GENETIC MODELING AND OPTIMIZATION IN HONING PROCESS

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Abstract : A genetic algorithm is a metaheuristic search method used in artificial intelligence and computing. genetic algorithm is utilized to grow top notch answers for improvement and pursuit issues by taking help of bio-operators such as natural selection, mutation and crossover. Genetic algorithms are excellent tools for searching through large and complex data sets. in 1980s joining ga and nn came up. since both being autonomous computing methods, why shall we combine them? Since, various parameters must be set before any preparation can begin in neural networking. However, there is no fixed method as how to set these parameters. for the success of the training these parameters are of prime importance. Genetic Algorithms And Neural Networks (GANN) are combined to find these parameters. the nature shows us that the accomplishment of an individual species isn't completely subject to her aptitudes and learning, yet additionally relies upon acquired genetic material
This research paper talks about the improvement of GANN models for the examination of the sharpening procedure connected to a real mechanical segment that is the connecting pole of a motorbike. The surface standard of the sharpened parts is estimated with the assistance of a talysurf intra machine. Acknowledged measure of surface harshness is center line average (ra) by tradition. honing speed, honing feed, honing time, grit size, temperature of the coolant, and the experience of human operator are six process parameters considered as the input variables in whole honing process. the genetic algorithm neural network model have three to four layer structure. one is input layer, anther is yield layer and next is two concealed layer.

Index Terms – **Honing, Genetic Artificial Neural Network and Optimization.**

1 INTRODUCTION

1.1 Genetic algorithms are seek algorithms in view of the mechanics of natural choice and natural genetics. They join survival of the first among string structures with an organized yet randomized information trade to shape seek algorithm with a portion of the innovative style of human hunt. In each generation, another arrangement of counterfeit animals (strings) is made utilizing odds and ends of the fittest of the old; an infrequent new part is striven for good measure. While randomized, genetic algorithms are no basic random walk. They productively misuse chronicled information to theorize on new hunt focuses with expected enhanced performance.

1.2 The central theme of my research is the development of GANN models for the analysis of the honing process with a balance between efficiency and efficacy necessary for survival in many different environments. We attempt to develop a robust GAAN model as the implications of robustness for artificial systems are manifold. If artificial system can be made more robust, the need of costly redesigns can be reduced or eliminated. If higher levels of adaptation can be achieved, existing systems can perform their functions longer and better. Designers of artificial systems both software and hardware, whether engineering systems, computer systems, or business systems can only marvel at the robustness, efficiency and the flexibility of biological systems. Features for self –repair, self guidance and re-production are the rule in biological systems, whereas they barely exist in the most sophisticated in systems.

1.3 Now let us discuss the concept of optimization. In short advancement is a mathematical model that endeavors to advance (boost or limit) a target work without abusing asset constraints. With reference to computer science it is a mathematical programming. Optimization of the process parameters is of practical importance. Genetic algorithm is an alternate to traditional optimization methods such as linear programming, geometric programming, dynamic programming, direct search methods and gradient-based methods. GAs has been found suitable for complex optimization problems where location of a global optimal is difficult. Genetic algorithm belongs to a class of stochastic optimization techniques. Due to the probabilistic nature of the solution procedure, the method doesn't always guarantee for optimality. The main features of GAs are as follows. The genetic algorithm is a multi path, which reduces the possibility of local minimum trapping. The algorithm evaluates a population of points, not a single point. It makes use of objective function, not derivatives to determine the fitness of the solution. Genetic algorithms obey probabilistic transition rules in the generation of a new population.

1.4 Genetic Algorithms (GAs) are versatile heuristic search algorithm in light of the transformative thoughts of natural choice and genetics. In that capacity they speak to an intelligent abuse of a random search used to take care of optimization issues.

1.5 They recreate the survival of the fittest among people over back to back generation for taking care of an issue. Every generation comprises of a populace of character strings that are similar to the chromosome (a chromosome contains set of arrangements in type of qualities) that we find in our DNA. Every person, (which is same as chromosome) speaks to a point in a search space and a conceivable arrangement. The people in the populace are then made to experience a procedure of development.

1.6 GA's are more robust and they do not break easily even if the input is changed slightly or in the presence of reasonable noise.

2 LITERATURE REVIEW

2.1 Ahmed and Haque [2001] used genetic algorithms to optimize process-planning parameters for rotational components. Machine capacity, limits of feed rate, depth of cut, cutting speed were considered as the constraints. Random values of different parameters were chosen within a selected range and graphs were plotted. It was observed that the initial population is spread over whole solution space instead of being localized. The values of different parameters were plotted after running the GA program 20 generation. The graphs showed that parameters move towards some specific values. After 40 generation, final values of parameters were plotted. It was found that all sets of values of a specific parameter in the final population come similar. It was concluded that as the number of generation increases, the rate of changes in fitness values decreases rapidly.

2.2 Baek et al. [2002] presented a surface roughness model of the face milling operations considering the profile and the run out error both axial and radial of each insert of the cutter body. The material removal rate was maximized through optimization of feed rate with surface roughness as a constraint.

2.3 Saravanan et al. [2003] used a genetic algorithm to find the values of the machining parameters that optimize the finished profile of a cylindrical block. They used binary coding to represent the variables including the wheel speed, work piece speed, depth of dressing and lead of dressing. Rank selection method was used for reproduction. Each individual was ranked increasing order of fitness from 1 to 20. Multi-point crossover was used in the crossover operation. It was observed that the value of the optimized objective function obtained by GA was better than that obtained through quadratic programming.

2.4 Dr. Manuj Darbari (2012) and Dr. Sunita Bansal developed a framework for intelligent Manufacturing systems in which the machine scheduling is achieved by MCDM and DRSA. The relationship between perception/knowledge base and profit maximization is extended for Multi objective function to be optimized. The multi objective optimization consists of three phases: Model Building, Optimization and Decision making. The focus is to optimize the part versus product planning. The part description is developed which starts from the component level manufacturing.

3 RESEARCH METHOD

3.1 Problem Formulation

Honing includes complex physical marvels, including shearing, plugging, heat transfer and lubrication. An assortment of information factors, for example, physical and mechanical properties of work piece and abrasive grits, feed, speed, coolant temperature and man-machine interaction influence the procedure.

GANN model is adaptable to plan and enhance the procedure parameters. Facilitate the triple hybrid approach is useful to outline the datasets in view of the consequences of the examinations. Each system is trained, approved and tried with the assistance of these datasets.

4 METHODOLOGY

The GA maintains a population of n chromosomes (solutions) with associated fitness values. Parents are selected to mate, on the basis of their fitness, producing offspring via a reproductive plan. Consequently, highly fit solutions are given more opportunities to reproduce, so that offspring inherit characteristics from each parent. As parents mate and produce offspring, room must be made for the new arrivals since the population is kept at a static size. Individuals in the population die and are replaced by the new solutions, eventually creating a new generation once all mating opportunities in the old population have been exhausted. In this way, it is hoped that over successive generations better solutions will thrive while the least fit solutions die out.

After an initial population is randomly generated, the algorithm evolves the through three operators:

4.1 selection which equates to survival of the fittest;

4.2 crossover which represents mating between individuals;

4.3 Mutation which introduces random modifications.

For the selected model the difference between the observed and predicted values of the response variable is checked to be within the specified tolerance limit.

Four following models have been developed :

1	(10)L	Fig-1
2	(15)L	Fig-2
3	(8,10)L	Fig-3
4	(8,15)L	Fig-4

The Matlab configurations of the four models are given in Fig 1,2,3,4

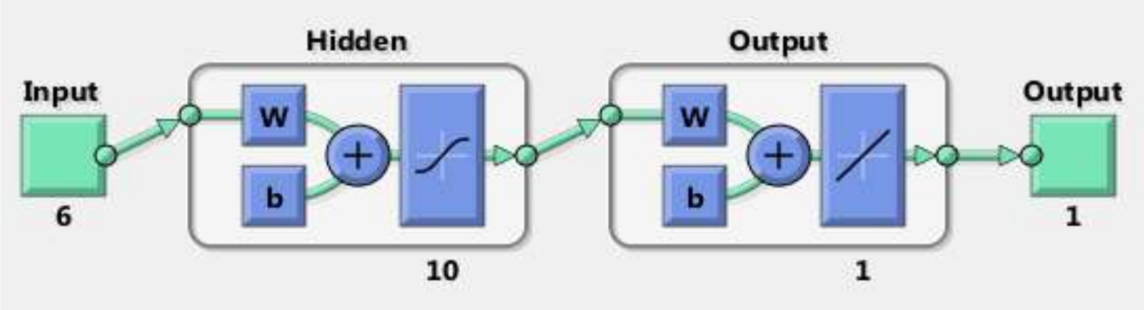
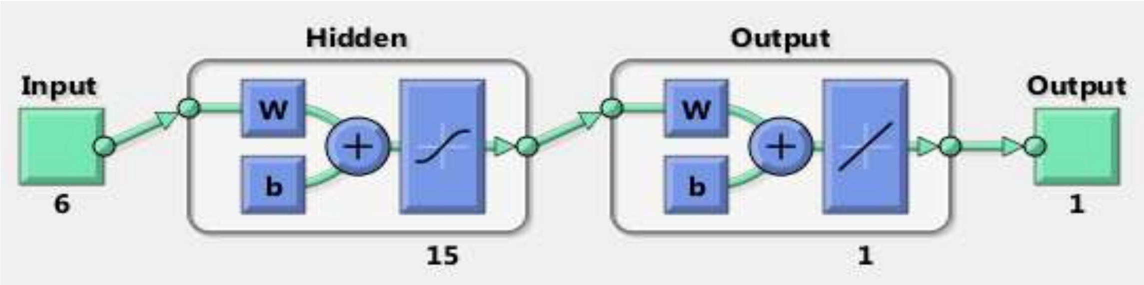


