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Study on drying of bitter gourd slices based on halogen dryer

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Abstract: In this study, the drying of bitter gourd slices with a halogen dryer was done at different thicknesses of bitter gourd (3, 5, and 7 mm) and temperatures (60, 65, and 70 °C). The effect of varying drying characteristics in the experiment was explored. Experimental results were evaluated based on the drying time and moisture content. The results indicate that the material drying thickness and drying temperature significantly impact the drying time and the equilibrium moisture content. Furthermore, the Multivariate Adaptive Regression Splines (MARS) model is also used to train and predict the moisture content of bitter gourd in this research. The temperature, thickness of the bitter gourd, and drying time were used as input parameters for the model. Two measures R^2 and Root Mean Ssquare Error (RMSE) were used to determine the accuracy of the trained MARS model. During training, the values of R^2 and RMSE obtained were 0.9846 and 3.7324, respectively. The test of trained MARS was successful, with a satisfactory correlation between experimental data points and predicted points. The results show that MARS can accurately predict the moisture content of bitter gourd in a halogen dryer.

Keywords: ANN; drying temperature; machine learning; MARS model; moisture content

Bitter melon is a plant family native to tropical and subtropical regions such as Africa, Asia, and Australia. Bitter melon is widely regarded as an essential food in Vietnam because of its high nutritional value. It is easy to grow, maintain, and process. It is also a type of herbal medicine with numerous therapeutic applications, including improving digestion and lowering blood sugar levels in humans, lowering the incidence of neural tube defects in newborns, lowering the risk of cardiovascular disease, digestion, and blood sugar levels in humans, and treating several types of cancer, including esophageal, papillary, and ovarian cancer. As a result, bitter melon has gained popularity in recent years, such as in (Jin et al. 2019; Yan et al. 2019; Wargovich 2000). Similarly, bitter melon has long been used as a traditional medicinal plant in Vietnam. It has been used to treat diabetes, cough, respiratory illnesses, skin problems, and scabies, among other health issues. It helps with liver cleansing, liver cell regeneration, and weight loss. The nutritional priorities and some of the abovementioned applications increase demand for dried bitter melon products. In Vietnam, dried bitter melon is commonly used as a type of herbal tea.

Drying is one of the earliest methods of food preservation and plays an important role in food industry

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operations. It is critical for increasing the shelf life of fresh goods, lowering packing costs, and reducing transportation loads. As a result, drying is now extensively used in an array of fields (Kadırgan et al. 2020; Septien et al. 2020), particularly in the field of food for the preservation of food products, which is researched by (Ahmed et al. 2013). The drying technique is one of the traditional methods for managing post-harvest agricultural products by removing moisture. During the drying process, heat, and mass transfer from the inner to the outer surfaces of the drying material will occur simultaneously under the impact of external environmental factors such as temperature, humidity, velocity, and time drying, as well as the properties and physical structure of the drying material. This is a thermodynamic and physical process interaction to reduce the moisture content to a minimally acceptable limit that inhibits microorganism growth and activity in agricultural products. To the extent required to ensure that the desired quality of the dried product can be preserved for a longer period, moisture content should be reduced. The relationships between the factors affecting the drying process must be modeled to accomplish this goal. However, it is possible to recognize that the drying process is significantly complicated due to influencing factors (Movagharnejad et al. 2007). Consequently, developing a mathematical equation that accurately captures the relationship between drying characteristics is difficult. Therefore, over the last few decades, drying has always piqued the interest of scientists. A predictable model obtained by relating a set of input and output variables has become an essential strategy in the drying field. An accurate prediction of the drying model is possible, resulting in optimized energy use and operating conditions, improved dried product quality, and thus efficient drying.

Aside from predictable models like artificial neural networks (ANNs) and support vector machine (SVM), a large number of researchers have been working on Multivariate Adaptive Regression Splines (MARS). Zhang and Goh (2013) employed MARS to model nonlinear and multidimensional connections in geotechnical engineering systems. In similar work, Zhang and Goh (2016) continued to develop MARS to predict pile drivability problems three years afterward. Overall, both studies concluded that the performance of MARS was very efficient in terms of capturing complex relationships between input and output data and generating simpler, easier-to-interpret models. Furthermore, MARS has also been used in several previous studies (Kisi 2015; Dey and Das 2016) due to its benefits. In the drying field, the application of MARS was established by (Friedman 1991) to determine the convex nonlinear relationships related to the drying process. Generally, MARS has many advantages and is extensively used in many fields, but its application in the drying process is uncommon. Therefore, this study aims to create and test the MARS method as an approximation tool for predicting the bitter melon drying process.

