DC Electro-Magneto-Mechanical Characterisation of 2G HTS Tapes for Superconducting Cable in Magnet System Using Artificial Neural Networks

Mohammad Yazdani-Asrami, *Member, IEEE*, Alireza Sadeghi, Seyyedmeysam Seyyedbarzegar, and Wenjuan Song, *Member, IEEE*

Abstract**-- Characterization of the exact critical current density (Jc) and stress values in twisted superconducting tapes plays an important role for analysing their magnetic, thermal, and mechanical behaviours. In this paper, a model based on Artificial Neural Network (ANN) is introduced to estimate the electro-magneto-mechanical characteristic of different superconducting tapes. For this purpose, magnetic flux density, temperature, strain, total thickness of tape, their width, thickness of stabilisers, and thickness of substrates are used as inputs to ANN model whilst minimum normalised Jc and maximum stress are considered as outputs. The required experimental data are extracted from published papers in literature. The ANN model was trained for Jc/stress estimation using extracted data for different inputs. Sensitivity analysis was conducted on ANN models which were used to estimate the Jc and stress values of tapes, to choose an optimum structure for ANN models to be used in future by other scientists in the superconductivity community. To check the reproducibility, repeatability, and stability of presented results, the estimations with ANN optimum structure were tested for 500 testing runs. We found that the ANN optimum structure was as 1 hidden layer with Levenberg-Marquardt training method and 7 inputs. Comparing to the literature, the proposed ANN model offers about 15% and 1.1% higher accuracy in Jc and stress estimations, respectively.**

Index Terms**-- ANN, Critical current, Magnetic field, HTS tapes, Stress, Strain, Temperature.**

I. INTRODUCTION

SUPERCONDUCTING technology is generally very promising for being used for applications in power systems, aviation industry, and healthcare sector in devices such as magnetic resonance imaging/nuclear magnetic resonance magnets [1]–[5], High Temperature Superconducting (HTS) cables [6]–[8], superconducting machines [9], [10], superconducting fault current limiters [11], [12], superconducting magnetic energy storage units [13], [14], and HTS transformers [15], [16]. In superconducting magnets, as one of the most successfully commercialised applications of superconductors, low temperature superconducting wires and also HTS tapes and cables are used in the form of coils to generate the required magnetic field with required properties [17], [18].

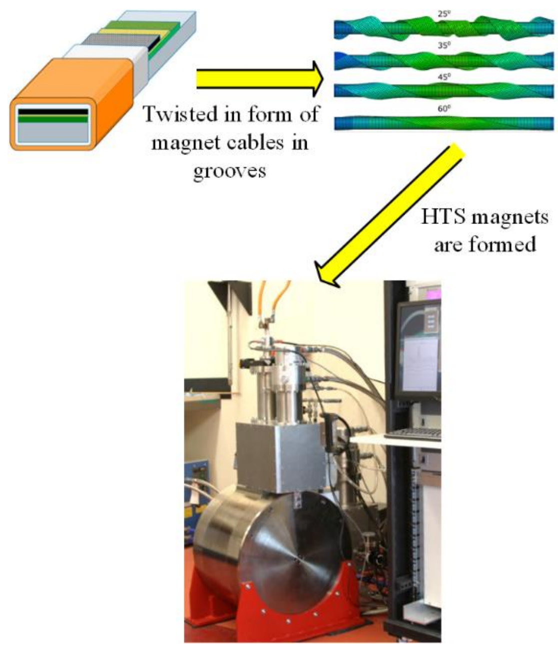


Figure 1. Twisting of HTS tapes in form of CORC cables in HTS magnets, figures adapted from [2]–[5].

As shown in Figure 1, usually in magnet applications, HTS tapes and cables are twisted to build up the coils and the magnet systems [2]–[5]. Twisting of HTS tapes causes local critical current density (Jc) reduction and stress increase. Thus, exact estimation of the Jc and stress values is a vital task during the design stage of superconducting magnets and cables which can be affected by multiple factors such as magnetic flux density, temperature, strain, thickness of tapes, and thickness of different layers in coated conductor [19], [20]. Performing experimental tests or using Finite Element Methods (FEMs) for characterising electro-magneto-mechanical behaviour of superconducting tapes is costly and time consuming whilst it can be handled easier and much faster by using

This manuscript was received 04 May 2022, revised 10 July 2022, accepted 22 July 2022.

M. Yazdani-Asrami, and W. Song, are with Propulsion, Electrification & Superconductivity group, Autonomous Systems & Connectivity division, James Watt School of Engineering, University of Glasgow, Glasgow, G12 8QQ, U.K. (Corresponding author's e-mail: m.yazdaniasrami@gmail.com, mohammad.yazdani-asrami@glasgow.ac.uk)

A. Sadeghi, and S. M. Seyyedbarzegar are with Department of Electrical Engineering, Shahrood University of Technology, Shahrood, Iran.

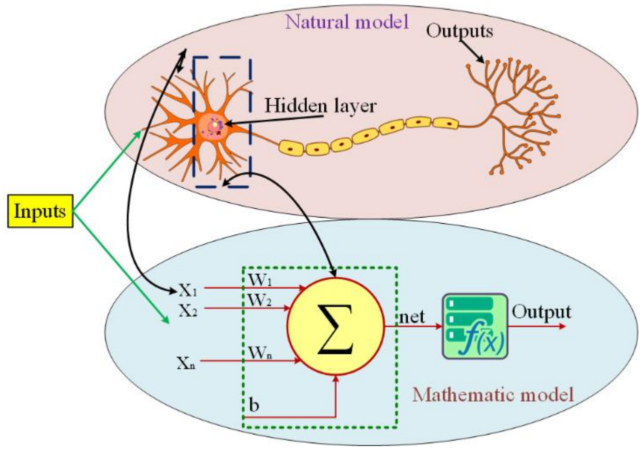


Figure 2. The internal structure of a simple ANN model containing inputs, weights, bias numbers, net signal, activation function, and model output

Artificial Intelligence (AI) technique-based models. These models are capable of considering multiple variables for determining the characteristic of HTS tapes without giving up on the accuracy or estimation speed. Last recently, AI models were used to design [21], monitor [22], and estimate [23] different characteristics and performances of superconducting devices. In [24], a novel AI approach was introduced to estimate the stress and Jc in HTS tapes. However, it did not consider the thickness of stabilisers and substrates in the model. However, the substrates work as mechanical protection of HTS layer in coated conductor tapes. Thus, considering their thicknesses for stress/Jc estimation could increase the accuracy of the model.

