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Lifetime Estimation of Enameled Wires Under Accelerated Thermal Aging Using Curve Fitting Methods

MUHAMMAD RAZA KHOWJA[1], GULRUKH TURABEE[2], PAOLO GIANGRANDE[1], (Senior Member, IEEE), VINCENZO MADONNA[1], (Member, IEEE), GEORGINA COSMA[3], (Member, IEEE), GAURANG VAKIL[1], (Member, IEEE), CHRIS GERADA[1,3], (Senior Member, IEEE), AND MICHAEL GALEA[1,4], (Senior Member, IEEE)

[1]Power Electronics, Machines and Control Research Group, University of Nottingham, Nottingham NG7 2RD, U.K.
[2]School of Science and Technology, Nottingham Trent University, Nottingham NG11 8NS, U.K.
[3]Department of Computer Science, School of Science, Loughborough University, Loughborough LE11 3TU, U.K.
[4]Key Laboratory of More Electric Aircraft Technology of Zhejiang Province, Ningbo 315100, China

Corresponding author: Muhammad Raza Khowja (raza.khowja@nottingham.ac.uk)

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ABSTRACT Estimating the lifetime of enameled wires using the conventional/standard test method requires a significant amount of time that can endure up to thousands of testing hours, which could considerably delay the time-to-market of a new product. This paper presents a new approach that estimates the insulation lifetime of enameled wire, employed in electrical machines, using curve fitting models whose computation is rapid and accurate. Three curve fit models are adopted to predict the insulation resistance of double-coated enameled magnet wire samples, with respect to their aging time. The samples' mean time-to-failure is estimated, and performance of the models is apprised through a comparison against the conventional 'standard method' of lifetime estimation of the enameled wires. The best prediction accuracy is achieved by a logarithmic curve fit approach, which gives an error of 0.95% and 1.62% when its thermal index is compared with the conventional method and manufacturer claim respectively. The proposed approach provides a time-saving of 67% (83 days) when its computation time is compared with respect to the 'standard method' of lifetime estimation.

INDEX TERMS Neural network, curve fitting, insulation lifetime, thermal aging, accelerated aging test, insulation resistance and dissipation factor.

I. INTRODUCTION

For safety-critical applications, like aircraft and marine, the electrical machines such as actuator motors and starter-generators) need to be highly reliable. In terms of insulation system of electrical machines, the weakest component is represented by a turn-to-turn insulation layer, whose breakdown might lead to over-temperatures that can trigger most severe faults (such as phase-to-ground and phase-to-phase insulation failures) and this eventually leads to motor outage [1], [2]. Today, industries such as aerospace and marine are heading towards more electrified solutions and quicker thermal lifetime evaluation that makes fast manufacturing of electrical machines an essential requirement. But, the major concern with the standard method [3], [4] of thermal lifetime evaluation is the amount of time required to estimate the lifetime of electrical machines which can take up to thousands of testing hours, lasting several months [5]. Therefore, fast and accurate tools are required which are capable of estimating motor insulation lifetime quickly and precisely, thus, enabling faster manufacturing of newly designed electrical machines [6], [7].

Neural networks (NN) have been employed successfully to resolve complex and diverse problems, including identification and control of non-linear systems, financial

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marketplace analysis, signal modelling and power system load-forecasting. This is done by training them in a supervised manner [8] that can approximate any continuous function as closely as required [9]. Recent studies have focused on the prediction of various non-linear diagnostic parameters of insulation systems (i.e. dissipation factor (Tanδ), Insulation Resistance (IR), Insulation Capacitance (IC), tensile strength, elongation, breakdown voltage etc.), through different NN architectures such as Radial Basis Function Network (RBFN), Backpropagation (BP), Long Short-Term Memory (LSTM), and curve fitting methods [5], [6], [10]–[14]. In [10], the tensile strength and elongation of XLPE cables were predicted with a RBFN using the Random Optimisation method as its training algorithm. Subsequently, the dielectric loss of transformer oil was predicted through a RBFN, however, in this case, the BP algorithms with Levenberg-Marquardt were adopted [11]. Similarly, LSTM, a newly developed recurrent neural network known for its capability of preserving internal memory, was employed by Shpreker *et al.* [12]. The IR of electrical equipment was predicted for early detection of potential failures, while variations in ambient humidity and air temperature were taken into consideration. In [6], [7], authors propose an alternative approach relying on a supervised NN that can significantly reduce the time required for lifetime evaluation under thermal aging tests. The supervised NN is based on a feedforward NN trained with Bayesian Regularisation Backpropagation (BRP) algorithm. The network predicts the wire IR and mean time-to-failure (MTTF) that reveals an accurate match of prediction outcomes with an error of 0.125%, when its thermal index is compared with standard method [3], [4] followed by the total time-savings of about 57%. In [5], [13], a Curve Fitting (CF) approach is adopted, on custom made motorettes, which considerably shortens the time required for thermal lifetime evaluation of low voltage electric motors. The mean value of differential IC is evaluated at the highest aging temperature (i.e. 290°C) along with its estimated MTTF using Weibull Probability Plot. The value of differential IC at which MTTF is reached is taken for other aging temperatures to predict the MTTF at 250°C and 270°C thermal exposures. This method has shown to result in an overall time-savings of about 1560 hours which is about 68% for the presented case-study. In addition, Gulrukh Turabee *et al.* [14] have introduced a comparative study of three CF approaches at 290°C aging temperature by predicting IR, under thermal stress, which is further explored in this paper.

According to the existing literature, a NN and CF methods can be used as efficient and effective tools that can provide alternatives to the conventional ‘standard method’ described in [3], [4]. This is mainly due to the intrinsic characteristics of the NN technique, such as its 1) ability to automatically learn the relationship between inputs and outputs; 2) size independency and complexity of the problem; 3) generalisation capacity; and 4) integration facility with other computational tools. Therefore, this paper proposes a surrogate approach that estimates the lifetime of electrical insulation systems using CF models which is then compared with NN approach proposed in [6], [7]. Three CF models (i.e. exponential, logarithmic and power CFs) are adopted to predict the IR of enameled wire, under thermal stress. By adopting CF approach, it is possible to accurately predict the lifetime of an insulation system, thus, enabling the proper design of electrical machines and avoiding the over-engineering [15]. For the purpose of validation, the predicted lifetime and thermal index have been validated experimentally against the conventional ‘standard method’.

