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Full Length Article

Critical current parameterization of high temperature Superconducting Tapes: A novel approach based on fuzzy logic

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ABSTRACT

In this study a novel method was presented to parameterize the critical current of Yttrium Barium Copper Oxide (YBCO) tapes based on their width, thickness, magnetothermal operational conditions, and the applied strain. For this purpose, a fuzzy-logic-based model was developed that take tapes structures and their operational conditions as inputs to calculate their critical current, as output. The results of critical current parameterization by fuzzy-logic-based model showed that the relative error of the proposed model is less than 3% comparing to experimentally acquired data. Then, the results of presented model was compared to results of semi-analytical fitting-based models and fully-analytical fitting based models. The comparisons showed the better performance in terms of accuracy and error of fuzzy logic model over fitting-based methods. At last, the results were also compared with the Artificial Neural Network (ANN)-based parameterization model and Adaptive Nero-Fuzzy Interference System (ANFIS)-based parameterization model. The proposed method had 6% to 8% higher accuracy and about 47% to 54% lower root mean squared error.

1. Introduction

High Temperature Superconducting (HTS) tapes and wires are killer technology for future power grids, cryo-electrified aircraft, ships, and spacecraft. This is due to their low energy loss, low total ownership cost, high level of compactness, low weight, and many other advantages [1,2]. For properly operation of power devices consisting of HTS tapes, critical current (Ic) is one of the most important parameters of these tapes. Critical current of HTS tapes depends on many factors such as magnetic field, operational temperature, applied strain, tape width, and tape thickness [3] and any change in these factors would lead to increase/decrease of critical current. Therefore, to avoid any malfunction of HTS devices, critical current parameterization is an important task during design stage of superconducting devices, especially for highly sensitive industries such as aviation and space [4,5].

Conventionally, critical current parameterization is conducted by performing experimental tests under specific field, temperature, and strain conditions [6–9]. These tests are usually performed to characterize the behavior of HTS tapes under different operational condition rather than using the tests results for design purposes of HTS devices. To take the advantage of these tests results, usually semi-analytical formulations are proposed that consist of some fitting parameters, specialized for each type of HTS tape or some specific operational condition [5,10–12]. This means that by using these semi-analytical methods for other type of HTS tapes or different working conditions, the results of critical current parameterization would consist of significant errors. To avoid this, last recently-two Artificial Intelligent (AI)-based methods were proposed that presented a general model with the capability of critical current parameterization for each type of Yttrium Barium Copper Oxide (YBCO) tapes [13,14]. Although these AI-based models were successful in presenting a general model for critical current parameterization, their accuracy could be still improved.

In this paper, another AI-based model is used for critical current parameterization of YBCO tapes based on data that experimentally collected. The novel proposed method operates based on fuzzy logic was firstly introduced in 1965 [15]. Before getting to analyze the results of critical current parameterization based on fuzzy logic, some analytical and semi-analytical formulations are proposed and by using the MATLAB fitting library, they are generalized for all types of YBCO tapes to show the readers the inability of these methods in estimating the critical current of various YBCO tapes.

2. General analytical Ic parameterization methods

To parameterize the critical current of YBCO tapes, many formulations and fitting equations have been proposed in literature based on

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variations of magnetic field, temperature, and strain. These formulations usually take the advantage of some fitting parameters to cope the experimental results with analytical simulations. The aforementioned parameters commonly vary for each tape and operational conditions and thus, for new conditions and tapes new experimental tests are needed to adapt the fitting parameters. The aim of this section is to discuss that how these formulation could be generalized for a group of YBCO tapes. Equation (1) shows the famous temperature dependency of critical current based on E-J power law [16].

$$f_1(T) = a_1\left(\frac{a_2 + T}{a_2 + a_3}\right)^{a_4} \tag{1}$$

where, a_i is coefficient that must be identified through fitting procedure and T is operational temperature. The aim of such generalization is to get rid of calculation or measurement of base temperature, critical temperature, critical current at base temperature, and other fitting parameters.

Another formulation for critical current parameterization is presented as equation (2) in [5] with respect to changes of field and temperature where B represents magnetic field (applied or self-field).

$$f_2(T,B) = a_5 \times \exp\left(-\frac{T}{a_6}\right) \times B^{a_7} \tag{2}$$

Equations (3) to (4) also provide formulations for critical current based on changes of field and strain (ε), respectively [10,12,16].

$$f_3(B) = a_8\left(1 - \frac{B}{a_9}\right) \times \exp\left(-\left(\frac{B}{a_{10}}\right)^{a_{11}}\right) \tag{3}$$

$$f_4(\varepsilon) = a_{12}\left(1 - a_{13}(\varepsilon - a_{14})^2\right) \tag{4}$$

In addition, equations (5) to (7) present an n$^{\text{th}}$ order polynomial and two different type for exponential formulations for critical current parameterization, based on the changes of temperature, field, and strain that is generally defined as x in these equations.

$$P_n(x) = c_1x^n + c_2x^{n-1} + \cdots + c_{n-1}x^2 + c_nx + c_{n+1} \tag{5}$$

$$E_1(x) = d_1 \exp(d_2x) \tag{6}$$

$$E_2(x) = k_1 \exp(k_2x) + k_3 \exp(k_4x) \tag{7}$$

where, c_i, d_i, and k_i are coefficients that must be identified during fitting procedure. About all the coefficients that presented in this section, would be discussed in results and discussion section of the paper.

3. An overview on fuzzy logic for critical current parameterization

When it comes to decision making by Boolean logic, there are only two possibilities: true or false. However, this approach may not be the optimal one for situations where there is uncertainty and insufficient information. The fuzzy logic has been used to manage these conditions. When making a choice, fuzzy logic assigns a degree of truth between [0,1] (1 being true and 0 being false), as opposed to Boolean logic, which assigns a 1 or 0 for true or false. The base of fuzzy logic is a fuzzy set. The fuzzy set is a set where each element has been given a degree of membership, which determines the trueness of the element to be part of that set. Usually, when one states a set, it is assumed that each element is part of that specific set. The degree of membership determines the trueness of an element belonging to that set. The likelihood that an element belongs to a given set increases with the element's degree's closeness to 1. A curve that explains how each element in the input space is transformed to a membership degree ranging from 0 to 1 is called membership function. The same can be shown using equation (8) [17–19]:

$$A\{x, \mu_A(x)|x \in X\} \tag{8}$$

where, $\mu_A(\mathrm{x})$ is the membershipfunctionof x inA.