Due to the application of HTS tapes in superconducting cables of magnet systems, accurate AI-based models with the capability of Jc and stress estimation, could help the researchers to design a magnet with a higher magnetic field homogeneity, low possibility of pre-mature quenches, lower local Jc reduction, and higher reliability [1]. This is especially the case for applications that a very accurate and multi-physical characteristic of HTS magnets are needed that is usually difficult or very time-consuming to acquire by FEMs. Therefore, in this paper, a novel method based on Artificial Neural Network (ANN) models is introduced - for the first time - to estimate the Jc/stress characteristic of different Second Generation (2G) HTS tapes whilst the thicknesses of stabilisers and substrates, strain, magnetic flux density, temperature, total thickness of the tape, and its width are considered as inputs for the proposed ANN model. Considering all of these properties as inputs makes the estimation of electromechanical characteristic more accurate. To accomplish such a goal, and after extracting the experimental results presented in [25]–[32], firstly, a series of preliminary results are illustrated to show the capability of ANN model in estimating the Jc and stress of the tapes. In addition, sensitivity analysis was conducted to choose an optimum structure for the proposed ANN model. It should be also mentioned that for training ANN model, 70% of the total data were used while the ratio of test data and validation data were 15% each. The next step is showing the stability and reproducibility of results by running the model for 500 times. At last, the results are compared with a method known as Adaptive Neuro Fuzzy Inference System (ANFIS) method based on the Root Mean Square Error (RMSE), and coefficient of fit-goodness (R^2). Using the proposed method of this paper, it is possible to determine Jc and stress of any generic superconducting tape, unlike what happens with conventional methods (Jc parameterizations and fitting methods) that usually refer to a single tape.

II. Methodology: the Proposed ANN model

A. *The overview of artificial neural networks*

An ANN is an AI-based model that uses data to characterise the behaviour of a complex and often non-liner systems that can be used for classification, clustering, vector quantisation, feature extraction, and even curve-fitting [33]. As shown in Figure 2, the simplest ANN system consists of three general layers. The first layer is known as "*Input*" layer which is the layer that receives the set of data based on which the ANN must characterise the system behaviour. After that there is/are "*Hidden*" layer(s) consisting of some "*neurons*" with the main objective to make a logical connection between inputs and output layers by using a set of weights, bias factor, and activation functions. At last, there is "*Output*" layer that presents result of the estimation, prediction, and classification tasks of ANN. Equations (1) and (2) express the correlation between input and output layers in an ANN system [34].

$$net = [w_1\ w_2 \ldots w_n]\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} + b = W^T x + b \qquad (1)$$

$$output = f(W^T x + b) \qquad (2)$$

where, W is weight vector, x is input vector, b is bias factor, and f is activation function.

Usually, ANN models consist of three phases, i.e. train, test, and validation. The training is a process in which ANN model uses inputs and outputs to recognise a specific pattern in understudied characteristic. Training data is part of dataset that participates in training phase of the ANN model. In fact, the number of training data plays an important role in final accuracy and speed of the ANN model. If all data are used in training stage, there is no remaining data for testing and validating the model and this could keep us blind about the real accuracy of the ANN model. Thus, to avoid this, the ratio of training data to total number of data is usually selected to be 50% to 70%. By doing this, ANN model is trained based on the majority of data that increase the final accuracy of the model while test and validation phases can be conducted as well. The importance of these phases originates in the fact that the performance of trained model is evaluated for the data out of training range that results in higher accuracy and higher level of adaptability of the final model. It should be also mentioned that, consistency, adaptability, and prediction capability are the most important features of the ANN models that could estimate the outputs out of the training range.

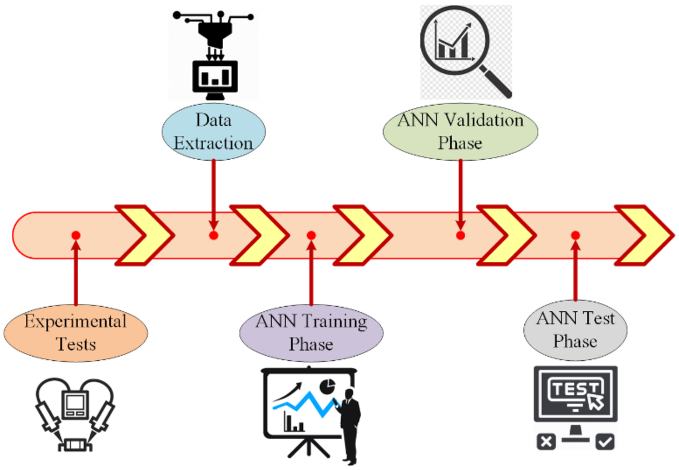


Figure 3. The procedure of developing an ANN-based predictor/estimator

Table 1. The range of the inputs for estimating the electro-magneto-mechanical characteristic of 2G HTS tapes under different conditions

Input	Range	Unit
Magnetic flux density	Self-field & 19	T
Temperature	4.2 & 77	K
Strain	0 to 0.8	%
Width of tapes	3.05, 4, 4.04, 4.1, and 4.19	mm
Thickness of tapes	101, 110, 112, 115, 153, and 161	μm
Stabiliser thickness	30, 36, 40, and 75	μm
Substrate thickness	50, 60, and 100	μm

B. Proposed ANN for the Jc and stress estimations

To use ANN for estimating stress/Jc, this paper has considered the following inputs: The thickness of tapes, width of tapes, the value of magnetic flux density, temperature, the applied strain, the thickness of stabiliser, and the thickness of substrate layer in different 2G HTS tapes. The data were extracted based on the experimental tests that were performed in [25]–[32]. As shown in Figure 3, after the experimental data extraction stage, training stage begins - initially based on Levenberg Marquardt algorithm on the experimental data. The next phase is the validation phase that is usually used to make a final assessment of the model performance and finally there is test phase. Table 1 tabulates the range of considered inputs in the proposed ANN model. The structure of the adapted ANN models for Jc and stress estimations are shown in Figure 4(a) and Figure 4(b), respectively. The initially tested networks – as preliminary models – have 1 hidden layer, in each layer there are 5 neurons, 7 inputs for Jc estimation and 6 inputs for stress estimation. Although more hidden layers results in a slight increase in accuracy of stress and Jc estimation, computational time would be increased significantly. Thus, the number for hidden layer selected to be 1 for the sake of speed and computation time concerns.

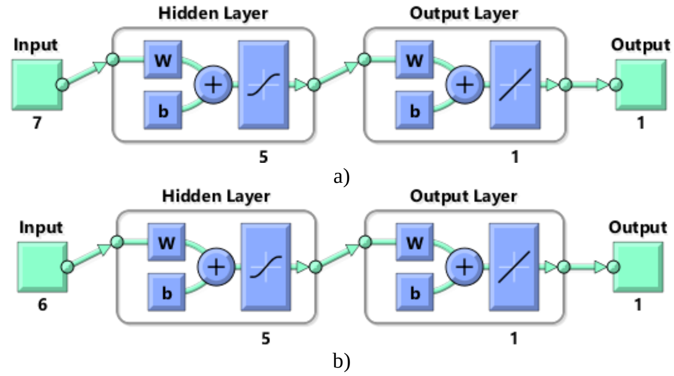


Figure 4. The structure of proposed ANN for the characteristic estimation of HTS tapes, a) Jc estimator, b) Stress estimator

The 7 inputs for the ANN model and their ranges are tabulated in Table 1. It should be also mentioned that in stress estimation, magnetic field is removed from the inputs and therefore, they are reduced to 6. Initially, the Levenberg-Marquardt method is used to train the model with 70% of the total data points.

