Information system for forecasting processes based on unsupervised, supervised neural networks

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ABSTRACT

In this paper, an Information system for forecasting processes based on unsupervised, supervised neural networks is developed. The unsupervised learning process is performed using Kohonen's Neural Networks (KNN) for clustering of the input space into affinity number of classes. For each class, the supervised learning process is performed using Feedforwared Neural Networks (FNN) The historical database that contains the data of the attributes of the forecasting process that cover two years is formed. The unsupervised process performs the role of front-end data compression.

The ANN is used to learn the relationship among past, current, future daily load and weather patterns that obtained from energy Distribution Company, Libya. All input patterns information are stored in distributed form among the various connection weights. The Comparison of the forecasted values of ANN and with without KNN with actual values is made to demonstratrate that the forecasting accuracy with KNN is very encouraging. By the proposed Information system the computation time for the neural network learning with KNN can largely reduced.

1 INTRODUCTION

The load demand is influenced by many factors, such as weather, economic and social activities and different load components (residential, industrial, commercial etc.).By analysis of only historical load data, it is difficult to obtain accurate load demand for forecasting. The relation between load demand and the independent variables is complex and it is not always possible to fit the load curve using statistical models. The numerical aspects and uncertainties of this problem appear suitable for ANN, and hybrid methodologies.

The daily load patterns in the same geographical area have been repeated for the same day type in the same season so, the ANN approach was proposed for load forecasting. The accuracy of a forecasting model is the most important factor in deciding its validity. To avoid incomplete or wrong load modeling, it is first of all essential to detect the row data of historical load and weather information from gross measurement and recording errors. Data of holiday and special days must also be omitted from the input data records because each of these days has a special load pattern. It is possible to detect most gross errors by simple checks on the row data because a bad data detection procedure must make use of redundancy in the set of load measurements. If there is no redundancy, there is no way to detect the bad data .It is beneficial to make an analysis of the residuals to detect any remaining bad data .in this way, the desired forecast may be obtained more accurately.

Artificial Neural Network (ANN) approach has several key features that make it highly suitable for load forecasting [34]. For example,

* It does not require any presumed functional relationship between electric load and other variables such as weather conditions.

* It provides a nonlinear mapping between weather variables and previous load patterns, and electric load with out the need for predetermined model.

* It is usually fault tolerant and robust.

In this paper, an Information system for forecasting processes based on unsupervised, supervised neural networks is developed. The unsupervised learning process is performed using Kohonen's Neural Networks (KNN) for clustering of the input space into affinity number of classes. For each class, the supervised learning process is performed using Feedforwared Neural Networks (FNN) The ANN is used to learn the relationship among past, current, future daily load and weather patterns that obtained from energy Distribution Company, Libya. All input patterns information are stored in distributed form among the various connection weights.

2 DAILY LOAD FORECASTING

ANN proved to be capable of finding internal representations of interdependencies within raw data not explicitly given or even known by human experts. This typical characteristic together with the simplicity of building and training ANN and their very short response time encouraged various groups of researchers to apply ANN to the task of load forecasting. Most of the papers [25- 46] present feasibility studies carried out at universities or research institutes often in cooperation with utilities. They mainly addresses peak load forecasting , total load forecasting, and hourly load forecasting with lead time from 1 to 48 hours [69].

Typically ANN map input data to a forecast of a load value. Therefore, a supervised technique using FNN with error back-propagation algorithm is the most frequent choice in load forecasting projects [26, 28, 37]. The self-organizing feature map is used by [41] which clusters the forecasting data to clusters with similar load profiles. Their network which predicts the load at peak hour is trained unsupervised only whereas in two papers by [25,26] the unsupervised network is used for clustering and supervised one for prediction.

For load forecasting, the input data of ANN span widely from pure temperature values [34] over combinations of hourly or aggregated load values, type of the day and weather data due to sophistically preprocessed data [32]. The amount of data applied in ANN load forecasting projects varies from a few days period to data sets collected over 5 years.

The computational demand of training FNN with error back propagation has been reduced by:

- restricting the validity of the solution to special seasons or day types.
- selection of the most significant training cases from raw data [38, 51, 53].
- modification and adaptation of the learning process [28, 52].
- adaptive training algorithm [27-55].

In this paper, KNN is used for data classification to identify the day classes/types which are essential for forecasting processes. Due to the dynamic nature of hourly loads and differences in load characteristics from region to region, it is required to analysis load data for each region separately and to design suitable neural networks for forecasting process for that region. Load analysis is performed to identify the day type/classes of that region. In this work, it is required to collect the effective hourly data of Libya energy system and save them in a dynamic database. Once the database is developed, their information can be update, delete, display, and insert. Also, from database we can identify the day types/classes of daily load patterns using KNN.

