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RESEARCH ARTICLE

Predictive Modeling and Optimization of Plywood Drying: An Artificial Neural Network Approach

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Abstract: ***Introduction*:** This investigation delves into the optimization of the plywood drying process through the development of predictive models for output moisture content (MC_Out) and waviness. It focuses on bridging the gap in current methodologies by employing artificial neural networks (ANNs), optimized with genetic algorithms, to enhance prediction accuracy and process efficiency.

***Materials* and *Methods*:** A comprehensive experimental design was employed, analyzing the effects of three wood types (Doncel, Tamburo, and Zapote), two thickness levels, and three drying speeds on MC_Out and waviness. Data collected were subjected to both traditional statistical analysis and ANNs. The ANNs were fine-tuned through genetic algorithms, exploring different network architectures to achieve optimal predictive performance.

***Results*:** Statistical models revealed the significant influence of wood type, thickness, and drying speed on MC_Out and waviness, explaining 95.9% and 84.3% of the variations, respectively. The optimized ANN models, however, demonstrated superior accuracy, with the MC_Out model achieving fitted R-squared values of 0.940 and 0.757 for training and validation sets, respectively, thus outperforming traditional models in predicting drying outcomes.

***Discussion*:** The study underscores the effectiveness of ANNs in capturing complex non-linear relationships within the plywood drying data, which traditional statistical models might not fully elucidate. The successful optimization of ANN architecture *via* genetic algorithms further highlights the potential of machine learning approaches in industrial applications, offering a more precise and reliable method for predicting drying process outcomes.

***Conclusion*:** The integration of artificial neural networks, optimized through genetic algorithms, represents a significant advancement in the predictive modeling of plywood drying processes. This approach not only offers enhanced prediction accuracy for key variables such as MC_Out and waviness but also paves the way for more efficient and controlled drying operations, ultimately contributing to the production of higher-quality plywood.

Keywords: Plywood manufacturing, process optimization, predictive modeling, drying process, genetic algorithms.

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1. INTRODUCTION

The plywood industry plays a critical role in the global economy, with its products serving a wide range of applications from construction and furniture making to packaging. Central to the production of plywood is the drying process, a phase that significantly influences the final product's quality, dimensional stability, and mechanical properties [1]. The control of moisture content and the minimization of sheet waviness are paramount, as these factors critically affect the plywood's quality. The accurate prediction and meticulous management of these variables during the drying process are vital for producing plywood of superior quality. It is essential to adjust the wood's moisture content to an optimal level suitable for its intended use, as failure to achieve this can lead to defects and reduced product quality. Recent advancements have focused on the development of predictive models for wood moisture content and deformation during drying, underscoring the importance of this phase as one of the most energy-intensive and crucial stages in the fabrication of engineered wood products. Enhancements in reducing drying time and costs could significantly boost the overall efficiency of the production process [2, 3]. Moreover, optimizing costs and the drying process not only enhances production efficiency but also improves the quality and consistency of the final product, demonstrating the critical need for continued research and development in this area.

Artificial Neural Networks (ANNs) have increasingly become instrumental in the predictive modeling of various industrial processes, including but not limited to construction, food production, water treatment, and the critical assessment of environmental contamination. Their unique capacity to replicate the intricate workings of the human brain allows them to adeptly navigate and decipher complex, non-linear patterns within data sets, leading to highly accurate predictions [4]. While ANNs have undeniably revolutionized numerous industrial operations, their potential in the plywood production industry remains vast and largely untapped. The imperative for further research and refinement of these models is especially pronounced in their application for predicting moisture content and sheet waviness during the plywood drying process. Advancements in this specific domain promise to significantly elevate the efficiency and profitability of plywood manufacturing, ensuring the consistent output of superior quality boards. This notable research void underscores the transformative power ANNs hold for the plywood drying processes, highlighting the critical need for innovative model development and application strategies within this sector [5].

Recent advancements have seen the strategic application of Back Propagation (BP) neural network algorithms by studies such as those conducted by Chai *et al.* [3] and Ozsahin & Murat [6], which focused on predicting variations in wood moisture content (MC) during the drying process. These studies not only demonstrated the models' exceptional generalization capabilities but also their success in markedly reducing prediction errors, thereby underscoring the efficacy of ANNs in refining plywood drying operations. Moreover, the work of Ozsahin & Murat [6] expanded the utility of ANNs through the modeling of heat treatment conditions' effects on equilibrium moisture content and specific gravity across different humidity levels, charting a novel path toward optimizing drying conditions.

