



Characterization of Rice Flour Quality using Artificial Neural Network – Genetic Algorithm for Production of *Zhero*: an Ethnic Himalayan Snack Product

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Abstract

Zhero is an indigenous popular snack product of Bhutia and Tamang tribe of Sikkim, India. The present study focusses on standardizing its process operations such as soaking and grinding for production of uniform quality rice flour to be used as raw material in *Zhero* preparation for commercial processing. The effects of soaking time, S_t (4 – 8 h) and temperature, S_T (15-25 °C) and grinding time, G_T (1 – 2 minutes) on the characteristics of rice flour have been studied. The process parameters were optimized using a multi-objective genetic algorithm (GA) along with a three-layer feed forward artificial neural network (ANN). The ANN model developed could satisfactorily predict all responses with R value of 0.999 for all training, testing, validation and global sets of data and MSE value 0.01883 for validated dataset. The final optimum conditions (S_t ; S_T ; G_T) were 4.2 h, 18 °C, and 1 min respectively. The predicted rice flour quality at optimized process conditions were: 23.85 % w b moisture content, 0.543 g/cm³ bulk density, 0.57 g/cm³ tapped density, 28.09° angle of repose, 0.31 mm particle size, Carr's index 5.055 and HR ratio 1.05. The experimental and ANN-GA model predicted responses had a relative percent error of < 10%, suggesting suitability of the developed model. This study represents a new attempt to conduct appropriate scientific research to determine the consistency of the production process and the quality of the final product, not only to confirm its origin and maintain its culture, but also to improve and standardize its technology for future commercial success.



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Abbreviations

ar	Angle of repose
Bd	Bulk density
ci	Carr's index
GT	Grinding time
hr	Hausner's ratio
Mc	Moisture content
ps	Particle size
St	Soaking time
ST	Soaking temperature
td	Tapped density

Introduction

Traditional foods serve as a symbol of heritage, trademark, and culture, in addition to providing an important opportunity for food diversification. It is the cuisine of a nation or ethnic group that is considered culturally and socially acceptable to consumers outside of that ethnic group. The processing and preparation of ethnic meals not only demonstrates local people's creativity and food heritage, but also their progressive learning to support life and the ecosystem altogether. Singh *et al.*¹ Traditional food are indispensable in eating habits of ethnic and tribal groups worldwide, with distinct flavours and tastes.

Zhero is an indigenous rice-based snack food of North Eastern region of India widely popular in Bhutia and Tamang tribes of Sikkim. Tamang and Thapa² The traditional processing method of *Zhero* is a crude method based mostly on experience of ethnic groups. The production of *Zhero* includes various unit operations viz., soaking, grinding, batter preparation (mixing), frying and packaging which are done using traditional methods, utensils and tools. Proper quality of rice flour and batter are crucial in the production of good quality *Zhero*. The traditional processing method is time consuming, labour-intensive and leads to unhygienic production and non-uniformity in the quality of rice flour, batter and final finished product. This necessitates proper scientific investigation of different unit operations involved and characterization of rice flour for ascertaining the uniformity in production process and best quality of finished product.

Any rice-based product's quality is determined by the physico-chemical characteristics and particle size distribution of the rice flour. Singh and Prasad³

These properties are inherently dependent on the soaking and grinding parameters followed during the processing of the final product. Ogunnigbo *et al.*⁴ In case of soaking, the rice flour quality is influenced by both soaking time and temperature. The moisture content of rice after soaking appears to be a significant factor in loosening and softening the structure of rice kernels, resulting in the formation of small particle flours with minimal starch degradation. Chiang and Yeh⁵ Grinding is an important size reduction process used to produce fine rice flour used in *Zhero* production. Grinding time is the key factor which determines the particle size of the rice flour used in *Zhero*. Singh and Prasad.³

Physico-chemical parameters of granular solids/powder influence its flow behaviour and storage. Rice flour properties such as bulk density, kernel density and porosity affect its handling characteristics. Bian *et al.*⁶ The flowability of rice flour after grinding is significantly influenced by its moisture level. Tran *et al.*⁷ The change in particle size distribution of grain flours affects the quality of their products. When rice flour is used to make rice foods, each product requires a different particle size distribution. Flour that is ground too finely can lead to transportation issues during manufacturing, whereas excessively large particles can give the final product an undesirably coarse texture. Generally, finer particles exhibit higher swelling power, forming a more rigid gel structure and providing greater stability compared to coarser particles. Qian and Zhang⁸ The particle size distribution of rice flour also plays a key role in determining its flowability. Jan *et al.*⁹ Investigating the combined effects of soaking and grinding on rice flour quality for *Zhero* batter production is a complex process that requires robust modelling approaches.

Parrenin *et al.*¹⁰ Such approaches are essential for standardizing flour quality to enable consistent, large-scale commercial production of *Zhero*.

Artificial neural network (ANN) offers significant learning ability and promise for determining and modeling the complicated non-linear relationship between multiple variables of a system. ANN can be regarded as a powerful tool for predictive modelling of responses arising from complex nonlinear behaviour of independent variables of a process. The multi-objective genetic algorithm (MOGA) is a search-based optimization method that optimizes multiple conflicting goals simultaneously under specific circumstances. Sadhu *et al.*¹¹ By employing a fitness function-based probabilistic frequentative global search method, this decision-making tool simulates biological evolution into a global optimum solution. Belna *et al.*¹² Any complicated process model can be predicted and optimized with the help of ANN and GA. Rajendra *et al.*¹³ There are numerous uses of ANN and GA, including drying, Kalathingal *et al.*¹⁴ plant processing, Kumar *et al.*,¹⁵ Jaddu *et al.*,¹⁶ Yang *et al.*¹⁷ and process optimization for developing products. Sadhu *et al.*¹¹

As per the literature survey, no research has been conducted on the standardization of traditional process, mechanization and quality of *Zhero* till date. Hence, proper study is required not just to validate its historical roots and conserve its culture, but also to enhance and standardise its technology for possible commercialization. In view of these research gaps, the adequate research is essential in addition to authenticate its originality and conserve its culture, but also to refine and standardise its technology for potential commercialization. The purpose of this study was to characterize the rice flour used in *Zhero* preparation and to optimize the soaking and grinding parameters using ANN-MOGA approach.

