IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received October 27, 2020, accepted November 8, 2020, date of publication November 16, 2020, date of current version November 27, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3037685

Prediction of Nonsinusoidal AC Loss of Superconducting Tapes Using Artificial Intelligence-Based Models

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This work was supported by the U.K. Engineering and Physical Sciences Research Council (EPSRC) under Grant EP/P002277/2.

ABSTRACT Current is no longer sinusoidal in modern electric networks because of widespread use of power electronic-based equipments and nonlinear loads. Usually AC loss is calculated for pure sinusoidal current, while it is no longer accurate when current is nonsinusoidal. On the other hand, efficiency of cooling system in large scale power devices is dependent on accurate estimation and prediction of the heat load caused by AC loss in design stage. Therefore, estimation of nonsinusoidal AC loss of high temperature superconducting (HTS) material would be of great interest for designers of large-scale superconducting devices. In this paper, at first nonsinusoidal AC loss of a typical HTS tape was calculated under distorted currents using H-formulation finite element method. Then, a range of artificial intelligence (AI) models were implemented to predict AC loss of a typical HTS tape. In order to find the best and more adaptive AI model for nonsinusoidal AC loss prediction, different regression models are evaluated using Support Vector Machine regression model, Generalized Linear regression model, Decision Tree regression model, Feed Forward Neural Network based model, Adaptive Neuro Fuzzy Inference System based model, and Radial Basis Function Neural Network (RBFNN) based model. In order to evaluate robustness of developed models cross-validation technique is implemented on experimental data. To compare the performance of different AI models, four prediction measures were used: Theil's U coefficients (U_Accuracy and U_Quality), Root Mean Square Error (RMSE) and Regression value (R-value). Obtained results show that best performance belongs to RBFNN based model and then ANFIS based model. U coefficients and RMSE values are obtained less than 0.005 and R-Value is become close to one by using RBFNN based model for testing data, which indicates high accuracy prediction performance.

INDEX TERMS AC loss, artificial intelligence, artificial neural network, current harmonics, HTS tape, loss prediction, numerical calculation, superconductivity.

I. INTRODUCTION

Transport AC loss of high temperature superconducting (HTS) material is one of the most important factors together with carrying current level to design HTS transformers, superconducting magnetic energy storage, HTS cables, and superconducting fault current limiters for power grid applications. The total loss and efficiency of superconducting coils of such large-scale power devices is key parameter for network performance [1], [2]. Modern power network suffers from pollution by voltage and current harmonics due to widespread use of switching and speed control devices, non-linear loads, and lighting control systems [3], [4]. Thus, current in the power grid is no longer sinusoidal, and exhibits a distorted waveform. Therefore, it is vital to estimate precise nonsinusoidal AC loss in any HTS device prior to fabrication and installation, e.g. in design stage.

Some papers in literature studied the effect of nonsinusoidal transport current AC loss on HTS tape, coil, winding, or even in component level using analytical, numerical

The associate editor coordinating the review of this manuscript and approving it for publication was Behnam Mohammadi-Ivatloo.

or experimental approaches [5]–[14]. Most of the research works in this field only considered an arbitrary distorted current waveform such as saw-tooth, square-shape, and triangular, instead of study the effect of each individual harmonic orders on the value of AC loss. The accurate calculation and prediction of nonsinusoidal AC loss is essential for any large-scale power applications, since the thermal stability and performance of cooling system absolutely depends on the value of AC loss as core heat load depends on the loading.

Artificial intelligence (AI) based methods are recently implemented in many different engineering problems. But application of AI models in applied superconductivity problems is certainly overlooked and has not been very popular. For example, artificial neural network (ANN) is an AI based method to solve complex problems such as data regression, classification, or clustering. ANN needs to be trained with data in order to be able to act as estimators and accurately model/represent the data pattern/behavior. ANN has a great potential to be used for solving applied superconductivity problems.

In [15], an analytical equation combined with ANN was linked to a finite element (FE) model in order to predict a semi-analytical formula for the calculation of AC loss of round wires under pure sinusoidal transport current in a fully superconducting rotating machine. The drawback of the proposed work is its complexity, as well as the need for simultaneous and couple working of ANN estimator with FE software. It makes this method slow and not robust enough, because any bug in the estimator side would feed the wrong information to the slow solving FE model. In [16], ANN was used to estimate AC losses of an HTS SMES for thermal stability studies. Firstly, the AC loss were calculated with a multi-scale model in FE software, and then back propagation ANN was implemented in MATLAB to estimate the loss. The current of the SMES was pure sinusoidal current. Results shown that the proposed simple back propagation ANN have between 2.5% to 15% error in estimation. In [17], ANN was used to design a MRI coil with complicated geometry. Using ANN, the design solving process got fast, and its accuracy increased. Still considering some of the parameters in the modeling process to achieve such high accuracy would be exhaustive. In [18], ANN was implemented in thermal design of a transient model for the ITER facility magnet, in order to predict the heat from the magnet to the liquid helium bath load caused by AC loss during plasma operation. The traditional calculation method for such study is exhaustively time consuming, thus, researchers decided to have incredibly faster estimation by giving up about 10% of accuracy.

There is a great potential to make AI involved in processing and estimating AC loss for superconductors, due to the highly nonlinear behavior of the HTS materials which makes FE solving process very slow, as well as expensive price and brittle nature of the HTS materials which make the experimental study very risky. Up to date, there is no literature on application of AI for nonsinusoidal AC loss predicting of HTS tapes. In this paper, firstly a 2D FE model was established in COMSOL Multiphysics to calculate AC loss of a typical HTS tape under current harmonics, with different amplitude, phase angles and harmonic contents to produce enough data for AI models. Secondly, in order to reduce the long computation time of the FE model, as well as complexity of having a harmonic order dependent FE model for AC loss under nonsinusoidal current, AI models including an ANN model were used to predict the nonsinusoidal AC loss for different harmonics. The proposed method is incredibly fast and accurate. The findings of the paper including the proposed best accurate model, will open the door for future online AC loss estimation for HTS electric machines.

TABLE 1. Specifications of HTS coated conductor.

