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Leveraging digitalization in HiMSEN production plant: implementation of NEMOS for emission compliance

Digitalizatiion, Connectivity, Artificial Intelligence & Cyber Security

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ABSTRACT

With the increasing demand for smart factory solutions in engine manufacturing, HD Hyundai Heavy Industries (HHI) has successfully implemented an integrated data acquisition system at the HiMSEN production plant. This system facilitates real-time data collection, structured storage, and analysis, supporting the digital transformation of production environments. By leveraging network technologies, industrial protocols, PLCs, and IoT, a streaming pipeline was developed to enable seamless data integration across various testbeds.

To further enhance digital knowledge management, NEMOS (NOx Emission Management & Optimization System) was introduced, addressing the limitations of manually recorded data. This system provides an intuitive operator interface, automates data entry through BOM integration, and enables real-time emission monitoring. Additionally, a stream processing server was implemented to synchronize emission data with engine operation parameters, allowing for accurate NOx compliance evaluations based on MARPOL Annex VI standards.

The collected data is utilized for predictive modeling and performance optimization, with applications such as HiBRAIN and Emission Analyzer Remote Control assisting in reducing operator workload and improving research collaboration. Analysis of emission prediction models has demonstrated the system's capability to track exhaust gas trends and optimize operational strategies, though further validation under diverse conditions is necessary.

This digitalization initiative is expected to accelerate the transformation of other HHI engine plants, enabling comprehensive operational and environmental data collection. These advancements will support the development of eco-friendly engines, enhance regulatory compliance, and drive continuous improvements in HiMSEN engine technology, reinforcing HHI's leadership in smart manufacturing and sustainable engineering.

1 INTRODUCTION

Since the initial production of the H21/32 type in 2001, HD Hyundai Heavy Industries (HHI) proprietary HiMSEN engine has reached a cumulative production of 15,000 units as of 2024, establishing itself as the market leader in the medium-speed engine sector for marine auxiliary power generation, with a 35% global market share (Figure 1). Leveraging decades of technical expertise and manufacturing experience, HiMSEN engines are exported to over 60 countries worldwide, ensuring stable performance tailored to diverse environmental conditions and operational requirements.

Figure 1. HiMSEN Engine Assembly & Test Shop

With the continuous increase in annual order volume, a significant number of four-stroke medium-speed HiMSEN engines, primarily dual-fuel engines, and two-stroke propulsion engines are scheduled for production this year, as illustrated in Figure 2. These units undergo commissioning and verification processes by the manufacturer before delivery, which are generally classified into “Shop Test” and “Sea Test”. The Shop Test is conducted before onboard installation to verify that the engine conforms to design specifications, including engine power, safety against fire, compliance with approved limits such as maximum pressure, and overall functionality[1].

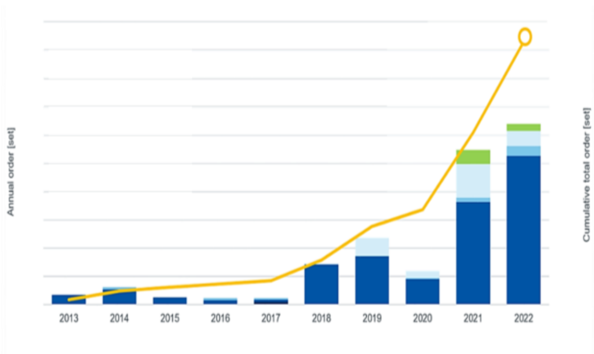

Figure 2. HiMSEN DF Engine Annual order & cumulative total order (As of Oct, 2022)

In particular, the Official Shop Test serve as foundational documentation for customers and act as a primary reference for future technical support. These results are essential for evaluating the performance status of onboard engines, providing a baseline for comparison with official shop test data at certain load and speeds levels. Furthermore, they play a crucial role in detecting abnormalities, as alarm and fault thresholds are configured to identify deviations that exceed predefined criteria.

