# FORECASTING ENERGY CONSUMPTION IN TAMIL NADU USING HYBRID HEURISTIC BASED REGRESSION MODEL

by

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*Energy consumption forecasting is vitally important for the deregulated electricity industry in the world. A large variety of mathematical models have been developed in the literature for energy forecasting. However, researchers are involved in developing novel methods to estimate closer values. In this paper, authors attempted to develop new models in minimizing the forecasting errors. In the present study, the economic indicators of the state including population, gross state domestic product, yearly peak demand, and per capita income were considered for forecasting the electricity consumption of a state in a developing country. Initially, a multiple linear regression model has been developed. Then, the coefficients of the regression model were optimized using two heuristic approaches namely genetic algorithm and simulated annealing. The mean absolute percentage error obtained for the three models were 2.00 for multiple linear regression model, 1.94 for genetic algorithm based linear regression and 1.86 for simulated annealing based linear regression.*

Key words: *energy forecasting, regression model, genetic algorithm, simulated annealing*

## Introduction

Developing energy-forecasting models is known as one of the most important steps in long-term planning. In order to achieve sustainable energy supply toward economic development and social welfare, it is required to apply precise forecasting model. Nowadays the increasing power consumption worldwide has led to the release of lot of pollutants to the atmosphere due to the emission of GHG to the atmosphere which in turn becoming the top most factor in affecting the fields of agriculture, natural ecosystems and the average earth temperature finally the human health [1]. Moreover, it is also essential for the planning and establishing of energy policy for a particular region in the world, or for a single country, either by international agencies or by the government itself. Hence, taking into account the limitations imposed by the future social and economic considerations towards a sustainable world, the total electricity consumption must be fulfilled by a optimum possible mix of the available conventional and renewable energy sources [2].

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Linear, quadratic, exponential, and logarithmic models have been formulated to study the effects of gross domestic production, population, stock index, export, and import on Iran's electric energy consumption along with artificial co-operative search algorithm based on three different scenarios from 1992 until 2013 [3]. The electricity demand of Iran was estimated based on economic indicators using particle swarm optimization (PSO) algorithm [4]. An optimized regression and improved particle swarm assisted ANN model was developed for electrical energy consumption forecasting from 2010-2030 based on gross domestic product, energy imports, energy exports, and population between 1967 and 2009 [5]. An energy prediction have been made for Mexico using population growth rate, gross domestic product per capita and energy intensity with different scenarios for the next 40 years using PSO and genetic algorithm (GA) models [2, 6].

An integrated algorithm was developed for forecasting monthly electrical energy consumption based on GA, computer simulation and design of experiments using stochastic procedures [1]. An integrated GA and ANN a forward feeding back-propagation method improved by GA were obtained for the forecasting of energy consumption [7, 8]. The industrial sector electricity consumptions and the totals are estimated, based on the basic indicators [9].

A methodology was developed for long-term electricity demand forecast in the residential sector of some Brazilian distribution utilities over 10 years. It was found that the average consumption per unit consumer depends on GDP, average household income and income distribution [10]. A long-term forecasting model was developed to obtain projections of electricity demand of Spain till 2030 given the expected evolution of the key factors [11]. It was focused on a bottom up approach towards modelling the aggregated energy demand of rural households of Bangladesh form the year 2010 to 2050 using population, GDP electrification index, public energy conservation index [12]. Analyzed a LEAP model and found how the energy, environmental and economic factors influence the energy demand with the help of baseline, new governmental policy and sustainable society scenarios in Korea by 2050 with reference to 2008 [13].

Scenarios were developed to analyze fossil fuels consumption and makes future projections based on a GA and three models in the quadratic form were developed to predict future residential energy output demand of Turkey [14]. The GA oil demand estimation model (GAODEM) was also developed to estimate the future oil demand values [15]. Simulated annealing (SA) algorithms have been used to choose the parameters of a SVM model to forecast the electricity load for Taiwan [16]. Linear, exponential, and quadratic models were developed and improved with a hybrid algorithm called PSO-GA for energy demand forecasting in China [17].

Two linear and three non-linear functions were formed to forecast and analyze energy in the Iranian metal industry, PSO and GA are applied to attain parameters of the models [18]. The PSO and GA optimal energy demand estimating (PSO-GA EDE) model was also developed [19, 20]. The electric power sector of Pakistan was analyzed with LEAP model based on historical electricity demand and supply over the period of 2011 to 2030 and resulted with the discount rate at 4%, 7%, and 10% [21]. An improved grey forecasting model using a small time-series data and the linear regression model was formed [22]. A hybrid dynamic approach was formed that combines a dynamic grey model with genetic programming to forecast energy consumption [23]. Models were developed using multiple linear regression analysis to predict the annual electricity consumption in New Zealand [24].

