



## ARTIFICIAL NEURAL NETWORKS APPLIED TO DRYING CURVES OF CAPSICUM CHINENSE

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### ABSTRACT

**Objective:** The objective of this study was to apply Artificial Neural Networks (ANNs) to predict the drying curves of *Capsicum chinense* at different temperatures, aiming to optimize the drying process and ensure the quality of the final product.

**Theoretical Framework:** Artificial Neural Networks (ANNs) have been widely used in modeling and predicting industrial processes, including the drying of agricultural products.

**Method:** An analogy was drawn between the chemical kinetics equations applied to the drying unit operation and the determination of the parameters: kinetic constant (k) and reaction order (n) for various temperatures. The parameters obtained in this analogy fed the neural network modeling. With the data extracted from the drying curves and the aid of GeoGebra software, the drying kinetics parameters, n (reaction order) and k (reaction rate constant), were determined. An RNA (Recurrent Neural Network) was developed in MATLAB to model the drying curves of the 'pimenta-de-cheiro' pepper (*Capsicum chinense*) at different drying temperatures (40°C to 70°C).

**Results and Discussion:** ANN training, performed with 245 data points and employing the Levenberg-Marquardt algorithm, resulted in high correlation coefficients (R = 1.0000 for training, 0.9999 for validation and 0.99995 for the overall set) and low mean squared error values (minimum MSE of  $9.94 \times 10^{-11}$ ). Furthermore, the ANN demonstrated generalization capacity when predicting drying curves for temperatures between 30°C and 80°C, confirming its applicability in modeling and optimizing the drying process of 'pimenta-de-cheiro' pepper. The neural network obtained was used to predict the drying curves of 'pimenta-de-cheiro' pepper (*Capsicum chinense*) at different drying temperatures (40°C to 70°C). Three-dimensional figures were obtained correlating the parameters temperature, kinetic constant (k) and reaction order (n). Due to the analogy made between the drying operation and chemical kinetics, in the drying operation, parameter (k) could be called drying kinetic constant, and parameter (n) could be called drying order.

**Research Implications:** ANN modeling is effective in predicting and optimizing industrial processes, especially in the analysis of large volumes of data and complex systems, contributing to effective quality control in food production and improvement of industrial processes.

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**Originality/Value:** Artificial Neural Networks (ANNs) stand out as innovative and effective tools in optimizing industrial processes, especially in the drying of agricultural products. Inspired by the functioning of human neurons, ANNs allow for precise and adaptive predictions to solve complex and dynamic problems.

**Keywords:** Artificial Neural Networks, Drying, *Capsicum chinense*.

## REDES NEURAIIS ARTIFICIAIS APLICADAS ÀS CURVAS DE SECAGEM DA PIMENTA-DE-CHEIRO (*CAPSICUM CHINENSE*)

### RESUMO

**Objetivo:** O objetivo do presente trabalho foi aplicar as Redes Neurais Artificiais (RNAs) para prever as curvas de secagem da pimenta-de-cheiro (*Capsicum chinense*) em diferentes temperaturas, visando otimizar o processo de secagem e garantir a qualidade do produto final.

**Referencial Teórico:** As Redes Neurais Artificiais (RNAs) têm sido amplamente utilizadas na modelagem e previsão de processos industriais, incluindo a secagem de produtos agrícolas.

**Método:** Foi realizada uma analogia entre as equações da cinética química aplicadas à operação unitária de secagem com a determinação dos parâmetros: constante cinética ( $k$ ) e ordem da reação ( $n$ ) para diversas temperaturas. Os parâmetros obtidos nesta analogia alimentaram a modelagem por redes neurais. Uma RNA foi desenvolvida no software MATLAB para modelar as curvas de secagem da pimenta-de-cheiro (*Capsicum chinense*) em diferentes temperaturas de secagem (40°C a 70°C).

