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Compressor performance prediction: gradient boosting regression model and sensitivity analysis

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ABSTRACT

This study introduces the use of gradient boosting regression (GBR) models to estimate the compressor performance of aero-engines. The model exhibits a mean absolute error (MAE) of 0.078, showcasing superior performance compared to previous studies. Through sensitivity analysis, optimal values for three key parameters were determined: 280 estimators, a max depth of 9, and a learning rate of 0.085. Furthermore, a comparison with a prior study revealed an impressive MAE value lower than 0.002, highlighting the GBR model's success in accurately predicting compressor performance. This demonstrates the model's effectiveness and predictive accuracy, making it a valuable tool for aero-engine compressor performance estimation.

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1. INTRODUCTION

The compressor in an aeroengine plays a critical role in the overall performance and efficiency of the propulsion system. The compressor increases the pressure of the incoming air, allowing for efficient combustion and higher thrust generation in the engine [1]. Analytical models have been developed for predicting gas turbine engine compressor performance. Pourfarzaneh *et al.* [2] introduced a dimensionless modeling approach validated through experimental data. Lee *et al.* [3] developed a performance prediction program validated for various gas turbine types. Recent advancements in computational fluid dynamics (CFD) have significantly improved the prediction of compressor performance [4]-[6]. However, despite improved performance, utilizing CFD remains prohibitively expensive, requiring specialized hardware and software. It is a solution considered using artificial intelligence technologies to save the CFD cost.

Artificial intelligence technologies have been utilized widely in different fields in recent years. Machine learning is used for real estate valuation breast cancer prediction [7], [8], and deep learning is used for stock prices and oil accident predictions [9], [10]. Furthermore, some research aimed at gas turbine engine studies using artificial intelligence technologies was spread.

Fei *et al.* [11] introduced an innovative feed-forward neural network with a Gaussian kernel function, demonstrating its superior performance to other data-driven modeling techniques. Yazar *et al.* [12] comprehensively compared various regression models to predict compressor and turbine map parameters, showcasing their potential in developing dynamic mathematical models for gas turbine engines. Liu and Karimi [13] advanced machine learning-based methods to forecast gas turbine performance through surrogate models utilizing high-dimensional model representation (HDMR) and artificial neural network (ANN). They particularly emphasized the utility of the ANN model for full-load performance prediction, laying the groundwork for continuous health monitoring and fault diagnosis. This methodology, adaptable to any gas turbine, quantifies performance degradation over time. Jayachandran *et al.* [14] presented a machine learning-based model to predict the net efficiency of gas turbines, with the random forest decision tree showing better accuracy in predicting overall efficiency. Future research directions include exploring k-means clustering, hybrid models, and utilizing ANNs with data from the ASTRA simulation tool. Ghorbanian and Gholamrezaei [15] investigated the application of ANNs for compressor performance prediction, comparing different types and concluding that the multilayer perceptron network technique is the most powerful candidate for interpolation and extrapolation applications. The other research on compressor performance based on the ANNs approach, such as [16]-[22]. In addition, a few studies on compressor performance were proposed using machine learning algorithms [23], [24]. These machine learning methods successfully estimate compressor performance and obtain significant prediction results.

This study investigated gas turbine engine studies based on artificial intelligence technologies widely utilized in different fields. The gradient boosting regression (GBR) model was developed to predict the gas turbine engine's compressor performance. In addition, the model accuracy was compared with Fei *et al.* [11] research to validate the model.

2. METHOD

2.1. Data

A compressor map visually displays a compressor's performance traits across different operational scenarios. Compressor maps provide valuable insights into key performance parameters like pressure ratio (π), corrected mass flow (G), efficiency (η), and corrected speed (N). In theory, pressure ratio (π) and efficiency (η) can be expressed as functions of corrected mass flow (G) and corrected speed (N), as shown in (1) and (2), respectively. A multistage axial flow compressor map was drawn and shown in Figure 1 [11].