Various drying systems are currently being developed and used in the manufacturing industry. Each type of drying system has benefits and drawbacks. In general, drying systems can be divided into two categories: (*i*) natural energy drying systems and (*ii*) artificial energy drying systems. Natural energy drying systems include solar energy, geothermal energy, and wind energy, among others. The advantages of these drying systems are that they use the available energy source, which helps to reduce costs. However, these still have significant disadvantages, such as the need for more initiative and the ability to control the drying process parameters. Therefore, meeting the high demands for quality drying products in the industrial system will be difficult. To overcome the shortcomings of the natural drying system, artificial energy drying system research and development are required. Convection drying, radiation drying (Adonis and Khan 2004; Hebbar et al. 2004), radio wave drying (Ling et al. 2018), and microwave drying (Abano 2016), and so on, recently are just a few examples of artificial energy-based drying systems. Among the drying systems discussed above, halogen lamp drying technology has been developed (Heinze and Isengard 2001; Planinić et al. 2005; Sumnu et al. 2005). Essentially, the findings of these published works demonstrated that drying technology utilizing halogen lamps had become more widely used in the drying process due to its simplicity and efficiency in controlling the drying temperature, which is one of the most important factors in the drying process.

According to the above-mentioned literature review and our knowledge, no works on MARS describe the drying process of sliced bitter melon on halogen lamps. Therefore, this research seeks to create and test the MARS as an approximating tool for predicting the drying process of bitter gourd slices under a halogen lamp.

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MATERIALS AND METHODS

Sourcing and preparation of the samples. The experiment was carried out in the laboratory of Vietnam's Industrial University of Ho Chi Minh city. Fresh bitter gourds were provided at a local market every morning. Before beginning the experiment, the samples were cleaned and dried naturally. To determine the initial moisture content, bitter gourd samples were dried in an oven at 150 °C until they reached a constant mass. The moisture content of the bitter gourd samples during the drying process as well as the moisture content of the bitter gourd samples before and after drying, was calculated using the following Equation (1) (Jin et al. 2019; Yasmin et al. 2022):

$$\omega_c = \frac{m_c - m_k}{m_k} \times 100 \tag{1}$$

where: ω_c – moisture content wet basis of drying material at the time of determination (%); m_c – mass of drying material at time t (g); m_k – mass of drying material at the time of determination $t + 1$ (g).

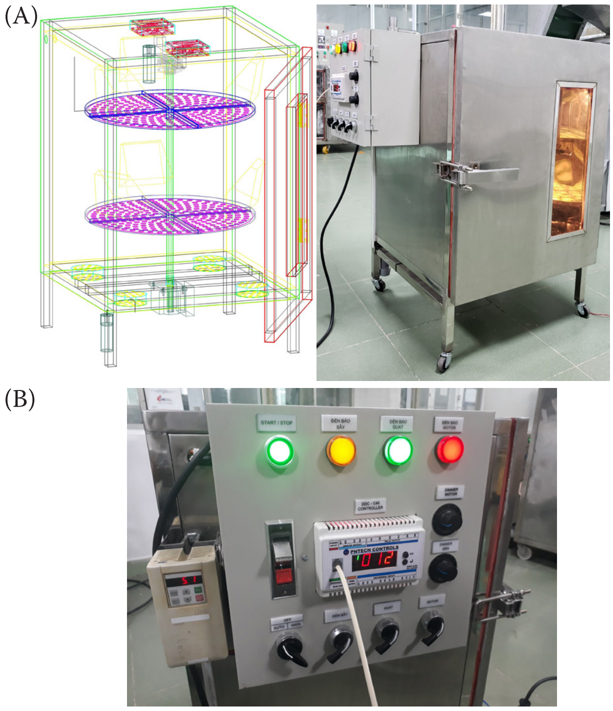

Figure 1. (A) Halogen dryer and (B) DDC-C46 (PNTech Controls) controller

The results show that, on average at a 95% confidence level, bitter gourd has an initial moisture content of about 94.48 ± 0.24% (w.b.). The result of the initial moisture content was very similar to research publications (Biswas et al. 2018; Yan et al. 2019; Jin et al. 2019).

