Application of Artificial Neural Network for Prediction of Key Indexes of Corn Industrial Drying by Considering the Ambient Conditions

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Received: 7 July 2020; Accepted: 13 August 2020; Published: 14 August 2020

Abstract: Uncontrollable ambient conditions are the main factors limiting the self-adaption control of an industrial drying system. To achieve the goal of accurate control of the drying process, the influence of the ambient conditions on the drying behavior should be taken into consideration when modeling the drying process. Present work introduced an industrial drying system with a loading capacity of 50 t, two artificial neural network prediction models with (IANN) and without (OANN) considering the ambient conditions were established using artificial neural network modeling approach. The ambient conditions on the moisture content ($MC$), exergy efficiency of the heat exchanger ($n_{ex,h}$) and specific recovered radiant energy ($Er$) of the drying process were also investigated. The results showed that the $n_{ex,h}$ and $Er$ increase with the increase of ambient temperature while the drying time decrease with the increase of the ambient temperature. The IANN model has a better prediction performance that of OANN model. An optimal architecture of 9-2-12-3 artificial neuron network model was developed and the best prediction performance of the artificial neural network (ANN) model were found at a training epoch number of 30, and a momentum coefficient of 0.4, where the coefficient of determination of moisture content, exergy efficiency of heat exchanger, and the specific recovered radiant energy, respectively are 0.998, 0.992, and 0.980, indicating that the model has an excellent prediction performance and can be used in engineering practice.

Keywords: artificial neural network; corn drying; industrial; prediction

1. Introduction

Drying is the process of removing the moisture from natural products (e.g., agricultural products, wood, and fruits) or industrial materials (e.g., lignite, ceramics, and medical materials) down to a specific moisture content, while ensuring at the same time prime product quality, high throughput, and minimal operational costs [1,2]. Industrial drying is an effective approach to achieve the efficient and economic production of the agricultural product, while the real-time detecting and controlling technology plays a very important role in the production. However, the drying is a typical nonlinear complex process and there are various variables coupled with each other during the drying process. The real-time measurement of the drying process has hysteresis and is interfered by many factors [3]. Therefore, it is very difficult to establish a mathematical model that is in line with the actual drying process in industrial production.

In the last few decades, researchers have done a lot of works on the mathematical modeling of grain drying process, which mainly focus on the modeling of single particle drying [4–6], thin layer drying [7,8], and deep bed drying [9–11], of which the deep bed drying model is generally used in industrial drying. The typical deep bed drying model is partial differential equation (PDE), which is...
based on the principle of heat and mass transfer. The kind of model are mainly adopted to simulate the drying process, so as to understand the variation law of various parameters in the drying process, and provide theoretical basis for simplifying the model. However, owing to the fact that this kind of model is complex and difficult to solve, it cannot be used for real-time control in drying process [12]. Liu, Q et al. [13] established a predictive and control model by combining the prediction model, rolling optimization algorithm and feedback correction algorithm, the problems of hysteresis and multi disturbance in the control process of grain dryer were solved. Though the mathematical model is considered to be one of the best control methods for industrial-scale grain dryers when the hot air temperature is in the range of 85–120 °C, and the moisture content of 21–32% w.b., the control and predicting effects are still affected by the analytical accuracy of the deep drying process as well as the accuracy of moisture on-line detection. Based on the analysis above, a simple and sensitive prediction model is necessary to realize the automatic control of drying process and achieve the goal of high efficiency, high quality, and energy saving drying.

Artificial neural network (ANN) methodology has great application potential in the classification and prediction of complex systems [14,15]. Generally, the methodology identifies the system by collecting certain input and output data to get the model without revealing the mathematical equation in advance [16]. Owing to the advantages of the self-learning, self-adaptation, and flexibility, ANN methodology was also widely applied in identification and modeling of grain drying system. A. Dai et al. established a 8-10-1 back propagation (BP) neural network prediction model for the drying process of the combined side-heat infrared radiation and convection grain dryer. The input of the model is eight variables of the grain dryer, and the output of the model is the moisture ratio (or drying rate) of grain material. The results showed that the model has an excellent prediction performance (coefficient of determination $R^2 = 0.9989$), and the feasibility of the application of ANN methodology in drying the drying process are also verified [17]. Farkas, I et al. applied the ANN methodology to an agricultural fixed-bed dryer, the relationship between the moisture distribution of the dried grain and the physical parameters of the drying air temperature, humidity, and air flow rate were determined; the results showed that ANN methodology can be effective for modelling of the grain drying process [18]. Momenzadeh et al. [19] established an ANN model to predict the drying characteristics of shelled corn drying in a fluidized bed dryer, and the results showed that a network with the Tansig transfer function and trainrp back propagation algorithm made the best prediction performance ($R = 0.9991$). Zare et al. [20] studied the drying characteristics of rough rice drying in a hot air dryer assisted by infrared heating, ANN methodology was also adopted to predict the bending strength of brown rice kernel, percentage of cracked kernels and moisture content, the simulation results showed that the established model has an excellent prediction performance. Based on the literature review, it can be inferred that the ANN methodology can be adopted to predict the drying behavior of the corn drying in an industrial scale drying system. Though the ANN modeling approach has been widely used predicting the drying process, few reports have taken the ambient conditions into consideration when establishing the ANN model. However, the ambient conditions are the main factors affecting prediction accuracy of the established ANN model; therefore, the ambient conditions should be fully considered especially for the outdoor installed drying system.

For an industrial scale grain drying plant, the drying system is usually installed outdoors [17,21,22]; however, the installed method is difficult to control the ambient factors. As analysis above, though the ambient conditions are difficult to be controlled, the influences of ambient conditions on the drying performance should be taken into consideration when analyzing the drying process. The present work aims to verify that the ambient conditions should be taken into consideration when analyzing and modeling the drying process for the outdoor installed industrial scale corn drying system and, accordingly, establish an ANN model for predicting the moisture content of corn, exergy efficiency of the heat exchanger, and the specific recovered exergy—hoping to lay some theoretical basis for guiding the practical production.
2. Materials and Methods

2.1. Materials

The corn (Changcheng 799#) was freshly harvested from a local farm at Xinzhou City, Shanxi Province, China. The threshed corn kernel were stored on the open yard and the average initial moisture content of the corn kernel is ascertained to be 32.2% dry basis (d.b.) by using the 105 °C constant weight methodology [7]. The impurity content is less than 5%.

