

ANN-Based sensitivity analysis for the prediction of energy consumption and head rice yield in a pneumatic paddy dryer

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Abstract

In this study, the performance of a pneumatic paddy dryer was investigated through a sensitivity analysis with an artificial neural network, in order to identify the relative importance of the process variables affecting the energy consumption and head rice yield (HRY). Experiments were conducted using Thai Jasmine 105 paddy rice, which was dried from 24% to 14% wet basis at drying air temperatures of 60°C, 80°C, and 100°C. Increasing the drying air temperature increased the drying rate from 0.46 to 1.11 kg_{water}/h. Drying at 60°C resulted in the lowest specific energy consumption (SEC) of 3.17 MJ/kg_{water} and the highest HRY (51.91%), but approximately 6 h was needed to reach the target moisture content for a batch of 20 kg. Higher drying temperatures substantially shortened the drying time but increased the SEC and reduced the HRY to 39.01–41.15%, suggesting a trade-off between drying rate, energy use, and milling quality. The model accurately predicted the moisture content, electrical energy consumption, and HRY, with coefficients of determination (R^2) ≥ 0.997 for both the training and testing datasets. Through a sensitivity analysis, the paddy grain temperature (T_{paddy}) was identified as the most informative predictor, accounting for approximately 38% of the total relative importance, followed by drying time (32%) and drying air temperature (21%). These findings indicate that T_{paddy} provides valuable information on the transient thermal state of the grain, and can serve as a key process variable for forecasting drying behavior. Rather than representing a standalone commercial drying solution, the framework presented here provides a basis for developing multi-stage drying strategies in which rapid pneumatic pre-drying can be followed by tempering or drying at lower temperatures to strike a balance between drying efficiency and HRY.

Keywords: Pneumatic paddy drying, Artificial neural network, Sensitivity analysis, Grain temperature, Specific energy consumption, Head rice yield

1. Introduction

Drying is an essential post-harvest operation for paddy rice with high moisture content, since inadequate moisture reduction can lead to rapid deterioration in the quality and storability of the grains. Mechanical drying systems are widely used to ensure a controlled process of moisture removal while maintaining acceptable milling quality [1, 2]. Of the various technologies that are available, pneumatic paddy dryers are especially prevalent due to their ability to dry high-moisture paddy at rapid rates with relatively low values for the specific energy consumption, typically ranging from 1.6 to 7.25 MJ/kg_{water} [3-5].

Previous studies of pneumatic and air-based drying systems have primarily focused on the influence of drying air temperature and airflow conditions on moisture removal, energy consumption, and milling quality, particularly in terms of head rice yield (HRY). In laboratory-scale investigations, short drying times have generally been used [3-6]; however, prolonged exposure to high drying air temperatures often results in excessive grain stress and a substantial reduction in head rice yield [7, 8]. Although the energy consumption of air dryers is comparable to that of conventional drying systems in Thai rice mills, their application remains limited by the degradation in quality caused by thermal and moisture-induced stresses within the paddy kernel [9].

In conventional methods of optimizing the drying process, the drying air temperature has been emphasized as the primary operating variable. However, the actual thermal state of the paddy grain is determined by the interaction among heat transfer, moisture evaporation, and exposure time, rather than solely by the drying air temperature. The transient grain temperature can consequently provide information on the process state related to the thermal history of the grain during drying. However, despite the physical relevance of this parameter, the predictive importance of the paddy grain temperature compared with conventional operating variables, such as drying air temperature and drying time, has not been systematically quantified.

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In recent years, artificial intelligence techniques, and particularly artificial neural networks (ANNs), have increasingly been applied to model the complex and nonlinear relationships affecting agricultural drying processes. Reliable ANN models have enabled sensitivity analyses to identify the most influential input variables affecting the performance of the system and the attributes of the product. This approach has been successfully applied to crop production and food drying studies to prioritize the key process parameters [10, 11]. Nevertheless, studies in which ANN-based sensitivity analyses are applied to pneumatic paddy drying systems remain limited, and the relative significance of the grain temperature in comparison with conventional control variables has not been thoroughly examined. Furthermore, ANNs have primarily been used for prediction in drying studies, whereas their use in a sensitivity-based framework for identifying informative process state variables and supporting the design of future drying strategies remains less widely explored.

The objective of this study is therefore to investigate the relative importance of the main operating variables in a pneumatic paddy drying system using an ANN-based sensitivity analysis framework. Experimental data obtained from drying Thai Jasmine 105 paddy rice were used to develop a predictive ANN model that took into consideration the ambient air conditions, drying air temperature, drying time, and paddy grain temperature as independent variables. The aim of the sensitivity analysis was to identify the most informative predictors of moisture reduction, energy consumption, and HRY. The results clarify the relative contributions of these variables and enable an assessment of the potential of the grain temperature as a process state variable for forecasting drying behavior. The findings may provide a basis for developing future multi-stage drying strategies in which rapid pneumatic pre-drying is combined with subsequent tempering or lower-temperature drying to balance drying efficiency and HRY.

