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Short Term Load Forecasting using Soft Computing Techniques

Chaturvedi D K*, Sinha A P** and Vikas Pratap Singh***

Soft computing techniques are extensively used for electrical load forecasting in the past such as ANN, Fuzzy Systems, GA etc.. ANN has some limitations, such unknown structure of ANN, Decision of neuron type, problem of training data and time, stuck in local minima etc. To overcome the drawbacks of ANN, a Generalized Neural Network (GNN) has been proposed. In this paper, different variants of GNN have been proposed to improve its performance such as GNN integrated with wavelet transform and trained with adaptive genetic algorithm and fuzzy system to forecast the short term week day electrical load. Performance of the proposed algorithm is compared with other GNN and its other variants on the basis of prediction error.

Keywords: *Load Forecasting, ANN, Generalized neural network, Wavelet, Adaptive Genetic algorithms, Fuzzy systems.*

1.0 INTRODUCTION

Short-term load forecasting (STLF) approaches available in the literature can be divided into two main categories: statistical methods and artificial intelligence based methods. The statistical category includes multiple linear regression [1], stochastic time series [2], ARIMAX and general exponential smoothing [3-5], state space model [6], and support vector regression (SVR) [7-8], whereas expert system [9], artificial neural network [10-14] and fuzzy inference [15-16] belong to the artificial intelligence category. The use of artificial neural networks (ANNs or simply NNs) for load forecasting has been proposed since the 1990s. Normally, ANN is trained using back propagation or its variants, but back-propagation learning has many limitations. A generalized neural network (GNN) has been developed to overcome the drawbacks of ANN and used for modeling [17], forecasting [18-20] and control applications [21-23].

Genetic algorithms (GAs) are more robust than the directed search (gradient back propagation) methods and also possess other useful characteristics. For example, hill climbing methods provide local optimum values and these values depend on the selection of a starting point. Also there is no information available on the relative Error with respect to global optimum. To increase the success rate in the hill climbing method, it is executed for large number of randomly selected different starting points. On the other hand, GA optimization is a random search [24] and does not need the derivative of error. Hence, any continuous or discontinuous function may also be used as a threshold function of NNs. Employing a random search GA guarantees global optimum.

To improve its performance, fuzzy rules can be used to guide it.

A GNN model with four wavelet components as inputs (called GNN-W) and trained using adaptive

*Professor, Dept. of Electrical EngineeringFaculty of Engineering, D.E.I. Dayalbagh, Agra, U.P.-282 005, India. Mobile : 09456433788, Email: dkc.foe@gmail.com
** Faculty, Dept. of Electrical Engineering, D.E.I. Dayalbagh, Agra, U.P.-282 005 India. Mobile : 09319196492, Email: Anandsinha.dei@gmail.com
***Energy Efficiency and Renewable Energy Division, Central Power Research Institute, Bangalore-560080. India. Mobile : 9458207770, Email: vikasforsmile@iitj.ac.in

GA with fuzzy concepts (GAF) is developed. The proposed GNN-W-GAF model is used for STLF and its performance compared with that of regular GNN and GNN-W with back-propagation training.

2.0 STLF USING GNN WITH BACK-PROPAGATION TRAINING MODEL (GNN-BKP)

The GNN consists of a single higher order neuron as shown in Figure 1 [17-19]. In the GNN model A1, A2 are summation and product aggregation functions and f1, f2 are sigmoid and Gaussian activation functions, respectively.

The GNN model was initially trained using error back-propagation (BKP) gradient search learning algorithm and applied to the STLF problem on datasets obtained from a 15 MVA, 33/11 kV substation at Dayalbagh Educational Institute (D.E.I.), Agra, India. Although the results obtained during the training and testing of the GNN model were quite promising (ref. Figure 2), they showed some room for improvement. This provided motivation to seek further improvement and the GNN was trained using adaptive GA – Fuzzy system.

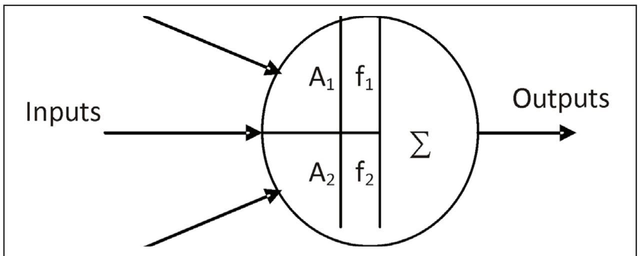


FIG. 1 GNN MODEL

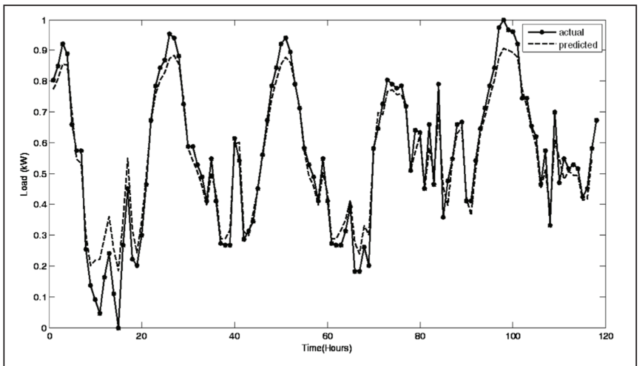


FIG. 2 TEST PERFORMANCE OF GNN-BKP MODEL

3.0 STLF USING GNN TRAINED WITH ADAPTIVE GENETIC ALGORITHM AND FUZZY SYSTEM (GNN-GAF)

Training a feed-forward GNN for the STLF problem using the back propagation learning mechanism has some drawbacks as below:

i. It is a slow learning process, especially when large training sets or large networks have to be used.
ii. Network may get stuck in local minima.
iii. The threshold function should be differentiable and non-decreasing.
iv. The training time in backprop depends upon
   a. Training parameters and initial weights.
   b. The error function used.
   c. The normalization range of training data and input output mapping.