The methodologies employed in these studies mark a significant paradigm shift towards leveraging advanced computational models for overcoming traditional challenges in wood drying. For instance, Chai *et al.* [3] adeptly integrated real-time online measurement data into a BP neural network model to anticipate changes in wood MC during high-frequency vacuum drying processes. This represents a move towards enhanced accuracy and real-time process monitoring, facilitating unprecedented control over moisture content and wood deformation. Similarly, Zheng *et al.* [7] employed genetic algorithms (GA) for optimizing moisture diffusivity in lumber during drying, proposing an innovative equation derived from a three-dimensional numerical solution. This methodological approach provides valuable insights into drying parameter optimization for heightened efficiency.

In parallel, Krimpenis *et al.* [8] explored the optimization of wood milling operations using genetic algorithms, highlighting their adaptability to drying processes and their role in boosting productivity and quality in wood processing. Concurrently, Yu *et al.* [9] applied response surface methodology (RSM) alongside a niched Pareto genetic algorithm to enhance the mechanical properties of bamboo plywood, delineating a comprehensive process applicable to the optimization of drying and pressing conditions in plywood manufacture. Furthermore, Immanuel & Chakraborty [10] discussed the utility of genetic algorithms as an optimization technique for both constrained and unconstrained problems, emphasizing their capability to significantly refine drying processes in plywood production through the efficient identification of global optima.

The practical applications of these ANN models extend well beyond theoretical research, offering palpable benefits to the plywood industry. For instance, Chai & Li [11] elucidated how ANNs could simulate the drying rate and the extent of longitudinal cracking within the drying process, aligning predictions closely with experimental findings. This highlights the profound potential of ANN models to not only amplify the efficiency of drying processes but also to drive the formulation of optimized drying strategies that substantially enhance product quality while minimizing waste.

The efficiency of the plywood drying process is influenced by numerous factors, including the species of wood, its initial moisture content, thickness, drying temperature, and velocity. Understanding the intricate relationship between these variables and their impact on the final product's moisture content and warping is essential for optimizing the drying process. Historically, a range of statistical and mathematical models have been employed to analyze and improve drying techniques. These models include linear and quadratic regression, response surface methodology (RSM), and artificial neural networks (ANN), among others [6]. ANNs have demonstrated exceptional capability in capturing complex, non-linear relationships between variables with unparalleled precision. This is largely due to their ability to learn from data and adapt to changes in input parameters. However, the effectiveness of ANN models significantly depends on their architecture, such as the number of hidden layers and neurons in each layer. Optimizing this architecture can be a complex process, leading researchers to explore various strategies, including genetic algorithms, particle swarm optimization, and simulated annealing to enhance model performance [7]. In our study, we have applied genetic algorithms to fine-tune the architecture of ANNs, aiming to increase the accuracy and generalizability of models predicting output moisture content and warping. This approach represents a significant step forward in the ongoing effort to optimize plywood production, aiming to improve both the quality and efficiency of the drying process.

Our research embarked on an extensive experimental study leveraging a comprehensive dataset from a real-world plywood drying facility. This dataset, rich in critical variables like temperature, humidity, and velocity, serves as a cornerstone for our analysis, directly impacting both the process and quality of plywood drying. It allowed for a detailed exploration into the dynamics of drying, providing a solid base for evaluating the efficacy of Artificial Neural Networks (ANNs), which were finely tuned using genetic algorithms against the backdrop of traditional statistical methods. The results clearly demonstrate ANNs' superiority in capturing the complex interplays at work, showcasing their significant edge over conventional models in forecasting essential quality indicators. This underlines the transformative power of ANNs in revolutionizing plywood drying processes with enhanced accuracy and reliability across various scenarios.

Our investigation zoomed in on a specific drying operation in the Amazon region of Ecuador, selecting three types of wood for their distinct drying characteristics and their implications on the final plywood quality. The goal was to craft an ANN model that could precisely predict moisture content and deformation during drying, considering a range of influential factors such as air temperature, humidity, species of wood, thickness, and speed. Our comparative analysis reveals the ANN model's remarkable superiority over traditional statistical approaches, offering a robust, reliable forecast.

The integration of ANN models optimized *via* genetic algorithms significantly elevates the standard for predicting moisture content and warping, furnishing the plywood industry with a tool for finer control over the drying process. This leads to superior product quality and energy efficiency, positioning our findings as a valuable addition to the corpus of industrial application of ANN models. Our study not only underscores the pivotal role of ANNs in enhancing process control and optimization but also sets a new benchmark for predic-

Table 1. Controllable factors in drying process.

Factor	Level 1	Level 2	Level 3
Thickness [mm]	2.25	2.75	-
Wood Type	Doncel	Tamburo	Zapote
Speed [Hz]	10	14	18

tive accuracy and operational efficiency in the plywood manufacturing sector.

