Optimal Simulated Design of RBF Neural Network Classifier Block 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 is done for the classification and qualitative assessment of the state of degradation of insulation in the respective phases of three-phase ac induction motor. 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, are presented in the previous research papers. The methodology adopted towards the optimal design process of the discrete neural network classifier blocks of discrete 'ANN' simulation model , which are designed on the basis of 'radial basis function' (RBF) type of neural network architecture for the qualitative assessment of the state of degradation of stator insulation is described in the present research paper.

Index Terms— induction motor, stator insulation, radial basis function, artificial neural network, Park's current transformation

I. INTRODUCTION

In the previous investigations [1-3], it is ascertained that there is no correlation between the results of any non destructive type of (d. c / a. c.) assessment parameters with destructive type of (d. c. /a. c. / impulse) breakdown levels. There is a need to establish an economical non destructive test method for an assessment of state of degradation of stator insulation caused due to various factors in an integrated way. In view of the above perspective, the present research work presents a novice nondestructive method to assess the state of degradation of stator winding insulation. 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 emphasis is towards the application of such unbalanced stator current numerical data to a suitable artificial intelligence (AI) based tool to determine the state of degradation of stator insulation. On experimental basis it is not feasible to collect the large set of unbalanced stator current data, which would model the entire range of state of degradation of insulation for the specific motor used in particular industry. However, in neural network based AI-technique, a large set of data pattern availability is required for the development of diagnostic model to detect the state of degradation of stator insulation. This is essential from the point of view of optimal design and efficient performance of the neural network classifier. Hence, there is need to generate large number of unbalanced stator current numerical data on the basis of computer simulation model to represent the various states of degradation of stator winding insulation occurring in respective phases. The formulation and execution of computer simulation program 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 (θ_0°), angle of major-axis (θ_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

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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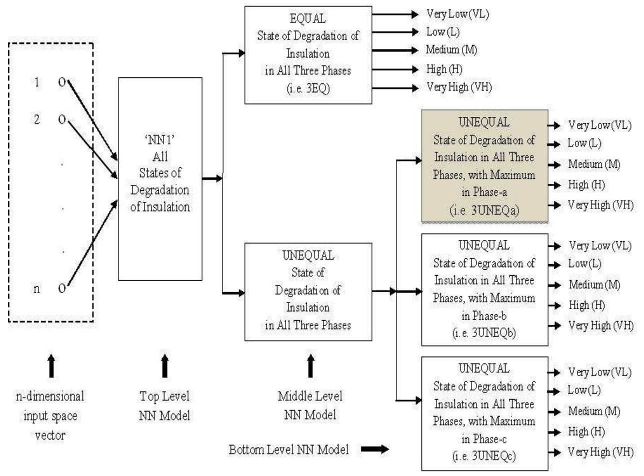

Fig.1 Schematic Block Diagram of Discrete 'ANN' Simulation Model

The 'n-dimensional input space vector' consists of 'n=6' numbers of extracted mathematical parameters 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, which is represented in the form of '6-dimensional input space vector', 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)').

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-b' as compared to 'phase-c' and 'phase-a' (i.e. 3UNEQb) then the '6-dimensional input space vector', is applied to the neural network classifier block '3UNEQb'. Otherwise, the same will be applied to the remaining neural network classifier block '3UNEQc'. 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 'radial basis function' (RBF) type of neural network architecture. The overall design strategy for the design of discrete 'ANN' simulation model is detailed in the next section. In the context of the design process, the description is restricted towards around only one particular neural network block of discrete 'ANN' simulation model. 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 'Figure 1'. The methodology adopted in the design process for each one of the simulated designs of the rest of the other discrete neural network classifier blocks more or less remains the same. Henceforth, only the overall simulation results of the rest of the other simulated designs of various discrete neural network classifier blocks are provided for the sake of comparative performance analysis. The various simulated designs of discrete neural network classifier blocks (i.e. NN1, 3UNEQ, 3EQ, 3UNEQa, 3UNEQb, and 3UNEQc) of discrete 'ANN' simulation model are designed at 'Neurosolutions' (Neurosolutions 5.0) platform [7].

III. STRATEGY FOR DESIGN OF DISCRETE 'ANN' SIMULATION MODEL

The major factors involved in the design process of the neural network classifier block are:

- The selection of neural network architecture (topology).
- The neural network design considerations such as determination of input and output variables, the number of hidden layers in the neural network, and size of 'training data (TR), cross validation data (CV), and testing data (TE) sets.'
- The practical considerations such as network efficiency, accuracy, robustness, and hardware implementation feasibility.
- The neural network training considerations such as initializing the network weights, selection of appropriate training parameters (e.g. learning rate (η) and momentum coefficient (α) etc), and selection of proper termination criterion (i.e. stopping condition (SC)).

There are numbers of parameters involved in the training process of neural network design, which can affect the performance of network. The selection of appropriate network parameter is as systematic and empirical process, which can be executed through experimentation. In the process of selection of an optimal value of a specific parameter the rest of the other parameters are set to their nominal default values whereas the value of specific parameter is varied gradually throughout its possible range of variation. At the time of variation in the value of parameter, its effect on the performance of the network is carefully monitored. The value of parameter, where the best performance is observed is chosen as an optimal value. The performance of the network is monitored on the basis of certain performance measures / indices such as 'mean square error (MSE), minimum average MSE (MIN AVE MSE) , normalized mean square error (NMSE), mean absolute error (MAE), classification accuracy (CA), and correlation coefficient (CC)'. Thus, each and every parameter of the network is selected by investigating the every single effect imposed by each one of them on the performance of network.

A. Radial Basis Function (RBF) Network

The 'radial basis function' (RBF) type of 'ANN' architecture is a nonlinear hybrid network, which comprises of single 'hidden-layer' (HL_1) with numbers of processing units (PU's). The processing units (PU's) belonging to the single hidden layer are often termed as cluster centers (CLC's). These cluster centers (CLC's) are assigned with 'Gaussian' (i.e. Bell shape) type of transfer functions rather than the standard 'Sigmoid' type of transfer functions employed by the processing elements (PE's) of 'multilayer perceptron' (MLP) type of 'ANN' architecture. The centers and widths of the Gaussians are set by unsupervised learning rules, and supervised learning is applied to the numbers of processing elements (PE's) belonging to output layer (OUT). These networks tend to learn much faster than MLP's.

