 doi:10.20944/preprints201711.0190.v1

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) , per capita demand, income 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 the direct causality exists between GSDP and the electricity demand of the state.

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

1. INTRODUCTION

Rapid economic development has led to improvement in the living standards and consequently to the electricity consumption in the state of Tamil Nadu. The electricity is a special energy which is hard to be stored and hence the mismatch between demand and supply needs to be addressed by the policy makers. The objective of the electricity demand modeling is to bridge the gap between the demand and supply. Hence there is need to forecast the electricity demand with reasonable accuracy. The electricity consumption in any region is influenced by many socio-economic factors such as population, prices, growth rate of the economy, GSDP, so the electricity time demand series experiences highly non linear characteristics. Thus electricity demand modeling is a difficult task.

The remainder of the paper is organized as below: Section2 describes the literature review regarding various techniques and models ; Section 3 presents the methodology used for this research . In Section 4 the results of the ANN-GA-PSO models have been described ; Section 5 discusses future estimation based on scenarios. Finally Section 6 highlights the conclusions.

2. Literature Review

The modeling techniques so far used can be divided into two categories such as parametric or non parametric techniques.

2.1 Parametric techniques : The linear regression, auto regressive integrated moving average (ARIMA), general exponential technique and stochastic time series techniques are some examples of parametric technique. The details are as follows :

 doi:10.20944/preprints201711.0190.v1

2.1.1 **Multiple Linear Regression (MLR)** based on least square method (LSM) has been used frequently for prediction of future energy demand. Parekh et al [1] applied MLR model to project the demand for petroleum products of India from 2011 to 2012. Zhang et al [2] forecasted the transportation energy demand in 2010,2015 and 2020 based on two scenarios. Limanond et al [3] developed log-linear regression models to project the transportation energy consumption in Thailand for 2010-2030.

2.1.2 **Auto regressive integrated moving average (ARIMA)** forecasting model is one of the popular models for the stationary time series analysis and there is no missing data within the time series. In ARIMA, Box and Jenkins [4] generated an underlying process based on the observations of the time series that precisely shows the process-generating mechanism. Ediger and Akar [5] forecasted the primary energy demand by fuel in Turkey using ARIMA model.

The main drawback of parametric technique is its incapability to adapt to abrupt change of any type of environment or social changes. A wide variety of models have been proposed for electricity demand modeling and forecasting based on time series techniques, support vector regression, expert systems, linear regression models, on linear projections . However none of the methods can yield the results with desired accuracy for all electricity demand forecasting problems because of their respective drawbacks. However, this shortcoming is overcome by applying non- parametric (artificial intelligence) based technique because of its potentiality to global search.

2.2 Non parametric techniques (artificial intelligence) have the capability for global search. 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 . Model performance under specific conditions should be analyzed and understood and incremental improvements made based on knowledge gained. These led to the rapid developments of combined and 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 GA, PSO, BFO etc are proposed by several researchers.

2.2.1 Artificial Neural Network (ANN)

ANN can be defined as 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. A artificial neural network (ANN) with 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. The training of the neural network is done by minimizing the cost function, usually a quadratic function of output error. A network having no hidden layer is called as SLNN (Single Layer Neural Network). The least mean squares (LMS) and back propagation (BP) algorithm are generally applied to train single layer and multilayer neural network respectively. It has been successfully applied to many emerging field such as control, image, videos etc

2.2.2 Hybrid ANN with Back Propagation (BP) Algorithm

From the previous research work published, a back propagation algorithm has always been considered as the conventional training of neural network for load forecasting problems. Yu-Jun He et al. 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).

2.2.3 Hybrid ANN with Genetic Algorithm (GA) optimization forecasting model 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.

2.2.4 Hybrid ANN with Particle Swarm Optimization algorithm(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.

2.2.5 GA- PSO hybrid algorithms : The combined model 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. 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 optimisation (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 . 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. 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.

3. Methodology

Based on the literature survey it is evident that if the coefficients of the equations in an artificial intelligence technique are optimized by a single optimization methods such as

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GA or PSO then it suffers from some well known drawbacks. These models consider only the inputs such as GSDP, population and price index ignoring other affecting factors. In the present study , we propose a hybrid algorithm called GA-PSO, which could optimize the coefficients of equations with better performance. The main differences of our approach from existing approaches can be summarized in the following ways :--

(1) 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 these two methods without their respective drawbacks.