Even though significant attempts have been made to predict the annual electricity demand, most of the papers used regression models to estimate the electricity need. These models could not estimate the exact demand and always had a notable error. Hence, in this work a new model has been developed to minimize the errors in estimating the future annual electricity demand. The detailed problem environment and methodology is given in the following section.

## Problem definition and methodology

Recent innovations almost all are required electric power to run or use either in turn to reduce human work or ease their work. Moreover, automation in all the fields are required electric power and new inventions are increasing the future electricity demand where the inventions are in non-linear nature. The other factors which play a vital role in creating uncertainty in electricity demand are population (POP), gross state domestic product (GDSP), yearly peak demand (YPD), and per capita income (PCI). It is necessary for the people who govern the country to know the future demand of electricity to avoid critical situation in the allocation of energy resources. Hence, forecasting of the energy demand is important to estimate the future requirement with minimum errors. In the present work, new models have been developed to overcome the existing problem of estimating the exact future demand. It is carried out in two stages, in the first stage a multiple linear regression model is developed and in the next stage the optimized regression coefficients are obtained using two meta heuristic algorithms namely GA and SA which reduces the errors in estimating the annual demand.

### *Regression techniques*

Regression models are quite common in load forecasting and used to model the relationship between the load and external factors and relatively easy to implement. A further advantage is that the relationship between input and output variables is easy to comprehend. A number of studies have employed the regression-based models for load forecasting. In general, regression methods attempt to forecast variations in some variable of interest, the dependent variable, on the basis of variations in a number of other factors, the independent variables. Mathematically, multiple regression models are of the form shown in eq. (1):

$$Y(t) = a_0 + a_1 x_1(t) + a_2 x_2(t) + .... + a_n x_n(t) + e(t) \tag{1}$$

where $Y(t)$ is the dependent variable, $x_1(t) \ldots x_n(t)$ – the explanatory variables correlated with $Y(t)$, $e(t)$ – a random variable with zero mean and constant variance, and $a_0 \ldots a_n$ – the regression coefficients which are determined by least square error technique.

### *Genetic algorithm*

A GA is a method for solving both constrained and unconstrained optimization problems based on a natural selection process that mimics biological evolution. The algorithm repeatedly modifies a population of individual solutions. At each step, the GA randomly selects individuals from the current population and uses them as parents to produce the children for the next generation. Over successive generations, the population evolves toward an optimal solution.

The GA has desirable characteristics as an optimization and offers significant advantages over traditional methods. It is inherently robust and has been shown to efficiently search the large solution space containing discrete or discontinuous variables and non-linear constraints. The optimal solution is sought from a population of solutions using random process [4]. Number of population, methods of selection, reproduction, cross-over, mutation and generation are considered as important factors in GA [5]. In this paper the fitness function is chosen to minimize the error value between the actual and multiple linear regression analysis (MLRA) predicted forecasting results. If the least error is obtained in the process of GA simulation, the iteration terminates, else it continues for various combinations of selection

