Prediction of equilibrium moisture content and swelling of Thermally modified hardwoods by artificial neural networks

Abasali Masoumi
masoumi@vt.edu

Virginia Polytechnic Institute and State University

Brian Bond
Virginia Polytechnic Institute and State University

Research Article

Keywords: Thermally Modified Wood, EMC, Swelling, ANN

Posted Date: April 2nd, 2024

DOI: https://doi.org/10.21203/rs.3.rs-4185877/v1

Additional Declarations: No competing interests reported.

Abstract

In this study artificial neural network (ANN) models were developed for predicting the effects of wood species, density, modifying time and temperature on the equilibrium moisture content (EMC) and swelling of six different thermally modified hardwood species. Lumber of Yellow-poplar (Liriodendron tulipifera); red oak (Quercus borealis); white ash (Fraxinus americana), red maple (Acer rubrum); hickory (Carya glabra), and black cherry (Prunus serotina) were selected. Using Keras and Pytorch libraries in Python, different feed forward and back propagation multilayer ANN models were created and tested. The best prediction models, determined based on the errors in training iterations, were selected and used for testing. Based on the performance analysis, the prediction ANN models are accurate, reliable and effective tools in terms of time and cost-effectiveness, for predicting the EMC and swelling characteristics of thermally modified wood. The multiple-input model was more accurate than the single-input model and it provided a prediction with R^2 of 0.9975, 0.92 and MAPE of 1.36, 7.77 for EMC and swelling.

INTRODUCTION

The utilization of thermally modified woods (TMW) has gained significant traction as a sustainable material across diverse applications (Espinoza et al. 2015; Bond et al. 2023). Thermal modification (TM), a process involving the controlled heating of wood within the temperature range of 180–240°C, changes its chemical, physical, and mechanical properties (Tjeerdsma and Militz 2005; Esteves and Pereira 2009; Militz and Altgen 2014; Hill et al. 2021). The primary objective of TM is to enhance the dimensional stability of wood, rendering it well-suited for applications in varying moisture conditions, particularly in outdoor applications. TMW exhibits altered equilibrium moisture content (EMC) and swelling compared to unmodified wood (Masoumi and Bond 2024).

Notably, hardwoods exhibit distinct chemical and anatomical properties than softwoods and across different plantations (Oladi et al. 2013). The Appalachian region in North America stands out as a hub for several hardwood species, with yellow poplar (YP) emerging as a prominent species, representing 35% of the region's growth and production (Appalachian Hardwood Species Guide, 2023).

Artificial Neural Network (ANN) models are pivotal for deciphering complex scenarios and revealing hidden relationships between input and output variables. This transformative technology, mirroring the human brain's learning process, excels in pattern recognition, classification, and prediction tasks across various domains like finance, healthcare, and image recognition (Sen et al. 2023).

The analysis of ANNs encompasses two key facets: architecture and mathematical functions. The architecture involves the arrangement and interconnections of layers and nodes, highlighting the network's information processing capacity. Simultaneously, mathematical functions, embedded in activation functions and weight adjustments, contribute to the network's adaptability and learning ability, crucial for its predictive prowess. Multilayer Perceptron (MLP) ANN models, particularly notable for their predictive capabilities, have been extensively researched and applied in diverse fields. Their proficiency in discerning complex patterns within data sets makes them adept at handling intricate relationships and non-linear dependencies, surpassing traditional analytical approaches (Sen et al. 2023). The novel deep learning principles have given rise to deep neural networks, capable of handling vast amounts of data and extracting hierarchical features. This dynamic landscape ensures that ANN models remain at the forefront of cutting-edge technological solutions, empowering to explore new frontiers in data analysis and decision-making.

Recent studies have reported the possibility of predicting EMC, swelling, and shrinkage of wood based on factors such as wood species, treatment time, and treatment temperature (Chen et al. 2022; Tiryaki et al. 2016). Chen et al. (2022) reported predicting the EMC and Specific gravity using a back-propagation Neural Network. Also, Nasir et al. (2019) reported the possibility of predicting the swelling coefficient and water absorption with the group method of data handling (GMDH) neural network. These studies have used single or few species in making models, however, a model containing a variety of species, particularly hardwoods that have very diverse properties is lacking in the literature.

