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# Comparison of mathematical and artificial neural network model to predict hot air-drying kinetics of garlic slices and determination of powder qualities

# Comparación de un modelo matemático y de red neuronal artificial para predecir la cinética de secado con aire caliente de rodajas de ajo y determinar las cualidades del polvo

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## Abstract

It is difficult to model the changes in moisture content when using hot air dryers that vary in temperature. This study focused on examining mathematical models and artificial neural networks (ANN) to forecast the moisture content of sliced garlic. Additionally, the study explored the impact of drying temperature on sliced garlic (2 mm). The trials were conducted using four different degrees of hot air temperature (50, 60, 70, and 80$^{o}$C). The quality of the powder used in these treatments was also assessed. The results indicated that out of the seven mathematical models, the two-term model provided the most accurate prediction of moisture ratio during the drying process, as evidenced by its greatest R-square value and lowest MSE. In addition, an artificial neural network (ANN) model with 4 hidden layers can also yield the most accurate model, meeting the same criteria as the mathematical model. When comparing the ANN model to the other model, both are capable of providing highly accurate predictions. Nevertheless, the use of an ANN model could yield more advantages in the up-scaling process. Furthermore, subjecting garlic slices to a drying process at a temperature of 60$^{o}$C can result in a product that possesses elevated levels of antioxidants, antioxidant activity, allicin content, and overall acceptance.
*Keywords*: garlic, artificial neural network, drying, modeling, antioxidant.

## Resumen

Es difícil modelar los cambios en el contenido de humedad cuando se utilizan secadores de aire caliente que varían en temperatura. Este estudio se centró en examinar modelos matemáticos y redes neuronales artificiales (ANN) para pronosticar el contenido de humedad del ajo rebanado. Además, el estudio exploró el impacto de la temperatura de secado en el ajo rebanado. Las pruebas se realizaron utilizando cuatro grados diferentes de temperatura del aire caliente (50, 60, 70 y 80$^{o}$C). También se evaluó la calidad del polvo utilizado en estos tratamientos. Los resultados indicaron que de los siete modelos matemáticos, el modelo de dos términos proporcionó la predicción más precisa de la proporción de humedad durante el proceso de secado, como lo demuestra su mayor valor R cuadrado y su MSE más bajo. Además, un modelo de ANN con cuatro capas ocultas también puede producir el modelo más preciso, cumpliendo los mismos criterios que el modelo matemático. Al comparar el modelo ANN con el otro modelo, ambos son capaces de proporcionar predicciones muy precisas. Sin embargo, el uso de un modelo de ANN podría generar más ventajas en el proceso de ampliación. Además, someter las rodajas de ajo a un proceso de secado a una temperatura de 60ºC puede dar como resultado un producto que posee niveles elevados de antioxidantes, actividad antioxidante, contenido de alicina y aceptación general
*Palabras clave*: ajo, red neuronal artificial, secado, modelado, antioxidante.

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# 1 Introduction

Garlic, scientifically known as *Allium sativum* L., is a pungent vegetable that is extensively used worldwide for its flavor-enhancing properties and medicinal benefits (Espinoza *et al*., 2020). Garlic is renowned for its health advantages mostly because of its diverse bioactive compounds, including allicin (El-Saber Batiha *et al*., 2020), polysaccharides (Ozma *et al*., 2023), and polyphenols (Dorrigiv *et al*., 2020). These chemicals not only give garlic its distinctive flavor but also contribute to its biological activity. Recently, there has been a growing popularity in various processed products of garlic, such as dehydrated garlic slices, garlic powder, raw garlic, black garlic, and garlic oil. The therapeutic benefits of garlic are ascribed to allicin and its breakdown products (Espinoza *et al*., 2020; Ozma *et al*., 2023; Subroto *et al*., 2021). Allicin does not exist in whole garlic, but it is quickly generated when fresh garlic is crushed or minced. Upon crushing, the allinase enzyme interacts with alliin, transforming it into allicin and pyruvic acid. Allicin undergoes decomposition when exposed to heat or organic solvents. It easily breaks down into different degradation products, including allylsulfides, vinyldithins, and ajoenes (Emadzadeh *et al*., 2021).

