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Article

Hybrid GA-PSO optimization of Artificial Neural Network for forecasting electricity demand

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Abstract

In the present study, a hybrid optimizing algorithm has been proposed using Genetic Algorithm (GA)and Particle Swarm Optimization (PSO) for Artificial Neural Network (ANN) to improve the estimation of electricity demand of the state of Tamil Nadu in India. The GA-PSO model optimizes the coefficients of factors of gross state domestic product (GSDP) , electricity consumption per capita, income growth rate and consumer price index (CPI) that affect the electricity demand. Based on historical data of 25 years from 1991 till 2015, the simulation results of GA-PSO models are having greater accuracy and reliability than single optimization methods based on either PSO or GA. The forecasting results of ANN-GA-PSO are better than models based on single optimization such as ANN-BP, ANN-GA, ANN-PSO models. Further the paper also forecasts the electricity demand of Tamil Nadu based on two scenarios. First scenario is the “as-it-is” scenario, the second scenario is based on milestones set for achieving goals of “Vision 2023” document for the state. The present research also explores the causality between the economic growth and electricity demand in case of Tamil Nadu. The research indicates that a direct causality exists between GSDP and the electricity demand of the state.

Keywords: Electricity Demand; ANN; PSO; GA; Hybrid Optimization; Forecasting

1. INTRODUCTION

Electricity reforms have liberalized the electricity sector in many countries.The salient features have been unbundling of generation, transmission and distributions entities; a competitive market with in countries and creation of an independent regulator for access to transmission infrastructure.

In the prevailing deregulated markets forecasting of electricity demand has emerged as a key research field. Many research tools and algorithms have been developed for electricity demand forecasting. The modeling techniques used so far can be divided into two categories : the parametric techniques and non parametric techniques. Studies using parametric techniques[1,2,3,4,5] such as Auto Regressive Integrated Moving Average (ARIMA), Exponential technique and Multiple Linear Regression are incapable of adapting to any type of environmental or social changes. A wide variety of models have been used for electricity demand modeling and forecasting based on time series techniques, support vector regression, expert systems and linear regression. However none of the methods can yield the results with desired accuracy for all the electricity demand forecasting problems because of their respective drawbacks. This shortcoming is overcome by applying non-parametric (artificial intelligence) based technique because of the potentiality to global search.

Cincotti .S et al [44] have highlighted the usability of computational intelligence for forecasting electricity prices. Among these artificial intelligence based methodology, artificial neural network (ANN) has emerged as one of the most prominent technique that has become very popular with the researchers. The ability to solve the complex relationships, adaptive control, decision making under uncertainty and prediction patterns makes ANN a powerful performer .This has led to the rapid developments of hybrid models.[1].Hybridization of different techniques with ANN has been successfully applied to both short term and long term energy demand forecasting. Hence, several variants of ANN which are generally hybridization of neural network with some learning techniques such as BP,GA and PSO are proposed by several researchers. The use of ANN with different optimization methods is also useful to forecast the electricity demand. Amjady.N and Keynia Farshid [46] presented a new short-term load forecast method which is a hybridization of a neural network with a novel stochastic search technique. According to them the modified harmony search algorithm can efficiently search the solution space in various directions thus avoiding being trapped in local minima and dead bands.

Hybrid ANN with Back Propagation (BP) algorithm has been considered as the conventional training of neural network for load forecasting problems. Yin F, Wang J and Guo C [47] have used similarity degree parameter to identify the appropriate historical load data as training set of neural network . A neural network with back propagation momentum training algorithm was also proposed in the aforementioned paper for load forecasting in order to reduce training time and to improve convergence speed. M.B. Abdul Hamid and T.K. Abdul Rahman [6] presented an Artificial Neural Network (ANN) trained for short term load forecasting model. This algorithm has specific benefits such as accuracy, speed of convergence, economic and historical data requirement for training etc. The major benefit of this algorithm over back propagation algorithm is in terms of improvement in mean average percentage error (MAPE).

Hybrid ANN with Genetic Algorithm (GA) optimization forecasting models have wide range of applications.GA is based on random search and optimization techniques guided by the principles of evolution and natural genetics. According to Goldberg[7], they are efficient, adaptive and robust search processes and produce near optimal solutions. GA is used for optimizing the weights of different demand equations using available data based on economic indicators. Canyurt et al [8] studied the future residential energy demand and total energy demand of Turkey based on various economic indicators. GA is used for energy demand model in linear, quadratic or exponential forms.Researchers such as Ceylon and Ozturk [9] , Haldenbilen and Ceylon [10] studied total energy demand of Iran and transport energy demand in the same way. Assarch et al [11] applied GA techniques to estimate the oil demand in Iran, based on socio-economic indicators in which the models are developed in exponential and linear forms.

Hybrid ANN optimized with PSO has been successfully applied for load forecasting. Tian Shu et al [14] have developed a new training method of radial basis function (RBF) neural network, based on quantum behaved PSO. Ning Lu et.al [15] have proposed the PSO based RBF neural network model for load forecasting . Yang Shang Dong et al[16] proposed a new PSO algorithm with adaptive inertia weight factor and incorporated Chaos with PSO. Ellen Banda and Komla A. Folly [23] have presented that the traditional load forecasting tools utilize time series models which extrapolate historical load data to predict the future loads. These tools assume a static load series and retain normal distribution characteristics. Due to their inability to adapt to changing environments and load characteristics, they often lead to large forecasting errors. In an effort to reduce the forecasting error, they have hybrid artificial neural network (ANN) and particle swarm optimization (PSO) is used in their paper. It is shown that the hybridization of ANN and PSO gives better results compared to the standard ANN with back propagation.

GA-PSO hybrid algorithm integrates the advantages of individual models, which was first proposed by Bates and Granger[17]. In the paper they have demonstrated that an appropriate linear combination of two forecasting models may yield better results than the individual models. For their application in electricity domain, Nazari et al [18] proposed a model using GA and PSO for forecasting energy demands of residential and commercial sectors in Iran. They studied the linear and exponential states using a genetic algorithm and PSO algorithm. According to their results, the exponential model derived from the PSO model is the best model. Unler[19] has proposed improvement of energy demand forecasts using swarm intelligence in the case if Turkey. He proposed a model using PSO-based energy demand forecasting to forecast the energy demand of Turkey. He argued that gross domestic product (GDP), population, import and export are useful basic energy indicators of energy demand. Younes M et al [20] provided a solution to the economic dispatch problem using a hybrid method genetic algorithm-particle swarm optimization (GA-PSO). They found that GA-PSO provides flexibility fast convergence ,less computational time for non linear characteristics of power systems. Araby EE El et al [21] developed a hybrid PSO technique for ancillary service in the deregulated electricity markets. They proposed that a two layered hybrid PSO-SLP (Successive Linear Programming) approach is suitable for non differentiable and discontinuous objective functions. Anwar Jarndal and Sadeque Hamdan [22] have described a combined approach of artificial neural networks (ANN) with particle-swarm-optimization (PSO) and genetic algorithm optimization (GA) for short and mid-term load forecasting .The model identifies the relationship among load, temperature and humidity using a case study of Sharjah City in United Arab Emirates. Linli J and Jiansheng W [24] have investigated the effectiveness of the hybrid Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) for optimizing neural network for rainfall forecasting. They have developed a hybrid Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) model for the automatic design of ANN by evolving to the optimal network configuration(s) within an architecture space, namely PSOGA-NN.The PSO is carried out as a main frame of this hybrid algorithm while GA is used as a local search strategy to help PSO jump out of local optima and avoid sinking into the local optimal solution early. The experimental results show that the GA-PSO-NN evolves to optimum or near--optimum networks in general and has a superior generalization capability with the lowest prediction error values . Experimental results reveal that the predictions using the GA-PSO-NN approach can significantly improve the forecasting accuracy.

