E-ISSN: 2717-3453 | P-ISSN: 2783-1442

Journal of Fuzzy Extension and Applications

www.journal-fea.com

J. Fuzzy. Ext. Appl. Vol. 3, No. 1 (2022) 31–44.

Paper Type: Research Paper

Application of the Fuzzy Inference System to Evaluate the Quality of Air Textured Warp Yarn

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Citation:

Bulut, U., & Özceylan, E. (2022). Application of the fuzzy inference system to evaluate the quality of air textured warp yarn. *Journal of fuzzy extension and application, 3* (1), 31-44.

Received: 22/11/2021 Reviewed: 10/12/2021 Revised: 13/12/2021 Accepted: 18/01/2022

Abstract

It has become one of the indispensable conditions to continuously improve the quality and achieve the quality standards in order to adapt to the increasingly competitive environment in the textile industry. However, the textile production process like many other industrial processes involves the interaction of a large number of variables. For a standard quality production, the relation between raw material properties, process parameters, and environmental factors must be established conclusively. The physical properties of air textured warp yarn that affect the quality of the yarn, construct the strength of the yarn. After the production process, different values of each yarn sample are revealed from the strength tests performed during the quality control process. Six criteria that affect the quality of the yarn and identify the strength of the yarn are defined as a result of strength tests. Those criteria are count, tenacity, elongation shrinkage, Resistance per Kilometer (RKM) and breaking force. The differences between the values of these criteria and linguistic variables cause uncertainty when defining the quality of the yarn. To take into consideration this uncertainty a Fuzzy Inference System (FIS) is developed using six criteria as inputs, 144 rules created, and the linguistic variables of Air Textured Yarn (ATY) samples of a textile manufacturer. The quality level of the products according to the different membership functions are identified with the proposed FIS generated by MATLAB version 2015a and recommendations are made to the manufacturer.

Keywords: Fuzzy ingerence system, Quality evaluation, Air textured warp yarn.

1 | Introduction

Air Textured Yarn (ATY) used as warp yarn which is the one of two component yarns, to turn yarn into a finished fabric and regarded as longitudinal set in a finished woven carpet in carpet weaving industry. Since the ATY forms the length of the carpet it directly affects the quality of the carpet to be produce [1]. Any yarn that does not reflect the quality values cause stretching, shrinkage, elongation, shortening, and irregularity problems in the carpet during or after weaving process. Thus, causes negative feedback from the customers, such as compliments, order cancelation or payment fault. To avoid these defects companies, who use ATY as a raw material, primarily prefer to work with ATY producers that produce high quality yarn groups and provide quality standardization.

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http://dx.doi.org/10.22105/jfea.2021.316204.1174

Main specifications of the yarn identified from the customers, such as denier, minimum strength and elasticity required, nodes per unit length, crimp properties and number of filaments. Any yarn does not match with these specifications will be rejected as poor quality. Machine parameters, parent yarn conditions and process parameters affect the quality. Under the same conditions, the properties of ATY can be determined with strength tests [2]. A comparison can be done between the test parameters of the yarn and quality standards values. Making a quality classification about yarn samples according to test parameters can provide to realize that if the yarn sample reflects the quality values and avoiding yarn faults before meet the customer. As a result of test parameters, quality of the yarn can be identified linguistically and uncertainty may occur because of these linguistic variables.

Aim of this study is to develop a fuzzy 'Quality Classification' model for a textile mill in Gaziantep. The company is producing three types of ATY (800 DEN, 1100 DEN and 1350 DEN). The six physical properties of ATY, namely count, tenacity, elongation, shrinkage, breaking force and Resistance per Kilometer (RKM), are the factors directly affect the quality of the yarn. The proposed quality classification model is generated with assigning these properties as inputs of the FIS for three types of the ATY (800 DEN, 1100 DEN and 1350). Different membership functions (triangular, trapezoidal, and z-shaped) are compromised for both input and output parameters. 144 rules are created and operated with if-then statement to relate between input and output parameters.

In the literature there are several fuzzy approaches have been successfully applied in textile industry. Majumdar et al. [3] studied adaptive neuro-fuzzy system to predict the cotton yarn strength from HVI fibre properties. Majumdar and Ghosh [4] introduced a model about the level of ring cotton yarns by translating perception and experience of a spinner into a FIS. Malik and Malik [5] developed an application for the prediction of strength transfer efficiencies of weft and warp yarns, with using adaptive neuro-fuzzy inference system. Amindoust and Saghafinia [6] developed a model for real-life supplier selection problem for a textile company in Malaysia with applying a modular FIS. Vu and Kim [7] studied a complete combination of the wearable application based on a textile sensor and FIS. Sarkar et al. [8] proposed a model to explain the effects of laser parameters on treated fabric parameters and predict other fabric properties with using FIS on MATLAB. However, there is no study about evaluating a quality level about ATY with factors affecting yarn quality, using a FIS. This study involves an extend research about quality of ATY with six factors affecting quality of the yarn, and proposes a fuzzy quality classification model with using these six factors and FIS. A real data set is attained into the literature with this research.

This study is divided into four sections. Firstly, the research takes a look at what is studied, why this topic is studied and the past studies about fuzzy approaches in textile industry at the Introduction section. Secondly it is explained that the method used for this research at the methodology section. In the case study section, there some tables and figures to illustrate the material and the application of case study. The results, recommendations and further attempts are explained at the conclusion section of the study.

2 | Methodology

In this study a FIS approach is developed to to evaluate a quality classification model with data selected from a textile mill in Gaziantep which is producing ATY.

A quality classification model is developed for three types of ATY (800 DEN, 1100 and 1350 DEN) with using FIS for ATY samples to analyze that if the yarn sample reflects the standard quality values and eliminate yarn faults for the company. FIS is a system based on the approach that mapping a set of given input variables to an output variable using fuzzy logic. FIS is presented within the context of fuzzy set theory and one of the useful tolls to solve uncertainty and complicated problems depend on fuzzy logic and close to human thinking [9]. The main structure of a FIS is shown in *Fig. 1*. FIS consists four [10] main components: 1) a fuzzification module that translates crisp inputs into fuzzy values, 2) an inference engine which implements a fuzzy reasoning mechanism to attain a fuzzy output, 3) a defuzzification module to translate this latter output to crisp value, and 4) a knowledge base that comprises both fuzzy rules known as the rule base and membership functions known as the database.

