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RESEARCH ARTICLE

COMPREHENSIVE STUDY & IMPLEMENTATION OF ENERGY PROGNOSIS USING NEURAL NET APPROACH

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ABSTRACT

According to current prevailing views, the field of energy will undergo significant structural changes in coming decades, making it radically different from what we know today. The classical approach to long term forecasting is often limited to the use of load and weather information occurring with monthly or annual frequency. So, in this work, the main objective of this work is prediction and forecast of historical energy data using ANN technique and curve fitting. It proposes a modern approach that takes advantage of daily information to create more accurate and defensible forecasts. The main scenarios are predictive modelling & scenario analysis. It uses ANN technique for predicting and optimizing the data. The other objective of this work is to minimize the error value up to 10^-5. It also uses time series analysis methods curve fitting and surface fitting methods. This research investigates the forecasting of residential energy consumption by applying the structural time series model to yearly data. It also provides power estimation at a particular time. The MATLAB software is used to set up a neural network model.

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INTRODUCTION

Given energy is generally accepted as being an important driver of economic growth, countries that focus on sustainable economic growth try to find ways to secure their future energy needs at a reasonable price. The rapid increase in demand from emerging economies, competition between nations to access energy resources, along with environmental problems, arouses another concern: whether or not there will be enough energy supply to meet future demand at reasonable cost. Arguably, this can be solved by long-term planning by developing scenarios for the future evolution of energy demand and the possibilities of meeting that demand in different ways. This can be achieved by a proper understanding of current and past energy demand and possible changes in terms of efficiency and structure, possible supply alternatives, possible technological change, etc. Consequently, energy demand analysis and forecasts are vitally important for long term planning and energy security. Today's sources of energy are still mainly fossil-based. Oil, natural gas and coal are the dominant fuels in the energy mix. And despite many efforts to lighten the carbon weight of global energy supply, it is generally agreed that the world demand for these fossil fuels will continue over at least the next few decades. Oil, natural gas and coal are natural resources. They are not found everywhere but are spread unevenly over the various geographical areas. Currently, the main sources of electrical energy such as thermal power and nuclear power generation usually result in environmental pollution and bring serious damage to the earth. Many emerging green energies therefore come into existence and bring public attentions. Solar energy is one of the pollution-free energies, and can be converted to electrical energy easily by solar cells.

Data mining is a process which finds useful patterns from large amount of data, the process of removing previously unknown, understandable and actionable information from large records and using it to make crucial business decisions. A forecast is a prediction of some future event(s). Forecasting problems are often classified as short-term, medium-term, and long-term. Load forecasting problems can be categorized into two groups: 1) short-term load forecasting (STLF); and 2) long-term load

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forecasting (LTLF). Short-term load forecasts, of which the forecast horizon is up to two weeks, are primarily used in power systems operations, such as unit commitment and economic dispatch. Long-term load forecasts, of which the forecast horizon may range from few months to several decades, are primarily used in power systems planning and financial planning. Predictive energy models can be developed using various Artificial Intelligence techniques, such as Artificial Neural Networks (ANN), fuzzy logic, data mining, mathematical programming and heuristic methods. The need to develop high accurate models for energy consumption forecasting is imminent, starting from simple data mining and noise suppression methods to more complete and efficient machine learning algorithms.

A lot of literature works related to this work have been proposed. Hong *et al*. (Yibin *et al*., 2014) proposed a modern approach that takes advantage of hourly information to create more accurate and defensible forecasts. The proposed approach had been deployed across many U.S. utilities, including a recent implementation at North Carolina Electric Membership Corporation. Yibin Li *et al*. (Sauer and Thomas Roessler, 2013) proposed that the system must schedule its workload based on current energy reserves and predictions of additional energy. In this case, the efficiency of scheduling was highly sensitive to the energy harvesting prediction. Liu *et al*. (Luis Hernández *et al*., 2013) proposed Artificial Neural Networks (ANN) technique to forecast the day-ahead wind power and Locational Marginal Price (LMP), and a hybrid Energy Storage System (ESS) consisting of two storage facilities was developed. Buhari *et al*. (Alvarez *et al*., 2011) proposed that Artificial neural network (ANN) has been used for many years in sectors and disciplines like medical science, defense industry, robotics, electronics, economy, forecasts, etc. The learning property of ANN in solving nonlinear and complex problems called for its application to forecasting problems. The rest of paper is ordered as follows. In section II, we discuss the structure of neural network, its architecture etc. In Section III, It defines proposed work related to energy forecasting scheme. In Section IV, it describes proposed results of system. Finally, conclusion is explained in Section V.

