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Optimal Simulated Design of MLP Neural Network Classifier Block for Assessment of State of Degradation in Stator Insulation of Induction Motor

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***Abstract*— In the present work the design of discrete 'ANN' simulation model is being 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 'multilayer perceptron' (MLP) 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, multilayer perceptron, artificial neural network, Park's current transformation**

I. INTRODUCTION

The state of stator winding insulation of induction motor is affected by the combination of thermal, mechanical and environmental stresses. The diagnostic tests and measurements to assess the condition of stator winding insulation in a particular machine are mainly classified in two broad categories viz. (1) Destructive tests and (2) Non-destructive tests. The destructive tests are the effective means to provide the direct measure of the status of insulation system. Another more subjective means of assessing the insulation condition requires the dissection and examination of some sample of insulation. Both the above methods damage the winding and in turn make the machine unserviceable. In the previous investigations 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 [1-3]. 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 state of degradation of insulation, occurring on account of several reasons, in an integrated way can be readily represented in terms of magnitude and degree of unbalance in the 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

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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 REVIEW STAGE

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.

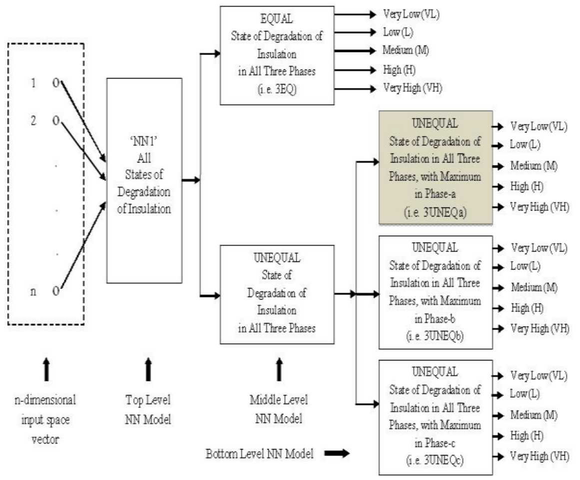

Fig.1 Schematic Block Diagram of Discrete 'ANN' Simulation Model

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

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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) 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.

Multilayer Perceptron (MLP) Network

The multilayer perceptron (MLP) network is one of the most important types of several 'ANN' architectures (topologies). The main advantage is that it is easy to use and can map or approximate the complex non-linear input-output relationship. The key disadvantage is that, it requires large size of training (TR) data- set to achieve the desired results. Hence, the multilayer perceptron (MLP) type of network is accountable for slow training process.

The complexity of the network can be understood on the basis of numbers of hidden layers, the number of processing elements belonging to the hidden layers and an output layer (i.e. size of the network), and the 'nonlinear activation function' assigned to them. The network can model the functions of almost any arbitrary complexity with the numbers of layers and the number of processing elements in each layer. The important characteristics of the multilayer perceptron (MLP) network are its processing elements (PE) with nonlinear activation functions and their massive

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interconnectivity. An appropriate methodology is being adopted in the design process of each one of the neural network classifier block, (Figure 1) based on 'multilayer perceptron (MLP)' type of an 'ANN' architecture. This is in view of obtaining the general optimal design. The general optimal design emphasizes the optimal reduction in the size of network and the selection of an appropriate nonlinear activation functions with fair deal of smooth nonlinear characteristics. The reduction in the size of the network reduces the complexity in the design. The simple designs with the appropriate nonlinear activation functions of smooth nonlinear characteristics facilitate the ease in the hardware implementation of the simulated design.

The steps involved in the general optimal design of neural network classifier block based on multilayer perceptron (MLP) 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 hidden layers (i.e. 'HL_1, HL_2 … HL_p').
e) The selection of number of processing elements (i.e. 'PE') in the hidden layers.
f) The selection of 'learning algorithm' (i.e. 'LA') and 'nonlinear activation function or computing node function or transfer function' (i.e. 'f') of 'processing elements or nodes' (i.e. 'PE') in each hidden layer and an output layer.
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 …) of the neural network.
h) The selection of 'termination or stopping criterion' (i.e. 'stopping condition (SC)').

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 multilayer perceptron (MLP) type of 'ANN' architecture are provided in the next section.