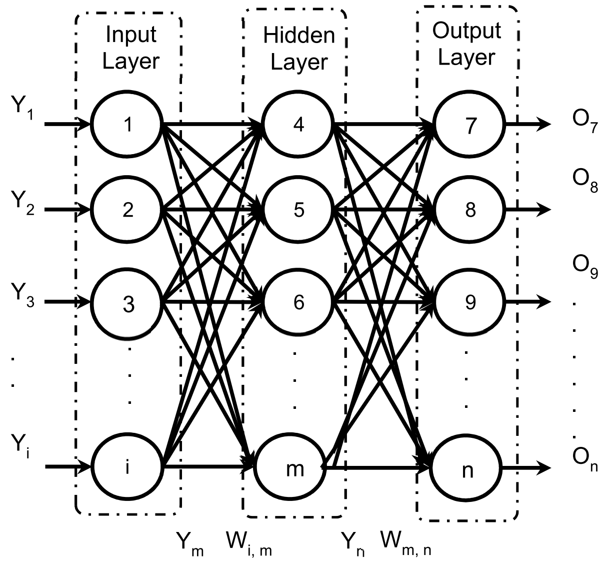

FIGURE 1. Architecture of BRP Neural Network with one hidden layer.

II. PREDICTION MODELS

A. NEURAL NETWORK MODEL

BRP, as shown in Fig. 1, is a multi-layer feedforward NN with one input, one output and one or multiple hidden layers. The input layer transmits the input signal through the hidden layer and reaches final output node. Hence, the output of the next layer is only influenced by the nodes of the previous layer. Having the advantage of a reliable and simple structure, this NN is a suitable algorithm to model non-linear systems. When a specified pattern is fed into input layers, the weighted sum W of the input Y to the mth node is represented by (1), in the hidden layer, calculating combined input to neuron.

$$\mathrm{S}_m = \sum_{i=1}^{n} W_{i,m} Y_m + \theta \tag{1}$$

where, n is the number of input layers. These inputs are propagated through a neuron which takes a linear combination of the inputs and transforms them through the sigmoid activation function. The weighted value from a bias node is represented by θ with an output value of 1 [14], [16].

An appropriate activation function (i.e. sigmoid function) decides the action potential of neuron i.e. (2). The output value from the activation function estimates the neuron’s output and is an input value for the neurons in the successive layer connected to it.

$$O_m = Y_n = \frac{1}{1+e^{-S_m}} \tag{2}$$

The difference between the expected and predicted value can be calculated using (3) where T_n is the predicted value and O_n represents an expected value.

$$\Delta_n = T_n - O_n \tag{3}$$

Weights can be modified using (4), where, $\Delta W_{m,n}$ is the change in weight between node m and n and l_r is the learning rate.

$$\Delta W_{m,n} = l_r Y_n \Omega_n \tag{4}$$

Ω_n is the error signal for node in the output layer and can be represented by (5).

$$\Omega_n = \Delta_n O_n (1-O_n) \tag{5}$$

B. CURVE FITTING MODELS

Curve Fitting is the process of creating a mathematical model that provides the best fit to specific curves in the dataset, in the form of mathematical equations. Curve Fitting models estimate the points anywhere along the curve, and can be utilized for estimating the lifetime of an insulation system by predicting the IR, followed by the time-to-failure associated with each sample. This section describes three different CF models which have been developed for predicting the lifetime of low voltage enameled wire at thermal exposures of 250°C, 270°C and 290°C, which is then extrapolated under normal stress levels through least mean square method [6], [7]. The details of CF models used to predict the lifetime are described below.

Let y(t) be the output of the curve fitting model, t be the input data given to the model, and A, B, m, c, P and d, are curve fitting constants which are to be determined using the given dataset.

1) EXPONENTIAL CF

The exponential function fits a curve through a given set of data points (for e.g. any insulation's diagnostic property), as described by (6). The exponential function, (6), is generally used when the rate of change of a parameter is proportional to the initial amount of the quantity. If the coefficient *B* is negative, the function exponentially falls, whereas, if coefficient *B* is positive, then *y* represents exponential growth [14].

$$y(t) = Ae^{Bt} \tag{6}$$

2) LOGARITHMIC CF

The Logarithmic function fits a curve through a given dataset in the form of (7). For this case, if the coefficient *m* is negative, the function represents logarithmic decline whereas, if the coefficient *m* is positive, the function represents a logarithmic growth or increase [14].

$$y(t) = m \cdot ln(t) + c \tag{7}$$

3) POWER SERIES CF

The Power series function fits a curve through a given dataset in the form of (8). In this case, if the coefficient *d* is negative, the function represents a decrease through a power law whereas, if *d* is positive, the function increases through a positive power law [14].

$$y(t) = Pt^d \tag{8}$$

III. ACCELERATED AGING TESTS

Electrical machines, when in operation, are subject to different stresses such as thermal, electrical, ambient and mechanical [17]. For low voltage electrical machines, thermal stress is the major cause of gradual insulation deterioration that can result in winding failure, eventually leading to the whole drive's outage [1], [18]. In practice, insulation system used in the windings of electrical machines are often made of organic materials. When these organic materials are exposed to thermal stress, they may progressively lose their electric withstanding capabilities. This is due to the onset of chemical reactions triggered by high temperatures [6], [19]. Insulation lifetime models are based on accelerated aging tests which are used to estimate the lifetime of enameled wires, where the samples of insulating material (such as twisted pair wire, random wound coils or custom-made motorettes) are subject to a constant thermal stress above their thermal index. Therefore, the aim of this work is to evaluate the lifetime of enameled wires, employed in electrical machines, using accelerated aging tests, based on the description of the test sample and procedure detailed in the following subsections.

A. TEST SAMPLE

The test sample holder is equipped with ten unaged twisted pair wires (without any resin or varnish application) as shown in Fig. 2. The samples were prepared according to the American Standard ASTM D2307 [4]. The wire has a thermal index of 220 °C (as claimed by the manufacturer) that guarantees 20,000 hours of insulation life at this temperature. The wire features a double layer of enamel i.e. a modified-polyester on base coat and a polyamide-imide insulation on top coat, which comes with a diameter of 0.4mm and insulation thickness of $\approx 25\mu$m. The length of each sample is fixed to 200mm with 20 twists on it, as recommended by the technical standards [3], [4]. The circuit of the sample holder is shown in Fig. 3. This circuit is designed such that one side of the wire is open circuited (i.e. a_2 and b_2 terminals), whereas, the second side of the wire is taken out for the measurement purpose. The terminal a_1 of each twisted pair wire is connected with a common copper bar which is connected with the ground terminal of MEGGER (black lead). The terminals a_2 of each wire are available for the measurement which is connected with the high voltage terminal of the MEGGER device (red lead), ensuring full voltage is applied between the two insulation layers.

