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**MANAGEMENT SUPPORT SYSTEM FOR PERFORMANCE
IMPROVEMENT AND MAINTENANCE OF TWO-STROKE
MARINE DIESEL ENGINES**

PH.D. THESES

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LIST OF SYMBOLS AND ABBREVIATIONS

Greek letters

	Meaning	Unit
θ	Crank angle (used in $dp/d\theta$ and crank-angle constraints)	$^{\circ}\text{CA}$
μ	Fuzzy membership grade (membership function output)	N/A
α	TMF/BECI balance parameter between extreme criteria contributions	N/A
λ	Aggregation/mixing parameter in hybrid scoring formulations (e.g. WASPAS/WISP form)	N/A
Δ	Difference between two values (e.g. Diesel-RK software predictions vs. Neural Network predictions: ΔSFC , ΔPM , ΔNO_x)	Same as the underlying variable

Latin letters

Symbol	Meaning	Unit
A	Set of alternatives (decision options / operating-point candidates)	N/A
A_i	i -th alternative (engine configuration/operating point)	N/A
$BECI_i$	Balanced Extreme Criteria Index (TMF component)	N/A
C	Set of criteria (e.g. SFC , NO_x , PM)	N/A
C_j	j -th performance criterion	N/A
C_i	TOPSIS closeness coefficient	N/A
$CAWI_i$	Criteria Aggregated Weighted Index (TMF component)	N/A
CD	Combustion Duration	$^{\circ}\text{CA}$
D	Injection dwell time between pilot and main injections	$^{\circ}\text{CA}$
$D+$	Distance to ideal solution (e.g. TOPSIS formulations)	Depends on normalization
$D-$	Distance to anti-ideal solution	Depends on normalization
$\underline{D}$	Pareto front Decision Matrix	N/A
DIS_i	Euclidean distance metric (TMF component)	N/A
$dp/d\theta$	Maximum pressure rise rate with respect to crank angle	$\text{bar}/^{\circ}\text{CA}$
EVO	Exhaust Valve Opening timing	$^{\circ}\text{CA-BBDC}$
EVC	Exhaust Valve Closing timing	$^{\circ}\text{CA-ABDC}$
F	Pilot injection fuel mass fraction	%
m_1	Exponent controlling NO_x penalty in SE formulation	N/A
m_2	Exponent controlling PM penalty in SE formulation	N/A
MAE	Mean Absolute Error	Depends on criterion
$MAPE$	Mean Absolute Percentage Error	%
MSE	Mean Squared Error	Depends on criterion
N	Population size (NSGA-II) / sample size depending on context	N/A
NO_x	Nitrogen oxides emission index	g/kWh
NO_{x0}	Reference/target NO_x level in SE formulation	g/kWh
P	Parent population (NSGA-II; P_t)	N/A
P_{fuel}	Common-rail fuel pressure	bar
P_{max}	Peak cylinder pressure	bar
PM	Particulate Matter emission index	g/kWh

LIST OF SYMBOLS AND ABBREVIATIONS

PM_0	Reference/target PM level in SE formulation	g/kWh
Q	Offspring population (NSGA-II; Q_t)	N/A
Q_i	VIKOR compromise index for alternative i	N/A
R	Merged population (NSGA-II; $R_t = P_t \cup Q_t$)	N/A
R^2	coefficient of determination	N/A
R^*	Best (minimum) R among alternatives (VIKOR)	N/A
R^-	Worst (maximum) R among alternatives (VIKOR)	N/A
R_i	VIKOR individual regret measure for alternative i	N/A
$RMSE$	Root Mean Square Error	
S^*	Best (minimum) S among alternatives (VIKOR)	N/A
S^-	Worst (maximum) S among alternatives (VIKOR)	N/A
SE	Synthetic Emission Index (Diesel-RK composite indicator)	N/A
SFC	Specific Fuel Consumption	kg/kWh
SFC_0	Reference/target SFC level in SE formulation	kg/kWh
S_i	VIKOR group utility measure for alternative i	N/A
SI_i	TMF synthesized index	N/A
SOI	Start of Injection	°CA-BTDC
t	Generation index (NSGA-II iteration counter)	N/A
v	VIKOR strategy weight (importance of group utility vs individual regret)	N/A
w_j	Weight of criterion j (generic MCDM notation)	N/A
w_{SFC}	Normalized weight assigned to SFC criterion	N/A
w_{NO_x}	Normalized weight assigned to NO_x criterion	N/A
w_{PM}	Normalized weight assigned to PM criterion	N/A
w'_{SFC}	Pre-normalized (raw) fuzzy weight output for SFC	N/A
w'_{NO_x}	Pre-normalized (raw) fuzzy weight output for NO_x	N/A
w'_{PM}	Pre-normalized (raw) fuzzy weight output for PM	N/A
x	Crisp input value (e.g. operator importance rating in fuzzy module)	N/A
x_{ij}	Performance value of alternative i with respect to criterion j (decision matrix element)	Depends on the criterion
$\underline{\underline{X}}$	Diesel-RK Decision Matrix	N/A
z	Output universe variable in defuzzification integral (centroid of area)	N/A
z^*	Defuzzified crisp output (centroid)	N/A

Subscripts

Symbol	Meaning
i	Index of alternative (operating point/configuration)
j	Index of criterion
t	Generation/iteration index in NSGA-II (e.g. P_t , Q_t)
max	Maximum value (e.g. P_{max})
0	Reference/target value (e.g. NO_{x0} , PM_0 , SFC_0)

Abbreviations

Symbol	Meaning
AI	Artificial Intelligence
ANNs	Artificial Neural Networks
BTE	Brake Thermal Efficiency
BN	Base Number (lubricant alkalinity reserve)

LIST OF SYMBOLS AND ABBREVIATIONS

CAC	Charge Air Cooler
CRITIC	Criteria Ranking by Intercriteria Correlation
DoE	Design of Experiments
DSS	Decision Support System
ECA	Emission Control Area
EGCS	Exhaust Gas Cleaning System (scrubber)
FLM	Fuzzy Logic Module (fuzzy weighting module)
HFO	Heavy Fuel Oil
HRR	Heat Release Rate
IMO	International Maritime Organization
LHS	Latin Hypercube Sampling
LNG	Liquefied Natural Gas
MCDM	Multi-Criteria Decision-Making
MDO	Marine Diesel Oil
MOEA	Multi-Objective Evolutionary Algorithm
NN	Neural Network
NPSH	Net Positive Suction Head
NSGA-II	Non-dominated Sorting Genetic Algorithm II
NSGA-III	Non-dominated Sorting Genetic Algorithm III
SAEAs	Surrogate-Assisted Evolutionary Algorithms
SCR	Selective Catalytic Reduction
TMF	TriMetric Fusion
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
VIKOR	ViseKriterijumska Optimizacija I Kompromisno Resenje
VLSF	Very-Low-Sulfur Fuel(s)
WPM	Weighted Product Method
WSM	Weighted Sum Method

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1. INTRODUCTION TO MARINE DIESEL ENGINES AND AIMS OF THE RESEARCH

Marine diesel engines serve as the cornerstone of international shipping, dominating propulsion technology of the world's commercial fleet, including container ships, bulk carriers and tankers [1, 2]. These engines operate under extreme thermodynamic and mechanical stresses (ranging from rapid load fluctuations during maneuvering to prolonged exposure to corrosive seawater), necessitating architectures that balance power density with exceptional durability and reliability [3].

To analytically manage this complexity, the marine diesel engine is conceptually decomposed into five interdependent functional systems: fuel injection, air management, lubrication, cooling and exhaust aftertreatment [4, 5]. This system-level framework is a foundational engineering methodology essential for structured design, effective operation, troubleshooting and predictive maintenance. Each subsystem is engineered to address specific operational challenges while collectively ensuring compliance with strict environmental regulations and enabling predictive maintenance through condition monitoring [6]. This chapter first demonstrates each subsystem's operational principles, failure modes and monitoring frameworks. It will then present the challenges in performance monitoring and predictive maintenance. Third, it highlights the role of intelligent Decision Support Systems (DSS) that integrate physics-based models with data-driven inference to navigate multi-objective trade-offs in fuel economy and emissions and frames the extension to component-health-aware decision-making via an expert system component. Finally, it states the research objectives, added value and outlines the methodological approach proposed to bridge the identified research gap.

