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Application of Artificial Intelligence Algorithms for Technical Textiles Design Based on Performance Requirements

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ABSTRACT

This paper presents a systematic approach to optimize technical textile selection using fuzzy logic as one of the AI techniques. Traditional methods for material design rely heavily on iterative prototyping, which is time-consuming and lacks adaptability to complex performance requirements. To address this, we propose a fuzzy inference system (FIS) that maps four critical performance parameters—tensile strength, elastic recovery, thermal conductivity, and moisture regain—to a suitability score for a predefined set of textiles. The system leverages MATLAB's Fuzzy Logic Toolbox to model linguistic variables (e.g., "high," "low") and employs a Mamdani FIS with tunable membership functions and rule bases. Case studies demonstrate the system's ability to recommend materials with high accuracy compared to expert evaluations, thereby significantly reducing design cycles. This framework is particularly valuable for industries requiring rapid, data-driven decisions, such as aerospace, healthcare, and sportswear.

1. Introduction

Technical textiles are materials that are designed to meet some specific performance requirements, such as thermal resistance, elastic recovery, tensile strength, or electrical conductivity. These textiles are critical in industries ranging from aerospace and healthcare to sportswear and construction. However, designing technical textiles involves navigating complex, often conflicting constraints (e.g., balancing strength and weight, or thermal insulation and breathability). Traditional design methods rely heavily on trial-and-error prototyping, which is time-consuming, costly, and limited in handling multi-objective optimization.

Artificial Intelligence (AI) has emerged as a transformative tool in technical textile design, enabling data-driven decision-making and predictive modeling. AI techniques such as machine learning (ML), neural networks (NNs), fuzzy logic, and genetic algorithms (GAs) can analyze vast datasets, simulate material behavior, and optimize designs based on performance metrics. For instance, ML models can predict how fiber composition affects tensile strength, while fuzzy logic systems handle subjective or imprecise design criteria (e.g., "high flexibility" or "moderate thermal resistance"). This paradigm shift not only accelerates innovation but also enhances sustainability by reducing material waste.

This next section explores the application of AI in the technical textile industry, focusing on its role in optimizing material properties, streamlining manufacturing, and enabling smart textiles.

2. Literature Review

The textile industry is among the oldest and most significant global industries. It encompasses the design, development, production, manufacturing, and distribution of textile products, including fibers, yarns, fabrics, and garments. Historically, the textile sector has marked several important milestones. During the 18th century, the Industrial Revolution significantly boosted textile production, transforming yarn and fabric manufacturing into a major industry. In the following century, the industry continued to advance, benefiting from technological innovations such as the steam engine, developments in textile machinery, and the advent of computers.

The textile industry is in a constant state of evolution, driven by emerging trends, a dynamic market, and advancements in machinery and technology. Over the past two decades, the sector has gained renewed momentum through ongoing progress in computer technology and research in artificial intelligence (AI). Although the application of AI in textiles began as early as the 1990s, its adoption has been relatively slow. This sluggish integration may be attributed to the industry's traditionally conservative approach in leveraging AI tools to harness the vast volumes of data generated by textile processes. As a global and highly diversified sector, the textile industry also faces the challenge of establishing international regulations to safeguard manufacturers' data. AI systems play a crucial role by converting large datasets into meaningful classifications, identifying patterns and trends that support intelligent decision-making [1]. Many textile industrialists and researchers are actively exploring the potential and diverse applications of artificial intelligence (AI) across various stages of the textile supply chain. As the demand for high-quality, fast-response, and technologically advanced textile products continues to grow, AI is increasingly being embraced by manufacturers to meet these evolving expectations [2, 3].

Textile processes such as spinning, weaving, and coloration involve numerous variables—both known and unknown—that are intricately interdependent. Developing precise mathematical models to accurately predict outcomes is often challenging and time-consuming. Traditional statistical and mechanistic models have limitations in addressing such complex problems and are therefore not always reliable for decision-making. Mechanistic models, for instance, often simplify problems to make equations more manageable, but this comes at the expense of accuracy. In contrast, artificial intelligence (AI) offers the ability to identify, classify, measure, and predict textile properties with significantly greater accuracy than conventional modeling approaches [4].

