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Optimization study on competence of power plant using gas/steam fluid material parameters by machine learning techniques

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ABSTRACT

The power plant significance is to envisage the complete load electric power production of a permanent load on a power supply to increase the yield from the accessible megawatts hours (MW hrs). This power plant productivity may rely upon conservation variables like pressure, temperature and humidity. Here, the preliminary way to increase overall efficiency can be precise by the combination of two thermodynamic cycles powered by gas and steam that reduces fuel costs also. In this proposal, machine learning techniques such as principal component analysis for reducing dimensions in the dataset where data points are plotted and K-Means, agglomerative for clustering method to predict the cluster for each data point, finally calculating the cluster center also. By statistical analysis, statistics of complete dataset can be done through features such as ambient pressure, relative humidity, ambient variable temperature, exhaust vacuum, power output. The foremost aspire of power plant is to accomplish overall efficiency carried through each and every components comes under power plant. These tremendous precise forecasts produce an upgrade production inventory that overestimates effectiveness and productivity of power station.

1. Introduction

In the last three decades, gas turbine steam locomotive solitary recognized as dominant equipment behind mechanical, aeronautical impetus and many power production industries. The Combined Cycle Power Plant becomes fame only as a consequence of enhance in thermal efficiency and also time required for production comparatively very fewer. The combined cycle power plant utilizes both steam and gas turbine combine to generate nearly 50% supplementary electricity other than conventional unique power plant. Pinar et al. [1] formed the full load electric energy production through machine learning techniques such as regression method where the bagging method with REPTree produce best results by way of Mean Absolute Error value as 2.818 and Root Mean Square Error value as 3.787. R. Bontempo et al. [2] presented hypothetical analysis of highly developed gas turbine cycles. In particular, three types of cycles are investigated which are intercooled, reheat and intercooled along with reheat cycles. These cycles attain utmost the whole work to increase the pressure ratio, such that increase in power production to generate better electricity Fig. 1.

A combined cycle power plant is basically a power plant based on electricity in which the combination of both (steam, gas) turbines to realize the overall competence of combined cycle power plant. This CCPP incorporates with one or more gas turbines which constrain the generators as well as drain into solitary boiler known as Heat Recovery Steam Generator (HRSG) to deliver a steam turbine whose production gives rise to high performance electricity. Yousuf Najjar et al. [3] reviewed the article for preceding one decade, approved twelve research analysis which enclose twelve gas turbine system for generating high energy that makes very well-organized. This mainly supports in some other applications of combined power plant industry namely LNG gasification, organic Rankine cycle, repowering, incorporated refrigeration and power, cryogenic power, closed gas turbine cycle.

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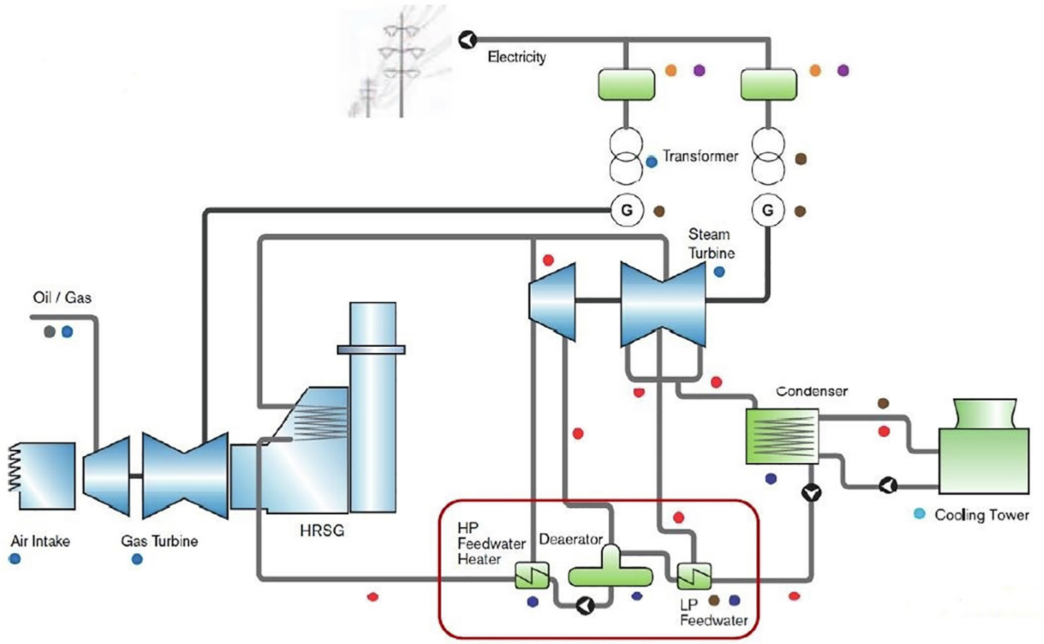

Fig. 1. Combined cycle power plant diagram.