IV. GENERAL OPTIMAL DESIGN OF LEVEL CLASSIFIER BLOCK BASED ON MLP TYPE OF 'ANN' ARCHITECTURE

The general optimal design of '3UNEQa' level-classifier block based on multilayer perceptron (MLP) type of NN-architecture (i.e. '3UNEQa-MLP) 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-MLP' 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 'data-set' must be statistically significant in order to cover the entire range of input and output variables of operating conditions. The number of data points must be large enough to provide the meaningful information about the problem under consideration.

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. This resultant data-set is further divided into 'three' sets i.e. training (TR) data-set, cross-validation (CV) data-set, and testing (TEST) data-set by means of process of 'data-tagging'. 'Neurosolutions' (Neurosolutions 5.0) platform provides the feature of 'data-tagging' application.

Initially, at the time of training process, the individual resultant 'data-set' of each neural network classifier block of discrete 'ANN' simulation model is divided into 'three' data-sets in the terms of ratio of '60:20:20' as a 'training (TR) data, cross-validation (CV) data, and 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 indices 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 indices 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

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done on the basis of some specific threshold values of the performance measures. The threshold values of performance measures used for the general optimal design of the level-classifier NN-blocks and category-classifier NN-blocks of discrete 'ANN' simulation model are shown in the 'Table I'. The performance measures specified for the general optimum design of category classifier blocks are far more precise and rigid as compared to the level classifier blocks. This is in view of the fact that the 'category classifier blocks belongs to 'top-layer' of discrete 'ANN' simulation model. Hence, it is necessary to maintain the '100%' accuracy in the result at the initial stage. Otherwise, any marginal error may affect the overall performance of the discrete 'ANN' simulation model.

TABLE I. PERFORMANCE MEASURES FOR DIFFERENT NEURAL NETWORK CLASSIFIER BLOCKS OF DISCRETE 'ANN' SIMULATION MODEL BASED ON MLP-NETWORK

NN-Classifier Blocks	Performance Measures (Indices)					
	MSE	MIN AVE MSE	NMSE	MAE	CA (%)	CC
Main Category-Classifier Block (i.e.NN1)	= 0.00025 ~ (2.5×10^{-4})	= 0.005 ~ (5×10^{-3})	= 0.0005 ~ (5×10^{-4})	= 0.0075 ~ (7.5×10^{-3})	~ 100.0	~ 1.0
Category-Classifier Block (i.e. 3UNEQ)	= 0.0004 ~ (4×10^{-4})	= 0.008 ~ (8×10^{-3})	= 0.0008 ~ (8×10^{-4})	= 0.012 ~ (1.2×10^{-2})	~ 100.0	~ 1.0
Level-Classifier Block (i.e.3EQ)	= 0.020 ~ (2×10^{-2})	= 0.025 ~ (2.5×10^{-2})	= 0.16	= 0.08	~ 90.0 - 100.0	~ 0.90 - 1.0
Level-Classifier Blocks (i.e.3UNEQa, 3UNEQb, 3UNEQc,)	= 0.0125 ~ (1.25×10^{-2})	= 0.015 ~ (1.5×10^{-2})	= 0.0500	= 0.075	= 97.0	~ 0.97 - 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 design of the rest of the level-classifier blocks and category-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 Hidden Layers (i.e. 'HL1, HL2 … HLp')

The number of hidden layers and the number of processing elements in the hidden layer decide the performance as well as the complexity of the network. Initially, the neural network configuration with only 'one' hidden-layer (i.e. 'HL1') and input-layer comprise of 'six' number of processing elements and an output-layer (i.e. 'OUT') comprise of 'five' number of processing elements is selected. The numbers of processing elements in the first hidden-layer (i.e. 'HL1') are selected as 'five'. At the outset of the training process it is observed that the multi-layer perceptron (MLP) type of 'ANN' configuration with 'single' hidden-layer delivers the reasonable performance. The performance of the network is reasonable in the sense that it fairly meets levels of the performance measures like 'MSE and MIN AVE MSE,' which are specified in 'Table-I'.

E. Selection of Number of Processing Elements in the First Hidden Layer (i.e. 'HL_1)

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 with the variation in the number of processing elements in the first hidden layer (i.e. 'HL_1'). The numbers of processing elements in the first hidden layer (i.e. 'HL_1') of the network are varied gradually from '2' to '20' and for each variation the network is trained with same randomized individual resultant '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.2.