Marine diesel engines are large compression-ignition machines engineered for high torque, high brake thermal efficiency and fuel flexibility, including operation on Heavy Fuel Oil (HFO), Very-Low-Sulfur Fuels (VLSF) and alternative fuels [1]. Operating on the Diesel/dual-cycle behavior, modern, slow-speed, two-stroke engines achieve ~50–55% brake thermal efficiency [7]. Two configurations dominate maritime applications: slow-speed two-stroke crosshead engines for main propulsion and medium-speed four-stroke trunk-piston engines for auxiliary power (and main propulsion on smaller vessels) [8]. These engines must perform reliably in corrosive environments, fluctuating loads and prolonged operation (conditions that challenge conventional maintenance practices) [6]. In this research, I address these challenges using data-driven, model-based and knowledge based methods: high-fidelity simulation coupled with intelligent decision-making frameworks to support real-time performance optimization and predictive maintenance.

1.1. Marine diesel engines: key subsystems functionality and integration

Marine diesel engines are compression-ignition power plants that convert the chemical energy of fuel into mechanical shaft power for propulsion and shipboard electricity, operating continuously under highly variable load profiles and harsh marine environments. Tightly coupled thermodynamic and mechanical processes govern their overall performance and emissions: air is drawn from the engine room, compressed by an exhaust-gas-driven turbocharger, cooled to increase charge density and delivered as scavenge air to support efficient cylinder filling and combustion. The resulting exhaust flow expands through the turbine, recovering exhaust enthalpy to sustain boost pressure and thereby closing the engine's dominant energy-recovery loop.

Figure 1.1. presents a simplified schematic of a turbocharged marine diesel engine, highlighting the coupled intake, compression, charge cooling, scavenge delivery path and the exhaust-driven turbine that recovers energy to sustain boost pressure.

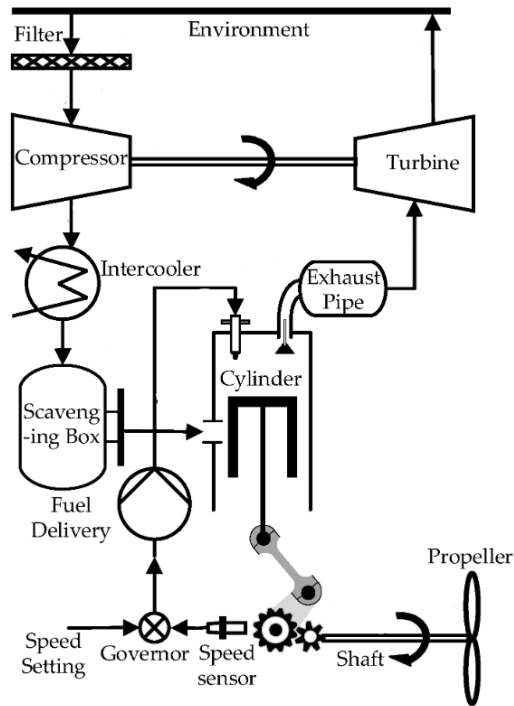


Figure 1.1. Simplified marine diesel engine layout

The following subsections decompose the marine diesel engine into five interdependent functional subsystems to enable structured analysis of operation, failure mechanisms and monitoring

1.1.1. Fuel injection subsystem

The fuel injection subsystem in marine diesel engines is a mission-critical subsystem responsible for the precise delivery, conditioning and combustion of fuel under extreme operational conditions. Comprising low and high pressure pumps, electronically controlled injectors, centrifugal purifiers and thermal management systems, it integrates mechanical and hydraulic principles to optimize combustion efficiency while complying with stringent emissions regulations [9].

The architecture of modern marine fuel injection subsystems is centered around precision control and robust fuel conditioning to meet the demands of fuels and emission regulations [10]. In large two-stroke engines such as those in the MAN B&W ME-C series and WÄRTSILÄ engines, fuel injection is managed by electronically controlled, hydraulically amplified injection [11, 12]. The core process involves two key stages [12]:

1. **Fuel Conditioning:** Incoming fuel must be conditioned to a precise viscosity and purity. This is achieved through controlled preheating and multi-stage filtration to remove water and particulate contaminants, ensuring proper atomization and protecting high-pressure components from wear and damage.
2. **High-Pressure Injection:** Modern systems use common-rail or electronically controlled unit injector technology to deliver fuel at pressures often exceeding 1,000 bar, which enables advanced

strategies like multi-pulse injections for optimizing the combustion process and minimizing emissions.

The fuel injection subsystem faces significant failure modes, including injector coking and pump cavitation, which are often accelerated by fuel contaminants or improper conditioning. These failures directly degrade engine performance, leading to a measurable increase in Specific Fuel Oil Consumption (*SFOC*) and complicating compliance with emissions regulations like IMO Tier III and the Carbon Intensity Indicator (*CII*) [13].

Ultimately, the fuel injection subsystem embodies the critical trade-offs between combustion efficiency, fuel flexibility and emission control. The interdependencies between fuel conditioning, injection precision and component degradation make it a primary candidate for the intelligent, model-based management and optimization frameworks explored in this research.

1.1.2. Air management subsystem

The air management subsystem is thermodynamically central to marine diesel performance and compliance, governing charge density, combustion quality and Nitrogen oxides (NO_x) formation. In slow-speed two-strokes, it comprises the turbocharger(s), charge-air (scavenge-air) cooler(s), filters/ducting, scavenge receiver and auxiliary blowers that support operation. From the turbocharger compressor, air passes through the cooler and into the scavenge receiver before entering the cylinder through the ports/valves, an architecture standardized in marine practice [14, 15].

The turbocharger is the core of this subsystem, recovering energy from the exhaust gas to compress the intake air. This process significantly improves the engine's Brake Thermal Efficiency (*BTE*) by repurposing waste exhaust enthalpy. Advanced two-stage turbocharging configurations further enhance performance by generating higher boost pressures, particularly under high-load conditions. The subsequent cooling of this compressed air in the Charge Air Cooler (*CAC*) is a critical step, as it substantially increases the charge air density and simultaneously lowers the peak combustion temperature. This reduction in-cylinder temperature is a primary method for suppressing the formation of NO_x , making the air system indispensable for compliance with IMO Tier III regulations [16].

The gas exchange process, governed by the engine's scavenging method, is equally critical for performance. In modern two-stroke engines, the dominant techniques are uniflow and loop scavenging. Uniflow systems, utilizing piston-controlled inlet ports and central exhaust valves, create a coherent air flow that typically yields superior scavenging efficiency. In contrast, loop scavenging relies on carefully engineered port timing and geometry to direct the air charge. While each design has its features, the completeness of the scavenging process directly influences the quality of the subsequent combustion cycle. Inadequate scavenging air pressure or poor efficiency can lead to residual gas contamination, which impairs combustion, increases fuel consumption and elevates emissions of unburnt hydrocarbons and particulates [15, 17].

1.1.3. Lubrication subsystem

The lubrication subsystem is a critical subsystem engineered to minimize friction, manage heat and protect engine components from wear and corrosion under extreme operating conditions [18, 19]. It fulfils several vital functions: supplying high-quality lubricant to moving parts to transform dry friction into liquid friction, dissipating heat, removing wear debris and providing corrosion protection and sealing [18]. In modern marine engines, this involves a complex arrangement of high-capacity pumps, purifiers, fine filters and in large two-strokes, electronically controlled cylinder oil injection systems.

A primary challenge for the lubrication system is managing contamination and chemical degradation, which are major drivers of engine wear. Key failure modes include [20]:

1. Soot contamination: During prolonged low-load operation, elevated soot levels can lead to abrasive wear if particles agglomerate and anti-wear additives are depleted.
2. Water contamination: Water contamination promotes microbial growth, which breaks down additives and produces corrosive organic acids.
3. Additive depletion: The neutralization of acids formed during the combustion of high-sulfur fuels depletes the lubricant's Base Number (BN). Once BN drops below a critical threshold, wear rates can accelerate significantly.

