IEEE MELECON 2002, May 7-9, 2002, Cairo , EGYPT.

Electric Load Forecast For Developing Countries

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ABSTRACT

The electric utility planning process begins with the electric load forecasting, because of the advanced need for new utility plants. These long lead times require the utility planning horizon to be at least ten years long. Since utility decisions involve an economic analysis of the operating and investment costs, the utility planning horizon may range from fifteen to thirty years into the future. Forecasting load demand is a difficult procedure and combines art with science. The key contribution of forecasters is their knowledge of electricity consumers and an understanding of the way they use electricity and other competing energy forms. The problem gains special aspects in developing countries, such as Egypt, because of the high demand growth rate as well as the wide differences in the modes and levels of consumption in the various regions (governo rates) in the country. During the recent years, some new mathematical tools have been published such as expert system (EXP.), Artificial Neural Network (ANN) and Fuzzy logic systems. These tools almost replaced the classic methods used by most utilities and research centers personnel for forecasting. In this study, a technique based on the Artificial Neural Network (ANN) method, is used to estimate Peak load and Light load for the Egyptian power system network as an example for developing countries. This technique is highlighted by the accuracy and sensitivity of the model with respect to the ANN parameters. The proposed technique can thus be applied to simple as well as extended power system networks.

Consequently, in this study, several structures for Neural Networks are proposed and tested. They proved to perform as one of the best and most sophisticated forecasting systems. In this study, the case of a number of neurons layers equal 7, gives the best results with high accuracy with the least error. The forecasted Peak loads and Light loads, up to year 2010, for the six Regions of the Egyptian Unified Network; Alexandria, Delta, Cairo, North Upper Egypt, South Upper Egypt and the Canal, are obtained directly from one case by using the actual and practical past ten years data.

Key Words

Planning, Load Forecasting, Econometric Method, Artificial Neural Network.

1. INTRODUCTION

Forecasts of peak demand and total energy consumption are the starting point in the planning cycle of an electric utility. Forecasting demand and energy for power systems in developing countries are difficult tasks. The difficulty stems from high growth rate of both electric demand and load as well as from the wide differences in the modes and levels of consumption from one city to the other cities and from one governorate to another. Electric utility companies need forecasting for budget planning, maintenance scheduling and fuel management. The choice of methodology depends on the objectives of the analysis as well as the availability of data and the skills of the forecasters.

The objective of the forecasting task in the present study is to provide forecasts of Peak loads and Light loads for different Egyptian regions networks that meet the planning requirements.

Artificial Neural Networks (ANN) has been developed in a wide variety of configurations. Despite this apparent diversity, network paradigms have a great deal in common. This paper introduces the concepts of the Artificial Neural Networks and their Applications in load forecasting as applied for the specified case. The feed-forward multi-layer network with the back-propagation algorithm [1] is presented with its training algorithm to learn the mapping function relating the input and output of a system, and is used for forecasting the yearly load, as applied for various regions of Egypt and for the whole unified system as an example for developing countries.

This serves the planning objectives not only for the whole system but also the planning objectives at the regions levels.

2. The Artificial Neuron

As known, the Artificial neuron [1] was designed to mimic the first-order characteristics of the biological neuron. In essence, a set of inputs is applied, each representing the output of another neuron. Each input is multiplied by a corresponding weight, analogous to a synoptic strength. All of the weighted inputs are then summed to determine the activation level of the neuron. Figure (1) shows a model that implements this idea. Despite the diversity of network paradigms, nearly all are based upon this configuration, where, a set of inputs, labeled $x_1, x_2, \ldots, x_n$, is applied to the artificial neuron. These inputs collectively referred to as the vector X, correspond to the signals into the synapses of a biological neuron. Each signal is multiplied by an associated weight, $w_1, w_2, \ldots, w_n$, before it is applied to the summation block label. Each weight corresponds to the "strength" of a single biological synoptic connection (the set of weights is referred to collectively as the vector W). The summation block, corresponding roughly to the biological cell body, adds all of the weighted inputs algebraically, producing an output, which is called NET. This may be compactly stated in vector notation as follows:

$$NET = XW$$

2.1. Multilayer Artificial Neural Networks

Larger and, more complex networks generally offer greater computational capabilities. Although networks have been constructed in every imaginable configuration, arranging neurons in layers mimics the layered structure of certain portions of the brain. These multilayer networks [1] have been proven to have capabilities beyond those of a single layer, and in recent years, algorithm has been developed to train them. Multilayer networks may be formed, by simply cascading a group of single layers; the output of one layer provides the input to the subsequent layer. Figure (2) shows such a network, again drawn fully connected. It will be proved in this work that there is a certain number of ANN layers that performs the forecast accurately, in a given case.