2. Materials and methods

2.1 Pneumatic dryer

In this study, a pneumatic dryer served as the primary apparatus for paddy drying. The system is illustrated in Figure 1, and had several components. A blower (Ventex, Model: 2RB 710 H16, 2.2 kW) generated airflow that was directed through a 4 kW electric heating unit to produce hot air, under regulation by a PID temperature controller (RKC, Model: REX-C100). An AC inverter (Hitachi, Model: C1-022SFC, 2.2 kW, 220V, one phase) controlled the speed of the blower, thereby controlling the airflow rate. Paddy from the storage tank was gravity-fed into the drying column via a ribbon screw feeder, ensuring a consistent feed rate of 3.3 kg_{dry-solid}/min. The paddy then encountered hot air at an air velocity of 8.5 m/s, exceeding the reported terminal velocity of the grains, and was conveyed upward through the drying column and then separated from the air stream in the cyclone separator. The energy consumption of each device was monitored using a power meter (NATIONINE, Model: DD28, 15/45A, two-wire single-phase). For data acquisition, an Arduino DUE was used as the microcontroller for a K-type thermocouple with a MAX6675 module and a DHT22 sensor (ASAIR, AM2302 module), which were used to measure the paddy temperature and ambient air conditions, respectively. The K-type thermocouple was positioned at the midpoint of the storage tank height within the bulk paddy layer to enable continuous monitoring of the paddy grain temperature during drying. The measured paddy temperature (T_{paddy}) was recorded at intervals of 15 min throughout the drying process, and was used as a time-varying input variable for the ANN model.

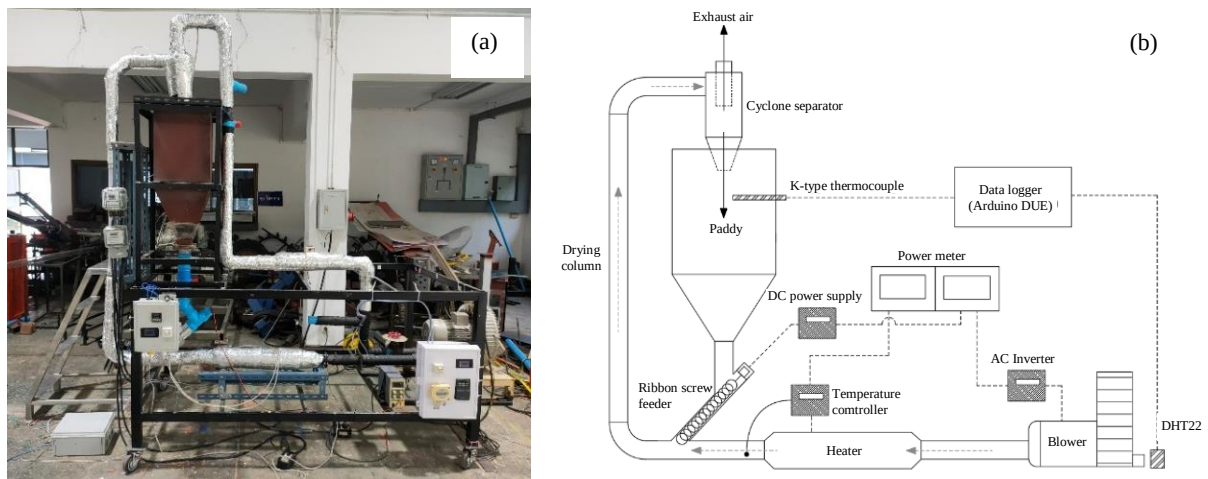


Figure 1 Pneumatic drying system: (a) experimental setup; (b) schematic diagram

2.2 Experimental procedure

Thai Jasmine 105 paddy rice, initially with a moisture content of 24% wet basis (%w.b.) and weighing 20 kg, underwent drying at a constant air speed of 8.5 m/s (via a pipe with a cross section of 1.5 in). The ribbon screw feeder operated at a consistent voltage of 12 V DC to maintain a speed of 50 rpm throughout the experiment. The dryer was operated in a recirculating batch mode. Based on a dry solid feed rate of approximately 3.3 kg_{dry-solid}/min, one complete circulation of the 20 kg batch required approximately 4.6 min. This value represents the average batch circulation time, and was estimated from the measured feed rate rather than measured directly as the residence time of individual kernels.

