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Forecasting of Electricity Demand by Hybrid ANN-PSO Models

Atul Anand, Anna University, Chennai, India
L. Suganthi, Anna University, Chennai, India

ABSTRACT

Developing economies need to invest in energy projects. Because the gestation period of the electric projects is high, it is of paramount importance to accurately forecast the energy requirements. In the present paper, the future energy demand of the state of Tamil Nadu in India, is forecasted using an artificial neural network (ANN) optimized by particle swarm optimization (PSO) and by Genetic Algorithm (GA). Hybrid ANN Models have the potential to provide forecasts that perform well compared to the more traditional modelling approaches. The forecasted results obtained using the hybrid ANN-PSO models are compared with those of the ARIMA, hybrid ANN-GA, ANN-BP and linear models. Both PSO and GA have been developed in linear and quadratic forms and the hybrid ANN models have been applied to five-time series. Amongst all the hybrid ANN models, ANN-PSO models are the best fit models in all the time series based on RMSE and MAPE.

KEYWORDS

Artificial Neural Network, Energy Demand, Forecasting, Particle Swarm Optimization, Tamil Nadu, Tamil Nadu Generation and Distribution Company Limited

INTRODUCTION

In order to ensure sustained growth for developing economies such as the state of Tamil Nadu in India, long term planning of energy resources is imperative to bridge the electrical energy gap. The allocation of capital resources requires an accurate model for forecasting electricity demand that can enable the optimal utilization of scarce resources. It is also useful for resource planning and for attracting investments in the field of energy. In recent reports on the energy policies of India, simple measures of GDP-elasticity and energy intensities have been used for demand forecasting for ten or more years (Government of India,2006). In this paper, the total electric energy demand is segregated into agriculture, residential, commercial, and industrial sectors. For each sector, hybrid artificial neural network (hybrid ANN) models have been developed using the state of art optimizing techniques, namely, particle swarm optimization (PSO) and Genetic Algorithm (GA). Hybrid ANN models have the potential to provide forecasts that perform well, compared to the more traditional modeling approaches. For each optimizing technique, both linear and quadratic forms have been developed. The four hybrid ANN models that are compared in this paper are: -ANN-PSO(Linear), ANN-PSO(Quadratic), ANN-GA(Linear) and ANN-GA(Quadratic). The results of each sector are compared with linear, autoregressive integrated moving average (ARIMA), and artificial neural network with backward propagation (ANN-BP) models. The best fit model for each sector is selected based on error indices such as root mean square error (RMSE) and mean absolute percentage error (MAPE).

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The study of the electric energy demand profile of the State of Tamil Nadu in Figure 1 shows a non-linear growth with undulations superimposed on the profile. For such a non-linear profile, in the past, many applications used the traditional statistical models, such as the autoregressive model, moving average model and the auto regressive moving average. These models perform well when the data lie within the range of past observations but they perform poorly while predicting extremes and also when the data lies near the limits. Moreover, conventional optimization might either fail to obtain a feasible solution or be trapped in local optima. However, with the advent of ANN and inspired by its strong ability of non-linear mapping, it has been applied to the field of energy forecasting. ANN does not require to specify a particular model form. Rather, the model is adaptively formed based on the features presented from the data. This data driven approach is suited for many empirical data sets where no theoretical guidance is available to suggest an appropriate data generating process. Therefore, ANN has been considered in the present study. Various independent socio-economic factors were considered to develop a forecasting model, as Table 1 shows, and Pearson correlations were found. On this basis, the per capita energy index, number of consumers, and consumer price index were taken as independent variables.

For non-linear demand profile, hybrid ANN models are designed to obtain near-optimal objective function values after optimization. The heuristic techniques such as GA and PSO are considered promising alternatives in this type of problem. They have been proved to be robust and powerful tools for many kinds of optimization problems (Unler, 2008). The detailed procedure for the hybrid ANN models which are proposed in the study is as follows:

- In the first step, PSO and GA optimization techniques are applied to the sectors of total electric demand, namely, agriculture, residential, commercial and industries sectors based on socio-economic indicators. PSO and GA optimization techniques are applied separately in linear and quadratic forms using the data from the year 1991 to 2000 for each time series. The optimizing techniques (PSO and GA) are used to train ANN which projects the demand from year 2001 to

Figure 1. Demand profile in the period 1991-2015

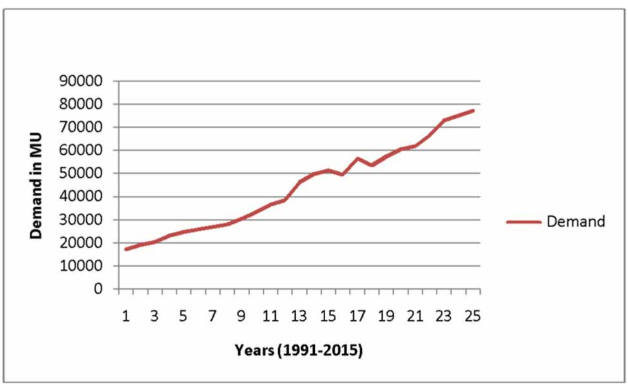


Table 1. Details of correlations among socio-economic factors

Pearson Correlations	Per Capita Energy Index	Consumers	Population	Consumer Price Index	Gross State Domestic Product	Per Capita Income
Total Electricity Demand	**0.68**	**0.76**	**0.65**	**0.8**	**-0.186**	**-0.082**

