Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Artificial Neural Networks as a Decision-Support System for Predicting the Quality Attributes of Thermally Modified Wood

Özlem BOZKURT
Namık Kemal University
Günay ÖZBAY
gunayozbay@aksaray.edu.tr

Aksaray University

Research Article

Keywords: Artificial Neural Networks, Wood Thermal Modification, Meta-Analysis, Predictive Modelling, Mass Loss, Decision-Support Systems

Posted Date: April 1st, 2026

DOI: https://doi.org/10.21203/rs.3.rs-8989634/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Version of Record: A version of this preprint was published at European Journal of Wood and Wood Products on August 29th, 2026. See the published version at https://doi.org/10.1007/s00107-026-02478-2.

Abstract

Thermal modification represents a key, environmentally safe way to enhance dimensional stability and biological resistance of wood. Yet, the complex, non-linear synergy of the hydrothermal process variables often renders traditional quality prediction models inadequate. This paper aimed to tackle this challenge by developing a robust decision-support model driven by an ANN, specifically a Multi-Layer Perceptron (MLP), to model the thermo-chemical properties of the wood cell wall matrix. A high-throughput meta-dataset comprising 200 validated experimental data points from the peer-reviewed literature (2000–2025) was used to investigate behavioural variability across softwood and hardwood taxa. The proposed MLP model combines 5 key input parameters (Species Type, Density, Temperature, Duration, and Medium) to predict 3 key performance metrics: ML, EMC, and MOR loss. Statistical validations highlight the model's strong generalizability, yielding R^2> 0.935 across all outputs, with Mass Loss achieving the highest precision (R^2 = 0.962). More refined sensitivity analysis (ANN weight partitioning) quantified the hierarchical influence of process variables and pinpointed temperature (45.2%) and treatment time (25.1%) as the predominant kinetic predictors of wood degradation. By integrating classical wood science theories with recent computational intelligence, this study has developed a powerful virtual prototyping engine that avoids destructive sampling and aligns with new Smart Manufacturing and global bioeconomy paradigms.

1. Introduction

Wood is a prime bio-based resource for the construction and manufacturing industries worldwide, owing to its renewability and carbon sequestration capacity (Pacheco-Torgal, 2025; Popescu et al., 2024; Akpan et al., 2021; Calovi et al., 2024; Cao et al., 2025; Schubert et al., 2022). Wood lignocellulosic structure is hierarchical and most commonly consists of cellulose, hemicelluloses, and lignin. Its mechanical properties and hygroscopic characteristics are determined by its hierarchical structure, from cell wall ultrastructure to macroscopic growth-ring architecture. Nonetheless, the natural hygroscopicity of wood leads to dimensional instability, moisture-induced swelling–shrinkage cycles, and heightened vulnerability to biological deterioration, limiting its use in high-value structural and outdoor applications. Thermal modification (heat treatment) is an environmentally friendly technique to enhance the dimensional stability and durability of wood without chemical preservatives. Wood is usually heated to a temperature between 150°C and 230°C in controlled atmospheres, such as steam, oil, or inert gases. At elevated temperatures, significant thermochemical transformations occur in the cell wall matrix. Hemicelluloses depolymerise and deacetylate, which results in acidic conditions that further catalyse carbohydrate degradation, whereas lignin undergoes condensation and structural rearrangement reactions (Kocaefe et al., 2015; Dong et al., 2020; Hill, 2007; Sandberg et al., 2017; Hill et al., 2021).

Notwithstanding these advantages, there is an intrinsic trade-off with thermal modification. The same degradation processes that enhance durability also result in mass loss and deterioration of mechanical properties, particularly the Modulus of Rupture (MOR), as documented in numerous experimental studies (Militz, 2002; Esteves & Pereira, 2009; Gündüz et al., 2008). The magnitude of these effects depends on

treatment temperature, duration, treatment medium, wood density, and species type. Anatomical differences between softwoods and hardwoods that affect heat transfer kinetics and degradation pathways further increase the variability in material properties. The influence of temperature and duration on wood quality has been extensively studied, but assessing final performance across different species and processing conditions is still very challenging (Guo et al., 2014; Salca & Hiziroglu, 2014; Cao et al., 2022). The interactions among process parameters and material characteristics are highly non-linear and interdependent, reflecting coupled thermo-chemical and structural mechanisms. Typically, statistical regression methods assume linear relationships or limited interaction effects, which is not ideal for describing this complexity, especially when strong interaction effects are present.