The central theme of research on genetic algorithms has been robustness, the balance between efficiency and efficacy necessary for survival in many different environments. The following are the advantages of GA:

i. It is a sophisticated search procedure based on the mechanics of natural genetics. The search is absolutely blind, but guided by pre-designated precise operators.
ii. It has a good potential as a problem solving tool, especially in finding near optimal solutions.
iii. GA based methods search from a population of potential solutions unlike other methods, such as hill climbing method, that process a single point of the search space.
iv. It uses pay off information (objective function), not derivatives or auxiliary knowledge.
v. It uses probabilistic transition rules, not deterministic rules.
vi. GAs work with coding of the parameter themselves.

3.1 Operators of GA

The chromosomes of GA consist of weights of GNN and they are modified using GA operators to get new population. The crossover and mutation are the most important operators of the genetic algorithm. Depending on the number of variables GA optimization can be slow. To improve the convergence of GA, adaptive GA (GAF) is developed, in which the GA parameters {crossover probability (Pc), mutation probability (Pm) and population size} are modified using fuzzy rules to improve its performance. The initial parameters of GAF are given below.

Population size: 50

Crossover probability, initial value: 0.9

Mutation probability, initial value: 0.1

Selection operator: tournament selection

Number of generations: 100

The application of GNN-GAF model is applied for load forecasting as shown in Figure 3. The GNN is trained for past three electrical load values as input and next hour load as output. The error function is calculated from predicted load of GNN and actual load and it is minimized using adaptive GAF. Flow chart for GNN-GAF is given in Figure 4.

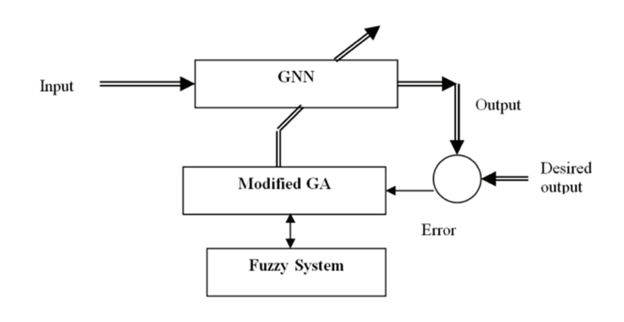


FIG. 3 GA AS LEARNING TOOL FOR GNN

3.2 Development of Adaptive Genetic Algorithm Using Fuzzy System (GAF)

Details of parameter variations and their influence on the optimization process have been studied by many researchers [25-30]. In all these studies the objective function is optimized using GA for different sets of parameters that are initialized at the time of starting. Normally, these GA parameters are kept constant during optimization. In the adaptive GA the parameters such as:

i. crossover Probability (P_c), and

ii. mutation probability (P_m)

are varied dynamically during the execution of the program. For this variation the fuzzy knowledge base that has been developed from experience to maximize the efficiency of GA, is used.

3.2.1. Basis of Variation Of P_c and P_m

Philosophy behind the variation of these parameters is that the GA optimization depends on the crossover and mutation operation. The high fitness value of chromosomes may require a low crossover probability and high mutation probability for further improvement; whereas, at low fitness value of chromosomes, a relatively high crossover probability and a low mutation probability are needed. The reason behind it is that at the time of starting high Pc and low Pm yield good results, because large number of crossover operations will produce better chromosome vectors whose fitness values are relatively high.

This process will continue for some finite number of generations, after that the fitness value of each chromosome vector becomes almost same (around 0.9). Beyond that, the effect of crossover is not significant due to little variation in the chromosome vectors of that particular population. Hence, at this stage, the population can be diversified by increasing the mutation rate of the chromosome vector to inculcate the new characteristics in the existing population.

Several methods of optimization have been proposed over the past few years. Some heuristics for an optimal setting of the mutation probability Pm, were proposed in [25]. Investigation of time dependencies on the mutation and the crossover probability is described in [26] and [27], respectively, and optimal settings for all these GA parameters are found by experimentation in [28].

In the present work, a fuzzy system is used to control the values of Pc and Pm. For this purpose, GA parameters have been defined onto three linguistic terms i.e. low (L), medium (M) and high (H). These are presented in Tables 1 and 2. The parameters are varied based on the value of the fitness function and its variance.

For this purpose the best fitness (BF) for each generation is considered. This value is expected to change over generations. If the BF does not change significantly over a number of generations (UN) then this information is also considered to affect changes in the GA parameters.

Diversity of population is one of the factors that influence the search for true optima. The variance of the fitness values of objective functions (VF) of a population is a measure of its diversity and hence, considered as a factor based on which the GA parameters are changed.

3.3 Development of Fuzzy System

Membership functions and membership values for the three input variables, i.e. BF, UN and VF, are selected based on experience and ease in computation. The support and overlapping of these membership functions are optimized.

