# Energy Forecasting Information System of Optimal Electricity Generation using Fuzzy-based RERNN with GPC

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## *Abstract*

In this paper, a hybrid fuzzy-based method is suggested for determining India's best system for power generation. This suggested approach was created using a fuzzy-based combination of the Giza Pyramids Construction (GPC) and Recalling-Enhanced Recurrent Neural Network (RERNN). GPC is a meta-heuristic algorithm that deals with solutions for many groups of problems, whereas RERNN has selective memory properties. The evaluation of the current load requirements and production profile information system is the main objective of the suggested method. The Central Electricity Authority database, the Indian National Load Dispatch Centre, regional load dispatching centers, and annual reports of India were some of the sources used to compile the data regarding profiles of electricity loads, capacity factors, power plant generation, and transmission limits. The RERNN approach makes advantage of the ability to analyze the ideal power generation from energy data, however the optimization of RERNN factor necessitates the employment of a GPC technique. The proposed method was tested using MATLAB, and the findings indicate that it is effective in terms of accuracy, feasibility, and computing efficiency. The suggested hybrid system outperformed conventional models, achieving the top result of 93% accuracy with a shorter computation time of 6814 seconds.

***Keywords:*** Energy Demand, Electricity Generation, Fuzzy based RERNN, GPC, Information System, Time Series.

## 1. Introduction

A technique for projecting future energy needs to achieve supply and demand equilibrium is known as energy forecasting. Energy Demand and price forecasts for fossil fuels, electricity (oil, natural gas, coal), and Renewable Energy Systems (RES) are all included in energy forecasting (solar, wind, hydro). Both predictable pricing values and probabilistic forecasting are forms of forecasting. Energy sector development and policy formation heavily rely on energy forecasts and planning. The main goal is the planning exercise and tool in various modern energy systems, and the selection of the forecasting model is largely dependent on the availability of data. The technique of forming predictions regarding potential future developments for particular historical entities is known as forecasting. In forecasting, expected future events or developments are estimated or calculated using a conceptual model. The conceptual model can, at its most informal level, be an empirical method built into people's lifetime practices and the specific cultural, social, and economic environments in which they reside, such as the creation of expectations regarding the repetitive actions and services to be performed on a specific single day. In this study, we assess the forecasting model's performance using the generation of power, which was constructed using a database that contains relevant information about previously generated energy data.

A few difficulties have arisen due to the rapid growth of the gross domestic product (GDP), per capita consumption, the world economy, and population, including the need to reduce the use of energy resources, increase delivery options, and address environmental problems like global warming [1]. A novel paradigm for projecting energy demand is offered that combines a flexible genetic algorithm with cointegration analysis. The factors of the linear and quadratic forms of a model based on artificial intelligence (AI) are optimized using historical annual data on electricity use from 1985 to 2015 [2]. A planned method can be used by a power provider to estimate energy consumption, deploy regional energy capacity effectively, and maintain a balance between the demand and supply of electricity for household buildings in workable cities [3][4]. Household consumption of energy forecasting will be analogous to multivariate time series forecasting. The prediction model may extract different properties from a specified window of many sensor signals and forecast energy usage. It’s still a problematic job due to strange internal patterns and unstated relationships between power attributes [5][6]. The amount of energy used is tracked as a time-series piece of data. Because the former incorporates a variety of power consumption methods, it is difficult to acquire knowledge of how electrical applications work [7]. Solar photovoltaic (PV) energy conservation system for attaining energy security through renewable sources and reaching energy independence by 2047. The major energy mix places a focus on cleaner energy in India's immediate future [8]. The precision of various deep learning methods and append the values of commercial building predictions of energy performance [9]. The best positioning of generation in distribution and charging stations for e-vehicles is organized by a two-stage fuzzy multi-objective strategy based on the Grasshopper optimization algorithm. It is used for the allocation of generation in distribution to improve the power factor of the substation, energy loss reduction, and profile improvement in the voltage system [10].

A hybrid methodology was developed that has distinct advantages in both linear and nonlinear modeling. An effective combined model is developed for increasing the energy forecasting accuracy to be achieved by either of the models used alone based on investigational outcomes with data sets [11]. A hybrid method proved efficient and achievable with the lowest percentage error between the statistics with more compared established models, so only around 8% between the observed and the corrected series models [12]. The development of energy usage prediction methods uses both linear and nonlinear methodologies, as well as optimization strategies, to connect the knowledge space with scientific uniqueness. These techniques enable decision-makers to make modifications based on power requirements and usage by calculating the progressive nature of power usage [13]. Energy storage and high-intermittent generating networks use reinforcement learning to suggest using deterministic look-ahead rule-based changes for arrangement and a straightforward Policy Function Approximation (PFA) for the real-time operation to create rules for energy dispatch with undefined prognoses [14]. An overview of real-time applications of machine learning for predicting growth trends in various energy systems uses three well-known forecasting engines to conduct a thorough review of supervised-based machine learning methods. Its objective is to provide practical techniques for predicting analysis and a number of other prediction tasks [15]. Least Squares Support Vector Regression (LSSVR) is the popular machine learning method used for developing prediction models that achieve high efficiency for hydropower energy consumption [16]. The paradigm of the Indian power system's traditional operation and planning is shifting as a result of grid integration plans on a large scale for wind and solar energy. In numerous Indian states, the negative effects are being seen as operational difficulties and generation reduction [17][18]. Renewable energy scenarios for energy forecasting models are based on deep learning to inform sustainable energy strategies and predictive data mining techniques, so smart energy networks can be used to forecast energy management systems. [19][20].

