ERJ
Engineering Research Journal
Faculty of Engineering
Minoufiya University

LONG-TERM LOAD FORECASTING AND ECONOMICAL OPERATION OF WIND FARMS FOR EGYPTIAN ELECTRICAL NETWORK

A. A. Abou El-Ela*, A. A. El-Zeftawy*, S. M. Allam*, and G. M. Atta**
* *Electrical Engineering Dept., Faculty of Eng., Shebin El-Kom, Egypt.*
** *Electrical Engineer*

ABSTRACT
Many of traditional methods have been presented for long-term load forecasting of electrical power systems. But, the results of these methods are approximated. Therefore, artificial neural network (ANN) technique for long-term peak load forecasting is modified and discussed as a modern technique in long-term load forecasting. The modified technique is applied on the Egyptian electrical network dependent on its historical data to predict the electrical peak load demand forecasting up to year 2017. This technique is compared with extrapolation of trend curves as a traditional method. Installed power generation capacities of Egyptian electrical network up to year 2017 are estimated dependent on the peak load forecasting of this network. Also, a proposed methodology to assess the economical operation of WFs beside conventional power system (CPS) is introduced. This methodology includes a mathematical model to develop the economical operation of wind farms on the whole power generation system capacity through the considered period.

تم استخدام كثير من الطرق التقليدية للتنبؤ بأحمال القوى الكهربية على المدى البعيد. وعند تطبيق هذه الطرق وجد أن نتائجها تقريبية و تختلف باختلاف الطريقة المستخدمة. لذا تم في هذا البحث اقتراح تحسين طريقه الشبكات العصبية الاصطناعية لتناسب التنبؤ لأحمال القوى الكهربية في جمهورية مصر العربية. و قد تم تطبيق الطريقة المحسنة (الشبكات العصبية الاصطناعية) التي تعتمد على البيانات السابقة لشبكة الكهرباء وذلك للتنبؤ بالأحمال المطلوبة حتى عام ٢٠١٧ في مصر. كما اشتمل البحث على نموذج رياضي لدراسة الاستخدام الاقتصادي لمزارع الرياح مع مصادر الطاقة التقليدية لتوليد الكهرباء. تم تطبيق النموذج الرياضي المقترح لتقدير القيمة الإقتصاديه لقدرات مزارع الرياح وتأثيرها على الطاقة التقليدية خلال فترة التخطيط المقترحة.

Keywords: Long-term load forecasting - Artificial neural network- economical operation of wind farms.

1-INTRODUCTION

Expected growth of load demand for electrical systems is one of the fundamental determinates for development and refurbishment. Power system expansion planning starts with a forecast of anticipated future load demand and energy requirements [1]. Electrical load forecasting problem is hard to deal with because of the non-linear and the random-like behavior of the factors affected on the electric load growth as well as the underminstic of load behavior and a great problem in data collection [2, 3]. The accuracy of a forecast is crucial to any electric utility since it dictates the timing and characteristics of major system addition [4]. High accuracy of the load forecasting for power systems improves the security of power system and reduces the generation costs [5]. Many studies on Long-term load forecasting have been made to improve the predication accuracy of peak load [6].

In this paper, an artificial neural network (ANN) with a feed foreword back-propagation algorithm is modified and discussed as a modern technique in long-term load forecasting. The modified technique is applied on the Egyptian electrical network depending on its historical data to predict the electrical peak load demand up to year 2017. ANN composed of neurons distributed in layers. As the trained propagation networks tend to give reasonable answers when presented with input that they have never seen, a new input will lead to an output similar to the correct output for input vector used in training similar to the new input being presented [7,8].

During the last decades there has been a great and urgent interest in developing renewable alternative energy technologies that could in the future replace present conventional sources of energy [9]. Besides solving many problems, Alternative energies provide many other benefits that make them worthwhile even at slightly higher cost [10]. With the first oil price shock in 1970, the interest in wind power re-emerged. The main focus was on wind power providing electrical energy instead of mechanical energy. This way, it became possible to provide a reliable and consistent power source by using other energy technologies, via the electric grid, as a back up [11]. Wind farms installed capacity evaluation requires a forecast for the network involves the peak loads and reserves. Also, a proposed technique to assess the economical operation of WFs beside conventional power systems is presented.