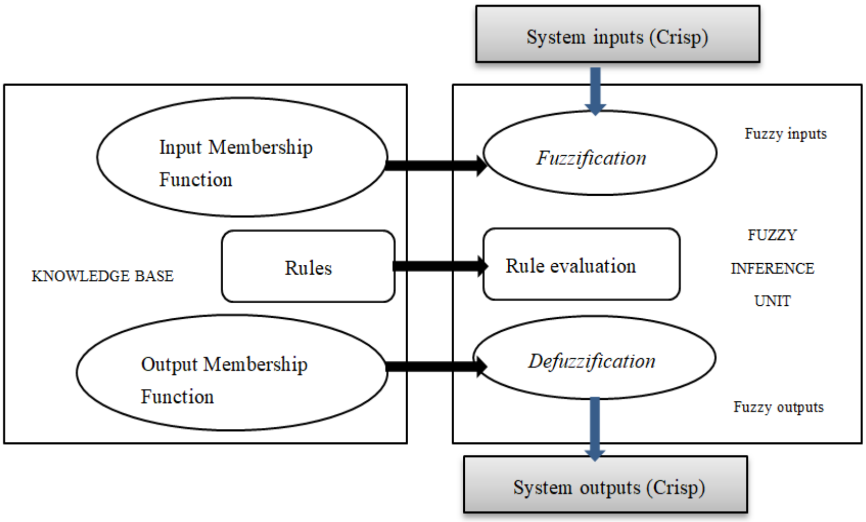

Fig. 1. Structure of FIS [11].

3 | Case Study

This research is motivated from an ATY manufacturer build in Gaziantep in 25.000 m^2 production plant. In a daily production, yarn samples are randomly selected from the production line and subjected to a series of tests to analyze if the values of tested yarn sample reflect the values of standard quality. There are three types of tensile tests applied from quality conrol and R&D department of the company which are tensile strength test, thermo-fisher shrinkage test and thermal resistance test as shown in *Fig. 2*.

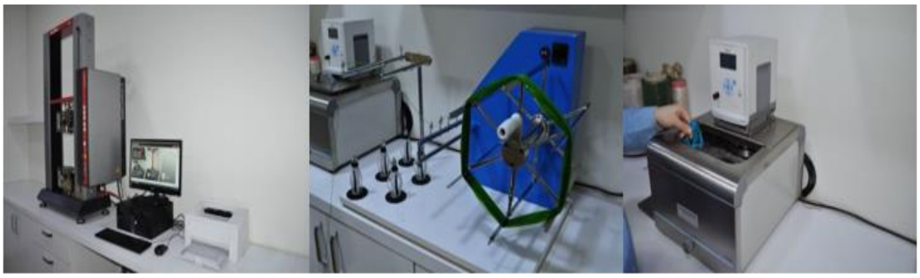

Fig. 2. Tensile test procedure.

The six physical properties of ATY; namely count, tenacity, elongation, shrinkage, breaking force and RKM, are the factors that directly affect yarn quality and construct the yarn strength. *Table 1* shows the terminology of yarn quality criteria. Value of physical properties of the yarn can be analyzed with tensile tests applied. Those six properties also have quantitave mesurable variables with test results values, these variables can easily adapt and subjected to the method used for this research.

Table 1. Yarn quality criteria.

Criteria	Terminology	Expressed as
Count	Count is expressed as the length per unit.	Denier
Tenacity	Tenacity is the breaking strength per denier.	Gram/Denier
Elongation	The ratio of extension of a specimen to its initial length.	Percentage
Shrinkage	The decrease in the length of a specimen caused by a specified treatment.	Percentage
Breaking force	The maximum force applied to a test specimen.	Kilogram
RKM	RKM is the abbreviation of RKM.	Percentage

Data used in this research is validated from the quality control department of the company. In an annual production period, between the months of January 2019 and January 2020, 663 yarn samples of 800 DEN ATY, 655 yarn samples of 1100 DEN ATY and 272 yarn samples of 1350 DEN ATY are subjected to tensile tests. *Table 2* is the brief view of test results of 800 DEN ATY samples (first and last five samples). Each ATY sample has been applied to tensile strength test, thermo-fisher shrinkage test and heat resistance test respectively. Values of tests results for each yarn sample can be either same or different with the same raw material properties, process parameters and environmental factors. Depending on these values, the quality of the yarn can be interpreted linguistically. However, uncertainty can be occurred due to the linguistic variables when defining the quality of ATY. To deal with these problems a quality classification model is developed with Mamdani FIS on MATLAB version 2015a and *Fig. 3* represents the flow chart of the model.

Table 2. Test results of 800 DEN ATY samples.

Sample	Count	Tenacity	Elongation	Shrinkage	Breaking Force	RKM
S1	787.00	4.00	11.00	8.90	3.23	36.52
S2	820.00	4.60	14.50	8.80	3.71	40.37
S3	800.00	4.40	12.50	9.50	3.54	39.45
S4	823.00	4.40	13.10	9.10	3.54	38.31
S5	827.00	4.30	12.50	9.70	3.43	36.94
.	.	.	.	.	.	.
S659	829.00	4.20	13.30	7.20	3.39	36.50
S660	822.00	4.20	13.00	7.50	3.37	36.50
S661	831.00	3.90	11.90	8.20	3.10	33.22
S662	827.00	3.80	11.00	8.20	3.05	32.88
S663	830.00	4.20	12.40	8.00	3.36	36.00

Count, tancity, elongation, shrinkage, breaking force and RKM are the six physical properties of ATY and factors directly affecting yarn quality. These physical properties are used as the input parameters of FIS evaluated. A MATLAB based coding is developed to execute the proposed fuzzy model of quality classification. *Fig. 4* shows the main structure of the model for 800 DEN ATY.

