Heliyon 10 (2024) e38003

Contents lists available at ScienceDirect

# Heliyon

journal homepage: www.cell.com/heliyon

Research article

# Optimization of process parameters for *Trifolium pratense L.* seed granulation coating using GA-BP neural network

Xuejie Ma [a], Min Liu [b], Zhanfeng Hou [a,c,*], Mengjun Guo [a], Zhihong Yu [a], Xin Tong [a], Haiyang Liu [a], Fang Guo [a]

[a] *College of Mechanical and Electrical Engineering, Inner Mongolia Agricultural University, Hohhot, 010018, China*
[b] *College Engineering and Technology, Jilin Agricultural University, Changchun, 130118, China*
[c] *Inner Mongolia Engineering Research Center of Intelligent Equipment for the Entire Process of Forage and Feed Production, Hohhot, 010018, China*

ARTICLE INFO

*Keywords:*
Red clover seed
Granulation coating
GA-BP
Experiment
Parameter optimization

ABSTRACT

Regarding the issue of low granulation qualification rates during the granulation coating of red clover seeds, this study theoretically analyzed the force conditions of seeds and powder particles under the action of liquid to obtain the main factors affecting seed coating quality. During the seed granulation coating process, an intermittent powder supply method combined with continuous liquid supply was utilized to control the ratio of powder to liquid. Using the granulation qualification rate as the evaluation index, single-factor experiments were conducted to investigate the effects of coating pan fill ratio, single powder supply amount, powder supply interval, and liquid supply amount on the quality of red clover seed granulation coating. Based on the results of the single-factor experiments, orthogonal experiments were conducted, revealing that the interaction of factors would influence the experimental results. To further optimize the quality of seed granulation coating, the mechanisms of powder and liquid in the adhesion process on granulation coating were explored. Orthogonal experiments were conducted on the process parameters of the granulation coating machine, and the GA-BP model was employed for optimization and solution. The optimal process parameter combination obtained was a coating pan fill ratio of 33.78 %, a single powder supply amount of 5.17 g, a powder supply interval of 7.7 s, and a liquid supply amount of 0.42 mL/s. Under this optimal parameter combination, granulation coating experiments with red clover seeds were performed, and the seed granulation coating quality was relatively high, with a granulation qualification rate of 97.7 %. The research results can provide a reference for optimization experiments on coating irregular seeds.

## 1. Introduction

Red clover (*Trifolium pratense* L.) is a perennial herbaceous plant of the legume clover genus, and is one of the important forage crops for artificial grassland establishment and ecological restoration in arid and semi-arid regions [1]. Due to its relatively small seed size, pre-sowing granulation coating treatment can improve seed suitability for sowing and germination rate [2]. Seed granulation coating technology involves the use of specific powders and liquids through mechanical processing or manual operations to produce uniform, regularly shaped small spherical seeds [3,4]. Granulation coating can improve the precision of mechanized precision seeding

* Corresponding author. College of Mechanical and Electrical Engineering, Inner Mongolia Agricultural University, Hohhot, 010018, China.
*E-mail address:* njau-hzf@163.com (Z. Hou).

https://doi.org/10.1016/j.heliyon.2024.e38003
Received 18 May 2024; Received in revised form 8 September 2024; Accepted 16 September 2024
Available online 17 September 2024
2405-8440/© 2024 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC license (http://creativecommons.org/licenses/by-nc/4.0/).

and emergence rate, while also providing protection against diseases, wind, and insect damage. Both domestically and internationally, grasseeds are widely sown using aerial broadcasting techniques [5–7]. However, granulation coating technology overcomes the issues of traditional broadcasting, such as seed drift and low emergence rates, creating favorable conditions for modern seeding practices [8].

Granulation coating technology has been extensively researched both domestically and internationally. Numerous scholars have conducted experimental studies on the efficiency and operational quality of granulation coating processes using various types of coating equipment [9,10]. Hou et al. utilized EDEM software to simulate the granulation coating effect of grasseeds under vibration force fields and designed a granulation coating machine suitable for grasseeds based on the simulation results [11–13]. Wang et al. employed a second-order rotatable central composite design to investigate the effects of process parameters on peanut seed coating qualification rate and breakage rate [14]. Researchers have conducted extensive experimental studies to address issues such as low coating quality and granulation qualification rates in granulation coating machines, employing various methods to improve seed granulation coating quality. However, most studies have overlooked the impact of powder and liquid addition processes on granulation coating quality. Due to the complex procedures involved in granulation coating experiments, conventional trials are inadequate for investigating the mechanisms of red clover seed granulation coating. This limitation has led to issues such as suboptimal coating quality and low qualification rates in the granulation coating process of red clover seeds.

In recent years, with the advancement of machine learning techniques, some scholars have employed genetic algorithms, neural networks, and other technologies to solve traditional models, yielding more accurate results [15–17]. In traditional orthogonal experiment optimization methods, the accuracy of experimental results is often affected by problem complexity and sample size [18,19]. Compared to traditional optimization experiments, neural network models possess stronger fitting capabilities and can fit arbitrary complex nonlinear functions. Through multi-layer network structures, neural network models extract complex nonlinear features from data, avoiding the multicollinearity issues encountered in linear regression, resulting in more reliable fitting outcomes [20,21]. For optimization algorithms, numerical methods primarily rely on iterative computations to solve problems. However, conventional iterative methods are prone to falling into local minima traps, resulting in "infinite loops" that impede further iteration. Genetic algorithms effectively overcome this limitation, offering a global optimization approach. Consequently, neural networks based on genetic algorithms yield more reliable optimization results compared to other algorithms. Currently, numerous scholars employ this method to optimize and solve complex models, with the GA-BP model—combining Back Propagation Neural Networks and Genetic Algorithms—finding particularly widespread application across various domains [22,23]. However, there is a lack of research utilizing the GA-BP model to address the complex nonlinear problems inherent in the granulation coating process investigated in this study.

To address the issue of low granulation qualification rates during the granulation coating process of red clover seeds, this study theoretically analyzed the force conditions of seeds and powder particles under the action of liquid to obtain the main factors affecting seed coating quality. Through single-factor experiments, the effects of different process parameters, including coating pan fill ratio, single powder supply amount, powder supply interval, and liquid supply amount, on the quality of red clover seed granulation coating were investigated using the granulation qualification rate as the evaluation index, to determine the suitable parameter range for red clover seed granulation coating.

To further improve the quality of seed granulation coating, orthogonal experiments were conducted on the process parameters of the granulation coating machine, and the GA-BP model was employed for optimization and solution. This allowed the identification of the process parameter combination that resulted in a relatively high granulation qualification rate. The complete granulation coating process technology was thus established, providing a reference for practical production.