Among the most critical aspects of the Shop Test in a mass-production environment is the ability to accommodate testing procedures within the constraints of the engine shipment plan. To ensure thorough validation, each engine's testbed occupancy is carefully managed based on the production schedule. During the allocated test period, comprehensive evaluations are conducted, including fuel consumption under various load conditions, emission measurements in accordance with IMO-regulated Tier levels (Tier I, II, and III), fuel mode transitions between gaseous and liquid fuels specific to dual-fuel engines, validation of NOx reduction performance via Selective Catalytic Reduction (SCR) systems, and MSS tuning operations[2,3]. To support these procedures, various standalone measurement devices are installed and operated on-site, each designed to capture specific parameters and display them locally via HMI or dedicated interfaces. The data collected from each device is then integrated and analyzed to generate official baseline performance datasets, which are delivered to customers as the primary reference for the corresponding engine.

In particular, recent years have seen a growing market demand for engines that not only comply with increasingly stringent international regulations but also deliver high output and operational efficiency. In this context, the ability to design and supply such advanced engines has become a critical differentiator among engine manufacturers. In response, HHI is actively developing next-generation engines powered by alternative fuels such as methanol and ammonia, aiming to meet future regulatory standards while maintaining high performance. Concurrently, extensive efforts are being made to conduct in-depth analysis of operational data from mass-produced HiMSEN engines. These analyses focus on identifying correlations among key performance indicators within the complex engine system, with the ultimate goal of deriving optimal control parameters. The outcomes of these initiatives are expected to contribute significantly to achieving higher efficiency, stable engine operation, and enhanced customer trust.

While conventional simulation methods and model-based system approaches remain effective for analyzing core engine performance, they often fall short when applied to emission-related phenomena, such as the generation and fluctuation of NOx and CH_4. This is primarily due to the highly nonlinear and variable nature of exhaust emissions, which are influenced by a multitude of interacting parameters and exhibit significant sensitivity to even minor variations in operating conditions. As a result, HHI has adopted data-driven methodologies to better capture the complex behaviors of emission formation during engine operation. By leveraging large volumes of time-series data acquired from mass-produced engines under various load and fuel conditions, machine learning and statistical modeling techniques are applied to identify hidden patterns and correlations between emission levels and key performance indicators. These efforts enable more accurate prediction of emissions under real-world conditions and support the derivation of optimal operational parameters that ensure both regulatory compliance and performance efficiency. In an environment of tightening IMO emission standards, such as those defined under MARPOL Annex VI, this data-centric approach has become essential for achieving sustainable and certifiable engine operation across a wide range of applications.

To support such data-driven emission analysis, the availability of high-resolution, real-time operational data has become increasingly critical—particularly during the Shop Test phase, where precise evaluation of engine behavior under varying load and fuel conditions is essential. Unlike static performance reports, real-time data captures the dynamic characteristics of engine operation, enabling more accurate assessments of emission trends, performance stability, and compliance with regulatory thresholds. However, earlier attempts to implement such data acquisition were constrained by the absence of a centralized and scalable infrastructure. In many cases, data was collected through isolated and heterogeneous systems, resulting in fragmented datasets that lacked consistency, traceability, and long-term usability. These limitations significantly hindered efforts to conduct holistic performance evaluations or to develop predictive models that reflect actual field conditions. Recognizing these challenges, HHI has focused on building an integrated data framework capable of aggregating and synchronizing real-time data streams from multiple on-site measurement devices, thereby enhancing the quality and utility of data for advanced analytics and optimization.

Recent technological advancements have facilitated the development of centralized data infrastructure, accelerating the shift toward digitalization and enabling industries to adopt automation, artificial intelligence (AI), and data management solutions [4]. The integration of smart sensors, data acquisition systems, Internet of Things (IoT), and cloud computing has played a crucial role in collecting operational data across sectors and optimizing data transmission to secured intranet networks. Once centralized, the integrated engine operation data ensures real-time accessibility, sustainability, and seamless availability for both field operators and engine research institutions[5]. By conducting in-depth analyses of this data, researchers can accelerate product development and identify key operational parameters for existing engines to enhance performance and efficiency. This data-driven interaction between the commissioning and research team fosters continuous improvement, while the early detection and prevention of potential operational issues help reduce workload and enhance overall operational reliability in the field.

This paper presents the deployment of an integrated data acquisition system established at the HiMSEN Production Plant to support digital transformation efforts in large-scale engine manufacturing. The system is based on a PLC-controlled hardware infrastructure, enabling reliable and structured collection of data from various engine testbeds and auxiliary systems via wired connections. This unified field-level system allows real-time operational data—including performance, control, and safety metrics—to be collected consistently during the mass production of HiMSEN engines. The data acquisition system serves as a foundational layer for advanced monitoring, performance validation, and regulatory compliance across a wide range of engine types and power ratings.

