



# Article Experimental Study on the Ventilation Resistance Characteristics of Paddy Grain Layer Modelled with Response Surface Methodology

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**Abstract**: The ventilation resistance of air flow through rice grain layers is one of the key parameters affecting drying uniformity as well as the energy consumption of the drying process. In order to reveal the variation of characteristics of the ventilation resistance with paddy grain moisture content, the air velocity and the bed layer depth are needed. A second order model was fitted to pressure drop using the response surface methodology and the results are compared with those of the Ergun model. The results showed that the pressure drop increases with the increase of paddy grain moisture content, air velocity and the bed layer depth, and the interactions between the air velocity and the bed layer depth, and the interactions between the air velocity and the bed layer depth are needed. The resulte drop model based on RSM was established and compared with the Ergun model. The results showed that the pressure drop model established by RSM is similar to that of the Ergun model.

Keywords: paddy grain; pressure drop; response surface methodology; Ergun model

# 1. Introduction

The pressure drop of the grain bed layer is the key parameter for designing and optimizing the structure of the drying chamber, and it is also one of the most important references for selecting the power of a fan [1,2]. During the drying process, owing to the bed layer porosity as well as the air viscosity, there must be a pressure drop when the air flows through the bed layer. A high-pressure drop may make it difficult for the air to flow through the bed layer and further lead to the increase of non-uniformity of the drying process, while a low-pressure drop may lead to wasting the power of the fan [3]. Accordingly, it is necessary to find out a reasonable pressure drop under the premise of ensuring product quality and maintaining a reasonable power demand of the fan.

In the last few decades, researchers have done many studies on the ventilation resistance of the grain bed layer by applying the traditional pressure drop models [4–7]. For example, Gunasekaran and Jackson [8] conducted an experiment on the flow resistance of sorghum bed layer by applying the Ergun model, the resistance of sorghum moisture content of 16.5, 18.5, and 23 %w.b. were determined under the grain bed depth of 150 to 1200 mm with the airflow ranges of 0.05 to 0.3 m/s. The results showed that the resistance of airflow increases with the increase of air velocity and bed layer depth, while resistance increases with the decrease of the hot air flow through the paddy grain bed layer; they found that the flow resistance of the hot air increases with the increase of hot air velocities. Zhang et al. [10] investigated the pressure drop of the air (with velocity ranges of 0.1 to 0.6 m/s) flow through the bed layer with depth ranges of 100 to 1000 mm, and



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**Copyright:** © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). found that the simulation accuracy of the pressure drop using Ergun model is reliable only when the air velocity is under 0.2 m/s. It can be summarized from the above analyses that the flow resistance of the grain bed layer are mainly determined by the traditional models and the characteristics of the air flow resistance are investigated by using single factor test. Though the works provided some valuable references for guiding the practical production, the air flow resistance prediction accuracy based on traditional models should be further improved and the interaction of the parameters on the flow resistance should be further investigated.

Respond surface methodology (RSM) is one of the most effective modeling tools to investigate the interactions of two or more variables on the responses, which is widely adopted to optimize the process parameters in the agriculture field [11,12]. Zeng et al. [13] conducted an experimental study on the vacuum drying extraction technology of konjac glucomannan using RSM, and an artificial neuron network (ANN) was also adopted and then compared with the RSM. The results showed that the model established by RSM is slightly better than that of an ANN. In order to improve the dynamic performance of orchard ditching fertilizer and to avoid resonance, Liu et al. [14] adopted the RSM to optimize the structure of the rack of orchard ditching-fertilizer machine. The results showed that the optimized structure has a better first-order modal frequency of 38.31 Hz than that of the traditional structure, and the optimized frequency is far away from the input frequency (35 Hz) of a tractor, indicating that the frequency of the structure optimized by RSM can avoid the resonance. Moreover, Kowalczyk et al. [15] adopted the RSM to optimize the production process of a micro-elemental feed additive for laying hens, the most favorable enrichment conditions of the process were determined by the model established by the RSM. It can be summarized that the RSM is widely used in the agricultural field, and it can be also adopted to model the ventilation resistance of paddy grain layer.

The present work adopted the RSM to model the ventilation resistance of paddy grain layer. In detail, an experiment followed by Box–Behnken Design was conducted to investigate the influences of the independent variable including paddy grain moisture content (*Mc*), air velocity ( $v_{air}$ ), and paddy layer depth (*L*) on the pressure drop ( $\Delta p$ ). The influences of the single factor as well as the interactions between any two independent variables on  $\Delta p$  were investigated and a ternary quadratic model for  $\Delta p$  was established and compared with the traditional Ergun model.

