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PREDICTING THE WEAVABILITY OF A NEW WOOLLEN FABRIC USING FUZZY LOGIC

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ABSTRACT

Weaving saturation can lead to several undesirable problems, such as problems with loom performance, premature wear of mechanical parts and loss of expensive raw materials. Therefore, when designing and creating new woollen fabrics, it is crucial to adjust yarn densities and qualities according to the weaves to pass weavability tests. This study focuses on the development of a practical fuzzy logic model to predict the saturation of new 100% Wool fabrics. To validate this fuzzy model, an experimental part was carried out. The fabric samples used in this study came from three different weave types (plain, twill and satin) and included five weft counts (Nm) and nine different densities. The results obtained using the fuzzy logic model developed were compared with the experimental values. The predictions generated by the fuzzy logic model were found to be satisfactory and accurate, demonstrating its effectiveness for predicting the saturation of a new 100% wool fabric.

Keywords: *Saturation Index, Weaving, Fuzzy Logic, Modelling, Weavability.*

1. INTRODUCTION

Weave saturation is a critical problem in textile manufacturing, particularly for woollen fabrics. It leads to defects; premature equipment wears and material losses. Current tools are not optimized to meet the specific needs of woollen fabrics, and traditional physical testing approaches do not reduce costs or accelerate design times. In this context, it becomes essential to develop a model based on modern technologies, such as fuzzy logic, to efficiently predict the weavability and saturation limits of wool fabrics.

In the field of textile modelling and simulation, several recent technological advances have helped to improve design and development processes. Here are some of these advances:

- ✓ 3D modelling 3D modelling technologies allow the creation of realistic virtual representations of textiles. This allows designers to visualize and manipulate fabrics virtually, making it easier to explore different design options and evaluate performance [1].
- ✓ Behaviour simulation: Simulation software can predict the behaviour of textiles under different conditions and constraints. For example, they can simulate tensile strength, deformation, abrasion resistance, breathability, weavability and so on. These simulations help to evaluate the performance of textiles even before creating physical prototypes [2], [3].
- ✓ Structure optimization: optimization software optimization techniques can be used to find the optimum structure for a textile based on specific objectives such as strength, flexibility, or lightness. These techniques allow a large design space to be explored and the best structural configurations to be identified [4].
- ✓ Integration of experimental data: Experimental data on textile properties, such as fiber strength, fabric stiffness, context, etc., can be integrated into simulation models. This makes it possible to better calibrate the models and improve their accuracy[5].
- ✓ Multi-physics analysis: Textiles can be subjected to different physical stresses

simultaneously, such as mechanical, thermal, or fluidic. Recent advances have made it possible to develop multi-physics simulation tools that take account of these complex interactions, enabling a more accurate assessment of textile behaviour in real-life conditions[6].

- ✓ Artificial intelligence and machine learning: Artificial intelligence and machine learning are increasingly being used to improve textile simulation models, making it possible to analyze large quantities of data, identify patterns and generate more accurate predictions[7],[8].

By combining these technological advances, it is possible to reduce reliance on costly physical testing, speed up the textile design process and optimize the performance of end products. By using artificial intelligence in these ways, textile simulation models can be improved in terms of accuracy, efficiency, and cost [9]. This enables designers and manufacturers to make more informed decisions and develop better quality textiles[10],[11].

The contribution of this research is crucial for the following reasons:

- ✓ Technological advances: It introduces a predictive model based on fuzzy logic, demonstrating high accuracy.
- ✓ Cost reduction: By eliminating the need for exhaustive physical testing, this research enables a significant reduction in the costs and lead times associated with textile design and production.
- ✓ Industrial applicability: The model is fast, reliable and easy to use in an industrial environment, making it particularly relevant for manufacturers seeking to optimize their development processes.
- ✓ Potential extension: This model could be adapted for other types of precious materials, paving the way for broader applications in the textile field.

2. LITERATURE REVIEW

Many efforts have been made to define and predict textile properties using AI. These technological advances offer numerous opportunities to improve the quality, performance, and functionality of textiles, while optimizing production processes and reducing costs and delivery times[12].

In their study, M. Alsayed, H. İ. Çelik and H. K. Kaynak investigated the factors influencing the air permeability of multi-filament fabrics, such as the number of filaments, weave density and weave type. Microfilaments were identified as having a significant impact on the air permeability of these fabrics due to their low porosity[13]. The aim of the study was to develop a fuzzy logic model to predict the air permeability of polyester multi-filament fabrics, using both conventional yarn and microfilaments.

The fabric samples used in the study included different fineness levels of microfilament and conventional filament, as well as different weave types and weave densities. The researchers compared the experimental results with the predictions of the fuzzy logic model and regression equations. The results showed that the fuzzy logic model had satisfactory accuracy, with a lower mean absolute error than the regression analysis. This confirms the superiority of the fuzzy logic model for predicting the air permeability of multi-filament fabrics.

In their study, M. KODALOĞLU and F. AKARSLAN KODALOĞLU examined the use of fuzzy logic to assess temperature physiology and occupational health in weaving companies[14]. The identification of risks in the work environment has been identified as a crucial factor in the prevention of work-related health problems, occupational diseases, and work-related accidents. The fuzzy logic approach offers a precise and adaptable method for assessing these risks and taking appropriate preventive measures. Using fuzzy logic, the researchers were able to consider various factors such as temperature, humidity, ventilation, exposure to chemicals, etc, to assess the health risks for workers in weaving companies. This approach makes it possible to obtain more precise and detailed assessments, considering the complexity and variability of working conditions.

In their study, T. Hussain, A. Jabbar and S. Ahmed found that adaptive neuro-fuzzy models slightly outperformed regression models in predicting compressed air consumption in the air-jet weaving process. These models have shown promising potential for estimating compressed air consumption, detecting air leaks and similar applications [15]. The researchers compared the performance of adaptive neuro-fuzzy models and regression models in predicting compressed air consumption in air-jet weaving. The results showed that adaptive neuro-fuzzy models were slightly superior in terms of prediction accuracy and reliability. This suggests that these models are more effective at estimating compressed air consumption and can be used to detect air leaks and similar problems.