The use of this network is recommended only when the number of exemplars is so small (< 100) or so dispersed that the clustering is ill-defined. For standard 'RBF's, the supervised segment of the network only needs to produce a linear combination of the output at the unsupervised layer. The hidden layers can be added to make the supervised segment as 'MLP' network instead of a simple linear perceptron. The number of patterns in the training set affects the number of centers, but this is mediated by the dispersion of the clusters. If the data is very well clustered, then few Gaussians are needed. On the other hand, if the data is scattered, many more Gaussians are required for good performance. The competitive learning has an intrinsic metric. The competitive learning keeps an intrinsic probability distribution of the input data. It has the drawback that some processing elements (PE's) may never fire, while others may always win the competition. In order to avoid these extreme situations one can include a conscience mechanism that keeps a count on how often a processing element wins the competition, and enforces a constant wining rate across the processing elements. The centers of the Gaussians are placed with a conscience mechanism.

The steps involved in the general optimal design of neural network classifier block based on 'radial basis function' (RBF) type of 'ANN' architecture are as follows:

(a) The selection of 'training (TR), cross-validation (CV) and testing (TEST)' datasets.

(b) The selection of 'performance measures or indices' (i.e. 'mean square error (MSE), normalized mean square error (NMSE), mean absolute error (MAE), classification accuracy (CA), and correlation coefficient (CC)').

(c) The selection of suitable 'error criterion' (i.e. 'Error Norm').

(d) The selection of number of processing elements (PE's) in the input-layer (IN) and output-layer (OUT).

(e) The selection of 'competitive rule' (i.e. 'CR') and 'metric function' (i.e. 'MF').

(f) The selection of number of 'cluster centers' (i.e. 'CLC').

(g) The selection of optimal learning parameters (e.g. 'learning constant or step size' (i.e. 'LC' or 'η'), and 'momentum coefficient or rate' (i.e. 'MC' or 'α'), etc …) for the 'processing elements or nodes' (i.e. 'PE') in the output layer (OUT) of the neural network.

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(h) The selection of ‘termination or stopping criterion’ (i.e. ‘stopping condition (SC)’).
(i) The performance evaluation tests of general optimal design of neural network classifier block based on various performance measures or indices over different data partioning schemes i.e. ‘Leave-N-Out (LNO) method, Variation in Groups (VG) method, and Variable Split Ratio (VSR) method’.

The details of the methodology adopted towards the application of these steps, in the design process of the general optimal design of ‘3UNEQa’ level-classifier block of discrete ‘ANN’ simulation model based on ‘radial basis function’ (RBF) type of ‘ANN’ architecture are provided in the next section.

IV. GENERAL OPTIMAL DESIGN OF LEVEL CLASSIFIER BLOCK BASED ON RBF TYPE OF ‘ANN’ ARCHITECTURE

The general optimal design of ‘3UNEQa’ level-classifier block based on radial basis function (RBF) type of NN-architecture (i.e. ‘3UNEQa-RBF) of discrete ‘ANN’ simulation model is obtained 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 general optimal design of ‘3UNEQa-RBF’ neural network classifier block is obtained by performing the systematic experimentations as per the steps described in the previous section. The description regarding an execution of these steps is detailed in the following sub-sections.

A. Training (TR), Cross-validation (CV), and Testing (TEST) Datasets

It is a common practice to select a set of training (TR) data, cross-validation (CV) data, and testing (TEST) data that are statistically significant to represent the system under consideration. The training (TR) data-set is used to train the neural network. The cross-validation (CV) data-set is used to compute the ‘error’ at the time of the training process of the neural network. The testing (TEST) data-set is used to assess the performance of the network, once it has been successfully trained. The ‘data-set’ must be statistically significant in order to cover the entire range of input and output variables of operating conditions.

In view of the above considerations, for the general optimal design of ‘3UNEQa’ level-classifier block, the resultant ‘data-set’ comprise of ‘8210’ numbers of stator current data pattern belonging to the sub-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’ is prepared among the entire ‘data-set’ comprise of ‘24700’ numbers of stator current data pattern. The resultant dataset is scaled down approximately by less than ‘ten’ percent (≤ 10 %). In the training process, the resultant dataset, which is reduced to ‘720’ numbers of stator current data is used.

In the training process, the resultant reduced ‘data-set’ is further divided into three data-sets by means of process of ‘data-tagging’. The ‘Neurosolutions’ (‘Neurosolutions 5.0’) platform provides the feature of ‘data-tagging’ application, by means of which it is possible to divide the individual resultant ‘data-set’ into ‘three’ sets by assigning the certain percentage of data (%) as a training (TR) data, cross-validation (CV) data, and testing (TEST) data. In the training process, initially about ‘sixty’ (60%) percent of data is tagged as training (TR) data whereas the ‘twenty’ (20%) percent of data is tagged as cross-validation (CV) data and the remaining ‘twenty’ (20%) percent of data is tagged as testing (TEST) data. Later, the consistency in the performance of the general optimal design of the neural network classifier block is tested on the basis of various performance measures over different data partioning schemes. The performance of the general optimal design of the neural network classifier block is measured on the basis of performance measures like - ‘mean square error (MSE), normalized mean square error (NMSE), mean absolute error (MAE), classification accuracy (CA), and correlation coefficient (CC)’. The different data partioning schemes are determined by means of various methods like- ‘Leave-n-out (LNO) method, variable split in ratio (VSR) method and variation in groups (VG) method’.

B. Selection of Performance Measures (Indices)

The selection of optimal values of design parameters is done on the basis of some specific threshold values of the performance measures. The threshold values of performance measures (indices) used for the general optimal design of the level-classifier NN-blocks of discrete ‘ANN’ simulation model are shown in the ‘Table I’.

