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Artificial Neural Network Modeling for Convective Drying Kinetics of Curry Leaves

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Abstract

The drying of curry leaves (*Murraya koenigii*) plays a significant role for their quality attributes, aromatic retention properties, and prolonged shelf stability for culinary and medicinal applications. The objective of this present research study was to investigate the impact of different drying temperatures of 40, 50, and 60 °C on drying kinetics of curry leaves through the application of a convective hot air oven drying technique. The experimental data (varying moisture ratio (MR) with respect to time) obtained by varying drying conditions were fitted into various mathematical models, whereby the Henderson and Pabis model provided the best description of the drying behavior, based on statistical parameters. Moreover, the artificial neural networks (ANNs) model was introduced and trained with obtained experimental data to accurately predict the MR values during the drying process. Predicted results demonstrated that the ANNs model obtained greater accuracy of fit with the experimental results compared to mathematical models, as confirmed by its superior performance matrices: coefficient of determination (R^2) of 0.99782 and root mean square error (RMSE) of 0.0156. Experimental and predicted data on MR, which exhibited a good fit of 99.56%, reflect the potential applicability of the ANN model for real-time monitoring and control of the curry leaf drying process in industries. This study has provided valuable information on the drying condition and technique to be adopted for better retention of bioactive compounds present in curry leaves. In addition, the developed ANN model can be integrated into the automated drying systems to predict the MR in a precise manner and for process optimization in order to realize better quality and consistency in the drying of curry leaves and other biological products.

Keywords

Curry leaves, Convective drying, Artificial neural network, Mathematical modeling

Introduction

Curry leaves or curry patta or kary patta, known scientifically as *M. koenigii*, are a quintessential element in Indian cuisine and traditional medicine. It is mainly grown in the Andaman Islands, Ceylon, China, India, Burma, Australia, and the Pacific Islands [1]. Curry leaves are valued for their unique scent from volatile oils and are used in small amounts to flavor foods. Traditionally, they have been employed as antiemetics, antidiarrheals, febrifuges, and blood purifiers [2]. The plant is considered both a tonic and a stomachic, with its leaves containing a wealth of bioactive compounds including carbohydrates, proteins, fibers, vitamins, ß-carotene and minerals. It contains a variety of bioactive compounds like glycosides, carbazole alkaloids, and triterpenoid alkaloids, which are beneficial for health. Furthermore, research suggests that curry leaves may possess anti-cancer properties, making them a promising candidate for further investigation in the realm of functional foods [2].

Drying is widely used and one of the most common traditional preservation method in practice [3]. For drying of various food materials, several drying methods have been developed, including hybrid techniques like intermittent microwave convective drying and solar, convective, freeze-drying, vacuum, osmotic, microwave, heat pump, and ultrasound drying [4]. Food quality is determined by the drying parameters chosen and the drying method used. Drying changes the fresh produce's physical, chemical, sensory, and nutritional characteristics which can affect the shelf life of foods. Among all the drying techniques, sun drying and convective hot air drying are the two most common and used methods for the drying of curry leaves. Although these techniques are affordable and relatively easy to use.

In recent years, food processing and quality control have recently been more focusing on advanced computational techniques such as ANN. ANN is a computational model inspired by the human neural structure. It is a powerful machine learning model capable of approximating complex non-linear relationships between input and output variables [5]. Consequently, ANN modifies weights and biases during the learning process to minimize errors between expected predictions and real target datasets [6]. In predicting the vacuum drying kinetics of moringa leaves, the ANN model performed better than seven semi-empirical models; and second was the Page model. Drying was probably most effective at 60 °C as indicated by the moderate energy needed for moisture movement in moringa leaves. It was concluded therefore that to dry moringa leaves for wider industrial use, the optimal drying temperature should not exceed 60 °C despite the increase in its drying rate (DR) and efficiency at higher temperatures [7]. During the study of the kinetics of drying thyme, not only the theoretical diffusion model but also eight empirical models were tested. ANNs outperformed both theoretical and empirical models, achieving the accuracy of 99.3% and an average value of the relative errors of 8.7% in predicting moisture evolution [8]. In the study on Ginkgo biloba seeds, microwave drying under different powers (200, 280, 460, and 640 W) was analyzed. The diffusivity coefficient values ranged from 3.318×10^{-9} to 1.073×10^{-8} m^2/s. The ANN model demonstrated strong predictive accuracy for both MR and color parameters, yielding high correlation coefficients ranging from 0.9056 - 0.9834 and low MSE values between 0.0014 and 2.2044. These established ANN models can be used for online prediction of moisture content and color changes during microwave drying of ginkgo biloba seeds [9].