This study aims to develop a single-input (as a more time and cost-effective model) and multiple-input model specifically tailored to predict EMC and swelling in thermally modified six different types of hardwood timber with different densities and anatomy. Using key features, such as wood species, density, treatment time and temperature, we seek to contribute to the ongoing exploration of ANN applications in predicting the intricate properties of TMW, thereby enhancing the understanding and utilization of this sustainable material in diverse applications.

EXPERIMENTAL

Data collection

The data used in this study was previously published by Masoumi and Bond (2024). Test specimens were prepared from randomly selected lumber. The lumber was kiln-dried to 6 to 8% MC prior to modification. Thermal modification of the lumber was conducted in an industrial dry-open vessel thermo-vacuum and the maximum modification temperature, duration and density of the lumber is presented in Table 1. Cubes of each treatment type of every species with dimensions of 1 in × 1 in × 1 in (L × R × T) were cut from the lumber. Physical experiments were conducted based on the ASTM D143-22 standard. Thirty cubes of each species were taken and conditioned by placing them in a climatic chamber in 21°C and 65% relative humidity (RH), which is equal to 12% RH for 20 days until unmodified specimens reached the equilibrium moisture content as measurements five days after this time showed no moisture absorption.

After conditioning, the samples were weighed, and their dimensions were measured using a 0.01-g accuracy balance and a 0.01-mm accuracy digital caliper. Samples were then submerged in distilled water for 20 days. Subsequently, samples were left to dry at room temperature for 3 days to avoid cracking and then placed in the oven at a temperature of 103 ± 2°C for 24 h. After each phase, the weight and dimensions of the samples were measured.

Table 1
Modification Temperature, Time and Density for Different Wood Species

Wood Species	YP	Red Oak	Ash	Red Maple	Hickory	Black Cherry
Temperature (°C)	A	B	C	C	C	D
Time (min)	A	C	C	C	C	B
Unmodified Density (g/cm^2)	0.44	0.74	0.74	0.61	0.77	0.56
Modified Density (g/cm^2)	0.37	0.46	0.32	0.45	0.59	0.46
As the modification schedule is proprietary, A,B,C,D represent the class of time and temperature.						

Artificial Neural Network Models

The authors utilized a dataset comprising 360 data points representing EMC and volumetric swelling of six hardwood species to predict EMC and swelling using a single input and multiple input Multilayer Perceptron (MLP) fully connected Artificial Neural Network implemented in Python 3.11. leveraging Keras and PyTorch. Keras and PyTorch are two powerful open-source machine-learning libraries. Keras is a python based and is used in deep learning for neural networks. PyTorch is an open-source machine learning library that can be integrated with Python and can debug neural networks easily. The mathematics of MLP is given in Eq. 4.

Model Architecture

The ANN model consisted of an input layer representing modified and unmodified, wood species, temperature, time, and density, and an output layer of EMC or swelling. The architecture involved an input layer, a hidden layer with ReLU activation (Rectified linear activation function that is the default function that will output the input directly, if it is positive, otherwise prints zero in output), and an output layer. The hidden layer is the layer of neurons that is neither the input nor the output layer and is what makes neural networks deep and enables them to learn complex data. The activation function is used to determine the output of a neuron by calculating the weighted sum of inputs and adds a bias to it. The model, implemented using the Keras and PyTorch deep learning libraries, adapted its input size based on the number of features extracted from the dataset. Various configurations were experimented with, including different architectures (single or multiple inputs, varying hidden layer neurons), optimizers (Adam and SGD), learning rates, epochs, and regularizations (L1, L2 and dropout). The models were assessed based on mean squared error (MSE), MAPE and R^2 values which are the best criteria for measuring the performance of ANNs (Sen et al. 2023). The ideal model has data with the lowest MSE, MAPE < 10 and R^2 above 0.90 and as close as to 1. Ultimately, the best model was chosen for prediction.