In their study, T. Tundo, and E. I. Sela investigated the use of fuzzy logic to solve production problems, focusing on the determination of fabric production using variables such as inventory, demand, and production costs[16]. Two methods were explored: the Tsukamoto method and the Sugeno method. The Tsukamoto method uses fuzzy sets to represent the input and output variables, while the Sugeno method uses constants or mathematical functions to model the relationships between the variables. The researchers compared the results obtained using these two methods with the company's actual data. The results of the study showed that the Tsukamoto method, using Weka rules, was the closest to actual fabric production. This means that this fuzzy logic approach, using fuzzy sets and specific rules, was better at predicting fabric production as a function of inventory, demand, and production cost variables.

In their study, M. A. I. Hussain, B. Khan, Z. Wang, and S. Ding developed a deep learning model using residual network (ResNet) for textile weave pattern recognition and classification [17]. The model was designed to be robust and able to generalize by incorporating data augmentation techniques. The researchers evaluated the model's performance using measures such as accuracy, balanced accuracy and F1 score. The experimental results demonstrated the robustness of the proposed model, with high performance even when the physical properties of the tissue were modified Compared with other approaches, including the VGGNet pre-trained model, the ResNet-based model achieved superior accuracy in weave pattern recognition. It also showed an improved ability to handle rotation and lighting effects.

L. S. Admuthe and S. Apte have adopted an approach combining two techniques, namely adaptive neuro-fuzzy inference system (ANFIS) and subtractive clustering, with the aim of predicting thread properties. ANFIS is an inference system based on neuro-fuzzy networks, which exploits the advantages of neural networks and fuzzy systems to model and predict complex relationships. Subtractive clustering, on the other hand, is a data clustering method aimed at identifying underlying structures in a data set[18]. In this context, it is used to prepare ANFIS input data by identifying groups of similar threads.

The study by S. A. Malik et al focuses on the analysis of polyester barrier fabrics (PES) and aims to establish a correlation between air permeability and influential parameters such as material, construction, and manufacturing process[9]. To this end, artificial neural network (ANN) models have been developed to map the relationships between input and output variables. Three ANN models were optimized according to the number of input variables, and the one that used all selected inputs showed the best results. The use of ANN makes it possible to adjust the permeability of barrier fabrics to specific needs, by optimizing loom, fabric, and yarn parameters. This approach avoids costly and time-consuming testing.

The article by L. K. Ncube, T. R. Chikowore and N. R. Sibanda presents the development of a fuzzy logic-based tool for managing textile weaving production in a context of increasing customer orders[19]. This tool, created using MATLAB, aims to optimize the use of limited raw materials and to make efficient decisions. Thanks to this fuzzy logic module, it is possible to determine the optimum number of orders that can be processed as a function of the raw materials available, and the number of orders received. Model validation results show that this tool could process 80% of orders received, a significant improvement on the 50% currently processed.

This potential improvement could lead to a 30% increase in production and a 1.2% increase in daily profits. Using fuzzy logic, this tool offers a solution for optimizing order management, maximizing the efficiency of raw material use and improving the overall performance of the textile production process.

The paper by Z. Gao and L. Chen [1] presents a comprehensive review of methods for the numerical analysis of 3D woven fabrics, focusing on recent advances in modelling methods at the meso and microscopic levels. It also analyses various virtual fibre models and discusses methods for detecting and modelling contact and friction interactions between fibres. The aim is to provide a reference for research into the simulation of 3D woven fabrics.

The work of S. Shahrabadi, Y. Castilla, M. Guevara, L. G. Magalhães, D. Gonzalez, and T. Adão [8] provides a review of defect types and automated optical inspection (AOI) systems based on machine learning techniques, demonstrating their effectiveness in the analysis of textile materials. The

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use of convolutional neural networks (CNNs), such as AlexNet and VGG16, has made it possible to achieve accuracy rates more than 98%.

All the above work has focused on the application of models to plastics materials. To our knowledge, no research has focused on wool, which is why the present work will develop a model based on fuzzy logic dedicated to 100% wool fabrics.

The aim of our new research is to develop a fuzzy logic-based model to predict weaving saturation for 100% wool fabrics. We will then compare the results of this model with experimental data obtained from loom experiments and tests.

Weavability refers to the ability of a material to be woven successfully in the textile manufacturing process (weaving). To achieve our goal, we draw on existing expertise in weavability and textile manufacturing technologies. We use the knowledge and fundamental principles that influence weaving, such as context, weaving parameters, interactions between threads, etc. In the experimental part of our research, we focus on exploring the limits of weavability and saturation indices in weaving. Understanding these limits is essential for optimizing textile manufacturing processes and guaranteeing the quality of end products. In addition, we will examine saturation indices, which determine the maximum yarn absorption or retention capacity of a new fabric. The results of our previous experiments will be presented to deepen our understanding of these important aspects of weavability.

Various studies have been carried out to determine saturation index formulae: Love's equations [20], Peirce's theory, Ashenhurst's theory [21], Law's rules [22] , Brierley's theory, Russell's index and Seyam and El Shiekh's saturation formulae [23],[24], Booten's index [25] and M. Dalal's saturation formulae [26] have been used to help define and formulate these indices and saturations.

This research was carried out under the following assumptions:

Assumption 1: The cross-section of the yarn is assumed to be cylindrical [21].

Assumption 2: If the number of threads is contracted, the threads are separated by only one thread thickness (equivalent to one diameter).

Assumption 3: Linear density and material density (g/cm3) are identical and homogeneous.

