Prediction of 2G HTS tape quench behavior by random forest model trained on 2D FEM simulations

D. Sotnikov, M. Lyly, and T. Salmi

***Abstract*—Detailed Finite Element Method (FEM) based simulations for 2G HTS tapes return high quality results, but the computation takes a long time due to the non-linearity of superconducting properties and they needed high mesh density. This work describes a method for prediction of quench behavior in a long 2G HTS tape based on a series of 2D FEM model simulations for short length of tape in many different conditions. The random forest model is trained by the set of results from the short-pieces FEM calculations. Subsequently the model can be applied to any length of HTS tape with similar thermal characteristics. Comparison of quench simulation in 10 cm long HTS tape between a detailed FEM model and a fully trained random forest model show that the predicted temperatures are within 0.68 %, while the computation time is significantly faster: The random forest model ran in less than 1 s, while the run time of the FEM model was 5:30 min.**

***Index Terms*—2G HTS tapes, quench, machine learning, random forest.**

I. Introduction

MODELLING of 2G high temperature superconductor (HTS) tapes is a difficult and a computationally high-cost process due to the non-linearity of material properties and the tape multi-component structure with very thin material layers [1]–[6]. Furthermore, the non-uniform critical current distribution along the tape leads to local differences in electrical conductivity. Each drop of the critical current value may bring a local quench (hot-spot) which can lead to tape overheating if not properly protected.

Two methods are often used for simulation of quench and the subsequent thermal processes in superconductors: 1) continuously connected homogenized pieces of superconductors (1D homogenization) [5], [7]; 2) detailed FEM analysis with all structures [4], [6]. The first method is based on the assumption of uniform temperature distribution in short piece of wire, and parallel connection of the tape's layers for getting homogenized electrical resistivity, thermal conductivity, and specific heat. This method is much faster than the 2D FEM analysis with all layers, but the results may not be accurate if the properties are not uniform along the tape length. Moreover, the temperature distribution may not be uniform across the tape thickness due to its high aspect ratio (typically 4 mm or 12 mm of width and about 0.1 mm of thickness) and non-symmetric structure of the constituent layers. We made an example computation to illustrate the non-uniform heat dissipation within HTS tape thickness (Fig. 1). The FEM model is based on [4], [6], [8], [9] and it was realized in Comsol Multiphysics [10] in accordance with recommendations from [6] and used the same mesh as presented in [4], [6]. The computational domain is a 2D longitudinal cross-section of an HTS tape. The tape critical current is 300 A, except that in the right side of the tape the critical current drops to 180 A. This domain corresponds to a symmetrical 10 mm piece of HTS tape with hot-spot in the middle (Fig. 2). Current of 300 A is applied to only superconducting layer on the left side and from there it distributes according to the tape layer resistivities. Fig. 1 shows how the temperature increases on the quench location at the tape right side and heat diffuses along the tape during the first 10 ms. There is up to 2 K difference between the top and bottom of the tape as it is presented in Fig. 1c.

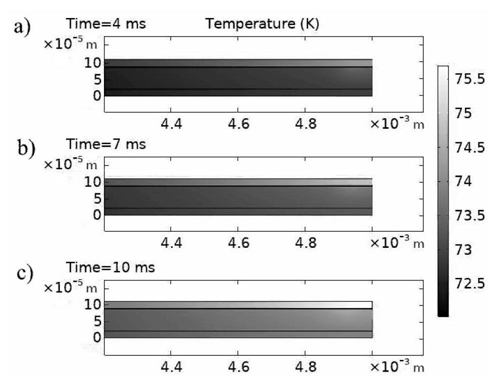

Fig. 1. 2D FEM simulation along the HTS tape length showing the temperature distribution at different time instants after starting a linear current ramp-up of the sample with initial temperature 72 K. The time instants correspond to currents of a) 120 A; b) 210 A; c) 300 A. At the right end of the tape the critical current is locally reduced to 180 A, while in the rest of the tape is 300 A.

The research was funded by Business Finland project #3972/31/2019 (SMARAGDI) and by Academy of Finland grant #334318 (HiQuench).

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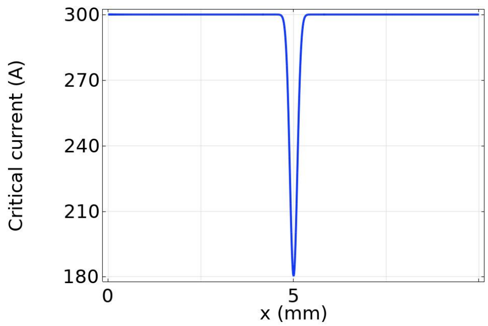

Fig. 2. Critical current drop modeled as a Gaussian function.

