Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/BA08.20250303
Published: December 20, 2025

Application of Improved Particle Swarm Optimization (PSO) on A Gas Turbine Model

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Abstract

This research investigated the predictive modeling and optimization of a gas turbine cogeneration facility using machine learning techniques combined with an advanced Particle Swarm Optimization (PSO) algorithm. Five machine learning models, K-Nearest Neighbors (KNN), Random Forest Regression (RFR), Decision Tree Regression (DTR), Support Vector Regression (SVR), and Gradient Boosting Regression (GBR), were used to train using turbine operational data to predict turbine thermal efficiency to examine their performance. The GBR had the best predicting accuracy with a Mean Absolute Error (MAE) of 0.00836, Mean Relative Error (MRE) of 0.00030, Mean Squared Error (MSE) of 0.00012, and R^2 of 0.99967. Then, an Improved PSO Algorithm was applied to the turbine flow rates in order to find gas turbine thermal efficiency maximization. Over several iterations, the majority of the PSO runs converged within 15 iterations to a maximum thermal efficiency of 32.62%. This value was very similar to the highest value of 32.63% identified in the dataset. Further analysis of the populations while the PSO algorithm converged showed that the metrics for population diversity were smooth between the exploratory to the exploitative phases. For the optimized maximum efficiency, each flow rates were achieved at the optimized condition. The pre- and post-optimization flow rate of gas into the turbine has had an upward adjusted entry flow rate, and boosted the compressor and boiler gas flows while decreased combustor outlet gas flows, which maintains the established limits of the gas turbine. The study produced a solid foundation to be used for the real-time prediction of performance and operational optimization of gas turbine facilities.

Keywords

Machine Learning, Gas Turbine, Improved Particle Swarm Optimization and Thermodynamics.

1. Introduction

The early modelling of gas turbines (GT) was achieved using simulations of declared first-principles equations and proprietary performance maps of the performance of actual designs. (Al-Hamdan and Ebaid 2005) created a combined operating-performance map created from an aero-derivative GT's turbine and a GT's compressor performance map through axis transformations, to model full-load efficiency measures. In order to forecast gas turbine performance with average errors under 2% and maximum errors under 4.3%, (Liu and Karimi 2020) created surrogate models based on high-dimensional model representation and artificial neural networks. (Haglind and Elmegaard 2009) demonstrated approaches to predict part-load operating measures from aero-derivative GTs, using either the performance maps and simplified performance maps of actual designs. (J. J. Lee, Kang, and Kim

2011) also made a general GT whole engine performance analysis program in a stage-stacking of performance maps; before again the only full validation was full-load performance. Some good examples of model validation are provided by (Song, Gu, and Ji 2015) who made a full-range performance model of a three-spool turbofan engine, with cooling for non-combustor hot section components, and validated the model at all working engine performance regimes. The speed of the data-based combinatorial methods came with surrogate-modeling methods. (Bartolini et al. 2011) used artificial neural networks (ANN) for micro-GT performance maps, albeit they were able to include the ambient parameters and the emissions. (Nikpey, Assadi, and Breuhaus 2013) developed an improved artificial neural network model for combined heat and power micro gas turbines that possessed even greater predictive accuracy than traditional regression methods. Again, (Nikpey et al. 2014) conducted an experimental study and ANN modeling of a recuperative micro gas turbine using natural gas-biogas mixtures and demonstrated strong performance predictions, regardless of fuel blending proportion. (Fast, Assadi, and De 2009) made multi-utility ANN models for industrial GTs with prediction errors of less 2%. (Rossi et al. 2014) created ANNs on top of physical models to establish baselines of consumption profiles of CHP plants for diagnostic capabilities in real-time. Other ML algorithms, such as K-Nearest Neighbors, Random Forest Regression, Decision Tree Regression, Support Vector Regression, and Gradient Boosting Regression were used to generate accurate predictions of GT power output, pressure ratio, and exhaust temperature for traditional combined-cycle and cogeneration plants. (Tüfekci 2014) created a model to predict the full load electrical power output of a combined cycle power plant using a variety of machine learning algorithms, including artificial neural networks, support vector machines, and random forest with a high degree of accuracy for forecasting performance. (Boksteen et al. 2014) developed a Bayesian calibration framework for power plant models, yielding higher predictability for loads by explicitly applying the uncertainties associated with models and measurement errors. (Kim and Joo 2005) developed an on-line performance monitoring framework for two combined cycle power plants, demonstrating that an on-line real-time performance monitoring system can successfully track operational parameters and monitor performance degradation in operation. Furthermore, on-line performance monitoring models using ML were developed for combined-cycle units, detecting performance deviations in real-time (Gu¨len, Griffin, and Paolucci 2002), and real-time diagnostic systems for heavy-duty industrial GTs were created. (J. H. Lee, Kim, and Kim 2017) produced a predictive model for estimating the power-generation capacity of a gas turbine combined-cycle cogeneration plant and validated its accuracy across various operational modes.