Over several decades, most studies have focused on individual species or restricted parameter ranges. Integrated modelling strategies capable of combining heterogeneous experimental datasets into a unified predictive framework remain relatively underexplored in multi-species thermal modification datasets. In this context, Artificial Intelligence (AI) and Machine Learning (ML) approaches offer the opportunity to model multivariate, non-linear relationships without imposing strict parametric assumptions.

Therefore, the present study compiles a curated meta-dataset derived from peer-reviewed literature published between 2000 and 2025, encompassing both softwood and hardwood species. An Artificial Neural Network (ANN)-based multi-layer perceptron (MLP) model is developed to predict key quality indicators, Mass Loss (ML), Equilibrium Moisture Content (EMC), and Modulus of Rupture loss (MOR loss), as functions of temperature, treatment duration, density, species type, and treatment medium. By modelling the coupled non-linear behaviour of thermally modified wood within a unified computational framework, this study provides a data-driven approach to improve predictive accuracy and support process optimisation.

2. Materials and Methods

2.1. Meta-Dataset Acquisition and Pre-processing

This research is supported by an empirical study, i.e., the use of a meta-dataset of peer-reviewed experimental papers from 2000 to 2025. Data were extracted from academic databases (Web of Science, Scopus, ScienceDirect) using the keywords “thermal wood modification”, “heat treatment”, and “wood property prediction”. Using these results, 200 high-quality high-throughput data points were extracted, including softwood (*Pinus sylvestris, Picea abies*) and hardwood (*Fagus sylvatica, Fraxinus excelsior*). The graphical data were digitised using high-precision software to ensure consistency with the numerical data extracted from the literature.

$X = [Species_{Type}, Density, Temperature, Duration, Medium]$

where the treatment medium is represented on a categorically encoded plane (Air, Steam, Oil, Nitrogen, Vacuum). Since the treatment medium used a different unit scale, all numeric features (zero or one in

each step) have been normalised. No bias could arise from differing scales (0, 1), and all numerical values are shown in [0, 1] on a min-max scale. A descriptive summary of the curated dataset, detailing the ranges, means, and standard deviations of both input and output parameters, is presented in Table 1. Moreover, this statistical summary helps maintain robust coverage of the data across the thermal modification spectrum. In addition to supporting principles such as open science and reproducibility, this manuscript is accompanied by Supplementary Material containing the full meta-dataset, including all source citations for the 200 data points.

Table 1
Statistical summary of the meta-dataset parameters used for ANN modelling (N = 200).

Parameter Category	Variable	Unit	Min	Max	Mean	Std. Dev.
Inputs	Density	kg/m^3	415.8	715.3	542.4	102.6
	Temperature	°C	150.0	230.0	192.5	18.4
	Duration	h	2.0	24.0	6.2	4.8
Outputs	Mass Loss (ML)	%	1.20	15.40	7.15	3.92
	EMC	%	4.15	10.20	7.22	1.54
	MOR Loss	%	3.00	45.00	21.40	10.85

2.2. Architecture of Artificial Neural Network (ANN)

The rationale for the proposed application of Artificial Neural Networks (ANNs) in this research stems from the complex, non-linear characteristics of wood thermal treatment processes. The dynamics of relationships within these systems are inherently non-linear and influenced by various processing variables that contribute to material degradation. Traditional regression models often overlook interaction effects among temperature, duration, and treatment medium because they typically assume linearity and allow only limited interactions. In contrast, recent advancements in ANN, particularly through the Multi-Layer Perceptron (MLP) architecture outlined in this study, offer a more robust approach by enabling the model to learn multivariate trends without being constrained by strict parametric limitations. This computational versatility allows the machine learning model to integrate diverse anatomical features, such as tracheids in softwoods and vessel structures in hardwoods, to develop a comprehensive predictive framework.