The knowledge base for modifying the GA parameters is given in Fuzzy Associative Memory (FAM) Tables 1-2. FAM is a Fuzzy Truth Table that shows relationship between input and output (value of P_c or P_m).

TABLE 1

FAM TABLE FOR CONTROLLING P_C

		UN		
		L	M	H
BF	L	H	H	H
	M	H	-	-
	H	H	M	-

		VF		
		L	M	H
UN	L	H	H	H
	M	H	-	-
	H	H	M	-

TABLE 2

FAM TABLE FOR CONTROLLING P_m

		UN		
		L	M	H
BF	L	L	L	L
	M	L	M	-
	H	L	M	-

		VF		
		L	M	H
UN	L	-	-	-
	M	-	-	-
	H	H	L	L

The range and maximum value of different membership functions such as low (L), medium (M) and high (H) for changing Pc and Pm using fuzzy system during training after accepting inputs such as BF, UN and VF of earlier population of adaptive GAF are shown in Table 3.

TABLE 3

DETAILS OF MEMBERSHIP FUNCTIONS

	Membership Value	**L**	**M**	**H**
P_c	Range	0.5-0.7	0.65-.8	0.7-1.1
	Max.	0.5	0.7	1.1
P_m	Range	0.001-0.062	0.055-0.075	0.062-0.12
	Max.	0.001	0.062	0.12
BF	Range	0-0.7	0.5-0.9	0.7-1.0
	Max.	0.0	0.7	1.0
UN	Range	0-6	3-9	6-12
	Max.	0	6	12
VF	Range	0-0.12	0.1-0.14	0.12-0.2
	Max. Value	0	0.12	0.2

3.4 Results of GNN-GAF

The GNN model is used to forecast the electrical demand of the 15 MVA, 33/11 kV substation of Dayalbagh Educational Institute, Dayalbagh, Agra, India. Load data for all working days from Monday to Friday, is gathered in a data set and used for training. The weekend (Saturday and Sunday) load is not considered in the data set because; it is very low and less varying as compared to normal working days' load. The GNN model is trained using GAF. The improvement in maximum fitness using GNN-GAF is shown in Figure 5. The fuzzy system is used to change crossover and mutation probabilities during execution of GNN-GAF as shown in Figure 6. The improvement in average fitness is also shown in Figure 7. A comparison of the load forecast by GNN-GAF with the actual load is shown in Figure 8. The complete data is divided in test data set (20%) and training data set (80%) to develop and check the performance of GNN-GAF. The GNN-GAF model gave better results than those obtained using GNN with back propagation (Sec. 2).