## 2. Materials and Methods

To fully understand the variation rules of ventilation resistance of the air flowing through paddy grain layer and further specify the optimization strategy for deep bed paddy drying process. A laboratory-scale experimental test was conducted based on the engineering application consideration; the detailed analysis steps are as follows.

# 2.1. Materials

The paddy grains sample with initial moisture content of 12.2 %w.b. are purchased from a local farmer at Leizhou Guangdong Province, China. The samples are, respectively manual humidified to 13.6 %w.b., 14.8 %w.b., 16.2 %w.b., 17.8 %w.b., 18.9 %w.b., 21.3 %w.b., 22.9 %w.b., 24.5 %w.b., and 25.6 %w.b. according to the methodology introduced in the literature [16]. Additionally, the prepared samples are sealed in plastic bags and stored in a refrigerator at approximately 4 °C for about 48 h prior to the experiments [13].

#### 2.2. Experimental Apparatus

As can be seen from Figure 1, the apparatus mainly consists of 6 parts including the centrifugal fan, frequency converter, air supply duct, screen mesh, test pipeline, and the fixing bracket. There are 10 pressure taps with a diameter of 10 mm on the test pipeline, the height of the test pipeline is 1100 mm, and the distance between any two adjacent pressure taps is 100 mm. Moreover, there is one air velocity tap closed to connection between the test pipeline and air supply duct and the connection is sealed by a rubber ring and silicone [17].

During the tests, the three levels of air velocities (0.1, 0.35, and 0.6 m/s) are produced by the centrifugal fan connected with a frequency converter. The air flows through the air supply duct, then flows cross the screen mesh, further flows cross the grain layer, and finally flows into the ambient space. The  $v_{air}$  was controlled by the frequency converter. The inlet  $v_{air}$  was measured by an anemometer. The air pressure was measured by a digital pressure gauge. The details of the instruments used in the tests are tabulated in Table 1. Compared with the industrial dryer—although the physical structure of the laboratory-scale apparatus is different, the grain bed is dynamic (actually for a single grain bed layer, and the velocities of the grain bed are very low during the cyclic drying process—the ratio of air volume to the mass of the bed layer for the industrial dryer and the apparatus are the same [18]. This indicates that the main results obtained by the laboratory-scale apparatus can provide some references for the industrial dryer, especially for power selection of the fan and to ascertain of the bed layer depth in the design link of the industrial dryer.



Figure 1. The schematic diagram of the laboratory-scale experimental apparatus.

Table 1. The details of the instruments used for the tests.

Instruments	Туре	Range/Value	Precision
Frequency converter	Delta VFD002M43B	2.2 kW	-
Centrifugal fan	XYFL-170	2.2 kW	-
Air supply duct	Round plastic pipe	$\phi$ = 300 mm	-
Screen mesh	Stainless steel screen	$2 \times 2 \text{ mm}$	-
Anemometer	SUMMIT-565	0.1–20 m/s	0.1 m/s
Digital pressure gauge	DP2000-5	0–1000 Pa	1 Pa
Electronic digital calliper	MNT-150	0–200 mm	0.02 mm

#### 2.3. Experimental Design

# 2.3.1. RSM Design

In the present work, three different paddy grain Mc of 12.2 %w.b., 18.9 %w.b., and 25.6 %w.b.; three different  $v_{air}$  of 0.10, 0.35, and 0.60 m/s; three different L of 0.10, 0.55, and 1.0 m, were considered to be the independent variables, while the  $\Delta p$  was regarded as the response. Owing to the fact that the Box–Behnken Design has the advantages of the less experimental operations comparing with Central Composite Design [19], and by comprehensive considering that the mass of each test is huge, the Box–Behnken Design method was adopted to analyze the effects of the interaction of independent variables (Mc,  $v_{air}$ , and L) on the response ( $\Delta p$ ) and further optimize the drying process. The experimental design representing the natural and coded values of independent variables are shown in Table 2. In order to develop the mathematical relations between the independent variables

and the response, the second-order polynomial model (Equation (1)) was adopted to establish the RSM model [20].

$$Y = \beta_0 + \sum_{i=1}^2 \beta_i X_i + \sum_{i=1}^2 \beta_i j X_i^2 + \sum_{i=1}^2 \beta_{ij} X_i X_j$$
(1)

where *Y* is the response,  $X_i$  and  $X_j$  are the independent variables affecting the response,  $\beta_0$ ,  $\beta_i$ , and  $\beta_{ij}$  are the regression coefficients for intercept quadratic liner and interaction terms.