The fuzzy logic takes in a crisp input and fuzzifies it and then pass it towards a fuzzy inference system. The Fuzzy Inference System (FIS) maps fuzzy input sets to fuzzy output sets by combining the rules from the fuzzy rule base and provides a crisp output after defuzzification. The flowchart is shown in Fig. 1. There are many inference systems available, but for critical current parameterization application, Sugeno inference system is used, as it is computationally very efficient. A Sugeno inference rule is shown as equation (9) [20].

$$IfInput1 = xandInput2 = y, thenOutputisz = ax + by + c \tag{9}$$

The AND logical operator in a fuzzy system can be presented as equation (10) [17]:

$$\mathrm{X\ AND\ Y} = \min(X, Y) \tag{10}$$

The OR logical operator in a fuzzy system can be also presented as equation (11) [17]:

$$\mathrm{X\ OR\ Y} = \max(X, Y) \tag{11}$$

The data must belong to one of the membership functions if it is to be used in a fuzzy logic model. In this case, the membership functions are clusters. Each cluster denotes which group the input belongs to, and the FIS produces an output based on this. In other words, clustering is nothing more than grouping similar data. The clustering methods used are Fuzzy C-means clustering and subtractive clustering method.

The Subtractive Clustering Method (SCM) is used in current research where instead of giving each data point a membership degree, a radius of impact is drawn around it and scored, as shown in Fig. 2. Each data point is visited, and a cluster is created based on how far each one is from the selected data point. This distance is considered when calculating the score. After visiting each point, the best cluster's center is chosen based on the score points shown in equation (12) [21].

$$\sigma_i = \sum_{j=0}^{j=0} e^{-q} \tag{12}$$

Where q is given by equation (13):

$$q = \frac{|x_i - x_j^2|}{\left(\frac{r}{2}\right)^2} \tag{13}$$

The membership degree in each cluster is calculated by equation (24):

$$\mu_{ij} = e^{(-0.5\times Z)} \tag{14}$$

Where z is given by equation (15):

$$Z = (x_i - c_j)^T \sum^{-1} (x_i - c_i) \tag{15}$$

Here, $\mathrm{c_j}$ is the cluster center defined by the matrix $\sum$ in equation (16):

$$\sum = \begin{bmatrix} 1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sigma_N \end{bmatrix} \tag{16}$$

To this far, the focus of this section was on providing a general overview on all models based on fuzzy logic. By presenting Fig. 3, the paper concentrates on implementation of a fuzzy-logic-based model for parameterization of critical current. By beginning from left hand side, firstly, the experimental inputs data and output data must be gathered as a matrix, known as critical current data, in MATLAB software package. Then, one has to fuzzifies all these data which means decomposing these data into one or more fuzzy sets through trapezoidal-shaped membership functions. In other words, fuzzification is considered as a step where based on the degree of membership

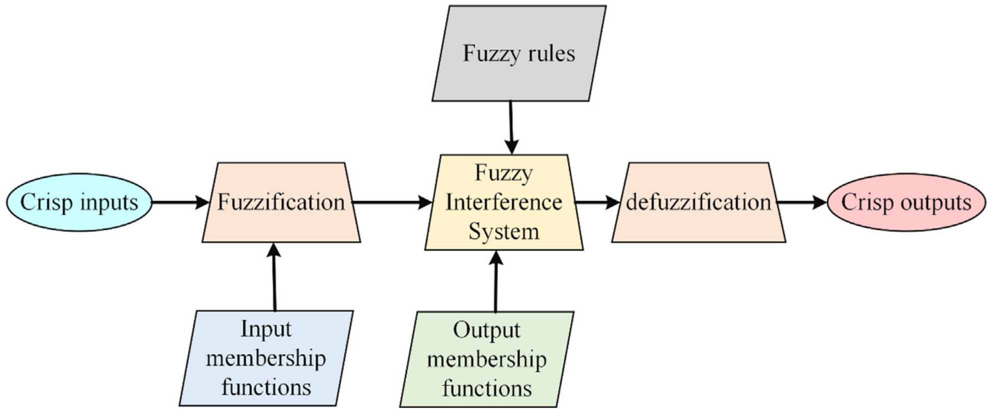


Fig. 1. Genearl Fuzzy logic flowchart.

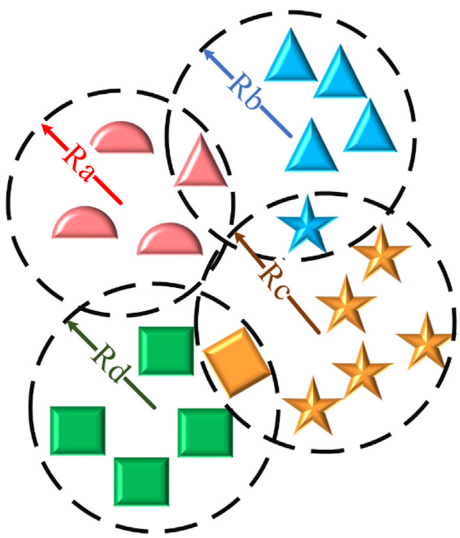


Fig. 2. SCM-based clusters for four different type of data.

functions, each critical current data is included in an appropriate fuzzy set. This could be conducted in MATLAB by using “genfis” function and also choosing SCM as the clustering method. Afterwards, a fuzzy system is generated that still needs interpretations which means converting fuzzy sets and rules into a crisp model that is known as defuzzification process. By doing so, a model is provided that could parameterize critical current of any HTS tape under any magnetic field, temperature, and strain.