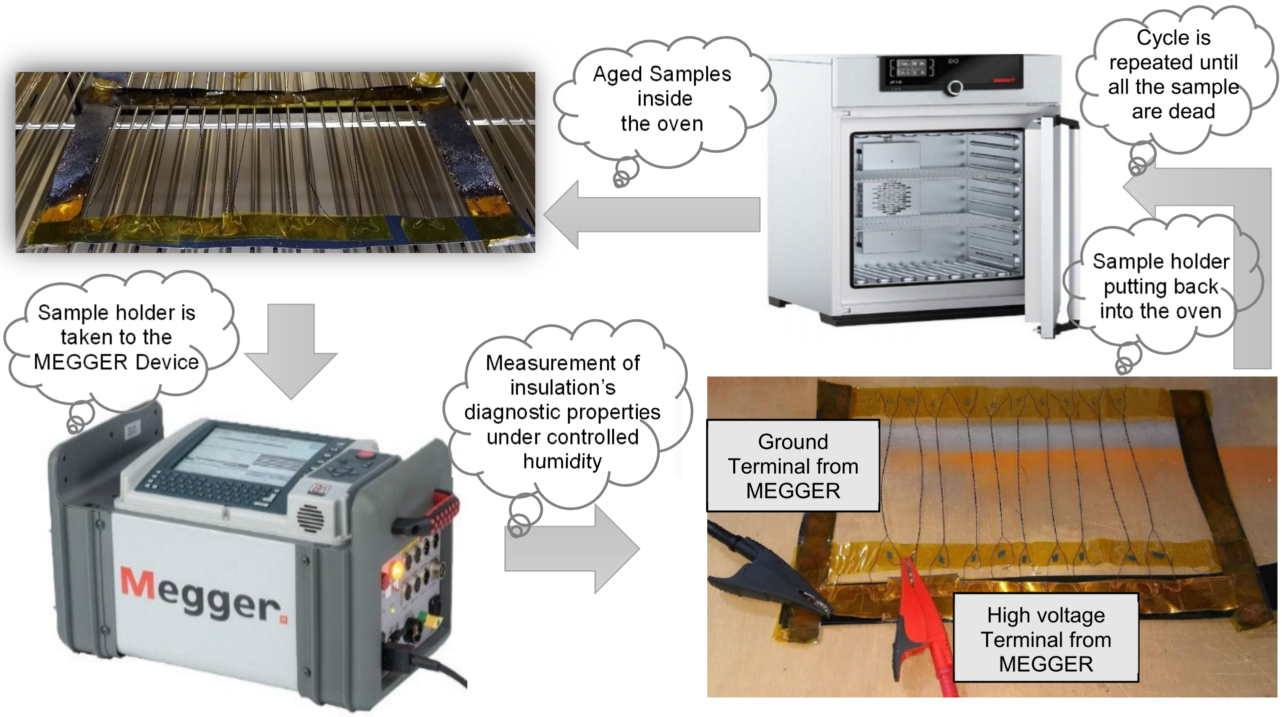

FIGURE 2. Measurement Setup for Accelerated Aging Tests.

B. THERMAL EXPOSURE AND EXPOSURE TIME

For this study, three thermal exposure points and time for each aging cycle were chosen according to the rule described by the Arrhenius law [20]–[22]. To enhance the statistical significance of the predicted time-to-failure, the Standard in [23] recommends that the number of aging cycles must be considered between 10 and 20 or higher [23]. In this Standard, the thermal exposure is obtained by using (9), where T_F is the aging temperature considered during the test procedure, T_i is the insulation thermal index, j is the number of desired aging cycles and 20,000 represents the life of insulation at thermal index as defined by the manufacturer. Based on (9), the exposure times ($t_{exposure}$) of 120h, 48h and 8h were obtained for the thermal exposures of 250°C, 270°C and 290°C respectively, which is at least 30°C higher than the thermal index of the enameled wire.

$$t_{exposure} = \frac{20,000 \times 2^{(T_i - T_F)/10}}{j} \tag{9}$$

C. MEASUREMENT SETUP AND TEST PROCEDURE

The measurement setup and thermal lifetime estimation procedure (i.e. thermal life identification) are shown in Fig. 2. The procedure recommends a series of heat exposures (whose temperature and duration have been determined according to [20]–[22]), followed by a diagnostic session during which an AC voltage (i.e. test voltage of 500V in step of 50V) is applied across the insulation for assessing the thermal degradation level. Therefore, thermal life identification consists of two separate and subsequent steps: 1) the thermal exposure

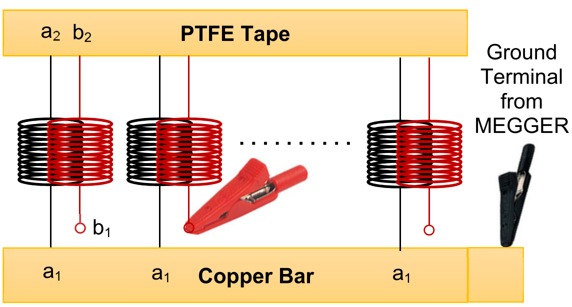

FIGURE 3. Twisted-pair wire circuit connections.

of the samples (i.e. twisted pairs) by using a temperature controlled oven, and 2) the diagnostic session via the dissipation factor tester (i.e. MEGGER device). During the diagnostic session, the diagnostic parameters, such as dissipation factor and insulation capacitance are measured and the end of life of the sample (i.e. insulation breakdown) is eventually detected. Indeed, each sample (i.e. twisted pair) is carried through repeated cycles of the thermal exposure and diagnostic measurements in sequence until the insulation breakdown occurs (i.e. the end of life is reached). With known measured values of dissipation factor and insulation capacitance, the insulation resistance of each twisted pair sample is determined by using (10), where, ω is the frequency of the applied voltage across the insulation layer, IR is the insulation resistance, IC is the insulation capacitance and Tanδ is the dissipation factor.

$$IR = \frac{1}{\omega \times IC \times Tan\delta} \tag{10}$$

IV. PREDICTION USING NN AND CF MODELS

This section discusses the prediction of insulation resistance using NN and CF methods. The NN proposed in [6], [7] was compared to the CF model in terms of prediction accuracy and time-saving. The insulation breakdown criteria is developed which helps in predicting the time-to-failure of every sample under dedicated aging thermal exposures. The training and prediction phase of the NN, its choices and considerations; insulation end of life criteria; selection of learning time for prediction using CF models; and prediction analysis and results using the NN network and CF methods are presented in the next sub-sections.