Drying experimental procedure. The drying experiment was executed using a halogen dryer, as shown in Figure 1. The dryer dimensions are 550 × 550 × 850 [(l × w × h (mm)], including 2 plates with 4 stainless steel trays. Because there are 3 halogen lamps per plate, each with a 100 W/bulb capacity, the maximum wattage of the halogen used in the drying model is 600 W. The maximum temperature in the dryer chamber was 90 °C. The stainless-steel trays were placed on a rotating shaft and the rotation speed was adjusted using an inverter device. The solid-state relay (SSR) device will keep the drying temperature constant. When the temperature reaches the preset level, the SSR device adjusts the halogen bulb's light intensity to reduce heat. In the drying model, there are 4 temperature sensors. One is at the outdoor locations to obtain the ambient temperature. Each compartment has two temperature sensors that measure the drying temperature inside the chamber. The last one is placed at the outlet to measure the temperature of the air outlet after the drying process. The moisture is removed from the chamber by two fans on the oven's top. The moisture reduction of the bitter gourd slices was loaded at 60-min intervals. The samples were dried until the moisture content was balanced. Each experiment was repeated three times, with an average value calculated.

Multivariate adaptive regression splines (MARS) modeling. MARS is a nonlinear and nonparametric regression architecture as a flexible method that uses fewer variables to replicate interactions between inputs and outcomes. This method eliminates doubt about the dependent and independent variables' functional relationship. MARS deduced this relationship from a set of coefficients and basis functions derived from regression data. MARS generates basis functions by iteratively inspecting them. Each spline function is defined on an interval, and the interval's endpoints are referred to as "knots" The MARS model is built in two steps: a forward phase and a backward phase. First, the model is established in the forward phase, and then basis functions are supplemented to increase the complexity until extreme complexity is reached. Second, the model's minimal significant basis function is removed using a backward computation.

Mathematically, the MARS model is based on piecewise linear basis functions of the following Equations (2 and 3):

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$$|x-t|_+ = \max(0, x-t) = \begin{cases} x-t & x>t \\ 0 & x\le t \end{cases} \quad (2)$$

$$|t-x|_+ = \max(0, t-x) = \begin{cases} t-x & x<t \\ 0 & x\ge t \end{cases} \quad (3)$$

where: t – the dataset knot; x – the predictor variable; the subscript$_+$ – the argument's positive condition.

These are known as truncated linear functions. Each function is piecewise linear with a knot at t, and two of these functions are known as a reflected pair. If the underlying variable is outside of the appropriate range, the accompanying basis function is set to zero and thus does not affect the model. The MARS model $f(X)$ is built as a linear combination of basis functions (BFs) and their interactions, which is expressed as Equation (4)

$$y = \sum_{i=1}^{n} a_i B_i(X) \quad (4)$$

where: y – the predicted variable, a_i – the coefficient estimated using the least-squares method; B_i – the i^{th} basis function; n – the number of basis functions; X – the vector of independent variables.

In this study, the MARS inputs are the independent variables of a drying duration time, temperature, and thickness of the material, and the MARS outputs the predicted moisture content (MC) of bitter gourd expressed in dry based on moisture content.

To assess and present the accuracy of the model, two different accuracy measures are employed, i.e., R^2 and root mean square error (RSME), as expressed by Equations (5 and 6). The R^2 is given by:

$$R^2 = 1 - \frac{\sum_{=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{=1}^{n} (y_i - \overline{y}_i)^2} \quad (5)$$

The RSME by:

$$RMSE = \sqrt{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \quad (6)$$

where: y_i – the measured value of the observed target in the experiment; $\hat{y}_i$ – the predicted value from the observation of the i^{th}-target; n – the number of validation points.

A model's accuracy assessment is a compromise between these two measured values. The higher the value of R^2 and the lower the value of RSME, the more accurate the model is.

Experimental setup. As previously stated, the drying parameters significantly affect the dried product's quality. For example, if the drying time for the food is too long, it not only causes some chemical reactions that result in changes in the structural, physical, and mechanical properties of the drying material, but it also wastes energy. Therefore, determining the optimal drying temperature is critical in addition to other drying parameters. According to several published studies, the drying temperature for bitter gourd ranges from 40 to 80 °C, depending on the thickness of the bitter gourd and the drying process (Biswas et al. 2018; Yan et al. 2019). Thereby, temperature drying and product thickness will be investigated as elements influencing the drying material during the drying process in this study. Three temperature levels were determined at 60, 65, and 70 °C. Also, the drying materials were bitter gourd slices with thicknesses of 3, 5, and 7 mm. Therefore, the following effects of the drying process will be investigated in this study: (*i*) the effect of drying material thickness; (*ii*) the effect of drying temperature, and (*iii*) the prediction of drying models for MC.

