

COMBUSTION EFFICIENCY PREDICTION IN GAS TURBINE COMBUSTOR USING SIGMOID NORMALIZATION AND FOOTBALL OPTIMIZATION BASED LSTM

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Abstract

An essential part of gas turbines is the combustion system, which burns the fuel and air mixture to produce thrust or power. Anomalies in combustors, such as problems with fuel nozzles, excessive vibration from acoustic waves and oscillations in the release of heat, and non-compliant emissions, are frequently caused by instability in combustion and uneven fuel distribution. To overcome these issues, FBO-LSTM is developed to predict combustion efficiency and power influence. A can combustor was designed with a 150 mm diameter casting, 210 mm length, and a 170 mm long combustor model, featuring variations in casting angle and dump gap. With a flow rate of 0.473 kg/s and 0.0096 kg/s, it has a vertical fluid and air input. Six scenarios were explored, varying casting angles and dump gap to analyse temperature, static pressure, velocity, power, and combustion efficiency. To normalize the input data, these simulated data are gathered. The data are then pre-processed using Sigmoid Normalization. Next, the LSTM is used to estimate the combustion power and efficiency using the pre-processed data. The Football Optimization (FBO) approach is utilized to select the optimal learning rate and batch size of the LSTM classifier. This technique achieved 96.2% of accuracy, 93.5% of selectivity, 89.7% of MCC and 3.8% of error, demonstrating considerable improvements in the findings. The error difference between the turbulence intensity of the dump gap and casting angle is 2% and 0.4%. Thus, this FBO-LSTM approach is a better choice to predict the power and efficiency of the combustor.

Keywords: Can Combustor; Football Game Optimization and Combustion Efficiency; Gas Turbine Combustor; LSTM; Sigmoid Normalization

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Introduction

Gas turbines are widely used in power generation worldwide and have been a crucial component of industrial production for over a century. However, their environmental impact has become a growing concern, largely due to the focus on improving combustion characteristics rather than addressing the harmful consequences of burning fossil fuels (Sundararaj *et al.*, 2019). The combustion process produces harmful emissions, including CO₂, H₂O, and NO_x, which degrade air quality and contribute to health problems. In response, there has been a global effort to develop low-emission combustion technologies to mitigate further environmental damage (Okafor *et al.*, 2020). This is particularly urgent due to the stringent NO_x emission regulations imposed by governments worldwide (Niszczota and Gieras, 2021). While natural gas, with its low nitrogen content, remains the dominant fuel for gas turbines, alternative low-heating-value gases like biogas and coal-bed methane (CBM) have not been fully exploited. These gases are often wasted, despite their potential to improve combustion efficiency. Recent research has shifted focus toward utilizing such low-heat value fuels, like CBM, to enhance gas turbine combustion and reduce emissions (Ursueguía *et al.*, 2021). This shift towards alternative fuels opens up new possibilities for improving the environmental performance of gas turbines.

Gas turbines with low NO_x emissions are receiving more attention, especially when it comes to combustor design. Numerous configurations, such as the lean direct injection (LDI) combustor (Meziane and Bentebliche, 2019) and the rich-quench-lean (RQL) combustor (Joo *et al.*, 2021), have been proposed by researchers and are often utilized to minimize NO_x emissions. The ultimate emission performance is greatly impacted by the choice of suitable structural characteristics and operating circumstances. NO_x generation is influenced by variables like equivalence ratio and combustion temperature. Several techniques, such as numerical simulation techniques and experimental testing, have been employed to ascertain the impact of these parameters on combustor emissions. By leveraging intricate chemical reaction processes, the chemical reactor network (CRN) technique allows for the prediction of pollutants in a less complicated and computationally costly manner than numerical simulation methods (Nguyen *et al.*, 2019). These approaches do have certain drawbacks, though, such as the requirement for large sums of money for research, as well as the requirement for intricate

flow models and the combination of several models. When the combustor is complicated, the CRN technique is prone to variations in forecast outcomes (Chang *et al.*, 2020).

Combustion chamber design system involves thermal design and three-dimensional combustion simulation to achieve low emissions and stable combustion under pressure conditions and high temperatures. Computational fluid dynamics (CFD) (Nassini *et al.*, 2021) is a crucial tool for simulation design, but faces challenges in fluid-thermal interaction and thermoacoustic oscillations. Although four-dimensional non-constant design simulation is still under research, three-dimensional design simulation is being utilized more frequently. Large-scale simulation data may be mined, and machine learning methods can be utilized to forecast non-constant phenomena in heat transport and flow. Conventional machine learning techniques, including logistic regression and Naive Bayes, K-neighbors, and decision trees, have limitations in data volume and computational power (Karthick, 2017). Deep learning methods, like convolutional neural network structures and recurrent neural network structures, are appropriate for cases with adequate processing and data resources, difficult challenges, and poor feature extraction efficiency. Genetic Algorithm (GA), they may take a long time to reach a solution (Shi *et al.*, 2019). Case-Based Reasoning (CBR) optimization struggles when encountering problems that differ significantly from past experiences (Niu *et al.*, 2020). But the FBO's unique focus on teamwork and dynamic problem-solving provides a novel and potentially more effective approach to optimization challenges. It is more adaptable and capable of handling dynamic, multi-objective, and complex optimization tasks. To overcome these issues, the FBO-LSTM approach is developed to predict the combustion efficiency and power.

The main contribution of this FBO-LSTM is given below:

- Optimized deep learning is developed for predicting combustion efficiency and power in the gas turbine.
- Sigmoid Normalization is utilized as a pre-processed technique to standardize the input data.
- The LSTM approach is used to predict the combustion efficiency and power in the gas turbine. For improving categorization accuracy, the hyper-parameters like learning rate and batch size of LSTM are selected optimally by Football game Optimization (FBGO).

- Recall, accuracy, and precision are used to assess the suggested LSTM-FBGO models' efficiency for validation and verification.

The sections of the paper are structured as follows: An overview of the literature is presented in Section 2 on gas turbine combustor performance. Proposed methodology and its architectures are given in Section 3. The outcome and discussion section are explained in Section 4. Lastly, Section 5 presents the concluding section.

Literature Review

Recent trends are being on to predict gas turbine combustor efficiency. Numerous models and several techniques were introduced to predict gas turbine combustor performance; a few of them are briefly discussed below.

Park *et al.* (2020) suggested an ANN to operate real-time data from industrial gas turbines to forecast the features of a gas turbine combustor. They projected combustor operation parameters, such as fuel mass flow, turbine inlet temperature, fuel distribution for each nozzle, NO_x, combustor operating pressure, and combustor inlet air temperature, based on their knowledge of the turbine exhaust temperature (TET) and key gas turbine design parameters. The average predicted root mean square error (RMSE) was less than 0.02296. However, pressure dynamics made the flame highly unstable.

Choi *et al.* (2020) suggested an innovative ResNet method for high-speed flame images for identifying a gas turbine's combustion instability. The efficacy of the suggested models was confirmed by a set of high-speed flame images taken in a gas turbine combustor throughout the process of changing from a stable to an unstable condition and back again. All test cases performed well, with processing times ranging from 5.2-12.2 ms and accuracy rates of 95.1%. The best combination, according to the data, is using recommended fusion layers in 16 time-steps with the ResNet-18 model. However, the training error of a properly deep model increased with the number of layers added.

Zhou *et al.* (2021) designed BIM (BASIS Image Monitor) was a CNN (Convolutional Neural Network) that uses monitoring combustion instabilities using time-averaged flame images. To cover a range of flame forms, experiments were conducted on the BASIS (Beihang Axial Swirler Independently-Stratified) burner using a variety of operational conditions. Experiments with 112 operational conditions were undertaken, and photographs were included in BIM for training and testing. After less than 20 minutes of training,

BIM achieved approximately 99% prediction accuracy. BIM-extracted features and Class Activation Maps (CAM) visualizations revealed statistical relationships between flame images and their stability. However, BIM attached flame could counteract weak flame-wall interaction and stabilize the flame, resulting in a false prediction.

Gangopadhyay *et al.* (2021) developed a deep learned architecture known as 3D convolutional selective autoencoder (3D-CSAE) to detect self-excited oscillations, used spatiotemporal data and high-speed filmed from a lab-based gas turbine engine combustor substitute known as a swirl-stabilized combustor. 3D-CSAE was made up of filters that learned the complicated visual and dynamic aspects of combustion instability from trained films in a hierarchical order. The 3D-CSAE on video frames is taken under a constrained set of operating parameters. 3D-CSAE hyper-parameters that effectively characterize hierarchical and multistage instability structure evolution used dynamic video data. The recommended model demonstrated a definite improvement in identifying the antecedents and the beginning of instability. However, underlying interactions between the flow-field and flame, the instantaneous flame edge in turbulent flow was not stationary.