fig-1



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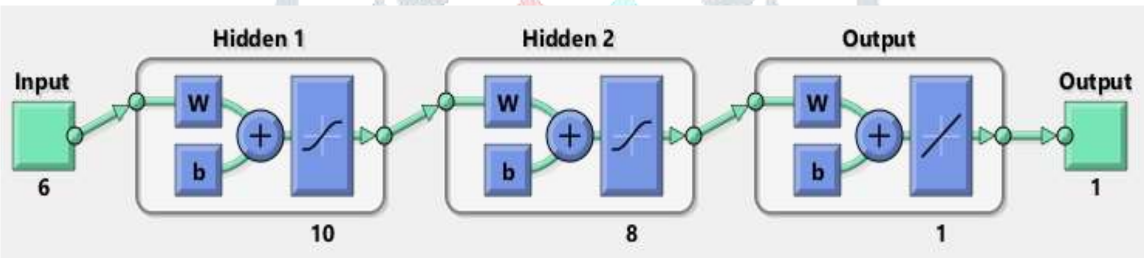

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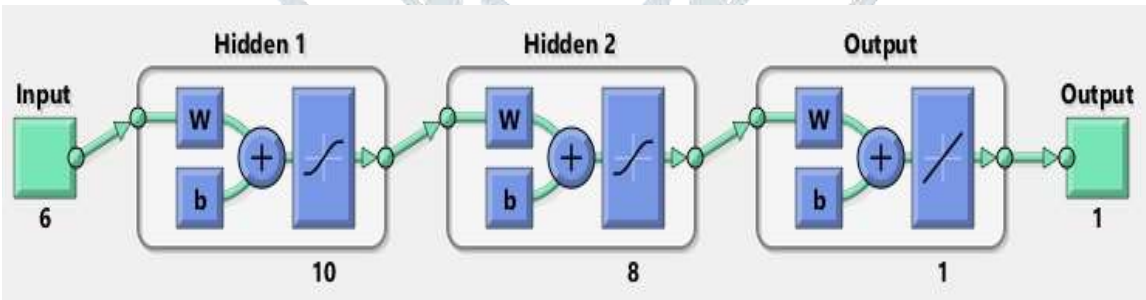


fig-4

The Matlab configurations of the four models Fig 1(10)L, Fig 2(15)L, Fig3(10,8)L, Fig4(15,8).

The programmer for the GANN is written in Mat lab 2014a. After initialization and configuration of neural network, its weight is optimized by the GA. MSE is continuously calculated, by changing previous weights of NN with new optimized weight values obtained from GA, in order to keep track of the generation fitness. With decrease in MSE, fitness of generation increases. With every iteration, gradient of iteration is also checked so that if gradient value comes less than or equal to the user given tolerance, than program terminates. The process flow is in figure 5.

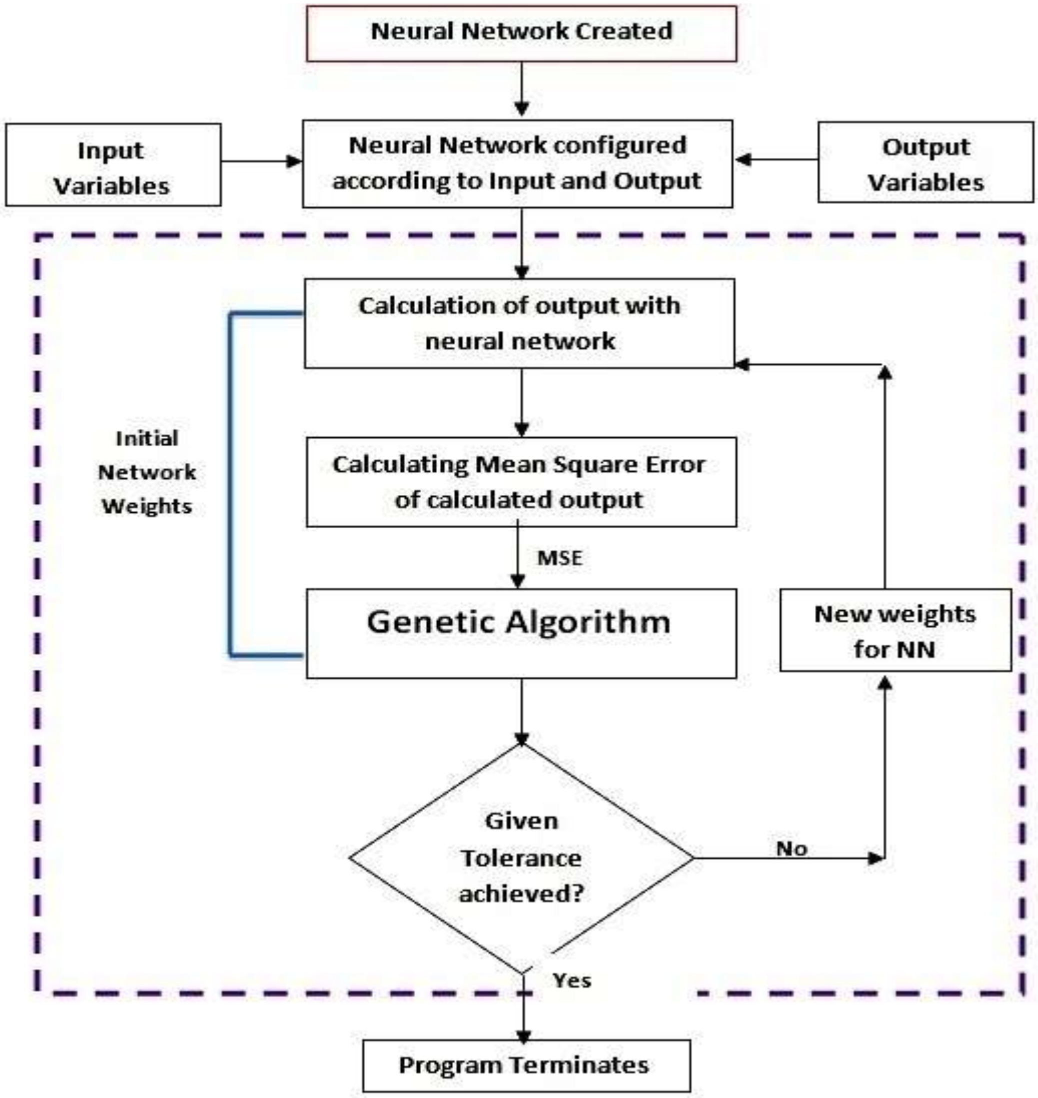


fig 5

5 PROPOSED WORK

Current study is done on Matlab 2014a software. Experimental data set is used for optimal results Two programs have been developed, one is for Initialization (setting weights and bias values of neurons by random numbers), Configuration (setting numbers of input and output and setting kernel (kernel is non-linear approximation function)in all models kernel function for hidden layer is tan-sig (tan-sig is tan-sigmoid function). For output layer the function is linear and for deploying Genetic Algorithm and the second program is used for calculating new output by setting the new weights of hidden layer neuron, obtained from genetic algorithm, and for calculation of mean square error, which acts as the objective of genetic algorithm for minimization. The second program works as an input handle to the genetic algorithm which continuously gives feedback to the genetic algorithm in form of Mean Square Error. The termination condition given to genetic algorithm is when gradient of MSE calculated reaches a value of 1e-5. Total no. of neurons taken in hidden layer are taken as ten (10). Figure6 below shows the decrease in MSE versus generations