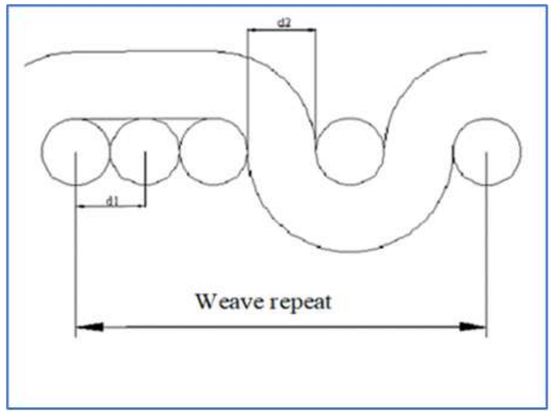

Figure 1: Warp cross section

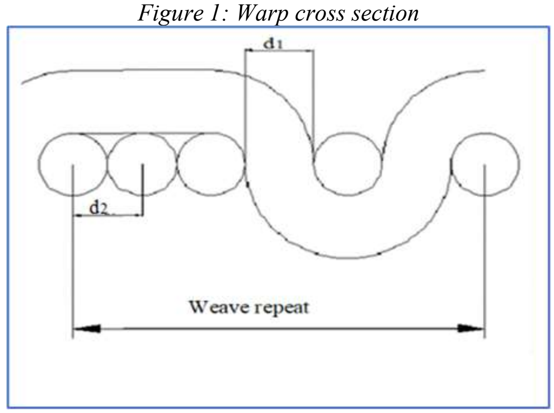

Figure 2: *Weft cross section*

The formulae corresponding to these saturation indices in the case of high tension are as follows[27]:

$$Ich = \frac{Cch}{\pi} \cdot \left(\sqrt{\frac{Tch}{\phi \rho_{fch}}} + \frac{ntr}{Rch} \cdot \sqrt{\frac{Ttr}{\phi \rho_{ftr}}} \right) \quad (1)$$

$$Itr = \frac{Ctr}{\pi} \cdot \sqrt{\frac{Ttr}{\rho_{ytr}}} \quad (2)$$

$$Ist = \frac{Isch \times Istr}{100} \quad (3)$$

With:

Ich = Isch: warp saturation index.
Itr = Istr: weft saturation index.
Ist: fabric saturation index.
Cch: Actual warp count.
Ctr: Actual weave count.
Rch: Warp weave ratio.
ntr: Number of weft face changes / warp ratio.
ρf ch: Density of warp yarn (g/cm3).
ρf tr: Density of weft yarn (g/cm3).
ρytr: Density of weft yarn (g/cm3).
Tch: Warp yarn count (in Tex).
Ttr: Weft yarn count (in Tex).

The literature review presented in the paper highlights significant advances in the use of artificial intelligence, particularly fuzzy logic, to predict various parameters in the textile field (air permeability, compressed air consumption, production management, etc.). However, to our knowledge, few if any studies have focused on the weavability of wool fabrics, a complex material characterized by specific properties such as elasticity and voluminous texture.

Weave saturation, a common problem, leads to defects, costly material losses and premature equipment wear. Currently, predicting weavability limits relies mainly on costly and time-consuming physical testing. This research is therefore needed to fill this gap by proposing a fuzzy logic model capable of predicting saturation and weaving feasibility for new wool fabrics, thus enabling significant savings in time and resources.

This study differs from previous work in several respects:

- ✓ Focus on wool: unlike the research by M. Alsayed et al [13], which focused on the permeability of polyester fabrics, this study focuses on the weavability of wool fabrics, a largely unexplored area.
- ✓ Saturation prediction: Existing fuzzy logic models have been applied mainly to aspects such as compressed air consumption [15], production management [19], or the assessment of physiological properties of textiles [14]. This study extends the application of fuzzy logic to the prediction of weaveability limits, offering a unique and practical solution.
- ✓ Integration of saturation indices: The integration of theoretical concepts established in the literature, such as saturation indices (Love, Peirce, Seyam and El Sheikh), into a fuzzy logic-based model is a novel advance that has not been exploited in previous work.
- ✓ Cost and time efficiency: The proposed model eliminates the need for exhaustive physical testing, thus reducing costs and speeding up the design process.
- ✓ Robust experimental validation: With a mean absolute error of just 1.22% (98.78% accuracy), this model demonstrates a significant practical advance.

These elements show that this research provides a practical and effective solution to a specific problem by extending the applications of fuzzy logic, filling an important gap and offering an innovative and effective solution to the problem of the weavability of woollen fabrics.

In this study, the main objective was to determine the weavability limits of the fabrics. The weavability limits refer to the maximum density at which a fabric can be woven without causing weaving problems, such as defects or thread breaks. To achieve this objective, several steps were taken.

First, fabric samples were woven on a loom using three basic weaves: plain, twill and satin. These basic weaves represent different configurations of weft and warp yarns. Next, the weave density, also known as " weft density ", gradually increased for each type of weave. This means that the number of weft threads per centimeter was increased until a maximum density was reached.

During the weaving process, measurements and observations were made to assess the quality of the fabric and to detect any weaving problems. When defects began to appear or weft threads could no longer be inserted correctly, the weave density was considered to have reached its limit of weavability for that fabric sample.

Once the fabric samples and experimental data had been collected, a fuzzy model based on artificial intelligence was developed. This fuzzy model uses fuzzy sets to represent and deal with the uncertainty and variability of the parameters involved in the weaving process. It has been trained using expert data, i.e. the knowledge and observations of textile professionals, to predict weavability limits when weaving new fabrics.

The advantage of this fuzzy model is that it can predict the weavability limits of a new fabric without having to carry out costly and time-consuming weaving tests on the actual machine. This saves time and resources, while avoiding potential mechanical damage caused by weaving tests.