Figure 1. Schematic architecture of A: basic single input; B: Basic Multiple input and C: Multiple input ANN model used in this study.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(\mathrm{y_i} - \mathrm{y_p}\right)^2 \quad (1)$$

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{n}\left(\mathrm{y_i} - \mathrm{y_p}\right)^2}{\sum_{i=1}^{n}\left(\mathrm{y_i} - \bar{\mathrm{y}}\right)^2} \quad (2)$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\left|\mathrm{y_i} - \mathrm{y_p}\right|}{\mathrm{y_i}}\right)100 \quad (3)$$

$$Y = \mathrm{g}\left(\theta + \sum_{j=1}^{m} v_{\mathrm{j}}\left[\sum_{j=1}^{n} f\left(W_{ij}\mathrm{x_i} + \beta_{\mathrm{i}}\right)\right]\right) \quad (4)$$

where Y is the prediction of dependent variable; g () is the activation functions of output neurons; θ is the bias value of output neuron; vj is the weight of the connection between the jth hidden and output neuron; f is the activation functions of hidden neurons; Wij is the weight of connection between the ith input neuron and jth hidden neuron; Xi is the input value of ith independent variable; and βj is the bias value of the jth hidden neuron.

Training and testing

The dataset was split into training and testing sets (80% for training, 20% for testing) using the train_test_split function. The neural network model was trained using mean squared error loss as the loss function and the Adam and SGD which are the most common optimizers. The training process involved iterating through 1000 epochs (iteration) and updating the model's parameters to minimize the training loss which shows how well the model is fitting the training data. Subsequently, the model was validated using the test set to evaluate its ability to predict. Test loss or mean squared error (MSE), R^2 and the Mean Absolute Percentage Error (MAPE) were used for evaluation and their mathematical expression are presented in Eq. 1–3. Test Loss or mean square error (MSE) indicates how well the model applies new data. A lower MSE suggests better accuracy. The R^2 score represents the proportion of variance in the dependent variable explained by the independent variables. A higher R^2 score (closer to 1) indicates better predictive performance. MAPE provides a measure of how far the predicted values are from the actual values as a percentage and should be defined and calculated before printing the data in the coding. In the training process the learning rate was set to lr = 0.0001–0.001 and 0.005, for fine-tuning model parameters for optimal performance.

RESULTS AND DISCUSSION

Model performance analysis

The data for performance analysis such as R^2, MSE, and MAPE values of the EMC and swelling parameters, shown in Table 2, indicate that the ANN models were successful. Both PyTorch and Keras performed similar accuracy in terms of R^2, MSE and MAPE in both single and multiple-input ANN models. The PyTorch has better flexibility and debugging capabilities to check and ensure the validity of Keras. The models implemented by both Keras and PyTorch provided similar results.The single input model was acceptable just in features of treatment and time ($R^2 > 0.90$ or MAPE < 10) for EMC, however for swelling, the single input model didn't' provide as good performance as all R^2 values were smaller than 0.90, and MAPE values were higher than 10. Swelling in wood, especially in TMW is affected by multiple features such as wood species and their anatomy and density that are unique to each species, modifying time and temperature that changes the physical properties to different extents by changing the chemical and structural properties differently in different species. In the multiple-input model, R^2 values were higher than 0.90 and MAPE values were smaller than 10% in predicted data for both EMC and swelling in TM hardwoods by having the R^2 and MAPE values of 0.9975, 0.92, and MAPE values of 1.36, 7.77 for EMC and swelling, respectively. Particularly, having R^2 value of 0.997 in EMC and MAPE of 1.36 shows very high accuracy of the performance in multiple input models in predicting EMC. R^2 value over 0.90 indicates an excellent correlation between the calculated and predicted data. MAPE is a decisive factor for evaluating for prediction performance (Aydin et al. 2015) and 10% is considered a highly accurate prediction.