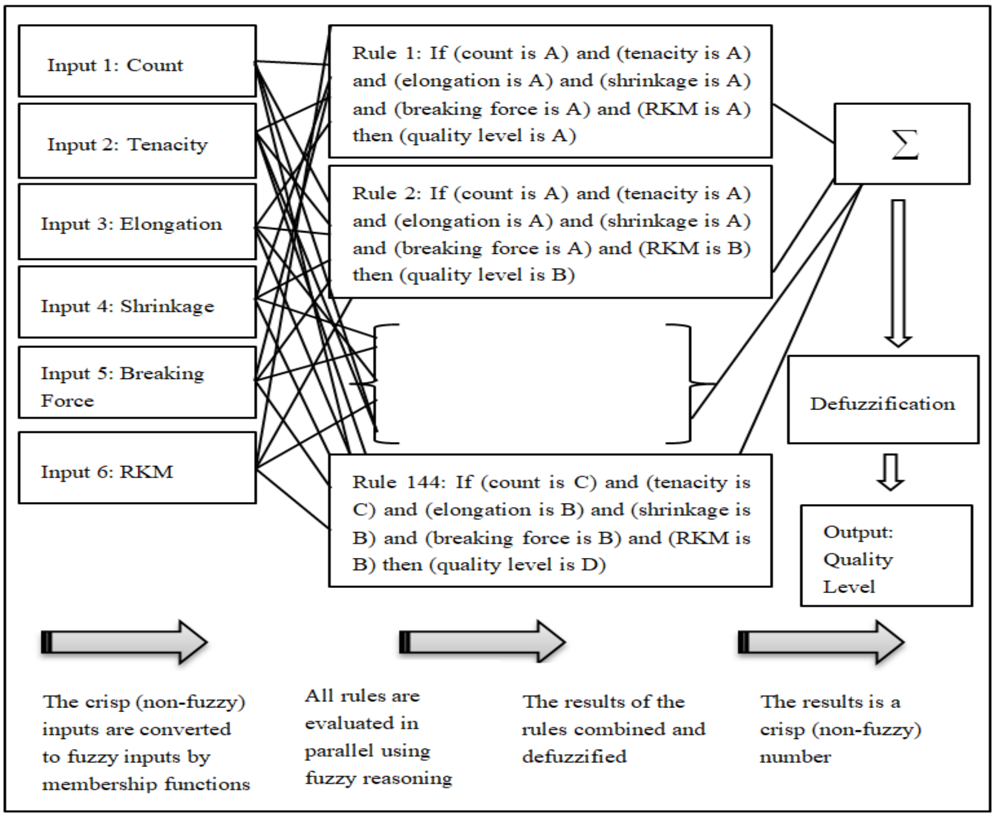

Fig. 3. Flow chart of proposed model.

Three linguistic fuzzy sets; namely best (A), average (B), non-acceptable (C), are generated for the input parameters of count and tenacity. For '800 DEN ATY Quality Classification' model two linguistic fuzzy sets; namely acceptable (A) and non-acceptable (B), are chosen for the input parameters of elongation, shrinkage, breaking force and RKM. Three forms of membership functions (triangular, trapezoidal, z-shaped) are used for the input parameters of count and tenacity. One form membership function (trapezoidal) is used for the input parameters of elongation, shrinkage, breaking force and RKM.

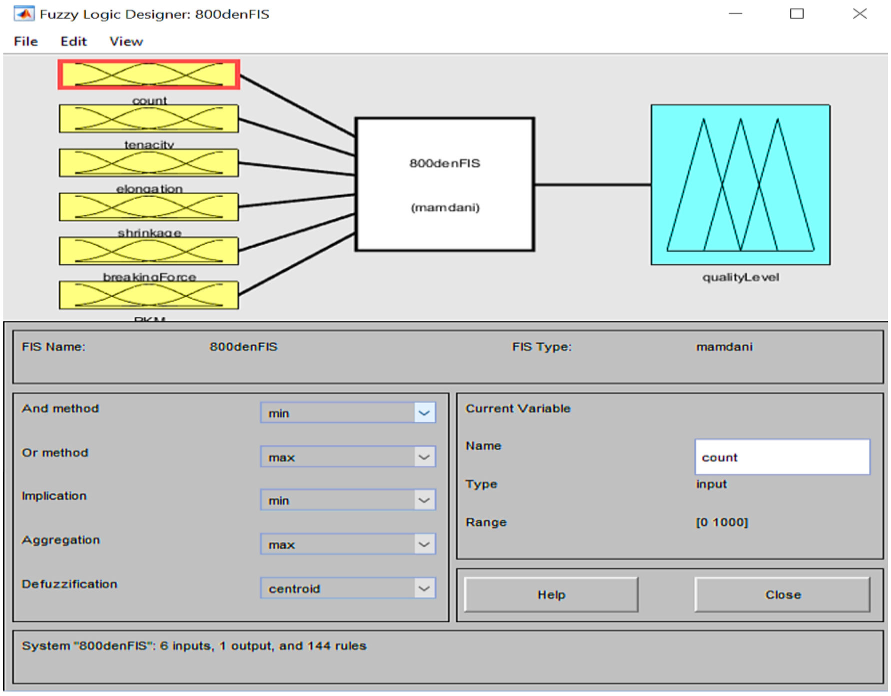

Fig. 4. The main structure of the '800 DEN ATY quality classification' model.

As an output parameter of quality classification; for linguistic fuzzy fuzzy sets, namely best (A), average (B), low (C) and non-acceptable (D), are chosen and one form of membership function (triangular) is used. The ranges of membership functions for both input and output parameters are generated according the quality standards values of 800 DEN ATY as shown in *Table 3*. Membership functions for both input and output parameters are consulted with Fuzzy Logic Toolbox of MATLAB. Types of membership functions and linguistic variables for input variables of '800 DEN ATY Quality Classification' model is shown in *Table 4*. *Fig. 5* represents the membership functions applied for input parameter of count; *Fig. 6* represents the membership functions applied for input parameter of tenacity and *Fig. 7* represents the membership functions applied for the output parameter of quality level.

Table 3. Quality standards of 800 DEN ATY.