Three experimental conditions were defined, based on constant drying air temperatures of 60°C, 80°C, and 100°C, throughout the drying process. At intervals of 15 min, three sets of rice samples were randomly collected from the cyclone outlet to assess the moisture content using the AOAC 945.15 standard and Eq. (1) [12, 13]. The temperature of the rice and the electrical energy consumption of each device were recorded simultaneously. The drying process for each condition continued until the rice moisture content reached 14%w.b., at which point the process was terminated. The paddy rice was then dehulled, and its quality was evaluated in terms of the HRY using Eq. (2) [5, 6].

$$MC_{wb} = \left(\frac{m_{wet} - m_{dry}}{m_{wet}} \right) \times 100 \quad (1)$$

$$HRY = \frac{m_{head}}{m_{total}} \times 100 \quad (2)$$

where MC_{wb} is the moisture content of the paddy (%w.b.), m_{wet} is its wet mass (kg), m_{dry} is its dry mass (kg), HRY denotes the head rice yield (%), defined as the percentage of milled rice kernels with a length equal to or greater than 80% of the full kernel length, m_{head} is the mass of head rice that is more than 80% of full grain (kg), and m_{total} is the total mass of rice (kg).

A naturally air-dried sample was used as the control treatment, in which paddy from the same batch was dried under ambient conditions to the target moisture content (14%w.b.) without exposure to heated air. The HRY for the control sample ($HRY_{control}$) was determined using the same milling and evaluation procedure as that applied to the pneumatic drying treatments. Three independent replicates were performed, and the results are reported as mean values $\pm$ standard deviation.

The drying performance was evaluated based on the drying rate (DR) and specific energy consumption (SEC) using Eqs. (3) and (4), respectively [5, 6].

$$DR = \frac{m_i - m_f}{t} \quad (3)$$

$$SEC = \frac{3.6E}{m_i - m_f} \quad (4)$$

where DR is the drying rate (kg_{water}/h), m_i is the mass of paddy before drying (kg), m_f is the mass of paddy after drying (kg), and t is the drying time (h). SEC is the specific energy consumption (MJ/kg_{water}), and E is the energy consumption of the system (kWh).

2.3 Data analysis

Statistical analyses were performed using IBM SPSS Statistics. A one-way analysis of variance (ANOVA) was conducted to identify significant differences among the drying conditions. When significant differences were detected ($p < 0.05$), Duncan's multiple range test was employed for pairwise comparisons. The experimental results were calculated as mean $\pm$ standard deviation, with different superscript letters indicating statistically significant differences at the 95% confidence level.

A multilayer perceptron ANN was developed using IBM SPSS Statistics to predict the drying performance and rice milling quality indicators. The input variables included the ambient air temperature (T_{surr}), ambient relative humidity of the air (RH_{surr}), temperature of the paddy grains during drying (T_{paddy}), drying air temperature (T_{air}), and drying time (denoted in the graphs as 'Time'). Since the drying air temperature was treated as a categorical variable, it was internally transformed in IBM SPSS into three indicator variables (60°C, 80°C, and 100°C) during training of the network. The output variables consisted of the moisture content of the paddy during drying (MC_{wb}), electrical energy consumption (kWh), and HRY. The architecture of the ANN consisted of a single hidden layer containing three neurons, with a hyperbolic tangent activation function in the hidden layer, and an identity activation function in the output layer. The network was trained using the scaled conjugate gradient algorithm with the default batch training settings in IBM SPSS Statistics.

A total of 106 experimental datasets were used, which were randomly divided into a training dataset (70%) for development of the model and an independent testing dataset (30%) for validation purposes. To reduce the risk of overfitting, the testing dataset was excluded from the training process, and was used solely to evaluate the predictive performance of the developed ANN model. Training of the network was automatically terminated using the default stopping criterion in IBM SPSS Statistics when additional iterations no longer improved the performance of the model, thus preventing unnecessary training and reducing the potential for overfitting. Although k-fold cross-validation was not available in the ANN module of IBM SPSS Statistics, the independent hold-out validation process adopted in this study provided an objective assessment of the performance of the model using previously unseen experimental data.

The predictive performance of the ANN model was evaluated based on the coefficient of determination (R^2) and the root mean square error (RMSE), which were calculated using Eqs. (5) and (6), respectively. An R^2 value approaching unity indicates a strong agreement between the predicted and experimental values, whereas a lower RMSE represents a smaller prediction error [14-17].

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{i=n} (Y_{exp} - Y_{pred})^2}{\sum_{i=1}^{i=n} (Y_{exp} - Y_{avg})^2} \right) \quad (5)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{i=n} (Y_{exp} - Y_{pred})^2}{n}} \quad (6)$$

where Y_{pred} represents variables predicted from the ANN model, Y_{exp} represents experimental data, Y_{avg} is the average value of a dependent variable, and n is the number of data samples.

A sensitivity analysis was also performed using the trained ANN model to quantify the influence of each input variable on the predicted outputs. The relative contribution of each input variable was calculated based on the normalized connection weights of the trained neural network, to give the proportional importance of each predictor in the prediction process [18, 19].

