7(2): 44-50, 2024

Journal of Food and Bioprocess Engineering

Journal homepage: https://jfabe.ut.ac.ir

Original research

Application of mathematical and genetic algorithm-artificial neural network models in microwave drying of sprouted quinoa

Sepideh Vejdanivahid [a], Fakhreddin Salehi [a, *]

[a] *Department of Food Science and Technology, Faculty of Food Industry, Bu-Ali Sina University, Hamedan, Iran*

A B S T R A C T

Quinoa is one of the pseudocereal grain that is rich in macro- and micronutrients. Sprouting is an effective process that improves the palatability, quality, nutritional value, and digestibility of quinoa seeds. In this research, the impact of microwave dryer power on the drying kinetics and moisture loss of sprouted quinoa was investigated. The sprouted quinoa seeds were dried as single layers at three different power levels (330, 440, and 550 W). The results showed that the drying time was decreased with increasing microwave power. Seven kinetic models were examined to simulate the experimental drying kinetics and the Page model showed the best performance. The effective moisture diffusivity coefficient (D_{eff}) was calculated to be in the range of 1.43×10^{-10} m^2/s to 2.93×10^{-10} m^2/s, and increased significantly with increasing microwave power ($p<0.05$). The average rehydration ratio of dried sprouted quinoa changed from 251.04% to 290.10%, and increased with increasing microwave power. In addition, in this study a genetic algorithm-artificial neural network (GA-ANN) method was used for prediction of the moisture loss of sprouted quinoa. The optimal network containing four neurons in hidden layer was able to predict the moisture loss of sprouted quinoa with a coefficient of determination (r) of 0.996. The highest values of water loss, water diffusion, and rehydration rate were obtained when drying with a microwave power of 550 W. The results of this study can be useful in selecting optimal drying conditions for microwave drying of sprouted quinoa and as a basis for other sprouted crops.

Keywords: Effective moisture diffusivity; Network structure; Page model; Quinoa; Rehydration

Received 06 Feb 2025; Received in revised form 23 Apr 2025; Accepted 25 Apr 2025

1. Introduction

Introducing resilient crop varieties that can thrive in harsh environmental conditions is an effective strategy for ensuring sustainable food production and securing supplies in arid regions. Quinoa (*Chenopodium quinoa* Willd) thrives in dry and salty conditions, making its cultivation highly significant (Samadzadeh et al., 2020). Quinoa is an Andean grain crop that has attracted increasing interest in recent years due to its eco-physiological characteristics and the nutritional value of its seeds. Quinoa plant was originally cultivated in South America, but is now used worldwide. The diversification of its cultivation areas on different continents is based on extensive research performed worldwide on its high nutritional, functional, and nutraceutical values and its adaptability to various climates and soils (Alandia et al., 2020; Okon, 2021; Pulvento and Bazile, 2023; Vejdanivahid and Salehi, 2024). Of the original producing countries, only Peru, Bolivia, and Ecuador are in the top ten most important exporters of this Andean grain. Quinoa's recent popularity has made it one of the world's most popular crops, and it is now used in many cuisines around the world as a substitute for rice or couscous (Arguello-Hernández et al., 2024). Quinoa has emerged as an optimistic agricultural option that numerous countries are investigating to alleviate water scarcity (Mirsafi et al., 2024). The purpose of a study by Soltanzadeh and Aahmadpour Borazjani (2022) was to measure the amount of input and output energy, the proportion of direct, indirect, renewable, and non-renewable energy, and the energy consumption efficiency of the quinoa production systems in the Iranshahr region of southern Iran. The results of the economic research showed that the average consumption cost of production one hectare of quinoa was $1668.93

*Corresponding author.
E-mail address: *F.Salehi@basu.ac.ir* (F. Salehi).
https://doi.org/10.22059/jfabe.2025.390056.1197

ha^{-1}, and the average net profit of farmer was about \$1451.86 ha^{-1}. Therefore, in terms of energy consumption and profitability, this plant is suitable for cultivation in the research area.