Table 2
Data for performance analysis of single and multiple input ANN

Single	Criteria	Input					Output
		Treatment	Species	Temperature	Time	Density	
input	R^2	0.95 (0.86)	0.03 (0.3)	0.86 (0.86)	0.91 (0.91)	0.66 (0.75)	EMC
	MSE	0.95 (0.95)	6.95 (6.94)	0.93 (0.96)	0.64 (0.64)	2.37 (1.76)	EMC
	MAPE	12.45 (11.79)	37.62 (37.88)	12.34 (12.41)	7.75 (7.74)	15.32 (12.60)	EMC
	R^2	0.2 (0.20)	0.54 (0.54)	0.20 (0.20)	0.2 (0.2)	0.70 (0.71)	Swelling
	MSE	21.38 (21.4)	12.16 (12.22)	21.38 (21.47)	21.045 (21.49)	7.84 (7.67)	Swelling
	MAPE	36.79 (37.5)	34.24 (34.5)	37.32 (37.98)	38.08 (38.47)	17.35 (17.18)	Swelling
Multiple input	R^2	0.9976 (0.9970)	All the features				EMC
	MSE	0.017 (0.02)					EMC
	MAPE	1.36 (1.54)					EMC
	R^2	0.92 (0.92)	All the features				Swelling
	MSE	2.0 (2.1)					Swelling
	MAPE	7.77 (8.25)					Swelling
*Keras Data is presented in parentheses							

The multiple input model performed an acceptable performance in predicting EMC and swelling of wood and the single input model was unable to predict accurately these results is in close accordance with the findings of Haftkhani et al. (2022) where they modeled the water absorption and swelling of TM fir (*Abies sp.*) wood and reported the superiority of the multiple input ANN model with R^2 and MAPE of 0.996 and 2.8. Ozsahin and Murat (2018) developed an ANN model for predicting EMC in TM fir (*Abies bornmuelleriana Maff*) and hornbeam (*Carpinus betulus L.*) and reported a MAPE value of 3.21. Also, in another study for the same species, Chen et al. (2022) reported R^2 of 0.99 and 0.98. The multiple-input ANN model was effective and reliable in predicting EMC and swelling. Tiryaki et al. (2016) confirmed predicting volumetric swelling by ANN models using wood species, treatment time, and temperature. Other studies have reported the effectiveness of ANN could predict TMW properties (Nasir et al. 2019).

Table 3
Experimental data and predicted results

Equilibrium Moisture content			Swelling		
Predicted	Actual	Error	Predicted	Actual	Error
7.41	7.4	-0.01	21.25	21.57	0.32
5.01	5	-0.01	10.49	10	-0.49
4.19	4.1	-0.09	10.80	9.06	-1.74
10.74	10.75	0.01	16.01	15.96	-0.05
4.98	5	0.02	10.61	8.92	-1.69
4.08	3.8	-0.28	10.29	13.79	3.50
10.28	10.25	-0.03	17.55	18.84	1.29
4.96	4.96	0.00	10.73	11.63	0.90
9.85	9.5	-0.35	13.84	13.55	-0.29
10.27	10.1	-0.17	12.88	13.57	0.69
11.65	11.56	-0.09	11.85	12.7	0.85
6.08	5.9	-0.18	4.43	4.82	0.39
7.40	7.6	0.20	20.32	23.67	3.35
6.08	6	-0.08	4.43	4.49	0.06
4.79	4.7	-0.09	8.22	7.35	-0.87
10.26	10.2	-0.06	12.53	14.29	1.76
9.55	9.6	0.05	20.12	20.37	0.25
10.74	10.7	-0.04	16.01	16.3	0.29
10.25	10.2	-0.05	13.13	12.88	-0.25
6.06	6.1	0.04	4.04	3.88	-0.16
…………………………………………………………………………					
4.98	5	0.02	10.61	10.91	0.30
4.19	4.2	0.01	10.80	7	-3.80
7.41	7.4	-0.01	21.25	16.54	-4.71
10.25	10.1	-0.15	13.49	13.58	0.09
10.73	10.75	0.02	16.12	15.67	-0.45