Materials and Methods

Material and Rice Flour Preparation

Local variety of rice (LS1) of Sikkim was used from the local markets of Ranipool, India. Rice was soaked in water at different temperature (15 °C -25 °C) and for different soaking time (4 to 8 h). The soaked rice was drained and shade dried for about 1.5-2 h based on preliminary trials to reduce the surface moisture. The dried rice was then ground for 1-2 mins at low speed (20875 rpm) using a kitchen

grinder (Phillips HL7757,750 W, Netherland). The ground rice flour was stored in LDPE pouches till further analysis. The ground rice flour was analysed for various physical properties. Rice flour used for *Zhero* preparation at villages was also collected and analysed for comparison. This was treated as the control sample.

Analysis of Rice Flour

The prepared rice flour and control flour were analysed for moisture content, particle size, angle of repose, bulk density, tapped density and flowability using following methods. All measurements were done in triplicate.

Moisture Content

Moisture content of rice flour was measured as per the method described by Düsenberg *et al.*¹⁸ using moisture analyser (HC103, Mettler Toledo, UK) at 105 °C.

Bulk Density and Tapped Density

The bulk density of rice flour was measured by carefully pouring the sample into a standard graduated cylinder, following the specified procedure. The sample was St added until the cylinder reached a 100 ml volume and then weighed. The cylinder was tapped around ten times on a level surface for proper compaction. After tapping, more material was added to bring the volume back to 100 ml, and the cylinder was weighed again. The bulk and tapped densities of the rice flour were then calculated using the recorded weights and the volume of the cylinder.

$$\text{Bulk density} = \frac{\text{Weight of flour (g)}}{\text{volume of flour (ml)}} \quad \dots(1)$$

$$\text{Tapped density} = \frac{\text{Weight of flour (g)}}{\text{volume of flour settled (ml)}} \quad \dots(2)$$

Angle of Repose

The angle of repose, Φ was measured as per the procedure described by Jan *et al.*⁹ On a level surface, a hollow cylinder was set, and rice flour was poured on top. In order to minimize the wall effect and assure consistent packing, the samples were tapped. The tube was progressively lifted off the ground so that the material could flow freely and form a cone. The following formula was used to determine Φ .

$$\text{Angle of repose } (\Phi) = \tan^{-1} \frac{2h}{D} \quad \dots(3)$$

where h is the height of the cone (mm), Φ is the angle of repose ($^\circ$); D is the diameter of the cone (mm).

Flowability

Flowability was calculated as per the method outlined by Jan *et al.*⁹ Flowability was measured using the Carr index and the Hausner ratio, that depends on inter-particle friction and are derived by the difference between the bulk and tap density of the powders. It was measured based on the given equation:

$$\text{Carr index} = 100 \times \frac{\rho_t - \rho_b}{\rho_t} \quad \dots(4)$$

$$\text{Hausner ratio (HR)} = \frac{\rho_t}{\rho_b} \quad \dots(5)$$

Where ρ_b is the bulk density (g/cm^3) and ρ_t is the tapped density (g/cm^3)

Particle Size Distribution

The particle size distribution of the rice flour sample was determined using the method described by Subba and Katawal¹⁹ An AstM-Standard sieve set, consisting of sieves with aperture sizes of 600, 425, 300, 212, and 150 μm , was employed. The sieve stack was arranged with the largest mesh size at the top and the smallest at the bottom. The sample was placed on the top sieve, and the entire assembly was subjected to mechanical shaking to promote particle separation. The material retained on each sieve was carefully collected and weighed to determine the particle size distribution. The fineness modulus and average particle size were calculated using equations (6) and (7), respectively, as presented by Sonay and Baxi.²⁰

$$\text{Fineness modulus (FM)} = \frac{\text{weight percent retained}}{100} \quad \dots(6)$$

$$\text{Average particle size} = 0.135(1.366)^{\text{FM}} \quad \dots(7)$$

Experimental Design

Box Behnken design was followed for soaking and grinding experiments using Design Expert 13.0 software. The experiments consisted of three independent variables viz., soaking temperature, soaking time and grinding time and seven dependent variables viz., moisture content, particle size, angle of repose, bulk density, tapped density, Carr index and Hausner ratio. There were three levels for each independent variable. The experimental design is given in Table 1. A total of seventeen experiments

were conducted during the study. The relative effects of the independent variables on the responses were evaluated by an artificial neural network (ANN). Each independent variable had three levels. Table 1 depicts the experimental design. The ANN models developed were used for optimization of process parameters applying a multi-objective genetic algorithm (MOGA) using MATLAB software (Version R2017a, The MathWorks, Inc., Natick, MA, USA).

Modelling and Optimization

MATLAB software (Version R2017a, The MathWorks, Inc., Natick, MA, USA) was employed to model and optimize the independent parameters using a multilayer feed-forward neural network (MLFFN) design and a genetic algorithm, respectively. Khawas *et al.*²¹ The selected MLFFN architecture consisted of an input layer, one hidden layer, and an output layer. The complete experimental dataset (17 runs) was replicated three times (51 data points) and partitioned into training, validation, and testing sets in an 80:10:10 ratio. Srikanth *et al.*²²

The input layer comprised three neurons corresponding to soaking temperature, soaking time, and grinding time, while the output layer consisted of seven neurons representing moisture content, particle size, bulk density, tapped density, angle of repose, Carr index, and Hausner ratio. The hidden layer contained 10 neurons, each connected by a bias value. The network was trained using the Levenberg–Marquardt backpropagation algorithm (trainlm). The hidden layer utilized a hyperbolic tangent sigmoid (tansig) transfer function, whereas the input layer had no transfer function and the output layer used a linear (purelin) transfer function. The mathematical representations of the tansig and purelin functions are provided in Equations (8) and (9).

$$\text{tansig}(n) = \frac{2}{(1 + \exp(-2 \times n)) - 1} \quad \dots(8)$$

$$\text{purelin}(n) = n \quad \dots(9)$$

To predict the dependent parameters, the network utilized the hidden layer to process information sequentially from the input layer to the output layer. During training, backpropagation was employed, propagating errors in the reverse direction to compute the difference between actual and predicted outputs. This error was then used to iteratively update the

weights and biases of both the hidden and output layers. Kalathingal *et al.*¹⁴ Through repeated forward and backward computations, optimized weights and biases were obtained, enabling accurate prediction of outputs within the range of the training data. Model validation was performed using the test dataset.