Item	Value
Manufacturer	SuperPower
Tape ID	SCS4050
Width of conductor (w_{sc}), mm	4
Thickness of conductor (t_{sc}), mm	0.1
Thickness of superconducting layer, μm	1
Substrate	Hastelloy
Thickness of substrate, μm	50
Stabilizer	Copper
Thickness of stabilizer, mm	0.04
Critical current (I_c) @ 77K, self-field, A	86

II. AC LOSS OF HTS TAPE UNDER NONSINUSOIDAL CURRENT

Knowledge of AC loss in an HTS tape is critical for technical and economical design of any large-scale superconducting power network devices. Since, it is not only dictating the efficiency of the device, but also the size of it, as well as efficiency of cooling system. Therefore, prediction of AC loss in design stage under nonsinusoidal current is crucial. On the other hand, usually AC loss measurement or calculation is offline and could be done on a piece of short sample, or a device but under experimental set up; whilst using AI based models helps to estimate loss under any new excitation during the operating condition of superconducting devices.

In this paper, the H formulation FE modelling method is used to calculate nonsinusoidal AC losses of a typical HTS tape under different distorted currents at different THDs, carrying current levels, harmonic orders, and phase angles. The parameters of the understudied tape were listed in Table 1. There are two independent variables in FE model, $\boldsymbol{H} = [H_x, H_y]^T$, where H_x and H_y are magnetic field components.

The E-J power law (1) was used to express the nonlinear relation of electric field E and current density J in superconducting layer, as follows [5]:

$$E/J = \left(E_0/J_c(B)\right)\left(\left|J/J_c(B)\right|\right)^{n-1} \tag{1}$$

where $E_0 = 1\ \mu$V/cm, and n = 25 is the power law constant derived from V-I characteristic, and $J_c(B)$ is critical current density dependent on external magnetic field, here a modified Kim model was adopted, as expressed in (2). J_{c0} is the self-field critical current density. The k, α, and

B_0 are curve fitting parameters as 0.41, 0.24, and 41 mT, respectively [8], [19].

$$J_c(B) = J_{c0}\left(1 + \left(k^2B_x^2 + B_y^2\right)\Big/B_0^2\right)^{-\alpha} \tag{2}$$

$$\partial(\mu_0\mu_r\boldsymbol{H})/\partial t + \nabla \times (\rho\nabla\times\boldsymbol{H}) = 0 \tag{3}$$

$$\begin{cases} \mu_0\mu_r\dfrac{\partial H_x}{\partial t} + \dfrac{\partial\left(\rho\left(\dfrac{\partial H_y}{\partial x} - \dfrac{\partial H_x}{\partial y}\right)\right)}{\partial y} = 0 \\ \mu_0\mu_r\dfrac{\partial H_y}{\partial t} - \dfrac{\partial\left(\rho\left(\dfrac{\partial H_y}{\partial x} - \dfrac{\partial H_x}{\partial y}\right)\right)}{\partial x} = 0 \end{cases} \tag{4}$$

Transport current at any time, I_t, was given by the integration of current density at corresponding time, $J(t)$, on the cross-section area Ω of superconducting layer, as shown in (5):

$$I_t = \int_{\Omega} J(t)d\Omega \tag{5}$$

Transport AC loss of superconducting tape, with unit of J/m/cycle, can be calculated by (6):

$$Q = 2\int_{T/2}^{T}\int_{\Omega} \boldsymbol{E}\cdot\boldsymbol{J}\,d\Omega dt \tag{6}$$

where T is the fundamental period of one cycle of applied current.

In this paper, THD was defined to denote distortion of transport current by each harmonic current component (I_{hk}) with respect to fundamental harmonic (I_{h1}), as follows:

$$\text{THD}_k\% = (I_{hk}/I_{h1}) \times 100 \tag{7}$$

$$I_{h1} = i_m \cdot I_c \tag{8}$$

where k is the order of current harmonic, $k = \{3, 5, 7\}$; and $\text{THD}_k = \{10\%, 20\%, 30\%, 40\%, \text{and } 50\%\}$. I_c is the critical current of tape; and $i_m = \{20\%, 30\%, 40\%, \text{and } 50\%\}$. It is worthy to point out that the THD of distorted current in simulations, reasonably covers the THDs of both industrial and domestic nonlinear loads in real world applications.

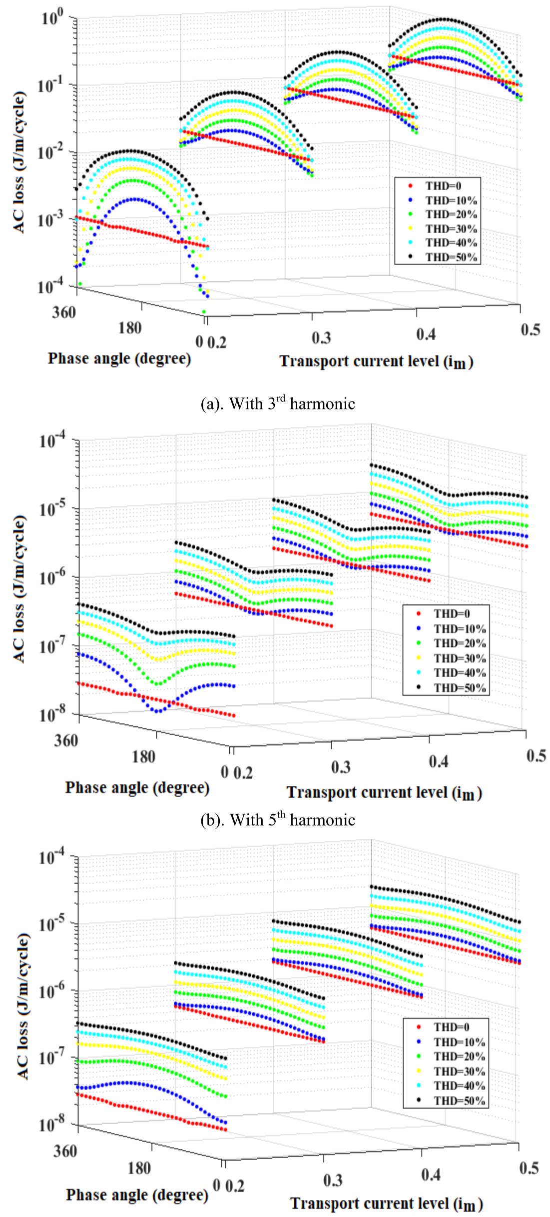
In this paper, φ_k denotes the phase angle of applied nonsinusoidal current. In order to study the effect of phase angle of current harmonics on AC loss in HTS tape, we always keep the phase angle of fundamental current φ_1 as 0, whilst varying phase angle φ_k of each harmonic current from 0 to 2π (i.e., 0° to 360°) by 10° steps.