Drying is a widely employed and expensive technique that effectively extends the shelf life of garlic worldwide. It achieves this by impeding the growth of microbes, decreasing enzyme activity, and slowing down unfavorable chemical reactions (Loan & Tai, 2023; Thuy *et al*., 2024). Garlic powder, a highly sought-after commercial garlic product, can be created by dehydrating garlic cloves or slices. The desiccated samples are subsequently ground into a fine powder. The standardization of garlic powder is based on allicin, as established by Lawson and Wang (2001). Nevertheless, there is significant variation in the quantity of allicin present across different brands. The variation in processing procedures, such as sample preparation, drying method, and drying conditions, is responsible for this phenomenon (Thuwapanichayanan et al., 2014).

Mathematical models are valuable tools, but they rely on certain assumptions that necessitate a deep understanding of process principles, estimation of multiple experimental variables, and the use of complex computing techniques (Langbauer *et al*., 2023; Loan & Tai, 2023; Yang et al., 2023). Moreover, nowaday, the researcher most focus on machine learning which could help further up-scale process(Lara-Cerecedo *et al*., 2023; Loan *et al*., 2023). In order to successfully estimate moisture content or moisture ratio under changing drying circumstances, the black-box modelling approach allows for investigation of these complex modelling challenges (Chokphoemphun *et al*., 2023; Loan *et al*., 2023; Yang *et al*., 2023). ANN, or Artificial Neural Network, is an example of a black-box methodology that offers advantages over traditional methods. Artificial neural networks (ANNs) enable the representation of complex and nonlinear systems, providing fast computation and seamless adaptability (Langbauer *et al*., 2023; Mohan *et al*., 2023; Yang *et al*., 2023). Therefore, the objective of this study was aimed to compare the effectiveness of mathematicall model and ANN model in prediction of changing of moisture content during drying process as well as study the effect of drying temperature on qualities and overall acceptance of garlic powder.

# 2 Materials and methods

## 2.1 Sample preparation

A local farm in the province of Tien Giang, Vietnam, provided the fresh garlic (*Allium sativum* L.). After drying the sample in a drying oven at 105°C until a constant weight reached, the initial moisture content of fresh garlic [63.23±1.23% (wet basis)] was determined. Three replications of each experiment were conducted. Fresh garlic was peeled manually, then an automatic fruit and vegetable slicer was used to slice into 2.0 ± 0.1 mm pieces and dried.

## 2.2 Drying experiment

The sample was subjected to drying at temperatures of 50°C, 60°C, 70°C, and 80°C until it reached a state of equilibrium moisture content. The weight of the sample was measured at regular 15-minute intervals during the drying process to determine the moisture content at various time points. Three replicates were conducted for each drying condition and the mean moisture content data was utilized.

## 2.3 Model fitting

The moisture ratio value (MR) was calculated as Equation 1 before fitting model. The variables in Equation are $M_t$, which represents the moisture content at time t as a percentage on a dry basis, $M_e$, which represents the equilibrium moisture content as a percentage on a dry basis, and $M_i$, which represents the initial moisture content as a percentage on a dry basis.

$$MR = \frac{M_t - M_e}{M_i - M_e} \tag{1}$$

Seven common thin-layer models were selected (Thuy *et al*., 2023; Thuy et al., 2022), which was used to fit the actual MR data as shown in Table 1.

Table 1. Seven mathematical modelling research of garlic slices in this study.

| No. | Model name | Equation |
|---|---|---|
| 1 | Newton | $MR = e^{-kt}$ |
| 2 | Henderson and Pabis | $MR = a\ e^{-kt}$ |
| 3 | Page | $MR = e^{-kt^n}$ |
| 4 | Logarithmic model | $MR = ae^{-kt} + c$ |
| 5 | Wang and Smith | $MR = 1 + at + bt^2$ |
| 6 | Two-term | $MR = ae^{-kt} + be^{-k_o t}$ |
| 7 | Diffusion approach | $MR = ae^{-kt} + (1-a)e^{-kbt}$ |

Regression analysis was conducted to find the drying constant (a, b, c, k, $k_1$,n) of each model. The highest coefficient of determination ($R^2$) and lowest mean square error (MSE) values were used to select the most suitable equation which expresses the drying kinetics of garlic slices.