TABLE 1. Curve fit constants for different Learning Time (LT).

CONSTANTS	LT 24h	LT 32h	LT 40h	LT 48h	LT 56h
A	1.7792	1.6203	1.5991	1.5274	1.452
B	-0.027	-0.02	-0.019	-0.017	-0.014
m	-0.464	-0.41	-0.417	-0.403	-0.384
C	2.475	2.2881	2.3062	2.2676	2.2145
P	3.2783	3.0127	3.256	3.2512	3.1621
d	-0.389	-0.354	-0.385	-0.384	-0.374

A. NN TRAINING AND PREDICTION PHASE

In the training phase of NN, the Bayesian Regularisation algorithm (BRP) is used where training is performed on a given set of samples (10 per aging temperature) having the form of (R_i, R_{i+1}) where R_i is the value of IR at aging time t_i whereas, R_{i+1} is the predicted value of IR at aging time t_{i+1}. In the prediction phase, to predict each sample's future value of IR R_{i+1} at aging time t_{i+1}, the model was trained on a set of data with input as aging time as (i.e. t_i, t_{i+1}) and output as IR (i.e. R_i, R_{i+1}). To achieve optimised prediction results, a training trade-off exercise was carried out using the BRP training algorithm described in [6].

B. CHOICES AND CONSIDERATIONS

In [6], the NN, number of neurons, and the insulation diagnostic property were chosen that will be used in this study. The BRP neural network was adopted which was tuned at 5 number of neurons to achieve its best performance in terms of predicting IR with respect to aging time, under thermal stress. For prediction analysis, several considerations were made during the accelerated aging test procedure. The test procedure was started and completed first at highest aging temperature (i.e. 290°C thermal exposure) until a breakdown in every sample is detected. This sets an insulation breakdown criteria for other aging temperatures (i.e. 250 °C and 270 °C). The tests were completed for 250°C and 270°C thermal exposures until the 7^{th} aging cycle, where the test procedure was purposely stopped, in order to predict the life of every sample, using NN and CF models. Once the prediction phase is completed, the experimental tests were resumed and completed for 250°C and 270°C aging temperatures (started from 8^{th} aging cycle until the insulation breakdown is detected in every sample). Subsequently, after successful competition of the test procedure, the failure times are post-processed using statistical methods, to validate the effectiveness of the proposed prediction methods against the experimental results.

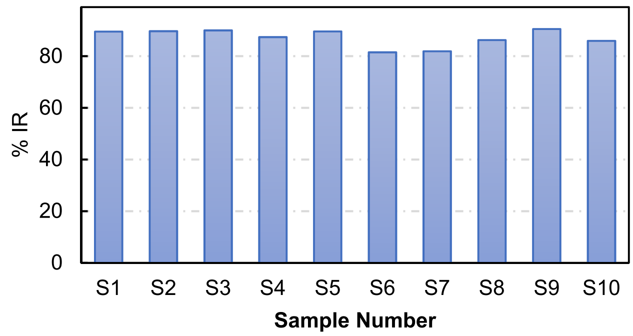

FIGURE 4. Insulation breakdown criteria (% IR at 290° C).

C. BREAKDOWN CRITERIA OF INSULATION

In order to obtain an insulation breakdown criteria, the %IR corresponding to the failure time of every sample, was determined at 290°C thermal exposure. The %IR was determined with respect to its unaged value of each twisted pair wire using (11), where $IR_{breakdown}$ is the IR at aging time one cycle before the sample's breakdown is detected and IR_{unaged} is the sample's IR value when the sample is virgin i.e. when the sample is not being exposed to any aging temperature. It was investigated that, for all the 10 samples, at 290°C aging temperature, the %IR was in the range of 82% to 90% (as shown in Fig. 4), where the mean ($\%IR_{br} = 87.22\%$) among all the samples was chosen as insulation breakdown criteria in predicting time-to-failure of every samples at remaining 2 aging temperatures i.e. 250 °C and 270°C [6], [7].

$$\%IR = 100 \times \frac{IR_{unaged} - IR_{breakdown}}{IR_{unaged}} \tag{11}$$

D. SELECTION OF LEARNING TIME FOR PREDICTION USING CF MODELS – A TRADE-OFF STUDY

As stated earlier, first, the experimental test procedure was conducted and completed at 290 °C aging temperature (i.e. the shortest thermal exposure). The trade-off analysis is then carried out in terms of selecting learning time, on the mean value of measured IR, for prediction analysis using three CF methods. Fig. 5a shows the variance (i.e. circles) of the IR along with its mean values (i.e. black line) with respect to the aging time, until 16th aging cycle where insulation breakdown of the last sample (S9 lasted the longest) was detected. For the trade-off study, 3rd to 7th aging cycles (i.e. 8h to 56h) were selected as degrees of freedom, which was given as an input in the CF models, in order to generate their corresponding mathematical model equations.