The performance of the trained model was evaluated based on the mean squared error (MSE) and the regression correlation coefficient (R). Training was terminated once the network achieved the highest R

and the lowest MSE across training, validation, and testing datasets. The MSE was calculated using the following equation:

$$MSE = \frac{\sum (y_p - y_a)^2}{n} \quad \dots(10)$$

where, n is the number of data sets, Y_a is the experimental response, Y_p is the predicted response of i^{th} set, and Y_m is the mean of experimental response.

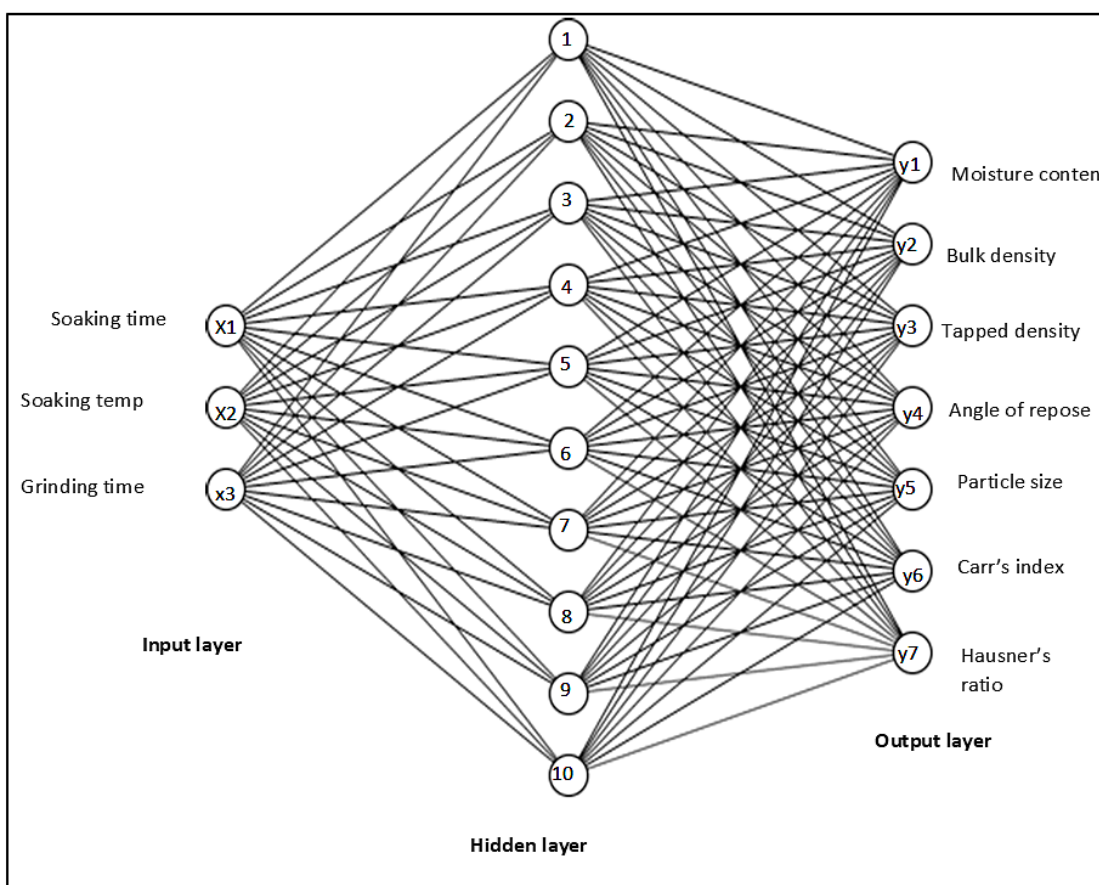


Fig. 1: Schematic diagram of developed neural network

Optimization using Genetic Algorithm

The genetic algorithm was implemented to optimize for maximum values. Hence, minimization objectives were reformulated as maximization problems by adjusting the fitness values. This adjustment was performed either by inverting the objective function or by altering its sign. The resulting responses were then improved through iterative processes including selection, reproduction, crossover, and mutation.

Erenturk and Erenturk.²³ For optimization, the fitness function was constructed by maximizing the HR ratio and minimizing moisture content, angle of repose, particle size, and Carr's index. Consequently, the fitness function is defined as follows:

$$z = - \left(\left(\frac{1}{1+y(1)} \right) + \frac{1}{1+y(4)} + \frac{1}{1+y(5)} + \frac{1}{1+y(6)} + y(7) \right) \quad \dots(11)$$

Where, $y(1)$ is moisture content, $y(4)$ is angle of repose, $y(5)$ is particle size, $y(6)$ is Carr's index and $y(7)$ is HR ratio. The ANN model was used to derive the expression for these variables. The program was run with 51 initial populations, and optimization was done in MATLAB® 2017a. While holding all other

factors constant, each of these was changed one at a time. An optimal process parameter and associated fitness value were obtained after 93 iterations. The resulting figure showed the change in fitness levels over each interval.