Chapter 2 organizes detailed related research on energy forecasting. Chapter 3 presents electricity demands in India. Chapter 4 presents a Hybrid Optimal Fuzzy-based RERNN with GPC for Energy Management systems. Chapter 5 presents the results and discussion. Chapter 6 provides the conclusion and future works.

## 2. Related Research Works

Electricity demand is the time series of prediction using the neuro-fuzzy system, which is used to define accurate forecasting values in power consumption. Predicting electricity demand is essential and necessary for managing and planning power resources [21]. In the literature [22], the neuro-fuzzy system model is projected to examine the ability to anticipate global solar energy under various weather scenarios. Different elements of time, topographical locations, and seasonally varying data may have an impact on solar photovoltaic (PV) power output. Consequently, reliable PV power forecasting is crucial for system stability and resilience. The researcher [23] developed a brand-new Type-2 Fuzzy system that simulates RES. In addition to presenting brand to the any nation's policymakers and associated institutions must consider energy use when developing their energy policies. The ARIMA model is used to anticipate energy consumption utilizing data on oil, coal, renewable energy sources, natural gas, and energy consumption from 1970 to 2015 [24]. Multi-area microgrids are used for novel predictive frequency management systems (MGs). The fuzzy-logic system (FLS) deep learning method simulates uncertainties based on adaptive learning laws to ensure robustness against perturbations. The learning rules are taken from an analysis of stability and robustness [25]. Battery charging and energy control are new models founded on interval type-3 fuzzy logic systems. The dynamics of batteries and solar panels are thought to be completely unknown, in contrast to the other approaches. The Lyapunov/invariant LaSalle's set theorems are used to examine their proposed method's robustness and asymptotic stability, and the alteration rules are extracted [26]. The ARIMA and Nonlinear Grey Model (NGM) models are used to forecast South Africa's energy consumption from 2017 to 2030 using energy consumption data from 1998 to 2016 [27].

The effect of increasing the capacity of renewable energy sources on sustainability characteristics has not been thoroughly evaluated in the Indian scenario. The study examines the ideal capacity of renewable energy installations using a suggested modeling framework. The plan includes a number of objectives, including a sustainability model connected to an optimization model [28]. In order to include operational features of various forms of hydropower in long-term power sector models, a new modeling methodology is presented, and then the mathematical model's formulation is offered for the examination of the body of literature and approaches. The current scenarios for the growth rate of electricity demand have been used to evaluate the potential development path for the power sector. Creating a potential rule to bolster national security standards allows for a further evaluation of the best way to deploy local hydro and renewable energy sources [29].

The system's clustering approach locates the cluster data that corresponds to the identified features and groups of linked electric appliances, removes noise from the credit for functionality, and finds flawed electric usage mechanisms [30]. In order to manage the variations brought about by the mainstreaming of renewable energy, we proposed and examined the effectiveness of demand-side measures. To create a linear programming model to put emergency and demand response economic programs into action and validate them [31].

## 3. Electricity Demand in India

In India, the electricity consumption in 2015 was 980 TWh, recording an average growth rate of 8.84%. In general, industries consume a lot of electricity, and it was estimated that the power consumption stood at 450 TWh (46%), with a significant increase up to 11%. Some of the crucial manufacturing industries that contribute to GDP are steel, aluminum, cement, petroleum products, pulp and paper, fertilizer, MSME (Ministry of Micro, Small, and Medium Enterprises), and other such industries. In 2015, the production of crude steel was 89 MT (Metric tons). It is a general tendency for energy intensity to decrease per ton of crude steel manufactured. By 2025–2026, India’s aluminum generation capacity remained at 2.36 MT, whereas the electricity intensity per ton was in the range of 14,000–17,000 kWh. In the case of cement manufacturing, the total electricity consumed was 300 MT with an electricity intensity/ton of 80 kWh.

### 3.1. Electricity consumption from residential buildings

Residential energy is consumed through many home appliances that help mankind for cooking, cooling, lighting, washing, and entertainment purposes. Energy demand depends on numerous factors, such as the location of the residence, weather conditions, socio-economic factors, and so on. A developing country like India has separated rural families from urban ones since these locations have different kinds of electricity consumption (EC) patterns. Further, the end-use of energy is subdivided by technology and the development of new agglomerations.

