

PAPER 156 – PREDICTION OF NO_x EMISSION IN GAS TURBINE POWER PLANT WITH HARRIS HAWKS OPTIMIZED ARTIFICIAL NEURAL NETWORK

T. I. Aмоса¹, O. Ibrahim², S. L. Ayinla^{1,3}, A. Bahashwan Abdullah Omar¹, F. Mochammed⁴
A. O. Yusuf³, H. O. Mahmud³

¹ Department Electrical & Electronics Engineering, Universiti Teknologi PETRONAS, Bandar Seri Iskandar, Malaysia.

²Department of Electrical & Electronics Engineering, University of Ilorin, Ilorin, Nigeria.

³Department of Computer Engineering, University of Ilorin, Ilorin, Nigeria.

⁴Department of Chemical Engineering, Universiti Teknologi PETRONAS, Bandar Seri Iskandar, Malaysia.

*Email: amosatemitopeibrahim@gmail.com

ABSTRACT

Predictive emission monitoring systems (PEMS) are critical instruments for verifying and strengthening the reliability of costly continuous emission monitoring systems used in gas-turbine power facilities. PEMS is built on the premise of predictive models that are trained on historical data to estimate emission components. The availability of a relevant and environmentally friendly dataset for gas turbine processes has prompted an investigation into the efficacy of models derived from different machine learning techniques. This inquiry aims to develop a predictive model for CO and NO_x emissions based on both ambient variables and technological process parameters. In the present study, a new machine learning-based model is proposed for the prediction of NO_x emissions in natural gas turbines. The model utilizes an Artificial Neural Network (ANN) that is optimized with the Harris Hawks Optimizer (HHO). The model is trained and validated on a dataset obtained from the University of California at Irvine (UCI) open data repository. The effectiveness of the proposed algorithm was evaluated by comparing it with conventional ANN. The proposed model obtained R² = 90.36%, RMSE = 3.9276, and MSE = 15.4260. The results showed that the proposed approach is effective and demonstrates competitive performance over ANN.

KEYWORDS: NO_x emissions, exhaust emission prediction, Intelligent emission monitoring, Harris hawk optimizer, Gas turbine combined cycle

19. INTRODUCTION

More energy consumption has a twofold detrimental impact on the environment, causing increased deforestation as well as increased carbon and flue gas emissions (Kaya et al., 2019). Air pollution is a significant problem that encompasses all components that have the potential to harm living things. The combustion process in the power sector is one of the primary sources of hazardous pollutants (NO_x and CO) emitted into the atmosphere. The nitrogen dioxide (NO₂) and nitric oxide (NO) emissions that arise from nitrogen and oxygen gas interactions in the air during combustion are referred to as NO_x. NO_x (NO₂ + NO) is regarded as the principal pollutant of the atmosphere because it causes tropospheric ozone, ozone layer depletion, photochemical smog, acid rain, and eventually global warming. Several agreements have been adopted in different United Nations (UN) climate change conventions by participating nations to raise environmental awareness in both public and political spheres. The Paris Climate Change Agreement and the Glasgow Climate Pact are two of such agreements that have established alternative roadmaps for achieving environmental sustainability. The Glasgow Climate Pact was adopted, with the goal of making the 2020s a decade of climate action and support. In this convention, several themes have been agreed upon in the decision package, including greater steps to strengthen climate change resilience and reduce greenhouse gas emissions. They also committed to working together to close the gap between existing emission reduction plans and what is needed to cut emissions so that global average temperature rises are restricted to 1.5 degrees. In fact, for the first time, countries are being urged to reduce unabated coal power and wasteful fossil fuel subsidies, in addition to the extant severe environmental laws, and tax implementation for carbon emissions.

In compliance with these resolutions, there is a specific focus on lowering emissions from power plants, as the combustion process in the power sector is a major source of hazardous pollutants (NO_x and CO) emitted into the atmosphere (Korpela et al., 2015; Skalska et al., 2010). In some regions of the globe, strong environmental restrictions limit these emissions to particular levels (Shakil et al., 2009). The Large Combustion Plant Directive and its replacement, the Industrial Emissions Directive (IED), which went into force in 2016 for

power plants with a capacity of more than 50 MW, is the European union regulations that limit flue gas emissions (NO_x, CO, and dust) (Kaya et al., 2019). The flue gas contents of NO_x and CO must be regularly monitored from any combustion plant surpassing a total capacity of 100 MW, according to IED (Korpela et al., 2017). Furthermore, when natural gas is utilized as a fuel, NO_x and CO emissions are regulated to 25 ppm_{dv} (parts per million by dry volume) by the EU.