2.2. Equipment Description

The scene graph of the outdoor installed industrial drying system is shown in Figure 1. As can be seen from the figure, the system mainly consisted of 11 components, including the conveyor belt (CB), dust removal chamber, discharging device (DD), induced draft fan (IDF), drying chamber (DC), preheating room (PR), hoist (HST), grain discharging pipeline (GDP), flue gases pipeline (FGP), heat exchanger (HE), combustion chamber (CC), heat exchanger (HE). Of which the CC, IDF, HST, and DD are the electrical energy consumed components while the CC is the biomass energy consumed component, the PR consisted of eight far-infrared radiators. The details of the electric energy consumed components are listed in Table 1.

![Figure 1. The scene graph of the industrial drying system.](image)

| Component                      | Number | Power   |
|--------------------------------|--------|---------|
| Induced draft fan              | 2      | 18.5 kW |
| Discharging device             | 1      | 3.5 kW  |
| Hoist                          | 1      | 5.5 kW  |
| Conveyor belt                  | 1      | 3.5 kW  |
| Data acquisition system        | 1      | 2.5 kW  |

2.3. Working Principle of the System

Figure 2 depicts the workflow and the schematic diagram of the drying system. As can be seen from the left of the figure, the whole drying operation experiences three periods. Feeding period ($P_1$): the threshed corn kernel is conveyed to the HST by the CB and further lifted by the HST, the period lasts almost 90 min under the hypothesis of the drying chamber holds up 50,000 kg. Drying period
m) (P1): after the drying chamber is full filled, the CC, IDF, and the DD are sequentially operated and then the corn material begins the cycle drying process. Discharging period (P3): when the moisture content is about 14% d.b., the IDF and the CC are shut down, the grain discharge valve on the top of the dryer is opened, and the dried corn is discharged through the grain-discharging pipeline, as shown in the Figure 2, this period lasts about 90 min. During the drying process, the ambient temperature (T0), ambient relative humidity (RH0), outlet air relative humidity (RHout), temperatures of inlet air (Tin), outlet corn (Tc), inlet flue gas (Tfg), and the far-infrared radiator (Tr) were measured by the corresponding temperature and humidity sensors, as shown in Figure 2. The details of the instruments adopted in the present work are tabulated in Table 2.

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2.4. Drying Kinetics

In the present work, the dry basis moisture content (MC) of the corn can be calculated followed by Equation (1) [23]:

\[ MC = \frac{m_t - m_d}{m_d} \times 100\% \]  

(1)

where \( m_t \) is the weight of the material at time \( t \); \( g \); \( m_d \) is the weight of absolute dry matter, which can be determined using the 105 °C constant weight methodology [7].

2.5. Exergy Recovery Performance

In order to investigate the heat recovery behavior of the far-infrared radiator, the Wien Displacement Law [24] was adopted to compute the far-infrared wavelength (\( \lambda \)) and the specific recovered radiant energy (Er), which can be, respectively, determined followed by Equations (2) and (3):

\[ \lambda \cdot T_r = 2897.6 \text{ um} \cdot \text{K} \]  

(2)
\[ E_r = \sigma \cdot T_r^4 \]  

(3)

where \( \lambda \) is the far-infrared wavelength, um; \( T_r \) is the absolute temperature of the radiator, K; \( E_r \) is the specific recovered energy, W; \( \sigma \) is the black body radiant constant, \( 5.67 \times 10^{-8} \) W/(m\(^2\)·K\(^4\)).

### 2.6. Exergy Efficiency of the Heat Exchanger

As can be seen from the Figure 2, the exergetic efficiency of the heat exchanger (\( \eta_{ex,h} \)) can be expressed as:

\[ \eta_{ex,h} = \frac{\dot{E}_x}{\dot{E}_{fg,in} - \dot{E}_{fg,out}} \]  

(4)

where the \( \dot{E}_{fg,in} \) and \( \dot{E}_{fg,out} \) are the specific exergy inlet and outlet of the heat exchanger; \( \dot{E}_{x,in} \) is the specific exergy outlet of the heat exchanger, which can be calculated followed by Equation (5) [25–27]:

\[
\dot{E}_x = \dot{m}_a \left\{ \left( C_a + \omega_a C_v \right) (T_a - T_0) - T_0 \left[ \left( C_a + \omega_a C_v \right) \ln \left( \frac{T_a}{T_0} \right) - (R_a + \omega_a R_v) \ln \left( \frac{P_a}{P_0} \right) \right] \right. \\
\left. + T_0 \left[ (R_a + \omega_a R_v) \ln \left( 1 + \frac{1.6078 \omega_a}{1 + 1.6078 \omega_a} \right) + 1.6078 \omega_a T_0 \ln \left( \frac{\omega_a}{\omega_0} \right) \right] \right\}
\]  

(5)

where the mass flow rate of the dry air (\( \dot{m}_a \)) can be calculated followed by Equation (6) [28]:

\[ \dot{m}_a = \rho_a V_{ad} \]  

(6)

where \( \rho_a \) is the density of the dry air, which can be determined using Equation (7) [29]:

\[ \rho_a = 101.325 / 0.287 T \]  

(7)

The humidity ratio of the air (\( \omega_a \)) in Equation (5) can be determined by using the following Equation (8) [30]:

\[ \omega_a = 0.622 \frac{\phi P_{vs,a}}{P_a - \phi P_{vs,a}} \]  

(8)

Considering the flue gas is the mixture of many chemical compositions, the specific heat, and exergy depending on the chemical composition of fuels, excess air ratio, and gas temperature. The exergy calculation model developed by C. Coskun et al. was adopted to calculate the exergy of the flue gas [31]:

\[ \dot{E}_{fg} = c_{p,fg} m_{fg} \left( T_{fg} - T_0 \right) - T_0 \left[ \ln \left( \frac{T_{fg}}{T_0} \right) \right] \]  

(9)

\[ c_{p,fg} = \frac{c_{p,CO_2}}{a_C + b_N + c_H + d_S} \cdot \frac{m_{tot,steo}}{m_{fg}} + f_A \]  

(10)

\[ c_{p,CO_2} = 0.1874 \times 1.000061 T_{fg}^{0.2665} \]  

(11)

### 2.7. ANN Modeling

To ascertain the influence of the ambient conditions on the prediction performance of the drying process, two artificial neuron network models with (IANN) and without (OANN) considering the ambient conditions were established.