PSO is a type of metaheuristic optimization technique that is triggered by the social behavior of bird flocking or fish schooling for effectively seeking optimum solutions with a good trade-off between exploration and exploitation processes in multidimensional complex search spaces. PSO is widely used for optimizing parameters in various engineering application areas. An optimized PSO technique using nominal average position of the swarm was developed by (Fang, Chen, and Shen 2011) for optimum multi-parameter gain tuning of PID for water turbine governors that showed better convergence properties relative to the conventional methods. (Mazhar, Liu, and Shukla 2019) used PSO to find optimum thermal parameters for phase change materials for grey water heat recovery systems which effectively improved energy recovery in thermal storage systems. (Krämer, Müller, and Kosterhon 2025) proposed a Deep Learning-Tuned Adaptive Inertia Weight (TAIW) technique that utilized the power of a neural network for adjusting the inertia weight factors dynamically using the individual search capability of each particle in an effective manner which showed better convergence properties for various benchmarking functions as well as for medical image registration tasks as compared to fixed inertia weight, linearly decreasing, and adaptive weight techniques. PSO methodology was successfully implemented by (Patel and Rao 2010) for optimizing design parameters of shell-and-tube heat exchanger geometric parameters with simultaneous improvement of both economic and thermal performance objectives. In recent times, PSO is a popular technique for optimizing the operation parameters of GT. (Emeka 2019) compared PSO to genetic algorithms in the context of a 100 MW GT and found that PSO converged on solutions much faster than the genetic algorithms, producing better tuning performance. Hybrid PSO Cuckoo Search techniques also eliminated the traditional controller designs for micro-GTs (Yang et al. 2021). Multi-objective PSO procedures, validating trade-offs of part-load efficiency and NO_x reductions, were also successful when applied (Ma et al. 2022). These procedures have now led to studies on the use of PSO in novel forms such as reinforcement-learning frameworks or adaptive neural fuzzy inference systems for dynamic GT control with reliability (Hadroug et al. 2021).

The purpose of this study is to investigate System A stated by (Pak and Suzuki 1997), and to examine the performance of five machine-learning (ML) models, KNN, RFR, DTR, SVR, and GBR, over the generated dataset to predict thermal efficiency based on combinations of mass-flow. The models created are evaluated based on their MAE, MSE, MRE, and R^2. The best model will guide an enhanced PSO algorithm to find the optimum operating point for maximum thermal efficiency and optimized mass flow rates to achieve that. Thus, the present work introduces a novel approach for advancing data-driven approaches for performance improvement of cogeneration gas turbine systems with a focus on predictive modeling and global optimization.

2. System Modelling

Figure 1 illustrates the Gas Turbine System along with its constraints. Mainly, intake air and fuel get compressed by the compressors and get mixed at the combustor with an equivalence ratio of 0.2. This lean mixture causes the combustor efficiency to be 98%. After the combustion, the mixture enters the turbine, produces work, and the residue passes through the waste heat boiler.