2.2. Back-Propagation Algorithm

Since ANN feed forward multi-layer networks with the back propagation algorithm have been used in the present study, a brief description of this is due.

The invention of the back-propagation algorithm has played a large part in the resurgence of interest in Artificial Neural Networks. Back-propagation is a systematic method for training multilayer Artificial Neural Networks. It has a mathematical foundation that is strong if not highly practical. Despite its limitations, back-propagation has dramatically expanded the range of problems to which Artificial Neural Networks can be applied, and it has generated many successful demonstrations of its power. The back-propagation training algorithm is an interactive method employing the gradient descent algorithm for minimizing the mean square error cost function between the actual network output and the target output for each pattern in the training set. The application of the generalized delta rule in the back-propagation algorithm requires two stages. In the first stage, after calculating the network output and comparing it with the target output, the delta error is calculated for the output layer [1]. In the second stage, this error signal is passed through each layer in the network in backward direction, from output layer to input layer, to calculate the appropriate weight changes. Figure (3) shows a multi-layer network suitable for training with back-propagation. The first set of neurons, (connected to the inputs), serves only as distribution points; they perform no input summation. The input signal is simply passed through to the weights on their outputs. Each neuron in subsequent layers produces NET and OUT signals.

3. Accuracy Tests Of The ANN Methods As Applied For Forecasts:

With the above ANN methodology used for load forecast, several tests are necessary to prove the accuracy of the results.

Multi tests were used for the comparison between the actual and forecasted peak load and light load on the Egyptian Electric Power System applying the published principles [2-6].

In this respect, load forecast in the present study has been carried out, first using one of the conventional methods e.g. historical trend method, for the period from year 1998 up to year 2010 using the available load data from year 1987 to year 1997 (historical data). With the loads of years from 1998 to 2000 known as actual loads the forecasted values for these years are compared. If the forecast is not within the specified accuracy, the historical forecast process is modulated until the accurate results are achieved. The obtained accurate results are then used for training the ANN network for forecast until yielding the same accurate results.

In other words, using candidate forecast methods; e.g. historical method, the present loads from past loads (ten years old data) can be predicated. Comparing this forecast with the actual present loads gives the error [7]. A load forecast is generally tested, by producing a forecast of present load levels, using past 10 years old data. Comparison of this forecast with present values of load is taken as an indication of the forecast procedure's probable accuracy over a future period of similar length. This same concept of error can be used in thinking about the error in a forecast of future loads, however it cannot be calculated because the actual values of the future are not known. This important aspect of load forecast error, which is called Average Absolute Value (AAV), is one of the statistical methods [8]. This method is used for evaluating the accuracy in the forecasting data.

4. Application of Artificial Neural Networks With Various Layers to the Egyptian Power System Networks Forecasts.

Several structures are considered during this study and some were acceptable in terms of accuracy. To evaluate the different structures, the forecast results obtained by the neural network method is compared to the results of forecasting methods used before. Several structures are developed over the research period. In this work the structures presented as the input data are the Peak load of the Egyptian Unified Network, the Peak load of Alexandria region, Delta region, Cairo region, North Upper Egypt region, South Upper Egypt region, and Canal region, in addition to the Light loads of the Egyptian Unified Network and the other regions. Adaptive training is used in this study since it is more suitable for the forecasting problem. Different scenarios are, used, for number of neurons layers of eleven, nine, seven and five. Thus, long term forecasts for the Egyptian power system and for the various regions are performed. The forecasting of an Egyptian Electric power system future load is then tested, and comparisons are made for forecasting errors, accuracy, and data needed, according to the data of Peak and Light loads of the Egyptian Unified Network and Peak and Light loads for the six regions. The input data are presented in Tables (1 and 2). This has been performed using the ANN networks with various layers. Thus, the Peak, and Light loads for the different regions; for the period from 1998 to 2010, are obtained.

5. Results Of Load Forecasting Using Neural Networks Suggested Method:

In the Egyptian network, historical growth of the Peak and Light loads for the unified power system (UPS), and Peak and Light loads for the different regions; Alexandria, Delta, Cairo, North Upper Egypt, South Upper Egypt and Canal during the preceding ten years are given in Tables (1) and (2).