The remainder of the paper is organized as follows: Section 2 introduces the Electricity sector in Tamil Nadu; Section 3 presents methodology used for research ; Section 4 shows the features of ANN-GA-PSO models; Section 5 brings out the results and discussion; Section 6:Conclusions.

2. The Tamil Nadu Electricity Sector

For the last many decades the energy sector has been the prime mover of the economy. Growth in the manufacturing sector was aided by sufficient availability of power. Till about a decade ago, the state had surplus electricity. However, availability of power has not kept pace with the increased industrial activity and the increased demand from the domestic consumer segment resulting in large deficit in power availability over the last few years. It can be observed from the Table 1 that the generation capacity has not kept pace with

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the electricity consumption which has increased significantly over the last many years. The state has resorted to buying power through short term contracts to tide over the shortage. This has increased the cost of power purchase for the state which is one of the reasons for the poor financial conditions of the state power utilities. The electricity demand -supply gap in Tamil Nadu is fairly high. According to Central Electricity Authority (CEA), the electricity deficit of the state in the year 2013 was around 17.5% as compared to 2.8% in the year 2008. Hence there is a dire necessity to forecast the electricity demand by the year 2023 to facilitate the investments in the sector.

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Table 1: Key electricity demand determinants

Year	Electricity (kWr) Consumption	Income Growth rate per capita(%)	GSDP (Billion Rs	Price Index	Demand (in mWh)
1991	295	10.97	4.81	48	17173
1992	303	11.9	5.27	55	19130
1993	334	12.9	5.74	65	20289
1994	350	13.9	6.2	79	23193
1995	421	14.8	6.6	82	24610
1996	435	15.7	7.1	85	25805
1997	449	16.8	7.5	89	26943
1998	459	17.9	8	92	27862
1999	496	18.8	8.5	94	30434
2000	510	14.7	10.9	101	33418
2001	539	15	10.88	103	36578
2002	708	15.2	15.01	107	38529
2003	740	15.3	17.56	109	46130
2004	780	15.5	18.66	110	49712
2005	860	17.23	17.73	115	51282
2006	960	19.99	20.44	117	49485
2007	1000	12.58	12.98	124	56493
2008	1000	13.73	14.4	136	53506
2009	1080	18.83	19.53	151	57212
2010	1040	17.27	18.07	166	60518
2011	1074	18.06	16.7	163.02	61897
2012	1118	18.29	17.66	159.01	66391
2013	1161	16.3	19.98	157.39	72987
2014	2130	17.89	42.27	143.52	74990
2015	2007	12.94	38.45	138.77	77218

2.1 Factors affecting Electricity demand

Electricity consumption of a state is a function of man affecting factors such as gross state domestic product (GSDP), consumer prices index, energy per capita and income parameters. The following factors reflect their major impacts on electricity demand :--

(1) **GSDP** : Even though the linkage between GSDP growth and electricity demand growth are not as strong as it was in the past, it is worth considering the impact on the society of high GDP

growth itself since they are linked to each other. A high GSDP growth rate year after year means higher manufacture of products and provision of services at an unprecedented pace leading to higher electricity demand. The electricity demand continue to grow in the state because of high level to continue in a business as usual scenario.

(2) **Electricity consumption per capita (E.Con)** has increased from 510 kWh in year 2000-01to 1,065 kWh in 2011-12 which is more than 100% increase. Hence per capita consumption has been taken as an independent factor.

(3) **Income growth rate (per capita)** : The vision 2023 document of the state of Tamil Nadu aims at doubling the per capita income by 2023. It is also seen that any increase in family income leads to spurt in consumption.

(4) Consumer Price Index (CPI) : Prices have an indirect impact on the electricity demand by affecting the purchase of luxury goods such as air conditioners, washing machines etc.

3. Methodology

In this section ,the electricity demand is modeled by ANN that is optimized by hybrid GA-PSO algorithm in the linear and quadratic forms. The results of ANN-GA-PSO and A-G-P-Q are compared with ANN with single optimization with GA and PSO algorithms.

3.1 Artificial Neural Network

ANN is a highly connected array of elementary processors called neurons . It resembles its origin from human brain that has large number of neurons interconnected in a highly complex, non linear and forming highly massive parallel network. An artificial neural network (ANN) with an input layer, one or more hidden layer and one output layer is known as multilayer perceptron (MLP). Each layer consists of several neurons and each neuron in a layer is connected to adjacent layer with some weights known as synaptic weights. We have considered a multi layer perceptron (MLP) that has three neurons layers [44] . While the first one is the input layer that is in the direct contact with the input data. The middle one is called the hidden layer and it has no contact with outside system. It connects data from the input layer and sends them to the next layer. The last one is the output layer that sends out results. Table 2 gives the network information of ANN about the input layer that is made up of four factors namely, electricity consumption(E.Con), income growth rate, GSDP and Consumer price index . The hidden layer has been used as the activation function. The output layer comprises of one unit representing electricity demand as the dependent variables. The in-sample data is split into two subsets, namely, the training set and the validation set. The training set is then used to train ANN-GA-PSO models till the training error ratio criterion of 0.001 is achieved. The Table 3 shows the sum of squares error, relative error, stopping rule and the training time of the ANN.

Table 2: ANN-GA-PSO Network Information

Input Layer	Factors	1	E.Con (electricity consumption)
		2	Income growth rate
		3	GSDP
		4	CPI
	Number of Units		59
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1		6
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	Electricity Demand
	Number of Units		1
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares

Table 3 : Model Summary : ANN-GA-PSO

Training	Sum of Squares Error	.004
	Relative Error	.001
	Stopping Rule Used	Training error ratio criterion (.001) achieved
	Training Time	0:00:00.23

3.2 PSO

Particle swarm optimization is a population based derivative free algorithm developed by Kennedy and Eberhart in 1995 [12]. A variant of the PSO method was developed by Shi and Eberhart in [13] in which a modification of the speed equation improves the convergence by inserting a time dependant variable.

$v_{t+1}=v_t+R_1*C_1*(g-x_t) +R_2*C_2*(p-x_t)$…………………………. (1)

$x_{t+1}=x_t+v_{t+1}$ ……………………………………………………………… (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”. This equation reveals the particle leader location to each particle. Decreasing the variable enables the slowing down of the speed of the particles around the leader location and provides a balance between exploration and exploitation. PSO finds an optimal point from the random set of points with the help of a fitness function, so that the random points are initialized between the ranges of values of the past two years which might find the point that matches the straight line formed by the data. This new point is the predicted value for the next year. This stochastic search based algorithm is successfully applied to some real time optimization problem in different emerging fields Tian Shu et al [14] have developed a new training method of radial basis function (RBF) neural network, based on quantum behaved PSO .Ning Lu et.al [15] have proposed the PSO based RBF neural network model for load forecasting .Yang Shang Dong et al[16] proposed a new PSO algorithm with adaptive inertia weight factor and incorporated Chaos with PSO. Particle swarm optimization (PSO) is a computational method that optimizes a problem by improving a solution with regard to a given measure of quality. It solves a problem by having a population of particles and moving these particles around in the search space according to a simple mathematical formula over the particle's position and velocity. Each particle's movement is influenced by its local best known position, but is also guided toward the best known positions in the search-space, which are updated as better positions are found by other particles. This is expected to move the swarm toward the best solutions . PSO is the metaheuristic optimization technique that makes few or no assumptions about the problem being optimized.