The aims of the present study are to examine the drying behavior of curry leaves at various temperatures conditions and to employ ANN model to simulate the experimental drying kinetics and MR observed in curry leaves throughout the drying procedure.

Materials and Methods

Fresh curry leaves were purchased from a local market at Longowal, Punjab. Then the leaves were rinsed with water to remove impurities and kept in the refrigerator for further use. The initial moisture content of curry leaves was determined using standard AOAC methods, in which 10 g of sample in triplicates were taken for drying at 105 ± 1 °C for 24 h [10]

Drying experiment

The drying experiment was carried out at three different temperatures of 40, 50, and 60 °C in a convective hot air dryer (Balaji enterprises-48T, Saharanpur, India). For every drying temperature, the experiment was conducted in triplicate. Throughout the dehydration procedure, the sample's weight was assessed by removing the trays from the hot air oven. The sample weight was determined using a balance that has an accuracy of 0.001 g (BT-423-S, Sartorius, Germany). The weighing interval was chosen at the beginning of each test, the time interval was 15 min. Every test was conducted until the sample weight remained constant. For dry agricultural products, the most popular physical models in table 1 are based on literature. Here six models are used to predict the MR.

Table 1: Various mathematical models for MR.

Model name	Equations
Lewis	$MR = exp\ (-kt)$
Page	$MR = exp\ (-kt^n)$
Modified Page - I	$MR = exp\ (-(kt)^n)$
Modified Page -II	$MR = k\ exp\ (-t/d^2)^n$
Henderson and Pabis	$MR = a\ exp\ (-kt^n)$
Wang and Singh	$MR = 1 + at + bt^2$
Two terms	$MR = a\ exp\ (-kt) + b\ exp\ (kt)$

Mathematical drying model

For the determination of equilibrium moisture content of curry leaves at each drying temperature, the specified sample was placed into the dryer until it achieved a constant weight. The MR of curry leaves during the drying process was determined as given by the equation 1 [11].

$$MR = \frac{M_t - M_e}{M_o - M_e} \quad (1)$$

Where, M_t is moisture content at any time (dry basis, d.b.), M_e is moisture content at an equilibrium condition (d.b). and M_0 is the monolayer moisture content (d.b.).

However, the DR of the given samples during drying was calculated using the given equation 2.

$$DR = \frac{M_{t+dt} - M_t}{dt} \quad (2)$$

Where, t is the duration of drying (min) and M_t and M_{t+dt} are the moisture content at any time t and moisture content at the duration t+dt (kg water/ kg dry matter) respectively [12].

To explore the drying kinetics of curry leaves, seven alternative empirical or semi-empirical drying models were fitted to the experimentally obtained MR and drying duration data for all the applied drying air temperatures (40, 50, and 60 °C). The constants and coefficients of the equation were found by fitting a nonlinear least square regression curve with the Levenberg–Marquardt (LM) approach using Origin Pro 2024 software. To evaluate the performance and fitting accuracy of the different models, several statistical indicators were employed. These included the RMSE, chi-square (χ^2), and the

R^2, which were determined using equations 3 to 5. A lower RMSE and χ^2, along with a higher R^2, were indicative of better model performance [13].

$$R^2 = \frac{\sum_{i=1}^{N}(MR_{exp,i} - MR_{pre,i})^2}{\sum_{i=1}^{N}(MR_{exp,i} - N)^2} \quad (3)$$

$$\chi^2 = \frac{\sum_{i=1}^{N}(MR_{exp,i} - MR_{pre,i})^2}{N - n} \quad (4)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(MR_{pre,i} - MR_{exp,i})^2} \quad (5)$$

Where, $MR_{exp,i}$ and $MR_{pre,i}$ are the i^{th} number of experimental and predicted dimensionless MR.