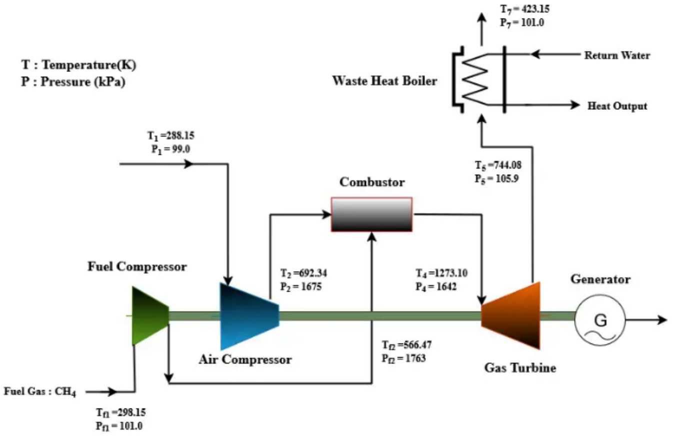

Figure 1. Gas Turbine System Model

For simulation purposes, first law of thermodynamics has been implemented with varying mass flow rates of air compressor inlet, air compressor outlet, fuel compressor, combustor outlet, and boiler, and so, a dataset of thermal efficiency variation with mass flow rates consisting of 32768 datapoints has been created. A summary of the dataset has been depicted in Table 1.

$$\dot{Q} + \dot{W} = \sum \dot{m}_{out} h_{out} - \sum \dot{m}_{in} h_{in} \tag{01}$$

Table 1. Dataset Summary

Mass Flow Rates	Air Compressor Inlet (kg/s)	Fuel Compressor (kg/s)	Air compressor Outlet (kg/s)	Combustor Outlet (kg/s)	Boiler (kg/s)	Thermal Efficiency (%)
Mean	53.486111	1.063889	52.527778	52.777778	52.111111	27.385041
Std	1.354790	0.212766	1.072921	1.091106	0.981995	1.922467
Max	55.555556	1.388889	54.166667	54.444444	53.611111	32.638056
Min	51.416667	0.738889	50.888889	51.111111	50.611111	22.132025

3. Methodology

3.1 Machine Learning

In the present study, we used the mass flow rates as input features and the thermal efficiency as the output label. The whole dataset was split into an 80:20 ratio for training and testing purposes. Then, five machine learning models were introduced to the dataset, and their hyperparameters were optimized by randomized search cv. Then, the performance metrics of the optimized models have been determined.

3.2 Improved PSO Method

PSO method considers the combination of mass flow rates as particle and collection of the particles as swarm, and searches for the best combination for maximum thermal efficiency possible for the given dataset. For improved PSO method, the adaptive inertia weight converges the model from exploration to exploitation. The constriction factor guarantees convergence, and velocity clamping prevents velocity explosion. Moreover, the improved model utilizes Latin hypercube sampling for better initial particle distribution. Basically, the method uses the optimized best-performing machine learning model to predict the thermal efficiency with its current particle, then compares it with the global best efficiency and moves the particle position according to the analysis in every iteration.

4. Model Validation

The thermodynamic analysis in this study was carried out by using Python (3.12) and Cantera. We had taken the simulation parameters of GT from (Pak and Suzuki 1997) as stated before. **Table 2** shows that our simulation and the simulation they did are almost similar. So, it can be said that our model setup was correct.

Table 2. Model Validation Results

Items	**Present Study**	**Study by Pak and Suzuki** (Pak and Suzuki 1997)
Net Work	10.03 MW	10 MW
Generated power output	27.13%	27.1%
Turbine Energy Output	86.36%	87.2%
Heat Output at Boiler	17.59 MW	16.93 MW
Power for compressing Air	57.8%	58.7%
Power for compressing fuel	1.43%	1.4%

5. Results and Discussions

5.1 Machine Learning Models

Figure 2 shows the predicted vs actual values of each model for the best hyperparameter combination. KNN is visibly the worst working model for our dataset, as it shows the most deviation from the ideal line. This statement is further validated by Fig 3 where the error, along with R^2 values, has been portrayed for every model. KNN offers the largest errors with MAE, MRE, and MSE values of 0.0854, 0.0031, 0.0119, respectively and the smallest R^2 value of 0.9967. The four remaining models show almost similar results which is hard to distinguish from Figure-1, but the error values can determine the best working model. From Figure 2 it is evident that GBR model shows the least errors and best R^2 values; with MAE, MRE, R^2 values of 0.00836, 0.0003, 0.00012 and 0.99967, respectively. Though the values of the performance metrics are nearly similar for RFR, DTR, SVR, and GBR, the differences can be visible by taking larger precisions of the values.