### 2.4 Artificial neural network (ANN)

This study employed a multi-layer feed forward back propagation model. The model was given drying time and temperature as input signals. The model outputs included the moisture ratio and moisture content. To achieve lower model complexity, the number of hidden layers (HLs) was limited to 1. The transfer function, also known as TANSIGMOID, was utilized for the hidden layer (HL) and its relative performance was examined (Dorofki *et al*., 2012). The model underwent training in MATLAB v.2021a utilizing Levenberg-Marquardt (LM) training functions. Model training was conducted using 70% of the available data. The remaining 30% of the data set was used for testing and validation, with an equal division between the former and latter. To save processing time, the number of iterations and validation tests were restricted to 1000. The ANN infrastructure with the minimum Mean Squared Error (MSE), maximum correlation coefficient (r), and minimum complexity was chosen.

### 2.5 Drying behavior

The effective diffusivity ($D_{eff}$ ) was calculated using the simplified form of Fick's Diffusion equation (Equation 2) (Demiray & Tulek, 2017).

$$\ln(MR) = \ln\left(\frac{8}{\pi^2}\right) - \left(\frac{\pi^2 t D_{eff}}{4L^2}\right) \tag{2}$$

The effective moisture diffusivity ($D_{eff}$) is defined as the ratio of the moisture flux to the moisture gradient and is measured in square meters per second ($m^2$/s). The drying time (t) is the duration of the drying process, measured in minutes. The thickness (L) refers to the distance or extent of the material being dried and is measured in meters (m). The diffusivity values were derived from the gradient of the ln(MR) vs time (t) plot. The relationship between moisture diffusivity and temperature was characterized by the Arrhenius equation (Equation 3). The activation energy (Ea, kJ/mol) was determined by plotting ln($D_{eff}$) against the reciprocal of absolute temperature (T, K).

$$D_{eff} = D_0 exp(\frac{-E_a}{RT}) \tag{3}$$

where, $D_0$ is the Arrhenius factor, $E_a$ is the activation energy (kJ/mol), R is the universal gas constant (8.314 kJ/mol.K) and T is the drying temperature (K).

### 2.6 Determination of qualities of garlic powder

The process of extracting and quantifying allicin was carried out utilizing the method that was explained earlier (Guo *et al*., 2023; Zhang *et al*., 2021). The total phenolic content and radical scavenging ability (DPPH%) were analyzed following the description of Van Tai *et al*. (2021). The overall acceptance based on 9-point scale (1-very dislike and 9-very like) on the overall color, flavor and texture of garlic powder was investigated. The results were expressed as Mean±STD.

## 3 Results and discussion

### 3.1 Drying characteristics of sliced garlic by fitting with mathematical models

The initial moisture content of sliced garlic was 63.23±1.23% (wet basis), which was change by different pattern during drying process at different temperature (Figure 1). At drying temperature of 50°C, the change of MR was drammatically reduced at the first 45 minutes, then the slight reduction in MR was found until the moisture of sliced garlic reaches equilibrium (after 2.5 hours). However, when the drying temperature increases, the remarkable reduction in MR and drying time also were found. The drying time were 75 min, 105 min, 120 min corresponding to used drying temperature at 80°C, 70 °C and 60°C. Evidently, the research on butterfly pea flowers butterfly pea flower (Thuy *et al*., 2021), purple sweet potatoes (Thuy et al., 2022), banana peel (Tai *et al*., 2021) and moringa leaves (Tai et al., 2024) had all demonstrated that the drying process transferred moisture more quickly when the air temperature was higher. According to these researchers, processing of water flow out of the food matrix could be more significantly powered by greater temperatures. Increased heat energy utilization speeds up the drying process, increasing the quantity of liquid vaporizing from the material's surface and hastening the diffusion of water from the specimen's inside to its surface. Sliced garlic's moisture content

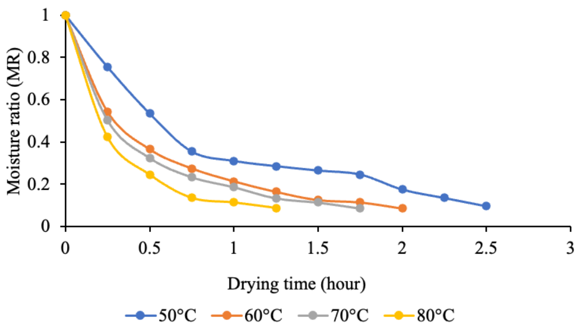


Figure 1. Moisture ratio versus drying time at different temperatures of sliced garlic.

also rapidly decreased. On the other hand, it is important to consider the possibility that the high drying temperature may alter the organoleptic and quality of the products.