Since it has become mandatory for power plant operators to monitor the NO_x and CO pollutants emitted during combustion operations in a power plant, three solutions for monitoring flue gas emissions from a combustion unit have been developed: i) intermittent measurements, ii) continuous emission monitoring system (CEMS), or iii) predictive emission monitoring system (PEMS) (Kaya et al., 2019). Emission testing facilities typically perform “intermittent measurements” with calibrated equipment at reasonable expenses. The emission monitoring equipment (such as a sensor set) is placed on-site in CEMS. CEMS delivers real-time emissions data collected directly from sensors. The accuracy of these measurements is dependent on adequate maintenance and calibrations of the equipment, which should be carried out according to industry standards (Kaya et al., 2019). PEMS, conversely, is an expert system that employs predictive models based on historical data to estimate emission components using some process variables like ambient temperature, turbine inlet temperature, etc. PEMS is regarded by many scholars as a backup, or alternative to CEMS for monitoring (Chien et al., 2005). Analytical equations derived from thermodynamic (or first) principles, mass and energy balance, and data-driven models, which include statistical and machine learning methods, are the two basic approaches to model development for PEMS. CEN/TC 264/WG 37 contains the standardization and technical specifications required for PEMS software certification, as well as performance and quality assurance for a PEMS to demonstrate suitability for its measuring task and to ensure that the PEMS continues to perform within the specified performance during operation.

For several decades, low research consideration has characterized the development of data-driven models for PEMS due to lack of applicable and ecologically valid datasets. However, the publication of an open source flue gas emission dataset (Kaya et al., 2019) on the University of California, Irvine, open data repository has prompted a challenge to develop and assess the performance of different models built using various machine learning algorithms. This paper presents a novel data-driven approach for learning PEMS model which is known for its promising solution for handling massive data (Sherstinsky, 2018). The primary aim of this study is to employ the Harris Hawks Optimized Artificial Neural Network (ANN-HHO) algorithm to develop a model capable of predicting NO_x emissions from gas turbines. The implementation and training were performed using MATLAB software. Using the Neural Net Tuning tool, ANN models was created, and HHO was applied to enhance model performance. Various statistical metrics, including MSE, RMSE, and R² were utilized to assess the models' performance.

The rest of this paper is structured as follows: Section 2 discussed various related works. Section 3 provides a detailed description of the materials and methods utilized to apply the ANN-HHO design in a power plant, including theoretical concepts. Experimental results are presented in Section 4, while Section 5 summarizes the study's conclusions.

20. RELATED WORKS

Over the last five decades, PEMS models have progressed from first principle-based models to AI-based models. AI-based models can be applied to process more data than traditional approaches and have been gaining popularity because of the advancements in computer technology and availability of larger datasets for training. Because AI-based PEMS models must employ process data linked to NO_x emission, this gives them greater flexibility in selecting and processing process data than the first principle or statistical models. In 1973, the first PEMS was developed and published (Hung, 1975). PEMS studies and commercial applications for a variety of sources and sectors have been extensively investigated since 1990. PEMS describe a relationship between a set of emission source process parameters (e.g., air pressure, turbine exhaust pressure) and the resulting flue gas emissions. However, lack of largescale datasets for training has been a major limitation for learning robust and accurate AI-based PEMS models for several decades.

The largest flue gas emission dataset was introduced by researchers in (Kaya et al., 2019). This data was collected over a five-year period to further PEMS research. Researchers were able to start an open discussion on the features of data and the quality of models derived from various machine learning methods to predict CO and NOx emissions after the dataset was published in the open data repository of the University of California, Irvine (UCI) in 2019. The authors provide the first attempt in literature to use extreme learning machine regressors (ELMs) to solve this challenge. The best result has a coefficient of determination $R^2 = 0.56$ and mean absolute error (MAE) 0.97 mg/m³ for CO prediction and $R = 0.67$ and MAE = 4.57 mg/m³ for NOx prediction. The study conducted by Li et al. in 2015, identified two notable limitations associated with ELM. Firstly, the inherent randomness in ELM results in amplified uncertainty during both approximation and learning processes. Secondly, if an inappropriate activation function is used, ELM is prone to experiencing generalization degradation (Lin et al., 2015). The author in (Wood, 2023) employed a set of twelve models, including multi-linear regression (MLR) and machine learning (ML) techniques, to accurately predict CO and NOx emissions in combined cycle gas turbines. Using Artificial Neuro Fuzzy Inference System (ANFIS) optimized with GA, the author in reference (Dirik, 2022) predicts the NOx emission in a combined cycle power plant. The performance obtained in this study improved due to the replacement of gradient-based backpropagation learning algorithm with meta-heuristic optimizer (GA) for learning the ANFIS model. Motivated by this, we also proposed to learn a prediction model for NOx emission in a combined cycle power plant using ANN optimized by HHO.