2- PROBLEM FORMULATION

A modified ANN technique is presented to predict the electrical peak load demand. Also, a proposed methodology to assess the economical operation of WFs beside the conventional power systems is introduced.

2-1 Modified ANN Technique

Figure 1 shows a single-layer neural network that presents a feed-forward back-propagation with tan-sigmoid hidden neurons and a purelin sigmoid target function according to the following step [12]: -

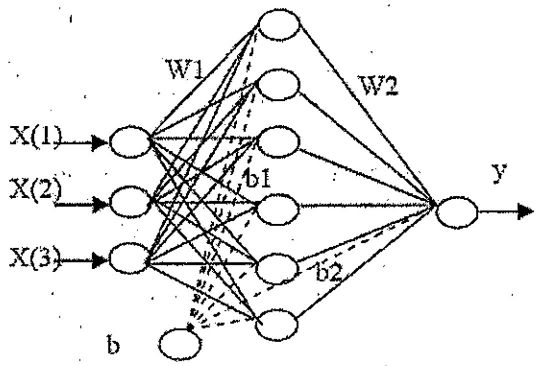

Figure 1 A single-layer neural network.

Step1: Initialization

The initial weights and biases for back-propagation networks are created with small random values. This function takes matrices input (P) (peak load demand data for each first three years), output (T) (peak load demand for the corresponding fourth year), hidden vector (S1), and transfer functions of each layer, and returns weight W, and biases (b) for each layer as: -

[W1, b1 W2, b2] = initff (P, S1, " tansig ", T, " purelin'); (1)

Step 2: Learning Rule

It can be used to adjust the weights and biases of networks in order to minimize the sum–squared error of the network. This is done by continually changing the values of the network weights and biases in the direction of steepest descent with respect to error. The change to be made in a layer's weights and bias are calculated by learnbp:

$$dW = Lr.\ P \qquad (2)$$

$$db = Lr.\ D \qquad (3)$$

The function learnbp returns a weight change matrix dW, and a bias change vector db for a layer whose current input vectors is P and delta vector is (D) and learning rate lr where: -

Lr (dW, db) = learnbp (P, D, Lr) (4)

Step3: Training

A function that can be used to train feed-forward network (trainbpx) with frequency of progress displays in epochs (df), maximum number of epochs to train (me), sum-squared error goal (eg), and learning rate (Lr) are: -

tp = (df – me–eg –Lr) (5)

(W, b, epochs, tr)= trainbpx (W, b, " F", P, T, tp) (6)

Given P,T, W, b, the transfer function and training parameter tp returns new weights and biases the number of epochs trained and a record of training errors tr. The training parameter tp, specify the number of epochs between displaying progress the maximum number of epochs to train the sum squared error goal and the learning rate. Training continues until either the error goal is met, or the maximum number of epochs has occurred.

Step4: Simulation

The function simulates a feed-forward network (simuff), takes network input P, matrix weight W, and vector biases b. Once these weights and bias have been determined, ANN is simulated by test data, usually the training and test data are different sets. The response of the perceptron should then be representative of the data by which it was trained as,

(a1,a2)= simuff
(P,W1, b1," tansig ", W2, b2," purelin"), (7)