The MLP model used in this study comprises an input layer with 5 neurons, two hidden layers, and an output layer with 3 neurons. The intricacies of chemical component degradation patterns are

represented in the first hidden layer, which contains 12 neurons, while the second hidden layer contains 8 neurons. To address the vanishing gradient problem, ReLU was used as the activation function for both hidden layers. In contrast, a linear activation function was used for regression predictions in the output layer. The Adam optimisation algorithm (Adaptive Moment Estimation) was selected for its efficiency in handling large datasets generated by wood modification procedures. Fundamentally, this sophisticated decision-support system, evaluated using Mean Squared Error (MSE), minimises reliance on expensive, destructive testing methods and promotes progress towards cyber-physical modelling in smart wood manufacturing. The schematic representation of this ANN architecture, including the specific neuron counts and layer connections, is presented in Fig. 1.

2.3. Model Training and Protocol of Validation

It stochastically partitioned the curated meta-dataset into two segments to promote robust generalisation of the proposed models and mitigate the risk of biased estimation, with 80% allocated to training and 20% to independent validation and testing. Using this partitioning method allows the model to be evaluated on data it has not yet seen, thereby providing a more realistic assessment of its predictive capacity. Second, to improve training stability and mitigate overfitting, a common challenge in complex neural network architectures, a stratified 5-fold cross-validation approach was employed. Because of this iterative validation, optimising the network's internal weights across multiple data folds can be done systematically. The predictive power and diagnostic performance of ANN models were extensively tested using the multi-criteria statistical framework. Analysis consisted of using the Coefficient of Determination (R^2) as a measure of the variance the model could capture, and the Root Mean Square Error (RMSE) to compute the standard deviation of the prediction residuals, as well as the Mean Absolute Percentage Error (MAPE) as a dimensionless measure of relative accuracy. These metrics provide a holistic corroboration of the model’s effectiveness in capturing the non-linear dynamics of the wood thermal modification process.

3. Results and Discussion

3.1. Predictive Performance and Statistical Validation

The ANN model was also critically evaluated using independent test datasets to assess its ability to explain the non-linear relationships characteristic of the hydrothermal process and of wood. The elaborate statistical approach, such as Coefficient of Determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), etc., is presented in Table 2. An R^2 of 0.93 or higher on all output variables in the unseen sample indicates strong generalisation capacity for the model. Such performance shows that the network goes beyond simple data training to represent the chemical and physical transformation trends of wood treatment. In particular, the model’s impressive performance in predicting mass loss (ML) (R^2 = 0.962) clearly demonstrates that kinetic thermal degradation is the most determinative factor in the magnitude of change. In addition, low MAPE values (3.20% to 5.42%) indicate

that the ANN provides accurate estimates across various wood species with different anatomical structures (Softwoods and Hardwoods). Low RMSE values indicate that the residuals are stochastically distributed, implying that the MLP model has made an efficient prediction of the synergistic interactions among temperature, process duration, and the outer medium. This statistical stability makes the model a reliable decision-support tool for the pre-calculation of quality yields in industrial processing, thereby saving time and costs in destructive experimental studies that might require extensive, expensive simulations.

Table 2
Performance metrics of the ANN model for the test dataset

Output Property	R^2	RMSE	MAPE (%)
Mass Loss (ML)	0.962	0.82	4.15
Equilibrium Moisture Content (EMC)	0.948	0.35	3.20
Modulus of Rupture Loss (MOR Loss)	0.935	2.14	5.42

3.2. Discussion and Theoretical Validation

This predictive accuracy ($R^2 > 0.93$) provides digital validation of well-established theories in wood science. The higher ML prediction accuracy is consistent with the results of Militz (2002) and Esteves & Pereira (2009), which suggest that thermal degradation occurs in a well-defined kinetic manner, primarily through hemicellulose depolymerisation. The model's capacity to "learn" these pathways shows that it can successfully bridge the transition from the degradation of thermally labile amorphous polysaccharides to more stable crystalline cellulose regions. This model shows greater flexibility than conventional linear regression, with both Softwoods and Hardwoods having low MAPE values, demonstrating that it represents a significant advancement over the classic linear regression. As noted by Gündüz et al. (2008) and Hill (2017), anatomical differences, most notably the tracheid structure in softwoods and the vessel architecture in hardwoods, will influence heat transfer rates and the sites of chemical reactions. Considering its initial density and species type, the MLP strengthened the model's ability to explain the unique thermo-chemical signatures of different wood taxa. The fact that residuals exhibit stochasticity further validates the claim of the "multi-objective" character of wood modification. The interaction between temperature and duration, which often causes marked deterioration in the modulus of Rupture (MOR), was accurately characterised. This agrees with the structural degradation described by Candelier et al. (2016), in which the carbohydrate matrix degradation is a vital parameter for the mechanical status of the lignocellulosic skeleton. In conclusion, our study indicates that AI can accurately mimic thermo-oxidative and hydrolytic reactions in the wood cell wall, providing an alternative to destructive testing that aligns with smart-manufacturing trends in the timber industry. The synergistic influence of treatment temperature and duration on wood degradation is visualised through a 3D neuro-thermal landscape in Fig. 2 (A). The model’s ability to map this landscape demonstrates strong congruence with the kinetic degradation pathways reported in the literature. To further decode the 'black box' nature of the neural network, a sensitivity analysis was performed Fig. 2(B). The results indicate that