2. Related work

Bolland et al. [4] revealed the comparative measures to enhance the efficiency of steam and gas turbines cycles in the power plant to generate high power electricity. The combined cycle power plant composed of dual as well as triple pressure reheat cycle, triple pressure critical reheat cycle were utilized to generate the outcome with high production of electricity. M Ameri et al. [5] surveyed the irreversibility of CCPP with analysis of energy. Here the experimental outcomes reveal that gas turbine, HRSG, combustion chamber and duct burner are the major resource of irreversibility which represents exceeding 83% in overall energy victims. The final outcome shows that CCPP increased with 7.38% whenever the duct number is used. A. L. Polyzakis et al. [6] performs recounting CCPP through optimization and comparing four kinds of gas turbine cycles namely simple, IC (intercooled), RH (reheated), integration (IC/RH). In this paper, the combined cycle power plant generates 300 MW while gas and steam turbine generates 200 MW, 100 MW respectively. Kotowicz et al. [9] presented combined cycle power plant using thermodynamics materials to achieve an net electric power of 0.63–0.65. The production of power is nearly 200 MW. Niu LU [11] utilizes linearization technique for power production in CCPP especially with gas turbine. R. Rajesh et al. [10] works by principle of Rankine and Brayton cycle for power generation using steam and gas turbine achieves an efficiency of 39.6% with overall net power production is 844 MW. Jesus L Lobo [13] predicted electric power generation in combined cycle power plant using the streaming learning with regression technique with parameters such as temperature, pressure, vacuum, power. Thamir et al. [12] exposed compression ratio technique for energy generation using both turbines in CCPP with an efficiency around 61%.

3. Workflow for proposed algorithm

First and foremost step in machine learning flow process is collection of dataset form the resource where finding large number of datasets for learning and validation process. Secondly, loading the dataset and describing the datasets such as features description utilized in training, testing and validation phases. In this review, statistical analysis plays major task for identifying power plant production from the combined process of gas and steam turbine to generate high power electricity depends on variables like pressure, temperature and humidity using techniques such as PCA for feature reduction along with clustering technique for clustering the data points found in the sample dataset. By validating the testing phase, the metrics like ambient pressure, relative humidity, ambient variable temperature, exhaust vacuum, power output with the intention to maximize the profit in CCPP. Final step is to calculate t-score and P-value in validation phase to predict the outcome with higher production to manufacture high power electricity.

The workflow for the proposed work can be summarized as follows: Fig. 2.

The power capacity utilization can be measured by load factor. It is the measure of utilization rate, and efficiency of energy usage depends on electricity. Here high load factor denotes that load is using electric system more powerfully whereas generators that underutilize the electric distribution will have a low load factor.

$$LoadFactor = \frac{Averageload}{Maximumload} w.r.t.time \quad (1)$$

Load factor = Average load/ Maximum load in a given time period. Load Factor in power plant is the most important parameter for calculating the overall performance, power capacity usage for generating high power output. On the other hand, if the load factor increases, the cost per unit (kWh) gets decreased for high power productivity.

4. Ml algorithm used in proposed work

4.1. Principle component analysis

PCA is a machine learning technique to condense the dimensionality of a dataset such as number of variables which results in reduction of information loss as well as enlarge in interpretability. This can be processed by creating innovative interrelated vari-