**Resultados e Discussão:** O treinamento da RNA, realizado o algoritmo de Levenberg-Marquardt, resultou em altos coeficientes de correlação ( $R = 1,0000$  para o treinamento, 0,9999 para a validação e 0,99995 para o conjunto geral) e baixos valores de erro quadrático médio (MSE mínimo de  $9,94 \times 10^{-11}$ ). Além disso, a RNA demonstrou capacidade de generalização ao prever curvas de secagem para temperaturas entre 30°C e 80°C, confirmando sua aplicabilidade na modelagem e otimização do processo de secagem da pimenta-de-cheiro. A rede neural obtida foi utilizada para previsão das curvas de secagem da pimenta-de-cheiro (*Capsicum chinense*) em diferentes temperaturas de secagem (40°C a 70°C). Foram obtidas figuras tridimensionais correlacionando os parâmetros temperatura, constante cinética ( $k$ ) e ordem da reação ( $n$ ) e razão de umidade. Pela analogia realizada entre a operação da secagem e a cinética química, na operação de secagem o parâmetro ( $k$ ) poderia ser denominado constante cinética de secagem e o parâmetro ( $n$ ) poderia ser denominado ordem de secagem.

**Implicações da Pesquisa:** a modelagem por RNA é eficaz na previsão e a otimização de processos industriais, especialmente na análise de grandes volumes de dados e sistemas complexos, contribuindo para um eficaz controle da qualidade na produção de alimentos e a melhoria dos processos industriais.

**Originalidade/Valor:** As Redes Neurais Artificiais (RNAs) destacam-se como ferramentas inovadoras e eficazes na otimização de processos industriais, especialmente na secagem de produtos agrícolas. Inspiradas no funcionamento dos neurônios humanos, as RNAs permitem previsões precisas e adaptativas para resolver problemas complexos e dinâmicos. Destaca-se neste trabalho como diferencial a analogia entre as curvas de secagem e as equações da cinética química.

**Palavras-chave:** Redes Neurais Artificiais, Secagem, Pimenta-de-Cheiro.

## REDES NEURONALES ARTIFICIALES APLICADAS A LAS CURVAS DE SECADO DE *CAPSICUM CHINENSE*

### RESUMEN

**Objetivo:** El objetivo de este estudio fue aplicar Redes Neuronales Artificiales (RNAs) para predecir las curvas de secado de *Capsicum chinense* a diferentes temperaturas, con el fin de optimizar el proceso de secado y asegurar la calidad del producto final.

**Marco Teórico:** Las Redes Neuronales Artificiales (RNAs) han sido ampliamente utilizadas en la modelación y predicción de procesos industriales, incluyendo el secado de productos agrícolas.



**Método:** Se desarrolló una RNA en MATLAB para modelar las curvas de secado de *Capsicum chinense* a diferentes temperaturas (50°C, 60°C y 70°C), utilizando datos experimentales extraídos de la literatura y procesados en el software GeoGebra.

**Resultados y Discusión:** El entrenamiento de la RNA, realizado con 245 datos y empleando el algoritmo de Levenberg-Marquardt, resultó en altos coeficientes de correlación ( $R = 1.0000$  para el entrenamiento, 0.9999 para la validación y 0.99995 para el conjunto general) y valores bajos de error cuadrático medio (MSE mínimo de  $9,94 \times 10^{-11}$ ). Además, la RNA demostró capacidad de generalización al predecir curvas de secado para temperaturas entre 30°C y 80°C, confirmando su aplicabilidad en la modelación y optimización del proceso de secado de *Capsicum chinense*.

**Implicaciones de la Investigación:** La modelación con RNAs es eficaz en la predicción y optimización de procesos industriales, especialmente en el análisis de grandes volúmenes de datos y sistemas complejos, contribuyendo al control de calidad efectivo en la producción de alimentos y a la mejora de procesos industriales.

**Originalidad/Valor:** Las Redes Neuronales Artificiales (RNAs) destacan como herramientas innovadoras y eficaces en la optimización de procesos industriales, especialmente en el secado de productos agrícolas. Inspiradas en el funcionamiento de las neuronas humanas, las RNAs permiten predicciones precisas y adaptativas para resolver problemas complejos y dinámicos.