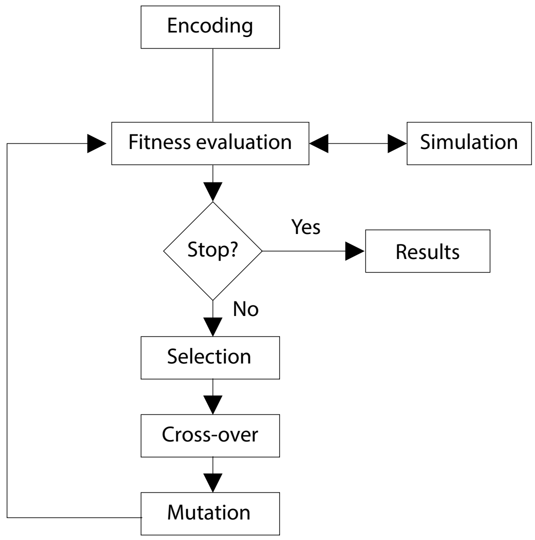


**Figure 1. Illustration of working of GA**

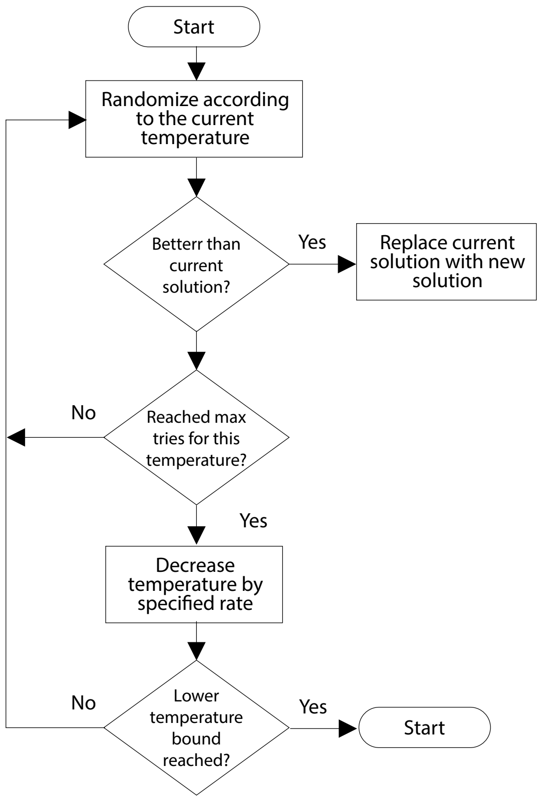


**Figure 2. Illustration of working of SA**

functions, cross-over and mutation values till the best optimal solution is reached for the fitness function. This process is illustrated in fig. 1.

### *Simulated annealing*

The SA algorithm is a way of finding optimum solutions to problems which have a large set of possible solutions, in an analogous fashion the physical annealing of solids to attain minimum internal energy states. The basic idea is to generate a path through the solution space, from one solution another nearby solution, leading ultimately to the optimum solution. In generating this path, solutions are chosen from the locality of the preceding solution by a probabilistic function of the improvement gained by this move. So, steps are not strictly required to produce improved solutions, but each step has a certain probability of leading to improvement. At the start all steps are equally likely, but as the algorithm progresses, the tolerance for solutions worse than the current one decrease, eventually to the point where only improvements are accepted.

In this way the algorithm can attain the optimum solution without becoming trapped in local optima. Figure 2 illustrates the working of SA where there are two major processes. First, for each temperature, the SA algorithm runs through a number of cycles and the number of cycles is predetermined by the programmer. As a cycle runs, the inputs are randomized. Once the specified number of training cycles has been completed, the temperature can be lowered. Once the temperature is lowered, it is determined whether or not the temperature has reached the lowest temperature allowed. If the temperature is not lower than the lowest temperature allowed, then the temperature is lowered and another cycle of randomizations will take place. If the temperature is lower than the lowest temperature allowed, the SA algorithm terminates.

At the core of the SA algorithm is the randomization of the input values. This randomization is ultimately what causes SA to alter the input values that the algorithm is seeking to minimize as the objective function which is the same as discussed in previous section.

### *Proposed methodology*

The proposed methodology is shown in fig. 3. The MLRA is used for modelling the energy consumption in this part of the study. The models taking different socio-economic and demographic variables into consideration are as shown in eq. (2):

$$E_{\text{predicted}} = w_0 + w_1 x_1 + w_2 x_2 + w_3 x_3 + w_4 x_4 \qquad (2)$$

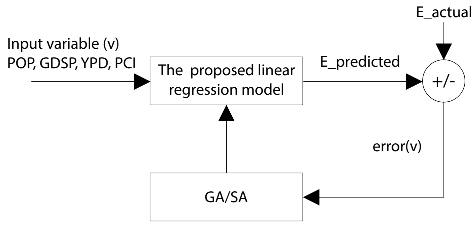


**Figure 3. Block diagram of the proposed GA/SA optimized linear regression model**

where, $x_1$, $x_2$, $x_3$, and $x_4$ are PD, POP, GSDP, and PCI, respectively, and $w_1$,$w_2$, $w_3$, and $w_4$ are the regression coefficients. The multiple linear regression equation thus formed is to be optimized for its coefficients using GA and SA by minimizing the mean absolute percentage error (MAPE) as objective function which is given in eq. (3):

