib} is material input capacity (kg/s), v_u is PCRD dryer air speed (m/s), v_{ucrb} is blower air velocity of PCRD material recirculation cyclone (m/s), T_{u3} is PCRD dryer air temperature (^oC), and g is gravity acceleration (m/s^2).

2.2.2. Artificial Neural Network

The ANN network structure used to predict Q_{ob} on PCRD is a multi input single output (MISO). The network topology used consists of 14 input neurons, 5 first hidden layers, 5 second hidden layers, 1 third hidden layer, and 1 output neuron. Input neurons are input variables used in mathematical models. The number of input neurons is equal to the number of variables that affect the mathematical model, namely M_{ib}, γ_{ib}, T_{ib}, D_p, L_p, D_{scrb}, L_{scrb}, D_{Acrb}, L_{Acrb}, L_{scrb}, D_{Acrb}, Q_{ib}, v_u, v_{ucrb}, T_{u3}, and g, and targets of network output is Q_{ob}. The ANN network structure formed can be seen in figure 2.

Variation input neurons are 9 variables, i.e. M_{ib} (21,31,41 % wb), v_u (15, 28, 31 m/s), T_{u3} (75, 100, 125 ^oC), L_p (9.38, 11.38, 13.38 m), L_{scrb} (0.27, 0.54, 0,81 m), D_{Acrb} (0.1016, 0.17, 0.22), L_{Acrb} (0.2, 0.37, 0.65 m), v_{ucrb} (10.75, 12.75, 15.75 m/s), Q_{ib} (0.00208, 0.00278, 0.00417 kg/s), while the other inputs are assumed to be constant, i.e. D_p (0.1016 m), D_{scb} (0.5 m), γ_{ib} (550 kg/m^3), T_{ib} (32 ^oC), and g (9.8 m/s).

The structure of the ANN network formed is trained and tested to determine the accuracy of the network. Training and testing of network structures are using 81 experimental data sets. The data is the same as the data used in the mathematical model. The experimental data was divided into 2 parts, namely 54 data sets for training, and 27 data sets for testing using trial and error methods.

The training and testing process uses a network topology with the first 5 hidden layers, second 5hidden layers, and 1 third hidden layer. ANN network training and testing simulations were carried out with the MATLAB Neural Network Toolbox (GUI) Graphical User Interface (GUI) Version 2014a application which was installed in a set of laptops with Intel Corei3-4030u CPU, 1.9 GHz, 4GB memory, and 500GB hard disk. The application has been developed by [4, 7-11].

To find out the performance value of the mathematical model and ANN in predicting Q_{ob}, a comparison of the index value of minimum error prediction performance is performed. According to [25] minimum error prediction performance is determined based on the mean square error, root mean absolute error (RMSE), mean relative error (MRE), and mean absolute error (MAE) values. To calculate the value of RMSE, MRE, and MAE used Equations 2 to 5.