This work describes a method for prediction of quench behavior in HTS tapes with the accuracy of 2D FEM simulations, but with significantly reduced computational cost. The model is based on a commonly-used machine learning algorithm known as Random forest. The model is trained with data from a series of 2D FEM simulations for short length of tape in many different conditions. Subsequently, it can be applied to any length of HTS tape with similar thermal characteristics. The following parameters are associated in each point of the tape structure: critical current, applied current (or time, if the DC transport current is a known function of time) and temperature. The trained model predicts the temperature distribution in the tape versus time, for a given current input function.

II. Material Properties

2G HTS tapes include several thin material layers [1]–[6]. Typically, the buffer layer is less than 0.5 µm [3], and it can be neglected in the computation. All the other layers: copper and silver stabilization layers, hastelloy substrate, and superconducting YBCO layer should be considered in the heat diffusion. The thicknesses of the layers in the analyzed case are summarized in Table I and specific properties of each material are presented in [4], [7], [8], [11].

TABLE I
Layer thicknesses of the considered HTS tape

Parameter	Unit	Value
Copper stabilizier (each side)	µm	20
Silver between substrate and copper	µm	1
Silver between YBCO and copper	µm	3
Hastelloy substrate	µm	60
YBCO	µm	2

The copper stabilization layer has the highest impact on heat diffusion: its thermal conductivity is the same as that of silver, but its thickness is 10 times larger. It has the same impact on the total resistivity of the tape. It is necessary to take into account also the non-linear resistivity of 2G HTS tape superconducting layer (ρ_{SC}) that is presented in equation (1) [4], [6], [8], [9].

$$\rho_{SC} = \frac{E_0}{J_c(T)}\left(\frac{J}{J_c(T)}\right)^{n-1}, \tag{1}$$

where E_0 is the critical electric field criterion used in the critical current measurement, J_c is the critical current density - a value of applied current density when superconductor transfers to normal state, and J is the current density in the superconductor. The critical temperature is from [9], and the other relevant parameters are summarized in Table II.

TABLE II
Parameters of 2G HTS tape

Parameter	Unit	Item	Value
Critical current initial (T = 72 K, B = 0 T)	I_{c0}	A	300
Critical temperature	T_c	K	90
Initial temperature	T_0	K	72
n-value	n		20
Critical current criteria	E_0	µV/cm	1

The tape J_c may vary along the tape length due to the tape manufacturing process characteristics, mechanical stress during coil fabrication, non-uniform applied magnetic field, or internal temperature gradients in conduction cooled systems. In this analysis we consider only known local reductions of initial J_c, and the general J_c temperature dependency, using (2) [8], [9]:

$$J_c(T) = \begin{cases} J_{c0}(\frac{T_c - T}{T_c - T_0}), & forT < T_c. \\ 0, & forT \geq T_c \end{cases} \tag{2}$$

III. Computation Methods

A. FEM Model

Normal operation of HTS tape is well described by electrical model [6], [8], [12] and applied to 2D geometry: redistribution of currents J between layers is going in accordance with temperature-dependent electrical conductivities $\sigma(T)$ (3).

$$J = \sigma E \tag{3}$$

$$q_e = EJ = \frac{1}{\sigma}J^2 \tag{4}$$

In case the applied current exceeds critical current, the tape resistivity increases, and part of the applied current penetrates to normal conducting layers, leading to electrical heating (5) [6], [8], [12]. Thermal model computes temperature increase in material layers based on their density ρ, heat capacity C_p and thermal conductivity k. The material properties also depend on temperature, and must be updated after each time step.

$$\rho C_p \frac{dT}{dt} - \nabla \cdot (k \nabla T) = q_e \tag{5}$$

For providing the training data for the Random forest model, a 5 mm-long-piece of 2G HTS tape is simulated. The critical current distribution is similar than the one presented in Fig. 2. It is reversed Gaussian function with center in point 5 mm. Gaussian function returns a plot with narrow peak that describes critical current drop typical for hot-spot, and at the same time this function is smooth which makes it easier to deal with it in the FEM computation. We applied the symmetry condition for heating model on the edge of the tape with coordinate 5 mm on x-axis - it corresponds to a 10-mm long tape with a hot-spot in the middle. In the simulated 5 mm length of the tape the minimum of critical current is on one end.

The optimal mesh size along the HTS tape was recommended 1.25 mm in [6]. But it is correct in case for uniform critical current distribution along the tape. In case of local drop of critical current even with a smooth shape of critical current drop is required a denser mesh. Otherwise, the current distribution near hot-spot is not determined properly. For this work we used 0.05 mm for each cell of mapped (rectangular) mesh along the tape.