E. PREDICTION RESULTS AND TIME-TO-FAILURE

The IR of each sample at all three aging temperatures is predicted using three CF methods and compared it with the

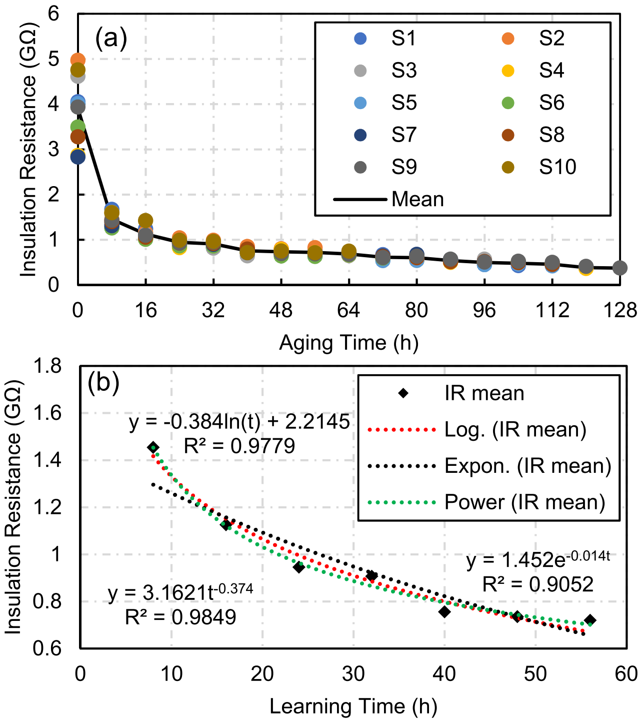

FIGURE 5. Measured IR at 290° C aging temperature (a) Variance and mean values (b) curve fit results when the learning time is 56h.

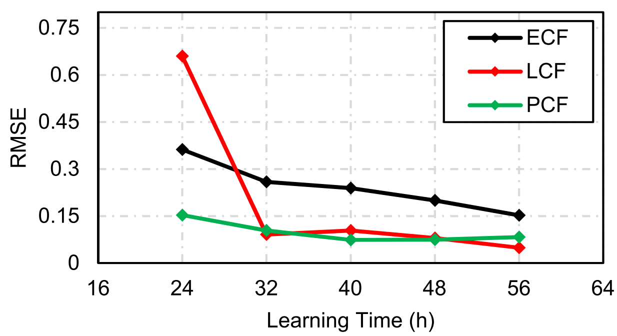

FIGURE 6. Root mean square error for different learning time, aged at 290° C.

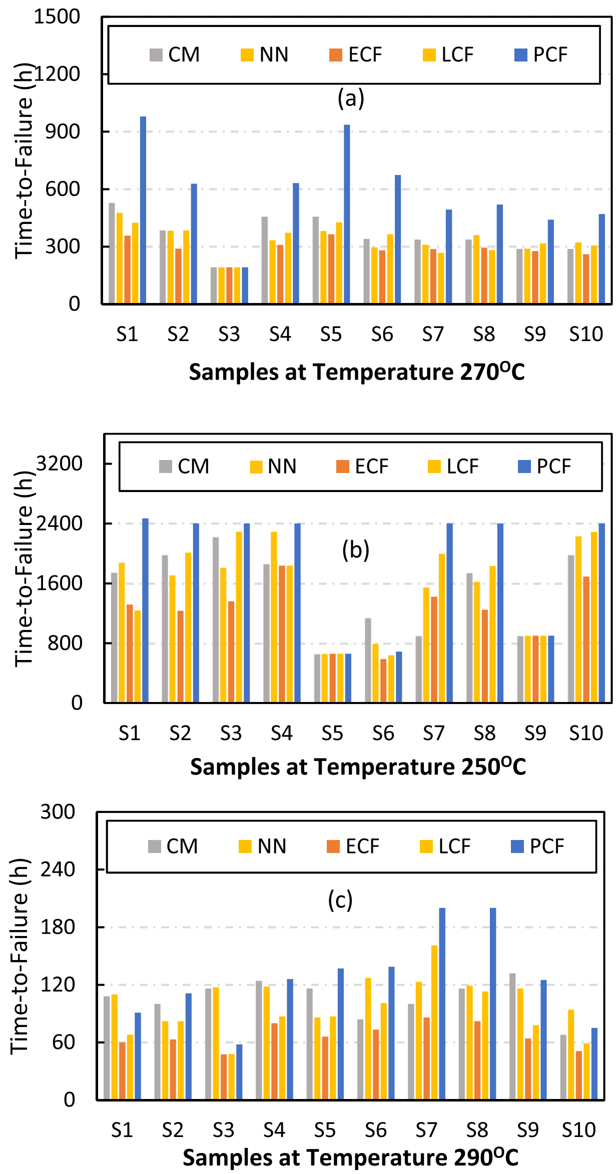

FIGURE 8. Samples' time-to-failure (a) 250° C aging temperature (b) 270° C aging temperature (c) 290° C aging temperature.

NN approach, initially introduced in [6], [7]. The NN was trained until the learning time reached the 7th aging cycle, whereas, the learning time at 5th aging cycle was considered for all three CF models. The samples that were failed before or at the considered learning times were discarded and not included in the prediction analysis. A total 3 samples were failed i.e. sample S3 at 270°C and sample S5 and S9 at 250°C. The time-to-failure of these 3 sample is considered as the time-to-failure of the samples obtained from the conventional method (CM), to fulfil the requirement of technical standards [3], [4] which recommends considering at least 10 samples per thermal exposure point. The time-to-failure of the rest of the 27 samples, at all three thermal exposures, is determined by predicting the IR values for a longer duration of time of 2400h, 888h and 160h at 250°C, 270°C and 290°C aging temperatures respectively (Fig. 7), in order to reach the IR breakdown criterion. The time-to-failure of each sample is reported in Fig. 8a to Fig.8c for aging temperatures of 250°C, 270°C and 290°C respectively. Fig. 7a to Fig. 7f show the predicted IR results using the NN approach and three CF methods, where, 2 samples of each aging temperature point, are shown. The black line is the IR data measured experimentally, red diamonds show the dataset which was trained for all three CF models, dotted line is the predicted trend and the black dashed line shows the IR threshold line of the insulation breakdown. Every sample is subject to face insulation breakdown as the IR reaches the threshold or border line (i.e. black dotted line). Once reached, their time-to-failures were recorded (Fig. 8).