3 GENERALIZED APPROACH FOR FORECASTING PROCESS

From the analysis of the forecasting methods, a generalized approach for forecasting using ANN is concludes. The steps of the Generalized approach for forecasting process using Neural Network can be described as:-

Phase 1: Data Collection

* Form a historical database that contains the data of the attributes of the forecasting process (input-output) that cover enough period immediately preceding the current time.

Phase 2: Data Classification

- Classify the historical database into groups according to a certain criteria (day type, season, similarity,…)
- Reject the redundant and inconsistent records from the database.
- Identify the forecasting parameters (period, class, …).

Phase 3: Training and testing

Identify the initial design of FNN that requires to determine the following parameters (no of input, output, hidden neurons, no of hidden layers, activation function, learning rate and momentum rate, and no of iterations).

- Form training and test sets of patterns for a class or day type from the database.
- Normalize the training and test sets.
- Train the neural network using the suitable learning algorithm.
- Test the trained FNN
- Calculate the testing performance measure of the FNN (absolute percentage error, average error and standard deviation)
- If the performance measures are not accepted then change the FNN design parameters and repeat.

Phase 4: Saving and updating

- Save the parameters of the trained FNN and its weights (Final ANN design).
- Update the historical database with the current recorded values.

In this work, Phase1 and 2 is presented in previous paper. The output of phase 1 is the historical database that contains recorded hourly loads, temperatures, humidity, atmospheric pressure. The database is used to form the training patterns for the KNN. Phase 2 is performed with KNN. The output of phase 2 is the classes of data patterns the corresponding to day types classification. Phase 3 and 4 are presented in this paper.

4 UNSUPERVISED/SUPERVISED LEARNING

An extra-large supervised learning system and a hierarchical system [9] are shown in Figs. 1 and 2. Fig.1 illustrates a situation where in almost every cluster there are a few local regions and separate supervised learning procedures are necessary. In Fig.2 large numbers of training set patterns are then sent forward to a supervised training phase. In fact, an unsupervised process performs the role of front-end data compression.

The unsupervised/supervised learning concept relieves the neural network of the burden of trying to associate many dissimilar patterns with the same output. If two groups, which are not alike, happen to end up in the same cluster, the message is that either pattern description is not adequate or vigilance factor is not adequately stringent. Using this concept, the supervised learning process is carried out on the cluster-wise data structure rather than on the entire data set.