Then, the proposed adaptive training for each selected number of layers for the ANN network is carried out. In this respect, a load model is proposed and the weights are estimated using back-propagation learning algorithm for feed forward neural networks.

Results of this study using back-propagation for the forecasting are summarized and shown in Tables (3-6) and Figures (4 and 5), which show the peak load and light load forecasts, between year 1987 to year 2010, for the Unified Power System (UPS) and the different six regions of Egypt.

These results of peak load and light load forecasting are obtained using the actual data given in Tables (1 and 2), where the vertical columns give the actual load and the calculated loads, with different number of neurons (11, 9, 7 and 5), for the six regions in addition to the actual load for the UPS (the Egyptian Unified Power System). The first ten horizontal rows of the tables represent the period, from year 1987/1988 to year 1996/1997. Then, the load forecasting from year 1997/1998 up to year 2009/2010 are given in the following thirteen rows (from row number 11 to number 23). Both the actual and forecasted loads are given for the period from 1997/1998 to 2000/2001 for the comparison process (accuracy test).

From the results shown in the tables and figures, it can be seen that, the case of a number of neurons equal 7 gives the best results with the least error.

Conclusion

With the Neural Networks, described in this work, evaluation of demand forecast using Artificial Neural Networks is addressed.

Long-term demand forecasting proved to be a very useful tool for electric utilities. The Neural Networks technique has several key features that make it highly suitable for this application. In this study, several structures for Neural Network's are proposed and tested. They proved to perform as one of the best and most sophisticated forecasting systems. In this study, the case of a number of neurons layers equal 7, gives the best results with high accuracy with the least error.

The forecasted Peak loads and Light loads, up to year 2010, for the six Regions of the Egyptian Unified Network; Alexandria, Delta, Cairo, North Upper Egypt, South Upper Egypt and the Canal, are obtained directly from one case by using the actual and practical past ten years data.

References

[1] Philip D. Wasserman, "Neural Computing-Theory and Practice", Anza Research Inc., by Van Nostrand Reinhold, 1989.

[2] MOUSTAFA H., "Egyptian Energy - Realism and Future Expectations", Third regional conference of CIGRE committees in Arab countries - Doha - Qatar, May 25- 27,1999.

[3] Spiegel M.r., "Theory and Problems of Statistics", Book, Schaum's outline series, McGraw-Hill, 1972.

[4] Chou Y.L., "Statistical Analysis", Book, Holt, Rinehart and Winston, book, New York, 1974.

[5] Sullivan R.L., "Power System Planning", Book, McGraw-hill Inc., 1977.

[6] Johnson R., "Elementary Statistics", Book, Duxbury press-northscitute-, Massachusetts, 1980.

[7] Willis H.L, "Load Forecasting for Distribution Planning Error and Impact

on Design", IEEE Trans., PAS, Vol. PAS 102, pp 675-686, 3 March. 1983.

[8] Willis H.L. and Northcote J.E.D., "Comparison Tests of Fourteen Distribution Load forecasting Methods", IEEE Trans. PAS, Vol. PAS 103, pp 1190-1197, 6 June, 1984.

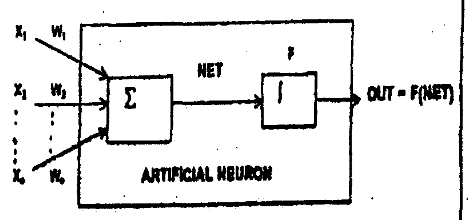

Fig. (1): The Artificial Neuron

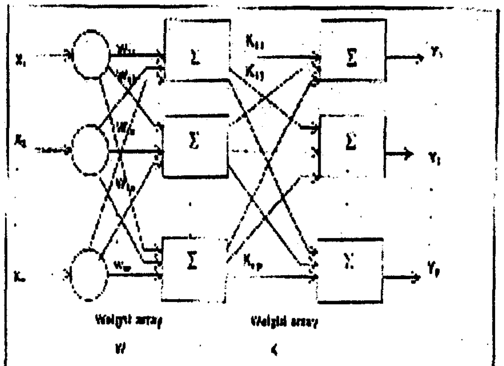

Fig.(2): Two Layer Network

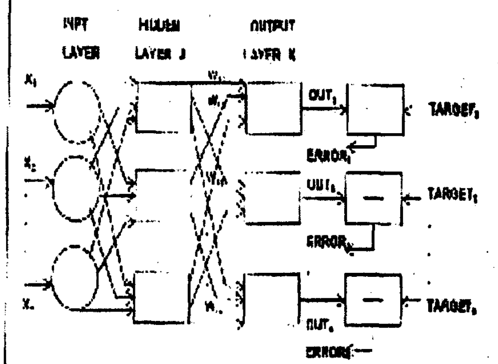

Fig.(3): The Two Layer Back propagation Network

Table (1)
Peak Load Development for Unified Egyptian Network and For Different Regions
(Alex., Delta, Cairo, North Upper Egypt, South Upper Egypt, and Canal)