2015. A comparison is made between the actual values and forecasted values of the electricity demand using ANN-PSO-Linear, ANN-PSO-Quadratic, ANN-GA, ANN-GA-Quadratic, ANN-BP, ARIMA and linear models. The performances of various models are compared and the best fit model is selected based on RMSE and MAPE;
- In the second step, total electric energy demand is forecasted based on the best fit model up to the year 2020. This study uses the technique mentioned in Fienberg and Genethlion's (2005) work using SCILAB. The coding has been done for the inertial weight model of PSO. IBM SPSS 2.0 software is used for running ANN.

The paper is divided into following sections, namely, Literature review, Forecasting Techniques, Determination of weight coefficients, Discussions, and Conclusions.

LITERATURE REVIEW

A review of the demand forecasting approaches suggests the existence of a large variety of techniques used by different sets of users. Bhattacharyya and Timilsina (2009) suggested that models can be categorized into two broad categories: simple approaches and sophisticated approaches. Simple models rely on simple indicators commonly used for forecasting such as growth rates, elasticities (especially income elasticity), specific or unit consumption and energy intensity. Westoby and Pearce (1984) noted that most of the work on energy forecasting used the "energy ratio" (which is popularly known as "energy intensity") and the "energy coefficient" (i.e. the elasticity of the energy demand with respect to the national income or GDP). Similarly, Codoni, Park and Ramani (1985) reported the use of the income elasticity of demand for an energy assessment study of Korea. Grover and Chandra (2006) report that Indian state agencies rely on income elasticities for forecasting primary energy and electricity demand. Harvey (1997) proposed an alternative method called the structural time series models, which have been applied to the energy demand, among others settings, by Hunt, Judge, and Ninomiya (2003). These studies have generally focused on the aggregated demand and considered variables such as GDP and price, but they do not capture the technological changes. The first systematic elaboration of the method and an application in France were reported by Chateau and Lapillonne (1978). Worrel (2004) argued in favour of disaggregation of the total energy demand into relevant homogenous end-use categories (Government of India -2006). Dahl (1994a) suggested that although models are found to test the per capita energy and total energy consumption, aggregation can cause heteroscedasticity when the population varies across the sample. Ibrahim (1985) reviewed the energy demand forecasting efforts in Arab countries using time series, single-equation models, and the aggregated approach noting that none of them meet the requirements of policy analysis. Similarly, Chern and Soberon-Ferrer (1986) analysed the structural changes in energy demand in developing countries. Ishiguro and Akiyama (1995) analysed the energy demand in five Asian countries, namely China, India, South Korea, Thailand and Indonesia both at the aggregate level and the sector level using a simple econometric model and provided forecasts for these countries up to 2005. Pesaran M.H, Smith R, Akiyama T (1998) conducted a major study that analyzed the energy demand in 11 Asian developing countries using an autoregressive distributed lag model for co-integration both at the aggregate and sector levels. Shiwei Yu and Yi-Ming Wei (2012) developed a PSO-GA optimal model to estimate primary energy demand of China. Unler Alper (2008) highlighted the use of PSO in linear and quadratic form for forecasting energy demand. Araby and Yorino (2010) showed the utility of hybrid PSO technique for electricity markets. Zhu and Wang (2011) developed a hybrid model with adaptive particle swarm optimization algorithm for electricity demand forecasting for China.

FORECASTING TECHNIQUES

The ARIMA Model

ARIMA is a times series model which is based on the assumption that the data possesses an internal structure such as trend analysis, auto-correlation or seasonality. The time series model predicts future values based on previously observed values. ARIMA methods assume that the time series are generated from linear processes. Linear models have advantages in that they can be understood and analyzed in great details and are easy to explain. However, they may be totally inappropriate if the underlying mechanism is non-linear. In fact, most real world systems are often non-linear (Granger & Terasvirta (1993). In this study, the ARIMA (1, 0, 1) model has been developed for each sub sector.

The Hybrid ANN-PSO Model

ANNs have been widely used in demand forecasting since 1990 (Kodeeswararamanathan et al., 2014). ANN is well suited for problems where the solutions require knowledge of factors whose relationships are difficult to specify (Kaastra & Boyd, 1996). According to Zhang et al. (1998) in such problems, good theoretical guesses of the underlying laws governing the systems are difficult to fathom (Guoqiang Zhang et al., 1998). The functional value in an ANN model can be written as:

$$y = f\left(x_1, x_2, \dots x_p\right)$$

where $x_1, x_2, \dots, x_p$ are the 'p' independent variables and y are is the independent variable:

$$y_{t+1} = f\left(y_t, y_{t-1}, \dots, y_{t-p}\right)$$

where y_t is the observation of time "t".

