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ORIGINAL

Fuzzy Logic Prediction Model for Mechanical and Absorption Behavior of Treated Woven Sisal Composites

Modelo de predicción mediante lógica difusa del comportamiento mecánico y de absorción de composites de sisal tejido tratado

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ABSTRACT

The transition towards environmentally friendly and sustainable materials has intensified interest in natural fiber-reinforced composites, with sisal fibers standing out due to their biodegradability and mechanical performance. Despite these advantages, their practical use remained hindered by poor interfacial adhesion and high moisture uptake, largely attributed to their hydrophilic nature and surface impurities. In this study, a dual chemical treatment using sodium hydroxide ($NaOH$) followed by potassium permanganate ($KMnO_4$) was applied to three types of woven sisal fabrics (plain, twill, and satin) to enhance fiber-matrix interaction and overall composite properties. Twenty-seven composite variants were produced and evaluated to investigate the influence of weave structure, treatment concentration, and immersion time on tensile strength and water absorption. To capture the intricate relationships between these variables, a fuzzy logic-based predictive model was developed. This model effectively forecasted material behavior, achieving low average absolute errors of 1,77 % for tensile strength and 3,46 % for water absorption, demonstrating its robustness and value as a tool for process optimization. This study contributed not only to the development of high-performance, bio-based textile composites, but also introduced an intelligent, cost-effective predictive framework capable of reducing experimental demands while guiding sustainable material development.

Keywords: Woven Composites; Sisal Fiber; Chemical Treatment; Performance Prediction; Fuzzy Logic Model.

RESUMEN

La transición hacia materiales sostenibles y respetuosos con el medio ambiente ha intensificado el interés por los compuestos reforzados con fibras naturales, destacando las fibras de sisal por su biodegradabilidad y rendimiento mecánico. A pesar de estas ventajas, su uso práctico sigue limitado por una pobre adhesión interfacial y una alta absorción de humedad, atribuida principalmente a su naturaleza hidrofílica e impurezas superficiales. En este estudio, se aplicó un tratamiento químico dual utilizando hidróxido de sodio ($NaOH$) seguido de permanganato de potasio ($KMnO_4$) a tres tipos de tejidos de sisal (liso, sarga y satén) con el objetivo de mejorar la interacción fibra-matriz y las propiedades generales del compuesto. Se produjeron y evaluaron veintisiete variantes de compuestos para estudiar el impacto de la estructura del tejido, la concentración del tratamiento y el tiempo de inmersión sobre la resistencia a la tracción y la absorción de agua. Para captar las complejas relaciones entre estas variables, se desarrolló un modelo predictivo basado en lógica difusa. Este modelo pronosticó eficazmente el comportamiento del material, logrando errores absolutos promedio de solo 1,77 % para la resistencia a la tracción y 3,46 % para la absorción de agua, lo que demuestra su robustez y utilidad como herramienta de optimización del proceso. Este estudio no solo contribuye al desarrollo de compuestos textiles de alto rendimiento basados en materiales biológicos, sino que también introduce un marco predictivo inteligente y rentable capaz de reducir la necesidad de ensayos experimentales y orientar el desarrollo de materiales sostenibles.

Palabras clave: Composites Tejidos; Fibra de Sisal; Tratamiento Químico; Predicción del Rendimiento; Modelo de Lógica Difusa.

INTRODUCTION

The growing demand for sustainable alternatives to synthetic materials has brought natural fiber-reinforced composites to the forefront of materials science research.(1) These bio-based composites present ecological benefits alongside satisfactory performance for diverse applications.(2) However, their overall effectiveness is strongly influenced by two critical factors: the internal structure of the textile reinforcement and the surface properties of the fibers employed.(3)

Sisal fiber, a renewable resource notable for its promising mechanical properties, has been extensively studied as a reinforcement in polymer composites. Despite its advantages, the natural hydrophilicity and presence of surface impurities in sisal fibers frequently result in weak bonding at the fiber-matrix interface, which undermines the composite's mechanical integrity and dimensional stability.(4)

Moisture ingress in composite materials primarily occurs via three mechanisms: diffusion through the polymer matrix, capillary action along the fiber-matrix interface, and penetration through microcracks generated during fabrication.(5) While diffusion is an intrinsic material behavior, capillary transport and microcrack infiltration can be mitigated through improved processing techniques.(6) Excessive moisture absorption negatively affects the composite's dimensional stability and mechanical performance, due to the contrasting hydrophilic nature of natural fibers and the hydrophobic characteristics of typical thermoplastic matrices.(7,8)

To address these challenges, chemical surface modifications such as alkaline and oxidative treatments are commonly applied to enhance the fiber-matrix compatibility.(9) Alkali treatment with sodium hydroxide (NaOH) removes surface impurities and increases fiber surface roughness, while oxidation with potassium permanganate ($KMnO_4$) introduces reactive functional groups that can strengthen interfacial bonding.(10)

Given the multifaceted and nonlinear interactions between fiber treatments, textile architecture, and composite performance, advanced modeling techniques are essential for accurate prediction and optimization.(11) Fuzzy logic modeling emerges as an effective tool to manage the inherent uncertainties and complex relationships among variables such as weave pattern, treatment concentration, and immersion time. This flexible approach enables reliable forecasting of composite behavior, particularly concerning mechanical properties and moisture absorption, thus reducing the need for extensive experimental trials.(12)

This research uniquely combines experimental work and fuzzy logic modeling to explore how sequential alkali and oxidative chemical treatments affect various woven sisal fabric structures. Unlike prior studies that typically focus on single treatments or non-woven fibers, this work investigates the synergistic effects of fabric weave and dual chemical modifications. Furthermore, the integration of an intelligent predictive model offers a novel approach to optimize the mechanical and moisture-resistance properties of natural fiber composites, thereby advancing both scientific understanding and practical applications. This study offers important contributions for several reasons:

- Technological innovation: this study develops a predictive model using fuzzy logic, providing high accuracy in its forecasts.
- Cost reduction: by reducing the need for numerous physical tests, it lowers development costs and accelerates textile development timelines.
- Industrial applicability: the model is simple, fast, and reliable, making it easy to integrate into industrial environments to enhance production processes.
- Broader perspectives: this methodological framework can be extended to other valorized materials, thus enabling broader applications in the textile field.

Significant research has been dedicated to utilizing artificial intelligence for the prediction and characterization of textile properties. Such advancements enable improvements in textile quality, performance, and functionality, while also contributing to more efficient production workflows and reductions in costs and delivery durations.

T. Tundo et al.(13) have explored the use of fuzzy logic to solve production problems. Two methods are examined: the Tsukamoto method and the Sugeno method. The objective is to determine fabric production using variables such as inventory, demand, and production costs. The Tsukamoto method uses fuzzy sets for input and output variables, while the Sugeno method uses constants or mathematical functions. By comparing the results obtained with actual company data, it is concluded that the Tsukamoto method with Weka rules is the closest to actual fabric production.

Hussain MAI et al.[14] presented a deep learning model using residual network (ResNet) for textile weave pattern recognition and classification. The model incorporates data augmentation techniques to improve its generalisability and was evaluated using metrics such as accuracy, balanced accuracy and F1 score. The experimental results demonstrate the robustness of the model, with high performance even when the physical properties of the fabric are modified. Compared with other approaches, notably the VGGNet pre-trained model, ResNet achieved better performance.