$$\pi = f(N, G) \tag{1}$$

$$\eta = f(N, G) \tag{2}$$

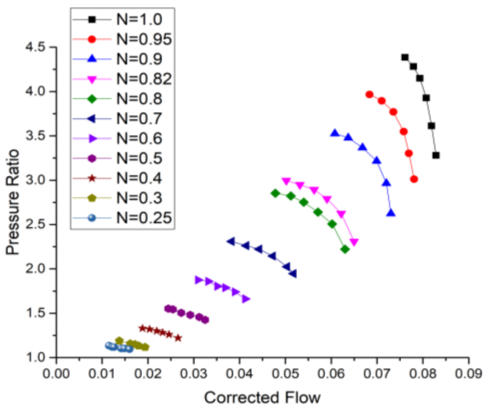

Figure 1. Compressor performance map

2.2. Gradient boosting regression model

GBR is a machine learning technique that constructs a predictive model by amalgamating numerous weak learners, often decision trees, to form a robust predictive model. This algorithm, pioneered by Friedman [25], encompasses ensemble learning, which amalgamates the predictions of multiple individual models (learners) to enhance overall prediction accuracy and generalization. Weak learners are models that perform slightly better than random guessing but lack robustness. Boosting is a technique where each new model in the ensemble rectifies the mistakes (residuals) made by the preceding models. Gradient descent optimization is an iterative optimization algorithm that minimizes a loss function (e.g., mean squared error for regression, log-loss for classification). The iteration process involves training the gradient boosting model in iterations. During each iteration, a new weak learner is integrated into the ensemble to rectify the errors made by the preceding models. The learning rate, also referred to as shrinkage, is a hyperparameter that regulates the contribution of each weak learner to the final prediction. Regularization: gradient boosting models often include regularization techniques to prevent overfitting, such as limiting the maximum depth of decision trees (max_depth), adjusting the minimum samples per leaf (min_samples_leaf), or using early stopping based on validation error. Prediction: once training is complete, the gradient boosting model can make predictions for new data by aggregating the predictions of all weak learners according to their weights.

Ensembles are built using decision tree models, with trees added incrementally to the ensemble to rectify prediction errors from previous models. Figure 2 illustrates an example of the gradient boosting model iteration procedure. This iterative process continues until satisfactory results are achieved, making gradient boosting a powerful machine learning algorithm that minimizes the loss gradient effectively.

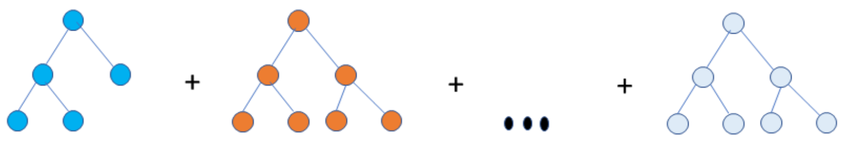

Figure 2. Gradient boosting model iteration procedure

Figure 3 shows the flowchart of the proposed GBR algorithm model for compressor performance prediction. This study divides the dataset into two subsets: 48 samples are allocated for model training, while 18 samples are designated for model testing. This data-splitting scheme aligns with the approach used in the study by Fei *et al.* [11]. The most critical step during model building is hyperparameter tuning. Different model parameters affect the model performance and accuracy. The critical parameters of the GBR model are as follows: a max_depth of 9, N_estimators set at 280, and a learning_rate of 0.085. The accuracy of the model is assessed through performance metric such as mean absolute error (MAE). In (3) defines the metrics where P_i represents the predicted value from the model and T_i represents the target value from the dataset.