ANN has been optimized with PSO technique. Particle swarm optimization (PSO) method, first published by Kennedy and Eberhart in 1995 (Westoby & Pearce, 1984), is based on a population of points that are at first stochastically deployed on a search field. A variant of the PSO method was developed by Shi and Eberhart in 1998 (Codoni et al., 1985) in which a modification of the speed equation improves the convergence by inserting a time dependent variable in the following equations:

$$v_{t+1} = v_t + R_1 * C_1 * \left(g - x_t\right) + R_2 * C_2 * \left(p - x_t\right) \tag{1}$$

$$x_{t+1} = x_t + v_{t+1} \tag{2}$$

where $C1$ and $C2$ are knowledge factors, $R1$ and $R2$ are random numbers, g is the location of the leader, p the personal best location, v_t is the velocity at iteration "t" and x_t is the position at iteration "t". PSO searches for the most fitted members in the search space by minimizing the error.

Normalization of Data

Raw data is not normally used directly in process modeling of ANN. This is due to the difference in magnitude of the process variables. The data was scaled to prevent data with larger magnitude from overriding the smaller and impede the premature learning process. For normalization of the raw data the year 1991 was taken as the base year and its parameters were used for comparing the raw data of the subsequent years as follows:

$$v_t^{norm} = \frac{V_t}{V_{Base}}$$

where t is the year v_t^{norm} is the normalized reading for the tth year and v_{Base} is the reading of the year 1991 taken as base year.

The forecasted electricity demand, y (Linear) in ANN-PSO (Linear) is given as follows:

$$y(linear) = \sum_{1}^{n} X_i(t) * W_i(t) \tag{3}$$

where $X_i(t)$ is the normalized value of the i^{th} socio economic factor and W_i(t) is corresponding weight. n is the total number of socioeconomic factors.

Hybrid ANN-PSO-Quadratic Model (QANN-P)

The weights of the input variables are calculated as per the Equation 3. The Equations 1 and 2 represents the generalized PSO model but in Quadratic PSO model the quadratic terms are introduced to the second and third terms in Equation 1 and the evolution equations become:

$$v_{t+1} = v_t + R_1 * C_1 * sign(g - x_t) * (g - x_t) \wedge 2 + R_2 * C_2 * sign(p - x_t) * (p - x_t) \wedge 2 \tag{4}$$

$$x_{t+1} = x_t + v_{t+1} \tag{5}$$

Therefore, the Quadratic PSO algorithm based on the evolution Equations 4 and 5 satisfies the requirements for describing the swarm intelligence behavior of bird flocking. The Quadratic PSO algorithm has the ability to simulate swarm intelligence of bird flocking and its difference with the standard PSO is in the introduction of the quadratic terms in the evolution equation. It improves the diversity of the swarm so that higher performance in global optimization. Quadratic PSO projects the input variables for the years 2001 to 2015 while using the data from 1991 to 2000 as input. Following equation is used for forecasting the demand using QANN-P:

$$\begin{aligned} y(Quadratic) = {} & X_1^2(t) * W_1(t) + X_2^2(t) * W_2(t) + X_3^2(t) * W_3(t) \\ & + W_{12}(t) * X_1(t) * X_2(t) + W_{23}(t) * X_2(t) * X_3(t) + W_{13}(t) * X_1(t) * X_3(t) \end{aligned} \tag{6}$$

where $X_i(t)$ is the normalized value of the i^{th} socio economic indicator, $W_i(t)$ is corresponding weight for the t^{th} year of the i^{th} indicator and $W_{ij}(t)$ is corresponding weight between the i^{th} and j^{th} indicators.

Hybrid ANN-GA Model (ANN-GA)

The performance of weights evolution using GA depends on the number of populations and generations. If these parameters were set too low, the evolution may converge to immature solution. However, the larger number of populations and generations would require longer computation time for convergence (Araby & Yorino, 2010). In order to find the weights of the input variables GA was run on SCILAB as per the parameters shown in Table 2, for the following linear equation for forecasted demand "y" during the "t" the iteration is as follows:

$$y(t) = \sum_{1}^{n} W_i(t) * X_i(t) \tag{7}$$

where W_i is the weight of the i^{th} parameter, X_i is the i^{th} socioeconomic factor and n is the total number of factors.

ANN-GA-Quadratic Model (QANN-GA)

Another version of Hybrid ANN-GA Model has been developed with the quadratic equation as follows:

$$y(t) = \sum_{1}^{n} X_i^2 * W_i \tag{8}$$

where $y(t)$, is the Energy Demand for the year 't', W_i represents the normalized weights, W_1, W_2, W_3 of PerCapita Energy Density (X_1), Consumer Price Index (X_2) and Number of Consumers (X_3) respectively.