**Palabras clave:** Redes Neuronales Artificiales, Secado, *Capsicum chinense*.

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## 1 INTRODUCTION

Peppers belong to the *Solanaceae* family, *Capsicum* genus, which comprises more than 150 varieties derived from five main species: *C. annuum*, *C. baccatum*, *C. chinense*, *C. frutescens* and *C. pubescens* (Dutra *et al.*, 2010). Discovered by Portuguese and Spanish navigators in the American continent, they were already widely used by native peoples due to their pungency superior to that of black pepper (*Piper*). During the colonial period, they integrated the indigenous diet in Brazil and gained multiple uses, from cooking to medicine and weapons of defense. The dispersion through maritime routes in the 15th and 16th centuries contributed to their popularization in Africa, Europe and Asia, consolidating their global relevance (EMBRAPA, 2024). Currently, in addition to being widely used in gastronomy, peppers play a significant economic role in global agribusiness, serving as raw material for the extraction of dyes, flavorings and oleoresins, essential for the food industry as they provide flavor and oxidative stability of lipids (Dantas *et al.*, 2017).

The sweet pepper, belonging to the species *Capsicum chinense*, is one of the most important varieties of the genus *Capsicum*, with great economic relevance due to its high demand both for *fresh consumption* and for the production of dried, ground peppers and sauces (Cardoso *et al.*, 2014). Originally found in the Amazon basin, this species is cultivated



commercially throughout Brazil, due to its adaptability to different soils and climates. The fruits of the sweet pepper present great variability in terms of size, shape and color, ranging from shades of yellow, orange and red when ripe. One of its most striking characteristics is the citrus aroma, which makes it distinct from other varieties of peppers, giving it a unique sensory profile.

Foods rich in water, such as peppers, require effective preservation techniques, with drying being one of the most widely used. This process reduces the water content of foods, minimizing enzymatic reactions, concentrating components such as sugars and acids, and decreasing water activity, which inhibits microbial growth responsible for spoilage ( Derlan *et al.*, 2013). In addition to its crucial role in preservation, drying has significant advantages, such as better conservation of products, weight reduction to facilitate storage and transportation, since the reduction in humidity is accompanied by a reduction in volume and weight, and its greater economic viability compared to other preservation methods.

A common approach to analyze the drying behavior of a material is through drying curves, which represent the process over time, showing the relationship between the moisture content of the substance and the time required for its drying under specific conditions ( Rajput , 2024). The analysis of drying curves can be deepened by drying kinetics, a widely used method. Van Brakel , for example, classified the behavior of different products during the process into sixteen distinct classes, offering a detailed view of the dynamics of moisture removal over time ( Bennamoun & Ndukwu , 2021). In this context, the effective drying rate model facilitates learning at the reaction mechanism level, allowing a better understanding of the process. The application of adequate mathematical assumptions and a well-planned parametric consideration in the design of dryers can result in an optimized process, with lower energy consumption and greater profitability (Cosme de Vera *et al.*, 2021).

Artificial Neural Networks ( ANNs ) have emerged as powerful tools in the analysis of mathematical models and in the optimization of industrial processes, such as the drying of food and agricultural products. In recent years, studies have demonstrated the effectiveness of ANNs in predicting the moisture content of various items, such as green peas, tomatoes, corn and pomegranate seeds ( Sharabiani *et al.*, 2021).

Specific objectives of this work were:

- a) To develop an ANN model to predict the drying curves of sweet pepper based on analogy to the chemical kinetic equations, using kinetic parameters such as the reaction order (  $n$  ) and the reaction rate constant (  $k$  ) and experimental drying data at different temperatures.



- b) Analyze the influence of temperature on the drying process through simulations with the ANN model, generating drying curves for a wide range of temperatures (30°C to 80°C) and evaluating the impact of temperature on the moisture ratio over time.
- c) Validate the ANN model by comparing the predicted results and the experimental data, ensuring the reliability and applicability of the method in industrial drying processes.

## 2 THEORETICAL FRAMEWORK

### 2.1 DRYING

Drying is a fundamental process that involves the simultaneous transfer of heat and mass between the material and the drying medium, usually carried out by an air current. The supply of heat is essential to vaporize a fraction of the water present, resulting in a partially dried solid material and allowing the conservation of product quality during storage for prolonged periods (Afonso & Correa, 1999; Pontes *et al.*, 2009; Gonelli, 2008).

Drying methods, in relation to the process flow, are broadly classified into two main categories: batch and continuous. In the batch method, the material is inserted into the drying equipment for a predetermined period, while in the continuous method there is a constant feed of the material and continuous removal of the dry product, with the process not being interrupted, except for failures or routine maintenance (Martins *et al.*, 2020).