RESULTS AND DISCUSSION

Effect of drying material thickness. To investigate the effect of material thickness on MC, dry experiments were conducted in this study at three different thicknesses of drying materials, namely 3, 5, and 7 mm, with a fixed temperature value and the same drying time. Figure 2 depicts the results.

Figure 2 (A, B, and C) show the effect of slice thickness on the drying kinetics of bitter gourd in a halogen lamp dryer at 60, 65, and 70 °C. These curves clearly show that the moisture removal rate was faster at a thin slice. Nearly 50% of the MC was removed in the first 2 hours. This is because the heat supplied at this stage is primarily for the removal of free water from the product. The remaining moisture was gradually detected after 5 to 7 h due to the trapped water inside. Figure 2 also illustrates a shorter drying time for thinner sliced bitter gourd and a longer drying time for thicker sliced bitter gourd at the same temperature. In particular, bitter gourd slices of 3 mm thickness reach a balanced MC after 4–5 h of drying time. Meanwhile, bitter gourd slices with a 7 mm thickness take a higher drying time, i.e., in 8–9 h at a temperature of 60 °C, in 6–7 h at a temperature

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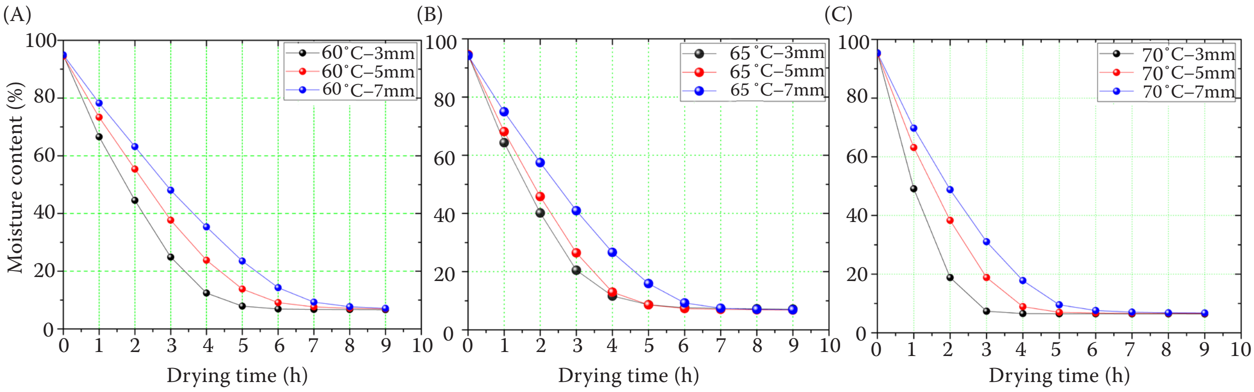

Figure 2. Effect of slice thickness (3, 5, and 7 mm) on moisture content of bitter gourd dried at (A) 60 ˚C, (B) 70 ˚C, and (C) 75 ˚C

of 65 °C, and 5–6 h at a temperature of 70 °C. This result demonstrates that the rate of MC change is proportional to the change in thickness. Similar results were reported by (Sadin et al. 2014) for drying tomato slices in an infrared dryer, (Ocoró-zamora and Ayala-aponte 2013) for drying papaya puree slices, and (Limpaiboon 2011) for drying pumpkin slices in a lab-scale tray dryer.

Effect of drying temperature. This research explored the effect of drying temperature on the drying process in this section of the experiment. To assess the influencing factors, the drying temperatures were set at 60, 65, and 70 °C, respectively, with the dried sample being the same thickness. The drying time was 9 h. Figure 3 depicts the outcomes.

The data from the MC versus drying time experiments were used to determine the effect of drying temperature on drying kinetics. Figure 3 shows that raising the drying temperature from 60 to 70 °C reduces the MC of bitter gourd significantly. This means that as the drying temperature rises, so does the total drying time. For example, the drying time of 3 mm thick-sliced bitter gourd was reduced from 6 to 3 h, i.e., at the time of reaching balanced MC, when the temperature was raised from 60 to 70 °C. A similar trend was evident for 5 mm and 7 mm thick-sliced bitter gourd at the same temperatures. This effect is due to the rigid texture of bitter gourd, which takes a long time to dry. Higher temperatures increased the thermal energy in the samples, requiring them to dry faster. Furthermore, similar behavior can be observed in the published paper (Yasmin et al. 2022) on the effect of drying temperature and drying material thickness on drying time.

