Design of MLP-NN Classifier Block with PCA-Type of Dimensionality Reduction Technique for Assessment of State of Degradation in Stator Insulation of Induction Motor

Amit J. Modak, H. P. Inamdar

Abstract— In the present work, the design of discrete 'ANN' simulation model was done for the classification and qualitative assessment of the state of degradation of insulation present in the respective phases of three-phase ac induction motor. The 'ANN' simulation model consists of numbers of discrete neural network classifier blocks. The extraction of mathematical parameters of stator current data pattern, which are simulating the specific state of degradation of insulation based on Park's current transformation model, were presented in the previous research papers. Further, the optimal design specifications of the various neural network classifier blocks, which were realized on the basis of 'multilayer perceptron' (MLP) and 'radial basis function' (RBF) types of neural network architectures were compared in the same papers. The striking generalizations, which were derived on the basis of the comparative performance analysis resemble that the general optimum design specifications, which are determined on the basis of 'MLP' network are preferred as an optimum choice over the 'RBF' network. The aim of the present research paper is to explore the possibility of any further reduction in the size of the 'MLP' network. The present investigation emphasis the use of 'principal component analysis' type of dimensionality reduction technique for the simplification and improvement in the design of discrete neural network classifier blocks, which were already designed on the basis of 'multilayer perceptron' (MLP) neural network architecture for the classification and qualitative assessment state of degradation of insulation in three-phase ac induction motor

Index Terms— induction motor, stator insulation, dimensionality reduction technique, principal component analysis (PCA), sensitivity analysis (SA), artificial neural network (ANN).

I. INTRODUCTION

In the previous investigations it is ascertained that there is no correlation between the results of any nondestructive type of (d. c / a. c.) assessment parameters with destructive type of (d. c. /a. c. / impulse) breakdown levels [1-3]. The emphasis is towards the development of artificial intelligence (AI) based non destructive test method, which is economical for an assessment of state of degradation in stator insulation of induction motor. In view of the above perspective, the present research work presents a novice AI-based nondestructive test method to assess the state of degradation of stator winding insulation, which is being caused due to various factors in an integrated way. The method is based on the concept that the degradation occurring in any one of the phases of stator winding insulation, effectively results in the state of unbalance in the three-phase stator current. The formulation and execution of computer simulation model to generate unbalanced stator current data pattern was mentioned in the previous research papers [4-6]. In these papers, on the basis of Park's current transformation model the unbalanced stator current data in three-phase machine variable form was first transformed into two-phase Park's current vector component form. The Park's current vector components were then presented in a graphical dq-data pattern form and certain mathematical parameters were deduced. The 'n-dimensional input space vector' consists of 'n=6' numbers of extracted mathematical parameters like – 'angle of orientation ($\theta_0°$), angle of major-axis ($\theta_m°$), length of major-axis (L_{MA}), length of minor-axis (L_{MB}), eccentricity (ε), and latus rectum (LR) as such represents the specific state of degradation of insulation present in the respective phases of three-phase ac induction motor [4-6]. The simulation analysis was conducted on three-phase, 10HP (7.5-kW), star (Y)-connected, six-pole, induction motor.

II. SUGGESTED APPROACH FOR DESIGN OF ANN SIMULATION MODEL BASED ON DIMENSIONALITY REDUCTION TECHNIQUES

The schematic block diagram of design of discrete 'ANN' simulation model is shown in the 'Fig.1'. The 'ANN' simulation model is designed for the purpose of classification and qualitative assessment of the state of degradation of insulation present in the respective phases of three-phase ac induction motor. The design of 'ANN' simulation model comprises of several discrete neural network classifier blocks. The discrete neural network classifier blocks are 'NN1, 3EQ, 3UNEQ, 3UNEQa, 3UNEQb, and 3UNEQ3c'. These discrete neural network classifier blocks are arranged in three levels viz., 'top-level NN-model, middle-level NN-model, and bottom-level NN-model'. Each one of these blocks is designed to perform some specific dedicated task.

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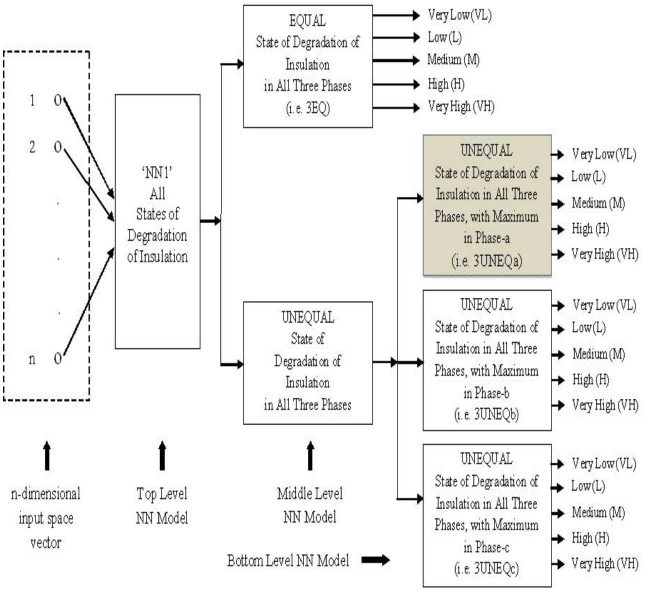

Fig. 1 Schematic Block Diagram of Discrete 'ANN' Simulation Model

The '6- dimensional input space vector' is applied as an input data to each one of these discrete neural network classifier blocks in the specific order. The neural network classifier block 'NN1' belongs to top-level of NN-model. The 'NN1' block is specifically designed to classify the state of degradation of insulation into two broad categories i.e. equal state of degradation of insulation in all three-phases (i.e. 3EQ) and unequal state of degradation of insulation in all three phases (i.e. 3UNEQ). The neural network classifier block '3EQ' belongs to one of the 'two' blocks of middle-level of NN-model. The '3EQ' block is specifically designed to qualitatively assess the equal state of degradation of insulation in all three-phases (i.e. 3EQ) into various qualitative levels such as 'Very Low (VL), Low (L), Medium (M), High (H), and Very High (VH)'. The neural network classifier block '3UNEQ' belongs to one of the 'two' blocks of middle-level of NN-model. The '3UNEQ' block is specifically designed to classify the unequal state of degradation of insulation in all three phases (i.e. 3UNEQ), into three sub-categories i.e. unequal state of degradation of insulation in all three phases but more in 'phase-a' as compared to 'phase-b' and 'phase-c' (i.e. 3UNEQa) , unequal state of degradation of insulation in all three phases but more in 'phase-b' as compared to 'phase-c' and 'phase-a' (i.e. 3UNEQb) , and unequal state of degradation of insulation in all three phases but more in 'phase-c' as compared to 'phase-a' and 'phase-b' (i.e. 3UNEQc) .