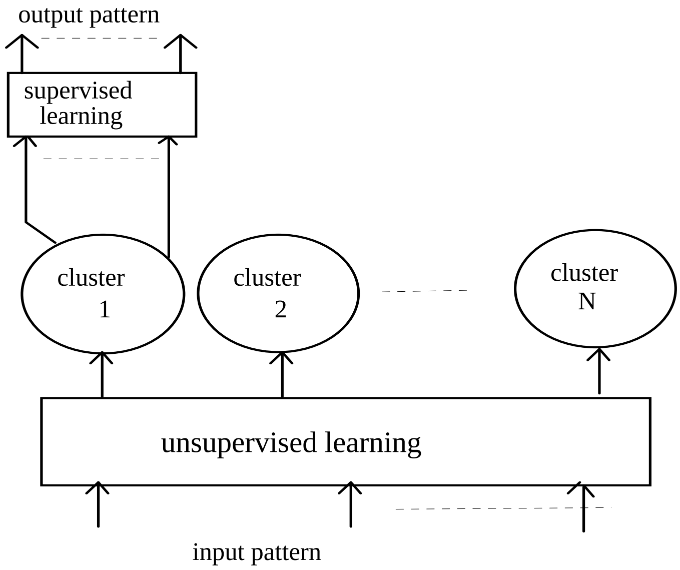


Fig.1 Unsupervised/supervised concept-type1

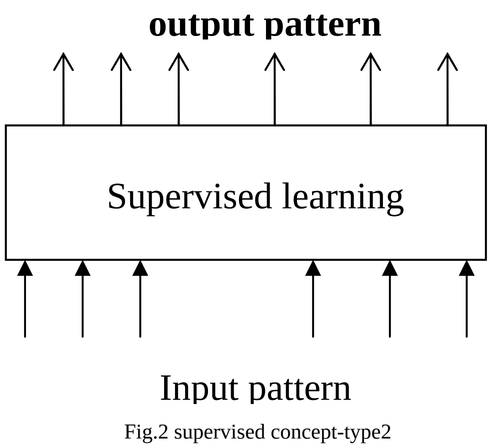


Fig.2 supervised concept-type2

5. OPERATION & TRAINING OF FNN

The multilayer feedforward network (FNN), also called Multilayer Perceptron , consists of a set of input units, a set of output units, and one or more layers of intermediate units. These intermediate unit layers are called hidden unit layers since the units in them do not directly communicate with the environment. The output of neurons of one layer feed forward to those of the adjacent layer. In order to train the FNN, one presents examples in turn to the neural network, each example consists of an input vector and a desired output vector. The output from the net when it is stimulated with a given input is compared with the desired output. If the net correctly models the process, the error between the output produced by the net and the desired output should be very small. If this error is not small, the weights associated with the connections are adjusted to iteratively reduce the error. This process of error minimization is essentially similar to unconstrained minimization of a function in optimization methods, and this case is known as the error back propagation method. The multilayer feedforward network compute a non-linear approximation of the underlying function specified by all training patterns. The characteristics of these ANN models are [50-55]:-

- Feedforward processing
- Supervised learning using error back propagation
- Multi-layer architecture used for
- Approximation of a nonlinear continuous or discrete function

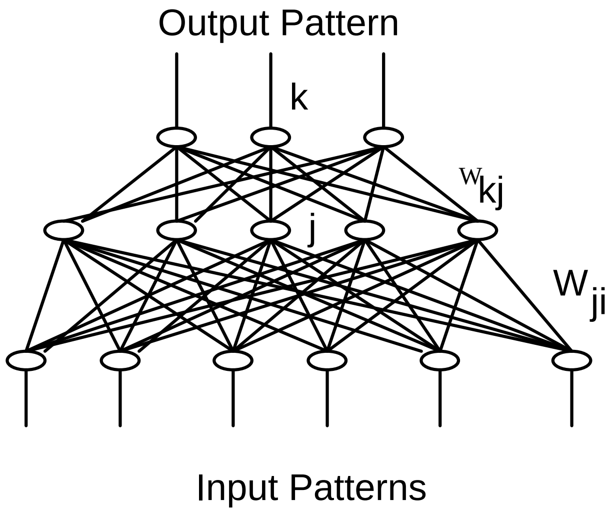


Fig. 8 A Multilayer Feedforward Neural Network.

6.1 OPERATION OF FEEDFORWARD ANN

A typical multilayer feedforward neural network with a single hidden layer is illustrated in Fig.5 For each neuron in the input layer, the neuron output is the same as the neuron input. For each neuron j in the hidden layer or the output layer, the net input net_j is given by

$net_j = \sum O_i \; W_{ji} + b_j$

Where, *Oi* is the output of neuron i. in the preceding layer, *bj* is the bais, and *Wji is the* weight from neuron i to j,

In the training process, the bais is regarded as connection weight between neuron j and a fictitious node whose output always remains at unity. The neuron output via a sigmodial function is given by:

$$O_j = f(net_j) = \frac{1}{1+e^{-net_j}}$$

6.2 TRAINING OF FEEDFORWARD ANN

In order to learn a neural network the rules for solving a problem, data sets describing the problem must be given. These data sets consist of input vectors and their desired/target output vectors. A full training set for a neural network describes the full range of expected inputs and associated desired outputs. The neural network is trained by a learning rule called the Back Propagation Learning Algorithm (BPLA) [51, 53]

6.3 BACK PROPAGATION LEARNING ALGORITHM

The BPLA is essentially an optimization method that uses an iterative gradient descent algorithm. Such algorithm is designed to minimize the mean square error between the actual output of the feedforward network and the desired output [25,26,69]. The algorithm is performed in two successive steps: forward propagation and back propagation. In the forward propagation phase, a pattern vector at the input layer together with its desired output pattern at the output layer are simultaneously applied to the network. The error detected at the output layer is then back propagated through the network to update the connection weights according to the Generalized Delta Rule (GDR) The process is repeated until the average system error goes under some prespecified values where the procedure is terminated. As the network is learnt, it becomes capable for classifying new input pattern vectors. Fig. 6 shows a flow chart of the BPLA