The physicochemical drying process can be divided into two distinct phases: in the constant-speed phase, drying is controlled by the transfer of heat from the air to the material, while in the decreasing-speed phase, the diffusion of water from the interior to the surface decreases, reducing the drying rate. During this process, moisture migrates from the interior of the material to the surface, where evaporation occurs into the surrounding air. These moisture transport mechanisms are directly related to external factors such as temperature, type and nature of the exposed surface, relative humidity, atmospheric pressure and airflow velocity.

An efficient way to analyze the drying process of a product is to develop mathematical models, which allow the description of the physical phenomenon and are commonly used in simulations (Pontes *et al.*, 2009). During drying, determining the moisture content is an indispensable and very important parameter for monitoring the changes that occur throughout the process. This analysis can be performed using typical drying curves, which are graphical representations of the moisture data of the material as a function of time, obtained experimentally (Cavichiolo, 2015).



Moisture can be represented in graphs as the moisture ratio (  $RU$  ), as seen in equation 1, where  $U^*$  is the water content of the material,  $U_i^*$  is the initial water content of the material and  $U_e^*$  is the equilibrium water content or hygroscopic equilibrium, that is, it is the moisture content that the product reaches when it equilibrates with the storage environment, being essential to evaluate water losses or gains under specific conditions of temperature and relative humidity. This equilibrium occurs when the water vapor pressure of the product equals that of the surrounding air (Afonso Junior & Correa, 2019; Goneli, 2008). In this case, the contents are represented in the decimal unit on a dry basis, and can be converted from the wet basis, from equations 2 and 3, where  $U_{BU}$  is the moisture on a wet basis,  $m_{total}$  is the total mass of the material,  $m_{dry}$  is the mass of dry material and  $m_{H_2O}$  is the mass of water in the material. However, other forms can be used for graphical representations, such as the drying rate (mass of water removed per unit time and area).

$$RU = \frac{U^* - U_e^*}{U_i^* - U_e^*} \quad (1)$$

$$U = \frac{m_{total} - m_{seco}}{m_{seco}} = \frac{m_{H_2O}}{m_{seco}} \quad (2)$$

$$U = \frac{U_{BU}}{1 - U_{BU}} \quad (3)$$

## 2.2 ARTIFICIAL NEURAL NETWORKS

The term *deep Deep learning* refers to an area of machine learning that involves neural networks with multiple layers. These networks are designed to learn increasingly complex and abstract representations of data using successive layers of processing. The goal is to enable artificial intelligence (AI) systems to perform tasks more efficiently than traditional methods, such as in areas such as image processing, speech recognition, and data analysis (Pouyanfar *et al.*, 2018).

The human brain is a complex organ that collects, stores, and processes information from the environment. The elementary computational units of the brain are neurons, which form complex networks. The dynamics of these networks cannot be directly explained by the relatively simple nature of an individual neuron. Therefore, different models and simulations of neurons, biological learning, and neural networks have been developed. Recently, the main applications of these models have shifted from focusing on analyzing the dynamics of natural systems to using neural models as a computing platform, known as ANNs (Artificial Neural



Networks), one of the most popular *frameworks* in machine learning research and applications ( Vasle & Moškon , 2024).

Artificial neural networks are composed of interconnected layers: an input layer, hidden layers, and an output layer. The neurons in the input layer receive the data and transmit it to the first hidden layer, where it is processed through weighted connections, that is, each connection has a weight that determines the relevance of the input. The processing in the hidden layers is performed in a non-linear manner, which allows the network to model complex relationships in the data ( Zakaria *et al.*, 2014 ). The output layer, in turn, presents the final result of the processing.

Learning in neural networks can be supervised, unsupervised, or reinforcement learning. In supervised learning, the neural network is trained with a set of labeled data, i.e. each input has a known corresponding output, and the goal is to minimize the error function between the output predicted by the network and the desired output. In unsupervised learning, the network does not receive output labels, but rather a set of data without this information. The goal is to identify underlying patterns or hidden structures in the data, such as clusters or probability distributions).