2.1. AI in the Manufacturing of Textiles

A wide range of publications highlight the use of neural networks in addressing various textile-related challenges, including visual defect detection, real-time process monitoring, prediction of textile properties, and modeling for design and prototyping.

Over the past two decades, neural networks have been widely employed for identifying textile defects, addressing limitations associated with human inspection [5]. Manual inspection tends to be slow, subjective, and susceptible to fatigue, often resulting in reduced productivity and increased rejection rates, which negatively affect output and inspection accuracy. Neural networks have proven to be effective tools for fault detection, owing to their capability to learn and reliably recognize defects. In many applications, neural networks are integrated with digital image analysis, employing various image processing techniques. A critical challenge in these systems lies in selecting appropriate input features for accurate modeling. Researchers typically extract relevant information from captured images to serve as input features for the neural network [6]. Multi-layer feedforward backpropagation neural networks are commonly used for learning and classifying different types of defects, enabling real-time fault identification and quality monitoring [4]. For optimal image acquisition, essential for effective neural network processing, devices such as cameras or scanners, along with proper lighting conditions, are required [7]. In addition to defect detection, neural networks are also applied in predicting and modeling textile properties, where physical and mechanical characteristics of fibers and yarns are used as input variables.

2.2. AI in Manufacturing of Yarn

Yarn quality plays a crucial role in determining the properties and overall quality of fabrics and garments. Yarn spinning is widely recognized as a complex manufacturing process influenced by numerous factors, including raw material characteristics, processing techniques, and equipment settings. Key physical properties of yarn—such as strength, elongation, evenness, and bending rigidity—significantly impact the performance and quality of textile products. With advancements in artificial intelligence, an increasing number of yarn production parameters are now being monitored and predicted through AI-based control systems integrated into spinning machinery, leading to improved production efficiency and consistent product quality [8, 9].

In the field of yarn quality control, AI has found wide applications since it is much better than human inspectors at detecting yarn defects, analysing failure rates, adjusting control settings to maximize the yarn production process, and maintaining yarn quality. AI-powered systems analyze programmable quality attributes of yarn, such as hairiness, unevenness, and tenacity of different types of yarn using digital image analysis [9,10]. As the quantity of available data increases, the system continues to optimize the AI recognition process and allows training results to be transferred to production lines [11]. The technology has also reduced yarn grading mistakes to as much as 60%, leading to better yarn grading [12].

Traditional approaches to yarn modeling are often tedious, producing overly simplistic and uniform representations that lack realistic visual and structural accuracy. To address this, researchers at Cornell University have developed an AI-based algorithm capable of automatically generating realistic models of fiber and yarn properties. Using Computed Tomography (CT) scanning, images of individual yarn strands are captured, and the AI algorithm transforms this scan data into detailed 3D fiber-yarn models. This advancement holds significant potential for fabric design and prototyping across various industries, including automotive and apparel manufacturing [13].

In parallel, predictive modeling techniques such as the Adaptive Neuro-Fuzzy Inference System (ANFIS) have been employed to estimate yarn properties like tenacity and unevenness. This method utilizes key cotton fiber attributes—such as fiber strength, length, fineness, and short fiber content—as input variables. Studies have shown that the ANFIS model can accurately predict yarn properties, making it a valuable tool for optimizing yarn production based on fiber characteristics [14]

2.3. AI in the Manufacturing of Fabric

Fabric inspection is still predominantly performed by human operators, who are prone to error due to fatigue and subjectivity. To overcome these limitations, researchers are increasingly employing AI-powered systems combined with image analysis to automatically detect and classify fabric defects. These intelligent systems not only identify and assess defects but also analyze data to improve fabric grading processes. The output is fast, making the technology suitable for continuous, real-time fabric monitoring. Depending on the type and severity of defects, classification accuracy can range from 75% to 85%. The implementation of automated fabric fault detection systems is expected to significantly enhance both the production efficiency and quality of apparel [15].

A computer vision system integrated with an Artificial Neural Network (ANN) has been effectively used for detecting and classifying fabric defects [14]. This combined system also plays a key role in pattern recognition during the design, development, and production of both woven and knitted fabrics. One notable example of such AI-driven quality control technology is Cognex ViDi, developed by Cognex Corp. This advanced system can automatically inspect fabric patterns and accurately identify pattern defects, making it a highly reliable tool in textile manufacturing [12]. As a camera-based inspection solution, Cognex ViDi is evolving rapidly and is being increasingly adopted in fabric production and printing industries for its precision and efficiency [12,13,16].