## 2. Overall structure and working principle of granulation coating machine

The granulation coating machine mainly consists of a powder feeding device, liquid feeding device, granulation device, and control

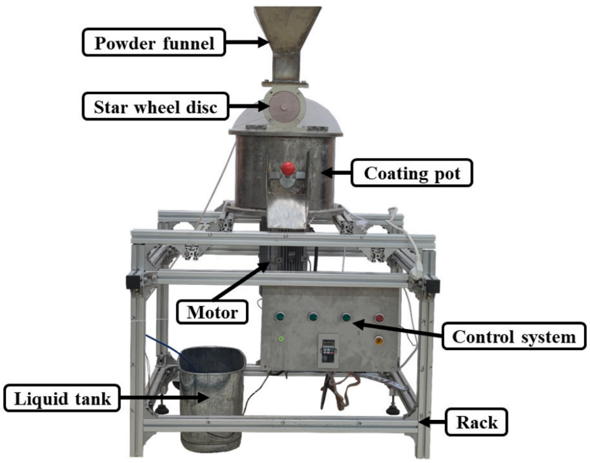


**Fig. 1.** Structure diagram of seed pelletizing coating machine.

system, as shown in Fig. 1. The powder feeding device comprises a powder hopper for storing powder and a star-shaped turntable for discharging powder, where the star-shaped turntable rotates under the control of a stepper motor. The liquid feeding device consists of a liquid tank and control valve. The granulation device primarily includes a coating pan and a motor that provides power. The three-phase asynchronous motor drives the spinning disc inside the coating pan to rotate, providing a space for mixing seeds, powder, and liquid.

During the granulation coating experiment, a certain mass of seeds is placed inside the coating pan, and the spinning disc is rotated by the motor. Then, the stepper motor drives the star-shaped turntable to rotate, allowing a metered amount of powder to fall from the hopper onto the spinning disc and thoroughly mix with the seeds. Afterward, the liquid switch is opened to provide an appropriate amount of liquid to the mixture of seeds and powder inside the pan. As the powder adheres and coats the seed surface under the action of the liquid, this powder feeding step is intermittently repeated. Throughout the coating process, the powder is supplied in batches with metered amounts controlled by software, while the liquid is continuously supplied. Under the rotation of the spinning disc, the powder evenly adheres to the seed surface, enabling the seeds to effectively and rapidly form granulated coated particles. From the granulation coating process, it is found that the mixing and adhesion of powder and seeds inside the coating pan affect the granulation coating effect of the seeds.

## 3. Theoretical analysis of granulation coating process

During the seed granulation coating process, the primary phenomenon is the adhesion of powder to the seed surface under the action of liquid. After the powder and seeds come into contact with the liquid, the contact forces between the materials become complex. By analyzing the non-contact adhesive force and contact adhesive force between materials, the interaction mechanism of materials after wetting can be revealed.

In the granulation coating process, van der Waals forces dominate among non-contact adhesive forces. These forces are the primary adhesive forces in the fluidization of fine particles, and the interactions produced by van der Waals forces are the essential characteristics of agglomeration between cohesive particles [24,25]. The continuous layer-by-layer adsorption on the surface of granulation powder particles is a fine particle fluidization bonding process dominated by intermolecular forces. As the liquid agent increases, the moisture content of the granulation powder rises, gradually intensifying the agglomeration effect between particles. The van der Waals force between materials can be expressed as:

$$F = \frac{A}{6\pi h^3} \tag{1}$$

where $F$ is the attractive force due to van der Waals force, N; $A$ is the constant for the interaction between the two materials, J; and $h$ is the adsorbed water film thickness, mm. The adsorbed water film thickness can be estimated from the particle specific surface area, according to the following formula:

$$h = \frac{\omega}{s\rho} \tag{2}$$

where $\omega$ is the particle moisture content, %; $s$ is the particle specific surface area, $m^2 \cdot g^{-1}$; and $\rho$ is the density of water.

Through the formula, it is known that particle moisture content is an important factor affecting the granulation performance of seeds. The factors influencing particle moisture content are the materials and liquid content. In subsequent granulation experiments, the liquid supply will be considered as one of the influencing factors.

In the contact adhesive force during the granulation coating process, the liquid bridge force is the main contributor. Many scholars have proposed models to describe the liquid bridge force. For example, Tatemoto et al. described the liquid bridge force as a function of the dimensionless liquid bridge volume and particle distance [26]. Girardi et al. conducted computational fluid dynamics discrete element method simulations using their proposed liquid bridge force model [27]. Among them, Yakov's liquid bridge force calculation formula was further simplified to:

$$F_s(\varphi) = 2\pi F_b \left(1 + \frac{4.125}{\pi}\sqrt{\varphi\varepsilon}\right) \tag{3}$$

where $F_s$ is the liquid bridge force, $F_b$ is the liquid surface tension, N/m; $\varphi$ is the liquid bridge volume ratio; and $\varepsilon$ is the bed void fraction.

In the millet seed granulation coating experiment, the adhesive liquid used was only water. Therefore, the liquid surface tension value in Equation (3) is the surface tension of water. The liquid bridge volume ratio is the ratio of the liquid bridge volume to the particle volume. Thus, it can be seen that the liquid amount and material volume play a decisive role in the liquid bridge force. Combined with the analysis results of Equations (1) and (2), the powder volume fraction also plays an important role in the granulation coating process.

## 4. Seed granulation coating process parameter experiments

### 4.1. Experimental materials and methods

According to the process flow, 100 g of red clover seeds were placed in the coating pan, followed by the addition of powder in batches and continuous supply of liquid. The powder was cumulatively supplied at a seed-to-powder ratio of 1:3 (300 g) to ensure the powder could adhere to the seed surface under the action of the liquid. The granulation qualification rate of the granulation coating experiment was evaluated against the requirements of GB/T 15671–2009 [28]. The granulation qualification rate $J$ was calculated using the following equation:

$$J = \frac{Z_{\mathrm{h}}}{Z_{\mathrm{b}} + Z_{\mathrm{h}}} \times 100\% \tag{4}$$

where $J$ is the granulation qualification rate, $Z_{\mathrm{h}}$ is the number of red clover seeds completely coated with powder and consisting of only one particle, and $Z_{\mathrm{b}}$ is the sum of the number of red clover seeds not completely coated and the number of coated red clover seeds with more than one particle.

Theoretical analysis of the seed granulation coating process indicates that the powder supply amount, powder supply interval, volume ratio between materials, and liquid supply amount all affect the granulation coating effectiveness. Combining this with actual production practices of granulation coating machines, preliminary experiments were conducted to screen the range of coating process parameters. Results showed that the seed granulation coating process requires a certain space, necessitating a coating pan fill ratio within 60 %. During granulation, excessive or insufficient supply of powder and liquid leads to poor granulation effects. Therefore, the selected ranges are 3–11 g for single powder supply amount, 3–11 s for powder supply interval, and 0.30–0.50 mL/s for liquid supply amount. Subsequently, single-factor and multi-factor orthogonal experiments were conducted to investigate the effects of coating pan fill ratio, single powder supply amount, powder supply interval, and liquid supply amount on seed granulation coating.