Equilibrium Moisture content			Swelling		
Predicted	Actual	Error	Predicted	Actual	Error
10.28	10.4	0.12	17.50	17.68	0.18
11.65	11.75	0.10	11.85	11.62	-0.23
9.79	10.3	0.51	12.98	13.45	0.47
10.28	10.3	0.02	17.50	18.43	0.93
6.08	6.1	0.02	4.43	4.65	0.22
6.10	6	-0.10	6.99	5.86	-1.13
11.72	11.76	0.04	11.57	11.51	-0.06
6.06	6.2	0.14	4.04	4.49	0.45
9.55	9.6	0.05	20.12	21.47	1.35
6.08	6	-0.08	4.43	3.74	-0.69
4.79	4.8	0.01	7.87	7.95	0.08
9.55	9.5	-0.05	20.08	21.2	1.12
9.55	9.6	0.05	20.08	19.6	-0.48

Fitting effect

Figure 2 shows the correlation between the experimental data values and the values predicted by the developed ANN models. There is a significant correlation between actual and predicted values in testing both in EMC and swelling with R^2 0.9975 and 0.92. The same accuracies are reported by other researchers such as Chen et al. (2022), 0.99, for EMC and Chai et al. (2018) 0.974. Figure 3 shows the training test for EMC and swelling. During training, the loss is printed every 100 epochs, it is essential to observe the loss trend to ensure that the model is converging as the decreasing trend indicates that the model is learning from the data. For EMC, the loss both in training and testing immediately dropped to its lowest value after epochs = 20 and kept a constant value toward the end of iterations, however, for swelling it dropped after 200 epochs as the loss is constant in training and testing, and in training the loss is higher than testing because EMC data are more uniform and swelling data are very diverse in all the tested hardwood species.

Figure 2. Fitting effect of actual vs predicted values in EMC and swelling.

Figure 3. Loss trend in Training Test for EMC and swelling

CONCLUSIONS

The PyTorch was used in this study as it has better flexibility and debugging capabilities to check and ensure the validity of Keras. The models implemented by both Keras and PyTorch provided similar results. The Multiple-input ANN model was successful in accurately predicting the EMC and swelling using various input features. ANN learns EMC data faster than swelling data. Hardwoods have different properties that lead to variation in their properties in a modification which makes it difficult to predict their properties. The accuracy of the prediction of the developed ANN models was 0.9975 and 0.92 for EMC and swelling, respectively which especially for EMC is higher than previously introduced models and for the swelling is inline with models in other species. The single-input model showed less accuracy in predicting the EMC and swelling using just one feature as an input. This is because multiple features are contributing to the EMC and particularly swelling changes.

Declarations

Author Contribution

The Author's contribution is as follows: Abasali Masoumi: Conceptualization, Investigation, data curation, formal analysis, software, writing the original draftBrian Bond: Supervision, funding and resources, review and editing

ACKNOWLEDGMENTS

The authors are grateful to the Bingaman Lumber company for providing thermally modified lumber and information regarding the thermal modifying process.

References

1. Appalachian Hardwood Manufacturers, Inc. (2023). "Appalachian Hardwood Species Guide," (https://www.appalachianwood.org/species/species.htm), Accessed 25 Nov 2023.
2. ASTM D143-22. (2022). "Standard test methods for small clear specimens of timber," current edition approved May 15, published June 2022. DOI: 10.1520/D0143-22.
3. Aydin G, Karakurt I, Hamzacebi C (2015) Performance prediction of diamond sawblades using artificial neural network and regression analysis. Arab J Sci Eng 40(7):2003–2012.
4. Bond, B., Gonzalez, J., Masoumi, A., Xavier Zambrano Balma, F., and Tylor, A (2023) Thermally modified wood as a sustainable alternative, in: *PTF BPI 2023*, *Processing Technologies for the Forest & Biobased Products Industries*, Simons Islands, GA, USA, pp. 1-15.
5. Chai H., Chen X, Cai Y, and Zhao J (2018). "Artificial neural network modeling for predicting wood moisture content in high frequency vacuum drying process," *Forests* 10(1), 1-10. DOI:

10.3390/f10010016

6. Chen Y, Wang W, and Li N (2022) Prediction of the equilibrium moisture content and specific gravity of thermally modified wood *via* an Aquila optimization algorithm back-propagation neural network model, *BioResources* 17(3), 4816-4836.
7. Espinoza O, Buehlmann U, and Laguarda-Mallo M. F (2015) Thermally modified wood: Marketing strategies of U.S. producers, *BioResources* 10(4), 6942-6952. DOI: 10.13576/biores.10.4.6942-6952
8. Esteves B. M, and Pereira H. M (2009) Wood modification by heat treatment: A review, *BioResources* 4(1), 370-404. DOI: 10.13576/biores.4.1.370-404
9. Haftkhani A.R, Abdoli F, Rashidijouybari I. et al. (2022) Prediction of water absorption and swelling of thermally modified fir wood by artificial neural network models. Eur. J. Wood Prod. 80, 1135–1150. https://doi.org/10.1007/s00107-022-01839-x
10. Hill C, Altgen M, and Rautkari L (2021) Thermal modification of wood—A review: Chemical changes and hygroscopicity, *Journal of Materials Science* 56(11), 6581-6614. DOI: 10.1007/s10853-020-05722-z
11. **Masoumi A, and Bond B (2024) Dimensional Stability and Equilibrium Moisture Content of Thermally Modified Hardwoods. BioResources 19(1), 1218-1228. DOI: 10.15376/biores.19.1.1218-1228**
12. Militz H, and Altgen M (2014) Processes and properties of thermally modified wood manufactured in Europe, *ACS Symposium Series* 1158, 269-285. DOI: 10.1021/bk-2014-1158.ch016
13. Nasir V, Nourian S, Avramidis S, Cool J (2019a) Prediction of physical and mechanical properties of thermally modified wood based on color change evaluated by means of “group method of data handling”(GMDH) neural network. Holzforschung 73(4):381–392
14. **Oladi R, Matini Behzad H, Sharifi Z, and Masoumi A (2013) Comparing the wood anatomy of the field elms (*Ulmus carpinifolia* Borkh.) native to Gorgan and Komijan,” *Journal of Forest and Wood Products* 66(1), 69-81.** DOI: 10.22059/JFWP.2013.35342
15. Ozsahin S, Murat, M (2018) Prediction of equilibrium moisture content and specific gravity of heat-treated wood by artificial neural networks. Eur. J. Wood Prod. 76, 563–572. https://doi.org/10.1007/s00107-017-1219-2
16. **Şen Z (2023). Artificial Neural Networks. In: Shallow and Deep Learning Principles. Springer, Cha**m. https://doi.org/10.1007/978-3-031-29555-3_7
17. Tjeerdsma B. F, and Militz H (2005) Chemical changes in hydrothermal treated wood: FTIR analysis of combined hydrothermal and dry heat-treated wood, *Holz als Roh- und Werkstoff* 63, 102-111. DOI: 10.1007/s00107-004-0532-8
18. Tiryaki S, Bardak S, Aydin A, Nemli G (2016) Analysis of volumetric swelling and shrinkage of heat-treated woods: experimental and artificial neural network modeling approach. Maderas Ciencia y Tecnología 18(3):477–492