III. Results and Discussions

A. Results of Jc/stress estimation by ANN model

Figure 5(a) plots the estimated value of Jc versus the real experimental values. In this stage, 15% of data are used for testing the ANN model. The more accurate the model is, the data points locate near the y=x line. Figure 5(b) shows the regression between the estimated values of stress and the real experimental values. As can be seen, the relation between experimental values and estimated ones is similar to y=x line. It proves that the proposed ANN model can be used for Jc/stress estimation of HTS tapes. The maximum relative error of Jc estimation is about 3% while this value for stress estimation is about 4%. However, the accuracy of the ANN model could be changed (either improved or worsen) by varying the ANN controlling parameters, such as number of neurons or type of activation functions. The impact of such parameter changes will be discussed in the following sub-sections. The next step is to select an optimum ANN structure for Jc/stress estimation.

At last, it should be mentioned that to make the problem more complex for our proposed ANN model, different HTS tapes from different manufacturers were used for training the model such as YBCO taped manufactured by SuperPower, SuNam, Bruker HST, Fujikura, and SuperOx. However, it can be seen from Figure 5, that even tough different tape structures from different manufacturers were used in our complex dataset, still the proposed ANN model can estimate the Jc/stress with high accuracy.

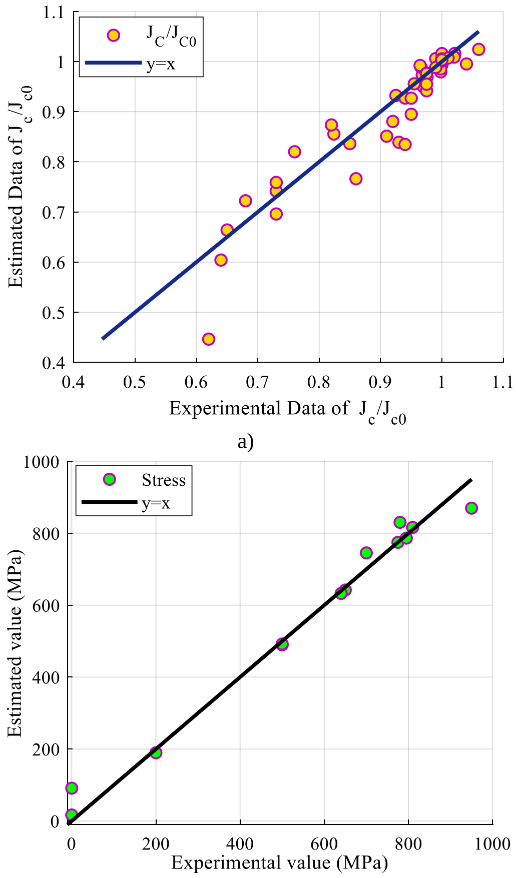


Figure 5. The regression performance of the proposed ANN model to characterise 2G HTS tapes, presented for test phase for: a) the normalised current density b) the stress

B. Sensitivity Analysis

The sensitivity analysis is accomplished according to three approaches. The first one is analysing impact of neuron number variations and impact of different activation functions. Four activation functions were used in this paper to evaluate their impact on the accuracy and computation speed of the proposed model. These activation functions are as follows and are illustrated in Figure 6 [35]:

- Pure linear: $F(x) = x$ (3)
- Saturated linear: $F(x) = \begin{Bmatrix} 0 & x < 0 \\ 1 & x > 0 \end{Bmatrix}$ (4)
- Hyperbolic tangent sigmoid: $F(x) = \tanh(x)$ (5)
- Log-sigmoid: $F(x) = \frac{1}{1+\exp(-x)}$ (6)

The next phase of the sensitivity analysis is for evaluating impact of number of inputs on the accuracy and computation speed of the proposed model. In this step, number of inputs changes from 1 to 7. In each case, the combinations of inputs are selected which offer the highest accuracy of Jc and stress estimation. After that the third phase investigates impact of training parameters on the final results such as different training methods and different ratio of training data to all data. The last two steps are conducted to show how data could change the accuracy of the estimations.

1) Impact of ANN parameters on the estimation results

In this part of sensitivity analysis, the training method is selected to be Levenberg- Marquardt while 70% of the data

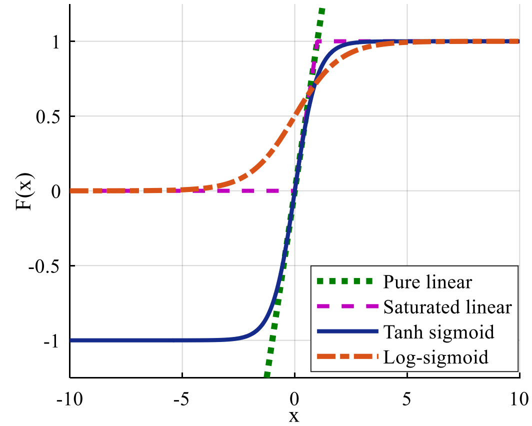


Figure 6. The activation functions used in the proposed ANN model

are used for training, 15% for testing, and 15% for validation. Figure 7(a) illustrates the impact of the number of neurons and type of activation functions on the R^2 values of the estimation. As can be seen, the increase in the number of neurons causes the R^2 increment, i.e. higher estimation accuracy. However, for neurons more than 5, computation time increases from about 1.1 seconds to around 3-6 seconds. Also, with respect to the nature of the data, tansig/purlin and logsig/purlin activation functions perform better. In fact, an ANN model needs two activation functions, one for relating inputs and hidden layers and another one for connecting hidden layers and outputs. In this study, the activation function before (/) is for inputs side and the function after (/) is for outputs side. For maximum 6 neurons, tansig/purlin performs better while for 7 neurons or more logsig/purlin activation function has better performance. The same behaviour can be seen in Figure 7(b), when comparing the RMSE for neurons higher than 4, the logsig/purlin performs better, in comparison to tansig/purlin. So, for Jc estimation, numbers of neurons are selected to be 5 and now is time to select the activation functions. The activation function is selected here to be tansig/purlin (~1.1 seconds) which is faster than logsig/purlin (1.5 seconds) in training phase. Figure 7(c) shows the variation of R^2 value for stress estimation. Here the best performance is related to the number of neurons in range of 3 to 10 while the best activation function in this range of neurons is tansig/purlin. Also, based on Figure 7(d), the hidden layers higher than 3 cause the extreme reduction of RMSE. Thus, for the sake of offering fast and accurate ANN model for stress estimation, numbers of neurons are set to 3 with tansig/purlin as the activation function. In accordance to the reported results, any ANN with numbers of neurons more than 3 and with activation function of tansig/purlin, is capable of estimating Jc and stress with a high accuracy and low RMSE.

2) Impact of number of inputs on the estimation results

Here ANN parameters are set as follows: number of neurons is 5, 70% training data, and Levenberg-Marquardt training method. Thus, 7 different scenarios are considered among all possible combinations. The reported combinations of inputs for Jc and stress estimations are the best-case scenarios with highest R^2 and lowest RMSE for each scenario. These combinations are tabulated in Table 2. The inputs combinations are chosen among multiple available scenarios.