Input	Range
Count	800 +- %5
Tenacity	4.00 +- %10
Elongation	>= 10.50
Shrinkage	<10
Breaking force	2.90<= breaking force >= 3.60
RKM	32<= RKM >=38

Table 4. Membership functions and linguistic variables of '800 DEN ATY 'Quality Classification' model.

		Linguistic Variable	Ranges	Membeship Function
Input 1	Count	A (Best level)	= 800	Triangular
		B (Avarage level)	760 <= Count <= 840	Trapezodial
		C (Low level)	Count < 760 and Count > 840	Z-shaped
Input 2	Tenacity	A (Best level)	= 4.00	Triangular
		B (Avarage level)	3.60 <= Tenacity <= 4.40	Trapezodial
		C (Low level)	Tenacity < 3.60 and Tenacity > 4.40	Z-shaped
Input 3	Elongation	A (Acceptable level)	=> 10.50	Trapezodial
		B (Non-acceptable Level)	< 10.50	Trapezodial
Input 4	Shrinkage	A (Acceptable level)	< 10.00	Trapezodial
		B (Non-acceptable Level)	=> 10.50	Trapezodial
Input 5	Breaking force	A (Acceptable level)	<=2.90 BF>= 3.60	Trapezodial
		B (Non-acceptable Level)	BF < 2.90 and BF > 3.60	Z-shaped
Input 6	RKM	A (Acceptable level)	<=32 RKM >= 38	Trapezodial
		B (Non-acceptable Level)	BF < 32 and RKM > 38	Z-shaped

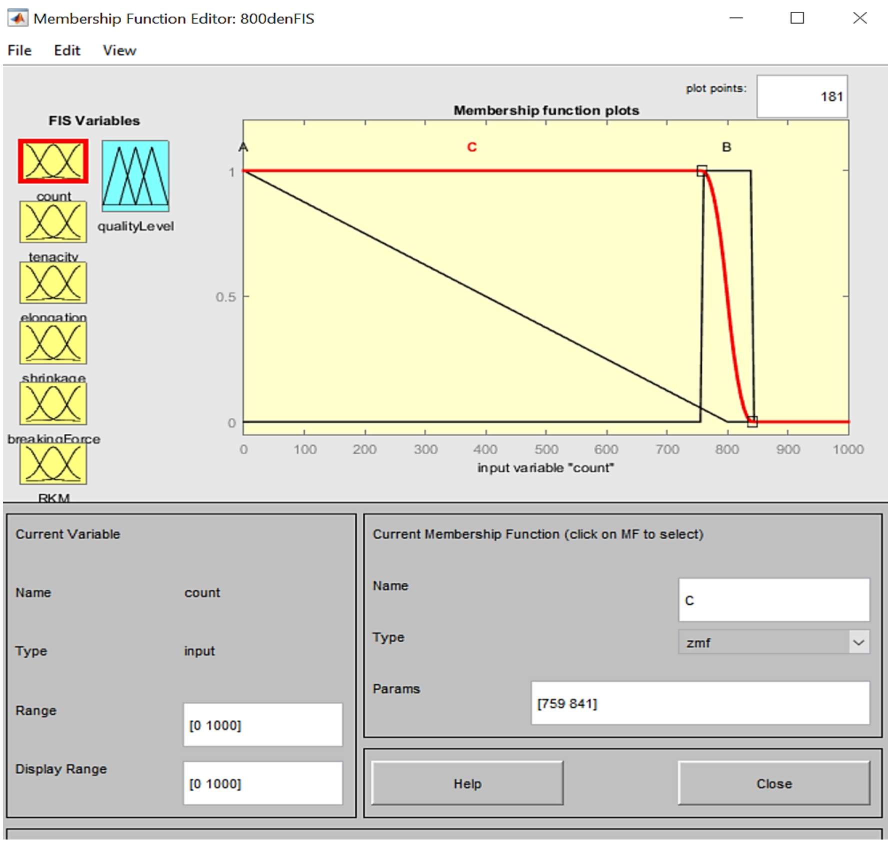

Fig. 5. Membership function of 'Count' for 800 DEN ATY.

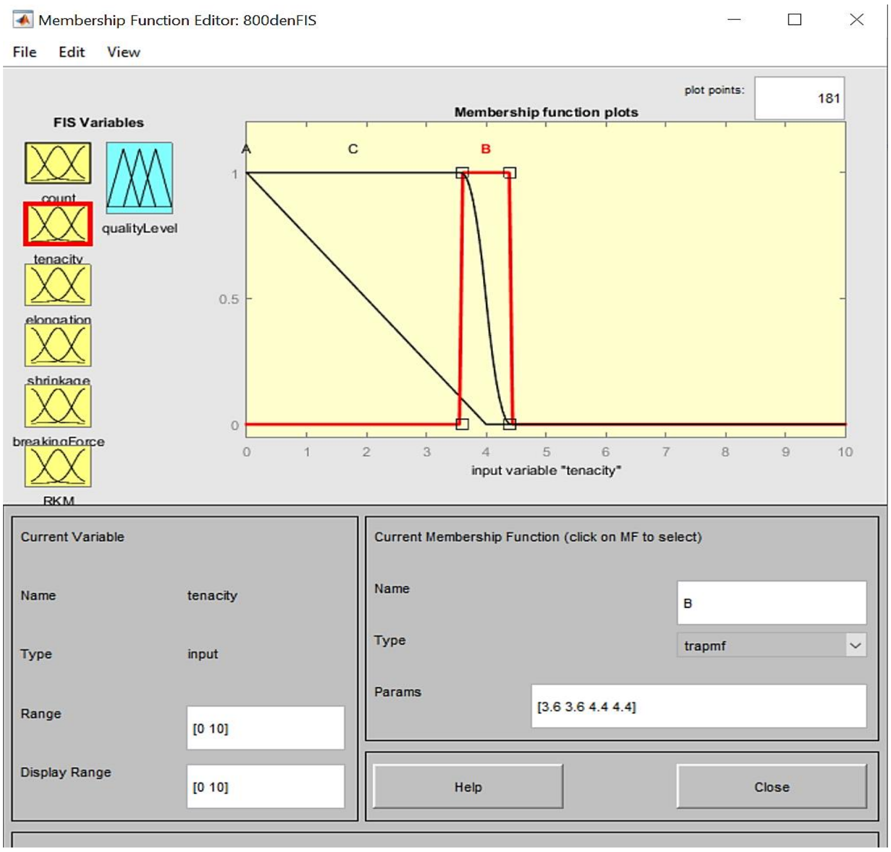

Fig. 6. Membership function of 'Tenacity' for 800 DEN ATY.