Table 1: Experimental design and response values

Run	Soaking time (h)	Soaking temp, °C	Grinding time (mins)	Moisture content, % w.b.	Bulk density g/cm ³	Tapped density g/cm ³	Angle of repose, °	Particle size, mm	Carl index	HR ratio
1	8	20	1	25.29 ^{aeg} (0.287)	0.48 ^{bdg} (0.014)	0.527 ^{bdg} (0.010)	26.5 ^{adg} (0.994)	0.272 ^{adg} (0.006)	8.92 ^{beg} (0.197)	1.098 ^{bfg} (0.041)
2	6	20	1.5	26.09 ^{beg} (0.296)	0.46 ^{adg} (0.013)	0.526 ^{adh} (0.008)	26.4 ^{adg} (0.990)	0.284 ^{adg} (0.006)	12.55 ^{cei} (0.277)	1.143 ^{cfi} (0.042)
3	8	15	1.5	23.78 ^{adg} (0.270)	0.54 ^{beg} (0.016)	0.603 ^{beh} (0.010)	24.2 ^{adg} (0.110)	0.277 ^{adg} (0.006)	10.45 ^{bdi} (0.023)	1.117 ^{bdi} (0.041)
4	4	20	1	25.9 ^{aeg} (0.294)	0.5 ^{bdg} (0.015)	0.500 ^{adg} (0.007)	27.8 ^{adg} (1.043)	0.241 ^{adg} (0.006)	0.00 ^{aeg} (0.000)	1.000 ^{afg} (0.037)
5	6	15	2	25.13 ^{bdg} (0.285)	0.48 ^{aeg} (0.014)	0.516 ^{aeg} (0.002)	28.5 ^{adg} (1.069)	0.289 ^{adg} (0.007)	6.98 ^{cdh} (0.154)	1.075 ^{cdh} (0.040)
6	6	20	1.5	25.49 ^{bdg} (0.290)	0.47 ^{adg} (0.014)	0.532 ^{adh} (0.003)	29.0 ^{adg} (1.088)	0.238 ^{adg} (0.006)	11.65 ^{cei} (0.258)	1.132 ^{cfi} (0.042)
7	6	25	2	25.75 ^{beg} (0.292)	0.47 ^{aeg} (0.014)	0.519 ^{aeg} (0.008)	28.2 ^{adg} (0.958)	0.261 ^{adg} (0.006)	9.44 ^{ceh} (0.209)	1.104 ^{ceh} (0.041)
8	6	20	1.5	26.09 ^{aeg} (0.296)	0.46 ^{adg} (0.014)	0.526 ^{adh} (0.008)	26.4 ^{adg} (0.990)	0.284 ^{adg} (0.007)	12.55 ^{cei} (0.277)	1.143 ^{cfi} (0.042)
9	4	20	2	25.79 ^{aeg} (0.293)	0.5 ^{bdg} (0.015)	0.55 ^{adg} (0.003)	27.5 ^{adg} (0.110)	0.287 ^{adg} (0.006)	9.09 ^{aeh} (0.201)	1.100 ^{afh} (0.041)
10	8	20	2	25.29 ^{aeg} (0.287)	0.48 ^{bdg} (0.014)	0.527 ^{bdg} (0.008)	26.5 ^{adg} (0.994)	0.272 ^{adg} (0.006)	8.92 ^{beh} (0.197)	1.098 ^{bfi} (0.041)
11	6	25	1	25.97 ^{bdg} (0.295)	0.48 ^{aeg} (0.014)	0.533 ^{aeg} (0.010)	30.3 ^{adg} (1.137)	0.239 ^{adg} (0.006)	9.94 ^{ceg} (0.220)	1.110 ^{ceg} (0.041)
12	4	15	1.5	25.26 ^{adg} (0.287)	0.5 ^{beg} (0.015)	0.515 ^{aeg} (0.006)	27.7 ^{adg} (1.039)	0.299 ^{adg} (0.007)	2.91 ^{adi} (0.064)	1.030 ^{adi} (0.038)
13	6	20	1.5	26.09 ^{beg} (0.296)	0.46 ^{adg} (0.014)	0.526 ^{adh} (0.006)	26.4 ^{adg} (0.990)	0.284 ^{adg} (0.007)	12.55 ^{cei} (0.277)	1.143 ^{cfi} (0.042)
14	4	25	1.5	23.5 ^{adeg} (0.267)	0.51 ^{beg} (0.015)	0.550 ^{aeh} (0.008)	28.3 ^{adg} (0.260)	0.273 ^{adg} (0.007)	7.27 ^{aei} (0.161)	1.078 ^{aei} (0.040)
15	6	15	1	25.86 ^{bdg} (0.294)	0.49 ^{aeg} (0.015)	0.540 ^{aeg} (0.007)	28.4 ^{adg} (1.066)	0.261 ^{adg} (0.006)	9.26 ^{cdg} (0.205)	1.102 ^{cdg} (0.041)
16	8	25	1.5	26.08 ^{adeg} (0.296)	0.516 ^{beg} (0.015)	0.567 ^{beh} (0.009)	31.6 ^{adg} (1.186)	0.333 ^{adg} (0.008)	8.99 ^{bei} (0.119)	1.099 ^{bei} (0.041)
17	6	20	1.5	25.49 ⁺ (0.290)	0.47 ^{adg} (0.014)	0.532 ^{adh} (0.006)	29.0 ^{adg} (1.088)	0.238 ^{adg} (0.006)	11.65 ^{cei} (0.258)	1.132 ^{cfi} (0.042)
18.	Control			22.75 (1.58)	0.503 (0.011)	0.573 (0.008)	29.3 (1.23)	0.292 (0.027)	5.15 (0.32)	1.15 (0.13)

Results

Experimentation

Rice flour samples were soaked and ground varying the soaking and grinding conditions as per the Box-Behnken design (Table 1). All the physico-chemical parameters of rice flour samples were evaluated. Table 1 depicts the values of all the responses measured.