Table 2.	Experimental	l design for	the RSM test
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	Code Levels				
Independent Variables	-1 0		1		
	Natural Levels				
<i>Mc</i> (%w.b.)	12.2	18.9	25.6		
$v_{air}$ (m/s)	0.10	0.35	0.60		
<i>L</i> (m)	0.10	0.55	1.0		

# 2.3.2. Model Validation

In statistics, the *p*-value is the probability of obtaining results as extreme as the results observed from a statistical hypothesis test, assuming that the null hypothesis is correct. The *p*-value is used as an alternative to rejection points to provide the smallest level of significance where the null hypothesis would be rejected [21,22]. A smaller *p*-value means stronger evidence for the alternative hypothesis [23].

Based on the analysis above, the *p*-value is used to validate hypothesis test of the model. The null hypothesis is defined as the response ( $\Delta p$ ) that cannot be explained by the obtained model, while the alternative hypothesis is defined as the response ( $\Delta p$ ) can be explained by the obtained model.

#### 2.3.3. RSM Model Validation Metrics

In the present work, the statistical indexes including determination coefficient ( $R^2$ ), mean absolute error (*MAE*), mean square error (*MSE*), and root mean square (*RMSE*) were adopted to evaluate the fitting performance of the  $\Delta p$  model developed by the RSM and the Ergun model, which can be, respectively, calculated followed by the following Equations (2)–(5) [24]:

$$R^{2} = 1 - \frac{\sum_{i=1}^{n} (Y_{pre,i} - Y_{\exp,i})^{2}}{\sum_{i=1}^{n} (Y_{\exp,i} - \overline{Y_{pre,i}})^{2}}$$
(2)

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |Y_{pre,i} - Y_{exp,i}|$$
(3)

$$MSE = \frac{\sum_{i=1}^{n} (Ypre, i - Yexp, i)^2}{n}$$
(4)

$$RMSE = \sqrt{MSE} \tag{5}$$

where,  $Y_{pre,i}$  is the value predicted by the models,  $Y_{exp,i}$  is the experimental value,  $Y_{exp}$  is the mean of the experimental values, and *n* is the number of the data points. Moreover, the experimental results are tabulated in Table 3.

Ston doud	Dun	Inde	Independent Variables				
Standard	Kull	<i>Mc</i> (%w.b.)	$v_{air}$ (m/s)	<i>L</i> (m)	$\Delta p$ (Pa)		
12	1	18.90	0.60	1.00	689.56		
15	2	18.90	0.35	0.55	194.26		
3	3	12.20	0.60	0.55	255.21		
1	4	18.90	0.60	0.10	83.13		
1	5	12.20	0.10	0.55	1375		
2	6	25.60	0.10	0.55	60.58		
4	7	25.60	0.60	0.55	485.12		
11	8	18.90	0.10	1.00	42.52		
14	9	18.90	0.35	0.55	167.28		
7	10	12.20	0.35	1.00	182.54		
9	11	18.90	0.10	0.10	12.62		
16	12	18.90	0.35	0.55	158.76		
5	13	12.20	0.35	0.10	17.11		
6	14	25.60	0.35	0.10	38.82		
17	15	18.90	0.35	0.55	168.76		
13	16	18.90	0.35	0.55	166.46		
8	17	25.60	0.35	1.00	396.69		

Table 3. Experimental design for the tests.

2.3.4. ANOVA Validation: Anderson-Darling (AD) Test for Normality

According to some of the literature, the distribution of residuals for a set of data can reflect the validity of a predicted model [25]. In detail, if the residuals follow a normal distribution (occurrences are random), the established model has a well-predicting capacity. The Anderson–Darling (AD) test is the statistical tool used to quantify the deviation for a set of residuals from a normal distribution. The validity of the distribution of residuals in the AD test at a 5% level of significance was used to confirm the model accuracy and to determine if a sample data set was taken from a population with a specific distribution [26]. In the present work, the AD test was conducted by the software Minitab 17.0, the null hypothesis is defined as the distribution of the residuals that do not follow the normal distribution, and the hypothesis can be rejected if the test statistic (AD value) is greater than a critical value [27].