Lyu *et al.* (2021) suggested a Long Short-Term Memory (LSTM) Network and a Convolutional Neural Network (CNN) to extract temporal correlations and spatial characteristics from high-speed images, and then output the detection of combustion instability. Interpret the model's detection process by visualizing the extracted spatial features and their temporal evolution. The impact of varying trained data volumes and CNN layer complexity on model performance. This model, CNNnet-18 + LSTM, got a high accuracy of 98.72%. However, CNN's accuracy does not increase significantly as its depth increases.

Bai *et al.* (2021) suggested a Convolutional neural network-based deep transfer learned for fault detection of gas turbine combustion chambers. A pre-trained convolutional neural network was trained on data from one gas turbine with high data quality, and it was then adjusted for defect detection in another gas turbine with low data quality. One data-rich gas turbine and another data-poor gas turbine shared fault knowledge using deep transfer learned. Combining data from both data-rich and data-poor gas turbines, the suggested method could greatly increase detection performance using data from the data-poor gas turbine directly. This method is effective, but accuracy needs to be improved.

Numerous methods and algorithms were proposed in the literature mentioned above to

anticipate the efficiency of the combustor. These approaches produce well-performing results, but they have certain drawbacks. The pressure dynamics make flame highly unstable (Park *et al.*, 2020), but using LSTM to model temporal dependencies and capture fluctuations in pressure and flame behavior over time results in more stable predictions. The training error of a deep model increases as more layers are added (Choi *et al.*, 2020). The proposed solution uses a simpler FBO-LSTM, helping to identify the optimal depth and parameters, thereby preventing overfitting and inefficiency. A BIM-attached flame may stabilize the flame and counteract a weak flame-wall contact, producing an inaccurate prediction (Zhou *et al.*, 2021). LSTM can capture temporal interactions between the flame and wall by processing data sequentially, enabling it to better model dynamic flame-wall contact. The instantaneous flame edge is not stationary (Gangopadhyay *et al.*, 2021), but LSTM can track its changing dynamics over time, providing more accurate predictions. CNN's accuracy does not increase significantly as its depth increases (Lyu *et al.*, 2021). Using LSTM for temporal predictions and optimizing with FBO improves accuracy and reduces training time. And the process consumes more time as well as has poor accuracy (Bai *et al.*, 2021). FBO to dynamically optimize the learning rate and batch size to ensure efficient training and improved performance. To get over these problems, a unique method is offered that uses an improved deep learning classifier to forecast combustor performance. The proposed combustor

efficiency prediction method is thoroughly explained in the next section.

Proposed Methodology

A combustor is a critical component of a gas turbine engine responsible for the combustion process that generates the high-temperature, high-pressure gas required to drive the turbine blades and produce mechanical power or electricity. Modern combustors are designed for fuel flexibility to accommodate different types of fuels, including natural gas, diesel, biofuels, and hydrogen, while maintaining performance and emissions standards. High temperatures within the combustor can lead to thermal stresses on components, necessitating robust design and material choices to ensure durability and reliability. The gas turbine combustor plays a crucial role in converting fuel energy into mechanical power efficiently and reliably. Continuous advancements in design, materials, and control technologies are essential to improving performance, reducing emissions, and enhancing the overall efficiency and reliability of gas turbine engines. Hence, AI based approach is utilized to predict the efficiency and power of the combustor in a gas turbine.

The workflow of a proposed method is depicted in Figure 1. A can combustor was designed with varying casting and dump gap shapes, including a 150 mm diameter casting and 210 mm length. It has a vertical fluid and air inlet, with a flow

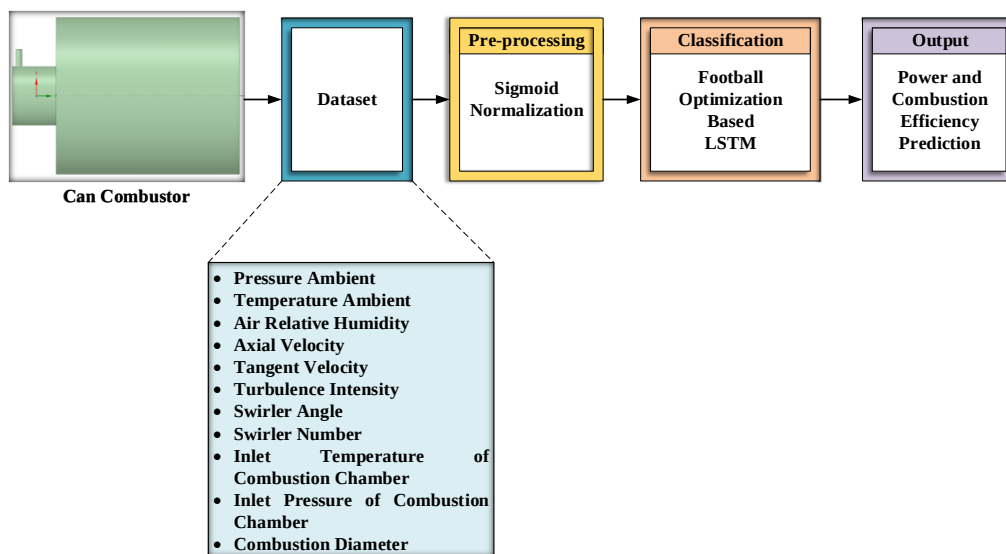


Figure 1. Systematic workflow of the proposed model

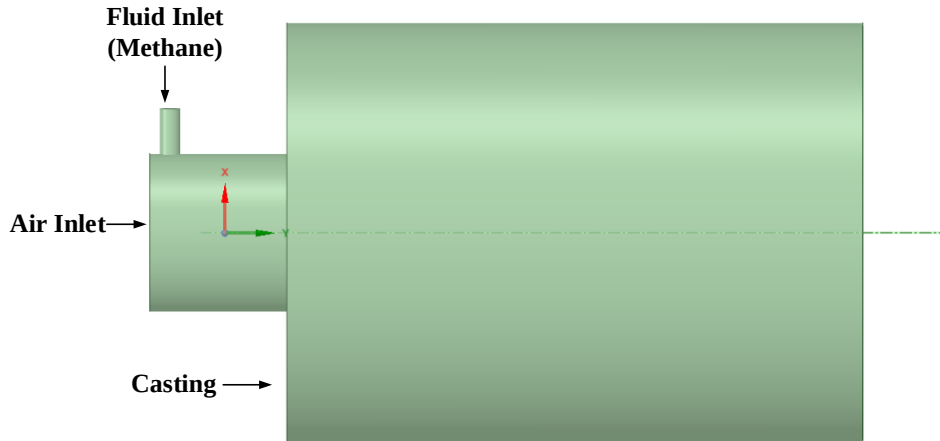


Figure 2. Schematic representation of Can – Combustor Model

rate of 0.473 Kg/s and 0.0096 Kg/s. The combustor model is 170 mm long and fixed inside the casting. Six scenarios were explored, varying casting angles and dump ratio to analyse temperature, static pressure, velocity, power, and combustion efficiency. These simulated data are collected and pre-processed using Sigmoid Normalization to standardize the input data. Next, the pre-processed data are given to LSTM to predict the combustion power and efficiency. Here, the learning rate and batch size of LSTM is optimally selected by football optimization. All prediction output will be evaluated and compared with can combustor simulation results to show the difference in error between predicted and simulated results (Singh and Singh 2020).

Data Collection from Simulated Combustor Model

The experimental setup includes a horizontal casting with a diameter of 150 mm and a length of 210 mm, an air (swirler) and fuel inlet, and a combustor model of 170mm. The swirler vane is positioned in front of the can combustor, and the air is uniformly entered through the nineteen swirler vanes. The fuel nozzles are evenly spaced around the casting perimeter. Methane was used as a fuel, and the fuel and air inlets are 300 K and 530 K with a flow rate of 0.0096 Kg/s and 0.473 Kg/s, respectively. Six scenarios were explored, varying casting angles and dump gap to analyse temperature, static pressure, velocity, power and combustion efficiency. The combustor is divided into four zones: dome, primary, secondary, and dilution holes. A stationary hollow casting ensures uniform fluid flow. The primary zone achieves the maximum flame temperature, while the dilution zone reduces

the final combustion process temperature to minimize CO emission and temperature. Analysis is conducted through varying casting shapes and dump gap and output from these model are collected and further given as input for prediction. The can combustor schematic representation shown in Figure 2.

Pre-processing

Simulated data requires pre-processing since it standardize the input raw data. Pre-processing uses Sigmoid Normalization in order to normalize the input data. A clear discussion of the proposed model was discussed as follows.

Sigmoid Normalization

It reduces the effect of the data outlier in a non-linear manner. Normalizing data in literature typically involves using one of the sigmoidal functions listed below:

Logistic Sigmoid (LS) function based normalization:

The logistic sigmoid function, which projects data between 0 and 1, provides the foundation for the data transformation. Larger values that are present at the data's tails are squashed, and the remaining mapped data is linear. The computation is made in this manner:

$$x'_{i,n} = \frac{1}{1+e^{-q_{i,n}}}, \quad \text{where } q_{i,n} = \frac{x_{i,n}-\mu_i}{v \cdot \sigma_i} \quad (1)$$

where v is the parameter, and during evaluation its value is set to 1. This non-linear normalization method is used when data is not evenly distributed around its mean. The data's outliers that deviate from the mean are exponentially squashed.