Neural Network Modelling

Using the experimental dataset, the neural network was trained and tested to evaluate its predictive performance. The model's accuracy was assessed using the regression correlation coefficient (R) and mean squared error (MSE). The training, validation, and testing datasets each achieved a maximum R value of 0.999, indicating an excellent correlation between predicted and experimental results, along with a minimum MSE of 0.0188. The optimal weights and biases obtained for the trained neural network are presented in Equations (12) – (15).

$$B_1 = \begin{bmatrix} 3.35675 \\ 2.720905 \\ -2.13372 \\ -0.16995 \\ 0.741599 \\ -0.69335 \\ -2.01844 \\ -1.82396 \\ 1.862408 \\ 3.259602 \end{bmatrix} \quad \dots(12)$$

$$B_2 = \begin{bmatrix} 0.226234 \\ 0.855284 \\ -0.37357 \\ -0.49648 \\ 0.260231 \\ -0.09206 \\ -0.66113 \end{bmatrix} \quad \dots(13)$$

$$H_2 = \begin{bmatrix} -0.2227 & 0.080058 & -1.0081 & -0.43704 & -0.05488 & 0.231938 & 0.996603 & -0.01474 & 1.212712 & -0.32641 \\ -0.60368 & -0.54072 & 3.48E-05 & -0.63712 & -0.46435 & 0.696586 & -0.40859 & -0.12994 & -0.52401 & -0.05844 \\ -0.43573 & -0.30751 & -0.4 & -0.67036 & -0.45625 & 1.05015 & -0.59342 & -0.27712 & -0.32405 & 0.506605 \\ 0.998453 & -0.66045 & 0.126002 & -0.02272 & 0.224708 & 0.490445 & -0.40756 & 0.099148 & -0.22269 & 0.172738 \\ -0.17771 & -0.48462 & 0.219256 & 0.171051 & 0.223257 & -0.15882 & 0.31267 & 0.147949 & -0.14169 & 0.516064 \\ -1.21783 & 0.068457 & -0.53062 & 1.080051 & 1.205079 & -0.20639 & 0.115861 & 0.671605 & 0.109533 & 1.624074 \\ -0.5504 & 0.231528 & -0.65406 & 0.188782 & 0.343617 & 0.301142 & -0.04097 & 0.098803 & 0.266608 & 1.054598 \end{bmatrix} \quad \dots(14)$$

$$H_1 = \begin{bmatrix} -2.369596099 & 1.459718384 & -0.070462821 \\ -1.931439274 & -2.616247111 & 0.578132817 \\ 1.14460389 & -2.697251144 & 0.794586936 \\ -0.387497951 & -2.766592971 & -2.051763798 \\ -0.807330531 & 2.461963541 & 1.946047738 \\ -1.551099897 & -3.979094857 & -0.928686127 \\ -2.902868731 & -2.091272347 & 0.38549882 \end{bmatrix} \quad \dots(15)$$

The matrices H_1 and H_2 represent the connection weights between the input and hidden layers, and between the hidden and output layers, respectively. Similarly, the biases in the hidden and output layers are represented by B_1 and B_2 . The regression analysis, error histogram, and performance metrics of the trained ANN are presented in

Fig 2. The regression plot (Fig 2b) demonstrates the agreement between predicted and experimental values for all types of datasets. The R-values for the analysis are close to 1 (0.999), confirming a very strong correlation. The error histogram (Figure 2d) indicates that the largest error observed is minimal (0.0297), suggesting high prediction accuracy.

Fig 2a shows the mean squared error (MSE) plotted against the number of training epochs, illustrating the progressive improvement of the network's learning. The optimal validation performance was obtained after 30 epochs, yielding a minimum mean squared

error (MSE) of 0.018826. Overall, these results confirm that the developed ANN model exhibits excellent predictive capability, with outputs closely matching the experimental data.