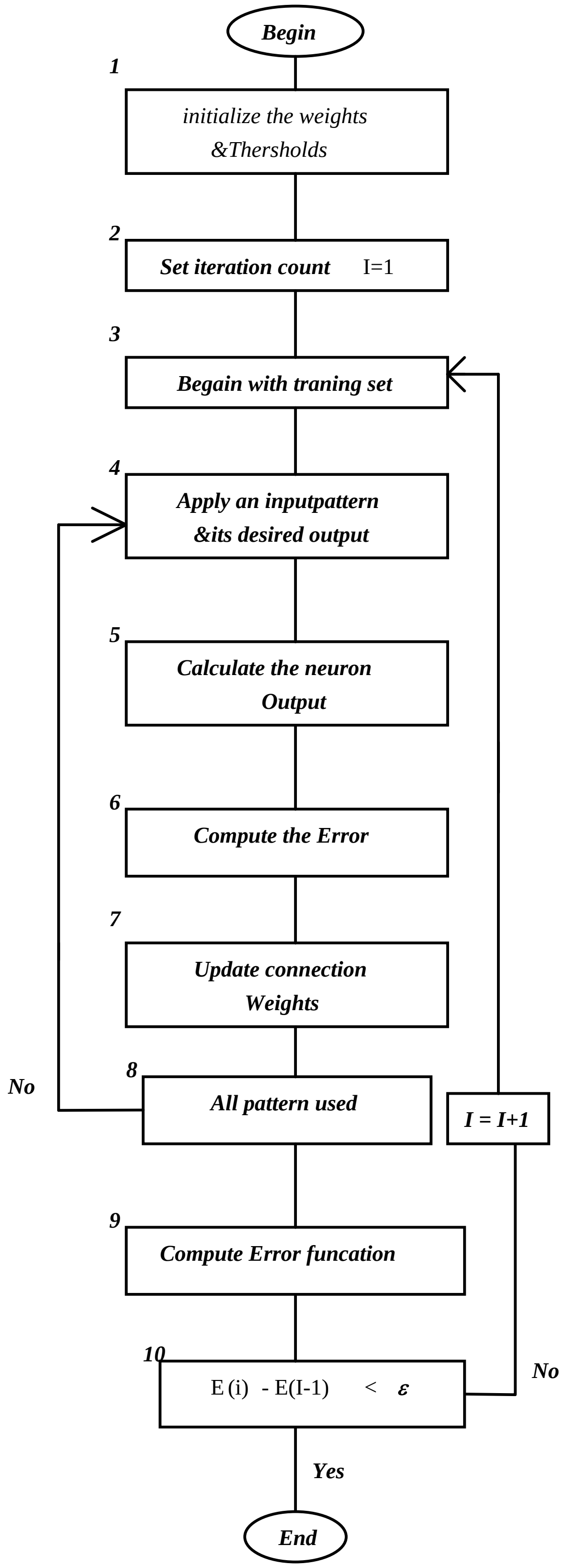


Fig.6 The Back Propagation Learning Algorithm (BPLA)

6.4 DATA NORMALIZATION

Since the data in the input-output patterns must be between 0 and 1, conversion has been made from real data to acceptable data of the neuron network according to the following equation:

$$NL = \frac{L - L\min}{L\max - L\min}$$

Where, NL is the normalized (converted) data value, L is the actual value, Lmax & Lmin are the recorded maximum and minimum data values in the data set. Once, the input-output patterns in the training and test sets are normalized, we start the training process.

6.4 ANN PERFORMANCE MEASURE IN FORECASTING PROCESS

The forecasting process results over a period are analyzed using the average and standard deviation values. The forecasted values using the trained neural network were analyzed by the Absolute Percentage Error (APE) which is given by;

$$APE_i = \frac{ABS(ACTUAL - FORECASTED)}{ACTUAL} * 100$$

The Average Value (AV) for the APE over N periods/values is given by;

$$AV = \sum_{i=1}^{N} APE_i$$

The Standard Deviation (SD) for a N periods/values is given by

$$SD = \sqrt{\frac{\sum_{i=1}^{N}(APE_i - AV)^2}{N}}$$

9 NEURAL NETWORK STRUCTURES FOR DAILY LOAD FORECASTING

In this paper Five input pattern formulations are explored:

(1) the first with 48 inputs including

(P_1............P48)-approach 1,

(2) the second formulation with 24 inputs including

(P_1............P24)-approach 2,

(3) the third formulation with 30 inputs including

(T_{max1} , T_{min1}, T_{a1}, T_{max2}, T_{min2}, T_{a2}, P1............P_{24})-approach 3

(4) the fourth formulation with 8 inputs including

(T_{max1} , T_{min1}, T_{a1}, T_{max2}, T_{min2}, T_{a2}, Pa............P_{24})-approach 4

(5) the fifth formulation with 11 inputs including

(W_{max} , W_{min} ,W_a , AP_{max} , AP_{min} , AP_a , H_{max} , H_{min} , H_a, Pa..........P_{24})-approach 5

where

T temperature (1 for previous day , 2 for actual day and a for average)