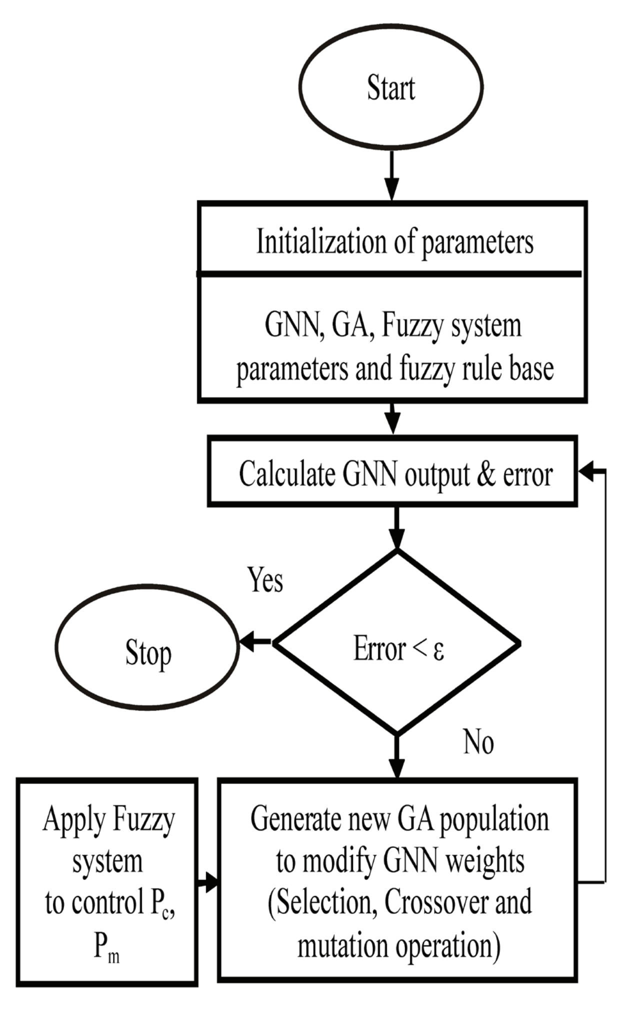


FIG. 4 FLOW CHART OF GNN-GAF

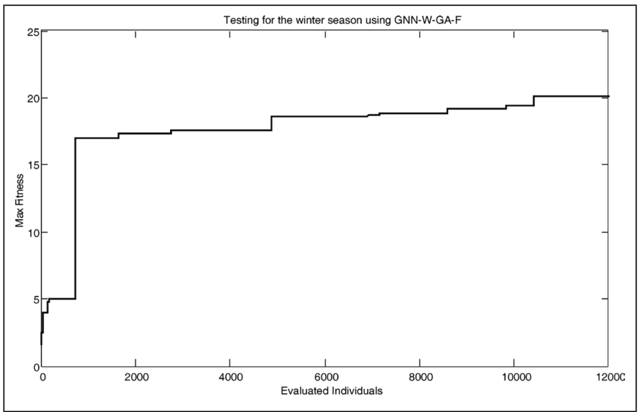
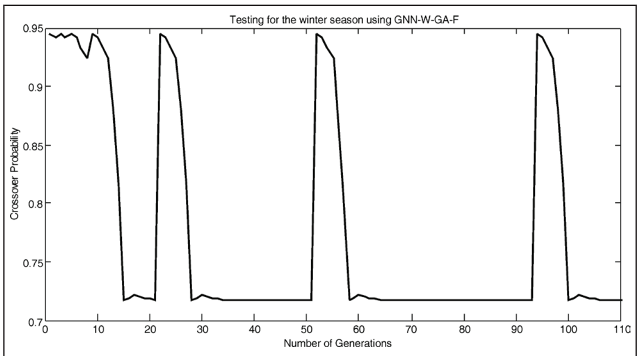
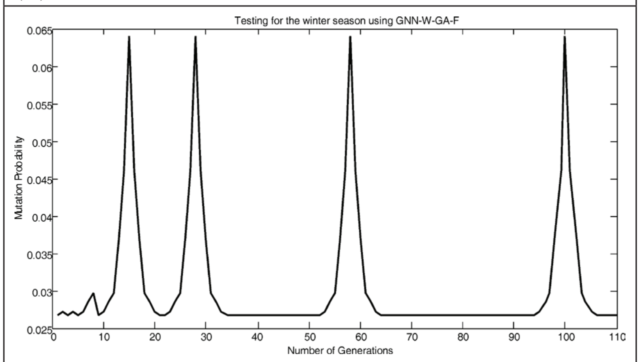


FIG. 5 CHANGE IN MAXIMUM FITNESS DURING TRAINING OF GNN-GAF MODEL



(A) CROSSOVER PROBABILITY



(B) MUTATION PROBABILITY

FIG. 6 VARIATION IN CROSSOVER AND MUTATION PROBABILITY DURING TRAINING OF GNN-GAF

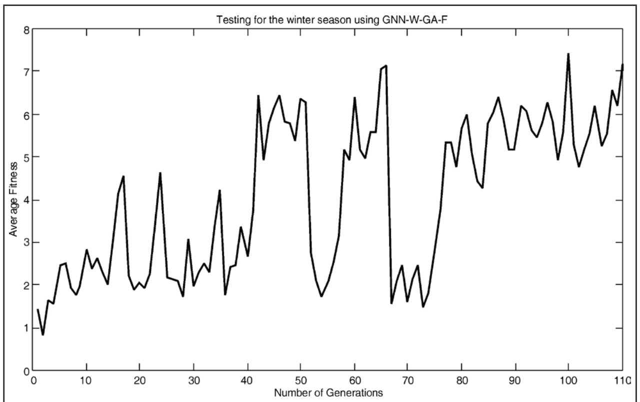


FIG. 7 AVERAGE FITNESS DURING TRAINING OF GNN-GAF

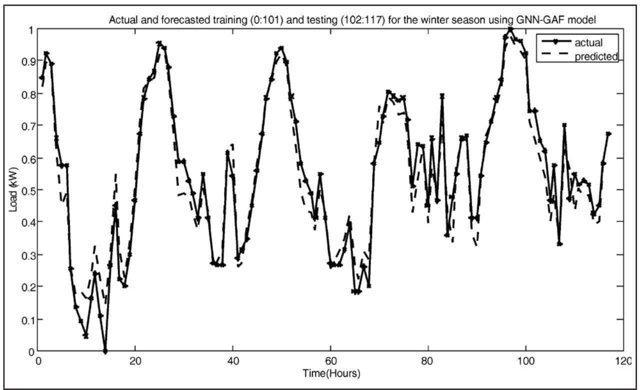


FIG. 8 TEST PERFORMANCE OF GNN-GAF MODEL

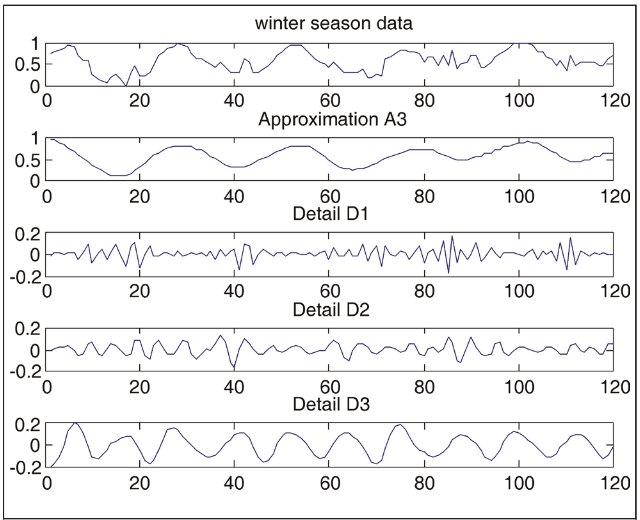


FIG. 8(A) WAVELET DECOMPOSITION OF HOUR LOAD DATA INTO WAVELET COMPONENTS

4.0 INTEGRATION OF WAVELET AND GNN-GAF SYSTEMS (GNN-W-GAF) FOR STLF

To further improve the performance of STLF, wavelet transform has been integrated with the GNN trained using adaptive GA and fuzzy system of section 3.