The nonsinusoidal current, $i_{\text{nonsin}}(t)$ is formulated as follows:

$$i_{\text{nonsin}}(t) = I_{h1}\sin(2\pi ft + \varphi_1) + T\text{HD}_k I_{h1}\sin(2\pi kft + \varphi_k) \tag{9}$$

where f is frequency of fundamental current, in this paper $f = 50$ Hz.

The nonsinusoidal AC losses of the understudied HTS tape were calculated using H-formulation in COMSOL Multiphysics, and illustrated in Fig. 1. In Fig. 1(a), to Fig.1(c), nonsinusoidal AC losses for 3rd, 5th, and 7th harmonics were shown in 3D view versus phase angle of harmonics (φ_k), as well as current carrying level (i_m). As it is depicted in Fig. 1, nonsinusoidal AC losses drastically increased in higher i_m, but the peak of AC loss occurs at different phase angles for different harmonic orders; i.e. maximum AC loss for 3rd and 7th harmonic occurs at 180°, whilst in case of 5th harmonic it occurs at 0°. Therefore, nonsinusoidal AC loss profiles are varying quite differently with phase angle and carrying current level. On the other hand, AC loss is much higher at higher THDs. The peak of AC loss increases with THD following a power law trend.



(a). With 3rd harmonic

(b). With 5th harmonic

(c). With 7th harmonic

FIGURE 1. Nonsinusoidal AC loss in HTS tape carrying harmonic current components at different phase angles and different I_{h1}/I_c ranges from 0.1 to 0.5. (a) carrying the 3rd harmonic. (b) carrying the 5th harmonic. (c) carrying the 7h harmonic.

Now, we use these AC loss data points which are calculated in this section as an input (training and testing) and also validation data for next section to be implemented in AI based models for predicting nonsinusoidal AC loss.

III. IMPLEMENTATION OF ARTIFICIAL INTELLIGENCE-BASED MODELS

The main purpose of this paper is to predict AC loss in HTS tapes while carrying nonsinusoidal current using AI based models. Different regression models such as mathematical and Computational Intelligence (CI) based models could be implemented. Many models were introduced for regression problems in literatures, but they have not been applied for superconducting problems, so it would be necessary to evaluate them to find the best model for AC loss prediction. Therefore, Support Vector Machine (SVM) regression model, Generalized Linear (GL) regression model, Decision Tree (DT) regression model, Feed Forward Neural Network (FFNN) based model with three hidden layers and Adaptive Neuro Fuzzy Inference System (ANFIS) based model and RBFNN based model were considered to find more adaptive and precise one to accurately predict AC losses of a typical HTS tape. Note that GL and DT models are mathematical based regression models while SVM, FNN, ANFIS and RBFNN models are CI based regression models.

A. OVERVIEW OF REGRESSION MODELS

1) GENERALIZED LINEAR REGRESSION MODEL

Simplest choice for modelling linear relationship between a response and predictive term is LR model. Since most of the physical phenomena are non-linear, it is impossible to simply solve them by LR, therefore it is necessary to improve LR performance by nonlinear parameters. LR can be generalized by using gamma distribution. The equations (10) and (11) show the LR and GLR [20].

$$\mu = \mathrm{b} \times \mathrm{X} \tag{10}$$

$$\mu^{-1} = \mathrm{b} \times \mathrm{X} \tag{11}$$

where, vector b defines coefficients of linear combination of the predictors X. The μ is the mean value of the normal distribution which is used for LR.

2) DECISION TREE REGRESSION MODEL

The DTR model works based on a tree structure. Important components of a DT are root node, decision node, leaf node, splitting and pruning. DT structure is plotted upside down, DT starts by a root nod, in the next levels nodes are split into one or more child nodes which is called decision node. Leaf nodes or Terminal nodes are the last nodes in the DT structure.

In the DTR, the mean value of the training data is assigned to the leaf nodes. When test data falls into the tree, its output is predicted by mean values [21].

3) SUPPORT VECTOR MACHINE REGRESSION MODEL

The SVM is basically a collection of set of hyper-planes in high dimensional space. SVM maps input data to higher dimension to increase separability of features between classes or data space. Main concept of SVM is to increase functional margin between hyper-plane and the nearest training data. SVM was introduced for solving complex classification problems, but it can also be applied for regression problems. Support Vector Machine Regression (SVMR) is based on the SVM's concepts and principles with some little changes in calculation of cost function. In the case of prediction (regression) the most important thing is to find a function that maps input data close to real numbers.

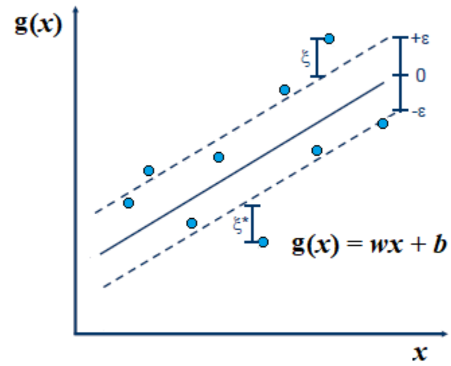


FIGURE 2. A typical regression of SVMR for training data.

Fig. 2 shows that points should be approximate within the decision boundary lines for good prediction. Red lines are the decision boundaries and blue line is the hyperplane that fits to the training data. The goal of SVMR is to minimize errors (ζ and ε) and close decision boundary to the hyperplane. Equation (12) shows the cost function of SVMR which should be minimized with constraints g(xi) - wxi – b $\leq \varepsilon + \zeta$i and wxi + b – g(xi) $\leq \varepsilon + \zeta$i∗ to find best regression model of the problem. To minimize:

$$\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\left(\zeta_i + \zeta_i^*\right) \tag{12}$$

where, w is a weight vector for the model, ζ_i and ζ_i^* are positive marginal values and C is controlling parameter. One the most important controlling parameters which can help to find better solution space for prediction and find more adaptive hyperplanes is kernel. Kernel maps solution space into higher dimensions linearly or non-linearly and could be based on linear, Gaussian, or Polynomial functions.

