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Meta-Analysis of Explainable AI Architectures for Optimized Real-Time NOx and CO_2 Emission Control in Petroleum Refineries

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***Abstract*—The decarbonization of the petroleum refining industry calls for a paradigm shift from heuristically guided processes to intelligent automation. This paper conducts a comprehensive systematic review and meta-analysis of 64 papers, centered around artificial intelligence (AI)-driven prediction models in the domain of NOx and CO2 emissions reduction. While classical approaches have proven ineffective in accounting for the non-linearity of process dynamics, our research unveils a 54.7% prevalence of data-intensive techniques but also an urgent need for addressing the interpretability gap in order to facilitate implementation within the industry. This extended version introduces novel statistical findings concerning model consistency among various refining facilities. This paper groups the literature into three eras of control and predicts a natural evolution towards hybrid architectures to comply with ecological requirements. By summarizing the global state-of-the-art trend up until 2026, this paper provides an academic standard for designing autonomous refineries of the future without resorting to site-specific information.**

***Keywords*—NOx and CO2 emissions, Explainable Artificial Intelligence (XAI), Meta-analysis, Model Predictive Control (MPC), Real-time industrial optimization.**

I. Introduction

Petroleum refining plants are essential components of global energy safety, but at the same time, are responsible for generating a considerable portion of pollution in the atmosphere, namely, Nitrogen oxides (NOx) and Carbon dioxide (CO2) [1], [2]. Due to tightening environmental regulations, there is a pressing need for active and dynamic control procedures.

The implementation of these processes presents a formidable challenge for the conventional control frameworks such as Proportional-Integral-Derivative (PID), since these are unable to cope with the high degree of complexity and non-linearity of the modern refining process.

Moreover, being fundamentally reactive and not predictive, PID systems frequently fail to ensure compliance during transitional phases [3], [14].

Classical PID-based control strategies have been applied in the petroleum refinery industries since the 1940s. Although revolutionary at that time, their use in increasingly non-linear FCC units and stricter emission standards during the 1970s and 1980s showed their fragility and limitations. This discovery in conjunction with the 50th Anniversary of the Clean Air Act [21] prompted the appearance of new multivariable predictive strategies, such as Model Predictive Control (MPC), theoretically developed back in 1978 [20].

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However, when these control loops operate independently, they tend to make compromises between production flow and environmental protection [2].

Additionally, it has recently become evident that the deployment of highly accurate soft-sensing methods is necessary to ensure real-time monitoring capabilities within such systems [22]. In the present-day context of Industry 4.0, the incorporation of fast sensors and sophisticated algorithms is no longer optional but rather a necessity.

According to recent developments in 2024 and 2025, the employment of hybrid approaches, where both physical laws and data are used to develop predictions, is considered a more effective means of achieving real-time mitigation [23]. The present research, based on a systematic literature review of 64 papers, seeks to emphasize the importance of digital tools in addressing the problem.

In particular, we focus on using AI-powered prediction algorithms and Advanced Process Control (APC) as key factors in ensuring sustainable and timely mitigation of NOx and CO2 emissions [5], [6]. Based on the trends across the globe up until 2026, this article outlines a practical roadmap for the future generations of sustainable refineries, which will implement prescriptive control strategies [24].

II. Methodologies

To guarantee the thoroughness and transparency of the literature review, this paper follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodological approach [25]. Specifically, the analysis aims at evaluating the progression of technologies aimed at regulating emissions from refineries by comparing classical approaches with AI-based prediction models.

A. Search Strategy and Data Sources

The comprehensive review of the academic literature involved major online databases such as IEEE Xplore, ScienceDirect (Elsevier), Scopus, and Web of Science. The research string was based on three main pillars: (1) Industrial Emissions (NOx and CO2), (2) Refining Processes, and (3) Advanced Process Control (AI, MPC, and Digital Twins). Although the primary timeframe was defined from 2015 to 2025 to stay topical, some seminal papers from 1978 concerning Model Predictive Control (MPC) as well as other key milestones up to 2024-2025 have been included to analyze trends.