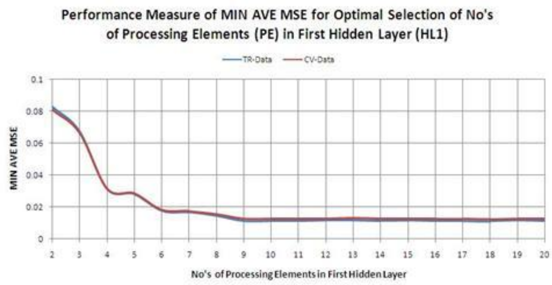

Fig.2 Performance Measure of 'MIN AVE MSE' for Optimal Selection of No's of Processing Elements of First Hidden layer

The minimum value of minimum average mean square error (i.e. 'MIN AVE MSE') is obtained for 'nine' number of processing elements (i.e. 'PE = 09') of first hidden layer for training (TR) and cross-validation (CV) data. Further, the minimum average mean square error (i.e. 'MIN AVE MSE') does not deviate much for number of processing elements more than 'nine' (i.e. 'PE ≥ 09') of first hidden layer for training (TR) and cross-validation (CV) data. The 'MIN AVE MSE' nearly remains the same at '0.01140986' and '0.01253543' value for training (TR) and cross-validation (CV) data, respectively. This is indeed meeting the requirements of the performance measure of the order of- '10^{-2}' of 'MIN AVE MSE' performance index specified in 'Table-I' for general optimal design of '3UNEQa' level-classifier block. Hence, the optimal numbers of processing elements of first hidden-layer for '3UNEQa' level classifier block based on multilayer perceptron (MLP) type of NN-architecture (i.e. '3UNEQa-MLP) are selected as 'PE = 09'. Thus, the general optimal design configuration of '3UNEQa' level-classifier block based on multilayer perceptron (MLP) type of NN-architecture (i.e. '3UNEQa-MLP) consists of 'input-layer' with 'six' numbers of processing elements, first 'hidden-layer' with 'nine' numbers of processing elements, and an 'output-layer' with 'five' numbers of processing elements (i.e. '6-9-5').

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F. Selection of Learning Algorithm and Activation Function

The next step in the general optimal design of '3UNEQa' level-classifier block based on multilayer perceptron (MLP) type of NN-architecture (i.e. '3UNEQa-MLP) of discrete 'ANN' simulation model is to select the learning algorithm (i.e. LA) and the proper activation function (i.e. computing node function / transfer function '*f*') of the processing elements belonging to first hidden layer and an output layer.

1) Selection of Learning Algorithm

The different types of learning algorithms (i.e. LA) like – Momentum (MOM), Conjugate-Gradient (CG), Quick-Propagation (QP), Levenberg-Marquardt (LM), Delta-Bar-Delta (DBD), and Step (STP) are verified for learning convergence. The learning algorithm 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 learning algorithms is shown in the 'Fig.3'.

On the basis of nature of convergence, it is observed that the convergence on training (TR) data is fast with 'Levenberg-Marquardt' (LM) and 'Momentum' (MOM) learning rule as compared to the rest of the other learning algorithms. However, in case of '6-9-5' multilayer perceptron (MLP) type of 'ANN' topology, the numbers of connection weights are quite significant. On account of this reason, in case of 'Levenberg-Marquardt' (LM) learning algorithm, the memory space requirement is quite large. Hence, the 'Momentum' (MOM) learning algorithm is preferred as an obvious choice over 'Levenberg-Marquardt' (LM) and rest of the other learning algorithms.

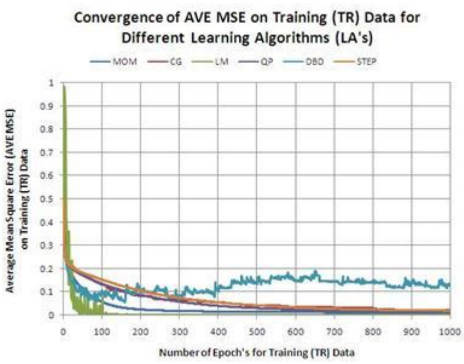

Fig.3 Convergence of AVE MSE on Training (TR) Data for Different Learning Algorithms

The 'Fig. 4' illustrates the variation of minimum average mean square (MIN AVE MSE) on training (TR) and cross-validation (CV) data for different learning algorithms for '3UNEQa' NN-level classifier block. In the case of 'Levenberg-Marquardt' (LM) learning algorithm, the 'MIN AVE MSE' is lowest on training (TR) as well as cross-validation (CV) data. However, the next lower-most minimum 'MIN AVE MSE' performance measure is observed for 'Momentum' (MOM) learning algorithm on both training (TR) as well as cross-validation (CV) data. It is somehow observed to be of small value as compared to the rest of other learning algorithms.