TABLE I PERFORMANCE MEASURES FOR LEVEL-CLASSIFIER NN-BLOCKS OF DISCRETE ‘ANN’ SIMULATION MODEL BASED ON RBF-NETWORK

NN-Classifier Blocks	Performance Measures (Indices)					
	MSE	MIN AVE MSE	NMSE	MAE	CA (%)	CC
Level-Classifier Block (i.e.3EQ)	= 0.075 ˜ $(7.5x10^{-2})$	= 0.09 ˜ $(9x10^{-2})$	= 0.3	= 0.15	˜ 90.0 - 100.0	˜ 0.90 - 1.0
Level-Classifier Blocks (i.e.3UNEQa, 3UNEQb, 3UNEQc,)	= 0. 0625 ˜ $(6.25x10^{-2})$	= 0.075 ˜ $(7.5x10^{-2})$	= 0.25	= 0.125	= 90.0	˜ 0.90 - 1.0

C. Selection of Error Criterion (Error Norm)

The ‘L_2’ error norm and cross entropy criterion is used in the learning procedure. Further, the same ‘L_2’ error norm and cross entropy criterion is used in the learning procedure for the general optimal designs of the rest of the level-classifier blocks of discrete ‘ANN’ simulation model. The ‘L_2’ error norm, which implements the quadratic cost-function, is by far the most widely applied cost-function in adaptive systems.

D. Selection of Number of Processing Elements (PE’s) in Input-layer (IN) and Output-layer (OUT)

The general optimal design of ‘3UNEQa’ level-classifier block based on radial basis function (RBF) type of ‘ANN’ architecture (3UNEQa-RBF) of discrete ‘ANN’ simulation model is obtained 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 extracted mathematical parameters i.e. ‘angle of orientation ($\theta_0{}^o$), angle of major-axis ($\theta_m{}^o$) , length of major

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axis (L_{MA}), length of minor axis (L_{MB}), eccentricity (ε), and latus rectum (LR)' are used as 'six-dimensional input space vector' to the neural network. Thus, the '3UNEQa' level-classifier block based on radial basis function (RBF) type of 'ANN' architecture (3UNEQa-RBF) of discrete 'ANN' simulation model is comprising of 'input-layer' with 'six' numbers of processing elements to accept the 'six-dimensional input space vector' to the neural network. The 'output-layer' (i.e. 'OUT') consists of 'five' numbers of processing elements each one of which is used to represent the specific qualitative level like - 'Very Low (VL), Low (L), Medium (M), High (H), and Very High (VH)'.

E. Selection of Competitive Rule (CR) and Metric Function (MF)

The performance of the network with 'two' competitive rules i.e. 'Standard-Full' (STDF) and 'Conscience-Full' (CSCIF) are verified with each one of the 'three' metric functions i.e. 'Dot-Product' (DP), 'Euclidean' (ED), and 'Boxcar' (BC). The numbers of computer simulation experimentations are done on 'Neurosolutions 5.0' to test the performance of the network for the specific combinations of competitive rules and metric functions. In each one of these computer simulation experiments, the numbers of cluster centers (CLC) are selected as '30' (default value) and 'AVE MSE' performance measure is observed on training (TR) and cross-validation (CV) data. The convergence to the global minimum of the network depends upon the convergence rule and the metric function used for the training. Hence, the convergence rate of each competitive rule and metric function is verified.

The competitive rule should be selected such that the convergence should be fast enough on training (TR) and cross-validation (CV) data, the errors (i.e. MSE, MIN AVE MSE, NMSE, and MAE) should be minimum, and classification accuracy (i.e. CA) should be maximum. The nature of convergence on training (TR) data for various competitive rules is shown in the 'Fig.2'.

On the basis of nature of convergence, it is observed that the convergence on training (TR) data is fast with 'Conscience-Full' (CSCIF) competitive rule as compared to the 'Standard-Full' (STDF) competitive rule. The 'Fig.3' illustrates the variation of minimum average mean square (MIN AVE MSE) on training (TR) and cross-validation (CV) data for different competitive rules for '3UNEQa' NN-level classifier block. In the case of 'Conscience-Full' (CSCIF) competitive rule, the 'MIN AVE MSE' is low as compared to the 'Standard-Full' (STDF) competitive rule on training (TR) as well as cross-validation (CV) data.

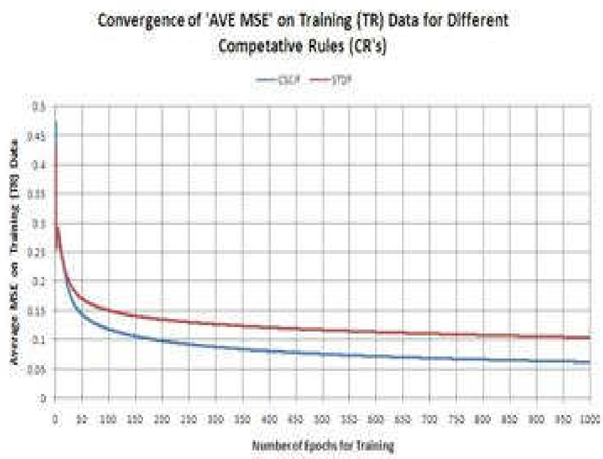

Fig.2 Convergence of AVE MSE on Training (TR) Data for Different Competitive Rules

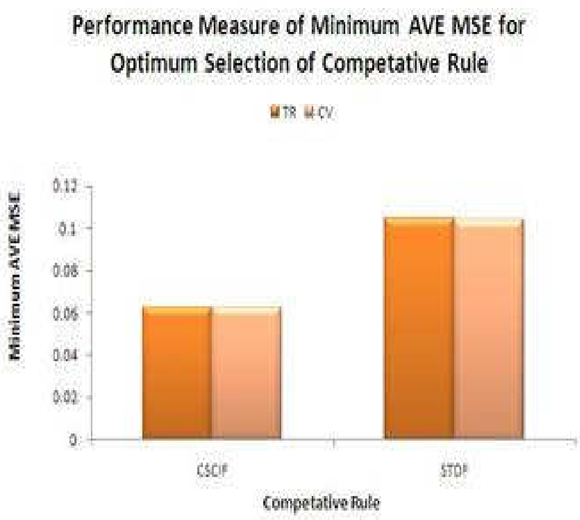

Fig.3 Variation of 'MIN AVE MSE' on Training (TR) and Cross-validation (CV) Data for Different Competitive Rules

In view of the fast convergence rate of 'AVE MSE' and 'MIN AVE MSE', the choice of 'Conscience-Full' (CSCIF) competitive rule, is preferred over 'Standard-Full' (STDF) competitive rule. The 'Table-II' shows the variations of average classification accuracy (CA) with different competitive rules.