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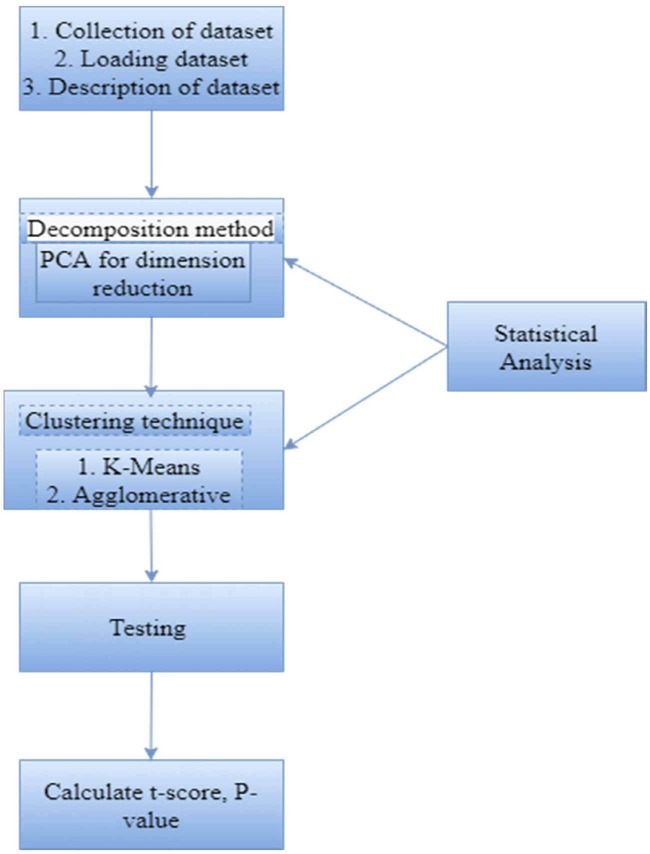

Fig. 2. Workflow for proposed method.

ables which makes exploit in variation very effectively. Dimension reduction is the process of reduction of large amount of data into partial data that almost used for modeling along with visualization. H. Kaya et al. [7] proposed his work for predicting full load power electricity of mutual gas and steam turbine through machine learning technique mainly regression such as multivariate, and additive, Artificial Neural Network and K means clustering to make global and local analytical model using specific features like temperature, humidity and pressure. In his review, smoother K-NN is probable to envisage total yield below 1% relative inaccurate in the given dataset which generates high power production. Jesus L Lobo et al. [13] introduced stream learning mechanism for power production with finding of errors using linear regression method in machine learning. PCA mechanism can be applicable on a dataset having three or more than three dimensions along with numeric variables

In this proposal, PCA is generally used in the decomposition process as follows:

Step 1: Apply PCA by appropriate data with same number of dimensions

Generate PCA outcome

Step 2: Apply PCA technique to fit good data into only two dimensions

Transform the good data using PCA fit above

Create data frame for reduced data

Step 3: Create a biplot for reduced data, good data.

4.2. Clustering technique

Clustering technique is an unsupervised machine learning approach (data has no pre-defined labels) for statistical analysis of dataset in many of the technical research fields Fig. 3.

The steps in the clustering technique can be operated as follows

Step 1: Collecting dataset from the specified resource.

Step 2: The dataset is loaded for further data pre-processing

Step 3: Apply clustering algorithm such as K-Means, as well as agglomerative clustering for cluster each data point

Step 4: Locate the center for cluster

Step 5: Finally calculate the mean silhouette co-efficient for number of cluster preferred.

Step 6: The mean silhouette co-efficient can be evaluated by comparing reduced data along with predicted data.

4.3. K Means clustering

K means clustering is a category of unsupervised machine learning technique used for clustering approach to separate 'n' objects into 'k' clusters where similar number of data points are clustered in one cluster. K means method tries to minimize the cluster inertia variance along with squared error function.

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} ||x_i^{(j)} - c_j||^2 \quad (2)$$

n- Number of cases, k- number of clusters, c_j- centroid for cluster j, J- objective function.

After dimension reduction through PCA, K- Means clustering approaches to predict the cluster for each data point to separate gas turbine, steam turbine also and finally calculate the centric point of the cluster.

4.4. Program for clustering used in the proposed work (testing phase)

```
//Predicting good data cluster
If x=1
Cluster becomes 0
Else x=preds
Cluster becomes 1
Create data frame as good data cluster
// testing portion for selecting good cluster
Int data_0, data_1
Initialize p= test (data_0, data_1);
Numerical_ selected []
Significant α=0.05 // fit threshold value
For (i=0; i<len(data_0.column); i++)
If p[i] ≤ α
P_value_dict={(t-score: round(stats[i]2,5), (P_value: round(p[i],5))}
ttest_dict(data_0.column[i])=P_value_dict
numerical_selected.append(data_0.column[i]) repeat for loop
Display significant features
Display data samples outside majority cluster
```

4.5. Gaussian mixture model:

Aishwarya et al. [14] explains the working procedure of Gaussian mixture model and how to implement in python coding. Gaussian Mixture is the probabilistic models which utilize the soft clustering approach for distributing the data points in dissimilar clusters. In this model, every recurrence enumerate mean and covariance matrix for every cluster by means of flexible task. The probability of blue cluster, green and cyan refers 1 and 0.