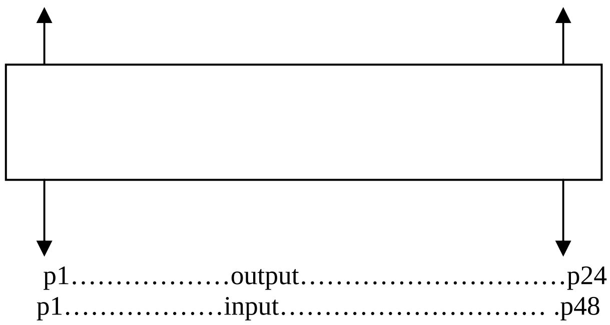


Fig. 7-a ANN structure for Approach 1

P1……………………………………………p24

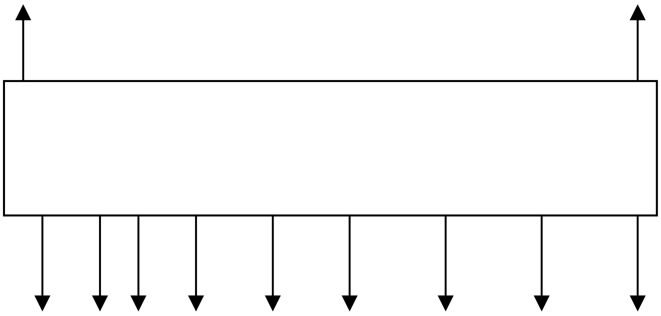


Fig. 7-b ANN structure for Approach 4

H humidity, W wind speed, AP atmospheric pressure.

Pa is the average daily load of previous day.

P_i average load from previous day at hour i.

In both cases the outputs are average hourly load

(P_1^f .... P_{24}^f).

Conceptual schemes for approaches 1 & 4 are shown in Fig. 7

The Five approach are tested on Database of Libya power system that contains hourly recording of :-

- Hourly Load (MW) ,
- Temperature (C),
- Relative Humidity,(%),
- Wind Speed, and
- Atmospheric Pressure (hpa)

Table –1 shows the Daily load forecasting (24 hours) for day 4/4/99 with approach-1. The Table contains :-

- Actual Load (AL),
- Forecasted Load with and without Kohonen (FLWK , FLOK) and
- Actual Error & Percent Error with and without Kohonen (EWK, PEWK, EOK, PEOK).

From the table we find that :-

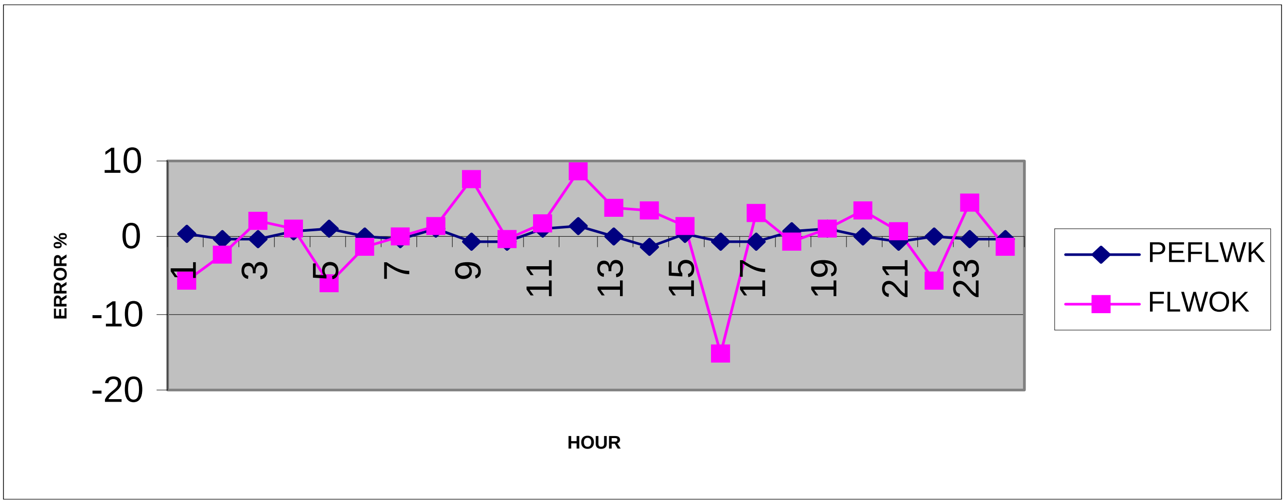
	Max error	APE
With Kohanen	1.67 %	0.581
Without Kohanen	**-15.3**	**3.465**

Fig.3 shows the percentage error for day 4/4/1999 with and without Kohonen. From Fig .3. the Percent Error is reduced using Kohanen's ,ANN.