Finally, to assess the effectiveness and accuracy of the fuzzy model, the experimental results obtained from the study of weavability limits were compared with the model's predictions. If the fuzzy model can accurately predict the weavability limits of new fabrics, this indicates that it can be used as a reliable tool in the process of designing and developing new textiles.

3. MATERIAL AND METHODS

3.1 Material and procedure

3.1.1 Materials

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Three variables were used to produce samples of 100% wool fabric: the type of weave (plain, twill and satin), the count of the weft yarns (measured in Nm) and the density of the weft (expressed as the number of picks per centimeter).
Characteristics of the loom and textile materials used for the various tests:
Dobby looms with positive transfer flexible lances.
Speed: 400 strokes/min.
Warp:
Worsted wool yarn with count: Nm = 60/2.
Warp count = 30 ends/cm
Weft:
Material: 100% wool.
Weft count and count (Nm) are variable.
Loom width: 180 cm.
Weft qualities:
100% wool Nm: 10, 15, 20, 25, 30, 35, 40, 45, 50 and 60.

3.1.2 Procedure

Different fabrics are produced and for each weave, the weft density is increased on the loom until the fabric is saturated: starting with normal weft density, then strong density and increasing to saturated weft for each type of weave and weft count with the following parameters:
Fixed parameters: warp qualities and characteristics:

Variable parameters (Weft): density and count (Nm).

Variable parameters (Weaves): plain, twill and satin.

We made various representative fabric samples by varying the weft quality, increasing the number of wefts per cm, and tensioning the warp until the fabrics reached saturation. For each weft quality, the saturation repeat is the average of five trials on the loom.

3.2. Fuzzy model

3.2.1 Presentation of Fuzzy Logic

The history of fuzzy logic[28] dates back to the 1960s, when Lotfi Zadeh, an Iranian-American mathematician and computer scientist, introduced this new branch of logic. He was inspired by the observation that many aspects of reality cannot be easily categorized in terms of true or false, but rather in terms of degrees of truth.

Traditional logic, based on the principle of the excluded third, considers that every proposition is either true or false, with no possibility of compromise. However, Zadeh realized that in many fields, such as linguistics, decision-making or the modelling of complex systems, it was more appropriate to use degrees of truth rather than binary values [29].

Zadeh introduced the concept of Fuzzy Logic to model and reason about vague or imprecise concepts. In fuzzy logic, propositions can have a truth value that varies between 0 and 1, reflecting the degree of certainty or uncertainty associated with each proposition. For example, instead of saying that it is raining or that it is not raining, the degree of rainfall can be expressed on a scale of 0 to 1. Fuzzy logic is based on sound mathematical principles, particularly the theory of fuzzy sets. It uses fuzzy operators such as fuzzy conjunction (AND), fuzzy disjunction (OR) and fuzzy negation (NOT), which allow fuzzy truth values to be manipulated in a coherent way.

Since its introduction, fuzzy logic has had many practical applications. It has been successfully used in areas such as systems control, pattern recognition, inference systems, artificial intelligence and decision making. It can be used to model and reason about complex real-life situations, where factors are often imprecise, incomplete or contradictory [30].

The history of fuzzy logic is therefore that of an innovative approach that has opened new perspectives in terms of modelling and reasoning, by considering the fuzzy and uncertain nature of many real-world phenomena. It continues to be an active and promising area of research, offering powerful tools for dealing with the complex and uncertain problems we face[31].

Fuzzy logic consists mainly of three stages: fuzzification, the inference engine and defuzzification. This is illustrated in Figure 3 below.

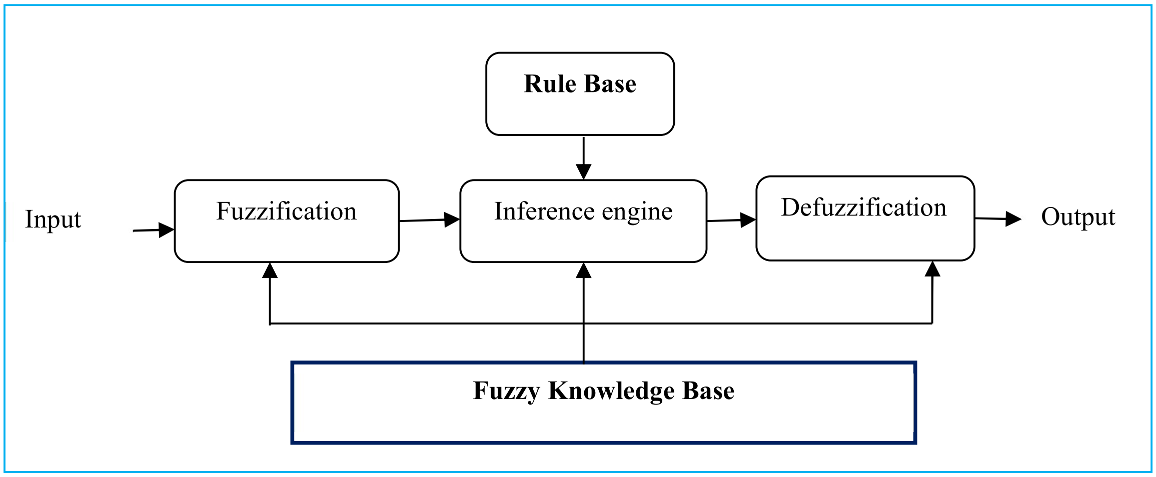

Figure 3: Fuzzy Inference Process

3.2.2 Fuzzification

Fuzzification involves converting crisp values into fuzzy values by assigning a degree of membership to different linguistic terms or fuzzy sets using membership functions. The choice of membership form depends on the specific problem and the data available. The triangular form is commonly used because it is easy to understand and interpret and allows intuitive modelling of linguistic variables. However, trapezoidal, and Gaussian forms of membership functions can also be used depending on the requirements of the problem and the characteristics of the data.