5. Dataset description

The dataset is collected from UCI machine learning repository [8] which is the most important resource of machine learning

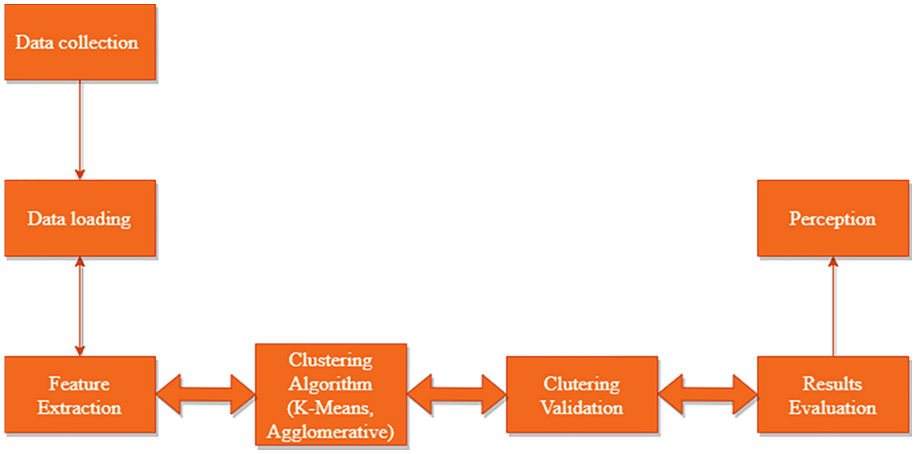

Fig. 3. Proposed work by machine learning method.

dataset through our searchable interface. The collected dataset should be stored in .csv files, the datasheet format should be in .xls. The dataset consists of 9568 samples obtained from nearly 6 years (2006–2011) of a Combined Cycle Power Plant (CCPP), when the power plant was scheduled to run with full load. The five parameters namely temperature, pressure, humidity, vacuum and power are identified through significant alpha level as 0.05 with feature size of 5081 rows* 5columns.

The CCPP mainly comprised of GT, ST and heat recovery steam generators. In that, the electricity is generated by both (gas, steam) turbines, grouped into one cycle finally transferred from one turbine to another. While the Vacuum is collected from Steam Turbine, the other three of the ambient variables affect the performance of GT. In order to be consistent with our baseline studies, 5x2 fold statistical tests can be carried out. The 2-fold cross validation is performed for each shuffling, and the resulting 10 measurements are used for statistical testing. The complete dataset statistics of each feature such as pressure, relative humidity, variable temperature, exhaust vacuum, power output can be evaluated via statistically analyzing the values namely count, mean, standard deviation, minimum, maximum predicted value. The power plant outcome can be analyzed by overall performance of features deliberate in both gases along with steam turbines to generate high electricity. Based on electricity production, the overall performance can be evaluated.

5.1. Features introduced in CCPP along with description and its types

Table 1.

Table 1
Features description and its types.

Features	Description of features	Types
Ambient pressure	Milli bars as unit	Input feature
Relative humidity	calculated in percentage	Input feature
Ambient variable temperature	measures in Celsius	Input feature
Exhaust vacuum	deliberated in cm Hg	Input feature
Power output (Full load power production)	deliberated in Megawatts	Target feature

5.2. Noteworthy metrics used in proposed work

(i) Silhouette co-efficient: The Silhouette co-efficient can be calculated by means of mean value of both outer cluster (x) and adjacent cluster (y) distance for every sample. The co-efficient for one sample can be simplified as

$$Co-efficient = \frac{(y-x)}{\max(x,y)} \tag{3}$$

Where x-outer cluster; y- Adjacent cluster

(ii) Centroid for cluster:

Centroid means central point distinct as multi dimensional average of cluster. The Centroid is a vector contains a number for every variable (A, B, C) However, every number is the mean of a variable for observations in that cluster Fig. 4 and Fig. 5.

For instance, the Centroid of points A, B and C can be intended as

$$centroid = \frac{x_1+x_2+x_3}{3}, \frac{y_1+y_2+y_3}{3}, \frac{z_1+z_2+z_3}{3}$$

(iii) t-score- t-score refers the consistent form of statistical calculation that takes individual score and converts it into standardized format which helps to compare the validation score in future. T-score can be calculated using the following formula.