Consequently, the condition and performance of the lubrication system are central to predictive diagnostics and maintenance optimization. Advanced condition monitoring methods are essential for early fault detection and are a cornerstone of modern predictive maintenance strategies [18, 20]. These data-driven approaches analyze key parameters like oil pressure, temperature and chemical properties to assess system health and enable timely intervention. Furthermore, research into advanced lubrication technologies, such as nanoparticle additives (e.g. SiO_2 , TiO_2), demonstrates their potential to form protective tribo-films, enhance load-carrying capacity and reduce wear by up to 40% in bench tests, offering a promising avenue for extending component life [21]. The modeling of lubrication systems, including the integration of possible faults, provides a critical database for developing sophisticated fault diagnosis and prognosis strategies [22].

1.1.4. Cooling subsystem

The cooling subsystem is a critical thermodynamic subsystem responsible for maintaining optimal operating temperatures across engine components, thereby ensuring structural integrity, controlling thermal stresses and preserving combustion efficiency. Modern marine diesel engines predominantly utilize dual-circuit architecture, separating a High-Temperature (HT) closed freshwater loop from a Low-Temperature (LT) open seawater loop [23]. This design is fundamental for managing heat rejection while mitigating corrosion. The HT circuit, typically maintained at 80–95 °C by thermostatic valves, circulates treated coolant with corrosion inhibitors through the engine block, cylinder liners, cylinder heads and turbocharger casings. This stable, elevated temperature is crucial for maximizing thermodynamic efficiency and reducing the condensation of corrosive acids in the cylinder liner. The LT seawater circuit, serviced by dedicated pumps, rejects this heat to the environment via a central cooler or plate heat exchanger. This physical separation is a primary protective barrier against galvanic corrosion, significantly reducing material degradation rates compared to direct seawater-cooled systems [23, 24].

Despite its robust design, the system is susceptible to several performance-degrading failure modes that have a direct impact on engine performance and fuel economy [25]. Accordingly, the main failure modes are as follows:

1. Fouling: This is a predominant issue with two distinct mechanisms. On the seawater side, biological fouling (e.g. barnacles, mussels) and silt accumulation act as a thermal insulator. On the freshwater side, mineral scaling (e.g. calcium sulfate) can occur. These deposits can reduce the overall heat transfer coefficient (U-value) by 25-40%, forcing the engine to operate at higher temperatures. This thermal inefficiency can directly increase Specific Fuel Oil Consumption (SFOC) by 2-4 [g/kWh] as combustion timing is compromised and mechanical friction increases.

2. Cavitation and corrosion: Cavitation erosion of pump impellers can occur when the Net Positive Suction Head (*NPSH*) falls below the pump's requirement, leading to pitting and failure. Additionally, despite inhibitor treatments, localized corrosion (particularly under-deposit pitting and galvanic corrosion at material interfaces) remains a persistent threat to the longevity of heat exchangers and piping.
3. Component degradation: The failure of thermostatic valves, which regulate the flow between the LT and HT circuits, can prevent the engine from reaching its optimal operating temperature. Similarly, the degradation of elastomeric seals (e.g. gaskets, hoses) over time, accelerated by thermal cycling and chemical breakdown, leads to coolant leaks and system depressurization.

The direct impact of cooling subsystem performance on engine efficiency, emissions and component lifespan makes its monitoring and maintenance a vital research area.

1.1.5. Exhaust aftertreatment subsystem

The exhaust aftertreatment subsystem is a thermally and chemically critical subsystem that manages post-combustion gas flow, recovers waste heat and enables compliance with IMO MARPOL Annex VI emission limits regulation. Core elements include high-temperature exhaust valves and manifolds, exhaust gas economizers/boilers for waste-heat recovery and aftertreatment such as Exhaust Gas Cleaning Systems (EGCS/scrubbers) and Selective Catalytic Reduction (SCR) units [26-28].

A primary function of the modern exhaust aftertreatment subsystem is emissions reduction. Exhaust Gas Cleaning Systems (scrubbers) are widely deployed to control sulfur oxides (SO_x), operating in either open-loop mode using seawater alkalinity or in closed-loop mode with added NaOH, particularly within Emission Control Areas (ECAs). For nitrogen oxides, SCR systems are the leading technology, using a catalyst and aqueous urea injection to achieve the more than 80% reduction required for IMO Tier III compliance. Simultaneously, exhaust gas economizers improve overall plant efficiency by recovering waste heat to generate steam for auxiliary systems [27, 28]. The performance of the exhaust aftertreatment subsystem directly influences fuel efficiency, emissions output and operational reliability, making it a fundamental component of predictive diagnostics and emission control strategies [6].

Understanding marine diesel engines as an integration of the five interdependent subsystems detailed in this chapter (fuel, air, lubrication, cooling and exhaust) enables a systematic approach to performance optimization, fault diagnosis and maintenance planning. This approach allows engineers to pinpoint issues more accurately and respond to abnormal operating conditions and emerging faults faster. As data collection from onboard sensors becomes more challenging, engine simulators provide a foundation for training neural network models to recognize failure patterns and performance monitoring. These models can differentiate between similar symptoms, such as an injector misfire and a turbocharger imbalance. Ultimately, this subsystem-oriented perspective is essential for developing the predictive, intelligent decision support framework that is central to the aims of this dissertation.

1.2. Challenges in performance monitoring and predictive maintenance of marine diesel engines

Implementing robust performance monitoring and predictive maintenance frameworks for marine diesel engines is critically constrained by a harsh and variable operating environment, persistent technical limitations in sensing and data infrastructure and significant economic and organizational

pressures, which collectively undermine data reliability and diagnostic accuracy [6]. The corrosive marine environment, with constant saltwater exposure and sulfuric acid condensation in exhaust systems, aggressively degrades both engine components and the sensors monitoring them, inducing signal drift and premature failure that corrupts the foundational data required for reliable analytics. Furthermore, the dynamic nature of marine operations, characterized by rapid load variations, creates a non-stationary operating regime where transient conditions often mask incipient component wear, generating false alarms in oil debris monitors and vibration analysis that undermine prognostic confidence [29]. Despite the proven potential of predictive maintenance to reduce operational costs by up to 20-30% compared to conventional approaches, budget trade-offs, competing risk priorities and organizational resistance to digital transformation continue to impede investment [30]. Fortunately, recent technological advances are directly addressing these limitations, creating a promising direction for research. Simulation platforms create virtual replicas of physical engines, enable real-time simulation of performance under varying conditions and have demonstrated reductions in false alarms by up to 40% during field trials by providing a contextual baseline for anomaly detection [6].

This landscape of challenges and emerging solutions directly frames the critical research gap this research addresses: the development of a surrogate-assisted, physics-informed and uncertainty-aware decision support framework that balances accuracy, computational efficiency and shipboard practicality by coupling Diesel-RK simulation software baselines with neural network surrogates, fuzzy operator-defined weighting and Multi-Criteria Decision-Making (MCDM) translates conflicting objectives (specific fuel consumption (*SFC*), Nitrogen Oxides Emissions Index (*NO_x*), particulate matter (*PM*) and operational limits) into a single, operating-point recommendation. In addition, an expert system maintenance component that translates abnormalities into transparent diagnostics and predictive, cost-aware interventions, creating more robust and generalizable performance management systems capable of operating reliably despite the harsh, dynamic and data-limited reality of the maritime environment.

1.3. The evolution of intelligent decision support systems in marine engine management

The evolution of Decision Support Systems marks a paradigm shift in marine engine management, moving from conventional static monitoring to intelligent, adaptive and predictive frameworks. Modern DSS integrates high-frequency sensor data with real-time simulations and adaptive algorithms, such as Artificial Neural Networks (ANNs), to dynamically optimize engine performance and predict fuel consumption [31]. The transformation is strengthened by technologies like predictive analytics and integrated sensors, which shift engine management from a reactive maintenance tool to a predictive operational capability.