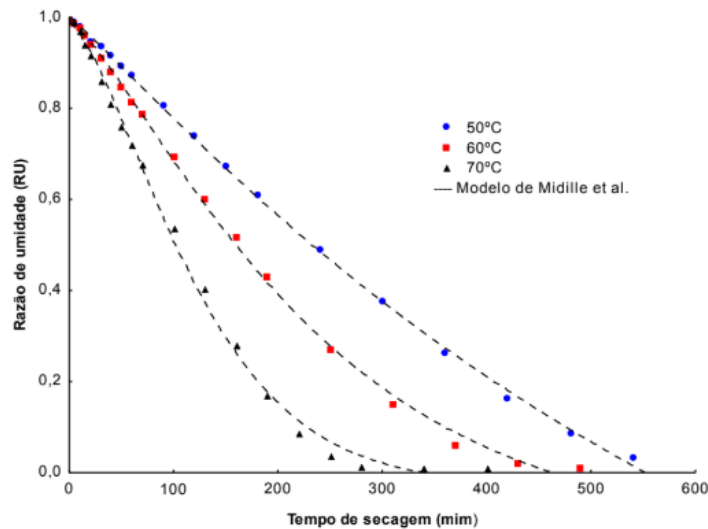
### 3 METHODOLOGY

#### 3.1 DATA PROCESSING

The work of Melo *et al.* (2015) was used as a source of experimental data in this study. The article investigates the drying kinetics of chili peppers at different temperatures (50, 60, and 70 °C), which allowed adjusting mathematical models and determining fundamental parameters, such as effective diffusivity and activation energy. The drying curves presented in the study (Figure 3) show a good separation between the experimental data for each temperature and an absence of excessive overlap between them, favoring the identification of distinct patterns and expanding the capacity of the neural network to learn and generalize the complex relationships involved in the drying process. The curves used present the moisture ratio (  $RU$  ) and the drying time as the axes of the graph.

**Figure 1**

Drying curves of allspice determined by the model of Midilli et al. at drying temperatures of 50, 60 and 70 degrees Celsius.



Source: MELO *et al.*, 2015.

An analogy was made between the chemical kinetics equations and the drying curves were applied to determine the parameters to be inserted into the data feed in the neural networks. With the data extracted from the drying curves and the aid of the *GeoGebra software*, the drying kinetics parameters,  $n$  (reaction order) and  $k$  (reaction rate constant), were calculated. According to Atkins and Jones (2010), the rate of a chemical reaction can be described by simple equations that allow the prediction of the composition of a mixture throughout its progression. For the authors, the reaction rate is defined as 'the change in the concentration of one of the reactants or products divided by the time it takes for the change to occur'. For a simple reaction  $A \rightarrow B$ , equation 4 of the reaction rate can be defined as:

$$\frac{dC_a}{dt} = -k \cdot C_a^n \quad (4)$$

Considering that the concentration ( $C_a$ ) can be replaced by the moisture ratio ( $RU$ ), which represents the concentration of water in relation to the dry material, it is possible to use Equation 5 to define the parameters  $n$  and  $k$ .

$$\frac{d(RU)}{dt} = -k \cdot (RU)^n \quad (5)$$



### 3.2 TRAINING OF THE ARTIFICIAL NEURAL NETWORK

The software used for the development of the Artificial Neural Network (ANN) was *MATLAB*, which offers powerful tools for creating neural networks, both deep and shallow, applicable in areas such as computer vision and autonomous driving, through the *Deep Learning Toolbox* and *Statistics and Machine Learning Toolbox*. With just a few lines of code, it is possible to create neural networks in *MATLAB* without the need for advanced expertise. The environment allows for rapid implementation, training, and visualization of neural network models, in addition to enabling the integration of these networks into existing systems and their deployment on servers, corporate systems, clusters, clouds, and embedded devices (MATHWORKS, 2024).

The training algorithm used was *trainlm* (Levenberg-Marquardt), a method widely used in training artificial neural networks, as long as the weight, net input and transfer functions are derivable. The Levenberg-Marquardt algorithm stands out for its robustness, being able to converge efficiently even on complex error surfaces that do not behave quadratically.

### 3.3 RESULTS AND DISCUSSIONS

Table 1 shows the *k* and *n* parameters obtained in the *GEOGEBRA* software, from the data of the chili pepper drying curves (Figure 1) and through Equations 4 and 5.