In a particular case, if '3UNEQ' block classifies the '6-dimensional input space vector', into the category of unequal state of degradation of insulation in all three phases but more in 'phase-a' as compared to 'phase-b' and 'phase-c' (i.e. 3UNEQa) then the '6-dimensional input space vector', is applied to the neural network classifier block '3UNEQa'. The neural network classifier block '3UNEQa' belongs to one of the three blocks of bottom-level of NN-model. The '3UNEQa' block is specifically designed to qualitatively assess an unequal state of degradation of insulation in all three phases but more in 'phase-a' as compared to 'phase-b' and 'phase-c' (i.e. 3UNEQa) into various qualitative levels such as 'Very Low (VL), Low (L), Medium (M), High (H), and Very High (VH)'. Thus, the design of '3UNEQa' block essentially consists of an input layer with 'six' processing elements to accept the '6-dimensional input space vector' and an output layer with 'five' processing elements to classify the unequal state of degradation of insulation in all three phases but more in 'phase-a' as compared to 'phase-b' and 'phase-c' (i.e. 3UNEQa) into various qualitative levels (i.e. 'Very Low (VL), Low(L), Medium(M), High (H), and Very High (VH)'). Like '3UNEQa' block, the '3UNEQb and 3UNEQc', neural network classifier blocks, are also specifically designed to qualitatively assess an unequal state of degradation of insulation in all three phases but more in their 'respective phase' as compared to the rest of the other 'remaining 'phases' into various qualitative levels such as 'Very Low (VL), Low (L), Medium (M), High (H), and Very High (VH)'.

The discrete neural network classifier blocks 'NN1' and '3UNEQ' are designed specifically to classify the state of degradation of insulation into various categories. Hence they are called as 'category-classifier' blocks. The task of classification of state of degradation of insulation assigned to these category classifier blocks emphasis the need of an optimal design considerations, which must ensure the possibility of the maximum efficiency and classification accuracy of about '100 %'.

The discrete neural network classifier blocks '3EQ', '3UNEQa, 3UNEQb, and 3UNEQc' are designed specifically to qualitatively assess the state of degradation of insulation into various qualitative levels. Hence they are called as 'level-classifier' blocks. The numbers of inputs are common for each one of these discrete neural network classifier blocks. The numbers of outputs for 'level-classifier' blocks (i.e. 'five') are more as compared to the numbers of outputs for 'category-classifier' blocks (i.e. 'two' for NN1 block and 'three' for 3UNEQ block). The more number of outputs for 'level-classifier' blocks leads to an increase in the size and complexity of the design, which ultimately posse the serious implications towards the hardware implementation of the neural network block. The task of qualitative assessment of state of degradation of insulation into various levels assigned to these 'level-classifier' blocks emphasis the need of an optimal design considerations, which must ensure the possibility of the reasonable efficiency and classification accuracy with an optimal reduction in the complexity of the design.

In order to meet the above stated design considerations, the general optimal design for each one of the blocks of the discrete 'ANN' simulation model is done. The general optimal designs of the discrete neural network classifier blocks are realized on the basis of 'multi-layer perceptron' (MLP) and 'radial basis function' (RBF) type of neural network topologies. The comparative performance analysis of the general optimal designs of the discrete neural network classifier blocks based on 'multi-layer perceptron' (MLP) and 'radial basis function' (RBF) type of neural network architectures is done to select appropriate neural network topology. The striking generalizations, which were derived on the basis of the comparative performance analysis further resemble that the general optimum design specifications, which are determined on the basis of 'MLP' network are preferred as an optimum choice over the 'RBF' network for the classification and qualitative assessment task of state of degradation of insulation in three-phase ac induction motor. However, there is a further need to explore the possibility of any reduction in the size of the 'MLP' network. The peculiarity of the present work, further lies in the fact that, it emphasis the use of dimensionality reduction techniques for the simplification and improvement in the design of discrete 'ANN' simulation model, which is already being designed on the basis of 'multilayer perceptron' (MLP) neural network architecture. The treatment of dimensionality reduction technique is introduced here.

A. Dimensionality Reduction (DR) Techniques

A neural network can perform any arbitrary nonlinear functional mapping task between the sets of variables. In principle, a single neural network can be used to map the raw input data directly onto the desired final output values. In practice, for all types of simple problems, such approach would generally give poor results for any number of reasons. In the feature extracted input dataset, it is necessary that the most superior features, which would provide the dominant cause and effect related information must be selected and irrelevant or redundant features must be discarded. This is important from the point of view of improvement in the performance of the neural network classifier and in turn avoids the curse of dimensionality. At first, just before initiating the training process, it is necessary to transform the feature extracted input dataset into some new representation. The input data presented to the neural network is pre-processed in a specific manner. Nevertheless the choice of preprocessing would be one of the most significant factors in determining the overall performance of the system. In the simplest case, the preprocessing may take the form of linear transformation of the input data. The more complex preprocessing does involve the reduction of the dimensionality of the input data. Since, the information content of the input data is somehow lost on account of the reduction of the dimensionality of the input data. At first, the reduction of the dimensionality of the input data may appear to contradict the improvement in the performance of the network.

The performance of the network can further be improved through the incorporation of *'prior knowledge'*. The term *'prior knowledge'* refers to the relevant information, which might be used to develop the solution and is additional to that already provided by the training (TR) data. The *'prior knowledge'* can either be incorporated into the structure of the network itself or at the time of preprocessing stage. The *'prior knowledge'* modifies the training process. The aspect of data preparation arises from the fact that the real data often suffers from the number of deficiencies such as missing input values or incorrect target values. Since, the training process of network may involve an iterative algorithm. It is generally convenient to process the entire training dataset by using the preprocessing transformation and then used this entire transformed dataset to train the network.

One of the most important forms of the preprocessing involves the reduction of the dimensionality of the input data. The principle motivation behind the 'dimensionality reduction' (DR) of the input data is that, it can help to alleviate the worst effects of the curse dimensionality. A network with fewer inputs has fewer adaptive parameters to be determined. The fewer adaptive parameters are more likely to be properly forced to the desired optimum specified values by means of dataset of limited size. This, in turn leads to the design of the network with better generalization properties. In addition, a network with fewer weights may be faster to train. In most of the situations, it is seen that the reduction in the dimensionality of the input space vector would result in the loss of information. A good preprocessing strategy is the one, which ensures the retention of the most of the relevant information. If too much information is lost in the preprocessing stage then the resulting performance of the network does offset any improvement, which may arise on account of the reduction in dimensionality of the input space vector.

The overall design strategy for the design of discrete 'ANN' simulation model based on 'principal component analysis (PCA)' type of dimensionality reduction techniques is detailed in the next section.