Using the normalized data for the inputs the weights are calculated using GA with parameters as shown in Table 3. The weights are calculated using GA subject to the condition that the values of normalized value of output (n-GA-Q) is as close as possible to the normalized value of the actual demand (nDemand). The weights and the normal input values are fed as nodes in the Artificial Neural Network.

Table 2. Parameters of GA

S.no	Parameters of GA	Values
1	Population Size	100
2	Probability of mutation	0.1
3	Probalility of cross mutation	0.7
4	Number of couples	110
5	Number of generations	10

Table 3. Parameters of PSO

S. No	Parameters	Value
1.	Number of Population	50
2.	Maximum Number of Iterations $(iter_{max})$	200
3.	Initial Inertia (w_{max})	0.8
4.	Final Inertia (w_{min})	0.2
5.	Personal Best Knowledge Factor (c_1)	2
6.	Global Best Knowledge Factor (c_2)	2

DETERMINATION OF WEIGHT COEFFICIENTS

In each hybrid, ANN-PSO approach each neural network (NN) defines the attributes of position and velocity. The position is related to weight of neural network. The velocity refers to updating of ANN's weights. The function of PSO in ANN is to get the best set of weights (particle position) where several particles are trying to move to get best solution. For neural network implementation, the fitness value corresponds to a forward propagation through the network and position vector of the network. The particle's best neighbor and global best particle are used to guide the particle new solutions. In the end the global best particle's position serves as the answer. Hence the function of PSO in ANN is to get the best set of weights. The iterative approach of PSO followed in the study is as follows:

Step 1: Initialize a population size, positions and velocities of agents, and the number of weights and biases. As shown in Table 3 the number of population is taken as 50.
Step 2: The current best fitness achieved by particle *p* is set as *pbest*. The *pbest* with best value is set as *gbest* and this value is stored. The personal best knowledge factor has been taken as 2.
Step 3: Evaluate the desired optimization fitness function *F(x)* for each particle as follows:

$$F(x) = \sqrt{\sum_{j=1}^{m} \left(E_{actual} - E_{predicted}\right)^2}$$

where E_{actual} and $E_{predicted}$ are the actual and predicted values of the electric energy demand respectively, m is the number of observations. The fitness function is formulated such that after each iteration, some new set of values are obtained that are added to the existing values, and a new set of values are obtained. The energy demand values that have minimal F(x) are taken for the next iteration of the PSO. The present study uses the 'Inertial Weight Model' developed by Shi and Eberhart with the 'Radius Improvement Model' developed by Salmon (Araby & Yorino, 2010).

Step 4: Compare the evaluated fitness value *F(p)* for each particle, p, with its *pbest* value. If *F(p)* < *pbest* then *pbest* = *F(p)* and *bestxp* =*xp*, *xp* represents the current coordinates of particle *p*, and *bestxp* represents the coordinates corresponding to particle *p's* best fitness so far.
Step 5: The objective function value is calculated for new positions of each particle. If a better position is achieved by a particle, *pbest* value is replaced by the current value. As in Step 1, *gbest* value is selected among *pbest* values. If the new *gbest* value is better than previous *gbest* value, the *gbest* value is replaced by the current *gbest* value and this value is stored. if *fp* < *gbest* then *gbest* = *p*, where *gbest* is the particle having the overall best fitness over all particles in the swarm.
Step 6: Change the velocity and location of the particle according to Equation 1 and Equation 2.
Step 7: If the maximum number of a predetermined iterations is exceeded, then optimization iterations are stopped else step 3 is repeated until convergence. Maximum number of iterations taken up is 200 (Table 3).

The normalized weights $\left(W_{12}, W_{13}, W_{23}\right)$ have been calculated using equation 6 for QANN-P model by using PSO in the quadratic form (Table 4).

Application of GA to Determine the Weight Coefficients

In order to determine optimum weights using GA following steps were taken:

Step 1: Generate an initial population of random weights.
Step 2: ANN was evaluated using the population weights. This was done by computing the raining error and assigning it to a fitness value depending on the solutions.
Step 3: Parents for genetic manipulation were selected and a new population of weights were created. The best existing weights (reproduction) were copied. New weights were created by crossover and mutation operators.
Step 4: The best population of weights that appeared in any generation was designated as the result of the performed GA. The maximum number of generation was taken up as 100 which was used to stop the iteration (as shown in Table 2).