GA-PSO hybrid algorithm that integrates the advantages of individual models was first proposed by Bates and Granger[17]. In the paper they have demonstrated that an appropriate linear combination of two forecasting models may yield better results than the individual models. In addition, the hybrid model has the similar nature of the combined model. For their application in electricity domain, Nazari et al [18] proposed a model using two metaheuristic algorithms, namely GA and PSO for forecasting energy demands of residential and commercial sectors in Iran. They studied the linear and exponential states using a genetic algorithm and PSO algorithm. According to their results, the exponential model derived from the PSO model is the best model. Unler[19] has proposed improvement of energy demand forecasts using swarm intelligence in the case if Turkey. He proposed a model using PSO-based energy demand forecasting to forecast the energy demand of Turkey. He argued that gross domestic product (GDP), population, import and export are useful basic energy indicators of energy demand. Younes M et al [20] provided a solution to the economic dispatch problem using a hybrid method genetic algorithm-particle swarm optimization (GA-PSO). They found that GA-PSO provides flexibility fast convergence ,less computational time for non linear characteristics of power systems. Araby EE El et al [21] developed a hybrid PSO technique for ancillary service in the deregulated electricity markets. They proposed that a two layered hybrid PSO-SLP (Successive Linear Programming) approach is suitable for non differentiable and discontinuous objective functions. Anwar Jarndal and Sadeque Hamdan [22] have described a combined approach of artificial neural networks (ANN) with particle-swarm-optimization (PSO) and genetic algorithm optimization (GA) for short and mid-term load forecasting . The model identifies the relationship among load, temperature and humidity using a case study of Sharjah City in United Arab Emirates. They have found that ANN is one of the powerful artificial intelligence techniques for load forecasting which is independent of the human experience. Linli J and Jiansheng W [24] have investigated the effectiveness of the hybrid Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) for optimizing neural network for rainfall forecasting. They have developed a hybrid Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) model for the automatic design of ANN by evolving to the optimal network configuration(s) within an architecture space, namely PSOGA-NN. The PSO is carried out as a main frame of this hybrid algorithm while GA is used as a local search strategy to help PSO jump out of local optima and avoid sinking into the local optimal solution early. The experimental results show that the GA-PSO-NN evolves to optimum or near--optimum networks in general and has a superior generalization capability with the lowest prediction error values . Experimental results reveal that the predictions using the GA-PSO-NN approach can significantly improve the forecasting accuracy.

When ANN is optimized by a single optimization methods such as GA or PSO then it suffers from well known drawbacks. In the present study ,we propose a hybrid algorithm called GA-PSO, which lead to better optimization results. In order to better optimize the coefficients, an effective hybrid optimization algorithm was developed based on GA and PSO which can fully combine the merits of single optimization models without their respective drawbacks. In order to test the accuracy of the models, we have compared the forecast results of ANN-GA-PSO models with other models using single optimization of ANN by GA, single optimization of ANN with PSO, ANN with backward propagation, ARIMA, HOLTS and linear regression. In order to test the accuracy of the models we have compared the mean absolute percentage error (MAPE) as a measure of quality in prediction. It is worth mentioning that , for the sake of comparison among different techniques electricity demand is derived using the same for all the modeling methods. Results point out that ANN optimized by both GA-PSO in quadratic form (A-G-P-Q) gives the best performance followed by ANN-G-P model. Consequently A-G-P-Q model is used to forecast the electricity demand till 2025 based on " as-it-is" scenario and scenario as per the "Vision document " of the state.

4. ANN-GA-PSO models

In order to forecast Tamil Nadu's electricity demand efficiently and precisely a hybrid GA-PSO based ANN model is proposed here in two form estimation method.

4.1 Two form estimation method

The authors have used the following equations for the GA-PSO optimization :--

$$D_{GA-pso-linear} = \sum_{i=1}^{M} (W_i * X_i + W_o) \quad .... (3)$$

$$D_{GA-Pso-Quadratic} = \sum_{i=1}^{M}(W_i * X_i + W_o + \sum_{i=1}^{M}(K_{ij} * X_i * X_j) + \sum_{i=1}^{M}(U_i * X_i^2)$$

.... (4)

where D is the electricity demand ;

X_i , X_j are the factors affecting i^{th} and j^{th} factors affecting electricity energy demand ; W_o , W_i, k_{ij} and U_i are the coefficients and M is the number of demand -affecting factors.[25]

PSO searches for the most fitted members by minimizing the error. PSO optimizes the weights of socio economic indicators by using both linear and quadratic regression models. Based on this two variations of PSO, models have been named ANN-PSO (Linear) and ANN-PSO (Quadratic) respectively **.** In PSO-Quadratic**,** the coefficients of the input variables are calculated as per the equation (4). 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 (1) and the evolution equations become

v_{t+1}=v_t+R_1*C_1*sign (g-x_t)*(g-x_t)^2 +R_2*C_2*sign (p-x_t)*(p−x_t)^2 .... (5)

x_{t+1}=x_t+v_{t+1} ……………………………………………………………………..(6)

Therefore, the Quadratic PSO algorithm based on the evolution equations (5) and (6) 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.

In GA operators ,N is the number of the individuals in the population ; f_i is the fitness value for the individual *i* . The population size particles are reproduced on the position of the particles using the following equation .

$$p_i = f_i / (f_s - f_{\max})$$

where f_{max} is the largest fitness value in the generation, p_i is the probability for the selection of the individual i. The crossover and the mutation operations are implemented with p_i and p_m according to following equations :--

$$X_A^{t+1} = \propto * X_B^t + (1-\propto) * X_A^t$$

$$X_A^{t+1} = \propto * X_A^t + (1-\propto) * X_B^t$$

where X_A^t *and* X_B^t are cross over chromosomes. $\propto$ is a parameter that is constant .

4.2 GA-PSO Hybrid optimization algorithm

The iterative approach of GA- 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.

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.

step 3: Evaluate the desired optimization fitness function *f(x) p* for each particle as the Sum of Square Error over a given data set.

step 4: Compare the evaluated fitness value *fp* of each particle with its *pbest* value.

If *fp* < *pbest* then *pbest* = *fp* 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). Fly each particle p accordingly. The best position is fed into the General Algorithm as selection.

step 7 : If the maximum number of a predetermined iterations is exceeded, then stop; otherwise Loop to step 3 until convergence. In the present study the convergence occurs around 50 iterations as shown in Fig 2.

Step 8 : The pop_size of M particles obtained by GA and M particles are combined to form new pop_size particles.

step 9 : Let $g_{en} = g_{en} + 1$, then step 3 is carried out.

step 10 : The best fitness values and solutions, namely , the position are outputted.