To evaluate the performance of fuzzy logic model for critical current parameterization, same as other methods, four indices were used that are Root Mean Squared Error (RMSE), Pearscon correlation coefficient (R), Absolute Error (AE), and Relative Error (RE) that are calculated based on equations (17) to (20).

$$RMSE = \sqrt{\sum_{i=1}^{N_s} \frac{(t_i - e_i)^2}{N_s}} \tag{17}$$

$$R = \frac{\sum_{i=1}^{N_s} (t_i - \bar{t})\left(e_i - \bar{e}\right)}{\sqrt{\sum_{i=1}^{N_s} \left(t_i - \bar{t}\right)^2 \sum_{i=1}^{N_s} \left(e_i - \bar{e}\right)^2}} \tag{18}$$

$$AE = |t - e| \tag{19}$$

$$RE = \left|\frac{e - t}{t}\right| \tag{20}$$

where, t is expected value, e is estimated value, $\bar{t}$ is mean value of expected data, $\bar{e}$ is mean value of estimated data, and N_s is number of data.

4. Results and discussions

4.1. Data variety of tapes

In this section the variety of data is evaluated based on the tape geometries, field, temperature and strain. The data are experimentally tested and reported in [6,7,22–24]. Fig. 4 illustrates that how data are distributed based on the width of HTS tapes and their thickness. As

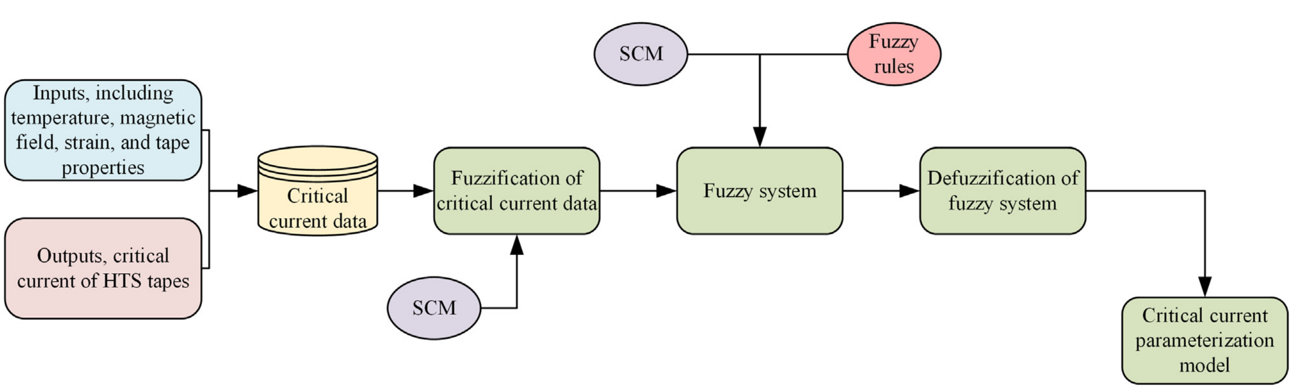


Fig. 3. The realization process of using a fuzzy logic model for parameterizing critical current of HTS tapes.

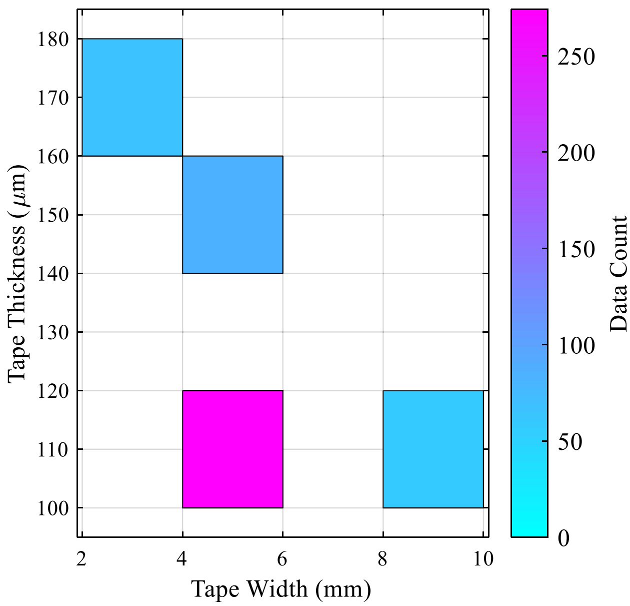


Fig. 4. Variety of data used for critical current parameterization based on the tapes geometry.

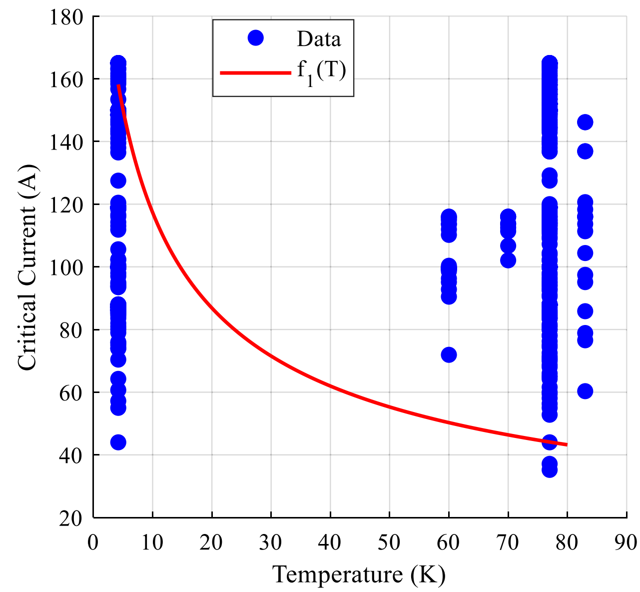


Fig. 5. Performance of f1 fitting equation for estimating the critical current of understudied HTS tapes.

shown in this figure, about 50% of data are related to HTS tapes with width in 4 mm to 6 mm range while their thickness is in 100 um to 120 um. 10% of data are related to bigger tapes that have width in 8 mm to 10 mm range while thickness is 100 um to 120 um. About 40% of data also belong to thicker HTS tapes with a thickness of 140 um to 180 um.