For Training Programme

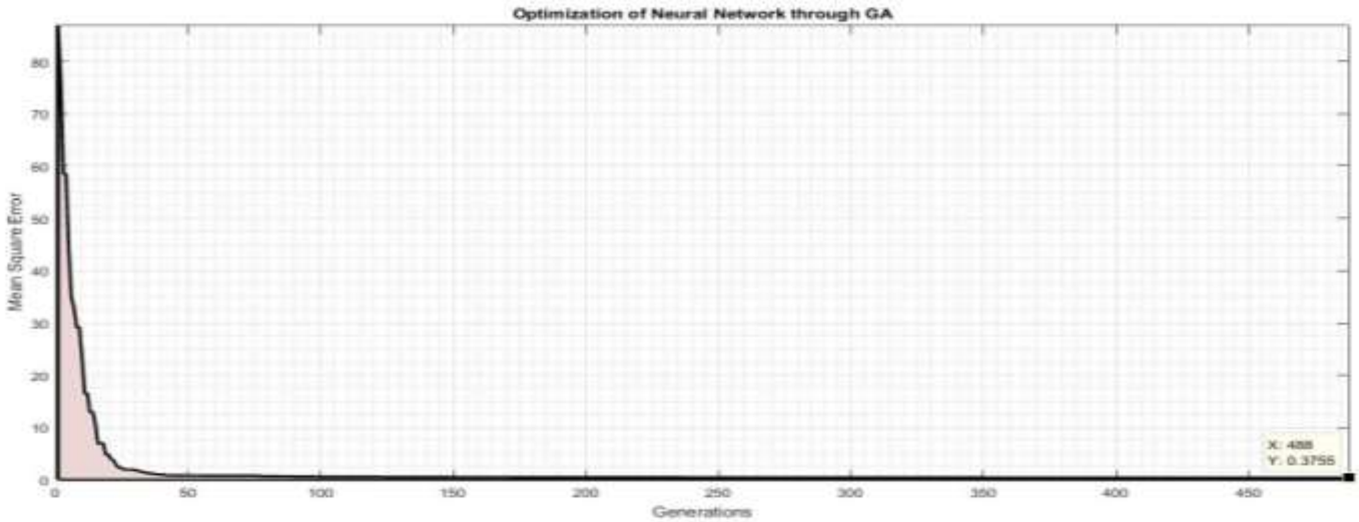


fig 6

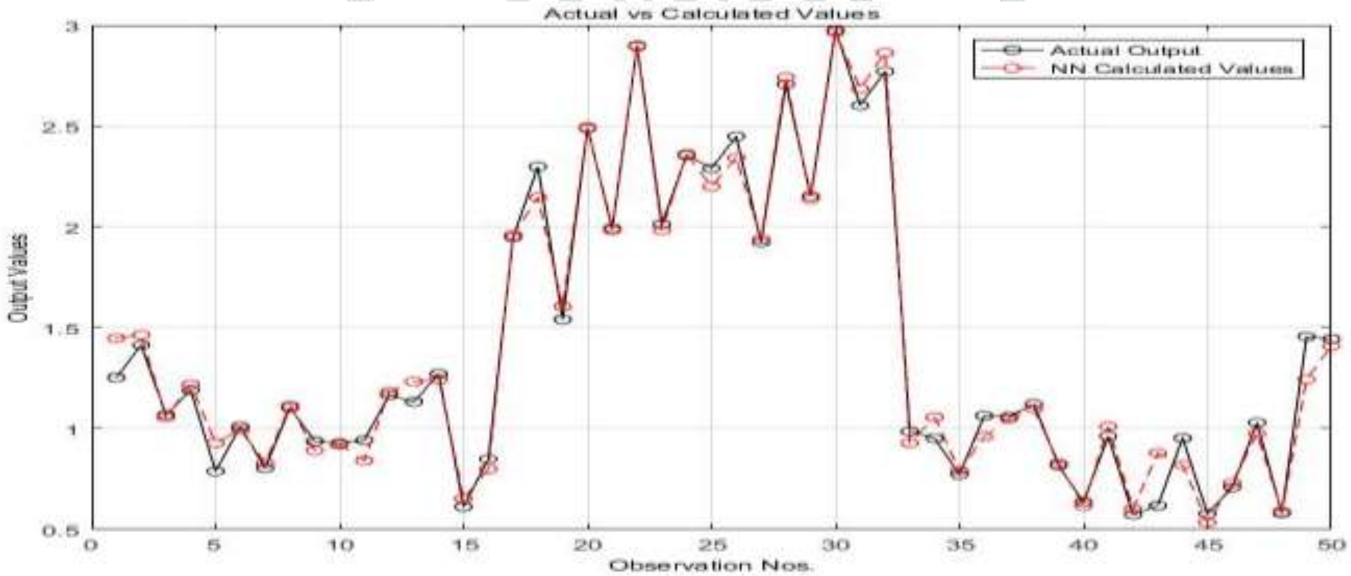
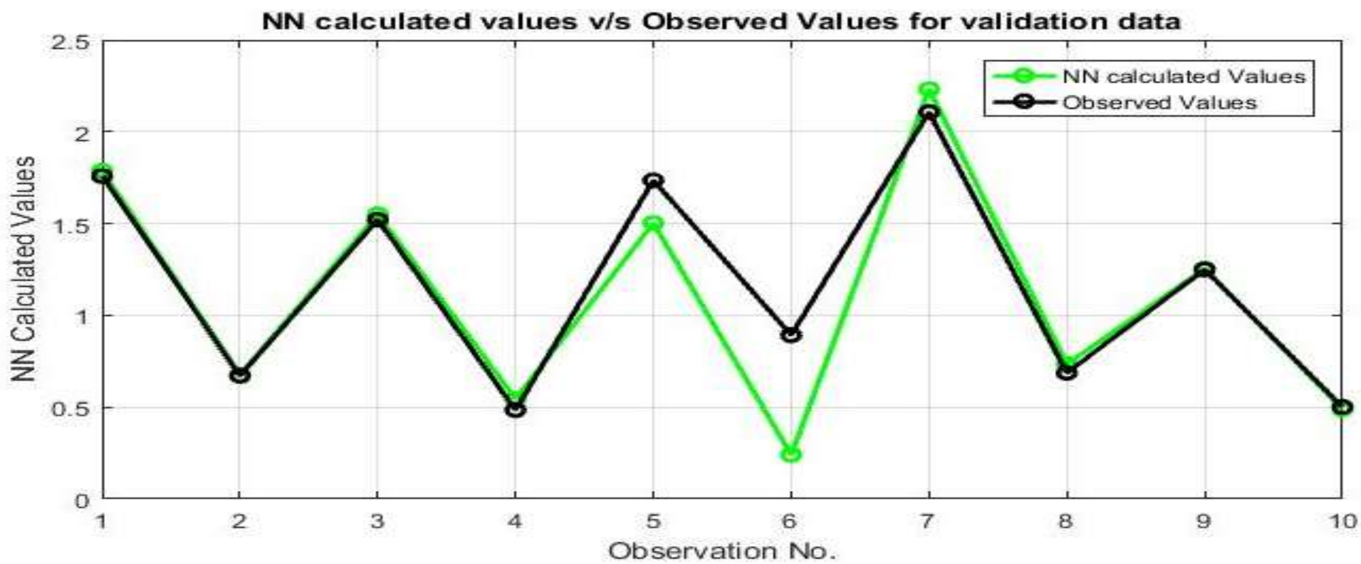


fig-7:GANN calculated training values vs observed (10)L



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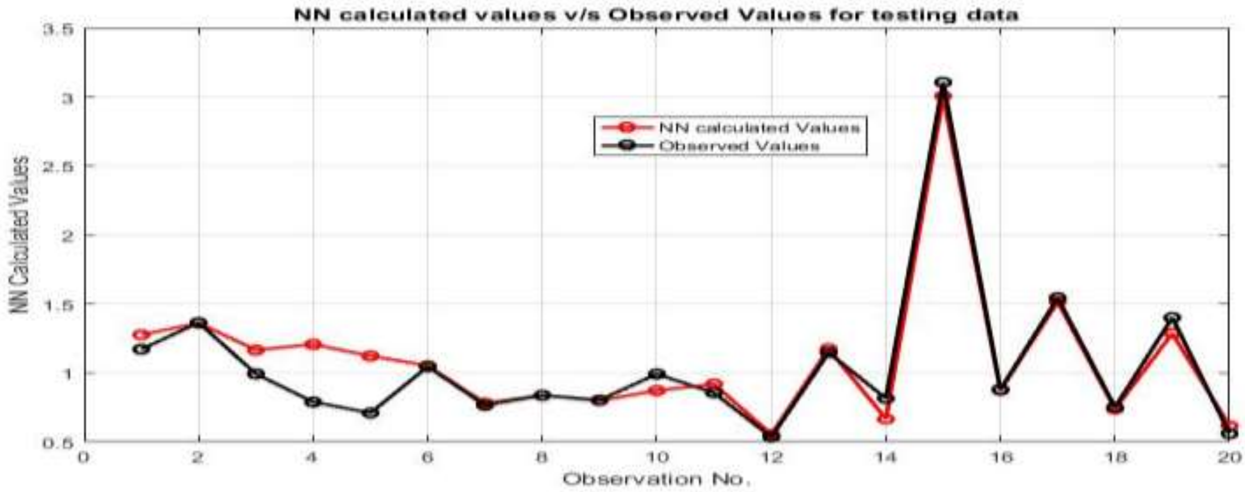