B. Random Forest Model

Random forest algorithm is an ensemble method based on decision tree method [13], [14], which continuously checks at each point whether the label of its features meet a specific criteria. The simplest example of a decision tree for a set of numbers is: if number (feature) is more than 0 (criteria) then it is positive number (label), else if it (feature) is less than 0 (criteria) then it is negative (label), otherwise it is 0 (label) (see an example of Random Forest method in Fig. 3). The training algorithm for the random forest method applies bootstrapping: randomly choosing sampling for minimization of error and avoiding over-fitting of predicted model.

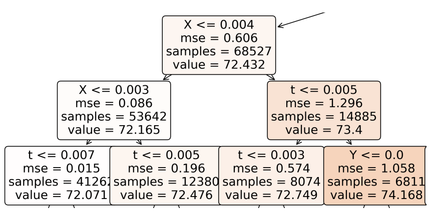

Fig. 3. Example of decision tree branch for the Random Forest model with displayed features X, Y and t, labels are equal to "value", and criteria are presented in comparison with features.

Random forest algorithm works very well for supervised learning tasks as we have in this work. Supervised means that the algorithm gets a training data as a set of known inputs and outputs, and it adjusts the weights until the model is fitted accurately. In our case the labeled dataset for input consists of selected points (w) (coordinates in the tape), and their known features (X) (critical current and time). The output, or label y, is the simulated temperature at this point (6):

$$X \cdot w = y. \tag{6}$$

The main task of algorithm is to create a model that could predict values (labels) for a new feature set. Random forest is a typical machine learning algorithm that includes training of the model and validation of it. During the training, algorithm uses a part of the input data for training, and the rest of the input data for testing and estimating the model accuracy.

In this work we use the Python library scikit-learn [15]) package for the random forest implementation. It has been applied for solving tasks in superconductivity also earlier [16]. For training we use the train_test_split module and assign 75 % of the input data for training, and 25 % for validation.

IV. Results

A. Data Acquisition

The final model should predict temperature in each point of the 2G HTS tape based on several parameters which impact on temperature. So, the w parameter in (3) is an array of two columns, set of x and y coordinates of all points in the tape. The y parameter is a temperature in each point.

For this computation we applied current linearly increasing from 0 A to 300 A in 10 ms. It corresponds to DC charge of superconducting device. So, one of column for training data we took time (due to linear dependence, we could take applied current as well). In the input labeled data set of random forest model we took only steps with integer millisecond.

The second feature is a critical current which is relevant only for the superconducting layer. We consider critical current constant in y direction (along the superconducting layer thickness), and varies only as a function of x. For the input data set simulations we took the tapes with different value of critical current in the hot-spot (values varied from 120 A up to 240 A), while the maximum remained 300 A (the same as presented in Fig. 2 with variable critical current drop in the center).

TABLE III
Example of Data for Random Forest Model

X		w		y
I_c, A	t, s	x, m	y, m	T, K
300	0.01	0	0	72.012414
300	0.01	5e-5	0	72.012441
300	0.01	0	4e-6	72.012414
300	0.01	5e-5	4e-6	72.012441
300	0.01	0	8e-6	72.012441

Some example data is presented in Table III. The final number of rows in the training data set table is 606 606 that is data for each point (mesh element) in 2D HTS tape model. It includes 10 time steps (1 ms per step) for each 20 critical current profiles. Running all those simulations with COMSOL takes several hours, but it has to be done only once. The same data can later be used also for other models.

B. Training and Prediction

We aimed to provide enough data to be able to train a high quality random forest model. Typically quality of the model should be checked by training with 70-75 % of data and use the rest of the data for validation. This was solved by using quick and powerful instrument for work with big data - the train_test_split module in scikit-learn package of Python [15]. It splits input datasets of X and y in datasets for train (for example, X_train and y_train) and for verification of model (X_test, y_test) by rows with ratio which is required. The data was split on 75 % for training and 25 % for test using train_test_split module.

The RandomForestRegressor from [15] was fitted using the training data. The comparison of 100 points of test data (FEM) and predicted data (Random Forest) is presented in Fig. 4, where "FEM" results are temperature of HTS tape points from

Comsol computation and "Random Forest" are temperature gotten by Random Forest method.

