Applying Fuzzy Logic Model for Bending Rigidity Evaluation of Woven Fabrics

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Abstract- **Fabric bending rigidity evaluation plays a very important role in determining end-use quality of products. This property has a non-linear behavior. Many techniques, such as mathematical, multiple regression, artificial neural network model, etc., have been used to predict mechanical properties of fabrics. This paper presents a method to model the bending rigidity of plain-woven fabrics using fuzzy logic. The input variables are yarn count, yarn diameter, yarn spacing, yarn bending rigidity and yarn length. The output variable is fabric bending rigidity. These results revealed the efficiency of fuzzy model to predict bending rigidity based on the mentioned parameters. Then the prediction accuracy of fuzzy logic model in comparison with three modeling methodologies based on mathematical, empirical and artificial neural network was evaluated. The comparison of the prediction performance showed that the fuzzy model is more powerful than the other models.**

***Keywords*: fuzzy logic, bending rigidity, woven fabric**

I. INTRODUCTION

Fabrics mechanical properties are valuable data for product development, quality control and market research in textile industry. These mechanical properties include tensile, bending, shearing, compression and surface properties. In order to make the fabrics one needs to understand the correlation between their structural geometry and mechanical properties. Several attempts have also been made to find out this correlation. One of the fabric parameters describing the mechanical properties is the bending rigidity. Bending rigidity not only has a decisive impact on the handle, tactile comfort and pleat formation of clothes, but also plays an important role in draping textile materials [1]. The bending rigidity assessment is essential for determining quality of fabrics. Peirce, as a pioneer, proposed a method for measuring the bending rigidity quantitatively [2]. Abbott compared five testing methods including: Peirce's cantilever test, Peirce's heart loop test, Schiefer flexometer, planoflex and MIT drapeometer, with subjective rating of stiffness. He found that the flexural rigidity calculated by the cantilever test had a significant correlation with the subjective rating [3]. Zhou and Ghosh used the non-linear bending behavior of fabrics measured by the Kawabata's evaluation system (KES) for fabric, to calculate the shapes of fabric bending curves in loop forms and compare with those measured by the cantilever and heart loop tests [4]. The studies in literature have shown that the relationship between fabric bending rigidity and fabric structure is nonlinear. In practice, the tool which is used to measure fabrics bending property is the Kawabata's evaluation system (KES) tester [5].

Modeling methodologies are essential to design fabrics and predicting their properties.

The modeling and prediction of fabric properties have become one of the most important and decisive tasks in the textile research field. Several models have been used to understand and predict the complex behavior of fabrics. There are three distinguished modeling methods for predicting the fabric properties, namely mathematical models, empirical models and artificial intelligent models.

Mathematical models based on the fundamental theories of woven fabrics knowledges often fail to reach satisfactory results. They can be used to explain the reasons that determine relationships between the fabric structure and property [2,6-8].

Empirical models, including statistical methods, are based on experimental data. Regression analysis is the most common statistical method for estimation of the relationship between input variables and output variables. This method has the advantage of simplicity in describing the quantitative relationship between textile material properties. Empirical models are very easy to use and have excellent predictive power, only if the coefficient value of determination of the model is close to 1 [9-12].

In order to model a nonlinear relationship between input and output data, it is possible to devise artificial

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intelligent models. Artificial intelligent models, such as neural networks and fuzzy logic are used to evaluate a great number of various engineering applications. Artificial neural network (ANN) methods are one of the artificial intelligent concepts that have been proved to be useful for textile products applications [13-15]. For example, the artificial neural network technique is used to model the relationship between the yarn properties, fabric parameters and weft shear stiffness of worsted fabrics [16]. Predicting bending rigidity of woven fabrics from their constructional parameters using artificial neural networks, has also been developed [17].

Fuzzy logic model has been used in parallel or complementarily with the artificial neural networks. Fuzzy logic model is one of the most important aspects of fuzzy system theory because of its simple form as a tool, and its power for predicting nonlinear relations. These methods have shown many advantages in characterizing some complex concepts related to the evaluation of textile products [18,19]. Neuro-Fuzzy model is another similar approach that has been used in the textile field [20,21].