# 2.3.5. Single Factor Experiments

In order to investigate influence of each independent variable on the response, the  $\Delta p$  under ten levels of Mc,  $v_{air}$ , and L were, respectively, measured followed by the 3 sets of experimental design, the single factor experiment design and the corresponding results are tabulated in Table 4.

	Single Factor Te			Single Factor Test 2			Single Factor Test 3		
Level	<i>Mc</i> (%w.b.)	v <sub>air</sub> (m/s)	L (m)	<i>Mc</i> (%w.b.)	v <sub>air</sub> (m/s)	L (m)	<i>Mc</i> (%w.b.)	v <sub>air</sub> (m/s)	L (m)
1	12.2				0.1				0.1
2	13.6				0.15				0.2
3	14.8				0.2				0.3
4	16.2				0.25				0.4
5	17.8	0.05	10.0	0.3	0 5	10.0	0.25	0.5	
6	18.9	0.35	0.35 0.5	18.9	0.35	0.5	18.9	0.35	0.6
7	21.3				0.4				0.7
8	22.9				0.45				0.8
9	24.5				0.5				0.9
10	25.6				0.6				1.0

Table 4. Experimental design for the single factor tests.

## 2.4. Ergun Model

Ergun model is one of most effective tools for revealing the relationship between fluid properties and porous media properties, which has been widely used in Hydrodynamics, thermodynamics, and engineering [28]. In order to investigate the ventilation resistance characteristics of the air flow through the paddy bed layer as well as to verify the  $\Delta p$  model developed by the RSM. The most widely used Ergun model ( $\Delta p_{Eur}$ ) was applied in the present work, which can be expressed as following expressions [29–31]:

$$-\frac{\Delta p_{\rm Eur}}{L} = \frac{150\mu(1-\varepsilon)^2}{d_{\sigma}^2\varepsilon^3}v_{air} + \frac{1.75\rho(1-\varepsilon)}{d_{g}\varepsilon^3}v_{air}^2 \tag{6}$$

where  $\mu$  is the dynamic viscosity of the air,  $1.81 \times 10^{-5}$  kg/(m·s) [32];  $\rho$  is the density of the air,  $\rho = 1.205$  kg/m<sup>3</sup> [33];  $\varepsilon$  is the porosity of the bed layer; and  $d_g$  is the equivalent diameter of a single paddy grain, m. The  $\varepsilon$  for different *Mc* levels of the paddy grains can be determined by a self-developed porosimeter; the details of the porosimeter can be found in our previous work [34].

On the other hand, the  $d_g$  for a single paddy grain with different *Mc* can be calculated according to the length ( $L_0$ ), width ( $W_0$ ), and height ( $H_0$ ) of the paddy grain. The calculation methodology introduced by Mohsenin et al. [35] are expressed as follows:

$$d_g = 3L_0 W_0 H_0 (L_0 W_0 + L_0 H_0 + W_0 H_0)^{-1}$$
(7)

Each parameter used for calculating the  $d_g$  was measured 3 times and the average value was used for the calculation. The  $d_g$  and  $\varepsilon$  for different Mc used for calculation in the Ergun model are shown in Figure 2.



**Figure 2.** The variations of the  $d_g$  and  $\varepsilon$  with *Mc*.

# 3. Results

# 3.1. ANOVA Analysis

In the present work, the software Design Expert 8.0.6 was applied to analyze the experimental results and the ANOVA analysis was employed to analyze the significance of the Mc,  $v_{air}$ , and L on the  $\Delta p$ . The results are tabulated in Table 5. It can be seen from the table that the sum of squares, mean square, F-value, and p-value for each of the terms of the model were calculated, of which the F-value and p-value are the criteria for evaluating the fitting performance of the specific term [36]. Specifically, the larger the F-value is, the more significant the term is and the better the fitting performance is; on the other hand, the p-value with the range of (0.01 < p < 0.05) indicates the term is significant (characterized by

the symbol "\*") while a *p*-value less than 0.01 indicates that the term is extremely significant (characterized by the symbol "\*\*").