Further, the moisture ratio of garlic slices under different drying temperatures were fitted with seven thin-layer mathematical models (Table 1). It was successful to estimate the moisture content and moisture ratio of dried samples using thin-layer modeling. Nonetheless, the model that was fitted was dependent on several variables, such as the kind of material, temperature, sample thickness, drying period, etc. Generally speaking, the greatest $R^2$ and the lowest RMSE, chi-square, or MSE are used to choose a fitness model (Arabhosseini *et al*., 2009). It could be seen from the Table 2 that all models could give the best prediction on the change of MR during drying process with high coefficient determination ($R^2$ > 90%). Among that, Wang and Sign model and Two-term showed the lowest and highest value of $R^2$, respectively. The lowest value of MSE also was found on the Two-term model at different level of temperature. Hence, it can be assumed that the two-term model effectively demonstrates the accuracy of the fit between observed and forecasted data. Two-term model also gave the best prediction on thin-layer drying behavior of bananas in a heat pump dehumidifier dryer (Dandamrongrak *et al*., 2002). Recently, the study of (Mbegbu *et al*., 2021) also demonstrated that this model could determine the drying kinetics and characteristics of scent and lemon basil leaves during drying in vacuum oven dryer. The moisture ratio of sliced turmeric also showed the best fit by two-term exponential model at drying temperature of 60°C (Jeevarathinam *et al*., 2022).

Table 2. Model constant and statistical values of fitting model with actual MR data.

| Model name | Model coefficient | $R^2$ | MSE ($x10^{-2}$) |
|---|---|---|---|
| 50°C | | | |
| Newton | k = 1.0431 | 96.01 | 0.310 |
| Henderson and Pabis | a = 0.9519; k = 0.9855 | 96.44 | 0.307 |
| Page | k = 1.0618; n = 0.7779 | 95.96 | 0.178 |
| Logarithmic model | a = 0.8771; k = 1.4888; c = 0.1253 | 98.33 | 0.162 |
| Two-term | a = 0.4745; b = 0.5395; k = 0.5229; $k_1$ = 2.3721 | 98.67 | 0.147 |
| Diffusion approach | a = 1.1179; k = 1.0499; b = 1.0326 | 96.01 | 0.388 |
| Wang and Smith | a = -0.8618; b = 0.2135 | 93.39 | 0.571 |
| 60°C | | | |
| Newton | k = 1.7344 | 96.02 | 0.342 |
| Henderson and Pabis | a = 0.9384; k = 1.6139 | 96.65 | 0.329 |
| Page | k = 1.5587; n = 0.6638 | 99.86 | 0.004 |
| Logarithmic model | a = 0.8765; k = 2.4437; c = 0.1082 | 99.33 | 0.007 |
| Two-term | a = 0.4753; b = 0.5246; k = 0.9182; $k_1$ = 5.2806 | 99.98 | 0.003 |
| Diffusion approach | a = 1.1533; k = 1.7273; b = 0.9869 | 96.02 | 0.456 |
| Wang and Smith | a = -1.2539; b = 0.4189 | 91.09 | 0.876 |
| 70°C | | | |
| Newton | k = 2.0197 | 96.18 | 0.357 |
| Henderson and Pabis | a = 0.9482 k = 1.9027 | 96.63 | 0.368 |
| Page | k = 1.7194; n = 0.6475 | 99.78 | 0.005 |
| Logarithmic model | a = 0.8803; k = 2.8921; c = 0.1094 | 99.46 | 0.007 |
| Two-term | a = 0.4716; b = 0.5284; k = 0.9720; $k_1$ = 5.4966 | 99.98 | 0.003 |
| Diffusion approach | a = 1.2384; k = 2.0195; b = 0.9995 | 96.18 | 0.499 |
| Wang and Smith | a = -1.4422; b = 0.5515 | 91.33 | 0.945 |
| 80°C | | | |
| Newton | k = 2.8701 | 98.12 | 0.228 |
| Henderson and Pabis | a = 0.9779; k = 2.8066 | 98.21 | 0.272 |
| Page | k = 2.2503; n = 0.6840 | 98.94 | 0.003 |

| | | | |
|---|---|---|---|
| Logarithmic model | a = 0.9081; k = 3.8266; c = 0.089 | 99.86 | 0.003 |
| Two-term | a = 0.1727; b = 0.8263; k = 0.5277; $k_1$ = 4.3295 | 99.91 | 0.002 |
| Diffusion approach | a = 0.8266; k = 4.3385; b = 0.1223 | 99.91 | 0.015 |
| Wang and Smith | a = -2.0318; b = 1.0774 | 95.22 | 0.072 |