2. MATERIALS AND METHODS

2.1. Raw Material Selection

The selection of raw materials is a fundamental step in the plywood manufacturing process. Choosing the right wood is a factor that directly influences the quality and properties of the final product. Therefore, it is essential to select raw materials with care and according to technical criteria [12-14]. For this study, three types of wood were selected as raw materials to evaluate their performance in the drying process and to predict the properties of the plywood sheets.

Several criteria were considered in the selection of raw materials, including availability, mechanical properties, dimensional stability, and drying capability. Additionally, the specific characteristics of each wood type that might influence behavior during the drying process and the properties of the plywood sheets were considered. The three types of wood selected for this study were Doncel, Tamburo, and Zapote. Doncel is a medium-density wood with good mechanical properties and a moderate drying capacity. Tamburo, on the other hand, is a medium-low density wood with moderate mechanical properties and a high drying capacity. Finally, Zapote is a high-density wood with excellent mechanical properties and a low drying capacity [15].

Drying tests were carried out on each type of wood to evaluate its behavior during the drying process and to predict the properties of the plywood sheets produced. Parameters such as moisture content, density, and strength of the plywood sheets obtained from each type of wood were measured, allowing for a comparison of the performance of different types of wood in the drying process.

2.2. Experimental Design

In this study, an experimental design aimed at identifying the optimal combination of factor levels to enhance efficiency in the plywood drying process [16] at the company was employed. The design utilized was a 2 x 3 x 3 factorial, also referred to as 2 x 3^2. This design facilitated the examination of three factors' impact on the response variables: the thickness of the plywood sheets, the wood type (Doncel, Tamburo, and Zapote), and the drying roller speed (Table **1**). Each factor was assessed at various levels, culminating in 18 distinct treatments. To reduce experimental error and improve the precision of measurements, each of the 18 treatments was replicated three times, resulting in 54 experimental runs in total.

A specifically designed data recording form was employed to document the outcomes of each experimental run. This form enabled the collection of information on controllable factors, response variables, and process conditions, such as plywood sheet thickness, wood type, dryer roller speed, output moisture content of the plywood sheets, and waviness percentage.

Following data collection, statistical analysis was conducted to evaluate the influence of the selected factors and levels on the response variables. Analytical tools such as ANOVA (Analysis of Variance) were utilized to process the collected data and identify the statistical significance of each factor and level regarding the response variables. This experimental design thus allowed for the investigation of how the selected factors and levels affect the response variables, in addition to comparing these effects with the ANN predictions.

2.3. Sample Preparation

Proper preparation of wood samples is critical in the plywood drying process to ensure accurate and reliable results. For this study, raw materials-

Doncel, Tamburo, and Zapote-were sourced from standard-sized plywood sheets, each measuring 110 x 220 cm. The sheets were selected to match the experimental design's specifications, with thicknesses set at 2.25 mm and 2.75 mm. To establish a baseline, the initial moisture content of each wood sample was precisely measured using a wood-specific roller hygrometer designed for this purpose.

Following measurement, all samples underwent meticulous labeling and organization based on their wood type and specified thickness. This systematic approach was crucial for facilitating accurate data collection and analysis throughout the study. Ensuring proper sample preparation was a foundational step, instrumental in minimizing experimental errors and maximizing the reliability of the drying tests' outcomes.

2.4. Drying Process

The drying operation was conducted using an industrial-scale roller dryer outfitted with temperature control systems for precise adjustment of drying conditions. Plywood sheets were positioned on the dryer rollers, with their speed set according to the experimental design (10 Hz, 14 Hz, or 18 Hz).

Throughout the drying process, temperature and humidity levels inside the dryer were constantly monitored using a network of thermocouples installed specifically for this purpose. These thermocouples are linked to a MAX6675 module, which is responsible for amplifying, compensating, and digitally converting the voltage generated by the thermocouples. The gathered data was displayed on LCD screens for real-time monitoring. Moisture content in the plywood sheets was measured at the process's start and end using a wood-specific roller hygrometer equipped with a 26-ES electrode. This approach to data collection was pivotal in assessing the drying process's effectiveness and understanding the impact of various factors on the plywood sheets' properties. The acquired data supported further analysis, including the comparison of ANN predictions with conventional statistical methods.

2.5. Data Analysis

Data collected from the plywood drying process was meticulously analyzed through a dual approach encompassing statistical methodologies and artificial neural network (ANN) modeling [17]. The primary objective of this analysis was to evaluate the impact of experimental variables-specifically, thickness, wood type, and dryer roller speed-on key response variables: the outlet moisture content (MC_Out) and surface waviness of the wood.