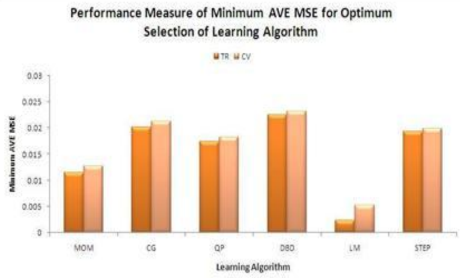

Fig.4 Variation of 'MIN AVE MSE' on Training (TR) and Cross-validation (CV) Data for Different Learning Algorithms for '3UNEQa-MLP' Neural Network

The 'Table-II' shows the variations of average classification accuracy (CA) with different learning rules. The average classification accuracy (CA) is highest in the case of 'Levenberg-Marquardt' (LM) learning algorithm (i.e. above '99.0 %') on both cross-validation (CV) as well as testing (TEST) data. However, the average classification accuracy (CA) for 'Momentum' (MOM) learning algorithm is observed to be more than '98%', which is well within the desired limits (i.e. ≥ '97.0 %' as specified in the Table 1) in the context of general optimal design of level classifier NN-block.

TABLE II . VARIATIONS OF CLASSIFICATION ACCURACY (CA) WITH DIFFERENT LEARNING ALGORITHMS

	Test on TEST Data						Test on CV Data					
LA	VHIGH	VLOW	LOW	HIGH	Medium	AVG	VHIGH	VLOW	LOW	HIGH	Medium	AVG
MOM	96.60574	99.63636	96.96312	100	98.91304	**98.42365**	96.79144	100	97.28601	100	98.44961	**98.50541**
CG	96.86684	99.27273	96.96312	100	99.27536	**98.47561**	97.86096	99.64413	97.28601	100	98.83721	**98.72566**
QP	96.34465	99.63636	96.52928	100	97.46377	**97.99481**	95.72193	100	96.86848	100	98.44961	**98.208**
DBD	97.38903	99.63636	96.96312	100	96.73913	**98.14553**	98.93048	98.57651	97.70355	100	98.06202	**98.65451**
LM	98.43342	100	99.56616	99.59514	99.63768	**99.44648**	99.19786	100	98.95616	100	99.6124	**99.55328**
STEP	99.63636	100	98.55072	96.09544	96.60574	**98.17766**	100	100	98.44961	97.07724	95.45455	**98.19628**

The activation function (i.e. computing node function / transfer-function - '*f*') of processing elements (i.e. 'PE') belonging to first hidden layer (i.e. PE = 9) and an output layer (i.e. PE = 5) is selected as 'Tanh Axon' as a default transfer-function while performing the numbers of computer simulation experiments to select the best suitable learning algorithm. In view of overall performance, as shown in the 'Fig.3 and Fig.4' and 'Table-II', it is noticed that the 'Momentum' (MOM) learning algorithm gives the best possible convincing optimal results.

2) Selection of Activation Function

The different types of activation functions like 'Axon, Bias Axon, Linear Axon, Tanh Axon, Linear Tanh Axon, Sigmoid Axon, Linear Sigmoid Axon, and Soft-Max Axon' are verified for the best performance and convergence. The 'Momentum' (MOM) learning algorithm is used in the training process while performing the numbers of computer simulation experiments to select the best suitable activation

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function. Similarly, on different transfer 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 transfer 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. 5', it is observed that the convergence on training (TR) data is quick with 'Tanh Axon' (TANH) transfer function as compared to the rest of the other transfer functions.

The 'Table-III' shows the variations of performance measures like - NMSE, MAE, and correlation coefficient (CC). In case of 'Tanh Axon' (TANH) transfer function, the 'NMSE' and 'MAE' performance measures are lowest on both cross-validation (CV) as well as testing (TEST) data. In case of 'Linear Tanh Axon' (L-TANH)' transfer function, the next lower-most values of 'NMSE' and 'MAE' performance measures are observed on both cross-validation (CV) as well as testing (TEST) data.