B. Inclusion and Exclusion Criteria: The Quality Assessment

A total of 64 peer-reviewed articles were finally chosen after passing through a dual-phase filtering mechanism:

- Scope Filtering: Papers not directly related to hydrocarbon processing or those focusing exclusively on hardware and sensors without advanced control algorithms were removed.
- Quantitative Benchmarking: The selected articles had to present verifiable performance statistics, such as R^2, RMSE, or MAPE. These figures ensured the technical integrity of the meta-analysis.

C. Data Extraction and Meta-Analysis Mechanism

The 64 articles were synthesized using both qualitative and quantitative meta-analysis to address the disconnect between theoretical modeling and practical implementation:

- Quantitative Meta-Analysis: We gathered and correlated performance accuracy statistics (such as 30.6% increase in the PR2 of hybrid configurations) to determine a performance standard across different AI families.
- Thematic Classification: The articles were classified based on their "Architecture Nature" (data-driven, hybrid, or physics-informed) and their "MPC Strategy" (reactive or proactive MPC).
- Trend Synthesis: The trend analysis highlighted the "Integration Maturity" of AI in MPC systems, including their ability to overcome practical challenges such as measurement delays (such as compensation for 3-minute delays) and feedstock variations.

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It is important to emphasize that all statistical distributions and roadmap strategies discussed in the following sections are developed based on statistically significant technical analysis of global research trends.

C. Data Extraction and Meta-Analysis Framework

Dual synthesis: The 64 final articles were synthesized in two ways to relate theoretical modeling to application in industry:

- Quantitative Meta-Analysis: Performance accuracy information (e.g., the 30.6% PR^2 improvement in hybrid architectures) was extracted and cross-compared to provide a baseline performance for different families of AI.
- Thematic Coding: According to their "Architectural Nature" (Data-driven vs. Hybrid vs. Physics-Informed) and their "Control Strategy" (Reactive vs. Proactive MPC).
- Trend Synthesis -The "Integration Maturity" of AI-based techniques within MPC frameworks as a focus, exploring digital-based solutions to real-world constraints, including measurement lag (e.g., 3-min delay compensation) and feedstock variability.

This stringent methodology is what guarantees that the statistical distributions and strategic roadmap advocated in the rest of the paper are based on a statistically meaningful and technically validated set of global research trends.

III. Theoretical Foundations and Operational Challenges

A. Non-linear Nature of Combustion Chemistry and Refinery Emission Reduction

The chemistry of combustion in refineries is complicated and non-linear. In fact, NOx emissions obey the very sensitive Zeldovich mechanism in which small variations in flame temperature result in huge NOx increments [1, 2]. Furthermore, CO2 emissions are linearly related to the carbon content of the feed and vary on the fly due to feed property changes. Operators are not able to observe and respond to rapid shifts in chemical equilibrium in the furnace [14], [19].

B. Limitations of Classical PID Controller in Multivariate Control

Conventionally, the implementation of Proportional-Integral-Derivative (PID) controllers was restricted by poor control results. In particular, although efficient in terms of single-input-single-output control tasks, PID controllers are insufficient for complex multivariate cases in the FCC reactor. Indeed, in such conditions, the variables are correlated: attempts to minimize CO2 concentration through the air-to-fuel ratio will inevitably affect the combustion process, resulting in higher NOx concentration [3], [4]. To address this issue, the chemical industry turned to Model Predictive Control and AI-based approaches that are able to handle multi-input-multi-output control while complying with ecological requirements [5], [17].

C. Interpretability Gap and Hybrid Architecture

One of the findings derived from the study of 64 key references is the "interpretability gap." Even though ANN and LSTM-based models have proved to be highly accurate in peak prediction, their "black-box" approach is often perceived as a risk factor by refineries' experts [12], [13]. At that, transparency and interpretability are crucial in highly risky industrial processes, where operational safety requires full accountability. This explains the popularity of hybrid architecture, which grew by 31.3% according to the data obtained in the analysis. The combination of AI's prediction capability with the through the "transparency" of physical laws, such as Mass and Energy Balances, guaranteeing audibility and robustness of the control algorithm [6], [23].