The general equation for a triangular membership function is:

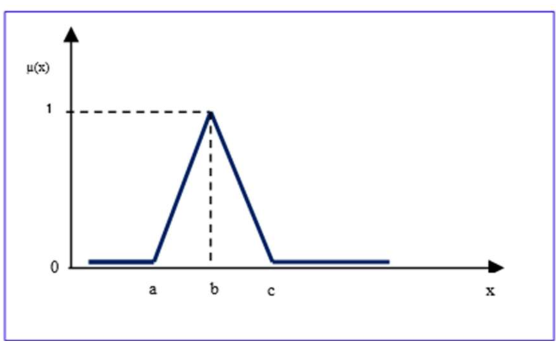

Figure 4: The Triangle Membership Function

$$\mu(x) = \begin{cases} 0 \text{ if } x \leq a \\ (x-a)/(b-a) \text{ if } a \leq x \leq b \\ (c-x)/(c-b) \text{ if } b \leq x \leq c \\ 0 \text{ if } x \geq c \end{cases} \quad (4)$$

The fuzzy prediction model was constructed using three fabric variables: yarn count (Nm), weft count (number of wefts per cm) and weave type (plain weave, twill, and satin). These variables were the most relevant for predicting saturation filling. They were used as inputs to the model, while the fabric saturation index was used as an output variable.

For fuzzification, five weft count values (Nm10, Nm20, Nm25, Nm35 and Nm60) were used as numerical (quantitative) input variables (Fig. 5). In addition, the loom saturation weights (9, 12, 15, 18, 23, 27, 34, 40 and 47) were also used as numerical (quantitative) input variables (Figure 6). The three weaving types (canvas, twill, and satin) were considered as linguistic (qualitative) input variables (Figure 7).

As for the output fuzzy sets, three fuzzy sets were defined for the saturation index: "weaving possible", "saturation" and "weaving impossible" (Figure 8).

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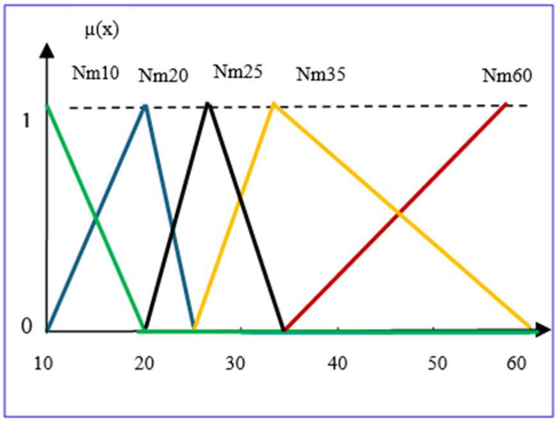

Figure 5: Input of yarn count yarn weft (Nm)

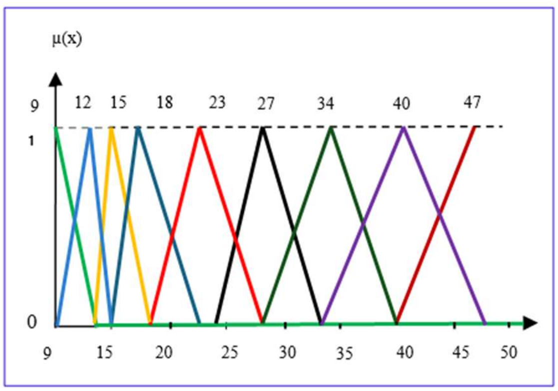

Figure 6: Input of Weft density

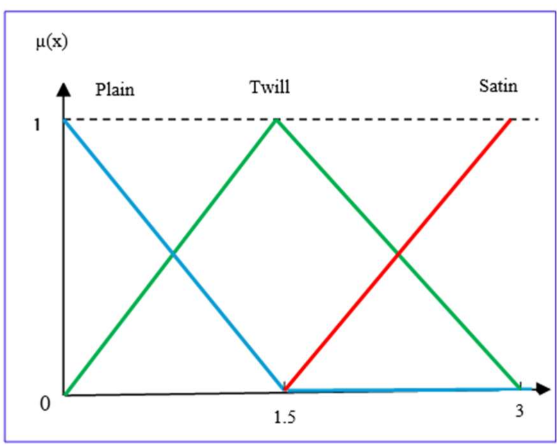

Figure 7: Input of weave type

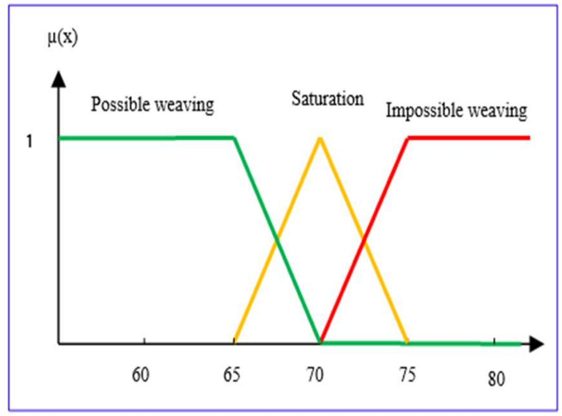

Figure 8: Output of saturation index

3.2.3 The Fuzzy Inference engine

Fuzzy inference is an approach that allows us to make decisions using rules formulated using linguistic terms.
The inference rules [27] are written as:

Rule 1*: if X1 is A11 and X2 is A12… and Xn is A1n then y is C1.*

.

.

Rule m *: if X1 is Am1 and X2 is Am2… and Xn is Amn then y is Cm*

X= (X1, X2,….,Xn): vector of inference
A=[Am,n]: characteristic matrix
C= (C1, C2,….,Cm): result vector

$$\mu m = \prod_{j=1}^{n} \mu_{m_j}(Xn) \quad (5)$$

μ_m : degree to belong of membership function decision class
μ_{mj}: degree to belong of membership function criterion.