Item	87/88	88/89	89/90	90/91	91/92	92/93	93/94	94/95	95/96	96/97	97/98
UPS Peak Load (MW)	6152	6279	6664	7004	7215	7503	7657	8099	8291	9235	9850
Peak load For Alexandria (MW)	848	894	929	965	1005	975	963	994	1033	1154	1206
Peak Load For Delta (MW)	1349	1375	1390	1458	1487	1645	1712	1760	1799	2094	2196
Peak Load For Cairo (MW)	2123	2154	2277	2296	2311	2371	2410	2597	2757	2974	3146
Peak Load For North Upper Egypt (MW)	429	436	530	550	579	593	608	664	688	718	826
Peak Load For South Upper Egypt (MW)	959	965	1011	1063	1106	1176	1204	1347	1395	1445	1557
Peak Load For Canal (MW)	444	455	527	672	727	743	760	787	819	850	919

Table (2)
Light Load Development for Unified Egyptian Network and For Different Regions
(Alex., Delta, Cairo, North Upper Egypt, South Upper Egypt, and Canal)

Item	87/88	88/89	89/90	90/91	91/92	92/93	93/94	94/95	95/96	96/97	97/98
UPS Light Load (MW)	2896	3163	3389	3514	3673	3947	4021	4316	4584	4975	5288
Light Load For Alexandria (MW)	373	424	453	468	531	525	535	590	640	670	690
Light Load For Delta (MW)	543	600	649	662	680	659	660	720	760	830	890
Light Load For Cairo (MW)	884	970	988	995	1008	1235	1250	1350	1395	1450	1650
Light Load For North Upper Egypt (MW)	220	230	265	275	292	336	360	390	440	570	586
Light Load For South Upper Egypt (MW)	651	703	733	757	785	835	856	890	959	990	999
Light Load For Canal (MW)	225	236	301	357	377	357	360	376	390	465	473

TABLE (3)