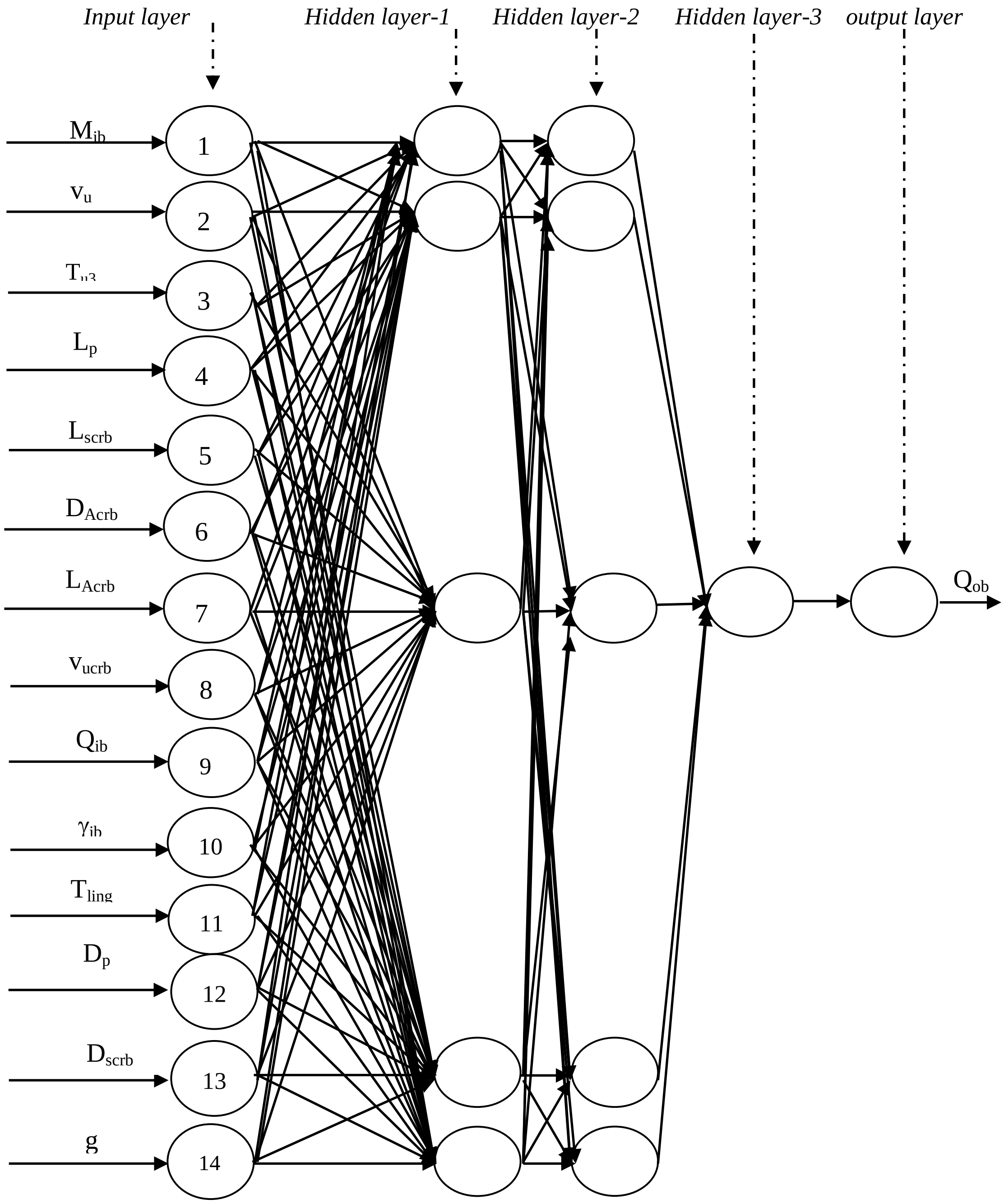


Figure 2 ANN structure for Q_{ob} predictions

$$MSE = \frac{\sum_{i=1}^{N} \left| M_{ob-prediksi,i} - M_{ob-observasi,i} \right|^2}{N} \quad (2)$$

$$RMSE = \left[\frac{\sum_{i=1}^{N} \left| M_{ob-prediksi,i} - M_{ob-observasi} \right|^2}{N} \right]^{0,5} \quad (3)$$

$$MRE = \frac{\sum_{i=1}^{N} \left| \frac{M_{ob-prediksi,i} - M_{ob-observasi,i}}{M_{ob-observasi,i}} \right|}{N} x100 \quad (4)$$

$$MAE = \frac{\sum_{i=1}^{N} \left| M_{ob-prediksi,i} - M_{ob-observasi,i} \right|}{N} \quad (5)$$

where:

MSE is mean square error, RMSE is the root mean absolute error, MRE is mean relative error (%), and MAE is mean absolute error values.

3. RESULTS AND DISCUSSION

Based on the results of the regression analysis on the mathematical model that has been developed (Equation 1), the value of determination coefficient (R^2) is obtained between predictive Q_{ob} (pred) against experimental Q_{ob} (exp) of 0.957, as in figure 3. The difference between predictive Q_{ob} (pred) towards experimental Q_{ob} (exp) is very small with an R^2 of 95.7%. This shows that the mathematical model in Equation 1 is very valid and feasible to predict Q_{ob} on PCRD.

