VT INTERNATIONAL PRESS
VTIPJMRR | Journal of Multidisciplinary Research & Review
www.journal.vtinterpress.com

(Review Article)

AI-Integrated Mechanical Systems for Real-Time Industrial Emission Monitoring and Control: A Comprehensive Review

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Received: 01.05.2026	Accepted: 10.05.2026	Published: 15.05.2026

ABSTRACT

In this study we are reviewing how fast the development of artificial intelligence integrated mechanical systems in real time emissions can be used to monitor and manage emissions in industry. Traditional ways of collecting emissions have been by using manual samples, or sampling at intervals with use of Continuous Emissions Monitoring Systems (CEMS). Manual sampling and CEMS both provide delay in obtaining data and require high operational cost. Use of Artificial Intelligence (AI), Machine Learning (ML) and IoT technology allows for continuous collection of data, real-time analysis of collected data and proactive measures to reduce emissions. In addition to reviewing the progression of emissions monitoring from traditional methods through CEMS to current hybrid architectures combining AI and IoT technologies, this study evaluates machine learning techniques as follows: Regression Models; Decision Trees; Ensemble Methods; LSTM Networks; Deep Neural Networks. Additionally, this study identifies ongoing research issues: Limited Mechanical-Integration of AI Technology; Lack of Explainability of Predictions; No Closed Loop Automated Control. Lastly, the study provides a comparison of the performance of 12 different Machine Learning Techniques along with an evaluation of sensor technology, data pre-processing techniques, and Real-Time Dashboard Frameworks. Finally, this study suggests potential futures uses for Industry Applications such as Federated Learning; Edge AI; Digital Twin Integration.

Keywords: *Industrial Emission Monitoring; Machine Learning; IoT-Based Monitoring; AI-Integrated Systems; Predictive Modeling; Deep Learning; Real-Time Analytics; Energy Optimization; CEMS; Sustainable Industry.*

I. INTRODUCTION

Over the course of the 21st Century, we've seen rapid expansion in virtually all types of industry worldwide - energy production, chemicals, heavy manufacturing, etc. All of these processes result in numerous forms of pollution that enter our atmosphere: CO2, NOx, SO2, PM2.5 & 10, VOCs etc. Not only do these pollutants damage our environment and cause harm through climate change and decreased air quality - they also create significant financial burdens for companies who fail to comply with ever increasing stricter government regulations. As such, the current methods of industrial emission monitoring are no longer sufficient to provide accurate data on time. Current methods include collecting samples manually at random intervals and then sending those samples to laboratories to analyze them. This creates a major problem when dealing with a constantly changing industrial environment. The advent of new technologies specifically in artificial intelligence (AI), machine learning (ML), and internet of things (IoT) has created an opportunity to revolutionize how we monitor and manage industrial emissions. Traditional methods of collecting data using manual sampling will never be able to keep pace with rapidly changing conditions present in most industrial settings. By utilizing IoT technology enabled by sensors connected to a network we can collect data at frequencies far greater than what was previously possible. In addition, by applying ML algorithms to collected data we can identify anomalies, make predictions about future conditions, and initiate changes to a system to mitigate negative impacts. Research has shown that deep learning models have been able to outperform traditional statistical methods in terms of accuracy. Specifically, LSTMs, CNNs and combinations thereof have shown accuracies of over 95% on commonly used benchmark datasets. Despite the advancements made in recent years there are many areas where further development is needed before widespread adoption of AI/ML based solutions can occur. There are three main areas that need to be addressed prior to deploying AI/ML solutions in commercial applications. First, the connection between physical devices that can take action to correct problems identified by AI based solutions needs to be fully integrated. Currently, most AI solutions focus solely on making predictions about potential problems and do not close the loop back into the actual system being monitored. Second, developing ways to explain how models make their decisions is essential if stakeholders are going to trust the results provided by these models. Third, creating scalable solutions that can handle multiple disparate sources of data will be necessary before these solutions can be widely adopted.