2-2 Proposed Methodology of WFs Economical Operation

A proposed methodology to evaluate the wind farms generation capacity, the corresponding capacity displacement of CPS, the annual savings in fuel costs and their impact on the whole power generation system over the considered planning period are estimated using the following suggested model,

$$P_{wf} = PSWFs * CCG = \sum^{nw} P_{wg} \qquad (8)$$

Where, PSWFs is the percentage sharing of wind farms in the capacity of conventional generation (CCG) and nw is the number of wind generators (WGs) in the wind farms which have a rated power (P_{wg}). The annual generation of this generator (E_{aw}). and the annual generation of the wind farm (E_{wf}) can be expressed as,

$$E_{aw} = CF_w * P_{wg} * 8760 \qquad (9)$$

$$E_{wf} = \sum^{nw} E_{aw} \qquad (10)$$

The capacity factor (CF_w) of a wind generator is given as a function of its cut-in, rated , furling wind speeds, scale and shape parameters of wind speed at the installation site by[13],

$$CF_w = \left[e^{-(V_c/c)^k} - e^{-(V_r/c)^k} \right] \Big/ \left[(V_r/c)^k - (V_c/c)^k \right] - e^{-(V_f/c)^k} \quad (11)$$

Where, c and k are the scale and shape parameters of Weibull distribution function of the wind speed which can be calculated as.

$$k = \delta / V_m \quad (12)$$

$$c = 1.12 V_m \quad (13)$$

However,

$$\delta = \left[\sum_{i=1}^{nv} f_i (V_i - V_m)^2 \right] \Big/ \left[\sum_{i=1}^{nv} f_i \right] \quad (14)$$

$$V_m = \left[\sum_{i=1}^{nv} f_i * V_i \right] \Big/ \left[\sum_{i=1}^{nv} f_i \right] \quad (15)$$

Where,

- V_c : The cut-in wind speed of WG, m/s.
- V_f : The furling wind speed of WG. m/s.
- V_r : Rated wind speed of WG, m/s.
- V_i : Instantaneous wind speed, m/s.
- V_m : The mean wind speed, m/s.
- f_i : The frequency of V_i, once/s.
- σ : The standard deviation.
- nv : The number of wind speed observation

Thus, the capacity displacement of CPS due to wind generation and its saving costs are given as [14],

$$CDG_c = \sum^{nv} P_{wg} (CF_w / CF_c) \quad (16)$$

$$SCD_c = C_c * CDG_c \quad (17)$$

Where,

- CDG_c : The capacity displacement of CPS, MW.
- SCD_c : The savings in capital cost of CPS, \$.
- CF_c : The capacity factor of CPS.
- C_c : The annual capital cost per 1kW of CPS, \$/kW.

The annual savings in fuel (F_c) and their costs (SFC) are given by,

$$F_c = K_f * E_{wf} / (H_f * \eta_o) \quad (18)$$

$$SFC = L_f * C_f * F_c \quad (19)$$

Where,

- F_c : The annual savings in conventional fuel.
- SCF : The savings in conventional fuel costs, \$.
- C_f : The cost per ton of F_c, \$/ton.
- H_f : The heat value of F_c, Kcal/Kg.
- K_c : The heat required for 1kWh (860 Kcal / kWh).
- η_o : The overall efficiency of the wind farm.
- L_f :The levelizing factor of conventional fuel at the end-of-year Cost and given by:

$$L_f(n) = \left[1 - \left((1+a)/(1+r) \right)^n \right] * r * (1+r)^n / (r-a) * n \quad (20)$$

Where, a, r are the escalating (inflation) and interest rates respectively.

3-APPLICATION AND RESULTS

The goal of this paper is to apply the modified ANN technique for long-term peak load forecasting to evaluate the installed capacities of the Egyptian CPS up to year 2017. Also, a proposed methodology is applied to assess the economical operation of WFs, with different sharing percentage related to the CPS up to that target period. All results are obtained using Matlab 6.5[15].

3-1 Long-Term Forecasting Technique

The extrapolation of trend curves method with different approximations (linear, logarithmic, and exponential) is applied as traditional technique for long-term load forecasting dependant on the historical data of electrical peak load demand of the Egyptian electrical network, from year 1993 to 2005 as shown in Tables 1 [16]. Figure 2 shows the extrapolation of trend curves for the Egyptian electrical peak load forecasting from year 2006 to 2017. From this figure, it can be found that: the route mean square error (R MS) between the predicted peak load demand and the different extrapolation of trend curves are equal to 0.9747, 0.9745, and 0. 9905, respectively. Also, the peak loads forecasting at year 2017 are equal to (23.7462 GW, 23.580 GW, and 40.378 GW) for linear, logarithmic, and exponential trend curves respectively.