Structure of neural network

Neural network is also called artificial neural network. In brief, artificial neural network is based on the idea of human neurons and uses a lot amount of artificial neurons to imitate the capabilities of neural network for the living creatures. Neural networks learn by example and relate a set of input variables to a set of output variables. ANNs can be classified by their architecture, processing and training. Whereas, architecture describes the neural connections, processing describes how networks produce output for every input and weight. On the other hand, training algorism describes how ANN adapts its weight for every training vector (Behera *et al*., 2012). Neural network architecture consists of three parts; input layer, hidden layers and output layers.

It can be transformed to mathematic equations to demonstrate the input and output relationship of artificial neurons.

Neuron Input:

$$n = w1p1 + w2p2 \ldots\ldots\ldots\ldots. + wnpn + b = wp + b$$

Neuron Output:
$a = f(wp + b)$
p: network input vector;
w: interconnect weights (synapse);
b: biases;
f: transfer function;
a: network output.

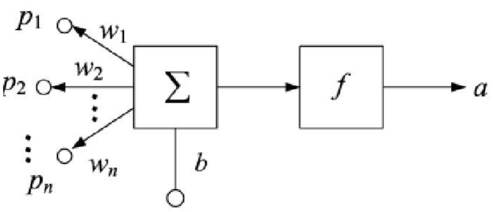


Fig. 1. Structure of Neural Network

To make the neural network operate correctly, it is necessary for the neural network to use a appropriate training method to learn iteratively until each input properly corresponds to the desirable output. The output of the neural network is tumultuous before the network was trained. The interconnect weights in the neural network will be gradually adjusted with an increasing number of training times in order to minimize the errors between the target values and the output values of the neural network. Back propagation network is one of the most widespread and representative learning rules in the neural network. It is based on a multilayered, feed-forward topology, with supervised learning. The basic structure of a back-propagation network is shown in Fig. 2.

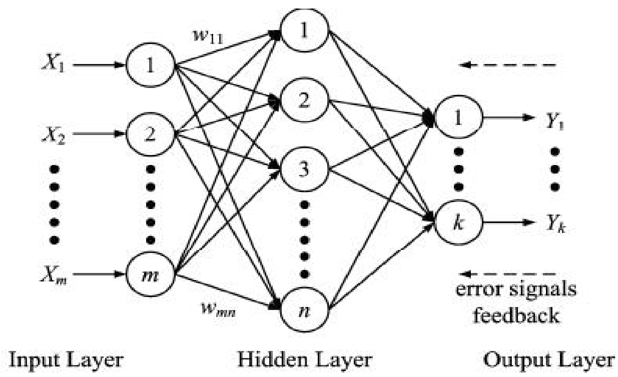


Fig. 2. Structure of Back-Propagation Network

The algorithm can be divided into feed-forward and back-propagation stages. In the feed-forward stage, the back-propagation network starts out with random weightings on its synapses. Then it is exposed to a training set of input data and the output should go along with every input. In the back-propagation stage, the network's weights are incrementally adjusted and the errors between target values and output values are propagated back to the network. The equation for calculating least mean square errors can be expressed as:

$$E(\hat{\theta} - \theta)^2 = E(\left(\hat{\theta} - E(\hat{\theta})\right) + (E(\hat{\theta}) - \theta))^2$$

$$MSE = VAR(\hat{\theta}) + BIAS^2$$

Where
$\hat{\theta}$= estimator
θ= estimated parameter
Var= Variance
Bias= Bias of Estimator

Fig. 3. Flowchart of Back-Propagation Network

The first step of training procedure is to setup initiated parameters related to network and also initialize weights of random numbers. In next step, it includes input of training data, output of hidden and output layers, error calculations and also weight adjustment of layers. After completion of training process, the convergence of target is checked. It this value is under limit then process is stopped otherwise it will be iteratively repeated until it reaches the desired limit. The output of the network after training is also a set of normalized data.