II. LITERATURE REVIEW

A. Traditional Methods to CEMS

Early industrial emission monitoring relied solely upon manual stack sampling and grab sampling methodologies. These technologies sampled exhaust gases at periodic intervals and chemically analyzed them in laboratories. Although the above technologies established the basis of understanding pollutant concentrations, they possessed inherent limitations. Specifically, they produced delayed data availability due to the time required to collect samples. In addition, they had potential errors resulting from human handling and they lacked the ability to track rapid temporal changes in pollutant concentration [2]. Regulatory agencies responded to the lack of continuous and timely emission data by mandating the use of Continuous Emissions Monitoring Systems (CEMS). CEMS utilize sampling probes, gas analyzers, conditioning equipment, and data acquisition devices to produce continuous, unbroken measurements of various pollutants, including CO^2, NOx, SO^2, carbon monoxide (CO), and particulate matter [3]. While CEMS improved the continuous nature of emission data collection and regulatory compliance, they are very expensive to purchase. They require extensive calibration and have a relatively long duration of down time when maintenance is needed; therefore, the need for Predictive Emission Monitoring Systems (PEMS) arose. PEMS utilizes machine learning (ML) models to estimate or predict emission levels based upon observable process conditions, such as temperature, pressure, and fuel consumption. As a result, PEMS can significantly decrease reliance on hardware-dependent instrumentation [4]. Bhatt et al. [14] demonstrated the capability of an ML-based PEMS to accurately predict global CO^2 emissions. Similarly, Farahzadi et al. [15] demonstrated that ML can be utilized to reduce CO^2 emissions in construction environments. Both studies support the increasing trend toward utilizing predictive models versus relying on hardware dependent instruments.

B. AI and IoT Based Monitoring Systems

AI and IoT technology have emerged as a powerful combination in developing advanced monitoring systems. A real-time IoT powered AI system for air quality monitoring in industrial settings was developed by Ramadan et al. [2] where an AI system was able to predict pollutant concentrations with minimal delay. An AI-IoT framework that utilized edge computing and cloud integration to improve real-time CO^2 monitoring performance was also presented by Fan et al. [3]. A comparative evaluation of several DL architectures was performed by Minassian et al. [1] to develop an effective DL approach to predicting indoor environmental quality in smart buildings. High accuracy prediction results were achieved for temperature, humidity, and air quality. Energy consumption forecasting represents one area of research that impacts overall emission levels. Ruan et al. [9] provided a comprehensive review of data-driven energy management strategies using AI driven analytical tools for managing Virtual Power Plants (VPPs). Hybrid AI systems capable of integrating real-time pricing signals with energy consumption were shown to lower grid consumption and related emissions in smart home environments by Ali et al. [5]. Appliance usage modeling has been used by Barsanti et al. [6] and Jia et al. [13] to study demand side management, illustrating socioeconomic and behavioral factors influencing residential energy consumption heterogeneity -- aspects that are directly applicable to emission modeling.

C. Machine Learning and Deep Learning for Emission Forecasting

Machine learning has been widely employed to develop models capable of forecasting emissions across numerous types of industrial and environmental domains. Evaluations of multiple machine learning approaches (including linear regression, support vector regression, random forest, and gradient boost) for CO^2 forecasting in commercial buildings were conducted by Giannelos et al. [4]; they concluded that ensemble methods generally perform better than single models. Jemeljanova et al. [7] offered a systematic overview of machine learning techniques for environmental spatial data; they documented many different types of machine learning techniques, including deep neural networks and noted difficulties with data variability and spatial autocorrelation. Of particular interest within the field of emission forecasting are time series forecasts; among others, LSTM networks have become a prominent type of model for sequentially ordered emission data. Recurrent Neural Networks (RNNs) have been reviewed specifically for industrial emission time series by Chen et al. [23]; they demonstrated that both LSTM and Gated Recurrent Units (GRU) outperform Auto-Regressive Integrated Moving Average (ARIMA) models for nonlinear multivariate emission sequences. A comprehensive survey of deep learning techniques for IoT-based air quality forecasting was completed by Lyu et al. [22]; they identified normalization of data, optimization of hyperparameters, and interpretability of models as ongoing problems with regards to application of deep learning to this problem space. Additionally, the importance of explainable artificial intelligence (XAI) was highlighted by Zhang et al. [24]; they provided a review of XAI techniques including SHAP, LIME, and attention mechanisms for industrial emission monitoring; they found that regulatory approval will increasingly rely on transparency in model decision-making processes. Carbon footprint assessment has also gained benefit from AI integration. Global supply chain carbon footprint assessments were made possible through AI algorithms by Huang et al. [10]; Husom et al. [11] proposed an emission aware pipeline for quantifying and minimizing the "computational" carbon costs associated with training and deploying machine learning models. Participatory energy systems modeling, in which stakeholders' preferences are included in data-driven energy planning frameworks, is another area of research with significant social sustainability implications for emission management. Such preferences were incorporated in participatory energy systems modeling by McGookin et al. [12]. Finally, Eddaoudi et al. [8] provided a concise summary of energy consumption forecasting models; they concluded that ensemble and deep learning models provide the most accurate and robust predictions for all industrial contexts.