(2) Four factors have been chosen based on full analysis of the electricity demand-affecting factors which are different from the economic indicators in the existing researches.

3.1 Two form estimation method

The authors have used the following equations [25].

$$\mathrm{D}_{\mathrm{GA-pso-linear}} = \sum_{i=1}^{M} (\mathrm{W}_{\mathrm{i}} * \mathrm{X}_{\mathrm{i}} + \mathrm{W}_{\mathrm{o}}) \quad \text{.................................} (3)$$

$$\mathrm{D}_{GA-Pso-Quadratic} = \sum_{i=1}^{M}(W_i * X_i + W_o + \sum_{i=1}^{M}(K_{ij} * X_i * X_j) + \sum_{i=1}^{M}(U_i * X_i^2) \quad \text{...} (4)$$

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

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 :--

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

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

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

3.2 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.

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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 between 50 and 60 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.

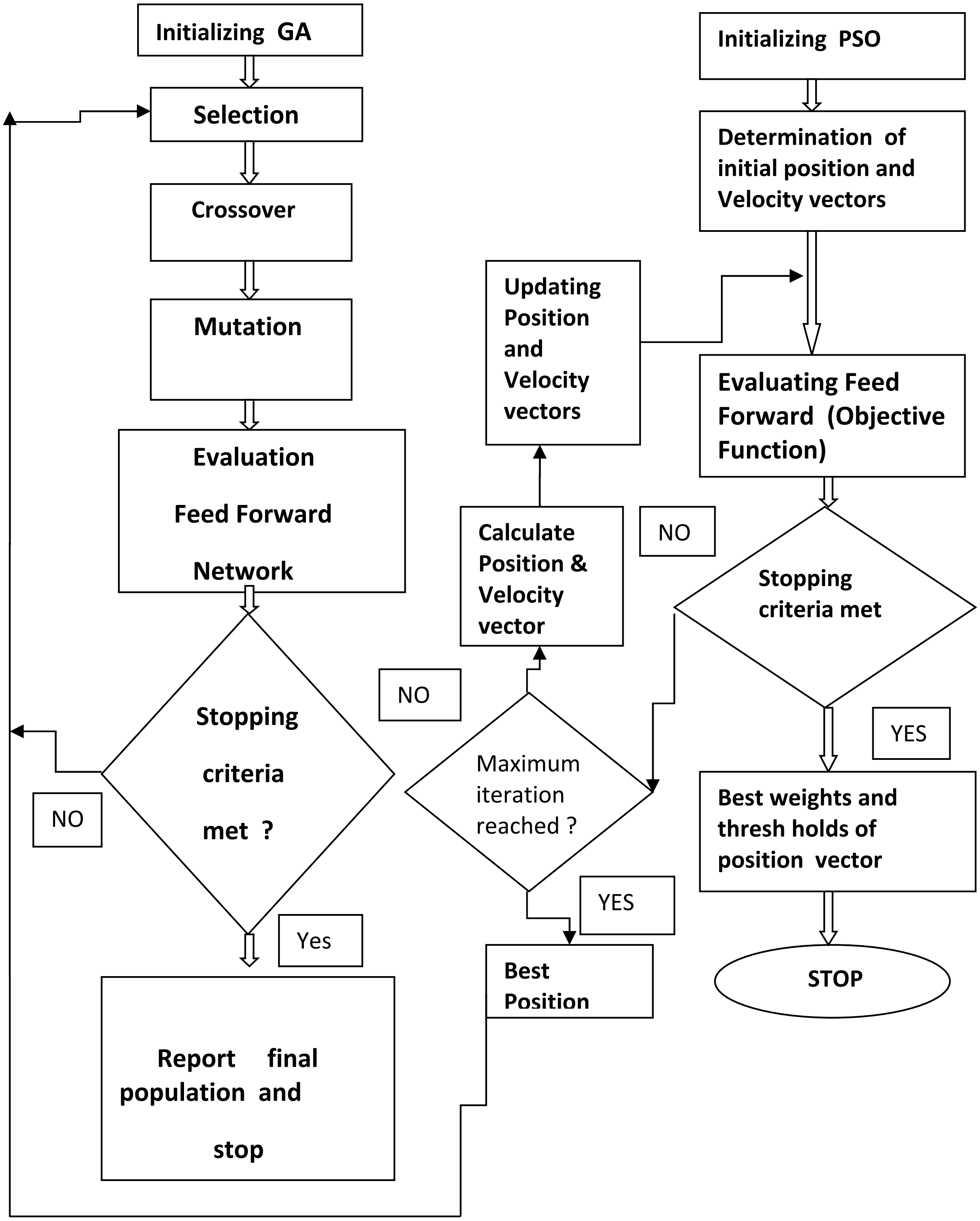

Fig 1 : Flowchart of ANN-GA-PSO

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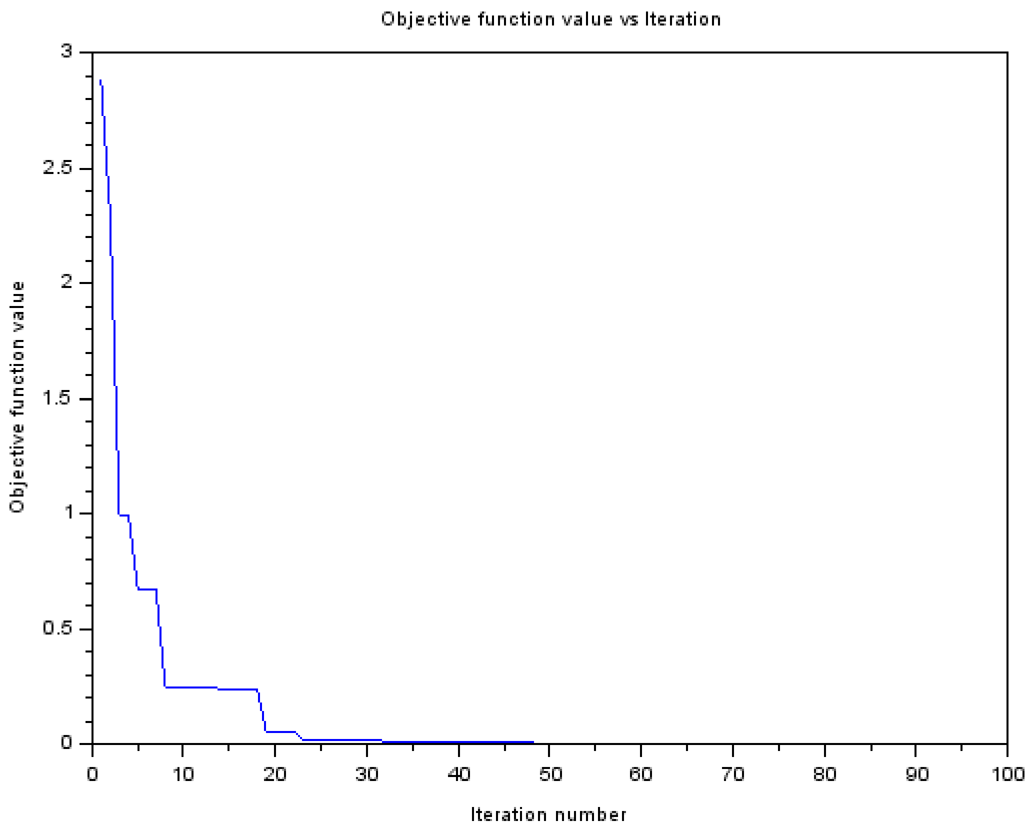

Figure 2 : Convergence Speed of ANN-GA-PSO algorithm

3.3 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. Tamil Nadu's electricity system is huge and complex. Hence scientific studies on electricity demand are more complicated to examine. The following factors reflect their major impacts on energy 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

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

(3) **Income** : The vision 2023document 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.