ANNs

ANNs are computing systems that mimic the architecture and processing mechanisms of the human brain's neural structure. Their strength lies in identifying intricate patterns and modeling non-linear interactions between input and output variables, which makes them highly effective for applications such as food processing, quality assessment, and process optimization [5]. In recent years, ANNs have been successfully applied to model and predict moisture content, DR, and energy consumption for various food products [14]. ANNs are comprised of the layer of interconnected nodes, called neurons, organized into layers, which work together to process the information. Integration of nonlinearity comes about with the activation function so that it can be able to recognize and replicate complex associations [15]. The ANN tunes these connections by modifying W and b with an optimization algorithm, such as gradient descent or its derivatives during training to minimize the discrepancy between forecasted and true value based on some loss criteria (e.g., mean squared error or cross-entropy loss) [16]. Once ANN is trained, it allows for the prediction of new but unseen data by flowing input data right from the first to the last layer. A trained network can make predictions from accepted patterns even when such data were not initially in the training set. The primary objective of training a neural network is to fine-tune the connection W between neurons to ensure that the network generates the correct output for a given input. Initially, these W are assigned random values before being updated through the learning process.

To train the ANN models in this current work, the LM training algorithm was used. Fast and stable convergence are features of the LM algorithm, which offers a type of numerical solution for reducing or minimizing the nonlinear functions. It works especially well for training small- to medium-sized ANNs [17]. For MR prediction, the ANN input layer may incorporate drying time and temperature, whereas the respective output layer gives information about the expected MR shown in figure 1. This means that by including relevant features, the latter will then be able to replicate existing relationships between input parameters and targeted water content using its hidden layers [18]. With the help of ANNs impressive pattern recognition and nonlinear modeling capabilities, this study seeks to come up with a reliable and efficient model that would be greatly instrumental in predicting MR in the future. This will facilitate improved control and optimization of curry leaf-drying methods.

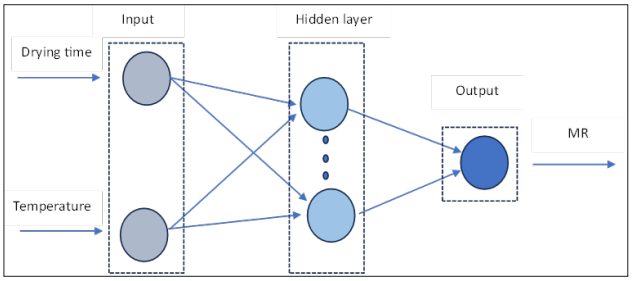


Figure 1: Architecture of ANNs.

ANN model assessment

After a comprehensive evaluation of the trained networks, the network configuration exhibiting the highest correlation coefficient (R) and the lowest MSE was selected for further predictions. To assess the predictive performance of the chosen network, independent test data was used after the completion of model training. The test results were analyzed to calculate various error metrics, including the MSE, mean absolute error (MAE), RMSE, and χ^2 value, using equation 6, 7, 8, and 9 respectively [19]. To illustrate the linear relationship between the actual MR and the estimated MR of the ANN trained model for curry leaves, Microsoft Excel 2019 software was utilized. The software enabled the graphical representation of the correlation between the actual and estimated mass, providing further insights into the performance of the ANN model.

$$MSE = \sum_{i=1}^{n}\frac{(y_i - y_p)^2}{n} \quad (6)$$

$$MAE = \sum_{i=1}^{n}\frac{|y_i - y_p|}{n} \quad (7)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_p)^2} \quad (8)$$

$$\chi^2 = \sum_{i=1}^{n}\frac{(y_i - y_p)^2}{y_i} \quad (9)$$

Where, y_i and y_p are the actual MR and predicted MR, respectively, and the number of observations is denoted *n* in the testing and training datasets.

Results and Discussion

Drying kinetics

This drying experiment intended to evaluate the effect of different convective drying temperatures on the MR values of the product over time. The temperatures conditions for convective hot air drying were set at 40 °C, 50 °C, and 60 °C respectively. The scatter plot graph indicates a clear trend of decreasing MR with increasing time across all temperatures. At the onset (0 min), the MR was approximately 1.0 for all samples, signifying a high moisture content. As the drying process progressed up to 300 min, a significant reduction in MR was observed. In the case of 40 °C exhibited a gradual decline in MR, indicating a steady drying process. At 50 °C, the decline in MR is steeper, signifying a more efficient DR than at 40 °C shown in figure 2. The MR decreases most sharply, reaching near-zero levels before 300 min at 60 °C, which implies the highest drying efficiency among the temperatures tested.