J. Lilly Mercy et al.[15] examined pineapple fiber-reinforced composites and highlighted the inverse correlation between moisture uptake and mechanical strength, with fiber orientation playing a pivotal role. Using a neuro-fuzzy model via MATLAB's ANFIS toolbox, they successfully linked static mechanical properties to factors including moisture content, fiber orientation, and volume fraction.

Swati Gangwar et al.[16] investigated epoxy composites reinforced with chemically treated kenaf fibers. Employing a Taguchi L27 design, they varied fiber content, NaOH concentration, and immersion time to optimize tensile, impact, and flexural strengths. Their hybrid multi-objective optimization combining grey relational analysis and fuzzy logic identified NaOH concentration as the dominant factor influencing mechanical behavior.

Mahmud et al.[17] contributed to sustainable composite development by combining PLA, jute fibers, and eggshell powder (ESP) fillers. Their fuzzy logic-based prediction model effectively guided the optimization process while reducing experimental efforts.

Pujari et al.[18] studied moisture absorption in epoxy composites reinforced with jute and banana fibers and concluded that jute composites absorbed less water. Artificial neural networks (ANN) provided better predictive performance than regression models for water uptake.

Sarkar et al.[19] compared two AI techniques—Adaptive Neuro-Fuzzy Inference System (ANFIS) and ANN to predict fabric moisture absorption. The ANFIS model had a stronger correlation with experimental data.

Mony Sankar Mondal et al.[20] developed a fuzzy logic expert system for predicting acoustic insulation in hybrid banana-glass fiber composites. The model achieved high prediction accuracy (R^2 = 0,9884), confirming the utility of fuzzy logic beyond mechanical property modeling.

Despite these advances, gaps remain in understanding how different woven fabric architectures influence moisture absorption and mechanical behavior after sequential chemical treatments, particularly in sisal fiber composites. Most studies focus on single treatments or short/unidirectional fibers, with limited exploration of combined alkali and oxidative treatments on woven textiles. Also, integrating fuzzy logic modeling with experimental investigations considering both weave structure and surface modifications is still uncommon.

To address these gaps, the present work evaluates the combined effects of fabric weave pattern and sequential chemical treatments on the tensile strength and water absorption of woven sisal composites. Three types of woven sisal fabrics—twill, plain weave, and satin were subjected to a two-step chemical treatment consisting of immersion in 0,5 % NaOH followed by $KMnO_4$ at concentrations of 0,03 %, 0,06 %, and 0,09 %. The influence of treatment conditions, fabric architecture, and immersion duration was assessed experimentally on 27 composite samples.

To handle the complex and nonlinear relationships between these variables, a fuzzy logic-based predictive model was developed. This modeling approach is particularly suitable for textile applications where multiple interacting factors affect material properties in ways that are difficult to quantify precisely. By enabling prediction of mechanical performance and moisture behavior, this model provides an efficient alternative to time-consuming experimental testing.

Overall, the fuzzy logic framework presented here facilitates the optimization and design of sustainable natural fiber composites, contributing to the advancement of eco-friendly, high-performance textile materials while minimizing research resource consumption.

METHOD

The Agave sisalana plant used in this study, as depicted in figure 1, was sourced from the southern area of Marrakech, Morocco. The chemical agents applied during the experimental procedures were of analytical grade: sodium hydroxide (NaOH, 99 %) and acetic acid (CH_3COOH, 99,88 %) were purchased from SOLVACHIMIE, while potassium permanganate ($KMnO_4$, 98 %) was acquired from LOBA CHIMIE.

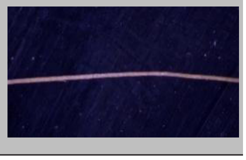
The composite matrix consisted of polyester resin supplied by DETAIL CHEMISTRY, along with methyl ethyl ketone peroxide serving as the curing catalyst and cobalt functioning as an accelerator. The resin exhibited a viscosity of 640 mPa·s and a density of 1200 kg/m³. For formulation, 1,9 % methyl ethyl ketone peroxide and 0,25 % cobalt were incorporated into the resin.

Treatment of sisal fiber

The sisal fibers used in this study were extracted from Agave sisalana leaves through mechanical decortication, a method that consists of scraping the leaf tissue to isolate the fibers, followed by drying. To enhance fiber-matrix interaction and remove surface impurities such as waxes and lignin, the fibers were treated with a dilute alkaline solution. Specifically, a 0,5 % sodium hydroxide (NaOH) solution was applied at 65 °C for 40 minutes. These treatment parameters were selected based on a factorial design approach detailed in our previous work.[21]

Additionally, the same study explored the synergistic effect of a subsequent oxidation treatment using potassium permanganate ($KMnO_4$) dissolved in acetone. The fibers were immersed in $KMnO_4$ solutions at varying concentrations (0,03 %, 0,06 %, and 0,09 %) and treated for 10, 20, or 30 minutes, maintaining a constant temperature of 40 °C. This dual treatment approach significantly improved mechanical performance and reduced water absorption, as shown in table 1. After chemical processing, the fibers were thoroughly washed, neutralized to remove any remaining reagents, and then rinsed with water. The final drying step was carried out in an oven at 105 °C for six hours to ensure complete moisture. Table 1 illustrates the morphological changes observed on the fiber surfaces before and after treatment,highlighting the improvements obtained through this optimized surface modification process.

Table 1. Microscopic Observation of Sisal Fibers Before and After Treatment

Fiber untreated	**Fiber treated with 0,5 % NaOH**	**Fiber treated with 0,5 % 3NaOH +0,0 % $KMnO_4$**	**Fiber treated with 0,5 % NaOH +0,06 % $KMnO_4$**	**Fiber treated with 0,5 % NaOH +0,09 % $KMnO_4$**
				

Preparation of sisal woven

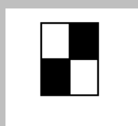
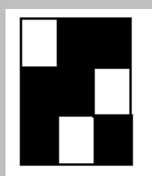
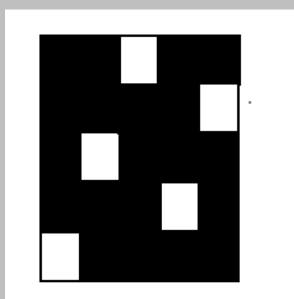
The composites were strengthened using three different weave patterns: plain weave, twill, and satin.

Plain weave are the most basic and widely used pattern. In this weave, the weft yarn crosses alternately over and under the warp yarns, creating a tight and balanced fabric with good durability and a uniform surface.

Twill weave is recognized by its diagonal rib pattern. Here, the weft thread passes under multiple warp threads before going over one or more, resulting in a fabric that is more flexible and better able to resist wear.

Satin weave is distinguished by its smooth and shiny surface. The weft yarn typically floats over four or more warp threads before going under one, minimizing the visible intersections. This structure produces a fabric that is soft, flexible, and has excellent draping qualities. Examples of these weave types can be seen in table 2.