Description of proposed work

It proposes a prediction and analysis of energy forecasting by historical data using ANN technique and curve fitting. The first step of training procedure is to setup initiated parameters related to network and also initialize weights of random numbers. In next step, it includes input of training data, output of hidden and output layers, error calculations and also weight adjustment of layers. After completion of training process, the convergence of target is checked. It this value is under limit then process is stopped otherwise it will be iteratively repeated until it reaches the desired limit. After this, analysis is done using further techniques. When discussing scenarios and forecasts it is important to note the difference between the two. Forecasts are predictions of the future. The best information available, e.g. from market analysis, is used to make a prediction of what will happen in the future. Scenarios, on the other hand, merely reflect thinking on how potentially the future may evolve. This is used in different ways. Quite often, scenarios are used to describe extreme views of the future, with one or more specific elements becoming highly dominant. It follows a step-by-step procedure comprising five major steps:

- Goal of forecast and the identification of resources for conducting it;
- Time prospect;
- Selection of a predicting technique;
- Conducting and implementation the prediction;
- Monitoring accuracy of the forecast.

In the back-propagation stage, the network's weights are incrementally adjusted and the errors between target values and output values are propagated back to the network. The first stage in the data mining process is that of deciding whether or not to go ahead with a given analysis. This is one of the most difficult and probably the most crucial of all the stages, as it is here that we decide whether or not we are going to spend our time and other resources investigating a given data set. Once we have decided to go ahead with our investigation, it is vital that the data be in a format that can be easily interpreted by the model building tool. Certain tools are given almost entirely to this stage of data mining and unsupervised clustering is also widely used in this stage of the process, particularly in the discovery of outliers. The more pre-processing applied to a given data set, the better the results from creating a data mining model of that data set are likely to be. The more pre-processing a tool offers, whether supervised or unsupervised, the better is likely to be the performance of models created by that tool or subsequently applied tools. After model building, it is used to predict the future data. After this, ANN is used for error minimization. It calculates the error by defining goal value and then it is minimized by iteration process.

Model building is the core of the data mining process. This is where verifiable results are obtained. The scope of this study is limited to supervised learner models. What this essentially means is that the models it creates will have been trained using examples of known cases (from the data set) and then verified using further information from the data which has not yet been presented to the model. This stage is known as the training and testing or validation stage and once completed the model produced can be used to predict future outcomes, instances which have neither been seen by the model nor by individuals. The final stage of the data mining process is that of interpretation. As with the decision phase, however, our interpretation of the results can be assisted using automated means.

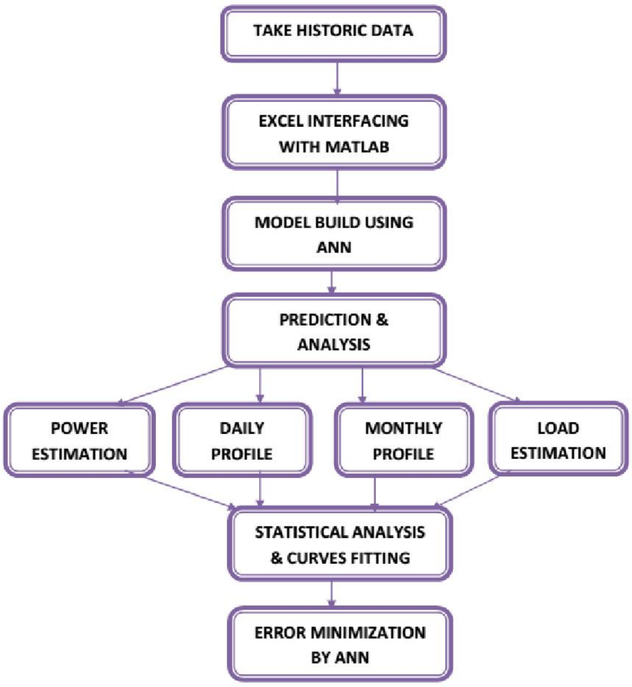


Fig. 4. Flow Chart of Proposed System using ANN

Historical data usually contain a certain amount of noise (random variation) that tends to obscure patterns in the data. Randomness arises from a multitude of relatively unimportant factors that cannot possibly be predicted with any certainty. The optimal situation would be to completely remove randomness from the data and leave only "real" variations (for example, changes in the level of patient demand). Unfortunately, it is usually impossible to distinguish between these two kinds of variations. The best one can hope for is that the small variations are random and the large variations actually mean something.

Averaging techniques smooth out some of the fluctuations in a data set; individual highs and lows are "averaged" out. A forecast based on an average shows less variability than the original data set do. The result of using averaging techniques is that minor variations are treated as random variations and essentially "smoothed" out of the data set.