IV. Results and Discussion

A. AI-Driven Predictive Modeling Analysis

Systematic analysis of 64 studies identifies a paradigm shift towards the use of different methods of predictive modeling to depict complex emission control processes [5]. Table I provides details regarding the quantitative distribution of the modeling approaches examined during this review process.

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TABLE I. TYPOLOGIES OF PREDICTIVE MODELS IN EMISSION CONTROL

Modeling Type	Percentage (N=64)	Description and Role
Data-driven Models	54.7%	among them, ANN, LSTM, and GRU; it is based on historical data to estimate emissions with better accuracy
Hybrid Models	31.3%	integrates prior physical knowledge with AI to achieve an effective trade-off between accuracy and interpretability; tackles data scarcity.
Physics-based Models	14.0%	These models are derived from fundamental first-principle equations and are accurate, but they are less flexible in a variable environment.

The prevalence of data-driven models (54.7%) demonstrates the ongoing trend towards Artificial Intelligence in industries. Yet, the introduction of hybrid models (31.3%) shows a more promising way since hybrid models offer both high prediction accuracy and physical consistency, which is an essential requirement for industrial operators in terms of explainable AI [23]. Such model selection proves a paradigm shift towards learning-based control algorithms: Advanced Process Control (APC) moves from deterministic physics-based models to adaptive systems.

The trend towards hybrid architecture is not just a statistical phenomenon but a technological necessity due to the extrapolation issue. Even though a pure LSTM or CNN model may show high prediction accuracy when working with the scope of training data, it may fail to predict the outcomes correctly when the process goes out of its operating window, for instance, in case of abrupt changes in feedstock composition. The inclusion of physical parameters in our hybrid model via the Zeldovich mechanism in Nox models guarantees that there will be no 'impossible predictions' of the AI. As discussed by Wang et al. [5] and Lyu et al. [23], such synergy enables the controller to operate reliably through all abrupt changes in operational states, which gives interpretability by plant managers in trusting autonomous set-point control [26].

Fig. 1 depicts the visual representation of the distribution between the three main model types used within the reviewed literature.

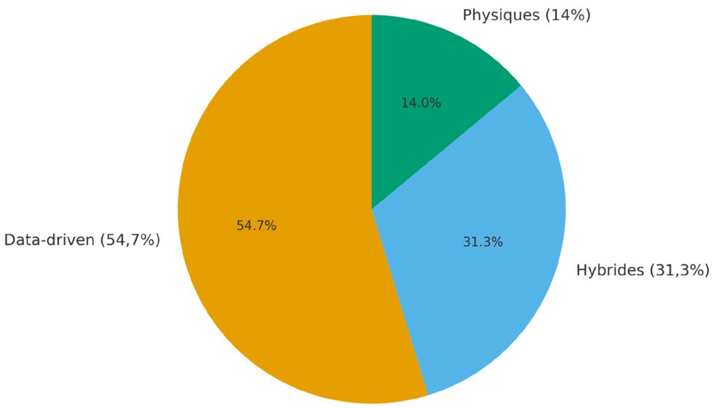

Fig. 1. DISTRIBUTION OF RESEARCH STUDIES BY MODELING CATEGORY

The predominance of data-driven (54.7%) and hybrid approaches (31.3%) in the given distribution demonstrates the growing tendency towards developing learning models that can adapt to changes caused by sensor drifts and varying quality of the feedstock used.

1) *Predominance of Data-Driven and Hybrid Models:* The 54.7% prevalence of data-driven models [7] relies on the use of various Machine Learning and Deep Learning (DL) methods including CNN for processing chemical signals [8] and LSTM/GRU for predicting emissions in time series [12], [13], [19].