Regarding the prediction of fabric physical and mechanical properties, researchers have applied backpropagation (BP) neural networks and fuzzy neural network models to evaluate the tactile qualities of fabrics, commonly referred to as fabric handle. These systems quantify the overall hand value using input data from both objective and subjective assessments. Fabric characteristics such as weight, thickness, elongation, tensile strength, shear, and surface roughness were measured objectively using the Kawabata Evaluation System for Fabrics (KES-FB) and subjectively through expert panel evaluations. Notably, the AI-based prediction methods showed a stronger correlation with the subjective assessments than the conventional KES-FB system [17].

Beyond fabric handle, AI systems—particularly those using feed-forward BP artificial neural networks—have also been employed to assess subjective fabric attributes such as comfort. These models use input parameters including weave type, thread density, yarn count, area density, and thickness to predict the thermal properties of fabrics. This approach allows for the estimation of thermal insulation performance in woven textiles prior to actual production, enabling informed design decisions [18].

2.4. AI in the Coloration and Finishing

Another significant application of AI in the textile industry is in the area of color management for dyed and printed textiles. Achieving accurate color matching has long been a complex challenge in textile coloration due to the numerous variables involved in the dyeing process. Traditionally, before the introduction of computer systems and automation, dye recipe formulation relied heavily on the expertise and experience of skilled professionals. This manual approach often resulted in inconsistencies and longer turnaround times.

Chen et al. (2021) introduced an automated color matching prediction model known as CMR-colour, which integrates three neural network architectures—including a Convolutional Neural Network (CNN), a deep learning model, along with two Artificial Neural Networks (ANNs). This hybrid model was designed to enhance the extraction of high-dimensional features from the spectral reflectance data of dyed textile substrates. The system effectively selects the appropriate dyes and determines the optimal concentration of each dye component to formulate the desired color recipe. Experimental results demonstrated that the CMR-colour model delivered highly accurate predictions, highlighting its strong potential and confirming its effectiveness in supporting precise color matching for dyeing and printing applications in the textile industry [19].

3. Motivation, Novelties, and Contributions

It is clear from the previous literature review that all AI techniques developed in the textile industry are concerned with aiding the user to determine the best-fitted fabric based on some performance parameters. So, the main contribution of this research is to develop an algorithm that can help the user to supply the desired requirements of performance, and the algorithm can infer the best-fitted fabric based on such requirements and based on some experience rules.

The original contributions of this study are:

(1) Developing an inference system based on fuzzy logic that enables the user to decide the best-fitted fabric based on some requirements.
(2) Graphical user interface development that allows the user to enter the desired requirements of performance and obtain the names of the best three fabrics.
(3) Evaluating the performance of the developed technique and the effectiveness of the proposed algorithm is clear.

The rest of this paper is structured as follows: Section 4 briefly introduces to the developed fuzzy inference system (FIS) technique. The implementation of the proposed Inference System on MATLAB is described in section 5. The results of the proposed inference system are presented in Section 6. Conclusions are introduced in section 7, followed by references.

4. Structure of The Proposed Fuzzy Logic Inference System

Fuzzy Inference Systems (FIS) provide a rule-based framework for decision-making, especially valuable when input data is imprecise or qualitative. In the context of technical textiles, FIS can simulate expert knowledge and reasoning by evaluating multiple fabric properties and making recommendations based on a set of linguistic rules [20].

The structure of the fuzzy inference system (FIS) is depicted in Figure 1. It is clear from this structure that FIS consists of three main operations: fuzzification, inference mechanism, and defuzzification [21]. Fuzzification is used to convert the crisp values of the preprocessed input of the model into suitable fuzzy sets represented by membership functions. The inference mechanism is the computational method that calculates the degree to which each rule fires for a given fuzzified input pattern by considering the rule and label sets. A defuzzifier compiles the information provided by each of the rules and makes a decision on this basis.