Classification

Data classification is the process of organizing data into categories that make it easy to retrieve, sort and store for future use. A LSTM approach is utilized in this method for classification purposes. This approach is used to predict the gas turbine combustion efficiency and power (Le *et al.*, 2019).

Long Short-Term Memory

An improvement on the RNN, Long Short-Term Memory adds more interactions to each cells to solve the problems caused by the aforementioned RNN shortcomings. A unique type of RNN, long-term dependencies can be learned by LSTMs, and they have the innate ability to retain information for extended distances. Organizationally, the LSTM model is set up like a chain. Its structure is different in the repeating module, though. The structure consists of four interacting layers, each with a distinct communication method, as opposed to a single neural network, as in a normal RNN. Figure 3 illustrates the architecture of the LSTM neural network.

Memory blocks known as cells make up an LSTM network in its conventional form. The cell after this receives both the condition of the cell and the hidden state. Data can pass virtually unmodified via the cell state, the primary data flow chain. Still, some linear changes could take place. Sigmoid gates can be used to add or delete data from the cell state. Comparable to a layer or a sequence of matrix operations with distinct individual weights is a gate.

They control the memorizing process through gates, LSTMs are designed to be independent of one another over time.

The process of creating an LSTM network begins with determining what data should be eliminated from the cell. The process of detecting and excluding data is determined by the sigmoid function, which takes the current input (X_t) at time t and the final LSTM unit's output (h_{t-1}) at time $t - 1$. The fraction of the previous output that has to be removed is also determined by the sigmoid function. The values of a vector known as the forget gate (f_t) range from 0 to 1, one for each integer in the cell state (C_{t-1}).

$$f_t = \sigma(W_f[h_{t-1}, X_t] + b_f) \quad (2)$$

In this case, σ is the sigmoid function, whereas W_f and b_f are the weight matrices and bias of the forget gate, respectively.

The subsequent stage entails selecting and modifying the cell state while saving data from the new input (X_t). This level is made up of the tanh layer and the sigmoid layer. While the *tanh* function weighs data that has gone by to evaluate its significance (-1 to 1), the sigmoid layer determines if newly received data should be updated or ignored (0 or 1). Multiplying the two values together yields the new cell state. Next, this new memory is joined with the old memory C_{t-1} to generate C_t .

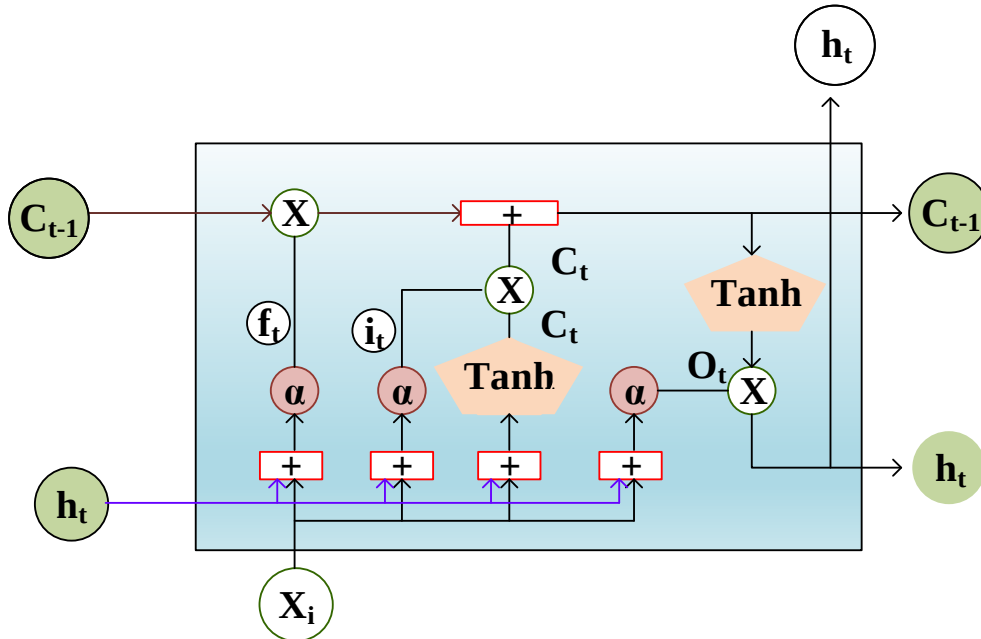


Figure 3. Architecture of the LSTM neural network

$$i_t = \sigma(W_i[h_{t-1}, X_t] + b_i) \quad (3)$$

$$N_t = \tanh(W_n[h_{t-1}, X_t] + b_n) \quad (4)$$

$$C_t = C_{t-1}f_t + N_t i_t \quad (5)$$

Where, C_{t-1} and C_t represent the cell states at times $t - 1$ and t , respectively, whereas W and b represent the cell state's weight matrices and bias.

The output values (h_t) are obtained from the output cell state (O_t) in the last stage, however they are filtered. Initially, a sigmoid layer ascertains which condition of the cell elements are output. The output of the sigmoid gate (O_t) is multiplied by the new values, which range from -1 to 1, generated by the $\tanh$ layer from the cell state (C_t).

$$O_t = \sigma(W_o[h_{t-1}, X_t] + b_o) \quad (6)$$

$$h_t = O_t \tanh(C_t) \quad (7)$$

Weight matrices and bias of the output gate are denoted by W_o and b_o , respectively.

Football Game Optimization (FBO)

FBO is a metaheuristic optimization method that models football players' behaviors. This framework forms a team of players, where each player's place on the football field represents a potential solution. The performance function (PEF) is used to calculate each player's performance. Under the guidance of a team coach, these players' movements mimic the two-phase procedure of receiving the ball and scoring the goal: coaching and random stroll. In order to minimize the overall harmonic distortion, the suggested method establishes the proper values of resistance and inductances for shunt and series filters (variables). The mathematical model of FBGO is given below:

Step 1: Initialization

The FBGO's population based optimization has been swapped for its learning rate (L_R) and batch size (B_S). Batch size varied from "0 to 100", and learning rate varied between "0.01 and 0.5". The formula for expressing the initialization procedure is given in Equations (8) and (9).

$$L_R = \{L_{R_1}, L_{R_2}, L_{R_3}, \dots, L_{R_n}\} \quad (8)$$

$$\{B_{S_1}, B_{S_2}, B_{S_3}, \dots, B_{S_n}\} \quad (9)$$

Where L_R is learning rate and B_S is batch size.

Step 2: Fitness Function

The fitness given by this optimization approach is to improve accuracy. The fitness value is determined by calculating the accuracy. Equation (10) and (11) shows the conceptual structure used to represent fitness function.

$$\text{Fitness } (F_i) = \max(\text{accuracy}) \quad (10)$$

$$\text{accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \quad (11)$$

In this case, FP is an abbreviation for false positive, TN is an abbreviation for true negative, TP is an abbreviation for true positive, and FN is an abbreviation for false negative.

Step 3: Updation

The value is adjusted for each population member's location until it achieves an optimal value. Therefore, updating the position of random walk in football can be mathematically modelled using Equations (12).

$$P_i^t = P_i^{t-1} + \delta_i \sigma + \gamma P_B^t - P_i^{t-1} \quad (12)$$

Where, σ_i is reduced for every iteration by $\sigma_i = \sigma_i \ominus$ and HD is hyper distance.

The team coach observes the players move and commits to memory the optimal locations and their cost function value (CFV), which will be lower than the team size. To increase the probability of a goal being achieved, the team coach uses the substitution plan to swap out inefficient players for more capable ones.

$$HD_i = P_i^{t-1} - P_{best}^{t-1} \quad (13)$$

$$\Re^t = \Re_{min} + \eta (\Re^{t-1} - \Re_{min}) \quad (14)$$

Using Equation (14) the value of $\Re$ is gradually lowered to its specified lowest value ($\Re_{min}$), and η resembles the constant.

$$\Im^t = \Im_{min} + \mathcal{E} (\Im^{t-1} - \Im_{min}) \quad (15)$$

According to Equation (15) where $\mathcal{E}$ is the succession constant, each skilful player whose Performance function exceeds the cost constraint value ($\Im$) will gradually have their performance function reduced as the iteration progresses. The various stages of the proposed FBO are specified as flowchart is shown in Figure 4.