4) FEED FORWARD NEURAL NETWORK BASED MODEL

The CI based methods usually find the best solution based on an iterative algorithm for finding the optimum value of cost function. In regression problems, cost function is similarity between real output (which is called target) and output of the algorithm (which is called predicted value). Artificial Neural Network (ANN) based methods show their abilities to develop reliable and accurate model to solve non-linear and complex problems in literatures [22]–[25]. One of the basic architectures of ANN is feed forward structure. As it can be seen in Fig. 3, Feed Forward Neural Network (FFNN) includes input layer, hidden layers, and an output layer. Each

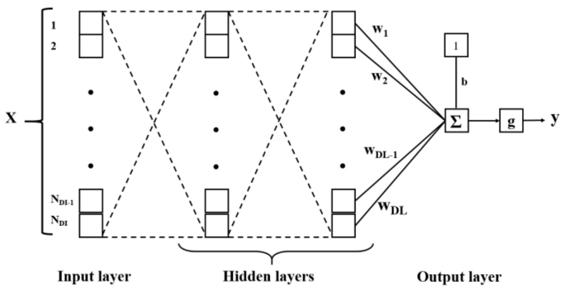


FIGURE 3. A typical structure of Feed Forward NN with two hidden layers.

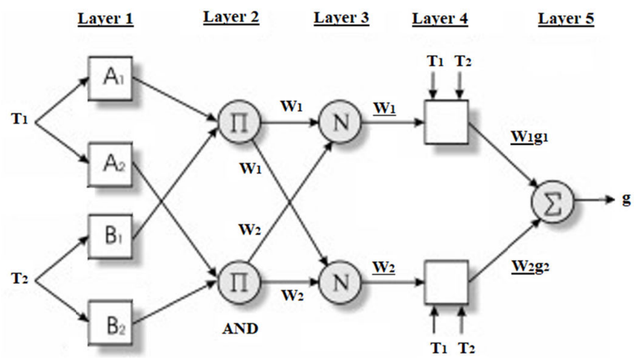


FIGURE 4. Typical structure of ANFIS [27].

layer consists of neurons which are connected to neurons of the next layer by synaptic weights [22]. Equation (13) shows the relation between output and the structure of FFNN.

$$X_J = g(W_{IJ}X_I) \tag{13}$$

where, X_I and X_J are the data in I^{th} and J^{th} layers that J=I+1, W_{IJ} is synaptic weight matrix between I^{th} and J^{th} layers and "g" is called activation or transfer function that could be either a linear or non-linear function.

5) ADAPTIVE NEURO FUZZY INFERENCE SYSTEM BASED MODEL

Another CI method that shows very promising performance is Fuzzy logic [26]. Fuzzy logic-based methods work based on human observation and not based on crisp values, so they are able to consider vagueness and imprecision of data. Developing optimum model for a complex problem is so exhaustive and it needs full knowledge about the physics, technology, and engineering of problem. Therefore, Adaptive Neuro Fuzzy Inference System known as ANFIS was introduced to automatically generate fuzzy set by using ANN structure. As Fig. 4 shows ANFIS includes five layers. At first layer, membership functions are determined for input values which is called Fuzzification layer. In the second layer that is called Rule layer, firing strength of the rules that are generated based on the first layer are predicted. The third layer normalizes the output of previous layer. At next layer, defuzzification procedure is done for the last layer which returns the final predicted value.

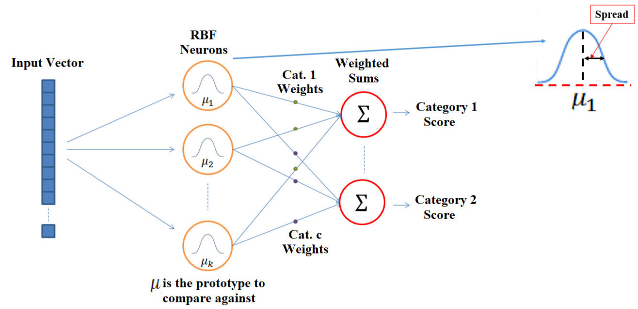


FIGURE 5. A simple frame of RBFNN.

6) RADIAL BASIS FUNCTION NEURAL NETWORK (RBFNN)

Although most of the aforementioned CI methods show promising results, choosing the best one depends on database.

The most important advantage and disadvantage of RBFNN are as follows:

- Advantage: Due to linear mapping from hidden layer to output layer, RBFNN doesn't trap into local minima. By this linearity, error surface becomes quadratic and therefore just has a single minimum.
- Disadvantage: Determining useful RBF centers are extremely depends on the distribution of input data. Therefore, RBFNN can present reliable outputs whenever experimental results are extracted by proper sampling rate.

The Main concept of the RBFNN is to assign input data to closest and most similar training center. RBFNN consists of functions which are based on Gaussian function and so-called Radial Basis Function (RBF). As shown in Fig. 5, RBFNN includes three layers. First layer is input layer and accept the input data. In the second layer, input data is mapped onto hidden layer. Each neuron in this layer is an RBF with a center and a radius (also called spread). Equation (14) shows the formulation of RBF. Center is determined during training step by a learning method but radius should be determined based on the knowledge of database.

$$h(x) = exp\left(-\frac{(x-c)^2}{r^2}\right) \tag{14}$$

where, c and r are center (μ) and radius (Spread), respectively.

The most important variables in RBFNN is its weights. The Euclidean distance between the new point and the center of each neuron is calculated and then RBF is applied to the distance to generate the weight or in other words, the influence of each neuron in output layer. Third layer is summation layer, it means that the output of neurons in hidden layer which are multiplied by their associated weights are added together to be presented as an output.

IV. AC LOSS PREDICTION: RESULTS AND DISCUSSIONS

In this paper, in order to develop AI based models for predicting AC loss of HTS tape under nonsinusoidal current, amplitude, phase angle, and total harmonic distortion of current harmonics are considered as input variables. For each order of harmonics (the 3rd, the 5th, and the 7th), 1110 experimental data are extracted based on the variation of input variables, therefore 3330 experimental data are available for developing AI based prediction models.