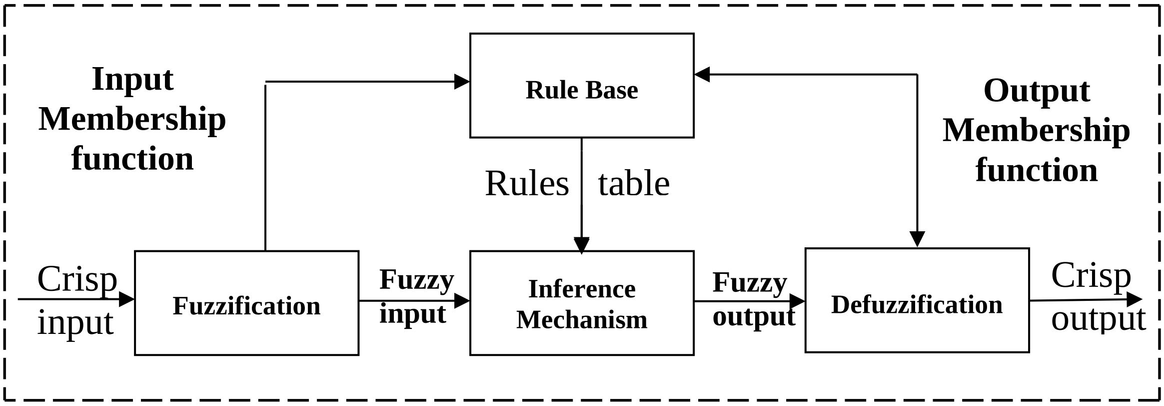

Fig.1. Typical Structure of Fuzzy Inference System (FIS)

In this study, a Mamdani-type FIS was developed using MATLAB's Fuzzy Logic Toolbox. The block diagram of the Mamdani-type FIS that was developed in this research is depicted in Figure 2. The figure declares the inputs to the FIS system developed and the output obtained from it.

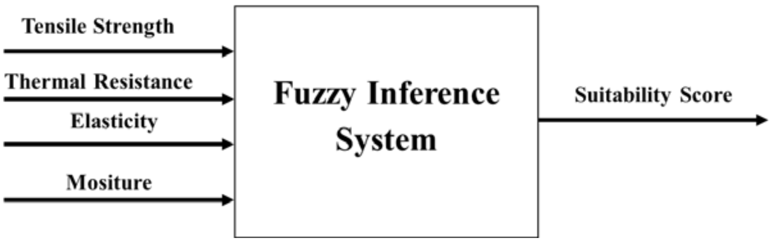

Fig.2. FIS inputs and outputs for textile selection

Inputs such as tensile strength, thermal resistance, elasticity, and moisture regain were mapped into fuzzy sets with linguistic variables like "Low," "Medium," and "High." Rules were defined based on expert knowledge, e.g.,

"IF tensile is Medium, elastic recovery is High, thermal conductivity is Low, and moisture regain is Low, THEN the score is Excellent."

The defuzzified output provided a crisp recommendation score for each textile type. The FIS proved especially effective in use cases requiring trade-offs between comfort and protection. This method supports designers in selecting optimal fabrics without relying solely on hard thresholds or exhaustive testing.

5. The implementation of the proposed Inference System on MATLAB

To evaluate the effectiveness of the proposed inference system, the proposed algorithms are developed and built for the selection of the most appropriate fabric that meets the performance requirements. Moreover, a graphical user interface (GUI) is built to facilitate the user to enter the required performance parameters such as tensile, elastic recovery, thermal conductivity, and the moisture regain, and the inference system provides the suitability score for all the entered fabrics to the FIS. From the suitability score, a score for each fabric, the user can select the highest score of suitability. Furthermore, the FIS provides the user with the best fabric recommendations.

The proposed fabric selector is developed on MATLAB 2013b with the aid of the MATLAB fuzzy toolbox included in the MATLAB environment. This algorithm can be developed on other versions of MATLAB [22].

Figure 3 shows the interface after running the program developed on MATLAB 2013b. It is clear from the figure that the user can enter the values of the required performance requirements, such as tensile strength, elastic recovery, thermal conductivity, and moisture regain. Then the FIS algorithm will provide the user with the best-fitted and recommended material and its score. Moreover, the algorithm will provide the user with the score for the different fabrics that have been entered into the algorithm.