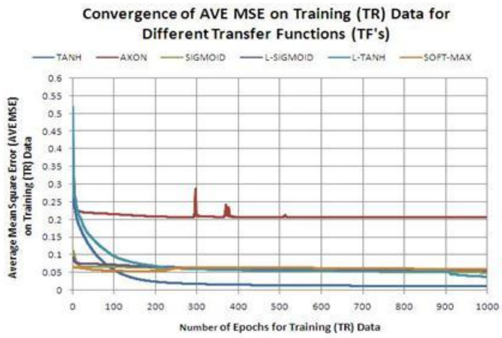

Fig. 5 Convergence of AVE MSE on Training (TR) Data for Different Transfer Functions

The 'Linear Tanh Axon' (L-TANH) transfer function is the linear piecewise approximation to 'Tanh Axon' (TANH) transfer function. However, it is noticed that, only in case of 'Tanh Axon' (TANH) transfer function, the lower-most values of the 'NMSE' and 'MAE' performance measures are observed well within the permissible limits. The permissible limits are specified in terms of threshold values of 'NMSE' (i.e. ≈ '0.05' as shown in the Table-I) and 'MAE' (i.e. ≈ '0.075' as shown in the Table-I) in the context of general optimal design of level classifier NN-block. The correlation coefficient (CC) is about 100% (i.e. '0.979988' and '0.981219' on cross-validation (CV) and testing (TEST) data, respectively) with the 'Tanh Axon' (TANH) transfer function, which is well within the permissible limit. The permissible limit is specified in terms of threshold value of 'CC' (i.e. ≈ '0.97 to 1.0' as shown in the Table 1) in the context of general optimal design of level classifier NN-block.

TABLE III. VARIATIONS OF PERFORMANCE MEASURES WITH DIFFERENT TRANSFER FUNCTIONS

Transfer Function	NMSE		MAE		CC	
	TEST	CV	TEST	CV	TEST	CV
TANH	0.043969	0.046223	0.047316	0.047754	0.981219	0.979988
AXON	0.794205	0.795143	0.289882	0.289047	0.442248	0.450433
SIGMOID	0.735802	0.733939	0.252884	0.251703	0.554428	0.568757
LINEAR -SIGMOID	0.760523	0.761524	0.230161	0.229977	0.393412	0.399307
LINEAR -TANH	0.054716	0.056834	0.06687	0.067181	0.980664	0.979602
SOFT-MAX	0.649079	0.64642	0.213484	0.212581	0.610542	0.614625

The 'Fig.6' illustrates the variations of average classification accuracy (CA) with different transfer functions. The average classification accuracy (CA) is highest in case of 'Tanh Axon' (TANH) and 'Linear Tanh' (L-TANH) transfer function (i.e. above '98.0 %') on both training (TR) as well as cross-validation (CV) data. Further, the average classification accuracy (CA) is observed to be well within the desired limits (i.e. ≥ '97.0 %' as specified in the Table-I) in the context of general optimal design of level classifier NN-block.

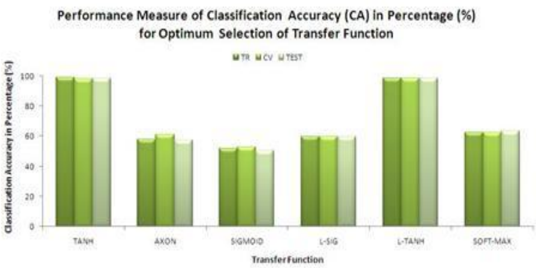

Fig.6 Variation of Average Classification Accuracy on Training (TR), Cross-validation (CV), and Testing (TEST) Data for Different Transfer Functions

In view of overall performance, as shown in the 'Fig.5 and Fig.6' and 'Table-III', it is noticed that the 'Tanh Axon' (TANH) transfer function of processing elements (i.e. 'PE') belonging to 'first hidden layer (i.e. PE = 9) and an output layer (i.e. PE = 5),' of the neural network gives the best possible convincing optimal results. Henceforth, in the context of the general optimal design based on multilayer perceptron (MLP) type of ANN-architecture (i.e. '6-9-5') of '3UNEQa' level-classifier block (i.e. '3UNEQa-MLP) of discrete 'ANN' simulation model, the 'Momentum' (MOM) learning algorithm and the 'Tanh Axon' (TANH) activation function are selected as an obvious choices.