In this section, 5-fold cross-validation technique is used to evaluate and validate the robustness of the proposed prediction models; therefore, all results are reported based on the average values with their standard deviation. For each harmonic order (the 3rd, the 5th, and the 7th), 1110 experimental data are partitioned into 5 equal sized subsamples. In each repetition of cross-validation, one subsample is used as testing data, one subsample is used as validating data and remained data are used as training data. The main purpose of this paper is to develop an AI based model to predict AC loss by using amplitude of harmonic current, phase angle of harmonic current, and its THD. The range of these variables are not same and in order to have the best training process, it is necessary to normalize them in a same range. Therefore, Min-Max normalization based on Equation (15) is used to normalize all data into the range of zero to one.

$$Normalized\ data = \frac{(D - D_{min})}{(D_{max} - D_{min})} \tag{15}$$

where, D is input data, Dmin and Dmax are minimum and maximum value of training data. Also, in order to evaluate forecast performance of developed model four prediction measures are used: Theil's U coefficients (U_Accuracy and U_Quality) [28], Root Mean Square Error (RMSE) and Regression value (R-value). Uncertainty entropy coefficients also called Theil's U coefficients which is based on the information entropy concept are used for evaluating the similarity between predicted and target (actual) values. Equations (16) and (17) show Theil's U accuracy and quality coefficients, respectively. The RMSE which is shown in equation (18) represents the square root of the difference between the original and predicted values of AC loss extracted by squared the average difference over the data set. In addition, final evaluation of proposed method for testing data are done by R-value. As equation (19) shows coefficient of determination or R-value represents the coefficient of how well the values fit compared to the original values.

$$U\_Accuracy = \frac{\sqrt{\sum_{i=1}^{n}\left(Target_i - Predicted_i\right)^2}}{\sqrt{\sum_{i=1}^{n}\left(Target_i\right)^2}} \tag{16}$$

$$U\_Quality = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Target_i - Predicted_i\right)^2}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Target_i\right)^2} + \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Predicted_i\right)^2}} \tag{17}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Target_i - Predicted_i\right)^2} \tag{18}$$

$$R - value = 1 - \frac{\sum_{i=1}^{n}\left(Target_i - Predicted_i\right)^2}{\sum_{i=1}^{n}\left(Target_i - mean\right)^2} \tag{19}$$

TABLE 2. Sensitivity analysis of model type for GLR based models for 3rd, 5th, and 7th harmonics. Bold values are the best in each harmonic.

Model type \ Harmonic	3rd	5th	7th
Constant	0.8472±0.0003	0.8370±0.0003	0.8331±0.0005
Linear	0.5566±0.0003	0.5005±0.0015	0.4843±0.0018
Quadratic	**0.3489±0.0024**	**0.2319±0.0007**	**0.1999±0.0005**
Interaction	0.4908±0.0016	0.3948±0.0005	0.3711±0.0003

TABLE 3. Sensitivity analysis of variables' distribution for GLR based models for 3rd, 5th, and 7th harmonics. Bold values are the best in each harmonic.

Distribution \ Harmonic	3rd	5th	7th
Normal	0.3490±0.0024	0.2319±0.0007	0.2000±0.0005
Poisson	**0.0832±0.0008**	**0.0766±0.0004**	**0.0300±0.0001**
Gamma	0.2291±0.0016	0.2058±0.0064	0.2085±0.0027
Inverse Gaussian	1.246e+39	1.0480e+39	0.964e+39

where, Targets are true values, Predicted are estimated values, mean is average of true values and "n" is the number of training data. It should be mentioned that target value for Theil's U coefficients and RMSE is zero and for R-value is one.

A. SENSITIVITY ANALYSIS OF THE PROPOSED AI BASED MODELS

The main goal of this paper is to find best and adaptive model for predicting AC loss of superconductors under nonsinusoidal currents, therefore, each model is justified in its best performance. In each repetition of cross-validation process, models are trained by training data and then, trained model is evaluated by validating data and U_Accuracy as prediction measure for all the harmonics. All obtained results are shown based on the average of U_Accuracy values for five separated runs and their standard deviation.

1) GLR BASED MODEL

Generalized Linear Regression (GLR) has two main controlling parameters, model specification and distribution function. Model specification (type) helps to find and select best functional form for a statistical model and determine which variables could be included. Most well-known model specifications are 'Constant', 'Linear', 'Quadratic', and 'Interaction'. Another parameter is distribution of variables which can be 'Normal', 'Poisson', 'Gamma', and 'Inverse Gaussian'. As it can be seen in Tables 2 and 3, best model specification for all harmonics is 'Quadratic' and by using this model type best distribution is 'Poisson'.

2) DTR BASED MODEL

Using best algorithm for selecting the best split predictor at each node of the tree, plays an important role for the DTR performance. Obtained results which are shown in Table 4 prove

TABLE 4. Sensitivity analysis of predictor algorithm for DTR based models for 3^{rd}, 5^{th}, and 7^{th} harmonics. Bold values are the best in each harmonic.

Algorithm \ Harmonic	3^{rd}	5^{th}	7^{th}
All splits	**0.1459±0.0130**	**0.0649±0.0043**	**0.0266±0.0012**
Curvature	0.1951±0.0192	0.0723±0.0091	0.0356±0.0051
Interaction	0.1956±0.0192	0.0703±0.0067	0.0356±0.0051

TABLE 5. Sensitivity analysis of Kernel type for SVMR based models for 3^{rd}, 5^{th}, and 7^{th} harmonics. Bold values are the best in each harmonic.

Kernel \ Harmonic	3^{rd}	5^{th}	7^{th}
Gaussian	**0.1785±0.0290**	0.1695±0.0134	0.1153±0.0069
Linear	0.6399±0.0024	0.5726±0.0012	0.5542±0.0026
Polynomial	0.2265±0.0018	**0.1143±0.0007**	**0.0688±0.0008**

TABLE 6. Sensitivity analysis of the type of activation function for FFNN based models for 3^{rd}, 5^{th}, and 7^{th} harmonics. Bold values are the best in each harmonic.