III. DESIGN OF DISCRETE 'ANN' SIMULATION MODEL BASED ON 'PRINCIPAL COMPONENT ANALYSIS' TYPE OF DIMENSIONALITY REDUCTION TECHNIQUE

The 'principal component analysis' (PCA) type of 'dimensionality reduction' (DR) technique is exercised in the overall design process. The treatment of dimensionality reduction technique i.e. principal component analysis (PCA) is introduced by means of 'XLSTAT 2008' software [7].

A. Principal Component Analysis (PCA)

In general, a reduction in the dimensionality of input space would be accompanied by a loss of the some information, which is instrumental in discriminating the different classes. The primary goal, in the context of the dimensionality reduction (DR) technique is to preserve as far as possible the relevant information. One of the approaches, which are already discussed, is based on the selection of a 'subset' for a given set of extracted features or inputs. The 'principal component analysis' (PCA) involves the mathematical procedure that transforms a number of possible correlated variables into smaller number of uncorrelated variables, which are subsequently termed as 'principal components'. The 'PCA' in mathematical term is defined as - an orthogonal linear transformation that transforms the data into a new coordinate system such that the greatest variance by any projection of data, which comes to lie on the first coordinate is termed as 'first principal component', the second greatest variance on the second coordinate is termed as 'second principle component', and so on. The 'PCA' in theoretical term is defined as – an optimum transformation for a given data, which is expressed in least square terms. The 'PCA' involves the calculation of the 'Eigen value decomposition' of a data covariance matrix or 'Singular value decomposition' of a data matrix, which is usually done after mean centering the data for each attribute. The results of a 'PCA' are usually discussed in terms of component scores.

The 'PCA' is a very useful method to analyze numerical data structured in '*M observations / N variables'* table. It allows one to:

1) Quickly visualize and analyze correlations between the 'N' variables.
2) Visualize and analyze the 'M' observations (initially described by the 'N' variables) on a low dimensional map, which offer an optimal view for a variability criterion.
3) Build a set of 'P' uncorrelated factors (P<=N), which can be reused as input for other statistical methods.

The details of the methodology adopted towards the application of the 'PCA' type of dimensionality reduction technique, in the design process of the optimal design of '3UNEQa-MLP-PCA' level-classifier block of discrete ANN simulation model are provided in the present section. This particular discrete neural network block is one of the four level-classifier blocks belonging to 'bottom-level' of discrete 'ANN' simulation model (i.e. 3UNEQa). It is marked in the form of overshadowed block in the 'Fig.1'. The overall simulation results of the rest of the other simulated designs of various discrete level-classifier neural network blocks, which are designed on the basis of 'multilayer perceptron' (MLP) type of network with 'principal component analysis (PCA)' type of dimensionality reduction technique, are provided for the sake of comparative performance analysis.

The treatment of 'PCA' is exercised by means of 'Pearson' rule [8]. The quality of projection from the initial 'six-dimensional' input feature space to a lower-dimensional feature space is represented in terms of mathematical objects like eignvalues and correlation circle. The 'Table 1' presents the variability of the principal components in terms of their eignvalues and variability (%), which is expressed in terms of cumulative and standalone percentage (%) value. The 'Fig. 2' provides the graphical representation of the same whereas the 'Fig.3' presents the correlation circle of initial 'six-dimensional' input feature space in the context of the optimal design of '3UNEQa-MLP-PCA' level-classifier neural network. As shown in the 'Table I, the eignvalues and variability (%) factor of the principle components, interpret that, it is possible to transfer the data from an initial 'six-dimensional' input feature space (i.e. 'L_{MA}, L_{MB}, ε, LR, θ_m°, and θ_0°') into the lower 'four- dimensional' input feature space for an optimal design of '3UNEQa- MLP-PCA' neural network level-classifier.

TABLE I PRINCIPAL COMPONENTS FOR OPTIMAL DESIGN OF '3UNEQa-MLP-PCA' NEURAL NETWORK

Principle Component	F1	F2	F3	F4	F5	F6
Eigenvalue	3.162	2.048	0.538	0.193	0.054	0.005
Variability (%)	52.698	34.133	8.965	3.216	0.902	0.087
Cumulative %	52.698	86.831	95.796	99.012	99.913	100.000

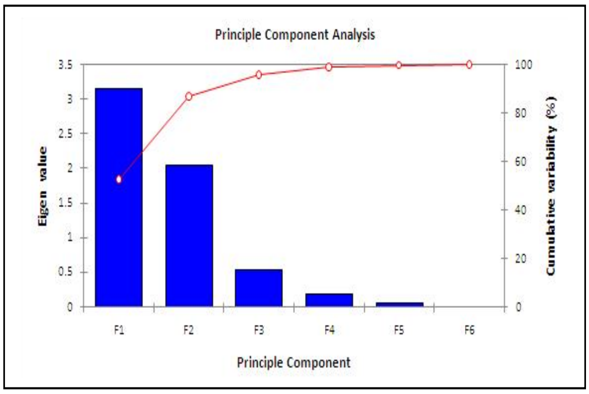

Fig. 2 Principal Components for Optimal Design of '3UNEQa-MLP-PCA' Neural Network

The cumulative variability of '99.012%' with 'four' (4) input features contains almost all the relevant information of the initial 'six' (6) input features. The eigenvalues, reflect the quality of the projection from an initial 'n-dimensional input space feature (n = 6) to a lower number of dimensions. In the present case, the first eigenvalue is '3.162' and represents '52.698 (%)' percentage (%) of the total variability. This means that – if the data is represented on only one axis, it is still possible to view the percentage (%) of the total variability of the data. Each eigenvalue corresponds to a factor, and each factor corresponds to a one dimension. A factor is a linear combination of the initial variables, and all the factors are un-correlated (CC = 0). The eigenvalues and the corresponding factors are sorted by descending order of how much of the initial variability they must represent (i.e. converted to %).

As shown in the Fig. 2, it is clear that, the first 'two' eigenvalues corresponds to a high percentage (%) of the variance. This further ensures that the map based on the first 'two' factors is a good quality projection of the initial 'six-dimensional' input feature space. In the present case, the first 'two' factors allow us to represent '86.831 (%)' percentage (%) of the initial variability of the data. This is a good result. Hence, the 'first map' is obtained between the first 'two' variables for the subsequent interpretations. The 'first map' is called the correlation circle (i.e. on axes F1 and F2).

The correlation circle (i.e. on axes 'F1' and 'F2') shows the projection of the initial variables in the factors space. When 'two' variables are far from the center and are close to each other, then they are significantly positively correlated (i.e. 'CC' close to '1') with each other. If they are orthogonal, then they are not correlated (i.e. 'CC' close to '0') with each other. If they are on the opposite side of the center, then they are significantly negatively correlated (i.e. 'CC' close to '-1') with each other. When 'two' variables are close to the center, it means that some information is carried on other axes, and that any interpretation might be hazardous. The correlation circle is useful in interpreting the meaning of axes as well. As shown in the 'Fig.3', it is clear that, all the variables are far from the center.