To explore the predictability of the modeling methodologies, Behara and Muttagi have used the published data of Leaf and Kandil [8] on fabric initial bending rigidity properties. The predictive power of each methodology was estimated by comparing the predicted fabric property values, obtained from mathematical, empirical and artificial neural network, with corresponding experimental results in terms of absolute error % of prediction [22]. This research has contributed to a better understanding of the fabrics bending rigidity, but quantitative prediction of this property is still an issue, that needs to be addressed to achieve the goal of engineering-based design of fabrics. Motivated by the analysis of artificial intelligence method, a novel approach is proposed to overcome some drawbacks of existing methods. Mathematical models are usually based on certain idealized assumptions, so their success potential is largely governed by the validity of these assumptions. The high error by empirical modeling may be due to small data size and inability of the multi-linear regression techniques to model the nonlinearities. They do not also provide as deep understanding of the relationships between the different variables as mathematical models. In this respect, artificial intelligence methods, which do not need incorporation of any assumptions or simplifications, are more efficient. This enables these methodologies to overcome the limitations of existing modeling methods. These methods also offer potentially great flexibility with respect to the ability to approximate a wide variety of functions.

The study of fabric bending rigidity can contribute to the design process of a fabric; in addition it can predict the problems that might arise during the weaving process. The bending rigidity deformation of woven fabric is very complicated because of the mechanical properties arrangement and interaction between its constituent yarns. The main objective of many scientific studies in textiles is to reveal the functional relationships that exist between structural parameters of fiber, yarn and fabric properties. The relationship between fabric structure and property is complex and inherently nonlinear. Most available methods are usually based on certain idealized assumptions, so their success potential is largely governed by the viability of these assumptions that are difficult to achieve from the practical point of view. These models can be used to explain the reasons that determine structure property relationships. Previous studies have contributed to better understanding of this phenomenon, but quantitative prediction of this property is still an issue that needs to be addressed to achieve the goal of engineering-based design of fabrics. Hence, the fuzzy models, which do not need any assumptions or simplifications, are more efficient. These models enable to overcome the limitations of existing modeling methods. Therefore, the proposed fuzzy model is to capture the relationship between the model inputs and corresponding outputs.

In this study the bending rigidity of a plain-woven fabric is predicted using five yarn parameters, extracted from previously published data [8], including: warp count, yarn diameter, yarn spacing, yarn bending rigidity and yarn length in a fuzzy logic model. Then the prediction accuracy of the model was evaluated.

A. Fuzzy Logic

The idea of fuzzy logic was first introduced by Zadeh [23]. Fuzzy logic can be prescribed as a mathematical model to study and define uncertainties. In the fuzzy modeling of a process, fuzzy logic is established based on the physical properties of a system, observed data, empirical knowledge, and so on. A typical fuzzy logic system consists of four major components: fuzzification, fuzzy rule base, fuzzy inference engine and defuzzification. These main steps involved in modeling a fuzzy system are shown in Fig. 1.

The fuzzification converts input data into suitable linguistic terms, which may be viewed as labels of the fuzzy sets. Each fuzzy set is characterized by appropriate membership functions that map each element to a membership value between 0 and 1. Membership function can have various forms, such as triangle, trapezoid and gaussian. A fuzzy rule represents a fuzzy relation between two fuzzy sets. It takes a form such as “If X is A then Y is B”. A fuzzy rule base contains a set of fuzzy rules, where

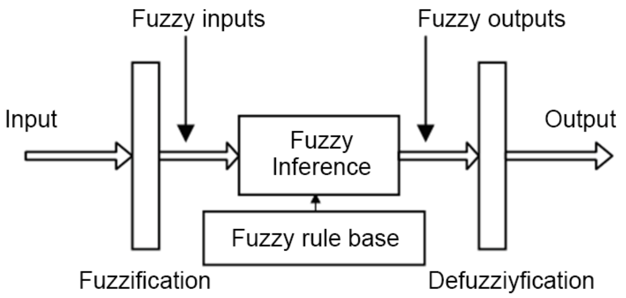


Fig. 1. Block diagram of a fuzzy logic model.

each rule may have multiple inputs and multiple outputs. Fuzzy inference can be realized by using a series of fuzzy operations. The defuzzification combines and converts linguistic conclusions (fuzzy membership functions) into crisp numerical outputs. Depending on the types of fuzzy reasoning and fuzzy if-then rules employed, three types of fuzzy inference system have been widely used in various applications: Mamdani fuzzy models [24], Sugeno fuzzy models [25], and Tsukamoto fuzzy models [26]. The output of each rule is also a fuzzy set. Output fuzzy sets are then assembled into a single fuzzy set. This step is known as "aggregation". Finally, the resulting set is resolved to a single output number by defuzzification, such as center of gravity, modified center of area, center of sums, and center of maximum and mean of maximum.