The developed fuzzy logic algorithm employs a **Mamdani Fuzzy Inference System (FIS)** architecture, characterized by its interpretable rule base and suitability for human-like decision-making. The FIS maps four input parameters to a single output "suitability score" using:

- **Inputs**:
  - Tensile Strength (T, 0–100 MPa)
  - Elastic Recovery (E, 0–100%)
  - Thermal Conductivity (K, 0–0.6 W/m·K)
  - Moisture Regain (M, 0–20%)

- **Output**: Suitability Score (S, 0–1), where higher values indicate better alignment with requirements.
- **Membership Functions (MFs)**

  Each input/output is fuzzified into linguistic variables using trapezoidal (trapmf), Gaussian (gaussmf), and Membership Functions (MFs). All the inputs MFs are defined using 3 MFs only: "Low, Medium, and High". The definition and the ranges of each input and output MF are defined as follows:

- **Tensile Strength**:
  - Low: trapmf [0, 0, 20, 40]
  - Medium: gaussmf [15, 50]
  - High: trapmf [60 80 100 100]

- **Elastic Recovery**
  - Low: trapmf [0, 0, 30, 60]
  - Medium: gaussmf [20, 60]
  - High: trapmf [70 85 100 100]

- **Thermal Conductivity:**
  - Low: trapmf [0 0 0.1 0.3]
  - Medium: gaussmf [0.1 0.3]
  - High: trapmf [0.2 0.4 0.6 0.6]

- **Moisture regain**
  - Low: trapmf [0 0 5 10]
  - Medium: gaussmf [4 8]
  - Low: trapmf [8 12 20 20]

- **Output (Suitability Score):**
  - Poor: trimf [0, 0, 0.5]
  - Good: gaussmf [0.5, 0.7]
  - Excellent: trimf [0.6, 1, 1]

Figure 4 shows the input membership function used in the algorithm for the best-fitted fabric. These MFs can be developed to be more than 3 MFs to optimize the decision of the FIS algorithm. Moreover, the ranges of the MFs can be changed to obtain more acceptable and accurate results from the FIS selector.