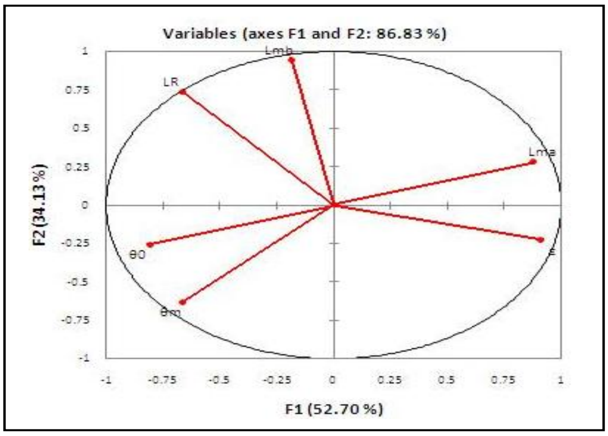

Fig. 3 Correlation Circle of Initial Six-Dimensional Input Feature Space for Optimal Design of '3UNEQa-MLP-PCA' Neural Network

The variables like - 'length of minor axis (L_{MB}) and latus rectum (LR)' of extended Park's current data patterns are quite close to each other. Hence, it is ascertained that both of them are significantly positively correlated (i.e. 'CC' close to '1'). Similarly, the variables like –'length of major axis (L_{MA}) and eccentricity (ε)' as well as 'angle of major axis (θ_m°) and orientation angle (θ_0°)' of extended Park's current data pattern are quite close to each other. Hence, it is ascertained that all of them, in their respective pairs, are significantly positively correlated (i.e. 'CC' close to '1') with each other. However, particularly, in the context of the selection of one variable at a time in between the different pairs, there is a need to draw further interpretation. The variables like – 'orientation angle (θ_0°) and length of minor axis (L_{MB})' are orthogonal to each other. Hence, they are not correlated (i.e. 'CC' close to '0') with each other. Similarly, the variables like – 'angle of major axis (θ_m°) and latus rectum (LR)' are orthogonal to each other. Hence, they are not correlated (i.e. 'CC' close to '0') with each other. The variables like - 'eccentricity (ε) and latus rectum (LR)' are on the opposite side of the center. Hence, both of them are significantly negatively correlated (i.e. 'CC' close to '-1') with each other. The either of the two variables could have been removed without any effect on the quality of the results. The 'Table 2' presents the corresponding correlation matrix, which provides the computational values of the correlation coefficients between all variables. It is observed that in most of the cases the variables are either partially positively correlated (i.e. 'CC' close to '+0.5') with each other or partially negatively correlated (i.e. 'CC' close to '- 0.5') with each other. There is a need to execute the principal component analysis (PCA) search procedure for the determination of optimum numbers of principle components (PC's) as inputs. The 'Neurosolutions 5.0' neural network design tool [9] is used to perform the numbers of computer simulation experimentations.

TABLE II CORRELATION MATRIX OF INITIAL SIX-DIMENSIONAL INPUT FEATURE SPACE FOR OPTIMAL DESIGN OF '3UNEQa-MLP-PCA' NEURAL NETWORK

Variables	θ0	θm	Lma	Lmb	ε	LR
θ0	1	0.721	-0.639	-0.004	-0.526	0.338
θm	0.721	1	-0.649	-0.398	-0.405	-0.010
Lma	-0.639	-0.649	1	0.189	0.805	-0.365
Lmb	-0.004	-0.398	0.189	1	-0.305	0.829
ε	-0.526	-0.405	0.805	-0.305	1	-0.774
LR	0.338	-0.010	-0.365	0.829	-0.774	1

The number of principal components (PC's) as inputs are varied from '1' to '6' PC's and performance of the general optimum design of '3UNEQa-MLP' network is verified. In the training process, the transformed data in the form of 'factor score' (FS) is tagged in the ratio of '80:10:10' (%) as 'TR: CV: TEST' (%) data, respectively. In the design process of '3UNEQa-MLP' general optimum design, the percentage ratio (i.e. '80:10:10 %') for data tagging is already being determined on the basis of 'variable split ratio' (VSR) type of data partioning scheme. The levels of performance measures like – 'MIN AVE MSE, MSE, NMSE, MAE, and CC' are relaxed marginally as compared to that of general optimum design. Since, it is expected that, the some of the relevant information might get lost in view of lower dimensional input feature space. The primary aim towards the application of principal component analysis (PCA) type of dimensionality reduction (DR) technique is to achieve almost the same 'average classification accuracy' (CA) performance measure with the lower dimensionality of input feature space.

The variation of 'MIN AVE MSE' and 'average classification accuracy' (CA%) performance measure on training (TR) and cross-validation (CV) data is illustrated in the 'Fig.4' and 'Fig.5' respectively, with different number of principal components (PC's) as inputs. The variations of performance measures like –'NMSE, MAE, and correlation coefficient (CC)' are shown in the 'Table III' with different number of principal components (PC's) as inputs.

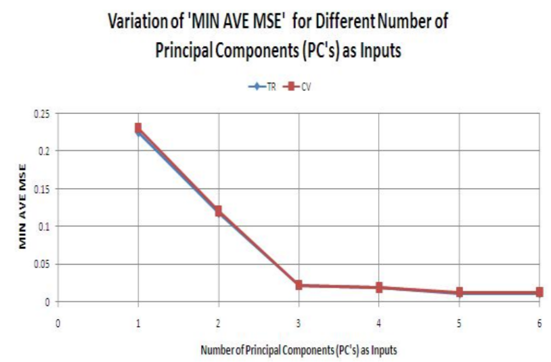

Fig.4 Variation of 'MIN AVE MSE' with Number of Principal Components as Inputs for '3UNEQa-MLP' Neural Network

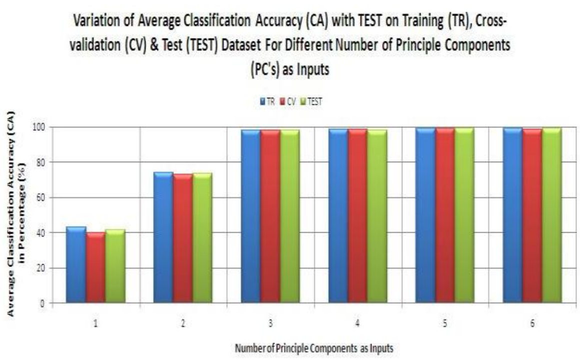

Fig.5 Variation of Classification Accuracy (CA) with Number of Principal Components as Inputs for '3UNEQa-MLP' Neural Network