Source	Sum of Squares	df	Mean Square	F-Value	<i>p</i> -Value		
Model	$5.480  imes 10^5$	9	60,885.15	148.56	<0.0001 **		
Мс	32,848.69	1	32,848.69	80.15	< 0.0001 **		
v <sub>air</sub>	$2.393 imes10^5$	1	$2.393  imes 10^5$	583.84	< 0.0001 **		
L	$1.681  imes 10^5$	1	$1.681  imes 10^5$	410.13	< 0.0001 **		
$Mc \cdot v_{air}$	8379.57	1	8379.57	20.45	0.0027 **		
$Mc \cdot L$	9255.40	1	9255.40	22.58	0.0021 **		
$v_{air} \cdot L$	83,096.71	1	83,096.71	202.76	< 0.0001 **		
$Mc^2$	256.14	1	256.14	0.62	0.4551		
$v_{air}^2$	6858.82	1	6858.62	16.74	0.0046 **		
$L^2$	85.53	1	85.53	0.21	0.6616		
Residual	2868.84	7		409.83			
Lack of Fit	2138.59	3	712.86	3.90	0.1106 (NS)		
Pure Error	730.26	4		182.56			
Std. Dev			20.24				
Mean			184.31				
$\mathbb{R}^2$			0.9948				
Adj R <sup>2</sup>		0.9881					
Pred R <sup>2</sup>		0.9358					
Adep Pre		43.223					
C.V.%		10.98					
PRESS			35,358.41				

**Table 5.** ANOVA evaluation of linear, quadratic, and interaction terms for response and coefficient of  $\Delta p$  model.

Note: The symbol "\*\*" indicates the term is extremely significant.

As can be seen from Table 5, the  $\Delta p$  model F value of 148.56 corresponds to a low *p*-value (p < 0.0001), which implies that the model was significant as the test failed to accept the null hypothesis that variations in the response could not be explained by the model. This indicates that the  $\Delta p$  model developed by the RSM is significant, and the experimental  $\Delta p$  can be explained by the obtained model. Moreover, the values of  $R^2$ , Adj  $R^2$ , and Pred  $R^2$  are similar and all close to 1 [37], which also indicates that the  $\Delta p$  model is in a well-fitting performance and can be used to predicted the  $\Delta p$ . The value of the C.V.% term is 10.98%, indicating that there are only 10.98% of the experimental data that cannot be explained by the  $\Delta p$  model developed by the RSM, in statistics, if the value of the C.V.% is greater than 15%, the data may be abnormal and should be eliminated [19]. On the other hand, the predicted residual sum of squares (PRESS) is a measure of how well the  $\Delta p$  model fits each point in the design. The high PRESS value (35358.41) in the present work may be caused by the abnormal 10.98% data. The influences of Mc,  $v_{air}$ , and L on the  $\Delta p$  model can be determined by the *F*-value as well as the *p*-value. It can be obviously summarized that the terms of Mc,  $v_{air}$ , L, Mc· $v_{air}$ , Mc·L,  $v_{air}$ ·L, and  $v_{air}^2$  have significant influences on the  $\Delta p$  while the  $Mc^2$  and  $L^2$  have no influence on the  $\Delta p$ . For the significant terms, by estimating the corresponding *F*-value, the contributors to the  $\Delta p$ , in ascending order of significance, are as follows:  $v_{air}^2$ ,  $Mc \cdot v_{air}$ ,  $Mc \cdot L$ , Mc,  $v_{air} \cdot L$ , L, and  $v_{air}$ .

#### 3.2. Anderson-Darling Normality Test Results

In the present work, the residuals are the difference between the experimental  $\Delta p$  and the predicted  $\Delta p$  by the established model (Equation (2)). The AD test was conducted by the software Minitab 17.0, and the probability distribution plot of the residuals is shown in the following Figure 3. As can be seen from the figure, the obtained AD value (0.484) is less than a critical value of 0.752, and the associated *p*-value (0.594) of the AD test is significant at a 5% level (*p*-value > 0.05) [25]. The results indicate that the residuals follow a normal distribution, and the deviation between the experimental  $\Delta p$  and predicted  $\Delta p$ 

are random [26]. Accordingly, it can be concluded that the null hypothesis can be rejected and the model predictions are correlated with the experimental data over the factor-space under evaluation in the present work.



Figure 3. The results of the Anderson–Darling normality test.