About the magnetic field, temperature, and strain of input data, it should be mentioned that based on experiments conducted in [6,7,22–24], magnetic field is in range of self-field to 19 T while temperature is considered in 4.2 K to 84 K range. 30% of data are related to 4.2 K temperature, 5% are related to data of 60 K to 70 K range, 60% are for data in 77 K temperature, and the rest is for data in 84 K. At last, strain in distributed equally for all ranges of 0% to 1.05%.

4.2. Performance of semi-analytical methods for critical current parameterization

In this section, the coefficients of semi-analytical fitting equations presented in section two of the paper are calculated and their performance is discussed. The coefficients of polynomial and exponential equations are also calculated, however, to prevent biasing of the paper toward the fitting equations, they are discussed and shown in Appendix section. Table 1 tabulates the calculated coefficients for presented fitting equations in section two. The aim was to access a general equation that could parameterize the critical current of any arbitrary HTS tape based on temperature, field, and strain, without any need to justify the fitting parameters for each tape.

Fig. 5 shows the performance of f_1 fitting equation to parameterize the critical current of HTS tapes, based on their operational temperature. As can be seen, the fitted equation hardly matches with experimental data of various HTS tapes. Here, different critical current values are shown in a specific temperature that has two main reasons, one is that these critical current values belong to different HTS tapes and another reason is that in each temperature different field and strain values are applied that resulted in critical current changes at constant temperature. This is a solid proof that fitting could not be used for critical current parameterization of HTS tapes based on just one factor, such as temperature.

At the next step, Fig. 6 is presented to show the performance of fitting equations in a two dimensional equation. Equation f_2 tends to parameterize the critical current of HTS taped based on the changes of temperature and magnetic field. As seen in this figure, presented formulation performs appropriately for data with high magnetic field (19 T) and low temperature (4.2 K) while it is unable to cope itself so that low magnetic field and high temperature (60 K to 84 K) data are also parameterized appropriately. This is originated in the nature

Table 1
Calculated coefficients of fitting equations of f1 to f4.

Fitting	Coefficient
$f_1(T)$	$a_1 = 80, a_2 = 3.963, a_3 = 92.5, a_4 = -0.5568,$
$f_2(T,B)$	$a_5 = 15.235, a_6 = 2.932, a_7 = 1.355$
$f_3(B)$	$a_8 = 320.55, a_9 = 155.35, a_{10} = 0.23, a_{11} = 0.025$
$f_4(\varepsilon)$	$a_{12} = 39.4, a_{13} = -0.01941, a_{14} = 11.5$

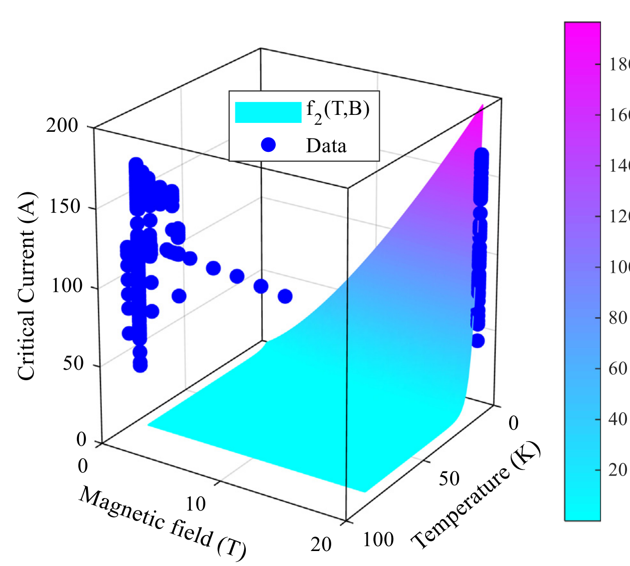


Fig. 6. Performance of f2 fitting equation for estimating the critical current of understudied HTS tapes.

of fitting methods and algorithms that try to present a formulation capable of estimating any data in fitting range. This would help and improve the performance of fitting algorithms through critical current parameterization of HTS tapes, if they just related to magnetic field, temperature, strain or any combination of them. We know that this is not the case and critical current relates to many other factors such as tape structure.

Fig. 7 displays the performance of f_3 equation in estimating the critical current of different HTS tapes. This fitting equation has a better performance than two previously discussed methods. However, it seems that for magnetic field out of 5 T to 15 T this equation has also high errors and low accuracy. Fig. 8 shows the performance of f4 fitting equation for estimating the critical current based on the changes of strain. As can be seen, this formulation has also failed to present coefficients that cope with critical current of all understudied tapes. The fitting here is just a simple mean value that reduces by increase of strain.

4.3. Critical current parameterization by means of fuzzy logic

Fig. 9 shows the results of critical current parameterization by means of fuzzy logic model. Although the results are shown based on the variations of strain, temperature, magnetic field, and tape properties are considered in model. Four clustering methods based on subtractive clustering approach were used here to parameterize critical current which have clustering radius of 1, 0.45, 0.3, and 0.1. The colorbars on right hand side show the difference between experimentally gained values and estimated values, known as Absolute Error (AE). As can be seen in this figure, SCM1 has the highest AE which is about 10 A while this value for SCM0.45, SCM0.3, and SCM0.1, is about 4 A, 4 A, and 3 A, respectively. This means that in worst-case scenario of SCM1, the parameterized critical current by fuzzy logic, has a 10 ampere value higher/lower than experimentally tested value. This means that, the SCM 0.1 has the highest accuracy in critical current parameterization, not only among the fuzzy logic-based approaches but also comparing to fitting methods. Mean Relative Error (MRE) values are also reported that confirm the high accuracy of SCM0.1 method with an 87% lower MRE than SCM1 approach, 50% lower MRE than SCM0.45, and 46% lower MRE than SCM0.3 method.