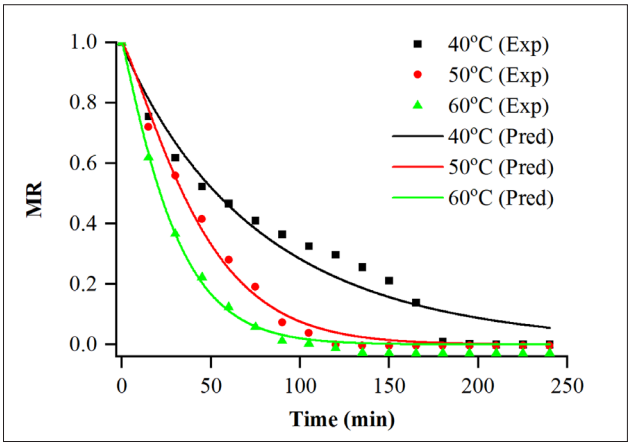


Figure 2: Drying kinetics of curry leaves at different temperatures.

The results suggest that temperature is a critical factor in the drying efficiency of food products. The higher the temperature, the more rapid the moisture loss, as evidenced by the sharper slopes for 60 ˚C. This can be attributed to the increased energy input at higher temperatures, which enhances the evaporation rate of water from the product. However, it is vital to consider the quality implications of higher drying temperatures, such as potential nutrient degradation or textural changes [20]. The optimal drying temperature must balance efficiency and product quality.

Selection for best mathematical models

Non-linear regression analysis was used to fit the experimental drying data into various models in table 1. The higher accuracy of the applied mathematical models was judged by the proposed statistical parameters such as R^2, RMSE, and χ^2 values. The results obtained in table 2 describe the performance of various thin-layer mathematical drying models with provides the values of empirical model constant and model parameters under different drying conditions (40 ˚C, 50 ˚C, and 60 ˚C).

Among the models considered, the Page model and the Henderson and Pabis model exhibited the best fit to the experimental data, with high R^2 values (>0.95) and low RMSE and χ^2 values across all temperatures. Experimental MR and pages, model predicted moisture are shown in figure 2. These findings are reasonable agreed with the earlier reported articles that have reported the suitability of these models for describing the drying behavior of various agricultural products [13, 21].

The Lewis model which is a special case of the Page model with n = 1, similarly provided a reasonably decent fit to the data, especially at higher temperatures (50 ˚C and 60 ˚C). However, its performance was slightly lower to the Page and Henderson and Pabis models, as evidenced by the lower R^2 and higher RMSE and χ^2 values. The modified Page I model and the modified Page II, modifications of the Page model, gave

Table 2: Empirical model constants and statistical parameters for thin layer drying of curry leaf.