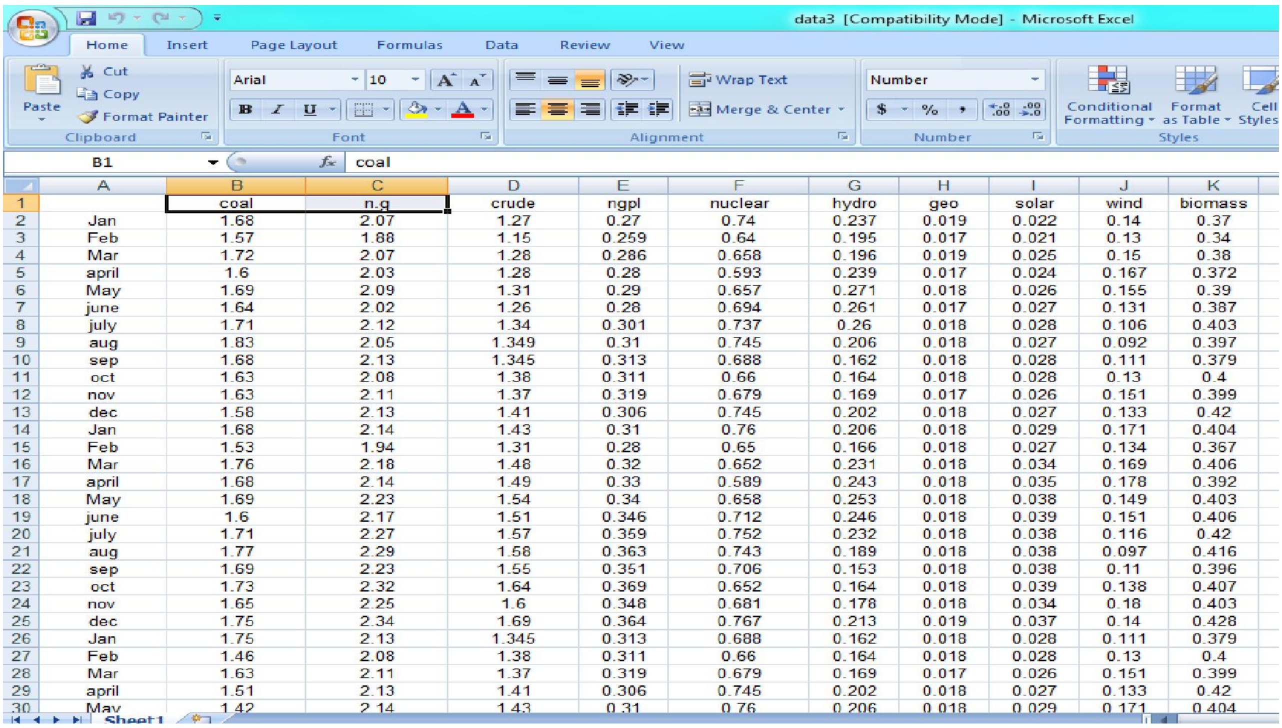
RESULTS AND DISCUSSION

This describes prediction and analysis for forecasting energy usage based on historical data. It has access to utility usage for the month of January to December, including information about different fields. The figure 5 shows the historic data values. It contains fields like crude oil, nuclear plant, hydro energy plant etc. The Table 4.1 describes the input parameters defined for the system. Their values may change. It describes the main results and analysis of energy forecasting data. Firstly, clear the workspace and then load the historic data by interfacing MATLAB with excel sheet. Data must contain energy production values etc. Then visualize the data with the help of 3-D plotting.

Table 1. Input Parameters of System

Parameter Name	Value
Inputs	5
Max Iterations	1000
Learning Rate	0.01
Momentum Rate	0.01
Goal Error	0.00001

In this, it provides the proposed results of system. The data is plotted w.r.t system load. It uses ANN method for prediction of data and also for error minimization. After this, it has to calculate power of a particular field. Use curve fitting method to explore this result. The result outputs are shown.