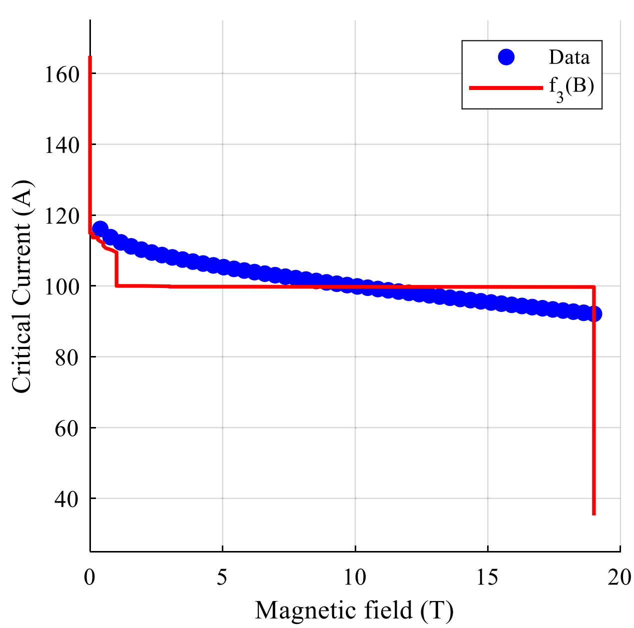


Fig. 7. Performance of f3 fitting equation for estimating the critical current of understudied HTS tapes.

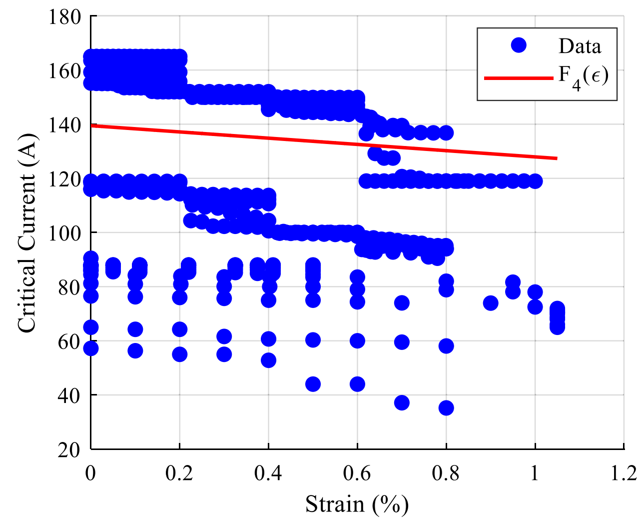


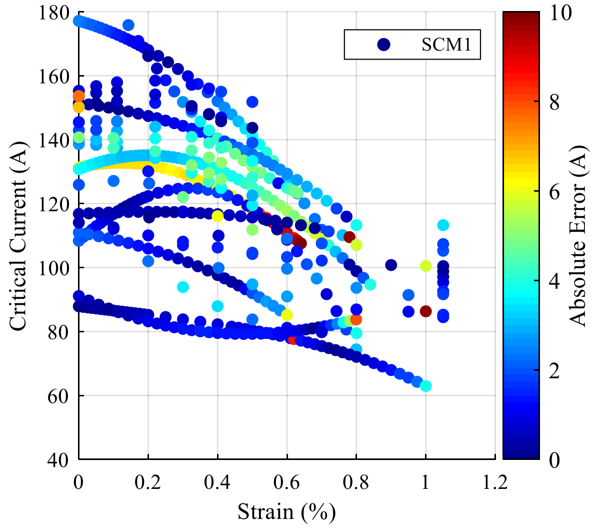
Fig. 8. Performance of f4 fitting equation for estimating the critical current of understudied HTS tapes.

The low AE and RE values of critical current parameterization by means of fuzzy logic method show the high capability of this AI-based tool in parameterization of critical current, regardless of the type and structure of HTS tapes and magnetothermal operational conditions. Therefore, by developing such model, one can parameterize the critical current of any HTS tape operating in any magnetothermal conditions. Another important property of fuzzy-based model is that it include tapes with 4 mm and more than 10 mm width.

4.4. Comparison of fuzzy logic critical current parameterization and analytical formulation

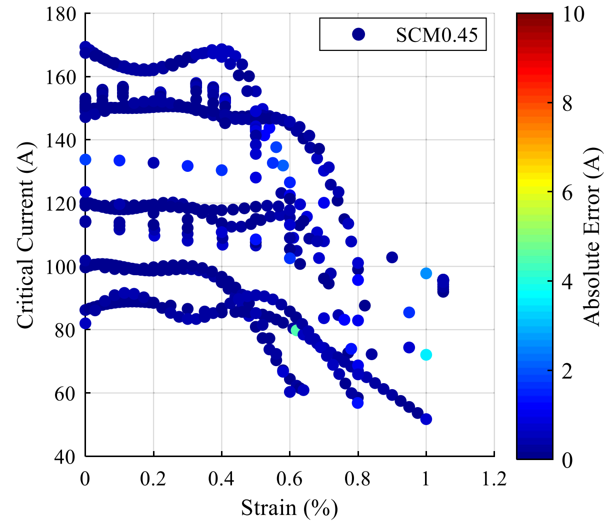
In this section, the results of critical current parameterization by different fitting methods are compared with the results of fuzzy logic method. Table 2 compares the R and RMSE values of the aforementioned methods. The best performance among the fuzzy based parameterization is related to SCM 0.1 with an 18% to 77% lower RMSE comparing to other fuzzy approaches. Among the fitting methods, $f_4(\mathcal{E})$ has the best performance with a 21% to 1260% higher R than other semi-analytical fitting methods and also 35% to 62% lower RMSE. However, this fitting equation parameterize the critical current just based on the strain value. Now by comparing the SCM0.1 with the results of fitting equations, it can be concluded that it has 45% to 1880% higher R value and also 90% to 96% lower RMSE. This shows another superiority of fuzzy logic model over semi-analytical fitting methods in parameterization of critical current. In other words, the fuzzy logic methods have an excellent coordination with experimentally tested data with high R value, low RMSE, AE, and MRE.