4.1 Wavelet Transform

Wavelet decomposition techniques have been integrated successfully with neural networks showing more accurate and acceptable results as compared to conventional methods [31-33]. It is a powerful tool that can be effectively utilized for the prediction of short-term loads by integrating it with the GNN-GAF model described above.

In the proposed approach the past load pattern is decomposed into 4-wavelet components (i.e. one approximate component (a3) and three detailed components (d1, d2, d3)) using Daubechies wavelets db8 as shown in Figure 8(a). These wavelet components, instead of the past load patterns, are then used to train GNN model for forecasting. The training patterns consist of decomposed wavelet components of given load pattern at time t, t-1, t-2 (past three points) as input and the forecasted wavelet component at t+1 as output. The training of GNN model is done with an adaptive Genetic Algorithm using fuzzy system (GAF) for different wavelet components. The block diagram of GNN-W-GAF model for STLF is shown in Figure 9.

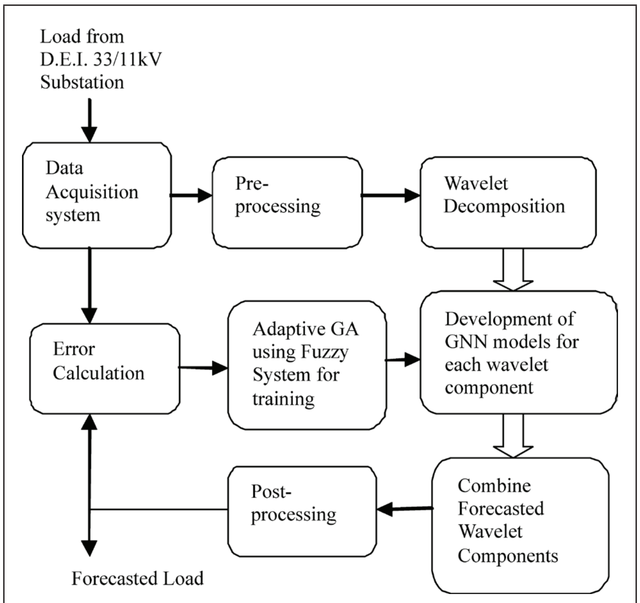


FIG. 9 DETAILED DIAGRAM OF GNN-W-GAF MODEL

The improvement in maximum and average fitness of adaptive GAF after modifying GNN weights is shown in Figures 10 and 11. The crossover and mutation probabilities of adaptive GAF are not constant but vary during execution as shown in Figure 12 as per the fuzzy rules to improve the optimization speed.

The training performance of GNN models for different wavelet components (i.e. low frequency approximate component (a3) and high frequency detailed wavelet components (d1, d2, d3)) using adaptive GAF are shown in Figure 13. The above developed model is used to forecast (a3, d1, d2, d3) wavelet components and then recombine them to get future load. A comparison of the forecast load with the actual load during testing using GNN-W-GAF is shown in Figure 14 with the same test data set as considered in other GNN variants. The GNN-W models are also trained using back propagation algorithm for different wavelet components for short term load forecasting and the results are shown in Figures 15-16. The GNN-GAF traing and testing performance shown in Figure 17.

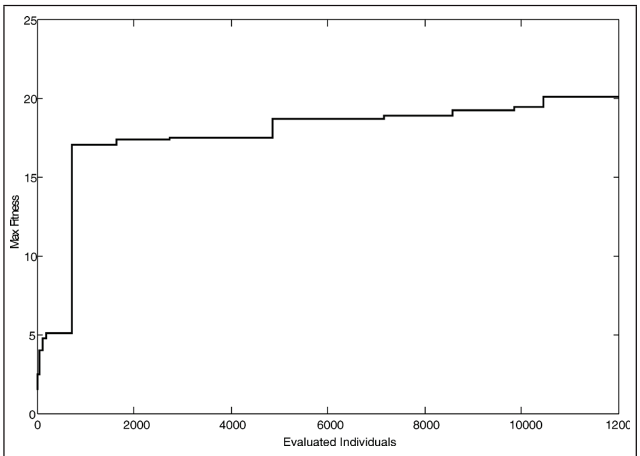


FIG. 10 MAXIMUM FITNESS OF GA FUZZY DURING TRAINING OF A3 COMPONENT USING GNN-W-GAF

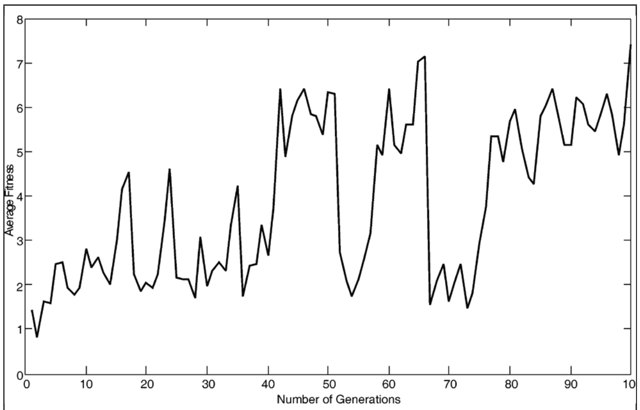
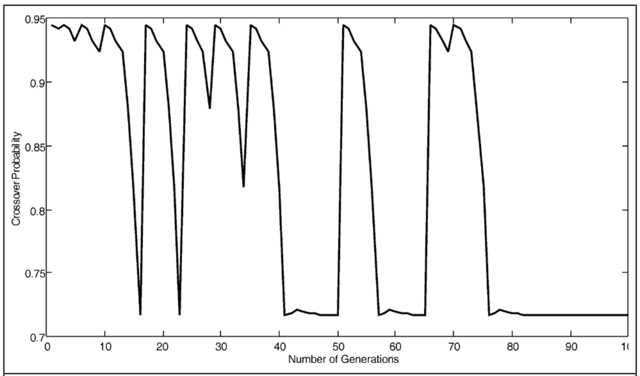
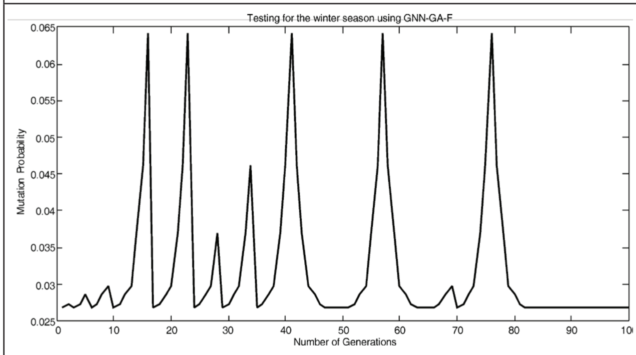