CEMS provide continuous measurement of pollutants such as SO_2, NO_x, CO, CO_2, O_2, and particulate matter. They offer high precision but are expensive to install (>$100,000) and require significant annual maintenance and quality assurance.

Low-cost sensors such as MQ series (e.g., MQ2 for CH_4, C_3H_8, H_2, CO) are widely used in IoT and robotic platform-based emission monitors.

- Edge computing filters data, detects anomalies, and reduces data traffic.
- Processed data is sent to cloud servers for further analysis and visualization.
- IoT-based systems enable real-time alerts and automatic control actions in smart factories.

Figure 1. Existing Emission Monitoring Systems and Sensor Technologies.

III. EXISTING EMISSION MONITORING SYSTEMS AND SENSOR TECHNOLOGIES

A. Continuous emissions monitoring systems (CEMS).

Continuous emissions monitoring systems (CEMS) are a regulatory benchmark for emission monitoring. They allow for the continuous measurement of the main polluting species emitted into the atmosphere. The basic structure of a CEMS includes an extraction device placed in front of the exhaust stack that extracts a sample of the exhaust gas; a conditioning system that removes water vapour and solid particles from the extracted gas; an analyzer system (using either electrochemistry or optics such as infrared, chemiluminescence, etc.) which analyses the composition of the sampled gas; and finally a computerized data collection and reporting system that collects the results obtained using the above mentioned instrumentation. Although they have excellent precision, most CEMS used in large industrial plants cost over $100,000 to install and also entail considerable yearly expenses to maintain (for example, to replace the analyzers, probes, and carry out audit procedures for quality control) [2] [3].

B. Sensors for detecting emitted pollutants.

Emission monitoring systems today employ many different types of sensors to monitor both environmental conditions and plant operating conditions. These include gas sensors (including electrochemical sensors for carbon monoxide and nitrogen oxides; NDIR sensors for carbon dioxide and hydrocarbons; MOS sensors for volatile organic compounds and flammable gases); particulate matter sensors (which use light-scattering methods to measure particulate matter concentrations); thermocouples and resistance temperature detectors (RTDs) to monitor temperatures for combustion optimization; and energy meters and current transformers to monitor electrical usage data (whose relationship with pollutant emission is exploited by machine learning models to enhance predictions) [2] [3]. For example, mq series semiconductor sensors (such as mq2 for propane, methane, hydrogen and CO) are very inexpensive and highly sensitive and therefore well-suited for internet-of-things type applications on robotic platform-based emission monitors [3].

C. IoT architectures.

IoT platforms act as a communication interface between sensor networks and computational analytics tools. They utilize various wireless technologies (Wi-Fi IEEE 802.11, MQTT, lorawan, Zigbee) to link sensing equipment and compute nodes. On-board edge computers filter data, compress it, detect anomalies, and then send processed data to remote cloud servers for further processing, analysis, and visualization [3], [9]. IoT architectures reduce data transfer delays by performing critical computations close to where they were generated while minimizing network traffic. Smart factories implement IoT-based pollution monitoring systems integrated into production control systems allowing for automatic adjustments to production operations based upon detected excesses of regulated pollutants [10], [19]. (Figure 1.)