In parallel with field-level integration, a complementary digital service platform, NEMOS (NOx Emission Management & Optimization System), has been developed to extend accessibility and usability of production data beyond the physical boundaries of the shop floor. NEMOS consolidates data not only from the HiMSEN Production Plant but also from external remote facilities in real time, enabling researchers and engineers to monitor, analyze, and collaborate on engine behavior and emissions trends across multiple locations. This system bridges the gap between production and research, enhancing transparency and accelerating data-driven decision-making for engine design, tuning, and validation.

Furthermore, this study demonstrates how the integrated data collected through the smart factory infrastructure is applied to real-world engine analysis and optimization. In particular, an MSS tuning model was developed and validated using operational data from mass-produced engines, yielding meaningful results in identifying optimal control settings that balance emission reduction and performance stability. Based on these findings, further refinement through additional data analysis and model enhancement is planned. The finalized service will be integrated into the NEMOS platform, enabling engineers to access intuitive, data-driven tools that support real-time decision-making and advanced tuning in the field.

2 HIMSEN PRODUCTION PLANT DATA ACQUISITION SYSTEM

As global manufacturing trends shift towards digitalization and data-driven optimization, mass-production environments are increasingly adopting smart technologies to improve operational efficiency and product quality. At the HiMSEN Production Plant, a comprehensive digital transformation has been successfully implemented to enhance engine assembly and testing processes. This transformation integrates real-time data collection, intelligent monitoring systems, and centralized data management, creating a scalable foundation for a smart factory. The following section outlines the structure and key features of this digital architecture, highlighting how it supports high-volume production while maintaining adaptability and precision.

2.1 Engine Data Collection with IoT Platform

Ship engines are produced under a high-mix, low-volume (HMLV) manufacturing system, where engine types, control units, and internal components vary based on ship owners' requirements and specific applications. Consequently, the list of collectable data differs for each engines. Given that different types of engines may be assembled on the same testbed depending on the operational schedule, the factory’s data acquisition system must be designed with sufficient flexibility to accommodate this diversity.

Using Microsoft Azure IoT services a signal framework is established tailored to each engine’s specifications, automating data collection. The system is structured into three main components:

- IoT Edge – Stores and retrieves engine information. Monitors start/stop status of the engine

- IoT Middleware – Provides a monitoring dashboard for real-time insights. Processes and stores collected data for analysis

- IoT Hub – Manages Edge modules for distributed processing. Handles device management, ensuring seamless communication between IoT components

RabbitMQ is employed for data communication between IoT components, ensuring efficient and rapid message transmission. The data sent from the Middleware is processed through the IoT Hub before being stored in the company’s time-series database, enabling streamlined data management and real-time monitoring.

2.2 Auxiliary Data Collection with PLC-based System

During shop tests, it is essential to consider changing environmental conditions to accurately predict engine performance, assess operational stability, and provide timely alerts for potential risks. To achieve this, data from auxiliary equipment, as shown in Table 1, must be collected alongside engine parameters.

Many of these auxiliary systems were introduced before the era of digitalization, and as a result, each component—including sensors, actuators, and electronic control units—is physically embedded with dedicated hardware. These systems are often only partially connected to private networks or individual HMIs (Human-Machine Interfaces), originally designed with limited external communication capabilities. Consequently, they were initially configured to operate in isolated environments, restricting seamless data integration and remote monitoring.

To facilitate data collection in this environment, a new PLC-based system has been introduced. Given the variations in existing testbeds and their associated auxiliary equipment, the system utilizes advanced networking technologies and protocols such as Industrial Ethernet, Industrial Wireless Networks, Fieldbus, TCP, OPC-UA, and RS-485 to ensure seamless data transmission and integration.

These PLCs are configured to synchronize data acquisition across different components, ensuring that all recorded data aligns within the same timeline. Ultimately, the collected data is transmitted to the intranet via OPC-UA, enabling centralized monitoring and analysis while maintaining compatibility with existing infrastructure.