TABLE II VARIATIONS OF CLASSIFICATION ACCURACY (CA) WITH DIFFERENT COMPETITIVE RULES

	Test on TEST Data						Test on CV Data					
CR	VLOW	VHIGH	LOW	Medium	HIGH	AVG	VLOW	VHIGH	LOW	Medium	HIGH	AVG
CSCIF	100	92.04545	92.41877	91.71429	90.69307	93.37432	99.2126	91.08527	93.01471	88.42975	88.68687	92.08584
STDF	100	90.5303	69.67509	86.85714	92.47525	87.90756	99.6063	91.47287	69.11765	84.573	90.50505	87.05497

The average classification accuracy (CA) is highest in the case of 'Conscience-Full' (CSCIF) competitive rule (i.e. above '90.0 %') on both cross-validation (CV) as well as testing (TEST) data. In view of the higher average classification accuracy (CA), the choice of 'Conscience-Full' (CSCIF) competitive rule, is preferred over 'Standard-Full' (STDF) competitive rule. The 'Euclidean' (ED) is selected as a default metric-function while performing the numbers of computer simulation experiments to select the best suitable competitive rule. Hence, the next step is to select the proper

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metric function with the optimal choice of 'Conscience-Full' (CSCIF) as a competitive rule.

On different metric functions, all the performance measures such as MSE, NMSE, MAE, correlation coefficient (CC) and average classification accuracy (CA) are observed carefully on cross-validation (CV) and testing (TEST) data. The metric function should be selected such that the convergence should be fast enough on training (TR) and cross-validation (CV) data, the errors (i.e. MSE, MIN AVE MSE, NMSE, and MAE) should be minimum, and classification accuracy (i.e. CA) should be maximum. The positive correlation between the desired output and actual output of the network is represented by correlation coefficient (i.e. CC). Hence, it should be approached to 'one' (i.e. 100 %).

On the basis of nature of convergence shown in the 'Fig.4', it is observed that the convergence on training (TR) data is quick with 'Boxcar' (BC) metric function as compared to the rest of the other metric functions.

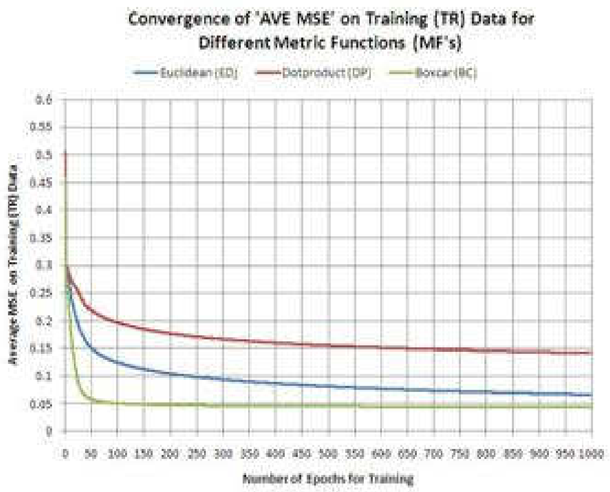

Fig.4 Convergence of 'AVE MSE' on Training (TR) Data for Different Metric Functions

The 'Table-III' shows the variations of performance measures like - NMSE, MAE, and correlation coefficient (CC). In the case of 'Boxcar' (BC) metric function, the 'NMSE' and 'MAE' performance measures are lowest as compared to the rest of other metric functions on both cross-validation (CV) as well as testing (TEST) data. The correlation coefficient (CC) is about 90% (i.e. '0.9185' and '0.924066' on cross-validation (CV) and testing (TEST) data, respectively) with the 'Boxcar' (BC) metric function.

TABLE III VARIATIONS OF PERFORMANCE MEASURES WITH DIFFERENT METRIC FUNCTIONS

Metric Function	NMSE		MAE		CC	
	TEST	CV	TEST	CV	TEST	CV
ED	0.227613	0.235555	0.120936	0.122805	0.884177	0.878876
DP	0.529034	0.527207	0.205384	0.205768	0.684864	0.68712
BC	0.14563	0.155475	0.068026	0.070125	0.924066	0.9185

The 'Fig.5' illustrates the variations of average classification accuracy (CA) with different metric functions. The average classification accuracy (CA) is high, in the case of 'Euclidean' (ED) and 'Boxcar' (BC) metric functions (i.e. above '90.0 %') on both cross-validation (CV) as well as testing (TEST) data. However, In view of the fast convergence rate of 'AVE MSE', the choice of 'Boxcar' (BC) metric function, is preferred over 'Euclidean' (ED) and 'Dot-product' (DP) metric function. Further, the variations of performance measures like - NMSE, MAE, and correlation coefficient (CC) support the optimum selection of 'Boxcar' (BC) metric function.