Quinoa is a dicotyledonous, C3 species in the *Amaranthaceae* family that produces achene fruits (chenopod grains) with a rounded seed of 1.5–4 mm (Garcia et al., 2015; Alandia et al., 2020). Quinoa seeds are consumed as a cereal grain and are characterized by their excellent nutritional value. They are considered to have a higher balance of essential amino acids, fatty acids, micronutrients, vitamins, and antioxidants than major cereals. As a gluten-free food grain with a low glycemic index, this pseudocereal is an alternative in special diets and industries (Al-Qabba et al., 2020; Alandia et al., 2020; Okon, 2021; Casalvara et al., 2024).

Sprouting is an effective process that improves the palatability, quality, nutritional value, and digestibility of edible seeds and is used in the production of edible food products (Xing et al., 2021; Salehi, 2023). Some researchers have reported that the vitamin content, phenolic compounds, and antioxidant capacity of raw quinoa seeds increased significantly 72 h after sprouting (Al-Qabba et al., 2020; Ng and Wang, 2021). One study showed that the total phenolic content of red and yellow quinoa increased by more than 200% within six days of sprouting, and then decreased slightly (Al-Qabba et al., 2020). Changes in the structural and physicochemical characteristics of quinoa starch during sprouting were reported by Xing et al. (2021). The surface of sprouted quinoa starch granules showed more pinholes and obvious crimples than native starch. The sprouting process has a significant effect on the structural and physicochemical properties of quinoa starch, providing a basis for the use of sprouted quinoa products in the food industry. Le et al. (2021) investigated the nutrient composition and functional content of different varieties of sprouted quinoa. Their results showed that quinoa sprouts had high contents of moisture, reducing sugar, potassium, magnesium, and vitamin C. They also contained all essential amino acids that were rich in leucine.

Drying is a preservation method that removes or decreases the moisture content of an agricultural crop. This process can influence the nutritional value of food products (Khodadadi et al., 2017; Khodadadi et al., 2024). As an efficient thermal processing method, microwave heating has faster heating rates and high energy efficiency compared to conventional processing methods (Salehi et al., 2024). During microwave drying, electromagnetic energy is converted into heat and interacts with the water molecules in the material. Water molecules in various substances are electric dipoles. So, when exposed to the magnetic field in a microwave dryer, they align themselves with the fluctuating electric field. The rapid molecular motion creates friction, which dissipates heat throughout the material (Khodifad and Dhamsaniya, 2020; Khodadadi and Masoumi, 2025). To stabilize the practicality of microwave technology in the drying process, options such as drying time, energy potency, and quality must be considered simultaneously (Sedani et al., 2021).

Mathematical models can only accurately estimate experimental data under very specific conditions, and no general equation exists that can describe the complete model (Martínez-Martínez et al., 2015). Artificial intelligence techniques can model nonlinear systems where the relationships between variables are unknown. An artificial neural network (ANN) is a type of artificial intelligence technique that can dynamically simulate the behavior of highly nonlinear systems (Salehi, 2020; Yang et al., 2023). Martínez-Martínez et al. (2015) used ANN-based models to characterize the drying process of switchgrass. The first ANN-based model described the moisture content change data more accurately than the six mathematical empirical equations commonly proposed in the literature. Furthermore, the second ANN-based model predicted the moisture content with a correlation coefficient of over 98.8%.

The selection of an appropriate ANN structure for estimating the drying process is important in terms of model accuracy and model simplicity. The architecture of an ANN has a significant impact on its performance. Many algorithms for finding an optimized ANN structure are derived based on specific data for a particular application domain (Liu et al., 2007). A genetic algorithm (GA) is used to perform optimization based on the resulting weights and biases of the ANN structure. A genetic algorithm–artificial neural network (GA-ANN) model is a useful tool for drying kinetics modeling and predicting food quality characteristics (Dil et al., 2016; Salehi, 2020).

As the world's population grows, food crops, which at a particular time appeared to be neglected or little known, begins to gain recognition. The aim of this study was to investigate and mathematical modeling of microwave drying curves and moisture diffusivity of sprouted quinoa. In addition, the GA-ANN method was used for prediction of the moisture loss of sprouted quinoa.