T (˚C)	Models and model parameters	R^2	RMSE	χ^2
Page model → $MR = exp(-kt^n)$				
40	k = 0.0159 ± 0.006, n = 0.9488 ± 0.0951	0.9575	0.0621	0.0038
50	k = 0.0091 ± 0.002, n = 1.2250 ± 0.0703	0.9923	0.0268	0.0007
60	k = 0.0220 ± 0.005, n = 1.1232 ± 0.0703	0.9936	0.0235	0.0005
Lewis model → $MR = exp(-kt)$				
40	k = 0.0126 ± 0.0006	0.9567	0.0607	0.0037
50	k = 0.0227 ± 0.0010	0.9851	0.0374	0.0014
60	k = 0.0346 ± 0.0013	0.9915	0.0263	0.0110
Henderson and Pabis → $MR = a\ exp(-kt^n)$				
40	k = 0.0117 ± 0.0078, a = 0.955 ± 0.010, n = 1.005 ± 0.136	0.9592	0.0630	0.0039
50	k = 0.0078 ± 0.0028, a = 0.977 ± 0.026, n = 1.256 ± 0.087	0.9932	0.0270	0.0007
60	k = 0.0217 ± 0.0063, a = 0.996 ± 0.024, n = 1.125 ± 0.078	0.9937	0.0243	0.0005
Modified Page I → $MR = exp(-(kt)^n)$				
40	k = 0.0127 ± 0.001, n = 0.944 ± 0.091	0.9575	0.0621	0.0038
50	k = 0.0216 ± 0.001, n = 1.226 ± 0.065	0.9927	0.0268	0.0007
60	k = 0.0334 ± 0.001, n = 1.227 ± 0.067	0.9937	0.0268	0.0005
Modified Page II → $MR = k\ exp(-t / d^2)$				
40	k = 0.9573 ± 0.0530, d = 2.413 ± 16.296, n = 0.070 ± 0.953	0.9592	0.0630	0.0039
50	k = 1.0296 ± 0.0364, d = 2.063 ± 7.796, n = 0.099 ± 0.755	0.9859	0.0388	0.0015
60	k = 1.0141 ± 0.0272, d = 2.030 ± 6.576, n = 0.114 ± 0.940	0.9917	0.0278	0.0007
Wang and Singh → $MR = 1 + at + bt^2$				
40	a = -0.008 ± 0.001, b = 0.0001 ± 0.0001	0.9397	0.0740	0.0054
50	a = -0.013 ± 0.001, b = 0.0001 ± 0.0001	0.9486	0.0717	0.0051
60	a = -0.004 ± 0.001, b = 0.0001 ± 0.0001	0.7907	0.1354	0.0183
Two terms → $MR = a\ exp(-kt) + b\ exp(kt)$				
40	k = 0.012 ± 0.001, a = 0.957 ± 0.045, b = 0 ± 0.000	0.9592	0.0630	0.0039
50	k = 0.023 ± 0.001, a = 1.029 ± 0.033, b = 0 ± 0.000	0.9859	0.0388	0.0015
60	k = 0.035 ± 0.001, a = 1.014 ± 0.026, b = 0 ± 0.000	0.9917	0.0278	0.1418

similar results to the original Page model. All these models worked equally well at all temperatures and thus may be applied to explain the drying kinetics of the material under study.

The Two-term model which combines the effects of two separate drying mechanisms, resulted a better fit with R^2 values comparable to the Page and Henderson and Pabis models. However, it should be noted that the parameter 'b' in this model was found to be negligible (approximately zero) across all temperatures, suggesting that the second term may not be necessary for describing the drying behavior of the material under investigation.

To accurately predict and optimize the drying process, it is crucial to choose the best drying model. The choice of model should be based not only on statistical parameters but also on the physical and theoretical considerations relevant to the specific drying system and material [22].

ANNs approach

The use of ANNs to predict and compute the MR values during the drying process of curry leaves was investigated. The ANNs were trained using a dataset obtained from experimental drying trials, which included various parameters such as drying temperature, drying duration, and relative humidity [23]. The performance of the ANNs model was judged with the help of statistical parameters such as R^2 and RMSE values.

The architecture of the developed neural network model is illustrated in figure 3. It consists of an input layer with two neurons as drying time and temperature, a hidden layer with ten neurons, and an output layer with a single neuron, the predicted MR. The connections between the layers are represented by W and b, which are adjusted during the training process to minimize the prediction error.

For the training data set, the model achieved an impressive R^2 value of 0.99916, indicating an excellent fit between the predicted and actual MR values. High R^2 values were also shown in the validation dataset, which was used for adjusting the model and optimization of hyperparameters. Overall, the results establish that the developed neural network model can accurately predict the MR during the drying process, achieving high predictive performance on both the training and testing data sets. The model's architecture and training process have been carefully designed and optimized to capture the complex relationships between the input features and the target MR values. The regression plot of trained model was shown in figure 4. ANN model achieves a 0.99782 accuracy for predicting the MR.

Mathematical model and ANNs comparison

The purpose of this study is to compare the effectiveness of a conventional mathematical model against a more advanced ANN technique in forecasting MR during drying. The mathematical model used was a linear regression equation, while the ANN was a feedforward neural network with a specific architecture and training algorithm. Both models are mathematical and ANNs models are well performed for predicting MR during the drying process. However, the ANNs model achieve the higher accuracy to predict the MR.