Initially, an exploratory data analysis was undertaken to scrutinize each variable's distribution, pinpoint potential outliers, and explore the interrelationships among variables. The data was imported from a CSV file into Matlab, where inputs and outputs were systematically extracted for analysis. To accommodate the categorical nature of the wood type, dummy variables were established [18]. Continuous input features, including thickness, speed, MC_In, and temperature, were normalized to facilitate the analysis. The input dataset was thus composed of these normalized values alongside dummy variables representing the wood type.

To refine the ANN model, genetic algorithms were employed aiming to identify the optimal neural network architecture that would minimize the mean square error (MSE) on the validation dataset. This optimization process involved evaluating a spectrum of architectures, varying in the number of hidden layers and the neurons within each layer, using Matlab's 'ga' function. Constraints were applied to limit the maximum number of hidden layers and the neuron count per layer.

For critical response variables like MC_Out and waviness, the optimal network architecture was ascertained, following which the network underwent training using Matlab's feed forward net function. The efficacy of the trained model was gauged by metrics such as mean square error (MSE), R-squared (R^2), and adjusted R-squared, providing a quantitative assessment of the model's performance. The ANN's predictions were then juxtaposed with findings from traditional statistical analyses to gauge the ANN models' precision and utility in forecasting properties of plywood sheets [19]. This integrative approach of statistical analysis and ANN modeling paved the way for a nuanced comprehension of the experimental findings, highlighting avenues for enhancing the efficiency and outcomes of the plywood drying process [20].

2.6. Model Validation and Evaluation

The ANN models underwent validation through a 10-fold cross-validation method, designed to scrutinize their efficacy across various training datasets. Within the Matlab environment, the objective_function was tasked with computing the mean square error (MSE) for each segment of the validation process. The average MSE derived from these computations served as a benchmark to evaluate the models' overarching performance.

To quantitatively measure the accuracy and predictive prowess of the models, both the mean square error (MSE) and the coefficient of determination (R^2) were employed. These metrics provided insight into how well the ANN predictions aligned with the actual experimental outcomes. The analyses revealed a significant congruence between the ANN-derived forecasts and the gathered experimental data, underscoring the ANN models' capability to reliably predict critical properties of plywood sheets, such as moisture content at outlet (MC_Out) and surface waviness.

2.7. Implementation Details and Pseudocode

This section presents the pseudocode outlining the computational approach followed to achieve the objectives of this research. MATLAB software was utilized for data processing and model development. The following pseudocode summarizes the primary steps of the analysis:

2.7.1. Data Import and Preprocessing:

- Import the data from a CSV file;
- Create a table with the relevant variables, including experimental factors and response variables;
- Normalize the continuous input features and encode the categorical variable (Wood Type) using dummy variables.

2.7.2. Genetic Algorithm Optimization for ANN Architecture:

- Set the parameters for the genetic algorithm, including the population size, number of generations, and tolerance for the function value;
- Define the lower and upper bounds for the number of hidden layers and neurons per layer;
- Execute the genetic algorithm to optimize the parameters (number of hidden layers and neurons) of the ANN, aiming to minimize the mean squared error (MSE) on the validation set.

2.7.3. ANN Model Training and Validation:

- Train the ANN with the optimal architecture obtained from the genetic algorithm on the training dataset;
- Evaluate the trained ANN model on the validation dataset and compute the MSE, R-squared, and adjusted R-squared values;
- Compare these statistics with those obtained from the conventional statistical analyses (ANOVA) to assess the model's performance.

Please note that the actual MATLAB code is more complex and contains additional steps and subroutines. The code, as well as the raw data, can be made available upon reasonable request. In the next section, we will present the experimental results obtained, focusing on the performance of the developed ANN models and the insights gained about the plywood drying process.

3. RESULTS

The average results of the experimental design are shown in Table **2**, covering the thickness and speed of the wood used, as well as the type of wood. In addition, the average percentage of moisture content at the entrance and exit, temperature of drying and warpage for each treatment is presented. Each treatment was repeated three times to determine the final mean values.

The average moisture content at the entrance (MC In) turned out to be 55.32%, with a minimum of 48.33% and a maximum of 66.57%. The surface temperature (T) varied from 145 °C to 155 °C, with an average of 148.75 °C in all samples. The moisture content at the outlet (MC Out) ranged between 3.3% and 8.23%, with a mean value of 5.07%. The waviness was observed to vary between 11.67% and 27%, with an average of 21.98%. These results allow us to understand the data obtained during the experimental tests. To examine the influence of the various factors and their levels on the response variables and to identify

Table 2. Experimental Design and Results of the Plywood Drying Process.