Table 4. Calculation of weights using PSO (Quadratic)

Year	Per Capita	Consumer	Populatio	X1^2	X2^2	X3^2	W12	W13	W 23
2001	1.739234	2.11078	1.284397	3.002919	4.429865	1.643856	3.64415	2.701863	2.225637
2002	1.740482	2.113684	1.285238	3.00315	4.438406	1.651702	3.645026	2.702687	2.230537
2003	1.743535	2.118801	1.291731	3.002158	4.444737	1.660925	3.648868	2.705969	2.234403
2004	1.742362	2.119748	1.299156	3.007993	4.44471	1.667298	3.652136	2.710261	2.236484
2005	1.74656	2.122802	1.306171	3.014499	4.454473	1.670075	3.658678	2.716603	2.240316
2006	1.757234	2.133471	1.307219	3.012913	4.461283	1.678114	3.670071	2.726663	2.250227
2007	1.765759	2.138782	1.32213	3.017055	4.468402	1.691601	3.679283	2.726751	2.255423
2008	1.766098	2.135789	1.322586	3.014853	4.472879	1.69542	3.68148	2.735885	2.260517
2009	1.765251	2.14489	1.328288	3.026726	4.484091	1.701831	3.690773	2.743303	2.263619
2010	1.772931	2.145303	1.337613	3.027097	4.494202	1.707186	3.687869	2.745971	2.268787
2011	1.776363	2.152834	1.34153	3.028766	4.498124	1.71523	3.693322	2.748153	2.272937
2012	1.781887	2.172139	1.33906	3.022918	4.498769	1.721589	3.702723	2.758801	2.277813
2013	1.780678	2.177584	1.345109	3.030564	4.506537	1.723886	3.703262	2.762279	2.278135
2014	1.758824	2.184461	1.354249	3.045545	4.524084	1.734389	3.69907	2.767402	2.272634
2015	1.751147	2.213611	1.370402	3.065134	4.522264	1.732671	3.695373	2.761724	2.258565

The weights W_1, W_2, W_3 are calculated as per Equation 7 for GA in linear form and as per Equation 8 for GA in quadratic form. The weights computed using GA in linear form are depicted in Table 5 where normalized demand (nDemand), normalized weights $(W_1, W_2 \text{ and } W_3)$ and normalized values of per capita energy (nPercapita), consumer price index (nConPrIndx) and number of consumers(nCon) are fed as input to the ANN. The projected value of the energy demand (ANN-GA) from the year 2001 to 2015 as obtained from ANN have been compared with the actual demand in Table 6.

With respect to ANN-GA model in quadratic form, Table 7 depicts the normalized weights $(W_1, W_2 \text{ and } W_3)$ and normalized forecasted value of electricity demand (n-GA-Q). The forecasted value of electricity demand (ANN-GA-Q) have been compared with actual demand (nDemand) from the years 2001 to 2015 in Table 8.

APPLICATION AND DISCUSSION

The proposed ANN-PSO and ANN-GA models in linear and quadratic forms have been implemented in SCILAB computing environment which gives easy access to compare with other forecasting methods. The demand data in the sectors of agriculture, residential, commercial, industries along with total electric energy demand from the years 1991 to 2015 have been used for the proposed hybrid ANN models using PSO and GA techniques. Forecasts for each sector by each model have been mentioned in Table 9, Table 10, Table 11, Table 12 and Table 13.

Table 5. Computation of weights using GA

Year	nPerCapita	nConPrIndx	nCon	nDemand	w1	w2	w3
2001	1.82	2.14	1.33	0.2298	-1.9	1.45	0.84
2002	2.4	2.22	1.35	0.2591	-1.7	1.81	0.67
2003	2.51	2.27	1.35	0.3004	-1.76	1.82	0.67
2004	2.64	2.29	1.37	0.3271	-1.77	1.81	0.67
2005	2.91	2.39	1.42	0.3626	-1.76	1.95	0.76
2006	3.25	2.43	1.45	0.3858	-1.72	2	0.76
2007	3.39	2.58	1.48	0.4023	-1.72	2	0.76
2008	3.39	2.83	1.51	0.4399	-1.72	2	0.76
2009	3.66	3.14	1.54	0.523	-1.7	2	0.76
2010	3.52	3.45	1.59	0.5296	-1.62	1.7	0.32
2011	3.64	3.39	1.58	0.5481	-1.62	1.7	0.32
2012	3.79	3.31	1.55	0.5258	-1.64	1.57	0.77
2013	3.93	3.28	1.54	0.5463	-1.61	1.03	1.11
2014	4.07	2.99	1.51	0.5777	-1.7	1.77	1.11
2015	4.27	2.89	1.54	0.6026	-1.67	1.92	1.5

Table 6. Forecasting of demand using ANN-GA

Year	PerCapita	ConPriceI	Consumer	Demand	ANN-GA
2001	539	103	1648341	9095	9084.51
2002	708	107	1675165	9412	9393.63
2003	740	109	1676113	9030	9050.17
2004	780	110	1702541	9382	9359.28
2005	860	115	1768052	9919	9925.99
2006	960	117	1801972	10349	10320.97
2007	1000	124	1839241	10912	10870.51
2008	1000	136	1872734	10520	10509.88
2009	1080	151	1913697	11940	11918.06
2010	1040	166	1972563	12625	12639.33
2011	1073	163	1967024	10425	10389.67
2012	1118	159	1932771	10085	10063.38
2013	1161	157	1919531	10091	10046.21
2014	1200	143	1874940	12301	12313.04
2015	1259	138	1909856	12500	12501.94