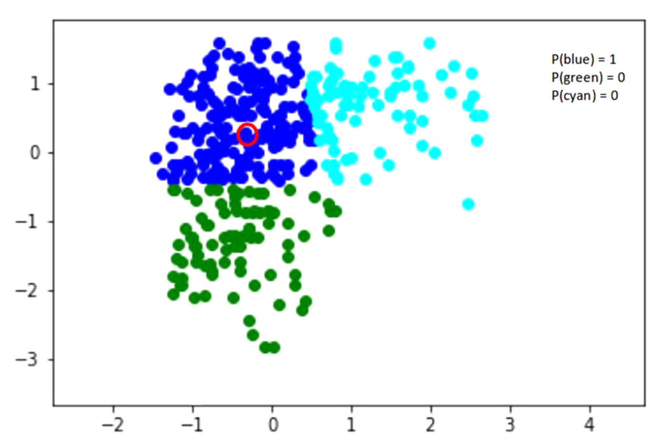

Fig. 4. Gaussian mixture clustering.

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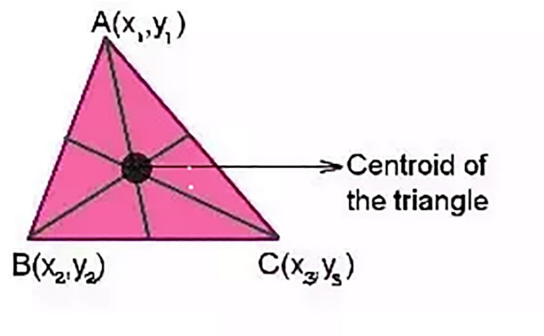

Fig. 5. Centroid for cluster.

Table 2
Truth table for P-Value.

TRUTH	Decision (Accept/Reject) Accept (H_0)	Reject (H_0)
H_0 – true	Correct decision- P	Type-I error
H_0 – false	Type-II error	Correct decision- P

P- Probability; H_0- null hypothesis

$$t = \frac{\bar{x} - \mu_0}{s/\sqrt{n}} \tag{4}$$

Where $\bar{x}$ - mean sample, μ_0 – mean population, n- sample size, s – standard deviation

For criteria if the sample is only one i.e n = 1, then the formula becomes

$$t = \frac{\bar{x} - \mu_0}{s} \tag{5}$$

(iv) P-Value- The P-Value can be intended test statistic of distribution under null hypothesis, testing type done and sample data. If p-value < 0.05, then statistically significant otherwise if > 0.05 then statistically not significant. In this proposal, p-value is the significant value as $\alpha = 0.05$.

The p-value is statistically significant based on the following table

Table 2

6. Experimental results and analysis

This phase is more significant since based upon the experimental results; we can moderate whether the model is good or bad. Principle component analysis can be carried out in decomposition process for placing the good data which are having similar features and finally generate the PCA results plot Fig. 6.

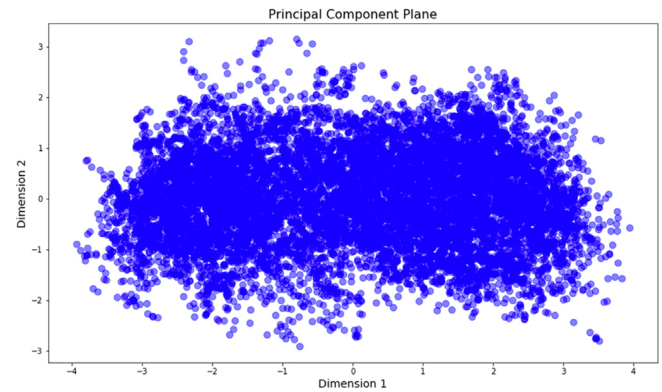

Fig. 7. PCA plane with different dimensions.

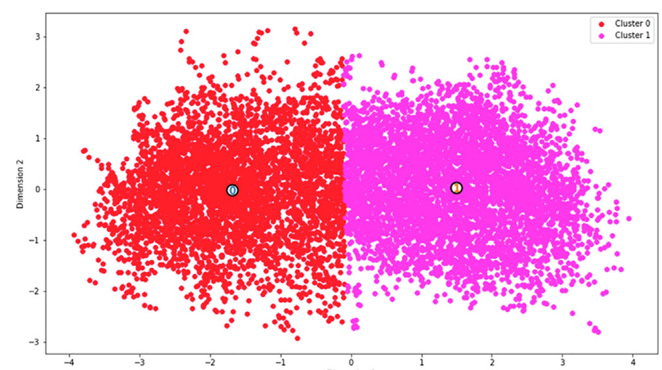

Fig. 8. Cluster Analysis.