21. MATERIALS AND METHODS

In this section, we described the ANN and HHO algorithms, as well as the machine learning approach employed in this study to predict greenhouse gases emitted in power plants. This study followed a data driven approach that uses historical data obtained from a combined cycle power plant. A combined cycle power plant is composed of gas turbines, steam turbines, and steam generators with heat recovery, where electricity is generated by combining gas and steam turbines in a single cycle (Dirik, 2022). The electricity is then transmitted from one turbine to the next, which can produce hazardous gaseous pollutants such as CO (carbon monoxide) and NOx (nitrogen oxides). NOx refers to a group of pollutants that include nitric oxide (NO₂) and nitrogen monoxide (NO), which are typically generated during the combustion process. This article is focused on NOx emissions from gas-fired power plants, which contribute to smog, acid rain, and tropospheric ozone pollution. By predicting the peak levels of such emissions, adequate preventive action is planned. To address this problem, ANN-HHO is employed to predict combined cycle emissions and their reductions, and to simulate NOx-level pollutant emissions based on environmental and control factors.

3.1 Artificial Neural Network

An artificial neural network is a biological-inspired computational intelligence algorithm that draws inspiration from human brain, and it is comprises of numerous artificial neurons. These neurons are linked by coefficients, known as weights, that form the neural structure of the network (refer to Fig. 1). Each neuron processes information by utilizing its weighted inputs, activation function, and one output. Essentially, a neuron is black-box model that determines what the outputs will be given the inputs. ANNs are sometimes referred to as connectionist models since the connection weights symbolize the memory of the system (Agatonovic-Kustrin & Beresford, 2000). While a single neuron can execute basic information processing tasks, the true strength of neural computing is derived from the interconnection of neurons within a network.

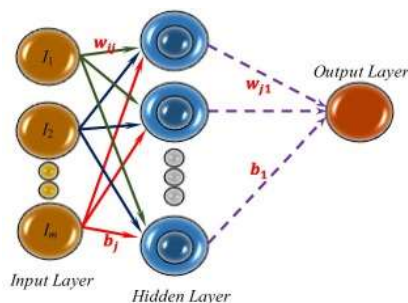


Figure 1. Illustration of ANN Structure.

The crucial characteristic of ANN is their capability to improve in a task through learning from experience. This feature enables ANN to be applied in a broad range of applications such as classification, prediction, detection, image processing, and pattern recognition. By minimizing the error between actual and expected outputs during training, ANN parameters, such as bias and weight, can be optimized (Khatir et al., 2021). While supervised, unsupervised, and reinforcement are the three learning approaches in machine learning, the most often used ANN is a fully connected, supervised network with backpropagation learning rule. However, it suffers from several limitations, particularly in their sensitivity to noisy data and vanishing gradient problem. Thus, there is a need to complement or replace this learning algorithm.

3.2 Harris Hawk Optimization Algorithm

Harris Hawks Optimization (HHO) algorithm was proposed in 2019 by Heidari et al. (Heidari et al., 2019), and has since then received huge research attention. HHO simulates collaborative behaviour and hunting style of the Harris Hawks in nature, i.e., surprise pounce. Harris's hawks employ the "surprise pounce" tactic, also referred to as the "seven kills" strategy, as their primary method of capturing prey. This strategy involves several hawks working together to attack a detected escaping rabbit from different directions, converging on it simultaneously outside of its cover. While the attack can be completed quickly in a matter of seconds, it may also involve multiple short-length, quick dives near the prey over several minutes, depending on the prey's escaping capabilities and behaviors. The Harris's hawks have the ability to imitate various hunting techniques depending on the situation and the fleeing patterns of their prey. In particular, researchers have identified four chasing tactics employed by these birds, namely, soft besiege, hard besiege, soft besiege with progressive rapid dives, and hard besiege with progressive rapid dives, as described in (Heidari et al., 2019).