3. Results and discussion

3.1 Performance results for the pneumatic paddy dryer

Figure 2 illustrates the temporal variation in the moisture content and temperature of the grains during drying in air at temperatures of 60°C, 80°C, and 100°C. Increasing the drying air temperature accelerated the removal of moisture and reduced the time required to reach the target moisture content of 14%w.b. The drying time at 100°C was reduced by 58.33% and 33.33% compared with 60°C and 80°C, respectively; this finding can be attributed to the greater temperature gradient between the drying air and the paddy grains, which enhanced heat transfer to the grain and promoted the migration and evaporation of moisture.

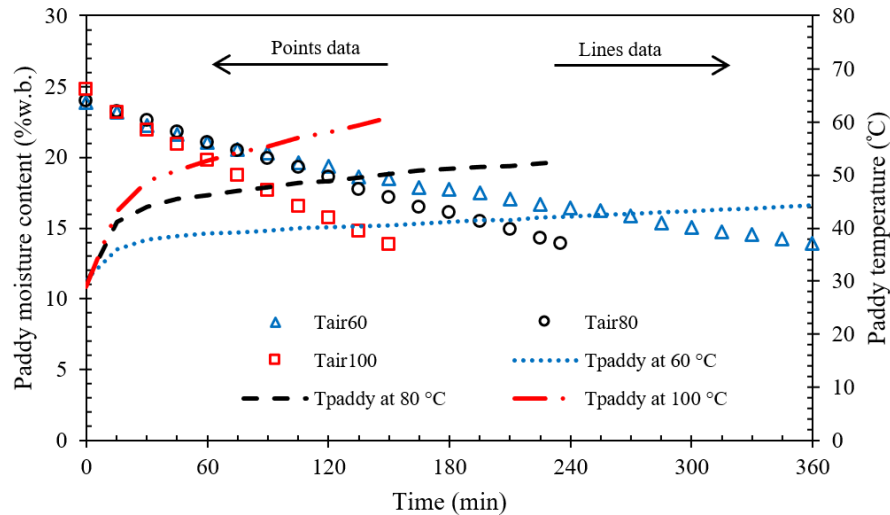


Figure 2 Moisture content and temperature of paddy grains during the drying process

Higher drying air temperatures also resulted in a more rapid increase in the temperature of the paddy grains, particularly during the initial stage of drying (0–30 min), when the temperature difference between the hot air and the grains was greatest. As drying progressed, T_{paddy} underwent a progressive increase, reflecting the dynamic response of the grain to heat transfer and moisture evaporation. This behavior indicates that the temperature actually experienced by the paddy grain is determined not only by the imposed drying air temperature but also by the duration of exposure. At elevated drying temperatures, the rapid removal of moisture from the grain surface relative to the migration of moisture from the interior may increase the internal moisture gradients and drying-induced stresses. Hence, both the air temperature and duration of drying contribute to the thermal and moisture history experienced by the grain.

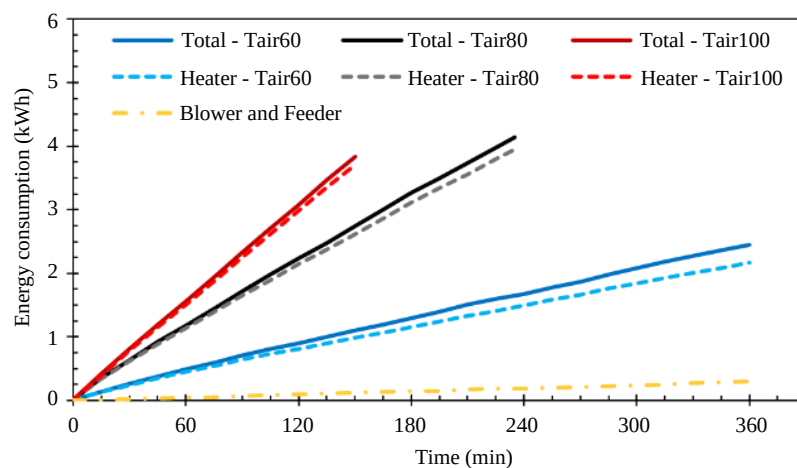


Figure 3 Energy consumption of the dryer

Figure 3 presents the cumulative electrical energy consumption of the pneumatic drying system as a function of drying time. The heater accounted for more than 90% of the total energy consumption, confirming that the generation of hot air was the major energy-consuming component of the system. The cumulative energy consumption differed among the drying conditions due to differences in both the energy demand and the duration of operation. Notably, the lowest cumulative energy consumption was found for the 60°C condition throughout the drying process, whereas in the higher-temperature conditions, greater energy input was required over their respective operating periods. These differences contributed directly to the variation in the SEC values presented in Table 1.