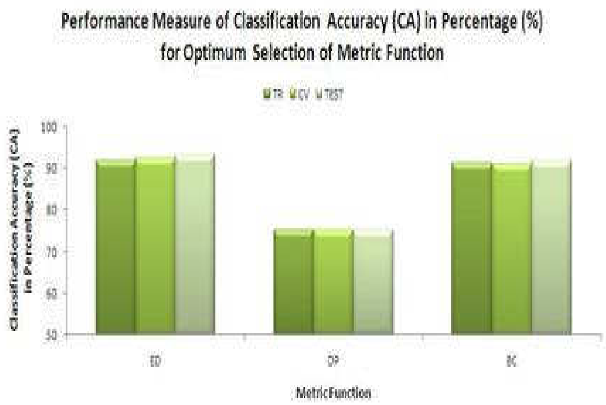

Fig. 5 Variation of Average Classification Accuracy on Training (TR), Cross-validation (CV), and Testing (TEST) Data for Different Metric Functions

The 'Conscience-Full' (CSCIF) is used as an optimal competitive rule while performing the numbers of computer simulation experiments to select the best suitable metric function. Further, the numbers of cluster centers (CLC) are selected as '30' (default value) while performing the numbers of computer simulation experiments to select the best suitable 'competitive rule' as 'Conscience-Full' (CSCIF) and 'metric function' as 'Boxcar' (BC). Hence, the next step is to select the proper numbers of cluster centers (CLC's) with the optimal choice of 'Conscience-Full' (CSCIF) as a 'competitive rule' and 'Boxcar' (BC) as a 'metric function'.

F. Selection of Number of Cluster Centers (CLC)

The numbers of cluster centers (CLC's) in the 'RBF' network represents the numbers of processing elements (PE's) in the hidden layer with the 'Gaussian' transfer function (i.e. bell-shape function). The optimal selection of the number of cluster centers (CLC's) in the hidden layer (i.e. 'HL_1') is done by observing the performance of the network with the variation in the number of cluster centers in the hidden layer. The numbers of cluster centers in the hidden layer of the network are varied gradually from '1' to '51'. For each one of these variations, the network is trained with the randomized resultant reduced 'data-set', which is tagged in terms of ratio of '60:20:20' as a 'training (TR) data, cross-validation (CV) data, and testing (TEST) data,' respectively.

The performance measure of 'MIN AVE MSE' over 'five' number of runs on training (TR) data and cross-validation (CV) data is illustrated in the 'Fig.6'. It is imperative that the 'MIN AVE MSE' performance measure decreases with the increase in the numbers of cluster centers on both training (TR) and cross-validation (CV) data. The 'MIN AVE MSE' performance measure attains the stable minimum value, when the number of cluster centers are more than 'thirty seven' (i.e. 'CLC $\geq$ 37') for single hidden layer on training

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(TR) and cross-validation (CV) data. This is indeed meeting the general requirements of the order of - ‘10^{-2}’ of ‘MIN AVE MSE’ performance index, as specified in ‘Table-I’, for the general optimal design of ‘3UNEQa’ level-classifier block.

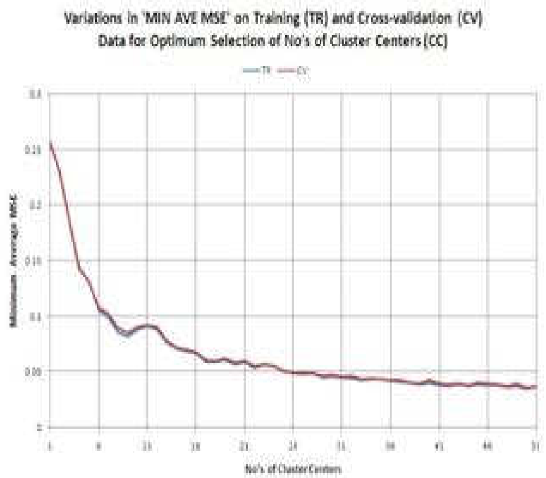

Fig.6 Variations in ‘MIN AVE MSE’ Performance Measure on Training (TR) and Cross-validation (CV) Data with Different Cluster Centers

The variation in the performance measures like- ‘NMSE, MAE, and correlation coefficient (CC)’ with different cluster centers on ‘cross-validation (CV),’ data are as shown in the ‘Fig.7’. It is imperative that the ‘NMSE and MAE’ performance measures decreases with the increase in the numbers of cluster centers on both training (TR) and cross-validation (CV) data, respectively. The ‘NMSE and MAE’ performance measures attains the stable minimum value, when the number of cluster centers are more than ‘thirty seven’ (i.e. ‘CLC ≥ 37’) for single hidden layer on training (TR) and cross-validation (CV) data. Similarly, the correlation coefficient (CC) performance measure increases with the increase in the numbers of cluster centers on both training (TR) and cross-validation (CV) data. The correlation coefficient (CC) performance measure approaches closely to the value ‘1’ (i.e. 100 %), when the number of cluster centers are more than ‘thirty seven’ (i.e. ‘CLC ≥ 37’) for single hidden layer on training (TR) and cross-validation (CV) data.

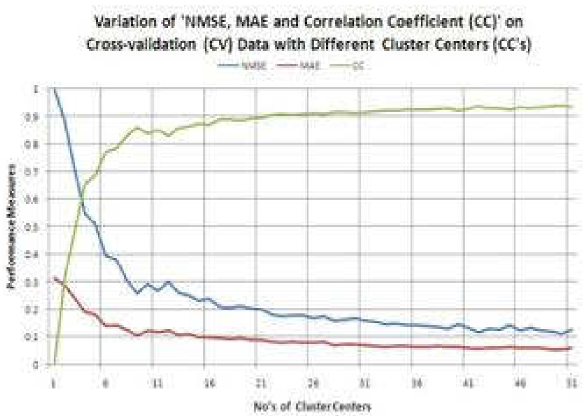

Fig.7 Variations in ‘NMSE, MAE, and CC’ Performance Measures on Cross-validation (CV) Data with Different Cluster Centers

In view of these trends in the variations in the performance measures , the optimal numbers of cluster centers (CLC’s) of single hidden-layer for ‘3UNEQa’ level classifier block based on radial basis function (RBF) type of NN-architecture (i.e. ‘3UNEQa-RBF) are selected as ‘CLC = 37’.