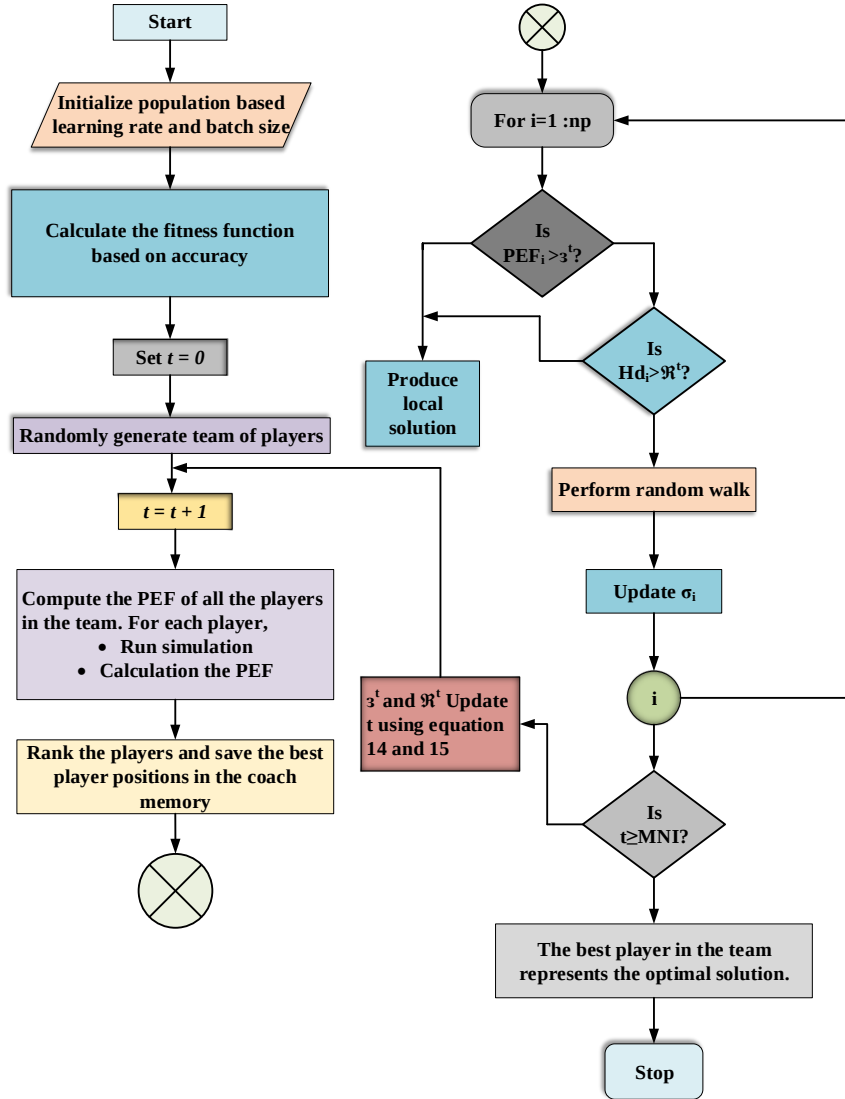


Figure 4. Architecture of the LSTM neural network

Step 4: Termination

Once the best option has been predicted, the entire selection procedure is ended.

Figure 5 illustrates the relationship between the FBO-LSTM. This flowchart provides data flows through the system, highlighting the key steps and interactions between FBO and LSTM. This technique have some parameters, the FBO used batch size and learning rate.

The Pseudo code of this proposed gas turbine combustor efficiency and power predicting method is given in Algorithm 1 (Srilakshmi *et al.*, 2024).

Algorithm 1: Pseudocode to predict combustion efficiency and power

Input: D = Combustion parameters

Pre-processing

```
{
  SN = Sigmoid Normalization (D) // standardize the input value
  IQR= Interquartile range (FWN) // detect outliers
}
```

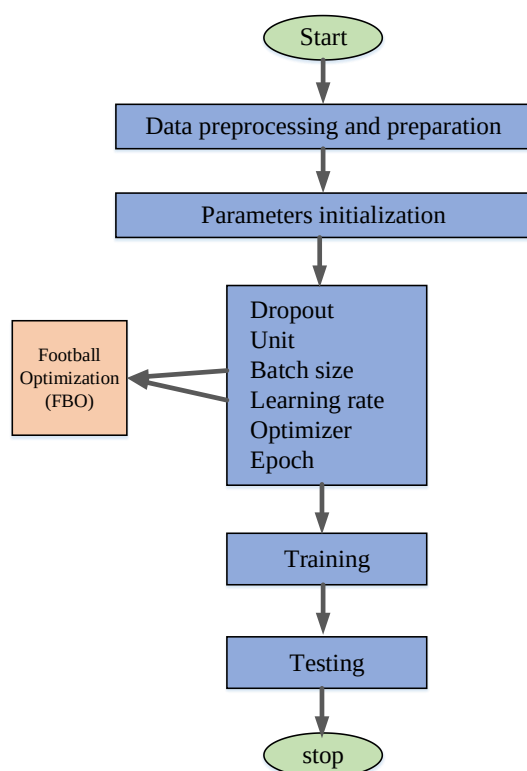
#Classification

```
{
  LSTM = Long Short-Term Memory (SN) // to predict the combustion efficiency and power
  FBO = Football game optimization (LSTM) // For selecting hyper parameters of LSTM
}
```

Output: Predicting combustion efficiency and power
End

Table 1. Statistical tests for proposed model

Source	SS (Sum of Square)	DF (Degree of Freedom)	MS (Mean Square)	F (Statistics)	Prob>F
1	4.64022e+07	8	5,155,817.45	3,950.42	0

**Figure 5. Relationship between FBO-LSTM**

Result and Discussion

In gas turbine engines, high pressure air is combined with fuel and burned in a combustor. The high temperature of the exhaust gas causes thrust when it is directed via a nozzle, turning the power turbine. Burners are also used in ramjet and scramjet propulsion systems. In this proposed method, data are gathered from a combustor, which is designed using ANSYS simulation, produces low temperature homogeneity and CO emission ansys simulation can combustor parameters. Below is a graphical depiction of these comparisons. For the testing, an Intel Core i5 processor, an Nvidia GeForce GTX 1650 graphics card, 16 GB of RAM, and Python 3.8 were utilized.

Table 1 shows the statistical test of the proposed system, the p-values are reported as 0, indicating statistically significant results. In table,

Table 2. Simulation parameter of LSTM

Parameters	Values
Activation	ReLu
Epochs	100
Loss	Mean square error
Learning Rate	0.01
Optimizer	Adam
Batch Size	64

Table 3. Simulation parameter of Football Game Optimization

Parameters	Values
Num_Teams	16
Max_Goal	3
Lower band	100
Upper band	100

the sum of squares (SS) is 4.64022e+07, the degrees of freedom (DF) is 8, the mean square (MS) is 5,155,817.45, the F-statistic is 3,950.42, and the Prob>F value is 0.

The simulation parameters for the LSTM and FBO are shown in Tables 2, and 3. Activation, optimizer, learning rate, loss, epochs, and batch size are the simulation parameters considered for the LSTM. The simulation parameters for FBO are Num_Teams, Max_Goal, Lower band and Upper band.

Figure 6(a) represents the accuracy values, which were calculated using the confusion matrix. Accuracy is defined as the degree of error in a system's prediction of a value. The proposed FBO-LSTM technique has a 96.2 % accuracy rate, compared to ANN at 91.3 %, CNN at 87.9 %, RNN at 85.3% and GRU at 81.7 %. The error comparison between the proposed and existing methods is shown in Figure 6(b). When the error is high, the system performs worse; when the error is low, the system performs better. The proposed method's error rate is 3.8%, ANN's is 8.7%, CNN's is 12.1%, RNN's is 14.7% and GRU's is 18.3%. It proves that the error rates of the proposed model are lower than those of existing models.

The graphical representation of the kappa parameter is shown in Figure 7(a). The existing approaches for ANN, CNN, RNN and GRU provide values of 83.6%, 76.3%, 75.4%, and 73.9% respectively. However the Kappa value of the FBO-LSTM Model is 89.7%. Figure 7(b) compares the MCC of the proposed and existing methods. MCC

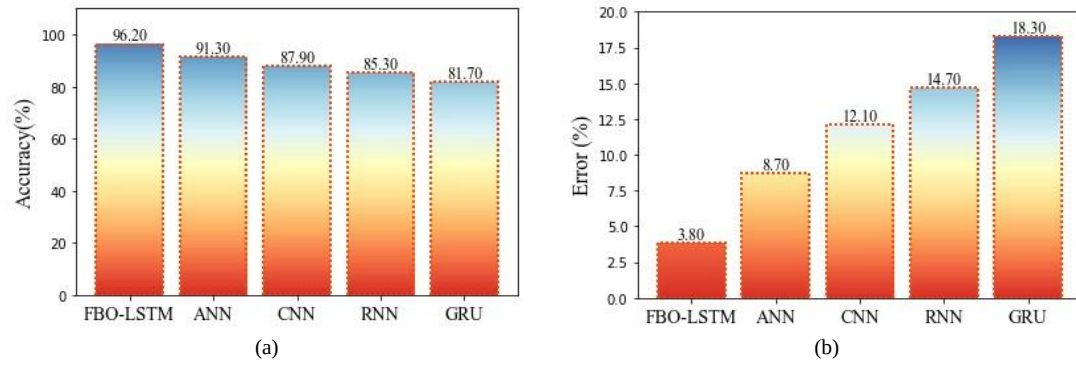


Figure 6. Comparison of the proposed and existing techniques for (a) Accuracy, (b) Error