RESULTS OF PEAK LOAD FORECASTING USING NEURAL NETWORKS

YEAR	UPS PEAK LOAD (MW)	ALEXANDRIA ACTUAL (MW)	ALEXANDRIA NUMBER OF NEURONS 11	%	9	%	7	%	5	%	DELTA ACTUAL (MW)	DELTA NUMBER OF NEURONS 11	%	9	%	7	%	5	%	CAIRO ACTUAL (MW)	CAIRO NUMBER OF NEURONS 11	%	9	%	7	%	5	%
87/88	6152	848	885		895		877		876		1349	1320		1331		1366		1353		2123	2098		2095		2116		2122	
88/89	6279	894	898		904		890		891		1375	1392		1396		1411		1407		2154	2171		2165		2170		2179	
89/90	6664	929	928		927		923		925		1390	1549		1542		1526		1535		2277	2334		2326		2310		2318	
90/91	7004	965	952		948		953		954		1458	1664		1655		1631		1642		2296	2460		2456		2439		2441	
91/92	7215	1005	966		961		971		971		1487	1728		1720		1697		1706		2311	2533		2533		2519		2517	
92/93	7503	975	984		980		996		993		1645	1808		1803		1786		1792		2371	2630		2635		2631		2622	
93/94	7657	963	995		990		1008		1004		1712	1848		1846		1834		1836		2410	2661		2688		2690		2678	
94/95	8099	994	1030		1028		1045		1040		1760	1972		1976		1984		1976		2597	2850		2862		2881		2863	
95/96	8291	1033	1058		1058		1067		1063		1799	2058		2065		2084		2072		2757	2978		2988		3011		2997	
96/97	9235	1154	1136		1139		1089		1113		2094	2264		2266		2284		2283		2974	3315		3300		3284		3311	
97/98	9850	1206	1193	3.631	1197	2.514	1198	2.235	1140	18.44	2396	2400	0.382	2389	0.669	2384	1.146	2405	0.86	3527	3552	1.781	3507	1.425	3431	6.838	3504	1.638
98/99	10919	1253	1300	11.6	1300	11.6	1223	7.368	1180	18.02	2289	2637	37.02	2592	32.23	2512	23.72	2596	32.66	3671	3981	20.03	3867	12.66	3638	2.132	3816	9.367
99/2000	11736	1385	1438	9.87	1430	8.38	1249	25.35	1221	30.54	2804	2916	7.698	2828	1.649	2619	12.71	2804	0	3993	4504	27.33	4305	16.68	3841	8.128	4170	9.465
2000/01	12376	1472	1607	21.63	1591	19.07	1275	31.56	1265	33.17	2753	3224	33.55	3107	25.21	2708	3.205	3041	20.51	4210	5106	42.93	4835	29.95	4049	7.714	4581	17.78
01/02	12730		1841		1822		1302		1318			3560		3506		2790		3364			5818		5573		4314		5147	
02/03	13110		2140		2138		1329		1380			3757		4097		2862		3817			6424		6560		4676		5939	
03/04	13910		2420		2436		1357		1431			3964		4779		2908		4303			6503		7494		5072		6773	
04/05	14720		2720		2699		1386		1468			4182		5645		2942		4873			6581		8394		5557		7721	
05/06	15560		3062		2872		1415		1479			4412		6753		2967		5548			6660		9205		6155		8790	
06/07	16400		3426		2902		1444		1489			4654		8071		2985		6302			6740		9869		6835		9908	
07/08	17260		3777		2931		1475		1500			4910		9566		2999		7144			6821		10438		7576		11053	
08/09	18090		4049		2960		1506		1510			5180		10989		3008		8008			6903		10967		8284		12109	
09/2010	18910		4236		2990		1537		1521			5465		12174		3016		8892			6985		11544		8926		13065	

TABLE (4)

RESULTS OF PEAK LOAD FORECASTING USING NEURAL NETWORKS

YEAR	UPS PEAK LOAD (MW)	NORTH UPPER EGYPT ACTUAL (MW)	NORTH UPPER EGYPT NUMBER OF NEURONS 11	%	9	%	7	%	5	%	SOUTH UPPER EGYPT ACTUAL (MW)	SOUTH UPPER EGYPT NUMBER OF NEURONS 11	%	9	%	7	%	5	%	CANAL ACTUAL (MW)	CANAL NUMBER OF NEURONS 11	%	9	%	7	%	5	%
87/88	6152	429	513		519		524		522		959	996		1000		1046		1026		444	554		561		581		560	
88/89	6279	436	526		528		532		531		965	1045		1046		1071		1060		455	586		589		600		587	
89/90	6664	530	557		553		553		553		1011	1151		1147		1136		1139		527	656		653		649		651	
90/91	7004	550	581		576		574		575		1063	1226		1222		1196		1205		672	708		703		693		703	
91/92	7215	579	596		590		587		588		1106	1267		1263		1234		1244		727	737		733		721		733	
92/93	7503	593	614		612		607		608		1176	1315		1313		1285		1295		743	773		771		760		772	
93/94	7657	608	624		623		618		619		1204	1338		1338		1313		1321		760	791		790		781		792	
94/95	8099	664	657		662		657		657		1347	1404		1408		1379		1402		787	847		850		835.7		853	
95/96	8291	688	681		689		686		685		1395	1445		1450		1448		1456		819	886		891		894.2		892	
96/97	9235	718	745		742		757		755		1445	1531		1529		1520		1569		850	981		978		956.8		974	
97/98	9850	876	792	18.79	761	25.73	804	16.11	800	17	1657	1584	10.46	1587	10.03	1535	17.46	1631	3.725	1069	1045	3.84	1025	7.04	1014	8.774	1018	8.16
98/99	10919	763	880	35.03	762	0.299	883	35.93	875	33.53	1853	1675	19.91	1613	26.85	1612	26.97	1725	14.32	1090	1157	10.37	1090	0	1166	11.81	1084	0.929
99/2000	11736	997	1000	0.528	762.8	41.24	980	2.993	963	5.986	1951	1789	16.33	1639	31.45	1693	26.06	1823	12.9	1408	1292	12.03	1143	27.49	1341	6.926	1152	26.56
2000/01	12376	1042	1160	19.25	763.5	45.43	1100	9.462	1066	3.915	1548	1935	65.7	1665	19.9	1777	38.9	1931	65.03	1548	1446	9.239	1174	33.88	1542	0.506	1228	28.99
01/02	12730		1415		764.3		1285		1211			2159		1692		1866		2074			1628		1206		1774		1331	
02/03	13110		1840		765.1		1579		1418			2515		1719		1959		2271			1786		1238		2040		1478	
03/04	13910		2395		765.8		1934		1641			2960		1746		2057		2482			1812		1272		2346		1644	
04/05	14720		3191		766.6		2393		1899			3581		1774		2160		2731			1839		1306		2698		1852	
05/06	15560		4304		767.4		2975		2199			4437		1803		2268		3029			1867		1341		3102		2121	
06/07	16400		5629		768.1		3647		2524			5449		1832		2382		3370			1895		1377		3568		2453	
07/08	17260		6977		768.9		4387		2873			6474		1861		2501		3761			1923		1415		4103		2867	
08/09	18090		8045		769.7		5096		3215			7286		1891		2626		4175			1952		1453		4718		3340	
09/2010	18910		8790		770.4		5741		3547			7853		1921		2757		4611			1981		1492		5426		3877	