5.2 Optimization by Improved PSO Algorithm

Figure 3(a) shows the thermal efficiency optimization process across iterations for multiple PSO runs. The convergence pattern demonstrates that PSO rapidly improves thermal efficiency in the first 10-15 iterations before stabilizing at the optimal value of 32.62%. The consistency across multiple runs indicates the algorithm's reliability and correctness.

Figure 3(b) illustrates the diversity metrics of the PSO algorithm. Both mean diversity and pairwise diversity start high and decrease exponentially as the algorithm progresses, eventually stabilizing at low values of 0.4-0.7; which means particles initially explore the search space widely and gradually converge toward the optimal solution, indicating a proper balance between exploration and exploitation phases.

Figure 4 illustrates the robust performance of the PSO algorithm, demonstrating both rapid convergence and effective population management. As shown in the Figure 4(a) the algorithm consistently stabilizes at a maximum thermal efficiency of 32.62% within the first 15 iterations across multiple runs, confirming its reliability. This efficiency is supported by the diversity metrics in Figure 4(b), which depict a smooth transition from high initial exploration to a focused exploitation phase, with diversity values settling between 0.4 and 0.7 to prevent premature convergence.

Table 3 compares flow rates across different system components before and after PSO optimization. The optimization appears to maintain or slightly improve flow rates across most parameters, with the most significant improvements visible in the higher flow rate components (around 55 kg/s). This demonstrates that PSO successfully optimized the system while maintaining operational constraints.

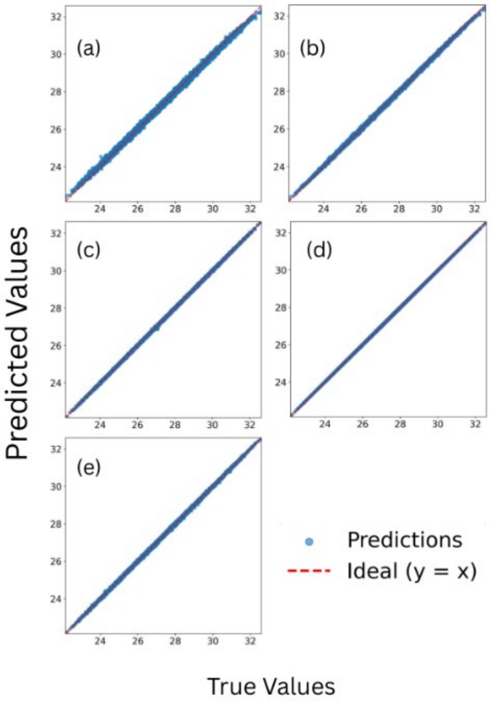

Figure 2. Predicted vs True Values for (a) KNN, (b) RFR, (c) DTR, (d) SVR and (e) GBR