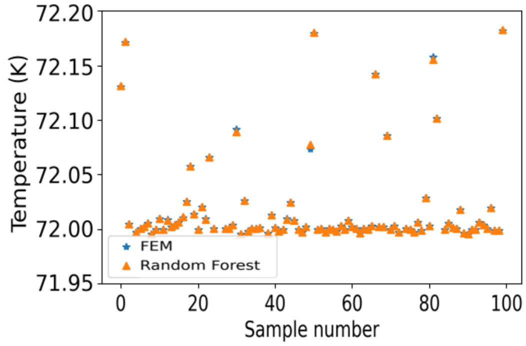

Fig. 4. Comparison of FEM model direct computation results and predicted data from trained Random Forest algorithm.

The mean absolute error was 0.00117 and mean squared error was 0.000108. This result fully satisfies the requested quality of computation.

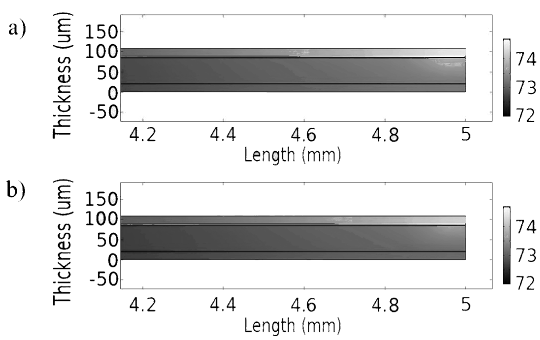

Fig. 5. Verification of predicted values by Random forest algorithm where: a) FEM; b) predicted.

For getting training data for analysis, several experiments with critical currents in range between 120.5 A and 238.2 A were provided. The result from random forest model was uploaded to Comsol for visualization and comparison of the data in equal environment. One of the results is presented in Fig. 5, where mean absolute error and mean squared error are 1.55e-3 and 4.83e-5 which means high quality of computed results.

C. Application of the Model to a Longer Tape

To demonstrate the benefits when simulating long tapes, the new method was applied to a 10 cm long tape with critical current distribution including 3 drops as presented in Fig. 6. The critical currents at the drops were 180 A, 190 A and 130 A. None of these values were among the input data for training the model. The current was applied by the same linear dependence as was described above: in 10 ms up to 300 A.

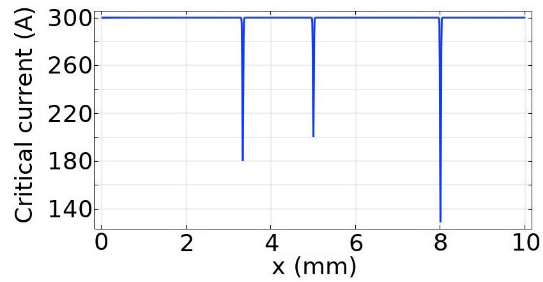

Fig. 6. Critical current distribution along the considered 2G HTS tape.

The trained random forest model returns temperature distribution very close to computation result from FEM (Fig. 7). The computation is time much faster: 1:28 minutes for random forest algorithm (including training) versus 5:30 minutes for FEM. We foresee that the difference in computation time will increase when increasing the length of the tape because 1:27 minutes took for uploading, processing and training data. After the training was computed, the random forest model run time was less than 1 s.

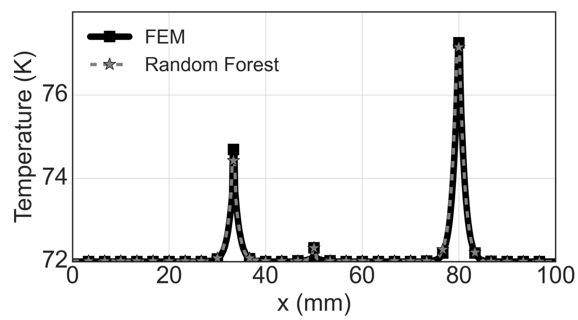

Fig. 7. Comparison of temperature distribution given by the COMSOL FEM simulation and the random forest model prediction that was generated in Python.

V. Conclusion

This paper describes a new machine learning method based approach for computation of quench behavior in 2G HTS tapes. It takes a set of FEM computations of 2G HTS tape short pieces as initial data with the critical current and applied current as features array, and temperature in each point as label array. The data was used for training a random forest algorithm and then predicting temperature evolution in 2G HTS tape of chosen geometry during quench.

In the shown example case of 10 cm long tape simulation, the trained model run time was less than 1 s, and the predicted temperatures were within 0.002 K from a detailed FEM simulation (Fig. 7). The corresponding FEM simulation run time was 5:30 min. In longer tapes, the advantage of faster computation time is likely to become even more significant.

The presented method is still completely new, and further works have to be done to explore the limits of its applicability and the requirements for the input data used for its training. Also other regression methods such as Linear, Ridge, Lasso, and XGB could be considered [17], and ultimately more HTS tape parameters can be included, such as current distribution and Lorentz force.

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