Example for the rules base:
WD: Weft density
WC: Weft yarn count
WT: Weave type
SI: Saturation index

$$\begin{array}{cc}
 & \begin{array}{ccc} & A=[Am,n] & \end{array} \qquad\qquad C \\
 & \begin{array}{ccc} \text{WD} & \text{WC} & \text{WT} \end{array} \qquad\qquad \text{SI}
\end{array}$$

$$\text{If} \begin{bmatrix} 9 & 10 & \text{Plain} \\ 12 & 10 & \text{Plain} \\ . & . & . \\ . & . & . \\ . & . & . \\ . & . & . \end{bmatrix} \text{then} \begin{bmatrix} \text{Saturation} \\ \text{Possible weaving} \\ . \\ . \\ . \\ . \end{bmatrix}$$

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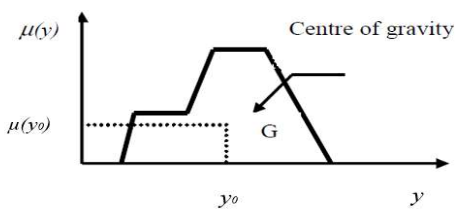
3.2.4 Defuzzification

Defuzzification is the process of converting the variables that describe the overall efficiency of a system, expressed in linguistic or fuzzy terms, into a numerical value. In this context, the center of gravity method is used to consider all the available information and obtain a precise value that represents overall efficiency.

$$Y_0 = \frac{\int_y y \times \mu(y)\,dy}{\int_y \mu(y)\,dy} \qquad (6)$$



The fuzzy control surfaces shown in Figure 9 were generated using MATLAB's Fuzzy software.

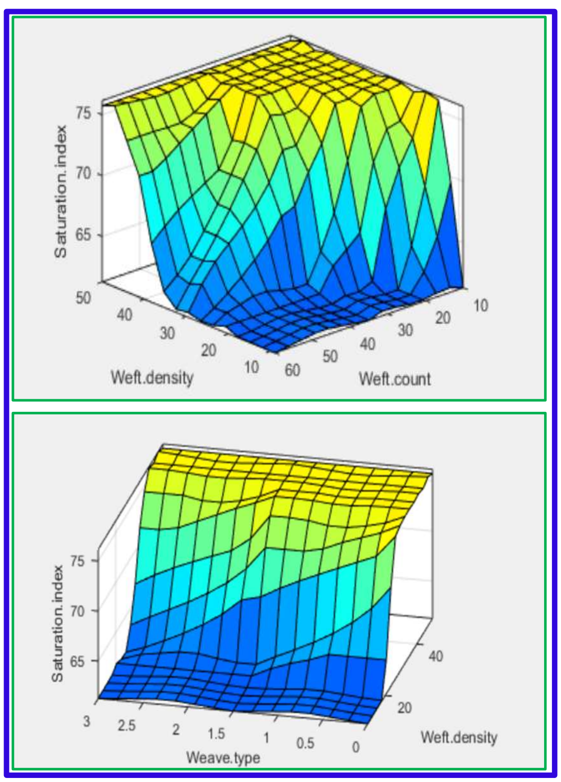


Figure 9: fuzzy control surfaces

Figure 9 shows graphically the relationship between weave type, weft count and weft density on the input side, and the weavability saturation index on the output side. These figures show the interactions and trends between these variables.

To validate the effectiveness of the fuzzy system developed, the values of Nm15, 30, 40, 45 and 50 and their saturation dummies were used to check the model's performance. This validation confirmed the ability of the fuzzy prediction model to provide accurate and reliable results.

Figure 10 shows the fuzzy prediction model and clearly explains the process used to make the predictions. The model uses fuzzy concepts and logic rules to estimate the saturation index as a function of weft count, weft density and weave type.

Here are three examples of predictions made by the model:

- ✓ If the weave is a plain weave with a weft count of Nm 30 and a weft repeat of 20, then the predicted saturation index is 68.6 (saturated weave).
- ✓ If the weave is a twill and the weft count is Nm 45 and the weft density is 34, then the predicted saturation index is 66.9 (saturated weave).
- ✓ If the weave is a satin weave and the weft count is Nm 50 and the weft density is 40.5, then the predicted saturation index is 66 (saturated weave). These examples demonstrate how the fuzzy logic model can consider the different variables and generate accurate predictions of saturation index as a function of weaving parameters.

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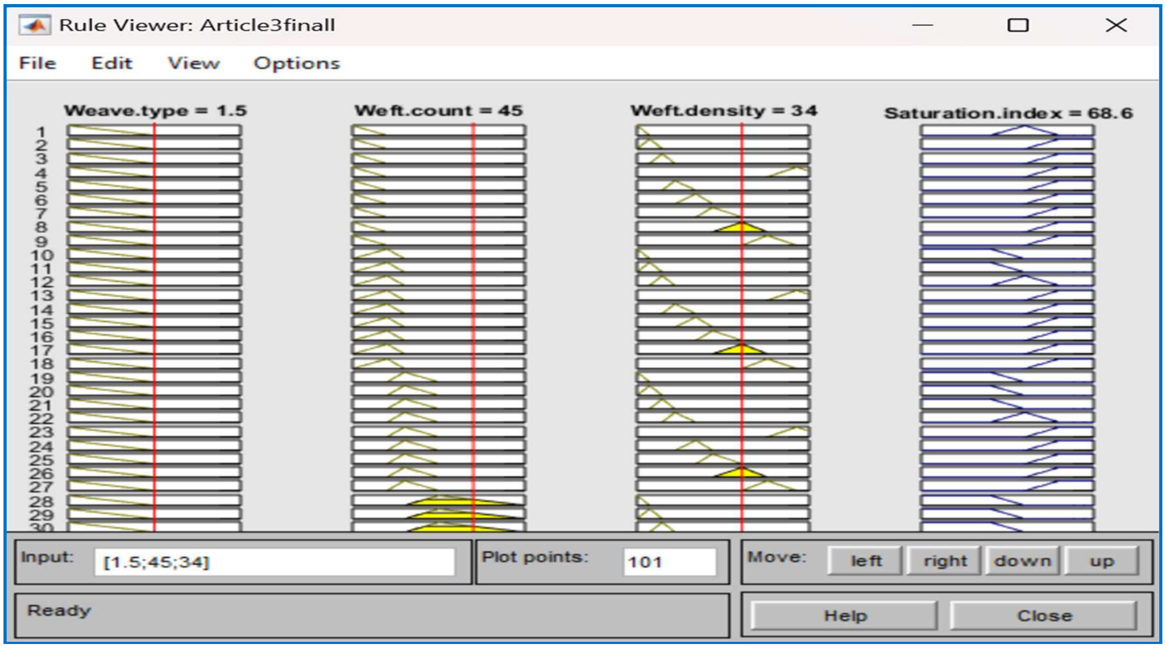