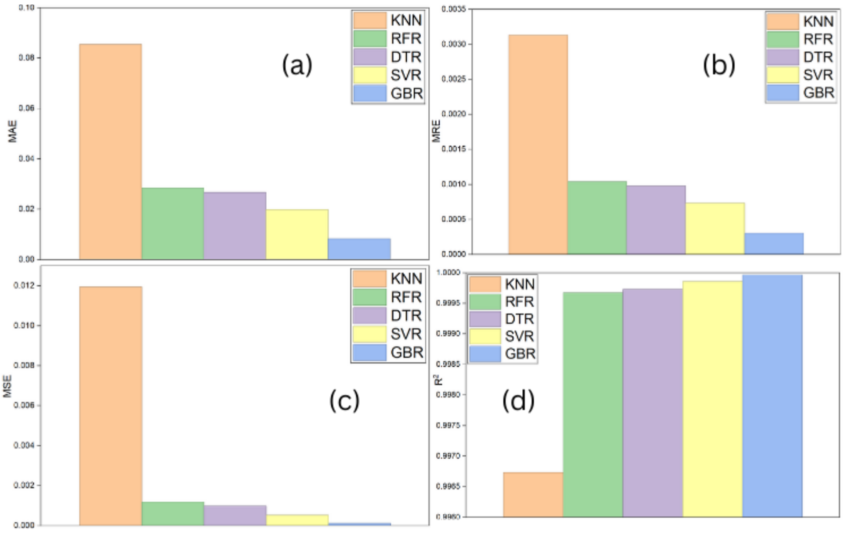

Figure 3. Performance Metrics (a) MAE, (b) MRE, (c) MSE, (d) R^2

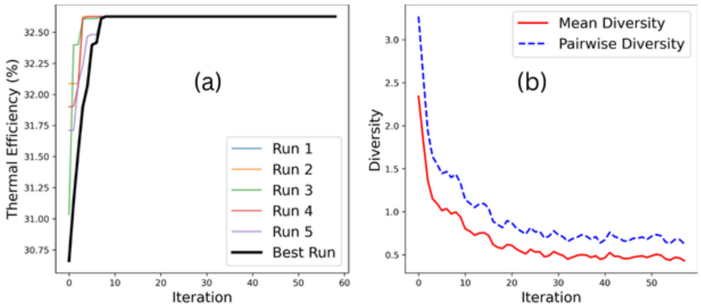

Figure 4. Performance of PSO Algorithm-(a) Convergence Plot, and (b) Population Diversity

Table 3. Comparison between optimal mass flow rates and original best mass flow rates from dataset

Mass Flow Rates	**Before PSO (kg/s)**	**After PSO (kg/s)**
Air Compressor Inlet	51.42	51.71
Fuel Compressor	0.74	0.77
Air Compressor Outlet	50.89	50.92
Combustor Outlet	54.44	54.30
Boiler	53.61	53.89

6. Conclusion

This study successfully established a comprehensive data-driven framework for the predictive modeling and operational optimization of gas turbine cogeneration systems. By integrating advanced machine learning techniques with meta-heuristic optimization, the research demonstrates a viable pathway for enhancing thermodynamic efficiency without relying solely on computationally expensive first-principles simulations. The key findings of the study are as follows:

1. Among the five machine learning models evaluated, Gradient Boosting Regression (GBR) emerged as the most robust predictor. It achieved the highest accuracy with a MAE of 0.00836 and R^2 of 0.99967. This indicates that the GBR model can capture the complex non-linear relationships between mass flow rates and thermal efficiency with near-perfect precision.
2. The Improved PSO algorithm demonstrated exceptional efficiency in exploring the solution space. The algorithm consistently converged to a maximum thermal efficiency of 32.62% within the first 15 iterations. The population diversity metrics confirmed a balanced transition from exploration to exploitation, preventing premature convergence to local optima.
3. To achieve the optimized efficiency, the algorithm identified a specific control strategy: increasing the mass flow rates for the air compressor and boiler while decreasing the combustor outlet gas flow. This configuration maximizes output while adhering to the established operational limits of the turbine system.

The implications of these findings extend significantly into industrial applications, particularly for the development of Digital Twin technologies and real-time supervisory control systems. The high inference speed and accuracy of the GBR model allow it to serve as a surrogate model for online performance monitoring, replacing slower physical simulations. Furthermore, the stability and speed of the Improved PSO algorithm suggest it is well-suited for dynamic control loops, where it can continuously adjust operational setpoints (such as fuel and air mass flow) to maintain peak efficiency in response to fluctuating load demands or environmental conditions. However, the proposed framework yields promising results, it is essential to acknowledge the limitations inherent in this study. The dataset employed was generated using thermodynamic simulations based on the theoretical model by (Pak and Suzuki 1997), rather than empirical data from an operating gas turbine. Consequently, the model does not account for real-world stochastic factors such as sensor noise, mechanical wear, or component degradation over time. Future research should focus on validating these algorithms against historical operational data from physical plants and incorporating noise-handling mechanisms to ensure robustness in a genuine industrial environment.