In terms of IR prediction accuracy, when compared with CM, both NN and LCF produced the promising results,

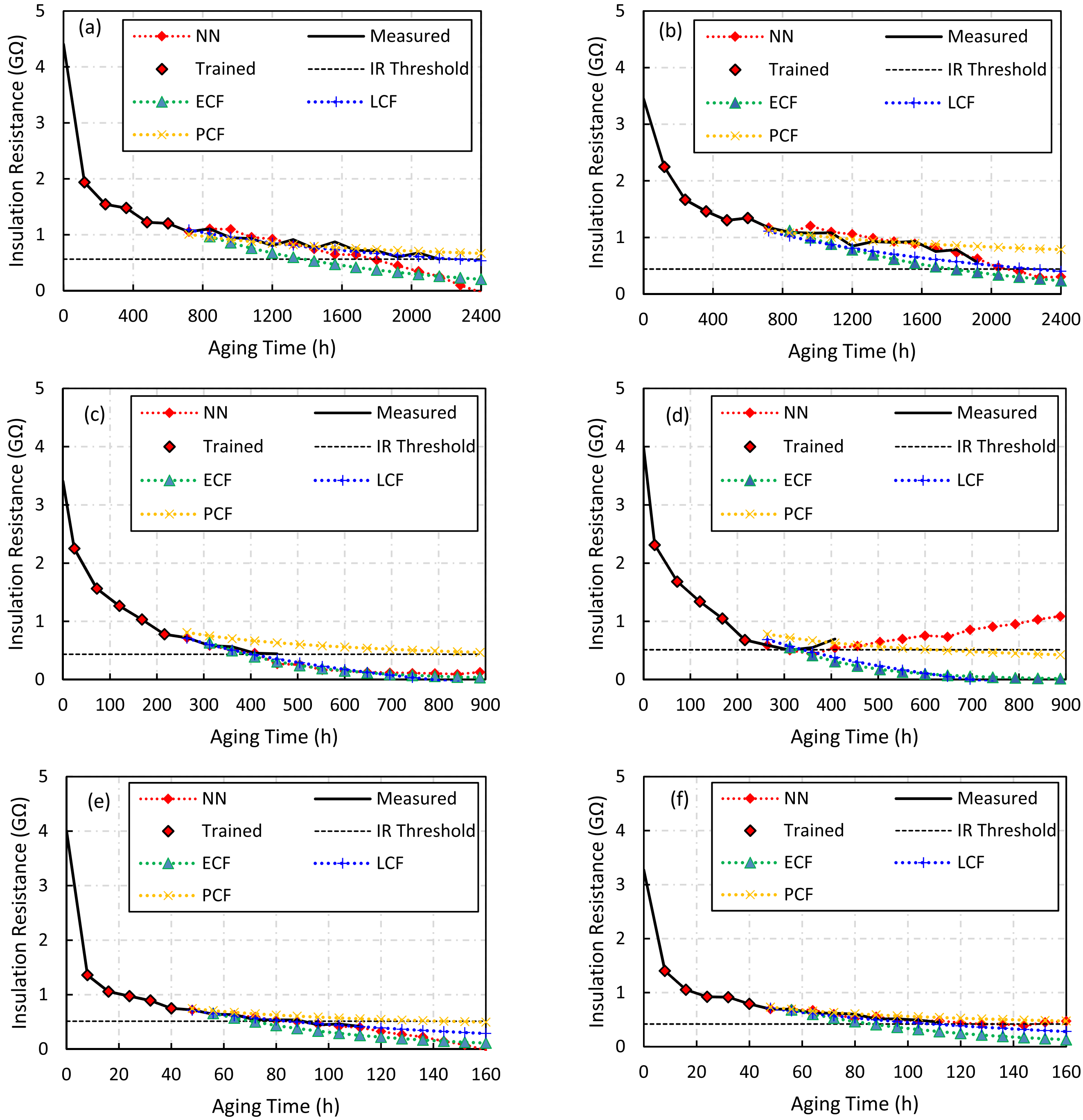

FIGURE 7. IR Prediction Results (a) Sample S3, at 250° C aging temperature (b) Sample S10, at 250° C aging temperature (c) Sample S1, at 270° C aging temperature (d) Sample S4, at 270° C aging temperature (e) Sample S5, at 290° C aging temperature (f) Sample S8, at 290° C aging temperature.

as opposed to the ECF and PCF methods. In fact, NN is able to predict the rising trend of IR of sample S4 at 270°C aging temperature (Fig. 7d). Both NN and LCF follow the measured IR values very closely, however, early breakdown is noticed in the ECF, whereas, the samples have failed comparatively late when IR is predicted using the PCF, as shown in Fig. 7b and Fig 7a respectively. Due to the delayed insulation breakdown, when predicted using the PCF, two samples (S7 and S8) have not reached the breakdown threshold at aging temperatures of 250°C and 290°C as shown in Fig. 8. Therefore, these two samples were purposely censored at 2400h and 200h, for aging temperatures of 250°C and 290°C respectively. This was done to estimate the PCF's MTTF. In terms of mean time-to-failure accuracy, the NN provides the best fit, when compared to the CM, giving the maximum and minimum percentage error of 7.34% and 2.03% respectively, as opposed

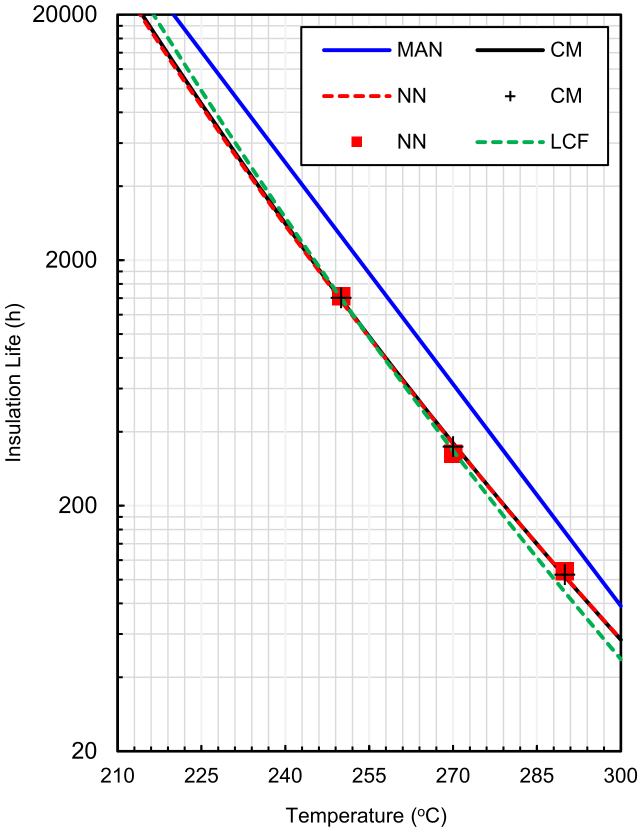

FIGURE 9. Plot of Arrhenius curves of MAN, CM, NN and LCF.

to the LCF, ECF and PCF. The second best candidate is the LCF which gives maximum and minimum percentage error of 13.75% and 3.75% respectively.