Table 1. Egyptian electrical network peak load data.

Year	Electrical Peak Load Data, GW
1993	7.503
1994	7.675
1995	8.149
1996	8.491
1997	9.235
1998	9.850
1999	10.919
2000	11.736
2001	12.376
2002	13.326
2003	14.401
2004	15.102
2005	16.019

Figure 2 Shows the extrapolation of trend curves for the Egyptian electrical peak load forecasting. In this Figure the load forecasting values are changed from an extrapolation curve to another at the same year due to the variations in the trend curves. Tables 2 illustrates the peak load forecasting for the network, up to year 2017 using different approximations.

From this Table, more accurate predicted electrical peak loads are obtained using the proposed modified ANN. The maximum error between the actual and predicted load demand is equal to 1.0 E-6. According to these predicted load results, the proposed modified of ANN is carried out to predict the electrical peak load demand for Egyptian network up to year 2017 as shown in Table 4.

Table 4. Predicted peak load demand using modified ANN technique.

Year	Predicted peak load, GW
2006	17.179
2007	18.385
2008	19.400
2009	20.270
2010	21.137
2011	21.801
2012	22.765
2013	23.558
2014	24.494
2015	25.192
2016	25.690
2017	26.300

Table 5 shows a comparison between the linear trend curve of the extrapolation method (as a conventional technique) and the proposed modified ANN technique as a modern technique for load forecasting of Egyptian network from year 2006 to year 2017. From this Table, it can be concluded that: the predicted peak load demand, using the modified ANN technique is more suitable than that from the linear trend curve compared with the actual load demand.

Table 5. A comparison between the linear trend curve and the proposed modified ANN technique for load forecasting of Egyptian network.

Year	Predicted Peak Load, GW	
	Linear Approx.	ANN Technique
2006	15.9516	17.179
2007	16.6602	18.385
2008	17.3688	19.400
2009	18.0774	20.270
2010	18.786	21.137
2011	19.4946	21.801
2012	20.2032	22.765
2013	20.9118	23.558
2014	21.6204	24.494
2015	22.329	25.192
2016	23.0376	25.690
2017	23.7462	26.300

Estimation of power capacities up to year 2017

The capacities of the Egyptian electrical power generations can be estimated using the predicted peak load demand of the network. The power generation installed capacities are the sum of the peak load demand, including the network losses, and the total system reserve. The power reserve can be computed as a percentage value of the network capacity from years 1993 to 2005 as shown in Table 6. ANN technique is modified to estimate the power reverse percentage from year 2006 to 2017, dependent on the history power reserve from years 1993-2005. The process of power reserve is estimated by training ANN using the historical data of reserve percentage for three years in the past as an initial data to estimate the 4^{th} year in advanced and so on. Table 7 illustrates the installed capacities of the network from years 2006 to 2017, the power installed capacity up to year 2017 is equal to 29.554 GW.

Table 6. Electrical installed capacities of Egyptian electrical network from years 1993 to 2005.

Year	Capacity , GW	Peak Load, GW	Reserve %
1993	11.911	7.503	37
1994	12.046	7.675	36.28
1995	12.978	8.149	37.209
1996	13.270	8.491	36.013
1997	13.330	9.235	30.720
1998	13.935	9.850	29.315
1999	14.582	10.919	25.120
2000	14.582	11.736	19.517
2001	15.286	12.376	19.037
2002	16.648	13.326	19.954
2003	17.671	14.401	18.5
2004	18.3919	15.102	17.98
2005	19.2744	16.019	16.88

Table 7. Electrical installed capacities of Egyptian network from the year 2006 to 2017.