3.4 Data Management

In this research study the GSDP data is measured in rupees and per capita energy intensity in Kwhr. The coefficients of predictors as obtained from GA-PSO optimization are depicted in Table 1. In this study IBM SS Software is used for ANN modelling. The factors are normalized according to the following equation for optimum functioning of ANN.

$$\mathbf{n(x)= (x\text{-}xmin)/xmin} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(7)$$

For validity examination of the proposed ANN-GA-PSO models , the following mean absolute percentage error (MAPE) serves as the evaluation index. The MAPE and forecasting accuracy (τ) have been defined as follows :

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

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

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

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

4. Results

Table 2 and Fig 6 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 3 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 4 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 7 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. Fig 3 forecasting values compares of A-G-P-Q with actual demand values on a logarithmic scale. 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.

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Table 1 : Coefficients of GA-PSO Linear

Year	PerCapita	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

Table 2 : 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

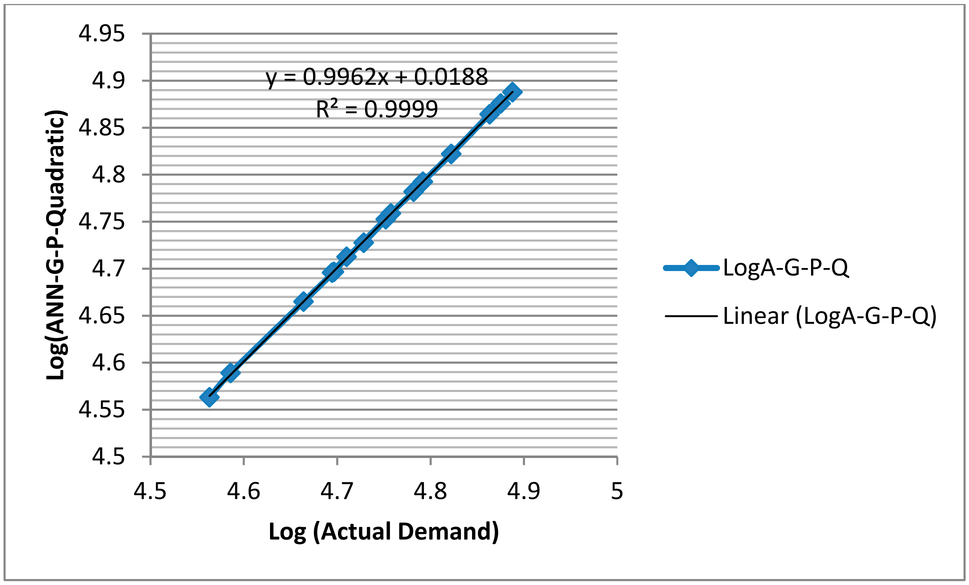

Fig 3 : Forecasting by A-G-P-Q model

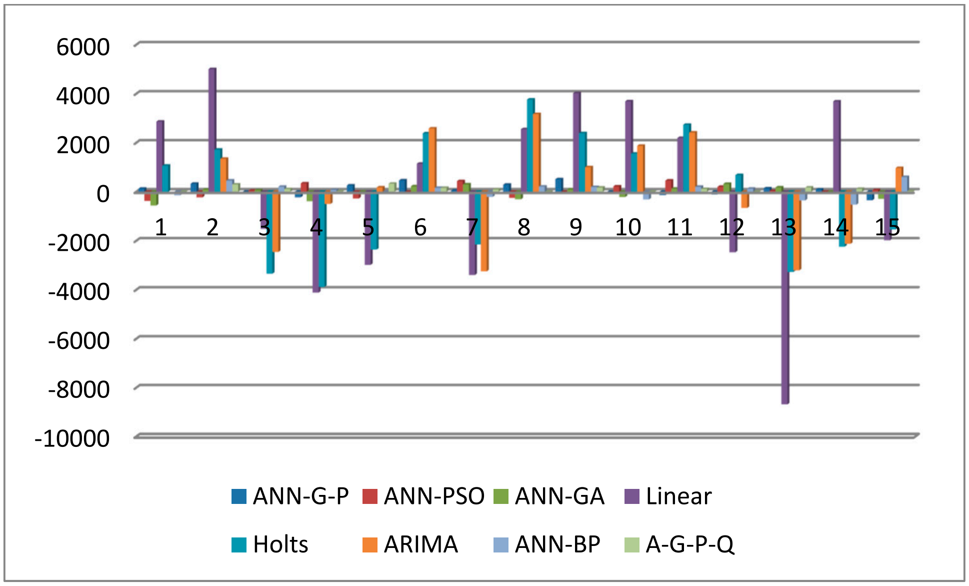

Fig 4 : Error Comparison of various models

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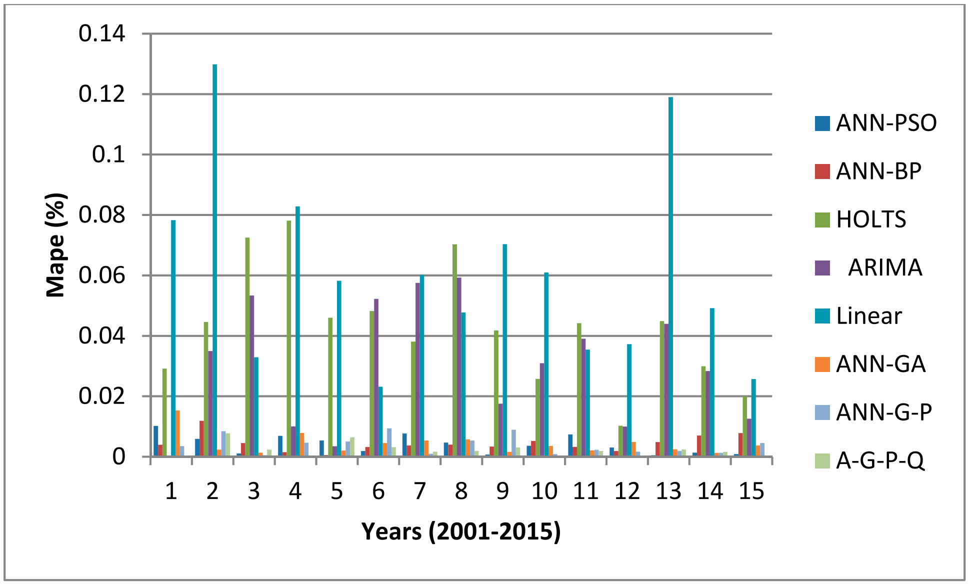

Fig 5 : MAPE Values

Table 3: 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 4 : Forecasting Accuracy (τ)

Linear	Holts	ARIMA	ANN-BP	ANN-GA	ANN-P	ANN-G-P	A-G-P-1
0	0.15	0	0.56	0.58	0.6	0.7	0.78