Table 1 Results for dryer performance and quality indicators for rice milling

Drying condition	DR (kg _{water} /h)	SEC (MJ/kg _{water})	HRY (%)
Control	-	-	59.13±1.77 ^a
T _{air} 60°C	0.46 ± 0.01 ^c	3.17 ± 0.07 ^c	51.91±1.79 ^b
T _{air} 80°C	0.71 ± 0.02 ^b	5.34 ± 0.10 ^a	39.01±0.94 ^c
T _{air} 100°C	1.11 ± 0.03 ^a	4.99 ± 0.09 ^b	41.15±1.03 ^c

*Values are expressed as mean ± standard deviation. For DR and SEC, statistical comparisons were performed among the three drying temperatures (60°C, 80°C, and 100°C). For HRY, comparisons included the naturally air-dried control and the three pneumatic drying treatments. Means followed by different superscript letters within each column are significantly different according to Duncan's multiple range test ($p < 0.05$).

Table 1 summarizes the drying performance, energy consumption, and rice milling quality (HRY) obtained under the three pneumatic drying conditions. Increasing the drying air temperature from 60°C to 100°C significantly increased the drying rate from 0.46 to 1.11 kg_{water}/h ($p < 0.05$), representing an approximately 2.4-fold increase. This result demonstrates the strong effect of the drying air temperature on moisture removal under this pneumatic drying configuration, and is consistent with the enhanced heat and mass transfer expected under a larger temperature gradient [7, 20]. In contrast, SEC exhibited a nonlinear response to drying air temperature, while HRY was significantly lower for all pneumatic drying treatments than for the naturally air-dried control.

Although drying at 60°C took longest, it produced the lowest SEC of 3.17 ± 0.07 MJ/kg_{water}. As shown in Figure 3, the lowest cumulative electrical energy consumption was found for the 60°C condition throughout the drying process. Thus, the lower energy demand of the heating system outweighed the additional energy associated with the prolonged drying period, resulting in the lowest SEC among the three drying conditions. When the drying air temperature was increased to 80°C, the additional heating requirement increased the cumulative energy consumption, while the corresponding increase in drying rate was insufficient to compensate for the higher energy input. Consequently, the highest SEC of 5.34 ± 0.10 MJ/kg_{water} was found for the 80°C condition. A further increase in the drying air temperature to 100°C substantially accelerated the moisture removal process and shortened the drying period: although the higher temperature increased the instantaneous heating demand, the shorter drying duration limited the accumulation of total energy consumption, resulting in a lower SEC of 4.99 ± 0.09 MJ/kg_{water} than at 80°C. These results demonstrate that under the pneumatic drying conditions considered here, SEC was determined by the combined effects of energy input and drying duration rather than by the drying air temperature alone.

From the perspective of energy performance, the values for the SEC obtained in the present study (3.17 to 5.34 MJ/kg_{water}) are within the range reported for paddy drying technologies in the literature. A recent review of these technologies reported SEC values ranging from approximately 2.58 to 14.71 MJ/kg_{water} for various drying systems, meaning that the values presented here are within the lower-to-middle portion of the reported range [9]. A thermal energy consumption of 3.17 MJ/kg_{water} has previously been reported for a small-scale mixed-flow dryer, with an electrical energy consumption of 0.97 MJ/kg_{water} for drying high-moisture paddy [6]. The SEC values obtained in the present study are therefore comparable with those reported for established paddy drying systems, particularly under the 60°C condition. However, direct numerical comparisons should be interpreted with caution, since differences in the dryer configuration, initial and final moisture contents, operating conditions, and system boundaries used for energy accounting can substantially affect the reported SEC values [6, 9].

Despite the improved drying rate, however, significantly lower HRY values were obtained for all pneumatic drying treatments compared to the naturally air-dried control ($p < 0.05$). This reduction in HRY can be associated with the rapid removal of moisture from the grain surface relative to the moisture migrating from the interior, which promotes internal moisture gradients and drying-induced stresses that can lead to fissure formation and subsequent kernel breakage during milling [7, 20]. Of the treatments considered here, 60°C produced the highest HRY (51.91 ± 1.79%), with values decreasing to 39.01 ± 0.94% and 41.15 ± 1.03% at 80°C and 100°C, respectively. Nevertheless, the HRY obtained at 60°C remained significantly lower than that of the naturally air-dried control (59.13 ± 1.77%), indicating that lowering the drying air temperature alone was insufficient to fully prevent quality degradation under this pneumatic drying configuration.