2. Material and Methods

2.1. Sprouting process of quinoa

For this study, we purchased white quinoa seeds harvested from Peru farms and packaged in Iran (OAB Company, Iran). First, the seeds were washed and soaked in tap water at approximately 25°C for 1 h. Then, the seeds were poured into a flat container and covered with a thin towel. The seeds were moistened with a water sprayer bottle every 6 hours. In total, the seeds were kept at a temperature of about 25°C for 72 h until they sprouted (Vejdanivahid and Salehi, 2024).

2.2. Microwave drying of sprouted quinoa

The sprouted quinoa was uniformly distributed as a single layer on a tray inside the microwave oven (Gplus, Model; GMW-M425S.MIS00, Goldiran Industries Co., Iran) and moisture loss was monitored accurately to 0.01 g (Kia Laboratory Weighing, model SL1000, Iran) at regular time intervals of 30 s. By reviewing various articles and conducting experiments, we discovered the most effective method for utilizing a microwave in the lab. The microwave drying experiments were carried out at different microwave powers of 330, 440, and 550 W. Each drying experiment was replicated three times, and the average values were used.

2.3. Mathematical modeling of drying kinetics

Researchers have developed mathematical models to describe nonlinear models, including theoretical, semi theoretical and empirical models (Yang et al., 2023). In this study, for mathematical modeling of the experimental drying curves of sprouted quinoa, first of all, the moisture ratio (MR) was calculated by using Eq. (1):

$$MR = \frac{M}{M_0} \quad (1)$$

Then, the seven commonly used semi-theoretical mathematical models, including Wang and Singh, Approximation of diffusion, Page, Newton, Midilli, Logarithmic, and Quadratic were fitted to the experimental MR results using Matlab software (version R2012a) and applying nonlinear regression method. The accuracy of the models was evaluated by using three well-known statistical criteria, including sum of squared error (SSE), coefficient of determination (r), and root mean square error (RMSE) (Salehi and Satorabi, 2021).

2.4. Effective moisture diffusivity coefficient (D_{eff})

Thin layer drying of agricultural products can be described by one-dimensional diffusion and using Fick's second law. The D_{eff} of sprouted quinoa during microwave drying was estimated following the procedure described by Salehi (2023).

2.5. Rehydration ratio

The dried sprouted quinoa was submerged in 250 ml glass beakers containing distilled water at 50°C. The beakers were transferred into the water bath (R.J42, Pars Azma, Iran) and the rehydration process was conducted at 50°C. The sprouted quinoa mass after the rehydration time (30 min) was recorded by a laboratory balance (Kia Laboratory Weighing, model SL1000, with an accuracy of ±0.01g, Iran). The rehydration percent of dried sprouted quinoa was calculated as the ratio of the weight of rehydrated sprouted quinoa divided by the weight of dried sprouted quinoa × 100 (Salehi et al., 2023).

2.6. Genetic algorithm–artificial neural network (GA-ANN) model

The Neurosolution software (release 5, NeuroDimension, Inc., USA) was used for GA-ANN modeling. The treatment time and microwave power (2 inputs) were used as inputs and moisture loss of sprouted quinoa during drying process was used as output. The experimental data order was first randomized and then total data were randomly separated into three partitions: training (30%), validating (20%), and testing data (50%). In the hidden layers and output layer a hyperbolic tangent activation function was used (due to the highest r-values in comparison to the other functions, sigmoid and a linear) (Eq. (2)).

$$f(x)=\frac{1}{1+e^{-x}} \tag{2}$$

The Levenberg–Marquardt (LM) optimization method was applied to network training. The crossover probability and the mutation probability operators were adjusted equal to 0.9 and 0.01, respectively. Also, a sensitivity analysis was done to supply the measure of relative significance between the inputs of the ANN model and to show how the model output changed in response to input changes.