India’s residential energy requirement is not set to increase drastically within 2050 since the home appliances invented so far have not penetrated every household. However, recent analysis has stimulated the increasing penetration rate of electrical tools in residential areas. The study investigated the energy consumption of a few home electrical devices such as the AC, Fridge, Television, Fan, Light, and heater. The current inventory was analyzed based on the information gathered from the Energy Administration in order to check the effectiveness of the minimum energy efficiency standards. According to a survey conducted by the National Sample Survey of India Organization (NSSO), the residential sector in India differs in energy consumption patterns on the basis of micro-household data, collected nationally.

### 3.2. Electricity consumption from industry

Steel, ammonia, paper, ethylene, aluminum, and cement are energy-demanding industries, while they also boost the development of other intensive industries such as plastics, glass, sodium carbonate, etc.

For instance, the steel industry follows three approaches: (1) An explosion kiln, which is a common route for an oxygen furnace (2) Iron ore directly mitigation on the electrical furnace; (3) an electric arc furnace route from scrap metal. The glass industry follows two methods, such as flat glass production and glass for containers. Some of the least energy-requiring industries are food and beverages, wood, tobacco, printing and textiles, medicine, rubber, and plastics, followed by electrical/electronic devices, metal, machinery, and other equipment in the rest of the manufacturing industries. Energy demand growth is mostly determined by the demand for material urbanization and the development of infrastructure. For instance, the construction of a building increases cement production in India by up to 78%, while it consumes 62% steel and 10% automobiles.

### 3.3. Electricity consumption from commercial buildings

The development of the commercial construction industry is expected to increase in the upcoming years. In 2016, it contributed a total of 53.8% of its value to the service industry in India. According to commercial acts, the land area used is estimated based on the data available in the economic census. An analysis was recently conducted to formulate the commercial construction sector.

### 3.4. Electricity consumption from agriculture

It is evident that agriculture is essential to India's economy given that 55.6% of the population works in agriculture and related industries. Further, agricultural activities contributed over 17.4% of the total GDP of the country in 2016–17. In 2012, agricultural activities consumed 17% of the overall electricity generated, which was a 12% overall increase in diesel from 2011. Irrigation pump-sets and tractors create the energy demand in this field. Additionally, there is little mechanization in the agriculture industry because tractors eliminate 19% of the potential market. The primary source of agricultural energy consumption is through two significant technologies, such as pumps and tractors, that are used on agricultural lands.

The electric pump stock requirement is predicted with the help of sales data and historical stock data. Electrical pumps are expected to hold a 95% market share by the year 2050, and the pump size will be 4 kW.

### 3.5. Electricity consumption from transport

Passenger transportation demand has shot up in recent years, and it was tracked using vehicle registration data from the past few years along with sales data. The researcher evaluated the transportation of buses and rail networks because the previous investigation inferred the existence of a close relationship between transportation and GDP. GDP can also predict the requirement for passenger travel. Moreover, current and future policy goals in the case of efficient transportation, such as cars, light-duty trucks, and public transport, demand fuel efficiency standards. It also takes expenses incurred on infrastructure into account when mission plans such as Smart City are proposed. India's overall passenger demand was 5503 billion passenger kilometers (bpkm) in 2015, and it is anticipated to reach 43,316 bpkm by

2050. Further, 2050 may see at least 17 cars owned by a population of 1,000, mostly from the US and other developed countries (809 cars per 1000 people), with Germany holding third place (568 cars per 1000 people). The public transportation modes are exceptionally compatible with app-based facilities such as Uber, Ola, etc.

## 4. GPC-based hybrid optimal fuzzy RERNN for energy management systems

GPC and a hybrid fuzzy-based RERNN are introduced in the current study. While GPC is a meta-heuristic algorithm that addresses a number of concerns, RERNN has selective memory features. The main goal of this strategy is to assess the existing production profile and load requirements in order to take future requirements and production capacity into account. Here is a step-by-step breakdown of the proposed system. **Fig. 1** shows the proposed system diagram of electricity generation using Fuzzy-based RERNN with GPC.

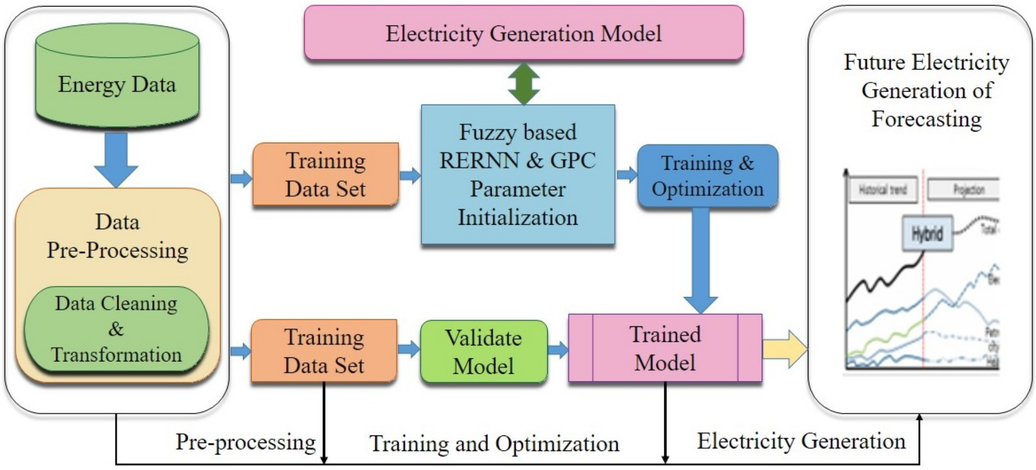


**Fig. 1.** Proposed system diagram of Electricity Generation using Fuzzy-based RERNN with GPC

### 4.1 Fuzzy

The fuzzy controller is made up of four independent modules or blocks, which are represented in **Fig. 2** as the inference engine, fuzzification block, defuzzification block, and rule base, the various modules are interconnected to offer a solution at the controller's exit and each has a unique set of tasks.