II. EXPERIMENTAL

The original data for model construction were collected from available scientific literature sources [8]. Table I outlines the inputs and outputs along with the range of the values investigated. In order to apply fuzzy logic for predicting fabric bending rigidity, we need to identify: inputs, outputs, fuzzification, fuzzy inference, and defuzzification. Yarn count (c), yarn diameter (d), yarn spacing (p), yarn bending rigidity (B), and yarn length (l) were used to evaluate and predict fabric bending rigidity (Bf).

In this study, we use the triangle membership functions for the input and output fuzzy sets. The triangular membership function is a function of a vector x and depends on three scalar parameters a, b, and c, which is defined as Eq. (1) (Matlab (7.8.0)). The parameters a and c locate the "feet" of the triangle and the parameter b locates the peak.

$$f(x;a,b,c)=\begin{cases} 0, & x\le a \\ \dfrac{x-a}{b-a}, & a\le x\le b \\ \dfrac{c-x}{c-b}, & b\le x\le c \\ 0, & c\le x \end{cases} \tag{1}$$

In the proposed method, a numerical approximation system is used to convert linguistic terms to their corresponding fuzzy numbers. The values of each range are used to define the triangular membership functions for the input variables. Fig. 2 shows the triangular membership curves of input variables. Input values were converted to four or five fuzzy intervals which have corresponding linguistic terms. For example, a set of five terms to represent warp yarn length could be given as: very small, small, medium, big, and very big (VS, S, M, B, and VB, respectively). Each output variable was partitioned into six fuzzy intervals. This number of membership functions was considered to be the lowest error percentage of prediction. Fig. 2 also shows the triangular membership curves for predicting fabric bending rigidity in the warp and weft directions.

Fuzzy rule base has IF-THEN rules that are defined for all the possible combinations of the fuzzy values of the linguistic variables involved. Fuzzy rules can be

TABLE I
QUANTITATIVE RANGE OF INPUT AND OUTPUT PARAMETERS FROM 33 FABRICS [8]

Variables				Average	Minimum	Maximum
Inputs	Warp	Count	Tex	39.2	19.7	60
		d_1	mm	0.221	0.16	0.279
		p_1	mm	0.459	0.364	0.594
		l_1	mm	0.68	0.509	0.835
		β_1	mN.mm^2	3.12	1.97	5.62
	Weft	Count	Tex	49.6	19.7	63.9
		d_2	mm	0.252	0.16	0.288
		p_2	mm	0.605	0.465	0.756
		l_2	mm	0.489	0.368	0.639
		β_2	mN.mm^2	3.77	1.97	6.81
Outputs		Bf_{warp}	mN.mm	11.45	5.92	28.5
		Bf_{weft}	mN.mm	12.66	3.48	23.49

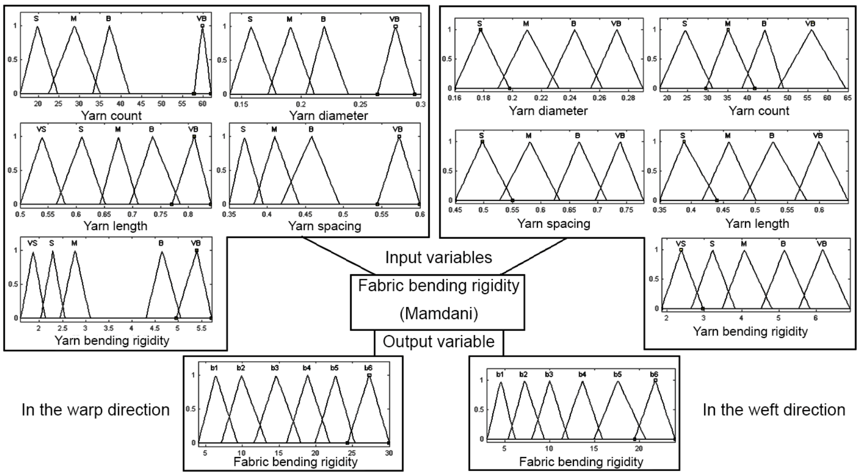


Fig. 2. Triangular membership curves of input and output variables.