F. MEAN TIME-TO-FAILURE (MTTF)

Once the time-to-failures were determined, the MTTF, corresponding to the 50% probability failure, were calculated using the logarithmic-average method as described in the American Technical Standard ASTM D-2307. The technical standard [4] suggests to calculate the time-to-failure by dividing the sum of the logarithms of the failure times of the individual samples, at each aging temperature, by the total number of samples in the group or a set. The failure time of the group is then an antilogarithm of the logarithmic mean, which is, represented by (12) and are reported in Table 2.

$$MTTF = Antilog\left(\frac{1}{N}\sum_{i=1}^{N} Log_{10}(TTF)\right) \tag{12}$$

where, MTTF is the mean time-to-failure, N is the number of samples, TTF is the time-to-failure of each sample.

G. TIME SAVING STUDY

In terms of time-saving, LCF is the most promising candidate as the time required to train the CF model is quiet less as compared to the NN approach (i.e. only 5 aging cycles are required). Time that has been saved using NN approach is 1440h and 264h at aging temperature of 250°C and 270°C respectively which saved about 1704h (71 days), in total, as illustrated in Table 3. On the other hand, time that has been saved using CF model is 1680h and 312h at aging temperature of 250°C and 270°C respectively which saved about 1992h (83 days). This has resulted in a time-saving of 57.4% and 67.1% when the prediction was performed by the NN and CF approaches respectively, compared to the conventional 'standard method' of lifetime estimation [3], [4].

TABLE 2. Comparison of mean time-to-failure.

AGING TEMP	CM	NN	ECF	LCF	PCF
250ºC	1405h	1426h	1156h	1419h	1693h
270ºC	347.6h	326.0h	286.9h	325.1h	549.0h
290ºC	104.7h	108.1h	77.2h	90.3h	111.5h
Error at 250ºC	-	-2.03%	18.95%	-3.75%	-26.44%
Error at 270ºC	-	7.34%	19.32%	7.47%	-65.42%
Error at 290ºC	-	-2.67%	36.76%	13.75%	-18.57%

TABLE 3. Time consumption and time-saving.

METHODS	250ºC	270ºC	290ºC	TOTAL
CM	2280h	552h	136h	2968h
NN	840h	312h	136h	1288h
CF	600h	240h	136h	976h
Time Saving in NN Method	1440h	264h	0h	1704h
Time Saving in CF Method	1680h	312h	0h	1992h

V. LIFETIME ESTIMATION MODEL

For a continuous mode of operation of any electrical machine, insulation system or subsystem is exposed by a constant winding temperature during their service [17], [24]. In this case, for low voltage electrical machines, thermal stress is the most dominant aging factor that gradually deteriorates the lifetime of insulation of the motor windings.

Therefore, a thermal lifetime model, based on the Arrhenius Law, is developed. According to the Arrhenius law [6], [20], the thermal life of a solid insulating material is given by (13)

$$L = A_1 e^{B_1/T} \tag{13}$$

where, A_1 and B_1 are material constants, whilst, L is the life of insulating material, in hours, at operating temperature T in Kelvin. Equation (13) illustrates that insulation life varies exponentially on the linear scale which, in actual, is a straight line when plotted on a logarithmic scale with B_1' as the slope of straight line and A_1' as the y-intercept. Hence, (13) can be rewritten in the form (14) and (15).

$$log_{10}L = \log_{10}A + (log_{10}e).\frac{B}{T} \tag{14}$$
$$Y = A_1' + B_1'X \tag{15}$$

Where:

$Y = log_{10}L$

$A_1' = log_{10}A$

$B_1' = (log_{10}e) \cdot B$

$X = 1/T$

TABLE 4. Constants and thermal index.

METHODS	A_1'	B_1'	T.I (ºC)	T.I Error CM	T.I Error MAN
MAN	N/A	N/A	220.00	-	-
CM	-12.74	8305.7	214.39	-	2.55%
NN	-12.66	8257.9	214.02	0.172%	2.72%
LCF	-13.48	8650.9	216.43	0.952%	1.62%

Using MTTFs (i.e. average life of 10 samples at specified aging temperature) reported in Table 2 and (13) to (14), the constants A_1' and B_1' and the thermal index are calculated for CM, NN and LCF methods which are reported in Table 4, with respect to the wire's thermal index as defined by the manufacturer. In Fig. 9, the Arrhenius curves are shown i.e. the thermal life of insulation is extrapolated to a lifetime of 20,000h for NN and LCF prediction methods (dotted lines), whereas, CM and MAN (Manufacturer) taken as control lines (solid lines). As stated earlier, the manufacture of the wire under investigation, has claimed the life of 20,000h at the thermal index value of 220°C, therefore, both NN and LCF prediction methods have been compared with thermal index as determined by the conventional method (T.I Error CM) as well as thermal index given by the manufacturer (T.I Error MAN). The obtained percentage errors of thermal index are 0.172% and 0.952% for NN and LCF respectively, when comparing insulation lifetime with CM. On the other hand, the obtained percentage errors of thermal index are 2.72% and 1.62% for NN and LCF respectively, when comparing insulation's lifetime defined by the manufacturer.

VI. CONCLUSIVE REMARKS

A new approach to estimate the lifetime of wire insulation, under thermal stress, is presented in this paper. Insulation life has been predicted using three curve fit models (i.e. exponential, logarithmic and power curve fits) and compared against the neural network approach and the conventional method of lifetime estimation. The insulation resistance of each sample was predicted under thermal stress of 250°C, 270°C and 290°C and the time-to-failure of each is estimated by an end of life criterion. The mean time-to-failure (MTTF) at each thermal stress was calculated through lognormal probability curve for 50% cumulative probability failure. By using MTTFs, thermal lifetime models were developed to compare the curve fit approach of lifetime estimation against the neural network and standard method. The lifetime model developed using the NN and LCF approaches gave the error of 0.95% and 0.17% respective when their thermal index were compared with the CM, where, the error of 2.72% and 1.62% were achieved when their thermal index were compared with MAN life claim. In addition, LCF approach has resulted in a significant time-saving method that saves about 83 days (67% time saving w.r.t standard method) as opposed to the neural network approach which saved about 71 days, when compared with the standard convetional approach. This suggests that both approaches come with their own trade-offs – one with a good accuracy but less time-saving (i.e. NN) and the other comes with a slightly lower accuracy but a higher time-saving rate (i.e. LCF). Therefore, by adopting NN and proposed LCF approaches, a significant amount of testing time can be saved without being compromised on the prediction accuracy.