Despite the favorable ranges of SEC values, however, the duration of processing represents an important limitation of the present laboratory-scale system. At 60°C, approximately 360 min (6 h) was required to reduce the moisture content of a 20 kg batch from approximately 24% to 14%w.b. Although the paddy was recirculated through the drying column at a dry-solid feed rate of approximately 3.3 kg_{dry-solid}/min, this value represents the internal circulation rate rather than the net production capacity of the dryer. The batch drying duration of approximately 6 h should not be interpreted as representative of commercial-scale throughput, since in its present configuration based on batch recirculation, the system would not be suitable as a single-stage commercial dryer for high-throughput paddy processing; instead, these results represent a laboratory-scale assessment of the relationships among drying temperature, energy consumption, drying rate, grain temperature, and rice milling quality. For scaled-up processes in the future, the focus should be on increasing throughput and reducing batch residence time while maintaining the favorable energy and quality characteristics observed in the present study.

Taken together, these results clearly indicate a trade-off among drying rate, energy consumption, and rice milling quality. Increasing the drying air temperature accelerated the removal of moisture but did not necessarily reduce SEC, since the energy demand for heating and the duration of operation jointly determined the total energy requirement. At the same time, the lower HRY obtained under pneumatic drying indicates that drying efficiency cannot be evaluated independently of the thermal and moisture conditions experienced by the grain. These observations suggest that drying air temperature alone may not be an adequate representation of the factors governing overall drying performance. An ANN analysis was therefore used to evaluate the relative importance of the drying air temperature, drying time, paddy grain temperature, and ambient air conditions in predicting drying performance and rice milling quality.

3.2 Accuracy of the artificial neural network model

The architecture of the developed ANN model is illustrated in Figure 4, and the agreement between the values predicted by the ANN and the experimental measurements is shown in Figure 5. The predicted values for paddy moisture content (MCwb), electrical energy consumption (kWh), and HRY were closely distributed around the reference line, indicating good agreement between the predictions and experimental observations. As summarized in Table 2, R^2 values of 0.997–0.999 were achieved for all three outputs

from the ANN, in both the training and testing datasets, with RMSE values ranging from 0.034 to 0.192. The predictive performance remained consistently high in the independent testing dataset, with R^2 values of 0.997 for MCwb and 0.999 for both kWh and HRY.

Although the developed ANN yielded excellent predictive performance, the model was established based on a relatively limited experimental dataset obtained under controlled laboratory conditions, and the predictive accuracy should be interpreted within the investigated operating range rather than extrapolated beyond the experimental domain. The use of an independent testing dataset that was not used for training provided an assessment of the model's predictive performance on previously unseen observations, and indicated satisfactory generalization under the conditions investigated here. Nevertheless, the possibility of overfitting cannot be completely excluded, as the dataset was relatively limited and k-fold cross-validation was not performed. Future studies using larger and more diverse datasets, together with repeated or k-fold cross-validation and appropriate regularization strategies, would provide a more comprehensive assessment of the robustness and generalization capability of the model.

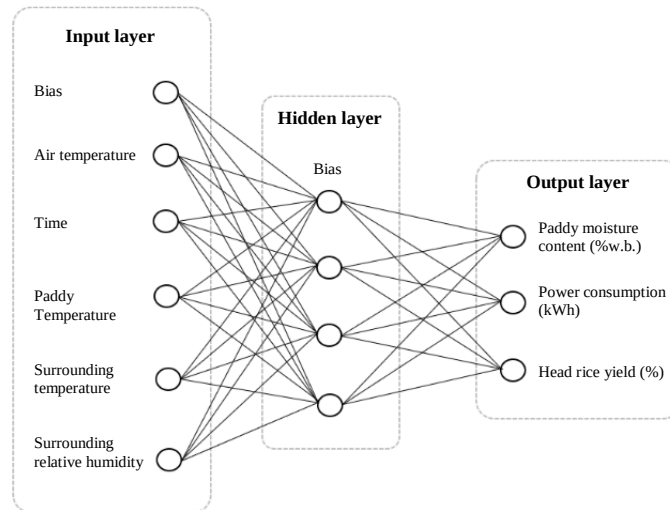


Figure 4 Architecture of the ANN model

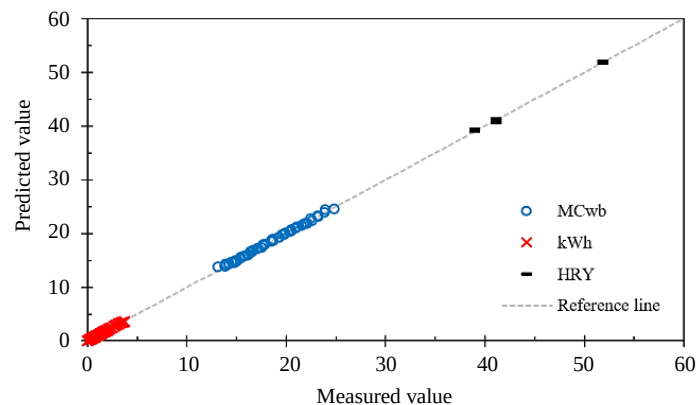


Figure 5 Comparison between predicted and measured values

Table 2 Predictive performance of the ANN model

Dataset	Statistical parameter	MCwb	kWh	HRy	Overall
Training data	R^2	0.997	0.999	0.999	0.999
	RMSE	0.169	0.034	0.161	0.136
Testing data	R^2	0.997	0.999	0.999	0.999
	RMSE	0.192	0.036	0.166	0.148

The high predictive accuracy indicates that the ANN model effectively captured the nonlinear relationships between operating variables and drying outcomes. Reliability at this level is essential for sensitivity analyses, as inaccurate or weak predictive models may lead to incorrect interpretations of the importance of each variable. The performance of the ANN model is comparable to or exceeds values reported in previous drying studies employing ANN-based approaches [21], confirming its suitability as a robust analytical tool for this study.