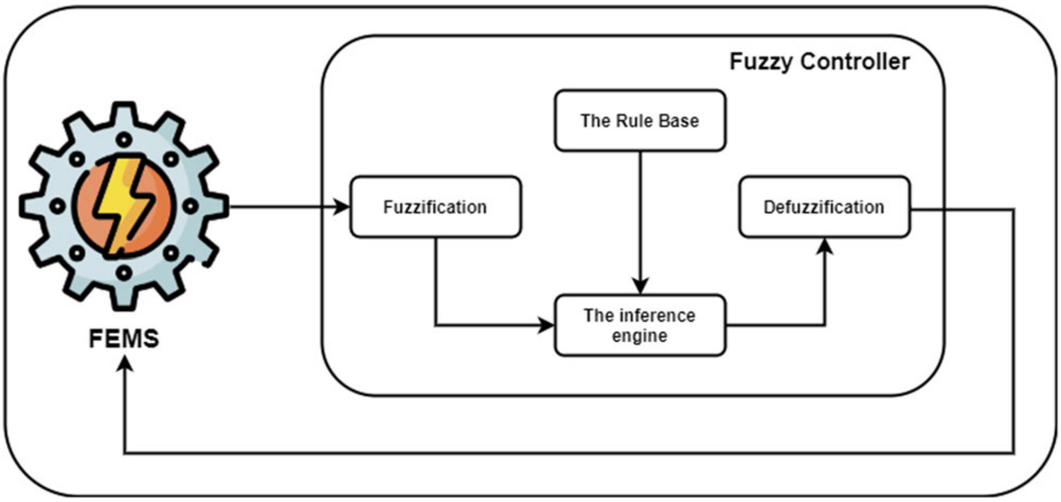


**Fig. 2.** Structure of Fuzzy Controller

The techniques showed how to create fuzzy rules from numerical data in general. In the initial stage, fuzzy regions are created from the input and output of the numerical data. This operation, which is a part of the data preprocessing, is carried out in the fuzzification block. Fuzzy rules will also be produced by the fuzzification block using the information gathered in the previous step.

The process of turning the input data into fuzzy sets is called fuzzification. The energy management system's sensors provide accurate, precise data as input. These values have undergone preprocessing so that the fuzzy system can understand them. In this kind of transformation, each input value is transformed into a membership degree between 0 and 1 using a membership function. The mapping space is divided uniquely depending on the function used.

The data domain was divided into triangular fuzzy regions, and the triangle membership function was utilized to estimate the values for energy production and consumption. Due to data dispersion, the step of the areas changes as the numerical data increases. Because the values in the data sets were not distributed in a uniform way, there were instances where the frequency of the data was higher and the step was smaller, leading to fuzzier regions, and instances where the frequency of the data was lower and the step was larger, leading to fewer fuzzy regions. It can be challenging to determine the working domain's ideal segmentation. Once the fuzzy regions have been located and the fuzzy rules have been developed, the fuzzy rule base is created. The space has N dimensions, where N is the amount of incoming data. As illustrated in **Fig. 3**, the Rule Base for a system with "AND" rules, two inputs, and one output ($x_1$, $x_2$; y), can be represented as a matrix.

Two rules were included in the matrix as examples. The following statements are arranged: "$R_1$: IF $x_1$ is $B_1$ and $x_2$ is $S_1$, THEN y is CE" and "$R_2$: IF $x_1$ is $B_1$ and $x_2$ is CE, THEN y is B1". The regions associated with input $x_1$ are depicted by lines, whereas the regions associated with input $x_2$ are depicted by columns. Each rule's regions of interest must be picked, and the region that corresponds to the output will be indicated on the position that was chosen. At this point, there may be conflicts between the mapped rules that already exist and the newly established rules. If this happens, it could be helpful to create a process for determining how trustworthy that rule is, and the more trustworthy rule should be given a position in the matrix based on how trustworthy it is.