Table 3. Results of the dynamic model using to predict the moisture ratio of garlic slices.

| Number of Hidden layer | Training | | Validation | | Test | |
|---|---|---|---|---|---|---|
| | r | MSE | r | MSE | r | MSE |
| 1 | 0.9323 | 0.0159 | 0.9726 | 0.0014 | 0.9672 | 0.0111 |
| 2 | 0.9946 | 0.0009 | 0.9200 | 0.0044 | 0.9904 | 0.0052 |
| 3 | 0.9950 | 0.0015 | 0.9895 | 0.0032 | 0.9988 | 0.0006 |
| 4 | 0.9995 | 0.0001 | 0.9986 | 0.0138 | 0.9996 | 0.0002 |
| 5 | 0.9830 | 0.0023 | 0.9957 | 0.0027 | 0.9981 | 0.0014 |
| 6 | 0.8719 | 0.0238 | 0.9808 | 0.0107 | 0.9837 | 0.0176 |
| 7 | 0.9860 | 0.0027 | 0.9973 | 0.0016 | 0.8583 | 0.0014 |
| 8 | 0.9957 | 0.0011 | 0.9900 | 0.0028 | 0.9730 | 0.0013 |

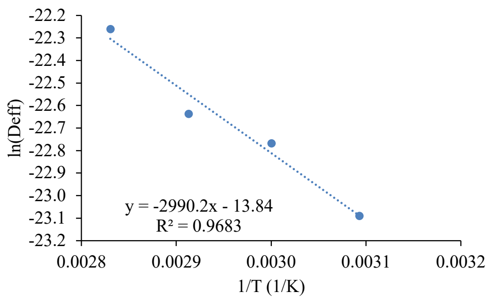


Figure 2. The graph of ln(Deff) versus 1/T.

The effective moisture diffusivity for fragrance and lemon basil leaves at various temperatures was determined by plotting the natural logarithm of the moisture ratio (MR) against time, using Fick's second law of diffusion. The curves were linearly fitted with $R^2$ values exceeding 90%, indicating that liquid diffusion governs the drying process. The effective moisture diffusivity ($D_{eff}$) values for garlic slices increased from 9.37 x $10^{-11}$ to 2.15 x $10^{-10}$ $m^2/s$ when the temperature rose from 50 to 80°C. The results were lower than the study of Guo *et al.* (2023). Figure 2 displays the relationship between the natural logarithm of $D_{eff}$ and the reciprocal of temperature for garlic slices subjected to various drying temperatures. The relationship between effective moisture diffusivity and temperature is evident, as indicated by the linear curve that demonstrates Arrhenius dependency. The graph allowed for the estimation of the activation energy (Ea) to be 24.86 kJ/mol.

### 3.2 *Drying characteristics of garlic slices by fitting with ANN model*

Predictions about the moisture ratio under different drying conditions were made using the ANN model, which included two input parameters, such as temperature and time and one output parameter: moisture ratio. Table 3 displays the statistical results of the test, validation and training. The correlation coefficient (*r*) between the training and testing models increases, as shown in this table, suggesting that a higher number of hidden layers may improve the model's fit to the actual data. Selvi *et al.* (2022) study found that the possibility of the networks was related to the quantity of neurons present in the deepest layers of the participants' bodies. As a result, underfitting resulted from fewer neurons, whereas overfitting resulted from an excessive number of neurons, providing an excessive amount of fitting (Loan *et al.*, 2023). To establish the most accurate way of multi-layer modeling with neural networks, the training datasets were used to find the best possible combination of neuronal and hidden layer counts. Having the lowest MSE and highest $R^2$ for garlic slices kinetic modeling, the ANN model with four hidden layers was determined to be the optimal structure. Figure 3 shows that the *r* values for this structure were 0.9995, 0.9986, 0.9996, 0.9884 for training, validation, test and overall data set, respectively.