**Table 1**

*Parameters adjusted based on experimental drying curves and equations 4 and 5.*

| Temp. (°C) | Humidity Ratio | Time (min) | n    | k (min <sup>-1</sup> ) |
|------------|----------------|------------|------|------------------------|
| 50         | 1 to 0         | 0 to 541.1 | 0.31 | $2.4 \times 10^{-3}$   |
| 60         | 1 to 0         | 0 to 490.8 | 0.63 | $4.1 \times 10^{-3}$   |
| 70         | 1 to 0         | 0 to 401.0 | 0.84 | $7.5 \times 10^{-3}$   |

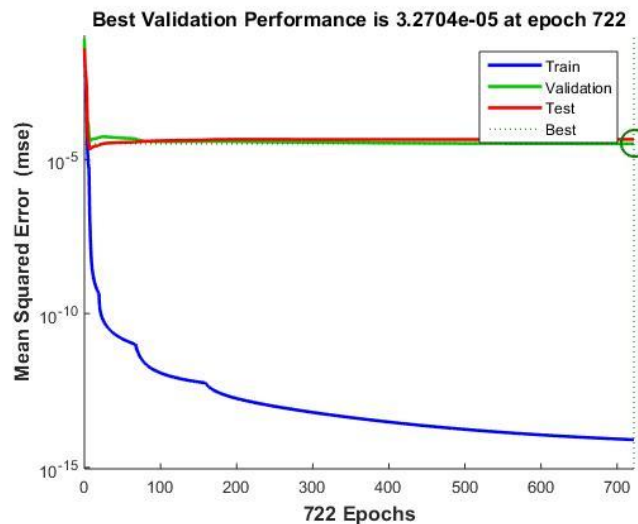
temperature parameter obtained in Table 1 fed the input of the neural network and the parameters (*k*) and (*n*) were the targets of the neural network. The neural network was trained and validated. To validate the data generated by the ANN, the performance and training graphs are shown in Figure 2. In them, it is possible to observe the evolution of the mean square error ( *Mean Squared Error - MSE* ) over 722 epochs (the number of times the training algorithm traverses the entire training dataset during the learning process). The blue curve represents the error on the training set, while the red and green curves correspond to the errors on the test and



validation sets, respectively. It can be seen that as the epochs progress, the error on the training set decreases significantly, indicating that the model is learning the patterns in the data effectively.

**Figure 2**

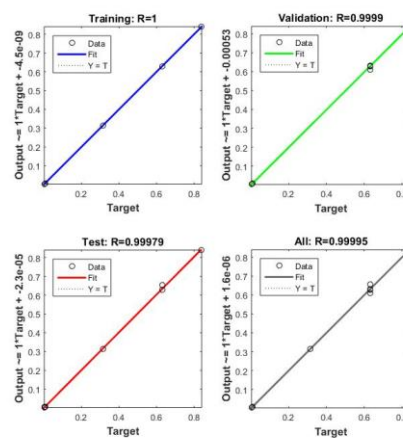
*Neural network performance graph.*



Linear regression graphs (Figure 3) were also analyzed to evaluate the performance of the ANN in predicting expected values, representing the relationship between the network output values and the target values for the training, validation, test and general sets.

**Figure 3**

*Linear regression plot of neural network.*



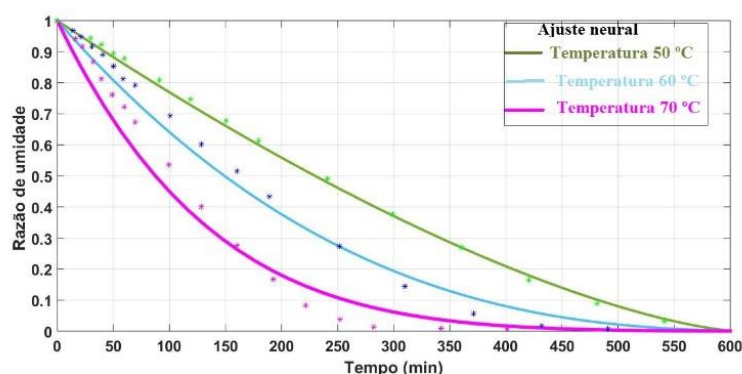


The correlation coefficients (R), which indicate the accuracy of the fit (with  $R=1$  being a perfect fit), revealed an  $R=1$  in the training graph, suggesting that the model accurately learned the patterns in the data. In the validation and test graphs, the R values were close to 1 (0.9999 and 0.99979, respectively), demonstrating excellent generalization of the model.