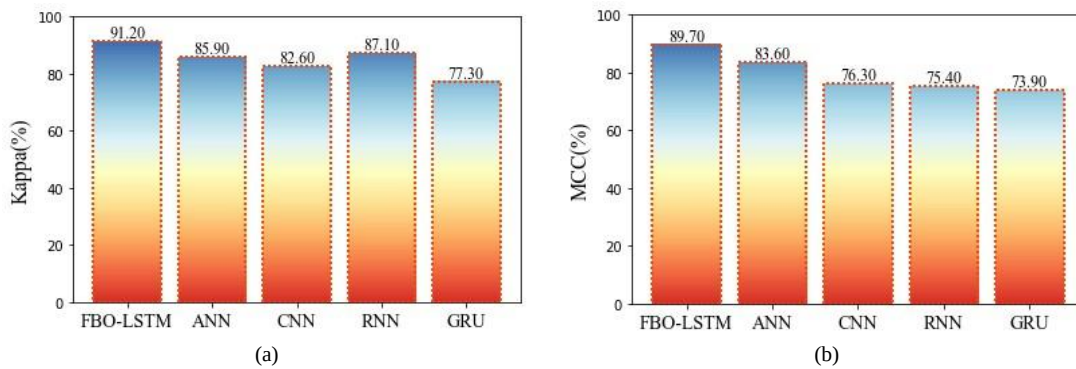


Figure 7. (a) Kappa, (b) MCC value of FBO-LSTM compared to several existing approach

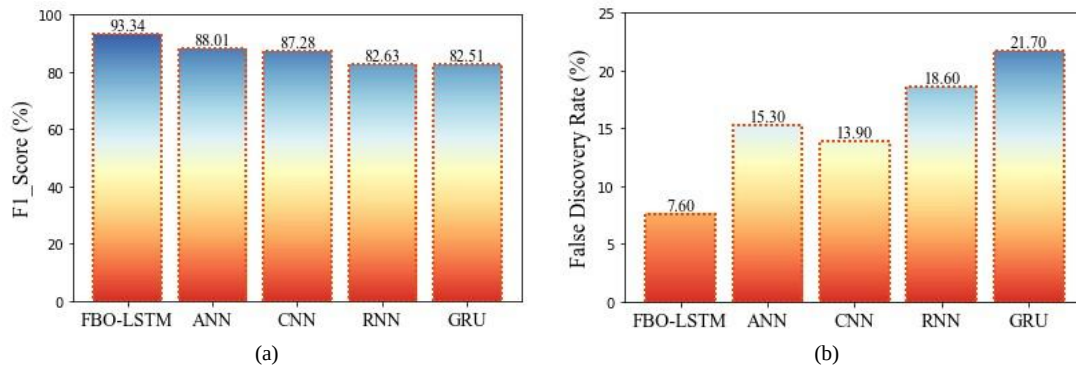


Figure 8. (a) F1_Score, (b) FDR comparison between proposed with existing algorithms

is used to assess or measure the difference between values that are expected and those that are actual. MCC in the proposed method has a value of 89.7%, ANN of 83.6%, CNN of 76.3%, RNN of 75.4% and GRU of 73.9%.

F1_Scores are analysed for both proposed and existing methods. Figure 8(a) displays a statistical analysis of the F1_score, revealing the system's binary types and the data set's accuracy level.

The F1_Score value for the proposed technique is 93.34 %, ANN is 88.01 %, CNN is 87.28 %, RNN is 82.63% and GRU is 82.51 %. Figure 8(b) shows the graphical representation of the False Discovery Rate (FDR) using the following proposed and existing techniques. FBO-LSTM, has a value of 7.60%, ANN, has a range of 15.3%, CNN, has a range of 13.9%, RNN, has a value of 18.6%, and GRU has a value of 21.7%.

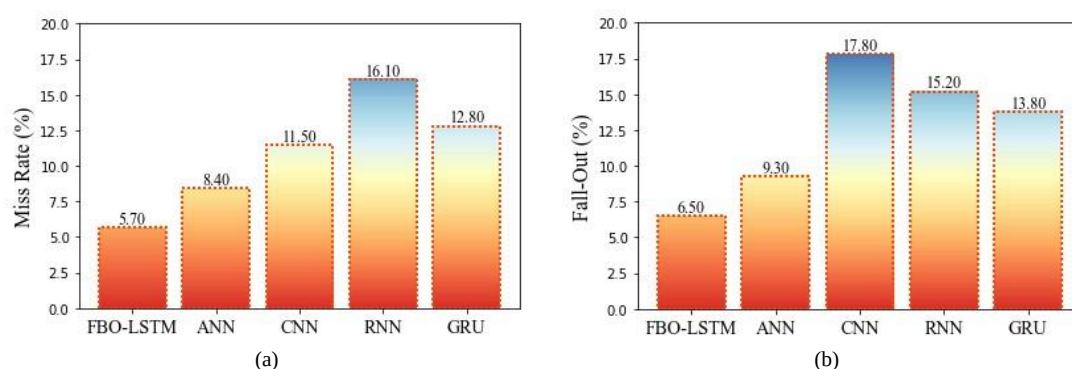


Figure 9. (a) Miss Rate, (b) Fall-Out Evaluation for proposed and Other Models

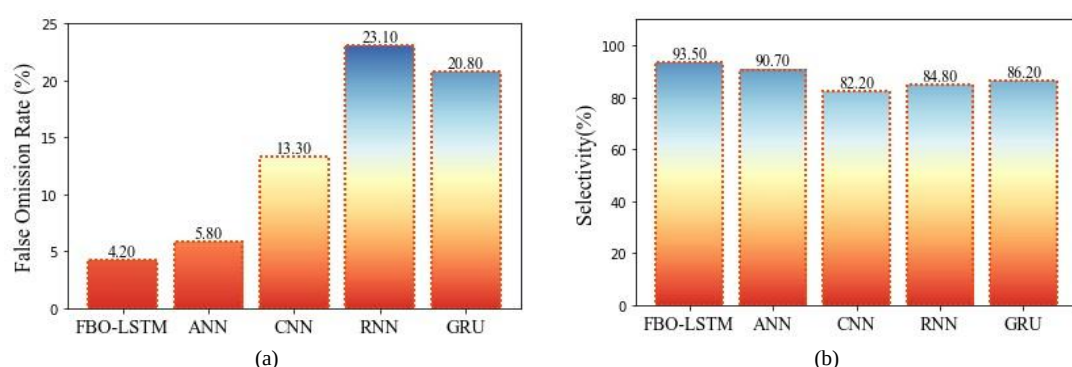


Figure 10. (a) Comparing (a) FOR, (b) Selectivity with FBO-LSTM and existing techniques

The Miss Rate graphical representation is depicted in Figure 9(a) which has the following existing techniques and the proposed technique. The value of the FBO-LSTM is 6.5%, the ANN has a value of 9.3%, and CNN has a value of 17.8%. The RNN has a value of 15.2% and the GRU has a range of 13.8%. The Fall Out graphical representation is shown in Figure 9(b) which has the following proposed and existing techniques named FBO-LSTM which has the value of 6.5%, the ANN has the range of 9.3%, the CNN has the range of 17.8%, the RNN has the value of 15.2% and the value of GRU is 13.8%.

The false omission rate (FOR) difference is given in Figure 10(a), which shows the number of false negative transactions as a fraction of all transactions having a negative outcome. The proposed method's FOR is 4.2%, ANN is 5.8%, CNN is 13.3%, RNN is 23.1% and GRU is 20.8%. It describes the pervasiveness of the false omission rate among all negative transactions. The selectivity graphical representation is shown in Figure 10(b) which has the following proposed and existing techniques named FBO-LSTM which has the value of 93.5%, the ANN has the range of 90.7%,

the CNN has the range of 82.2%, RNN has the value of 84.8%, and the value of GRU is 86.2%.

The Negative predictive value (NPV) for the proposed and existing methods is shown in Figure 11(a). FBO-LSTM strategy, has an NPV of 95.8%. However the NPV values for the existing method currently in use ANN, CNN, RNN and GRU algorithms are 94.2%, 86.7%, 76.9% and 79.2%. The Positive Predictive Value (PPV) graphical representation is depicted in Figure 11(b) which has the following proposed technique and the existing techniques. The value of the FBO-LSTM is 92.4%, the ANN has the value of 84.7%, and CNN has the value of 86.1%. The RNN has the value of 81.4% and the GRU has the range of 78.3%. Figure 11(c) shows the graphical depiction of the Hit rate and includes both the proposed and the existing methods. The FBO-LSTM value is 94.3%, the ANN is 91.6%, and the CNN is 88.5%. The RNN's range is 83.9%, whereas the GRU's value is 87.2%.