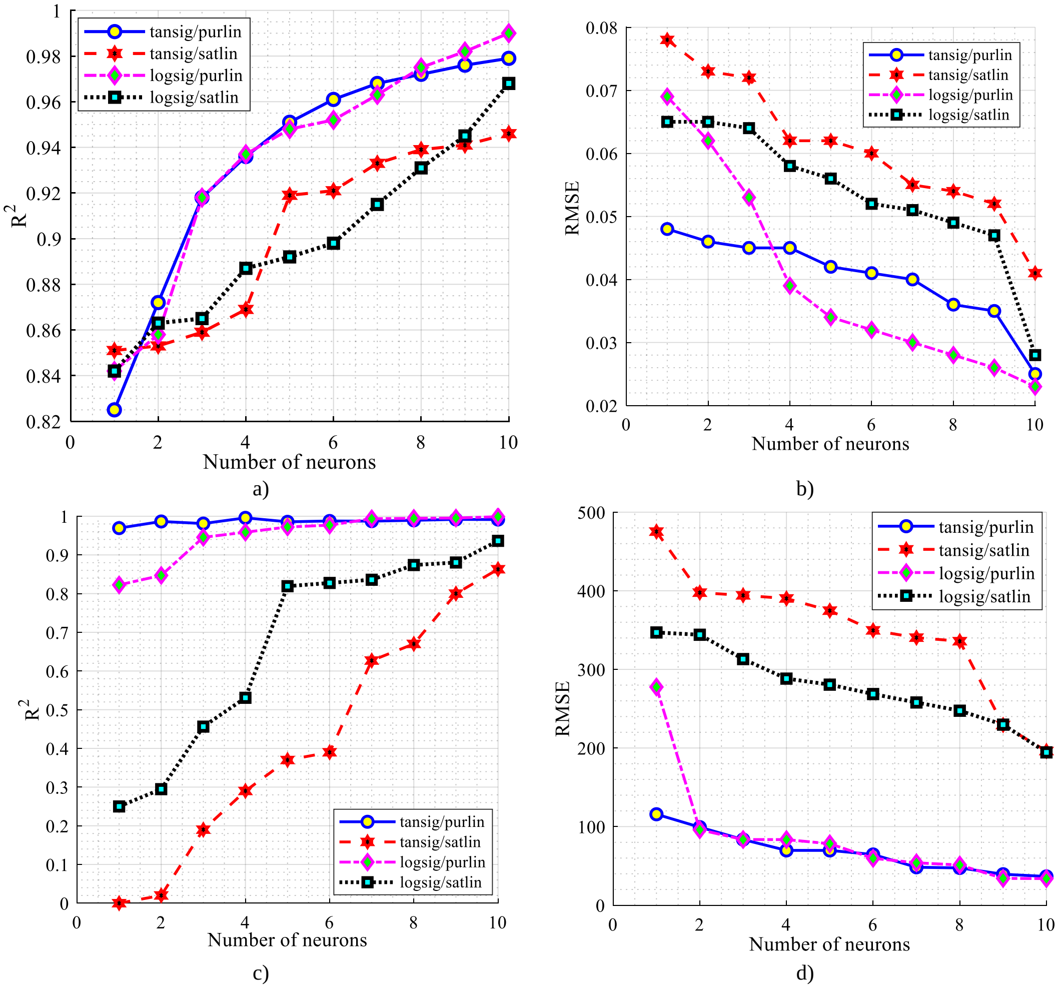


Figure 7. Sensitivity analysis for the variation of neuron numbers and activation functions in the proposed ANN, log sig stands for log-sigmoid function, tansig stands for tangent sigmoid, purlin stands for pure linear, and stalin stands for saturated linear function, a) R^2 of Jc estimation, b) RMSE of Jc estimation, c) R^2 of stress estimation, d) RMSE of stress estimation

For instance, in S2 of Jc estimation, there are 21 different scenarios with different combination of inputs that the reported one show the best performance. By applying each one of these scenarios, it can be observed that the highest R^2 belongs to the scenario with seven inputs, as shown in Figure 8(a) and Figure 8(b) for Jc and stress estimation, respectively. Also, by reducing the inputs, the R^2 is reduced and the worst-case scenario is when just 1 input are fed to ANN model.

3) Impact of training process/parameters on the estimation results

Firstly, the ratio of training data is changed for three values, 50%, 70% and 90% of all data for both Jc and stress estimations. As listed in Table 3, the ratio of training data has a significant impact not only on the training accuracy but also on final test and validation results. For Jc estimation, the superiority of performance belongs to the ANN model when 70% of data are used to train the model. By doing this, RMSE is about 10% lower in comparison to the situation in which 50% of data are used for training and 7% lower comparing to situation in which 90% of data are used for training. For stress estimation the better performance of ANN model can be achieved when 70% of data are used in training stage. Thus, 70% of the data is used to train the model in this paper.

Table 2. Considerations for scenarios of different numbers of inputs for Jc estimation. In case of stress estimation, in S4 to S6, the flux density is replaced by thickness of substrate and also there is no S7 for stress estimation

Scenario	Number of inputs	Type of Inputs
S1	1	Strain
S2	2	Strain- thickness of stabiliser
S3	3	Strain- temperature-thickness of stabiliser
S4	4	Strain - temperature - flux density - thickness of stabiliser
S5	5	Thickness and width of tapes- strain- flux density, temperature
S6	6	Thickness and width of tapes- strain- flux density, temperature, thickness of stabiliser

S7	7	Thickness and width of tapes-strain- flux density, temperature, thickness of stabiliser-thickness of substrate

Table 3. The impact of training data ratio on the accuracy of the proposed ANN model

Train data ratio respect to all data	Jc estimation			Stress estimation		
	train	test	validation	train	test	validation
50%	0.054	0.048	0.047	32.68	46.93	45.43
70%	0.036	0.044	0.039	27.98	45.43	38.66
90%	0.046	0.047	0.041	31.68	49.87	40.19

It should be mentioned that other parameters of ANN model are fixed at what found in previous sections. There are many different training methods to train an ANN model, among them the following ones are the most commonly used for complex problems [35]: Levenberg-Marquardt (LM), Bayesian Regulation (BR), Broyden, Fletcher Goldfarb, and Shanno (BFGS), Conjugate Gradient Backpropagation (CGB), Conjugate Gradient Backpropagation with Fletcher-Reeeves Updates (CGBFRU), Conjugate Gradient Backpropagation with Polak-Ribiere Updates (CGBFPU), Gradient Descent with Adaptive Backpropagation (GDAB), Gradient Descent with w/momentum adaptive Backpropagation (GDXB), One Step Secant (OSS), and finally, Scaled Conjugate Gradient Backpropagation (SCGB). In Table 4, a sensitivity analysis is conducted to show their impact on the train, test, and validation phases of the ANN model for the Jc estimation. As can be seen, the best performance of training is for LM method with the highest R^2 and the lowest RMSE. Also, in the test and validation phases, the best performance belongs to the LM method. At last, by considering the computation time, as an important factor, the LM method has the fastest performance with shortest estimation time. It should be also emphasised that the LM has a highest R^2 with the minimum simulation time.

C. *Stability Analysis of the estimation results*

The term of stability indicates not only the high accuracy of the reported estimations is not a random phenomenon that somehow end up with high accuracy but also can be repeated and reproduced if the exact same parameters are applied to the model. To do this, each estimation is conducted with 5 neurons for Jc estimation and 3 neurons for stress estimation, tansig/purlin activation function, 7 inputs for Jc estimation, and 70% ratio of training data and repeated for 500 times running.