Figure 10: Rule viewer of developed fuzzy mode

4. Results and discussion

Figures 11, 12 and 13 show experimental results in the form of saturation curves for fabric samples in the three weave types: plain weave, twill weave and satin weave. When analyzing fabric saturation, three important factors are generally considered: weave type, weft count and number of picks per centimeter. Weft count refers to the thickness or fineness of the yarn used in fabric manufacture, measured in Nm. The number of picks per cm represents the number of weft threads present in one cm of fabric.

In our experiment, by setting the weave type, we observed a significant correlation between the weft count and the number of picks per cm, as evidenced by the high coefficients of determination (R^2): $R^2 = 0.9966$ for plain weave, $R^2 = 0.9935$ for twill and $R^2 = 0.9962$ for satin.

When the yarn used for the weft is finer, i.e. it has a higher Nm count, it has a greater surface area per unit mass. Consequently, to achieve fabric saturation, it is necessary to increase the number of picks in the fabric, i.e. to increase the number of weft threads per cm.

The positive correlation we observe between weft count and the number of picks per centimeter is therefore consistent and predictable. It highlights the fact that to achieve fabric saturation, it is necessary to adjust the number of picks according to the count of the weft yarn used.

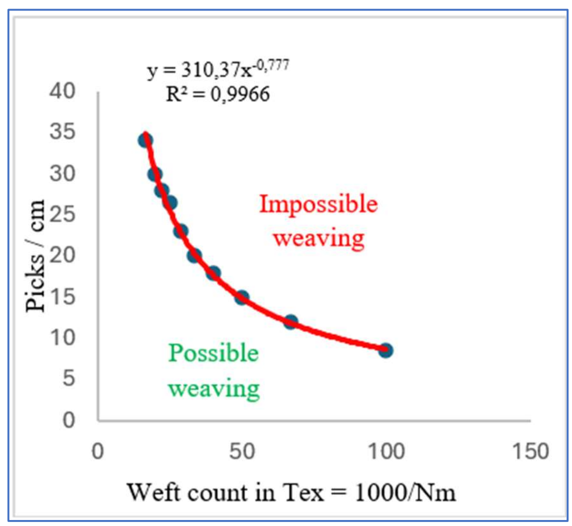

Figure 11: Saturation curve of plain weave

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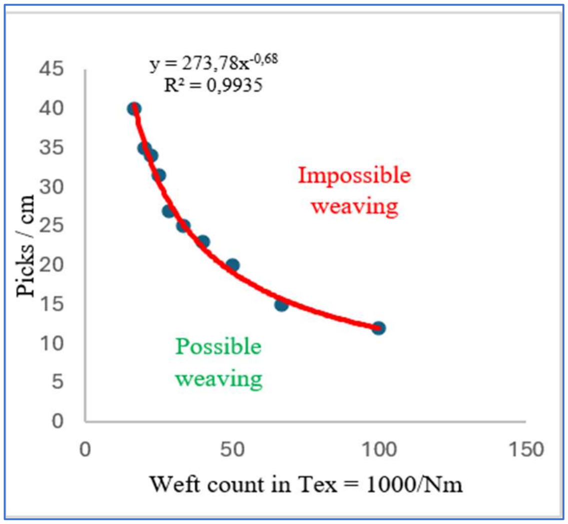

Figure 12: Saturation curve of twill weave

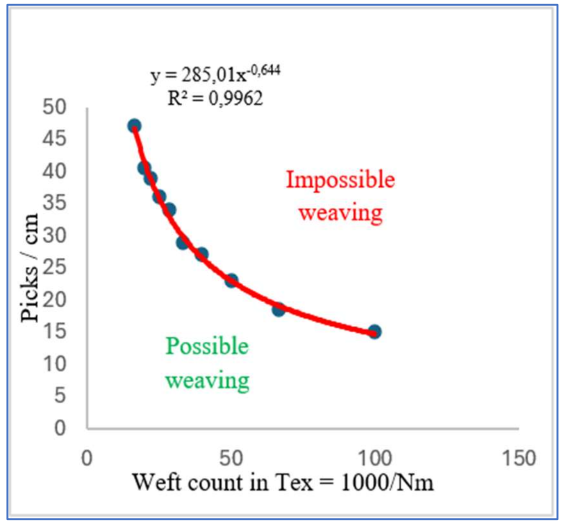

Figure 13: Saturation curve of satin weave

Table1:Comparison of predicted and experimental values for saturation index

				Saturation index %		
Sample	Weave	Nm	Picks/cm	**Experience**	**Fuzzy logic**	**Err %**
1	Plain	15	12,00	67,4	67,2	0,32%
2		30	20,00	65,8	66,9	1,69%
3		40	26,50	70,4	71,7	1,81%
4		45	28,00	68,3	68,6	0,46%
5		50	30,00	67,8	66,4	2,07%
6	Twill	15	15,00	67,8	67,2	0,85%
7		30	25,00	68,5	67,5	1,45%
8		40	31,50	70,7	70,9	0,25%
9		45	34,00	70,5	68,6	2,64%
10		50	35,00	67,6	66,0	2,31%
11	Satin	15	18,50	67,3	67,2	0,19%
12		30	29,00	66,7	67,1	0,59%
13		40	36,00	69,0	69,2	0,35%
14		45	39,00	69,4	68,6	1,14%
15		50	40,50	67,5	66,0	2,21%
				Mean absolute error %		**1,22%**