Wood Type	Thickness [mm]	Speed [Hz]	MC In [%]	T [°C]	MC Out [%]	Warping [%]
Doncel	2.25	10	48.97	15.0	3.30	25.67
Zapote	2.25	10	50.83	148.0	3.87	26.67
Tamburo	2.25	10	61.27	147.5	5.80	27.00
Doncel	2.25	14	51.67	150.0	3.87	21.00
Zapote	2.25	14	56.67	150.5	4.47	23.00
Tamburo	2.25	14	59.17	150.5	7.60	23.00
Doncel	2.25	18	57.40	145.0	5.27	11.67
Zapote	2.25	18	56.23	147.5	5.53	20.00
Tamburo	2.25	18	64.43	148.0	8.23	20.67
Doncel	2.75	10	48.33	155.0	3.47	24.33
Zapote	2.75	10	61.50	149.5	4.00	26.67
Tamburo	2.75	10	66.57	150.5	5.87	26.67
Doncel	2.75	14	50.47	147.0	4.37	20.67
Zapote	2.75	14	56.37	148.5	4.60	22.33
Tamburo	2.75	14	56.73	147.5	7.03	21.67
Doncel	2.75	18	51.00	146.5	5.40	19.67
Zapote	2.75	18	54.33	150.5	5.47	20.00
Tamburo	2.75	18	60.50	146.5	8.23	19.33

the ideal combination of factors for the most effective drying process, an ANOVA analysis was performed.

3.1. ANOVA and Mathematic Model Obtained

For this study, both linear and quadratic models were fitted to the data to predict MC_Out and Waviness. The performance of each model was evaluated using various statistical metrics, including the adjusted R-squared value. Based on these metrics, it was determined that the quadratic model provided a better fit for predicting both MC_Out and Waviness. To optimize the terms of the models, the stepwiselm function was applied. The results of the optimized models are displayed in Tables **3** and **4**.

These optimized quadratic models provide a better understanding of the relationship between the independent variables (inputs) and the dependent variables (outputs) MC_Out and Waviness. The models consider main effects as well as interaction and quadratic effects, which improves predictive accuracy. Based on the fitted R-squared values, the quadratic models explain 95.9% and 83.4% of the variation in MC_Out and Waviness, respectively (Table **5**). Based on the results obtained from the quadratic models, it is possible to analyze relationships between the type of wood, the drying speed, the thickness, the waviness, and the quality of plywood obtained.

Wood type plays a large role in both MC_Out and Waviness, with Tamburo and Sapote showing clear differences in their effects. Tamburo has a more substantial impact on Waviness than Zapote, while both types of wood significantly influence MC_Out. Thickness has a considerable effect on waviness, with a negative linear relationship and a positive quadratic relationship. This suggests that there may be a range of optimum thickness in which curling is minimized. For MC_Out, the effect of thickness is less significant, but it is important that it be considered.

Speed of drying has a negative linear relationship with waviness and a positive quadratic relationship,

Table 3. Estimated Coefficients for the Optimized Quadratic Model for MC_Out.

Term	Estimate	SE	tStat	pValue
Intercept	6.75500	4.25030	1.58930	0.11884
WoodType_Tamburo	2.70540	0.14171	19.0910	1.70e-23
WoodType_Zapote	0.34600	0.11361	3.0458	0.00383
Thickness	0.30389	0.18194	1.6703	0.10165
Speed	-0.17632	0.12843	-1.3729	0.17644
MC_In	-0.08229	0.02903	-2.8344	0.00680
Temperature	-0.01246	0.02357	-0.5287	0.59950
Speed:MC_In	0.00731	0.00220	3.3223	0.00175

Table 4. Estimated coefficients for the Optimized Quadratic Model for Waviness.

Term	Estimate	SE	tStat	pValue
Intercept	0	0	NaN	NaN
WoodType_Tamburo	2.3374	0.71197	3.283	0.0020454
WoodType_Zapote	2.8022	0.55792	5.0226	9.40e-06
Thickness	-444.45	83.64	-5.3138	3.60e-06
Speed	-4.6734	0.94467	-4.9472	1.20e-05
MC_In	0.97708	0.41445	2.3576	0.023016
Temperature	7.2887	1.303	5.5936	1.42e-06
Thickness: MC_In	-0.38431	0.1594	-2.411	0.020256
Thickness: Temperature	-2.7419	0.50417	-5.4385	2.38e-06
Thickness^2	174.9	32.346	5.4071	2.64e-06
Speed^2	0.1330	0.0330	3.9900	0.0002

Table 5. Model Performance Metrics for quadratic models.