G. Selection of Optimal Learning Parameters

The optimal selection of learning parameters of the processing elements belonging to first hidden layer and an output layer of the neural network is 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 i.e. 'learning constant or step-size' ('η'), and 'momentum coefficient or rate ('α')' of the processing

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elements belonging to first hidden layer and an output layer of the neural network. 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 first hidden layer (i.e. 'HL_1') and an output layer ('OUT') of the neural network. Initially, the momentum coefficient of the processing elements (i.e. PE = 9) belonging to first hidden layer is set to some arbitrary default value of '0.7'. Similarly, the 'learning constant' (i.e. 'η' or 'LC') and '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 '0.1' and '0.7', respectively. In fact, these initial arbitrary default values are decided by the 'Neurosolutions 5.0' neural network design tool [7].

In view of the above default settings, the learning constant of the processing elements (i.e. PE = 9) belonging to first hidden 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 = 9) belonging to first hidden 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 default settings. The learning constant of the processing elements (i.e. PE = 9) belonging to first hidden layer is varied from '1.0' to '10.0' in steps of '1.0' unit (i.e. 1.0:1.0:10). If the 'MIN AVE MSE' does not converge to the minimum value over an entire variable range (i.e. 1.0:10) of the learning constant then the numbers of computer simulation experimentations are performed further with the same default settings. The learning constant of the processing elements (i.e. PE = 9) belonging to first hidden layer is varied further over an exceeding range in the multiples of ten's, (i.e. '0.1:1:10:100:1000:10000: …'). The extensive training process, which involves the numbers of computer simulation experimentations, typically suggests the 'trial and error' procedure for an optimum selection of the learning parameters. This 'trial and error' procedure, leads to the 'heuristic' modeling approach, in the context of the general optimum design of any neural network classifier block.

In the context of the general optimal design based on multilayer perceptron (MLP) type of ANN-architecture (i.e. '6-9-5') of '3UNEQa' level-classifier block (i.e. '3UNEQa-MLP) of discrete 'ANN' simulation model, the simulation result shown in the 'Fig.7', indicate that the performance measure of 'MIN AVE MSE' converges to minimum value at learning constant 'LC = 0.8' 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 = 9) belonging to first hidden layer is selected as '0.8'.

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 first hidden layer with the optimum value of learning constant selected as '0.8'. 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 = 0.3' 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 '0.3'. Likewise, the numbers of computer simulation experimentations are performed for optimum selection of 'learning constant' and 'momentum coefficient' of the processing elements (i.e. PE = 5) belonging to output layer.

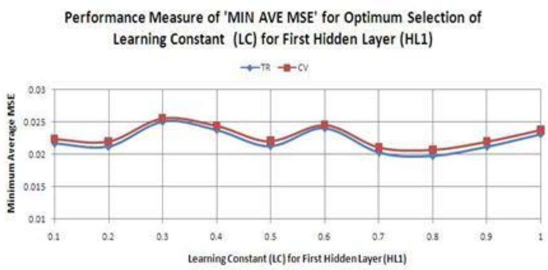

Fig.7 Performance Measure of 'MIN AVE MSE' for Variation in Learning Constant (LC) of Processing Elements belonging to First Hidden Layer

The optimum values of learning constant and momentum coefficient of the processing elements (i.e. PE = 9) belonging to first hidden layer are selected as '0.8' and '0.3', respectively. On the basis of simulation results it is being observed that the performance measure of 'MIN AVE MSE' converges to minimum value at 'learning constant (LC) = 0.7 and momentum coefficient (MC) = 0.3', 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' and 'momentum coefficient' of the processing elements (i.e. PE = 5) belonging to output layer are selected as '0.7' and '0.3', respectively.

In the context of the general optimal design of multilayer perceptron (MLP) type of ANN-architecture (i.e. '6-9-5') of '3UNEQa' level-classifier block (i.e. 3UNEQa-MLP), 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 multilayer perceptron (MLP) type of ANN-architecture. There is need to decide the appropriate stopping criterion or

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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 multilayer perceptron (MLP) type of ANN-architecture (i.e. '6-9-5') of '3UNEQa' level-classifier block (i.e. 3UNEQa-MLP) 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 result of the variation in performance measure of 'MIN AVE MSE' on training (TR) and cross-validation (CV) data for different 'number of epochs' is shown in the 'Fig. 8'.