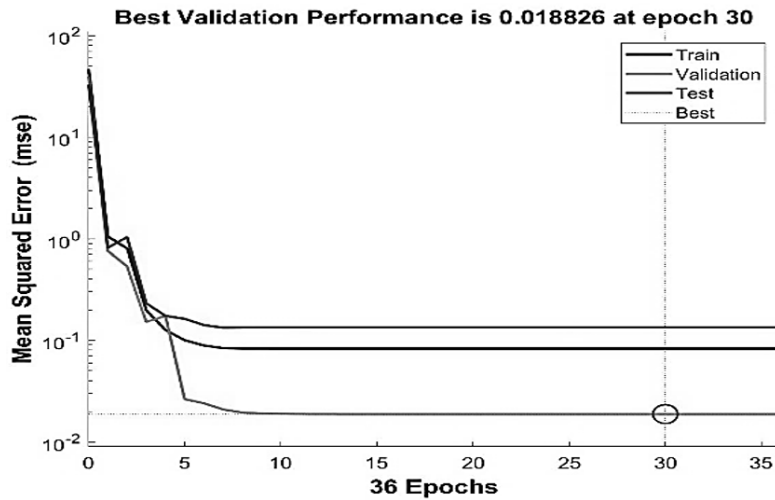


Fig. 2 (a): Performance validation

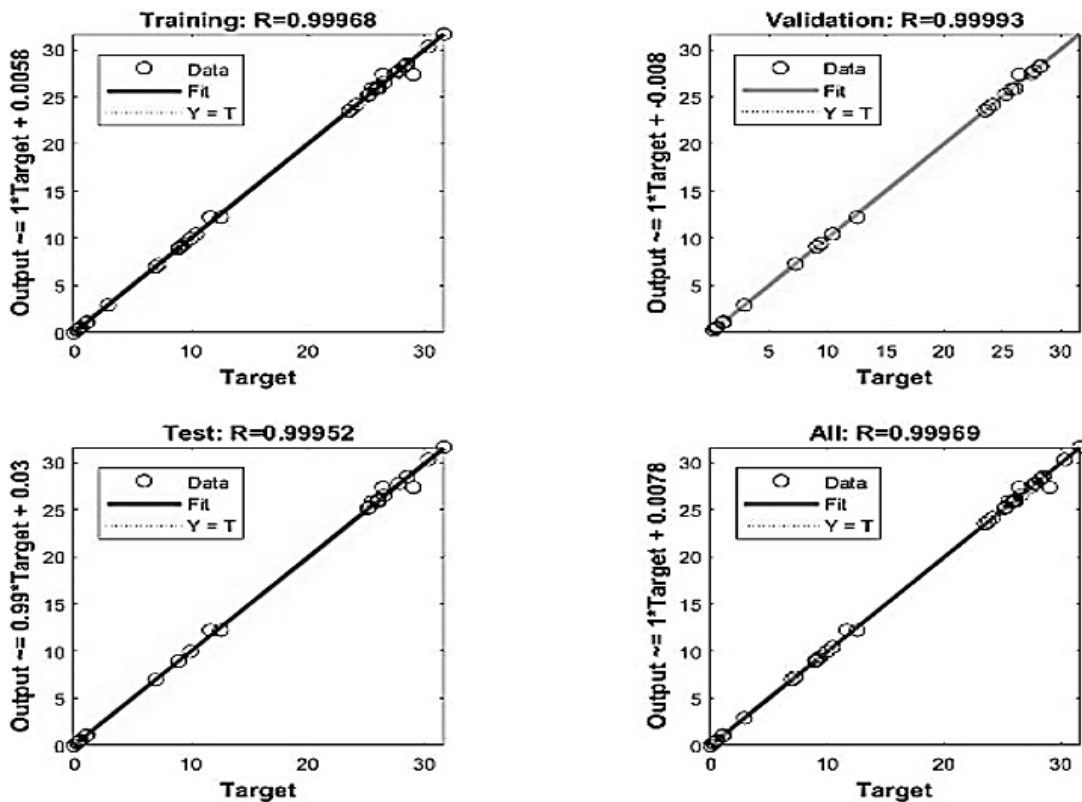


Fig. 2 (b): Regression

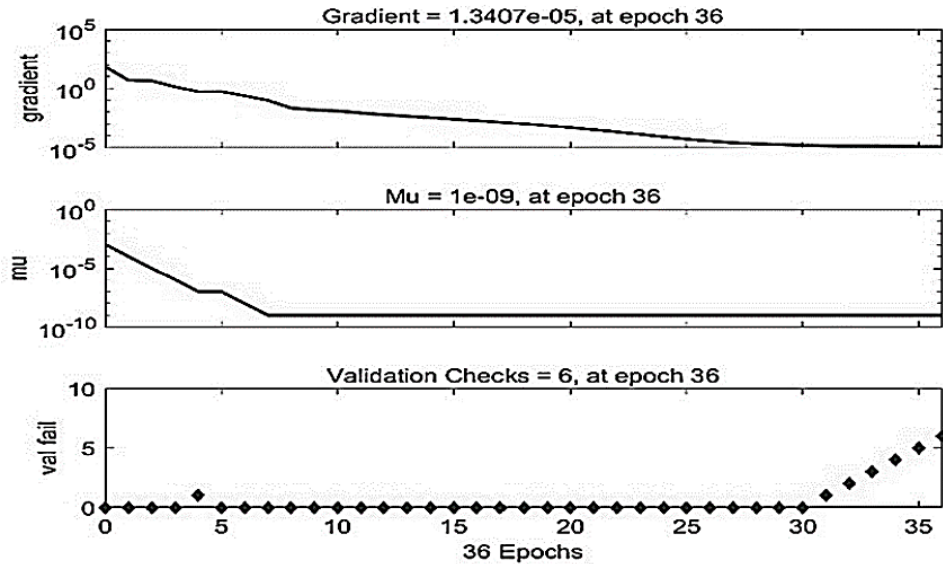


Fig. 2 (c): Training state

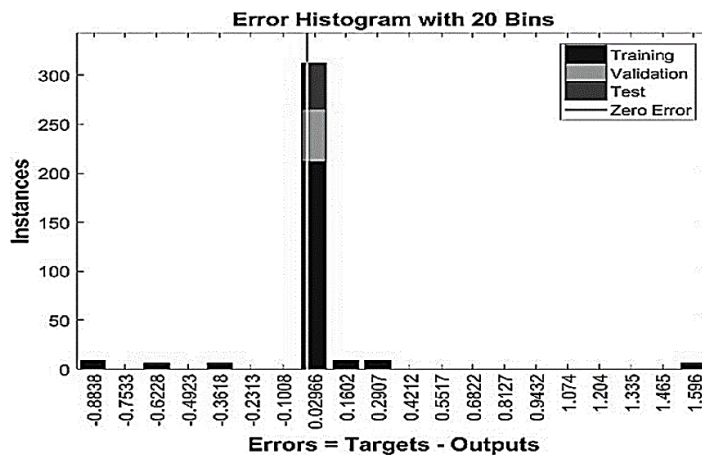


Fig. 2 (d): Error histogram

Fig. 2: Post-training (a) performance, (b) Regression, and (c) Training state (d) Error histogram analysis for the generated ANN model

Relative Influence of Process Parameters on Quality of Rice Flour

The relative significance of the independent variables (xSt, xST, xGT) for predicting responses (yMC, yBD, yTD, yAR, yPS, yCI and yHR) were determined by using neural network model. In order to analyse the effect of xSt, on Ymc the coded value of xSt was set at ±1, and the other three independent variables xST and xGT were set to zero. Similar to this, the relative impact of independent parameters on the response MC(yMC), BD(yBD), TD(yTD), AR(yAR), PS(yPS), CI(yCI) and HR(yHR) were obtained by computing

the values of $\Delta ymc(St)(ST)(Gt)$, $\Delta ybd(St)(ST)(Gt)$, $\Delta ytd(St)(ST)(Gt)$, $\Delta yar(St)(ST)(Gt)$, $\Delta yps(St)(ST)(Gt)$, $\Delta yci(St)(ST)(Gt)$, $\Delta yhr(St)(ST)(Gt)$ using Equations (16) to (18).²⁴ The obtained relative influence of xSt, xST and xGT is presented in Table 2.