Figures

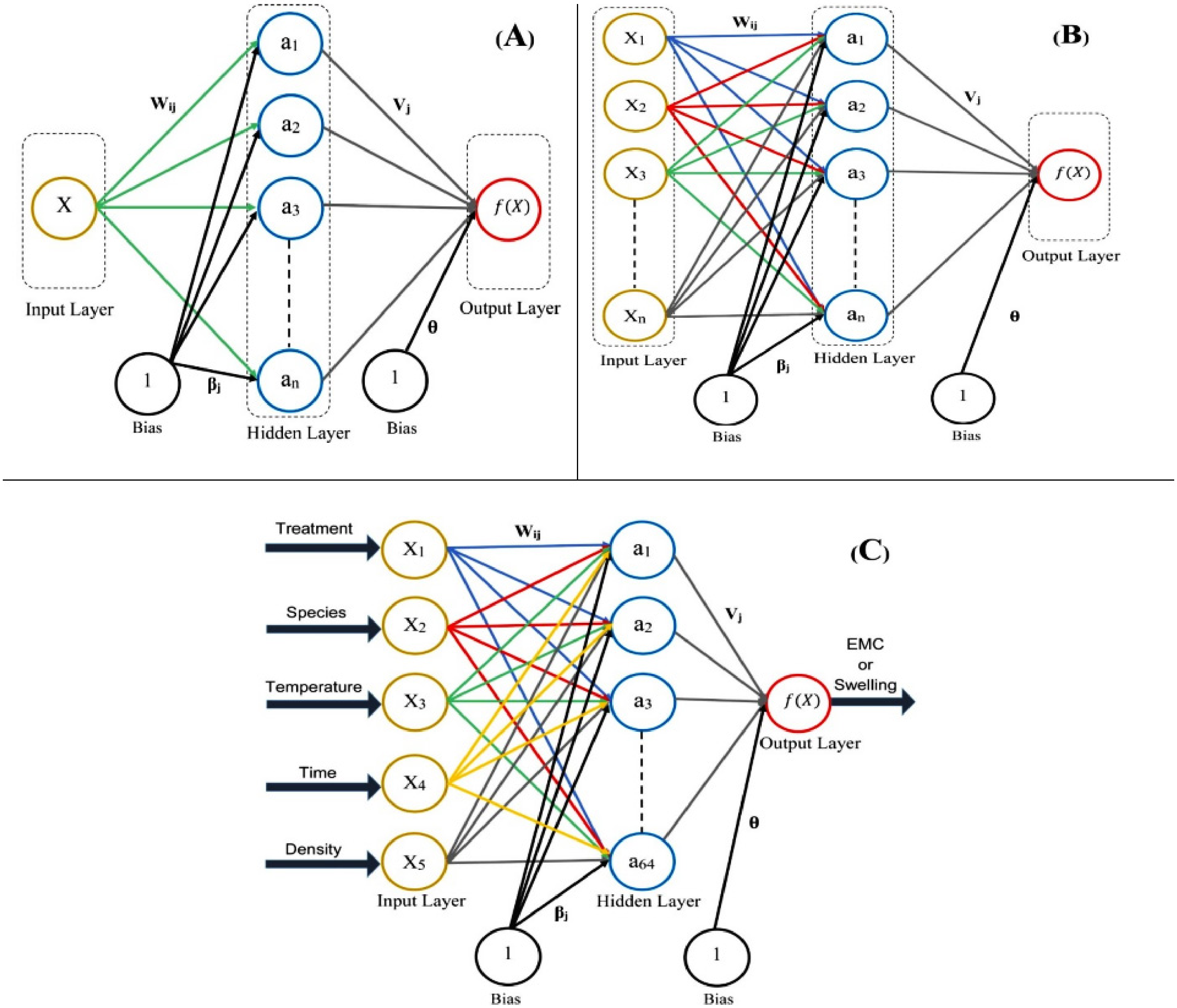

Figure 1

Schematic architecture of A: basic single input; B: Basic Multiple input and C: Multiple input ANN model used in this study.