$$MAPE = \frac{100\sum \frac{|AV - FV|}{AV}}{n} \qquad (3)$$

### *Imlementation of the proposed methodology*

The proposed methodology has been demonstrated on forecasting the total energy consumption of Tamil Nadu, a state of India, by taking 30 years of data from 1983 to 2012 considering POP, GSDP, YPD, and PCI as variables. These variables considered in the forecasting of electricity for Tamil Nadu have been obtained from Department of Economics and Statistics, Tamil Nadu State Government. Initially a MLRM is formed to estimate the total energy consumption (TEC) based on socio economic indicators. The regression coefficients were estimated by statistical analysis using least square method. The data set from 1983 to 2012 was used in the regression model. The linear regression equation obtained is shown in eq. (4):

$$TEC = 1.24PD + 1.534POP + 0.214GSDP - 0.952PCI - 69083 \qquad (4)$$

Equation (5) represents the general form of the previous equation where the coefficients of the variables YPD, POP, GSDP, PCI, and constant are replaced with the terms $w_1$, $w_2$, $w_3$, $w_4$, and $w_0$, respectively. Using GA and SA, the optimized values of the previous terms are obtained by considering minimizing the MAPE as objective function:

$$TEC = w_1 PD + w_2 POP + w_3 GSDP - w_4 PCI - w_0 \qquad (5)$$

The GA and SA both were coded with MATLAB 2009. The convergence of the objective function and sensitivity analysis are examined for varying the parameters of GA (population size, methods of selection, reproduction, cross-over, mutation, and generation) and SA (temperature function and temperature update function).

## Results and discussions

In this section, the effect of various parameters involved in GA and SA on MAPE were discussed. In section *Results of GA based weight optimization* dealt with the effect of MAPE by varying the selection process, (stochastic uniform, roulette wheel, tournament, and uniform selection) and cross-over probability (from 0.80 to 0.90 with a step value of 0.05). Mutation probability does not have much effect on MAPE, it is fixed as 0.045. In section *Results of SA based weight optimization* the effect of MAPE is studied by varying the SA parameters like annealing function (fast annealing and Boltzmann annealing) and temperature update function (exponential, logarithmic, and linear function).

### *Results of GA based weight optimization*

The GA was implemented in MATLAB software and the results are discussed in this section. First the selection functions were varied and the one which produced the least fitness value was chosen as the best selection function. Similarly, the best cross-over and mutation fractions were obtained. Table 1 illustrates the results of GA using different selection functions and it is viewed that stochastic uniform method produced least MAPE value. The cross-over fraction was varied as 0.80, 0.85, and 0.90 by considering the stochastic uniform method as selection function.

**Table 1. Weight optimization using GA by varying the selection function**

| Selection function | Stochastic uniform | Roulette | Tournament | Uniform |
|---|---|---|---|---|
| Objective function value | 3.0225 | 3.1937 | 5.3452 | 3.5885 |
| Weights | $w_1 = 1.2157$ | $w_1 = 1.2488$ | $w_1 = 1.2108$ | $w_1 = 1.0978$ |
| | $w_2 = 1.5343$ | $w_2 = 1.5258$ | $w_2 = 1.5083$ | $w_2 = 1.5266$ |
| | $w_3 = 0.1988$ | $w_3 = 0.1194$ | $w_3 = 0.1567$ | $w_3 = 0.0289$ |
| | $w_4 = 0.8507$ | $w_4 = 0.3153$ | $w_4 = 0.5605$ | $w_4 = 0.2997$ |
| | $w_0 = 69033$ | $w_0 = 69091$ | $w_5 = 69127$ | $w_0 = 69083$ |

The corresponding summary of results is shown in tab. 2. It is understood from the tab. 2 that cross-over probability 0.85 produced least MAPE value. The linear regression equation obtained in eqs. (3) and (4) were modified using the weights optimized by GA and the resultant equation is given in eq. (6):

$$TEC = 1.2157PD + 1.5343POP + 0.1988GSDP - 0.8507PCI - 69033 \tag{6}$$

**Table 2. Weight optimization using GA by varying the cross-over fraction**

| Reproduction cross-over | 0.9 | 0.85 | 0.8 |
|---|---|---|---|
| Objective function value | 3.099 | 3.0225 | 3.0822 |
| Weights | $w_1 = 1.2711$ | $w_1 = 1.2157$ | $w_1 = 1.2185$ |
| | $w_2 = 1.5326$ | $w_2 = 1.5343$ | $w_2 = 1.5330$ |
| | $w_3 = 0.1590$ | $w_3 = 0.1988$ | $w_3 = 0.1628$ |
| | $w_4 = 0.5910$ | $w_4 = 0.8507$ | $w_4 = 0.6088$ |
| | $w_0 = 69189$ | $w_0 = 69033$ | $w_0 = 69079$ |

The eq. (6) obtained using GA-MLRM was used to forecast energy consumption for the period 2013-2016 which is shown in tab. 3 and is found that there is 13.67% improvement in prediction of output as compared with MLRM where MAPE of MLRM and GA-MLRM are 6.5% and 5.61%, respectively. The estimation errors of GA based regression model are less than that of estimated by regression method.