Table 1. List of Auxiliary components

Equipment	Purpose
Power Meter	Engine performance

Micro Pilot Consumption	Engine performance
Fuel Oil Consumption	Engine performance
GRU (Gas Regulating Unit)	Engine performance
Exhaust Back Pressure	Engine performance
SCR	IMO Tier compliance
Ambient Condition	Engine performance
Bearing & Winding temp.	Engine safety
Exhaust Emission	IMO Tier compliance
(Option) Vibration/Noise	Engine safety

3 THE NEMOS

In addition to the engines and auxiliary equipment installed and operated in the HiMSEN Production Plant, a separate gas analyzer (HORIBA MEXA series) is utilized to analyze gaseous exhaust emissions generated during engine operation. Unlike fixed installations, this gas analyzer is designed to be mobile, allowing relocation between testbeds and across factory sites.

However, due to its mobility, manual input from field operators is required to identify which engine the measured emission data corresponds to. Furthermore, since it operates on a separate power source, it must be capable of transmitting and receiving remote signals to determine the active status of the device. Comprehensive equipment management is also necessary to track maintenance history, internal component replacements due to failures, aging and wear conditions, and span gas calibration records before each measurement.

To evaluate compliance with IMO NOx emission regulations (MARPOL Annex VI) using raw NOx concentration (ppm) data obtained from the gas analyzer, additional data such as ambient conditions, engine operation parameters, and fuel consumption must be considered. While the digitalized infrastructure of the HiMSEN Production Plant provides access to relevant data, a dedicated stream processing server was implemented to ensure precise time synchronization between emission data and engine operation data, enabling accurate calculation of NOx emissions (g/kWh).

To overcome these challenges, NEMOS was developed to enable real-time emission assessment during the shop test. The system offers comprehensive monitoring by integrating operational and emission data collected from multiple sources at varying frequencies. Its intuitive user interface (UI), as shown in Figure 3, allows operators to log steady-state conditions at each load level, while BOM data integration automates input based on the engine's unique ID, reducing reliance on manual entry. Upon completion of the test, emission data is automatically processed and compiled, facilitating report generation that minimizes operator workload while ensuring accuracy and statistical reliability.

3.1 Gas Analyzer Data Collection with wireless Communication

Multiple gas analyzers are deployed across various production sites, each assigned a distinct IP address via Private LTE (PLTE) infrastructure,