temperature is the predominant factor (45.2% contribution), followed by treatment duration (25.1%), which reinforces the thermo-chemical sensitivity theories proposed by Hill (2017). Finally, the model's fidelity was verified by comparing the probability density distributions of the experimental and predicted datasets (Fig. 2C). The significant overlap between these distributions confirms that the ANN architecture successfully captured the variance and stochasticity of the meta-analytic data, providing a robust surrogate model for industrial wood modification processes.

3.3. Practical Implications and Industrial Significance

More than any prior computational validation, this research presents a transformative advancement for the global wood modification sector. By transitioning from traditional empirical "trial-and-error" techniques to a decision-support framework using Artificial Neural Networks (ANNs), this study seeks to enhance the efficiency of raw materials and energy use through sophisticated virtual prototyping. Our proposed Multi-Layer Perceptron (MLP) model serves as an advanced simulation tool for industrial manufacturers, enabling them to emulate the dynamic relationships among various hydrothermal factors —such as temperature and duration—and their impacts on different wood species without resorting to destructive physical testing. This predictive capability significantly minimises timber waste and lowers operational costs typically associated with extensive research and development (R&D) phases in new product development.

The strong predictive capacity demonstrated in our analysis ($R^2 > 0.93$) underscores a mathematically robust methodology for proactively calculating essential quality metrics such as Mass Loss (ML) and Modulus of Rupture (MOR). Such precision facilitates the optimisation of material characteristics, ensuring both structural integrity and exceptional dimensional stability. Furthermore, sensitivity analysis reveals that temperature (45.2%) and treatment duration (25.1%) are the primary factors influencing these processes, providing a quantitative framework for industrial automation.

By integrating these neural weightings into cyber-physical systems, the timber industry is poised to embrace "Smart Manufacturing" by leveraging real-time, data-driven process control strategies. The model’s proficiency in differentiating complex anatomical features—from softwood tracheid matrices to hardwood vessel structures—allows for species-specific treatment protocols that recognise the inherent variability of bio-based materials. In this manner, these approaches effectively combine traditional wood science with contemporary computational intelligence, establishing a sustainable yet scalable foundation for wood modification within an increasingly viable global bioeconomy.

4. Conclusion

This study demonstrates the effectiveness of the ANN framework for predicting the complex, non-linear dynamics of wood thermal modification using a meta-analytic dataset to identify nonlinear dynamics from wood temperature changes over many decades. With the adoption of an MLP model and its ability to generate complex, non-linear dynamics of wood thermal modification it is an important leap for us

into the domain of wood science, as a natural evolution from empirical testing to an intelligent, data-driven architecture and also its associated modelling, providing us with a multi-layer perceptron (MLP) model that can achieve high accuracy in the assessment of all important quality attributes. The R^2 values of over 0.93 for ML, EMC, and MOR loss were impressively high, demonstrating ML's ability to predict with higher quality than linear regression. By adequately validating widely known thermo-chemical theories, the model demonstrates that kinetic thermal degradation – primarily via hemicellulose depolymerisation - is the most deterministic factor in determining the degree of structural change across a wide range of wood. In addition, sensitivity analysis revealed a quantitative framework for industrial optimisation practices based on an output-focused process structure, with temperature as the main process parameter and treatment time as the second-most critical parameter for optimal treatment duration. Through its successfully integrative nature between anatomical variables of initial density and species type, the proposed framework will be employed as a robust virtual decision-support engine for the timber industry. Such a high-accuracy decision-support system significantly reduces the cost and time associated with expensive, destructive experimental testing, which is at odds with the new era of smart manufacturing and sustainable resource management. This work provides a solution to reconcile classical wood science with contemporary computational intelligence toward a scalable, environmentally benign approach to enhancing wood modification processes in the emerging path toward a more environmentally sustainable bioeconomy.