Figure 4 shows the validation graph of the data generated by the neural network (Humidity Ratio versus Time).

**Figure 4**

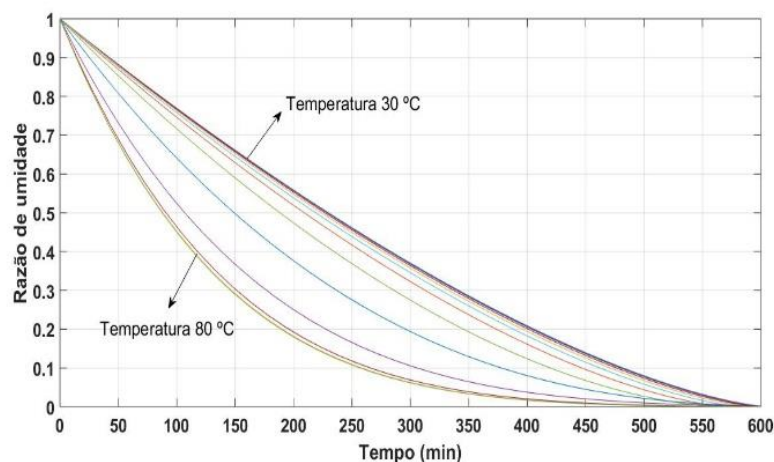
*Validation graph of data generated by the neural network (Humidity Ratio versus Time).*



Applying the trained neural network, drying curves of 30°C-80°C were generated, obtained by the neural network for different temperatures.

**Figure 5**

*Neural network generated graphs of 30°C-80°C drying curves.*



The curves illustrate the relationship between drying time and moisture content, showing that higher temperatures accelerate moisture removal from the material. It can be seen

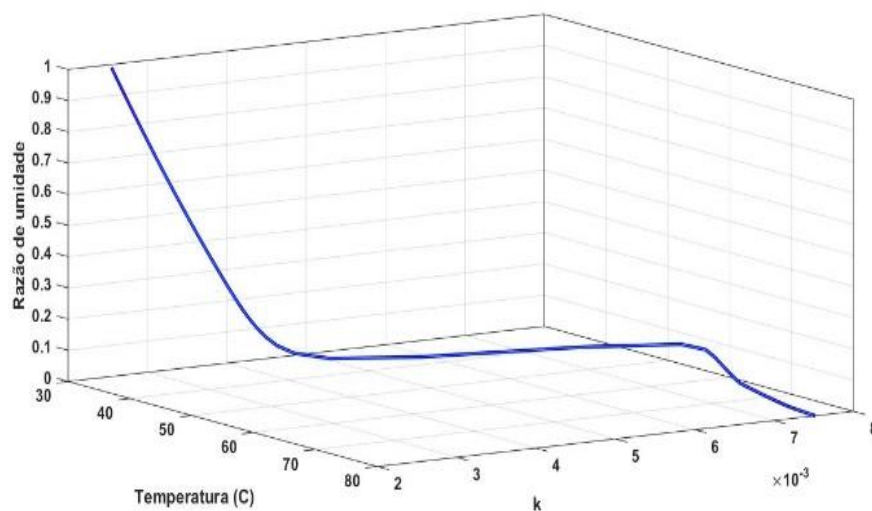


that the curve corresponding to a temperature of 30°C shows a more gradual reduction in moisture content over time, while the curve corresponding to 80°C shows a more pronounced decline, indicating faster drying. This behavior confirms the direct influence of temperature on the drying process, since higher temperatures promote a higher moisture evaporation rate. In addition, the curves show typical exponential drying behavior, in which moisture removal occurs more quickly at the beginning and progressively slows down over time. This phenomenon is explained by the reduction in the moisture gradient between the material and the external environment as the process progresses.

Figures 6, 7 and 8 were obtained, three-dimensional correlating the parameters temperature, kinetic constant ( $k$ ) and reaction order ( $n$ ) and humidity ratio ( $RU$ ).