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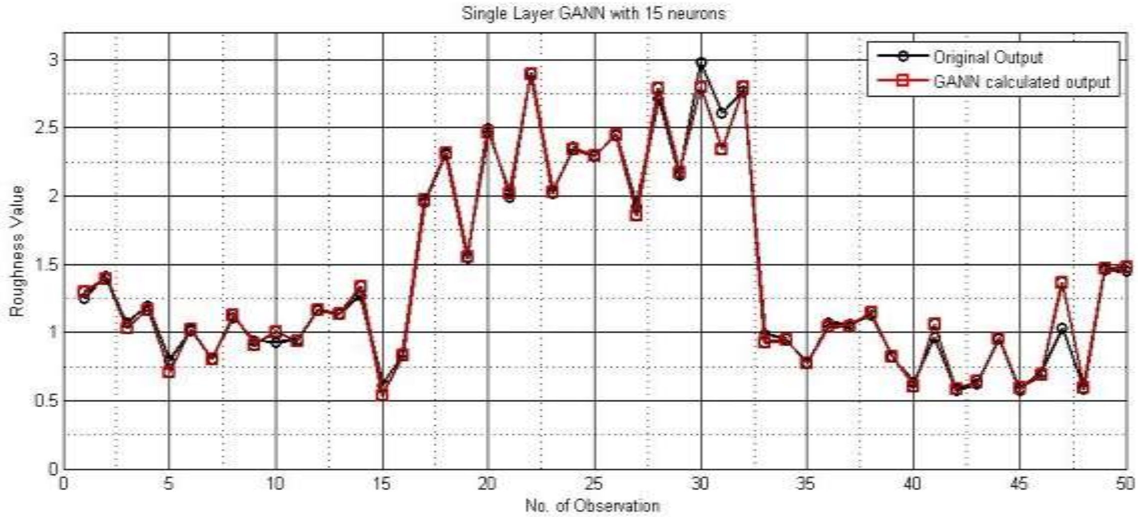

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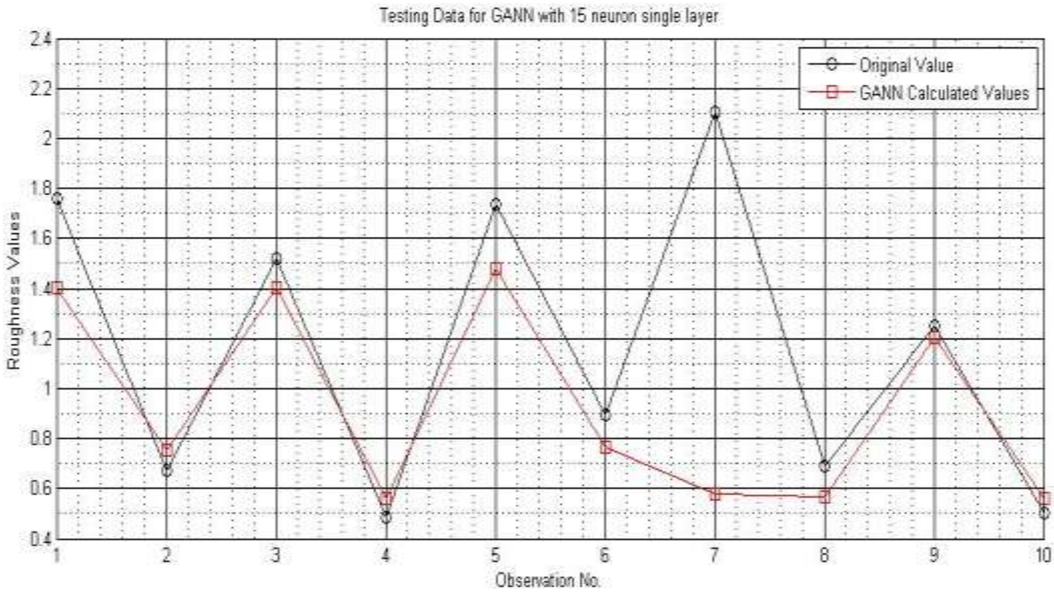

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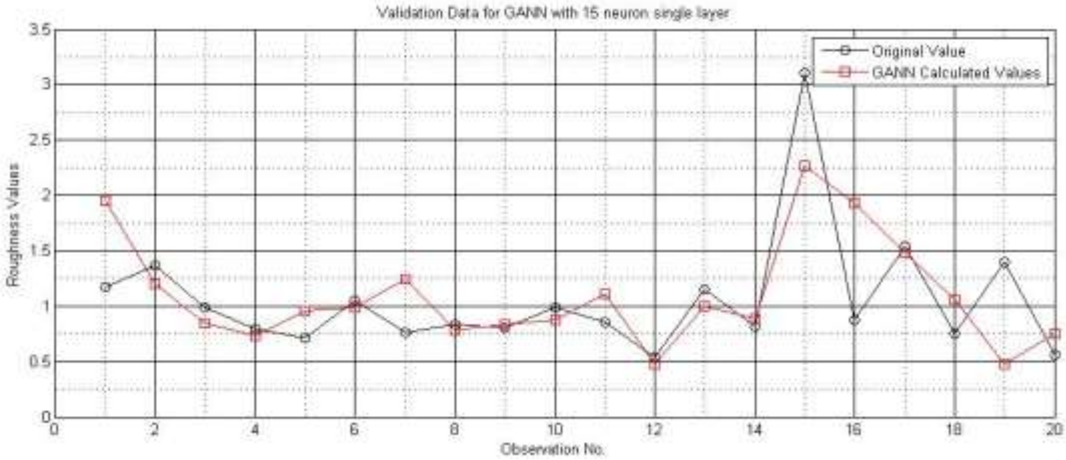

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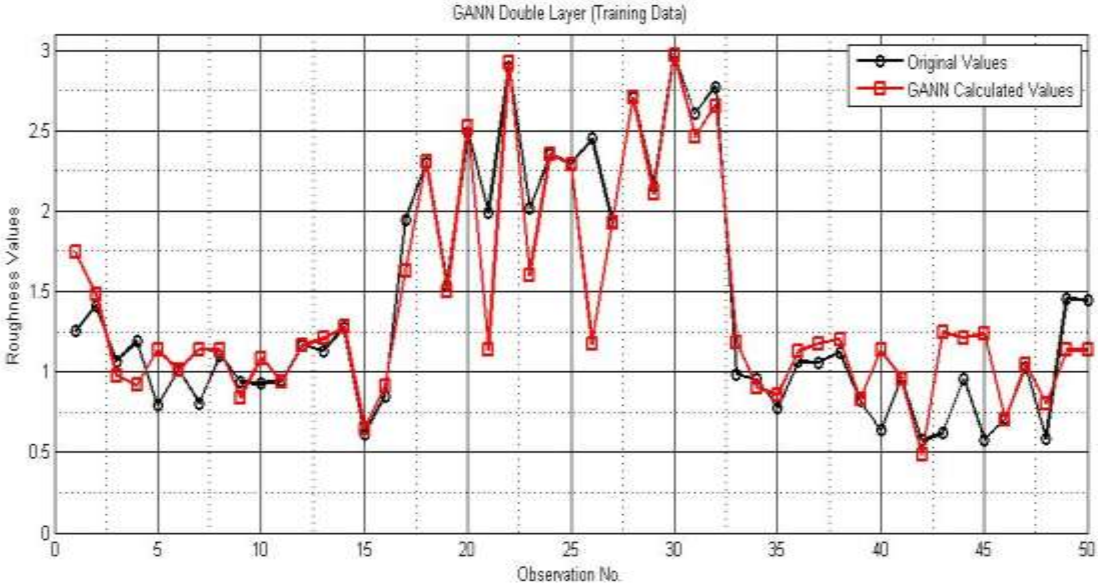