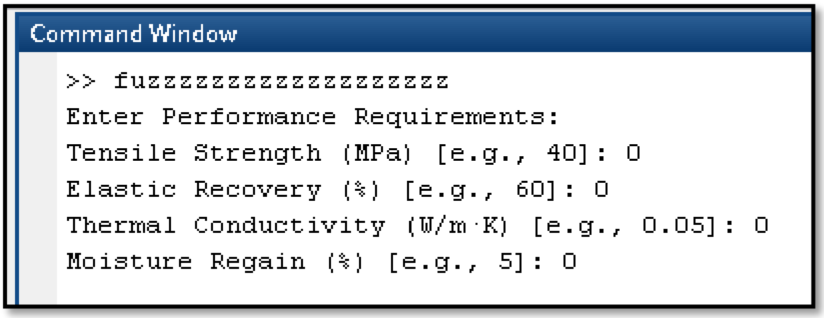

Fig.3. MATLAB command window for entering the required performance parameters

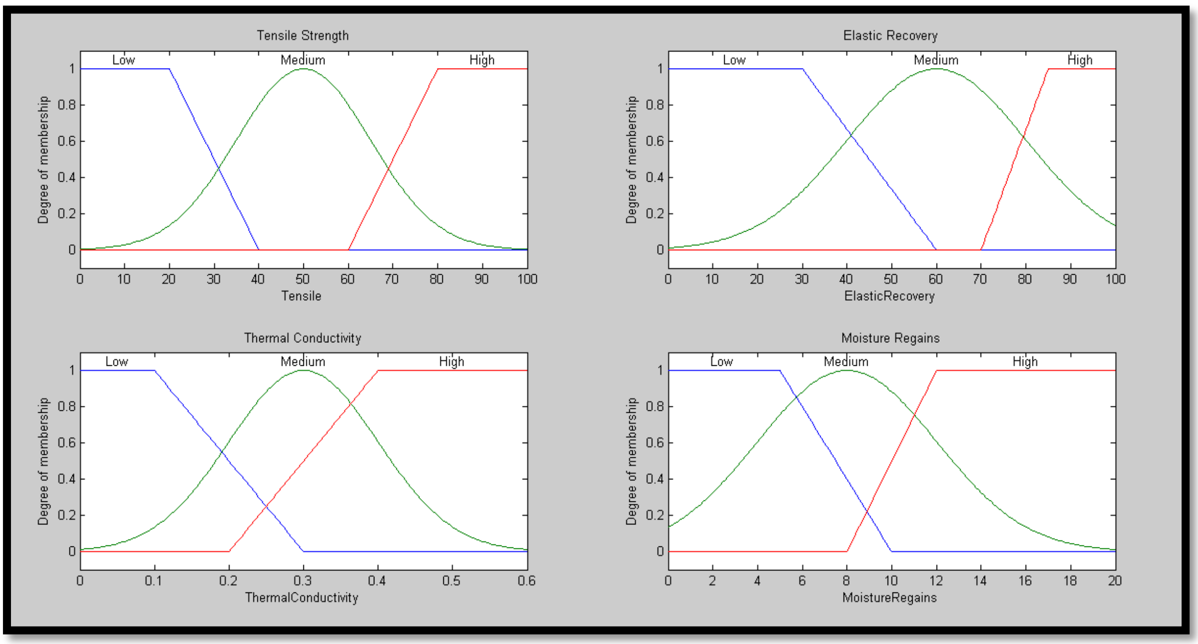

Fig.4. Inputs Membership Functions

The Fuzzy Rule Base

The system uses IF-THEN rules to encode domain expertise. Each rule follows the format:
IF **Tensile** is A AND **Elastic** is B AND **Conductivity** is C AND **Moisture** is D, THEN **Suitability** is Z.
Where A, B, C, D are input MFs (Low, Medium, High), and Z is the output MF (Poor, Good, Excellent). The rule base used in the algorithm is defined in Table 1. These rules can be optimized by the expert user for more accurate results of the fiber selector.

Table 1. Fuzzy Rule Base

Rule No.	Tensile	Elastic	Thermal	Moisture	Output	Interpretation
1	Low	Low	Low	Low	Excellent	All low-spec requirements → High suitability
2	Medium	Medium	Medium	Medium	Good	Balanced specifications → Moderate suitability
3	High	High	High	Low	Poor	High thermal conductivity → Low suitability
4	High	High	Low	High	Excellent	High strength + Low thermal → Ideal
5	Medium	High	Low	Low	Excellent	Moderate strength + High elasticity → Optimal

For the rule aggregation, all rules use AND (logical conjunction), and a uniform weight (1.0) is used for all rules. For the Inference and Defuzzification, the max operator for aggregation is used to combine the rule outputs. To convert fuzzy output to a crisp score, the centroid method is used, which is defined as [23]:

$$S_{crisp} = \frac{\int \mu_S(z).zdz}{\int \mu_S(z)dz}$$

Where $\mu_S(z)$ is the aggregated output of the MF.

6. The Results of the Proposed Inference System.

The proposed algorithm is developed and implemented on MATLAB 2013b. In the implemented techniques, twelve types of fabrics (Cotton, Polyester, Naylon, Polypropylene, Kevlar, Wool, Polyacrylic, Viscose, Spandex, Nomex, Coolmax, HDPE) are defined in the program in terms of its parameters such as tensile strength (T), elastic recovery (E), thermal conductivity (K), and moisture regain (M) as shown in figure-5.

```
% Data columns: [Tensile, ElasticRecovery, ThermalConductivity, MoistureRegains]
data = [
    48     59.5    0.05     9;       % Cotton
    6.5    97.5    0.065    0.6;     % Polyester
    6.5    97.5    0.275    4.25;    % Naylon
    4.5    87.5    0.55     0.025;   % Polypropylene
    22.5   12.5    0.04     0.1;     % Kevlar
    5.5    92.5    0.0425   15.5;    % Wool
    3.5    90      0.04     1.75;    % Polyacrylic
    1.55   67.5    0.05     12;      % Viscose
    0.8    97.5    0.055    1;       % Spandex
    6      50      0.05     5;       % Nomex (ElasticRecovery adjusted)
    5      87.5    0.06     0.75;    % Coolmax
    35     1.15    0.33     0.01;    % HDPE
];
```

Fig.5. Parameters of 12 Fabrics used in the Simulation

After running the FIS, the user is asked to enter the required performance parameters, and the code provides the user with the score of suitability for the 12-fabric defined in the program.