FIG. 11 AVERAGE FITNESS CHARACTERISTICS OF GA FUZZY DURING EXECUTION OF A3 COMPONENT USING GNN-W-GAF

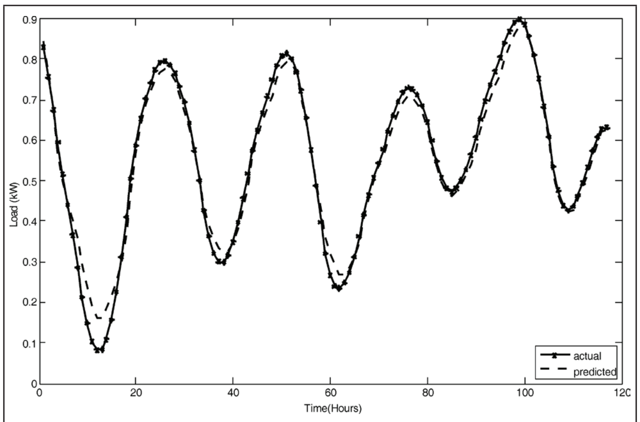


(A) CROSSOVER PROBABILITY

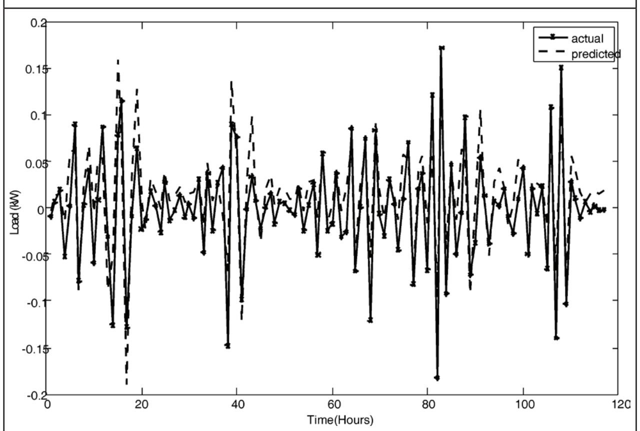


(B) MUTATION PROBABILITY

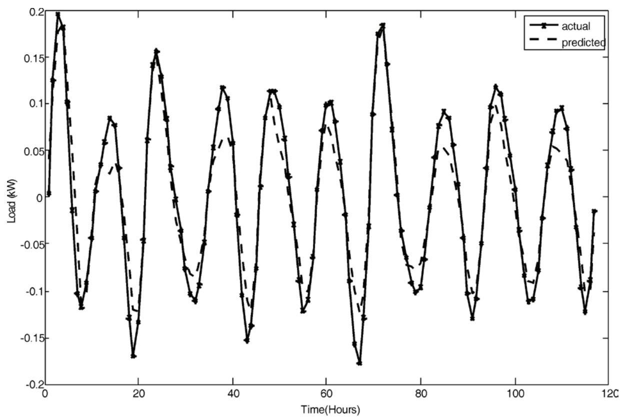
FIG. 12 VARIATION IN CROSSOVER AND MUTATION PROBABILITY DURING TRAINING OF A3 COMPONENT USING GNN-W-GAF



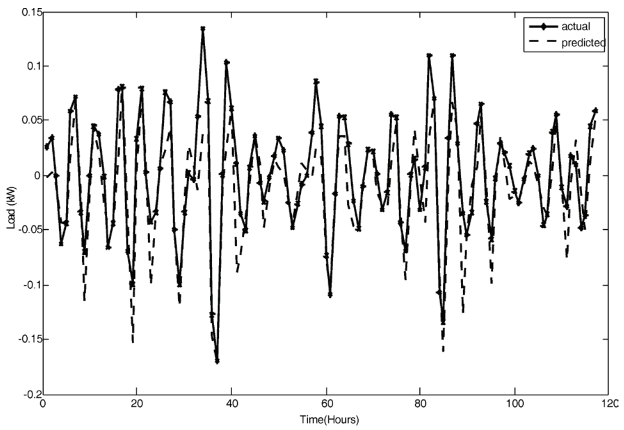
(A) FORECAST OF A3 COMPONENT USING GNN-W-GAF