Performance of MARS models for prediction of bitter gourd moisture content. This study's experimental data were used to train and test the MARS model for predicting the bitter gourd moisture ratio during the drying process. 270 data points were collected for each of the nine conditions. The experimental data were randomly divided into two groups. One set of data was used for training, while the other was used to test the model. MARS was trained using three independent variables, namely

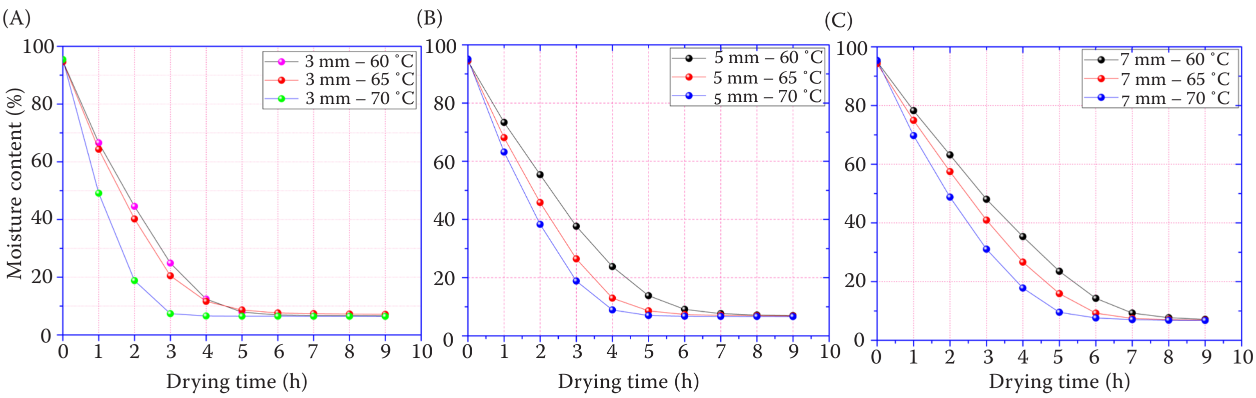

Figure 3. Effect of the drying temperature on moisture content of bitter gourd dried at (A) 60 °C, (B) 65 °C, and (C) 70 °C

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drying time, thickness, and temperature, and one dependent variable, namely MC. The best performance of trained MARS was noted when the test error (RMSE), and the SD were minimum and the R^2 was maximum. As a result, the overall RMSE, SD, and R^2 values for training the MARS were 3.7324, 3.7477, and 0.9846, respectively. The RMSE, SD, and R^2 values show that MARS is highly accurate in approximating the drying process. Figure 4 depicts the MC of bitter gourd between the measured experimental values and the predicted model value in the training data figure. A diagonal line inclined at 45 degrees from the horizontal represents a perfect prediction in Figure 4. This demonstrates that most of the data points along the training line are very close to this line, indicating good prediction during training. Table 1 outlines the BFs of the trained MARS model for the MC of bitter gourd and their corresponding equations. A well-trained MARS model was developed as an Equation (7):

$$\begin{aligned} y = & -1.2042 - 4.1889 \times BF1 + 11.624 \times BF2 + \\ & + 4.1851 \times BF3 - 2.8498 \times BF4 + 3.78 \times BF5 + \\ & + 0.94328 \times BF6 + 1.4729 \times BF7 + \\ & + 3.5937 \times BF8 - 0.71734 \times BF9 + \\ & + 0.94738 \times BF10 - 0.49447 \times BF11 - \\ & - 0.2128 \times BF12 + 5.4788 \times BF13 - \\ & - 0.90839 \times BF14 + 3.4626 \times BF15 - \\ & - 2.109 \times BF16 - 2.7649 \times BF17 + \\ & + 3.5752 \times BF18 \end{aligned} \tag{7}$$

where: BF – basic function

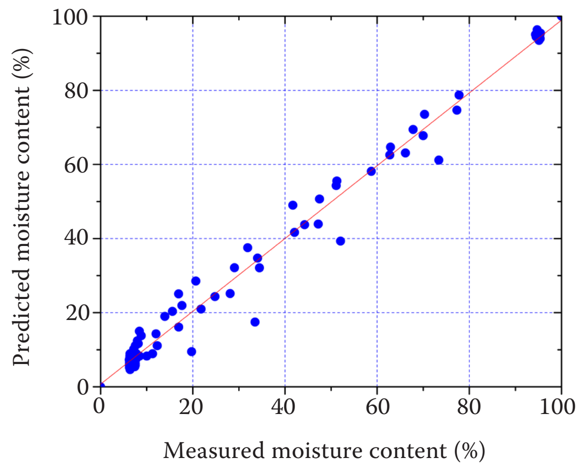

Figure 4. Comparisons between predicted and measured values of multivariate adaptive regression splines for moisture content