TABLE (5)
RESULTS OF PEAK LOAD FORECASTING USING NEURAL NETWORKS

YEAR	UPS LIGHT LOAD (MW)	ALEXANDRIA ACTUAL (MW)	ALEXANDRIA NUMBER OF NEURONS 11	%	9	%	7	%	5	%	DELTA ACTUAL (MW)	DELTA NUMBER OF NEURONS 11	%	9	%	7	%	5	%	CAIRO ACTUAL (MW)	CAIRO NUMBER OF NEURONS 11	%	9	%	7	%	5	%
87/88	2896	373	308		301		314		340		543	494		505		514		455		884	815		842		838		793	
88/89	3163	424	356		359		357		357		600	517		517		519		508		970	905		896		893		878	
89/90	3389	453	387		394		386		375		649	536		532		531		546		988	963		942		942		949	
90/91	3514	468	401		408		400		387		662	547		542		540		564		995	990		969		970		987	
91/92	3673	531	417		423		416		401		680	561		557		554		586		1008	1021		1004		1007		1034	
92/93	3947	525	439		439		438		427		659	590		589		586		618		1235	1072		1072		1075		1110	
93/94	4021	535	445		442		459.9		434		660	599		599		596		625		1250	1087		1092		1095		1129	
94/95	4316	590	464		453		482.9		462		720	641		644		641		653		1350	1152		1178		1179		1200	
95/96	4584	640	479		464		507		485		760	687		689		688		675		1395	1232		1265		1264		1257	
96/97	4975	670	487		501		532.4		514		830	757		756		762		701		1450	1425		1404		1401		1326	
97/98	5178	690	495.3	61.43	541	47	559	41.32	528	51.1	890	783	30.84	785	30.26	799	26.22	713	51.01	1650	1470	23.5	1475	22.85	1477	22.58	1356	38.38
98/99	5478		503.7		642		525		545			809.6		811		845		729			1617		1572		1592		1394	
99/2000	5793		512.3		825		554		560			837.1		837.8		875		743			1779		1648		1714		1426	
2000/01	6123		521		1135		597		573			865.6		865.4		906.5		756			1957		1684		1836		1453	
01/02	6467		529.8		1617		661		584			895		894		939.1		768			2152		1721		1952		1475	
02/03	6826		538.8		2315		756		593			925.5		923.5		972.9		779			2367		1759		2058		1492	
03/04	7199		548		3241		898		600			956.9		953.9		1008		788			2604		1798		2147		1506	
04/05	7587		557.3		4351		1104		605			989.5		985.4		1044		796			2865		1837		2220		1516	
05/06	7990		566.8		5526		1397		609			1023		1018		1082		803			3151		1878		2274		1524	
06/07	8408		576.4		6610		1800		612			1058		1052		1121		809			3466		1919		2312		1530	
07/08	8840		586.2		7481		2323		614			1094		1086		1161		813			3813		1961		2335		1534	
08/09	9286		596.2		8105		2964		615			1131		1122		1203		817			4194		2004		2346		1537	
09/2010	9748		606.3		8514		3686		617			1170		1159		1246		820			4613		2048		2348		1539	