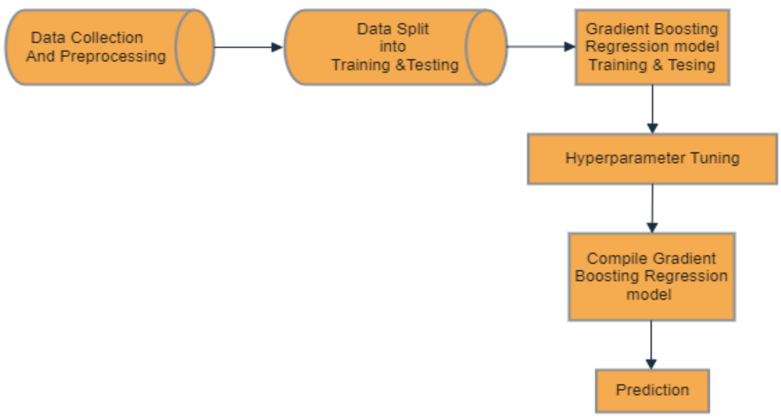

Figure 3. Flowchart of the proposed gradient boosting regression model

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |T_i - P_i| \tag{3}$$

3. RESULTS AND DISCUSSION

3.1. Model performance

The GBR model's performance, as demonstrated in Table 1, was validated by comparing it with the outcomes reported by Fei *et al.* [11]. Notably, the present study's MAE value was lower than Fei's model's. This comparison underscores the efficacy of our GBR model in accurately predicting compressor performance, indicating its potential for practical applications.

Table 1. Performance MAE statistics result of the GBR model

MAE
0.078
0.080 [11]

The comparison of compressor performance predictions at N=1 between the GBR model and Fei's study, as depicted in Figure 4, reveals notable improvements in the GBR model's performance. Specifically, the GBR model demonstrates superior accuracy compared to Fei's study, particularly evident in the range of corrected flow around 0.076 to 0.078, where the prediction deviation is significantly reduced. Furthermore, the GBR model exhibits increasing accuracy with higher corrected flow values, with predictions aligning closely with actual values from the testing dataset, significantly above 0.080 corrected flow. These findings highlight the GBR model's robustness and capability to accurately predict compressor performance across varying flow conditions, showcasing its potential for enhancing predictive accuracy and reliability in practical applications within the compressor industry.

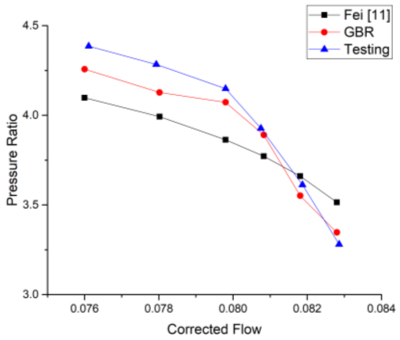

Figure 4. Prediction of compressor performance

3.2. Sensitivity analysis
3.2.1. Effect of the number of estimators

The number of estimators is a critical hyperparameter in GBR models, directly influencing the model's performance and complexity. In essence, each estimator represents an individual decision tree in the ensemble, and increasing the number of estimators can have both positive and negative effects. Figure 5 shows the observed variation in MAE values across different numbers of estimators, ranging from 180 to 330, which provides valuable insights into model behavior. Interestingly, a significant reduction in MAE occurs when the number of estimators reaches 280, indicating improved predictive accuracy and model performance. This finding suggests that adding more boosting stages beyond this point may not necessarily lead to further enhancements in prediction quality, as evidenced by the stable low MAE values even at 330 estimators. The stability of the lowest MAE value as the number of estimators increases to 330 highlights an intriguing aspect of model convergence and optimization. It suggests that the model's capacity to generalize and capture underlying patterns may have reached a plateau beyond which additional complexity does not significantly improve performance. These results underscore the importance of hyperparameter tuning in GBR models, specifically the number of estimators, to achieve optimal predictive accuracy while effectively managing computational resources.

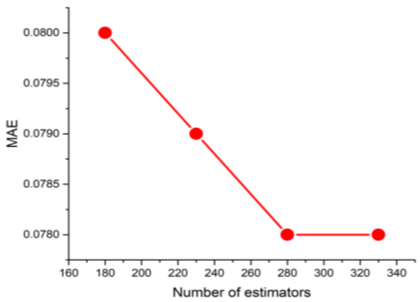

Figure 5. Sensitivity of the GBR model to the number of estimators

3.2.2. Effect of the max-depth

The max_depth hyperparameter in GBR models is pivotal in managing model complexity and ensuring optimal performance. It dictates the maximum depth of each decision tree in the ensemble, directly influencing the trees' complexity and the overall model's ability to capture intricate patterns in the data. Figure 6 shows the observed range of max_depth values from 4 to 10, which provides a comprehensive view of how varying this hyperparameter impacts model performance. During the model training and testing phases, the MAE values were closely monitored across different max_depth values. A notable trend emerged where the model's MAE reached its lowest value when the max_depth parameter was set to 9. This finding suggests that a max_depth of 9 strikes a balance between capturing essential features in the data while avoiding overfitting, resulting in improved predictive accuracy and generalization ability. The significance of this optimal max_depth value underscores the critical role of hyperparameter tuning in GBR models. Fine-tuning max_depth within a reasonable range can substantially improve model performance without sacrificing computational efficiency.