3.3 Optimizing ANN with Harris Hawk Optimizer

HHO is a population-based gradient-free meta-heuristic optimization algorithm inspired by the collaborative conduct and hunting style of Harris Hawks. Stimulating the dynamic pattern and behaviours of this intelligent specie of bird via mathematical model, an optimization algorithm is generated. HHO is well suited for improving ANN by optimizing the error function. However, HHO was used in this work to address the drawbacks of backpropagation learning algorithm in ANN, such as slow convergence and the tendency to be trapped in local minima. HHO is a stochastic search technique for optimization based on the concepts of harmonized foraging of one of the most intelligent birds, Harris' Hawks in hunting escaping preys (rabbits in most cases). In the HHO algorithm, the Harris's hawks serve as the candidate solutions, with the best solution in each step being identified as the intended prey or close to the optimum. These hawks randomly perch on various locations and employ two strategies to detect prey. In Table 1, we present the setting/parameters of the proposed hybrid algorithm.

Table 1. ANN-HHO Parameters setting for the proposed ANN-HHO algorithm.

Algorithm	Setting/Parameters	Types/value
HHO	Number of search agent	30
	Maximum iteration	100
	Lower bound	-10
	Upper bound	10
	default constant	1.5
ANN	Input layer	9
	hidden size	10
	Output layer	1
	Epoch	1000
	Activation function	Sigmoid

3.4 Datasets

This study makes use of the Gas Turbine CO and NOx Emission Dataset from the University of California at Irvine (UCI) open data repository (Kaya et al., 2019). The data was obtained in northwestern Turkey during a five-year period, and it consisted of hourly average sensor readings of eleven variables (nine input and two target

variables) with a total of 36,733 occurrences. The nine independent variables may be divided into two categories: environmental variables (such as temperature, humidity, and pressure) and process factors (such as turbine energy yield and air filter difference pressure). Table 2 summarizes the engine variables names, acronyms, and basic statistics of the variables contained in dataset utilized in our study. For this study, we use the data obtained between 2011-2013 for training and validation, and only the first 6-month data from 2014 for testing.

Table 2. Summary of the features contained in the UCI CO and NOx emission dataset.

Variable name	Acronym	Unit	Mean	Min	Max
Ambient Temperature	AT	deg. Celsius	17.71	-6.23	37.10
Ambient Pressure	AP	mbar	1013.07	985.85	1036.56
Ambient Humidity	AH	%	77.87	24.08	100.20
Air Filter Difference Pressure	AFDP	mbar	3.93	2.09	7.61
Gas Turbine Exhaust Pressure	GTEP	mbar	25.56	17.70	40.72
Turbine Inlet Temperature	TIT	deg. Celsius	1081.43	1000.85	1100.89
Turbine After Temperature	TAT	deg. Celsius	546.16	511.04	550.61
Compressor Discharge Pressure	CDP	mbar	12.06	9.85	15.16
Turbine Energy Yield	TEY	MWH	133.51	100.02	179.50
Carbon Monoxide	CO	mg/m ³	2.37	0.00	44.10
Nitrogen Oxides	NO _x	mg/m ³	65.29	25.90	119.91

22. RESULTS AND DISCUSSION

In this section, we discuss the result of the proposed ML-based modelling and prediction of NOx emission from gas turbine power plant using ANN and the proposed ANN-HHO. The obtained result is summarized in Table 3.

Table 3: Simulation result of ANN and ANN-HHO model

Model	Data split		Performance metrics					
	Train	Test	MSE		RMSE		R ²	
ANN	65	35	20.1687	20.3097	4.4910	4.5066	0.9140	0.9119
	70	30	19.5909	19.2445	4.4262	4.3846	0.9169	0.9156
	80	20	19.1679	21.1168	4.3781	4.5953	0.9180	0.9091
ANN-HHO	65	35	13.5591	18.3471	7.3643	9.5712	0.9153	0.8854
	70	30	12.9506	15.4260	3.5987	3.9276	0.9191	0.9036
	80	20	14.6665	18.2373	3.8297	4.2705	0.8310	0.7899

Table 3 shows the results of various training-testing dataset split ratios for the conventional ANN and ANN-HHO models. The ANN model shows the best result with a split ratio of 70-30%, with MSE, RMSE, and R² values of 19.2445, 4.3846, and 90.56%, respectively. In comparison, the ANN-HHO model shows values of 15.4260, 3.9276, and 90.36% for MSE, RMSE, and R², respectively. Although the R² value does not change significantly, the proposed model exhibits a lower MSE and RMSE, indicating lower overall error and a closer fit to the actual data. Therefore, the ANN-HHO model gave a robust NOx emissions prediction in a gas turbine process based on ambient variables and technological process parameters.