G. Selection of Optimal Learning Parameters

The optimal selection of the learning parameters i.e. ‘learning constant or step size’ (‘LC’ or ‘η’), and ‘momentum coefficient or rate’ (‘MC’ or ‘α’) of the processing elements belonging to output layer of the ‘RBF’ network is also responsible for the global minimum and would decide the convergence rate to minimum. The numbers of computer simulation experimentations are performed for optimal selection of learning parameters of the processing elements belonging to the output layer. The ‘Momentum’ (MOM) learning algorithm is used for the training process and ‘Tanh Axon’ (TANH) transfer function is assigned to the processing elements belonging to output layer (OUT) of the ‘3UNEQa-RBF’ neural network. The ‘Conscience-Full’ (CSCIF) is used as an optimal ‘competitive rule’ whereas the ‘Boxcar’ (BC) is used as optimal ‘metric function’. Further, the numbers of cluster centers (CLC) are selected as ‘37’ (optimal value) while performing the numbers of computer simulation experimentations.

Initially, the ‘momentum coefficient’ (i.e. ‘α’ or ‘MC’) of the processing elements (i.e. PE = 5) belonging to output layer is set to some arbitrary default value of ‘0.7’. In fact, the initial arbitrary default value is decided by the ‘Neurosolutions 5.0’ neural network design tool [7].

In view of the above optimal and default settings, the learning constant of the processing elements (i.e. PE = 5) belonging to output layer is varied from ‘0.1’ to ‘1.0’ in steps of ‘0.1’ unit (i.e. 0.1:0.1:1.0). The performance measure of ‘MIN AVE MSE’ is observed for each variation of the learning constant on training (TR) and cross-validation (CV) data. The value of learning constant for the processing elements (i.e. PE = 5) belonging to output layer is finally selected as an optimum value, at which the ‘MIN AVE MSE’ converges to the minimum value. If the ‘MIN AVE MSE’ converges to the minimum value at learning constant ‘LC = 1.0’, then the numbers of computer simulation experimentations are performed again with the same optimal and default settings. The learning constant of the processing elements (i.e. PE = 5) belonging to output layer is varied further over an exceeding range in the multiples of ten’s, (i.e. ‘0.1:1:10:100:1000:10000: …’). The simulation result shown in the ‘Fig.8’, indicates that the performance measure of ‘MIN AVE MSE’ converges to minimum value at learning constant ‘LC = 0.7’ over the initial variable range (i.e. 0.1:1.0) on training (TR) and cross-validation (CV) data . Hence, the optimum value of learning constant (i.e. ‘η’ or ‘LC’) of the processing elements (i.e. PE = 5) belonging to output layer is selected as ‘0.7’.

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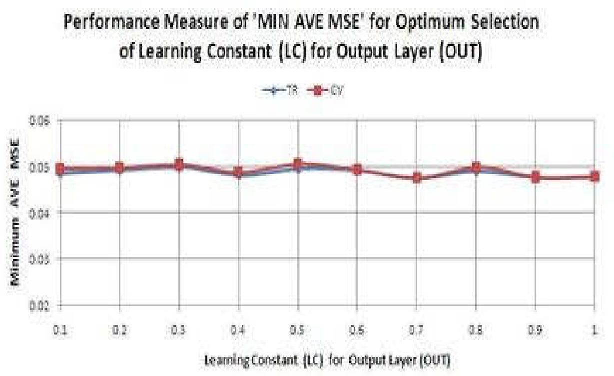

Fig.8 Performance Measure of 'MIN AVE MSE' for Variation in Learning Constant (LC) of Processing Elements belonging to Output Layer

In a similar manner, the numbers of computer simulation experimentations are performed for an optimum selection of momentum coefficient (i.e. 'α' or 'MC') of the processing elements (i.e. PE = 9) belonging to output layer with the optimum value of learning constant selected as '0.7'. On the basis of simulation results, it is being observed that the performance measure of 'MIN AVE MSE' converges to minimum value at momentum coefficient 'MC = 0.4' over the variable range (i.e. 0.1:1.0) on training (TR) and cross-validation (CV) data. Hence, the optimum value of momentum coefficient (i.e. 'α' or 'MC') of the processing elements (i.e. PE = 9) belonging to first hidden layer is selected as '0.4'.

In the general optimal design based on 'radial basis function' (RBF) type of ANN-architecture of '3UNEQa' level-classifier block (i.e. 3UNEQa-RBF) of discrete 'ANN' simulation model, the 'Per-Epoch' (Batch Mode) type of the 'frequency of weight updates' approach is used in the training process. The overall training process, which includes the numbers of computer simulation experimentations is initially consists of the standard presentation of 'thousand' (1000) numbers of 'Epochs' over 'five' (5) numbers of 'Runs' to the processing elements (i.e. PE = 6) belonging to input-layer (IN) of radial basis function (RBF) type of ANN-architecture. There is need to decide the appropriate stopping criterion or stopping condition to limit the number of epochs to a predetermined value.

H. Selection of Stopping Criterion

In the context of different 'numbers of epochs', the general optimal design of radial basis function (RBF) type of ANN-architecture of '3UNEQa' level-classifier block (i.e. 3UNEQa-RBF) is trained for number of times and the corresponding variations in performance measures like 'MIN MSE' and 'MIN AVE MSE' on training (TR) and cross-validation (CV) data are observed. The simulation results of the variation in performance measures of 'MIN AVE MSE' on training (TR) and cross-validation (CV) data for different 'number of epochs' are shown in the 'Fig.9'.

The threshold values for performance measures of 'MIN MSE' and 'MIN AVE MSE' are considered approximately '7.5' times of the order of '10^{-2}' (i.e. $\approx 7.5 \times 10^{-2}$) as an effective stopping condition for the training process of level-classifier blocks belonging to bottom layer of discrete 'ANN' simulation model. The simulation results as shown in the 'Fig.9', suggest that the performance measures like - 'MIN AVE MSE' approaches towards the threshold values for '1000' number of epochs. Further, there is no significant change in either 'MIN MSE' or 'MIN AVE MSE' for the 'number of epochs' beyond '1000'. However, in the view of the satisfactory stopping condition, as a margin of safety, the 'multiplicity' order in the tune of '3' to '4' times the 'number of epochs' is maintained. Hence, the '3000' number of epochs is selected as an optimum stopping condition.