The Decision Support System operates on three interconnected pillars as follows:

1. Real-time condition monitoring: By combining Artificial Intelligence (AI) based abnormality detection, rule-based diagnostics and expert support, platforms such as Wärtsilä Expert Insight platform help detect issues early and support actions that improve asset efficiency; Wärtsilä reports ~2-5% fuel-efficiency gains and fewer unplanned maintenance events in service agreements using this approach [32].
2. Predictive health monitoring and maintenance: Digital services such as MAN PrimeServ Assist platform combine continuous data acquisition, abnormality detection and expert advisory on the

MAN CEON backbone to prevent failures and reduce unplanned downtime, enabling condition-based maintenance and better maintenance planning [33].

3. Integrated regulatory compliance: DSS are increasingly embedded with regulatory intelligence. Equipment-supplier systems combine emissions-control hardware with monitoring and control to help ships meet MARPOL Annex VI regulations. For example, Alfa Laval PureSO_x scrubbers support SO_x compliance in open/closed/hybrid modes [34].

However, full-scale implementation faces challenges beyond technology. A significant barrier is the industry-wide shortage of skilled personnel capable of deploying and maintaining these advanced systems [1]. Furthermore, successful adoption requires a user-centered design that fulfills operators' basic psychological needs, such as autonomy and competence, to ensure they are motivated to use the decision support systems effectively [35].

Future DSS architectures are trending toward digital twins and AI-enabled predictive analytics [36]. These systems will leverage big data and machine learning to provide deeper insights and greater operational possibilities, while ensuring they support and empower the crew [35, 37].

In my research, DSS is positioned not only as a technological enabler but also as a central pillar in the adaptive management support system, aligning optimization, maintenance and regulatory compliance through integrated decision intelligence.

1.4. Goals of the research

This research aims to develop an end-to-end decision support system for large two-stroke marine diesel engines. This system is designed to provide reliable operational and maintenance guidance under non-stationary, data-limited conditions. The research purposes are the following:

1. To configure and validate a high-fidelity engine model using Diesel-RK software (a full-cycle diesel engine simulation environment) to represent a slow-speed, two-stroke engine across key load points, defining operational constraints [e.g. Tier III emission limits, peak cylinder pressure (P_{max}), maximum pressure rise rate ($dp/d\theta$), exhaust gas temperature (T_{exh})].
2. To construct a Design of Experiments (DoE) over the main control variables: Start of Injection (SOI), Injection Fraction (F), Dwell (D), Common-Rail Fuel Pressure (P_{fuel}) and exhaust valve timings (EVO/EVC) and generate the corresponding Diesel-RK decision matrix (SFC , NO_x , PM).
3. To develop and validate a Neural network surrogate model capable of accurately predicting objectives, from control inputs within the studied operating range.
4. To integrate the surrogate model with Non-dominated Sorting Genetic Algorithm II (NSGA-II) in order to compute constrained Pareto fronts for multiple operating scenarios (e.g. Emission Control Areas compliance vs. open-sea, varying load profiles).
5. To benchmark a suite of Multi-Criteria Decision-Making (MCDM) algorithms (e.g. TOPSIS, VIKOR, PROMETHEE II, TriMetric Fusion) on fixed Pareto sets, assessing rank stability, sensitivity to weights and consensus measures to identify the most robust methods for marine engine trade-offs.
6. To design an operator-defined fuzzy weighting module that maps between (0-10) importance ratings for SFC , NO_x and PM into normalized weights using a Mamdani Fuzzy Logic Module (FLM) with triangular membership functions, ensuring symmetry, dominance limits and trade-off mediation.

7. To integrate the fuzzy weights with the selected MCDM method(s) for scenario-based, operator-centric selection from the Pareto set.
8. To develop a rule-based maintenance/prognostics database that links selected operating points to health indicators (e.g. soot loading, cylinder pressure trends, turbocharger).
9. To formalize diagnostic knowledge and parameters for on-board decision support by providing actionable advice and maintenance scheduling per subsystem (fuel, lubrication, cooling, air, exhaust).
10. To deliver and validate the newly developed DSS software by integrating all computational modules into a single, coherent and fully traceable Decision Support System and to demonstrate system-level performance and decision quality through realistic case studies.

1.5. Added value of the research

This dissertation elaborated a coherent Decision Support System for two-stroke marine diesel engines, bridging the gap between high-fidelity simulation and actionable operational intelligence under non-stationary, data-limited conditions. It moves beyond separated approaches by integrating Diesel-RK physics, a Neural Network surrogate module, NSGA-II based optimization algorithm, Multi-Criteria Decision-Making, an operator-defined fuzzy weighting module and a rule-based maintenance expert into a unified, closed-loop decision support system. Figure 1.2 provides a high-level overview of the newly developed Decision Support System and its condition-aware workflow, showing how monitored engine state is first classified and then followed by either performance optimization (normal condition) or maintenance reasoning (abnormal condition).

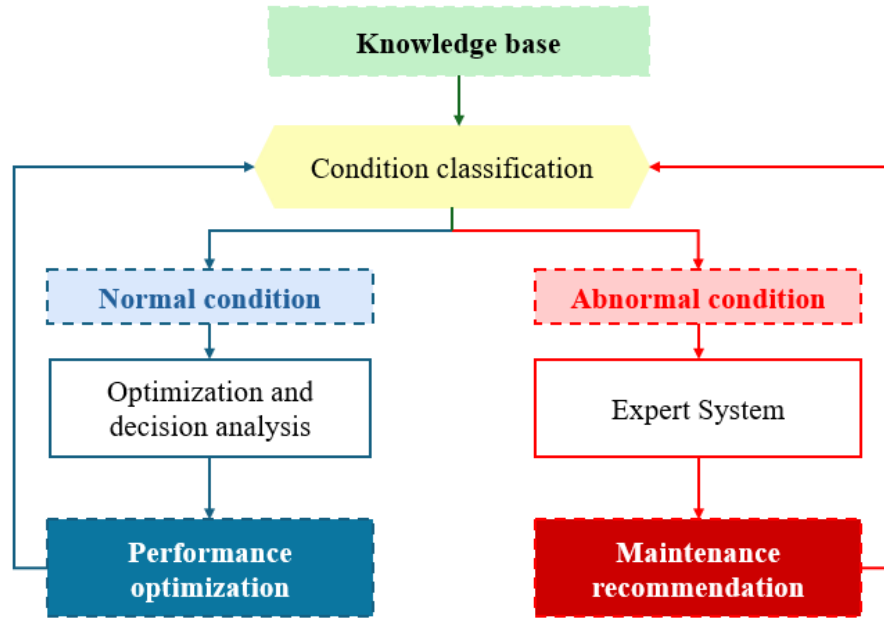


Figure 1.2. High-level architecture of the integrated DSS for two-stroke marine diesel engines

The contribution of the elaborated framework is threefold.

First, it establishes a surrogate-assisted, multi-objective optimization procedure that generates a high-resolution Pareto set of emission–efficiency trade-offs, creating a library of optimal operating alternatives under realistic operating constraints.

Second, it delivers a marine-tailored decision module by 1.) benchmarking fourteen MCDM algorithms on a robust Diesel-RK dataset to identify stable, consensus-aligned ranking behavior and 2.) embedding an operator-centric fuzzy weighting module that enables instant re-ranking of the pre-computed Pareto set as operational priorities shift, thereby avoiding computationally expensive re-optimization while maintaining transparency and explainability for shipboard use.

Third, it provides a health-aware supervisory link between performance optimization and a rule-based expert system link condition indicators with the recommended operating points to issue diagnostic inferences and prescriptive maintenance actions, explicitly connecting short-term control decisions with long-term reliability and life-cycle cost.

Collectively, these innovations constitute a condition-aware and explainable, newly elaborated DSS software with direct practical value. It delivers crew-interpretable guidance, ensures computational viability, provides objective trade-offs and enables predictive maintenance. The result is a fully integrated, holistic performance and maintenance management system elaboration that unifies physics-based simulation, surrogate-assisted optimization, preference-driven decision ranking and rule-based maintenance intelligence into a single operational framework, yielding enhanced safety, improved operational performance and a more predictable, cost-effective maintenance strategy.