Table 2. Weave structures

Weave structure	**Diagram**
Plain	
Twill	
Satin	

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Fabrication of composite

The composite specimens were produced using the vacuum bagging process. To facilitate demolding, the mold surface was first coated with a layer of wax. The textile reinforcements were then positioned within the mold, and a plastic film was sealed over the top to create an airtight environment. A vacuum pump was activated to remove the air from the system, thereby generating the necessary vacuum pressure. Resin was then introduced and drawn into the fiber structure through vacuum assistance, ensuring thorough impregnation. Once the fibers were fully saturated, the composites were left to cure at room temperature for approximately 8 hours.

Mechanical Properties

Tensile tests were performed using a Universal Testing Machine (model GT-C01-3) fitted with a 50 kN load cell. The tests followed the UNE-EN ISO 527-4:1997 standard, applying a constant crosshead speed of 2 mm/min. This method provided key data on the tensile strength and elastic modulus of the composites, reflecting their mechanical response under tensile loading. For each treatment variant, ten specimens measuring 250 mm × 25 mm × 3 mm were prepared and tested.[22]

Water Absorption

Water uptake measurements of sisal-reinforced polyester composites were conducted in accordance with ASTM D570-98. Five replicates per sample type were tested, with specimen dimensions of 25,4 mm × 76,2 mm.[23] Samples were first dried at 105°C for one hour to ensure moisture removal and then allowed to reach room temperature. After immersion in water for 24 hours, samples were carefully removed, surface moisture was blotted away using a dry cloth, and the specimens were weighed to determine the amount of absorbed water.

Water absorption was determined according to the following equation (1):[23]

$$Mt(\%) = \frac{(We - Wi)}{Wi} \times 100 \qquad \textbf{(1)}$$

Mt is the water absorption rate, Wi is the initial weight of the sample, and We represents the weight of simple after immersion in water.

Fuzzy model

Fuzzy logic is a mathematical and artificial intelligence approach designed to handle concepts that cannot be easily classified as simply true or false. Instead, it allows for intermediate values, reflecting the uncertainty and ambiguity often found in real-world problems.[22]

Unlike traditional binary logic which relies on clear-cut rules and definitions, fuzzy logic embraces the idea that concepts can exist in degrees or ranges.[23] This is achieved through fuzzy sets, where each element's membership is expressed by a membership function that assigns a value between 0 and 1, indicating how strongly the element belongs to the set.

This approach has found applications in various fields including control systems, decision-making, pattern recognition, robotics, and broader AI tasks. Its main advantage lies in its ability to model situations where precise boundaries are hard to define.[24,25,26]

The fuzzy logic process generally consists of three key parts: fuzzification, an inference engine, and defuzzification,[27,28] as depicted in figure 1.

1. Fuzzification transforms crisp numerical inputs into fuzzy values. Variables are represented by membership functions that describe the degree to which these values belong to linguistic categories or fuzzy sets.
2. The selection of membership function shapes depends on the problem context and data characteristics. Triangular membership functions (figure 2) are popular due to their straightforward nature and ease of interpretation. Nonetheless, other shapes like trapezoidal or Gaussian functions can also be used depending on the complexity and needs of the application.

Fuzzy Knowledge Base

The fuzzy prediction model was developed using three input variables: concentration, time, and woven fabric structure. The outputs predicted by the model were tensile strength and water absorption, which proved to be the key factors influencing the fabric's mechanical and moisture related properties.

During the fuzzification process, three discrete concentration values (0,03 %, 0,06 %, and 0,09 %) were considered (figure 3), along with three-time intervals of (10, 20, and 30 minutes) (figure 5) as quantitative inputs. Additionally, three fabric structures plain, twill, and satin were incorporated as qualitative linguistic variables (figure 4). For the outputs, fuzzy categories such as low, medium, and high were assigned to both tensile strength and water absorption, illustrated in figure 6 and 7.

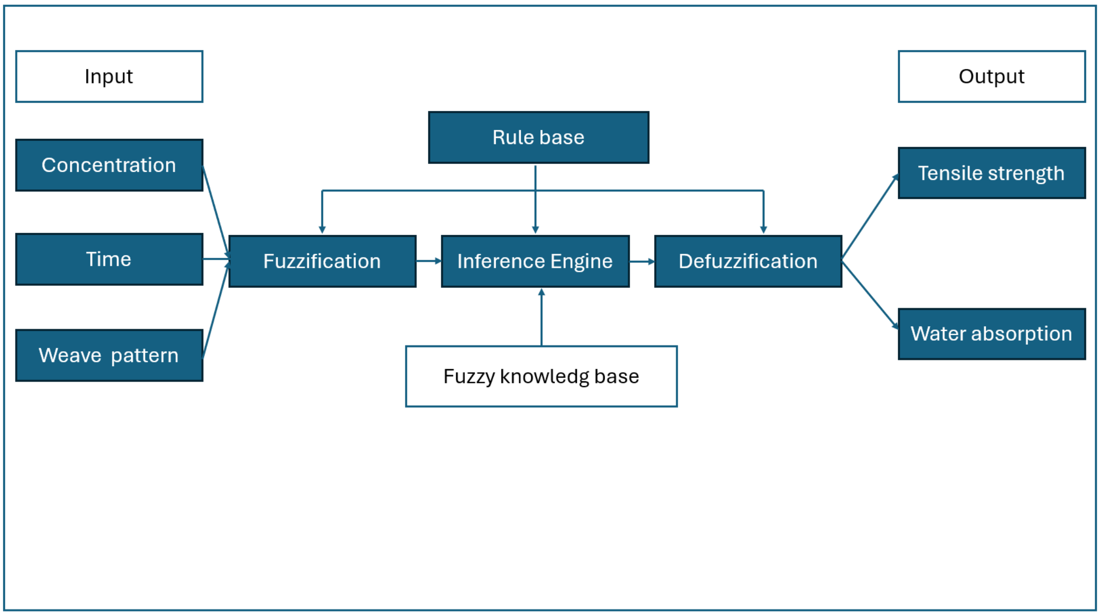

Figure 1. Fuzzy inference process

The triangular membership curve is outlined using the formula shown in equation (2):