3.3 Sensitivity analysis and dominant drying variables

Before interpreting the ANN sensitivity results, the relationships among the input variables were examined using Pearson correlation analysis (Table 3). A moderate positive correlation was found between T_{paddy} with drying air temperature ($r = 0.655$, $p < 0.001$), whereas the correlation with drying time was weak and not statistically significant ($r = 0.186$, $p = 0.178$). This pattern indicates

that T_{paddy} was related to (but not simply a direct surrogate for) the drying air temperature and drying time. Instead, T_{paddy} represents the transient thermal response of the paddy to the combined effects of heat transfer, moisture evaporation, and exposure conditions during drying.

Table 3 Pearson correlation coefficients among ANN input variables

Variable	T_{air}	Time	T_{paddy}	T_{surr}	RH_{surr}
T_{air}	1	-.412**	.655**	0.036	-0.041
Time	-.412**	1	0.186	.617**	-.451**
T_{paddy}	.655**	0.186	1	.466**	-.401**
T_{surr}	0.036	.617**	.466**	1	-.958**
RH_{surr}	-0.041	-.451**	-.401**	-.958**	1

A sensitivity analysis using the ANN was conducted to quantify the relative predictive contribution of each input variable to the model outputs. The normalized importance values are presented in Figure 6. Of the variables investigated here, T_{paddy} had the highest relative importance, accounting for approximately 38% of the normalized importance, followed by drying time (32%) and drying air temperature (21%). The contributions of the ambient air temperature and relative humidity to the ANN predictions were lower. These results suggest that T_{paddy} is the most informative predictor within the present dataset and model structure. It is important to note that the sensitivity values represent the relative predictive contribution of each variable to the trained ANN, and should not be interpreted as direct evidence of causal or absolute physical dominance. The ranking observed here is nevertheless physically interpretable when considered together with the measured temperature response and the heat and mass transfer processes occurring during pneumatic drying.

The relatively high importance of T_{paddy} can be interpreted based on its position within the coupled heat and mass transfer process. The drying air temperature represents the thermal condition imposed by the dryer, whereas T_{paddy} represents the resulting thermal state of the biological material. The measured value of the grain temperature is governed by the balance between convective heat transfer from the hot air, heat consumption associated with moisture evaporation, internal moisture transport, and the duration of exposure. Consequently, T_{paddy} provides information on the actual thermal history experienced by the grain that cannot be represented by the drying air temperature alone. This interpretation is supported by previous studies showing that grain temperature and its temporal variation are closely associated with changes in the rice milling quality during drying [22, 23].

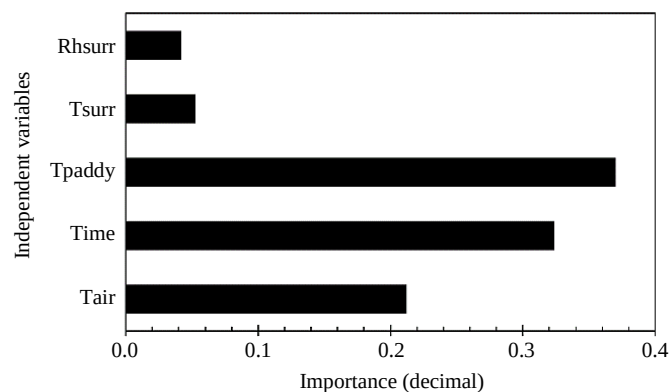


Figure 6 Relative importance of independent variables affecting drying performance

From the perspective of heat and mass transfer, we note that the grain temperature governs not only the evaporation rate but also the development of internal moisture gradients within the rice kernel. During high-temperature drying, moisture is removed rapidly from the grain surface, whereas moisture diffusion from the kernel interior proceeds at a slower rate. This imbalance creates localized shrinkage near the surface while the core remains relatively wet, generating tensile stresses within the kernel. When these stresses exceed the mechanical strength of the rice grain, microscopic fissures are initiated; these then propagate during milling, resulting in kernel breakage and a reduction in HRY. This mechanism agrees well with the results of both classical studies [24, 25] and recent investigations demonstrating that the grain temperature history and internal moisture gradients are the principal factors controlling formation of fissures and milling quality during rapid drying [5, 7, 8, 26, 27].