1.6. Thesis outlines

Following the introduction, Chapter 2 reviews management support systems for marine diesel engines, covering decision support approaches, MCDM applications and limitations, expert systems for predictive maintenance, surrogate modeling with evolutionary optimization and uncertainty handling in operational decision-making. Chapter 3 develops the surrogate-based multi-objective optimization workflow: Diesel-RK dataset generation, neural network surrogate training and validation, NSGA-II Pareto-front construction for $SFC-NO_x-PM$ trade-offs and Diesel-RK revalidation of selected solutions. Chapter 4 benchmarks fourteen MCDM algorithms for marine applications and identifies the most stable and robust method(s) through consensus and sensitivity analysis, then adapts the selected approach for real-time engine decision support. Chapter 5 introduces the operator-defined fuzzy weighting module and integrates it with the selected MCDM method to enable scenario-aware, preference-driven ranking. Chapter 6 develops the rule-based expert system for predictive maintenance and maintenance planning. Chapter 7 integrates all components into a holistic management Decision Support System. Chapter 8 illustrates the Decision Support System through scenario testing and full numerical examples, including the operational workflow and user interface. Finally, Chapter 9 summarizes the dissertation's main contributions and research implications.

2. LITERATURE REVIEW ON MANAGEMENT SUPPORT SYSTEMS FOR MARINE DIESEL ENGINES

The core challenge in marine diesel engine management is using heterogeneous operational data to find an optimal operating point that balances conflicting objectives. This decision must simultaneously navigate the complex trade-offs between fuel economy and minimizing emissions, all while adhering to the dynamic constraints of IMO Tier III regulations and Emission Control Areas. Consequently, this chapter is structured to analyze the integrated decision-making framework required to solve this multi-objective optimization problem. This chapter follows the end-to-end decision framework. Section 2.1. examines DSS and digital twins that produce validated, ship-specific criteria and constraints; Section 2.2. details surrogate-assisted evolutionary optimization that efficiently maps the Pareto set feeding MCDM; Section 2.3. analyses MCDM methods and categories to translate those criteria into transparent, preference-aware rankings; Section 2.4. addresses uncertainty and parameter robustness, ensuring the final choice remains defensible across operating conditions. Section 2.5. incorporates expert systems for explainable reasoning and predictive maintenance, completing a holistic management framework.

2.1. Decision support systems in marine diesel engines: current trends

The field of marine diesel engine management is increasingly growing with advanced Decision Support Systems that leverage real-time data, simulation models and artificial intelligence to assist operators in optimizing engine performance and maintenance. A prominent trend is the integration of engine simulation models with machine learning to improve the energy efficiency of ships. For example, Karatuğ et al. [31] developed an innovative DSS that combines a high-fidelity engine model (Ricardo Wave) with an Artificial Neural Network (ANN). The system uses historical voyage data to train the ANN offline and the resulting model achieves excellent accuracy (99%) in predicting fuel consumption. This approach enables cost-effective, real-time monitoring of critical engine parameters without extensive new sensor installations, addressing the common challenge of data limitation in ship operations. The DSS provides ship operators with actionable guidance on engine settings to reduce fuel use and emissions during voyages [31]. Such systems illustrate the push towards data-driven optimization for meeting strict fuel economy and emissions targets. Another cutting-edge trend is the adoption of digital twin technology as a core of decision support. A digital twin is a virtual replica of the engine that mirrors its state and performance. Cui et al. [38] highlight that digital twins are emerging as "pivotal innovation" in maritime engineering, offering new ways to enhance engine safety and reliability. This capability supports predictive maintenance and operational decision-making. For instance, forecasting when engine components will wear out or how efficiency will change under different loads. Current research provides roadmaps for integrating digital twins into engine management frameworks to address gaps in conventional monitoring. In practice, companies are beginning to deploy such systems: SIREHNA's ship DSS [39], for example, offers a digital twin-based dashboard for performance simulation and voyage optimization (an approach aligned with Shipping principles). IoT connectivity and cloud platforms enable these DSS to gather fleet-wide engine data, allowing shore-based experts to collaborate with ship crews. Overall, the current trend in marine engine DSS is toward intelligent, connected systems that merge simulation, AI and big data analytics to support decision-making. These innovations are driven by real-world needs for better fuel economy, regulatory compliance and reduced downtime, marking a significant evolution from earlier manual or ad-hoc decision processes.

Beyond performance optimization, DSS are also transforming maintenance strategies, shifting them from reactive to proactive. In the maintenance domain, data-driven decision support emphasizes condition-based and predictive maintenance. Researchers have applied machine learning to predict engine faults or performance degradation before they occur, enabling interventions to be planned in advance. For instance, Maione et al. [40] propose a DSS framework that benchmarks multiple Machine Learning (ML) algorithms for predicting failures in a marine diesel engine's subsystem. In their case study, the system was tested on an engine's oil circuit, where clogging or sub-optimal filtering can lead to engine damage. The results clearly showed that this approach effectively supports predictive maintenance: the DSS achieved high prediction accuracy while identifying the fastest algorithm, confirming that considering both error and speed helps choose the most suitable model for real-time fault prediction. Moreover, the authors demonstrate that the framework is flexible and can be extended to different engine components by using appropriate performance metrics. In essence, such a system can continuously diagnose the engine's condition by comparing these expectations with actual measurements (flagging any significant deviations). This kind of proactive DSS enables ship engineers to receive early warnings of abnormal behavior and schedule maintenance or adjustments before a failure or performance loss escalates.

A variety of AI techniques are being explored to enhance decision support for engine reliability. Knowledge-driven and hybrid approaches are particularly notable. Fuzzy logic is one such technique gaining traction for marine engine management. Babichev et al. [41] developed a fuzzy inference system to determine the current technical state of a marine diesel based on manufacturer-specified criteria. In their implementation for a Wärtsilä 6L46C engine, key operating parameters (e.g. temperatures, pressures, etc.) were input into a Mamdani-type fuzzy model. The output of the system is a continuous health index from 0 to 1 representing the engine's condition. Simulation tests showed that as the input parameters vary from their minimum acceptable values to maximum, the "technical state" index correspondingly shifts from poor condition up to good condition. This range and behavior indicate that the fuzzy inference system is behaving in line with expert expectations, effectively aggregating multiple sensor inputs into a single health score. Such a fuzzy-DSS can support maintenance decisions in a more accurate way than simple alarm thresholds.

Data-driven machine learning methods are also widely used for DSS focused on fault detection and diagnosis. One example is the application of support vector machines in combination with evolutionary optimization. Niu et al. [42] developed a method using a Genetically Optimized Support Vector Machine (SVM). Since real fault data is rare, they trained the model on data from an engine simulator. The optimized system proved highly robust to sensor noise, showcasing the potential of data-driven models to diagnose faults before they become serious.

In addition to technical innovations, researchers are recognizing the importance of integrating business data with physical sensor data in maintenance decision support. Maintenance decisions should ideally balance technical needs with economic and logistical considerations. Parida et al. [43] argued for a fusion of business and physical data in maintenance DSS, noting that traditionally, operations data and maintenance data were separated, blocking optimal decision-making. For example, a DSS that combines equipment condition indicators (vibrations, temperatures, etc.) with information like spare parts availability, repair crew scheduling and cost impact can help prioritize maintenance actions that yield the best business outcome. By harmonizing these, companies can create a single source for asset management. This approach ensures that the DSS recommendations are not only technically sound (e.g. indicating when a component is likely to fail) but also contextually appropriate. In practice, modern fleet management systems are increasingly pulling such diverse data streams into unified dashboards for maintenance planning. The outcome is a more cost-effective and operationally efficient maintenance regime, where both engineering analytics and business intelligence support decisions.