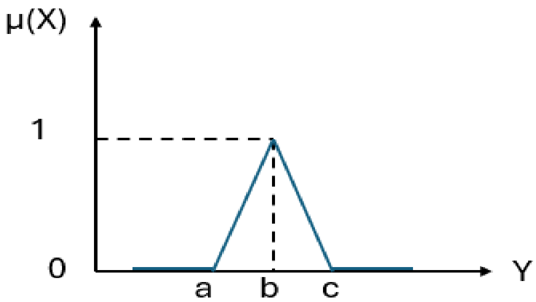

Figure 2. Triangle Membership Function

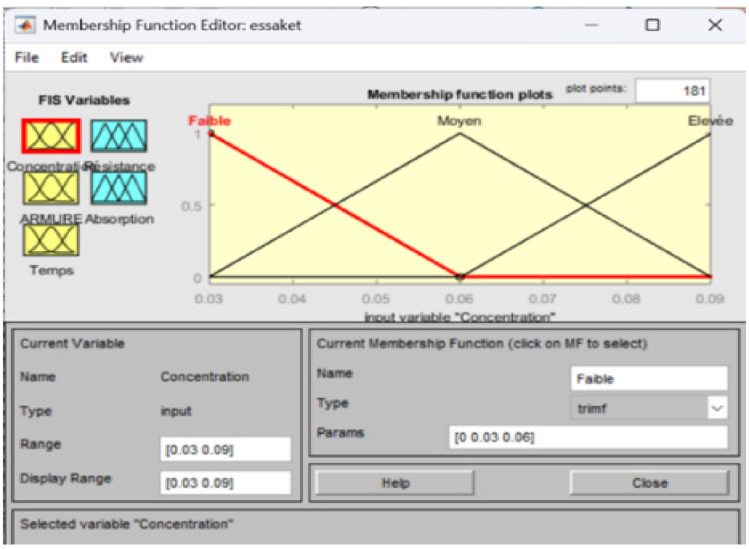

Figure 3. Input of chemical concentration

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$$\mu(x) = \begin{cases} 0 & \text{si } x \leq a \\ \dfrac{x-a}{b-a} & \text{si } a < x \leq b \\ \dfrac{c-x}{c-b} & \text{si } b < x < c \\ 0 & \text{si } x \geq c \end{cases} \quad (2)$$

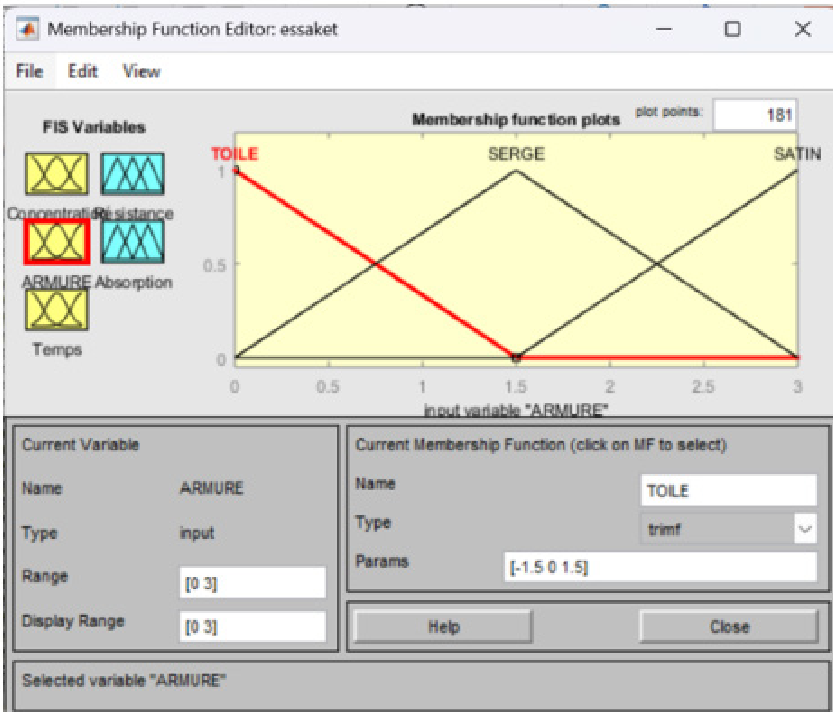

Figure 4. Input of fabric weave

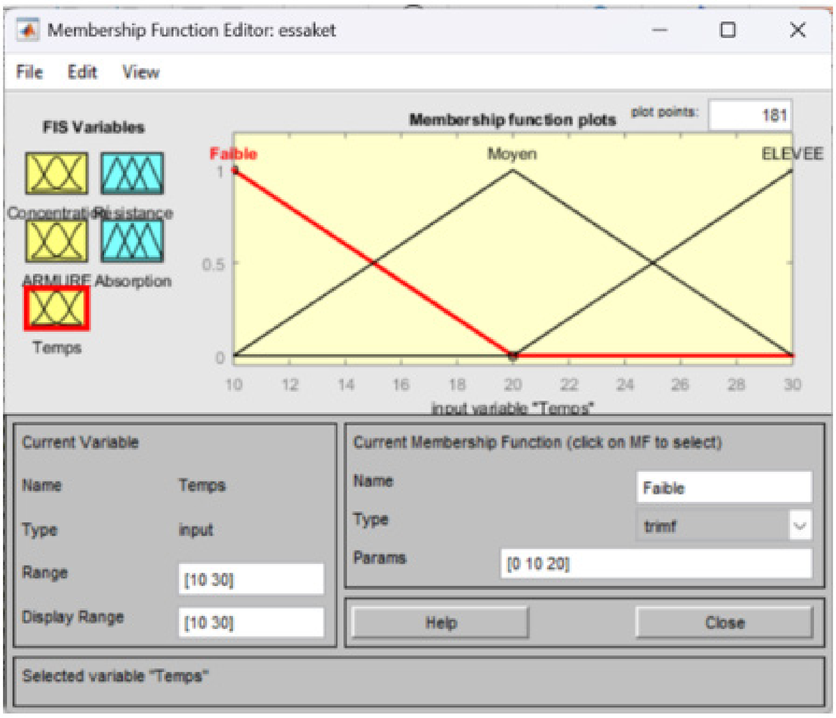

Figure 5. Input of immersion time

Fuzzy inference enables decision-making based on a set of rules formulated using qualitative, linguistic expressions. These rules typically follow a structured format such as:[27, 23]

R_1: if X_1 corresponds to A_{11}, X_2 corresponds to A_{12}, ..., and X_n corresponds to A_{1n}, then the output y is C_1

R_m: if X_1 corresponds to A_{m1}, X_2 corresponds to A_{m2}, ..., and X_n corresponds to A_{mn}, then the output y is C_m

$X = (X_1, X_2, ..., X_n)$: input vector representing the inferred variables

$A = [A_{mn}]$: matrix of reference fuzzy sets (characteristic matrix)

$C = (C_1, C_2, ..., C_m)$: output vector containing possible conclusions or decisions