(B) FORECAST OF D1 COMPONENT USING GNN-W-GAF



(C) FORECAST OF D2 COMPONENT USING GNN-W-GAF



(D) FORECAST OF D3 COMPONENT USING GNN-W-GAF

FIG. 13 PERFORMANCE OF GNN-W-GAF FOR DIFFERENT WAVELET COMPONENTS

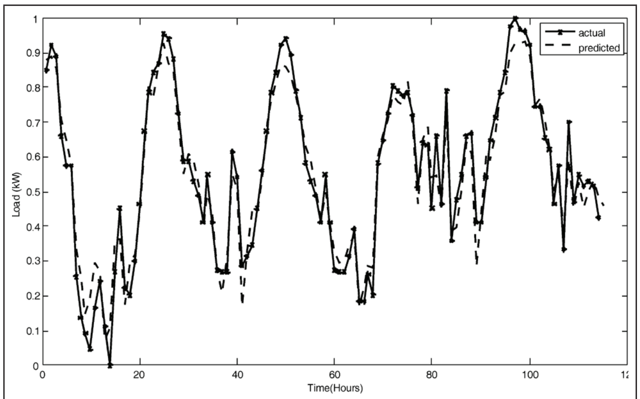
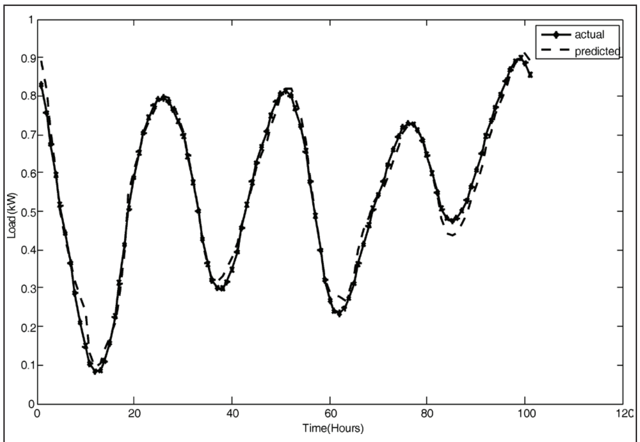
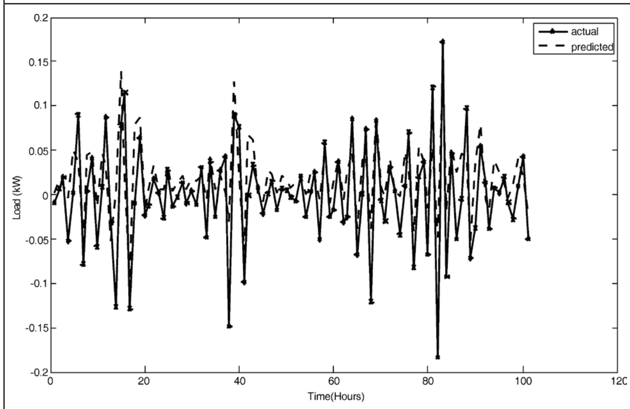


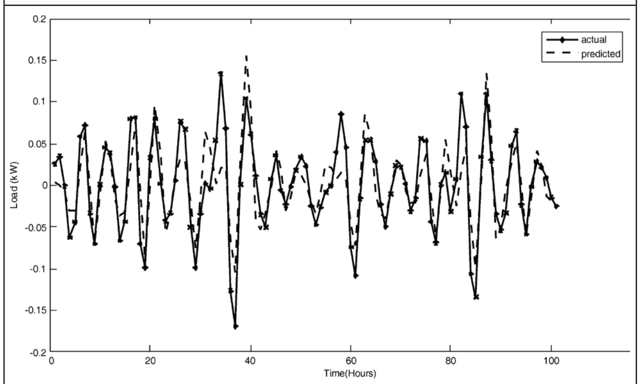
FIG. 14 TEST PERFORMANCE OF GNN-W-GAF MODEL FOR STLF



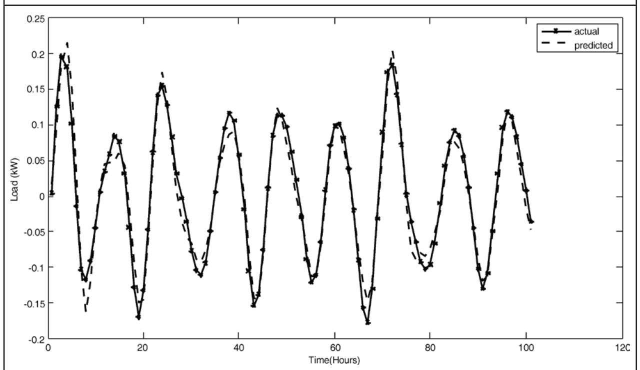
(A) FORECAST OF A3 COMPONENT USING GNN-W-BKP