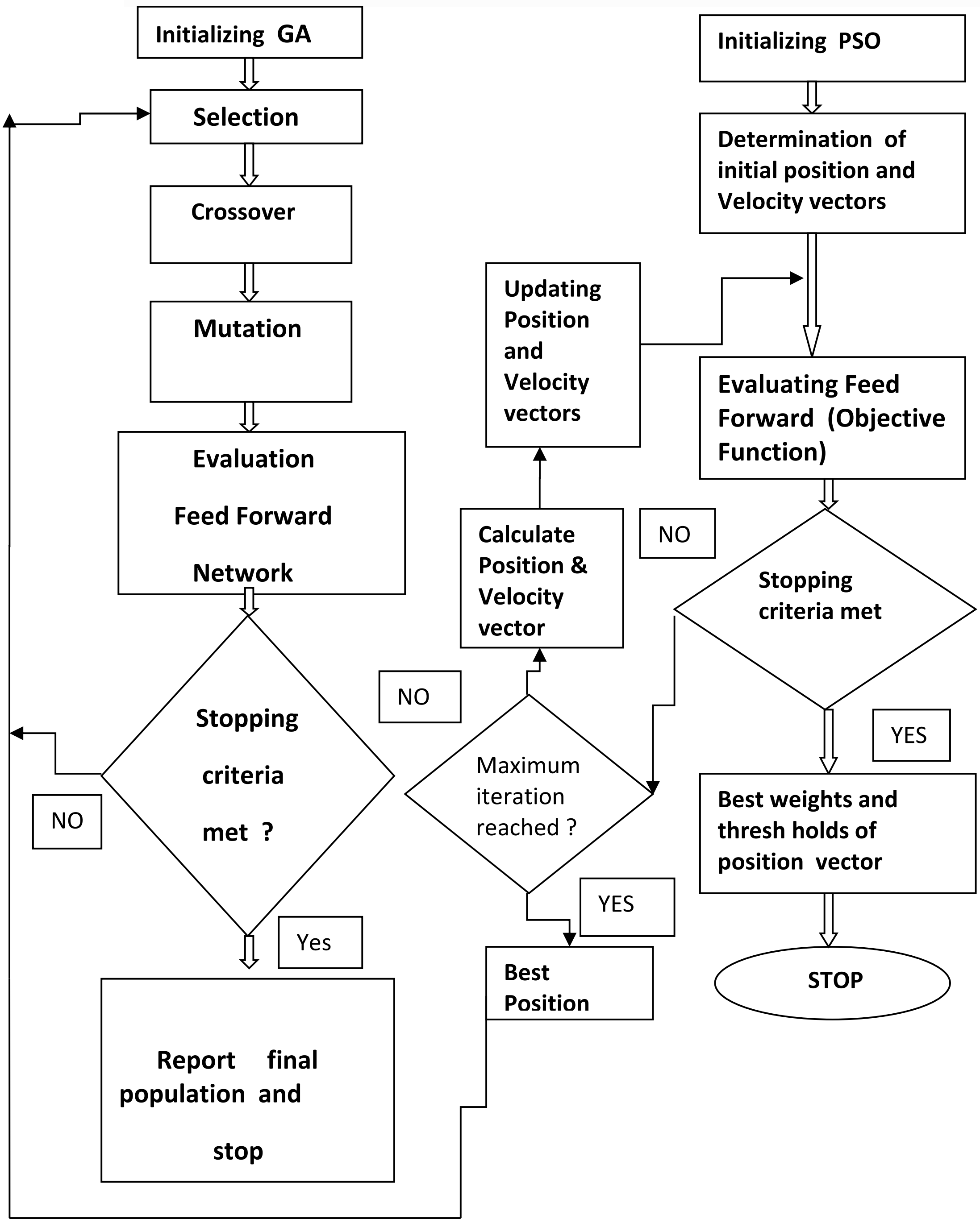

Fig 1: Flowchart of ANN-GA-PSO

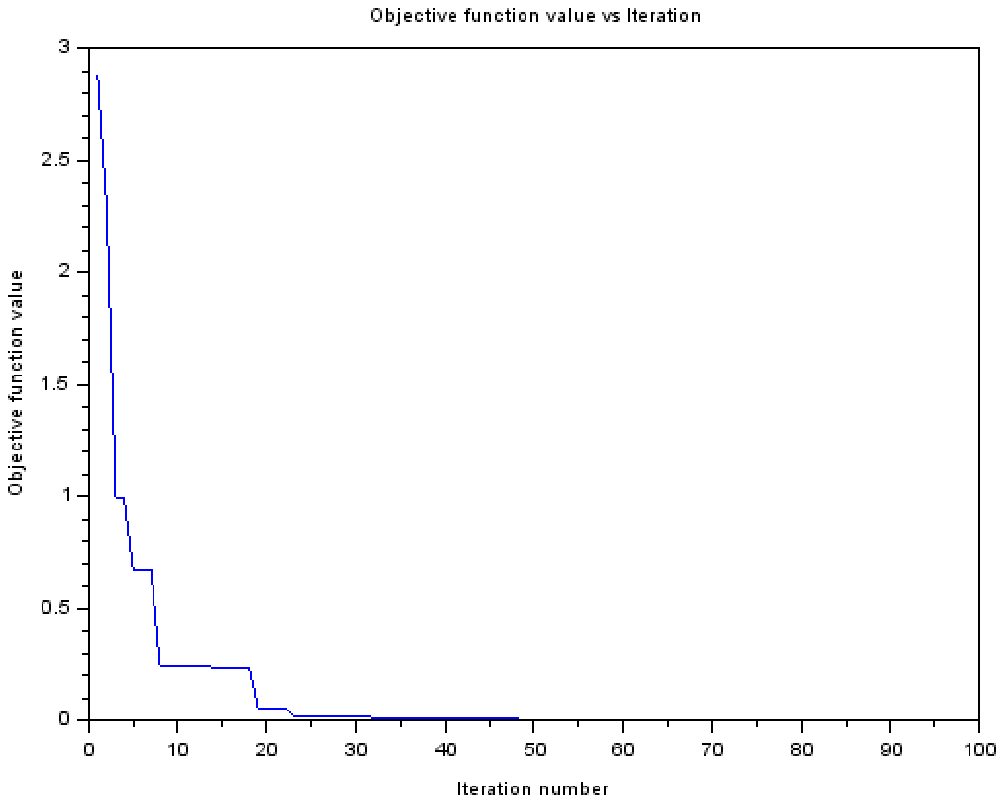

Figure 2: Convergence Speed of ANN-GA-PSO algorithm

4.3 Computational environment and data management

All the GA and PSO techniques have been developed in open source SCILAB environment. For application of ARIMA ,HOLTS and Linear models standard econometric tool boxes have been used. IBM SS Software version 2 has been used for ANN simulation. It is designed to provide the necessary tools as a part of standard ANN algorithms and relevant analysis. In this research study the GSDP data is measured in rupees and per capita energy intensity in KWh. The coefficients of predictors as obtained from GA-PSO optimization are depicted in Table 4. The factors are normalized according to the following equation for optimum functioning of ANN.

n(x)= (x-xmin)/xmin ....(7)