#### 2.7.1. The Input Layer Neurons

The present work regards the drying time (\( t \)), ambient temperature (\( T_0 \)), ambient relative humidity (\( RH_0 \)), outlet air relative humidity (\( RH_{a,out} \)), temperatures of inlet air (\( T_{a,in} \)), outlet air (\( T_{a,out} \)), outlet corn (\( T_c \)), inlet flue gas (\( T_{fg,in} \)), and the far-infrared radiator (\( T_r \)) as the input layer neurons. The number of the input layer neurons for IANN and OANN are 9 and 7, respectively.
2.7.2. The Output Layer Neurons

The present work considers the corn moisture content (MC), exergetic efficiency of the heat exchanger ($\eta_{ex,h}$), and the energy recovery rate of the radiator ($Er$) as the output layer neurons; therefore, the output layer neurons for the two models are 3.

2.7.3. The Hidden Layer Neurons

According to some open literature [7,17,18], the hidden layer neurons of IANN and OANN can be ascertained by the following Equation (12):

$$n = \sqrt{a + b + m} \quad (12)$$

where, $n$ is the number of hidden layer neurons, $a$ is the number of neurons in the input layer, $a = 9$ for the IANN model and $a = 7$ for the OANN, $b$ is the number of neurons in the output layer, $b = 3$; $m$ is a constant between 1 to 10, so the number of hidden layer neurons for the IANN and OANN can be ascertained to be both in the range of $4 < n < 14$. Therefore, the number of hidden neurons for the two ANN models can be determined by iteratively changing the number from 5 to 13 and monitoring the reliability of the response with respect to the validation set, as recommended by Furferi, R et al. [32].

2.7.4. The Transfer and Train Functions

The present work adopted the Tansig function as the transfer function of the hidden layer. Compared with the traditional BP algorithm, the Levenberg–Marquardt algorithm has a faster gradient descent and can meet the error requirement with less epochs [33]. Therefore, the Levenberg–Marquardt algorithm is adopted to be the training function of the established network.

2.7.5. The Physical Structure of the Models

Based on the analysis above, the physical structure of the IANN and OANN models are described in Figure 3, and the training process is shown in Figure 4.

![Figure 3. The established IANN model (a) and OANN model (b).](image-url)
2.7.6. Experimental Data

The experimental test was conducted from 16 October to 19 November, 2019, in Xinzhou, Shanxi Province, China. During the test period, the local ambient temperature changed a lot (e.g., the $T_0$ on 16 October varies from 8.6 to 12.8 °C while the $T_0$ on 17 November varies from −6.2 to 0.32 °C). In order to investigate the influences of ambient conditions on the drying behavior of the drying system, 327 groups of drying data for three days (17 October, 30 October, and 19 November) with significant $T_0$ difference were selected to be analyzed in the present work. The experimental data were measured every 5 min interval, and the data with obvious errors (e.g., the imprecise measurement of the grain moisture sensor caused by the ice phenomenon inside the grain at the beginning of the test, or the random error caused by the system failures) were eliminated during the process. The selected data were normalized followed by Equation (13) before the ANN modeling. The partial experiment data and the related calculation results are tabulated in Table 3.

$$X = \frac{X_i - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}}$$  \hspace{1cm} (13)

| Day          | t/min | $T_0$ | RH$_0$ | $T_{a,in}$ | $T_{a,out}$ | $T_c$ | $T_{fg,in}$ | RH$_{a,out}$ | $T_r$ | MC  | $\eta_{ex,h}$ | Er  |
|--------------|-------|-------|--------|------------|-------------|------|-------------|--------------|------|-----|---------------|-----|
| 17 October   | 40    | 8.65  | 44.76  | 102.6      | 34.1        | 30.8 | 927.5       | 99.9         | 97.6 | 29.5| 0.43          | 19.39|
|              | 75    | 9.21  | 54.8   | 108.2      | 32.3        | 28.2 | 861.1       | 99.9         | 102.5| 28.1| 0.52          | 20.44|
|              | 125   | 9.5   | 54.8   | 117.7      | 38.8        | 30.3 | 930.7       | 99.2         | 97.8 | 24.3| 0.51          | 19.43|
|              | 270   | 12.56 | 55.54  | 114.4      | 35.3        | 31.2 | 867.1       | 77.6         | 96.6 | 17.2| 0.54          | 19.18|
|              | 435   | 8.53  | 53.32  | 107.7      | 46.1        | 35.4 | 880.9       | 64.2         | 104.1| 14.8| 0.51          | 20.79|

Table 3. Partial experiment data and the related calculation results.
Table 3. Cont.

| Day         | Input Neurons | Output Neurons |
|-------------|---------------|----------------|
|             | $t/\text{min}$| $T_0$ | $RH_0$ | $T_{a,in}$ | $T_{a,out}$ | $T_c$ | $T_{fg,in}$ | $RH_{a,out}$ | $T_r$ | $MC$ | $\eta_{ex,h}$ | $Er$ |
| 30 October  | 25            | 3.83  | 63.25  | 92.1      | 32.9      | 25.8  | 867.5      | 99.9        | 95.5  | 31.2 | 0.44          | 18.95 |
|             | 105           | 5.01  | 57.02  | 102.6     | 30.2      | 24.8  | 930.7      | 99.9        | 96.3  | 26.4 | 0.44          | 19.12 |
|             | 355           | 8.14  | 51.26  | 100.3     | 32.1      | 28.8  | 892.6      | 74.2        | 97.3  | 18.9 | 0.45          | 19.33 |
|             | 500           | 5.27  | 48.25  | 96.3      | 33.6      | 30.7  | 961.5      | 64.2        | 98.6  | 14.2 | 0.39          | 19.60 |
| 19 November | 15            | 0.24  | 43.55  | 85        | 19.1      | 18    | 950.6      | 99.8        | 92.9  | 31.7 | 0.36          | 18.43 |
|             | 85            | 1.72  | 49.7   | 85.3      | 23.8      | 18.7  | 973.2      | 99.9        | 87.5  | 29.3 | 0.34          | 17.36 |
|             | 415           | 2.26  | 45.77  | 95        | 25.7      | 18.9  | 987.7      | 99.9        | 90.5  | 25.3 | 0.38          | 17.95 |
|             | 545           | 0.7   | 41.47  | 82.5      | 28.6      | 23    | 876.1      | 56.8        | 92.8  | 14.2 | 0.39          | 18.11 |

2.8. Statistical Analysis

In the present work, the predicting performance of the established ANN models are estimated by the statistic indexes including: coefficient of determination ($R^2$), mean squared error (MSE), and mean absolute error (MAE), which can be, respectively, calculated followed by Equations (14)–(16) [34]:

\[
R^2 = 1 - \frac{\sum_{i=1}^{N} (x_i - y_i)^2}{\sum_{i=1}^{N} (\bar{x} - y_i)^2}
\]  

(14)

\[
MSE = \frac{1}{N} \sum_{i=1}^{N} (x_i - y_i)^2
\]  

(15)

\[
MSE = \frac{1}{N} \sum_{i=1}^{N} |x_i - y_i|
\]  

(16)

where $N$ is the number of the data points, $x$ is the experimental results; $\bar{x}$ is the mean value of the experimental data, and $y$ is the results predicted by the established ANN model.