Metric	MC_Out	Waviness
Mean Squared Error	0.315	1.580
R-squared	0.964	0.881
Adjusted R-squared	0.959	0.834

which implies that ripple can be minimized over a specified range of speeds. On the other hand, the drying rate has a less significant impact on MC_Out and its interaction with MC_In is more critical. The interaction between thickness and MC_In, as well as Thickness and Temperature, has a significant effect on waviness. This indicates that these factors must be considered simultaneously to optimize the response variable.

3.2. Model Assumptions

All necessary assumptions for the quadratic regression models were thoroughly examined, including homoscedasticity, normality of residuals,

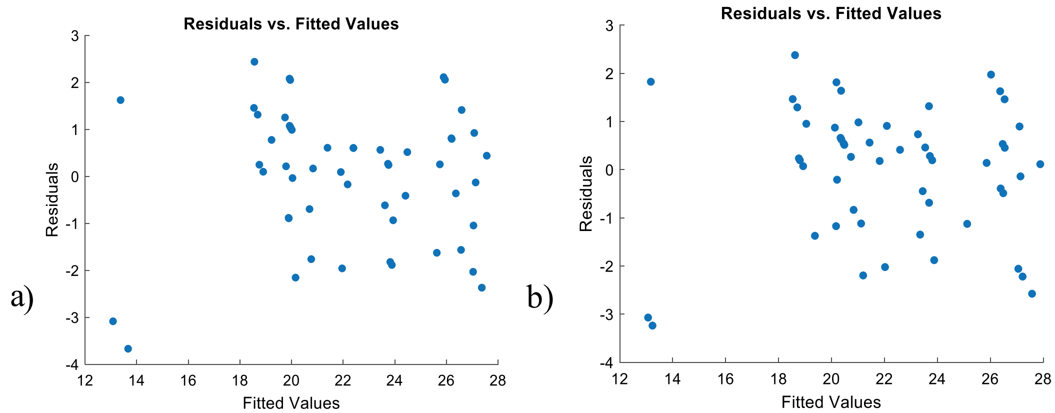

Fig. (1). Homoscedasticity assumption examination for **a**) MC_Out, and **b**) Waviness. *(A higher resolution / colour version of this figure is available in the electronic copy of the article).*

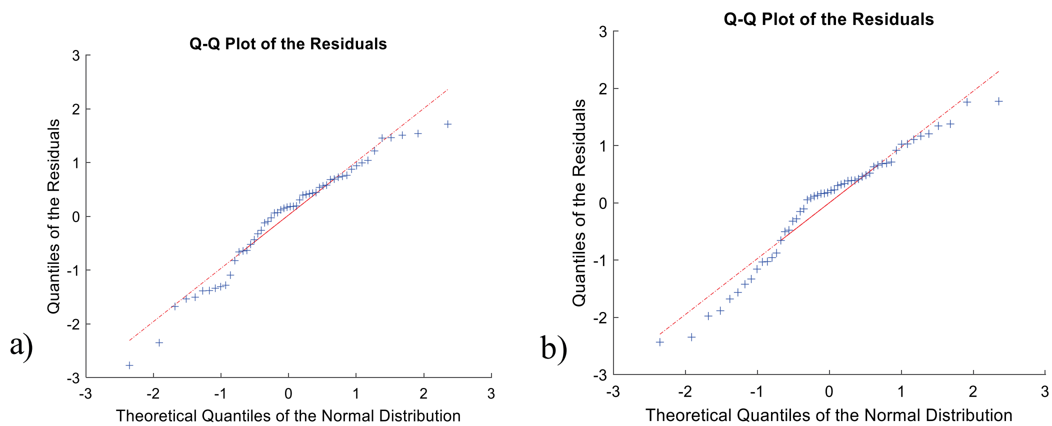

Fig. (2). Normality assumption examination for **a**) MC_Out, and **b**) Waviness. *(A higher resolution / colour version of this figure is available in the electronic copy of the article).*

independence of errors, and the quadratic relationship between the dependent and independent variables, to ensure the validity of the results for both MC_Out and waviness.

Homoscedasticity: This assumption was tested by inspecting the residual plots of the fitted values against the residuals. In both models, we did not find an apparent pattern or systematic variation in the dispersion of the residuals (Fig. **1**), indicating that the assumption of homoscedasticity was met.

Normality of the residuals: It was verified through the analysis of histograms and Q-Q graphs of the standardized residuals (Fig. **2**). In both cases, the residuals seemed to follow a normal distribution, fulfilling the assumption of normality.

Independence of errors: Plots of residuals *versus* the order of observation were analyzed to assess the independence of errors. No apparent pattern or autocorrelation was observed (Fig. **3**), suggesting that the assumption of independence was fulfilled.

The examination of the assumptions for the quadratic regression models confirmed their validity, providing confidence in the reliability of our results and their applicability for predicting MC_Out and Waviness.