2.7. Statistical analysis

Data were analyzed using one-way analysis of variance (ANOVA), and when significant differences were detected, means were compared using Duncan multiple range test with a 95% confidence level ($p<0.05$). The data analysis was carried out with IBM SPSS Statistics 21 software (SSPS Inc., USA).

3. Results and Discussion

3.1. Drying process

Quinoa is very rich in dietary fiber, protein, vitamins, unsaturated fatty acids, and minerals, with an amazing balance of essential amino acids. It is also considered a gluten-free grain and can be used in the diet of people with celiac disease (Okon, 2021). The typical moisture loss curves of the sprouted quinoa at different power levels are shown in Fig. 1. The maximum moisture loss rates of the sprouted quinoa were obtained for the power level of 550 W while the minimum moisture loss rates belonged to the microwave power of 330 W. The higher power enhances both kinetic energy and absorbed energy causing more vapor pressure difference between the center and surface of the samples and consequently increasing the moisture removal rates (Azimi-Nejadian and Hoseini, 2019). Najib et al. (2022) investigated the drying process of lentils that have been soaked and sprouted, utilizing a microwave-assisted infrared oven. Their findings indicated that microwave power was the most influential factor in drying speed, followed by infrared power, while the duration of sprouting had little impact. The value of specific energy consumption varies by microwave and infrared powers and has the least amount for microwave power of 0.42 kW and infrared power of 0.375 kW.

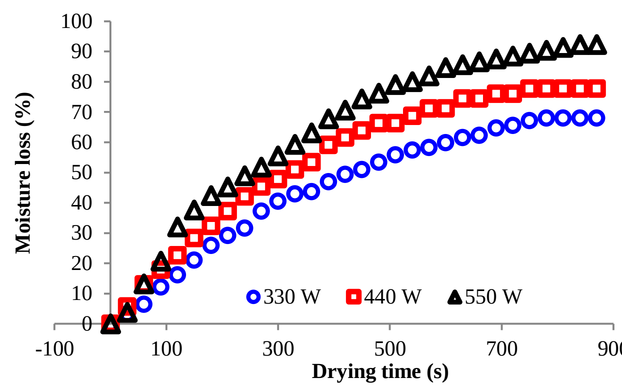

Fig. 1. Moisture loss curves for microwave-dried sprouted quinoa at different power levels.

3.2. Evaluation of mathematical thin-layer models

The obtained experimental moisture ratio values were fitted to the mathematical thin layer models and the results of statistical analysis are reported in Table 1. From the result and based on the statistical criteria including SSE, r, and RMSE, of all the practiced models, the Page model was found as the more suitable model to describe the microwave thin layer drying curves of the sprouted quinoa.

The drying constant and coefficient for the Page model obtained from fitting the moisture removal curves at different microwave power levels are shown in Table 2. Furthermore, to examine the Page model capability to simulate the drying curves, the experimental moisture ratio data was compared with those estimated by the model

Table 1. The statistical analysis of the used thin-layer models for prediction of the sprouted quinoa drying curves (microwave power=550 W).

Model name	Sum of squared error	Coefficient of determination	Root mean squared error
Wang and Singh	0.0146	0.9932	0.0228
Approximation of diffusion	0.0051	0.9976	0.0138
Page	0.0048	0.9988	0.0131
Newton	0.0052	0.9976	0.0134
Midilli	0.0049	0.9978	0.0136
Logarithmic	0.0049	0.9978	0.0133
Quadratic	0.0109	0.9949	0.0201

Table 2. Drying constants of Page model for sprouted quinoa under microwave drying.

Microwave power	k	n	Sum of squared error	Coefficient of determination	Root mean squared error
330 W	0.1014	0.9323	0.0117	0.9956	0.0200
440 W	0.1690	0.8875	0.0134	0.9960	0.0216
550 W	0.1698	1.0013	0.0065	0.9984	0.0152

and the results for one randomly selected drying curve are shown in Fig. 2. As can be seen from this figure, the points were generally banded around the 45° straight line declaring that the Page model had a good capability to describe the microwave drying behavior of the sprouted quinoa.