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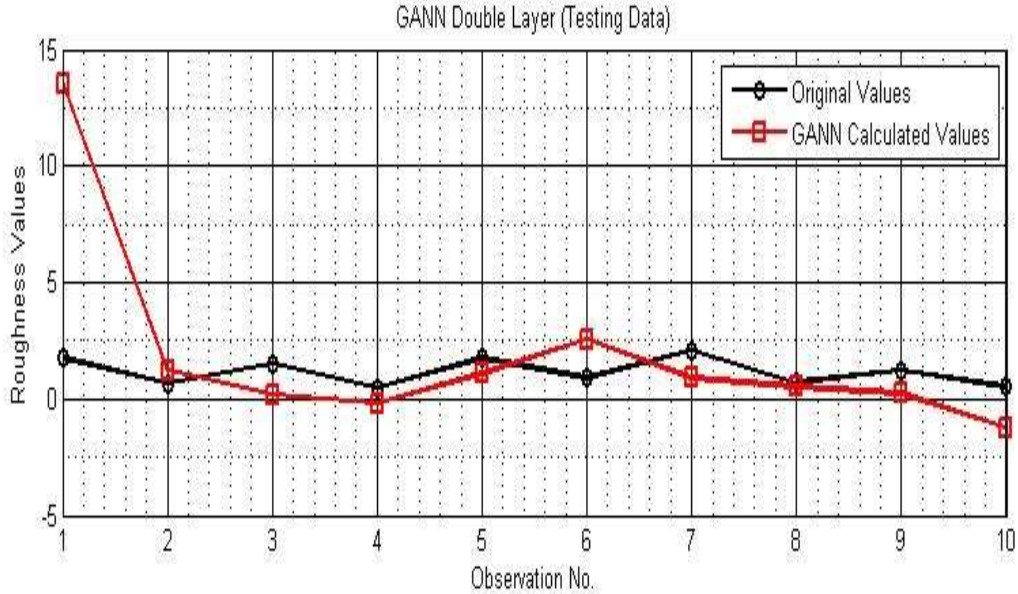

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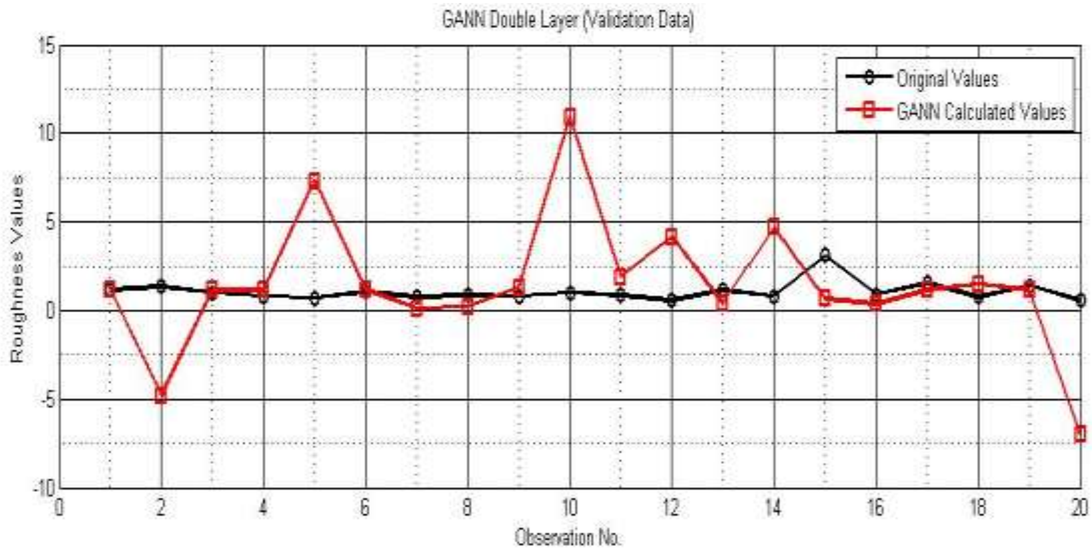

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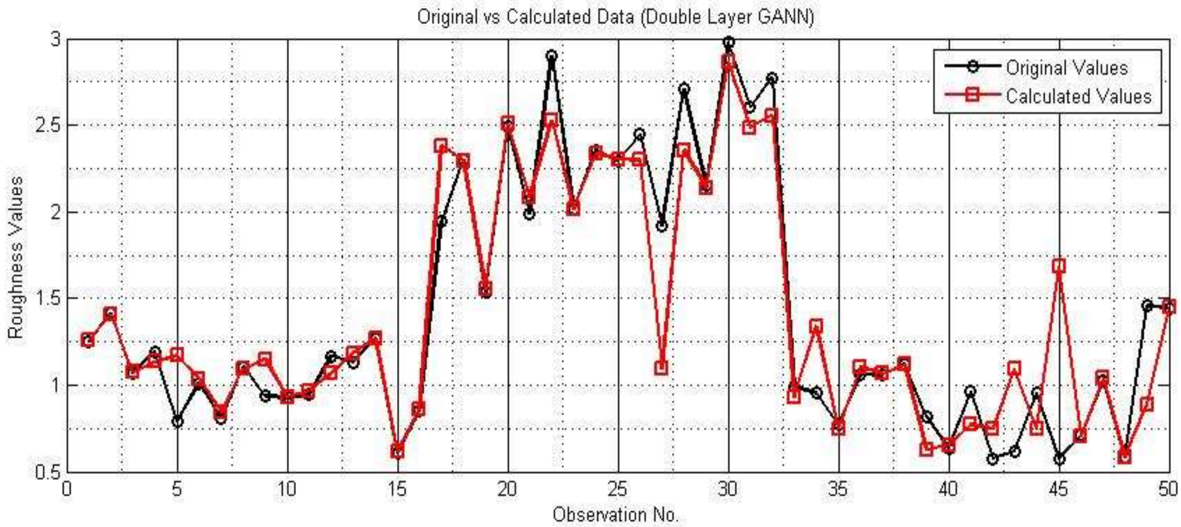

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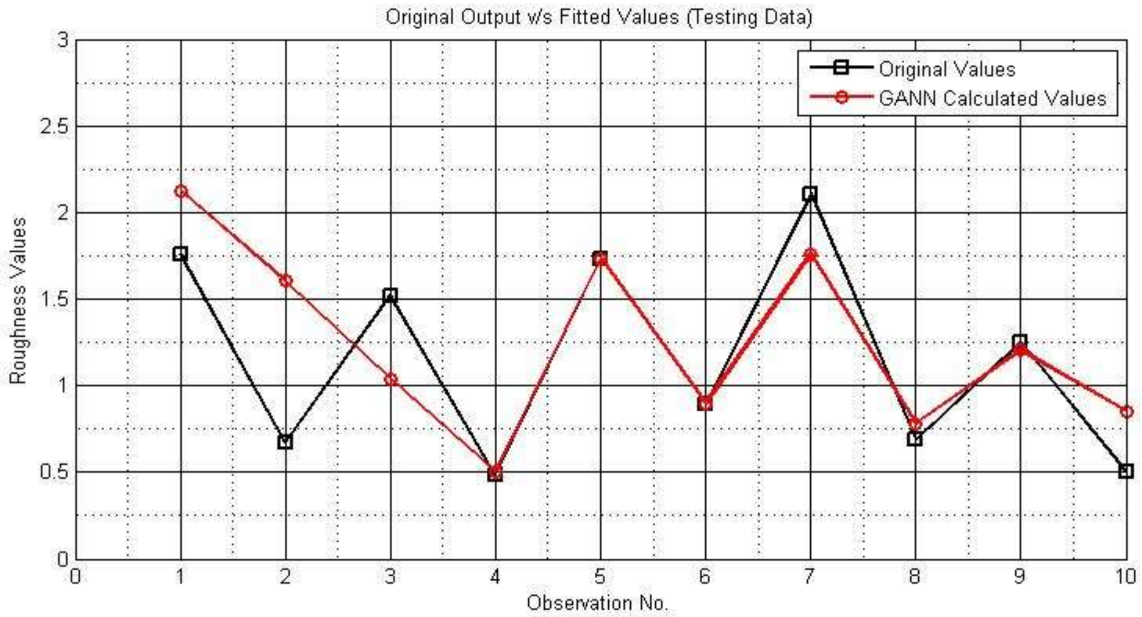