Since the accurate prediction of NOx emissions is crucial in industries that rely on gas turbines, such as power generation or aerospace, the proposed model can be used to optimize emissions and avoid regulatory penalties, leading to more efficient and environmentally friendly engine design. Therefore, the significance of the proposed model is its usefulness in accurately predicting NOx emissions, making it a valuable tool for industries that depend on gas turbines.

23. CONCLUSION

The aim of this research is to create an ANN-based model using a publicly available dataset on combined cycle power plant exhaust, and to improve its performance through HHO algorithm to accurately predict NOx levels. The study utilizes a machine learning approach to develop a data-driven model for estimating NOx emission

concentrations in exhaust gases. The performance of the constructed models was evaluated based on statistical metrics such as R^2 , MSE, and RMSE. The ANN model achieved $R^2 = 90.56\%$, RMSE = 4.3846, and MSE = 19.2445 on the test data, while the ANN-HHO model attained $R^2 = 90.36\%$, RMSE = 3.9276, and MSE = 15.4260. The results demonstrate that the hybrid ANN-HHO model outperforms the ANN model in predicting NO_x, as evidenced by lower system error values. The result indicates that the proposed model has the potential to accurately predict NO_x levels in exhaust emissions.

REFERENCES

- Agatonovic-Kustrin, S., & Beresford, R. (2000). Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research. *Journal of pharmaceutical and biomedical analysis*, 22(5), 717-727.
- Chien, T., Chu, H., Hsu, W., Tu, Y., Tsai, H., & Chen, K. J. A. E. (2005). A performance study of PEMS applied to the Hsinta power station of Taipower. 39(2), 223-230.
- Dirik, M. (2022). Prediction of NO_x emissions from gas turbines of a combined cycle power plant using an ANFIS model optimized by GA. *Fuel*, 321, 124037. <https://doi.org/10.1016/j.fuel.2022.124037>
- Heidari, A. A., Mirjalili, S., Faris, H., Aljarah, I., Mafarja, M., & Chen, H. (2019). Harris hawks optimization: Algorithm and applications. *Future Generation Computer Systems*, 97, 849-872. <https://doi.org/10.1016/j.future.2019.02.028>
- Kaya, H., Tüfekçi, P., & Uzun, E. J. T. J. E. C. S. (2019). Predicting CO and NO_x emissions from gas turbines: novel data and abenchmark PEMS. 27, 4783-4796.
- Khatir, S., Tiachacht, S., Le Thanh, C., Ghandourah, E., Mirjalili, S., & Abdel Wahab, M. (2021). An improved Artificial Neural Network using Arithmetic Optimization Algorithm for damage assessment in FGM composite plates. *Composite Structures*, 273, 114287. <https://doi.org/10.1016/j.compstruct.2021.114287>
- Korpela, T., Kumpulainen, P., Majanne, Y., Häyrinen, A., & Lautala, P. (2017). Indirect NO_x emission monitoring in natural gas fired boilers. *Control Engineering Practice*, 65, 11-25.
- Korpela, T., Kumpulainen, P., Majanne, Y., & Häyrinen, A. J. I.-P. (2015). Model based NO_x emission monitoring in natural gas fired hot water boilers. 48(30), 385-390.
- Lin, S., Liu, X., Fang, J., & Xu, Z. (2015). Is Extreme Learning Machine Feasible? A Theoretical Assessment (Part II). *IEEE Transactions on Neural Networks and Learning Systems*, 26(1), 21-34. <https://doi.org/10.1109/TNNLS.2014.2336665>
- Shakil, M., Elshafei, M., Habib, M. A., & Maleki, F. (2009). Soft sensor for NO_x and O₂ using dynamic neural networks. *J Computers Electrical Engineering*, 35(4), 578-586.
- Sherstinsky, A. (2018). Fundamentals of Recurrent Neural Network and Long Short-Term Memory Network.
- Skalska, K., Miller, J. S., & Ledakowicz, S. J. S. o. t. t. e. (2010). Trends in NO_x abatement: A review. 408(19), 3976-3989.
- Wood, D. A. (2023). Long-term atmospheric pollutant emissions from a combined cycle gas turbine: Trend monitoring and prediction applying machine learning. *Fuel*, 343, 127722.