TABLE (6)
RESULTS OF PEAK LOAD FORECASTING USING NEURAL NETWORKS

YEAR	UPS LIGHT LOAD (MW)	NORTH UPPER EGYPT ACTUAL (MW)	NORTH UPPER EGYPT NUMBER OF NEURONS 11	%	9	%	7	%	5	%	SOUTH UPPER EGYPT ACTUAL (MW)	SOUTH UPPER EGYPT NUMBER OF NEURONS 11	%	9	%	7	%	5	%	CANAL ACTUAL (MW)	CANAL NUMBER OF NEURONS 11	%	9	%	7	%	5	%
87/88	2896	220	223		227		207		223		651	567		571		602		582		225	218		214		204		198	
88/89	3163	230	226		229		222		226		703	623		619		630		623		236	235		236		228		227	
89/90	3389	265	230		231.1		233		231		733	657		652		651		652		301	249		252		248		250	
90/91	3514	275	233		233.2		239		234		757	672		668		663		667		357	257		260		258		263	
91/92	3673	292	238		236		245		239		785	688		687		676		684		377	266		270		272		278	
92/93	3947	336	247		248		254		248		835	710		714		699		709		357	285		286		295		303	
93/94	4021	360	250		251		256		251		856	715		721		705		715		360	291		291		302		310	
94/95	4316	390	262		266		264		261		890	735		743		729		736		376	319		314		330		334	
95/96	4584	440	274		277		269		269		959	751		756		751		751		390	353		347		358		355	
96/97	4975	570	279		288.4		272		280		990	771		757		782		769		465	425		429		405		381	
97/98	5178	586	284	82.51	300.2	78.09	301.9	77.62	285	82.24	999	779	63.22	757.8	69.32	797	58.05	776	64.08	473	450	9.274	499	10.48	455	7.258	393	32.26
98/99	5478		289.1		312.5		335.1		291			782		758.5		818		784			568		652		480		409	
99/2000	5793		294.3		325.3		372		296			785.1		759.3		835		791			683		905		538		424	
2000/01	6123		299.6		338.6		412.9		300			788.3		760		846		796			797		1307		610		437	
01/02	6467		305		352.5		458.3		304			832		760.8		857		801			834		1922		703		448	
02/03	6826		310.5		367		508.8		306			1115		761.6		868.1		804			872.4		2825		824		458	
03/04	7199		316.1		382		564.7		308			1787		762.3		879.4		806			912.5		4073		985		467	
04/05	7587		321.8		397.7		626.8		309			2903		763.1		890.9		808			954.5		5678		1205		474	
05/06	7990		327.6		414		695.8		310			4273		763.8		902.4		810			998.4		7555		1504		480	
06/07	8408		333.5		431		772.3		311			5528		764.6		914.2		811			1044		9514		1905		484	
07/08	8840		339.5		448.6		857.3		311.9			6276		765.4		926.1		811.8			1092		11313		2422		488	
08/09	9286		345.6		467		951.6		312.9			6780		766.1		938.1		812.6			1143		12772		3048		491	
09/2010	9748		351.8		486.2		1056		313.8			6894		766.9		950.3		813.4			1195		13834		3751		493	