**Table 3. Actual and forecasted value of TEC for the period 2013-2016 for MLRM and GA-MLRM**

| Year | TEC [Million kWh] | PD [MW] | POP ('000') | GSDP (Rs crores) | PCI (Rs crores) | Forecasted value | | Error [%] | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | MLRM | GA-MLRM | MLRM | GA-MLRM |
| 2013 | 74872 | 12131.12 | 68265 | 447943 | 60738.03 | 88715.29 | 87835.01 | 18.48927 | 17.31356 |
| 2014 | 89793 | 12654.02 | 68654 | 480619 | 63880.45 | 93961.51 | 92890.29 | 4.64235 | 3.449366 |
| 2015 | 94128 | 13176.93 | 69030 | 499521.5 | 67022.86 | 96240.25 | 95187.45 | 2.244021 | 1.125543 |
| 2016 | 99691 | 13699.84 | 69396 | 526844.3 | 70165.27 | 100305.6 | 99143.22 | 0.616502 | 0.549479 |

### *Results of SA based weight optimization*

The optimization of the weights by SA was implemented in MATLAB software and the results are discussed in this section. First the annealing functions were varied and the one which produced the least fitness value (since minimization was the objective) was chosen as the best annealing function. The tab. 4 illustrates the fitness values obtained using different annealing functions.

**Table 4. Results of optimization of regression weights using SA**

| Annealing function | Fast annealing | Boltzmann annealing |
|---|---|---|
| Objective function value | 3.0134 | 3.0457 |
| Weights | $w_1 = 1.0436$ | $w_1 = 1.0584$ |
| | $w_2 = 1.5326$ | $w_2 = 1.5391$ |
| | $w_3 = 0.1909$ | $w_3 = 0.1721$ |
| | $w_4 = 0.7735$ | $w_4 = 0.6485$ |
| | $w_0 = 69057$ | $w_0 = 69004$ |

The weights are further optimized by choosing different temperature update functions with the best annealing function and the results are shown in tab. 5.

**Table 5. Results of optimization of regression weights using SA**

| Temperature update function | Exponential temperature update | Logarithmic | Linear |
|---|---|---|---|
| Objective function value | 3.0134 | 3.0765 | 3.0423 |
| Weights | $w_1 = 1.0436$ | $w_1 = 1.0604$ | $w_1 = 1.1226$ |
| | $w_2 = 1.5418$ | $w_2 = 1.5478$ | $w_2 = 1.5382$ |
| | $w_3 = 0.1909$ | $w_3 = 0.2207$ | $w_3 = 0.1942$ |
| | $w_4 = 0.7735$ | $w_4 = 0.9920$ | $w_4 = 0.8128$ |
| | $w_5 = 69057$ | $w_5 = 69054$ | $w_5 = 6.9001$ |

The linear regression equation obtained in eqs. (3) and (4) were modified using the weights optimized by SA and the resultant equation is given in eq. (7):

$$TEC = 1.0436PD + 1.5418POP + 0.1909GSDP - 0.7735PCI - 69057 \tag{7}$$

Similar to the section *Results of GA weight optimization*, the TEC values are forecasted using the optimized weights obtained in SA-MLRM and represented in tab. 6. It is observed that the proposed SA-MLRM provided 18.24% improvement in forecasting TEC as compared with MLRM and 5.3% improvement as compared with GA-MLRM.