Table 4 shows the relative values of the independent variables GA-PSO optimization that are used for ANN simulation where E.Con, Income, GSDP, CPI are the input variables. Table 5 indicates the coefficients of equation 3 by using GA-PSO optimization

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Table 4: Normalized Values of GA-PSO-Quadratic

Year	E.Con	Income	GSDP	CPI	Sq-E.Con	Sq-Incom	Sq-GSDP	Sq-CPI
2001	0	0.153846	0	0	0	0.023669	0	0
2002	0.313544	0.153846	0.363636	0.038835	0.09831	0.023669	0.132231	0.001508
2003	0.372913	0.153846	0.636364	0.058252	0.139064	0.023669	0.404959	0.003393
2004	0.447124	0.230769	0.727273	0.067961	0.19992	0.053254	0.528926	0.004619
2005	0.595547	0.307692	0.636364	0.116505	0.354677	0.094675	0.404959	0.013573
2006	0.781076	0.538462	0.818182	0.135922	0.61008	0.289941	0.669421	0.018475
2007	0.855288	0	0.181818	0.203883	0.731517	0	0.033058	0.041568
2008	0.855288	0.076923	0.272727	0.320388	0.731517	0.005917	0.07438	0.102649
2009	1.003711	0.461538	0.818182	0.466019	1.007435	0.213018	0.669421	0.217174
2010	0.929499	0.307692	0.636364	0.61165	0.863969	0.094675	0.404959	0.374116
2011	0.992579	0.384615	0.545455	0.582524	0.985213	0.147929	0.297521	0.339335
2012	1.074212	0.384615	0.636364	0.543689	1.15393	0.147929	0.404959	0.295598
2013	1.153989	0.230769	0.818182	0.524272	1.33169	0.053254	0.669421	0.274861
2014	2.953618	0.384615	2.818182	0.398058	8.723858	0.147929	7.942149	0.15845
2015	2.723562	0	2.454545	0.349515	7.417791	0	6.024793	0.12216
2016	3.022263	0.153846	2.909091	0.38835	9.134076	0.023669	8.46281	0.150815
Year	X12	X13	X14	X23	X24	X32	X34	Demand
2001	0	0	0	0	0	0	0	0
2002	0.048237	0.055944	0.012176	0.055944	0.005975	0.055944	0.014122	0.053338
2003	0.057371	0.097902	0.021723	0.097902	0.008962	0.097902	0.03707	0.261141
2004	0.103183	0.167832	0.030387	0.167832	0.015683	0.167832	0.049426	0.359068
2005	0.183245	0.195804	0.069384	0.195804	0.035848	0.195804	0.074139	0.40199
2006	0.420579	0.440559	0.106166	0.440559	0.073189	0.440559	0.111209	0.352862
2007	0	0	0.174379	0	0	0	0.03707	0.544453
2008	0.065791	0.020979	0.274024	0.020979	0.024645	0.020979	0.087379	0.462792
2009	0.463251	0.377622	0.467749	0.377622	0.215086	0.377622	0.381289	0.56411
2010	0.286	0.195804	0.568529	0.195804	0.1882	0.195804	0.389232	0.654492
2011	0.381761	0.20979	0.578201	0.20979	0.224048	0.20979	0.317741	0.692192
2012	0.413158	0.244755	0.584037	0.244755	0.209111	0.244755	0.345984	0.815053
2013	0.266305	0.188811	0.605004	0.188811	0.120986	0.188811	0.42895	0.99538
2014	1.136007	1.083916	1.175712	1.083916	0.153099	1.083916	1.121801	1.050139
2015	0	0	0.951925	0	0	0	0.857899	1.11105
2016	0.464964	0.447552	1.173695	0.447552	0.059746	0.447552	1.129744	1.211196

Table 5: Coefficients of GA-PSO Linear

Year	E.Con	Income	GSDP	CPI	x1	x2	x3	x4	x5
2016	2167	14.88	43.06	142.9	-1.93	0.91	-1.005	-1.63	-1.14
2017	2341	17.11	48.23	147.22	-1.94	0.54	-1.56	-0.41	-1.25
2018	22	19.68	54	151.64	-1.98	-0.1	-0.179	-1.64	-1.12
2019	2730	22.63	60.5	156.19	-2	0.39	-1.05	-0.86	0.77
2020	2949	26.03	67.76	160.87	-2	-1.4	-0.68	-0.76	0.99
2021	3185	29.93	75.89	165.7	-1.99	0.19	-1.58	-1.23	-0.63
2022	3439	34.4	85	170.7	-2	-1	-1.95	-1.2	-0.31
2023	3715	39.58	95.2	175.8	-1.99	0.28	0.28	-1.71	0.62
2024	4012	45.52	106.6	181	-2	0.41	-0.9	-0.21	-0.49
2025	4333	52.35	119.42	186.5	-2	-1.26	0.127	-0.76	0.03

4.4 Evaluation of the forecast performance

Root Mean Square Error (RMSE) or Mean Absolute Error (MAE) are commonly used as a measure of forecasting performance. However ,Fatai and Armstrong have negated RMSE or MAE as both are scale dependent and RMSE is affected by outliers that are common in electricity forecasting. Weron Rafal [45] have asserted that MAPE is the most popular evaluation index that works well in load forecasting. Therefore in order to compare predictive accuracy of the ANN-GA-PSO models, we have used mean absolute percentage error (MAPE) as the evaluation index. The MAPE and forecasting accuracy (τ) have been defined as follows :

$$\text{MAPE} = \frac{100}{n} \sum_{t=1}^{n} \left| {(A_t - F_t)}/{A_t} \right|$$

$$\tau = 1 - \left| {(A_t - F_t)}/{A_t} \right| \quad \text{if} \quad \left| {(A_t - F_t)}/{A_t} \right| < 1$$

$$\tau = 0 \quad \text{if} \quad \left| {(A_t - F_t)}/{A_t} \right| \geq 1$$

where A_t is the actual value and F_t is the forecast value.

The total electricity demand of Tamil Nadu from year 2001 to 2015 haas been used as a benchmark to test the effectiveness and superiority of the proposed ANN-GA-PSO models. First, ARIMA (1,0,1) ,HOLTS and linear models have been employed to calculate

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electricity demand . Secondly the simple optimization of ANN is performed by GA and PSO separately and the results are tabulated under ANN-GA and ANN-PSO respectively. The optimum weight coefficients of GA-PSO optimization are obtained from equation 3 and equation4 for ANN-GA-PSO in linear and quadratic forms respectively. For the sake of verifying the validity and superiority of the proposed ANN-GA-PSO models the comparison is also made with ANN-BP model.

5. Results

Table 6 and Fig 3 shows results of ANN-G-P and A-G-P-Q models in both linear and quadratic forms along with simple optimization models ,ANN-PSO and ANN-GA. Fig 4 compares the errors of linear , Time series models (Holts and ARIMA), ANN-GA, ANN-PSO, ANN-G-P and A-G-P-Q models. Table 7 and Fig 5 compares the MAPE values of different models. It can be seen that MAPE of A-G-P-Q (0.2%) and ANN-G-P (0.3%) are far better than single optimized models of ANN-GA (0.42%) and ANN-PSO(0.4%).Table 8 depicts the forecasting accuracy (τ) of different models. It is clear that τ of A-G-P-Q model at 0.78 followed by ANN-G-P at 0.7 are far superior to single optimization models. Figure 6 compares the result of the ANN-G-P (Linear) and A-G-P-Q (Quadratic) model against the actual values of the electricity demand from the year 2001 to 2015. ANN-G-P and A-G-P-Q are in close agreement with the actual values. The forecasts of A-G-P-Q are compared with actual demand on a logarithmic scale in Fig 7. It is seen that the relationship between the two is linear and the slope is 0.99. Thus A-G-P-Q model is best suited for forecasting the electricity demand for the year 2016 to 2025.