The Training Time comparison graphical representation is depicted in Figure 12(a) which has the following proposed techniques and the existing techniques. The value of the FBO-LSTM is 68.6 sec, the ANN has the value of 57.3 sec, and CNN

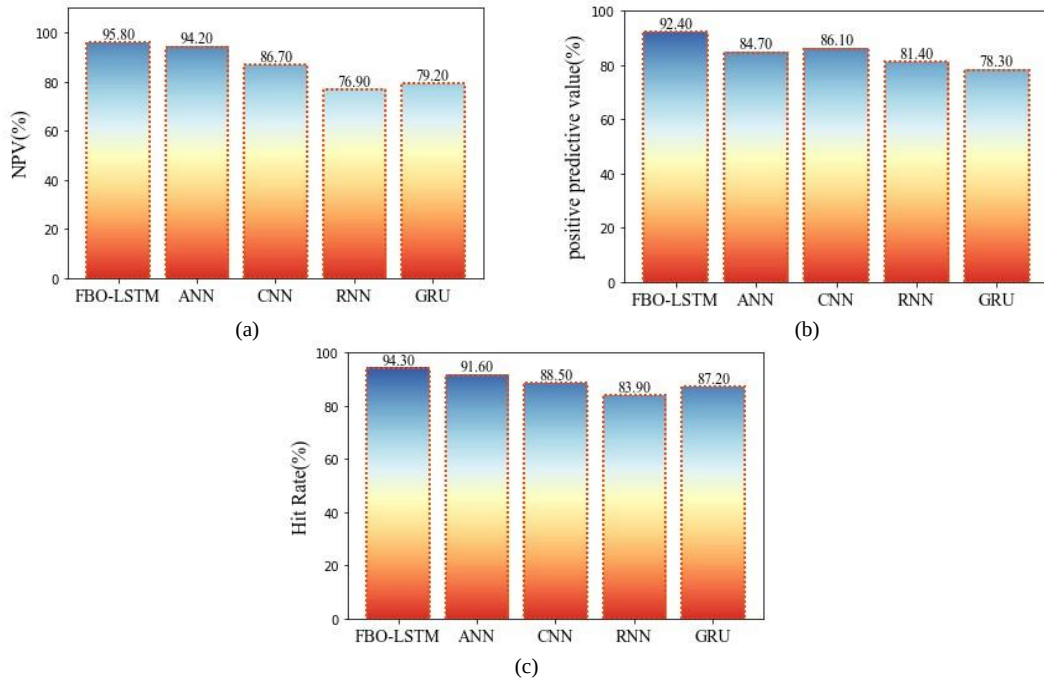


Figure 11. (a) NPV, (b) PPV, (c) Hit Rate value of FBO-LSTM compared to several existing methods

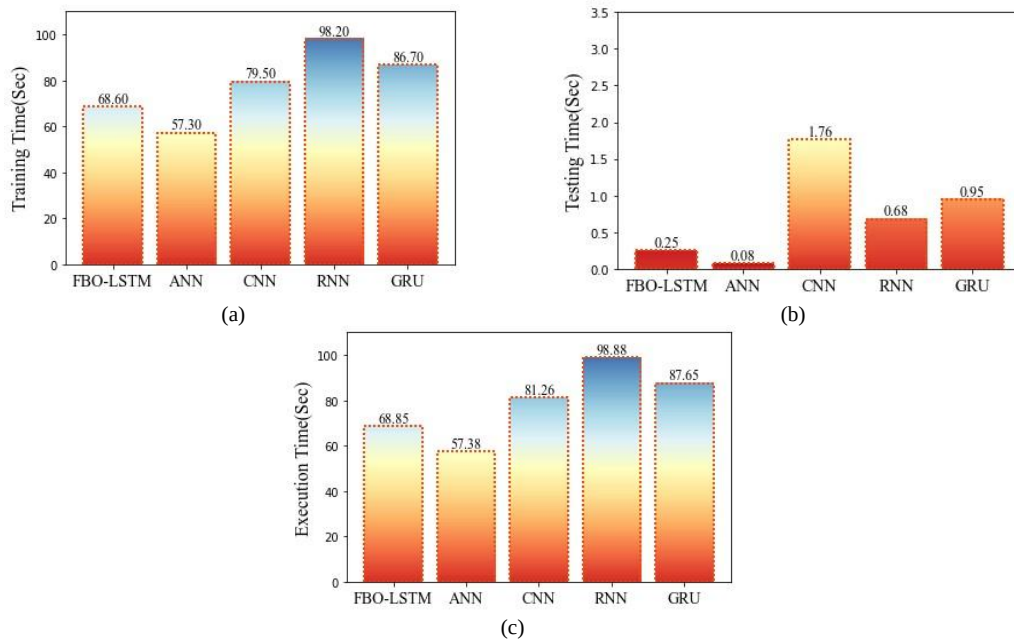


Figure 12. Comparison of (a) Training Time, (b) Testing Time, (c) Execution Time

has the value of 79.5 sec. The RNN has the value of 98.2 sec and the GRU has the range of 86.7 sec. The graphical representation of the testing time comparison is shown in Figure 12(b). Where the comparison of the proposed and existing approaches are made such as the FBO-LSTM

has the value of 0.25 sec, the ANN has 0.08 sec, the CNN has the value of 1.76 sec, RNN has the range of 20.68 sec and the GRU is 0.95 sec. The execution time comparison of the proposed and the existing approach is shown in the Figure 11 (c) where the FBO-LSTM has the value of

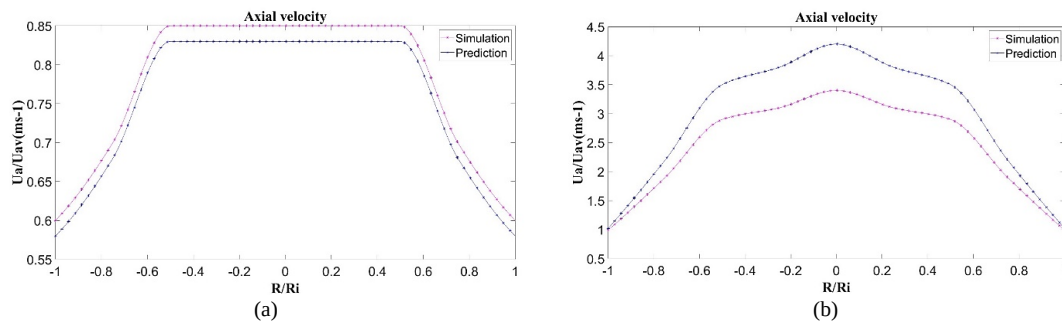


Figure 13. Comparisons of simulation and prediction for (a) Axial velocity of 90 degree, (b) Axial velocity of 0.5 dump gap

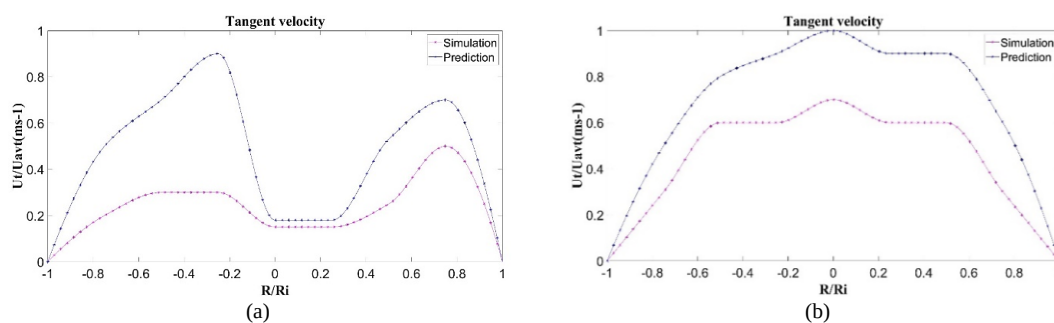


Figure 14. Comparisons of simulation and prediction for (a) Tangent velocity of 90 degree, (b) Tangent velocity of 0.5 dump gap

68.85 sec, the ANN has 57.38 sec, the CNN has 81.26 sec, RNN is 98.88 sec and the GRU has the range of 87.65 sec.

Comparison between Simulation and Prediction

A combustor is designed to attain low temperature uniformity and CO emissions. The simulation for the combustion chamber was designed using the ANSYS 16.1 CFD with processor Intel(R) Core (TM) i5-10300H CPU @ 2.50GHz 2.50 GHz, 16.0 GB RAM, and 64-bit operating system. Prediction output will be evaluated and compared with can combustor simulation results to show the error difference.

Figure 13(a) represents the comparisons of simulation and prediction result for axial velocity of the gas turbine combustor angle of 90 degree. The X- and Y-axis indicate the combustor's radius and axial velocity, respectively. Simulated and predicted constant axial velocity begins at -0.5 radius and end at +0.5 radius. The simulation can combustor with the same radius of -1 and a combustor axial velocity of 0.6. The comparison between the simulation and prediction results for the axial velocity of the 0.5 gas turbine combustor dump gap is shown in Figure 13(b). At -1 and

+1 radius, the lowest axial velocity was obtained. The maximum axial velocity in both the simulation and prediction is 3 and 4.