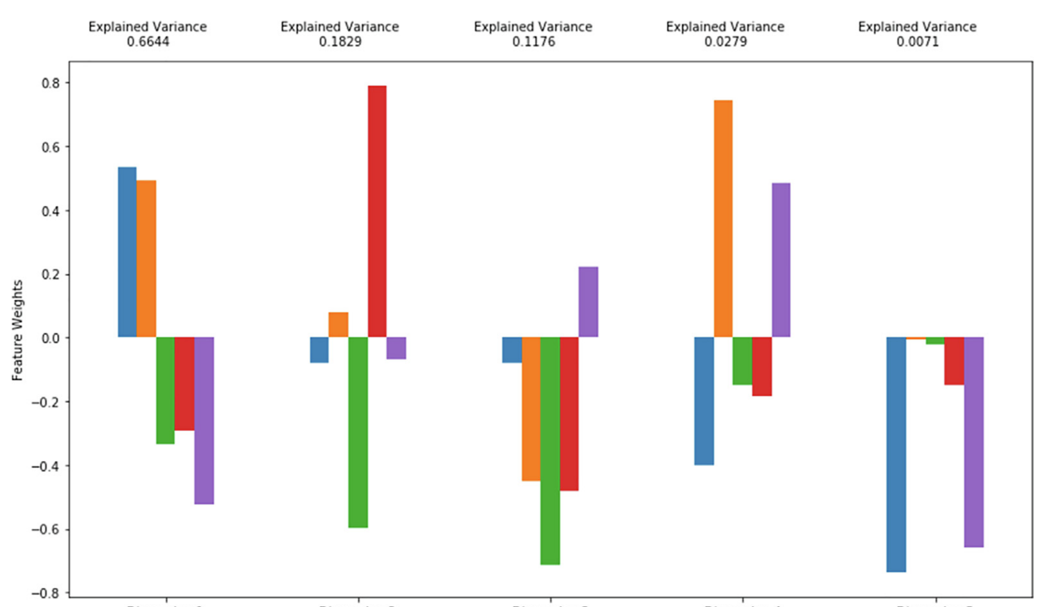

Fig. 6. Decomposition process using PCA.

Table 3
Basic statistics of dataset for predicting power parameters.

	Temperature(AT)	Vacuum (V)	Pressure (AP)	Humidity (RH)	Power (PE)
Mean	19.65	54.31	1013.26	73.31	454.37
variance	55.54	161.49	35.27	213.17	291.28
Std	7.452473	12.707893	5.938784	14.600269	17.066995
Min	1.810000	25.360000	992.890000	25.560000	420.260000
max	37.110000	81.560000	1033.300000	100.160000	495.760000

Table 4
Covariance Matrix.

	Temperature(AT)	Vacuum (V)	Pressure (AP)	Humidity (RH)	Power (PE)
AT	55.54	79.94	−22.45	−59.031	−120.6
V		161.49	−31.21	−57.92	−188.6
AP			35.27	8.63	52.546
RH				213.17	97.13
PE					291.28

Table 5
Correlation matrix.

	Vacuum (V)	Pressure (AP)	Humidity (RH)	Power exhaust (PE)
T	0.85	0.51	0.54	−0.94
V		0.41	0.30	−0.88
RH				0.38
AP			0.10	0.52

Table 6
Statistical analysis for Energy features.

	Temperature(AT)	Vacuum (V)	Pressure (AP)	Humidity (RH)	Power (PE)
count	9.568000e + 03	9.568000e + 03	9.568000e + 03	9.568000e + 03	9.568000e + 03
mean	3.415259e-16	−2.186999e-16	5.361082e-15	6.205901e-16	−1.760869e-15
std	1.000052e + 00	1.000052e + 00	1.000052e + 00	1.000052e + 00	1.000052e + 00
min	−2.394126e + 00	−2.277901e + 00	−3.430019e + 00	−3.270589e + 00	−1.998406e + 00
25%	−8.240958e-01	−9.888705e-01	−7.003615e-01	−6.836860e-01	−8.563765e-01
50%	9.309729e-02	−1.751604e-01	−5.373067e-02	1.141150e-01	−1.649474e-01
75%	8.143721e-01	9.627745e-01	6.737290e-01	7.891378e-01	8.241478e-01
max	2.342804e + 00	2.144779e + 00	3.374760e + 00	1.839173e + 00	2.425568e + 00

Table 7
t-score, P- value calculation.