	A	B	C	D	E	F	G	H	I	J	K
1		coal	n.g	crude	ngpl	nuclear	hydro	geo	solar	wind	biomass
2	Jan	1.68	2.07	1.27	0.27	0.74	0.237	0.019	0.022	0.14	0.37
3	Feb	1.57	1.88	1.15	0.259	0.64	0.195	0.017	0.021	0.13	0.34
4	Mar	1.72	2.07	1.28	0.286	0.658	0.196	0.019	0.025	0.15	0.38
5	april	1.6	2.03	1.28	0.28	0.593	0.239	0.017	0.024	0.167	0.372
6	May	1.69	2.09	1.31	0.29	0.657	0.271	0.018	0.026	0.155	0.39
7	june	1.64	2.02	1.26	0.28	0.694	0.261	0.017	0.027	0.131	0.387
8	july	1.71	2.12	1.34	0.301	0.737	0.26	0.018	0.028	0.106	0.403
9	aug	1.83	2.05	1.349	0.31	0.745	0.206	0.018	0.027	0.092	0.397
10	sep	1.68	2.13	1.345	0.313	0.688	0.162	0.018	0.028	0.111	0.379
11	oct	1.63	2.08	1.38	0.311	0.66	0.164	0.018	0.028	0.13	0.4
12	nov	1.63	2.11	1.37	0.319	0.679	0.169	0.017	0.026	0.151	0.399
13	dec	1.58	2.13	1.41	0.306	0.745	0.202	0.018	0.027	0.133	0.42
14	Jan	1.68	2.14	1.43	0.31	0.76	0.206	0.018	0.029	0.171	0.404
15	Feb	1.53	1.94	1.31	0.28	0.65	0.166	0.018	0.027	0.134	0.367
16	Mar	1.76	2.18	1.48	0.32	0.652	0.231	0.018	0.034	0.169	0.406
17	april	1.68	2.14	1.49	0.33	0.589	0.243	0.018	0.035	0.178	0.392
18	May	1.69	2.23	1.54	0.34	0.658	0.253	0.018	0.038	0.149	0.403
19	june	1.6	2.17	1.51	0.346	0.712	0.246	0.018	0.039	0.151	0.406
20	july	1.71	2.27	1.57	0.359	0.752	0.232	0.018	0.038	0.116	0.42
21	aug	1.77	2.29	1.58	0.363	0.743	0.189	0.018	0.038	0.097	0.416
22	sep	1.69	2.23	1.55	0.351	0.706	0.153	0.018	0.038	0.11	0.396
23	oct	1.73	2.32	1.64	0.369	0.652	0.164	0.018	0.039	0.138	0.407
24	nov	1.65	2.25	1.6	0.348	0.681	0.178	0.018	0.034	0.18	0.403
25	dec	1.75	2.34	1.69	0.364	0.767	0.213	0.019	0.037	0.14	0.428
26	Jan	1.75	2.13	1.345	0.313	0.688	0.162	0.018	0.028	0.111	0.379
27	Feb	1.46	2.08	1.38	0.311	0.66	0.164	0.018	0.028	0.13	0.4
28	Mar	1.63	2.11	1.37	0.319	0.679	0.169	0.017	0.026	0.151	0.399
29	april	1.51	2.13	1.41	0.306	0.745	0.202	0.018	0.027	0.133	0.42
30	May	1.42	2.14	1.43	0.31	0.76	0.206	0.018	0.029	0.171	0.404