TABLE III VARIATIONS OF PERFORMANCE MEASURES WITH NUMBER OF PRINCIPAL COMPONENTS AS INPUTS FOR '3UNEQa-MLP' NEURAL NETWORK

Number of Inputs	NMSE		MAE		CC	
	TEST	CV	TEST	CV	TEST	CV
1	0.874145	0.891083	0.278528	0.282052	0.350695	0.332894
2	0.463004	0.457676	0.163645	0.162001	0.732324	0.732260
3	0.074531	0.066102	0.063964	0.062393	0.968073	0.972282
4	0.053717	0.053969	0.059809	0.059437	0.978520	0.978413
5	0.042903	0.046885	0.058296	0.058958	0.984846	0.983094
6	0.043963	0.045511	0.057458	0.057847	0.984419	0.983864

As shown in the 'Fig.4', it is observed that the 'MIN AVE MSE' performance measure approaches to minimum value on training (TR) as well as cross-validation (CV) data for 'four' (4) number of principle components (PC's) given as inputs. Similarly, as shown in the 'Fig.5', it is observed that the 'average classification accuracy' (CA %) is above '98 %' with 'four' (4) number of principle components (PC's) as input feature space. The performance measures like - 'NMSE and MAE' decreases just near to the acceptable limit with 'four' (4) number of PC's as input on cross-validation (CV) and testing (TEST) data. On the contrary, the correlation coefficient (CC) performance measure increases just above the acceptable limit (i.e. ≥ 0.97) with 'four' (4) number of PC's as inputs on cross-validation (CV) and testing (TEST) data. It is inferred that the number input features can be reduced from 'six' to 'four'. The same methodology, which was adopted for the general optimal design of '3UNEQa-MLP' level classifier block is also adopted towards obtaining the optimum design specifications for '3UNEQa-MLP-PCA' level-classifier neural network design with '4' No's of PC's as inputs.

The optimal selection of the number of processing elements in the first hidden layer (i.e. 'HL_1') is done by observing the performance of the network (i.e. 3UNEQa-MLP-PCA) with 'four' (4) number of principle components (PC's) as inputs. The computer simulation experimentation is done for the variation in the number of processing elements in the first hidden layer (i.e. 'HL_1'). The optimal numbers of processing elements of first hidden-layer for '3UNEQa' level classifier block based on multilayer perceptron (MLP) type of NN-architecture with principal component analysis (PCA) (i.e. '3UNEQa-MLP-PCA) are selected as 'PE = 09'. Thus, the optimal design configuration of '3UNEQa' level-classifier block based on 'multilayer perceptron' (MLP) type of 'ANN' architecture with 'principal component analysis' (PCA) type of 'dimensionality reduction' (DR) technique (i.e. 3UNEQa-MLP-PCA) is consisting of 'input-layer' with 'four' numbers of processing elements as principal components (PC's), first 'hidden-layer' with 'nine' numbers of processing elements, and an 'output-layer' with 'five' numbers of processing elements (i.e. '4-9-5'). The 'Momentum' (MOM) learning algorithm and the 'Tanh Axon' (TANH) activation function are selected as obvious choices for the selection of new optimal learning parameters (i.e. 'learning constant or step size' (i.e. 'η'), and 'momentum coefficient or rate' (i.e. 'α'), etc …) of the processing elements belonging to 'first hidden layer and output layer') and the stopping condition (i.e. SC). The new design specifications determined for the optimal design of '3UNEQa-MLP-PCA' neural network classifier block are listed in 'Table IV'.

TABLE IV DESIGN SPECIFICATIONS OF OPTIMAL DESIGN OF '3UNEQa-MLP-PCA' NN- LEVEL CLASSIFIER BLOCK

Design Parameter	Specification
Data Tagging: 80% Training (TR), 10% Cross Validation (CV), 10 % Testing (TEST)	TR: CV: TEST (%) » 80:10:10 (%)
Number of Processing Elements (PE's) as Optimal Number of Principal Components (PC's) as Inputs in Input Layer (i.e. 'IN')	04
Error Criterion	'L_2' Norm
Stopping Condition (i.e. 'SC')	'2500' Epochs
Number of Hidden Layers (i.e. 'HL_1, HL_2, …')	01 (i.e. 'HL_1')
Number of Processing Elements (PE) in First Hidden Layer (i.e. 'HL_1')	09
Transfer Function (i.e. 'TF')	'Tanh Axon' (i.e. 'TANH')
Learning Algorithm (i.e. 'LA')	'Momentum (i.e. 'MOM')
First Hidden Layer: Learning Constant or Step-Size (i.e. 'LC' or 'η')	0.4
First Hidden Layer: Momentum Coefficient or Rate (i.e. 'MC' or 'α')	0.8
Output Layer : Learning Constant or Step-Size (i.e. 'LC' or 'η')	0.8
Output Layer: Momentum Coefficient or Rate (i.e. 'MC' or 'α')	0.7
Number of Connection Weights : (i.e. 4 x 9 + 9 x 5 + 9 + 5)	95
Number of Processing Elements (PE) in Output Layer (i.e. OUT)	05
Neural Network Topology	4-9-5-MLP-PCA

In order to verify and compare the training and testing results of the newly designed classifier, the transformed dataset in the form of factor score (i.e. FS) of lower dimensionality with the 'four' number of principal components (PC's) as inputs is used. The optimal design of '3UNEQa-MLP-PCA' neural network level classifier block with the design specifications listed in 'Table IV', is re-trained over 'five' (5) numbers of runs (times) with different random weight initializations and later tested on 'Testing (TEST), Cross-validation (CV), and Training (TR)' datasets. The different data partioning schemes like 'Variable Split Ratio (VSR) method, Variation in Groups (VG) method and Leave-N-Out (LNO) method' are used to assess the performance of the network.

The 'Fig.6' shows the variation of 'MSE' performance measure with variable percentage of data tagged for training (TR) data for '3UNEQa - MLP - PCA' design. The 'Table V' shows the variation of 'NMSE, MAE, and CC' performance measures for the same design. On the basis of these simulation results, it is observed that, the dataset must be partitioned as '50 % -50 %' for training (TR) and testing (TEST) data for the best results.