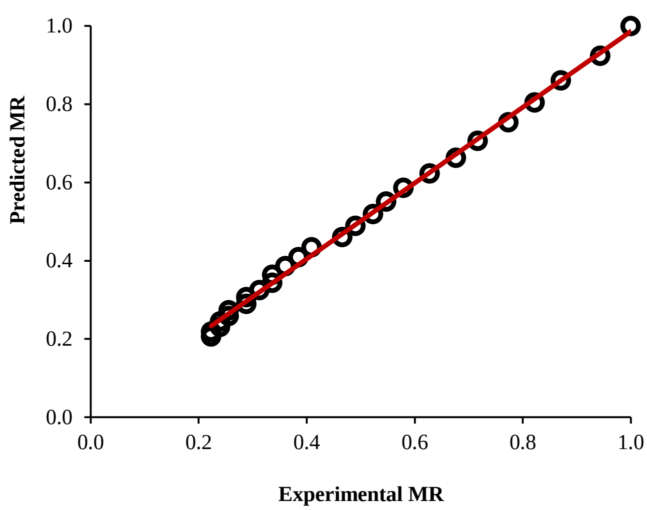

Fig. 2. Comparison between experimental data and predicted moisture ratios (MR) values by Page model (microwave power=440 W).

3.3. Effective moisture diffusivity coefficient (D_{eff})

Microwave energy has been used very successfully in food processing, especially in the drying of foods to preserve the quality of valuable food products (Khodifad and Dhamsaniya, 2020; Salehi et al., 2024). The calculated average values for the D_{eff} of the sprouted quinoa at various microwave power levels from plotting the graph of ln(MR) versus process time and using Eq. (2) are presented in Table 3. Based on statistical analysis, microwave power has a significant effect on moisture diffusivity ($p< 0.05$), and an increase in power increases the moisture diffusivity coefficient. Generally, with microwave technology, the drying rate increases as microwave power and temperature increase (Sedani et al., 2021). As the results show, the moisture diffusivity changed from 1.43×10^{-10} m^2/s to 2.93×10^{-10} m^2/s. Vejdanivahid and Salehi (2024) used adaptive neuro-fuzzy inference system to estimate mass transfer during convective drying of microwave-treated quinoa sprouts. Their results showed that microwave pretreatment for 30 s increases moisture removal rate, increases D_{eff}, and reduces drying time of quinoa sprouts. With microwave pretreatment of quinoa sprouts for 30 s, they were observed that the D_{eff} increased significantly from 5.73×10^{-11} m^2s^{-1} to 10.49×10^{-11} m^2s^{-1} ($p<0.05$).

Table 3. The values of effective moisture diffusivity coefficient values for the sprouted quinoa under microwave power drying (Different letters within the column indicated statistically significant differences between various treatments ($p<0.05$)).

Microwave power	Effective moisture diffusivity coefficient (m^2/s)	Coefficient of determination
330 W	$1.43\times10^{-10}\pm1.18\times10^{-11\ c}$	0.991
440 W	$2.01\times10^{-10}\pm1.28\times10^{-11\ b}$	0.985
550 W	$2.93\times10^{-10}\pm2.55\times10^{-11\ a}$	0.996

3.4. Rehydration ratio

Microwave drying is especially recommended for drying seeds, fruits, and vegetables as it reduces the drying duration and energy consumption. However, for biological materials, an analysis of the quality parameters of the dried final product is highly recommended (Sedani et al., 2021). Rehydration capacity is a crucial characteristic of dried food products. The porous structure of the material directly influences its attributes, such as rehydration capacity, hardness, and crispness. The calculated average values for the rehydration ratio of the dried sprouted quinoa at various microwave power levels are presented in Table 4. An increase in microwave power increases the rehydration ratio of dried sprouted quinoa. But, based on statistical analysis, microwave power has no significant effect on the rehydration ratio of samples ($p > 0.05$). As the results show, increasing microwave power from 330 W to 550 W increased the rehydration ratio from 251.04% to 290.10%.