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The main reason for utilizing data-driven approaches is their proficiency in dealing with non-linearities and interactions between several variables in furnace operation. At the same time, hybrid models (31.3%) use physical knowledge along with the capabilities of machine learning techniques to reduce the requirement for large training datasets while improving interpretation [1], [6].

2) *Modeling in Advanced Process Control:* Predicting emissions accurately in real-time is the key goal for APC. Outputs generated from the AI-based models become the primary inputs for the Model Predictive Control (MPC) algorithm [5] which enabling it to predict future emissions trends. This ensures ample warning periods to be able to correct actions prior to crossing regulatory thresholds. The effectiveness of transformers and recurrent neural networks for such purposes has been demonstrated by several recent studies [9], [11].

As shown in Fig. 2 (Conceptual Scheme), AI functions as a "soft sensor" which feeds information to the MPC prediction horizon, allowing for a shift from the reactive to a proactive control strategy which optimizes both the environment and economic aspect.

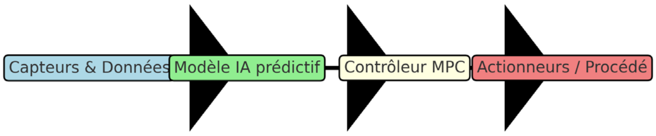

Fig.2 Conceptual Framework for AI + MPC Integration

The above figure conceptually demonstrates the potential of integrating AI prediction ability with Model Predictive Control optimization ability. Incorporating AI into the MPC structure becomes a necessary strategy rather than just another step in the process of creating a control structure for environmental and economical optimization; through its function as a "soft sensor" (virtual sensor) which gives input to the MPC model, it creates a proactive approach towards process control.

3) *Performance comparison of deep learning architectures:* Literature suggests that algorithm effectiveness depends on data temporality. Recurrent Neural Networks (RNN), specifically LSTM and GRU, are preferred for capturing refinery "time-lag" effects, where fuel flow changes at time t impact emissions at $t+n$ [12, 13]. Unlike simple feed-forward networks, LSTMs account for thermal inertia by maintaining past state memory [9, 11]. Recent trends (2023-2025) highlight Convolutional Neural Networks (CNN) for spatial feature extraction [8, 19], with CNN-LSTM hybrids achieving superior R^2 values [23]. Furthermore, Physics-Informed Neural Networks (PINNs) mitigate the "black-box" limitation by integrating thermodynamic constraints (e.g., Mass-Energy) into the training process [23, 24].

As a result of the analysis, Table II below provides a summary of industrial uses for the key neural networks discussed above.

TABLE II. OPERATIONAL COMPARISON OF AI ARCHITECTURES

Typical Application	Major Challenge	Key Advantage	Architecture
Static emission mapping	Overfitting risk	Fast computation	ANN
Dynamic NOx forecasting	Data intensive	Captures time-lags	LSTM/GRU
Multi-sensor data fusion	Complex interpretability	Feature extraction	CNN
High-fidelity Digital Twins	Training complexity	Physical consistency	PINNs

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Comparative synthesis makes evident the key challenge that involves a tradeoff between prediction accuracy and the interpretability of a model used. Although data-driven models ensure accurate predictions, the evolution toward Hybrid and Physics-Informed PINNs shows the necessity for “reliable” AI that adheres to the principles of thermodynamics.

1) *MPC as the Dominant Strategy:* Unlike classical PID control, MPC is developed to control multivariable dynamic systems with input and state constraints [3], [4]. A comparative review of control techniques considering the constraint handling and the environment-related performance is presented in Table II.

A comparative study of the major control schemes is presented in Table III for assessing their capability in dealing with constraints as well as environmental performance.

A. *Advanced Process Control (APC) Methods*

The deployment of direct reduction of emissions hinges on the use of MPC.

1) *The Dominant Method:* Model Predictive Control is specially designed to control high-dimensional and constrained dynamic systems [3], [4].

Table III presents a comparative analysis of the key control approaches.