(B) FORECAST OF D1 COMPONENT USING GNN-W-BKP

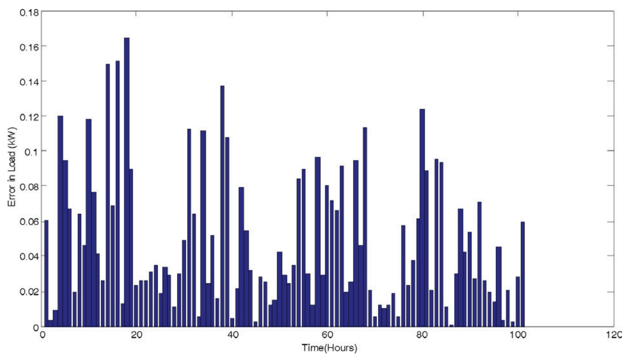


(C) FORECAST OF D2 COMPONENT USING GNN-W-BKP

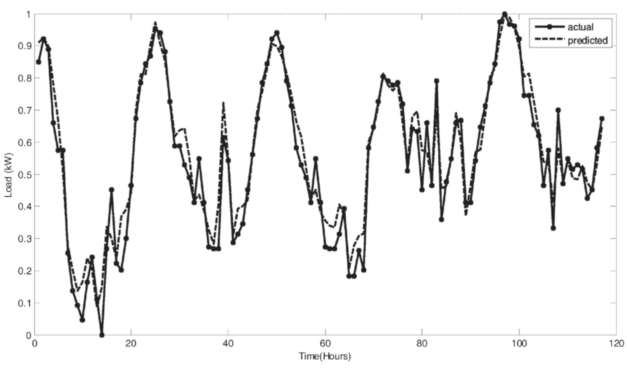


(D) FORECAST OF D3 COMPONENT USING GNN-W-BKP

FIG. 15 PERFORMANCE OF GNN-W-BKP FOR FORECASTING THE WAVELET COMPONENTS

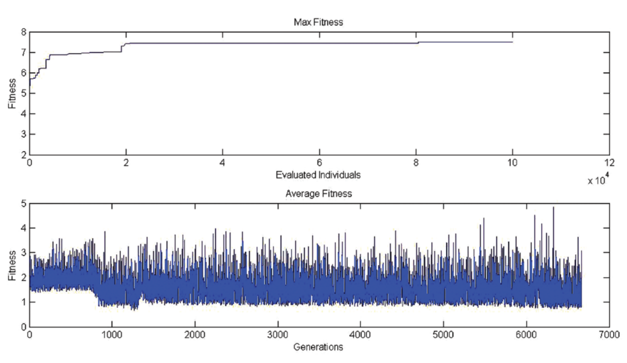


(A) ERROR DURING TRAINING FOR THE WINTER SEASON

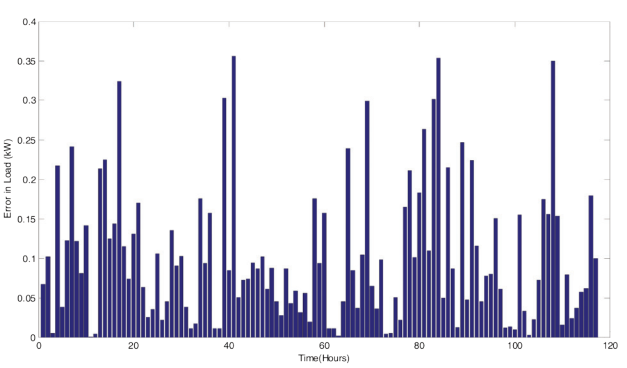


(B) TEST PERFORMANCE

FIG. 16 GNN-W-BKP MODEL FOR STLF



(A) MAXIMUM FITNESS AND AVERAGE FITNESS USING GNN-GAF MODEL



(B) ERROR DURING TESTING

FIG. 17 GNN-GAF MODEL

Once the GNN-W-GAF models are developed for different wavelet components, they are used for forecasting. The forecast RMS errors during testing for a3, d1, d2, d3 are calculated for GAF and back propagation training algorithms and tabulated in Table 4. Finally, these forecasted wavelet components are combined to get forecasted load. The forecasted load is then compared with actual load and testing absolute error is tabulated in Table 5. It can be seen from Table 5 that the performance of GNN-W-GAF for STLF is the best among all other GNN variants.

TABLE 4

TESTING ERROR FOR DIFFERENT WAVELET COMPONENTS

Wavelet components	RMSE	
	GNN-W-GAF	GNN-W-BKP
a_3	0.0297	0.0260
d_1	0.0342	0.0417
d_2	0.0308	0.0324
d_3	0.0254	0.0185

TABLE 5

COMPARISON OF DIFFERENT VARIANTS OF GNN FOR STLF

Models	Min. Error (kW)	Max. Error (kW)	RMSE (kW)
ANN-W-BKP	0.0001057	0.3409	0.126
GNN - BKP	0.00020	0.3382	0.1329
GNN - GAF	0.00042	0.3554	0.1032
GNN-W - BKP	8.767e-005	0.1649	0.0610
GNN-W - GAF	0.00120	0.1270	0.0486

5.0 CONCLUSIONS

The paper deals with short term load forecasting using different variants of GNN trained with back-propagation and adaptive GAF to overcome the drawbacks of ANN and back propagation (BKP) training algorithm. To further improve the accuracy of forecasting short term load, GNN model is combined with wavelet transform and GNN-W models have been developed. The GNN-W-GAF has been trained through exposure to a set of input and output data. The real time data collected from D.E.I. Substation has been used for training and testing all these models.

The back propagation and GAF training algorithms have been compared for GNN and GNN-W. For GA optimization, sum squared error function was computed and used as fitness function of GA. The results show that the GNN with the help of GAF performs well with non-derivative learning mechanism. It helps to minimize the error (i.e. the fitness value of objective function reaches near to one). The results show that the RMSE of GNN-W-GAF is minimum as compared to GNN and GNN-W trained with back-propagation (BKP), and GNN trained with GAF.

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