The next step is comparing the results of critical current parameterization by fuzzy logic with the results of polynomial fitting methods. For this purpose, polynomial equations of 1st order to 9th are considered for each factor including field, temperature, and strain and their R and RMSE values are reported. As reported in Table 3, by considering temperature, as independent variable of polynomial, the best performance belongs to 4th order equation with R value of 0.81 and RMSE of 0.114. The SCM0.1 has 22% higher R value and 82% lower RMSE than 4th polynomial with independent variable of temperature. If magnetic field is considered as independent variable, the best performance of polynomial fittings relates to 9th order with R and RMSE of 0.79 and 0.120 which are 25% lower than R value of SCM0.1 and 82% higher than RMSE value of SCM0.1 approach. At last, by considering strain as independent variable, the best performance is shown by 8th order polynomial with R and RMSE value of 0.156 and 0.242,



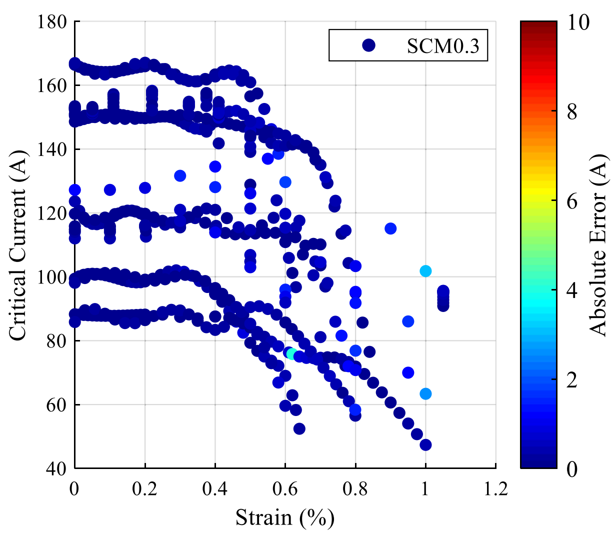
Mean Relative Error=11.58%

a) SCM1



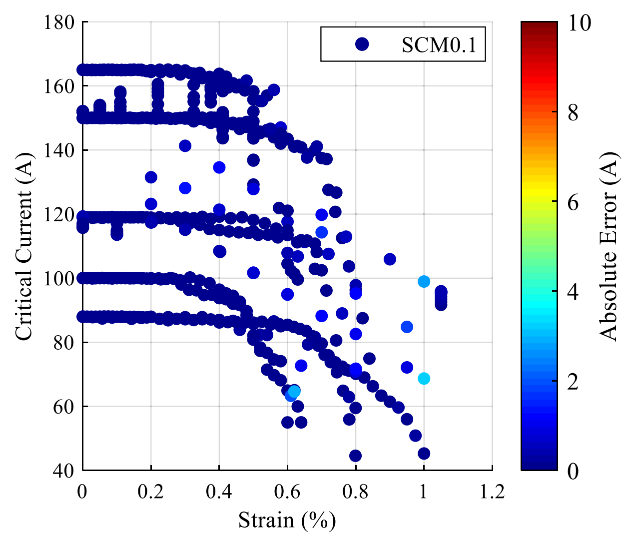
Mean Relative Error=2.98%

b) SCM0.45



Mean Relative Error=2.79%

c) SCM0.3



Mean Relative Error=1.49%

e) SCM0.1

Fig. 9. Results of critical current parameterization by means of fuzzy logic and with respect to the absolute error of estimated values versus experimental ones.

Table 2
Comparison of accuracy and error of fuzzy-based models and semi-analytical fitting equations for critical current parameterization.

Method	SCM1	SCM0.45	SCM0.3	SCM0.1	$f_1(T)$	$f_2(T,B)$	$f_3(B)$	$f_4(\varepsilon)$
RMSE	0.098	0.030	0.027	0.022	0.626	0.576	0.363	0.235
R	0.85	0.98	0.99	0.99	0.05	0.13	0.56	0.68

respectively, which are 530% lower than R value of SCM0.1 and 90% higher than RMSE value of SCM0.1 approach. At last, it should be mentioned that to avoid biasing the paper toward the fitting methods, the calculated coefficients are presented in Appendix section.

After comparing polynomial fitting equations with the results of fuzzy logic, the next step is to evaluate the performance of two exponential equations with fuzzy logic. Table 4 shows the RMSE and R values of critical current parameterization by means of exponential equations. Significantly, the SCM0.1 and also other fuzzy approaches have upper hand comparing to exponential equations. SCM0.1 has 24% to 792% higher R value and 81% to 95% lower RMSE value in comparison to exponential equations.

Table 3
Accuracy and error of critical current parameterization by means of polynomial fitting methods.

Variable	Temperature (K)		Magnetic Field (T)		Strain (ε)	
Index	RMSE	R	RMSE	R	RMSE	R
P_1	0.151	0.669	0.156	0.646	0.247	0.114
P_2	0.121	0.785	0.137	0.725	0.246	0.121
P_3	0.115	0.808	0.129	0.758	0.246	0.122
P_4	0.114	0.810	0.125	0.773	0.244	0.137
P_5	0.115	0.807	0.122	0.781	0.244	0.144
P_6	0.115	0.805	0.121	0.785	0.242	0.155
P_7	0.116	0.805	0.121	0.787	0.242	0.155
P_8	0.127	0.764	0.120	0.789	0.242	0.156
P_9	0.119	0.794	0.120	0.790	0.243	0.142

Table 4
Accuracy and error of critical current parameterization by means of polynomial exponential methods.

Variable	Temperature (K)		Magnetic Field (T)		Strain (ε)	
Index	RMSE	R	RMSE	R	RMSE	R
E_1	0.153	0.658	0.514	0.656	0.247	0.111
E_2	0.154	0.656	0.119	0.796	0.245	0.128

4.5. Comparison of fuzzy logic with ANFIS and ANN methods

Table 5 shows the results of critical current parameterization of HTS tapes by fuzzy logic method, Adaptive Neuro-Fuzzy Interference System (ANFIS) model [14], and Artificial Neural Network (ANN) model [13]. SCM0.1 has higher R value comparing to ANFIS and ANN-based models with 6% to 8% higher R value. Meanwhile RMSE value of SCM0.1 is about 47% to 54% lower than RMSE of ANFIS and ANN model. It should be also noted that except SCM1, all other SCM methods have a better performance in parameterization of critical current. Therefore, it should be noted that fuzzy logic methods, especially SCM0.1 and SCM0.3 has highest accuracy among the reported models and techniques in literature.