extracted from expert knowledge or numerical data. Since no expert knowledge was available in the approximation of the relationship between output variables and their corresponding input variables, the fuzzy rule base of this modeling method is a collection of fuzzy IF-THEN rules acquired from numerical input-output data. It is noted that in the case of rule extraction from data, an effective data partition in input–output space can lead to reducing the number of rules and thus improving the computational efficiency of the fuzzy models. This fuzzy rule base was used for fuzzy inference engine. 29 Fuzzy rules are evaluated simultaneously to determine the fabric bending rigidity. Table II shows some of the defined rules:

Afterwards, the definition of the fuzzy rule base is implemented by using Mamdani's fuzzy inference method. Mamdani's fuzzy inference method is the most commonly applied fuzzy methodology. This method is a type of fuzzy inference in which the fuzzy sets from the consequent of each rule are combined through the aggregation operator and the resulting fuzzy set is defuzzified to yield the output. It is necessary to determine fuzzy rules to make apparent the effect of relationships between the input membership functions and the output results.

Defuzzification converts the resulting fuzzy outputs from the fuzzy inference engine to a number. There are several defuzzification methods. Centroid, SOM (smallest of maximum) MOM (mean of maximum), and LOM (largest of maximum) methods were used in this study. The centroid method for defuzzification gave the best prediction accuracy for fabric bending rigidity. The output of this defuzzifier is a number Z*, for the discrete case, which defined as Eq. (2) (Matlab (7.8.0)):

$$Z^* = \frac{\sum_i \mu_c(z_i) z_i}{\sum_i \mu_c(z_i)} \tag{2}$$

Where, Z* is the defuzzified output value, z_i is the output value in the ith subset, and $\mu(z_i)$ is the membership value of the output value in the ith subset. For the continuous case, the summations in Eq. (2) are replaced by integrals. All the input/output data were used for validating the effectiveness of the model. The fuzzy logic tool box of Matlab (7.8.0) was used in this study.

III. RESULTS AND DISCUSSION

This model was designed to evaluate the fuzzy logic model efficiency in predicting the fabrics bending rigidity. Therefore, it was necessary to compare the results obtained from fuzzy logic with experimental data. Among of studied parameters, yarn count, diameter, spacing, bending rigidity,

TABLE II
SOME OF THE DEFINED RULES

1. If [yarn count is small] and [yarn diameter is small] and [yarn spacing is medium] and [yarn length is small] and [yarn bending rigidity is very small] then [fabric bending rigidity is b1].
2. If [yarn count is medium] and [yarn diameter is medium] and [yarn spacing is big] and [yarn length is medium] and [yarn bending rigidity is very small] then [fabric bending rigidity is b3].
3. If [yarn count is very big] and [yarn diameter is very big] and [yarn spacing is medium] and [yarn length is big] and [yarn bending rigidity is medium] then [fabric bending rigidity is b4].

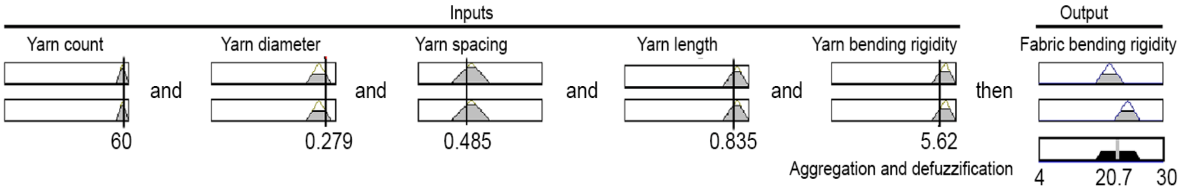
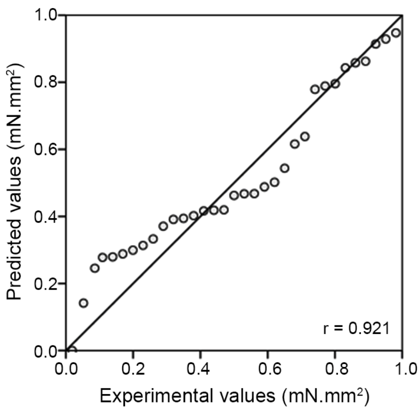