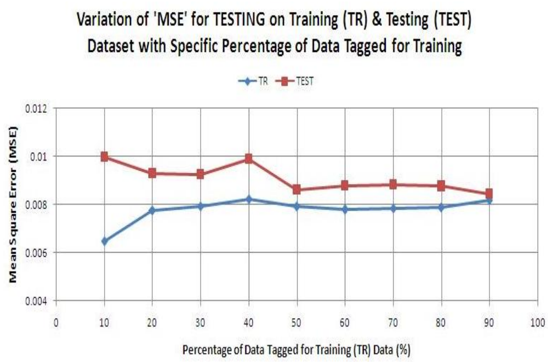

Fig.6 Variation of 'MSE' Performance Measure with Variable Percentage of Data Tagged for Training (TR) Data for

‘3UNEQa - MLP - PCA’ Design

TABLE V. VARIATION OF ‘NMSE, MAE, AND CC’ PERFORMANCE MEASURES WITH VARIABLE PERCENTAGE OF DATA TAGGED FOR TRAINING (TR) DATA FOR ‘3UNEQa – MLP - PCA’ DESIGN

Percentage of Data	NMSE		MAE		CC	
TR(%)-TEST (%)	TEST	TR	TEST	TR	TEST	TR
10 (%)-90(%)	0.061488	0.039789	0.061414	0.057638	0.975819	0.986030
20(%)-80 (%)	0.057058	0.047619	0.061346	0.059453	0.977909	0.982624
30(%)-70(%)	0.056536	0.048575	0.060383	0.058529	0.977659	0.981704
40(%)-60(%)	0.059684	0.049369	0.059343	0.057735	0.975750	0.980874
50(%)-50(%)	0.053333	0.049345	0.060359	0.059572	0.979116	0.981116
60(%)-40(%)	0.053968	0.047826	0.059485	0.058567	0.978921	0.982028
70(%)-30(%)	0.055046	0.049505	0.061004	0.060345	0.979340	0.981881
80(%)-20(%)	0.053041	0.048349	0.058750	0.057972	0.979183	0.981431

The variation of ‘MIN AVE MSE’ performance measure for different groups of dataset is represented in the ‘Table VI’. The variation of ‘MIN AVE MSE’ performance measure over a marginal range (i.e. between ‘0.015’ and ‘0.02’) confirms the consistency in the performance of network for different groups of dataset.

TABLE VI VARIATION OF ‘MIN AVE MSE’ PERFORMANCE MEASURE FOR DIFFERENT GROUPS OF DATASET FOR ‘3UNEQa – MLP - PCA’ OPTIMAL DESIGN

GROUP NO	VG	Avg TrnMSE (MIN)	Avg CVMSE (MIN)
1	1234	0.014269	0.015381
2	2341	0.014905	0.017249
3	3412	0.015652	0.017618
4	4123	0.016181	0.015360
5	2134	0.015870	0.017115
6	3241	0.014376	0.016839
7	4312	0.015810	0.018045
8	4132	0.015956	0.016261
9	2143	0.014227	0.016389
10	3214	0.014737	0.017407
11	4321	0.015763	0.014987
12	1432	0.015648	0.016048

The variation of ‘average classification accuracy’ (CA) performance measure for different numbers of predefined subset of exemplars to be skipped (i.e. ‘102, 116, 131, 145, 160, 174, 189, and 205’) during the ‘Leave-N-Out’ (LNO) type of data partioning training scheme is shown in the ‘Fig. 7’.

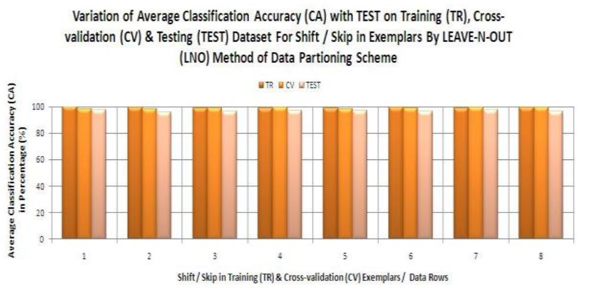

Fig. 7 Variation of ‘Average Classification Accuracy’ (CA) Performance Measure for ‘Leave-N-Out’ (LNO) Type of Data Partioning Training Scheme of ‘3UNEQa – MLP –PCA’ Optimal Design

The variation of ‘average classification accuracy’ (CA) performance measure over a marginal range on ‘training (TR), cross-validation (CV), and testing (TEST),’ dataset confirms the consistency in the performance of network for different ‘Leave-N-Out’ (LNO) data partioning scheme. This further ensures that the network is truly learned and generalized. Thus, the optimal design of ‘3UNEQa-MLP-PCA’ neural network level classifier block with the design specifications listed in ‘Table IV’ is determined for qualitative assessment of an unequal state of degradation of insulation in all three phases but more in ‘phase-a’ as compared to ‘phase-b’ and ‘phase-c’ (i.e. 3UNEQa) into various qualitative levels such as ‘Very Low (VL), Low (L), Medium (M), High (H), and Very High (VH)’.

The overall simulation results of the rest of the other simulated designs of various discrete neural network classifier blocks based on multilayer perceptron (MLP) type of ‘ANN’ architecture with principal component (PCA) type of dimensionality reduction technique are provided in the ‘Table-VII’ for the sake of comparative performance analysis.

IV. COMPARATIVE PERFORMANCE ANALYSIS OF OPTIMAL SIMULATED DESIGNS OF LEVEL-CLASSIFIER NN-BLOCKS BASED ON ‘MLP’ AND ‘MLP-PCA’ DESIGN STRATEGIES

The comparative performance analysis of the design specifications and the performance measures of the general optimal simulated designs of the level-classifier neural network blocks (i.e. 3UNEQa, 3UNEQb, and 3UNEQc) of discrete ‘ANN’ simulation model, which are designed on the basis of ‘multilayer-perceptron’ (MLP) type of ‘ANN’ architecture and their corresponding optimal simulated designs based on ‘principal component analysis’ (PCA) type of ‘dimensionality reduction’ (DR) technique are briefly summarized in ‘Table VIII’.

TABLE VII OPTIMAL SIMULATED DESIGNS OF LEVEL-CLASSIFIER NN-BLOCKS BASED ON ‘MLP-PCA’ NETWORK ARCHITECTURE

Specifications / Performance Measures	Optimal Simulated Design Specifications and Performance Measures of Level-Classifier Neural Network Blocks		
	3UNEQa-MLP-PCA	3UNEQb-MLP-PCA	3UNEQc-MLP-PCA
NN-Topology TR: CV: TEST (%) (Primary Data Tagging Percentage)	4-9-5 80:10:10	4-7-5 70:15:15	4-9-5 70:15:15
Error Criterion (EC)	L_2-Norm	L_2-Norm	L_2-Norm
Stopping Criterion (SC)	2500 Epochs	5000 Epochs	4000 Epochs
Learning Algorithm (LA)	Momentum	Momentum	Momentum
Transfer Function (TF)	TANH	TANH	TANH
MIN MSE (SC)	0.012755	0.012776	0.013519
MIN AVE MSE (SC) TR: TEST (%) (VSR Data Tagging)	0.015680 50:50	0.017333 60:40	0.014819 70:30
MSE (VSR)	0.008606	0.007550	0.007792
NMSE (VSR)	0.053333	0.046654	0.047922
MAE (VSR)	0.060359	0.039020	0.054939
CC (VSR)	0.979116	0.978287	0.980964
AVE CA (%) (VSR)	98.3277	98.0295	98.4984
TR: CV: TEST (%) (VG Data Tagging)	50:25:25	60:20:20	70:15:15
MIN AVE MSE (VG) (MIN.; MAX.)	(0.014987 ; 0.018045)	(0.014655 ; 0.020206)	(0.013582 ; 0.016006)
AVE MSE (LNO) (MIN.; MAX.)	(0.012570 ; 0.015106)	(0.007562 ; 0.015650)	(0.008775 ; 0.011837)
AVE CA (%) (LNO) (MIN.; MAX.)	(95.9390 ; 97.7988)	(97.3452 ; 98.5952)	(96.7188 ; 98.9474)
No. of Connection Weights	95	75	95