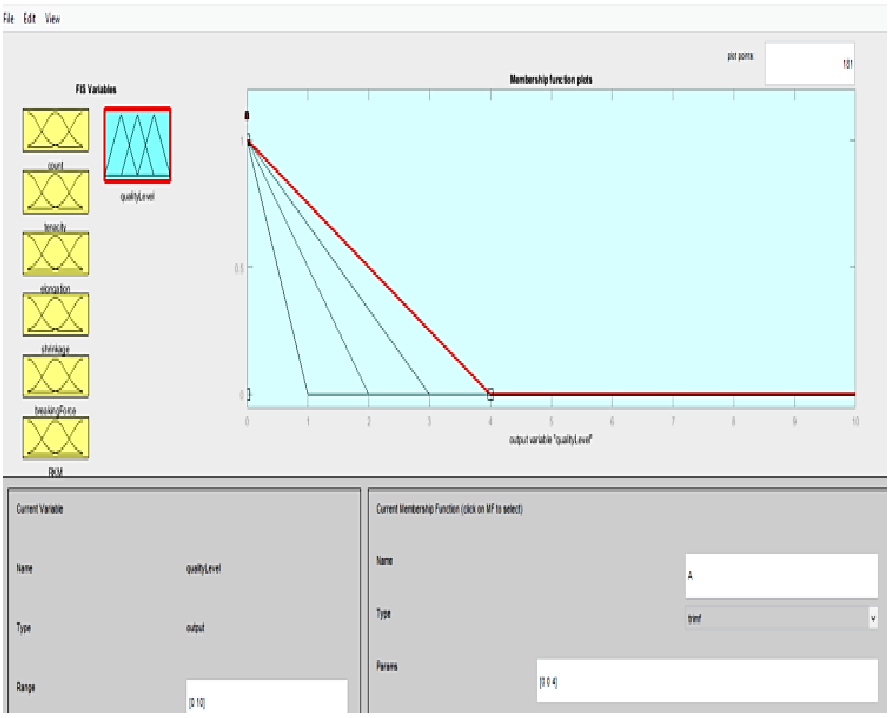

Fig. 7. Membership function of 'Quality Level' for 800 DEN ATY.

Following total 144 rules are created for fuzzification with the help of expert knowledge of the quality control manager of the company. As an example of rule base if (count is B) and (tenacity is A) and (elongation is A) and (shrinkage is A) and (breaking force is A) and (RKM is A) then (output is A). A Mamdani max-min inference approach is applied for combination of fuzzy sets into a single fuzzy set. Finally centroid defuzzification method is used to convert the output into non-fuzzy crisp numeric value. *Fig. 8* represents the rule viewer of the FIS. The rule viewer is the interface that shows the change in output parameter as a result of changes in input parameters. The decision makers can take the final decision by this interface to select optimum input parameters.

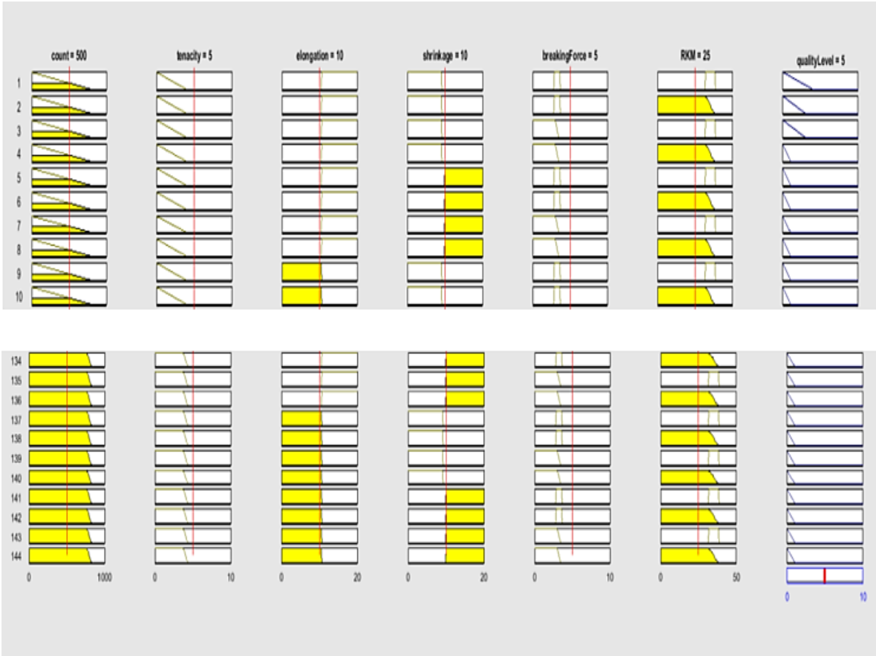

Fig. 8. Rule viewer of 800 DEN ATY quality classification model.

For '1100 DEN ATY Quality Classification' application, four linguistic fuzzy sets, namely best (A), average (B), low (C) and non-acceptable (D) are evaluated for the output parameter of quality classification. One form membership function (triangular) is develoed for the output parameter. The ranges of membership fuctions for both input and output parameters are generated according to quality standards of 1100 DEN ATY as shown in *Table 5* and test results of 1100 DEN ATY samples (first and last five samples) shown in *Table 6*. *Table 7* represents the linguistic variables, types of memberhip functions developed for input variables of quality classification model of 1100 DEN ATY samples. *Fig. 9* shows the membership functions applied for the input parameter of 'Elongation' and *Fig. 10* shows the membership function applied for the input parameter of 'RKM' which are consulted with Fuzzy Logic Toolbox of MATLAB.

Table 5. Quality standards of 1100 DEN ATY.