Several recent studies have utilized drying conditions and time as input variables in artificial neural network (ANN) modeling to forecast moisture content (Caiyan *et al.*, 2023; Hadjout-Krimat *et al.*, 2023; Subramanyam & Narayanan, 2023; Yang *et al.*, 2023). These studies employ a static model similar to the one used in this investigation. The artificial neural network (ANN) model was trained using experimental data using the 'nntool' function in MATLAB. The LM training algorithm (TRAINLM) using 4 neurons in the hidden layer demonstrated the most satisfactory results during the training phase among the investigated configurations. This was determined based on the criteria of least error and reduced relationship complexity, as previously discussed (Figure 4). Table 4 displays the precise values of the weights and bias that are optimal for the network specifically designed for garlic slices.

Table 4. ANN topology weights and bias for moisture ratio prediction for garlic slices.

| Hidden layer | $w_{input1}$ | $w_{input1}$ | Bias | $w_{output}$ | $Bias_{output}$ |
|---|---|---|---|---|---|
| 1 | -3.5112 | 1.2592 | 4.2096 | 1.1218 | 2.5218 |
| 2 | 2.0404 | 1.8275 | 1.1645 | -0.2925 | - |
| 3 | 1.0278 | -1.1205 | -2.3519 | 3.6602 | - |
| 4 | 1.1675 | -6.9239 | 6.5060 | 0.7127 | - |

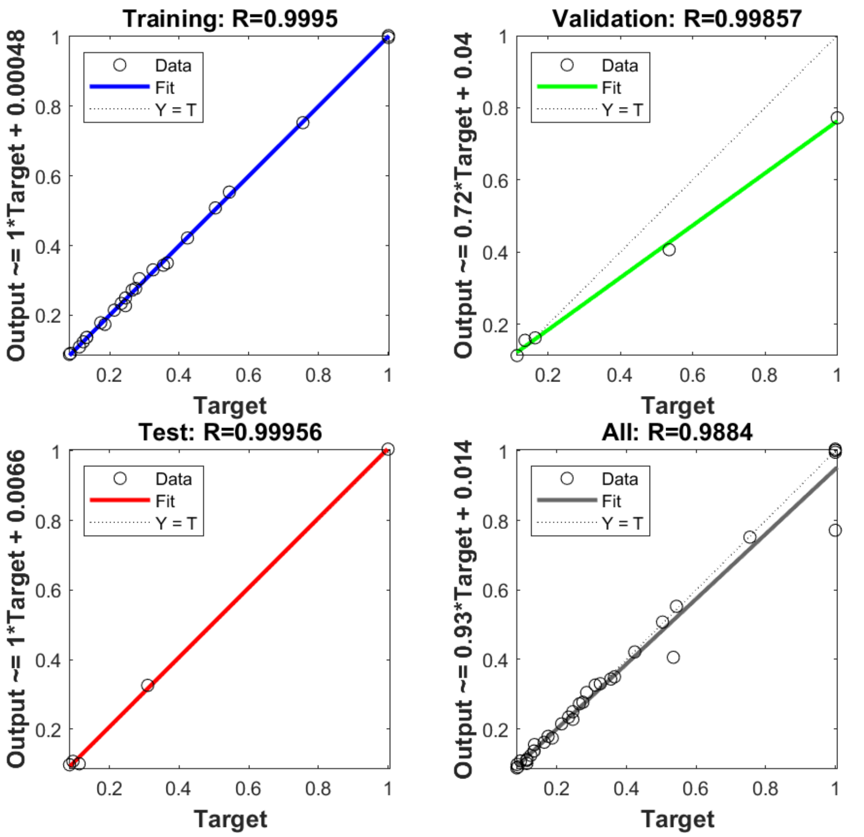


Figure 3. Artificial neural network (ANN) model to predict and actual data for garlic slices.

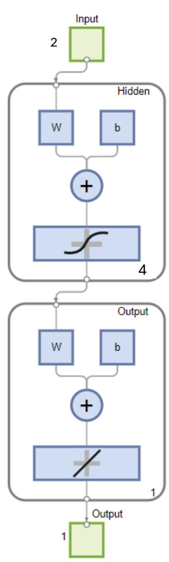


Figure 4. ANN model topology with a hidden lazy with 4 neurons.