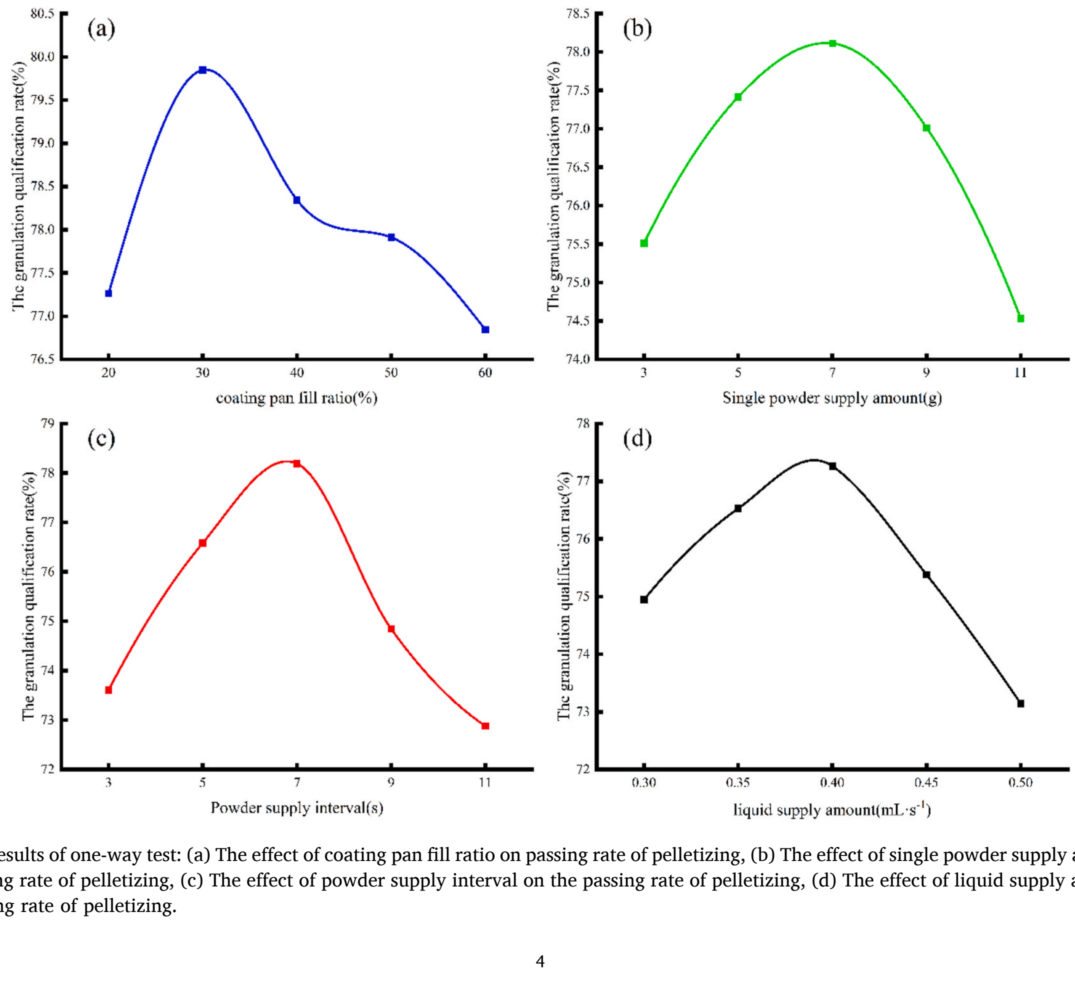


**Fig. 2.** Results of one-way test: (a) The effect of coating pan fill ratio on passing rate of pelletizing, (b) The effect of single powder supply amount on the passing rate of pelletizing, (c) The effect of powder supply interval on the passing rate of pelletizing, (d) The effect of liquid supply amount on the passing rate of pelletizing.

### 4.2. Single factor experiments

During the granulation coating process, the volume ratio of seeds to powder in the coating pan, i.e., the coating pan fill ratio, affects the granulation qualification rate. The pass rate of pelletization was determined using the statistical method described in Equation (4). To investigate the relationship between this factor and the granulation qualification rate, the single powder supply amount was fixed at 7 g, the powder supply interval at 7 s, and the liquid supply amount at 0.40 mL/s. The coating pan fill ratio was adjusted to 20 %, 30 %, 40 %, 50 %, and 60 %, and granulation coating experiments were conducted at these five levels. The experimental data are shown in Fig. 2a. As can be seen from the figure, when other factors were fixed at one level, the granulation qualification rate increased as the fill ratio increased from 20 % to 30 %. However, when the fill ratio increased from 30 % to 60 %, the granulation qualification rate decreased with increasing fill ratio. Therefore, the granulation qualification rate was highest, and the seed granulation coating effect was best when the coating pan fill ratio was 30 %.

During the granulation coating process, the size of the single powder supply amount affects the granulation qualification rate, without changing the total powder supply. To investigate the relationship between this factor and the granulation qualification rate, the coating pan fill ratio was fixed at 40 %, the powder supply interval at 7 s, and the liquid supply amount at 0.40 mL/s. The single powder supply amount was adjusted to 3, 5, 7, 9, and 11 g, and granulation coating experiments were conducted at these five levels. The experimental data are shown in Fig. 2b. As can be seen from the figure, when other factors were fixed at one level, the granulation qualification rate increased as the single powder supply amount increased from 3 g to 7 g. However, when the single powder supply amount increased from 7 g to 11 g, the granulation qualification rate decreased. Therefore, the granulation qualification rate was highest, and the seed granulation coating effect was best when the single powder supply amount was 7 g.

During the granulation coating process, the powder supply interval affects the granulation qualification rate. To investigate the relationship between this factor and the granulation qualification rate, the single powder supply amount was fixed at 7 g, the coating pan fill ratio at 40 %, and the liquid supply amount at 0.40 mL/s. The powder supply interval was adjusted to 3, 5, 7, 9, and 11 s, and granulation coating experiments were conducted at these five levels. The experimental data are shown in Fig. 2c. As can be seen from the figure, when other factors were fixed at one level, the granulation qualification rate increased as the powder supply interval increased from 3 s to 7 s. However, when the powder supply interval increased from 7 s to 11 s, the granulation qualification rate decreased. Therefore, the granulation qualification rate was highest, and the seed granulation coating effect was best when the powder supply interval was 7 s.