Table 6: Performance of different models

Year	ActTotal	ANN-pso	Linear	Holts	ANN-BP	ANN-G-P	ARIMA	ANN-GA	A-G-P-Q
2001	36578	36206	39441	37643	36434	36705		36018	36582
2002	38529	38302	43532	40247	38987	38854	39876	38618	38827
2003	46130	46180	44614	42787	46337	46109	43671	46192	46238
2004	49712	50054	45595	45829	49786	49484	49214	49323	49731
2005	51282	51007	48299	48925	51254	51540	51458	51179	51611
2006	49485	49394	50630	51870	49643	49949	52069	49707	49640
2007	56493	56927	53094	54343	56282	56546	53244	56795	56586
2008	53506	53257	56060	57267	53719	53792	56676	53201	53404
2009	57212	57172	61235	59603	57404	57720	58214	57303	57383
2010	60518	60737	64208	62076	60205	60465	62391	60302	60522
2011	61897	62353	64090	64631	62098	61757	64313	62024	62011
2012	66391	66593	63920	67069	66515	66282	65730	66713	66378
2013	72987	73023	64302	69712	72635	73126	69779	73164	73160
2014	74990	74890	78675	72748	74464	75084	72866	74898	75109
2015	77218	77285	75235	75681	77818	76870	78189	76930	77242

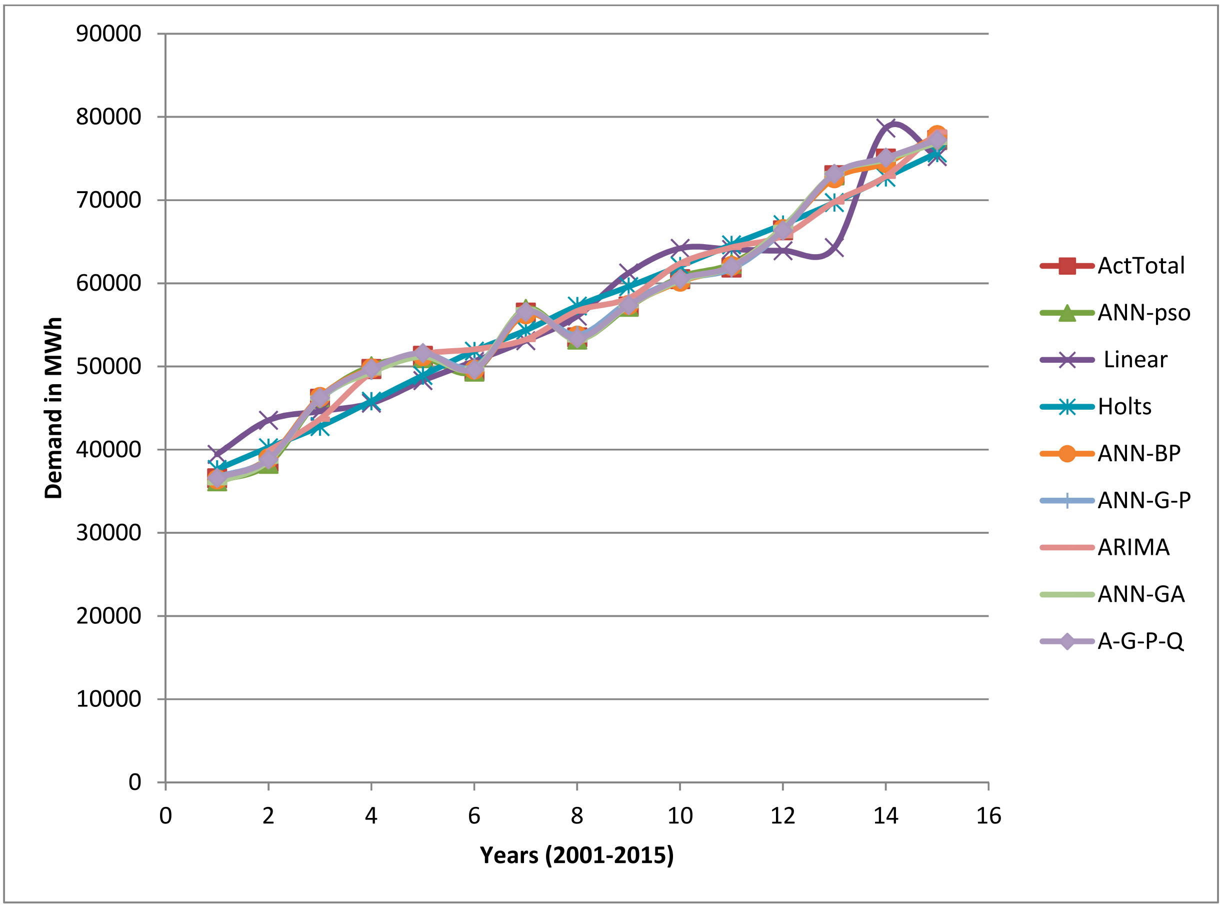

Fig 3: Performance of models

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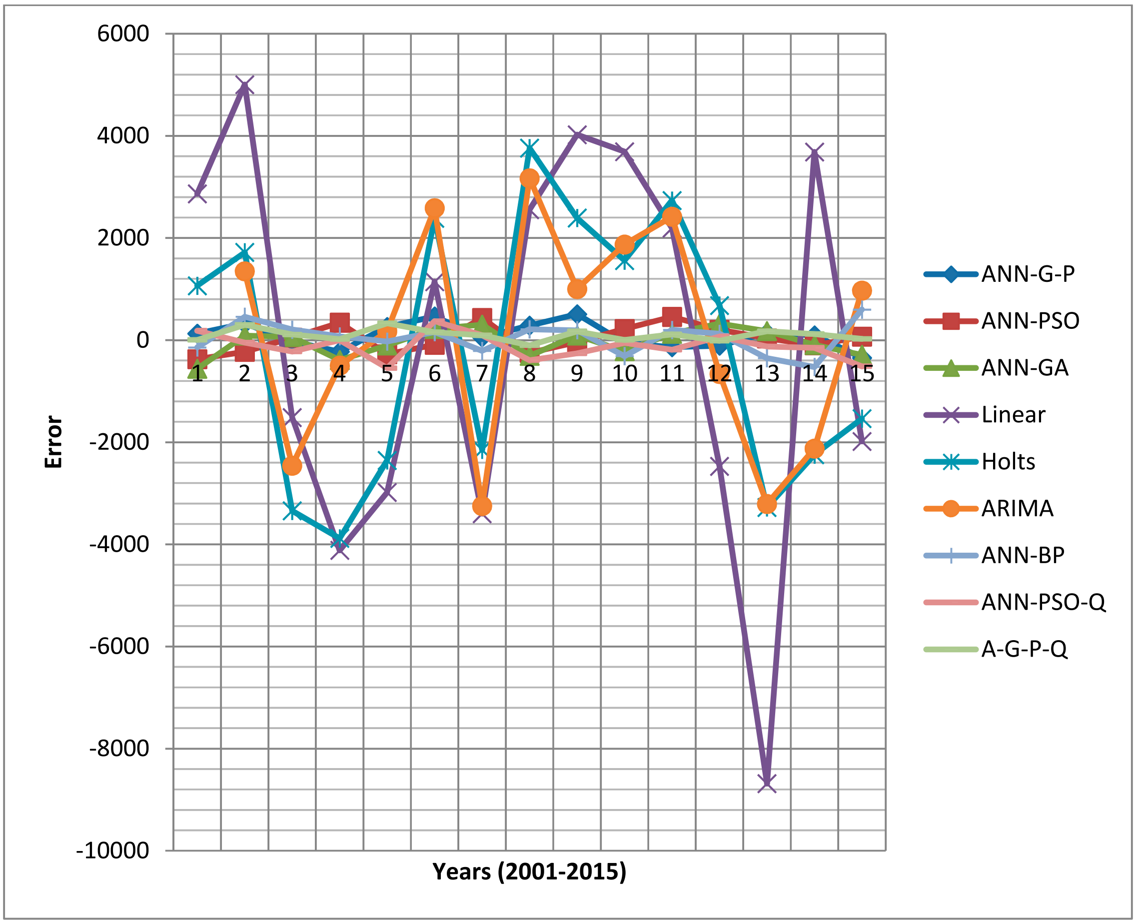