The following are the few of the striking generalizations, which are established on the basis of the comparison between the specifications and performance measures.

(1) In the context of the stopping criterion (SC), the levels of 'MIN MSE' and 'MIN AVE MSE' performance measures are marginally higher and just lying outside the permissible acceptable limits for 'MLP-PCA' network as compared to the 'MLP' network. Further, in the case of 'MLP-PCA' network, by an average, the number of 'epochs' required for the stopping criterion are more as compared to the 'MLP' network.

(2) The performance tests based on the variable split ratio (VSR) method of data partioning scheme suggest that, the 'seventy' percent (70%) of data tagging for the training (TR) data and remaining 'thirty' percent (30%) of data tagging for the cross-validation (CV) and testing (TEST) data is preferred as an optimum selection for most of the cases of 'MLP' networks while in the case of 'MLP-PCA' networks, by an average, the 'sixty' percent (60%) of data tagging for the training (TR) data and remaining 'forty' percent (40%) of data tagging for the cross-validation (CV) and testing (TEST) data is preferred as an optimum selection. Thus, in the case of 'MLP-PCA' network, even on account of large number of 'epochs' required for the stopping criterion, the 'effective time elapsed per epoch per exemplar' is quite less as compared to the 'MLP' network.

TABLE VIII OPTIMAL SIMULATED DESIGNS OF LEVEL-CLASSIFIER NN-BLOCKS BASED ON 'MLP' AND 'MLP-PCA' NETWORK ARCHITECTURE

Specifications / Performance Measures	Optimal Simulated Design Specifications and Performance Measures of Level-Classifier Neural Network Blocks					
	3UNE Qa-MLP	3UNE Qa-MLP-PCA	3UNE Qb-MLP	3UNE Qb-MLP-PCA	3UNE Qc-MLP	3UNE Qc-MLP-PCA
NN-Topology	6-9-5	4-9-5	6-11-5	4-7-5	6-8-5	4-9-5
TR: CV: TEST (%) (Primary Data Tagging Percentage)	60:20:20	80:10:10	60:20:20	70:15:15	60:20:20	70:15:15
Error Criterion (EC)	L_2-Norm	L_2-Norm	L_2-Norm	L_2-Norm	L_2-Norm	L_2-Norm
Stopping Criterion (SC)	3000 Epochs	2500 Epochs	4000 Epochs	5000 Epochs	2000 Epochs	4000 Epochs
Learning Algorithm (LA)	Momentum	Momentum	Momentum	Momentum	Momentum	Momentum
Transfer Function (TF)	TANH	TANH	TANH	TANH	TANH	TANH
MIN MSE (SC)	0.011704	0.012755	0.011437	0.012776	0.010086	0.013519
MIN AVE MSE (SC)	0.012867	0.015680	0.011669	0.017333	0.010889	0.014819
TR: TEST (%) (VSR Data Tagging)	80:20	50:50	70:30	60:40	70:30	70:30
MSE (VSR)	0.006873	0.008606	0.006297	0.007550	0.005723	0.007792
NMSE (VSR)	0.042185	0.053333	0.038580	0.046654	0.035238	0.047922
MAE (VSR)	0.055509	0.060359	0.053161	0.039020	0.043590	0.054939
CC (VSR)	0.985093	0.979116	0.986386	0.978287	0.985589	0.980964
AVE CA (%) (VSR)	98.7252	98.3277	98.9655	98.0295	98.7827	98.4984
TR: CV: TEST (%) (VG Data Tagging)	80:10:10	50:25:25	70:15:15	60:20:20	70:15:15	70:15:15
MIN AVE MSE (VG) (MIN.; MAX.)	(0.009608 ; 0.013906)	(0.014987 ; 0.018045)	(0.008585 ; 0.011839)	(0.014655 ; 0.020206)	(0.008170 ; 0.012197)	(0.013582 ; 0.016006)
AVE MSE (LNO) (MIN.; MAX.)	(0.013919 ; 0.020245)	(0.012570 ; 0.015106)	(0.007320 ; 0.011531)	(0.007562 ; 0.015650)	(0.007590 ; 0.012882)	(0.008775 ; 0.011837)
AVE CA (%) (LNO) (MIN.; MAX.)	(88.9376 ; 97.7709)	(95.9390 ; 97.7988)	(96.7251 ; 99.2593)	(97.3452 ; 98.5952)	(95.7716 ; 98.5714)	(96.7188 ; 98.9474)
No. of Connection Weights	113	95	137	75	101	95
Percentage (%) Reduction in Size	---	15.93 %	---	45.25 %	---	5.94 %

(3) The performance tests based on the variable split ratio (VSR) method of data partioning scheme suggest that, the levels of 'MSE, NMSE, and MAE' performance measures are marginally higher for 'MLP-PCA' network as compared to the 'MLP' network. However, the levels of all these performance measures are lying just within the acceptable permissible limits for 'MLP-PCA' network. Further, the level of cross-correlation coefficient (CC) performance measure is quite comparable in both the cases.

(4) The performance tests based on the 'variable split ratio' (VSR) method of data partioning scheme suggest that, the average classification accuracy (CA) performance measure is just above 'ninety eight' percent (98 %) for both 'MLP' as well as 'MLP-PCA' network. Thus, in the case of 'MLP-PCA' network, the average classification accuracy (CA) performance measure is achieved well within the desired limit. This is irrespective, on account of the lower dimensionality input feature space for 'MLP-PCA' network.

(5) The performance tests based on the 'variation in group' (VG) method of data partioning scheme suggest that, the variation in the 'MIN AVE MSE' performance measure is marginal for different groups of dataset for 'MLP' as well as 'MLP-PCA' network. This particular fact ensures the consistency in the performance of the networks, which are designed on the basis of 'MLP' as well as 'MLP-PCA' network topology. However, the marginal variation in the 'MIN AVE MSE' performance measure is particularly noticed at higher level for 'MLP-PCA' network as compared to the 'MLP' network. In fact, it varies just outside the acceptable permissible limit (Table VIII). This marginal deterioration in the performance of the 'MLP-PCA' network is expected because of the loss of marginal relevant information on account of lower dimensionality input feature space.