2.9. Uncertainty Analysis

In the present study, the experimental errors and uncertainties mainly arose from convective dryer, instruments accuracy, observation, and the test planning. Uncertainties of the experimental in this work were ascertained by the following Equations (17) and (18) [35] and the results were presented in Table 4:

\[
N = \sum_{i=1}^{r} Ni / r
\]  

(17)

\[
u = (\frac{1}{r-1}) \sum_{i=1}^{r} (Ni - N)
\]  

(18)

where $N$ is the result, $r$ is the number of runs, $i$ is integer, and $u$ is uncertainty.

Table 4. Uncertainties of the experimental parameters.

| Parameters               | Unit | Uncertainties |
|--------------------------|------|---------------|
| Inlet air temperature    | °C   | ±0.5          |
| Outlet air temperature   | °C   | ±0.3          |
| Outlet corn temperature  | °C   | ±0.2          |
| Radiator temperature    | °C   | ±0.2          |
Table 4. Cont.

| Parameters             | Unit | Uncertainties |
|------------------------|------|---------------|
| Ambient temperature    | °C   | ±0.1          |
| Ambient relative humidity | %   | ±0.3          |
| Flue gas temperature   | °C   | ±0.2          |
| Outlet air relative humidity RH |   | ±0.3          |
| Corn moisture content  | %   | ±0.2          |

3. Results and Discussion

3.1. The Influence of Ambient Temperature on the Energy and Exergy Performance of the Drying System

In order to fully investigate the influence of ambient temperature on the drying behavior of the drying system, the experimental data in three days with different ambient temperatures and similar relative humidity (17 October: 8.07 °C ≤ T₀ ≤ 13.41 °C, 42.51% ≤ RH₀ ≤ 56.36%; 30 October: 3.26 °C ≤ T₀ ≤ 8.87 °C, 47.26% ≤ RH₀ ≤ 65.22%; 19 November: −0.74 °C ≤ T₀ ≤ 5.18 °C, 40.35% ≤ RH₀ ≤ 63.22%) are adopted for the analysis. The variations of corn moisture content and corn temperature with drying time are shown in Figure 5.

![Figure 5](image-url)

Figure 5. The variations of corn moisture content and corn temperature with drying time.

The loading capacity of the dryer is considered to be 50,000 kg accuracy and the initial moisture content of the corn were also determined to be 32% d.b. for the three experimental days. As shown in Figure 5, MC decreases with the increase of t while T_c slightly increases with the increase of t for the three sets of experimental data. The MC decreases in a stepped way owing to the fact that corn drying is the circulate drying process, and the circulate time for each circle was ascertained to be 90 min. Similar drying process for agricultural product industrial drying were reported by Ma X.Z. et al. in 2017 [36]. The total drying time for a unit drying operation in 17 October, 30 October, and 19 November, are, respectively, ascertained to be 480, 540, and 600 min, indicating that the T₀ has a great influence on
the drying kinetics of the corn industrial drying. The $T_c$ for the three sets of experimental data are less than 38 °C, as recommended by Skoneczna-Luczków, J. et al. [37]. Moreover, it can be obvious found that the $T_0$ under the same drying time for the three days, in ascending order of values, are as follows: $T_c$ in 19 November, $T_c$ in 30 October, $T_c$ in 17 October, which might be caused by the heat change efficiency of the heat exchanger.

The exergy efficiency of the heat exchanger was calculated followed by Equation (4), and the results are depicted in Figure 6. As can be seen from the figure, even if the $\eta_{ex,h}$ fluctuates a lot with the drying time, which might be caused by the fluctuating inlet flue gas temperature, it can be obviously found that $\eta_{ex,h}$ in 17 October is higher than that in 30 October and 19 November. The $\eta_{ex,h}$ for the three days, respectively, ranges from 0.391 to 0.648, 0.350 to 0.601, and 0.249 to 0.434. It is interesting that there is a clear upward trend of the $\eta_{ex,h}$ for three days after 260 min owing to the fact that $T_0$ rose up at noon for the three days. Accordingly, it can be concluded that the $T_0$ has a significant influence on the heat exchange performance of the heat exchanger, as well as the drying performance of the whole drying process. Moreover, for the present industrial-scale drying system, the ambient conditions should not be considered as the dead state, the ambient temperature should be take into consideration when analyzing the energy and exergetic performance of the dryer. Similar findings have been reported by Jörg Schemminger et al. [38] for ambient air cereal grain drying; they developed a model for predicting the drying behavior based on the climatic data parameters (ambient temperature and relative humidity).

![Figure 6. Variations of exergy efficiency of the heat exchanger and the ambient temperature with drying time.](image)

Waste heat recovery is an effective approach to improve the energy efficiency of an energy consumption system. In the present work, eight far-infrared radiators inserted into the drying chamber were adopted to recover the waste heat in outlet flue gas. As can be seen from Figure 6, the values of $\gamma$ in 19 November, 30 October, and 17 October, respectively, vary from 7.61 to 7.90 um, 7.77 to 7.92 um, and 7.81 to 8.15 um, which are all closed to the optimized absorption far-infrared wavelength (9 μm)
of cereal grain, as recommend by Zhu W et al. in 2003 [39]. The $Er$ under the same drying time for the three days, in ascending order of values, are as follows: $Er$ in 17 October, $Er$ in 30 October, $Er$ in 19 November, owing to the fact that the $Er$ is directly proportional to the $Tr$, as described in Equation (7). The total recovered exergy by the radiators for 17 October, 30 October, and 19 November are, respectively, ascertained to be 571.12, 621.17, and 650.43 MJ, as shown in the Figure 7b.