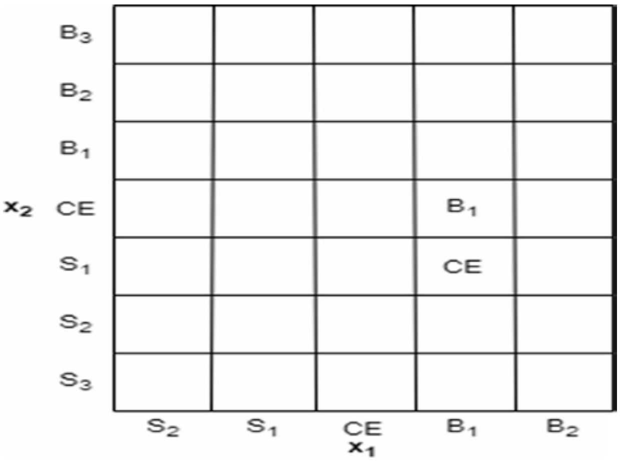


**Fig. 3.** Form of Fuzzy Rule Base

## 4.2 RERNN modeling

The data domain was divided into triangular fuzzy regions, and the triangle membership function was utilized to estimate the values for energy production and consumption. Due to data dispersion, the step of the areas changes as the numerical data increases. Because the values in the data sets were not distributed in a uniform way, there were instances where the frequency of the data was higher and the step was smaller, leading to fuzzier regions, and instances where the frequency of the data was lower and the step was larger, leading to fewer fuzzy regions. It can be challenging to determine the working domain's ideal segmentation.

### 4.2.1. RERNN process of steps

**1. Initialization**

Set the EV's settings, including the weight vectors and node count, to their initial values. $W = [W_1, W_2, \quad \dots \quad W_n]$. Read the nodes in the hidden layer as well as the iteration numbers i.

**2. Generation of random values**

After the initialization procedure, produce the input vectors at random. Here, the parameters of the EV system that are created at random namely, battery power, and EM torque with speed, and battery SOC are used as inputs.

**3. Analyse iterations**

Perform the following iteration if the current iteration fails to converge.

**4. Find the learning rate**

Use the generalized Armijo search method, where the search condition is verified using equation (1), to calculate the learning rate.

$$E(w^k + L_R p^k) \le E(w^k) + \alpha_1 L_R E_w^k (p^k)^t, \ \alpha_1 \ge 0 \qquad (1)$$

**5. New weight computation**

Utilize the gradient descent method to compute the weights as shown in equation (2).

$$w^{k+1} = w^k + L_R P^k \qquad (2)$$

**6. Maximum iteration checking**

Repeat unless the algorithm converges or reaches the maximum number of iterations.

**7. Final Computation**

Calculate the conjugate gradient descents and choose the learning direction using equations (3) and (4).

$$P^k = -E_w^k + \beta P^{k-1} \tag{3}$$

$$\beta = \frac{\alpha E_w^k (P^{k-1})^t}{P^{k-1}(P^{k-1} - E_w^k)}, \alpha \in (0,1) \tag{4}$$

Go to step 4 if the difference between the current and prior iterations exceeds E.

### 4.3. Giza Pyramid Optimization

A meta-heuristic technique called GPC addresses numerous problems [32]. This approach's major objective is to evaluate the existing workload, including the production profile, in order to learn more about the demands and production methods. **Fig. 4** describes and illustrates the proposed method's step-by-step process in detail.