During the granulation coating process, the liquid supply amount affects the granulation qualification rate. To investigate the relationship between this factor and the granulation qualification rate, the single powder supply amount was fixed at 7 g, the coating pan fill ratio at 40 %, and the powder supply interval at 7 s. The liquid supply amount was adjusted to 0.30, 0.35, 0.40, 0.45, and 0.50 mL/s, and granulation coating experiments were conducted at these five levels. The experimental data are shown in Fig. 2d. As can be seen from the figure, when other factors were fixed at one level, the granulation qualification rate increased as the liquid supply amount increased from 0.30 mL/s to 0.40 mL/s. However, when the liquid supply amount increased from 0.40 mL/s to 0.50 mL/s, the granulation qualification rate decreased. Therefore, the granulation qualification rate was highest, and the seed granulation coating effect was best when the liquid supply amount was 0.40 mL/s.

### 4.3. Multi-factor orthogonal experiments

Comprehensively observing the seed granulation coating process, it is known that the results of the red clover seed granulation coating experiments are affected under different process parameters. However, the single factor experiments did not consider the coupled effects of multiple factors on the experimental results. Therefore, orthogonal experiments were conducted to investigate the interactive effects of factors on seed granulation coating. From the single factor experiments, it is known that when the coating pan fill ratio is 30 %, the single powder supply amount is 7 g, the powder supply interval is 7 s, and the liquid supply amount is 0.40 mL/s, the granulation qualification rates are the maximum values in their respective groups, indicating the highest granulation qualification rate during granulation coating in this group. Considering the interactive effects between factors, orthogonal experiments were designed based on the principles of orthogonal experiments. The coating pan fill ratio, single powder supply amount, powder supply interval, and liquid supply amount were selected as the experimental factors, and the granulation qualification rate, which measures the granulation coating effect, was used as the evaluation index. The factor levels are shown in Table 1, and the experimental design and results are shown in Table 2.

For the results of the red clover seed granulation coating experiments, considering the influence patterns of multiple factors on the granulation qualification rate, as shown in Fig. 3. Under the action of multiple factors, the variation of the granulation qualification

**Table 1**
Table of experimental factors.

| Levels | Factors | | | |
|---|---|---|---|---|
| | Coating pan fill ratio $B$ (%) | Single powder supply amount $C$ (g) | Powder supply interval $D$ (s) | Liquid supply amount $E$ (mL·s$^{-1}$) |
| −1 | 20 | 5 | 5 | 0.35 |
| 0 | 30 | 7 | 7 | 0.40 |
| +1 | 40 | 9 | 9 | 0.45 |

**Table 2**
Test plan and results.

| No. | *B* (%) | *C* (g) | *D* (s) | *E* ($mL·s^{-1}$) | The granulation qualification rate *J* (%) |
|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0 | 92.6 |
| 2 | 1 | 0 | 0 | −1 | 71.1 |
| 3 | −1 | 0 | 0 | −1 | 68.5 |
| 4 | 0 | 0 | 1 | −1 | 68.8 |
| 5 | 0 | 0 | −1 | 1 | 71.4 |
| 6 | 0 | 1 | 1 | 0 | 78.2 |
| 7 | 0 | 0 | 1 | 1 | 89.4 |
| 8 | 1 | 0 | 1 | 0 | 90.1 |
| 9 | −1 | 0 | 1 | 0 | 79.1 |
| 10 | 0 | 0 | 0 | 0 | 93.4 |
| 11 | 1 | 0 | 0 | 1 | 89.9 |
| 12 | 1 | 1 | 0 | 0 | 79.6 |
| 13 | −1 | 0 | 0 | 1 | 76.4 |
| 14 | 0 | 0 | 0 | 0 | 92.4 |
| 15 | 0 | −1 | 1 | 0 | 93.4 |
| 16 | 0 | −1 | −1 | 0 | 92.4 |
| 17 | 0 | −1 | 0 | 1 | 96.6 |
| 18 | −1 | 0 | −1 | 0 | 80.4 |
| 19 | 0 | 0 | 0 | 0 | 94.4 |
| 20 | 0 | −1 | 0 | −1 | 90.3 |
| 21 | 1 | −1 | 0 | 0 | 91.3 |
| 22 | −1 | 1 | 0 | 0 | 73.4 |
| 23 | 0 | 1 | 0 | 1 | 78.4 |
| 24 | 1 | 0 | −1 | 0 | 76.1 |
| 25 | 0 | 0 | −1 | −1 | 70.4 |
| 26 | 0 | 1 | −1 | 0 | 64.4 |
| 27 | −1 | −1 | 0 | 0 | 95.4 |
| 28 | 0 | 1 | 0 | −1 | 60.4 |
| 29 | 0 | 0 | 0 | 0 | 91.2 |

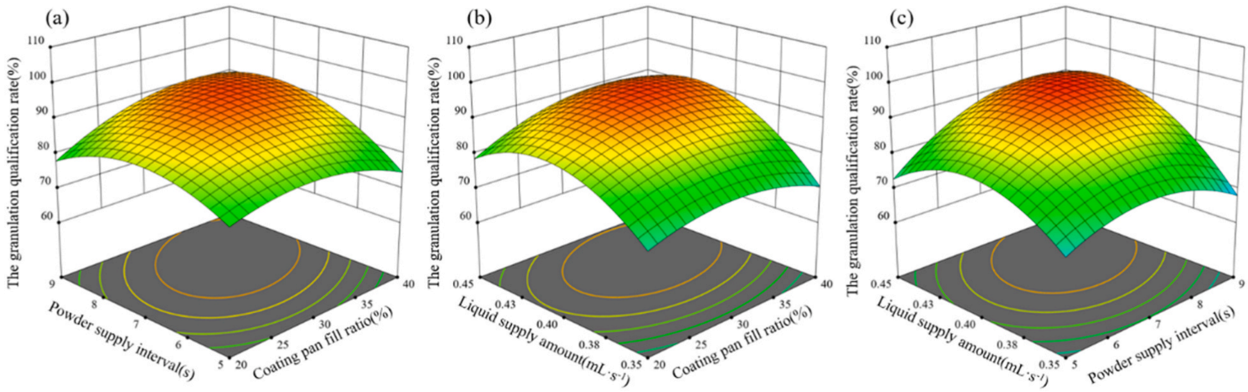


**Fig. 3.** Response surface of the granulation qualification rate: (a) Interaction between the powder supply interval and the coating pan fill ratio, (b) Interaction between the liquid supply amount and coating pan fill ratio, (c) Interaction between the powder supply interval and liquid supply amount.

rate is consistent with the single factor experimental results, and the influence degrees of the factors on the granulation qualification rate are different. As shown in Fig. 3a, analyzing the response surface plots of the powder supply interval and coating pan fill ratio on the granulation qualification rate, when the single powder supply amount and liquid supply amount factors are at the zero level, fixing the powder supply interval, as the coating pan fill ratio increases, the granulation qualification rate shows a trend of first increasing and then decreasing; fixing the coating pan fill ratio, as the powder supply interval increases, the granulation qualification rate shows a trend of first increasing and then decreasing.