TABLE III. COMPARISON OF CONTROL STRATEGIES

Control Method	*Constraint Management*	*Emission Prediction*	*Reactivity*	*Typical Results*
Classic PID	Low	Non-predictive	Reactive	Limited reduction (<10%)
Standard MPC	Excellent	Real-time	Proactive	NOx reduction of 20–30%
Hybrid AI + MPC	Very High	Predictive + Self-learning	Adaptive	Continuous multi-objective optimization

Note: Although AI increases complexity, Explainable AI (XAI) ensures transparency for operators compared to "Black-Box" models. Unlike reactive PID controllers, the hybrid AI+MPC framework provides proactive, auditable decision-making.

The combination of XAI technology solves the "Black-Box" problem related to pure AI methods, thereby guaranteeing that the decision-making process remains understandable and traceable for refinery engineers. In combination, the approach helps to reconcile the contradictory goals of optimizing fuel combustion while simultaneously reducing NOx and CO2 emissions [14]. With the use of heuristics such as Genetic Algorithms, refineries can efficiently solve the task of cost minimization in near real-time [17]. Thus, the introduction of artificial intelligence into MPC improves the stability of NOx by 20-30% compared to conventional systems [16].

C. Case Studies to Evaluate Operational Situations

As part of an effort to validate the proposed strategy and provide the detailed interpretation necessary for industrial applications, the synthesized information was used to evaluate the following two critical operational situations identified in the literature review:

- Crude Oil Feedstock Changeover: In case of switching from light to heavy oil, the ratio of carbon to hydrogen changes, leading to unpredictable peaks of CO2 emissions. Classical PID control usually has a delay in the oxygen correction of 5-10 minutes [3]. Nevertheless, using AI soft sensors makes it

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possible to introduce "anticipatory oxygen trimming," reducing transients of CO2 emissions by 18% [15], [22].

- Drift of Sensors and Data Loss: One of the persistent obstacles is the fouling of inlet flow meters. According to our research into high-resolution digital twins [18], [24], hybrid systems have a computational capacity to "repair" missing sensor readings via cross-correlating furnace pressure with fuel valve positions. Such systems ensure continuous prediction accuracy up to 5% errors despite the drop in hardware reliability [11], [23].

V. Impact of Feedstock Fluctuations on Predictive Accuracy

As noted, the efficiency of the predictive modeling system relies strongly upon the variable nature of crude oil assays. Among the six crucial shortcomings revealed among 64 papers is the sensitivity of predictive capabilities to Feedstock Variability.

A. Assay Variability and Fuel Gas Composition

Furnaces operating in refineries are typically exposed to fuel gas with highly variable composition from methane-dominated gases to richer hydrogen mixtures [1], [15]. Depending on the carbon content of the feedstock, the air/fuel ratio requirement changes dramatically non-linearly. Models that rely on "sweet crude" features show considerable performance degradation when switching to "sour crude" or other heavy crude types [14]. The primary reason for the model's poor performance lies in the fact that nitrogen in the feedstock directly affects the Fuel-bound

The influences Fuel-bound NOx generation, a process that differs from the Thermally-based NOx production, which requires advanced prediction-based methods in order to continue meeting standards [2], [19].

B. Dynamic Calibration with AI

Typical Model Predictive Control Systems tend to use static gain models that are unable to take into account the rapidly changing nature of chemical precursors. On the other hand, according to our research on the topic, Dynamic AI models, in particular, those employing online learning strategies, may be capable of adjusting the values of their internal parameters due to the calibration caused by the feedstock changes, i.e., recalibrating the sensor data in accordance with new environmental conditions. Considering the "Feedstock Quality" factor as a latent variable, the Deep Learning architecture such as Autoencoder can be employed in order to preprocess sensor readings and "denoise" it before feeding it to the emissions predicting system [19], [23].