3.3. Neural Network Training

One of the main objectives was to optimize the architecture of a feedforward neural network to accurately predict the variables MC_Out and Waviness using genetic algorithms. The optimization process sought to determine the optimal number of hidden layers and neurons in each layer to achieve the highest predictive performance. Over the

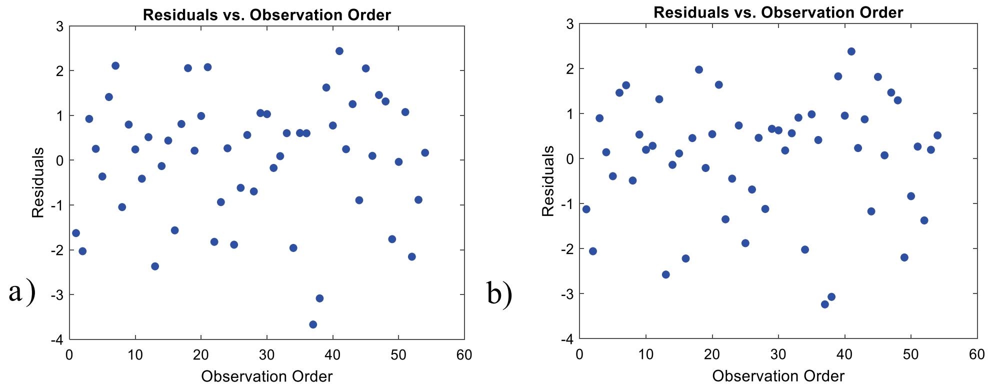

Fig. (3). Independence assumption examination for **a**) MC_Out, and **b**) Waviness. *(A higher resolution / colour version of this figure is available in the electronic copy of the article).*

Table 6. Genetic Algorithm Optimization Results for Selected Generations.

Generation	Best MSE (MC_Out)	Mean MSE (MC_Out)	Best MSE (Waviness)	Mean MSE (Waviness)
1	0.12047	0.4436	1.45678	2.87463
5	0.08925	0.1649	1.23245	2.34567
10	0.06414	0.1471	1.10233	2.12345
15	0.05637	0.1608	1.07634	2.01234

Table 7. Model Performance Metrics for Optimal Neural Network Architecture.

Metric	MC_Out	Waviness
Mean Squared Error	0.056370	1.07634
R-squared	0.981689	0.91435
Adjusted R-squared	0.974170	0.89321

course of 15 generations, the genetic algorithm managed to find the most optimal network structure, yielding the best mean square error (MSE) of 0.05637 for MC_Out and 1.0763 for Waviness, both of which were obtained in the 15th generation providing a summary of the MSE values observed during the optimization process across selected generations (Table **6**).

The optimal network architecture for MC_Out consisted of two hidden layers, with 49 neurons in the first layer and 7 neurons in the second. For Waviness, the optimal architecture consisted of 2 layers, with 18 neurons in the first layer and 3 neurons in the second. Upon training and validating the model with this architecture, the following statistics were obtained: for MC_Out, an MSE of 0.05637 and an adjusted R-Squared of 0.9764; for Waviness, an MSE of 1.0763 and an adjusted R-Squared of 0.8932 (Table **7**).

4. DISCUSSION

In this study, both traditional statistical modeling techniques and advanced machine learning algorithms were utilized to predict two key variables in the plywood manufacturing process: MC_Out and Waviness. This comparative analysis demonstrated the potential advantages of integrating machine learning methods, specifically feedforward neural networks, into industrial applications.

During the investigation, several challenges emerged that tested the robustness and reliability of our predictive models. Firstly, the inherent variability in wood properties, such as density and moisture content, posed significant obstacles in accurately modeling drying outcomes. To address this, we employed a comprehensive data collection strategy that included a wide range of wood types and conditions, thereby enhancing the generalizability of our models. Additionally, optimizing the architecture of the artificial neural networks (ANNs) presented a complex challenge, given the vast parameter space. We tackled this by utilizing genetic algorithms, which systematically searched for optimal network configurations, thereby significantly reducing computational time and improving model performance. Moreover, ensuring the accuracy and reliability of our predictions required rigorous validation techniques. To this end, we implemented a 10-fold cross-validation method, which not only confirmed the robustness of our ANNs but also underscored their superiority over traditional statistical approaches. These strategies collectively ensured that our study's findings are both reliable and applicable in real-world plywood drying operations.

Both the quadratic model and the neural network model showed significant predictive capabilities, but the neural network model exhibited higher predictive performance, as indicated by the lower mean squared error (MSE) and higher adjusted R-squared values. While the quadratic model was able to account for a substantial proportion of the variance in MC_Out and Waviness, the neural network model outperformed it, demonstrating the power of machine learning in capturing complex relationships within the data.