Table 5 tabulates the statistical values for the mean and standard deviation of the RMSE and R^2 after 500 times repetition of Jc estimation. As can be seen, the mean value of R^2 and RMSE in test phase is very close to the previously discussed ones. On the other hand, the lower standard deviation means the stability of the results is higher, typically this index shows the difference of each data from the mean of the all data points. The mean and standard deviation are also shown for training and validation phases to show the stability of estimations in these phases too. The same is shown for stress estimation in Table 6. As can be seen, the reported mean

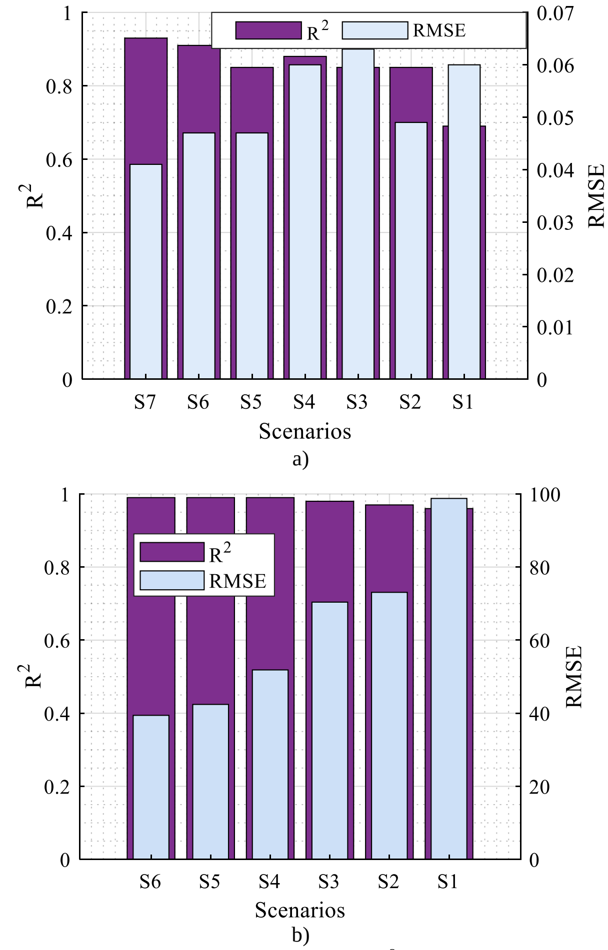


Figure 8. The impact of the number of inputs on R^2 and RMSE, a) Jc estimation b) Stress estimation

Table 4. The impact of different training methods on the R^2, RMSE, and estimation time of the ANN model for Jc estimation for a grid with 5/3 neurons, and 70% of training data.

Phase	**Train**		**Test**		**Validation**		**Computation time (s)**
Parameter	***R^2***	***RMSE***	***R^2***	***RMSE***	***R^2***	***RMSE***	*****
LM	0.96	0.031	0.93	0.042	0.93	0.022	1.12
BR	0.95	0.032	0.82	0.072	0.92	0.046	2.12
BFGS	0.85	0.053	0.91	0.47	0.91	0.076	3.29
CGB	0.81	0.066	0.88	0.057	0.73	0.068	1.92
CGBFRU	0.84	0.062	0.91	0.047	0.91	0.046	1.93
CGBFPU	0.8	0.068	0.8	0.064	0.8	0.061	1.52
GDAB	0.74	0.073	0.8	0.073	0.78	0.081	1.48
GDXB	0.84	0.063	0.77	0.077	0.76	0.048	2.03
OSS	0.82	0.064	0.88	0.044	0.88	0.065	1.85
SCGB	0.84	0.061	0.92	0.48	0.81	0.059	1.67

values for R^2 and RMSE are very close to the values based on which the parameters of the ANN were chosen.

To show the distribution of the R^2 and RMSE values after 500 times of repetition, Figure 9 is presented. According to Figure 9(a), for test phase of Jc estimation, around 370 of the 500 data points have the R^2 value more than 0.9 which means 74% of the data have a high accuracy, near the reported values. This number and percentage are around 320 and 64% for RMSE value lower than 0.06, in test phase of Jc estimation, according to Figure 9(b). For stress estimation

Table 5. Stability analysis of the critical current estimation by ANN after 500 times repetition for a ANN with 5 neurons, and 70% of training data, and Levenberg-Marquardt training method.

Results	Phase	RMSE	R^2
Mean	Train	0.036	0.944
	Test	0.044	0.932
	Validation	0.039	0.935
Standard deviation	Train	0.011	0.038
	Test	0.017	0.064
	Validation	0.017	0.062

Table 6. Stability analysis of the stress estimation by ANN after 500 times repetition for an ANN with 3 neurons, and 70% of training data, and Levenberg-Marquardt training method.

Results	Phase	RMSE	R^2
Mean	Train	27.98	0.991
	Test	45.43	0.980
	Validation	38.66	0.981
Standard deviation	Train	24.01	0.022
	Test	33.63	0.057
	Validation	27.14	0.045