Another major driver of DSS development is the push for energy efficiency and emissions reduction in shipping. Decision support tools are being created to help crews and fleet managers continuously improve fuel economy during operations. Zeng et al. [44] describe a data-driven intelligent energy-efficient management system for ships that demonstrates this trend. Their system incorporates an ensemble machine learning module alongside a physics-based empirical model of the ship's propulsion. In practice, it collects a wide range of voyage data (speed, draft, weather, engine settings, etc.) and uses the hybrid ML-physics model to perform real-time regression analysis on key performance indicators: specifically, the main engine's shaft power output and the fuel consumption rate. By comparing model predictions with actual values and analyzing the influence of each input factor, the DSS can identify conditions or behaviors that are suboptimal for efficiency. Zeng et al. report that after analyzing feature impacts, the system was able to draw valuable conclusions. In summary, these approaches are increasingly reflected in commercial solutions as well. For instance, Kongsberg's EcoAdvisor [45] is a proactive DSS that monitors a vessel's operations and environment, then provides real-time suggestions to crews on how to sail more efficiently (speed profiles, engine settings, etc.).

Overall, current trends in engine management decision support systems can be summarized as a movement toward intelligent, data-centric and collaborative decision-making tools. Modern DSS integrates high-quality simulations with intelligent models to predict performance and detect faults with unprecedented accuracy. These systems incorporate expert knowledge to handle cases where data alone is insufficient or to provide explainable insights. These systems fuse operational sensor data with business and logistical information to ensure decisions are optimal in the broader context of ship operations. And through technologies like digital twins and IoT connectivity, these systems create a bridge between the physical machinery and its virtual counterpart, enabling real-time monitoring, forecasting and optimization across an entire fleet. This is a significant leap from earlier generations of ship operation, where decisions relied heavily on crew experience and periodic reports. With the tightening of emissions regulations and the ever-present drive to reduce costs, the adoption of such advanced DSS is only expected to accelerate. The "smart ship" paradigm is rapidly becoming a reality, fundamentally enhancing how marine diesel engines are managed for safety, efficiency and reliability. Each of these developments contributes to a future where marine engines operate under close to optimal conditions at all times, guided by the insights generated from vast amounts of data, leading to a new era of decision support in maritime engineering.

2.2. Surrogate modeling and evolutionary optimization approaches for marine engine performance

The optimization of marine diesel engines for improved efficiency and reduced emissions is a well-established field of research, increasingly reliant on computational methods and Surrogate-Assisted Evolutionary Algorithms (SAEAs) have emerged as a powerful tool to navigate this complex space [46]. This section reviews the current state of the art of surrogate modeling and evolutionary optimization.

The computational burden of high-fidelity simulation tools necessitates the use of efficient surrogate models. Foundational work by Niu et al. [42] demonstrated the profound computational savings (over 98%) by replacing the high-fidelity simulation model with a trained SVM surrogate model during the multi-objective optimization process. Subsequent research has expanded on this paradigm. Yang et al. [47] successfully employed a Kriging model with NSGA-III and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to optimize a diesel engine for Euro VII compliance, demonstrating the continued relevance of this methodology. Similar multi-fidelity surrogate approaches, such as Co-Kriging combined with NSGA-II, have been developed for

efficiently optimizing offshore engineering structures while balancing computational cost and accuracy [48]. Surrogate-guided multi-objective optimization has also been leveraged in internal combustion engine design, for instance, in optimizing injection parameters and combustion chamber forms using Multi-objective Genetic Algorithm frameworks [49].

Recent advances in surrogate modeling have progressed along different, distinct paths relevant to marine engine optimization. Qu et al. [50] applied Bayesian Neural Networks in marine four-stroke to optimize exhaust gas recirculation (EGR) settings, achieving remarkably high predictive accuracy (coefficient of determination (R^2) ≈ 0.99 , Mean Absolute Percentage Error ($MAPE$) ≈ 2.3 – 3.1%) while enabling power increases of 4.17% , Brake-Specific Fuel Consumption ($BSFC$), reductions of 4.27% and NO_x reductions of 12.37% . Zhang et al. [51] employed eXtreme Gradient Boosting XGBoost surrogates for dual-fuel engine optimization, reporting exceptional predictive performance ($R^2 = 0.9979$ training, 0.9874 testing) and achieving better computational efficiency gains compared to full GT-Power software simulations. The optimized configurations demonstrated $BSFC$ reductions of 17.6 – 28.6% and brake-specific NO_x abatement of 26.8 – 69.1% . Multi-fidelity and ensemble meta-models represent another trajectory, offering substantial computational savings by combining low-cost physics models with sparse high-fidelity evaluations. Wei et al. [52] demonstrated that multi-fidelity meta-modelling for natural gas-hydrogen/diesel dual-fuel engines could reduce overall computation time by up to 50% while achieving hydrocarbon reductions of 46% , NO_x reductions of 68% and thermal efficiency improvements of 5% . Pal et al. [53] developed surrogate-assisted frameworks that explicitly model heteroscedastic noise. When applied to a diesel engine calibration problem, their methods achieved a reduction in the evaluation budget of over 80% by efficiently directing sampling and preventing overfitting to noisy data.

The Non-dominated Sorting Genetic Algorithm II (NSGA-II) is widely recognized as a benchmark Multi-Objective Evolutionary Algorithm (MOEA) for engine optimization due to its effectiveness in handling non-convex, multi-objective spaces [54]. It is particularly well-suited for problems involving a limited number of objectives (typically 2–3), where it demonstrates strong convergence and diversity characteristics.

In contrast, NSGA-III was specifically developed to address the limitations of NSGA-II in many-objective optimization problems (four or more objectives), where maintaining solution diversity becomes increasingly challenging. NSGA-III introduces a reference-point-based selection mechanism that systematically distributes solutions across the Pareto front, making it more appropriate for high-dimensional design spaces such as advanced energy systems or multi-constraint engine optimization problems [55].

NSGA-II continues to dominate two and three objective engine calibration and emissions optimization problems due to its robustness, simplicity of implementation and reliable Pareto diversity generation. Its widespread adoption with Response Surface Methodology (RSM), Gaussian Process Regression (GPR) and Neural Network (NN) surrogates across bench and Computational Fluid Dynamics (CFD) validation studies confirms its practical utility [56 - 59]. However, NSGA-III becomes advantageous when additional competing objectives, such as cost, durability and multi-pollutant trade-offs are simultaneously considered, where NSGA-II may suffer from loss of selection pressure and reduced Pareto front resolution.

The generation of a Pareto front via robust algorithms like NSGA-II is only half the solution. The ultimate goal for an engineer is to select a single, implementable configuration. This is where Multi-Criteria Decision-Making becomes paramount. As highlighted in recent reviews and applications [60 - 63], MCDM methods provide a structured, mathematically rigorous framework for this final selection.

2.3. Applications and limitations of MCDM algorithms in marine engineering

The integration of Multi-Criteria Decision-Making is paramount for translating a Pareto optimal front into a single, implementable configuration for marine diesel engines. While optimization identifies a set of non-dominated solutions, MCDM provides the structured, mathematically rigorous framework necessary to select the final design or operating point by reconciling conflicting objectives [60, 62]. Despite its critical role, the application of MCDM in marine engineering often lacks the systematic robustness found in other engineering fields.

A prevalent limitation can be noticed in current practice in the reliance on a single MCDM method and most commonly TOPSIS. This approach is vulnerable to the inherent biases and mathematical assumptions of the chosen algorithm, as different methods are found on distinct principles for aggregating criteria and measuring preferences. Recent studies have demonstrated that MCDM outputs can be highly sensitive to method design, weight assignment and criterion interdependences [51, 52]. For instance, TOPSIS relies on Euclidean distance measures and assumes independence between criteria, which may misrepresent situations where criteria interact or exhibit compensatory behavior.

Recent advances in marine engine optimization have increasingly integrated surrogate modelling techniques with multi-objective optimization and MCDM, creating end-to-end computational frameworks that bridge simulation, optimization and decision-making. This integration addresses a critical research gap: the need for systematic coupling of surrogate models, optimizers and decision-making processes to create robust, implementable solutions.