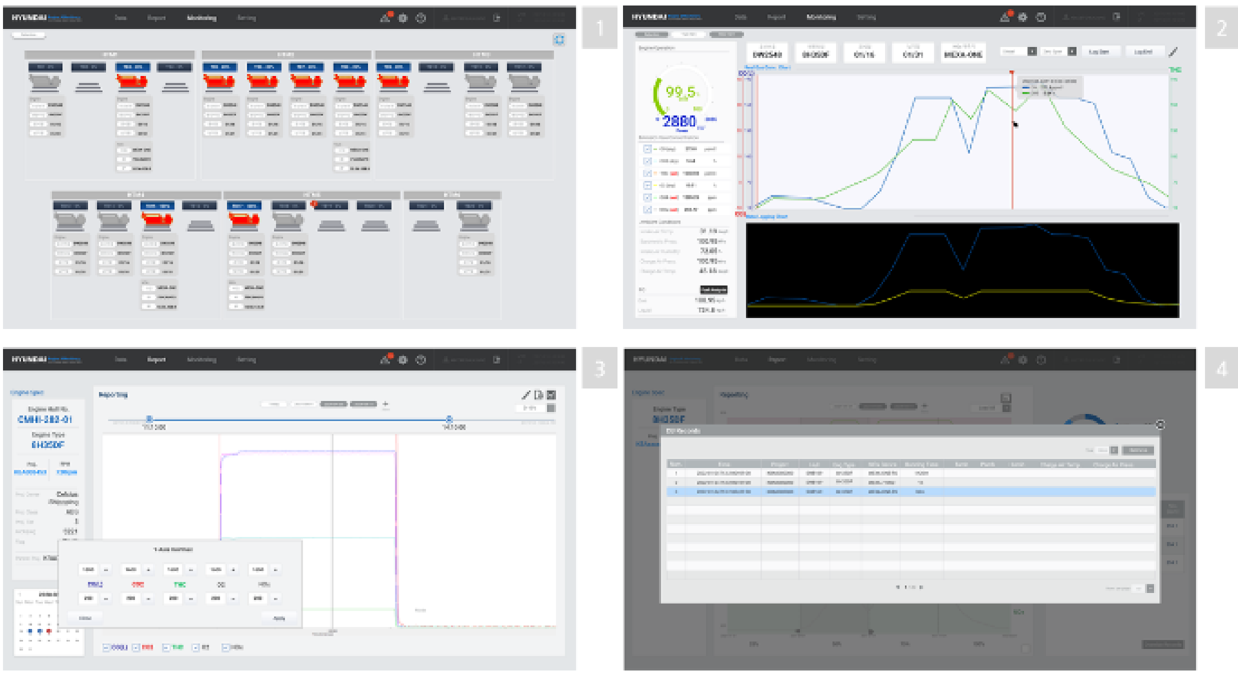

Figure 3. NEMOS UI, 1) Installed Engine by Plant Testbed, 2) Real-time emission monitoring, 3) Report & Summary 4) DB lists

enabling TCP/IP-based status monitoring and data exchange. To ensure seamless operation, the system periodically checks whether the equipment is powered on and functioning properly and dynamically initializes a dedicated kernel for active analyzers, facilitating continuous data acquisition until the device is deactivated. The collected information is then relayed to a message queue, where it is autonomously processed within containerized services hosted in the Data Center.

The stream data transmitted to the message queue is buffered to handle potential communication disruptions, allowing real-time storage in InfluxDB, a time-series database. Additionally, during the initial system deployment, key metadata - including installation location, model specifications, purchase year, and PLTE router configuration - is structured within a relational database (RDB). A predefined API service allows for manual updates to equipment records, ensuring precise asset management as operational conditions evolve.

For medium-speed dual-fuel (DF) engines operating at rated speed, emission values are typically recorded 10–20 minutes after reaching a stable load condition. However, while there are fundamental criteria for determining stabilization, the judgment often relies on the experience of skillful operators, and this process is not systematically documented. By leveraging the data recorded by experienced operators, the NEMOS can aid in establishing additional criteria, contributing to the standardization of stabilization assessment through a structured methodology.

3.2 Streaming Data Pipeline

Reliable real-time data is fundamental to the success of smart factory implementation, impacting efficiency, cost, automation, and security. To ensure data reliability, it is crucial to design a system capable of processing real-time data promptly while ensuring no data loss even in temporary network disruptions. To achieve this, the system must temporarily store data locally and process it once connectivity is restored. This necessity led to the development of a streaming data pipeline, which efficiently manages data flow and ensures stable transmission to the database, maintaining data integrity and reliability throughout the process.

Figure 4 illustrates system architecture of NEMOS for engine emission monitoring and analysis. The system consists of three major components:

- Factory (Data Sources & PLC Integration): Various sensors and meters collect engine-related operational data. The PLC integrates and transmits data to the Develop Center
- Develop Center (Data Processing & Analysis): Data Receiver handles data serialization and time synchronization to ensure real-time processing. Data Processor conducts NOx regulation checks to ensure compliance with emission global standards. Also, the steady-state condition check provides field operators with a signal indicating the engine stabilization point, allowing them to accurately determine when the engine has reached a stable operating state.
- Internal Database (Data Storage & Visualization): The Internal Database integrates engine specification data from the in-house system, serving as metadata to filter and enhance the analysis of operational data.