Table 7. Computation of weights using GA (Quadratic)

2001	539	103	1648341	-0.0015	0.001369	0.00209	0.52961	0.5289
2002	708	107	1675165	-0.00157	0.00226	0.0023	0.54807	0.5479
2003	740	109	1676113	-0.0036	0.0031	0.0069	0.525825	0.5248
2004	780	110	1702541	-0.0035	0.00769	0.0018	0.546323	0.5458
2005	860	115	1768052	-0.0025	0.0026	0.0053	0.577593	0.577
2006	960	117	1801972	-0.00346	0.002237	0.0045	0.602632	0.601
2007	1000	124	1839241	-0.00226	0.0014	0.00716	0.635416	0.6349
2008	1000	136	1872734	-0.0036	0.0062	0.0088	0.61259	0.611
2009	1080	151	1913697	-0.009	0.0069	0.033	0.695277	0.6923
2010	1040	166	1972563	-0.0093	0.008321	0.0025	0.735166	0.7345
2011	1073	163	1967024	-0.0057	0.00469	0.00482	0.607058	0.6068
2012	1118	159	1932771	-0.00215	0.0055	0.0034	0.587259	0.5868
2013	1161	157	1919531	-0.00437	0.0024	0.004344	0.587608	0.5874
2014	1200	143	1874940	-0.0042	0.006047	0.00613	0.716299	0.716
2015	1259	138	1909856	-0.00191	0.000219	0.00531	0.727887	0.7269

Table 8. Calculation of demand by QANN-GA

2001	539	103	1648341	9095	0.5302	9105.125
2002	708	107	1675165	9412	0.549	9427.977
2003	740	109	1676113	9030	0.5235	8990.066
2004	780	110	1702541	9382	0.5467	9388.479
2005	860	115	1768052	9919	0.5756	9884.779
2006	960	117	1801972	10349	0.6019	10336.43
2007	1000	124	1839241	10912	0.633	10870.51
2008	1000	136	1872734	10520	0.6103	10480.68
2009	1080	151	1913697	11940	0.6962	11955.84
2010	1040	166	1972563	12625	0.7347	12617
2011	1073	163	1967024	10425	0.6078	10437.75
2012	1118	159	1932771	10085	0.5849	10044.49
2013	1161	157	1919531	10091	0.5887	10109.75
2014	1200	143	1874940	12301	0.714	12261.52
2015	1259	138	1909856	12500	0.7274	12491.64

Table 9. Agriculture sector electricity demand forecast

Year	Actual	ANN-PSO	QANN-P	ANN-GA	QANN-G	ARIMA	Linear	ANN-BP
2001	9095	9119	9102	9084	9105	9114	8635	9067
2002	9412	9411	9428	9394	9428	9050	9195	9435
2003	9030	9033	9016	9050	8990	9217	9223	9046
2004	9382	9411	9411	9359	9388	9321	9551	9377
2005	9919	9926	9926	9926	9885	10205	10240	9899
2006	10349	10338	10372	10321	10336	10497	10760	10344
2007	10912	10905	10939	10870	10870	10896	11011	10938
2008	10520	10527	10527	10510	10481	11094	10973	10499
2009	11940	11935	11952	11918	11956	11063	11116	11933
2010	12625	12639	12656	12639	12617	12027	11137	12648
2011	10425	10424	10441	10390	10438	11877	11257	10429
2012	10085	10080	10115	10063	10044	10773	11154	10081
2013	10091	10115	10132	10046	10110	11037	11179	10112
2014	12301	12279	12313	12313	12261	10680	11261	12301
2015	12500	12536	12468	12502	12491	12289	11895	12524

Table 10. Residential sector electric demand forecast

Year	QANN-G	ANN-GA	ACTUAL	QANN-P	ARIMA	ANN-PSO	Linear	ANN-BP
2001	174	171	173	175	201	175	134	172
2002	184	178	180	180	180	177	194	180
2003	183	195	190	191	147	189	189	190
2004	184	187	185	182	166	185	216	183
2005	196	190	190	187	185	190	221	190
2006	194	194	194	199	230	192	213	195
2007	219	219	216	211	216	217	247	216
2008	236	231	237	237	265	235	276	239
2009	400	402	403	402	374	404	309	400
2010	494	495	498	498	510	502	415	402
2011	506	511	509	510	512	511	494	329
2012	520	518	518	519	514	517	580	319