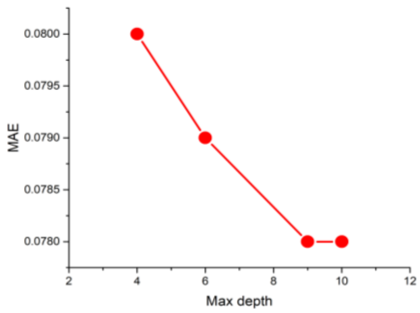

Figure 6. Sensitivity of the GBR model to the max-depth

3.2.3. Effect of the learning rate

The learning rate is a critical hyperparameter in the GBR model, dictating the impact of each tree on the ensemble during training. Figure 7 reveals the range of learning rates explored, from 0.065 to 0.1, and sheds light on how this parameter influences model performance. Observing MAE values across different learning rates during model training and testing provides essential insights into optimal learning rate selection. The trend observed indicates that increasing the learning rate initially reduces MAE, with the lowest MAE achieved at a learning rate of 0.085. This finding underscores the importance of finding the right balance; a moderate learning rate optimizes model convergence and accuracy without compromising stability or risking overfitting. However, a rapid rise in MAE is noted beyond this optimal learning rate, indicating diminishing returns or even a deterioration in model performance as the learning rate becomes too high. This observed relationship between learning rate and MAE highlights the delicate trade-off between model optimization and avoiding overfitting.

Proper hyperparameter tuning is crucial for model success. Learning rate is a critical hyperparameter that significantly impacts model performance. Setting it too high can lead to divergence while setting it too low can result in slow convergence. Careful optimization is essential to achieve optimal results.

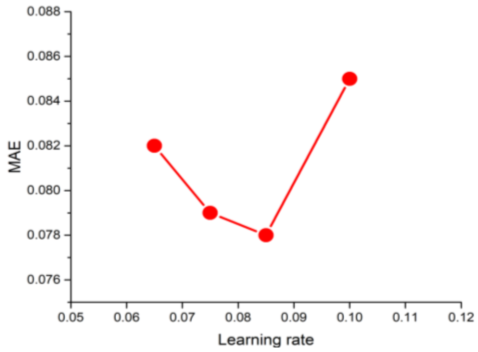

Figure 7. Sensitivity of the GBR model to the learning rate

This study thoroughly investigated the performance of the GBR model through a detailed analysis of key model parameters, including the number of estimators, max depth, and learning rate. These parameters play a pivotal role in shaping the model's training and testing outcomes, directly impacting its overall performance and predictive accuracy. The investigation delved into understanding the model's sensitivity to these parameters, aiming to identify the optimal configurations that would yield the best results. This involved conducting a comprehensive sensitivity analysis by adjusting the parameters' ranges and observing their effects on the model's performance metrics. Such an analysis is crucial in gaining valuable insights into how changes in these parameters influence the model's behavior during the training and testing phases.

The sensitivity analysis provided researchers with critical information for fine-tuning the model parameters. By carefully adjusting the ranges and observing the corresponding variations in model performance, researchers could make informed decisions about the optimal settings for each parameter. This iterative process of analysis and adjustment maximizes the model's predictive accuracy and ensures that it performs optimally across different scenarios and datasets.

Following the sensitivity analysis, the study successfully identified the optimal parameters for the GBR model. These optimal configurations were summarized and presented in Table 2, providing a clear reference for future research and practical implementations. By establishing the ideal parameter values, researchers can streamline the model development process and enhance its performance without unnecessary trial and error.