$$\Delta(Ymc)St = (Ymc)_{+1} - (Ymc)_{-1} \quad \dots(16)$$

$$\Delta(Ymc)ST = (Ymc)_{+1} - (Ymc)_{-1} \quad \dots(16)$$

$$\Delta(Ymc)GT = (Ymc)_{+1} - (Ymc)_{-1} \quad \dots(16)$$

Table 2: Effect of independent parameters (in coded form)

xSt	xST	xGT	Ymc	ΔYmc	Ybd	ΔYbd	Ytd	ΔYtd	Yar	ΔYar	Yps	ΔYps	Yci	ΔYci	Yhr	ΔYhr
-1	0	0	25.47	0.33	0.492	-0.005	0.528	0.017	28.9137	-2.87	0.2919	-0.025	14.6631	-8.66	1.106	-0.004
1	0	0	25.80		0.487		0.541		26.0432		0.2669		6.0025		1.1019	
0	-1	0	25.24	0.86	0.485	0.001	0.533	0.008	28.0985	1.043	0.2822	0.0007	6.6257	2.79	1.0846	0.028
0	1	0	26.10		0.486		0.541		29.1419		0.2829		9.4173		1.1125	
0	0	-1	25.69	0.105	0.481	-0.009	0.556	-0.027	27.7036	-0.51	0.2533	0.012	9.8929	-0.60	1.1348	0.054
0	0	1	25.80		0.472		0.529		27.1863		0.26578		9.2905		1.1891	

Discussion

The moisture content of rice flour for different treatments of St, GT and ST varied in the range 23.78 - 26.09 % w. b. (Table 1). This value is close to the moisture content of control flour (22.75 ± 1.58 % w. b). From the analysis given in Table 2, (ΔYmc) $ST > (\Delta Ymc) St > (\Delta Ymc) GT$ trend was observed which suggests that xST has the highest effect on moisture content and grinding time has the least effect on moisture content of samples. The moisture content of the flour increased significantly with increased soaking time and temperature. Kajihaua *et al.*²⁵ reported a similar tendency for sprouted sesame seed flour, as did⁵ for rice flour. This effect may be due to the increased rate of moisture diffusion into the rice kernels at higher temperature and longer time. According to Yeh *et al.*²⁶ moisture diffusivity increases with temperature thereby leading to increased moisture diffusion in the rice kernels at higher temperature.

The particle size of rice flour varied between 0.261 and 0.333 mm depending on the combination of independent variables (Table 1). The control flour had a particle size of 0.292 ± 0.027 mm, which is within the range for different treatments. From Table 2, it can be observed that (ΔYps) $St > (\Delta Yps) GT > (\Delta Yps) ST$ which suggests that soaking time has the highest negative effect on particle size followed by the positive effects of grinding time and soaking temperature. Longer soaking time might have led to more moisture diffusion into the rice kernels making them softer and easily fragmentable to fine powder form.³ also cited similar behaviour where particle size distribution was influenced by semi wet grinding and soaking. Particle size of flour increased with increase in grinding time and soaking temperature which may be due to lump formation from finely ground rice flour caused by the heat released during longer grinding time. However, the effects of soaking and grinding conditions on the particle size were found to be non-significant which is in accordance with the findings reported by Kijima *et al.*²⁷

The bulk density of prepared flour samples varied in the range 0.46-0.54 g/cm³ for different combination of independent variables (Table 1). These values are in agreement with the values determined for control rice flour (0.503 ± 0.011). Similarly, Table 2 showed a trend of (ΔYbd) $GT > (\Delta Ybd) St > (\Delta Ybd) ST$, indicating that xGT has the greatest negative influence on

bulk density. Likewise, for tapped density the values ranged between 0.5 and 0.603 as cited in Table 1 for different combination of independent variables. The control rice flour also showed similar range of tapped density values of 0.573 ± 0.008 g/cm³ (Table 1). From the comparison of relative influence of independent variables of tapped density, $(\Delta Y_{td})_{GT} > (\Delta Y_{td})_{St} > (\Delta Y_{td})_{ST}$ trend was observed (Table 2). This could be attributed to the greater particle size of lumps at higher grinding times. According to Jung *et al.*²⁸ the physical and chemical qualities of food powder determine its bulk properties, such as bulk density and flowability. The bulk density decreased with increasing soaking time Antarlina *et al.*²⁹ showed similar results for white sorghum flour. At higher levels, the effects of soaking and grinding parameters on bulk density and tapped density were not significant (Table 1).

The angle of repose range of rice flour samples was 24.2° -31.6° for different combination of St, GT and ST (Table 1). The control *Zhero* rice flour had an angle of repose of $29.3^\circ \pm 1.23$, which was within the measured range of the flour samples investigated in this experiment. From the analysis shown in Table 2, a trend of $(\Delta Y_{ar})_{St} > (\Delta Y_{ar})_{ST} > (\Delta Y_{ar})_{GT}$ was observed citing highest and lowest negative effect of xSt and xGT on angle of repose respectively. Soaking temperature showed positive effect on angle of repose of rice flours. This trend is similar to the trend observed for particle size. It could be due to more moisture absorption by rice kernels at longer soaking duration which might have led to formation of fine cohesive rice resulting in higher angle of repose. As per the report by Jan *et al.*⁹ angle of repose is influenced by the particle size reduction. During the process, the reduction in particle size is more because of the involvement of soaking process. The interstitial spaces between larger particles are occupied by smaller particles, and with the increase in contact points leading to greater cohesiveness, the angle of repose was observed to increase as particle size decreased. As shown in Table 1, all of the independent variables impact on angle of repose were found to be non-significant.