As shown in Fig. 3b, analyzing the response surface plots of the liquid supply amount and coating pan fill ratio on the granulation qualification rate, when the single powder supply amount and powder supply interval factors are at the zero level, fixing the liquid supply amount, as the coating pan fill ratio increases, the granulation qualification rate shows a trend of first increasing and then decreasing; fixing the coating pan fill ratio, as the liquid supply amount increases, the granulation qualification rate shows a trend of first increasing and then decreasing.

As shown in Fig. 3c, analyzing the response surface plots of the powder supply interval and liquid supply amount on the granulation qualification rate, when the coating pan fill ratio and single powder supply amount factors are at the zero level, fixing the powder supply interval, as the liquid supply amount increases, the granulation qualification rate shows a trend of first increasing and then decreasing; fixing the liquid supply amount, as the powder supply interval increases, the granulation qualification rate shows a trend of first increasing and then decreasing.

### 4.4. GA-BP model analysis

The response surface method experiments actively collect data based on multivariate linear regression to obtain regression equations with good properties. Although the variation of the granulation qualification rate under the interaction of two factors showed certain regularity, it could not be clearly described by a simple linear relationship. In recent years, with the development of machine learning, compared with the regression model obtained by the response surface method experiments, modern intelligent optimization algorithms can also perform good regression fitting and modeling. The GA-BP algorithm combines the global search capability of genetic algorithms with the nonlinear fitting ability of BP neural networks. This algorithm effectively handles multi-parameter optimization problems, making it suitable for solving complex process parameter optimization issues such as seed granulation coating. Compared to traditional optimization methods, the GA-BP algorithm can better address potential interactions between parameters, thereby enhancing optimization effectiveness. The neural network structure includes a series of interconnected neuron layers, mainly composed of three layers: input layer, hidden layer, and output layer, with each layer connected by neurons to another layer. These neurons pass information from one layer to another. In this way, the information reaches the output layer.

Using the results of orthogonal tests as the dataset, the GA-BP algorithm is used for regression fitting and modeling. The dataset (29 sets) is randomly divided into a training set (21 sets, 70 %), a test set (4 sets, 15 %), and a validation set (4 sets, 15 %). The *mapminmax* function is selected to normalize the input and output data to eliminate the influence of dimensions.

The GA-BP algorithm fully utilizes the advantages of the genetic algorithm in global search. It takes the genetic algorithm as the main body and optimizes the structure and parameters of the BP neural network. Through operations such as selection, crossover, and mutation, the genetic algorithm evolves each individual (a set of BP network parameters) toward a direction of higher fitness. In the GA-BP settings, the population size is 100, the number of iterations is 1000, the *normGeomSelect* function is used, the crossover coefficient is 0.8, and the mutation coefficient is 0.2 [29,30]. Selecting the optimal topology structure is the key to the successful application of neural networks. The input layer is set with 4 neurons: Single powder supply, Powder supply interval, liquid supply amount, and Coating pan fill ratio, and the granulation qualification rate is set as the output layer. The number of hidden layer nodes n in the hidden layer is calculated by the following equation:

$$n = \sqrt{n_1 + n_2} + c \tag{5}$$

where $n_1$ and $n_2$ are the number of neurons in the input layer and output layer, respectively, and c is a constant ranging from 1 to 11. After calculation using Equation (5), the value range of $n$ is 3–13.

The algorithm running platform for this research is MATLAB (MathWorks, U.S.) software. The prediction performance of the machine learning model is evaluated using the coefficient of determination $R^2$, mean squared error (*MSE*), and mean absolute error (*MAE*). A larger $R^2$ indicates a higher degree of model fitting, while smaller *MSE* and *MAE* values indicate better model accuracy and stability. Due to the limited number of training samples, errors may occur during regression fitting. Therefore, the training was repeated three times, and the experimental results are shown in Fig. 4.

From Fig. 4, it can be seen that when the number of hidden layer nodes is 12, the regression model algorithm has the maximum $R^2$ and the minimum *MSE* and *MAE*, indicating that the model fitting degree is higher and the model accuracy and stability are better at this point. Therefore, the GA-BP with 12 hidden neurons is selected as the regression model for this research, and the topological

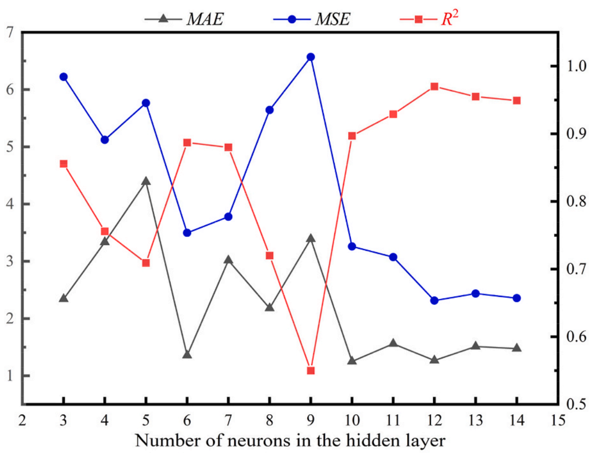


**Fig. 4.** Comparison of regression models.

structure of the established GA-BP model is 3–12-1. As shown in Fig. 5, the *Mean Squared Error* of the model is selected for performance evaluation. From the figure, it can be seen that the *Mean Squared Error* of the model shows a decreasing trend during the training process, indicating that the model's fitting effect on the training data is gradually improving as the training progresses. The best performance is obtained at the 2nd step, at which point the neural network training is basically completed, indicating that the GA-BP training has a relatively fast and stable convergence speed. This model can be used for experiments.

The training, validation, and testing performance of GA-BP in this research is analyzed as shown in Fig. 6. From the figure, it can be seen that the correlation coefficients for training, validation, testing, and all data are 0.991, 0.994, 0.999, and 0.971, respectively, indicating a strong model fitting effect and good generalization ability. The close correlation coefficients of the data indicate that no significant overfitting or underfitting has occurred. GA-BP performs outstandingly in this research, obtaining a high-precision model with strong generalization ability, which can be used for subsequent experimental research.

The GA-BP has good fitting accuracy. Using the trained model as the fitness function, a MATLAB script was written to conduct iterative optimization using the Genetic Algorithm. The individual with the closest fitness was then selected, and the final results obtained were: a coating pan fill ratio of 33.78 %, a single powder supply amount of 5.17 g, a powder supply interval of 7.7 s, and a liquid supply amount of 0.42 mL/s. Under this optimal parameter combination, granulation coating experiments with red clover seeds were performed, and the average granulation qualification rate was 97.7 %. The experimental results indicate that the red clover seed granulation coating experiment based on the GA-BP optimization model meets the requirements of GB/T 15671–2009.