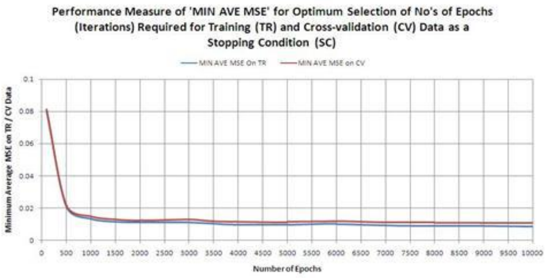

Fig.8 Variation of 'MIN AVE MSE' Performance Measure with 'Numbers of Epochs'

The threshold values for performance measures of 'MIN MSE' and 'MIN AVE MSE' are considered approximately '1.5' times of the order of '10-2' (i.e. ≈ 1.5 x 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 'Figure 8', suggest that the performance measure like - 'MIN AVE MSE' approaches towards the threshold value 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.

V. PERFORMANCE TESTS OF GENERAL OPTIMAL DESIGN OF MULTILAYER PERCEPTRON TYPE OF NETWORK

The general optimal design of '3UNEQa' level-classifier block based on multilayer perceptron (MLP) type of NN-architecture (i.e. '3UNEQa-MLP) 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-MLP' neural network classifier block are listed in 'Table-IV'. 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-MLP' neural network level classifier block with the design specifications listed in 'Table 4', 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.

TABLE IV. DESIGN SPECIFICATIONS OF GENERAL OPTIMAL DESIGN OF '3UNEQA-MLP' 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
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')	0.8
First Hidden Layer: Momentum Coefficient or Rate (i.e. 'MC' or 'α')	0.3
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')	0.3
Number of Connection Weights: (i.e. 6 x 9 + 9 x 5 + 9 + 5)	113
Number of Processing Elements (PE) in Output Layer (i.e. OUT)	05
Time Required Per Epoch Per Exemplar	'51.2' ms
Neural Network Topology	6-9-5-MLP

The variation of performance measures like – 'NMSE, MAE, and CC' over a marginal range ('Table V') 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. Further, as and when the percentage of data tagged for training (TR) exceeds over 'eighty' percent (i.e. 80%), the performance of the network marginally improves on testing (TEST) data.

TABLE V. VARIATION OF 'NMSE, MAE, AND CC' PERFORMANCE MEASURES WITH VARIABLE PERCENTAGE OF DATA TAGGED FOR TRAINING AND TESTING DATA

Percentage of Data	NMSE		MAE		CC	
TR(%)-TEST (%)	TEST	TR	TEST	TR	TEST	TR
10 (%)-90(%)	0.055283	0.037965	0.056441	0.053198	0.978551	0.986804
20(%)-80 (%)	0.043330	0.037451	0.051664	0.050417	0.983266	0.986273
30(%)-70(%)	0.044762	0.037538	0.057234	0.055833	0.984128	0.987669
40(%)-60(%)	0.043876	0.037962	0.054297	0.053293	0.983731	0.986701
50(%)-50(%)	0.044327	0.038103	0.056415	0.055233	0.984018	0.987106
60(%)-40(%)	0.044597	0.037758	0.057399	0.056085	0.984257	0.987565
70(%)-30(%)	0.043949	0.035881	0.052831	0.051667	0.983549	0.987388
80(%)-20(%)	0.042185	0.039925	0.055509	0.054881	0.985093	0.986173
90(%)-10(%)	0.042484	0.038831	0.053973	0.053022	0.984324	0.986146

The variation of 'MIN AVE MSE' performance measure ('Fig.9') over a marginal range (i.e. between '0.01' and '0.015') 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. '36, 41, 46, 51, 56, 61, 66, and 72') during the 'Leave-N-Out' (LNO) type

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of data partioning training scheme. The performance of the network is tested to verify the consistency over all predefined subset of exemplars to be skipped with respect to 'average classification accuracy' (CA) performance measure. The variation of 'average classification accuracy' (CA) performance measure ('Fig. 10') for different numbers of predefined subset of exemplars to be skipped (i.e. '36, 41, 46, 51, 56, 61, 66, and 72') during the 'Leave-N-Out' (LNO) type of data partioning training scheme are reasonable and confirms the consistency in the performance of network.