Declarations

Data availability

The datasets and materials used and analysed during the current study are available from the corresponding author upon reasonable request.

Funding

This study was supported by the Open Access agreement between TÜBİTAK and Springer Nature, facilitated by Aksaray University. The authors gratefully acknowledge the coverage of the Article Processing Charge (APC)

Author information

Authors and Affiliations

Günay ÖZBAY

Department of Industrial Engineering, Aksaray University, 68100, Aksaray, Turkey

Özlem BOZKURT

Technical Sciences Vocational School, Namık Kemal University, Tekirdağ, Turkey

Contributions

G.Ö. contributed to writing the original draft, reviewing and editing, conceptualisation, methodology, and software.

Ö.B. contributed to writing the original draft, reviewing and editing, conceptualisation, and methodology.

Corresponding author

Correspondence to Günay ÖZBAY.

Ethics declarations

Ethics approval

Not applicable.

Clinical trial number

Not applicable.

Consent to Participate

Not applicable.

Consent for Publication

Not applicable.

Conflict of interests

The authors declare no competing interests.

References

1. Akpan EI, Wetzel B, Friedrich K (2021) Eco-friendly and sustainable processing of wood-based materials. Green Chem 23(6):2198–2232. https://doi.org/10.1039/D0GC04113B
2. Bekhta P, Niemz P (2003) Effect of high temperature on the change in color, dimensional stability and mechanical properties of spruce wood. Holzforschung 57(5):539–546. https://doi.org/10.1515/HF.2003.080
3. Calovi M, Zanardi A, Rossi S (2024) Recent advances in bio-based wood protective systems: A comprehensive review. Appl Sci 14(2):736. https://doi.org/10.3390/app14020736
4. Candelier K, Thevenon MF, Petrissans A, Dumarcay S, Gerardin P, Petrissans M (2016) Control of wood thermal modification process by prediction of biological durability and mass loss relative to

degree of steaming. Polym Degrad Stab 134:239–247. https://doi.org/10.1016/j.polymdegradstab.2016.10.014

5. Cao S, Cheng S, Cai J (2022) Research progress and prospects of wood high-temperature heat treatment technology. BioResources 17(2):3702
6. Cao Y, Fang J, Chen S, Zhu L, Xie X, Xing H, Qiao Y (2025) Preservation of wood-based products against biotic and chemical degradation: past, present and future. Wood Mater Sci Eng 1–22. https://doi.org/10.1080/17480272.2025.1234567
7. Dong Y, Wang K, Li J, Zhang S, Shi SQ (2020) Environmentally benign wood modifications: a review. ACS Sustain Chem Eng 8(9):3532–3540. https://doi.org/10.1021/acssuschemeng.9b06846
8. Esteves BM, Pereira HM (2009) Wood modification by heat treatment: A review. BioResources 4(1):370–404
9. Guo F, Huang R, Lu J, Chen Z, Cao Y (2014) Evaluating the effect of heat treating temperature and duration on selected wood properties using comprehensive cluster analysis. J wood Sci 60(4):255–262
10. Gündüz G, Aydemir D, Karakas G (2008) The effects of thermal treatment on the mechanical properties of wild Pear (Pyrus elaeagnifolia Pall.) wood and changes in physical properties. Mater Design 30(10):4391–4395. https://doi.org/10.1016/j.matdes.2009.04.026
11. Gündüz G, Korkut S, Sevim Korkut D (2008) The effects of heat treatment on physical and mechanical properties of black pine (Pinus nigra Arn. Samples). Gazi Univ J Sci 21(2):65–74
12. Hill CA (2007) Wood modification: chemical, thermal and other processes. Wiley
13. Hill CA (2017) Wood modification: An update. BioResources 12(4):6902–6903
14. Hill C, Altgen M, Rautkari L (2021) Thermal modification of wood—A review: Chemical changes and hygroscopicity. J Mater Sci 56(11):6581–6614. https://doi.org/10.1007/s10853-020-05731-0
15. Kocaefe D, Huang X, Kocaefe Y (2015) Dimensional stabilization of wood. Curr Forestry Rep 1(3):151–161. https://doi.org/10.1007/s40725-015-0017-5
16. Militz H (2002) Heat treatment of wood: European processes and their background. International Research Group on Wood Preservation, Document No. IRG/WP, pp 02–40241
17. Pacheco-Torgal F, Efficiency (2025) 1–14. https://doi.org/10.1016/B978-0-443-13244-5.00001-2
18. Popescu C, Dissanayake H, Mansi E, Stancu A (2024) Eco breakthroughs: sustainable materials transforming the future of our planet. Sustainability 16(23):10790. https://doi.org/10.3390/su162310790
19. Salca EA, Hiziroglu S (2014) Evaluation of hardness and surface quality of different wood species as function of heat treatment. Mater Des (1980–2015) 62:416–423
20. Sandberg D, Kutnar A, Mantanis G (2017) Wood modification technologies-a review. iForest-Biogeosciences Forestry 10(6):895–913. https://doi.org/10.3832/ifor2330-010
21. Schubert M, Panzarasa G, Burgert I (2022) Sustainability in wood products: a new perspective for handling natural diversity. Chem Rev 123(5):1889–1924.