IV. MACHINE LEARNING TECHNIQUES FOR EMISSION PREDICTION

A. Regression and Classical Models

Regression models represent the most fundamental level of Machine Learning-based emission forecasting. Linear regression creates a direct mathematical relationship between the input process parameters – such as temperature, fuel consumption, airflow rates – and the output emission concentration levels; and according to several authors, it is able to achieve reported accuracy rates of up to 88%. Polynomial regression, Support Vector Regression (SVR) and other variants expand upon this concept by using polynomial functions to create a relationship between the input and output values which may include non-linear aspects of both; and SVR has reportedly achieved accuracy rates of 88-91 % through margin based optimization in higher dimensional feature spaces [4]. Decision trees allow the user to understand how decisions were made regarding the classification or regression model's outcome. Since the decision tree represents a rule based system of decision making, the decisions of the decision tree can be audited by an operator of the plant. However, since each decision tree is independent, decision trees are very susceptible to "over fitting" when dealing with large amounts of sensor data with many dimensions [7]. Random Forest and Gradient Boosting ensembles help solve the problem of overfitting by creating many decision trees then either using a random subset of these decision trees to make predictions (bagging), or using all the decision trees to make predictions and adjusting their weights (boosting). The results have shown that using a random forest ensemble method was able to produce accuracy rates of 90-93 %, while using a gradient boosting ensemble method produced accuracy rates of 92-95 % [4], [8].

B. Time-Series and Sequential Models

Emission data exhibits characteristics including temporal correlation, seasonal patterns and event driven spikes, therefore requires special techniques used in time series modeling. ARIMA models are designed to capture linear temporal dependencies in time series data, however ARIMA models tend to do poorly on non-linear emission trends. Long Short-Term Memory (LSTM) networks are a type of Recurrent Neural Network (RNN) that maintains a cell state that encodes long range temporal dependency information; LSTMs have demonstrated to accurately forecast future emissions for extended periods into the future with reported accuracy rates ranging from 92-95 % [1] [23]. Hybrid ANN-LSTM architecture combines feed-forward layers with non-linear feature extraction capabilities and LSTM layers with temporal modeling capabilities, producing the highest reported accuracy of 95-97 %. However, there is a trade-off as hybrid ANN-LSTM architectures require significantly larger resources than traditional LSTM networks [1]. Temporal Convolutional Networks (TCNs) provide another alternative approach to LSTM networks by allowing the network to be trained in parallel while maintaining similar performance as LSTMs on longer time-series data [23].