Table 4. The rehydration ratio values for the sprouted quinoa under microwave drying (Same letters within the column indicated statistically non-significant differences between various treatments (p>0.05)).

Microwave power	Rehydration ratio (%)
330 W	251.04±33.87 [a]
440 W	282.05±75.99 [a]
550 W	290.10±27.10 [a]

3.5. Genetic algorithm–artificial neural network (GA-ANN) modeling results

ANN has been effectively used to model and predict food drying parameters, especially in areas where mathematical modeling methods fail (Salehi, 2020; Yang et al., 2023). In this study, the GA-ANN model was developed for the estimation of the moisture loss of sprouted quinoa during microwave drying. In this research, the ANN model was trained using the GA to find the best network structure. It was found that GA-ANN with four neurons in one hidden layer could estimate moisture loss with a high correlation coefficient value (r=0.996). The calculated r-values for the estimation of moisture loss during microwave drying of sprouted quinoa show a high correlation between estimated and experimental values.

The mean square error value versus the number of learning generations is shown in Fig. 3. As can be seen, the error value decreases in the first few generations and after about 39 generations, the error value reaches a constant value. The rapid decrease in the mean square error graph in the initial training cycles indicates rapid learning of the network.

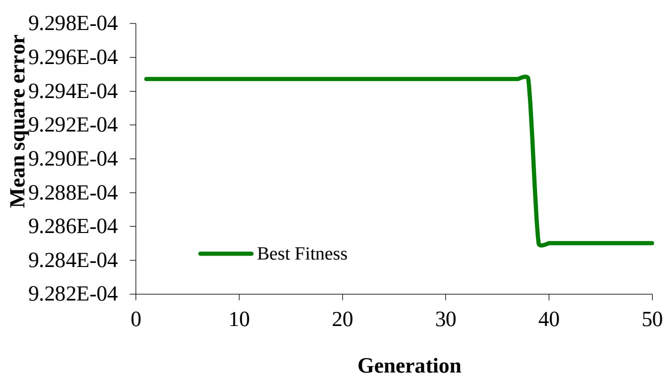

Fig. 3. Mean square error values as a function of the learning generation during training and validation of network.

To predict moisture loss during microwave drying of sprouted quinoa, the optimized GA-ANN model was used to calculate error values. The mean squared error (MSE), normalized mean squared error (NMSE), mean absolute error (MAE), minimum absolute error, and maximum absolute error were 4.854, 0.008, 1.682, 0.007, and 5.696, respectively. In summary, the predictions of the GA-ANN model have high agreement with the testing datasets and they are useful for understanding and controlling the factors affecting the drying rate of sprouted quinoa during microwave drying.

In GA-ANN modeling, the testing data (50%) were used to predict the trained network performance on unseen data. The estimation performance of the GA-ANN model for unseen data of moisture loss is presented in Fig. 4. As can be seen from this figure, the points were generally banded around the 45° straight line declaring that the GA-ANN model had a good capability to describe the microwave drying behavior of the sprouted quinoa. The results showed that a satisfactory agreement between the predicted and experimental data could be achieved by using the GA–ANN model. In a study, Yang et al. (2023) combined an ANN with a GA to obtain a model and optimal process parameters for dry breaking of walnuts. The ANN optimized by the GA was applied to simulate the effects of infrared temperature, air velocity, moisture content, and loading direction on the five response variables, from which the objective functions of drying time, specific energy consumption, high kernel rate, whole kernel rate, and shell-breaking rate were developed. Their results showed that the ANN model showed sufficient prediction ability for drying time, specific energy consumption, high kernel rate, whole kernel rate, and shell-breaking rate, with coefficients of determination of 0.996, 0.998, 0.990, 0.991, and 0.993, respectively.