The simulation and prediction results for the tangent velocity of the gas turbine combustor at a 90-degree angle are compared in Figure 14(a). The radius and tangent velocity of the combustor are shown by the X- and Y-axes, respectively. When compared to the tangent velocity of the simulation, the prediction tangent velocity achieved a high velocity. Prediction and simulation have high tangent velocities of 0.9 and 0.5, respectively. Figure 14(b) illustrates the comparison between the simulation and prediction results for the tangent velocity of the 0.5 gas turbine combustor dump gap. 0.6 and 1 is the high tangent velocity of the simulation and prediction, respectively. -0.6 and 0.6 radius provide the same tangent velocity.

Figure 15(a) compares the simulation and prediction results for the gas turbine combustor's turbulence intensity at a 90-degree angle. The X- and Y-axes represent the combustor's radius and turbulence intensity, respectively. The predicted turbulence intensity reached a high velocity in comparison to the simulation's turbulence intensity. Prediction and simulation have high turbulence

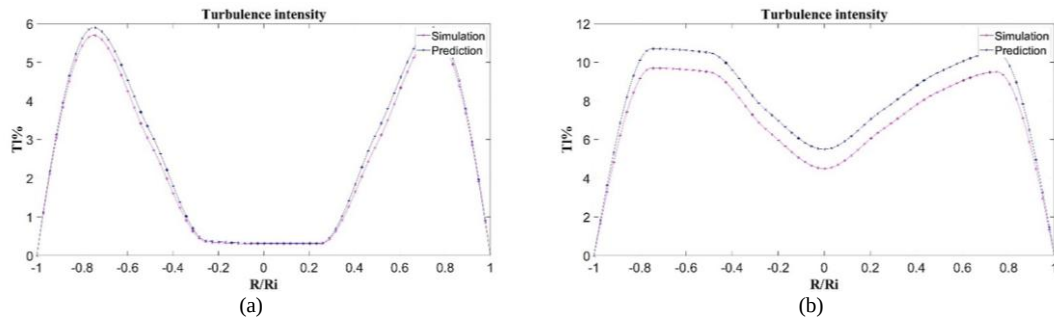


Figure 15. Comparisons of simulation and prediction for (a) Turbulence intensity of 90 degree, (b) Turbulence intensity of 0.5 dump gap

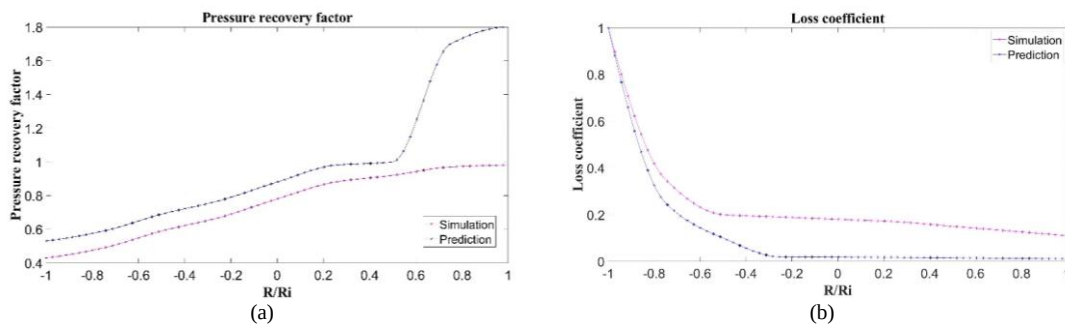


Figure 16. Comparisons of simulation and prediction for (a) Pressure recovery factor, (b) Loss coefficient

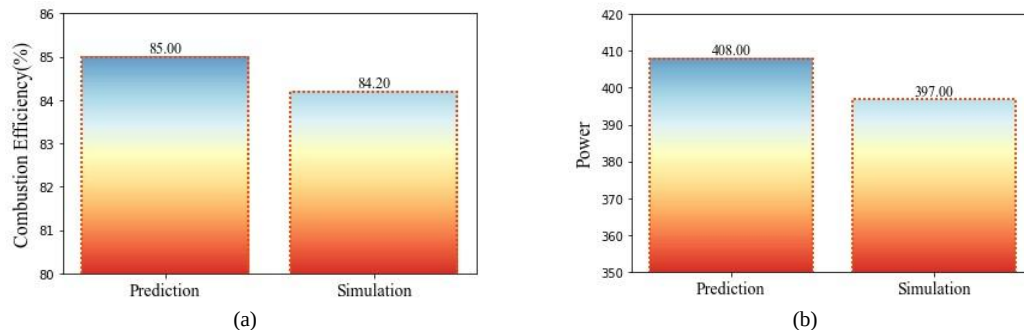


Figure 17. Analysis of prediction and simulation for (a) Combustion efficiency, (b) Power

intensity of 6 and 5.6, respectively. The comparison of the simulation and prediction results for the turbulence intensity of the 0.5 gas turbine combustor dump gap is shown in Figure 15(b). 9 and 11 is the high turbulence intensity of the simulation and prediction, respectively. A 0.5 dump gap in turbulence intensity is shown to have a 2% difference in error between the simulation and prediction results. The same turbulence intensity was attained in both simulation and prediction at -0.8 and 0.8 radius.

Figure 16(a) compares the simulation and prediction results for the gas turbine combustor's

pressure recovery factor. Pressure recovery factor seems to be lower at the inlet portion and higher at the outer segment. Prediction and simulation have high pressure recovery factor of 1.8 and 0.9, respectively. The comparison of the simulation and prediction results for the loss coefficient of the gas turbine combustor dump gap and 90 degree of casting angle is shown in Figure 16(b). Loss coefficient gradually decreases from the inlet and it is very low at the outlet portion of the combustor. Prediction and simulation have loss coefficient of 0.01 and 0.10, respectively.

The can combustion efficiency for the prediction and simulation methods is represented in Figure 17(a). The can combustor efficiency obtained 85% efficiency and the simulation approach obtain 84.20% of efficiency. The power of can-combustor representation is depicted in the Figure 17(b). The can combustor power obtained 408 KW in prediction and 397 KW power obtained in simulation approach.

Comparison of State of Art Method

A comparison of the proposed model's performance with several other models is shown in Table 4. Accuracy (%), precision (%), NPV (%), and selectivity (%) are among the metrics evaluated. A few state-of-the-art methods, such as ResNet, CNN-LSTM, and CNN are compared with the proposed method.

Table 4 analysis shows that the proposed strategy's accuracy and error rates are better than those of the existing methods, its predictive values are noticeably higher. Existing methods are insufficient for handling unsupervised data and do not work well with independent predictors. So, FBO-LSTM was employed in this paper to predict gas turbine combustion efficiency and power.

Ablation Study for the Proposed Method

The results of the ablation examination with different learning rates and batch sizes are shown in Table 5.

The results of the ablation study with different learning rates and batch sizes for predicting combustion efficiency and power are shown in Table 5. Efficiency is assessed by changing the LSTM learning rate between 0.01, 0.02, and 0.05 and the batch size between 64, 50, and 45.

The FBO-LSTM outperformed the others in terms of learning rate and batch size at 0.01 and 64.

Practical Implications

In a combined cycle power plant (CCPP), the FBO-LSTM approach can significantly enhance efficiency and reduce operational costs by predicting combustion efficiency and power in real-time. By analyzing input parameters like ambient pressure, temperature, and flow velocity, the model helps optimize combustion performance, detect anomalies such as uneven fuel distribution, and suggest adjustments to variables like dump gap and casting angle. This leads to more efficient combustion, reduced fuel consumption, and lower NOx and CO2 emissions, helping the plant comply with environmental standards. Additionally, by predicting potential issues and enabling predictive maintenance, the system minimizes unscheduled downtime, extends component lifespans, and reduces maintenance costs, ultimately improving the plant's reliability and financial performance.