Fig 4: Error comparison of various models

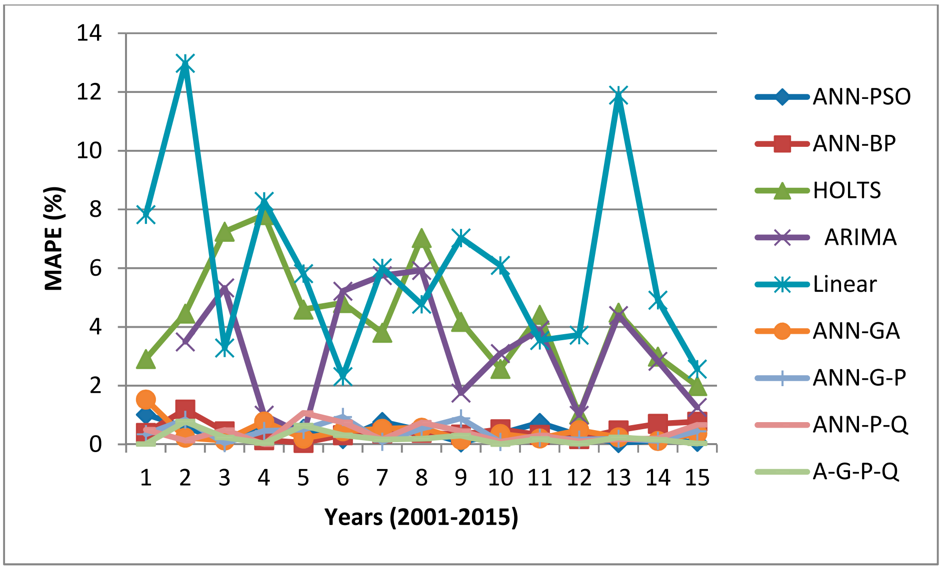

Fig 5: MAPE (in %)

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Table 7: MAPE VALUES (%)

Linear	Holts	ARIMA	ANN-BP	ANN-GA	ANN-P	ANN-G-P	A-G-P-Q
6.07	0.85	3.02	0.44	0.42	0.4	0.3	0.22

Table 8: Forecasting Accuracy (τ)

Linear	Holts	ARIMA	ANN-BP	ANN-GA	ANN-P	ANN-G-P	A-G-P-Q
0	0.15	0	0.56	0.58	0.6	0.7	0.78