# 3.3. The Interactions of the Independent Variables on the Pressure Drop

Based on the ANOVA analysis in Section 3.1, the  $Mc \cdot v_{air}$ ,  $Mc \cdot L$ , and  $v_{air} \cdot L$ , respectively, have significant influences on the  $\Delta p$ . The response surface as well as its corresponding contour plots are depicted in the following Figures 4–6. As can be seen from Figure 4a, the  $\Delta p$  increases with the increase of  $v_{air}$  under constant Mc, which might be due to the fact that the inertia resistance of the air increases with the increase of  $v_{air}$ , just as reported by Zhang et al. [10]. On the other hand, the  $\Delta p$  increases with increase of Mc under constant  $v_{air}$ , which might be caused by the increased  $\varepsilon$  in high Mc, just as reported by Li et al. that the  $\varepsilon$  of paddy layer increases with increase of paddy moisture content [38]. Though the suitable  $\Delta p$  for the engineering application should be further investigated by comprehensively considering the power of the fan, the contours shown in Figure 4b can be the reference for the single factor analysis.



**Figure 4.** The interaction of *Mc* and  $v_{air}$  on the  $\Delta p$  (**a**) and the contour plots (**b**).



**Figure 5.** The interaction of *Mc* and *L* on the  $\Delta p$  (**a**) and the contour plots (**b**).



**Figure 6.** The interaction of  $v_{air}$  and *L* on the  $\Delta p$  (**a**) and the contour plots (**b**).

Figure 5 depicts the interaction of *Mc* and *L* on the  $\Delta p$ , similar with the trend shown in above Figure 4.  $\Delta p$  increases with increase of *L*, which might be caused by the fact that the path of air flow through the paddy grain layer increases with the increase of *L* and further lead to the increase of  $\Delta p$ ; a similar finding has been reported by Rocha et al. for  $\Delta p$  of paddy rice layer [39]. On the other hand, the  $\Delta p$  increases with increase of *Mc*; the same reason analyzed in Figure 4 can be also used to explain the trend. Interestingly, the  $\Delta p$ under different *Mc* with the *L* under 0.4 m almost remains constant, indicating that the  $\Delta p$  is slightly affected by the *Mc* when the *L* is small, which can be regarded as a design reference of the bed layer depth. Moreover, it can be seen from Figure 5a that the  $\Delta p$  linearly varies the single factor *L* or *Mc*, while the  $\Delta p$  non-linearly varies with the interaction terms of *Mc*·*L*, just as shown in the following Figure 5b.

The interaction of  $v_{air}$  and L on the  $\Delta p$  are shown in the following Figure 6. As can be seen from Figure 6a that the  $\Delta p$  varies from the minimum 17.11 Pa to the maximum 689.56 Pa, the variation range is much larger than that of the interaction terms of  $Mc \cdot L$  and  $Mc \cdot v_{air}$ , indicating that the influence of term  $L \cdot v_{air}$  on  $\Delta p$  is more significant than that of  $Mc \cdot L$  and  $Mc \cdot v_{air}$ , just as analyzed in Section 3.1. Accordingly, in order to reach the objective of the efficient and energy-saving drying, efforts should be firstly made to optimize the drying parameters related to the L and  $v_{air}$  in the engineering drying application. Especially when the air with high  $v_{air}$  flow through the bed layer with large L, the  $\Delta p$  rapidly increases with the interaction term of  $L \cdot v_{air}$  (as shown in Figure 6b, in other words, the larger driven force for supplying the drying medium is needed when the  $L \cdot v_{air}$  is high.

# 3.4. The Comparison of the $\Delta p$ Model Developed by RSM and Ergun Model

In order to verify the feasibility of the  $\Delta p$  model developed by RSM, the comparison analysis focused on the RSM experiments for the  $\Delta p$  model developed by RSM and Ergun model was conducted, and the statistical indexes including  $R^2$ , *MAE*, *MSE*, and *RMSE* were calculated. The detailed analysis is in Section 3.4.1.

# 3.4.1. The Comparison of the $\Delta p$ in the RSM Experiments

Based on the ANOVA analysis results shown in Table 5, the second-order polynomial expression of the  $\Delta p$  model developed by the RSM ( $\Delta p_{RSM}$ ) are expressed as following Equation (8):

$$\Delta p_{\rm RSM} = 174.60194 - 2.20717Mc - 981.35993v_{air} - 403.3567L + 27.32537Mc \cdot v_{air} + 15.95439Mc \cdot L + 1281.17778v_{air} \cdot L - 0.17375Mc^2 + 645.768v_{air}^2 - 22.25679L^2$$
(8)

The 17 sets of independent variables tabulated in Table 5 were substituted into the above  $\Delta p_{RSM}$  model and the predicted  $\Delta p_{RSM}$  values were obtained. On the other hand, the 17 sets of independent variables were also substituted into the  $\Delta p_{Eur}$  model shown in Equation (2) by transmitting the *Mc* into the corresponding  $\varepsilon$  (just as tabulated in Figure 2), and the predicted  $\Delta p_{Eur}$  values were obtained and compared with the corresponding predicted  $\Delta p_{RSM}$ . The comparison between the  $\Delta p_{RSM}$  and the  $\Delta p_{Eur}$  were evaluated by the validation metrics (Equations (2)–(5)), and the statistical results are tabulated in Table 6.