## 5. Discussion

To address the issue of low granulation qualification rates during the granulation coating of red clover seeds, the force conditions of the powder and seeds under the action of liquid were theoretically analyzed to obtain the main factors affecting the granulation qualification rate. Experiments were then conducted to analyze the effects of various parameters on the granulation qualification rate. In the adhesion process between seeds and powder, van der Waals forces, as non-contact adhesive forces, are significantly influenced by different types of powders and liquids in terms of the interaction constants between materials and the thickness of adsorbed water films. Hydrophilic powders tend to form thicker adsorbed water films, which theoretically reduces van der Waals forces. This characteristic necessitates more liquid to promote initial adhesion to the seed surface. Liquid bridge forces, as contact adhesive forces, are primarily affected by the liquid surface tension, liquid bridge volume ratio, and bed porosity. In the actual granulation coating process, van der Waals forces and liquid bridge forces act simultaneously, with their relative importance potentially varying across different stages of the coating process. This dynamic change presents challenges for process parameter optimization. During the parameter optimization experiments, it was observed that the multitude of influencing factors complicated the resolution of experimental results. To improve the granulation qualification rate of red clover seeds during granulation coating, a neural network machine learning model (GA-BP) was introduced to optimize the experimental results.

Compared to the traditional optimization experiments using the response surface methodology (*RSM*) for parameter optimization, the GA-BP model analyzes and processes the data. Although this requires a large amount of iterative calculations and more time, it can more accurately solve the nonlinear relationships between variables, which is beneficial for improving the accuracy of experimental results [30]. From the theoretical foundations of the two models, the *RSM* experimental analysis method establishes an effective prediction model through different experiments, while the GA-BP is a black-box model that focuses on data analysis, making it easier to explore data relationships than designing an experimental system [31]. This research explores the feasibility of using the GA-BP model for data analysis of the red clover seed granulation coating process parameter optimization experiments through a neural network machine learning model. The experimental results show that the neural network method can be used in the parameter optimization

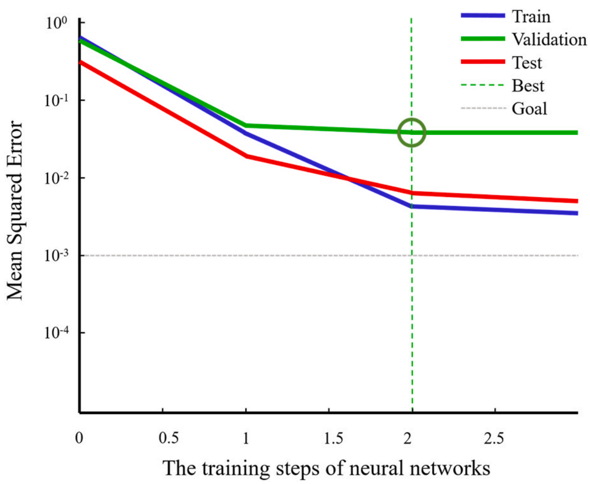


**Fig. 5.** Model mean squared error performance evaluation.

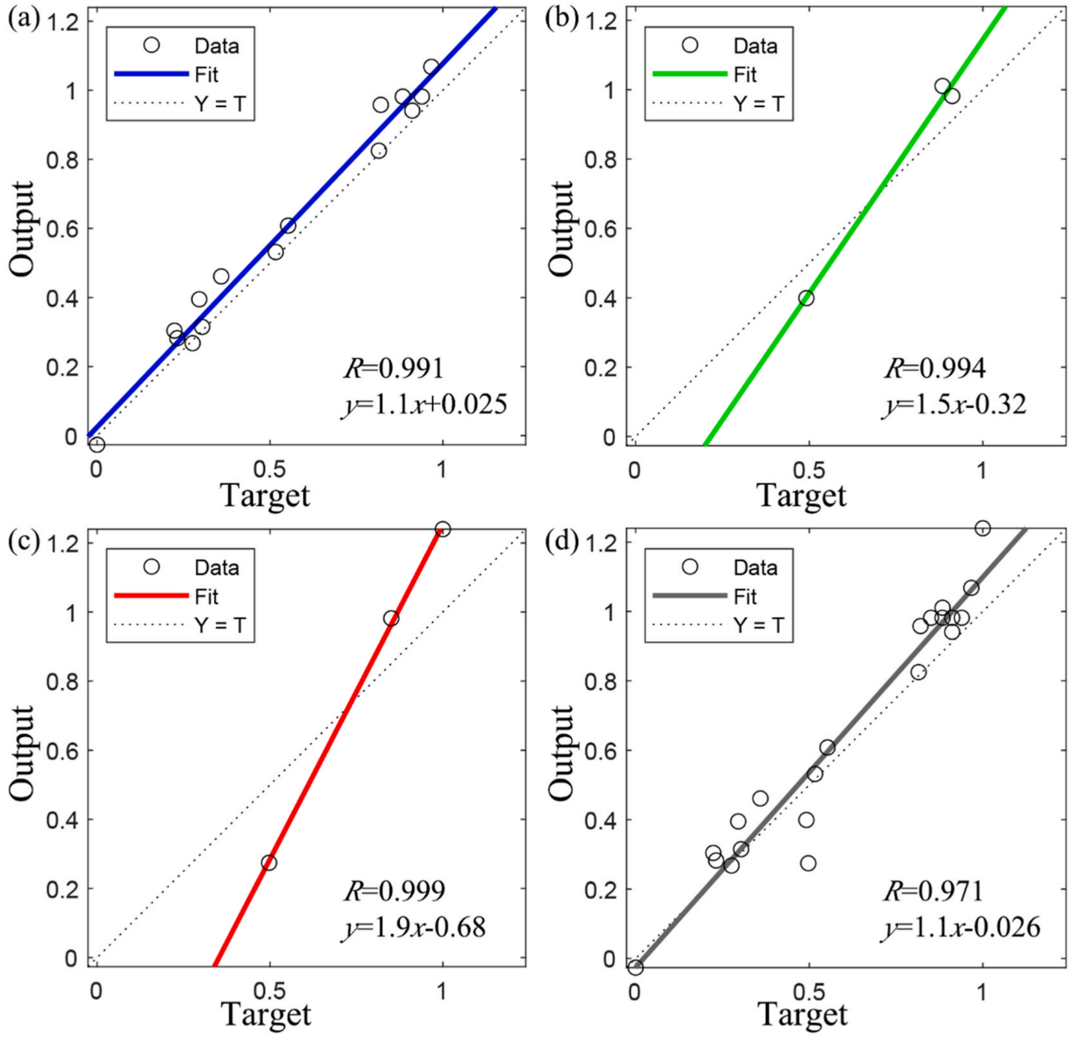


**Fig. 6.** Regression analysis: (a) training, (b) validation, (c) test, (d) all.

experiment field to improve simulation accuracy, and this method can provide a reference for other fields involving multi-factor optimization experiments.