Year	Peak Load, GW	Reserve %	Total Capacity GW
2006	17.179	16.10	20.4523
2007	18.385	15.45	21.7423
2008	19.400	15.00	22.8312
2009	20.270	14.52	23.7078
2010	21.137	14.08	24.5785
2011	21.801	13.65	25.2045
2012	22.765	13.00	26.1669
2013	23.558	12.75	27.0013
2014	24.494	12.5	27.9937
2015	25.192	12.01	28.6340
2016	25.690	11.53	29.2361
2017	26.300	11.00	29.5539

3-2 Economical Operation of W Fs with CPS

The plan strategy of Ministry of Electricity and Energy in Egypt has been stated that, the penetration level of wind farms capacity must be 3% of the total CPS up to year 2017 [17]. Using the installed power generation capacities that has been estimated in Table 7, wind farms capacities are estimated up to year 2017 as shown in Figure 3. This Figure illustrates these capacities at different percentage sharing of wind farms (PSWFs).

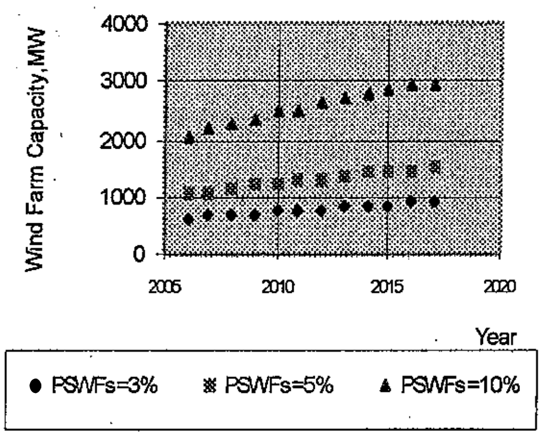

Figure 3. Capacities of wind farms at different PSWFs up to year 2017.

Red-sea coast at Zafarana in Egypt was selected as an appropriate site to establish large-scale wind farms of 20 GW in Egypt. Therefore, this site will be considered for planning wind farms beside the CPS up to year 2017 with employing 600 kW for each wind generation unit.

Table 8. Number of wind generators and their annual Energy generation for different PSWFs up to year 2017.

Year	Number of wind generators			Annual wind farm generation, GWh		
	PSWF s =3%	PSWF s =5%	PSWFs =10%	PSWFs =3%	PSWF s =5%	PSWFs =10%
2006	1023	1705	3409	1293.07	2155	4308.9
2007	1087	1812	3624	1374.00	2290.3	4580.7
2008	1142	1903	3805	1443.00	2405.4	4809.5
2009	1186	1976	3951	1499.00	2497.7	4994.1
2010	1229	2048	4096	1553.45	2588.6	5177.3
2011	1260	2101	4200	1592.64	2655.7	5308.8
2012	1308	2181	4361	1653.00	2756.8	5512.3
2013	1350	2250	4500	1706.00	2844.3	5688.0
2014	1400	2333	4666	1769.60	2948.9	5897.8
2015	1432	2386	4772	1810.00	3016.0	6031.8
2016	1462	2437	4873	1847.96	3080.3	6159.5
2017	1478	2463	4926	1868.00	3113.2	6226.5

The proposed methodology in section 2.2 is carried out to assess the economical operation of WFs beside the CPS considering the following values: The average value of c and k, are equal to 7.5 m/s and 2.32 m/s respectively. The average values of CFc , Hf, and ηo, are equal to 0.68, 11500 Kcal/Kg, and 0.30, respectively. Table 8 shows the number of wind generation units and their annual energy generation (GWh) for different PSWFs up to year 2017. The number of wind generation units and their annual energy generation are increased with increasing of PSWFs. The capacity displacement of WFs (MW), and the annual savings in conventional fuel (ton) are computed for different PSWFs as shown in Figures 4 and 5.