Input	Range
Count	1100 +- %5
Tenacity	4.00 +- %10
Elongation	>= 12.00
Shrinkage	<9
Breaking force	3.90<= breaking force >= 4.65
RKM	31<= RKM >=38

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Table 6. Test results of 1100 DEN ATY samples.

Sample	Count	Tenacity	Elongation	Shrinkage	Breaking Force	RKM
S1	1083.00	4.20	13.00	8.00	4.65	38.27
S2	1079.00	4.10	13.00	8.10	4.53	37.43
S3	1091.00	4.10	12.50	7.50	4.48	36.56
S4	1078.00	4.10	12.30	7.80	4.46	36.87
S5	1077.00	3.90	11.20	9.30	4.27	35.31
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S651	1110.00	3.80	12.40	7.10	4.16	33.75
S652	1109.00	3.70	13.00	6.80	4.12	33.14
S653	1100.00	3.80	12.70	6.80	4.19	33.95
S654	1100.00	3.80	12.30	6.20	4.21	34.31
S655	1101.00	3.90	13.50	6.90	4.30	34.50

Table 7. Membership functions and linguistic variables for '1100 DEN ATY 'quality classification' model.

		Linguistic Variable	Ranges	Membeship Function
Input 1	Count	A (Best level)	= 1100	Triangular
		B (Avarage level)	1045 <= Count <= 1155	Trapezodial
		C (Low level)	Count < 1045 and Count > 1155	Z-shaped
Input 2	Tenacity	A (Best level)	= 4.00	Triangular
		B (Avarage level)	3.60 <= Tenacity <= 4.40	Trapezodial
		C (Low level)	Tenacity < 3.60 and Tenacity > 4.40	Z-shaped
Input 3	Elongation	A (Acceptable level)	=> 12.00	Trapezodial
		B (Non-acceptable Level)	< 12.00	Trapezodial
Input 4	Shrinkage	A (Acceptable level)	< 9.00	Trapezodial
		B (Non-acceptable Level)	=> 9.00	Trapezodial
Input 5	Breaking force	A (Acceptable level)	<=3.90 BF>= 4.65	Trapezodial
		B (Non-acceptable Level)	BF < 3.90 and BF > 4.65	Z-shaped
Input 6	RKM	A (Acceptable level)	<=31 RKM >= 38	Trapezodial
		B (Non-acceptable Level)	BF < 31 and RKM > 38	Z-shaped

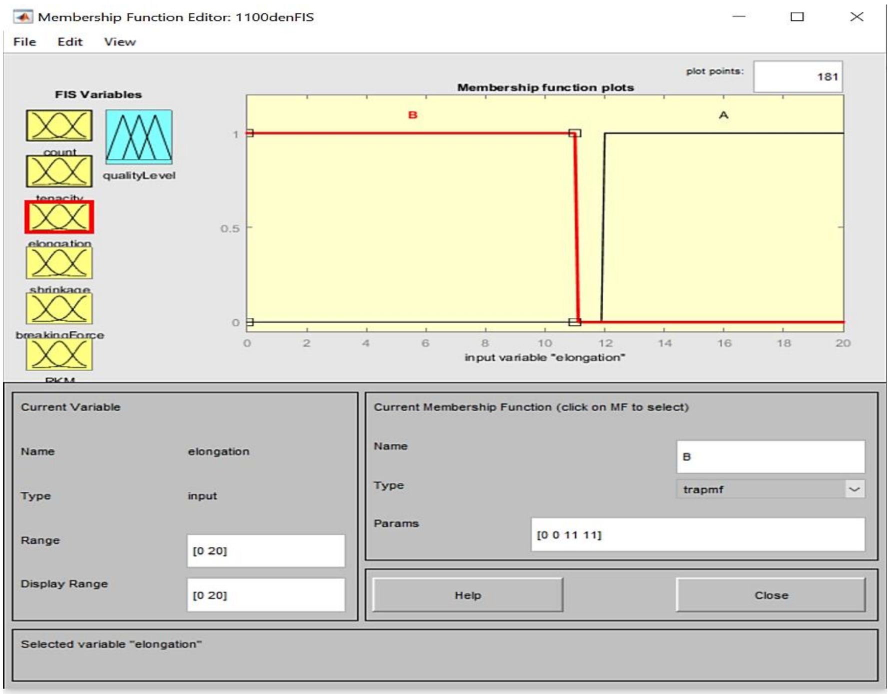

Fig. 9. Membership function of 'Elongation' for 1100 DEN ATY.

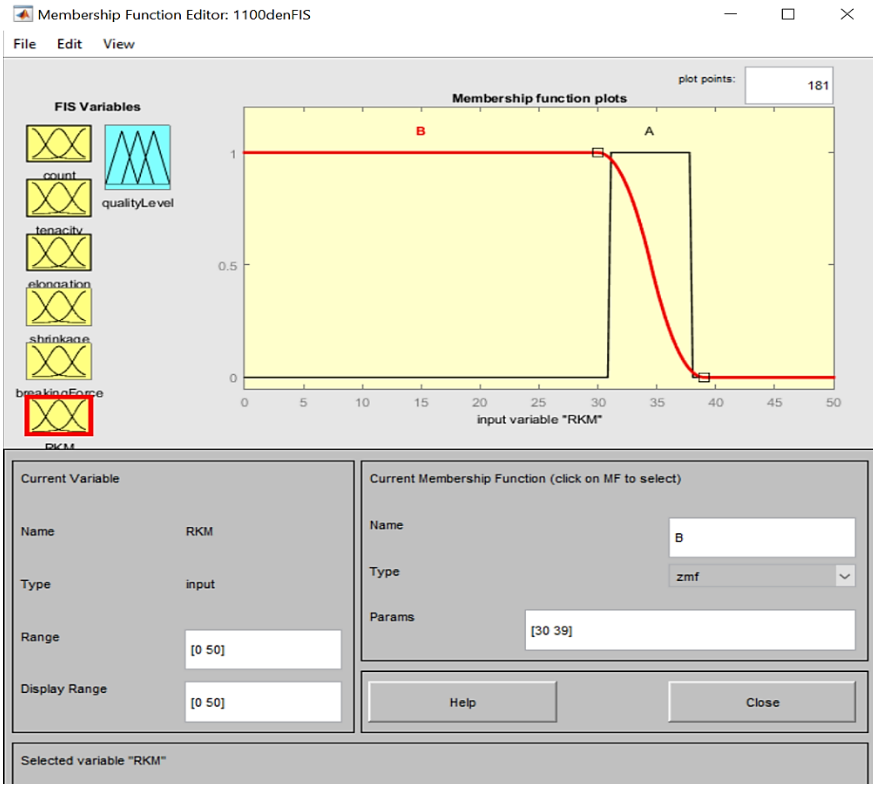

Fig. 10. Membership function of 'RKM' for 1100 DEN ATY.