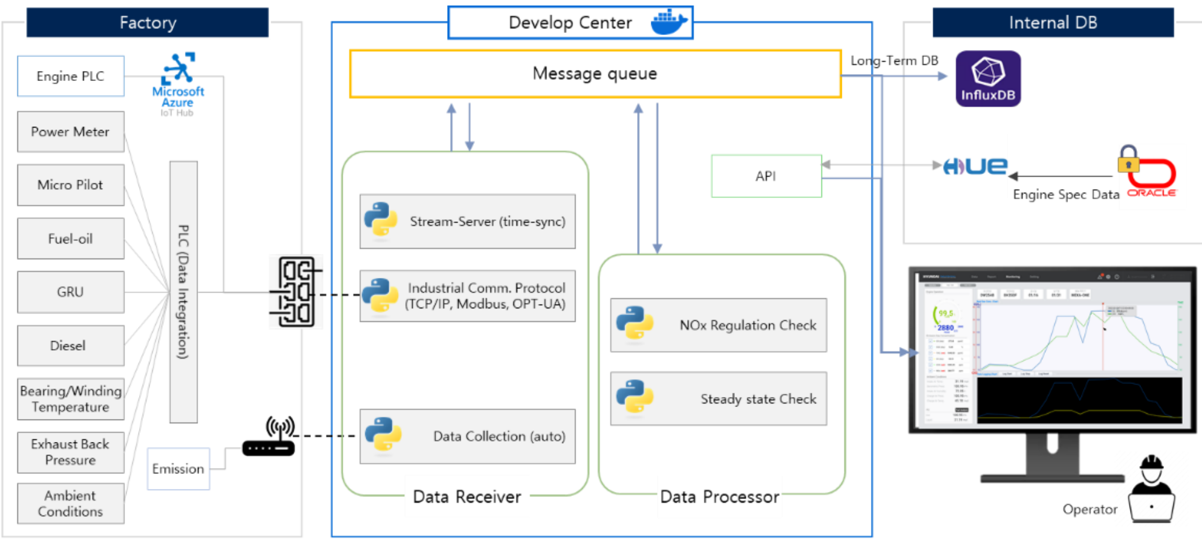

Figure 4. System Architecture of NEMOS

4 DATA-DRIVEN MODELING OF CONTROL VARIABLE EFFECTS ON MSS-TUNED DUEL-FUEL ENGINES

In recent years, the adoption of liquefied natural gas (LNG) as a marine fuel has significantly increased due to its advantages in reducing sulfur oxides (SOx), nitrogen oxides (NOx), and carbon dioxide (CO_2) emissions compared to conventional fuels. However, the environmental benefit of LNG can be substantially offset by the emission of unburned methane, commonly referred to as methane slip[7]. Methane (CH_4) is a potent greenhouse gas with a global warming potential (GWP) that is 29.8 times greater than CO_2 over a 100-year timescale and up to 86 times over a 20-year timescale, according to the Intergovernmental Panel on Climate Change (IPCC)[8]. The presence of methane slip in gas-fueled marine engines has thus emerged as a critical environmental concern, undermining the long-term sustainability of LNG propulsion systems.

To mitigate this issue, technologies such as Methane Slip Solution (MSS) have been developed, which utilize multistage micro-pilot fuel injection strategies to reduce unburned methane in the exhaust gas. However, determining the optimal injection parameters—such as timing, duration, and pressure settings—for various engine load conditions is a highly complex task. It requires extensive experimentation and analysis due to the nonlinear interactions between control inputs, combustion behavior, and emission outputs. The process is further complicated by engine-to-engine variability in production and the sensitivity of methane formation dynamics to minor control deviations. As a result, a significant amount of time, cost, and engineering resources is traditionally required to identify and validate tuning parameters that effectively minimize methane slip without compromising engine performance or stability.

In line with global efforts to reduce methane emissions from gas-fueled engines, Hyundai Heavy Industries–Engine & Machinery Division (HHI-EMD) has pursued several technical strategies, including the implementation of Cylinder Cut-Off (CCO) and Crevice Volume (CV) reduction, to mitigate methane slip. Among these, the application of multi-phase injection (MPI) using micropilot fuel has shown promising potential in minimizing unburned methane during gas mode operation. This study focuses on the analysis of operational data obtained under MPI configurations, with the objective of developing a methodology that can rapidly identify optimal tuning points for Methane Slip Solution (MSS). By leveraging a structured data-driven approach, the proposed method significantly reduces the time required for MSS tuning in mass-produced engines. Furthermore, it enables a deeper understanding of the interdependencies among key control parameters, thereby laying the groundwork for future in-depth analysis of engine performance and emission behavior under various operating conditions.

4.1 MSS Tuning Real-data Preparation

For this study, real-time operational data was collected from the HiMSEN Production Plant during actual MSS tuning procedures conducted by field engineers. The integrated dataset was acquired through the NEMOS platform, which streams structured time-series data from the shop floor to research environments. This dataset includes three primary categories of variables: control parameters manually adjusted by operators (e.g., injection timing and duration), system state variables internally regulated by the engine controller, and emissions data (e.g., NOx, CH_4) reflecting the engine′s environmental output. These variables were synchronized and serialized at fixed intervals through the NEMOS data pipeline to ensure temporal consistency.

To analyze the impact of operator-driven tuning, changes in control variables were segmented based on predefined thresholds. This allowed for the identification of meaningful before-and-after intervals, enabling the training of time-series models to capture the dynamic relationships among control inputs, system behavior, and resulting emissions. Prior to model development, the dataset underwent preprocessing, including removal of missing values and smoothing using a moving average filter to reduce transient noise and improve signal stability.