Table 2. Optimal parameters of the GBR model

number of estimators	max depth	learning rate
280	9	0.085

4. CONCLUSION

The compressor performance model constructed using the GBR approach was developed successfully, and it obtained improved model performance compared to previous studies. This stark contrast underscores the advantages of employing the GBR model for such tasks. Following a meticulous sensitivity analysis, the study identified optimal values for three key parameters: the number of estimators, learning rate, and max depth. Meticulously explored and refined within specific ranges, these values were instrumental in fine-tuning the model for superior predictive accuracy and performance.

Future work related to this study could concentrate on several key areas to further enhance the model's capabilities. One avenue of exploration involves fine-tuning hyperparameters beyond those scrutinized in the current study. Researchers can unlock further model accuracy and robustness improvements by delving into other potential parameters and optimizing their settings. Additionally, conducting broader sensitivity analyses with an expanded range of parameter values presents another promising direction for future research. This approach allows for a more comprehensive understanding of how hyperparameter variations impact the model's performance across different scenarios and datasets. Employing advanced optimization techniques, such as Bayesian optimization or genetic algorithms, could also prove beneficial in optimizing the model's parameters more efficiently and effectively.

REFERENCES

[1] R. O. Bullock, *Aerodynamic design of axial flow compressors*. Washington, DC, USA: National Aeronautics and Space Administration, 1965.

[2] H. Pourfarzaneh, A. Hajilouy-Benisi, and M. Farshchi, "An analytical model of a gas turbine components performance and its experimental validation," in *Turbo Expo: Power for Land, Sea, and Air*, Oct. 2010, pp. 335–340, doi: 10.1115/GT2010-23369.

[3] J. J. Lee, D. W. Kang, and T. S. Kim, "Development of a gas turbine performance analysis program and its application," *Energy*, vol. 36, no. 8, pp. 5274–5285, Aug. 2011, doi: 10.1016/j.energy.2011.06.032.

[4] M. Kethidi, A. Kovacevic, N. Stosic, and I. K. Smith, "Evaluation of various turbulence models in predicting screw compressor flow processes by CFD," in *7th International Conference on Compressors and their Systems 2011*, Elsevier, 2011, pp. 347–357.

[5] J. J. Moore, D. L. Ransom, and F. Viana, "Rotordynamic force prediction of centrifugal compressor impellers using computational fluid dynamics," *Journal of Engineering for Gas Turbines and Power*, vol. 133, no. 4, Apr. 2011, doi: 10.1115/1.2900958.

[6] E. L. L. Pereira, C. J. Deschamps, and F. A. Ribas, "Performance analysis of reciprocating compressors through computational fluid dynamics," in *Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering*, Nov. 2008, vol. 222, no. 4, pp. 183–192, doi: 10.1243/09544089JPME194.