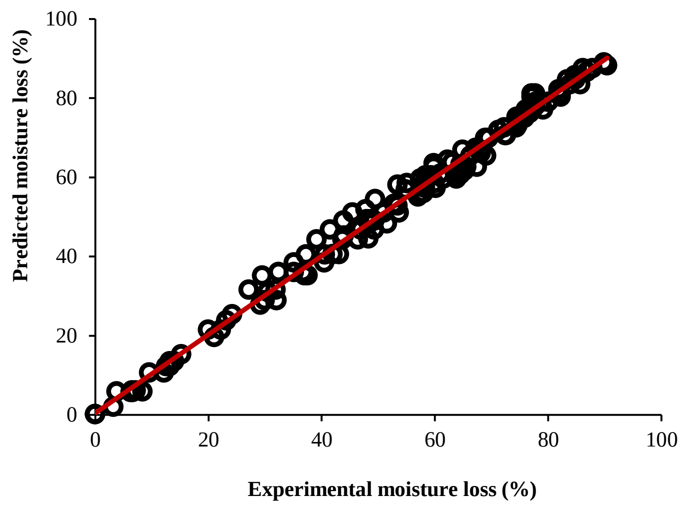

Fig. 4. Comparison between experimental data and predicted moisture loss of sprouted quinoa during microwave drying by genetic algorithm–artificial neural network model.

The core of the ANN training process is the optimization of weights and biases. The initial weights and biases of the ANN network are randomly generated. The GA first pre-optimizes the initial weights and biases of the ANN, and then the neural network is trained using the optimized weights and biases to accelerate the convergence speed of the network and obtain the global optimum values (Salehi, 2020; Yang et al., 2023). The best GA-ANN network weight and bias values for moisture loss changes of sprouted quinoa during microwave drying are reported in Table 5, which could be used in a computer program to predict this parameter.

The results indicated that the developed GA-ANN drying model can efficiently estimate the moisture loss of sprouted quinoa during microwave drying. Also, in this study the sensitivity analysis was used to examine the sensitiveness of GA-ANN structures toward various inputs. Sensitivity analysis results demonstrated that the treatment time was the major sensitive input for estimating moisture loss of sprouted quinoa during microwave drying.

Table 5. The weight and bias data of the best model structure for estimation of moisture loss of sprouted quinoa during microwave drying.

Hidden neurons	Bias	Input neurons		Output neuron
		Treatment time (min)	Microwave power (W)	Moisture loss (%)
1	3.8122	3.3971	-0.1216	2.9799
2	1.1801	0.3532	0.8902	0.6760
3	1.4303	-0.7577	-0.6883	-0.8303
4	0.5927	1.8148	-0.3497	0.4299
Bias				-2.6502

4. Conclusion

Quinoa is known for its high nutritional value and adaptability. Microwave power-assisted drying significantly reduces the drying duration compared to other technologies. In this study, the impact of microwave power level on drying characteristics of single thin layer drying of sprouted quinoa via a microwave oven dryer were investigated. The curves of moisture loss rate included a short accelerating rate period in the beginning followed by a long falling rate period. The minimum process duration of the sprouted quinoa was obtained for the power level of 550 W while the maximum value belonged to the microwave power of 330 W. Among different mathematical models fitted to the experimental moisture ratio data, the Page model was found as the best one to describe the curves. By increasing the microwave power level from 330 W to 550 W, the effective moisture diffusivity coefficient significantly increased from 1.43×10^{-10} m^2/s to 2.93×10^{-10} m^2/s ($p < 0.05$). An increase in microwave power increases the rehydration ratio of dried sprouted quinoa. The GA-ANN structure has two inputs of treatment time and microwave power. The optimal network with a general structure of 2-4-1 was constructed to estimate the moisture loss of sprouted quinoa during microwave drying. The modeling results indicated that the mathematical and GA-ANN models could give a better estimate of the moisture ratio and moisture loss of sprouted quinoa during microwave drying. Sensitivity analysis results showed that treatment time is the most sensitive factor in predicting the moisture loss of sprouted quinoa.

Funding

This research was supported by a grant from the Bu-Ali Sina University, Hamedan, Iran (Grant No. 1004498).

Acknowledgements

We acknowledge Bu-Ali Sina University Research Council for its financial support of this research.

Conflict of interest

The authors declare that there is no conflict of interest.

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