Activation function \ Harmonic	3^{rd}	5^{th}	7^{th}
Gaussian	0.2914±0.0929	0.1226±0.0402	0.0852±0.0644
Pure line	0.5585±0.0024	0.5014±0.0022	0.4889±0.0080
Triangular basis	0.3948±0.0488	0.2255±0.1076	0.1836±0.0667
Logarithm sigmoid	**0.1821±0.0991**	**0.0990±0.0410**	**0.0444±0.0232**
Hyperbolic tangent sigmoid	0.2062±0.1084	0.1207±0.0404	0.0508±0.0256

that using 'All splits' algorithm will lead to better performance in comparison with 'curvature' and 'interaction' algorithms. By using 'All splits' algorithm, all possible splits are considered as predictor and it helps to search all solution space.

3) SVMR BASED MODEL

One of the most important advantage of SVMR is using Kernel. It can map feature space into higher dimension and helps regression model to find more adaptive space to the target values. Most common used Kernels for SVMR are 'Gaussian', 'Linear', and 'Polynomial' types. According to the obtained results in Table 5, Gaussian and Polynomial kernels present similar performance, but in the most of the harmonics 'Polynomial' kernel is better than other kernels.

4) FFNN BASED MODEL

Two main parameters of FFNN structure are number of hidden layers and Activation Function (AF) which is applied on each neuron in the layers. In order to find proper AF, at first FFNN is initialized with one hidden layer consisted of 3 neurons. Table 6 shows that best performance could be obtained by using 'Logarithm sigmoid' AF.

Then, sensitivity analysis has been done on the number of layers by using 'Logarithm sigmoid' AF for all neurons.

TABLE 7. Sensitivity analysis of the type of membership function for FFNN based models for 3^{rd}, 5^{th}, and 7^{th} harmonics. Bold values are the best in each harmonic.

Membership function \ Harmonic	3^{rd}	5^{th}	7^{th}
Gaussian	**0.0075**±0.0009	**0.0121**±0.0002	**0.0033**±0.0002
Trapezoid	0.0353±0.0013	0.0258±0.0004	0.0076±0.0001
Generalized bell-shaped	0.0114±**0.0005**	0.0177±**0.0001**	0.0041±**0.0001**
Triangular	0.0274±0.0014	0.0081±0.0006	0.0092±0.0002

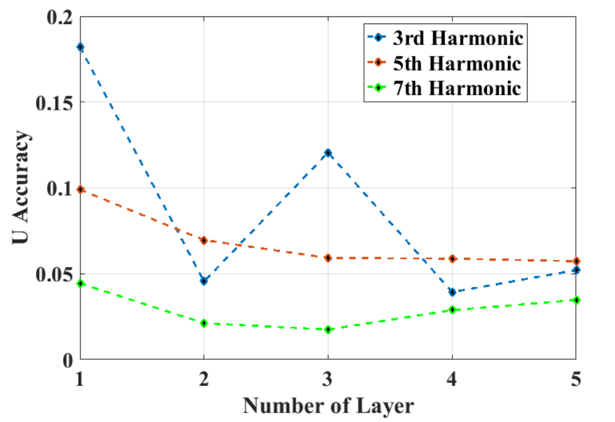


FIGURE 6. Sensitivity analysis of the number of hidden layers for FFNN based models for 3^{rd}, 5^{th}, and 7^{th} harmonics.

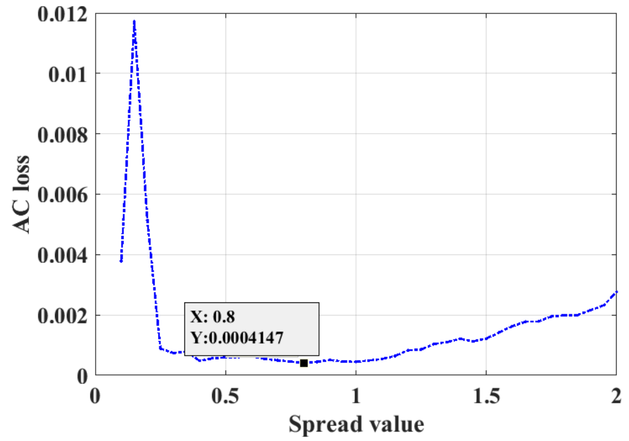


FIGURE 7. A sample of finding the best spread value for the proposed RBF model.

Fig. 6 shows that best performance could be achieved by increasing the number of hidden layers. In other hand, computational cost will be increased by the structure deepens, while results are not changed significantly. Therefore, best structure could be obtained by four hidden layers.

5) ANFIS BASED MODEL

It is absolutely important in any Fuzzy sets to use Membership Functions (MFs) most adaptive to the nature of data and the solution space. It helps the rules of Fuzzy sets to

TABLE 8. Individual proposed models for 3^{rd}, 5^{th}, and 7^{th} harmonics.

Harmonic	3^{rd}	5^{th}	7^{th}
Range of Spread	[0.25 , 0.6]	[0.5 , 1]	[0.5 , 1]
U_Accuracy	0.0035±0.0011	0.0061±0.0012	0.0005±0.0000

TABLE 9. Obtained results for training data by using proposed AI models for 3rd, 5^{th}, and 7^{th} harmonics.

		3^{rd} Harmonic		
model	U_Accuracy	U_Quality	RMSE	R_Value
GLR	0.5600±0.0007	0.3063±0.0005	0.1145±0.0002	0.5648±0.0009
DTR	0.1010±0.0043	0.0506±0.0022	0.0207±0.0008	0.9858±0.0012
SVMR	0.1858±0.0288	0.0944±0.0177	0.0379±0.0063	0.9414±0.0285
FFNN	0.1032±0.1659	0.0064±0.0048	0.0040±0.0038	0.9999±0.0000
ANFIS	0.0016±0.0001	0.0008±0.0000	0.0003±0.0000	1.0000±0.0000
RBF	0.0004±0.0002	0.0002±0.0004	0.0000±0.0000	1.0000±0.0000
		5^{th} Harmonic		
model	U_Accuracy	U_Quality	RMSE	R_Value
GLR	0.497±0.0014	0.2663±0.0008	0.2663±0.0008	0.6453±0.0015
DTR	0.0585±0.0016	0.0293±0.0007	0.0293±0.0007	0.9951±0.0002
SVMR	0.1654±0.0012	0.0831±0.0077	0.0831±0.0077	0.9582±0.0054
FFNN	0.0483±0.0593	0.0352±0.0395	0.0352±0.0395	0.9983±0.0007
ANFIS	0.0016±0.0000	0.0007±0.0000	0.0007±0.0000	1.0000±0.0000
RBF	0.0026±0.0019	0.0013±0.0009	0.0013±0.0009	1.0000±0.0000
		7^{th} Harmonic		
model	U_Accuracy	U_Quality	RMSE	R_Value
GLR	0.4870±0.0006	0.2599±0.0004	0.1274±0.0003	0.6585±0.0007
DTR	0.0207±0.0007	0.0103±0.0003	0.0054±0.0001	0.9994±0.0000
SVMR	0.1147±0.0011	0.0579±0.0031	0.0324±0.0057	0.9818±0.0018
FFNN	0.0126±0.0042	0.0061±0.0024	0.0074±0.0063	0.9983±0.0031
ANFIS	0.0003±0.0000	0.0001±0.0000	0.0000±0.0000	1.0000±0.0000
RBF	0.0002±0.0000	0.0001±0.0000	0.000±0.0000	1.0000±0.0000