5. Conclusions

Critical current parameterization of High Temperature Superconducting (HTS) tapes plays a vital role in design, condition monitoring, and protection of HTS power devices implemented in power grids, electric aircraft, and electric spacecraft. Many methods have been proposed to for parameterization of HTS tapes which can be categorized into three groups, experimental tests, semi-analytical models, and Artificial Intelligent (AI) techniques. Based on third class, this paper presents a novel method for parameterization of critical current, known as fuzzy logic model. The most important findings of this paper based on the proposed method are:

- Low accuracy, adaptability, and reliability of semi-analytical and fully-analytical fitting methods in parameterization of critical current.
- The absolute error of fuzzy logic models for critical current parameterization was between 3 A to 10 A while their mean relative error were between 1% to 11%.
- By comparing the results of critical current parameterization of HTS tapes and semi-analytical and fully-analytical fitting methods, it can be seen that fuzzy method has about 80% to 90% lower Root Mean Squared Error (RMSE) and 45% to more than hundreds of percent higher accuracy.
- By comparing the results of critical current parameterization by fuzzy logic model and Adaptive Neuro-Fuzzy Interference System (ANFIS) model and Artificial Neural Network (ANN) model, reported in literature, it can be seen that the fuzzy method has also better performance comparing to these AI-based models.
- RMSE value of fuzzy model is about 40% to 50% lower than ANFIS method.
- RMSE value of fuzzy model is about 45% to 54% lower than ANN method.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A: Coefficients of polynomial fittings and exponential fittings

To avoid distracting the readers from the main bulk of the results, the coefficients of polynomial and exponential equations reported in

Table 5
Accuracy comparison of critical current parameterization based on fuzzy logic with methods reported in literature.

Method	SCM1	SCM0.45	SCM0.3	SCM0.1	ANFIS [14]	ANN [13]
R	0.85	0.98	0.99	0.99	0.92	0.93
RMSE	0.098	0.030	0.027	0.022	0.047	0.042

Table 6
Polynomial coefficients for critical current parameterization based on temperature.

order	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}
P_1	−77.36	161.10	-	-	-	-	-	-	-	-
P_2	−0.047	3.113	143.8	-	-	-	-	-	-	-
P_3	−0.0025	0.3191	−10.9	196.5	-	-	-	-	-	-
P_4	0.0001771	−0.04204	3.291	−89.87	478.6	-	-	-	-	-
P_5	−1.40e + 05	4.126e + 07	−4.57e + 09	2.292e + 11	−4.649e + 12	1.581e + 13	-	-	-	-
P_6	−1.506e + 04	3.327e + 06	−1.666e + 08	−1.134e + 10	1.303e + 12	−3.485e + 13	1.243e + 14	-	-	-
P_7	1175	−2.444e + 05	1.161e + 07	4.767e + 08	−2.645e + 10	−1.79e + 12	9.023e + 13	−3.456e + 14	-	-
P_8	−11.92	2970	2.537e + 05	7.915e + 06	−1.913e + 07	−6.65e + 09	6.99e + 11	−2.592e + 13	9.704e + 13	-
P_9	−0.0952	13.69	308.2	9.032e + 04	−1.68e + 06	3.966e + 08	−3.824e + 09	−2.651e + 11	−8.429e + 11	8.38e + 12

Table 7
Polynomial coefficients for critical current parameterization based on magnetic field.

order	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}
P_1	−2.935	136.9	-	-	-	-	-	-	-	-
P_2	0.765	−17.6	140.6	-	-	-	-	-	-	-
P_3	−0.1653	4.617	−31.21	142.1	-	-	-	-	-	-
P_4	0.04971	−1.658	16.05	−50.46	142.9	-	-	-	-	-
P_5	−0.01307	0.509	−6.605	34.94	−71.12	143.4	-	-	-	-
P_6	0.004075	−0.1765	2.73	−19.18	63.13	−90.62	143.6	-	-	-
P_7	−0.001557	0.07382	−1.311	11.28	−49.95	111.5	−115.1	143.8	-	-
P_8	0.001219	−0.06067	1.158	−11.04	56.89	158.9	230.5	−158.7	144	-
P_9	−0.0006785	0.03561	−0.735	7.851	−47.53	167.2	−336.4	365.9	−194.5	144.1

Table 8
Polynomial coefficients for critical current parameterization based on strain.

order	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}
P_1	−117.2	163.4	-	-	-	-	-	-	-	-
P_2	46.16	−158.3	169.1	-	-	-	-	-	-	-
P_3	28.1	4.46	−142.5	168	-	-	-	-	-	-
P_4	−414.8	862	−518.5	–33.8	163.8	-	-	-	-	-
P_5	68.45	−585.7	1011	−571.5	−27	163.5	-	-	-	-
P_6	2234	−6669	7012	−2941	363.7	−109.5	164.8	-	-	-
P_7	−1.078e + 04	4.051e + 04	−5.996e + 04	4.38e + 04	−1.601e + 04	2591	−253.5	166.2	-	-
P_8	4015	−2.707e + 04	6.73e + 04	−8.285e + 04	5.463e + 04	−1.88e + 04	2945	−270.6	166.4	-
P_9	4743	−1.76e + 04	1.392e + 04	2.542e + 04	−5.791e + 04	4.589e + 04	−1.707e + 04	2773	−264.1	166.3

Table 9
Coefficient of exponential fitting formula based on temperature, magnetic field, and strain.

Polynomial type	E_1		E_2			
Coefficient	d_1	d_2	k_1	k_2	k_3	k_4
Temperature	161.4	−0.005967	0	−8.51	161.4	−0.005967
Magnetic field	137.4	−0.02804	106.7	−0.01372	37.71	−14.68
Strain	170.9	−1.052	−14.48	−12.83	178.6	−1.142

section 4, are shown and discussed here and in Tables 6–9. To find these coefficients, MATLAB software package is used.