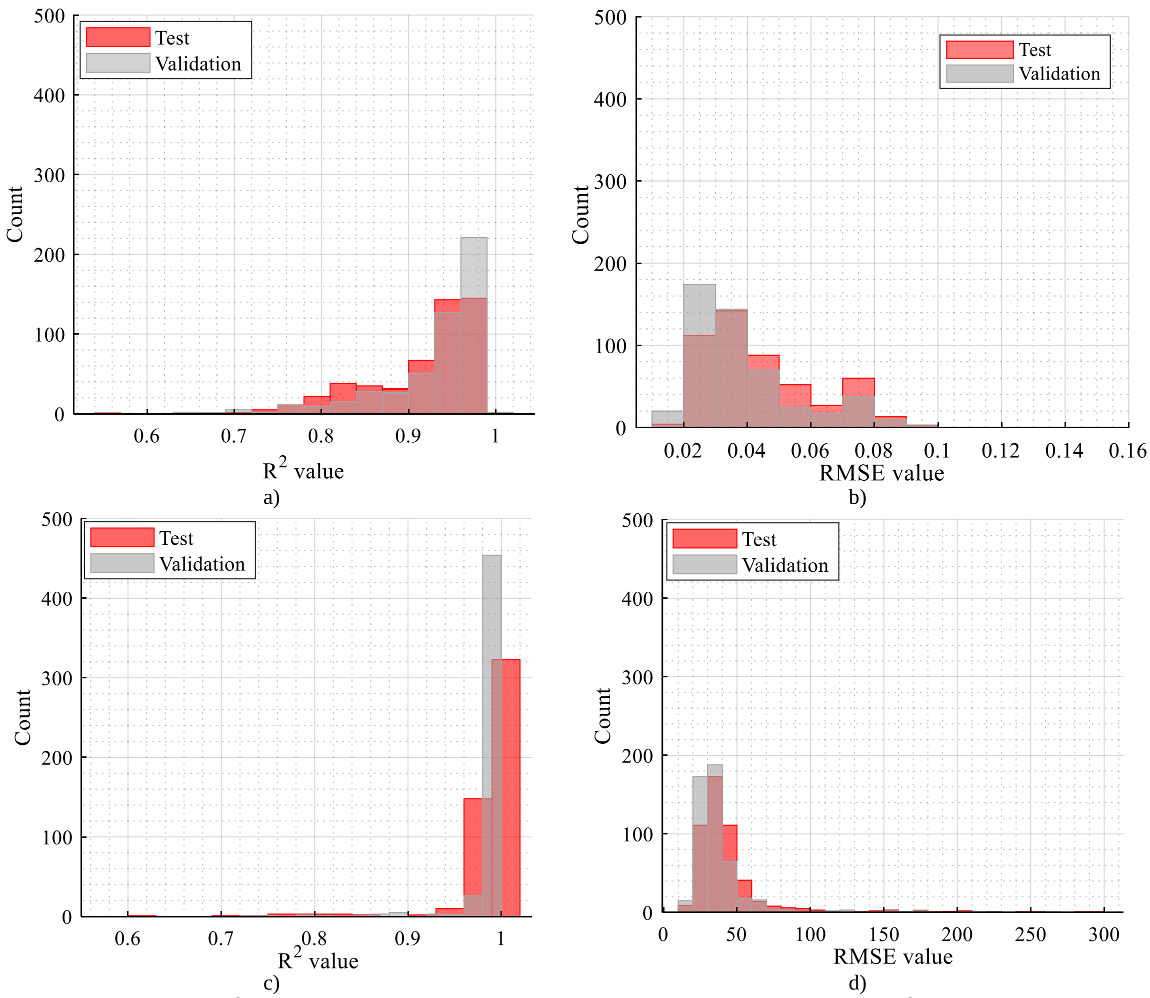


Figure 9. Distribution of R^2 and RMSE values for Jc and stress estimations after 500 times repetition a) R^2 of Jc estimation, b) RMSE of Jc estimation, c) R^2 of stress estimation, d) RMSE of stress estimation

and according to Figures 9(c) and 9(d), in test phase, 480 of data have a R^2 values higher than 0.9 which mean 96% of data are estimated with an accuracy higher than 90%. On the other hand, this value for RMSEs under 50 is about 90%. The reported values indicate that the proposed ANN model has very high stability for Jc/stress estimation.

D. Selecting optimum structure for ANN model

The optimum structure of the proposed ANN model is shown in Figure 10(a) for Jc estimation and in Figure 10(b) for stress estimation. The training method in both cases is selected as LM method while 70% of data are used for training the model. As shown in Figure 10(a), the Jc estimation requires 5 neurons in each layer while this value for stress estimation is 3.

IV. RESULTS COMPARISON WITH OTHER METHODS

A. Comparison with ANFIS method in [24]

To show the capability of the proposed structure of ANN model, Table 7 is presented. In this table, firstly the 7 inputs are used to form an ANN model. Another ANN model is also used for estimating with only 5 inputs. At last, the results are compared with the estimations of ANFIS method [24] to show the improvements that the proposed ANN with 7 inputs is offering. For Jc, the proposed 7 inputs ANN has about 10% higher R^2 value in comparison to 5 inputs ANN and 15% higher than the proposed method of [24]. The RMSE of the 7 inputs ANN is also 10% and 26% lower than two other methods, respectively. By considering estimation computation time, both the 7 inputs and the 5 inputs ANN model has superiority to ANFIS method with 82.4% lower estimation time. The computation times are reported based on running the models on a personal computer with settings as follows: 16GB RAM and Intel Core-i7 3.40 GHz CPU.

For stress estimation, the R^2 value of all methods are very close to each other and by this metric, no method has superiority over others. However, by comparing the RMSE, it can be seen that the value of RMSE in proposed ANN method with 7 inputs is 18.5% lower than ANN with 5 inputs and 6% lower than method published in [24]. When considering estimation computation time as an index, the ANN model with 7 inputs has around 60% lower estimation time. According to the reported results, it can be seen that the ANN model with 7 inputs has a better performance for Jc estimation in comparison to ANN with 5 inputs and ANFIS method published in [24], in terms of accuracy, error, and estimation computation time. On the other hand, the ANN with 7 inputs has also superiority in stress estimation over ANN with 5 inputs and ANFIS, in terms of error and estimation computation time while in terms of R^2 index, all three methods offer a close performance.

B. Comparison with Fitting Methods

ANN models have a significant advantage over fitting methods when they are used for Jc/stress estimation. They can estimate the electro-magneto-mechanical characteristics of 2G HTS tapes with respect to multiple factors such as flux density, temperature, type of tape, strain, etc. In addition, ANN is capable of considering all interdependencies among inputs simultaneously. This is not the case for fitting methods and they usually have two inputs. Although some methods and software give a solution to this for fitting methods and present an n-dimensional equation for curve fitting, they are either too slow, or based on artificial intelligence models to determine the coefficient of polynomial fittings. To compare the best performance of fitting methods for Jc and stress estimations with the ANN model, Figure 11(a) and Figure 11(b) are presented to illustrate the R^2 value of the estimation, based on a general form of polynomial fit shown in equation (7):

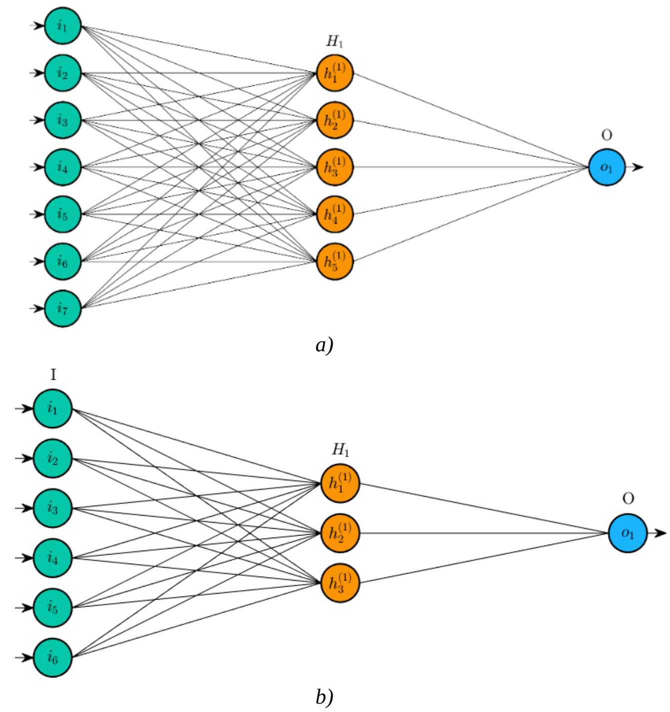


Figure 10. The proposed optimum structures for ANN to be used in a) Jc estimation, b) stress estimation