Table 11. Commercial sector electric demand forecast

Year	ANN-BP	Actual	ANN-GA	ANN-PSO	Q-ANN-G	Q-ANN-P	Linear	ARIMA
2001	974.97	978	979	970	979	980	1051	1054
2002	1032.02	1038	1039	1032	1032	1044	1070	1098
2003	1081.27	1080	1092	1096	1087	1070	1050	1087
2004	1097.65	1103	1104	1094	1102	1106	1087	1104
2005	1184.28	1179	1181	1175	1175	1178	1128	1136
2006	1217.75	1216	1217	1214	1216	1216	1178	1159
2007	1323.26	1331	1331	1338	1329	1329	1234	1204
2008	1337	1353	1363	1348	1358	1355	1303	1221
2009	1037.18	1043	1039	1037	1053	1044	1391	1290
2010	1589.04	1592	1599	1588	1590	1594	1499	1614
2011	1618.18	1611	1611	1621	1604	1609	1577	1629
2012	1725.58	1711	1705	1712	1705	1707	1636	1665
2013	1914.53	1917	1920	1935	1934	1915	1943	1925

Table 12. Industries sector electricity demand forecast

Year	Actual	ANN-PSO	Q-ANN-P	ANN-GA	Q-ANN-G	Linear	ANN-BP	ARIMA
2001	12085	12002	12143	12186	12114	10960	12025	11552
2002	12588	12528	12758	12607	12459	13364	12639	13894
2003	14168	14017	14004	14047	17127	17127	14323	16603
2004	14547	14568	14456	14499	14554	17240	14535	15943
2005	18001	17985	17947	17958	17959	18107	17929	17114
2006	20977	21018	20946	20857	20999	19010	21069	19083
2007	22948	23038	22825	22900	22888	19766	22837	20576
2008	23115	23137	23139	23319	23128	20867	23358	22164
2009	24849	24846	24667	24765	24815	22823	24950	23481
2010	25107	25093	25152	25225	24909	23711	24999	24674
2011	18186	18214	18183	18164	18119	23113	18142	23578
2012	21105	21021	21130	21080	21121	21792	21004	19338
2013	15605	15693	15655	15401	15619	15038	15407	15879
2014	15387	15444	15310	15442	15421	14654	15246	14696
2015	17072	16963	17182	17188	17029	18167	17138	17438

Table 13. Total electricity demand forecast

S.No	Year	Actual	ANN-PSO	ANN-GA	QANN-G	QANN-P	ARIMA	Linear
1	2001	36577	36456	35342	34483	36630	41525	37643
2	2002	38529	38041	57598	42589	38296	39275	40247
3	2003	46130	46323	35857	27580	46161	41540	42787
4	2004	49712	49898	72298	16331	49990	46339	45829
5	2005	51282	51678	30070	7127	51210	49769	48925
6	2006	49485	49478	28284	33230	49853	52421	51870
7	2007	56493	56725	45852	59521	56585	53798	54343
8	2008	53506	53167	44152	41971	53837	57398	57267
9	2009	57212	57113	48771	46144	57564	58432	59603
10	2010	60518	60585	40133	26584	60689	60480	62076
11	2011	61897	62044	61170	49578	62080	63373	64631
12	2012	66391	66274	48170	51588	66459	66397	67069
13	2013	72987	73224	36304	28095	73260	70177	69712
14	2014	74990	74704	45852	47724	74685	74547	72748
15	2015	77218	77181	73947	53408	77690	78158	75681

Accuracy Measures

The mean absolute percentage error (MAPE) and root mean square error (RMSE) measure the residual errors, which give a global idea of the difference between the predicted and actual values. In the present study, the RMSE, MAPE, have been used for comparison and have been defined as follows:

$$MAPE = \Sigma \left[\frac{\frac{Y_{actual} - Y_{estimated}}{Y_{actual}}}{n} \right] * 100$$

$$RMSE = \sqrt{\Sigma \frac{\left(Y_{actual} - Y_{estimated}\right)^2}{n}}$$

where Y_{actual}, $Y_{estimated}$ are the actual and estimated values and n is the number of observations.

Forecasts Comparisons

The results of ANN-PSO model in both linear and quadratic forms have been compared with ARIMA and linear models using RMSE and MAPE (Table 14). The hybrid ANN models (with PSO and GA optimisation) consistently outperform the ARIMA and linear models in all the sectors. ANN-PSO and ANN-GA models have better performance than ANN-BP which indicates that optimisation by PSO and GA improves the performance of ANN-BP. Amongst the four hybrid ANN models (ANN-PSO, ANN-GA, QANN-P and QANN-G), ANN-PSO is the best fit model in all the sectors based on RMSE and MAPE.