Several recent studies exemplify this integrated approach, which are the following:

1. XGBoost and MOEA/D Integration: Zhang et al. [51] demonstrated an efficient optimization framework for dual-fuel marine engines using eXtreme Gradient Boosting (XGBoost) surrogate modelling coupled with Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) and CV-TOPSIS (a TOPSIS variant). The XGBoost surrogate achieved very high predictive accuracy ($R^2 > 0.95$) when calibrated against GT-Power simulations and experimental data, enabling a computational speed up of over 10 times while maintaining reliability. The framework achieved simultaneous reductions of 17.6–28.6% in *BSFC* and 26.8–69.1% in brake-specific Nitrogen Oxides Emissions Index across different engine loads, demonstrating the practical viability of surrogate-based optimization with MCDM ranking for final solution selection [51].
2. GWO-tuned SVR for Dual-Fuel Engines: Wei et al. [52] integrated CFD simulations with Grey Wolf Optimizer (GWO) algorithm, Support Vector Regression (SVR) surrogates, Multi-Objective Grey Wolf Optimization MOGWO and entropy-weighted TOPSIS for marine methanol-diesel dual-fuel engine optimization. The GWO-tuned SVR achieved $R^2 > 0.95$ across performance metrics and the entropy weighting approach reduced subjective bias in TOPSIS criterion weighting. The optimized configuration achieved 26.2% NO_x reduction and 13.4% improvement in Indicated Specific Fuel Consumption (*ISFC*) compared to baseline operations [52].
3. Bayesian Neural Networks for EGR Systems: Qu et al. [50] employed Bayesian Neural Network surrogates within NSGA-III optimization for a marine four-stroke engine EGR system. The Bayesian approach provided uncertainty-aware predictions that enhanced optimizer reliability, while TOPSIS facilitated final decision-making from the Pareto front. The verified optimal solution achieved +4.17% power increase, -4.27% *BSFC* reduction and -12.37% NO_x reduction, with AVL-BOOST software engine simulations [50].
4. ANN Integration: Nutakki et al. [64] applied ANN surrogates within NSGA-II optimization for a novel heat integration system integrated with marine engines generating liquefied hydrogen. The framework optimized efficiency and CO_2 emissions at the system level (not merely cylinder

metrics), with TOPSIS used for final working-fluid selection. This work demonstrates the extensibility of surrogate-MCDM frameworks beyond single-engine optimization to coupled marine thermal systems [64].

These before mentioned studies collectively demonstrate a methodological trend toward Neural Network Surrogate and systematic integration of surrogate-optimizer-MCDM frameworks that reduce computational cost while maintaining decision fidelity.

MCDM methods have been validated in various engineering contexts [65, 62], including the newly introduced TriMetric Fusion method [61]. In marine engine applications specifically, several landmark studies have established the utility of these methods, which are the following:

1. **Pre-injection Strategy Optimization:** Rodríguez et al. [60] conducted a systematic study on the Wärtsilä 6L 46 four-stroke marine diesel engine using three well-established MCDM methods, Weighted Sum Method (WSM), Weighted Product Method (WPM) and TOPSIS. This study evaluated 125 pre-injection scenarios using CFD simulations validated against sea trial data. Linear max, linear sum, vector and logarithmic normalization methods provided consistent optimal pre-injection configurations. The selected configuration achieved 34.7% reduction in NO_x emissions with only 6.7% increase in specific fuel consumption, demonstrating a favorable emissions-performance trade-off [60]. However, the study also revealed that pre-injection strategies achieving up to 24% NO_x reduction simultaneously increased CO emissions by 7.6% and raised SFC by 23.5% due to lower peak pressures, highlighting the multi-dimensional nature of optimization trade-offs [60].
2. **Powertrain-Level Applications:** MCDM has been applied at both subsystem and propulsion-architecture levels in marine powertrains. Interval type-2 fuzzy VIKOR (VISeKriterijumska Optimizacija Kompromisno Resenje) has ranked alternatives for auxiliaries of ship main diesel engines under uncertain, linguistic criteria [66]. At the plant/architecture level, Nazemian et al. [67] employed Analytic Hierarchy Process (AHP) for weighting and Measurement of Alternatives and Ranking according to Compromise Solution (MARCOS) for ranking to evaluate hybrid/battery and alternative-fuel power management topologies for bulk carriers against techno-economic and operational criteria, providing structured multi-criteria decision analysis to inform strategic powertrain choices under regulatory pressure [67]. Additionally, multi-criteria frameworks have compared diesel-mechanical and diesel-electric options across cost, environmental impact and risk dimensions [68].

The MCDM field is rapidly advancing, as evidenced by recent contributions from Quevedo-Reina et al. [69] on complex ANN surrogates for offshore structures and Nickabadi et al. [70] on Kriging (Gaussian process regression) surrogate modelling for ship propulsion shafts. Recent works have explored multi-objective performance optimization in marine diesel engines, incorporating trade-offs between fuel efficiency and emissions reduction. The comprehensive survey prepared by Cruz et al. [71] correctly identifies key challenges in managing uncertainty and computational scalability in dynamic (non-stationary) optimization settings.

Despite recent progress in MCDM supported engine decision frameworks for marine applications, few critical gaps remain in current research and practice, as follows:

1. **Lack of Multi-Method Comparison:** Most studies employ a single MCDM method (typically TOPSIS) without systematic comparison across multiple algorithms to assess ranking stability and method-dependent bias [51, 52].
2. **Limited Two-Stroke Engine Focus:** Most prior studies have focused on four-stroke engines, leaving two-stroke marine engines (critical for deep-sea shipping) less studied despite their distinct operational characteristics and optimization challenges.

The selection of the appropriate MCDM method for marine applications is not trivial. The literature distinguishes between Scoring-Based, Distance-Based, Pairwise Comparison, Outranking and

Hybrid/Intelligent Systems-Based categories. Depending on how they handle trade-offs, aggregate criteria and derive rankings [62, 65]. These categories differ in their mathematical foundations, assumptions and practical implications for decision-making [62, 65].

Multi-Criteria Decision-Making frameworks offer a mathematically structured means of navigating complex decision environments. MCDM does not seek to produce a single "correct" answer. Instead, it provides a formal structure for aggregating diverse economic, environmental and operational criteria while acknowledging that preferences, trade-offs and uncertainties must be explicitly modelled rather than assumed. However, the multiplicity of available MCDM algorithms introduces a practical challenge: different methods can lead to different rankings for the same dataset. This divergence is not due to computational error but from each algorithm's underlying assumptions regarding distance metrics, normalization, compensatory behavior and preference aggregation. As such, algorithm selection must be aligned with the structure of the decision environment and the nature of the trade-offs involved.

2.4. Handling uncertainty and parameter optimization in marine engine management

Traditional MCDM approaches in marine engineering have relied heavily on fixed-weight methods that assume precise quantification of operator preferences. However, recent advances in linguistic decision-making have shown significant promise for handling the inherent imprecision in operator evaluations. Shi et al. [58] use a 2-tuple linguistic DEMATEL (Decision-Making Trial and Evaluation Laboratory) method to rank marine diesel engine maintenance practices by turning uncertain, linguistic expert judgments into a causal–effect structure of 32 practices. The approach allows experts to express opinions in words while the model provides precise numerical processing and aggregates multiple experts, making it suitable for complex trade-offs involving emissions, fuel efficiency and reliability.

Fuzzy Analytic Hierarchy Process (Fuzzy-AHP) has emerged as another powerful approach for handling linguistic preferences in marine engineering applications. The methodology addresses the cognitive burden of traditional AHP by using fuzzy sets to represent the inherent uncertainty in human judgment, with singleton membership functions that capture expert assessments across multiple criteria. This approach has been efficient for scenarios where decisions must balance multiple performance characteristics under uncertain operating conditions [72, 73]. The integration of Taguchi methodology with MCDM approaches has emerged as a powerful paradigm for handling uncertainty in marine diesel engine optimization. Recent work by researchers developing a Taguchi-based hybrid MCDM approach for diesel engine optimization [74] demonstrated significant advances in handling uncertainty through the MEREC-MARCOS methodology. This integrated approach combines the Taguchi method for experimental design with the MEREC (Method based on Removal Effects of Criteria) and MARCOS (Measurement Alternatives and Ranking according to COmpromise Solution) methods, providing a comprehensive framework for multi-criteria optimization under uncertainty. The methodology proved particularly effective for addressing uncertainty in diesel engine optimization, achieving optimal performance characteristics while accommodating variations in operating conditions and fuel properties.