The value of HR for rice flour samples ranged between 1.00 and 1.143 for different combination of independent variables whereas Carr's index varied between 2.91 and 12.55 (Table 1). The values of

HR and CI for control rice flour were found to be 1.15 ± 0.13 and 5.15 ± 0.32 respectively. results fall within the range of those recorded for the rice flour samples under study. The values of HR and CI values for all studied samples were < 1.18 and < 15.0 respectively which indicated good to excellent flowability of the *Zhero* rice flour. Nabavi *et al.*³⁰ These Hausner's ratio and Carr's index are directly related to density and particle size of ground flour. From the present study, the trend observed was $(\Delta Y_{ci})_{St} > (\Delta Y_{ci})_{ST} > (\Delta Y_{ci})_{GT}$ for Carr's index and $(\Delta Y_{hr})_{GT} > (\Delta Y_{hr})_{St} > (\Delta Y_{hr})_{ST}$ for HR, which implies that soaking conditions have highest effect on CI and HR. According to, Jan *et al.*⁹ enhanced interparticle forces or mechanical interlocking contribute to increased particle cohesion, resulting in reduced flowability as indicated by higher values of the Hausner Ratio and Carr's Index. From the above discussion, it can be concluded that bulk and tapped density are directly related to grinding conditions, which also affect flour flowability, resulting in a favourable effect on HR values.

Optimisation using GA

The developed ANN model was combined with MOGA to optimize the independent variables viz., soaking time, soaking temperature and grinding time. After 93 iterations, the optimal process parameters and fitness values were determined. The generated plot showed the change in fitness levels over each interval. The optimization was carried out to maximise the HR ratio while minimising moisture content, angle of repose, particle size and Carr's index. Fig. 3 illustrates the changes in fitness values over successive generations and the mean fitness value was -8.05319×10^6 . After GA, the optimized values were obtained at 4.2 h soaking time, 18 °C soaking temperature and 1.0 min of grinding time. At the optimal conditions, the expected values of responses obtained were 23.85 % w b moisture content, 0.543 g/cm³ bulk density, 0.57 g/cm³ tapped density, 28.09° angle of repose, 0.31 mm particle size, Carr's index 5.055 and HR ratio 1.05. These results were validated by conducting experiments under the optimized process conditions. The relative percentage error (RPE) between the experimental and predicted responses obtained was in the range of 1.01-4.44% ($< 10\%$) which indicates good validation of model. (Table 3).

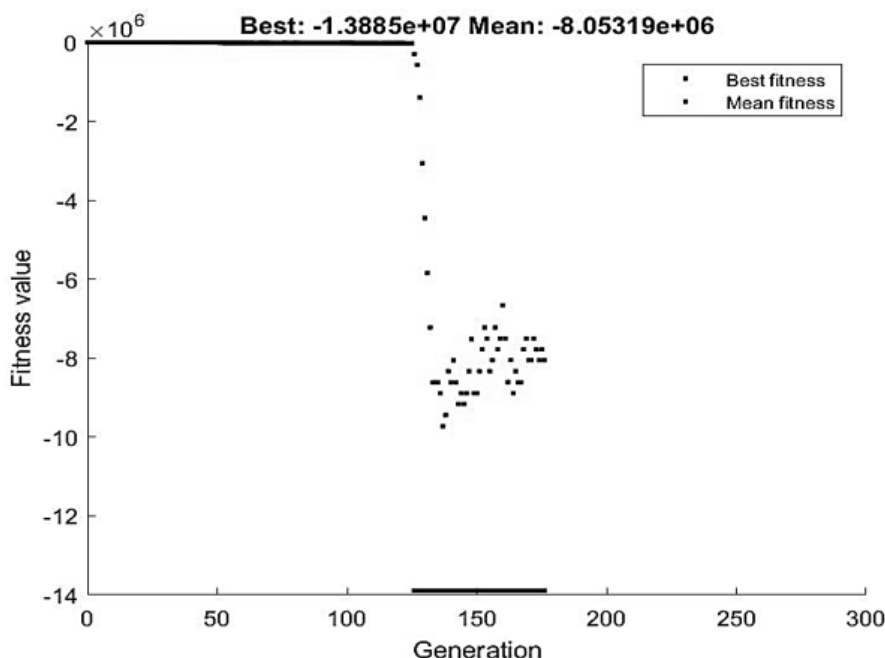


Fig. 3: Fitness values across generations during MOGA optimization

Table 3: Validation of the ANN-GA optimized results

Statistical parameters	Moisture content, % wb	Bulk density, g/cm ³	Tapped density, g/cm ³	Angle of repose, °	Particle size, mm	HR ratio index	Carr's
Actual value (y_a)	24.46 (0.53)	0.533 (0.05)	0.565 (0.012)	27.81 (0.31)	0.301 (0.012)	1.10 (0.18)	5.108 (0.234)
Predicted value (y_p)	23.85	0.543	0.576	28.095	0.315	1.055	5.055
RPE (%)	2.56	1.84	1.91	1.01	4.44	4.27	1.05

Conclusion

In this study, an attempt was made to optimise the process parameters using ANN-MOGA for rice flour production of *Zhero* (an ethnic Himalayan snack). According to the research outcomes, a multilayer feed forward back propagation neural network comprising three input, ten hidden, and three output neurons was able to identify the relationship between different responses and the input parameters (soaking temperature, grinding temperature, and grinding time). The optimum soaking and grinding conditions for *Zhero* preparation were 4.2 h soaking time, 18 °C soaking temperature and 1 min of grinding time, which were found using a multi-objective ANN-GA approach. A strong statistical

agreement between the predicted and validated values indicated that the proposed model was acceptable. In order to optimize the standardized process for *Zhero*, the quality parameters of rice flour can be successfully estimated using the developed ANN coupled with GA model. The results of this study will serve as a St step towards standardizing the *Zhero* production process, which will pave the path for its commercialization and mechanization while maintaining uniform quality.

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The authors do not have any conflict of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request

Ethics Statement

This research did not involve human participants, animal subjects, or any material that requires ethical approval.

Informed Consent Statement

This Study did not involve human participants, and therefore, informed consent was not required.

Clinical Trial Registration

This research does not involve any clinical trials.

Permission to Reproduce Material from Other Sources

Not Applicable.

Author Contributions

- **Apeksha:** Conceptualization, Methodology, Visualization, Investigation, Software, Data curation, Formal analysis, Writing – original draft
- **Sujata Jena:** Conceptualization; funding acquisition; project administration; supervision; writing-review and editing.
- **Sitesh Kumar:** Software, Data curation, Formal analysis

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