Figure 6 shows the command window after the user enters the required parameters, and the code gives the score for the 12 fabrics and provides the user with the recommended material.

```
Enter Performance Requirements:
Tensile Strength (MPa) [e.g., 40]: 77
Elastic Recovery (%) [e.g., 60]: 28
Thermal Conductivity (W/m·K) [e.g., 0.05]: 0.03
Moisture Regain (%) [e.g., 5]: 2

Recommended Material: Viscose (Score = 0.84)
----------------------------------------
Material    Score
----------------------------------------
Cotton      0.50
Polyester       0.75
Naylon      0.73
Polypropylene       0.50
Kevlar      0.57
Wool        0.76
Polyacrylic     0.81
Viscose     0.84
Spandex     0.80
Nomex       0.84
Coolmax     0.78
HDPE        0.50
----------------------------------------
```

Fig.6. The output of the program after running

Figure 7 shows the score of suitability calculated for the 12-fabric types, and the best material is plotted in red color and the others are shown in blue one.

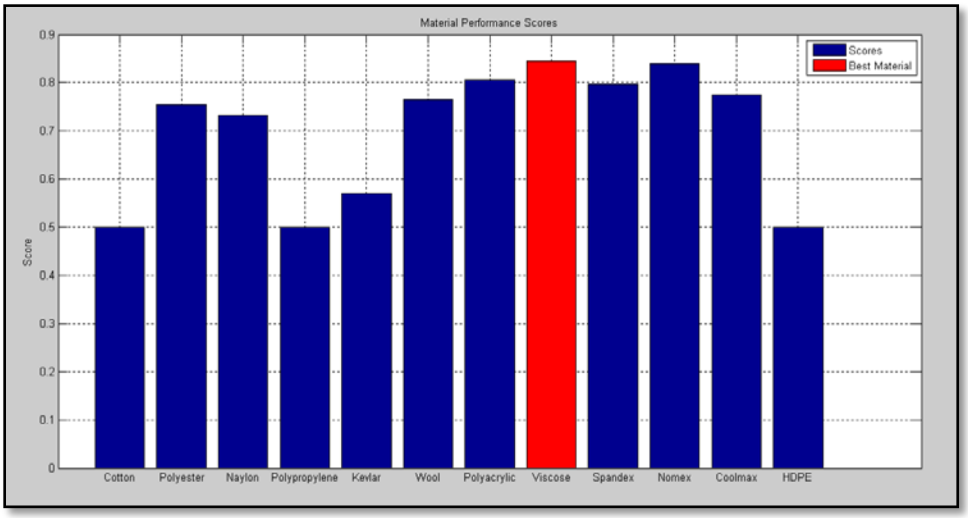

Fig.7 Suitability Score of 12 Fabrics

Moreover, the developed graphical user interface (GUI) allows the user to supply the program with the required parameters, such as Tensile, Elastic Recovery, Density, Elongation, Conductivity, Moisture, and the FIS will select the appropriate fabric types based on the rules and the parameters entered for each fabric.

Figure 8 depicts the GUI that appears to the user to enter the parameters. In the GUI, the user can click on the select fabric button to obtain the best-fitted fabric. Additionally, the GUI provides the best three fabrics and also draws the parameters for the three fabrics.

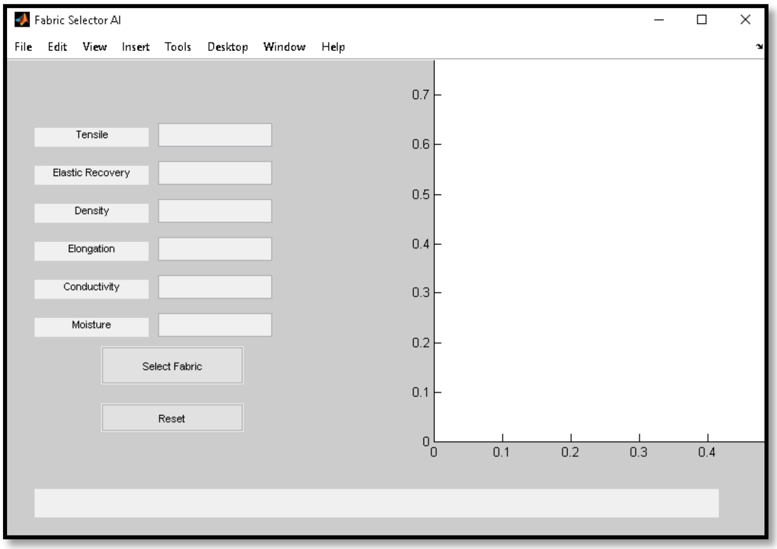

Fig.8. The GUI for Fabric Selector

Figure 9 shows the GUI that appears after clicking on the select fabric button. It is clear that based on the entered values, the GUI provides the best match fabric and gives the plot for the parameters of the best-fitted materials. The materials are ordered as HDPE, Cotton, and Kevlar.