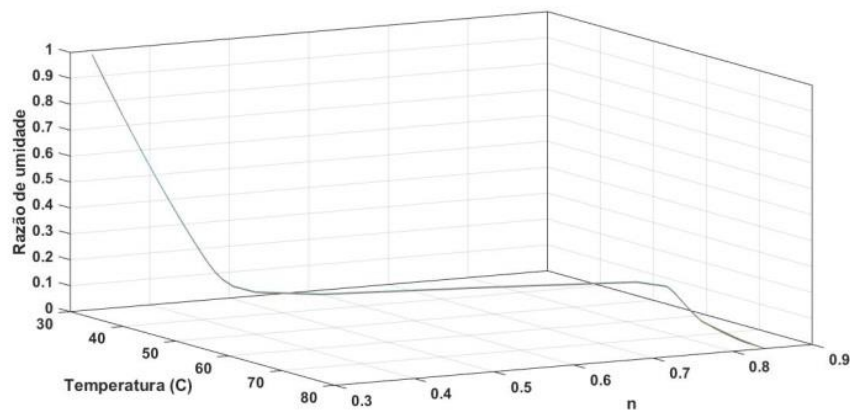
**Figure 6**

*Three-dimensional graph representing the variation of the rate constant  $k$  as a function of temperature and humidity ratio, highlighting the thermal influence on the reaction kinetics.*

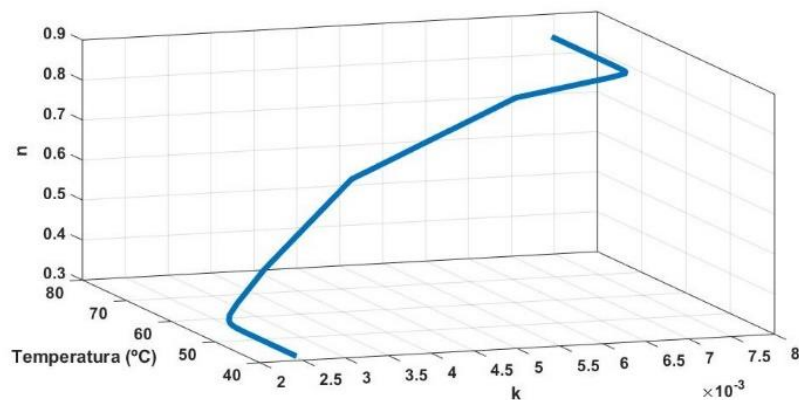


**Figure 7**

Three-dimensional graph illustrating the direct relationship between reaction order  $n$  and temperature, with the moisture ratio represented on the three-dimensional axis as the third parameter.

**Figure 8**

Three-dimensional graph showing the evolution of the rate constant  $k$  as a function of temperature and reaction order  $n$ , highlighting the exponential growth trend.



It is observed that the rate constant  $k$  increases with temperature, as predicted by the *Arrhenius model*. The speed at which a chemical reaction occurs typically increases with increasing temperature, and by exposing the components under study to high temperatures and intermittent measurements over time, the relationship between the reaction rate of degradation mechanisms and temperature can be estimated (Oliveira, 2012). This reinforces that the neural network was able to correctly capture the exponential relationship between these variables.



## 4 CONCLUSIONS

The study demonstrated the effectiveness of the application of Artificial Neural Networks (ANNs) in the modeling and prediction of the drying curves of sweet pepper (*Capsicum chinense* and ). The neural network developed, using the Levenberg-Marquardt training algorithm (*trainlm*), was able to predict with high accuracy the kinetic behavior of the drying process, evidenced by correlation coefficients close to 1 ( $R=0.99995$ ). The neural network was able to generalize the patterns of the experimental data, adequately adjusting to the drying curves at different temperatures.

The results obtained confirmed the direct influence of temperature on the drying process and the neural network could predict the kinetic parameters, such as the reaction order ( $n$ ) and the reaction rate constant ( $k$ ), which followed trends compatible with the kinetic theory of chemical reactions, especially the Arrhenius model. The rate constant  $k$  increased exponentially with temperature, while the reaction order  $n$  remained within a plausible range, reinforcing the robustness of the model.

By the analogy made between the drying operation and chemical kinetics, in the drying operation the parameter ( $k$ ) could be called the drying kinetic constant and the parameter ( $n$ ) could be called the drying order.

The application of ANNs in this study proved to be an effective tool for predicting drying curves with high accuracy and for analyzing kinetic parameters under different thermal conditions. Furthermore, the use of artificial neural networks represents a promising approach for modeling complex processes, such as food drying, offering valuable insights for the food and agricultural industries.

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