For '1100 DEN Quality Classifaction' model total 144 rules are created for the fuzzification step of the model. *Fig. 11* represents the rule viewer of 1100 DEN ATY Quality Classification model. A Mamdani max-min inference approach is applied for combination of fuzzy sets into a single fuzzy set. Finally centroid defuzzification method is used to convert the output into non-fuzzy crisp numeric value.

Fig. 11. Rule viewer of 1100 DEN ATY quality classification model.

Quality classification model is also developed for 1350 DEN ATY samples. Four linguistic fuzzy sets, namely best (A), average (B), low (C) and non-acceptable (D) are evaluated for the output parameter of '1350 DEN ATY Quality Classification' model. One form membership function (triangular) is develoed for the output parameter. The ranges of membership fuctions for both input and output parameters are generated according to quality standards of 1350 DEN ATY as shown in *Table 8*. Test results of 1350

DEN ATY samples (first and last five samples) are shown in *Table 9*. *Table 10* represents the linguistic variables, types of memberhip functions developed for input variables of quality classification model of 1100 DEN ATY samples. *Fig. 12* shows the membership functions applied for the input parameter of 'Shrinkage' and *Fig. 13* shows the membership function applied for the input parameter of 'Breaking Force' which are consulted with Fuzzy Logic Toolbox of MATLAB.

Table 8. Quality standards of 1350 DEN ATY.

Input	Range
Count	1350 +- %5
Tenacity	4.20 +- %10
Elongation	>= 12.50
Shrinkage	<9
Breaking force	5.00<= breaking force >= 6.50
RKM	30<= RKM >=38

Table 9. Test results of 1350 DEN ATY samples.

Sample	Count	Tenacity	Elongation	Shrinkage	Breaking Force	RKM
S1	1340.00	4.80	13.20	8.80	6.49	43.25
S2	1335.00	4.50	13.10	7.50	6.13	40.43
S3	1337.00	4.50	13.20	6.10	6.13	40.29
S4	1339.00	4.50	13.40	6.00	6.13	40.29
S5	1344.00	4.40	13.60	8.90	5.95	38.77
.	.	.	.	.	.	.
S268	1363.00	4.30	13.90	7.70	5.74	37.49
S269	1373.00	4.20	12.40	8.10	5.62	36.46
S270	1376.00	4.20	13.50	7.80	5.67	36.68
S271	1370.00	4.30	13.90	7.30	5.74	37.36
S272	1360.00	4.20	13.10	8.00	5.63	36.87

Table 10. Membership functions and linguistic variables of '1300 DEN ATY 'Quality Classification' model.

		Linguistic Variable	Ranges	Membeship Function
Input 1	Count	A (Best level)	= 1350	Triangular
		B (Avarage level)	1282 <= Count <= 1418	Trapezodial
		C (Low level)	Count < 1282 and Count > 1418	Z-shaped
Input 2	Tenacity	A (Best level)	= 4.20	Triangular
		B (Avarage level)	3.78 <= Tenacity <= 4.62	Trapezodial
		C (Low level)	Tenacity < 3.78 and Tenacity > 4.62	Z-shaped
Input 3	Elongation	A (Acceptable level)	=> 12.50	Trapezodial
		B (Non-acceptable Level)	< 12.50	Trapezodial
Input 4	Shrinkage	A (Acceptable level)	< 9.00	Trapezodial
		B (Non-acceptable Level)	=> 9.00	Trapezodial
Input 5	Breaking force	A (Acceptable level)	<=5.00 BF>= 6.50	Trapezodial
		B (Non-acceptable Level)	BF < 5.00 and BF > 6.50	Z-shaped
Input 6	RKM	A (Acceptable level)	<=30 RKM >= 38	Trapezodial
		B (Non-acceptable Level)	BF < 30 and RKM > 38	Z-shaped

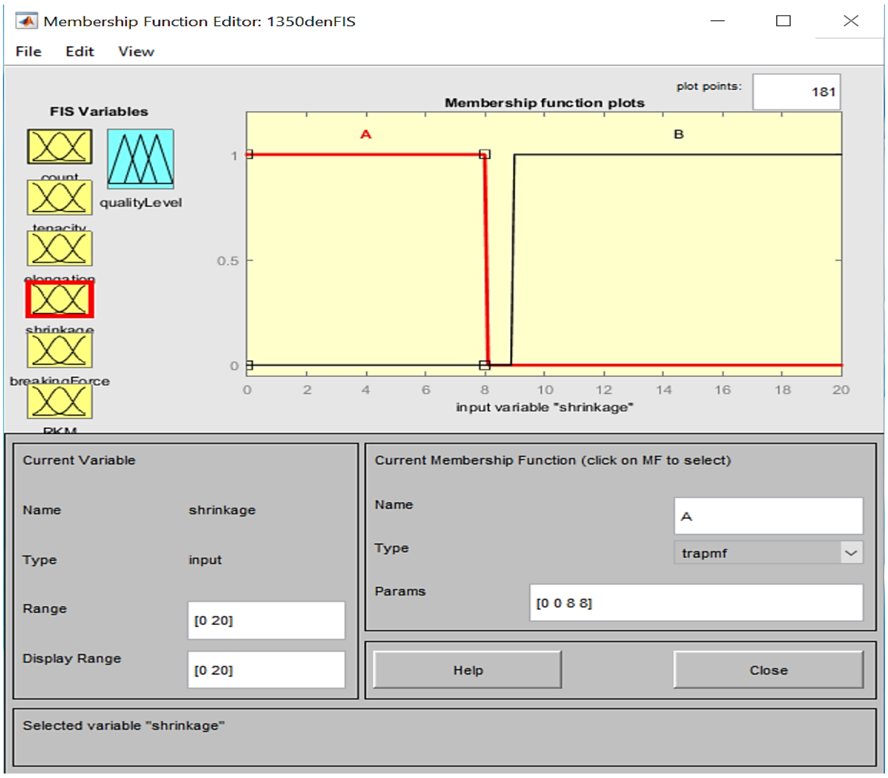

Fig. 12. Membership function of 'Shrinkage' for 1350 DEN ATY.