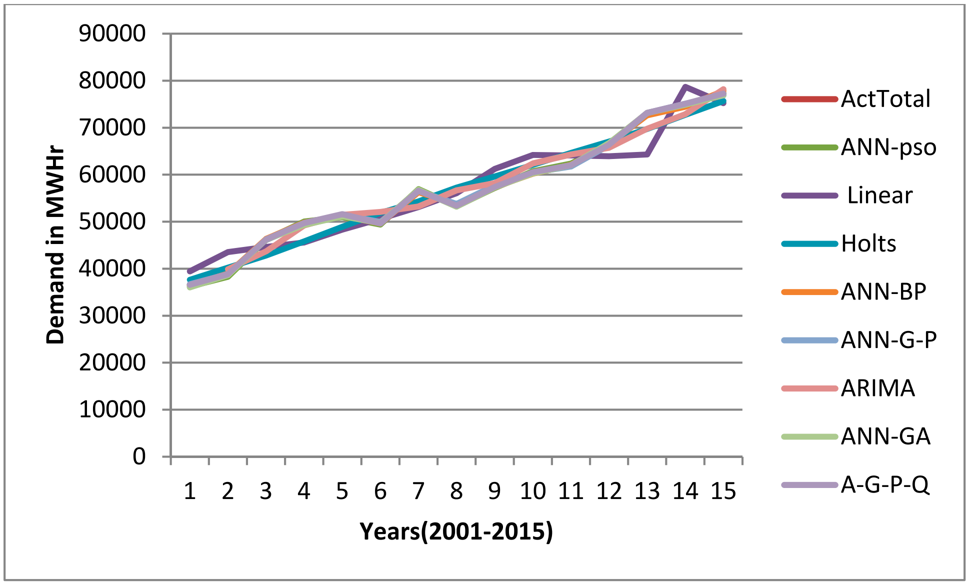

Fig 6 : Performance of models

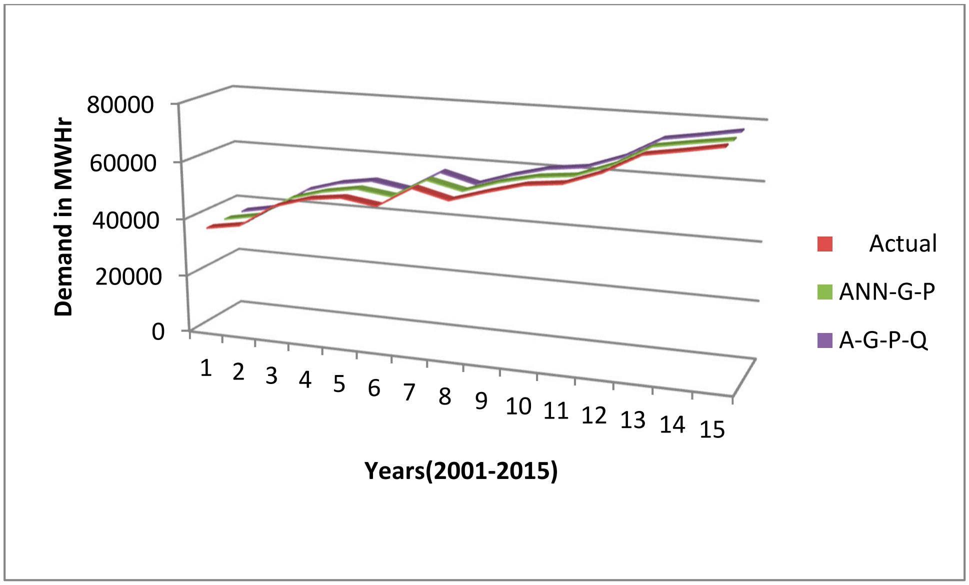

Fig 7 : Comparison of ANN-G-P & A-G-P-Q

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5. Discussion :

The future estimation of the electricity demand of Tamil Nadu has been done under two scenarios. Scenario 1 (as it is) assumes the per capita energy intensity be 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 per capita energy intensity as 8% ,income growth as 15% , GSDP as 12% and CPI at 3%. Table 4 shows the tabulated results of the forecasted electricity demand for scenario 1 and scenario 2 using A-G-P-Q model. The Fig 8 shows the forecasted electricity demand as per scenario 1 and scenario2. 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 GWhr as compared to 87.8 GWhr as per scenario 1 and scenario2 respectively. The state of Tamil Nadu will have to find resources for fulfilling the demand of 87.8 GWhr if it wants to achieve the goals set up by the Vision 2023 document.

Table 5: Scenario -1 and Scenario 2

Year	Scenario1	Scenario2
2016	80881.1	80536.8
2017	81212.8	83324.1
2018	81142	82726
2019	82137.4	84301.3
2020	83043.7	81074.1
2021	82751.5	83469.4
2022	83029.4	85330.9
2023	83826.2	87581.5
2024	83400.7	85636
2025	84263	87825