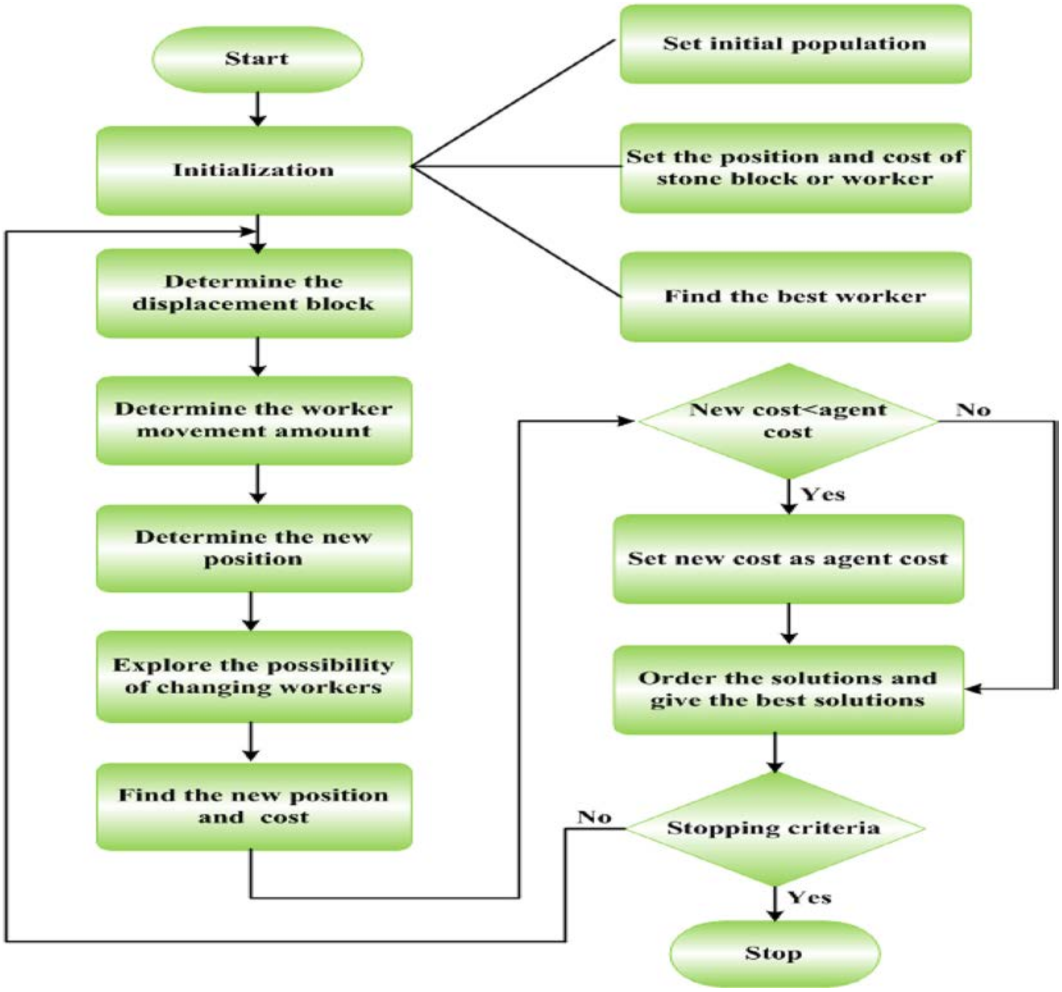


**Fig. 4.** Flow chart of Giza Pyramid Construction

**1. Value Initialization:** To determine the demand for and iterations of this system, start with the population of the Giza pyramid.

**2. Random input generation:** Create the vectors for the inputs as shown in the equation (5)

$$Random^{ab} = \begin{bmatrix} A_p^{11}H_i^{11} & A_p^{12}H_i^{12} & \mathrm{K} & A_p^{1b}H_i^{1b} \\ A_p^{21}H_i^{21} & A_p^{11}H_i^{11} & \mathrm{K} & A_p^{2b}H_i^{2b} \\ \mathrm{M} & \mathrm{M} & \mathrm{M} & \mathrm{M} \\ A_p^{a1}H_i^{a1} & A_p^{a2}H_i^{a2} & \mathrm{K} & A_p^{ab}H_i^{ab} \end{bmatrix} \quad (5)$$

Here, $a_p^{ab}$ and $h_i^{ab}$ indicate the state and control vectors' random solutions.

**3. Fitness performance:** The fitness function is used to evaluate the present load and production profile in order to take into account the current requirement with production form.

**4. Generation:** Create the starting population, their location, and the labor cost (in stone blocks).

**5. Determination:** Choose the ideal employee to serve as the Ruler's representative.

**6. Calculate the update value:** Determine the volume of worker movement and the number of stone blocks that were moved.

**7. Estimate the value:** Calculate the number of new employees.

**8. Investigation:** Look at the potential of replacing the employees, and figure out the new position and the new cost.

## 5. Results and Discussion

This section goes into great length about the experimental validation of the suggested method. The goal of the study is to identify the ideal product combination for upcoming electricity programs in India. RERNN and GPC are combined in the newly announced hybrid method. RERNN features a selective memory component, whereas GPC is a multi-issue meta-heuristic method. This approach's major objective is to evaluate the production profile and load requirements in order to comprehend the existing requirements in production form.

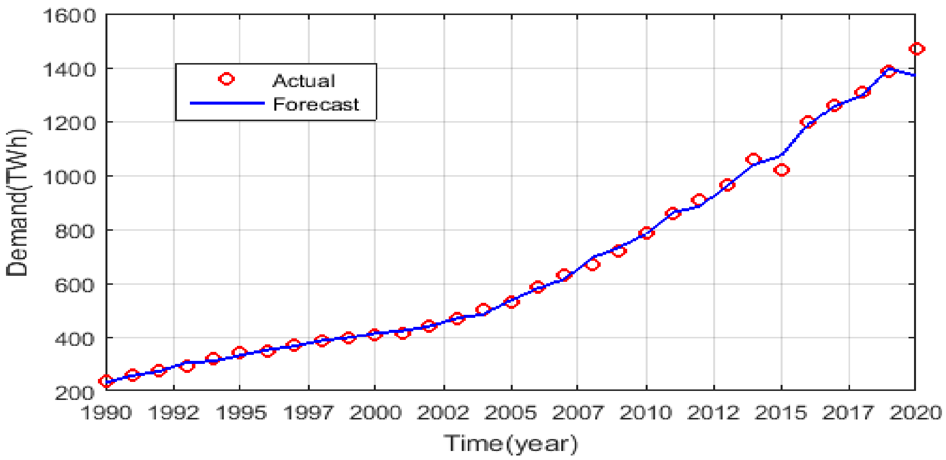


**Fig. 5.** Actual with Forecast Demand in India

**Fig. 5** depicts India's actual and forecasted demand. The demand was 200 TWh in 1990, as predicted, and increase to 400 TWh and 800 TWh in 2000 and 2010, respectively.