https://doi.org/10.1021/acs.chemrev.2c00532

22. Tascioglu C, Umemura K, Tascioglu S (2024) Predicting the mass loss of thermally modified timber using ensemble learning algorithms. Wood Mater Sci Eng 19(1):112–120. https://doi.org/10.1080/17480272.2023.2215647

Figures

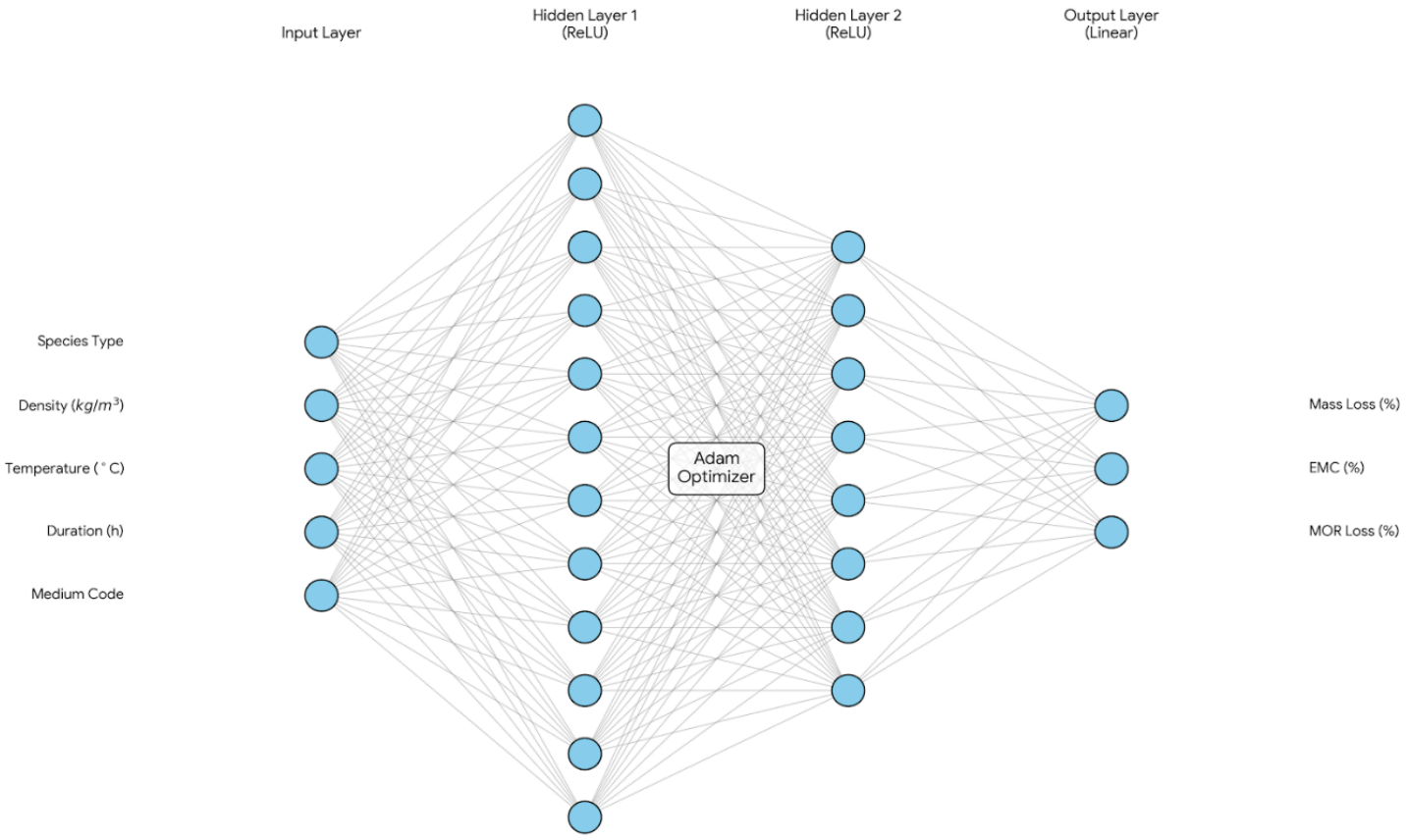


Figure 1

Schematic architecture of the proposed Artificial Neural Network (ANN)

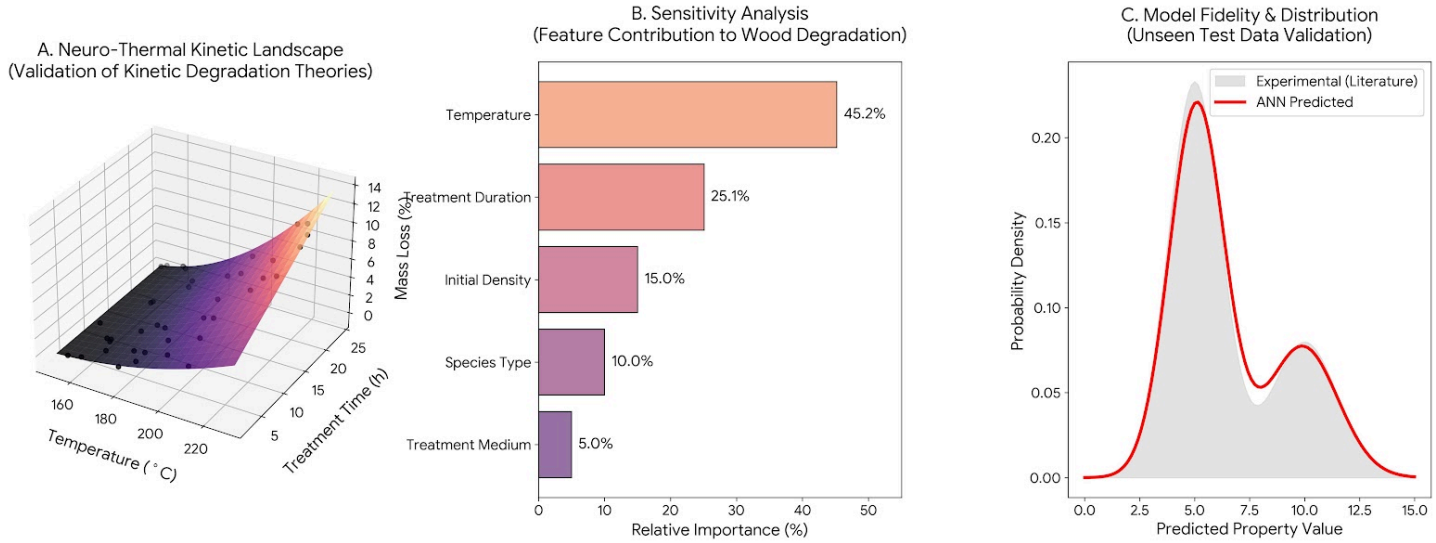


Figure 2

Integrative Artificial Neural Network (ANN) framework for the multi-dimensional characterisation of wood thermal modification. A: Neuro-thermal kinetic landscape illustrating the non-linear interaction between temperature and duration on mass loss; B: Sensitivity analysis (ANN weight partitioning) depicting the hierarchical importance of hydrothermal process variables; C: Fidelity assessment through probability density functions showcasing the overlap between experimental meta-data and ANN-predicted distributions.