	Temperature (AT)	Vacuum (V)	Pressure (AP)	Humidity (RH)	Power (PE)
t-score	25377.53314	20080.87096	2946.2519	1930.01406	25574.33742
P-value	0.00000	0.00000	0.00000	0.0000	0.00000

The features weight can be evaluated by different variance for different dimensions. For dimension 2, the specified weight as 0.8 which is maximum. Apply PCA technique by appropriate good data with only two dimensions, then transforming the same good data using PCA fit above. Creating data frame for the reduced data using dimensionality reduction method. Construct biplot for good data, reduced data along with PCA technique for placing the data into different dimensions Fig. 7.

After implementation, the outcome of clustering can be displayed by identifying the reduced data, predicted data as well as centers of different clusters grouped from the known features Fig. 8.

6.1. Overall statistical analysis

In this proposal, statistical analysis can be done for finding energy generation in combined cycle power plant Table 3.

The temperature cannot be under 0, where as it ranges from 1 to 37. Now, the overall highly generated power output is nearly 496 MW through data analysis.

6.2. Covariance matrix evaluation for clustering

The power exhaust calculation through covariance matrix is 291.28 Table 4.

6.3. Correlation matrix

Correlation matrix execute clustering for both rows and columns i.e [i, j] and [j, i]. The correlation between vacuum and temperature is nearly 0.85. The correlation between vacuum and power exhaust is 0.88 Table 5.

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Table 8
Comparison table for power production.

Authors	Materials (gas/ oil/ steam)	Methods used	Parameters calculated in CCPP to generate electricity Temperature	Humidity	Pressure	Vacuum	Power Exhaust	Efficiency	Power output
M. Ameri et al. [5]	Gas turbine, thermal	Exergy analysis	✓	NA	✓	NA	✓	45.5%	420 MW
Kaya H et al. [7]		ANN, K-means clustering	✓	✓	✓	✓	✓	NA	NA
Yousuf Najjar et al. [3]	Gas turbines	12 research investigation	✓	NA	✓	NA	NA	NA	NA
Pınar Tüfekci et al. [1]		Bagging algorithm	✓	✓	✓	✓	✓		473 MW
A. L. Polyzakis et al. [6] & R. Bontempo et al. [2]		Simple cycle, Inter Cooler (IC), Reheated cycle, IC/RH.	✓	NA	✓	NA	✓	53.5%	300 MW
Niu L U et al. [11]	Gas turbine	Linearization model					✓	✓	
Thamir K et.al. [12]	Steam turbine, Gas turbine	Compression ratio	✓	NA	✓	NA	✓	61%	NA
Kotowicz et.al [9]	Gas turbine	Thermodynamic analysis	✓	NA	NA	NA	✓	63%	200 MW
R Rajesh et.al. [10]	Gas, steam turbine	Working principle of Rankine, Brayton cycle	✓	NA	✓	NA	✓	39.6%	843.75 MW
Jesus L Lobo et al. [13]		Linear Regression	✓	✓	✓	✓	✓	NA	NA
Current Work	Gas, steam turbine	Machine Learning technique	✓	✓	✓	✓	✓	80%	496 MW per year

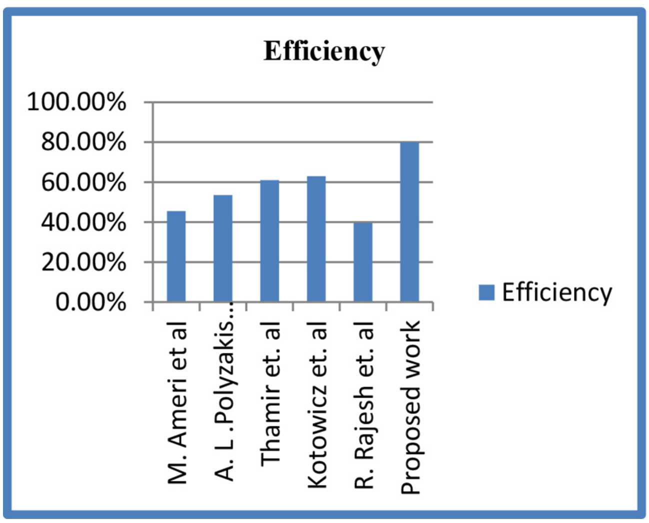

Fig. 9. Efficiency calculation.