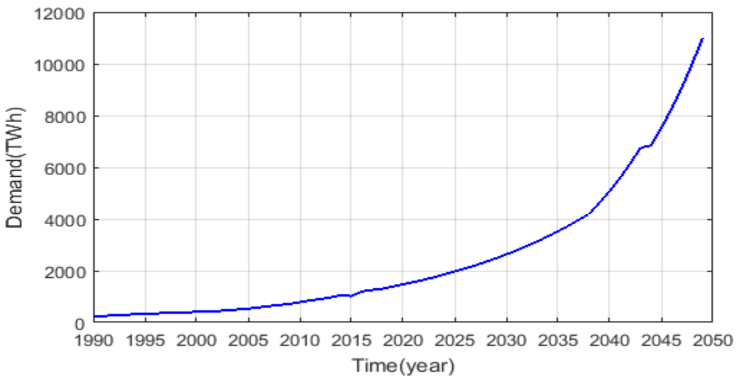


**Fig. 6.** Forecasting Demand in India

**Fig. 6.** shows the forecasted demand in India. The demand for the year 1990 was 380 TWh, while it is set to increase to 2000 and 10,500 in the years, 2025 and 2050, respectively.

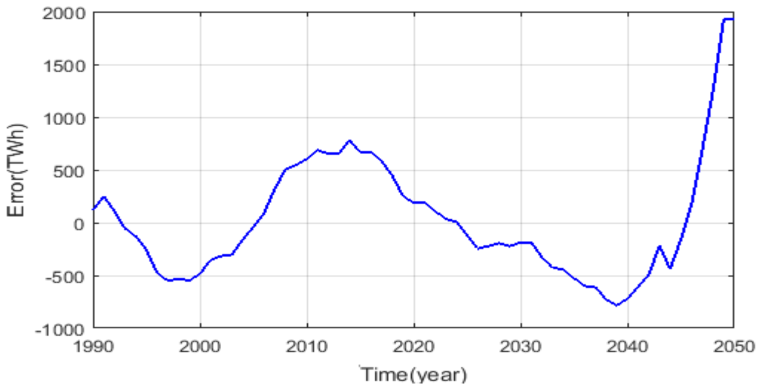


**Fig. 7.** Error Demand in India

**Fig. 7.** shows the error demand in India. For the years 1990 and 2010, the error demands stood at 110 TWh and 600 TWh, respectively, while they will be 2,000 TWh for the year 2050.

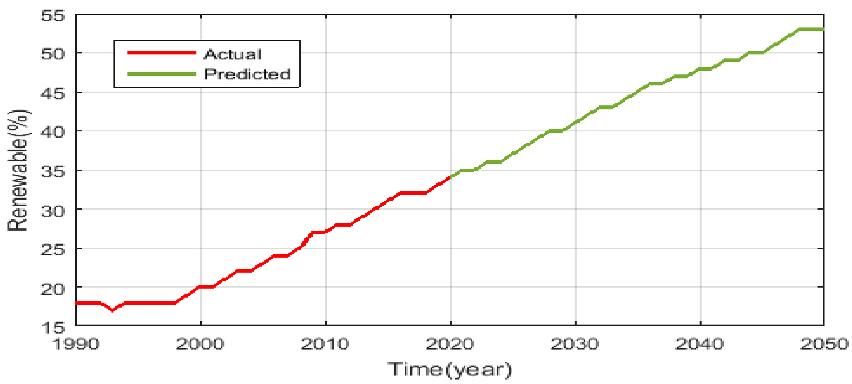


**Fig. 8.** Actual and predicted renewable energy for global nations

Fig. 8 shows the actual and predicted renewable energy across the globe. Between the years 1990 and 2020, the actual renewable energy produced was in the range of 17% to 35%, while it is predicted to increase in the range of 35–55% during the years 2020 to 2050.

**Table 1.** World Electricity Consumption

| **Final Consumption** | **2019** | **2030** | **2040** | **2050** |
|---|---|---|---|---|
| Energy (ExaJoule) | 575 | 648 | 692 | 725 |
| Electricity (kWh) | 80.4 | 143.74 | 176.08 | 197.56 |

**Table 2.** Capacity of power stations in India

| **Sector** | **Coal** | **Gas** | **Nuclear** | **Hydro** | **Renewable** | **Misc.** |
|---|---|---|---|---|---|---|
| Capacity (MW) | 199,864.50 | 24,956.51 | 6,780.00 | 45,789.22 | 91,153.81 | 34,272.96 |
| Percentage (%) | 49.62 | 6.19 | 1.68 | 11.37 | 22.63 | 8.51 |

**Table 3.** Electricity (GW) demand from 2015 to 2050

| **Economic Sectors** | **2020 (%)** | **2030** | **2040** | **2050** |
|---|---|---|---|---|
| Domestic | 42.2 | 142.8 | 313.7 | 668.2 |
| Industrial | 26.8 | 107.5 | 272.4 | 663.3 |
| Commercial | 8.4 | 27.6 | 221.0 | 552.5 |
| Agricultural | 9.3 | 29.2 | 119.1 | 298.3 |
| Transport | 7.5 | 23.4 | 101.9 | 279.6 |
| Misc. | 5.8 | 48.7 | 164.5 | 412.9 |
| Aggregate | 100 | 379.2 | 2452.1 | 2874.8 |