Fig. 5. Historic Data Used

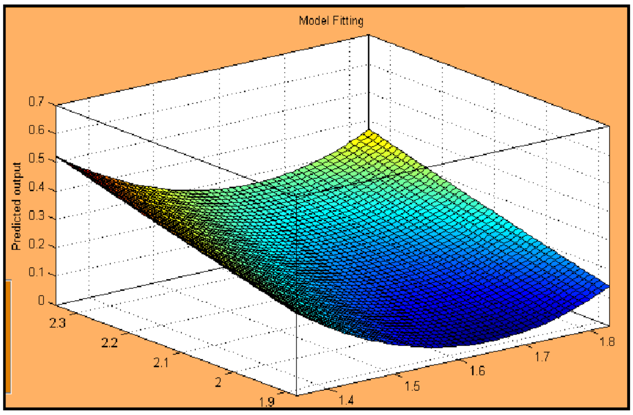


Fig. 6. Model Fitting with Normalized Output having Mean=0 and SD=1

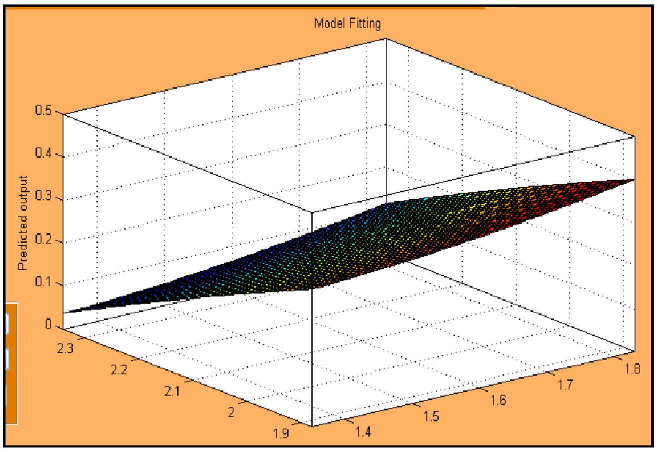


Fig. 7. Model Fitting with Un-normalized Output

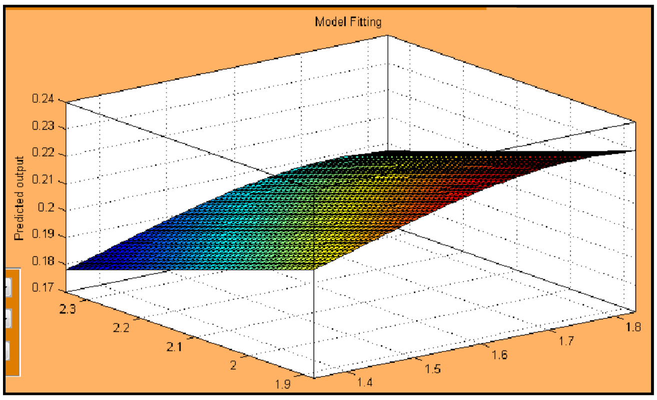


Fig. 8. Model Fitting with Normalized Output (-1,1)

Table 2. Power Analysis of Each Field

Field	Power Used (MW)
Residential	1724.8
Commercial	1792.7
Industrial	2551.2
Transportation	3140.4
Power Sector	2677.9
Natural Gas	932.4
Petroleum	57.8
Geo	-53
Solar	3.2
Biomass	2.2

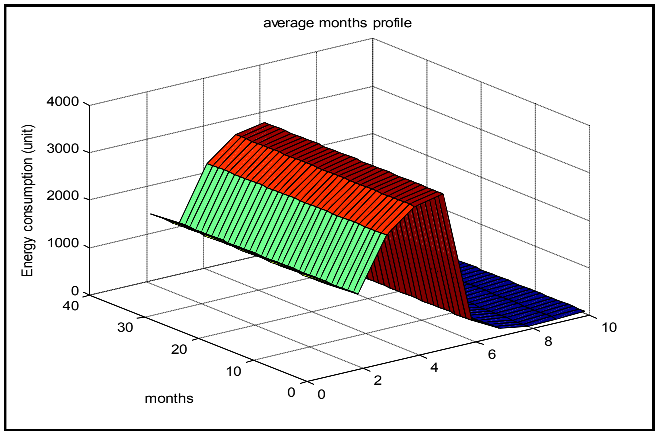


Fig. 9. Average Monthly Profile of Data

The following custom plotting routine takes data as an input, calculates the estimated mean and 95% confidence interval of the mean and standard deviation. The profile seems to have a very tight confidence interval, suggesting that the general trend throughout the day is similar. By looking at average profiles for each month of the field, it can make some observations on daily trends. It can see that the morning energy spike is not prominent on the weekends. The performance analysis is shown below. Table 2 shows the power analysis at a particular field. Different fields have different units of consumption of power. The main scenarios are predictive modelling & scenario analysis. It uses ANN technique for predicting and optimizing the data. The other objective of this work is to minimize the error value upto 10^-5. Table 3 & 4 provides the error values w.r.t. iterations with and without normalized conditions. The number of iterations may vary but error value is under 10^-5.

Table 3. Error Minimization by ANN with No Normalization Condition

Iterations	MSE
1	0.3235
100	0.0000029
500	0.0000017
1000	0.0000011
1282	0.0000010

Table 4. Error Minimization by ANN with Normalization Condition

Iterations	MSE
1	0.462
10	0.4919
20	0.2709
29	0.0000019

Conclusion

This work investigates the energy prognosis using time series methods. The main objective of this work is prediction and forecast of historical energy data using ANN technique and curve fitting. The ANN method is used for prediction and error minimization of data. It explored historical energy usage data to develop a forecasting system. It uses the data of 10 fields that provides different usage of energy throughout. Statistics and visualizations revealed that there are usage trends throughout the day, and the trends seem to depend on the day of the week. It has access of data of each field. This knowledge can be used for a gross forecast of the energy usage. In this, single day profile and average month profile is evaluated. It also calculates power of any particular hour observed. The performance parameters like mean, standard deviation and confidence interval is also evaluated. It minimizes the error value up to 0.000001 using ANN. Different functions are used for modelling of data.

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