Table (1) 24-hourly load forecasting for workday of 4 /4/1999 using approach-1

HOUR	AL (MW)	**FLWK (MW)**	**FLOK (MW)**	**PEWK %**	**PEOK %**	**EWK (MW)**	**EOK (MW)**
1	1319	1313	1396	0.45	-5.87	6	-77
2	1287	1291	1317	-0.37	-2.33	-4	-30
3	1287	1290	1259	-0.28	2.17	-3	28
4	1232	1223	1219	0.67	0.97	9	13
5	1212	1200	1285	0.95	-6.00	12	-73
6	1288	1287	1305	0.01	-1.39	1	-17
7	1473	1478	1471	-0.38	0.03	-5	2
8	1652	1635	1630	1.01	1.36	17	22
9	1763	1774	1628	-0.6	7.64	-11	135
10	1742	1753	1748	-0.68	-0.34	-11	-6
11	1765	1743	1730	1.241	2.00	22	35
12	1776	1747	1622	1.67	8.66	29	154
13	1758	1757	1691	0.0568	3.77	19	67
14	1719	1740	1659	-1.220	3.46	-21	60
15	1690	1682	1664	-0.4733	1.51	8	26
16	1560	1568	1800	-0.5128	-15.3	-8	-240
17	1737	1744	1682	-0.4029	3.15	-7	55
18	1791	1778	1800	0.725	-0.50	13	-9
19	1851	1833	1830	0.981	0.82	18	21
20	2082	2081	2012	0.0480	3.42	1	70
21	1878	1888	1862	-0.5324	0.83	-10	16
22	1790	1785	1892	0.2793	-5.69	5	-102
23	1775	1779	1694	-0.225	4.56	-4	81
24	1665	1668	1688	-0.180	-1.38	-3	-23

Fig .3 Errors For Day 4/4/99 with and without Kohanen's using approach-1



By Similar, the Same analysis is performed on Libya Database to obtain the week load forecasting using approach-1 as shown in Table 2. From Table 2, the Max percentage error for week days from 3/4/99 to 9/4/99 with and without Kohanen are (1.67, -15.3) respectively .

Table (2) Summary forecasting error for a week from 4/4/99 to 9/4/99.

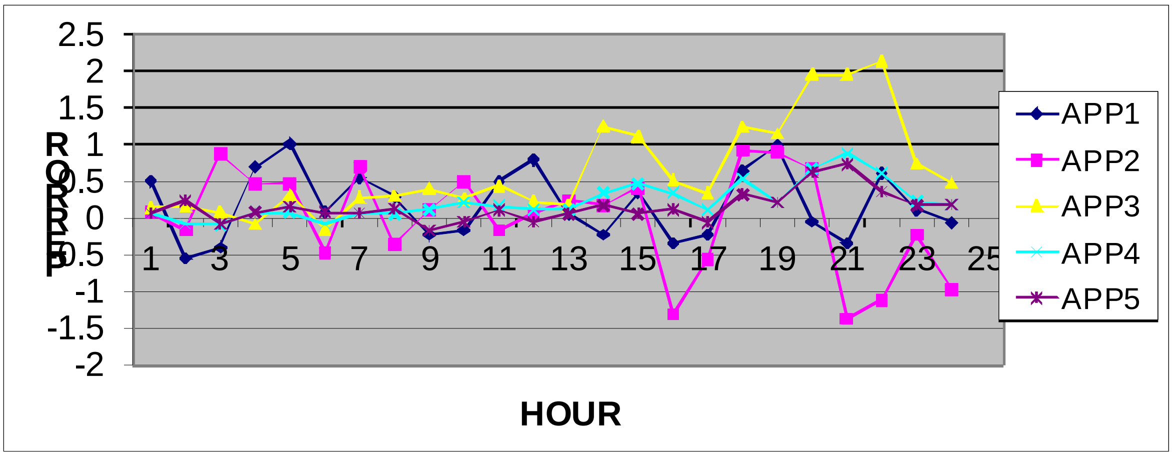
DAY	SAT 3/4/99	SUN 4/4/99	MON 5/4/99	TUS 6/499	WED 7/4/99	THR 8/4/99	FRI 9/4/99
WITH KOHANEN							
MAX	1.428	1.670*	1.195	1.011	1.010	0.482	0.444
MIN	0.064	0.011	0.055	-0.047	-0.051	0.544	0.053
AV	0.5968	0.58110	0.5367	0.40654	0.333	0.1642	0.17687
WITH OUT KOHANEN							
MAX	7.828	-15.3*	11.12	11.33	3.580	3.460	8.420
MIN	-0.710	0.034	-0.415	-0.34	0.434	-0.063	-0.21
AV	3.3953	3.46458	5.4195	4.0677	2.2446	0.6161	2.64675

Table 3 Summery of load forecasting for a week from 3/4/99 to 9/4/99 using Five approaches

Approach No	1	2	3	4	5
WITH KNN					
MAX	1.67	1.873	4.444	1.0086	1.666
AV (MAX)	0.59682	0.74826	0.773429	0.2747	0.2836
WITHOUT KNN					
MAX	-15.3	-15.550	-12.266	-10.755	-10.755
AV (MAX)	5.4195	4.8228	2.12635	2.1830	1.7432

Table 3 shows the summery of load forecasting for a week from 3/4/99 to 9/4/99 using Five approaches. Fig.4 shows the Forecasting of Day 6/4/99 using the Five approaches with KNN (working Day) Fig.5 shows the forecasting of Day 9/4/99 using the five approaches with KNN(Weekend).