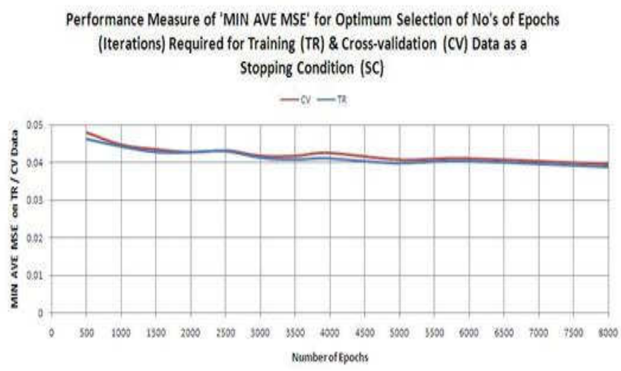

Fig.9 Variation of 'MIN AVE MSE' Performance Measure with 'Numbers of Epochs' for General Optimal Design

V. PERFORMANCE TESTS OF GENERAL OPTIMAL DESIGN OF RADIAL BASIS FUNCTION TYPE OF NETWORK

The general optimal design of '3UNEQa' level-classifier block based on 'radial basis function' (RBF) type of NN-architecture (i.e. '3UNEQa-RBF) of discrete 'ANN' simulation model is thus obtained by performing the numbers of computer simulation experimentations, which are described in the previous sections. The design specifications determined for the general optimal design of '3UNEQa-RBF' neural network classifier block are listed in 'Table IV'.

TABLE IV DESIGN SPECIFICATIONS OF GENERAL OPTIMAL DESIGN OF '3UNEQa-RBF' NEURAL NETWORK LEVEL CLASSIFIER BLOCK

Design Parameter	Specification
Data Tagging 60% Training (TR) , 20% Cross Validation (CV), 20 % Testing (TEST)	TR: CV: TEST (%) » 60:20:20 (%)
Number of Processing Elements (PE) in Input Layer (i.e. 'IN')	06
Error Criterion	'L_2' Norm
Stopping Condition (i.e. 'SC')	'3000' Epochs
Competitive Rule (i.e. CR)	Conscience-Full (CSCIF)
Metric Function (i.e. MF)	Boxcar (BC)
Number of Cluster Centers (CLC's) in Single Hidden Layer (i.e. 'HL_1') Transfer Function (i.e. 'TF') of Processing Elements (PE's) belonging to Output Layer	37 'Tanh Axon' (i.e. 'TANH')
Learning Algorithm (i.e. 'LA') of Processing Elements (PE's) belonging to Output Layer	'Momentum (i.e. 'MOM')
Output Layer : Learning Constant or Step-Size (i.e. 'LC' or 'η')	0.7
Output Layer: Momentum Coefficient or Rate (i.e. 'MC' or 'α')	0.4
Number of Processing Elements (PE) in Output Layer (i.e. OUT)	05
Number of Connection Weights: (i.e. 6 x 37 + 37 x 5 + 37 + 5)	449
Time Required Per Epoch Per Exemplar	'164.4' ms
Neural Network Topology	6-(37)-5-RBF

The general optimal design of the network is tested on the data, which is not used during the training process i.e. testing (TEST) data. The design of the network must be more generalized. The general optimal design of '3UNEQa-RBF' neural network level classifier block with the design

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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 variation of performance measures like 'average classification accuracy' (CA) over a marginal range ('Fig. 10') confirms the consistency in the performance of network for different datasets, which are formed on the basis of variable percentage of data tagged for the training and testing.

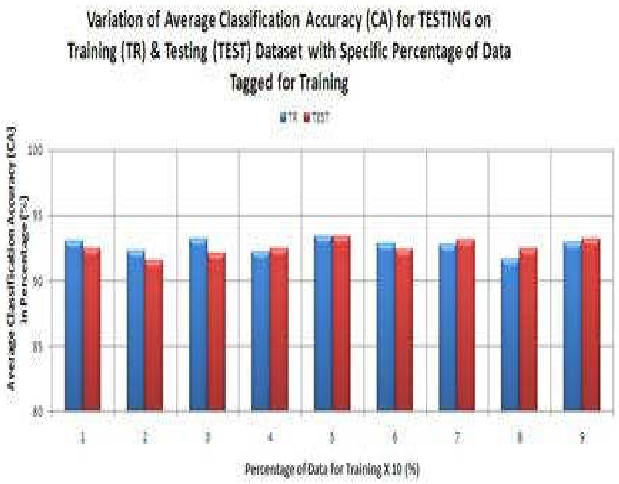

Fig.10 Variation of Average Classification Accuracy (CA) Performance Measure with Variable Percentage of Data Tagged for Training and Testing Data

The 'average classification accuracy' (CA) is above '90.0%' on testing (TEST) data, which is well within the permissible limit for all datasets. The permissible limit is specified in terms of threshold value of 'average classification accuracy' (i.e. '$\geq$ 90.0 for 'CA', as shown in the Table 1) for the general optimal design of level classifier NN-block. Further, the marginal improvement in the performance of the network is observed on testing (TEST) data, when the percentage of data tagged for training is 'fifty' percent (i.e. 50%).

The variation of 'MIN AVE MSE' performance measure ('Table V') over a marginal range (i.e. between '0.04' and '0.05') confirms the consistency in the performance of network for different groups of dataset. The numbers of computer simulation experimentations are done to test the performance of the network for different numbers of predefined subset of exemplars to be skipped (i.e. '90, 102, 115, 127, 140, 152, 165, and 180') during the 'Leave-N-Out' (LNO) type of data partioning training scheme.