**Table 6.** The statistical results of the RSM experiment for comparing  $\Delta p_{RSM}$  and  $\Delta p_{Eur}$ .

Statistical Indexes	RSM Model	Ergun Model
Statistical muexes	$\Delta p_{RSM}$	$\Delta p_{Eur}$
Determination coefficient ( $R^2$ )	0.9948	0.9868
Mean-square error (MSE)	10.9021	15.7041
Mean absolute error (MAE)	2868.9372	7292.4115
Root-mean-square error( <i>RMSE</i> )	12.9908	20.7115

As can be seen from Table 6, the index  $R^2$  (0.9948) of the RSM model is higher than that of the Ergun model (0.9868), while the indexes *MAE*, *MSE*, and *RMSE* of the RSM model are, respectively, lower than the corresponding index of the Ergun model, which indicates that the pressure drop model developed by the RSM is better fitted than the Ergun model.

# 3.4.2. The Single Factor Analysis of the $\Delta p$

In order to validate fitting performance of the  $\Delta p_{RSM}$  and  $\Delta p_{Erg}$ . The second-order polynomial RSM model was transmitted into three first-order quadratic models by substituting the independent variables shown in Table 3 into Equation (8), the single factor pressure drop models based on the  $\Delta p_{RSM}$  are as follows:

$$\Delta p_{Mc} = -72.8038915 + 19.7482445Mc - 0.17375Mc^2 \tag{9}$$

$$\Delta p_{\mathbf{v}_{air}} = 14.4119253 + 175.678453 \mathbf{v}_{air} + 645.768 \mathbf{v}_{air}^2 \tag{10}$$

$$\Delta p_I = -12.72658565 + 346.593494L - 22.25679L^2 \tag{11}$$

Based on the above Equations (6), (9)–(11), the variations of  $\Delta p$  with Mc,  $v_{air}$ , and L can be obtained and, respectively, depicted in the following Figures 7–9. As can be seen from Figure 7 that the  $\Delta p$  is proportional to the Mc, and the variation range of the  $\Delta p$  was ascertained to be 86.38–197.57 Pa. It can be summarized from Figure 2 that the equivalent diameter  $d_g$  increases with the Mc while porosity of the bed layer  $\varepsilon$  decreases with the

increase of the *Mc*, indicating that the volume of the air pathways decreased with the increase of *Mc* [40], and further lead to the flow resistance of the air passing through the bed layer will be increased with the increase of the *Mc*. On the other hand, it can be seen from Figure 7 that the  $\Delta p_{RSM}$  are more closed to the experimental  $\Delta p$  than the  $\Delta p_{Erg}$ .



**Figure 7.** The variations of  $\Delta p$  with *Mc* under the constant  $v_{air}$  of 0.35 m/s and *L* of 0.5 m.



**Figure 8.** The variations of  $\Delta p$  with  $v_{air}$  under the constant *Mc* of 18.9 %w.b. and *L* of 0.5 m.



**Figure 9.** The variations of  $\Delta p$  with L under the constant  $v_{air}$  of 0.35 m/s and Mc of 18.9 %w.b.

Figure 8 depicts the variations of  $\Delta p$  with  $v_{air}$  under the constant Mc of 18.9 %w.b. and L of 0.5 m. Similar with the variation trend of the  $\Delta p$  shown in the above Figure 7,  $\Delta p$  also increases with increase of  $v_{air}$ , and the variation range of the  $\Delta p$  was ascertained to be 38.44–352.92 Pa. Moreover, it can be seen from Figure 8 that the  $\Delta p_{Erg}$  with the  $v_{air}$  of 0.1 m/s and 0.15 m/s are more closed to the corresponding experimental  $\Delta p$  than the  $\Delta p_{RSM}$ , indicating that the Ergun model has a better prediction performance than the developed RSM model when the  $v_{air}$  is under 0.2 m/s. The same conclusions have been made by Mahmood et al. [41] and Ye et al. [10]. However, in this case, the developed  $\Delta p_{RSM}$ model has a better performance than the Ergun model when the  $v_{air}$  is above 0.2 m/s, which may be more suitable for guiding the actual process.