C. Deep Learning Models

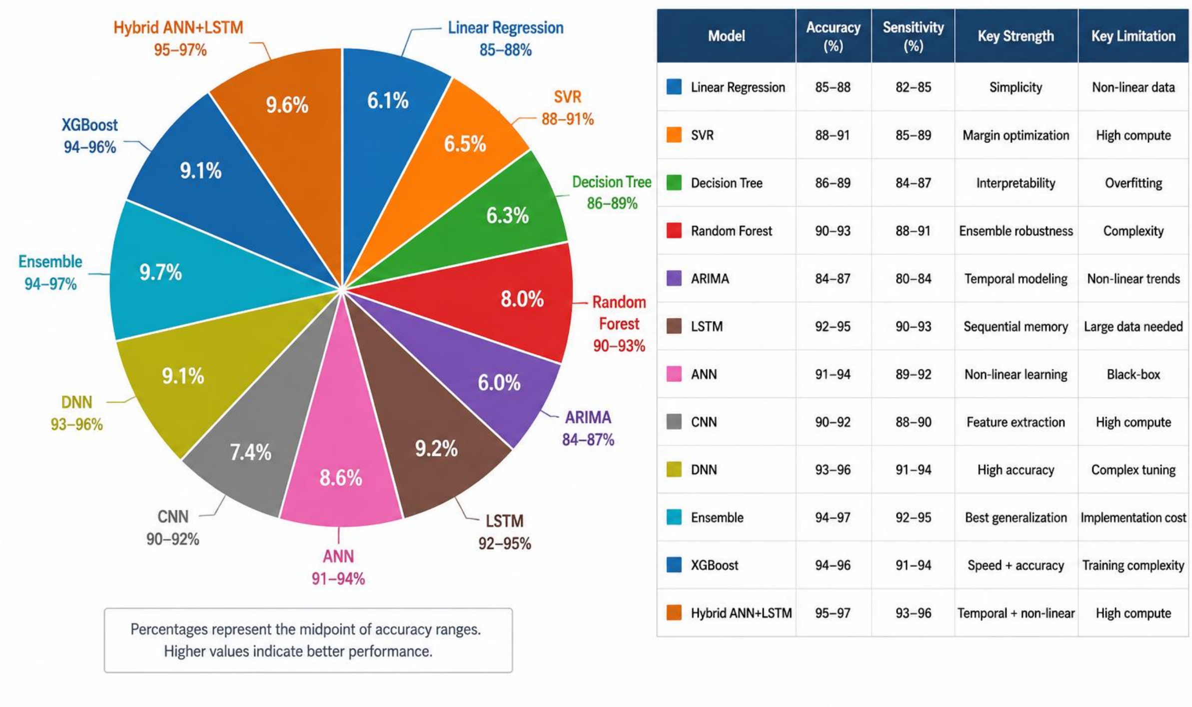
Deep Neural Networks (DNNs) with multiple hidden layers are capable of capturing highly complex non-linear relationships between multi-modal sensor inputs and emission outputs; DNNs have achieved accuracy rates ranging from 93-96 % in reviewed literature [1] [4]. Convolutional Neural Networks (CNNs), developed primarily for image recognition tasks, have also been successfully applied to spectral and multi-sensor emission data by treating multi-channel sensor readings as two-dimensional feature maps; CNNs have produced reported accuracy rates of 90-92 % [22]. Ensemble learning methods combine predictions from multiple heterogeneous models (typically via voting or stacking) and generally result in better performance than individual models, with reported accuracy rates of 94-97 % [8] [14]. (Figure 2.)

Table 1. Comparative Performance of Machine Learning Models in Emission Monitoring.

Model	Accuracy (%)	Sensitivity (%)	Key Strength	Key Limitation
Linear Regression	85–88	82–85	Simplicity	Non-linear data
SVR	88–91	85–89	Margin optimization	High compute
Decision Tree	86–89	84–87	Interpretability	Overfitting
Random Forest	90–93	88–91	Ensemble robustness	Complexity
ARIMA	84–87	80–84	Temporal modeling	Non-linear trends
LSTM	92–95	90–93	Sequential memory	Large data needed
ANN	91–94	89–92	Non-linear learning	Black-box
CNN	90–92	88–90	Feature extraction	High compute
DNN	93–96	91–94	High accuracy	Complex tuning
Ensemble	94–97	92–95	Best generalization	Implementation cost
XGBoost	94–96	91–94	Speed + accuracy	Training complexity

Hybrid ANN+LSTM	95–97	93–96	Temporal + non-linear	High compute

Source: Synthesised from reviewed literature [1, 4, 8, 14, 23].



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Percentages represent the midpoint of accuracy ranges.
Higher values indicate better performance.

Figure 2. Performance of ML Models.