**Table 6. Actual and forecasted value of TEC for the period 2013-2016 for MLRM and SA-MLRM**

| Year | TEC [million kWh] | PD [MW] | POP ('000') | GSDP (Rs crores) | PCI (Rs crores) | Forecasted value | | Error [% ] | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | MLRM | SA-MLRM | MLRM | SA-MLRM |
| 2013 | 74872 | 12131.12 | 68265 | 447943 | 60738.03 | 88715.29 | 87385.46 | 18.48927 | 16.71314 |
| 2014 | 89793 | 12654.02 | 68654 | 480619 | 63880.45 | 93961.51 | 92338.12 | 4.64235 | 2.834427 |
| 2015 | 94128 | 13176.93 | 69030 | 499521.5 | 67022.86 | 96240.25 | 94641.37 | 2.244021 | 0.545397 |
| 2016 | 99691 | 13699.84 | 69396 | 526844.3 | 70165.27 | 100305.6 | 98536.64 | 0.616502 | 1.157942 |

Table 7 shows the values of weighting factors obtained for the three models and tab. 8 explains the MAPE error of the three models for the testing period of 2006-2012. It shows that the SA-MLRM model has the least MAPE and can be applied to predict the energy consumption of Tamil Nadu state.

**Table 7. The obtained weight factors by the three models**

| Weight factors | MLRM | GA-MLRM | SA-MLRM |
|---|---|---|---|
| $w_0$ | –69083 | –69033 | –69057 |
| $w_1$ | 1.240 | 1.2157 | 1.0436 |
| $w_2$ | 1.534 | 1.5343 | 1.5418 |
| $w_3$ | 0.214 | 0.1988 | 0.1909 |
| $w_4$ | –0.952 | –0.8507 | –0.7735 |

Using the method of least squares, linear models of the economic indicators have been formulated and were predicted for the future years from 2020-2050 in a gap of 5 years. Then the TEC for the future years of Tamil Nadu state were predicted by the three models using the eq. (4) along with the weight factors shown in the tab. 7. The tab. 8 shows, the MAPE of SA-MLRM is the least one, and hence the future energy demand predicted using this particular algorithm may give the closer values of the future energy consumption.

The predicted values of TEC by the three models are shown in tab. 9. Finally it has been observed that the SA-MLRM model predicted the closest values of the future energy consumption for the State with lowest MAPE error, which may also be referred for the decision making in the energy policies of the Tamil Nadu state.

**Table 8. Relative error between actual and predicted value using all three models**

| Year | Actual data (MU) | Predicted data (MU) | MLRM MAPE [%] | GA-MLRM MAPE [%] | SA-MLRM MAPE [%] |
|---|---|---|---|---|---|
| 2006 | 56726 | 57635 | –1.60188 | –1.54513 | –1.59802 |
| 2007 | 63563 | 61910 | 2.60120 | 2.70113 | 2.58703 |
| 2008 | 66848 | 64391 | 3.67555 | 3.82077 | 3.68628 |
| 2009 | 66966 | 67079 | –0.16851 | 0.04197 | –0.01717 |
| 2010 | 72887 | 71179 | 2.34331 | 2.60325 | 2.55128 |
| 2011 | 76071 | 76497 | –0.56000 | -0.21247 | –0.06605 |
| 2012 | 77819 | 80210 | –3.07214 | –2.66125 | –2.50447 |
| Average MAPE [%] | | | 2.00 | 1.94 | 1.86 |

**Table 9. Forecasted energy consumption values using all three models for the future years**

| Future years | TEC [MU] (MLRM) | TEC [MU] (GA-MLRM) | TEC [MU] (SA-MLRM) |
|---|---|---|---|
| 2020 | 125142 | 123221 | 122258 |
| 2025 | 139276 | 137280 | 136289 |
| 2030 | 153409 | 151339 | 150321 |
| 2035 | 167543 | 165399 | 164352 |
| 2040 | 181676 | 179458 | 178383 |
| 2045 | 195810 | 193518 | 192415 |
| 2050 | 209943 | 207577 | 206446 |

## Conclusion

An improved multiple linear regression model has been proposed in this work using two meta heuristic methods namely genetic algorithm and simulated annealing. Optimized coefficients values were obtained by changing the parameters of both genetic algorithm and simulated annealing by considering minimizing MAPE as objective function. The proposed models have been implemented to forecast the total energy consumption of Tamil Nadu state for the given population, gross state domestic product, yearly peak demand, and per capita income values during the period between 1983 and 2012. The MAPE values are calculated for the period between 2013 and 2016 using both the models. It is proved that the proposed GA-MLRM and SA-MLRM techniques have produced an accuracy of approximately 94% in forecasting TEC for the period 2013 to 2016. The obtained result reveals that simulated annealing-multiple linear regression model can be used as a suitable algorithm to estimate the future energy consumption.

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