This study successfully improved the qualification rate of red clover seed granulation coating under laboratory conditions through theoretical analysis and experimental optimization. However, translating these research findings to industrial applications still faces a series of potential challenges that require further investigation and resolution. Firstly, in scaled-up production, industrial-grade equipment may differ significantly from laboratory equipment in design and performance. These differences could affect the uniform distribution of powder and liquid, thereby impacting coating quality. Parameter optimization specific to industrial equipment will be necessary. Moreover, industrial production requires increased efficiency while ensuring quality. The optimal powder supply intervals and liquid supply rates obtained in this study may need further optimization to find a balance between quality and efficiency. Additionally, factors such as temperature and humidity in industrial environments may differ from laboratory conditions, potentially affecting the powder and liquid adhesion process. Future research could focus on optimizing raw material use and energy consumption while maintaining granulation qualification rates. This may involve more precise process parameter control and more efficient equipment design.

## 6. Conclusions

This paper focuses on the granulation coating of red clover seeds, analyzing the force conditions of powder particles under the action of liquid to identify the main experimental factors affecting the granulation qualification rate of seeds. The GA-BP model is then employed to optimize the optimal parameter combination of these main experimental factors, thereby determining the best process parameters for the granulation coating of red clover seeds:

1) By analyzing the force conditions of seeds and powder particles under the action of liquid, combined with the results of single-factor experiments, the process parameters affecting the quality of red clover seed granulation coating were determined to be coating pan fill ratio, single powder supply amount, powder supply interval, and liquid supply amount.
2) Through orthogonal experiments, it was found that the interaction of factors would influence the experimental results. The GA-BP neural network model was introduced to investigate the granulation qualification rate of red clover seeds under the combined action of multiple factors. The topological structure of the selected GA-BP model was 3–12-1, and the correlation coefficient was 0.971, indicating that the model can be used for subsequent experimental research.
3) To further improve the quality of seed granulation coating, the GA-BP model was used to optimize the results of the process parameter optimization orthogonal experiments, obtaining a process parameter combination of coating pan fill ratio of 33.78 %, single powder supply amount of 5.17 g, powder supply interval of 7.7 s, and liquid supply amount of 0.42 mL/s. Using this process parameter combination, the average granulation qualification rate of red clover seeds was approximately 97.7 %.

In industrial production, it may be necessary to process seeds of different varieties or batches, which may vary in shape and surface characteristics. This seed diversity might require dynamic adjustment of process parameters based on seed properties. Developing an intelligent process control system capable of adapting to different seed characteristics could be a worthwhile direction for exploration.

## Funding

This work was funded by the Key R&D and achievement transformation plan project of Inner Mongolia (2023YFDZ0006), the Program for improving the Scientific Research Ability of Youth Teachers of Inner Mongolia Agricultural University (BR220128), and the Research Program of Science and Technology at Universities of Inner Mongolia Autonomous Region (NJZZ23046, NJZY21461), the High level Talent Introduction and Research Launch Project of Inner Mongolia Agricultural University (NMGIRT2403), the Natural Science Foundation of Inner Mongolia Autonomous Region (2023QN05034), and the Inner Mongolia Autonomous Region Military-Civilian Integration Key Research Projects and Soft Science Research Projects (JMZD202201).

## Data availability

Data included in article.

## CRediT authorship contribution statement

**Xuejie Ma:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation. **Min Liu:** Methodology, Investigation. **Zhanfeng Hou:** Methodology, Investigation, Funding acquisition. **Mengjun Guo:** Software, Methodology. **Zhihong Yu:** Supervision, Methodology. **Xin Tong:** Investigation, Conceptualization. **Haiyang Liu:** Investigation, Conceptualization. **Fang Guo:** Supervision, Project administration.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## References

[1] P. McKenna, N. Cannon, J. Conway, J. Dooley, The use of red clover (Trifolium pratense) in soil fertility-building: a Review, Field Crops Res. 221 (2018) 38–49, https://doi.org/10.1016/j.fcr.2018.02.006.
[2] H. Sidhu, D. Wiesenborn, B. Johnson, E. Monono, E. Eriksmoen, Coating of hulled seeds improved field plantability and grain yield of extra-large confectionary sunflower achenes, Crop Sci. 59 (2019) 1182–1190, https://doi.org/10.2135/cropsci2018.06.0400.
[3] J. Köhl, P. Butterbach, R.-U. Ehlers, T. Gaildry, L.G. Haas, S.P.C. Groot, L. van der Heijden, I. Houwers, E. de Lange, G. Lopez, A. van Nieuwenhoven, M. Notten, M. Storcken, Screening criteria for microbial bioprotectants for seed coating to protect seeds and seedlings from diseases, Biol. Control 190 (2024) 105450, https://doi.org/10.1016/j.biocontrol.2024.105450.
[4] X. Ma, M. Liu, Z. Hou, J. Li, X. Gao, Y. Bai, M. Guo, Calibration and experimental studies on the mixing parameters of red clover seeds and coated powders, Processes 10 (2022), https://doi.org/10.3390/pr10112280.
[5] H. Jarrar, A. El-Keblawy, C. Ghenai, P.C. Abhilash, A.K. Bundela, Z. Abideen, M.S. Sheteiwy, Seed enhancement technologies for sustainable dryland restoration: coating and scarification, Sci. Total Environ. 904 (2023) 166150, https://doi.org/10.1016/j.scitotenv.2023.166150.
[6] S. Pedrini, Z. Webber, H. D'Agui, K. Dixon, M. Just, T. Arya, S. Turner, Customise the seeds, not the seeder: pelleting of small-seeded species for ecological restoration, Ecol. Eng. 196 (2023) 107105, https://doi.org/10.1016/j.ecoleng.2023.107105.
[7] R. Piri, A. Moradi, H. Balouchi, A. Salehi, Improvement of cumin (Cuminum cyminum) seed performance under drought stress by seed coating and biopriming, Sci. Hortic. (Amst.) 257 (2019) 108667, https://doi.org/10.1016/j.scienta.2019.108667.
[8] M. Sohail, T. Pirzada, C.H. Opperman, S.A. Khan, Recent advances in seed coating technologies: transitioning toward sustainable agriculture, Green Chem. 24 (2022) 6052–6085, https://doi.org/10.1039/d2gc02389j.
[9] I. Rocha, Y. Ma, M. Vosátka, H. Freitas, R.S. Oliveira, Growth and nutrition of cowpea (Vigna unguiculata) under water deficit as influenced by microbial inoculation via seed coating, J. Agron. Crop Sci. 205 (2019) 447–459, https://doi.org/10.1111/jac.12335.
[10] I. Rocha, Y. Ma, P. Souza-Alonso, M. Vosátka, H. Freitas, R.S. Oliveira, Seed coating: a tool for delivering beneficial microbes to agricultural crops, Front. Plant Sci. 10 (2019), https://doi.org/10.3389/fpls.2019.01357.
[11] Z. Hou, Y. Qiu, Z. Chen, H. Liu, F. Guo, L. Mi, Optimization of process parameters of pelletizer for agropyron seeds under vibration force field, INMATEH - Agric. Eng. 60 (2020) 147–154, https://doi.org/10.35633/INMATEH-60-17.