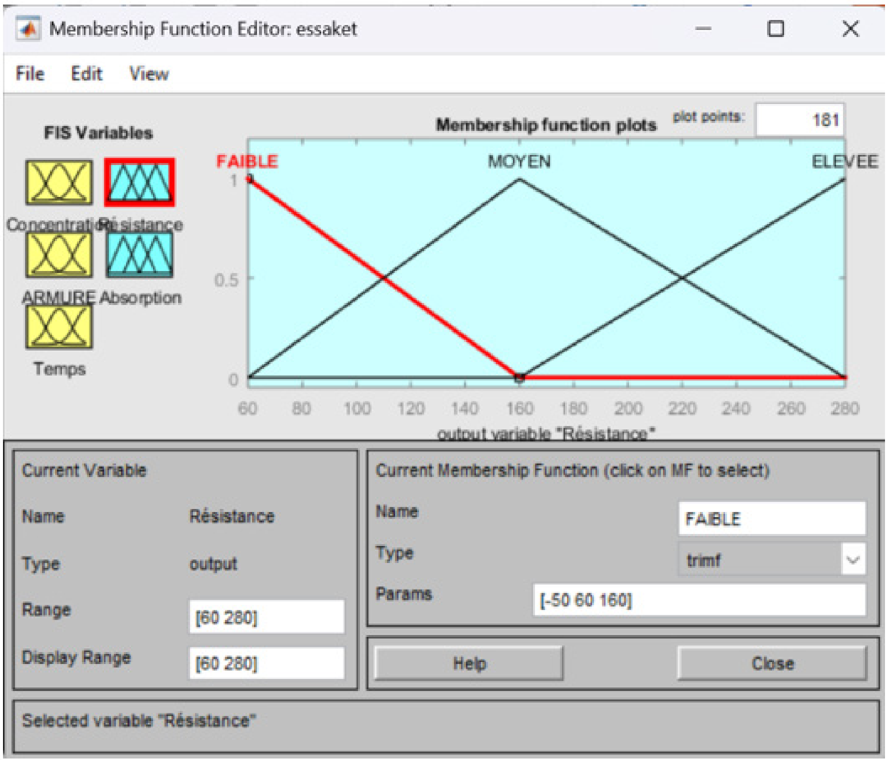

Figure 6. Output tensile strength

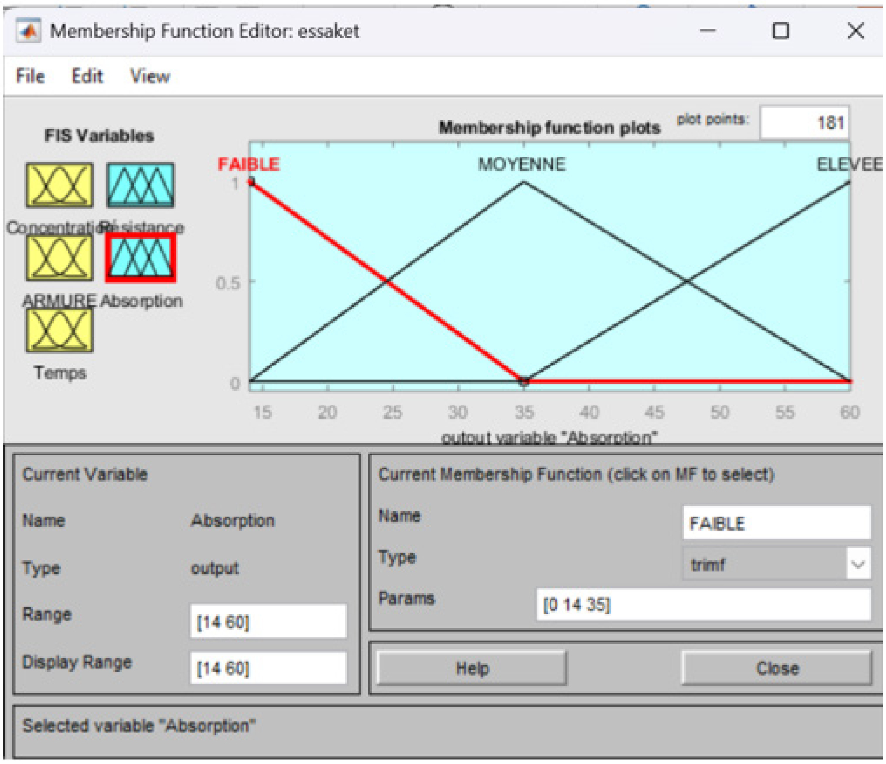

Figure 7. Output water absorption

The overall degree of matching between the input and the fuzzy rule *m* is computed using equation (3):

$$\mu_m = \prod_{j=1}^{n} \mu mj(Xj) \qquad (3)$$

Where:
μ_m: aggregated membership degree for decision rule m
$\mu_{mj}(X_j)$: membership value of the *j*-th input criterion with respect to the fuzzy set defined by rule m

Defuzzification refers to the step where the system's overall performance initially described using fuzzy or linguistic terms is transformed into a specific numerical value. In the present study, the centroid (or center of gravity) method is employed. This approach integrates all the relevant fuzzy information to derive a crisp output that best represents the system's efficiency.[24] The defuzzified output value is determined using the well-established center of gravity method, as shown in the following equation (4):

$$Y_0 = \frac{\int \mu(y)dy}{\int y \cdot \mu(y)dy} \qquad (4)$$

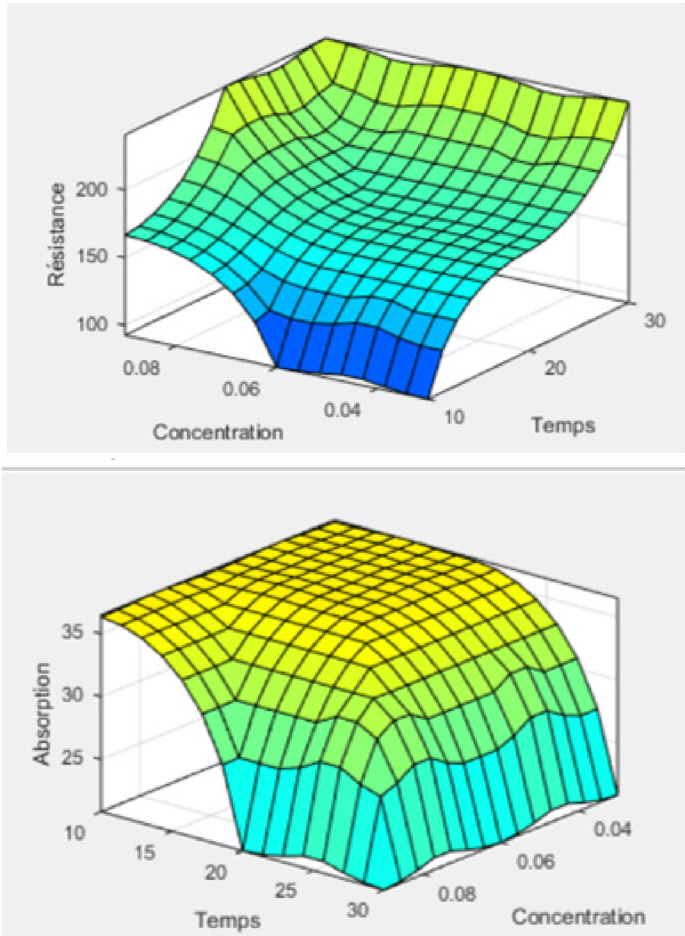

Figure 8. Illustrates the control surfaces generated through the fuzzy logic environment available in MATLAB

Figure 8 graphically illustrates the relationship between $KMnO_4$ concentration, immersion time, and weave structure (as input variables), and tensile strength and water absorption capacity (as output variables).To assess the performance of the developed fuzzy system, $KMnO_4$ concentrations of 0,03 %, 0,06 %, and 0,09 % were tested in combination with corresponding immersion durations across the three types of woven structures. The fuzzy logic-based predictive model is depicted in figure 9, which clearly outlines the modeling process.

Prediction example:If the fibers are treated with a 0,06 % $KMnO_4$ solution for 20 minutes, and the weave type is satin (structure 3), the predicted tensile strength is 167 MPa, and the estimated water absorption is 36,3 %.