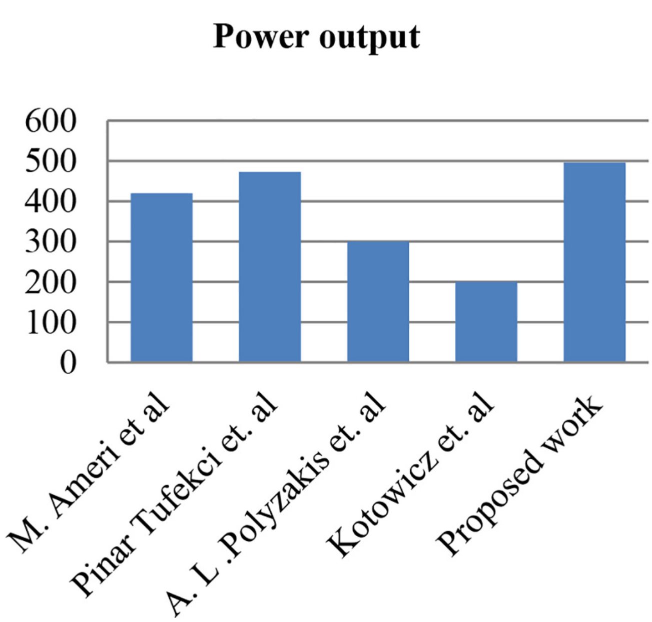

Fig. 10. Comparison for power production calculation.

6.4. Statistical representation (Median, mode, mean, minimum, maximum)

The analysis of statistical representation such as count, mean, minimum, maximum values are evaluated especially generating high power output based on five features medium (AT, V, AP, RH, PE) with range of alpha as 0.05 Table 6.

6.5. t-score, P-value calculation

The overall energy production over 6 years can be calculated using statistical analysis by t-score (squared) value with net generation as 25,574 Megawatts over 6 years. The net production of power generation approximately 496 MW hours which seems to be better manufacture than existing work Table 7.

The capacity of gas turbine and steam turbines can vary from different industries. For instance, In India, the power production with collective capacity of 200 GW at Kudankulam nuclear power plant. The total installed power station capacity in India is 370,048 MW, the capacity of gas turbine noticed as 500 KW to 250 MW, the average steam turbine is represented as 37 MW as well as CCPP as 26 GW, steam turbine generate electricity of 85% during the year 2014 especially in U.S countries. The overall efficiency of the organization can be increased by 50–60 % to generate high power if the loads of work are numerous. Thus, we can say that the overall efficiency for simple cycle as 34% and also combined cycle is 64%.

6.6. Features comparison for power production in combined cycle power plant

The CCPP shows high efficiency in production of electric power which seems to be much better than single shaft gas turbine. The Table 8 shows the parameters comparison of parameters, techniques used, usage of materials such as gas, oil, steam, for competence of energy productivity among different researchers. The efficiency and performance comparison calculation can be evaluated in Table 8 Fig. 9.

The efficiency of power plant can be deliberate using heat rate generation during production in every organization. If heat rate increases in thermal units (Btu), then the percentage of efficiency decreased and vice-versa. The power generated in proposed work is 496 MW which outperforms the experimental results when comparing other works with an efficiency of 80% Fig. 10.

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7. Conclusion and future scope

Combined Steam and gas turbine acts as a main role for outlook energy production in many industries to augment the overall competence of combined cycle power plant. In this examination, the first cycle is PCA method to reduce the features via variance, constructing biplot for reduced features and also good data, the second cycle prefers K-means clustering where all the data points are clustered to detach good data and reduced data for forecasting high electric energy to be generated. For machine learning technique, python tools could be utilized. The optimum performance of high quality electricity can be achieved by features calculation namely ambient temperature and pressure also, relative humidity, vacuum and power exhaust statistically by machine learning modus operandi. The features evaluation can be highlighted by means of t-score value for each feature in regarding with steam and gas turbine power plant to breed electricity. The power plant production can be evaluated therefore the efficiency calculation is around 80% and electricity production as 496 MW via statistical analysis that outperforms the existing work. The future scope is usage of supplementary learning technique like support vector machine, regression trees intended for better production of electrical energy.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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