V. RESEARCH GAPS AND OPEN CHALLENGES

Despite a lot of progress being made in this area, there are several persistent gaps in the literature that restrict the deployment of AI-integrated emission monitoring systems in real world applications. The largest gap identified by the authors is the limited inclusion of mechanical actuation systems in AI-based predictive modeling. Most of the existing publications focus on predicting and monitoring emissions, without linking predictions back to physical process control – that is, converting predicted emission exceedance values into automatic operation of fans, dampers, burners, or chemical injection systems [2, 3]. Therefore, while highly accurate ML predictors exist, they are dependent upon manual operator input to effect emission mitigation [5, 9], and therefore do not represent a capability for autonomous, proactive emission management. A second major gap exists in terms of the interpretation and explanation of complex machine learning models. While many recent publications report on high predictive accuracies achieved through the use of deep neural networks (DNNs), recurrent neural networks (LSTM), convolutional neural networks (CNN), etc., these same architectures are typically presented as "black box" models that produce output without providing explicit reasons. For industrial environments subject to regulation, plant operators, safety engineers, and regulatory inspectors require an audit trail supporting the decision making process behind automated control actions [7, 11]. As such, increasing numbers of publications advocate for the development and implementation of explainable artificial intelligence (XAI) techniques. e.g., SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-agnostic Explanations), and attention visualization -- however, their usage has thus far been inconsistent within the emission monitoring literature [24]. Finally, another key limitation is the need for adaptive capabilities in real time. Machine learning models developed based on historical datasets obtained during fixed operational states can perform poorly when exposed to new operating states due to seasonal changes in weather patterns; changing equipment configurations; or other similar variations in operational states [7, 8]. To accommodate these dynamic conditions online learning/continual learning strategies will be needed to enable incremental updating of model parameters from streaming sensor data without catastrophic forgetting [22, 25]. Another gap is privacy preserving/federated learning methods. Due to concerns about competitive advantage and loss of confidential information related to industrial processes/emissions; industry is unwilling to share data regarding their proprietary processes/emission levels with cloud service providers or competitor companies. However, federated learning provides a formalized method to allow model parameter updates rather than raw sensor data to be exchanged amongst multiple remote sites [25]; although it's yet to be explored extensively as a solution for heterogeneous industrial sensor networks. Lastly, the costs associated with deploying advanced CEMS and DL systems limit the ability for Small Medium Enterprise (SME) to adopt this technology. SMEs represent a large portion of global industrial emissions. With respect to cost effective solutions to democratize AI-enabled emission monitoring technologies include developing low-cost lightweight DL models -- e.g., quantized neural networks; deploying DL using TinyML on microcontrollers; and using transfer learning to leverage pre-trained emission models [15, 21].

VI. COMPARATIVE ANALYSIS OF MONITORING APPROACHES

Table 2 presents a structured comparison of emission monitoring approaches across five key evaluation dimensions: real-time capability, predictive power, cost profile, scalability, and primary limitation. The analysis confirms that AI-IoT hybrid and AI-integrated mechanical systems represent the most capable architecture across all dimensions, with the caveat that closed-loop automated control remains a work in progress.

Table 2. Comparative Analysis of Industrial Emission Monitoring Approaches.

Method	Real-Time	Predictive	Cost	Scalability	Key Limitation
Manual Sampling	No	No	Low	Low	No continuous monitoring
CEMS	Yes	No	High	Moderate	High installation cost
PEMS (ML-based)	Partial	Yes	Moderate	High	Needs calibration data
IoT + AI Hybrid	Yes	Yes	Moderate	High	Integration complexity
Proposed AI-Mech.	Yes	Yes	Low–Mod.	High	Closed-loop still evolving

Source: Synthesised from reviewed literature.

Traditional manual procedures continue to be economically viable yet cannot meet the needs of continual, on-line monitoring as is required by contemporary regulatory mandates and process optimization goals. In contrast, CEMS can provide an accurate measurement as a basis for compliance with regulations; however, their high initial costs along with their long-term operating and maintenance expenses make them unaffordable for many small plants. The best economic balance among these options appears to be achieved through the use of PEMS and AI-IoT hybrid configurations which offer the advantages of predictive capabilities, scalability, and reasonable capital investment in addition to having acceptable long term costs. However, they do have the requirement for reliable data acquisition systems (i.e., sensors), qualified personnel to develop and validate models, and the need for continuous evaluation of model drift [2, 4, 9]