Fig.4 Work day Forecasting using the five approaches with KNN(6/4/99).



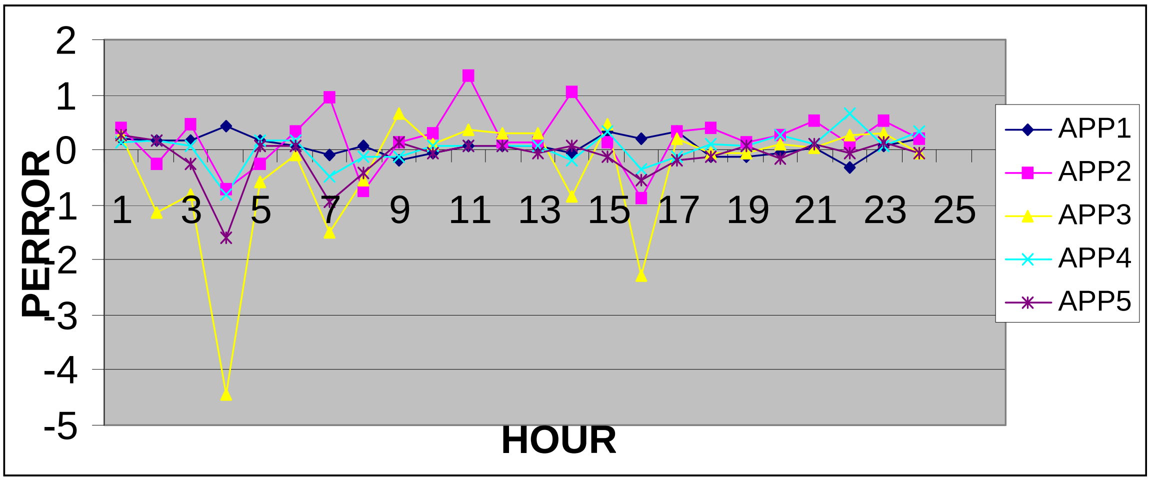


Fig.5 Weekend forecasting using the five approaches with KNN (9/4/99)

From Figures 4 &5 we conclude that approaches 5 is the best for work day forecasting and approach 4 is the best for holiday forecasting. So, approaches 4 and 5 are the suitable for load forecasting with FNN.

Fig.6 shows the forecasting for a week from 3/4/99 to 9/4/99 using the Five approaches without KNN (working Day) Fig.7 shows the forecasting for a week from 3/4/99 to 9/4/99 using the five approaches without KNN (Weekend). From Figures 6 &7 we conclude that approaches 4 and 5 are the suitable for load forecasting without FNN.

From the results, The Hourly Load of Libya energy system is affected with the environment parameters such as:-Temperature, Relative Humidity, Wind Speed , and Atmospheric Pressure. To get accurate forecasting the environmental parameters must be included.

Fig.6 Work day Forecasting using the five approaches without KNN(6/4/99).