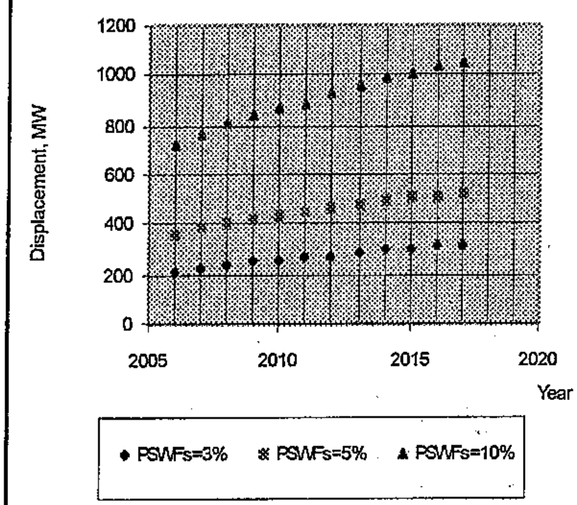

Figure 4. Capacity displacement, MW

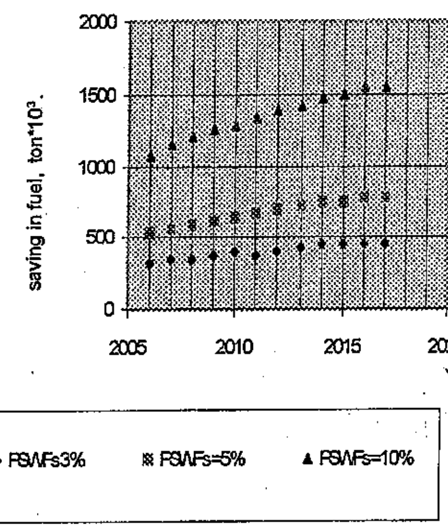

Figure 5. Annual saving in conventional fuel, ton*10^3.

Also, the annual capital costs due to the capacity displacement of WFs and the savings in conventional fuel costs are computed for different PSWFs up to year 2017 as given in Table 9.

4-CONCLUSIONS

A modified ANN technique has been efficiently and accurately applied on the Egyptian network to predict the peak load demand up to year 2017. However, the Ann technique has been reformulated efficiently (modified) to be suitable for our network. Once the accurate predication of peak load demand has been computed, the total installed generation capacities, up to year 2017 are obtained accurately.

Also, a proposed methodology is presented to assess the economical operation of wind farms beside the conventional power system. Zafarana on the Red-sea coast has been selected as an appropriate site that can host large-scale wind farms in Egypt for applying the proposed methodology with 3% of the total capacity has been efficiently introduced. Also, the saving in capital and operation costs for different PSWFs has been introduced.

Finally, the WFs concern as a great and urgent interest renewable alternative energy, especially in the zones, which have fast wind like Zafarana zone in Egypt. This concern is due to the raising prices of conventional energy, the dependence on oil, the decreasing supply of fossil fuels, and the negative environmental effects caused by their consumption.

Table 9. The annual savings in capital and fuel costs due to the wind farms Installation through years 2006-2017.

Year	Savings in capital costs, $\$*10^6$				Annual savings in fuel coasts, $\$*10^6$			
	C_c $/KW	PSWFs =3%	PSWFs =5%	PSWFs =10%	C_f $/ton	PSWFs =3%	PSWFs =5%	PSWFs =10%
2006	105	22.785	37.91	75.88	145	46.70	77.87	155.73
2007	112	25.76	43.01	86.05	160	54.72	91.20	182.69
2008	117	28.31	47.15	94.38	175	62.95	104.83	209.80
2009	123	30.955	51.53	103.02	193	72.11	120.10	249.26
2010	130	33.93	56.42	112.88	210	81.27	135.45	271.03
2011	136	36.312	60.52	121.09	230	91.31	152.26	304.36
2012	143	39.611	66.07	132.20	250	103.00	171.75	343.53
2013	150	42.90	71.55	143.10	280	119.00	198.52	397.00
2014	158	46.93	78.21	156.29	310	136.71	227.85	455.76
2015	165	50.16	83.49	166.93	342	154.24	257.18	514.23
2016	174	53.94	89.96	179.76	370	170.20	284.16	568.10
2017	183	57.46	95.53	191.11	415	194.00	322.04	644.12

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