References

Al-Hamdan, Qusai Z., and Munzer S. Y. Ebaid. “Modeling and Simulation of a Gas Turbine Engine for Power Generation.” *Journal of Engineering for Gas Turbines and Power* 128(2): 302–11. 2005. doi:10.1115/1.2061287.

Bartolini, C. M., F. Caresana, G. Comodi, L. Pelagalli, M. Renzi, and S. Vagni. “Application of Artificial Neural Networks to Micro Gas Turbines.” *Energy Conversion and Management* 52(1): 781–88. 2011. doi:10.1016/j.enconman.2010.08.003.

Boksteen, Sowande Z., Jos P. van Buijtenen, Rene Pecnik, and Dick van der Vecht. “Bayesian Calibration of Power Plant Models for Accurate Performance Prediction.” *Energy Conversion and Management* 83: 314–24. 2014. doi:10.1016/j.enconman.2014.03.073.

Emeka, Ugwuoke Philip. “Comparison of GA and PS Optimization Mechanisms for Optimizing 100MW Delta IV Ughelli Gas Turbine Power Plant Operating Parameters.” *American Journal of Energy Engineering* 6(4): 44–49. 2019. doi:10.11648/j.ajee.20180604.12.

Fang, Hongqing, Long Chen, and Zuyi Shen. "Application of an Improved PSO Algorithm to Optimal Tuning of PID Gains for Water Turbine Governor." *Energy Conversion and Management* 52(4): 1763–70. 2011. doi:10.1016/j.enconman.2010.11.005.

Fast, M., M. Assadi, and S. De. "Development and Multi-Utility of an ANN Model for an Industrial Gas Turbine." *Applied Energy* 86(1): 9–17. 2009. doi:10.1016/j.apenergy.2008.03.018.

Gu¨len, S. C., P. R. Griffin, and S. Paolucci. "Real-Time On-Line Performance Diagnostics of Heavy-Duty Industrial Gas Turbines." *Journal of Engineering for Gas Turbines and Power* 124(4): 910–21. 2002. doi:10.1115/1.1413465.

Hadroug, Nadji, Ahmed Hafaifa, Abdelhamid Iratni, and Mouloud Guemana. "Reliability Modeling Using an Adaptive Neuro-Fuzzy Inference System: Gas Turbine Application." *Fuzzy Information and Engineering* 13(2): 154–83. 2021. doi:10.1080/16168658.2021.1915451.

Haglind, F., and B. Elmegaard. "Methodologies for Predicting the Part-Load Performance of Aero-Derivative Gas Turbines." *Energy* 34(10): 1484–92. 2009. doi:10.1016/j.energy.2009.06.042.

Kim, Si-Moon, and Yong-Jin Joo. "Implementation of On-Line Performance Monitoring System at Seoincheon and Sinincheon Combined Cycle Power Plant." *Energy* 30(13): 2383–2401. 2005. doi:10.1016/j.energy.2005.01.001.

Krämer, Katharina, Stefan Müller, and Michael Kosterhon. "Deep Learning-Tuned Adaptive Inertia Weight in Particle Swarm Optimization for Medical Image Registration." In SCITEPRESS, 307–18. 2025. doi:10.5220/0013122000003912.

Lee, Jae Hong, Tong Seop Kim, and Eui-hwan Kim. "Prediction of Power Generation Capacity of a Gas Turbine Combined Cycle Cogeneration Plant." *Energy* 124: 187–97. 2017.doi:10.1016/j.energy.2017.02.032.

Lee, Jong Jun, Do Won Kang, and Tong Seop Kim. "Development of a Gas Turbine Performance Analysis Program and Its Application." *Energy* 36(8): 5274–85. 2011. doi:10.1016/j.energy.2011.06.032.