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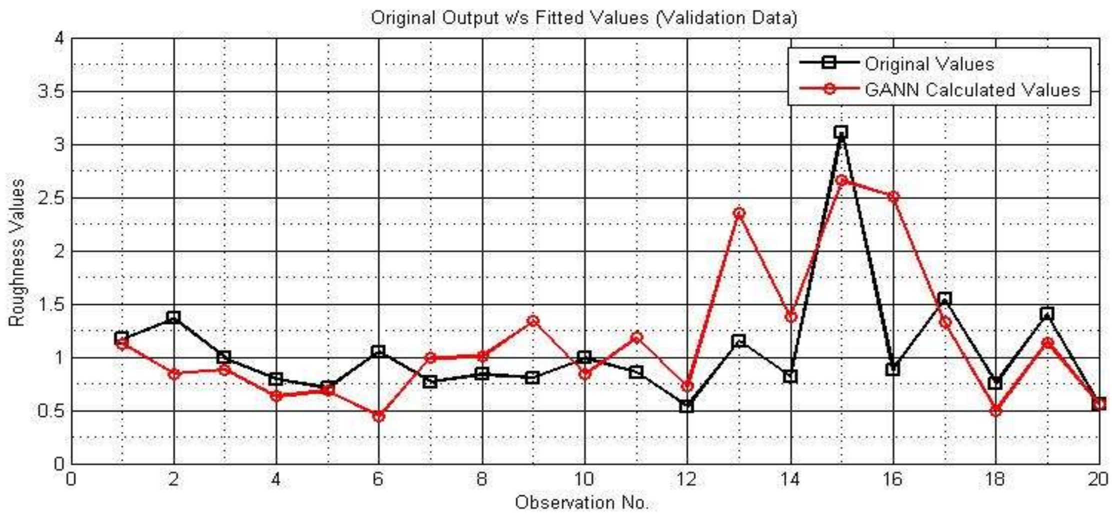
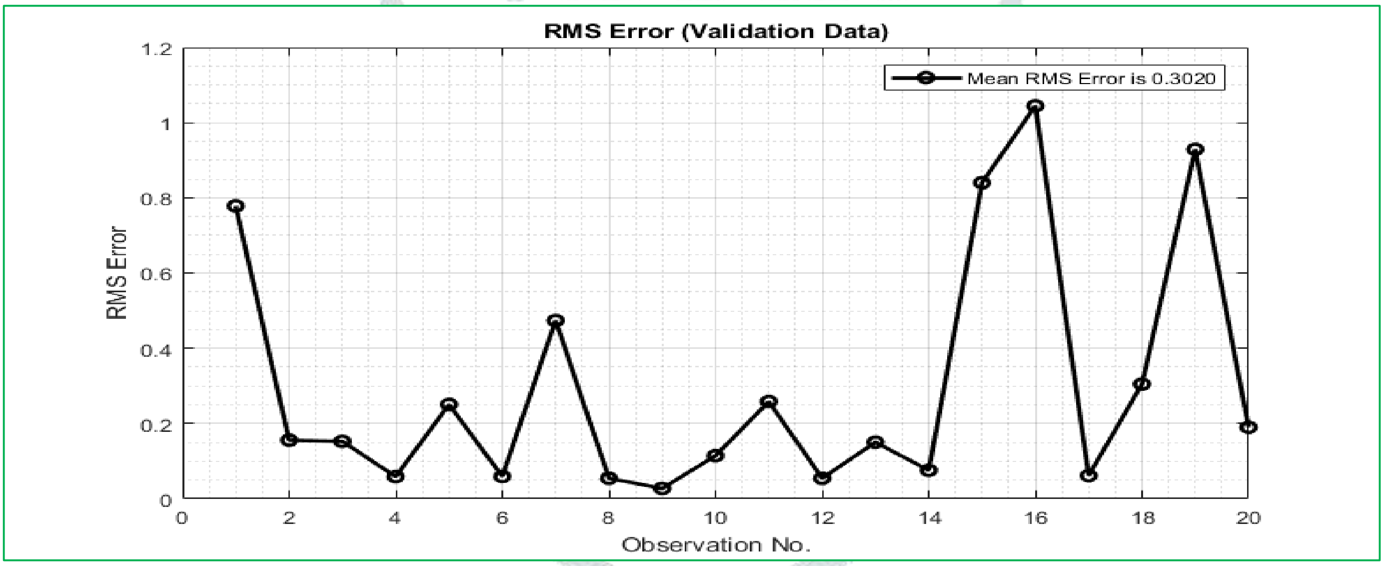


fig-18

From figure, 7 to 18 it can be seen that GANN calculated values corresponding to the respective input values are pretty close to the observed values. Model is neither loosely fitted nor it is over fitted.

15 LAYER MODEL



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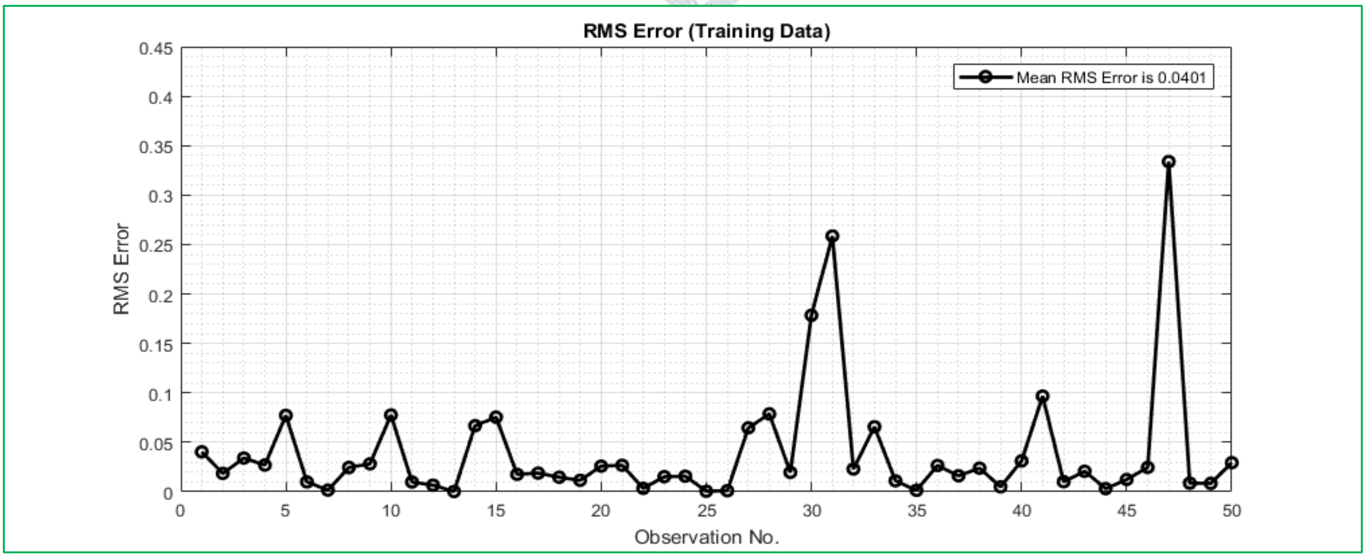

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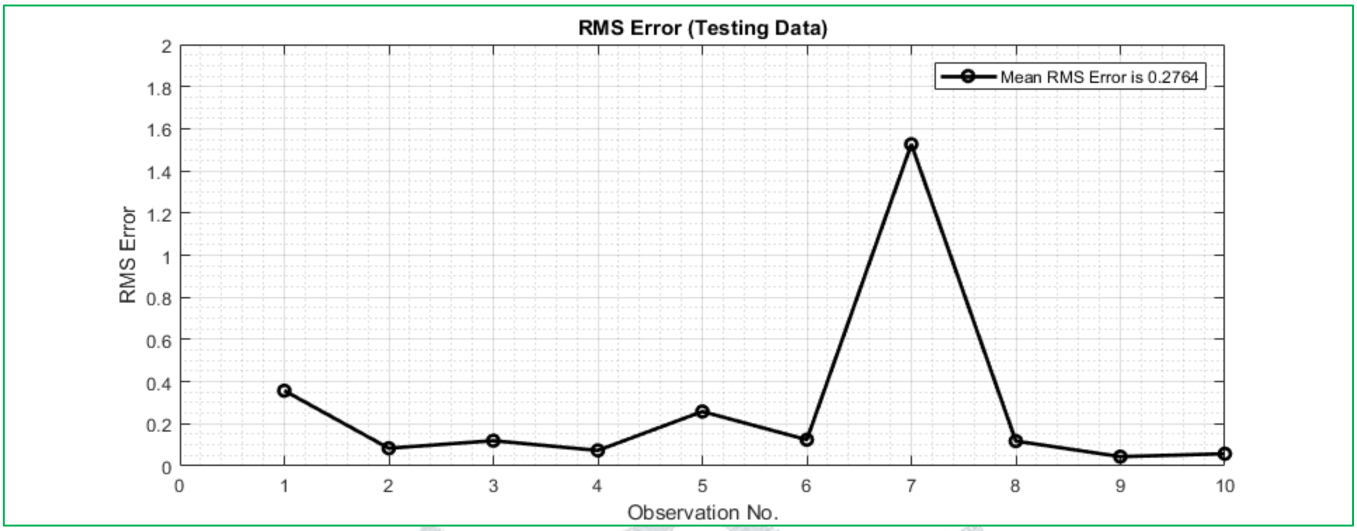
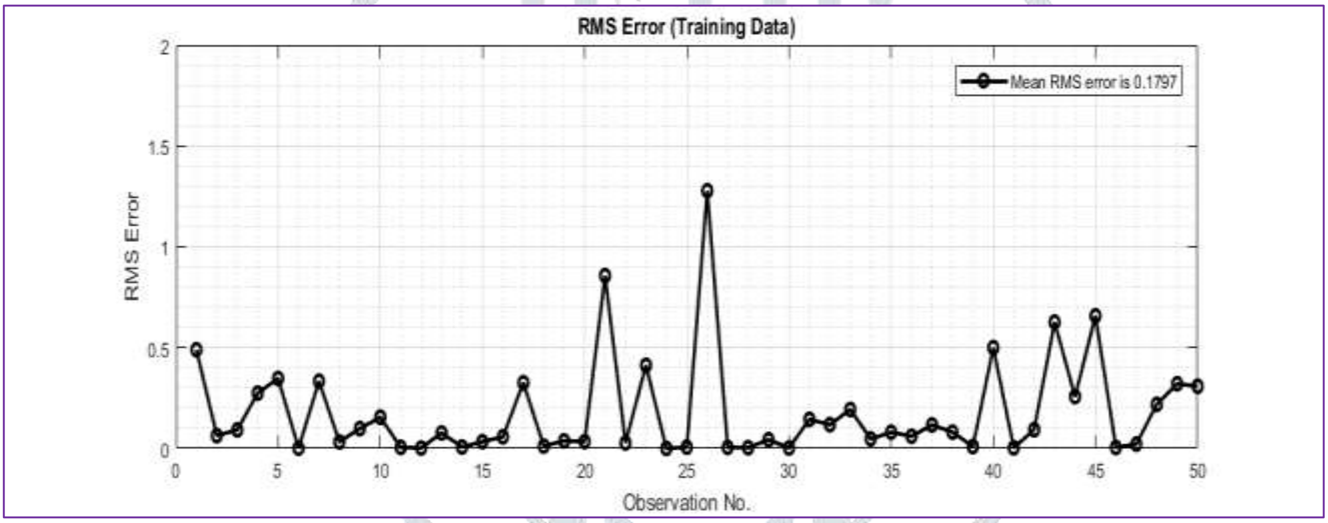