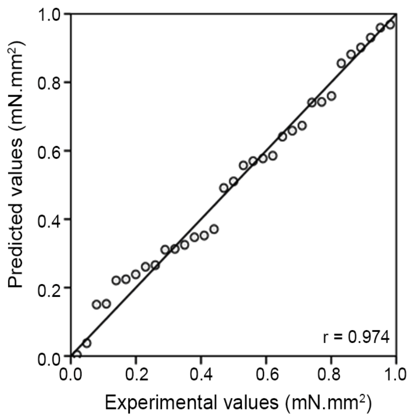
Fig. 3. An example of fuzzy logic reasoning procedure.

TABLE III
EXPERIMENTAL AND PREDICTED VALUES OF FABRICS BENDING RIGIDITIES IN WARP AND WEFT DIRECTIONS

Bf_{warp} (mN.mm)			Bf_{weft} (mN.mm)		
Experimental value	Predicted value	Error%	Eperimental value	Predicted value	Error%
7.76	8.68	11.86	12.32	13.7	11.20
8.64	8.66	0.23	14.76	16	8.40
10.8	8.59	-20.68	23.49	21.7	-7.62
9.88	9.36	-5.26	7.54	7.4	-1.86
8.26	8.72	5.57	17.96	16	-10.91
10.58	10.10	-4.54	20.31	18.1	-10.88
7.02	6.57	-6.41	8.06	8.73	8.31
6.27	6.57	4.78	4.56	4.59	0.66
6.36	6.60	3.77	6.09	6.16	1.15
6.34	6.57	3.63	4.38	4.6	5.02
9.3	8.52	-8.39	3.48	4.61	32.47
9.48	9.45	-0.32	9.41	8.74	-7.12
7.11	6.59	-7.31	9.25	8.74	-5.51
6.21	6.60	6.28	6.16	7.22	17.21
5.92	6.61	11.66	8.17	8.74	6.98
6.23	6.62	6.26	15.64	16	2.30
7.32	6.62	-9.56	16.99	16	-5.83
6.28	8.53	35.83	6.88	7.39	7.41
9.12	8.57	-6.03	14.37	11.9	-17.19
9.43	8.52	-9.65	7.85	7.41	-5.61
9.54	8.53	-10.59	13.33	13.7	2.78
9.68	8.52	-11.98	9.79	11.3	15.42
19.59	18.90	-3.52	22.09	21.8	-1.31
18.48	18.90	2.27	20.55	21.7	5.60
20.45	20.70	1.22	22.5	21.8	-3.11
17.25	16.70	-3.19	20.25	16	-20.99
18.25	16.70	-8.49	19.62	17.8	-9.28
28.5	16.70	-41.40	16	17.8	11.25
14	14.80	5.71	13.06	13.7	4.90
16.47	16.70	1.40	13.68	13.7	0.15
20.5	17.70	-13.66	12	12	0.00
15.2	16.70	9.87	10	12	20.00
11.6	12.50	7.76	7.36	7.38	0.27
Mean absolute error %		8.76	Mean absolute error %		8.14



(a)



(b)

Fig. 4. Correlation of experimental and predicted values of fabrics bending rigidities.

and length are the main parameters influencing the fabric bending rigidity.

We applied the triangular membership function due to its better performance. Fuzzy rule base contains rules that include all possible fuzzy relations between inputs and outputs. The performance of a fuzzy rule base depends not only on the input variable selections but also on the generation of fuzzy rules. We constructed the Mamdani-type fuzzy rules, relating input variables to the output variable. The product and centroid methods were employed as the inference operator and defuzzification methods, respectively. For testing the model, the input values were fed into the fuzzy logic model and the output values were compared with the targeted output (obtained from Leaf's experimental data). With this model, an example is given to illustrate the reasoning procedure of fuzzy logic. As shown in Fig. 3, the yarn count, yarn diameter, yarn spacing, yarn length, and yarn bending rigidity equals 60 Tex, 0.279 mm, 0.485 mm, 0.835 mm, and 5.62 mN.mm^2, respectively. The output, fabric bending rigidity in the warp direction is 20.7 mN.mm.