cover all possible events. Table 7 shows that 'Gaussian' and 'Generalized bell-shaped' MFs are the best options for this research work. By using 'Gaussian' MF, lowest value of U_Accuracy can be obtained, while low value of U_Accuracy with least value of standard deviation can be achieved by using 'Generalized bell-shaped' MF.

6) RBFNN BASED MODEL

As mentioned in section (III.A.6.) the most important parameter for RBFNN is spread of radial basis function. In each repetition of cross-validation, proper spread value has been found by seeking from 0.001 to 5. As it can be seen in Fig. 7 which is one of the variations of the spread value for validating data for 5th harmonic, best spread value is 0.8. Sensitivity analysis on spread value as presented in Table 8 shows that best performance of RBFNN could be achieved when the spread value is considered in the range of 0.5 to 1.

B. NONSINUSOIDAL AC LOSS PREDICTION FOR SPECIFIED HARMONIC ORDER

According to the results of sensitivity analysis process, best parameters are considered for AI models. In this step, in order to evaluate proposed AI models, 5-fold cross-validation technique is used. In each repetition, models are trained by training data and then, performance of trained model is evaluated using testing data. Evaluations are done based on four prediction measures which are presented in equations (16) to (19).

TABLE 10. Obtained results for testing data by using proposed AI models for 3rd, 5^{th}, and 7^{th} harmonics.

		3^{rd} Harmonic		
model	U_Accuracy	U_Quality	RMSE	R_Value
GLR	0.5592±0.0025	0.3058±0.0012	0.1144±0.0003	0.5657±0.0029
DTR	0.1429±0.0162	0.0719±0.0083	0.0292±0.0033	0.9713±0.0060
SVMR	0.1859±0.0288	0.0944±0.0177	0.0380±0.0064	0.9413±0.0285
FFNN	0.1058±0.1681	0.0073±0.0058	0.0043±0.0037	0.9999±0.0000
ANFIS	0.0060±0.0014	0.0030±0.0007	0.0012±0.0002	0.9999±0.0000
RBF	0.0034±0.0019	0.0017±0.0009	0.0006±0.0003	1.0000±0.0000
		5^{th} Harmonic		
model	U_Accuracy	U_Quality	RMSE	R_Value
GLR	0.4982±0.0034	0.2673±0.0034	0.2673±0.0034	0.6445±0.0037
DTR	0.0638±0.0009	0.0320±0.0003	0.0320±0.0003	0.9942±0.0001
SVMR	0.1680±0.0084	0.0846±0.0107	0.0846±0.0107	0.9568±0.0092
FFNN	0.0484±0.0595	0.0358±0.0399	0.0358±0.0399	0.9982±0.0000
ANFIS	0.0029±0.0007	0.0014±0.0004	0.0014±0.0004	1.0000±0.0000
RBF	0.0067±0.0019	0.0034±0.0009	0.0034±0.0009	1.0000±0.0000
		7^{th} Harmonic		
model	U_Accuracy	U_Quality	RMSE	R_Value
GLR	0.4864±0.0025	0.2599±0.0011	0.1276±0.0008	0.6593±0.0031
DTR	0.0262±0.0045	0.0131±0.0009	0.0069±0.0004	0.9990±0.0001
SVMR	0.1162±0.0045	0.0588±0.0019	0.0329±0.0050	0.9812±0.0012
FFNN	0.0133±0.0046	0.0064±0.0031	0.0075±0.0063	0.9981±0.0033
ANFIS	0.0008±0.0002	0.0004±0.0001	0.0002±0.0000	1.0000±0.0000
RBF	0.0005±0.0000	0.0002±0.0000	0.0001±0.0000	1.0000±0.0000

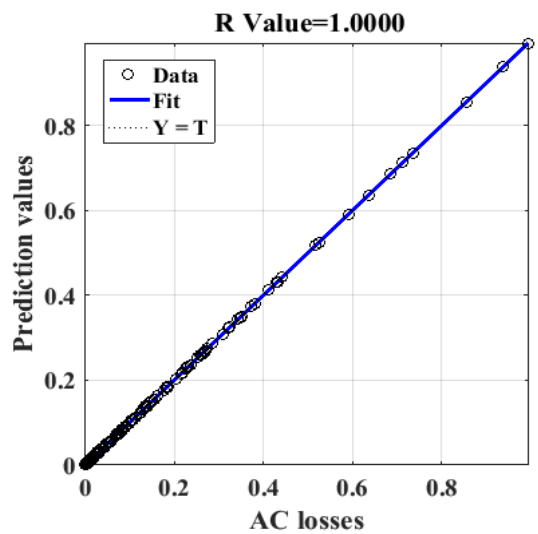


FIGURE 8. Fitted predicted values versus Targets.

Table 9 and 10 show the performance of proposed models for training and testing data in the 3^{rd}, the 5^{th}, and the 7^{th} harmonics, respectively. Obtained results for training data show that ANFIS and RBF based models present best performance. Although, the performance of these two models are so similar but according to the obtained results for testing data RBF based model shows better performance.

C. A GENERAL AI BASED MODEL FOR ALL HARMONIC ORDERS

Obtained results for testing data show that RBF based model is very accurate and reliable. Therefore, in this section to achieve final goal of this paper which is to introduce a general model to predict nonsinusoidal AC loss of HTS tape under different current harmonics, RBF based model is introduced.