4.2 Variable Selection and Preprocessing

To construct a relevant dataset for modeling CH4 emissions, we selected five primary variables from the MPI control domain:

- Main pilot injection timing
- Main pilot injection duration
- Pre-pilot injection timing
- Pre-pilot injection duration
- Charge air pressure

Each variable was extracted from second-level time-series shop test logs. Preprocessing included smoothing and normalization for system and emission variables to ensure effective convergence during learning.

4.3 Control Event Segmentation and Dataset Construction

To build a reliable model, training data must reflect meaningful variations in engine control parameters. Manual tuning performed by operators during engine optimization provides useful reference points where control variables significantly change as show in Figure 5. By segmenting these moments, we construct a training dataset that accurately represents the dynamic relationship between engine control variables and emission concentrations.

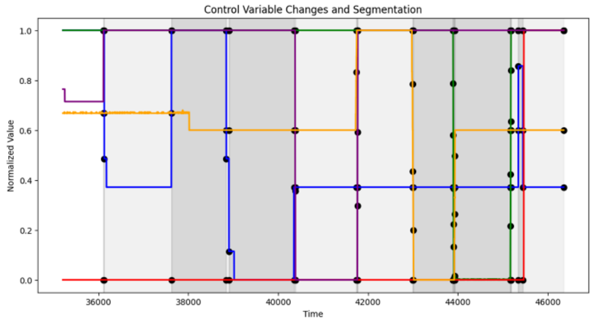

Figure 5. MSS tuning control variable changes performed by operators

4.4 Dual-Model Learning Structure

To accurately capture the behavior of CH4 emissions, a two-tier model architecture was developed:

- BaseModel: Learns the general behavior of CH4 emission under steady-state conditions using sequences without control intervention. This reflects baseline engine behavior under fixed load and speed.

- ControlEffectModel: Trained specifically on control-influenced segments, this model captures how variations in control input gradually alter CH4 output. The model's output is combined with the BaseModel prediction to reconstruct total CH4 prediction over time.

Loss minimization is applied over the composite prediction relative to actual emission data.

4.5 Modeling Temporal Influence of Control

To represent the gradual influence of control changes, three temporal response models were explored. The following equations define the temporal influence weights used to model control effects on CH_4 emission in dual-fuel engines. These formulations are used to modulate the maximum effect of a control input Δy_{max} over time as shown in Equation 1.

$$y_{pred}(t)=y_{base}(t) + w(t) * \Delta y_{max} \quad (1)$$

$$w(t)=\exp(-(t-\mu)^2/(2\sigma^2)) \quad (2)$$

$$w(t)=\exp(-pt) \quad (3)$$

$$w(t)=1/\exp(-k(t-\mu)) \quad (4)$$

Where:

- y_{pred}: The baseline CH_4 emission prediction at time t obtained from the BaseModel
- w(t): Time-varying influence weight applied to control effect
- p: Exponential decay rate, $p > 0$
- μ (mu): Center of influence (in time steps)
- σ (sigma): Spread of influence (standard deviation in Gaussian)
- k: Slope parameter controlling the steepness of the sigmoid transition
- t: Time index (t = 0, 1, ..., 59)

Each model predicts a dynamic weight curve over the 60-step window, modulating the control effect.

Empirical evaluation showed that the sigmoid-based control influence model most accurately mirrored real engine behavior. The final model, combining the sigmoid kernel-based control effect and baseline emission prediction, demonstrated the lowest MAE and R^2 in comparison with actual CH4 measurements.

Table 2. Temporal Influence simulation models

Model	MAE	R^2	Equation
Gaussian	181.3283	0.7742	Eq.2
Exponential Decay	167.1868	0.8144	Eq.3
Sigmoid	162.0370	0.8191	Eq.4

4.6 Evaluation

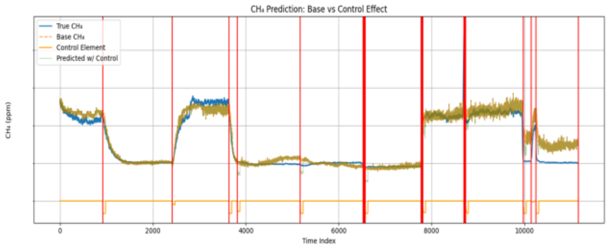

Figure 6. Predicted emission concentration based on LSTM model

Figure 6 displays four key elements: the actual CH_4 measurements(True CH_4), the baseline predictions from the BaseModel (Base CH_4), the influence of control inputs (Control Element), and the resulting CH_4 prediction that combines both components (Predicted CH_4 with Control). The red vertical lines mark the timing of control actions, while the yellow-colored bars at the bottom represent the magnitude and direction of control variable changes applied at those moments.