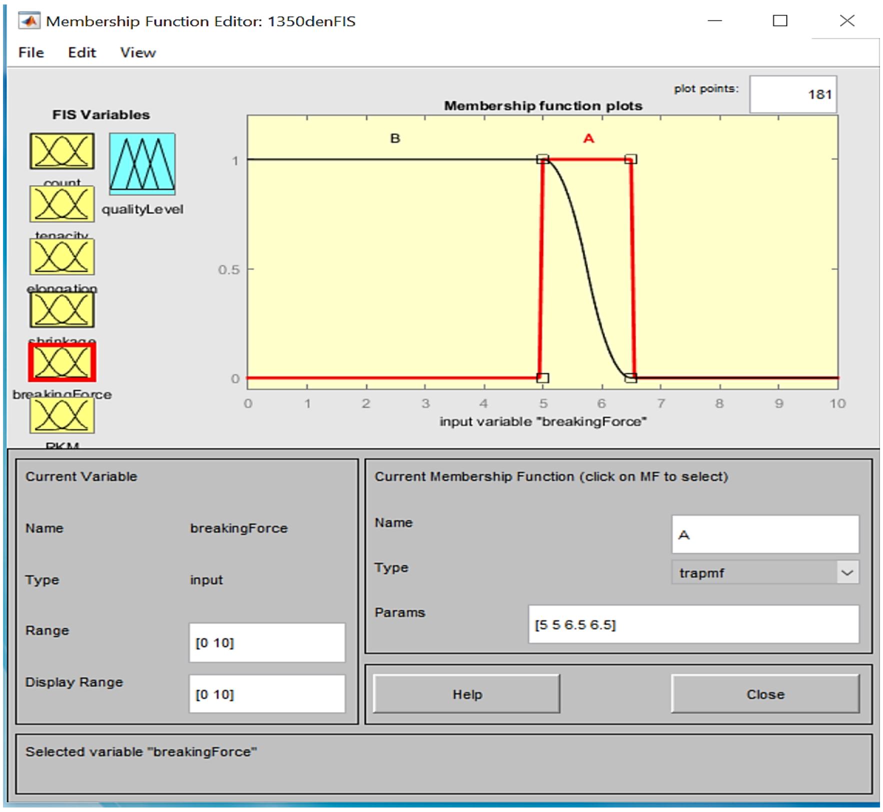

Fig. 13. Membership function of 'Breaking F orce' for 1350 DEN ATY.

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Total 144 rules are consulted for the fuzzification of '1350 DEN Quality Classifaction' model. *Fig. 14* represents the rule viewer of '1350 DEN ATY Quality Classification' model. A Mamdani max-min inference approach is re-applied for the combination of fuzzy sets into a single fuzzy set. At the final part of the application, centroid defuzzification method is used to convert the output into non-fuzzy crisp numeric value.

Fig. 14. Rule viewer of 1350 DEN ATY quality classification model.

4 | Conclusion

A FIS is proposed to model the quality level of ATY. The model is evaluated by using factors affecting quality of ATY as inputs into a FIS. The developed fuzzy rules give a very good understanding about the interaction between the factors. Different membership functions are used for input parameters and one form membership function is used for output parameter. The ranges of membership functions are compromised according the quality standards of the yarn. The fuzzy 'Quality Classification' model is implemented for three types of ATY samples (800 DEN, 1100 DEN and 1350 DEN). The Mamdani inference engine is used for the model. As a result of the model; for 800 DEN ATY, it is seen that two of yarn samples are at the best level (A), 382 of yarn samples are at the average level (B), 54 of yarn samples are at the low level (C), 225 of yarn samples are at the non-acceptable level (D) of the quality classification. When the model is practiced for 1100 DEN ATY, it is seen that 606 of yarn samples are at the average level (B), seven of yarn samples are at the low level (C), 42 of yarn samples are at the non-acceptable level of quality classification model. As a result of '1350 DEN ATY Quality Classification' application 188 of yarn samples are at the average level (B), 40 of yarn samples are at the low level (C), 44 of yarn samples are at the non-acceptable level (D) of the model. The test results have been interpreted linguistically from the quality control of the problem and do not coincide with the results of the fuzzy model. As an example, without a 'Qulity Classification' model the quality control manager determined 13 of 800 DEN yarn samples as faulted yarn, but with the proposed model 225 of yarn samples are determined at the non-acceptable level of the model. It is seen that faulted yarns are not often realized before thet-y reach the customers. A quality classification model can help the company to estimate the yarn on which level is it. Therefore, yarn faults can be eliminated before they reach the customer. Quality control manager can take the final decision with the help of the model. Thus, there will be improvements on quality control process and with these impovements there may be decreases in costs. Also, all yarns that are ready for sale are sold at the same price. As an example, a yarn group with has very good values according to the quality standard values and a yarn group with average values are priced at the same selling price. A better pricing strategy can be done with the help of the quality classification model. The system is quite easy to develop and it can be modified easily any type of product which has any different denier. This study has potential limitations. Physical properties of the yarn that affect the quality of the yarn used as criteria of FIS evaluated but environmental conditions (temperature and humidity) are not considered as affecting factors while preparing this study. Three membership functions (triangular, trapezoidal and z-shaped) are used for both input and output parameters of the fuzzy model, other types of membership functions can be developed while constructing the model. Recommendations for future studies are evaluating the model with Sugeno inference engine to compare the results and developing a decision support system for the company

Conflicts of Interest

All co-authors have seen and agree with the contents of the manuscript and there is no financial interest to report. We certify that the submission is original work and is not under review at any other publication.

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