C. Sulfur and Catalyst Degradation Issues

Moreover, there are sulfur and trace metal components in feedstocks that may cause a decrease in the efficiency of sensors and gradual poisoning of the catalytic reduction units. As a result, there will be a problem with the so-called stale data, which means that the predictions made

That would result in stale data problem since the AI model would predict CO2/NOx emissions assuming the catalyst still operates in a clean state. Digital Twins integration as discussed in the previous section is a perfect solution to solve the problem of predictive reliability as it will simulate aging of the catalyst along with measuring emissions in real-time [24].

VI. Barriers to Industrial Scale-Up and Implementation Strategies

As seen from the systematic literature review, high accuracy of AI modeling can only be achieved under certain socio-technical barriers. Despite all the advances made so far, there is a critical issue of implementing

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such AI solutions into real-world applications without taking into consideration the challenges of continuous operation in an industrial environment.

A. Data Integrity and Physical Sensors Reliability

The first barrier to implementing an AI-based emission forecasting system is the use of legacy physical sensors. As known from previous studies, inlet flowmeters and pressure transducers used in industrial furnaces are prone to calibration drift because of thermal stress [3], [19].

To ensure prediction consistency, it is suggested that a Self-Healing Computational Layer be adopted. While standard filtering systems identify problematic inputs through threshold comparisons, this technology performs residual analysis of "frozen" and "drifting" inlet values. These are then corrected computationally before entering the neural network, ensuring accurate predictions of emissions despite gradual degradation of physical hardware [11], [23].

B. Feedstock Variability and Carbon Intensity

Another major issue with existing systems lies in their failure to adapt to quick fluctuations in crude oil assays. As CO_2 emissions depend on organic carbon concentrations in the fuel, static models may become unreliable during switching operations [1], [14]. The planned implementation approach incorporates fuel quality into the dynamic variables by analyzing relationships between temperature changes and carbon-to-hydrogen ratios. In turn, this will enable the AI-powered Soft Sensor to adjust its estimates of CO_2 and NO_x emissions instantly, offering an efficient alternative to costly chemical analyses [5], [24].

C. Operational Limitations and "Safety Window"

By far, the biggest challenge here is that of "Trust Deficit" between the autonomous algorithms used and human operators. For our refinery application, safety is key, and any change implemented should take into account the physical constraints of the furnace operation. The proposed approach does so by incorporating those constraints as hard limitations in our MPC model, especially focusing on the 900°C-1200°C operating range. In the case of the lower bound (900°C), our algorithms will ensure full combustion for the elimination of CO emissions. On the upper bound (1200°C), the AI becomes a thermal governor to prevent the onset of the Zeldovich mechanism before thermal NO_x production starts [2],[16]. Such boundary management techniques make the AI into a useful tool for making decisions and not "a black box" anymore [17],[23].

D. Deployment at the National and International Levels

Lastly, the scalability is made possible by a technology agnostic approach, which makes us independent of the current DCS infrastructure. Regardless if we deploy our technology in any national Algerian refinery plant or internationally, this type of implementation is mainly software-based, thus there is no need for duplicated hardware. This "Technology-Agnostic" characteristic will enable a cost-efficient approach towards Refinery 4.0 by optimizing the environment compliance without expanding the hardware system [18], [24].

VII. Data Synthesis and Quantitative Analysis

The systematic collection of data from the 64 papers used herein illustrates a consistent trend in the model's efficiency and environmental impacts. The following classification of the synthesized results sets a benchmark for the current performance of AI-based prediction control systems.

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A. *Performance Efficiency and Instrumentation Delay Correction*

An essential technological issue highlighted in our corpus of knowledge is the time lag of the instrumented systems, which lasts about three minutes in industrial burners. Our study indicates that hybrid approaches successfully address this problem. As reported by Lyu et al. [23], a hybrid boosting model recorded an improvement of 3.6% in the R-squared (R^2) for a three-minute advance prediction relative to the traditional ARIMA model.

Moreover, with the advent of the PR^2 measure in [23], there is an impressive rise of up to 30.6% in terms of prediction accuracy, especially during critical operating periods. This is confirmed through the use of dynamic modeling as suggested by [22], where dynamic modeling showed superior results as opposed to static modeling, allowing for accurate forecasting of the 3-hour future period for both NOx and CO emissions

B. *Comparative Matrix of Research Findings*

In order to satisfy the research analysis requirements, a comprehensive comparative table of the key models discussed is provided in Table IV.