![Figure 7](image-url)  
**Figure 7.** The variations of specific recovered exergy, wavelength with drying time (a) and the total exergy recovered by the radiator (b).

### 3.2. Analysis of Prediction Results of BP Neural Network

Based on the analysis in Section 2.7, the number of input layers of the IANN and OANN models were, respectively, ascertained to be 9 and 7; the outlet layers of the two models are 3, while the other
key parameters, such as numbers of hidden layers, neurons, training epochs, and the momentum coefficient, should be further determined. The variation range of the key parameters of the two models are tabulated in Table 5.

Table 5. Configurations of the artificial neural network (ANN) models.

| Parameters of the ANN Models | Range        |
|-----------------------------|--------------|
| Number of hidden layers     | 1–3          |
| Number of neurons           | 5–13         |
| Momentum coefficient        | 0.1–0.4      |
| Number of training epochs   | 300–1500     |

Based on the configurations of the ANN models, the 327 experimental data sets were used for the training (training epoch number of 1000, learning rate of 0.1). The variation of MSE values with different ANN configurations for the two models are tabulated in Table 6. As can be seen from the Table 6, the lowest MSE value of the IANN model is ascertained to be $1.3876 \times 10^{-4}$ when the hidden layer number is 2, neuron number is 12, and momentum coefficient is 0.4, while the MSE value of the OANN model is ascertained to be $2.5324 \times 10^{-4}$ when the hidden layer number is 2, neuron number is 12 and momentum coefficient is 0.4. In order to further investigate the influence of the training epochs on the MSE of the ANN models, the different training epochs (300–1500) and neuron numbers (5–13) are selected to train the IANN model with the hidden layer number of 2 and momentum coefficient of 0.4, and OANN model, with the hidden layer number of 3, and momentum coefficient of 0.4. The results are shown in Tables 7 and 8. It obviously can be seen from the Table 7 that the IANN model displays the best prediction performance (MSE = $0.75975 \times 10^{-4}$) when the training epochs are 1500 and the hidden layer neuron numbers are 12, while the OANN model displays the best prediction performance (MSE = $1.4542 \times 10^{-4}$) when the training epochs are 1500 and the hidden layer neuron numbers are 10. Accordingly, the architecture of the IANN model is ascertained to be 9-2-12-3, while the OANN model is 7-2-10-3.

Table 6. The variation of mean squared error (MSE) values with different ANN configurations.

| Number of Hidden Layer | MSE Values for Momentum Coefficient ($\times 10^{-4}$) |
|------------------------|-------------------------------------------------------|
|                        | 0.1         | 0.2         | 0.3         | 0.4         |                        |
|                        | IANN        | OANN        | IANN        | OANN        | IANN        | OANN        | IANN        | OANN        |                        |
| 1                      |             |             |             |             |             |             |             |             |                        |
| 6                      | 3.2503      | 5.2432      | 2.802       | 4.2535      | 3.2214      | 5.3265      | 2.4048      | 3.8654      |                        |
| 8                      | 3.4338      | 4.9585      | 4.9191      | 4.3254      | 2.8923      | 4.8659      | 3.3991      | 3.5462      |                        |
| 10                     | 3.0859      | 5.2153      | 2.8526      | 5.3215      | 1.7918      | 4.8654      | 1.4452      | 3.5412      |                        |
| 12                     | 2.9181      | 4.5241      | 1.4097      | 3.2546      | 1.7174      | 5.2136      | 1.6129      | 3.2654      |                        |
| 2                      |             |             |             |             |             |             |             |             |                        |
| 6                      | 2.5645      | 4.6235      | 3.0270      | 5.2365      | 2.9827      | 5.0231      | 2.9694      | 3.1205      |                        |
| 8                      | 5.1399      | 5.6865      | 3.5683      | 4.9565      | 3.2241      | 4.8654      | 3.9953      | 3.6215      |                        |
| 10                     | 1.9517      | 3.6542      | 2.3201      | 5.3214      | 2.5523      | 4.5621      | 2.212       | 3.0365      |                        |
| 12                     | 2.1699      | 4.2156      | 1.8036      | 4.2356      | 2.6759      | 4.3562      | 1.3876      | 2.9654      |                        |
| 3                      |             |             |             |             |             |             |             |             |                        |
| 6                      | 3.7975      | 4.3655      | 5.4039      | 5.2142      | 4.1843      | 4.8654      | 2.7318      | 2.8542      |                        |
| 8                      | 2.2898      | 4.3568      | 2.6400      | 4.3652      | 1.7453      | 4.2154      | 3.246       | 2.7321      |                        |
| 10                     | 3.8677      | 4.6856      | 2.1785      | 4.1025      | 2.7466      | 4.0354      | 2.587       | 2.6245      |                        |
| 12                     | 2.6241      | 3.2345      | 1.6469      | 3.8695      | 1.6639      | 3.9564      | 1.5512      | 2.5324      |                        |

Training epoch number of 1000 and learning rate of 0.1. The bold number in the table is the lowest MSE value.
Table 7. Influence of epochs and neuron number of established IANN model on MSE values.

| Epochs | MSE Values for Neuron Number ($\times10^{-4}$) |
|--------|---------------------------------|
| 300    | 3.7578, 4.5403, 2.4953, 3.5101, 2.3489, 4.7521, 2.7562, 1.7478, 2.1324 |
| 400    | 2.9890, 2.6272, 2.5036, 3.7639, 1.7403, 2.4159, 2.2206, 0.97334, 1.3887 |
| 500    | 5.8078, 1.6159, 3.2015, 2.5594, 2.2823, 3.0795, 2.1183, 0.89931, 2.1599 |
| 600    | 4.5154, 2.6319, 2.0265, 1.2636, 1.8356, 1.7178, 2.2507, 1.3522, 1.0449 |
| 700    | 4.1400, 2.6848, 3.0314, 1.6838, 1.2706, 2.0658, 2.0319, 1.3243, 1.4640 |
| 800    | 3.9628, 2.6995, 2.4877, 1.7637, 1.8480, 1.2178, 2.5307, 1.3522, 1.0449 |
| 900    | 3.1647, 3.5374, 2.5279, 1.9526, 1.2706, 2.0658, 2.0319, 1.3243, 1.4640 |
| 1000   | 3.7801, 2.387, 2.8735, 3.3274, 2.3157, 1.6443, 1.7539, 1.1109, 1.2262 |
| 1100   | 3.9321, 2.6832, 2.2898, 1.7675, 2.8269, 1.7395, 1.7649, 1.2327, 1.3550 |
| 1200   | 3.6763, 2.7611, 2.2023, 2.1266, 2.0861, 2.7173, 2.0194, 1.0018, 0.8389 |
| 1300   | 3.6221, 2.4292, 2.0158, 3.3011, 1.8011, 1.6036, 2.0977, 1.1542, 0.8389 |
| 1400   | 4.1916, 2.5568, 1.8191, 1.4018, 1.9659, 1.7178, 1.5259, 1.3142, 1.1663 |
| 1500   | 3.4770, 2.8762, 4.7773, 1.7395, 1.789, 1.4142, 2.0901, 0.75975, 1.7163 |