**Table 4.** Electricity (GW) consumers from 2015 to 2050

| **Economic Sectors** | **2020 (%)** | **2030** | **2040** | **2050** |
|---|---|---|---|---|
| Domestic | 41.93 | 85.4 | 284.8 | 511.9 |
| Industrial | 26.89 | 58.5 | 262.6 | 508.8 |
| Commercial | 7.99 | 16.3 | 201.5 | 409.2 |
| Agricultural | 9.25 | 18.7 | 102.8 | 203.4 |
| Transport | 7.19 | 15.9 | 187.7 | 391.5 |
| Misc. | 6.75 | 28.03 | 149.5 | 314.6 |
| Aggregate | 100 | 222.83 | 1188.9 | 2339.4 |

Table 1 displays the trends in global electricity usage from 2019 to 2050. The capacity of India's power plants is displayed in Table 2. For the nation of India, we discovered the varied capacity of power plants for coal, gas, nuclear, hydroelectric, and renewable energy. The demand for power from 2015 to 2050 is shown in Table 3. The consumption pattern of electricity from 2015 to 2050 is shown in Table 4. The comparative table value based on the normalized MSE is displayed in Table 5. Table 6 displays the computation time for India based on several experiments. Table 7 lists the performance metrics for 50 and 100 trials in India.

**Table 5.** Comparative table based on normalized MSE

| Trails | ANFIS (Gulnar Perveen et al., 2019) | Fuzzy based GOA (Srinivasa Rao Gampaa et al., 2020) | JS-LSSVR (Jui-Sheng Chou et al., 2021) | NCPRT2FS (Jafar Tavoosi et al., 2021) | Proposed Fuzzy based RERNN with GPC |
|---|---|---|---|---|---|
| 50 | 16.83 | 16.73 | 16.27 | 15.95 | 15.41 |
| 100 | 19.37 | 19.28 | 18.99 | 17.55 | 16.14 |
| 250 | 17.28 | 16.93 | 16.83 | 16.74 | 16.62 |
| 500 | 18.88 | 18.65 | 18.17 | 17.31 | 16.46 |
| 1000 | 20.59 | 20.36 | 20.31 | 20.18 | 20.04 |

**Table 6.** Comparison of Computation time using various trails

| Trails | Computation time (Sec) | | | | |
|---|---|---|---|---|---|
| | ANFIS | Fuzzy based GOA | JS-LSSVR | NCPRT2FS | Proposed Fuzzy based RERNN with GPC |
| 100 | 7096 | 6963 | 6862 | 6560 | 6814 |
| 250 | 24823 | 25459 | 24380 | 25189 | 13962 |
| 500 | 40414 | 40129 | 38806 | 38314 | 27955 |
| 1000 | 66963 | 66842 | 66725 | 66366 | 55958 |

**Table 7.** Comparison of Performance Measures for 50 and 100 trials

| Performance Measures (%) | 50 trails | | | | |
|---|---|---|---|---|---|
| | ANFIS | Fuzzy based GOA | JS-LSSVR | NCPRT2FS | Proposed Fuzzy based RERNN with GPC |
| Accuracy | 85 | 89 | 90 | 92 | 94 |
| Specificity | 78 | 84 | 87 | 91 | 93 |
| Recall | 86 | 90 | 92 | 94 | 95 |
| Precision | 76 | 86 | 93 | 93 | 94 |
| | 100 trails | | | | |
| Accuracy | 73 | 83 | 92 | 92 | 93 |
| Specificity | 67 | 79 | 84 | 94 | 94 |
| Recall | 63 | 77 | 89 | 90 | 91 |

## 6. Conclusion

A fuzzy-based hybrid RERNN-GPC model is proposed for finding the optimal production mix that meets the demands of the future electricity system in India. By combining RERNN and GPC, this study introduces a hybrid methodology. While GPC is a multi-problem meta-heuristic algorithm, RERNN features a selective memory feature. This approach's major objective is to evaluate the current load requirement with a power generating profile in order to comprehend the current requirement with a production facility. The proposed hybrid approach predicts the ideal generating mix for India's future energy system. The system found an ideal solution with the help of the suggested hybrid technique, which requires less computing time. To prove the superiority of the suggested system, the new method was simulated using MATLAB, and the results were contrasted with their current methods. Also exhibited and discussed are the findings in relation to future global electricity generation. With a computation time of 6814 seconds, the suggested hybrid approach outperformed existing methods with a best result of 93% accuracy. In the future, for the promotion of energy efficiency, new technologies for energy production, limiting energy consumption, and raising awareness of energy issues, a combination of private initiative and government intervention will be crucial to raising public awareness of energy efficiency and opening the door to a future with sustainable energy. So, the advanced deep learning algorithms will be integrated to enhance energy forecasting and energy policies with the help of smart grids and smart meters.

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