[12] M. Liu, Z. Hou, X. Ma, X. Zhang, N. Dai, Determination and testing of pelletized coated particles, INMATEH - Agric. Eng. 66 (2022) 247–256, https://doi.org/10.35633/inmateh-66-25.

[13] X. Ma, Z. Hou, M. Liu, Calibration of simulation parameters of coated particles and analysis of experimental results, INMATEH - Agric. Eng. 67 (2022) 233–242, https://doi.org/10.35633/inmateh-67-23.

[14] J. Wang, H. Xie, Z. Hu, L. Hu, B. Peng, M. Liu, Parameter optimization on mechanical coating processing of rotary table-roller coating machine for peanut seeds, Nongye Gongcheng Xuebao/Transactions Chinese Soc, Agric. Eng. 33 (2017) 43–50, https://doi.org/10.11975/j.issn.1002-6819.2017.07.006.

[15] J.M. Buades Rubio, A. Jaume-i-Capó, D. López González, G. Moyà Alcover, Solving nonograms using neural networks, Entertain. Comput. 50 (2024) 100652, https://doi.org/10.1016/j.entcom.2024.100652.

[16] H. Dagne, V.P. S, H. Palanivel, A. Yeshitila, S. Benor, S. Abera, A. Abdi, Advanced modeling and optimizing for surface sterilization process of grape vine (Vitis vinifera) root stock 3309C through response surface, artificial neural network, and genetic algorithm techniques, Heliyon 9 (2023) e18628, https://doi.org/10.1016/j.heliyon.2023.e18628.

[17] J. Sun, J. Kainz, State of health estimation for lithium-ion batteries based on current interrupt method and genetic algorithm optimized back propagation neural network, J. Power Sources 591 (2024) 233842, https://doi.org/10.1016/j.jpowsour.2023.233842.

[18] R.K. Gupta, R.C. Singh, Optimizing high-speed rotating shaft vibration control: experimental investigation of squeeze film dampers and a comparative analysis using Artificial Neural Networks (ANN) and Response Surface Methodology (RSM), Expert Syst. Appl. 249 (2024) 123800, https://doi.org/10.1016/j.eswa.2024.123800.

[19] R. Pravina, H. Uthayakumar, A. Sivasamy, Hybrid approach based on response surface methodology and artificial neural networks coupled with genetic algorithm (RSM-GA-ANN) for the Prediction and optimization for the Photodegradation of dye using nano ZnO anchored glass fiber under solar light irra, J. Taiwan Inst. Chem. Eng. 153 (2023) 105248, https://doi.org/10.1016/j.jtice.2023.105248.

[20] B. Karmakar, S.P. Saha, R. Chakraborty, S. Roy, Optimization of starch extraction from Amorphophallus paeoniifolius corms using response surface methodology (RSM) and artificial neural network (ANN) for improving yield with tenable chemical attributes, Int. J. Biol. Macromol. 237 (2023) 124183, https://doi.org/10.1016/j.ijbiomac.2023.124183.

[21] H.-L. Lau, F.W.F. Wong, R.N.Z.R.A. Rahman, M.S. Mohamed, A.B. Ariff, S.-L. Hii, Optimization of fermentation medium components by response surface methodology (RSM) and artificial neural network hybrid with genetic algorithm (ANN-GA) for lipase production by Burkholderia cenocepacia ST8 using used automotive engine oil as substrate, Biocatal. Agric. Biotechnol. 50 (2023) 102696, https://doi.org/10.1016/j.bcab.2023.102696.

[22] D. Xiang, D. Wang, S. Wang, L. Yan, Y. Chen, Analysis and optimization of laser cladding Ti-B4C composite coatings based on the interaction and GABP-NSGAII algorithm, Surf. Coating. Technol. (2024) 131186, https://doi.org/10.1016/j.surfcoat.2024.131186.

[23] C. Jin, Z. Li, M. Huang, J. Wen, X. Ding, M. Zhou, C. Cai, Laboratory and simulation study on the Cd(II) adsorption by lake sediment: mechanism and influencing factors, Environ. Res. 197 (2021) 111138, https://doi.org/10.1016/j.envres.2021.111138.

[24] Y. Badran, R. Ansart, J. Chaouki, O. Simonin, Macro-scale numerical investigation of the contribution of Van der Waals force to the pressure-drop overshoot in fine-particle fluidized beds, Powder Technol. 436 (2024) 119505, https://doi.org/10.1016/j.powtec.2024.119505.

[25] Y. Du, S.A. Bradford, C. Shen, T. Li, X. Bi, D. Liu, Y. Huang, Novel analytical expressions for determining van der Waals interaction between a particle and air–water interface: Unexpected stronger van der Waals force than capillary force, J. Colloid Interface Sci. 610 (2022) 982–993, https://doi.org/10.1016/j.jcis.2021.11.157.

[26] M. Horio, T. Kai, T. Tsuji, H. Hatano, Fluidization centennial and the decades of research and development in Japan, Powder Technol. 415 (2023) 118093, https://doi.org/10.1016/j.powtec.2022.118093.

[27] M. Girardi, S. Radl, S. Sundaresan, Simulating wet gas–solid fluidized beds using coarse-grid CFD-DEM, Chem. Eng. Sci. 144 (2016) 224–238, https://doi.org/10.1016/j.ces.2016.01.017.

[28] X. Ma, M. Liu, Z. Hou, X. Gao, Y. Bai, M. Guo, Numerical simulation and experimental study of pelletized coating of small grain forage seeds, Nongye Gongcheng Xuebao/Transactions Chinese Soc, Agric. Eng. 39 (2023) 43–52, https://doi.org/10.11975/j.issn.1002-6819.202211002.

[29] N. Gammoudi, M. Mabrouk, T. Bouhemda, K. Nagaz, A. Ferchichi, Modeling and optimization of capsaicin extraction from Capsicum annuum L. using response surface methodology (RSM), artificial neural network (ANN), and Simulink simulation, Ind. Crops Prod. 171 (2021) 113869, https://doi.org/10.1016/j.indcrop.2021.113869.

[30] X. Ma, M. Guo, X. Tong, Z. Hou, H. Liu, H. Ren, Calibration of small-grain seed parameters based on a BP neural network: a case study with red clover seeds, Agronomy 13 (2023), https://doi.org/10.3390/agronomy13112670.

[31] A.P. Singh, D.K. Singh, Multi response optimization for micro-EDM machining of AISI D2 die steel using RSM and neural network, Mater. TODAY-PROCEEDINGS 43 (2021) 1449–1455, https://doi.org/10.1016/j.matpr.2020.09.183.