Table 8. Influence of epochs and neuron number of established OANN model on MSE values.

| Epochs | MSE Values for Neuron Number ($\times10^{-4}$) |
|--------|---------------------------------|
| 300    | 6.3524, 5.9654, 5.6548, 5.1264, 4.9546, 3.6584, 3.2345, 3.215, 4.3254 |
| 400    | 6.1256, 5.8645, 5.3642, 4.2568, 3.9564, 2.8645, 3.3654, 2.9564, 3.9854 |
| 500    | 6.5426, 6.2153, 5.2648, 4.8654, 4.2315, 3.6524, 3.9654, 2.9852, 4.6524 |
| 600    | 6.1546, 5.6425, 5.1265, 4.0365, 4.2125, 2.9952, 2.8675, 3.2465, 3.6584 |
| 700    | 5.8642, 5.3549, 5.0365, 4.2156, 3.6854, 2.3654, 3.3264, 3.2156, 3.4528 |
| 800    | 5.6521, 5.6824, 4.9564, 3.2156, 3.6584, 3.1257, 3.6542, 3.6214, 4.1253 |
| 900    | 5.5215, 5.1265, 4.8542, 3.6879, 2.9654, 2.6584, 3.3215, 2.8654, 3.6254 |
| 1000   | 5.2698, 5.3216, 4.6245, 3.6954, 3.2564, 2.6542, 3.0215, 2.8654, 3.2154 |
| 1100   | 5.3165, 4.9632, 4.3568, 4.0264, 3.9854, 2.9548, 2.3652, 2.6854, 2.9548 |
| 1200   | 4.9632, 4.8654, 4.3564, 4.2565, 2.6584, 1.6548, 3.8654, 1.9654, 2.6458 |
| 1300   | 4.8652, 4.5687, 4.0215, 3.8652, 3.2152, 2.2154, 3.6584, 2.6542, 2.3254 |
| 1400   | 4.8652, 4.3242, 4.3265, 3.3264, 3.6542, 1.6854, 3.2548, 2.3254, 2.6542 |
| 1500   | 4.6624, 4.2156, 4.2364, 3.9682, 3.2644, 1.4542, 3.6524, 1.8824, 2.0312 |

Hidden layer number of 2 and learning rate of 0.4. The bold number in the table is the lowest MSE value.

Based on the obtained architecture of the two models, the data sets were trained by the models and the training results are shown in Figure 8. As can be seen from the Figure 8a, the IANN model gets the best prediction performance when the training epochs are 30, where the model gets the lowest MSE value ($2.125 \times 10^{-4}$) and the $R$-values for the data sets used for training, validating, and testing the model are 0.99852, 0.99623, and 0.99788, respectively. On the other hand, the OANN model gets performs a best prediction performance when the epochs are 31, where the model gets the lowest MSE value ($2.112 \times 10^{-4}$) and the $R$-values for the data sets used for training, validating, and testing the model are 0.99779, 0.99225, and 0.99231, respectively. Indicating that the established models have sufficient reliability and can be used for predicting the $MC$, $\eta_{ex,h}$, and $Er$. However, compared with the OANN model, the IANN model has a better prediction performance with the higher values of MSE and $R$-values, indicating that the IANN model has a better prediction performance. It can be summarized that the ambient conditions should be taken into consideration when establishing the prediction model. Moreover, in order to achieve the repeatability of the model, the weights of the established IANN model are listed in Table 9.
Figure 8. The training results of the 9-2-12-3 IANN model (a) and the 7-2-10-3 OANN model (b).

Table 9. The weights of the established model.

| Weight Matrix |  
|---------------|---|
|               |   |

(a) 
(b)
Table 9. The weights of the established model.

| Weight | Matrix |
|--------|--------|
| $i_{w1,1}$ | $-0.13887 -1.4159 -0.59037 0.1114 -0.75533 -0.065606 -0.40298 0.10036 0.048895 0.31505 -0.11427 -2.9315^T$ |
| $i_{w2,1}$ | $-0.043673 0.88573 0.40884 -0.11595 -1.6174 0.19736 0.21143 -0.1711 -0.38451 -0.9736 -0.18843 -0.21793$ |
| $i_{w1,2}$ | $-0.029184 -0.94861 -0.04776 -0.072804 0.67878 0.10712 -0.10786 0.016793 1.1512 0.43835 -0.12774 -0.27362$ |
| $i_{w2,2}$ | $1.325 0.87228 1.2523 -0.36426 0.69924 0.28796 -0.014829 0.32952 -0.31587 -0.9736 -0.18843 -0.21793$ |
| $b_{1}$ | $[1.5332 0.7684 -0.18591 0.20253 1.0812 0.078345 0.11536 0.011221 -0.51627 -1.1868 -2.0232 -3.1241]^T$ |
| $b_{2}$ | $[-0.5767 0.052421 0.11789]^T$ |
3.3. The Application of the IANN Model

To further verify the practicability of the established IANN model, the 117 experimental data sets acquired in 12 November (−3.01 °C ≤ T₀ ≤ 59.4 °C, 40.35% ≤ RH₀ ≤ 63.23%) were trained by the model. The comparison between experimental values and predicting results of the MC, Er, and η_{ex,h} are depicted in the following Figure 9. Obviously, it can be seen from the figure that the regression coefficient of determination (R²) for MC, Er, and η_{ex,h}, respectively, are 0.998, 0.992, and 0.980, mean squared error (MSE) of 0.067, 0.00296, and 0.0057, mean absolute error (MAE) of 0.16, 0.04, and 0.0063. The values of the above statistic indexes indicate that the 9-2-12-3 IANN model has an excellent prediction performance and can be used in engineering practice. Moreover, the prediction results of the first cycle (the measured MC between 28.9% d.b. and 32% d.b.) are slightly deviated from the experimental results, which might be caused by the fact that there is a measurement error for the on-line moisture meter in the high moisture region of cereal grains [40].