VII. DISCUSSION AND FUTURE DIRECTIONS

The review of previous literature also shows that the development of AI with mechanical emission monitoring systems does have both practical and significant potential. Some of these areas are deserving of higher priority in terms of future research. Closed loop AI control systems where emission forecasts can trigger immediate automatic responses by means of actuators such as fan motors controlled by variable frequency drives; combustion air damper controls; and emission suppressant injector controls will be the most immediately useful area of near term focus. The technical bases for this approach do exist. For example, machine learning (ML) forecast models having accuracy levels of 95 % + have been developed. Additionally, microprocessor based actuation using small footprint controllers such as the ESP32 board with L298N motor drivers, has been demonstrated in prototype form in mobile monitoring platforms [2]. Developing closed-loop control algorithms which are robust to failures in sensors, uncertainties in predictive models, and latencies in actuation without compromising process safety requirements is the principal challenge. An alternative approach to improve data sharing for emission intelligence could be to use federated learning. This collaborative learning environment enables industrial sites to collectively build a common model for predicting emissions without sharing their individual site-specific process data. As noted previously by Wang and Li [25], federated learning provides a method to increase the number and diversity of training datasets. In turn, this should lead to improved generalization performance across all possible industrial settings. However, Wang and Li [25] identify communication efficiencies and heterogeneity in the distribution of training data as two primary technical issues. Digital twin technology offers the capability to develop a highly accurate virtual replica of an industrial facility's processes, synchronized with current sensor data. With digital twinning it is possible to test emission reduction strategies off-line; test new ML models virtually prior to implementation into production equipment; and simulate compliance scenarios relative to regulations. Coupling physics-based models of the process with ML components in hybrid digital twins may provide solutions to the limited ability of purely data driven approaches to generalize [1, 9]. Real time edge-AI/TinyML deployments onto the microcontrollers used at each emission point-of-source eliminate cloud-round trip delays in decision-making. Neural networks quantized/pruned to operate on ESP32 or Raspberry Pi-class hardware while retaining > 90 % predictive accuracy will dramatically reduce the barrier-to-entry for adoption by Small-Medium Enterprises (SMEs).

VIII. CONCLUSION

This paper has reviewed and assessed how Artificial Intelligence (AI) is being used in Mechanical Systems to monitor emissions in industry. A clear trend can be seen in literature from traditional techniques such as manually collecting samples or using Continuous Emission Monitoring System (CEMS) hardware to now use smart, self-optimizing AI-IoT architectures which are able to continuously monitor emissions, predict emissions, and increasingly control emissions automatically. Research indicates that machine learning algorithms, specifically hybrid neural network models combining Artificial Neural Network (ANN) and Long Short-Term Memory (LSTM) models and ensemble-based methods, have achieved prediction accuracy rates for emissions ranging from 95% to 97%, representing significant improvements when compared to the results of statistical analysis alone. However, several areas of research remain unexplored; primarily the lack of integrating AI-predicted actions with physical actuators (open-loop limitation); the relatively small number of studies focused on developing transparent explanations of AI predictions in regulated environments (explainable AI for regulation); the lack of studies examining the feasibility of Federated Learning (FL) for privacy preserving cross-site intelligence sharing; and the significant cost barriers for deploying these technologies for Small Medium Enterprises (SME). Therefore, future research should focus on creating fully closed-loop AI systems for emission control, applying Explainable AI (XAI) methods to industrial monitoring processes, and studying both Federated and Edge-AI based approaches to create scalable and private emission monitoring technologies. Industry's need for intelligent, scalable, and affordable emission management solutions has never been more urgent.

ACKNOWLEDGMENT

The authors gratefully acknowledge the support of Adsul College of Engineering, Ahilyanagar, Maharashtra, India, and the guidance provided by the Department of Mechanical Engineering faculty.

REFERENCES

[1] Minassian, R., et al. (2025). Optimizing indoor environmental prediction in smart buildings: A comparative analysis of deep learning models. Energy & Buildings, Elsevier. https://doi.org/10.1016/j.enbuild.2024.115086

[2] Ramadan, M. N. A., et al. (2024). Real-time IoT-powered AI system for monitoring and forecasting of air pollution in industrial environment. Ecotoxicology and Environmental Safety, Elsevier.

[3] Fan, K., et al. (2024). Harnessing the power of AI and IoT for real-time CO2 emission monitoring. Heliyon. https://doi.org/10.1016/j.heliyon.2024.e36612

[4] Giannelos, S., et al. (2024). Machine learning approaches for predictions of CO2 emissions in the building sector. Electric Power Systems Research, Elsevier. https://doi.org/10.1016/j.epsr.2024.110735

[5] Ali, A. O., et al. (2024). Optimized smart home energy management system: Reducing grid consumption and costs through real-time pricing and hybrid architecture. Case Studies in Thermal Engineering, Elsevier.