(6) The performance tests based on the 'leave-n-out' (LNO) method of data partioning scheme suggest that, the variation in the 'AVE MSE' performance measure is marginal and varies just outside the acceptable permissible limit for different numbers of shift / skip in exemplars of dataset for 'MLP' as well as 'MLP-PCA' network. This particular fact ensures the consistency in the performance of the networks, which are designed on the basis of 'MLP' as well as 'MLP-PCA' network topology. However, the marginal variation in the 'AVE MSE' performance measure is particularly noticed at lower level for 'MLP-PCA' network as compared to the 'MLP' network.

(7) The performance tests based on the 'leave-n-out' (LNO) method of data partioning scheme suggest that, the variation in the 'average classification accuracy' (% CA) performance measure is marginal for different numbers of shift / skip in exemplars of dataset for 'MLP' as well as 'MLP-PCA' network. This particular fact ensures the consistency in the performance of the networks, which are designed on the basis of 'MLP' as well as 'MLP-PCA' network topology. However, the marginal variation in the 'average classification accuracy' (% CA) performance measure is particularly noticed at higher level for 'MLP-PCA' network (i.e. '95 % to 98 %') as compared to the 'MLP' network (i.e. 88 % to 98 %).

(8) In the case of 'MLP-PCA' network, the average classification accuracy (CA) performance measure is achieved well within the desired limit (i.e. ≥ 98.0 %). This is irrespective, on account of the lower dimensionality input feature space for 'MLP-PCA' network. The lower dimensionality input feature space is accountable for the reduction in the number of connection weights and in turn the size of the network. The size of the network is reduced by '15.93 %, 45.25

%, and 5.94%' for 3UNEQa, 3UNEQb, and 3UNEQc level classifier blocks, respectively. This particular fact is very important in view of the feasibility in the hardware implementation of the design specifications.

V. CONCLUSIONS

The methodology adopted in the design process of the various simulated designs of discrete neural network classifier blocks (i.e. 3UNEQa, 3UNEQb, and 3UNEQc') of discrete 'ANN' simulation model, based on 'multilayer perceptron' (MLP) type of neural network architecture with 'principal component analysis' (PCA) type of dimensionality reduction (DR) technique, is presented in the paper. The treatment of dimensionality reduction technique i.e. 'principal component analysis (PCA)' is introduced by means of 'XLSTAT 2008' software. The levels of performance measures like – 'MIN AVE MSE, MSE, NMSE, MAE, and CC' are relaxed marginally as compared to that of general optimum design. Since, it is expected that, the some of the relevant information might get lost in view of lower dimensional input feature space. The primary aim towards the application of 'principal component analysis' (PCA) type of 'dimensionality reduction' (DR) technique is to achieve almost the same 'average classification accuracy' (CA) with the lower dimensionality of input feature space.

The optimal design specifications, based on 'multilayer perceptron' (MLP) type of 'ANN' architecture with 'principal component analysis' (PCA) type of 'dimensionality reduction' (DR) technique does exceed the desired performance criterion, over a marginal range, for '3UNEQa, 3UNEQb, and 3UNEQc' level-classifier blocks. However, the purpose behind the design process of the level-classifier neural network blocks, based on the 'dimensionality reduction' (DR) technique is very well justified by means of comparative analysis between the design specifications and performance measures based on different design strategies. The striking generalizations, which are derived on the basis of the comparative performance analysis further resemble that the optimum design specifications, which are determined on the basis of 'MLP' network with the dimensionality reduction (DR) techniques are preferred as an optimum choice over the simple 'MLP' network for the classification and qualitative assessment task of state of degradation of insulation in three-phase ac induction motor.

REFERENCES

1. G. C. Stone, H. G. Sedding, B.A. Lloyd and B.K. Gupta, "The ability of diagnostic tests to estimate the remaining life of stator insulation," IEEE Trans. Energy Conversion, vol.3, no.4, Dec.1988, pp. 833 - 841.
2. Yoshida, H. and K. Umemoto, "Insulation Diagnosis for Rotating Machine Insulation," IEEE Trans. Electrical Insulation, vol. 21, no.6, Dec. 1986, pp. 1021-1025.
3. Tsukui, T., M. Takamura and Y. Kako, "Correlations between Nondestructive and Destructive Tests on High-Voltage Coil Insulations for Rotating Machines," IEEE Trans. Electrical Insulation, vol. 15, no. 2, April 1980, pp. 118-124.
4. A.J. Modak and H.P. Inamdar, "Performance Evaluation of Computer Simulated Extracted Features of Induction Motor with Healthy State of Insulation Present in Any Two-Phases," International Journal of Computer and Electrical Engineering (IJCEE), International Association of Computer Science and Information Technology Press (IACSIT), Singapore, vol.4, no.1, February 2012, pp. 65-74, DOI:10.7763/IJCEE.2012.V4.453, (ISSN: 1793-8163)
5. A.J. Modak and H.P. Inamdar, "Computer Simulated Extracted Parameters of Induction Motor for Equal Variation in State of Degradation of Insulation in all Three-phases," Proc. 7th IEEE Int. Conf. Industrial Electronics and Applications (ICIEA), Singapore, July 2012, pp. 1349-1350, IEEE Catalog Number: CFP1220A-CDR, (ISBN: 978-1-4577-2119-9/12)
6. A.J. Modak and H.P. Inamdar, "Performance Evaluation of Computer Simulated Extracted Features of Induction Motor for Variation in State of Degradation of Insulation in Any Two-Phases with Healthy State of Insulation in Remaining Phase," International Journal of Applied Engineering (IJAE),Eureka Press, Singapore, vol.1, no.2, December 2011, pp.104-114 (ISSN: 2010 4391)
7. [XLSTAT, 2008] : Addinsoft: XLSTAT Version 2008, http:// www.xlstat.com, Addinsoft Inc. 28 West 27th Street, Suite 503, New York, NY 10001, USA.
8. Kovach Computing Services, http://www.kovcomp.co.uk, Kovach Computing Services,85,Nant-y-Felin,Pentraeth,Isle of Anglesey LL75 8UY Wales, U.K. 2, Aug. 1987, pp. 740–741 [Dig. 9th Annu. Conf. Magnetics Japan, 1982, p. 301].
9. [NEUROSOLUTIONS, 5.0]: NEUROSOLUTION Version 5.0, http:// www.neurosolutions.com, Neuro Dimension, Inc. 3701 NW 40th Terrace, Suite 1, Gainesville, FL 32606.

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