References

[1] Yazdani-Asrami M, Sadeghi A, Song W, Madureira A, Pina JM, Morandi A, et al. Artificial intelligence methods for applied superconductivity: material, design, manufacturing, testing, operation, and condition monitoring. Supercond Sci Technol 2022;35:54. https://doi.org/10.1088/1361-6668/ac80d8.

[2] Yazdani-Asrami M, Sadeghi A, Song W. Ultra-Fast Surrogate Model for Magnetic Field Computation of a Superconducting Magnet using Multi-Layer Artificial Neural Networks. E.A: J. Supercond. Nov. Magn; 2023.

[3] Liu Q, Kim S. Temperature-field-angle dependent critical current estimation of commercial second generation high temperature superconducting conductor using double hidden layer Bayesian regularized neural network. Supercond Sci Technol 2022;35:035001.

[4] Sadeghi A, Xu Z, Song W, Yazdani-Asrami M. Intelligent Probability Estimation of Quenches Caused by Weak Points in High Temperature Superconducting Tapes, Energies. E.A 2023;16(1):193.

[5] Senatore C, Barth C, Bonura M, Kulich M, Mondonico G. Field and temperature scaling of the critical current density in commercial REBCO coated conductors. Supercond Sci Technol 2016;29:014002.

[6] Barth C, Mondonico G, Senatore C. Electro-mechanical properties of REBCO coated conductors from various industrial manufacturers at 77K, self-field and 4.2K, 19T. Supercond Sci Technol 2015;28:045011.

[7] Shin HS, Dedicatoria MJ, Awaji S, Watanabe K. Characteristic strain response of I c in SmBCO coated conductor tapes under magnetic field at 77 K. IEEE Trans Appl Supercond 2012;22. https://doi.org/10.1109/TASC.2012.2182978.

[8] Van Der Laan DC, Ekin JW, Douglas JF, Clickner CC, Stauffer TC, Goodrich LF. Effect of strain, magnetic field and field angle on the critical current density of y Ba2Cu3O7-δ coated conductors. Supercond Sci Technol 2010;23:2–9. https://doi.org/10.1088/0953-2048/23/7/072001.

[9] Russo G, Yazdani-Asrami M, Scheda R, Morandi A, Diciotti S. Artificial Intelligence-based Models for reconstructing the critical current and index-value surfaces of HTS tapes. Supercond Sci Technol 2022;35:124002.

[10] Fleiter J, Sitko M, Ballarino A. Analytical formulation of Ic dependence on torsion of YBCO and BSCCO conductors. IEEE Trans Appl Supercond 2013;23:3–6. https://doi.org/10.1109/TASC.2012.2228292.

[11] Jaroszynski J, Constantinescu A-M, Miller G, Xu A, Francis A, Murphy T, et al. Rapid assessment of REBCO CC angular critical current density Jc(B, T = 4.2 K, θ)

using torque magnetometry up to at least 30 tesla. Supercond Sci Technol 2022;35:095009.
[12] Higgins JS, Hampshire DP. Critical Current Density of YBa2Cu3O7 Coated Conductors Under High Compression in High Fields. IEEE Trans Appl Supercond 2011;21:3234–7.
[13] Yazdani-Asrami M, Sadeghi A, Seyyedbarzegar S, Song W. DC Electro-Magneto-Mechanical Characterisation of 2G HTS Tapes for Superconducting Cable in Magnet System Using Artificial Neural Networks. IEEE Trans Appl Supercond Early Acce 2022;32(7):1–10.
[14] Yazdani-Asrami M, Sadeghi A, Seyyedbarzegar SM, Saadat A. Advanced experimental-based data-driven model for the electromechanical behavior of twisted YBCO tapes considering thermomagnetic constraints. Supercond Sci Technol 2022;35, 054004. 10.1088/1361-6668/ac57be.
[15] Zadeh LA. Fuzzy sets. Inf Control 1965;8:338–53. 10.1016/S0019-9958(65)90241-X.
[16] Sadeghi A, Seyyedbarzegar SM, Yazdani-Asrami M. Transient analysis of a 22.9 kV/2 kA HTS cable under short circuit using equivalent circuit model considering different fault parameters. Phys C Supercond Its Appl 2021;589:1353935. https://doi.org/10.1016/j.physc.2021.1353935.
[17] Lee CC. Fuzzy logic in control systems: fuzzy logic controller. IEEE Trans Syst Man Cybern 1990;20:408–14. 10.1109/21.52551.
[18] Kaufman A, Gupta MM. Introduction to fuzzy arithmetic. New York: Van Nostrand Reinhold Company; 1991.
[19] Dubois DJ. Fuzzy sets and systems: theory and applications. Academic Press; 1980.
[20] Sugeno Michio. An introductory survey of fuzzy control. Inf Sci (Ny) 1985;36:59–83. https://doi.org/10.1016/0020-0255(85)90026-X.
[21] Pang MB, Zhao XP. Traffic flow prediction of chaos time series by using subtractive clustering for fuzzy neural network modeling. In: 2008 Second Int Symp Intell Inf Technol Appl; 2008. p. 23–7.
[22] Cheggour N, Ekin JW, Thieme CLH, Xie YY, Selvamanickam V, Feenstra R. Reversible axial-strain effect in Y-Ba-Cu-O coated conductors. Supercond Sci Technol 2005;18. https://doi.org/10.1088/0953-2048/18/12/016.
[23] Sugano M, Nakamura T, Manabe T, Shikimachi K, Hirano N, Nagaya S. The intrinsic strain effect on critical current under a magnetic field parallel to the c axis for a MOCVD-YBCO-coated conductor. Supercond Sci Technol 2008;21. https://doi.org/10.1088/0953-2048/21/11/115019.
[24] Shin HS, Dedicatoria MJ. Variation of the strain effect on the critical current due to external lamination in REBCO coated conductors. Supercond Sci Technol 2012;25. https://doi.org/10.1088/0953-2048/25/5/054013.