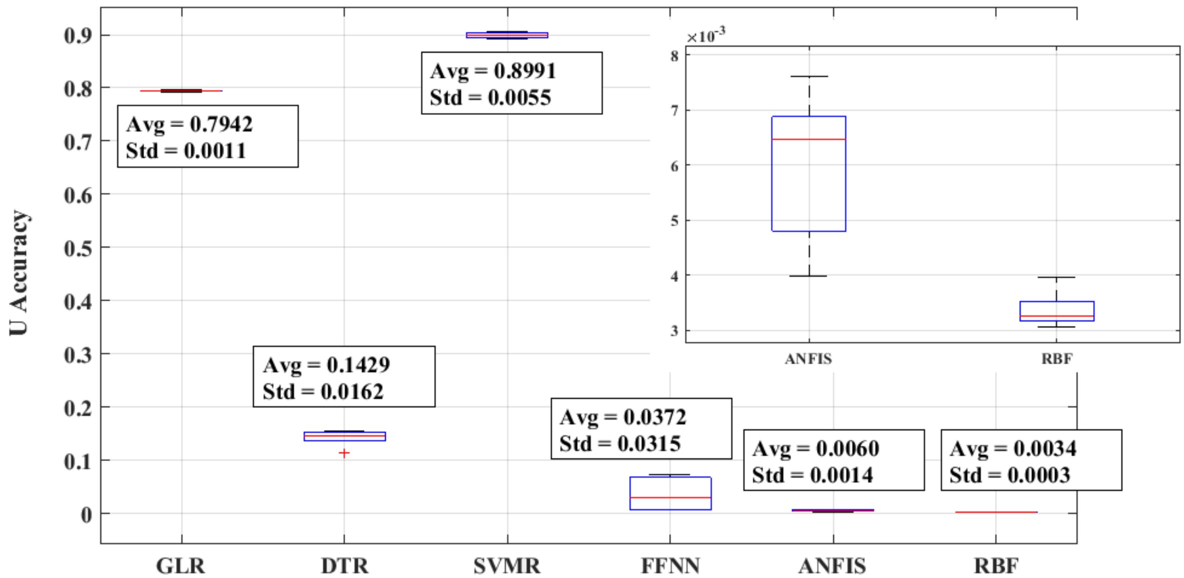


FIGURE 9. Comparison between proposed RBF based model and other AI based model according to U_Accuracy measure.

TABLE 11. Obtained results for evaluating RBF based models for all experimental testing data.

		Training data		
model	**U_Accuracy**	**U_Quality**	**RMSE**	**R_Value**
RBF	0.0006±0.0004	0.0003±0.0002	0.0000±0.0000	1.0000±0.0000
		Testing data		
model	**U_Accuracy**	**U_Quality**	**RMSE**	**R_Value**
RBF	0.0034±0.0003	0.0017±0.0001	0.0003±0.0000	1.0000±0.0000

Same as previous sections, cross-validation is used to evaluate prediction performance of proposed model. All 3330 experimental data are partitioned into five equal sized subsamples. In this step, order of harmonic is considered as input variable in addition to three mentioned variables, therefore, four input variables are used to develop RBF based model.

According to the sensitivity analysis spread value is considered as 0.5. Table 11 shows the performance of proposed model based on four measure factors and Fig. 8 presents the regression results for testing data in one repetition of cross-validation.

Obtained results for RBF based model show that U_Accuracy, U_Quality and RMSE are close to zero and R_Value is one. In addition, Fig. 9 which is based on U_Accuracy measure illustrates that RBF based model is accurate and reliable in comparison with other AI based models. According to Fig. 9 performance of DTR-, FFNN-, ANFIS- and RBF based models are so promising. Among them best performance is belong to RBF, while ANFIS is so close to it. FFNN based model has acceptable average value but its standard deviation is not good enough.

V. CONCLUSION

Application of artificial intelligence in applied superconductivity is certainly overlooked. In this paper, several artificial intelligence-based models and approaches were introduced and implemented for predicting AC loss of a typical HTS tape. For this purpose, nonsinusoidal AC losses of the tape were modeled using finite element method based on H-formulation in COMSOL Multiphysics. Three main orders of current harmonics i.e. 3^{rd}, 5^{th} and 7^{th} orders were considered to distort the transport current. Amplitude, phase angle, and total harmonic distortion of current harmonics were considered as study parameters.

Six deferent AI based models are considered to find more adaptive and robust prediction model, which are Support Vector Machine (SVM) regression model, Generalized Linear (GL) regression model, Decision Tree (DT) regression model, Feed Forward Neural Network (FFNN) based model with three hidden layer and Adaptive Neuro Fuzzy Inference System (ANFIS) based model and RBFNN based model. For each harmonic order, sensitivity analysis has been done to find best controlling parameters for AI based models. Trained models are tested for 3^{rd}, 5^{th} and 7^{th} orders and also for all harmonic orders condition.

Our investigations based on obtained results for training and testing data with cross-validation technique show that best prediction performance is belong to RBFNN. RBFNN based model presents less than 0.001 and 0.005 U_Accuracy value for training and testing data, respectively. Also, R_Value for both of them is close to one. After RBFNN, ANFIS based model could be a good choice for predicting AC loss with less than 0.009 U_Accuracy value.

The AI-based models presented and implemented in this paper, open new doors for introducing and using them in the field of applied superconductivity. In addition, the optimal model of this paper will enable online loss prediction of HTS coils and windings in superconducting rotating machine of future electric aircrafts.

The future work is to use fuzzy logic/system for setting a smart system capable of predicting the AC loss of HTS rotating machine while nonsinusoidal current is a spectrum of 20 harmonic components. This proposed fuzzy model will be compared with the presented ANFIS and ANN models of this paper from accuracy point of view. Note that fuzzy model is an expert system, which not only needs data to be set, but also need a deep knowledge of the problem/system as well.

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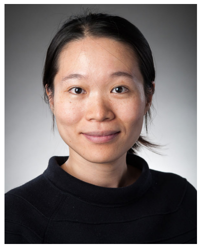

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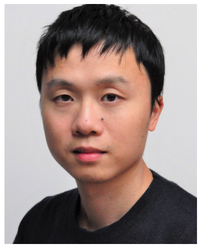

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