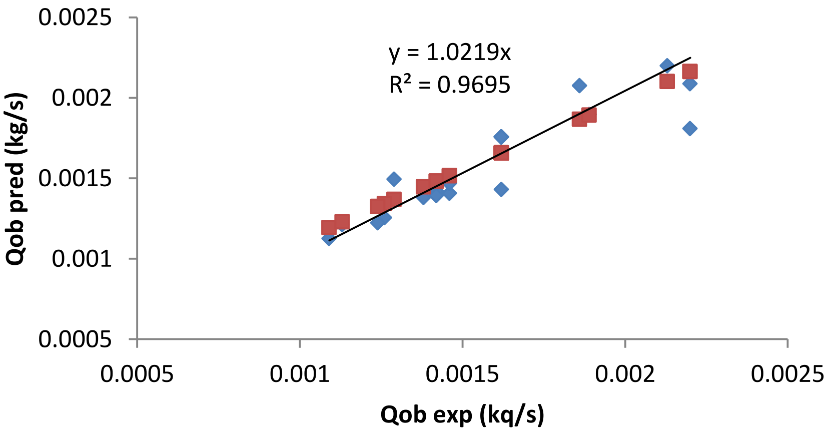


Figure 3 Comparison of Q_{ob} pred. and Q_{ob} exp. of mathematical modeling

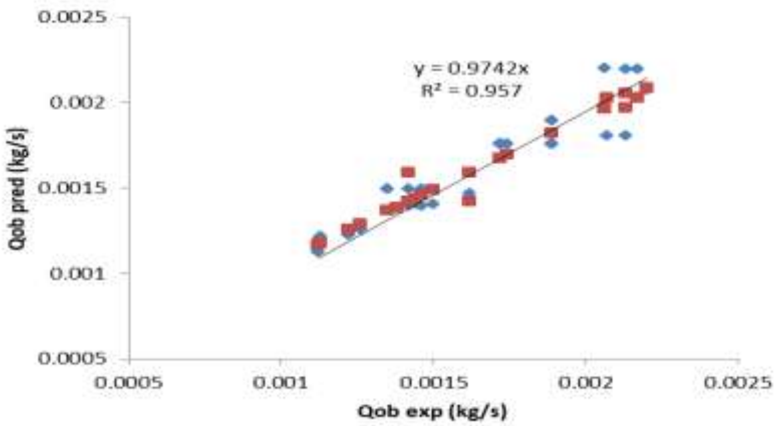


Figure 4 Comparison of Q_{ob} pred. and Q_{ob} exp. of mathematical modeling

Then the level of validity of the mathematical model is tested using different data from the data used in the initial testing. The test results of the model validity, obtained a value of determination coefficient (R^2) which is almost the same as the initial test that is 0.9695 or 96.95%, as shown in figure 4. This shows that the mathematical model is very valid to predict Q_{ob} in the modified wet sago starch dryer type PCRD.

The results of the regression analysis conducted to determine the effect of each input variable on material output capacity (Q_{ob}) can be seen in Table 1. Data in Table 1 shows that each input variable has a very high influence on Q_{ob}. It is seen that the value of R^2 in each input variable has a value greater than 90%. Therefore, the input variables used have a very close relationship with Q_{ob} on PCRD.

Table 1 Effect of variable variations on Q_{ob}

Jenis Variabel Variasi	R^2
The material input moisture content (M_{ib})	0.978
Material input capacity (Q_{ib})	0.977
PCRD dryer air temperature (T_{u3})	0.984
PCRD drying pipe length (L_p)	0.999
Height of PCRD material recirculation cyclone cylinder (L_{scrb}),	0.963
Pipe diameter of upper outlet on PCRD material recirculation cyclone (D_{Acrb})	0.979
Pipe length of upper outlet on PCRD material recirculation cyclone (L_{Acrb})	0.949
Blower air velocity of PCRD material recirculation cyclone (v_{ucrb})	0.997
PCRD dryer air speed (v_u)	0.993

ANN network topology training results consisting of 14 input neurons, 5-5-1 hidden layer neurons, and 1 output neuron (target), Levenberg-Marquadrant network training algorithm, the transfer of the logsimoid function has resulted in an R^2 value between predicted Q_{Ob} and experimental Q_{Ob} of 0.9993 or 99.93%, as figure 5. This shows that the ANN network structure that is formed is very accurate for predicting Q_{Ob} in modified starch dryers PCRD type.