Table 1. Basis functions and corresponding equations of Multivariate Adaptive Regression Splines Model for moisture content prediction

Basis function	Equation
1	max (0, x3 –4)
2	max (0, 4 –x3)
3	max (0, 5 –x2) × max (0, 1 –x3)
4	max (0, x1 –65)
5	max (0, 65 –x1)
6	BF4 × max (0, x3 –2)
7	BF4 × max (0, 2 –x3)
8	max (0, x2 –5) × max (0, 6 –x3)
9	BF1 × max (0, x1 –65)
10	BF5 × max (0, x3 –7)
11	BF5 × max (0, 7 –x3)
12	max (0, 5 –x2) × max(0, 65 –x1)
13	max (0, 5 –x3)
14	max (0, x3 –3) × max (0, 65 –x1)
15	max (0, 3 –x3) × max (0, 7 –x2)
16	BF13 × max (0, x2 –5)
17	BF13 × max (0, 5 –x2)
18	max (0, x3 –1)

BF – basis function, x – the predictor variable

To validate the predictive capacity of the trained MARS model, the experimental validation data of three levels of temperature and 7 mm of thickness are used for testing. Figure 5 illustrates the results of these tests. Figure 4 clearly shows that the almost-predicted points of MARS agree excellently with the measured experimental points for all lev-

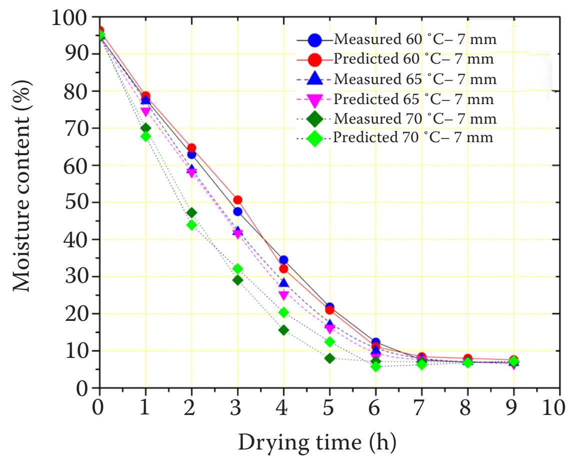

Figure 5. The predictive capacity of trained-multivariate adaptive regression splines model by using different experimental validation data

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els of the drying process. The best agreement was obtained during the drying process at 60 °C, and a 7 mm thickness. The drying process had the lowest agreement at 70 °C and 7 mm thickness. Generally, the analysis results show that MARS can accurately predict the drying behavior of bitter gourd.

CONCLUSION

This analysis assessed the drying characteristics of bitter gourd slices dried in a halogen dryer at temperatures of 60, 65, and 70 °C, as well as bitter gourd thicknesses of 3, 5, and 7 mm. The drying temperature and drying material slice thickness had a significant impact on the drying time and final MC. Almost all bitter gourd samples were dried using a drying process with falling rate periods. According to the findings, it can be stated that the drying characteristics of bitter gourd in the drying process at 60–70 °C, the effect of drying temperature and material thickness on MC, and drying time. The higher the drying temperature or the thinner the drying material is, the shorter the drying time is.

Furthermore, the MARS model was also used to predict the MC reduction of bitter gourd slices during halogen lamp drying. The MARS model was used to capture and predict the drying behavior of bitter gourd in a halogen dryer, as well as the relationship of bitter gourd MC at drying temperatures of 60, 65, and 70 °C and material thicknesses of 3, 5, and 7 mm. The MARS model during the training stage produced results with an R^2 value of 0.9846, an RSME of 3.7324, and a SD of 3.7577. Validation of the predictable MARS model was also carried out. According to the results, MARS is an appropriate method for predicting the MC of bitter gourd in a halogen dryer.

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