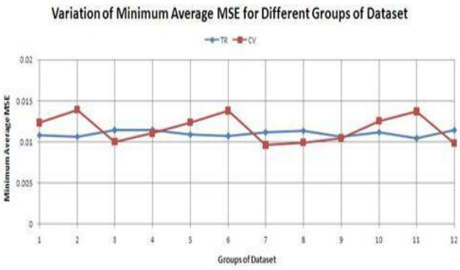

Fig.9 Variation of 'MIN AVE MSE' Performance Measure for Different Groups of Dataset for '3UNEQa – MLP' General Optimal Design

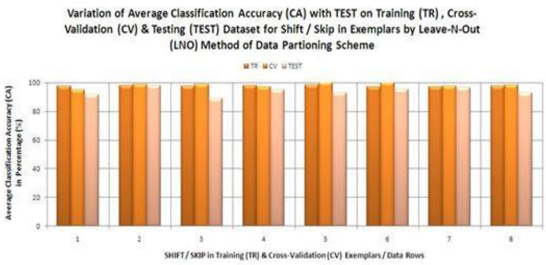

Fig.10 Variation of 'Average Classification Accuracy' (CA) Performance Measure for 'Leave-N-Out' (LNO) Type of Data Partioning Training Scheme

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 multilayer perceptron (MLP) type of 'ANN' architecture are provided in the 'Table-VI' for the sake of comparative performance analysis.

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 'multilayer-perceptron' (MLP) type of neural network architecture, is introduced in the present research paper. The general optimal simulated designs of 'category-classifier' and 'level-classifier' neural network blocks of discrete 'ANN' simulation model, which are designed on the basis of multilayer-perceptron (MLP) type of 'ANN' architecture does satisfy the desired performance criterion. 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 proposed general optimal design of '3UNEQa-MLP' 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.

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

Specifications / Performance Measures	Optimal Simulated Design Specifications and Performance Measures of Level-Classifier Neural Network Blocks					
	NN1-MLP	3UNEQ-MLP	3EQ-MLP	3UNEQa-MLP	3UNEQb-MLP	3UNEQc-MLP
NN-Topology	6-2-2	6-6-3	6-9-5	6-9-5	6-11-5	6-8-5
TR: CV: TEST (%) (Primary Data Tagging Percentage)	60:20:20	60:20:20	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	L_2-Norm	L_2-Norm
Stopping Criterion (SC)	500 Epochs	1000 Epochs	1200 Epochs	3000 Epochs	4000 Epochs	2000 Epochs
Learning Algorithm (LA)	Momentum	Momentum	Momentum	Momentum	Momentum	Momentum
Transfer Function (TF)	TANH	TANH	TANH	TANH	TANH	TANH
MIN MSE (SC)	1.871E-06	0.000371	0.013107	0.011704	0.011437	0.010086
MIN AVE MSE (SC)	0.002263	0.007666	0.020316	0.012867	0.011669	0.010889
TR: TEST (%) (VSR Data Tagging)	50:50	70:30	50:50	80:20	70:30	70:30
MSE (VSR)	2.22467E-13	0.000179	0.021283	0.006873	0.006297	0.005723
NMSE (VSR)	9.49174E-11	0.000808	0.159647	0.042185	0.038580	0.035238
MAE (VSR)	3.28493E-07	0.010160	0.071445	0.055509	0.053161	0.043590
CC (VSR)	1.00	0.999605	0.932716	0.985093	0.986386	0.985589
AVE CA (%) (VSR)	100	100	93.3333	98.7252	98.9655	98.7827
TR: CV: TEST (%) (VG Data Tagging)	50:25:25	70:15:15	50:25:25	80:10:10	70:15:15	70:15:15
MIN AVE MSE (VG) (MIN. - MAX.)	(0.000902 - - 0.004196)	(0.000341 - - 0.004945)	(0.003477 - - 0.044947)	(0.009608 - - 0.013906)	(0.008585 - - 0.011839)	(0.008170 - - 0.012197)
AVE MSE (LNO) (MIN. - MAX.)	----	(0.000160 - - 0.000205)	(0.014524 - - 0.018791)	(0.013919 - - 0.020245)	(0.007320 - - 0.011531)	(0.007590 - - 0.012882)
AVE CA (%) (LNO) (MIN. - MAX.)	----	(100 - - 100)	(83.3333 - - 100)	(88.9376 - - 97.7709)	(96.7251 - - 99.2593)	(95.7716 - - 98.5714)
No. of Connection Weights	20	63	113	113	137	101

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