The model incorporates a sigmoid-based temporal influence kernel to reflect the gradual effect of control interventions over time. As shown, the predicted CH_4 values closely track the true measurements during and after control adjustments, demonstrating the model's capability to adapt to dynamic engine behavior. According to Table ~, this model configuration achieves a coefficient of determination ($R2=0.8191$, $MAE=162.0370$) The results demonstrate that the model effectively captures exhaust gas concentration trends under both scenarios:

- When control variables continuously change, the model adapts dynamically and accurately tracks fluctuations.
- When control variables remain stable over a long period, the model maintains a consistent prediction, aligning well with the raw data trends.

These findings validate the model’s ability to generalize across different engine operating conditions while maintaining high prediction accuracy.

Although this analysis was conducted on a single engine type with a limited dataset, future accumulation of operational data from field applications is expected to enable more detailed and comprehensive analyses. To achieve this, reliable data collection and storage must be prioritized, ensuring the integrity and consistency of the dataset. Additionally, the accuracy of operator key-in inputs plays a crucial role in refining the model’s predictive capabilities, highlighting the necessity of meticulous data management for continuous improvement.

5 CONCLUSIONS

HHI has successfully established a data integration system for the HiMSEN Production Plant, marking a significant step toward digitalization in engine manufacturing and testing. This paper highlights the challenges encountered during its implementation and explores how the collected data is leveraged to enhance performance and operational efficiency. By integrating ICT-based infrastructure, the system enables real-time data acquisition, structured storage, and advanced analytical capabilities, contributing to the advancement of HiMSEN engine technology and reinforcing HHI’s leadership in smart factory solutions.

1 A comprehensive data acquisition system has been successfully implemented at the HiMSEN Production Plant, integrating network technologies, industrial protocols, PLCs, and IoT to enable real-time data collection and structured storage.

2 To further enhance digital knowledge management, NEMOS was introduced, allowing operators to input critical operational data while facilitating collaboration between field operators and research teams.

3 Data-driven analysis, such as the Prediction of Emission Concentration, demonstrated the system’s ability to track exhaust gas trends and optimize emissions, with continuous data accumulation and integration of external factors expected to further improve predictive modeling and engine performance optimization.

The digital transformation of other Hyundai Heavy Industries engine plants is expected to accelerate, enabling the comprehensive collection of operational and environmental data. This will not only support the design and development of eco-friendly engines but also facilitate the creation of precise performance models for HiMSEN engines, serving as a key driving force in advancing the licensing business. By continuously enhancing data-driven methodologies, Hyundai Heavy Industries will further optimize engine performance, sustainability, and production efficiency, reinforcing its leadership in the global engine manufacturing industry.

DEFINITIONS, ACRONYMS, ABBREVIATIONS

AI: Artificial Intelligence

BOM: Bill of Material

DF: Dual Fuel

ECA: Emission Control Area

GRU: Gas Regulating Unit

HiEMS: Hyundai Intelligent Equipment Management Solution

HiBRAIN: Hyundai Integrated Brilliant Artificial Intelligence Net

HiCAMS: Hyundai Intelligent Camera-Based Alarm Monitoring System

HiDTS: Hyundai Intelligent Digital Twin Ship

HMLV: High-Mix, Low-Volume

HHI: HD Hyundai Heavy Industries

HMI: Human-Machine Interface

ICT: Information and Communication Technology

IMO: International Marine Organization

IoT: Internet of Things

ISS: Integrated Smart Ship Solution

LSTM: Long Short-Term Memory

MSS: Methane Slip Solutions

MPI: Multi-phase Injection

NEMOS: NOx Emission Management & Optimization System

OPC UA: OPC Unified Architecture

PCA: Principal Component Analysis

PLC: Programmable Logic Controller

PLTE: Private LTE

RDB: Relational Database

SCR: Selective Catalytic Reduction

TCP/IP: Transmission Control Protocol/Internet Protocol

UI: User Interface

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