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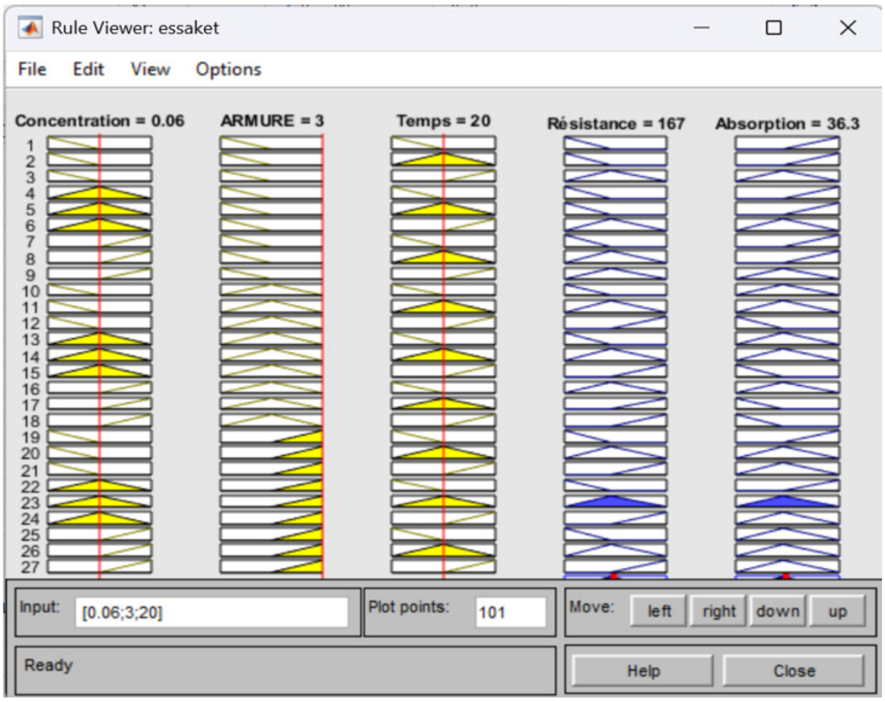

Figure 9. Graphical Interface for Rule Inspection in the Fuzzy Mode

RESULTS

Figures 10, 11, and 12 display the experimental saturation curves for composites reinforced with three different woven structures: plain weave, twill, and satin.

The investigation centers on the influence of three critical variables fabric architecture, $KMnO_4$ treatment level, and exposure time on the performance of the developed composites.[29] The $KMnO_4$ concentration refers to the level of chemical treatment applied to the fibers, while the immersion time indicates how long the fibers are exposed to this treatment.

By holding the weave type constant, our findings reveal a strong link between $KMnO_4$ concentration, immersion time, and the tensile strength of the composites. The coefficients of determination for the different weaves further support this correlation: plain weave (R^2 = 0,9494), twill (R^2 = 0,9442), and satin (R^2 = 0,9606). This demonstrates that higher concentrations and longer immersion times contribute to notable improvements in tensile strength.

Additionally, there is a significant positive correlation between these treatment parameters and the composites' water absorption characteristics, with R^2 values of 0,9111 for plain weave, 0,9139 for twill, and 0,9523 for satin. This indicates that chemical treatment effectively lowers water absorption, enhancing the durability and performance of the materials.

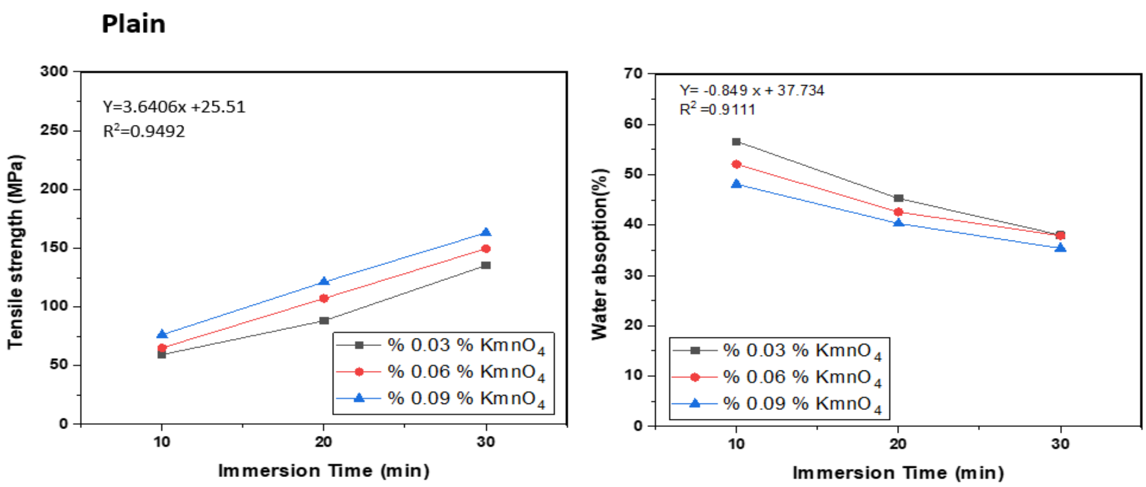

Figure 10. Tensile strength and water absorption for plain weave

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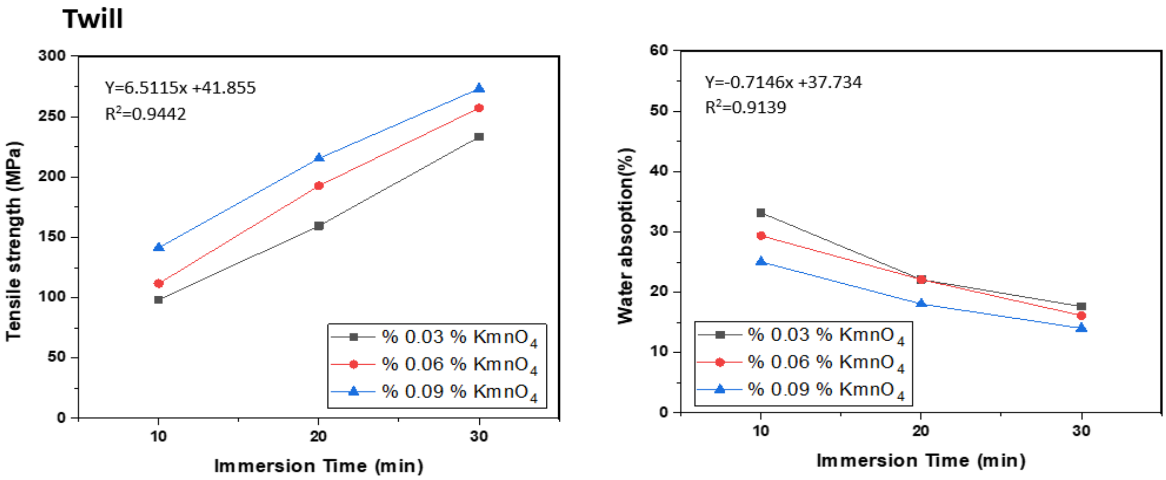