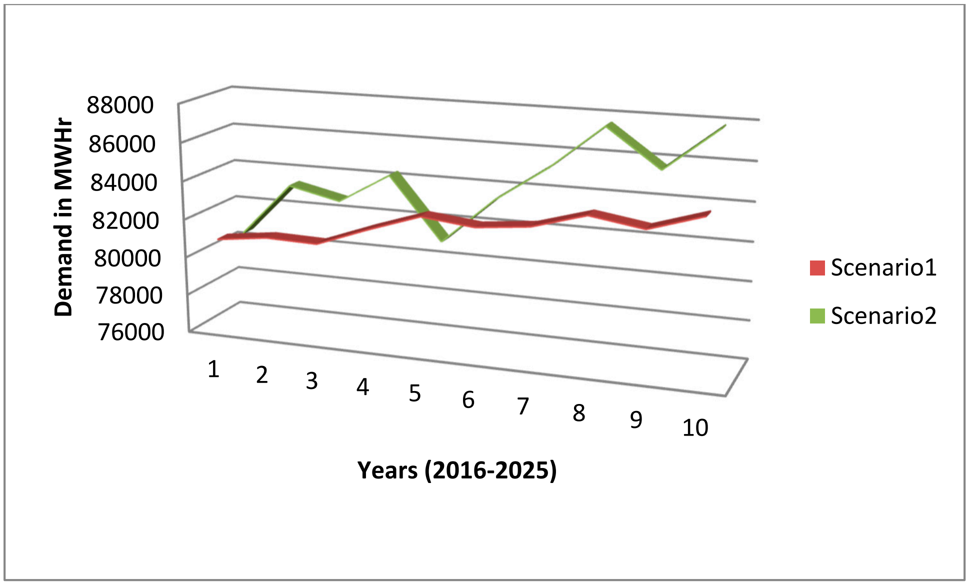

Fig 8 : Forecasts as per scenario 1 and 2

5.1 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. In the present study, as shown in Fig 9, total energy and GDP are co integrated, a one percent increase in total energy consumption leads to an increase of 0.86 in GDP, while a one unit increase in GDP will raise total energy consumption by 0.79 units .

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

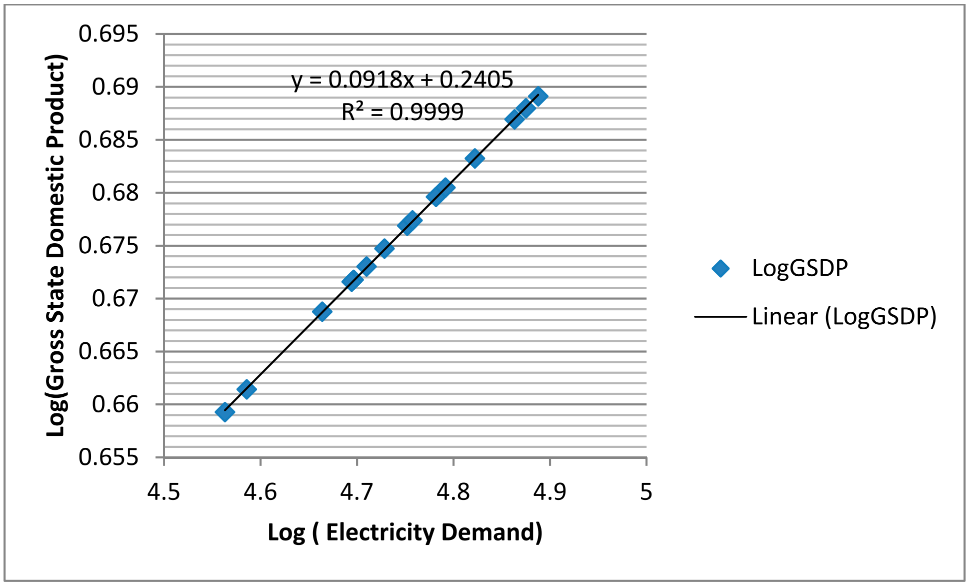

Fig 9 : Relationship between Electricity demand and GSDP

6. Conclusions

This study proposed a novel algorithm based on PSO and GA for training ANNs in linear and quadratic forms for forecasting of electricity demand for the period from 2016-2025. In particular, proposed linear and quadratic A-G-P models have demonstrated about 28% and 48% improvement over conventional ANN-GA model and 25% and 43% improvement over conventional ANN-PSO model. A-G-P models can be trained extremely quickly, which makes it possible to perform a large number of evaluations. This method can highly solve the problem of over fitting and falling in local minimum in data set with less data set. The ANN-GA-PSO models are used to explore the relationship between electricity demand and GSDP of the state which in the case of Tamil Nadu is seen as cointegrated. These results can be further used to increase the investments to achieve the energy goals for the year 2023 as set out in the Vision document of the state.

Acknowledgements : The author will like to thank the Tamil Nadu Electricity Board , Electronics Corporation of Tamil Nadu and the Centre for Development of Advanced Computing for their continuous support. Dr Venu , Eshani and Amay for their assistance in trouble shooting in programming.

Author Contributions : Prof Suganthi proposed the idea and gave inspiration for the development . Atul Anand collected the data and established the forecasting model.

Conflict of Interest : The authors declare that there is no conflict of interest.

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