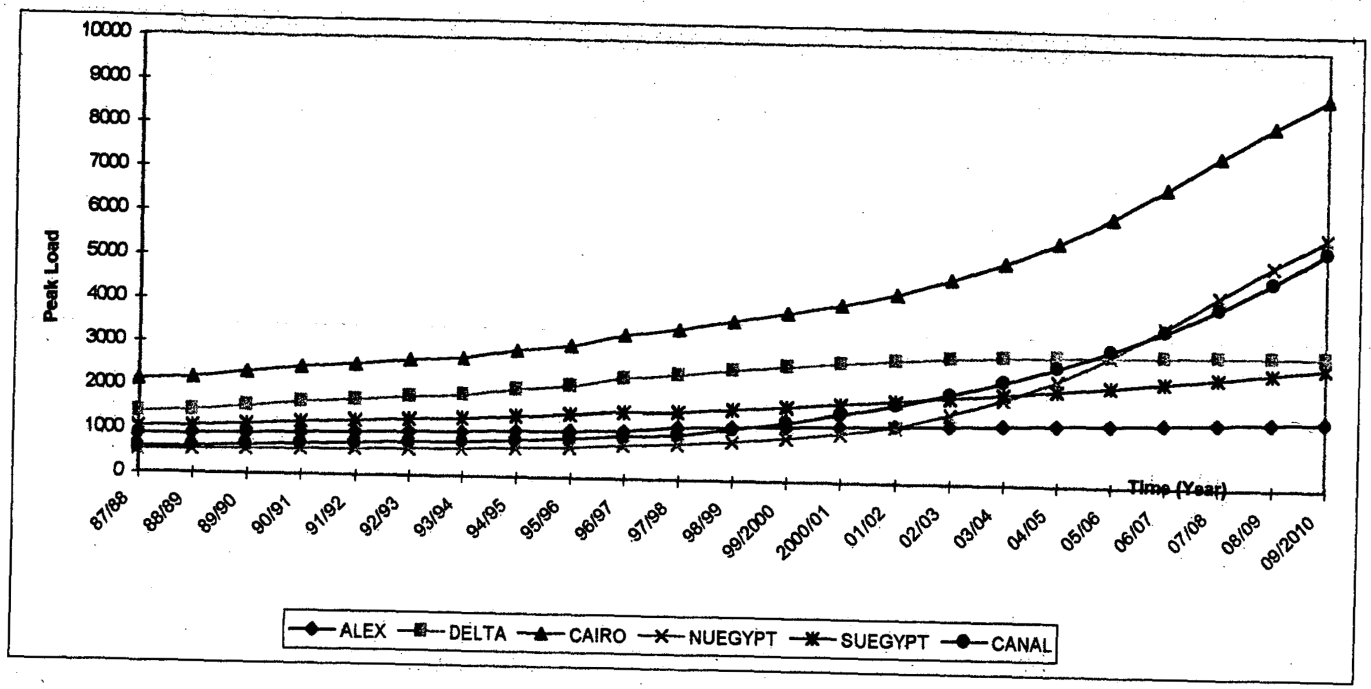

Figure (4) Results of Peak Load Forecasting Using Neural Networks

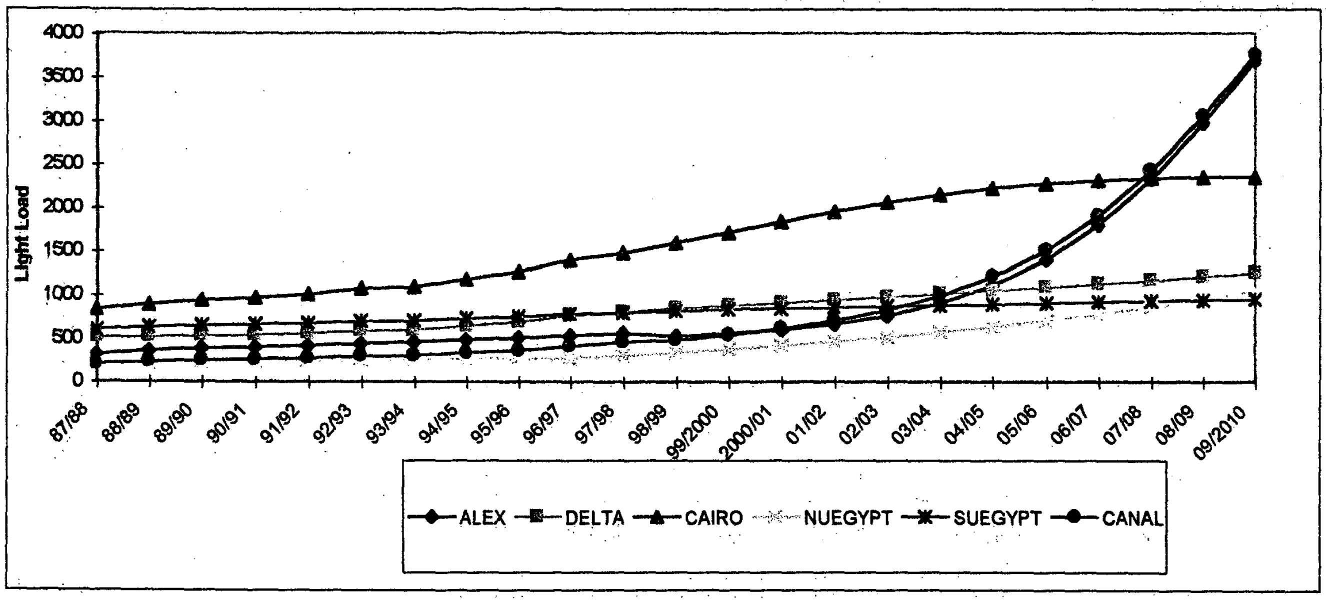

Figure (5) Results of Light Load Forecasting Using Neural Networks