TABLE V VARIATION OF 'MIN AVE MSE' PERFORMANCE MEASURE FOR DIFFERENT GROUPS OF DATASET

GROUP NO	VG	Avg TrnMSE (MIN)	Avg CVMSE (MIN)
1	1234	0.042540	0.041807
2	2341	0.046013	0.047875
3	3412	0.042282	0.046646
4	4123	0.038122	0.038518
5	2134	0.042077	0.041818
6	3241	0.042002	0.042844
7	4312	0.040363	0.044189
8	4132	0.039417	0.039382
9	2143	0.042748	0.043215
10	3214	0.042751	0.047005
11	4321	0.040765	0.044016
12	1432	0.038415	0.038285

The performance of the network is tested to verify the consistency over all predefined subset of exemplars to be skipped with respect to 'AVE MSE' performance measure.

The variation of 'AVE MSE' performance measure ('Fig. 11') for different numbers of predefined subset of exemplars to be skipped (i.e. '90, 102, 115, 127, 140, 152, 165, and 180') during the 'Leave-N-Out' (LNO) type of data partioning training scheme are over a marginal range. This confirms the consistency in the performance of network and as such ensures that the network is truly learned and generalized.

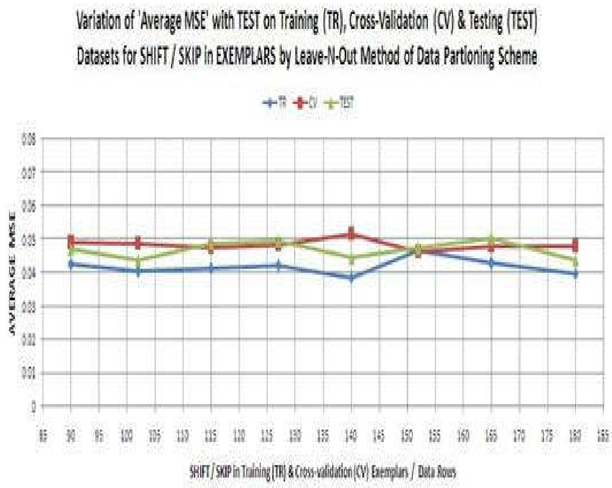

Fig.11 Variation of 'AVE MSE' Performance Measure for 'Leave-N-Out' (LNO) Type of Data Partioning Training Scheme

The methodology adopted in the design process for each one of the simulated designs of the rest of the other discrete neural network classifier blocks is more or less remains the same. The overall simulation results of the rest of the other simulated designs of various discrete neural network classifier blocks based on radial basis function (RBF) type of 'ANN' architecture are provided in the 'Table VI' for the sake of comparative performance analysis.

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TABLE VI OPTIMAL SIMULATED DESIGNS OF NN-CLASSIFIER BLOCKS BASED ON 'RBF' NETWORK ARCHITECTURE

Specifications / Performance Measures NN-Topology	3EQ-RBF 6-(18)-5	3UNEQa-RBF 6-(37)-5	3UNEQb-RBF 6-(42)-5	3UNEQc-RBF 6-(42)-5
TR: CV: TEST (%) (Primary Data Tagging Percentage)	60:20:20	60:20:20	60:20:20	60:20:20
Error Criterion (EC)	L_2-Norm	L_2-Norm	L_2-Norm	L_2-Norm
Stopping Criterion (SC)	1200 Epochs	3000 Epochs	1000 Epochs	1500 Epochs
Competitive Rule (CR)	CSCIF	CSCIF	CSCIF	CSCIF
Metric Function (MF)	Boxcar (BC)	Boxcar (BC)	Boxcar (BC)	Boxcar (BC)
MIN MSE (SC)	0.052027	0.040899	0.032818	0.034503
MIN AVE MSE (SC)	0.063580	0.041786	0.034345	0.036526
TR: TEST (%) (VSR Data Tagging)	70:30	50:50	60:40	50:50
MSE (VSR)	0.021720	0.021116	0.021328	0.021703
NMSE (VSR)	0.196238	0.122329	0.125260	0.128616
MAE (VSR)	0.060057	0.058430	0.057001	0.058397
CC (VSR)	0.911311	0.936250	0.934771	0.933050
AVE CA (%) (VSR)	90.00	93.3934	92.5401	93.3674
TR: CV: TEST (%) (VG Data Tagging)	70:15:15	50:25:25	60:20:20	50:25:25
MIN AVE MSE (VG) (MIN.; MAX.)	(0.014765 ; 0.068150)	(0.038285 ; 0.047875)	(0.031077 ; 0.037383)	(0.035597 ; 0.042156)
AVE MSE (LNO) (MIN.; MAX.)	(0.007642 ; 0.015428)	(0.043864 ; 0.050561)	(0.055039 ; 0.061069)	(0.039822 ; 0.042515)
AVE CA (%) (LNO) (MIN.; MAX.)	(100 ; 100)	(82.3504 ; 86.2309)	(76.5316 ; 83.7930)	(84.5709 ; 89.1122)

VI. CONCLUSIONS

The methodology adopted in the design process of the various simulated designs of discrete neural network classifier blocks of discrete 'ANN' simulation model, based on 'radial basis function' (RBF) type of neural network architecture, is introduced in the present research paper. The general optimal design specifications based on 'radial basis function' (RBF) type of 'ANN' architecture does meet the desired performance criterion for level-classifier blocks. The general optimum design specifications, based on 'radial basis function' (RBF) type of network architecture, are specifically obtained on the reduced individual resultant datasets. The purpose behind the design process of the level-classifier neural network blocks, based on the 'RBF' neural network architecture, is to test the performance of the network on the basis of clustering mechanism. A concrete example of 'supervised' learning approach is provided by 'classification' problem while 'clustering' problem provides an example of 'unsupervised' learning approach. The multilayer-perceptron (MLP) type of neural network topology is best suitable for 'classification' application. The radial basis function (RBF) type of neural network topology is best suitable for 'clustering' application.

The proposed general optimal design of '3UNEQa-RBF' neural network level classifier block is trained and later tested on various datasets so as to ensure that its performance does not depend on specific data partioning scheme. The performance of the proposed design specification of the network found to be consistent over all datasets with respect to various performance measures. This particular fact ensures the generality of the proposed design specifications. 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.

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