## 3.3 *Comparison between ANN model with thin-layer mathematical model*

In contrast to ANN, the selected mathematical model (Two-term) exhibited a higher $R^2$ value and overall MSE, despite providing a significantly improved fit to the experimental data. According to the findings of Caiyan *et al.* (2023), the trained ANN demonstrated better predictive capabilities compared to the tested models, regardless of the applied conditions. Previous studies have shown that ANN model can accurately predict the drying kinetics of various products, such as paddy by cabinet tray dryer (Subramanyam & Narayanan, 2023), onion puree by Refractance Window Dryer (Zalpouri *et al.*, 2023), pumpkin (Karlović *et al.*, 2023). The ANN model's utilization of a nonlinear transfer function rendered it more appropriate for nonlinear regression prediction, resulting in superior $R^2$ values and diminished MSE values in comparison to the thin-layer model. ANN models demonstrate superior performance when the

Table 5. The qualities and overall sensory acceptance of garlic powder.

| Drying temperature (°C) | TPC (mgGAE/g) | DPPH% | Allicin content (mg/g) | Overall acceptance |
|---|---|---|---|---|
| 50 | 5.92±0.54 | 57.45±1.35 | 12.60±1.45 | 5.67±1.32 |
| 60 | 6.45±0.35 | 64.45±4.56 | 11.34±0.86 | 8.56±0.86 |
| 70 | 6.78±0.67 | 67.45±4.76 | 9.45±0.69 | 7.56±1.24 |
| 80 | 6.54±0.23 | 62.34±2.35 | 8.56±1.02 | 6.86±1.54 |

system exhibits nonlinear and intricate interactions (Daliran *et al*., 2023; Zhong et al., 2023). Compared to other models that were assessed, the ANN approach generated a more accurate prediction of the MR. It is interesting to note that the Diffusion approach model was able to strongly rival the outstanding predictive abilities of ANN, maybe due to the simpler processing of the data. Augmenting the magnitude and frequency of drying factors might lead to the malfunctioning of semi-empirical models and require the implementation of ANN. Hence, the created dynamic ANN model can be employed in a predictive control system to accurately forecast the future reactions of the sample based on certain process control parameters.

### *3.4 Garlic powder qualities under different drying temperatures*

Drying temperature is one of important parameters to determine quality of product. From Table 5, the total phenolic content, antioxidant activity, allicin content, and overall acceptance were influenced by drying temperature. The highest content of TPC and antioxidant activity were found in the sample from hot-air temperature of 70°C, while the reduction of allicin content was observed when the drying temperature increases. Long time of drying could lead to reduce the antioxidant (Tai *et al*., 2024; Thuy *et al*., 2021), which could be explained for the lowest value of TPC was found on sample from drying temperature of 50°C. The higher proportion of phenolic acids can be attributed to the rise in drying temperature, which likely caused an increase in inter-conversion reactions among polyphenols. Furthermore, the thermal treatment appears to have an impact on phenolic compounds. Phenolic chemicals mostly exist in a bound state, where they are connected to the structural components of the cell wall. Thermal processing, pasteurization, and freeze-drying liberate the phenolic chemicals that are bound using these techniques (Wongsa *et al*., 2023). However, the phenolic compounds also were degradation under heating process, which led to reduce TPC in garlic powder at drying temperature of 80°C. Antioxidant activity also positive related with TPC in this study. Moreover, the allicin content was independed with the drying temperature. Allicin is the non-heat stable compound (Wongsa *et al*., 2023; Zheng *et al*., 2023), therefore it was reduced when the higher temperature supplied. However, among four drying temperatures, the overall acceptance was highest in the sample was dried at 60°C. At this temperature, the allicin content, TPC and DPPH% also were comparable with the highest value. Therefore, it was chosen for drying sliced garlic in this study.

## Conclusion

The drying process is a crucial stage in the manufacturing of garlic powder. The experimental experiments revealed that an increase in temperature significantly affected the rate of drying, as evidenced by the subsequent increase in mass transfer parameters. The drying temperature also caused a modification in the quality of the powder. At a temperature of 60°C, the powder exhibits a high concentration of total phenolic content, 2,2-diphenyl-1-picrylhydrazyl (DPPH), allicin content, and the maximum level of overall acceptance. Out of the 8 models that were investigated, the two-term model demonstrated the highest accuracy in predicting the drying kinetics of instant brown rice. When the two-term model and artificial neural network (ANN) were compared, it became evident that the prediction capability of the trained ANN was highly comparable.

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