fig-21

MODEL (10,8) L



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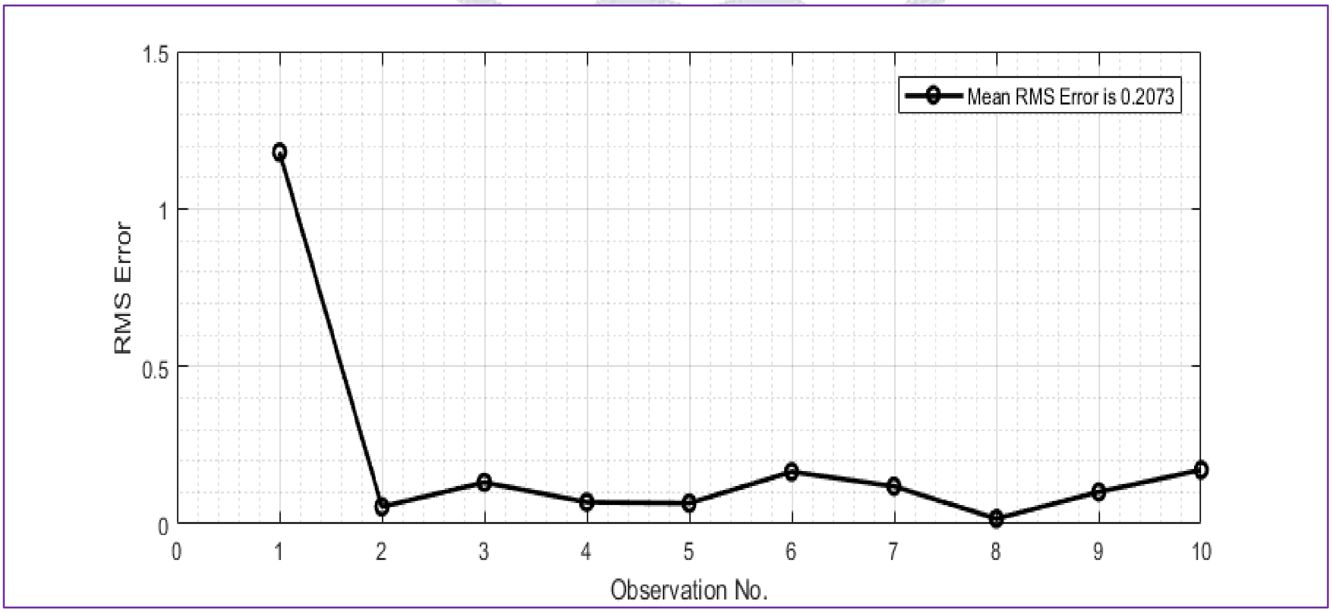

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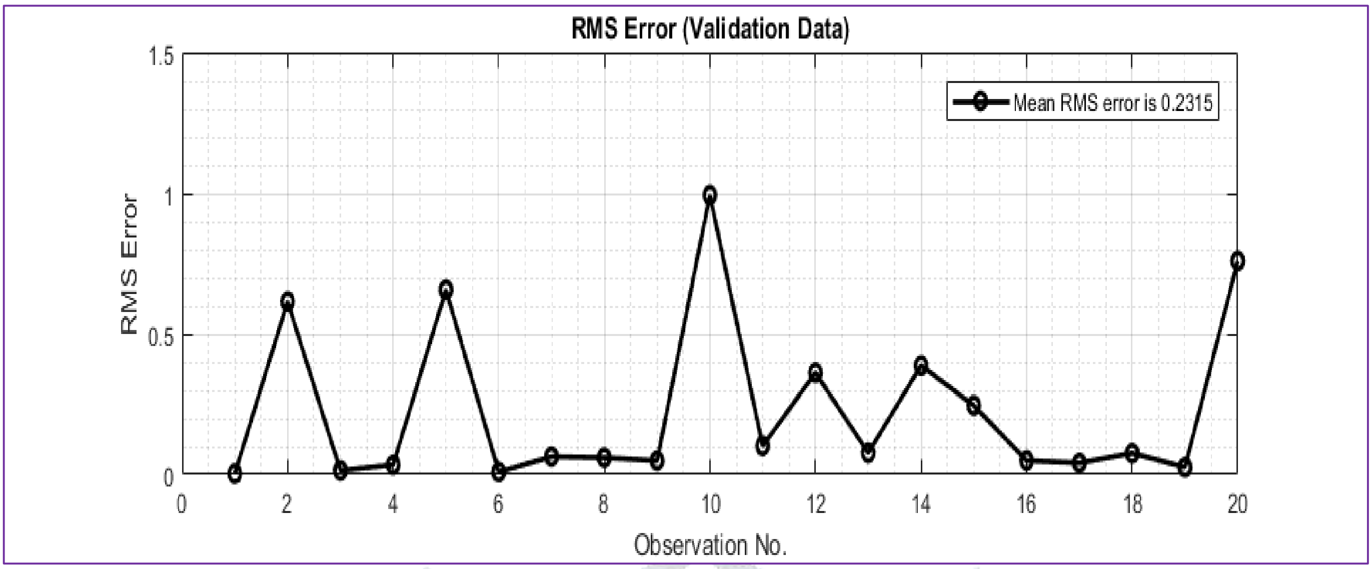
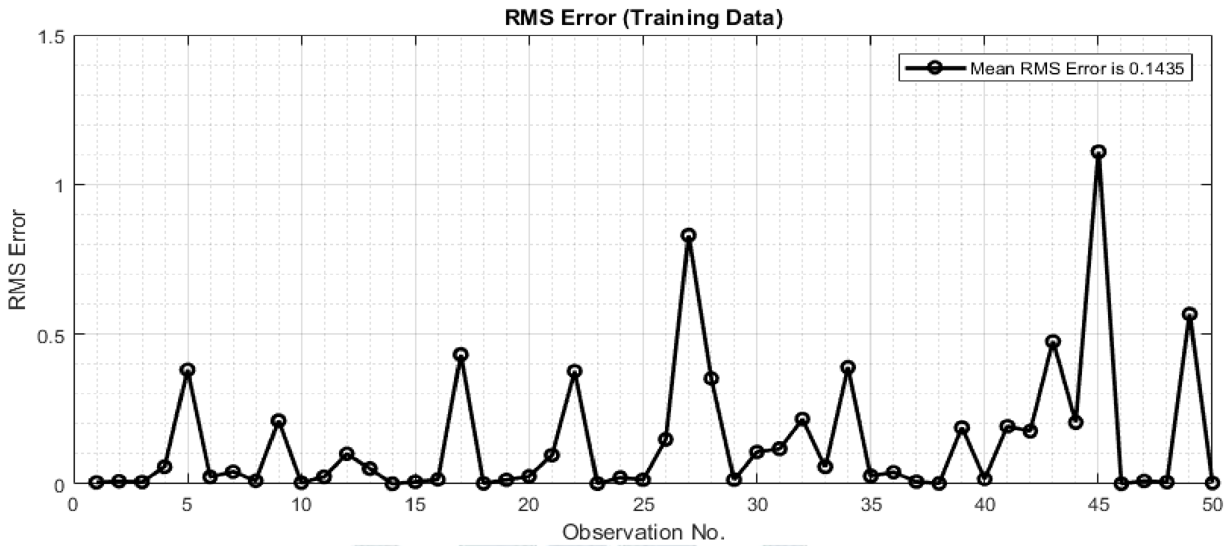