Figure 11. tensile strength and water absorption for twill weave

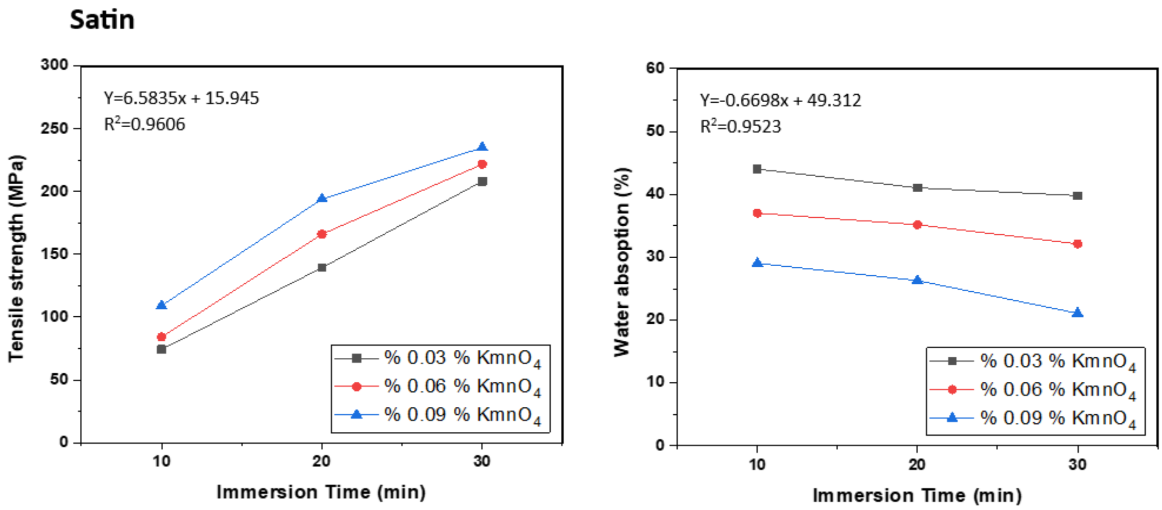

Figure 12. tensile strength and water absorption for satin weave

Table 3 summarizes both the experimental data and the corresponding predictions generated by the fuzzy logic model for a total of 27 fabric samples.

The percentage errors between the observed and predicted values were computed, revealing an average absolute deviation of 1,77 % for tensile strength and 3,46 % for water absorption. Such minimal deviations confirm the model's ability to accurately reproduce experimental trends.

This suggests that the fuzzy system effectively models the intricate relationships within the dataset and mirrors the actual experimental trends with a high degree of accuracy.

Overall, the results underscore the robustness of the fuzzy logic approach, confirming its potential as a reliable predictive tool in evaluating the mechanical and moisture-related performance of woven composites.

Figure 13. Tensile Strength - Experimental vs Fuzzy Logic

Sample	Weave structures	Concentration (%)	Time (min)	Tensile strength (Mpa)			Water absoption %		
				Experience	Fuzzy logic	Err%	Experience	Fuzzy logic	Err%
1	Plain	0,03	10	59,34	60,50	1,95 %	56,63	55	2,88 %
2		0,03	20	88,21	87,10	1,26 %	45,30	44	2,87 %
3		0,03	30	135,34	138,60	2,41 %	38,02	37,3	1,89 %
4		0,06	10	65,11	66,30	1,83 %	52,09	49	5,93 %
5		0,06	20	107,23	110,20	2,77 %	42,60	41,8	1,88 %
6		0,06	30	149,55	154,00	2,98 %	37,90	36,3	4,22 %

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7		0,09	10	76,21	77,30	1,43 %	48,11	47	2,31 %
8		0,09	20	121,12	122,50	1,14 %	40,30	40,8	1,24 %
9		0,09	30	163,11	164,40	0,79 %	35,40	35	1,13 %
10	Twill	0,03	10	98,16	97,30	0,88 %	33,16	34,16	3,02 %
11		0,03	20	159,50	163,10	2,26 %	22,11	21,7	1,85 %
12		0,03	30	233,17	235,10	0,83 %	17,63	18,1	2,67 %
13		0,06	10	111,75	110,60	1,03 %	29,35	30	2,21 %
14		0,06	20	192,73	199,10	3,31 %	22,11	25	13,07 %
15		0,06	30	257,12	264,40	2,83 %	16,13	15,8	2,05 %
16		0,09	10	141,32	143,90	1,83 %	25,03	22	12,11 %
17		0,09	20	215,34	218,80	1,61 %	18,05	18,9	4,71 %
18		0,09	30	273,16	276,85	1,35 %	14,03	14,3	1,92 %
19	Satin	0,03	10	74,25	75,00	1,01 %	44,02	46	4,50 %
20		0,03	20	139,42	144,10	3,36 %	37,02	36	2,76 %
21		0,03	30	208,30	212,50	2,02 %	29,04	28	3,58 %
22		0,06	10	84,16	83,60	0,67 %	41,03	40	2,51 %
23		0,06	20	166,11	167,00	0,54 %	35,17	36,3	3,21 %
24		0,06	30	221,90	226,50	2,07 %	26,30	27	2,66 %
25		0,09	10	109,16	111,80	2,42 %	39,80	40,5	1,76 %
26		0,09	20	194,12	197,80	1,90 %	32,13	31,4	2,27 %
27		0,09	30	235,16	238,10	1,25 %	21,09	20,6	2,32 %
			Valeur absolue moyenne:			1,77 %			3,46 %

Figures 13 and 14 illustrate the distribution of 27 experimental samples across three distinct treatment zones applied to composites reinforced with chemically modified woven fibers: the effective treatment zone, the saturation zone, and the ineffective (or detrimental) treatment zone. These zones reflect the underlying physicochemical transformations induced by potassium permanganate ($KMnO_4$) on lignocellulosic fibers, which in turn directly influence the composites' mechanical strength and water absorption capacity.[31] The figures also offer a comparative overview of the experimental data versus predictions generated by a fuzzy logic-based model.