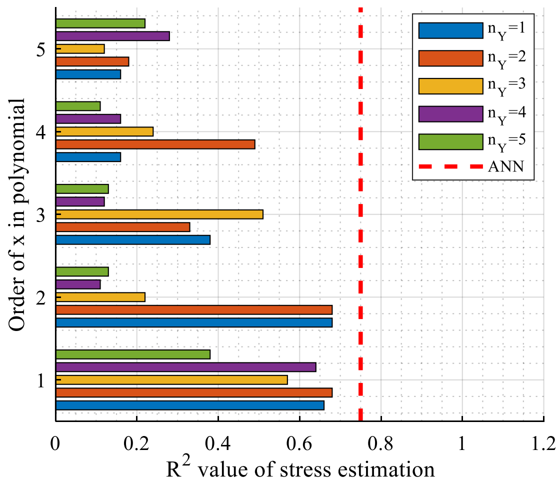
Table 7. A comparison of the accuracy and RMSE of the ANN when thickness of stabiliser and the substrate are considered as inputs and when they are not considered as inputs and also comparison with the method of [24]

models	indices	Proposed ANN with 7 inputs	ANN with 5 inputs	[24]
critical current	R^2	0.93	0.84	0.81
	RMSE	0.042	0.047	0.057
	Time (s)	0.278	0.315	1.573
stress	R^2	0.99	0.98	0.98
	RMSE	39.42	40.05	41.99
	Time (s)	0.316	0.277	0.780

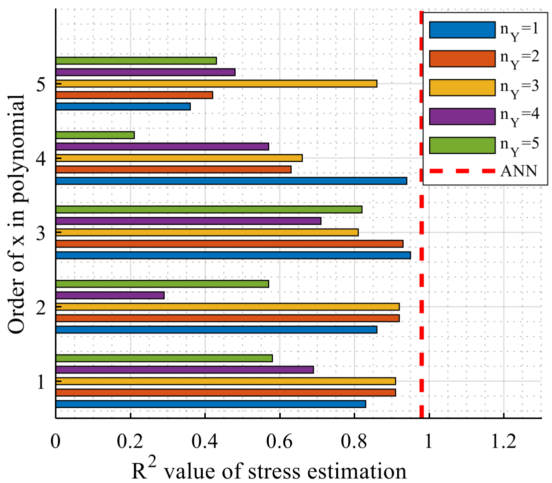
$$F = a_1x^n + b_1^n y + c_1x^n y + c_2x^{n-1}y^2 + \cdots + a_n x + b_n y + c_{nm} \tag{7}$$

where, F is the proposed fitting polynomials, a_i is the coefficient of the polynomial fit for terms that just have x, b_i is the coefficient of the polynomial fit for terms that just have y, c_i is the coefficient of the polynomial fit for terms that are a combination of x and y, and x, y are the inputs which could be any of the 7 inputs of ANN.

Here x and y are considered as thickness of stabiliser and strain, respectively, as this scenario offers the best performance for Jc/stress estimation in ANN model with two inputs and fitting methods. The maximum R^2 of Jc estimation by fitting methods is about 0.68 which is 10% lower than R^2 value of ANN method with two inputs. The highest R^2 value for stress estimation by fitting methods is about 0.94 which is 3% lower than the reported value for ANN with two inputs. Thus, it can be stated that ANN has also superiority in comparison to fitting methods, even when only two inputs are considered. By comparing the results and considering the



a)



b)

Figure 11. R^2 value of polynomial fitting methods based on thickness of stabiliser and substrates, a) For Jc estimation b) For stress estimation

ANN properties, it can be seen that the ANN model is more practical during the design stage of the superconducting devices and fitting methods could not accomplish the same task that offered ANN models. This is due to the fact that fitting methods are not capable of considering many inputs for Jc or stress estimation with high accuracy and low computation time.

V. Conclusion

Electromechanical characteristic of twisted high temperature superconducting (HTS) tapes plays a significant role at the design stage of the HTS cables and magnets. Analysing the stress and critical current density of twisted HTS tapes requires electromagnetic finite element models parallel with thermo-mechanical considerations that leads to long simulation time and extreme computational burden. To overcome this issue, this paper presented a fast and accurate model based on Artificial Neural Networks (ANN) to solve the electro-magneto-mechanical problems of twisted HTS tapes. Unlike finite element-based methods, proposed ANN model is capable of considering all electromagnetic and thermo-magneto-mechanical properties of HTS tapes with a fast-computational speed.

The results show the superiority of the proposed ANN model in comparison to previously presented models in [24] based on other AI-methods as well as curve fitting approaches. A comprehensive sensitivity analysis is conducted to select the optimum range, type, and values of parameters of the proposed ANN model. At last the stability of the results were tested after 500 repeated estimations. The most important findings of this paper are as follows:

- The estimations by ANN have a better performance in comparison to the method that proposed in [24], in terms of higher R^2, lower RMSE, and lower estimation time.
- When comparing with fitting methods, the better performance of the proposed ANN-based model can be clearly observed, especially when fitting methods have only two inputs.
- The most appropriate activation function for stress and critical current estimations is pure linear/log sigmoid with a R^2 value higher than 0.92 for estimating both critical current density and stress.
- The stability of the results is also tested and proven after repeating the estimations for 500 times which indicates the reproducibility and repeatability of the estimations.

References

[1] M. Parizh, Y. Lvovsky, and M. Sumption, “Conductors for commercial MRI magnets beyond NbTi: requirements and challenges,” *Supercond. Sci. Technol.*, vol. 30, no. 1, p. 014007, 2016.

[2] N. M. Strickland *et al.*, “Cryogen-free 1kA-class Ic measurement system featuring an 8 T HTS magnet,” *J. Phys. Conf. Ser.*, vol. 507, no. 2, p. 022037, 2014.

[3] A. Usoskin, U. Betz, J. Gnilsen, S. Noll-Baumann, and K. Schlenga, “Long-length YBCO coated conductors for ultra-high field applications: gaining engineering current density via pulsed laser deposition/alternating beam-assisted deposition route,” *Supercond. Sci. Technol.*, vol. 32, no. 09, p. 094005, 2019.

[4] X. Wang, S. A. Gourlay, and S. O. Prestemon, “Dipole Magnets above 20 Tesla: Research Needs for a Path via High-Temperature Superconducting REBCO Conductors,” *Instruments*, vol. 3, no. 4, p. 62, 2019.

[5] V. A. Anvar *et al.*, “Enhanced critical axial tensile strain limit of CORC® wires: FEM and analytical modeling,” *Supercond. Sci. Technol.*, vol. 35, no. 5, p. 055002, 2022.

[6] A. Sadeghi, S. M. Seyyedbarzegar, and M. Yazdani-Asrami, “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.*, vol. 589, no. July, p. 1353935, 2021, doi: 10.1016/j.physc.2021.1353935.

[7] A. Morandi, “HTS dc transmission and distribution: Concepts, applications and benefits,” *Supercond. Sci. Technol.*, vol. 28, no. 12, p. 123001, 2015, doi: 10.1088/0953-2048/28/12/123001.

[8] M. Yazdani-Asrami, S. M. Seyyedbarzegar, A. Sadeghi, W. T. B. de Sousa, and D. Kottonau, “High Temperature Superconducting Cables and their Performance against Short Circuit Faults: Current

Development, Challenges, Solutions, and Future Trends," *Supercond. Sci. Technol.*, vol. 35, no. 8, p. 083002, 2022.

[9] M. Yazdani-Asrami, M. Zhang, and W. Yuan, "Challenges for developing high temperature superconducting ring magnets for rotating electric machine applications in future electric aircrafts," *J. Magn. Magn. Mater.*, vol. 522, p. 167543, 2021, doi: 10.1016/j.jmmm.2020.167543.