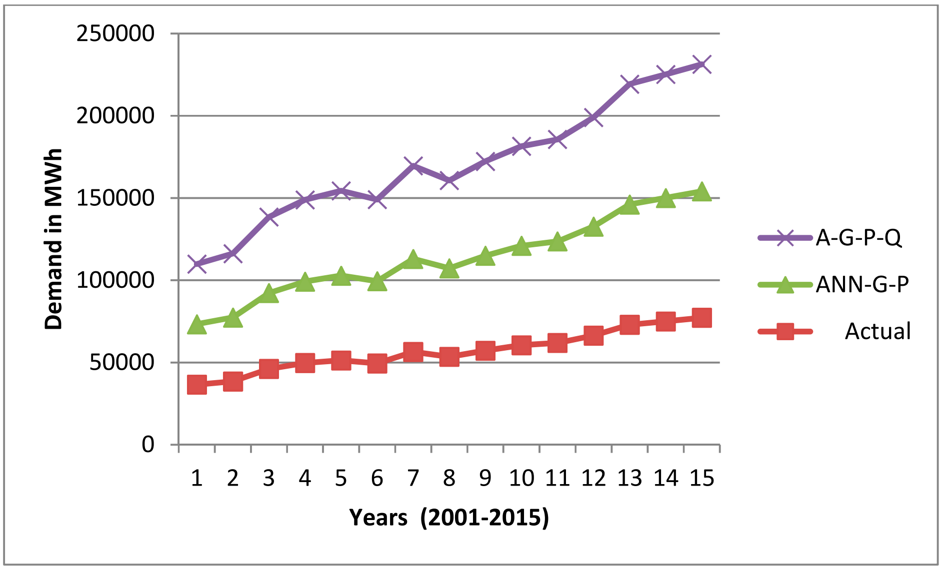

Fig 6: Comparison of ANN-G-P & A-G-P-Q

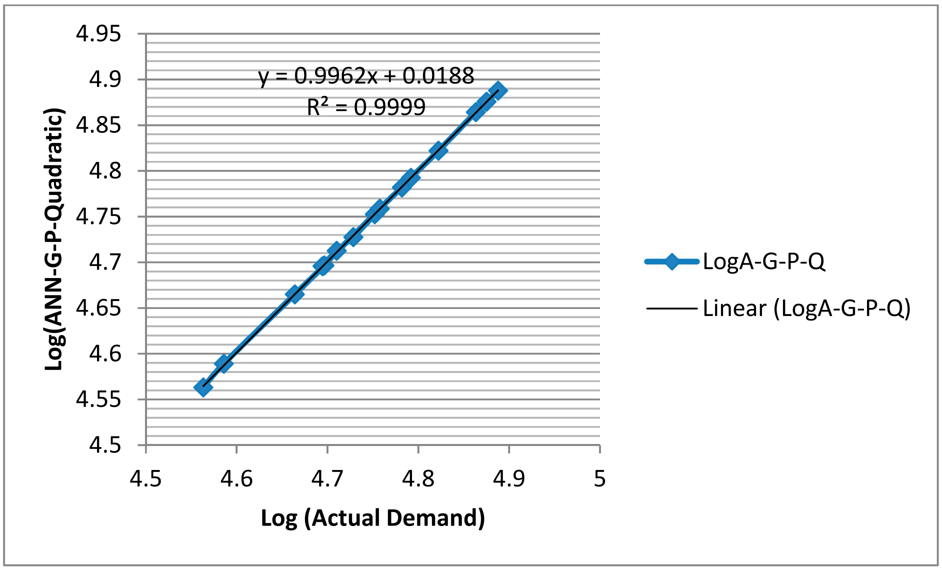

Fig 7: Forecasting by A-G-P-Q model

5.2 Future estimation

The future estimation of the electricity demand of Tamil Nadu has been evaluated under two scenarios. Scenario 1 (as it is) assumes the energy consumption to grow at the rate of 5% , income at the rate of 12%, GSDP at 11% and CPI at 2%. Scenario 2 considers the VISION Document 2023[26] goals of the state as expected growth rate of energy consumption as 8% ,income growth as 15% , GSDP as 12% and CPI at 3%. Table 9 shows the tabulated results of the forecasted electricity demand for scenario 1 and scenario 2 using A-G-P-Q model. Fig 8 shows the forecasted electricity demand as per scenario 1 and scenario 2.The projected electricity demand as per scenario2 are on the higher side throughout except for the year 2020. The electricity requirement for the year 2025 is 84 GWh as compared to 87.8 GWh as per scenario 1 and scenario2 respectively. The state of Tamil Nadu will have to find resources for fulfilling the demand of 87.8 GWh if it wants to achieve the goals set up by the Vision 2023 document.

Table 9: Demand Forecast

Year	Scenario1	Scenario2
2016	80881	80537
2017	81213	83324
2018	81142	82726
2019	82137	84301
2020	83044	81074
2021	82752	83469
2022	83029	85331
2023	83826	87581
2024	83401	85636
2025	84263	87825

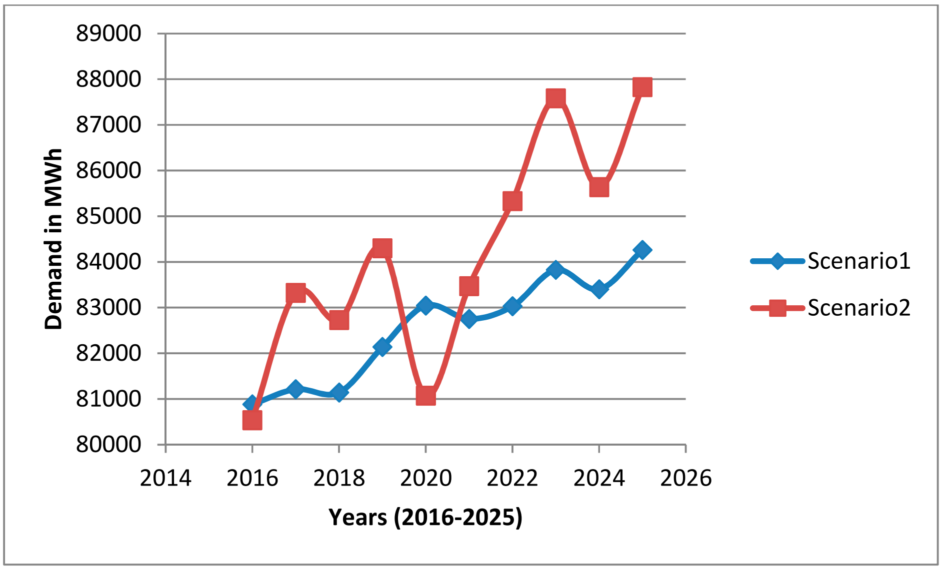

Fig 8: Forecasts as per scenario 1 and scenario 2 using A-G-P-Q model

5.3 Relationship between GSDP and Electricity demand

According to Daria Kostyannikova [27] ,the causality and cointegration results are not uniform across countries and measures of energy consumption. This can be explained by different economic policies and energy structures in each country. Based on the direction of causality between total energy consumption and economic growth, the following policy implications can be made. In countries where unidirectional causality runs from energy consumption to economic growth ,even though energy consumption is not the only factor that determines economic development, it is important that the governments increase investment in energy sector and reduce inefficiency in the supply and use of energy. Our present study shows that electricity demand and GSDP are co-integrated . As shown in Fig 9 one percent increase in total energy consumption leads to an increase of 0.86 in GDP while a one percent increase in GSDP will raise total energy consumption by 0.79 percent .

Our research shows that in case of Tamil Nadu, causality exists between GSDP and electricity demand. Hence it will be possible to increase the GSDP by investing in bridging the electricity demand gap.

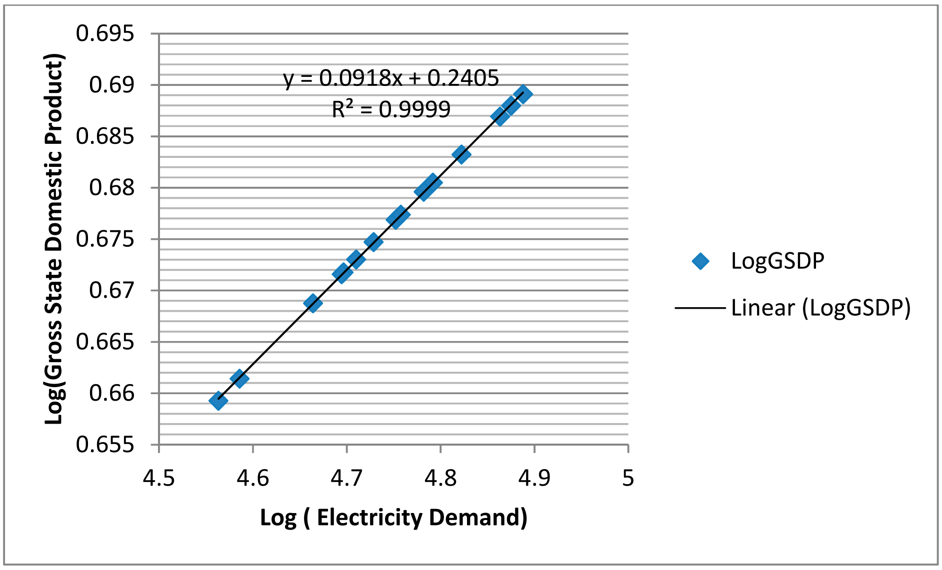

Fig 9: Relationship between Electricity demand and GSDP

6. Conclusions

This study has proposed a novel algorithm based on PSO and GA for optimizing ANNs in linear and quadratic forms for forecasting of electricity demand . ANN has been optimized by hybrid optimizing algorithm of PSO and GA in linear and quadratic forms. Single optimized ANN (ANN-GA,ANN-PSO) have been compared with hybrid optimized ANN's (ANN-GA-PSO,A-G-P-Q).ANN-GA-PSO models in linear and quadratic forms have demonstrated 28% and 48% improvement over ANN-GA model and 25% and 43% improvement over ANN-PSO model. ANN-GA-PSO models can solve the problem of over fitting and falling in local minimum in data set ANN-GA-PSO models have been used to explore the relationship between electricity demand and GSDP of Tamil Nadu state which is seen as co- integrated. ANN-GA-PSO models can be used for resource planning and for bridging the energy gap in the state to achieve the goals set out in the Vision document of the state.

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