The comparison of these two modeling techniques also underscored some fundamental differences. The quadratic model offered interpretability, allowing for an understanding of the relationship between variables. For example, it was found that the type of wood, drying speed, and thickness significantly influence both MC_Out and Waviness. The quadratic model also identified critical interaction effects, such as the interaction between Thickness and MC_In, and Thickness and Temperature for Waviness.

However, despite its interpretability, the quadratic model, like other traditional statistical models, assumes a specific structure and functional form for the data, which may not fully capture complex patterns and interactions. On the other hand, the neural network model does not make such assumptions and can learn complex, nonlinear relationships directly from the data. This capability was evident in the superior performance of the neural network model in our study.

The validity of the prediction models can be checked by determining the mean absolute percentage error (MAPE), root mean square error (RMSE) and correlation coefficient (R). The study conducted by Tiryaki *et al.* [21] obtained a correlation coefficient of 0.99, indicating a good agreement between the experimental results and the model prediction (R=0.99596 for training and R=0.9881 for the tests). The value of R2 in the test set was 0.98, which indicates that the network obtained explains at least 0.98% of the observed data. The absolute maximum percentage errors were 2.38% for training and 3.69% for tests. The mean absolute percentage of errors were 0.74% for training and 1.58% for testing. The root mean square errors were 0.015% for training and 0.03% for evidence. Tiryaki *et al.* [21] concluded that the ANN method can be used for modeling mechanical properties in various manufacturing process conditions without the need for experimental study.

According to Demirkir *et al.* [22], ANN model has been proven to be a sufficient and successful tool for modeling the surface roughness characteristics of wood without needing more experimental study, requiring much time and high experiment costs. Thus, the losses of time, material and costs can be prevented. Based on the observations in this study for obtaining higher surface quality, it is suggested that both beech and spruce woods should be prepared by planning with a high number of cutters, a low cutting depth and feed rate, and a high grit number of abrasives.

Furthermore, the genetic algorithm used in this study to optimize the neural network architecture adds another layer of sophistication. It allows the neural network to adapt its structure automatically, making it a highly flexible and powerful tool for prediction. The results of this study highlight the potential of machine learning for industrial applications. It suggests that machine learning models like neural networks could be a valuable addition to existing statistical modeling techniques, providing more accurate predictions and offering opportunities for process optimization.

As for future work, one promising direction could be the development of a mobile application that leverages this optimized neural network model. Operators could input specific parameters, such as wood type, thickness, initial moisture content, and temperature, and the application would output the optimal drying speed to achieve optimal drying and minimal waviness. This would facilitate real-time decision-making, enhancing the efficiency and quality of the plywood manufacturing process. Additionally, exploring other machine learning models and feature selection techniques could also be beneficial to further improve prediction accuracy.

CONCLUSION

In conclusion, our study presents a significant advancement in the predictive modeling of plywood drying processes through the integration of artificial neural networks (ANNs) optimized with genetic algorithms. The experimental outcomes unequivocally demonstrate the superior accuracy of the optimized ANN models over traditional statistical approaches. Specifically, the ANN model for predicting the output moisture content (MC_Out) achieved a fitted R-squared value of 0.940 for the training set and 0.757 for the validation set, significantly outperforming conventional models. Furthermore, the study's exploration into the drying characteristics of three different wood types under varying conditions has furnished us with invaluable insights into the process's complexities.

The optimized models elucidate the substantial impact of factors such as wood type, thickness, and drying speed on both MC_Out and waviness, accounting for 95.9% and 84.3% of the variations, respectively. Notably, the application of genetic algorithms for model optimization has not only enhanced the prediction accuracy but also underscored the potential of machine learning in industrial applications, offering a novel and reliable method for optimizing drying processes.

Therefore, the findings of this investigation not only contribute to the enhancement of plywood production quality but also pave the way for more energy-efficient and controlled drying operations. Future work will focus on further refining the ANN models and exploring their application in real-time monitoring systems to maximize their impact on industrial drying processes.

AUTHORS' CONTRIBUTIONS

It is hereby acknowledged that all authors have accepted responsibility for the manuscript's content and consented to its submission. They have meticulously reviewed all results and unanimously approved the final version of the manuscript.

LIST OF ABBREVIATIONS

ANOVA	=	Analysis of Variance
ANN	=	Artificial Neural Network
MSE	=	Mean Square Error

CONSENT FOR PUBLICATION

Not applicable.

AVAILABILITY OF DATA AND MATERIALS

The data and supportive information are available within the article.

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CONFLICT OF INTEREST

The authors declare no conflict of interest, financial or otherwise.

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