The correlation and sensitivity results highlight an important distinction between the roles of T_{air} , time, and T_{paddy} . T_{air} determines the external thermal driving condition, while time determines the duration over which this condition acts. T_{paddy} represents the resulting thermal state of the grain arising from these process conditions together with moisture evaporation and internal transport. Thus, the higher importance of T_{paddy} identified by the ANN does not mean that T_{air} or time are physically unimportant; instead, it suggests that T_{paddy} provides a more direct representation of the thermal state that emerges from their interaction with the drying material. This distinction is particularly relevant to the results presented here, since T_{air} and time were associated with the speed of drying and energy consumption, whereas T_{paddy} was also closely connected to the thermal exposure experienced by the grain and, consequently, to the conditions associated with quality deterioration.

The results of the correlation analysis provide further support for this interpretation. The correlation between T_{paddy} and T_{air} was moderate ($r = 0.655$), but there was only a weak and nonsignificant correlation between T_{paddy} and time ($r = 0.186$). Hence, the 38% importance assigned to T_{paddy} cannot be explained simply by duplication of the information contained in the drying time. Instead, the sensitivity result suggests that the measured grain temperature carries additional information about the transient response of the grain during drying. Nevertheless, since the ANN-based importance reflects predictive association rather than causality, this interpretation

should be regarded as a mechanistic explanation supported by the experimental observations rather than as proof that T_{paddy} independently causes the observed responses.

From an engineering perspective, these results suggest that the grain temperature should be considered as an additional control-oriented process variable, rather than relying exclusively on the drying air temperature. Conventional methods of controlling air temperature regulate the thermal input to the dryer, but the actual thermal response of the grain depends on heat transfer, moisture evaporation, internal moisture transport, and exposure time. Real-time monitoring of T_{paddy} could therefore provide an additional feedback signal for adjustments to the heating intensity or the duration of drying according to the actual thermal condition of the grain. This approach would be particularly useful when the objective is to balance rapid moisture removal with the avoidance of excessive thermal exposure associated with quality deterioration. The findings presented above therefore provide a mechanistic basis for further investigation of grain-temperature-oriented control strategies, rather than a direction demonstration of their effectiveness.

The sensitivity results should be interpreted within the experimental domain of the present study. The ANN was trained using data obtained from a laboratory-scale pneumatic dryer processing only Thai Jasmine 105 paddy over a limited moisture range, with drying air at a fixed velocity of 8.5 m/s and only three temperatures (60°C, 80°C, and 100°C). The relative importance ranking cannot therefore be generalized to other dryer configurations, operating ranges, grain varieties, airflow conditions, or drying temperature ranges without further validation.

The sensitivity analysis presented here identifies predictive importance but does not establish independent causal effects among the input variables. Studies should therefore be conducted in future to validate the observed ranking using larger datasets and broader operating conditions, together with cross-validation and complementary statistical or model-based analyses. In further work, real-time grain-temperature monitoring could also be integrated with dynamic heat and mass transfer models, model predictive control, and artificial intelligence optimization to investigate whether grain-temperature-oriented control can simultaneously reduce energy consumption, shorten drying time, and preserve HRY.

4. Conclusions

In this study, experimental pneumatic paddy drying was investigated via an ANN-based sensitivity analysis to identify the process variables that most strongly influence the drying performance, energy consumption, and rice milling quality. Increasing the temperature of the drying air accelerated moisture removal and reduced the drying time but lowered HRY, indicating an inherent trade-off between drying efficiency and product quality. Of the conditions investigated here, drying at 60°C provided the most favorable results, as it yielded the lowest SEC with the highest HRY. The ANN accurately predicted the moisture content, electrical energy consumption, and HRY, enabling a reliable evaluation of the importance of these variables.

Within the operating range investigated here, the paddy grain temperature (T_{paddy}) emerged as the most informative predictor, with a larger contribution than drying time and drying air temperature. Rather than representing an independent control variable, T_{paddy} reflects the transient thermal state of the grain resulting from the coupled effects of heat transfer, moisture evaporation, and exposure duration, thereby providing richer process state information than drying air temperature alone.

The principal contribution of this study is a demonstration that ANN-based sensitivity analysis can be used not only for prediction but also for identifying physically meaningful process state variables for pneumatic paddy drying. These findings suggest that when developing drying strategies, grain temperature should be considered as an additional feedback variable rather than relying exclusively on the temperature of the drying air, to strike a better balance between the drying rate, energy efficiency, and rice milling quality. Although the proposed framework was developed under laboratory-scale conditions and further validation will be required for other dryers and operating conditions, it provides a practical foundation for grain-temperature-oriented monitoring, advanced process control, and intelligent optimization of pneumatic paddy drying systems.

5. References

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