[10] K. S. Haran *et al.*, "High power density superconducting rotating machines - Development status and technology roadmap," *Supercond. Sci. Technol.*, vol. 30, no. 12, p. 123002, 2017, doi: 10.1088/1361-6668/aa833e.

[11] W. Song, X. Pei, J. Xi, and X. Zeng, "A novel helical superconducting fault current limiter for electric propulsion aircraft," *IEEE Trans. Transp. Electrif.*, vol. 7, no. 1, pp. 276–286, 2020.

[12] J. Xi, X. Pei, W. Song, B. Xiang, Z. Liu, and X. Zeng, "Experimental tests of DC SFCL under low impedance and high impedance fault conditions," *IEEE Trans. Appl. Supercond.*, vol. 31, no. 5, pp. 1–5, 2021.

[13] Y. Zhai *et al.*, "Research on the Application of Superconducting Magnetic Energy Storage in the Wind Power Generation System for Smoothing Wind Power Fluctuations," *IEEE Trans. Appl. Supercond.*, vol. 31, no. 5, 2021, doi: 10.1109/TASC.2021.3064520.

[14] J. X. Jin, X. Y. Chen, R. Qu, H. Y. Fang, and Y. Xin, "An integrated low-voltage rated HTS DC power system with multifunctions to suit smart grids," *Phys. C Supercond. its Appl.*, vol. 510, pp. 48–53, 2015, doi: 10.1016/j.physc.2015.01.006.

[15] M. Yazdani-Asrami *et al.*, "Fault current limiting HTS transformer with extended fault withstand time," *Supercond. Sci. Technol.*, vol. 32, no. 3, 2019, doi: 10.1088/1361-6668/aaf7a8.

[16] Muhammad Azizi Abdul Rahman, "Distribution Network Modelling and Analysis of the Application of HTS Transformer," 2012.

[17] Q. Wang *et al.*, "Progress of ultra-high-field superconducting magnets in China," *Supercond. Sci. Technol.*, vol. 35, no. 2, p. 023001, 2021.

[18] N. Mitchell *et al.*, "Superconductors for fusion: a roadmap," *Supercond. Sci. Technol.*, vol. 34, no. 10, p. 103001, 2021.

[19] F. Gömöry and J. Šouc, "Current–voltage curve of the high temperature superconductor with local reduction of critical current," *Supercond. Sci. Technol.*, vol. 34, no. 12, p. 12LT01, 2021.

[20] M. Yazdani-Asrami, S. A. Gholamian, S. M. Mirimani, and J. Adabi, "Investigation on Effect of Magnetic Field Dependency Coefficient of Critical Current Density on the AC Magnetizing Loss in HTS Tapes Exposed to External Field," *J. Supercond. Nov. Magn.*, vol. 31, pp. 3899–3910, 2018.

[21] B. Shen *et al.*, "Development of an HTS magnet for ultra-compact MRI System: Optimization using genetic algorithm (GA) Method," *IEEE Trans. Appl. Supercond.*, vol. 30, no. 4, 2020, doi: 10.1109/TASC.2020.2974417.

[22] M. Yazdani-Asrami *et al.*, "Artificial intelligence methods for applied superconductivity: material, design, manufacturing, testing, operation, and condition monitoring," *Supercond. Sci. Technol.*, vol. E.A, 2022, doi: https://doi.org/10.1088/1361-6668/ac80d8.

[23] M. Yazdani-Asrami, M. Taghipour-Gorjikolaie, W. Song, M. Zhang, and W. Yuan, "Prediction of nonsinusoidal ac loss of superconducting tapes using artificial intelligence-based models," *IEEE Access*, vol. 8, pp. 207287–207297, 2020, doi: 10.1109/ACCESS.2020.3037685.

[24] M. Yazdani-Asrami, A. Sadeghi, S. M. Seyyedbarzegar, and A. Saadat, "Advanced experimental-based data-driven model for the electromechanical behavior of twisted YBCO tapes considering thermomagnetic constraints," *Supercond. Sci. Technol.*, vol. 35, no. 5, p. 054004, 2022, doi: https://doi.org/10.1088/1361-6668/ac57be.

[25] C. Barth, G. Mondonico, and C. Senatore, "Electro-mechanical properties of REBCO coated conductors from various industrial manufacturers at 77 K, self-field and 4.2 K, 19 T," *Supercond. Sci. Technol.*, vol. 28, no. 4, p. 45011, 2015, doi: 10.1088/0953-2048/28/4/045011.

[26] H. S. Shin, M. J. Dedicatoria, S. Awaji, and K. Watanabe, "Characteristic strain response of I c in SmBCO coated conductor tapes under magnetic field at 77 K," *IEEE Trans. Appl. Supercond.*, vol. 22, no. 3, pp. 0–3, 2012, doi: 10.1109/TASC.2012.2182978.

[27] N. Cheggour, J. W. Ekin, C. L. H. Thieme, Y. Y. Xie, V. Selvamanickam, and R. Feenstra, "Reversible axial-strain effect in Y-Ba-Cu-O coated conductors," *Supercond. Sci. Technol.*, vol. 18, no. 12, 2005, doi: 10.1088/0953-2048/18/12/016.

[28] M. Sugano, T. Nakamura, T. Manabe, K. Shikimachi, N. Hirano, and S. Nagaya, "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.*, vol. 21, no. 11, 2008, doi: 10.1088/0953-2048/21/11/115019.

[29] M. Sugano, K. Shikimachi, N. Hirano, and S. Nagaya, "The reversible strain effect on critical current over a wide range of temperatures and magnetic fields for YBCO coated conductors," *Supercond. Sci. Technol.*, vol. 23, no. 8, p. 085013, 2010, doi: 10.1088/0953-2048/23/8/085013.

[30] J. Fleiter, M. Sitko, and A. Ballarino, "Analytical formulation of Ic dependence on torsion of YBCO and BSCCO conductors," *IEEE Trans. Appl. Supercond.*, vol. 23, no. 3, pp. 3–6, 2013, doi: 10.1109/TASC.2012.2228292.

[31] H. S. Shin and M. J. Dedicatoria, "Variation of the strain effect on the critical current due to external lamination in REBCO coated conductors," *Supercond. Sci. Technol.*, vol. 25, no. 5, 2012, doi: 10.1088/0953-2048/25/5/054013.

[32] D. C. Van Der Laan, J. W. Ekin, J. F. Douglas, C. C. Clickner, T. C. Stauffer, and L. F. Goodrich, "Effect of strain, magnetic field and field angle on the critical

current density of y Ba2Cu3O7-δ coated conductors," *Supercond. Sci. Technol.*, vol. 23, no. 7, pp. 2–9, 2010, doi: 10.1088/0953-2048/23/7/072001.

[33] Z. Zhang, D. Zhang, and R. C. Qiu, "Deep Reinforcement Learning for Power System Applications: An Overview," *CSEE J. POWER ENERGY Syst.*, vol. 6, no. 1, pp. 213–225, 2020.

[34] C. C. Aggarwal, *Neural Networks and Deep Learning: A text book*. Springer, 2018.

[35] D. Graupe, *PRINCIPLES OF ARTIFICIAL NEURAL NETWORKS*. World Scientific Publishing, 2013.