Liu, Zuming, and Iftekhar A. Karimi. "Gas Turbine Performance Prediction via Machine Learning." *Energy* 192: 116627. 2020. doi:10.1016/j.energy.2019.116627.

Ma, Yujia, Jinfu Liu, Linhai Zhu, Qi Li, Yaqiong Guo, Huanpeng Liu, and Daren Yu. "Multi-Objective Performance Optimization and Control for Gas Turbine Part-Load Operation Energy-Saving and NOx Emission Reduction." *Applied Energy* 320: 119296. 2022. doi:10.1016/j.apenergy.2022.119296.

Mazhar, Abdur Rehman, Shuli Liu, and Ashish Shukla. "An Optimizer Using the PSO Algorithm to Determine Thermal Parameters of PCM: A Case Study of Grey Water Heat Harnessing." *International Journal of Heat and Mass Transfer* 144: 118574. 2019. doi:10.1016/j.ijheatmasstransfer.2019.118574.

Nikpey, H., M. Assadi, and P. Breuhaus. "Development of an Optimized Artificial Neural Network Model for Combined Heat and Power Micro Gas Turbines." *Applied Energy* 108: 137–48. 2013. doi:10.1016/j.apenergy.2013.03.016.

Nikpey, H., M. Assadi, P. Breuhaus, and P. T. Mørkved. "Experimental Evaluation and ANN Modeling of a Recuperative Micro Gas Turbine Burning Mixtures of Natural Gas and Biogas." *Applied Energy* 117: 30–41. 2014. doi:10.1016/j.apenergy.2013.11.074.

Pak, P. S., and Y Suzuki. "Exergetic Evaluation of Methods for Improving Power Generation Efficiency of a Gas Turbine Cogeneration System." *International Journal of Energy Research* 21(8): 737–47. 1997.doi:10.1002/(SICI)1099-114X(19970625)21:8%3C737::AID-ER283%3E3.0.CO;2-2.

Patel, V. K., and R. V. Rao. "Design Optimization of Shell-and-Tube Heat Exchanger Using Particle Swarm Optimization Technique." *Applied Thermal Engineering* 30(11): 1417–25. 2010.doi:10.1016/j.applthermaleng.2010.03.001.

Rossi, Francesco, David Velázquez, Iñigo Monedero, and Félix Biscarri. "Artificial Neural Networks and Physical Modeling for Determination of Baseline Consumption of CHP Plants." *Expert Systems with Applications* 41(10): 4658–69. 2014. doi:10.1016/j.eswa.2014.02.001.

Song, Yin, Chun-wei Gu, and Xing-xing Ji. "Development and Validation of a Full-Range Performance Analysis Model for a Three-Spool Gas Turbine with Turbine Cooling." *Energy* 89: 545–57. 2015.doi:10.1016/j.energy.2015.06.015.

Tüfekci, Pınar. "Prediction of Full Load Electrical Power Output of a Base Load Operated Combined Cycle Power Plant Using Machine Learning Methods." *International Journal of Electrical Power & Energy Systems* 60: 126–40. 2014.doi:10.1016/j.ijepes.2014.02.027.

Yang, Rui, Yongbao Liu, Youhong Yu, Xing He, and Hongsong Li. "Hybrid Improved Particle Swarm Optimization-Cuckoo Search Optimized Fuzzy PID Controller for Micro Gas Turbine." *Energy Reports* 7: 5446–54. 2021. doi:10.1016/j.egyr.2021.08.120.

Biographies

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Shakib Arafat Tapu is a Mechanical Engineering Undergraduate Student at Bangladesh University of Engineering and Technology. He has done work in electromechanical systems, machine learning and kinematics while leading a sub division of Team Interplanetar- BUET Mars Rover team. He has also worked on thermal engineering and management systems while doing his role as Co-Chair of ASHRAE BUET Student Branch. He is currently working on developing Electrohydrodynamic Cooling Systems and optimizing the system parameters using machine learning. Apart from academic course works, he is also enthusiastic and working on Robotics, Bio-Engineering and Advanced Thermal Engineering applications.