Conclusions

Gas turbines are a common type of power generation machinery found all over the world. Despite being widely utilized, the system has a limited functioning window, is rather sophisticated, and requires frequent tuning by the maker and operator. The compressor, combustor, and turbine are the three main parts of a gas turbine. A high pressure working fluid is created from the air as it passes through the compressor and air intake system. To create power, it expands in the turbine, reacts with the fuel in the combustor, and runs the generator. Shafts connect the turbine and compressor, which rotate

Table 4. Analysis of the state-of-the-art approach in comparison

Methods	Accuracy	Error	Fall-Out	Miss Rate
Proposed FBO-LSTM	96.2%	3.8%	6.5%	5.7%
ResNet	95.1%	6%	7.2%	12.5%
CNN-LSTM	84.1%	5.89%	6.47%	14.01%
CNN	91.89%	5.57%	8.13%	13.2%

Table 5. Study of ablation for the proposed method

Performance	Learning Rate				Batch Size	
	0.01	0.02	0.05	64	50	45
Accuracy	96.2%	94.20%	94.02%	96.2%	94.54%	94.68%
NPV	95.8%	96.40%	95%	95.8%	96.51%	96.01%
MCC	89.7%	88.50%	87.02%	89.7%	88.47%	86%
Kappa	91.2%	89%	88.58%	91.2%	88.8%	88.01%

at a very high speed. The performance map of each individual component determines the overall system performance. Lean-premixed turbulent combustion has low emissions, but because of pressure dynamics, the flame is highly unstable. To overcome this issues, Optimized deep learning is developed for predicting combustion efficiency and power in gas turbine. In this paper, A can combustor, specifically engineered with variations in casting and dump gap shapes, incorporates a 150 mm diameter casting and spans a length of 210 mm. Notably, the design features a vertical fluid and air inlet with precise flow rates of 0.473 Kg/s and 0.0096 Kg/s respectively. Housing the combustor model securely within the 170mm length casting, this configuration allowed for in-depth exploration across six distinct scenarios. By manipulating casting angles and dump ratios, comprehensive analysis encompassing temperature profiles, static pressure distributions, velocity dynamics, power output, and combustion efficiency metrics was executed. During the investigative phase, simulated data sets were precisely cataloged and subsequently pre-processed utilizing Sigmoid Normalization techniques to ensure standardized input data conditions. It was pertinent to employ this rigorous pre-processing step before feeding the data into the Long Short-Term Memory (LSTM) model for predicting combustion power output and efficiency levels. Remarkably, the critical selection of the optimal learning rate and batch size parameters for the LSTM model was facilitated by leveraging the innovative football optimization technique. Following the predictive phase, all model-generated outputs were subjected to a thorough evaluation process, culminating in a comprehensive comparison with the can combustor simulation results. This rigorous evaluation served to highlight any discrepancies or variations between the predicted values and the actual simulated outcomes, shedding light on the efficacy and accuracy of the predictive models employed in this intricate research endeavor. The performance metrics that are utilized to compare existing and proposed models to determine the most effective ones are accuracy, precision, Error, Selectivity, FNR (False Negative Rate), and MCC. Proposed technique achieved an impressive 96.2% accuracy rate and only 3.8% error rate, demonstrating considerable improvements in the findings. Additionally, FBO-LSTM outperforms other models as demonstrated by a Selectivity of 93.5%, NPV of 95.8% and MCC of 89.7%.

Limitations and Future Scope

The FBO-LSTM approach has several limitations such as complex structure and lack of

interpretability and combustion emitted relatively low NOX compared to baseline CI mode combustion. Future work can focus on domain adaptation of data distribution and incorporation of inlet velocity fluctuation information when training neural network.

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Compliance with ethical standards. This article is a completely original work of its authors; it has not been published before and will not be sent to other publications until the journal's editorial board decides not to accept it for publication.

Reference

- Bai, M., Yang, X., Liu, J., Liu, J., and Yu, D. (2021). Convolutional neural network-based deep transfer learning for fault detection of gas turbine combustion chambers. *Applied Energy*, 302:117509. <https://doi.org/10.1016/j.apenergy.2021.117509>
- Chang, S.H., Bak, H.S., Yu, H., and Yoo, C.S. (2020). A numerical study of combustion and NO X emission characteristics of a lean premixed model gas turbine combustor. *Journal of Mechanical Science and Technology*, 34:1795-1803. <https://doi.org/10.1007/s12206-020-0341-y>
- Choi, O., Choi, J., Kim, N., and Lee, M.C. (2020). Combustion instability monitoring through deep-learning-based classification of sequential high-speed flame images. *Electronics*, 9(5):848. <https://doi.org/10.3390/electronics9050848>
- Gangopadhyay, T., Ramanan, V., Akintayo, A., Boor, P.K., Sarkar, S., Chakravarthy, S.R., and Sarkar, S. (2021). 3D convolutional selective autoencoder for instability detection in combustion systems. *Energy and AI*, 4:100067. <https://doi.org/10.1016/j.egyai.2021.100067>
- Joo, S., Kwak, S., Lee, J., and Yoon, Y. (2021). Thermoacoustic instability and flame transfer function in a lean direct injection model gas turbine combustor. *Aerospace Science and Technology*, 116:106872. <https://doi.org/10.1016/j.ast.2021.106872>
- Le, X.H., Ho, H.V., Lee, G., and Jung, S. (2019). Application of long short-term memory (LSTM) neural network for flood

- forecasting. *Water*, 11(7):1387. <https://doi.org/10.3390/w11071387>
- Lyu, Z., Jia, X., Yang, Y., Hu, K., Zhang, F., and Wang, G. (2021). A comprehensive investigation of LSTM-CNN deep learning model for fast detection of combustion instability. *Fuel*, 303:121300. <https://doi.org/10.1016/j.fuel.2021.121300>
- Meziane, S. and Bentebbiche, A. (2019). Numerical study of blended fuel natural gas-hydrogen combustion in rich/quench/lean combustor of a micro gas turbine. *International journal of hydrogen energy*, 44(29):15610-15621. <https://doi.org/10.1016/j.ijhydene.2019.04.128>
- Nassini, P.C., Pampaloni, D., Meloni, R., and Andreini, A. (2021). Lean blow-out prediction in an industrial gas turbine combustor through a LES-based CFD analysis. *Combustion and Flame*, 229:111391. <https://doi.org/10.1016/j.combustflame.2021.02.037>
- Nguyen, T.H., Park, J., Jung, S., and Kim, S. (2019). A numerical study on NO_x formation behavior in a lean-premixed gas turbine combustor using CFD-CRN method. *Journal of Mechanical Science and Technology*, 33:5051-5060. <https://doi.org/10.1007/s12206-019-0944-3>
- Niszczoła, P. and Gieras, M. (2021). Impact of the application of fuel and water emulsion on CO and NO_x emission and fuel consumption in a miniature gas turbine. *Energies*, 14(8):2224. <https://doi.org/10.3390/en14082224>
- Niu, Y., Kang, J., Li, F., Ge, W., and Zhou, G. (2020). Case-based reasoning based on grey-relational theory for the optimization of boiler combustion systems. *ISA Transactions*, 103, 166-176. <https://doi.org/10.1016/j.isatra.2020.03.024>
- Okafor, E.C., Somarathne, K.K.A., Rathnanan, R., Hayakawa, A., Kudo, T., Kurata, O., and Kobayashi, H. (2020). Control of NO_x and other emissions in micro gas turbine combustors fuelled with mixtures of methane and ammonia. *Combustion and Flame*, 211:406-416. <https://doi.org/10.1016/j.combustflame.2019.10.012>
- Park, Y., Choi, M., Kim, K., Li, X., Jung, C., Na, S., and Choi, G. (2020). Prediction of operating characteristics for industrial gas turbine combustor using an optimized artificial neural network. *Energy*, 213:118769. <https://doi.org/10.1016/j.energy.2020.118769>
- Karthick, S. (2017). Semi supervised hierarchy forest clustering and KNN based metric learning technique for machine learning system. *Journal of Advanced Research in Dynamical and Control Systems*, 9:2679-2690.
- Shi, Y., Zhong, W., Chen, X., Yu, A. B., and Li, J. (2019). Combustion optimization of ultra supercritical boiler based on artificial intelligence. *Energy*, 170:804-817. <https://doi.org/10.1016/j.energy.2018.12.172>
- Singh, D. and Singh, B. (2020). Investigating the impact of data normalization on classification performance. *Applied Soft Computing*, 97(Part B):105524. <https://doi.org/10.1016/j.asoc.2019.105524>
- Srilakshmi, K., Rao, G.S., Balachandran, P.K., and Senjyu, T. (2024). Green energy-sourced AI-controlled multilevel UPQC parameter selection using football game optimization. *Frontiers in Energy Research*, 12:1325865. <https://doi.org/10.3389/fenrg.2024.1325865>
- Sundararaj, R.H., Kumar, R.D., Raut, A.K., Sekar, T.C., Pandey, V., Kushari, A., and Puri, S.K. (2019). Combustion and emission characteristics from biojet fuel blends in a gas turbine combustor. *Energy*, 182:689-705. <https://doi.org/10.1016/j.energy.2019.06.060>
- Ursueguía, D., Marín, P., Díaz, E., and Ordonez, S. (2021). A new strategy for upgrading ventilation air methane emissions combining adsorption and combustion in a lean-gas turbine. *Journal of Natural Gas Science and Engineering*, 88:103808. <https://doi.org/10.1016/j.jngse.2021.103808>
- Zhou, Y., Zhang, C., Han, X., and Lin, Y. (2021). Monitoring combustion instabilities of stratified swirl flames by feature extractions of time-averaged flame images using deep learning method. *Aerospace Science and Technology*, 109:106443. <https://doi.org/10.1016/j.ast.2020.106443>