[7] A. Barlybayev, A. Sankibayev, R. Niyazova, and G. Akimbekova, "Machine learning for real estate valuation: Astana, Kazakhstan case," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 35, no. 2, pp. 1110–1121, Aug. 2024, doi: 10.11591/ijeecs.v35.i2.pp1110-1121.
[8] S. S. Reddy, N. Pilli, P. Voosala, and S. R. Chigurupati, "A comparative study to predict breast cancer using machine learning techniques," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 27, no. 1, pp. 171–180, Jul. 2022, doi: 10.11591/ijeecs.v27.i1.pp171-180.
[9] Z. Sidek, S. S. S. Ahmad, and N. H. I. Teo, "Associating deep learning and the news headlines sentiment for Bursa stock price prediction," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 31, no. 2, pp. 1041–1049, Aug. 2023, doi: 10.11591/ijeecs.v31.i2.pp1041-1049.
[10] Y. S. A. ElWahab, M. M. Nasr, and F. K. Al Sheref, "An intelligent oil accident predicting and classifying system using deep learning techniques," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 29, no. 1, pp. 460–471, Jan. 2023, doi: 10.11591/ijeecs.v29.i1.pp460-471.
[11] J. Fei, N. Zhao, Y. Shi, Y. Feng, and Z. Wang, "Compressor performance prediction using a novel feed-forward neural network based on Gaussian kernel function," *Advances in Mechanical Engineering*, vol. 8, no. 1, p. 1687814016628396, 2016, doi: 10.1177/1687814016628396.
[12] I. Yazar, H. S. Yavuz, and A. A. Yavuz, "Comparison of various regression models for predicting compressor and turbine performance parameters," *Energy*, vol. 140, pp. 1398–1406, 2017, doi: 10.1016/j.energy.2017.05.061.
[13] Z. Liu and I. A. Karimi, "Gas turbine performance prediction via machine learning," *Energy*, vol. 192, p. 116627, Feb. 2020, doi: 10.1016/j.energy.2019.116627.
[14] A. V. T. Jayachandran, H. Omar, A. Tkachenko, and A. Krishnakumar, "Machine learning predictor for micro gas turbine performance evaluation," *Aeronautics and Aerospace Open Access Journal*, vol. 4, no. 4, pp. 172–180, Dec. 2020, doi: 10.15406/aaoaj.2020.04.00120.
[15] K. Ghorbanian and M. Gholamrezaei, "An artificial neural network approach to compressor performance prediction," *Applied Energy*, vol. 86, no. 7–8, pp. 1210–1221, Jul. 2009, doi: 10.1016/j.apenergy.2008.06.006.
[16] M. Gholamrezaei and K. Ghorbanian, "Application of integrated fuzzy logic and neural networks to the performance prediction of axial compressors," *Proceedings of the Institution of Mechanical Engineers, Part A: Journal of Power and Energy*, vol. 229, no. 8, pp. 928–947, Dec. 2015, doi: 10.1177/0957650915596877.
[17] W. Wang, Y. Yao, and Z. Ma, "Model of compressor performance prediction based on error back-propagation artificial neural work," *Fluid Mach*, vol. 33, no. 4, 2005.
[18] P. C. Vilalta, H. Wan, and S. S. Patnaik, "Centrifugal compressor performance prediction using gaussian process regression and artificial neural networks," *ASME International Mechanical Engineering Congress and Exposition, Proceedings (IMECE)*, vol. 59452, p. V008T09A045, 2019, doi: 10.1115/IMECE2019-11936.
[19] J. Ma, X. Ding, W. T. Horton, and D. Ziviani, "Development of an automated compressor performance mapping using artificial neural network and multiple compressor technologies," *International Journal of Refrigeration*, vol. 120, pp. 66–80, 2020, doi: 10.1016/j.ijrefrig.2020.08.001.
[20] O. Cortés, G. Urquiza, and J. A. Hernández, "Optimization of operating conditions for compressor performance by means of neural network inverse," *Applied Energy*, vol. 86, no. 11, pp. 2487–2493, 2009, doi: 10.1016/j.apenergy.2009.03.001.
[21] Y. Yu, L. Chen, F. Sun, and C. Wu, "Neural-network based analysis and prediction of a compressor's characteristic performance map," *Applied Energy*, vol. 84, no. 1, pp. 48–55, 2007, doi: 10.1016/j.apenergy.2006.04.005.
[22] T. Palmé, P. Waniczek, H. Hönen, M. Assadi, and P. Jeschke, "Compressor map prediction by neural networks," *Journal of energy and power engineering*, vol. 6, no. 10, pp. 1651–1662, 2012.
[23] L. Zhong, R. Liu, X. Miao, Y. Chen, S. Li, and H. Ji, "Compressor performance prediction based on the interpolation method and support vector machine," *Aerospace*, vol. 10, no. 6, p. 558, 2023, doi: 10.3390/aerospace10060558.
[24] J. Marx, S. Gantner, J. Städing, and J. Friedrichs, "A machine learning based approach of performance estimation for high-pressure compressor airfoils," *Turbo Expo: Power for Land, Sea, and Air*, vol. 51029, p. V02DT46A004, 2018, doi: 10.1115/gt2018-75372.
[25] J. H. Friedman, "Greedy function approximation: a gradient boosting machine," *Annals of Statistics*, vol. 29, no. 5, pp. 1189–1232, 2001, doi: 10.1214/aos/1013203451.

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