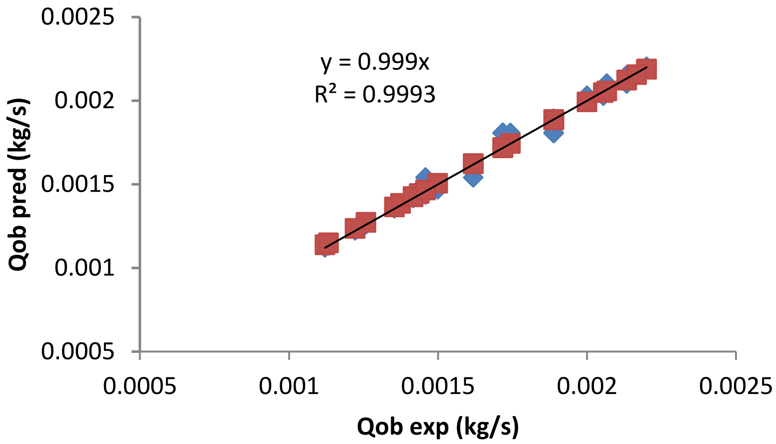


Figure 5 Comparison of predictive material output capacity (Q_{ob} pred) with experiments (Q_{ob} exp) of ANN Training

ANN topology that has been trained then tested using 27 different sets of experimental data. Network test results with the same topology as the ANN test obtained an R^2 value of

0.9989 or 99.89%, as figure 6. When compared with the value of R^2 of training, the value of R^2 of the test is lower, probably due to the smaller amount of data and the selection of less proportional data. However, the R^2 value produced by the ANN test approached the training ANN, with a very small difference in value so that the ANN model that had been formed was very valid to predict Q_{ob} in the modified wet sago starch dryer PCRD type. The results of this research are the same as the results of the research using the ANN model to predict the final moisture content of materials on PCRD conducted by [7].

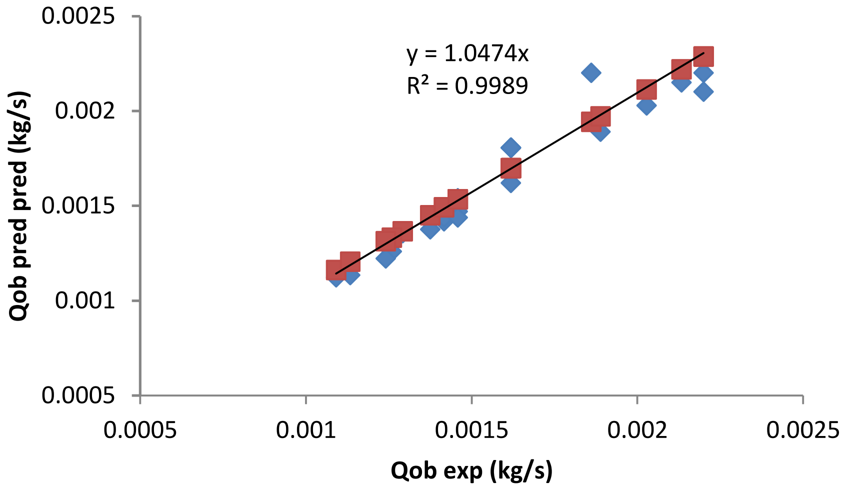


Figure 6 Comparison of predictive material output capacity (Q_{ob} pred) with experiments (Q_{ob} exp) of ANN Testing

The analysis results of the performance index values between the mathematical model and ANN can be seen in Table 2. The results of the analysis are obtained using Equations 2 to 5. The data in Table 2 show that the error values of ANN training (MSE, RMSE, MAE, and MRE) are smaller when compared with error values (MSE, RMSE, MAE, and MRE) in the mathematical model. This shows that ANN has a better performance index value when compared to the mathematical model. The comparison results between mathematical models and ANN in this research are the same as the comparisons results conducted by [18] for mushroom drying in a microwave vacuum drier, where the ANN model has a higher level of accuracy with an R^2 value of 0.99 and an MSE value of 8.8×10^{-4}. Likewise with research conducted by [20], where the ANN model is the best when compared to the mathematical model in the process of drying apple slices pretreated with high intensity ultrasound. In addition, a comparison of mathematical models and ANN has also been carried out by [19] where ANN is the best model with a value of R^2 greater than the mathematical model.

Table 2 Comparison of performance indexes of mathematical models and ANN training

Modeling	MSE	RMSE	MAE	MRE (%)
Mathematical model pred-1	1.18×10^{-8}	1.08×10^{-4}	8.10×10^{-5}	4.589
ANN Training	2.75×10^{-9}	5.25×10^{-5}	3.66×10^{-5}	2.075

4. CONCLUSIONS

The best model to predict the output capacity of materials in a modified starch dryer type pneumatic conveying ring dryer is ANN model with a network topology of 14 input neurons, 5 first hidden layers, 5 second hidden layers, 1 third hidden layer, and 1 output neuron (14- 5-5-1-1). This is based on a very small MSE value and a very high correlation coefficient.

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