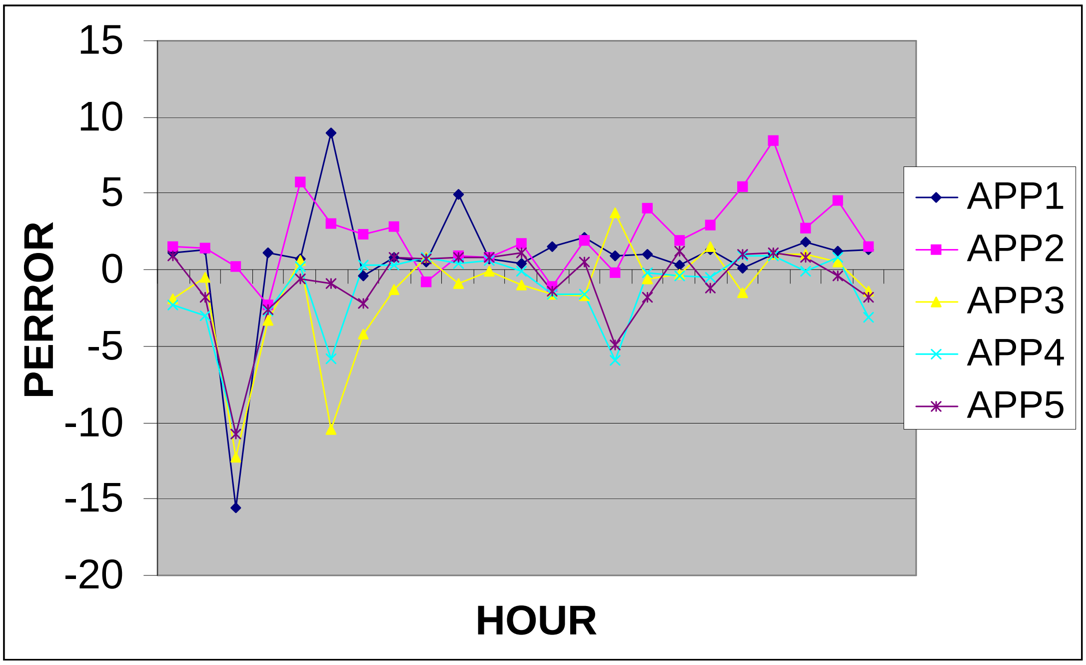
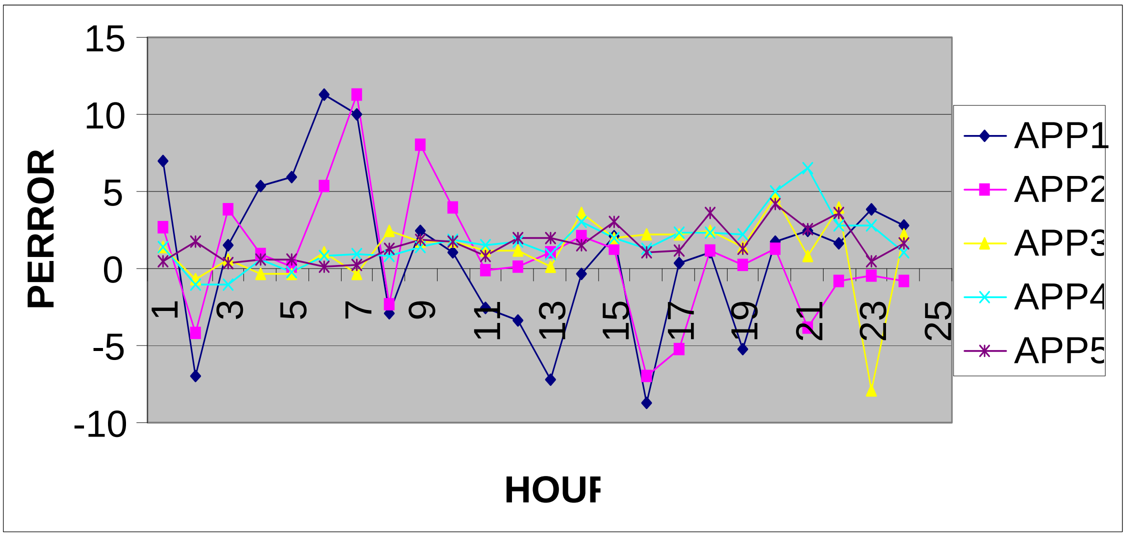


Fig.7 Weekend forecasting using the five approaches without KNN (9/4/99)



10 CONCLUSION

An Information system for forecasting processes based on unsupervised, supervised neural networks is developed. The unsupervised learning process is performed using Kohonen's Neural Networks (KNN) for clustering of the input space into affinity number of classes. For each class, the supervised learning process is performed using Feedforwared Neural Networks (FNN). The historical database that contains the data of the attributes of the forecasting process that cover two years is developed using the recorded actual data collected from Libya energy system. From the results, we found that KNN is very effective in day type classification and has the capability to identify new classes.

In this paper Five input pattern formulations are explored for daily load forecasting.. The FNN is used to learn the relationship among past, current, future daily load and weather patterns that obtained from the energy system of Libya. All input patterns information are stored in distributed form among the various connection weights. The Five approach are tested on Database of Libya power system that contains hourly recording of :- Hourly Load, Temperature, Relative Humidity, Wind Speed , and Atmospheric Pressure.

The Comparison of the forecasted values of FNN and with without KNN with actual values is made to demonstrate that the forecasting accuracy with KNN is very encouraging. By the proposed Information system the computation time for the neural network learning with KNN can largely reduced. The Hourly Load of Libya energy system is affected with the environment parameters such as:-Temperature, Relative Humidity, Wind Speed , and Atmospheric Pressure. To get accurate forecasting the environmental parameters must be included.

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