![Figure 9](image-url)  
*Figure 9. The comparison of experimental values and predicting results for the MC (a), Er (b), and η_{ex,h} (c).*

Based on the established 9-2-12-3 IANN model, a control model of the drying process is proposed, as shown in the Figure 10. During the drying process, the experimental data collected by the corresponding sensor are used to train, and get, the optimal IANN model. As can be seen from Figures 2 and 10, the drying process is controlled by the DD and the flue gas valve on the flue gas pipeline.
When one of the inputted factors changes, the established IANN model can automatically calculate and analyze the predicted corresponding output indexes at the same time. Accordingly, the intelligent optimized controller optimizes and calculates the grain discharging electric motor (or flue gas valve), and the optimal rotational speed of the electric motor (or optimal openness of the valve) is given to the frequency converter, so as to control the drying process, and realize the optimal control of the MC, Er, and \( \eta_{ex,h} \). The proposed control model based on the IANN model may strengthen the practical implications.

![The proposed control model structure of industrial corn drying system.](image)

**Figure 10.** The proposed control model structure of industrial corn drying system.

### 4. Conclusions

The present work considers the ambient temperature as one of the key parameters affecting the drying performance of the industrial corn drying. The artificial neuron network was applied to predict the drying performance of the drying system. The drying kinetics, the exergy exchange performance, as well as the heat recovery performance of the drying system were investigated. The detailed conclusions depending on the results are listed as follow:

1. The exergy efficiency of the heat exchanger is significantly affected by the ambient temperature, where the exergy efficiency is proportion to the ambient temperature. Moreover, the exergy efficiency of the heat exchanger varies from 0.249 to 0.648 for the whole drying process;
2. The far-infrared wavelength of the radiators are found to be ranged from 7.61 to 8.15 \( \text{um} \), and the recovered radiant exergy for 17 October, 30 October, and 19 November are, respectively, ascertained to be 571.12, 621.17, and 650.43 MJ;
3. Based on the analysis of the ambient conditions on the drying performance of the drying system, two prediction models with (IANN) and without (OANN) considering the ambient conditions were established and compared with each other. The results showed that IANN model has a better prediction performance, which indicates that the ambient conditions should be taken into consideration when establishing the prediction model;
4. The best performance for prediction of moisture content, specific recovered exergy, and exergy efficiency for corn industrial drying are found to be at the training epochs of 30, where the regression coefficient of determination for \( MC, Er, \) and \( \eta_{ex,h} \), respectively, are 0.998, 0.992, and 0.980; mean squared error of 0.067, 0.00296, and 0.0057; mean absolute error of 0.16, 0.04, and 0.0063.
This indicates that the established IANN model has excellent prediction performance and can be used in engineering practices.

**Author Contributions:** Data curation, B.L., C.L. (Chengjie Li) and J.H.; Formal analysis, B.L.; Funding acquisition, C.L. (Changyou Li); Investigation, B.L., C.L. (Chengjie Li) and J.H.; Methodology, B.L.; Project administration, C.L. (Changyou Li); Software, B.L. and J.H.; Supervision, C.L. (Changyou Li); Writing—original draft, B.L. All authors have read and agreed to the published version of the manuscript.

**Funding:** This work was supported by the National Natural Science Foundation of China No. 31,671,783; No. 31,371,871) and Science and Technology Planning Project of Guangdong Province, China (No. 2014B020207001).

**Acknowledgments:** The authors would like to thank the editors and reviewers for their valuable and constructive comments.

**Conflicts of Interest:** The authors declare that we have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**References**

1. Defraeye, T. Advanced computational modelling for drying processes—A review. *Appl. Energy* 2014, 131, 323–344. [CrossRef]
2. Li, B.; Li, C.; Huang, J.; Li, C. Exergoeconomic Analysis of Corn Drying in a Novel Industrial Drying System. *Entropy* 2020, 22, 689. [CrossRef]
3. Mujumdar, A.S. *Handbook of Industrial Drying*, 3rd ed.; Taylor & Francis Group: Boca Raton, FL, USA; CRC Press: Boca Raton, FL, USA, 2006. [CrossRef]
4. Huang, H.; Yu, H.; Xu, H.; Ying, Y. Near infrared spectroscopy for on/in-line monitoring of quality in foods and beverages: A review. *J. Food Eng.* 2008, 87, 303–313. [CrossRef]
5. Amjad, W.; Crichton, S.O.J.; Munir, A.; Hensel, O.; Sturm, B. Hyperspectral imaging for the determination of potato slice moisture content and chromaticity during the convective hot air drying process. *Biosyst. Eng.* 2008, 166, 170–183. [CrossRef]
6. Patel, K.K.; Khan, M.A.; Kar, A. Recent developments in applications of MRI techniques for foods and agricultural produce—An overview. *J. Food Sci. Technol.* 2015, 52, 1–26. [CrossRef]
7. Li, B.; Peng, G.L.; Luo, C.W.; Meng, G.D.; Yang, L. Vacuum drying kinetics characteristics of Chinese prickly ash based on Weibull distribution. *Food Ferment. Ind.* 2017, 43, 58–64. [CrossRef]
8. Li, H.; Chang, Q.; Gao, R.; Dai, Z.; Chen, X.; Yu, G. Thin-layer drying characteristics and modeling of lignite under supercritical carbon dioxide extraction and the evolution of pore structure and reactivity. *Fuel Process. Technol.* 2018, 170, 1–12. [CrossRef]
9. Aregba, A.W.; Nadeau, J.P. Comparison of two non-equilibrium models for static grain deep-bed drying by numerical simulations. *J. Food Eng.* 2007, 78, 1174–1187. [CrossRef]
10. Ebrahimifakhar, A.; Yuill, D. Inverse estimation of thermophysical properties and initial moisture content of cereal grains during deep-bed grain drying. *Biosyst. Eng.* 2020, 196, 97–111. [CrossRef]
11. Doder, D.; Djakovic, D. Modeling of intermittent convective drying of walnuts in single layer and its influence on deep bed drying simulation. *Therm. Sci.* 2019, 23, 272. [CrossRef]
12. Hu, Z.; Wang, H.; Xie, H.; Wu, F.; Chen, Y.; Cao, S. Mathematical models of crossflow grain drying and their applications. *Trans. Chin. Soc. Agric. Eng.* 2010, 26, 76–82. [CrossRef]
13. Liu, Q.; Bakker-Arkema, F.W. A model-predictive controller for grain drying. *J. Food Eng.* 2001, 49, 321–326. [CrossRef]
14. Davoudi, K.F.; Freeman, S.A.; Mosher, G.A. Use of Neural Networks to Identify Safety Prevention Priorities in Agro-Manufacturing Operations within Commercial Grain Elevators. *Appl. Sci.* 2019, 9, 4690. [CrossRef]
15. Mucha, W. Application of Artificial Neural Networks in Hybrid Simulation. *Appl. Sci.* 2019, 9, 4495. [CrossRef]
16. Aghbashlo, M.; Hosseinpour, S.; Ghasemi-Varnamkhasti, M. Computer vision technology for real-time food quality assurance during drying process. *Trends Food Sci. Technol.* 2014, 39, 76–84. [CrossRef]
17. Dai, A.; Zhou, X.; Liu, X.; Liu, J.; Zhang, C. Model of drying process for combined side-heat infrared radiation and convection grain dryer based on bp neural network. *Trans. Chin. Soc. Agric. Mach.* 2017, 48, 351–360. [CrossRef]
18. Farkas, I.; Reményi, P.; Biró, A. Modelling aspects of grain drying with a neural network. *Comput. Electron. Agric.* 2000, 29, 99–113. [CrossRef]
19. Gülşah, C.; Yıldız, C. The prediction of seedy grape drying rate using a neural network method. *Comput. Electron. Agric.* 2011, 75, 132–138. [CrossRef]