Table 14. Comparison of forecasts of various models for different sectors

S.no	Model	Agriculture Demand		Residential Demand		Commercial Demand		Industries Demand	
		RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1	ANN-PSO	16.95	0.12	1.94	0.17	59	0.29	59	0.29
2	ANN-GA	23.9	0.2	2.35	0.85	109.7	0.52	109.7	0.52
3	QANN-P	22.95	0.19	2.49	0.86	96.3	0.47	96.3	0.47
4	QANN-G	26.69	0.22	3.43	1.17	75.75	0.32	75.75	0.32
5	ANN-BP	61.39	0.15	162.24	40.3	119.2	0.57	119.2	0.57
6	ARIMA	724.7	4.92	22.56	17.25	1927	8.2	1927	8.2
7	LINEAR	738	617	46.83	13.34	2157	9.8	2157	9.8

Forecasting comparison of the total electricity demand is listed in Table 15. It is evident that QANN-P model outperforms other models in terms of RMSE and MAPE values. From Figure 2 it is evident that QANN-P aligns with the actual demand over the years 2001 to 2015.

Hence QANN-P is used to forecast the electricity demand for the years beyond 2015.

Table 16 lists the forecasts from the years 2001 to 2020 using QANN-P model and Figure 3 shows the profile of the projected demand using QANN-P model against the actual demand from the years 2001 till the year 2020.

CONCLUSION

ANN-PSO both in linear and quadratic form gives better results when compared with the ANN –BP or time series model such as ARIMA. As is seen in the five-time series the forecasting ability of ANN improves when optimized with PSO. Hence for power utilities in developing economies such as Tamil Nadu Generation and Distribution Company (TANGEDCO) both linear and quadratic versions of ANN-PSO models are ideal for forecasting electricity demand. For optimizing ANN, PSO performs better than GA hence PSO can be the better optimizing technique. For further studies a combined optimizing technique based on PSO and GA can be considered.

Table 15. Comparison of forecasts of total electricity demand

Error	ANN-BP	ANN-GA	QANN-G	ANN-PSO	QANN-P	ARIMA	Linear
RMSE	258.16	47.63	6256	236	65	2626	9398
MAE	198	15496	20,000	196	218.9	2108	2338
MAPE	0.72	27	34	0.37	0.38	4.22	4.28

Table 16. Forecasting electricity demand by QANN-P model

Year	P- Cap-En	Co-Pr-Ind	N-Cons	QANN-P
2001	554.6318	472.6592	1616811	36630
2002	586.9038	514.69	1637313	38296
2003	604.9707	527.9458	1657332	46161
2004	632.8892	550.1697	1699559	49990
2005	680.9822	598.7729	1703774	51210
2006	709.9936	644.1522	1726785	49853
2007	754.7332	658.1305	1764567	56585
2008	778.6538	680.9808	1766763	53837
2009	793.0188	716.231	1795486	57564
2010	823.5501	749.5662	1817832	60689
2011	831.9718	759.9379	1853117	62080
2012	856.7116	779.4751	1878436	66459
2013	901.9753	814.7637	1905657	73260
2014	922.002	835.0401	1923826	74685
2015	930.8125	851.1199	1966485	77690
2016	949.2263	859.4808	1995669	74204
2017	981.104	884.6208	2044049	76370
2018	1009.227	914.1552	2093418	78862
2019	1056.216	948.3732	2129758	81538
2020	1074.459	961.182	2159453	84714

Figure 2. Total demand by ANN-PSO models

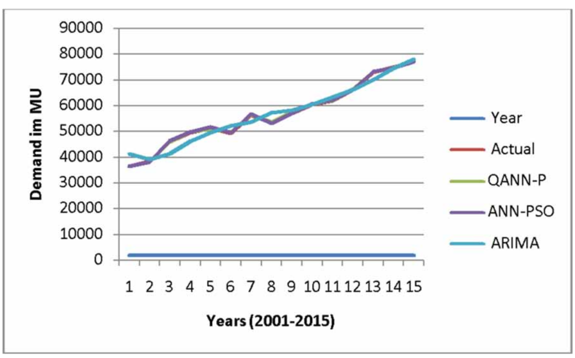
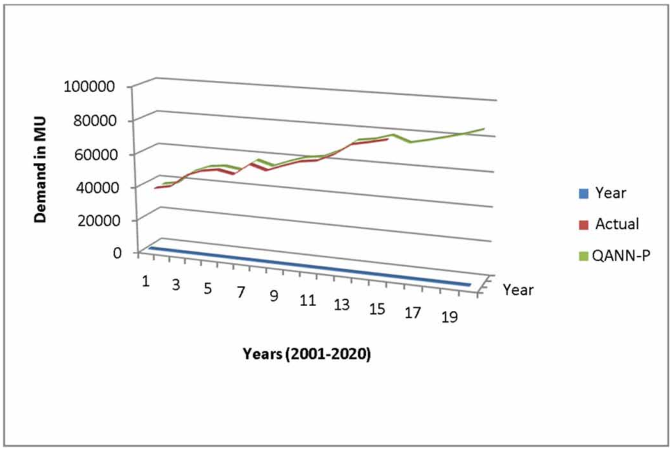


Figure 3. Comparison of QANN-PSO forecast with actual demand



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