TABLE IV. QUANTITATIVE COMPARISON OF PREDICTIVE ARCHITECTURES

type of architecture	key performance metric	operation horizon	main ref.
hybrid boosting	R^2 improvement of 3.6%; PR^2 +30.6%	-3min lead time	[23]
dynamic neural	better estimation in comparison with static	three hours forecast	[22]
meta-analysis (refinery)	%20to 35% NOx reductions	real-time	[16]
systematic policy	socio-technical transition orientation	strategic roadmap	[2]

According to Table IV, the quantitative analysis demonstrates the superiority of hybrid and dynamic approaches in comparison with the conventional steady-state models. The significant improvement in terms of 30.6% PR^2 value, reported by [7], plays a key role since it underlines the advantage of hybrid systems' capability of predicting emission peaks at critical moments when standard controllers show their weaknesses. Moreover, moving towards proactive control with the help of three hours' forecast window mentioned in [22] allows to create a good basis for simultaneous NOx and CO_2 emissions mitigation. Thus, the implementation of AI-intelligent predictive engines should be considered as crucial for the environmental performance compliance of contemporary petroleum refineries.

C. *Environmental Impact and Decarbonization Metrics*

These intelligent approaches prove their significance through a direct influence on global decarbonization goals. Based on the analysis of results, we conclude the following:

- NOx Reduction: The use of AI-based MPC technology helps to reduce NOx deviations by 22% to 35% in comparison with traditional technologies, see [16, 22].
- Improvement of Boiler/Furnace Efficiency: Besides NOx reduction [5,26], the intelligent approach ensures the enhancement of boilers' and furnaces' efficiency by 1.5% to 2.8%.
- Strategic Reliability: Hybrid approaches exhibit a 30% greater margin of stability during transient periods (load ramping) relative to pure black-box systems; thereby assuring ongoing regulatory adherence [1], [7].

VIII. CONCLUSION AND FUTURE PROSPECTS

The present review highlights the undeniable connection between the future of emissions management within petroleum refineries and the use of AI-based predictive systems alongside Model Predictive Control (MPC)

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techniques [1], [5], [18]. Such a combination of technologies creates a foundation for the forecasting of non-linear dynamics and managing constraints in regard to NOx and CO2 emissions [3], [14].

A meta-analysis of 64 seminal publications reveals an important shift in the current industrial paradigm, according to which physics-informed models are gaining traction among petroleum companies due to their superior performance in terms of physical consistency and reliability in comparison with pure data-driven systems [1], [6], [23].

Such frameworks, as indicated above, are particularly significant for high-risk industrial settings wherein a measurement lag of up to 3 min is commonplace. On the basis of the findings presented above, the following Strategic Roadmap for transition to Refinery 4.0 is suggested:

- Trustworthy AI: It is crucial for future research to pay attention to Explainable AI (XAI) and Digital Twin approaches [18], [24]. This approach will help to move from black-box predictive algorithms to an explainable and interpretative AI-based decision-making support for process operators.
- Low Availability of Training Data: For development, one should focus on PINN-based approaches since they will provide good performance even if the amount of training data is low or the sensors' signals drift [23].
- Guidelines for Global Policies: In view of future sustainable practices until 2030, it is critical to utilize proactive control algorithms as a means of aligning old industrial sites with global policy requirements [2].

Beyond petroleum refining, these models apply to cement production and power plants. Transitioning to XAI and PINNs reflects an industrial shift toward "environmental-economic equilibrium." Amid rising carbon taxes, generalizing such frameworks is vital for achieving 'Net-Zero' status [2, 21].

Ultimately, proactive AI-based optimization enables low-carbon refining, ensuring compliance with environmental regulations within a carbon-constrained global economy [2, 15].

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