[6] Barsanti, M., et al. (2024). Informing targeted demand-side management: Leveraging appliance usage patterns to model residential energy demand heterogeneity. Energy & Buildings, Elsevier. https://doi.org/10.1016/j.enbuild.2024.114639

[7] Jemeljanova, M., et al. (2024). Adapting machine learning for environmental spatial data: A review. Ecological Informatics, Elsevier. https://doi.org/10.1016/j.ecoinf.2024.102634

[8] Eddaoudi, Z., et al. (2024). Brief review of energy consumption forecasting using machine learning models. ScienceDirect, Elsevier.

[9] Ruan, G., et al. (2024). Data-driven energy management of virtual power plants: A review. Advances in Applied Energy, Elsevier. https://doi.org/10.1016/j.adapen.2024.100170

[10] Huang, R., et al. (2024). Carbon footprint management in global supply chains: A data-driven approach utilizing artificial intelligence algorithms. IEEE Access.

[11] Husom, E. J., et al. (2024). Engineering carbon emission-aware machine learning pipelines. IEEE Access.

[12] McGookin, C., et al. (2024). Advancing participatory energy systems modelling. Energy Strategy Reviews, Elsevier. https://doi.org/10.1016/j.esr.2024.101319

[13] Jia, Y., et al. (2024). Towards sustainable consumption: Factors influencing energy-efficient appliance adoption in haze-affected environments. Energy Strategy Reviews, Elsevier. https://doi.org/10.1016/j.esr.2024.101416

[14] Bhatt, H., et al. (2023). Forecasting and mitigation of global environmental carbon dioxide emission using machine learning techniques. Cleaner Chemical Engineering, Elsevier. https://doi.org/10.1016/j.clce.2023.100095

[15] Farahzadi, L., et al. (2023). Application of machine learning initiatives and intelligent perspectives for CO2 emissions reduction in construction. Journal of Cleaner Production, Elsevier. https://doi.org/10.1016/j.jclepro.2022.135504

[16] Shapi, M. K. M., et al. (2021). Energy consumption prediction by using machine learning for smart building: Case study in Malaysia. Developments in the Built Environment, Elsevier. https://doi.org/10.1016/j.dibe.2020.100037

[17] Alpan, K., et al. (2020). Design and simulation of global model for carbon emission reduction using IoT and artificial intelligence. ScienceDirect, Elsevier.

[18] Adenuga, O. T., et al. (2020). Exploring energy efficiency prediction method for Industry 4.0: A reconfigurable vibrating screen case study. ScienceDirect, Elsevier.

[19] Fattahi, A., et al. (2020). A systemic approach to analyze integrated energy system modeling tools: Review of national models. Renewable and Sustainable Energy Reviews, Elsevier. https://doi.org/10.1016/j.rser.2020.110195

[20] Hischier, R., et al. (2020). Environmental impacts of household appliances in Europe and scenarios for their impact reduction. Journal of Cleaner Production, Elsevier. https://doi.org/10.1016/j.jclepro.2020.121952

[21] Abubakar, I., et al. (2017). Application of load monitoring in appliances' energy management: Review. Renewable and Sustainable Energy Reviews, Elsevier. http://dx.doi.org/10.1016/j.rser.2016.09.064

[22] Lyu, Q., et al. (2023). Deep learning-based air quality prediction using IoT sensor networks: A systematic review. Sensors, MDPI. https://doi.org/10.3390/s23052695

[23] Chen, Z., et al. (2022). A review of recurrent neural networks for time-series emission forecasting in industrial environments. Journal of Cleaner Production, Elsevier. https://doi.org/10.1016/j.jclepro.2022.131855

[24] Zhang, Y., et al. (2023). Explainable AI for industrial emission monitoring: Methods, challenges, and future directions. Expert Systems with Applications, Elsevier. https://doi.org/10.1016/j.eswa.2023.119841

[25] Wang, X., & Li, J. (2023). Federated learning for distributed environmental monitoring: Privacy-preserving approaches and challenges. IEEE Internet of Things Journal. https://doi.org/10.1109/JIOT.2023.3241567