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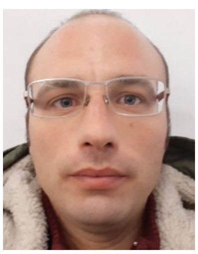
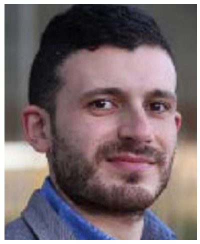
MUHAMMAD RAZA KHOWJA received the B.Eng. degree (Hons) in electrical power engineering and the M.Sc. degree in electrical engineering in from the Mehran University of Engineering and Technology, Jamshoro, Pakistan, in 2011 and 2012, respectively, and the Ph.D. degree in electrical and electronics engineering from the University of Nottingham, U.K., in 2018. He is currently a Research Fellow with the Power Electronics, Machines, and Control Group, University of Nottingham. His main research interests include integrated passive components, design and development of high-performance electrical machines for aerospace applications, and characterization of insulating materials for electrical machine's applications.

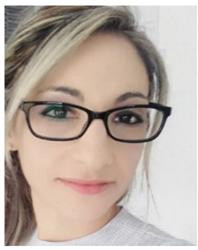
GULRUKH TURABEE received the B.S. degree in computer science from the Institute of Business Administration, Karachi, Pakistan, in 2017, and the M.Res. degree in computer science from Nottingham Trent University, U.K., in 2019. Her research interests are in the field of artificial intelligence and machine learning, including deep learning, applied to the biomedical and electrical engineering applications.



PAOLO GIANGRANDE (Senior Member, IEEE) received the bachelor's (Hons.), master's (Hons.) and Ph.D. degrees in electrical engineering from the Politecnico of Bari, in 2005, 2008, and 2011, respectively. Since 2012, he has been a Research Fellow with the Power Electronics, Machines and Control Group, University of Nottingham, U.K. In 2018, he was appointed as a Senior Research Fellow with the Accelerated Lifetime Testing Laboratory, Institute of Aerospace Technology, Nottingham, where he is currently the Head. His main research interests include sensorless control of ac electric drives, design and testing of electromechanical actuators for aerospace, thermal management of high-performance electric drives, and lifetime modeling of electrical machines.



VINCENZO MADONNA (Member, IEEE) received the B.Sc. degree in electronic engineering from the University of Calabria, Rende, Italy, in 2012, and the M.Sc. degree in electrical engineering from the University of Bologna, Bologna, Italy, in 2016. He is currently pursuing the Ph.D. degree in electrical machines design with the Institute for Aerospace Technology (IAT), University of Nottingham, Nottingham, U.K. In 2012, he was an Exchange Student with KU Leuven, Belgium, and in 2015, he was a Visiting Researcher with the University of Nottingham. He is currently a Marie Curie Fellow with the IAT and the Power Electronics, Machines and Control Group, University of Nottingham. His research interests include design, thermal management, and lifetime prediction modeling of electrical machines. He received the qualification of an Italian Chartered Engineer in 2016. He serves as a Reviewer for the IEEE Transactions on Industrial Electronics, the IEEE Transactions on Transportation Electrification, and various IEEE-sponsored international conferences.



GEORGINA COSMA (Member, IEEE) received the B.Sc. degree (Hons.) in computer science from Coventry University, U.K., in 2003, and the Ph.D. degree in computer science from the University of Warwick, U.K., in 2008. She is currently a Senior Lecturer/Associate Professor with the Department of Computer Science, Loughborough University, U.K. She is the Principal Investigator of The Leverhulme Trust Project Grant Novel Approaches for Constructing Optimised Multimodal Data Spaces (RPG-2016-252). Her research interests focus on data science, deep learning, computational intelligence, nature-inspired feature selection, and feature engineering. She is a member of various IEEE communities, including the IEEE Computer Society, IEEE Computational Intelligence Society, Big Data Community, Brain Community, Cloud Computing Community, Internet of Things Community, and Smart Cities Community.

GAURANG VAKIL (Member, IEEE) received the Ph.D. degree in variable speed generator design for renewable energy applications from the Power Electronics, Machines and Drives Group, IIT Delhi, New Delhi, India, in 2016. He subsequently worked as a Research Associate with the Power Electronics, Machines and Controls Group, University of Nottingham, Nottingham, U.K., where he was appointed as an Assistant Professor with the Department of Electrical and Electronics Engineering in 2016. His main research interests include design and development of high-performance electrical machines for transport and propulsion, optimizing electric drive-train for pure electric and hybrid vehicles (aerospace and automotive), high-power density machines, and magnetic material characterization.

CHRIS GERADA (Senior Member, IEEE) received the Ph.D. degree in numerical modeling of electrical machines from the University of Nottingham, Nottingham, U.K., in 2005. He subsequently worked as a Researcher with the University of Nottingham on high-performance electrical drives and on the design and modeling of electromagnetic actuators for aerospace applications, where he has been the Project Manager of the GE Aviation Strategic Partnership since 2006. In 2008, he was appointed as a Lecturer in the electrical machines with the University of Nottingham, where he became an Associate Professor in 2011 and a Professor in 2013. His main research interests include the design and modeling of high-performance electric drives and machines. He is the past Chair of the IEEE IES Electrical Machines Committee. He is an Associate Editor of the IEEE Transactions on Industry Applications.

MICHAEL GALEA (Senior Member, IEEE) received the Ph.D. degree in electrical machines design from the University of Nottingham, Nottingham, U.K., in 2013. He was appointed as a Lecturer with the University of Nottingham in 2014, where he became an Associate Professor in 2018 and a Professor in electrical machines and drives in 2019. He is currently the Head of the School of Aerospace, University of Nottingham, Ningbo, China, where he is also the Director of aerospace. He currently lectures in electrical machines and drives and in aerospace systems integration and manages a number of diverse projects and programs related to the more/all electric aircraft, electrified propulsion, and associated fields. His main research interests include design and development of electrical machines and drives (classical and unconventional), reliability and lifetime degradation of electrical machines, and the more electric aircraft. He is a Fellow of the Royal Aeronautical Society. He is on the Executive Board of the U.K. Magnetics Society.