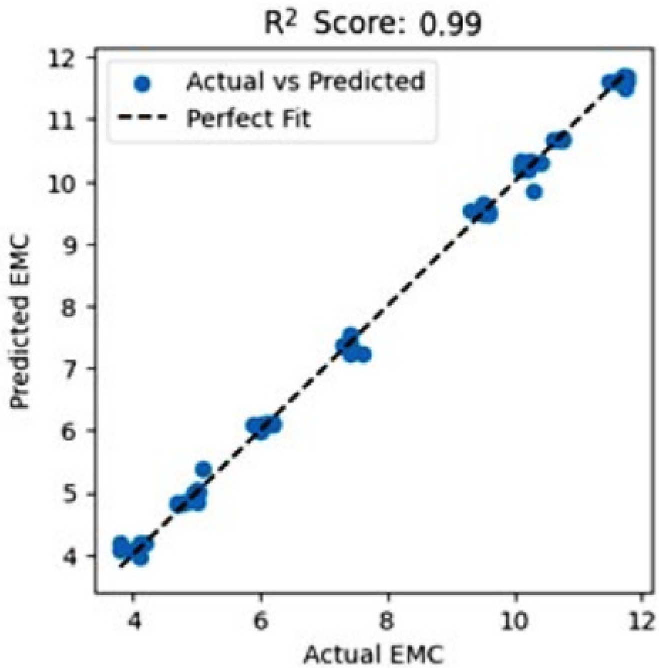

Figure 2

Fitting effect of actual vs predicted values in EMC and swelling.

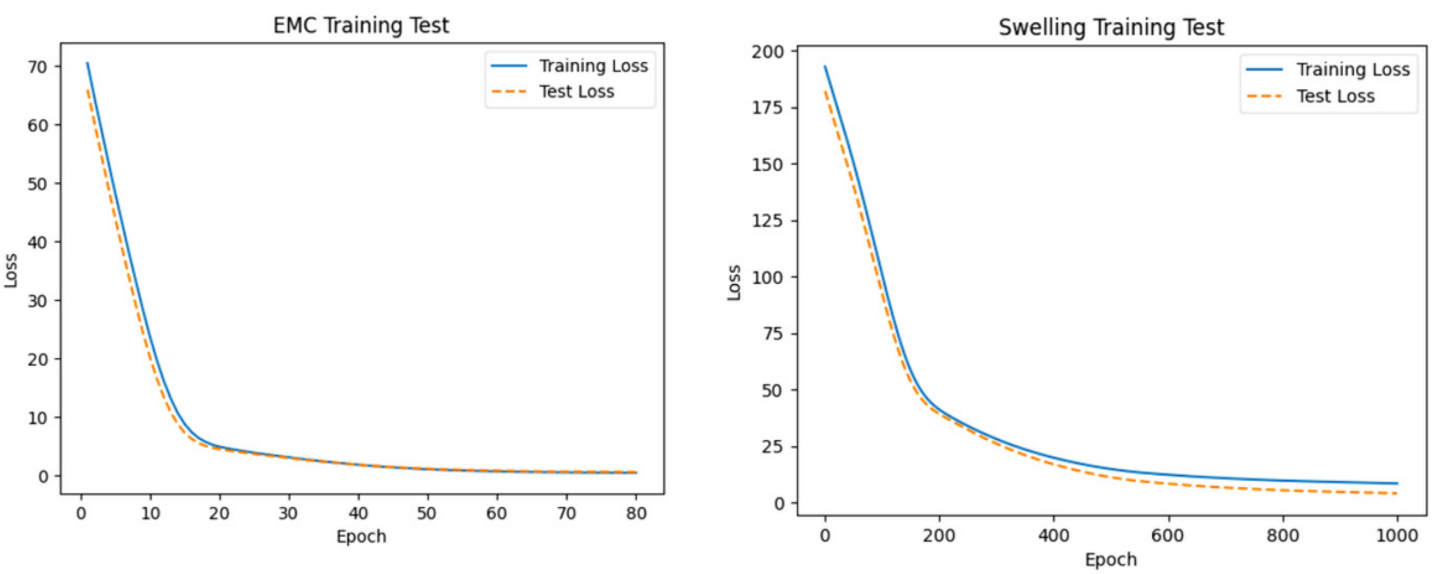

Figure 3

Loss trend in Training Test for EMC and swelling