fig-24

MODEL (15,8) L



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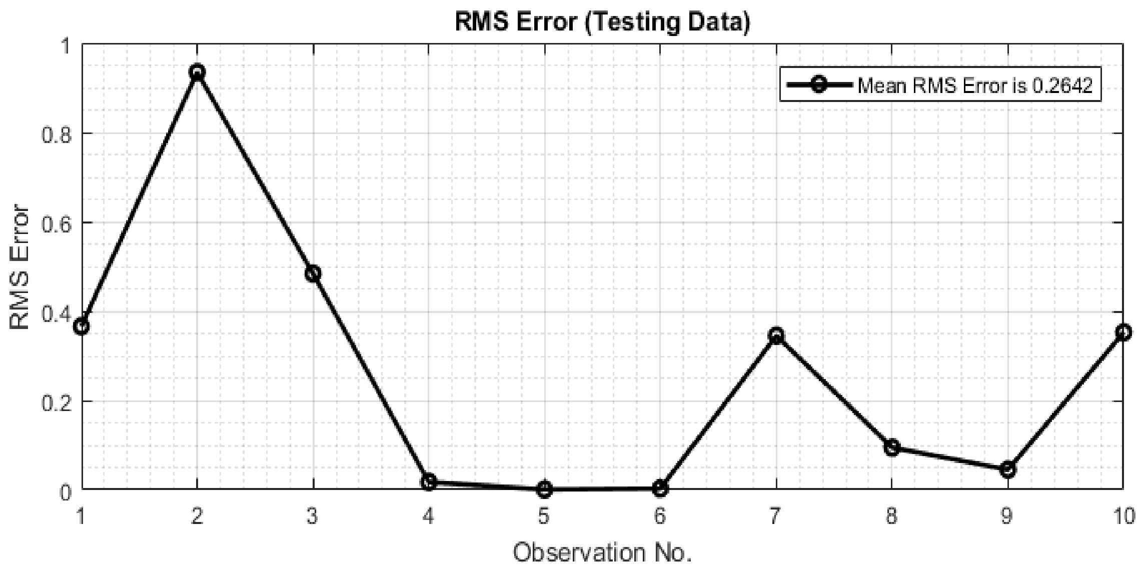

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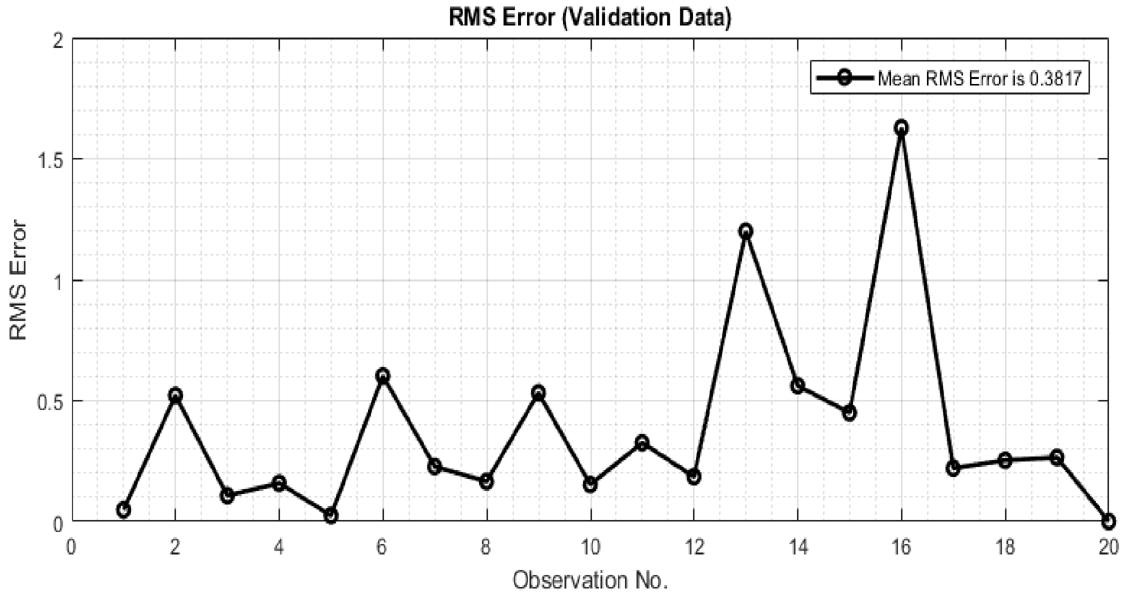

fig-27

The prediction error statistics like root mean square error (RMSE) are used to select the best model. The RMSE graphs are given for the various models in Fig-(20,21,22), (23,24,25) ,(26,27,28) for models (15)L, (8,10)L, (8,15)L respectively.

The table for MSE for the models is given in Table No1 . Minimum error suggests the best model.

TABLE-1

Sr. No	Model	Training MSE	Testing MSE	Validation MSE
1	(15,8)L GANN	0.1435	0.2642	0.3817
2	(10,8)L GANN	0.1797	0.2073	0.2315
3	15L GANN	0.0401	0.2764	0.302
4	10L GANN	0.0508	0.1052	0.0295

The comparative graphical representation for RMSE values for the Four Models is given in Fig-28.

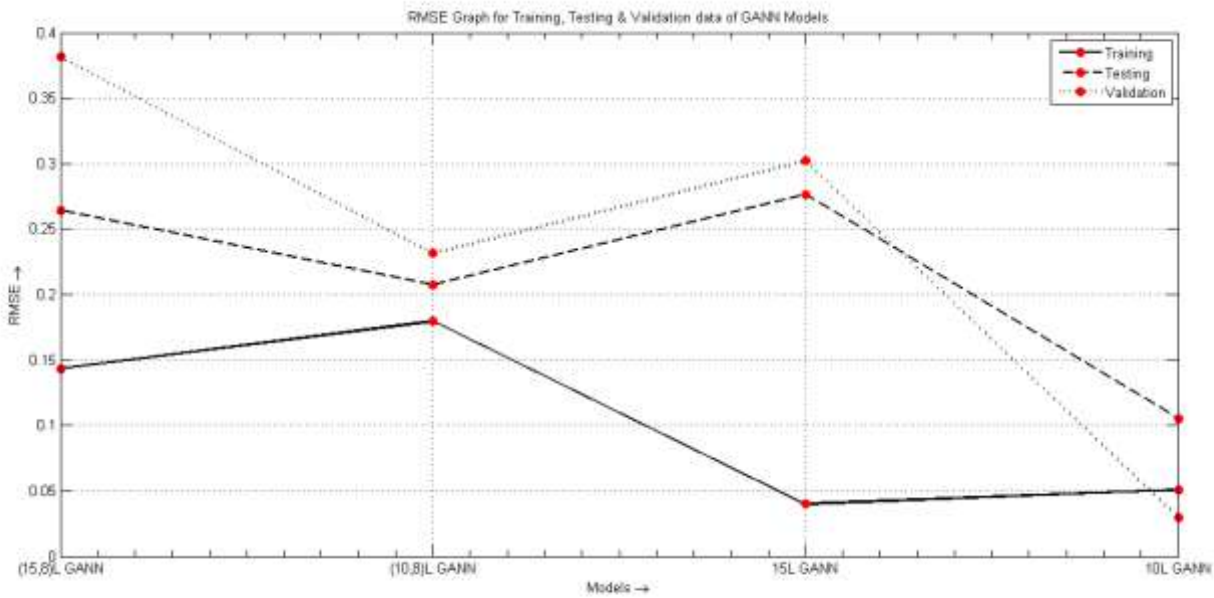

fig-28

6 RESULTS AND ANALYSIS

It is seen from the calculated and observed values that the values are closed together and the models are neither loosely fitted nor over fitted.
If we compare (15, 8) L GANN model with (10, 8) L GANN model than the difference in RMSE for (15,8)L is larger than (10,8)L GANN model. Also overall RMSE for (15,8)L is greater than (10,8)L model thus (10,8)L model is preferable. 15L model in the same way is also not preferable due to large RMSE difference in training, testing and validation. But, 10L GANN model is best suited because its overall RMSE is least as compared to other three models as well as difference of RMSE is also small for training, testing and validation.

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