20. Zare, D.; Naderi, H.; Jafari, A. Experimental and Theoretical Investigation of Rough Rice Drying in Infrared-Assisted Hot Air Dryer Using Artificial Neural Network. In Proceedings of the 2012 Dallas, Dallas, TX, USA, 29 July–1 August 2012. [CrossRef]

21. Jafari, H.; Kalantari, D.; Azadbakht, M. Semi-industrial continuous band microwave dryer for energy and exergy analyses, mathematical modeling of paddy drying and it’s qualitative. *Energy* 2017, 138, 1016–1029. [CrossRef]

22. Li, B.; Li, C.; Li, T.; Zeng, Z.; Ou, W.; Li, C. Exergetic, Energetic, and Quality Performance Evaluation of Paddy Drying in a Novel Industrial Multi-Field Synergistic Dryer. *Energies* 2019, 12, 4588. [CrossRef]

23. Syahrul, S.; Hamdullahpur, F.; Dincer, I. Thermal analysis in fluidized bed drying of moist particles. *Appl. Therm. Eng.* 2002, 22. [CrossRef]

24. De, L.J.A.S.; Santos, J. Generalized Stefan-Boltzmann law. *Int. J. Phys.* 1995, 34, 127–134. [CrossRef]

25. Khanali, M.; Aghbashlo, M.; Rafiee, S. Exergetic performance assessment of plug flow fluidised bed drying process of rough rice. *Int. J. Exergy* 2013, 13, 387–408. [CrossRef]

26. Dincer, I.; Sahin, A.Z. A new model for thermodynamic analysis of a drying process. *Int. J. Heat Mass Transf.* 2004, 47, 645–652. [CrossRef]

27. Yildirim, N.; Genc, S. Energy and exergy analysis of a milk powder production system. *Energy Convers. Manag.* 2017, 149, 698–705. [CrossRef]

28. Beigi, M.; Tohidi, M.; Torki-Harchegani, M. Exergetic Analysis of Deep-Bed Drying of Rough Rice in a Convective Dryer. *Energy* 2017, 140. [CrossRef]

29. Tohidi, M.; Sadeghi, M.; Torki-Harchegani, M. Energy and quality aspects for fixed deep bed drying of paddy. *Renew. Sustain. Energy Rev.* 2017, 70, 519–528. [CrossRef]

30. Soufiyan, M.M.; Dadak, A.; Hosseini, S.S.; Nasiri, F.; Dowlati, M.; Tahmasebi, M. Comprehensive exergy analysis of a commercial tomato paste plant with a double-effect evaporator. *Energy* 2016, 111, 910–922. [CrossRef]

31. Coskun, C.; Oktay, Z.; Ilten, N. A new approach for simplifying the calculation of flue gas specific heat and specific exergy value depending on fuel composition. *Energy* 2009, 34, 1898–1902. [CrossRef]

32. Furferi, R.; Governi, L.; Volpe, Y. Modelling and simulation of an innovative fabric coating process using artificial neural networks. *Text. Res. J.* 2012, 12, 1282–1294. [CrossRef]

33. Aghbashlo, M.; Mobli, H.; Rafiee, S.; Madadlou, A. The use of artificial neural network to predict exergetic performance of spray drying process: A preliminary study. *Comput. Electron. Agric.* 2012, 88, 32–43. [CrossRef]

34. Chokphoemphun, S.; Chokphoemphun, S. Moisture content prediction of paddy drying in a fluidized-bed dryer with a vortex flow generator using an artificial neural network. *Appl. Therm. Eng.* 2018, 145, 630–636. [CrossRef]

35. Yogendrasasidhar, D.; Setty, Y.P. Drying kinetics, exergy and energy analyses of Kodo millet grains and Fenugreek seeds using wall heated fluidized bed dryer. *Energy* 2018, 151, 799–811. [CrossRef]

36. Ma, X.Z.; Fang, Z.D.; Li, C.Y. Energy efficiency evaluation and experiment on grain counter-flow drying system based on exergy analysis. *Trans. Chin. Soc. Agric. Eng.* 2017, 33, 285–291. [CrossRef]

37. Skoneczna, L.J.; Ciesielczyk, W. Exergetic analysis for a complete node of a fluidized bed drying of poppy seeds. *Chem. Process. Eng.* 2015, 36, 437–447. [CrossRef]

38. Jrg, S.; Duncan, M.; Werner, H. Ambient air cereal grain Drying-Simulation of the thermodynamic and microbial behavior. *Therm. Sci. Eng. Prog.* 2019, 13, 100382. [CrossRef]

39. Zhu, W.; Zhang, Z. Research on characteristics of infrared absorption of grain. *Grain Storage* 2003, 32, 38–41.

40. Li, C.; Ma, X.; Mai, Z. Analytical study on on-line model of moisture in hot air drying process of grain. *Trans. Chin. Soc. Agric. Eng.* 2014, 30, 10–20. [CrossRef]