The error percentage of prediction was calculated using

TABLE IV
THREE MODELING METHODOLOGIES [22]

	Model
Mathematical	$Bf_{warp} = \beta_1 p_2 \div p_1[p_2(1-c_1) - 0.8758D\theta_1]$ $Bf_{weft} = \beta_2 p_1 \div p_2[p_1(1-c_2) - 1.0778D\theta_2]$
Empirical	$Bf_{warp} = 69.363 + d_1(-385.299) + d_2(-181.981) + l_1(-13.631)$ $l_2(232.493) + p_1(-289.970) + p_2(24.084) + tex_1(1.529)$ $+tex_2(0.491) + \beta_1(-0.703) + \beta_2(1.336)$ $R^2 = 0.842$ $Bf_{weft} = 18.916 + d_1(300.38) + d_2(-438.798) + l_1(132.455)$ $l_2(159.367) + p_1(-174.684) + p_2(-137.467) + tex_1(-0.798)$ $+tex_2(1.137) + \beta_1(-0.334) + \beta_2(2.425)$ $R^2 = 0.903$
Artificial neural network	Radial basis function (RBF)

the Eq. (3):

$$\text{Error }(\%) = \frac{y_i - y_i'}{y_i'} \times 100 \tag{3}$$

Where, and are predicted and experimental values, respectively. The mean absolute error (MAE) values were computed for the model. The experimental and predicted values of bending rigidities in warp and weft directions of the sample fabrics are given in Table III. The mean prediction error percentages for fabric bending rigidity are 8.76% and 8.14% in warp and weft directions, respectively. The correlations between the experimental and predicted values of these two bending rigidities of the fabrics are shown in Fig. 4. As can be seen, there is a good relationship between these values.

In order to comparing prediction error of proposed model with the former presented models (Table IV), in this study we applied the only 7 parameters from 33 mentioned data, that had been used for other modeling methods according to previous works [22].

Table V indicates that the prediction errors of fabric bending rigidity in the warp direction are 12.9%, 11.15%, and 8.79% for mathematical, empirical, and artificial neural network models, respectively. Fuzzy model produces the least error of 7.87% comparing to the other three models. Also, Table V shows an error of 5.40% for prediction of fabric bending rigidity in the weft direction. As shown in Table V, fuzzy logic model has a lower prediction error in the weft direction too. Therefore, this paper developed a fuzzy model which provides an easy way to predict bending rigidity of woven fabrics. This property is not only complicated but also has nonlinear behavior. This method is evaluated on the basis of constructional parameters and it can be observed that its predictive errors and the range of errors are very low. Moreover, unlike most available methods, these methods do not need predefined

TABLE V
COMPARATIVE SUMMARY OF DIFFERENT PREDICTION MODELS

Model		Bf_{warp}	Bf_{weft}
Mathematical	Range	-23.70 to 23.80	-12.60 to 17.90
	Mean absolute error %	12.90	10.20
Empirical	Range	-19.22 to 28.44	-24.83 to 77.06
	Mean absolute error %	11.15	25.35
Artificial neural network	Range	-13.22 to 11.40	-4.94 to 31.68
	Mean absolute error %	8.79	9.91
Fuzzy logic	Range	-13.66 to 11.66	-9.28 to 8.31
	Mean absolute error %	7.87	5.40

mathematical equations of the relationship between the model inputs and corresponding outputs, and use the data alone to determine the structure of the model and unknown model parameters.

IV. CONCLUSION

In this research we have introduced a model based on fuzzy logic to predict the bending rigidity of woven fabrics. Bending rigidity of woven fabrics can be effectively calculated with this model. Fuzzy logic model is powerful to solve non-linear problem and it is a cheap and easy-to-use system.We found that prediction performance was best for fuzzy logic model in comparison with mathematical, empirical and neural network models. Consequently, fuzzy logic could be used as a useful modeling tool for engineers and researchers to predict fabrics mechanical properties. There was no hybrid fuzzy-neural network system to predict the bending rigidity of woven fabrics. However, Fuzzy-neural computing systems can be a future research direction in this area.

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