Table 1 and Fig. 14 show the experimental results of the fabric saturation index, which are the measurements obtained during actual tests. These results are compared with the values predicted by a fuzzy logic model developed specifically for this context. The fuzzy logic model is an inference system that uses fuzzy concepts to represent and deal with uncertainty in data. To evaluate the performance of the fuzzy logic model, the percentage errors between the experimental results and the predicted values are calculated. The average absolute error of the fuzzy model is 1.22%. This means that, on average, the predictions of the fuzzy logic model deviate from reality by only 1.22%. Such a low error percentage indicates that the fuzzy logic model is highly accurate and reliable in its predictions.

This result is important because it suggests that the fuzzy logic model can be used with confidence to make accurate predictions in the specific domain of tissue saturation index. It can be used to estimate the tissue saturation index for new samples where experimental measurements are not available.

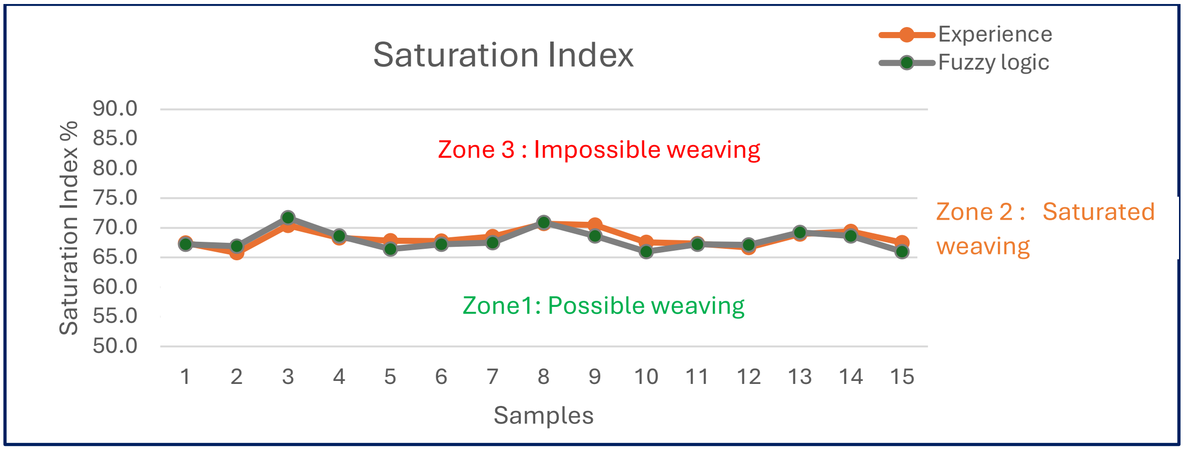

Figure 14: The values of the experimental and expected saturation index

The agreement between the experimental curve and that predicted by the fuzzy logic model is a significant result that underlines the validity and relevance of the model in this specific field. This indicates that the fuzzy logic model can reproduce the relationships and behaviour observed in real data, which is essential for providing accurate predictions.

An important aspect is the ability of the fuzzy logic model to capture the general shape of the experimental curve. This means that the model can capture general variations and trends in the data, which is essential for understanding and predicting the behaviour of the system under study. The model's ability to reproduce the experimental curve also suggests that it has been able to integrate the relevant information contained in the experimental data and use it to generate accurate predictions.

This observation reinforces confidence in the use of the fuzzy logic model to make decisions and predictions in this field. The model's ability to deliver results that closely match real data is an indicator of its performance and accuracy. This means that the model can be reliably used to simulate scenarios, optimize processes, or make informed decisions.

Using the fuzzy logic model, it is possible to explore different combinations of variables and parameters to better understand the system under study. This can lead to significant improvements in various fields of application, such as industry, engineering, finance, or medicine.

The results of this study are based on several rigorous criteria. The fuzzy logic model was experimentally validated by comparing its predictions with data from real trials. The results show a close match, with an average absolute error of just 1.22%. The variables used in the model (yarn count, dobby and weave type) proved sufficient to predict saturation limits accurately. Furthermore, the trends observed in the experimental and simulated curves confirm the model's ability to capture the complex interactions between these variables. These elements demonstrate the reliability and robustness of the proposed approach.

5. CONCLUSION

The development of the fuzzy logic model on MATLAB was motivated by the need to reduce the costs and time associated with weavability testing in the textile industry. Traditionally, after new fabrics have been designed and created, it is necessary to carry out tests to assess their suitability for successful weaving. However, these tests can be time-consuming, costly and lead to material loss. The fuzzy logic model we have developed uses fuzzy concepts and logic rules to estimate the weavability of a given fabric. It considers various parameters, such as fabric type, yarn density and other specific material characteristics, to generate accurate predictions. The average absolute error of 1.22% indicates that the model's predictions are in very good agreement with actual weavability test results. This means that the model is reliable and can be used as an accurate predictive tool, enabling informed decisions to be made about fabric feasibility without the need for physical testing.

By using the model, textile manufacturers can save time and resources by avoiding costly and time-consuming testing. They can also reduce the material losses associated with such testing, by optimizing production parameters right from the design stage. What's more, the fuzzy logic model offers a faster approach to assessing fabric weavability. Results can be obtained in a matter of moments, speeding up the textile development and production process. Following these results, the development of other models for valuable and expensive materials is strongly recommended.

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