The variations of  $\Delta p$  with *L* under the constant  $v_{air}$  of 0.35 m/s and *Mc* of 18.9 %w.b. are depicted in Figure 9. It can be seen from the figure that the  $\Delta p$  linearly increases with the increase of *L*, and the  $\Delta p$  gets the minimum (27.68 Pa) and maximum value (276.83 Pa), respectively, at the *L* of 0.1 and 1m. On the other hand, it can be also seen from Figure 9 that, for the all levels of *L*, the fitting performance of the  $\Delta p_{RSM}$  is better than that of the  $\Delta p_{Erg}$ . In order to further investigate the fitting performance of the  $\Delta p_{RSM}$  and the  $\Delta p_{Erg}$  in the above three single factor experiment, the statistical indexes mentioned in Section 2.3.3 were also calculated and the results are tabulated in the following Table 7.

Table 7. The statistical results for the single factor experiments.

Statistical Indexes		RSM Model	l	Ergun Model			
Statistical indexes	$\Delta p_{Mc}$	$\Delta p_{vair}$	$\Delta p_L$	$\Delta p_{Mc}$	$\Delta p_{vair}$	$\Delta p_L$	
Determination coefficient ( $R^2$ )	0.9755	0.9909	0.9918	0.8539	0.9846	0.9737	
Mean-square error ( <i>MSE</i> )	35.9195	89.4276	64.5378	213.7543	151.9289	206.1363	
Mean absolute error (MAE)	5.6094	8.4528	6.3943	13.9521	10.1731	12.6444	
Root-mean-square error ( <i>RMSE</i> )	5.9933	9.4566	8.0335	14.6203	12.3259	14.3574	

As can be seen from Table 7 that the  $R^2$  value of each single factor model based on the  $\Delta p_{RSM}$  is higher than that of the corresponding model based on the  $\Delta p_{Erg}$ , while the other indexes (*MSE*, *MAE*, and *RMSE*) of each single factor model based on the  $\Delta p_{RSM}$  are lower than the corresponding index of the corresponding model based on the  $\Delta p_{Erg}$ . Which indicates that the single factor model  $\Delta p_{Mc}$ ,  $\Delta p_{vair}$ , and  $\Delta p_L$  based on the  $\Delta p_{RSM}$  has better fitting performance than that of the corresponding single factor model based on the  $\Delta p_{Erg}$ . By combining the results obtained in Section 3.4.1, it can be concluded that the developed ventilation resistance model based on the RSM has a better predicting performance than the traditional Ergun model.

#### 4. Conclusions

By considering the moisture content (*Mc*), air velocity ( $v_{air}$ ), and grain bed layer depth (*L*) as the key factors affecting the ventilation resistance of the air, one must regard the pressure drop ( $\Delta p$ ) as the key index characterizing the ventilation resistance of the air. The present work investigated the influences of each factor and the interactions of the factors on the pressure drop; a second-order polynomial model was also obtained based on the RSM. The detailed conclusions depending on the main results are listed as follows:

- (1) The relations among the Mc,  $\varepsilon$ , and  $d_g$  were revealed and the mathematical expressions were also given in the present work.
- (2) The  $\Delta p$  increases with the increase of Mc,  $v_{air}$ , and L and the contributors to the  $\Delta p$ , in ascending order of significance, are as follows:  $Mc < L < v_{air}$ .
- (3) The interaction analysis indicates that the interactions of the  $v_{air}$  and L has the most significant influence on the  $\Delta p$ , and the match principle between the  $v_{air}$  and L should be firstly considered when optimizing the drying process.
- (4) A second-order polynomial  $\Delta p$  model based on the RSM was obtained, and its fitting performance was verified to be better than that of the traditional Ergun model by evaluating the  $R^2$ , *MSE*, *MAE*, and *RMSE*.
- (5) The developed  $\Delta p$  model based on the RSM shows a better fitting performance than the Ergun model when the  $v_{air} \ge 0.2$  m/s, while the Ergun model shows better when the  $v_{air}$  is under 0.2 m/s.

The present work revealed the influences of the variables that can be directly measured in an engineering drying application on the pressure drop and established a prediction model of the pressure drop. Thus, the main results would be helpful for further optimizing the drying process. Further study is recommended to investigate the pressure drop variation characteristics by taking the air temperature as well as the paddy grain flow velocity into consideration.

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