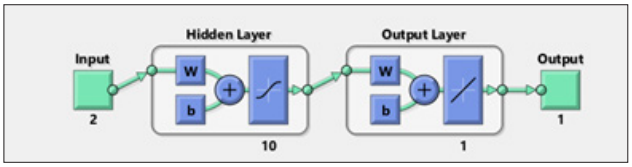


Figure 3: The result ANN model structure for MR prediction.

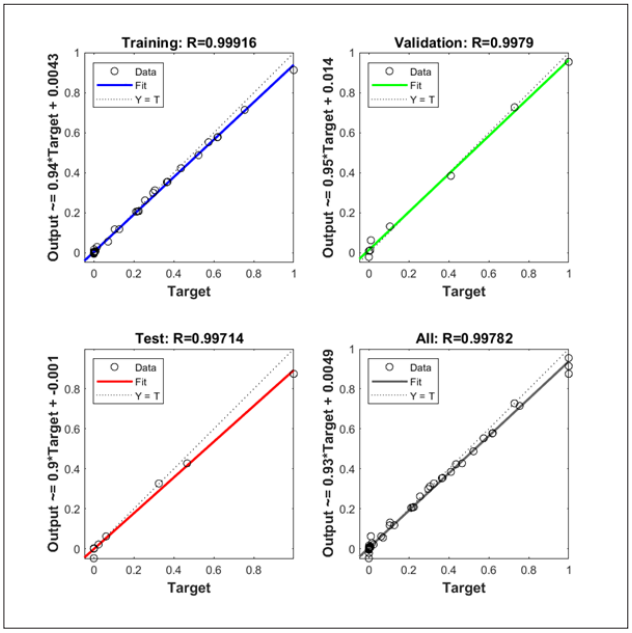


Figure 4: The regression plot for trained ANN.

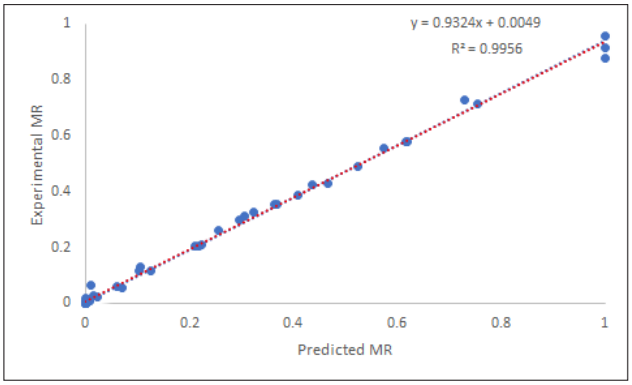


Figure 5: Correlation between experimental and predicted MR.

These findings show that there is outstanding concordance in the ANN and that the model accurately corresponds to the experimental MR under different conditions. The correlation between experimental and predicted MR through ANN modeling is shown in figure 5. The performance of trained ANN model for MR prediction of curry leaves during drying process showed strong performance with a high R^2 value of 0.9978. The MR of curry leaf was predicted with great accuracy using the pretrained ANN model. The RMSE, MAE, MSE, and χ^2 values were 0.0156, 0.0066, 0.00024, and 0.0122 respectively. Similar to the current study, Bai et al. [9] reported that for MR prediction of Ginkgo Biloba seeds with a higher R^2 value of 0.9834.

Conclusion

In this study, the drying kinetics of curry leaves were analyzed using both conventional thin-layer mathematical models and an ANN approach. The Henderson and Pabis model was best fitted to the experimental drying data with higher R^2, reduced RMSE and χ^2. The study explained that curry leaves dry kinetics and as the temperature increases the moisture loss also increases. Among all the mathematical model Page and Henderson and Pabis models which could be preferred for estimation of MR and developed ANN model achieves the highest accuracy with R^2 of 0.9978 which is better than mathematical models for predicting the MR. ANN model was applied to predict the MR. The result showed that ANN model can precisely predict the MR with correlation coefficient higher than 0.997. The correlation between experimental and predicted MR was 99.56%. Accordingly, ANN model can be further used for automation of drying process. The utilization of statistical tools such as mathematical models and advanced machine learning algorithms including ANN proved to be effective in estimating the MR of leaves. The ANN model has a lot of potential for real-time monitoring and automation in industrial drying systems since it is very accurate and can be changed to fit different needs. This will make the systems more energy-efficient and improve the quality of the products.

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Conflict of Interest

None.

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