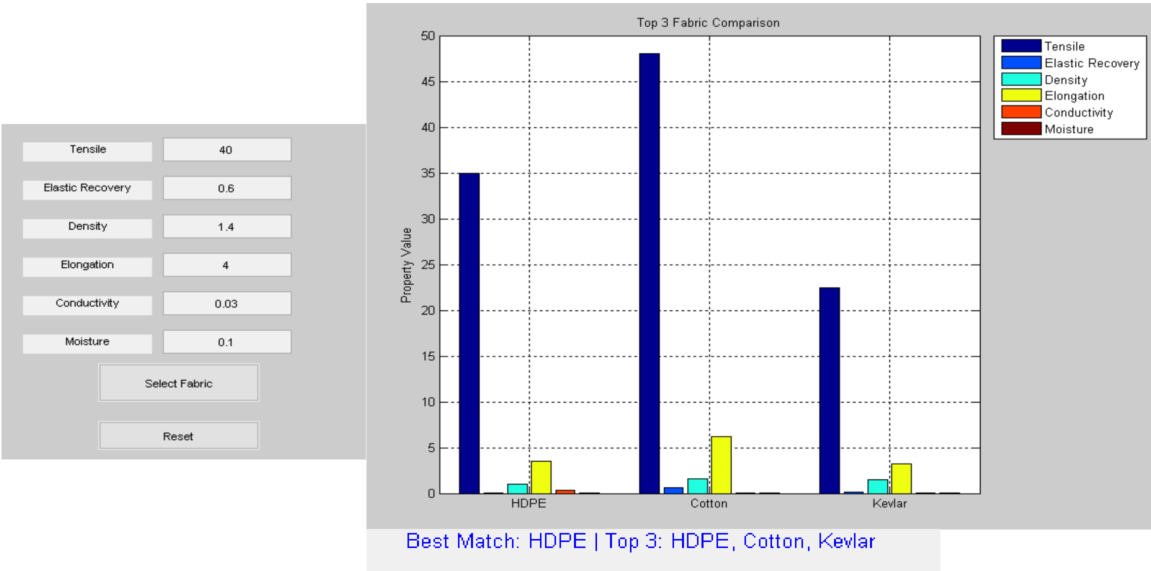

Fig.9. The Output of the GUI for Fabric Selector

From the above results, it is clear that the algorithm results can be optimized by increasing the number of fabrics used as a data set for the program. Moreover, the performance of the algorithm can be improved by changing the fuzzy membership function to 5 MF or 7 MF and changing the fuzzy rule base. Furthermore, accurate values for the fabrics used extracted from expertise in the textile industry can enhance the algorithm's performance.

7. Conclusion and Future Work

This paper has presented a comprehensive approach to optimizing the selection of technical textiles using a fuzzy inference system (FIS) implemented in MATLAB. The system offers an intelligent, rule-based method for selecting fabrics based on performance requirements such as tensile strength, elastic recovery, thermal conductivity, and moisture regain. By translating expert knowledge into fuzzy rules and linguistic variables, the developed tool enhances decision-making accuracy and reduces the time and cost associated with traditional prototyping methods. The system's GUI further simplifies interaction, allowing users to input parameters and receive recommendations effectively. Evaluation results indicate that the algorithm provides reliable and interpretable suggestions, closely aligning with expert evaluations. However, there remains further advancement. The current system uses a limited set of fabric types and relies on a relatively simple rule base and three membership functions for each input. Expanding the input database to include a broader range of fabrics and refining the membership functions and rule sets based on expert consultations can significantly improve system accuracy. Additionally, implementing adaptive or learning-based mechanisms to update the rule base dynamically could further enhance performance.

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