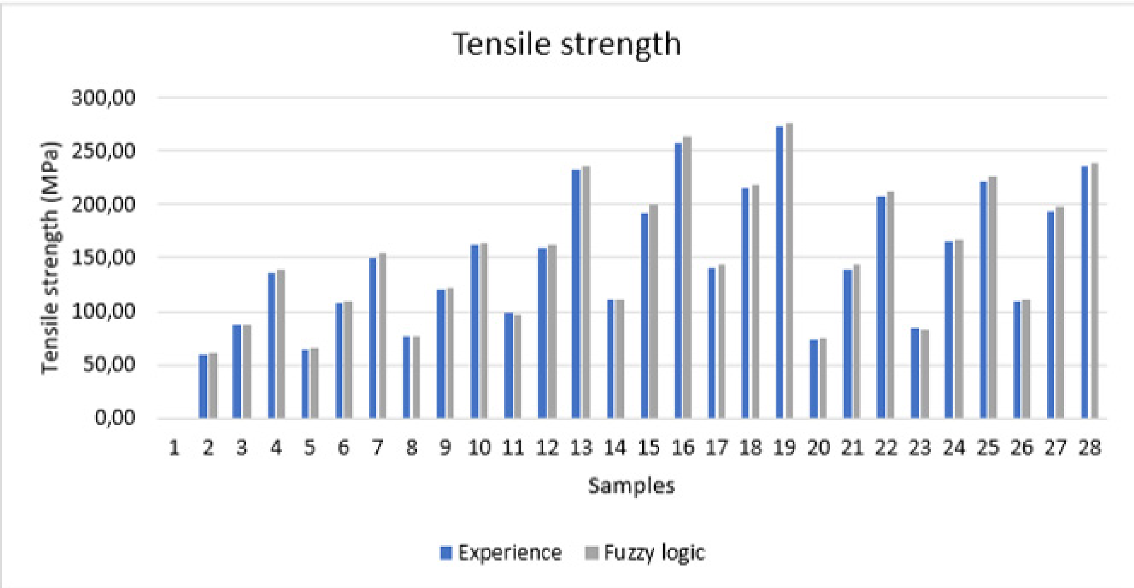

Figure 13. Tensile Strength – Experimental vs Fuzzy Logic

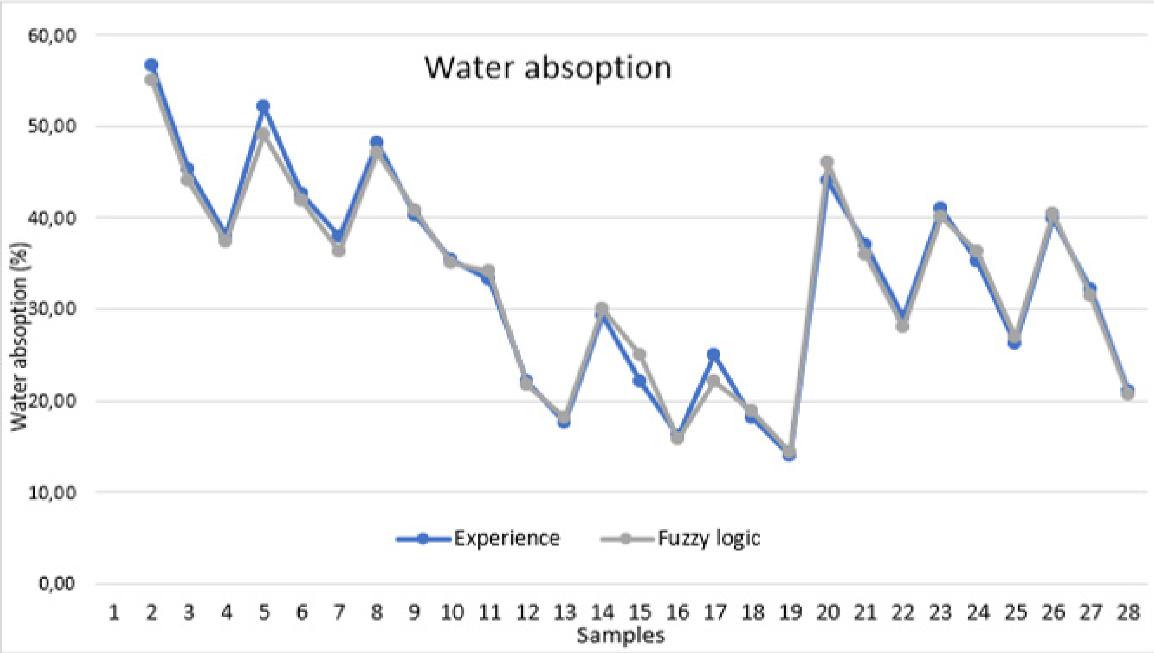

Figure 14. Water absorption – Experimental vs Fuzzy Logic

The fuzzy logic model shows a strong predictive capacity, closely matching experimental results across varying concentrations, immersion durations, and fiber weave structures. It accurately captures the nonlinear trends in both tensile strength and water uptake, affirming its relevance for modeling systems governed by uncertainty and complexity such as natural fiber composites undergoing chemical surface modification. The model achieves low average absolute errors (1,77 % for tensile strength and 3,46 % for water absorption), highlighting its robustness as a process optimization tool.

In the effective treatment zone, which encompasses moderate $KMnO_4$ concentrations and immersion times, samples show substantial improvements in performance. For instance, Twill samples 13 to 18 and Satin samples 23 and 24 exhibit high tensile strength values (up to 273 MPa for sample 18) and significantly reduced water absorption rates (below 25 %). At the molecular level, such treatment promotes selective oxidation of lignin and hemicellulose, while preserving the crystalline regions of cellulose. This controlled degradation removes surface impurities and exposes hydroxyl groups, improving matrix–fiber interfacial bonding and reducing porosity.

The saturation zone is characterized by diminishing returns, where further increases in treatment intensity (concentration or time) no longer result in significant mechanical or functional improvements. Representative samples in this zone (e.g., 8, 9, 17, 21, 26, and 27) display a performance plateau. This effect is explained by the exhaustion of accessible reactive sites on the fiber surface.[32] Once most hydroxyl and other oxidizable functional groups are consumed, $KMnO_4$ has minimal further impact. Consequently, both tensile strength and hydrophobicity stabilize, despite harsher treatment parameters.

The ineffective treatment zone includes two subcategories:

1. Under-treatment, observed in samples 1 to 7 (Plain weave), leads to minimal enhancement in mechanical strength and persistently high-water absorption (up to 56 %). Inadequate chemical reaction leaves the fiber surface rich in lignin, waxes, and hemicellulose, resulting in poor adhesion and moisture resistance.
2. Over-treatment, affecting samples such as 25, 14, and 16, results in degradation of the cellulose backbone. Excessive oxidation beyond surface-level modification damages the β-1,4-glycosidic bonds of cellulose, causing structural breakdown, increased porosity, and compromised mechanical integrity. This is reflected in reduced tensile strength and sometimes a resurgence in water uptake.

From a physicochemical standpoint, the delineation of these zones is rooted in the complex interactions between the oxidizing agent ($KMnO_4$) and the fiber's lignocellulosic matrix. The effective zone represents optimal conditions where hemicellulose and lignin are selectively oxidized, enhancing interfacial compatibility.[33] The saturation zone reflects the limit of surface reactivity, and the ineffective zone highlights the detrimental effects of excessive or insufficient treatment either due to lack of activation or irreversible cellulose damage.

In summary, the graphical analysis confirms that optimal composite performance is achieved within the effective treatment zone, where chemical treatments enhance fiber surface properties without compromising internal structural integrity. The fuzzy logic model proves to be a valuable predictive framework for identifying and maintaining this processing window, thus supporting the development of high-performance, chemically tailored natural fiber composites.

CONCLUSIONS

Globalization has sped up supply chains and heightened the demand for process optimization, especially in composites reinforced with woven fabrics. In this context, quickly and accurately validating the mechanical and functional properties of treated materials is essential to minimize development costs and time.

The fuzzy logic model developed in MATLAB has shown strong performance in predicting tensile strength and water absorption for treated composites, with mean absolute errors of 1,77 % and 3,46 %, respectively. This approach offers a practical solution for optimizing treatment variables such as $KMnO_4$ concentration, immersion duration, and weave type, reducing the need for extensive physical testing.

Encouraged by these encouraging results, the model is scheduled for industrial trials within a textile production environment. This phase is vital to verify the model's practical effectiveness and its potential role in production workflows. Successful validation will establish the model as a reliable decision-making tool to enhance the quality and performance of natural fiber composites.

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