Objective weighting methods such as Entropy and CRITIC (Criteria Ranking by Intercriteria Correlation) methods offer systematic alternatives to subjective preference assessment, particularly valuable when expert knowledge is limited or when consistent operator preferences cannot be assumed. These methods derive weights directly from the decision matrix data, eliminating human bias while providing a mathematically sound criteria importance assessment. However, recent studies have revealed significant limitations in marine applications [75, 72].

Research on marine diesel injection optimization has shown that Entropy and CRITIC methods can yield divergent optimal solutions that may not align with operational priorities. In comparative studies, CRITIC heavily prioritized NO_x emissions while Entropy favored Specific Fuel Consumption (*SFC*), demonstrating that objective methods, while mathematically rigorous, may produce results that conflict with practical marine engineering requirements [63]. This divergence highlights the critical need for integrated approaches that combine the mathematical rigor of objective weighting with domain expertise and operational context. Although fuzzy theory is recognized as a robust framework for handling imprecision, a survey of maritime MCDM shows that many studies still default to fixed weights or ad-hoc numerical conversions of linguistic terms, leaving a critical research gap in systematically ensuring robustness under preference uncertainty [76].

2.5. Expert systems for predictive maintenance in marine engines

Expert systems represent a class of knowledge-driven decision support systems that emulate human diagnostic reasoning and they have established a long-standing history in marine engine maintenance applications [77]. In the last five years, their role has evolved significantly with the integration of data-driven elements, but the core principle remains: capture the expertise of marine engineers in a system that can advise on fault diagnosis and maintenance actions. Modern marine engine expert systems are increasingly deployed for predictive maintenance, aiming to detect incipient faults and recommend preventative actions before catastrophic failures occur. Recent advances in expert system architectures for marine engines have focused on hybrid designs that combine traditional rule-based reasoning with modern machine learning techniques [78]. The evolution of expert systems has been particularly notable in the integration of evidential reasoning frameworks and knowledge based approaches, as documented in comprehensive surveys of prognostic and health management systems [79]. These systems address critical challenges in marine diesel engine diagnostics through sophisticated uncertainty handling and adaptive learning mechanisms.

One of the most significant recent developments in marine engine expert systems is the evolution of the Belief Rule Base (BRB) methodology, introduced by Xu et al. [80] and subsequently enhanced by several research groups. The BRB system represents a sophisticated approach to fault diagnosis that combines multiple rule subsystems, each utilizing evidential reasoning to infer fault probabilities with calibrated uncertainty quantification. Recent research by Ming et al. [81] introduced the BRB-P (Belief Rule Base with Probability Table) method, which addresses critical limitations of traditional BRB systems in marine applications. This enhanced approach incorporates interpretability constraints, including credibility of expert knowledge, penalty factors and rule-activation factors during optimization. A revolutionary advancement in expert system design for marine engines is the development of knowledge graph-based reasoning systems. The adaptive causal path reasoning model for marine diesel engine fault diagnosis introduced by Shen et al. [82] represents a significant leap forward in interpretable fault diagnosis. This system addresses critical limitations in traditional expert systems by providing explainable multi-hop reasoning paths that follow a three-hop causal chain: fault, the cause and then the recommendation.

Modern marine engine expert systems increasingly employ hybrid architectures that combine symbolic reasoning with data-driven learning. These hybrid systems address the knowledge acquisition bottleneck that has traditionally limited expert system deployment by incorporating machine learning components that can update knowledge bases automatically. The hybrid approach has been particularly effective in addressing the challenge of novel failure modes. Unlike pure expert systems that struggle with scenarios outside their rule base, hybrid systems can learn from new data while maintaining the interpretability of traditional expert systems. This is achieved through

techniques such as Self-Organizing Maps for feature extraction combined with expert system analysis of higher-level features, as documented in recent marine engineering applications [83].

Expert systems remain a cornerstone of predictive maintenance for marine engines, providing explainable, expert-like reasoning for fault diagnosis and maintenance decision support. Recent advances in belief rule-based systems, knowledge graph-based reasoning and hybrid architectures are significantly enhancing their effectiveness. The integration of these systems positions expert systems as essential components of intelligent marine engine management systems. As the maritime industry continues to embrace marine industry principles, expert systems are evolving to become more adaptive, explainable and integrated with data-driven learning capabilities, ensuring their continued relevance in predictive maintenance applications.

This chapter has provided a critical review of the literature related to management support systems for marine diesel engines, tracing the integrated decision-making framework from high-fidelity simulation and surrogate-assisted optimization to multi-criteria decision-making and predictive maintenance. The review confirms a strong trend towards intelligent, data-driven systems that leverage digital twins, AI and evolutionary algorithms to navigate the complex trade-offs between fuel economy, emissions and reliability. However, the review of literature studies points out research gaps, particularly concerning the development of a holistic, robust and practically implementable decision support framework for large two-stroke marine diesel engines. The existing research gaps can be summarized as follows:

1. Lack of fully integrated framework: while individual components like surrogate modelling, NSGA-II and MCDM are well-researched separately, there is a shortage of studies that seamlessly integrate them into a closed-loop system.
2. Insufficient focus on two-stroke engine specifics: the majority of surrogate-MCDM studies focus on four-stroke or automotive engines. There is a distinct lack of research dedicated to the unique operational characteristics and control variables of slow-speed two-stroke engines, which form the backbone of international shipping.
3. Comprehensive MCDM benchmarking selection: most studies rely on a single algorithm (typically TOPSIS) without a systematic, comparative benchmark of multiple methods (e.g. TOPSIS, VIKOR, PROMETHEE, TriMetric Fusion) to assess their robustness, rank stability and consensus for marine-specific trade-offs.
4. Static and non-transparent decision-making in dynamic environments: current MCDM implementations in marine engineering often utilize fixed, pre-defined weights, failing to accommodate the dynamic and subjective nature of operator priorities at sea. There is a critical need for an intuitive, fuzzy logic-based weighting module that allows operators to express preferences dynamically for conflicting objectives, ensuring the final operating point recommendation is both optimal and context-aware, while maintaining complete transparency for the crew.
5. Disconnect between performance optimization and predictive maintenance: although performance optimization and predictive maintenance are both active research areas, these are often treated as separate directions. Explicitly linking the selected optimal operating points to component health indicators and prognostics.

These identified gaps collectively frame the research opportunity addressed in this dissertation: the development of a novel, surrogate-assisted and uncertainty-aware decision support system that bridges these divides.

3. SURROGATE-BASED MULTI-OBJECTIVE OPTIMIZATION OF MARINE DIESEL ENGINE PERFORMANCE

This chapter demonstrates the development of the surrogate-based optimization module of the elaborated management support framework. The central methodological challenge involves reconciling the computational expense of a high-fidelity thermodynamic model of a two-stroke marine diesel engine. Accordingly, to enable fast objective evaluation during the optimization, a data-driven surrogate model, based on a Neural Network (NN), is developed to emulate the behavior of a high-fidelity two-stroke marine diesel engine model. This NN surrogate is trained on a systematically generated dataset, enabling it to approximate the engine's response to key control parameters with significantly reduced computational time. Subsequently, the validated surrogate model is integrated into the NSGA-II evolutionary algorithm to perform a constrained multi-objective optimization. This process demonstrates the trade-off Pareto front related to Specific Fuel Consumption (SFC) to emission indices of Nitrogen Oxides (NO_x) and Particulate Matter (PM), all within defined operational and regulatory constraints.

Consequently, this chapter establishes the methodological foundation for performance optimization of the two-stroke marine diesel engine studied in this dissertation. It formalizes a mapping from a compact set of practically adjustable control variables, including Start Of Injection (SOI), Fuel Mass Fraction (F), Dwell Time (D), Common-Rail Fuel Pressure (P_{fuel}), Exhaust Valve Opening (EVO) and Exhaust Valve Closing (EVC), to multiple, often conflicting, performance indicators. The resulting Pareto front constitutes a library of technically feasible, non-dominated operating strategies. This library serves as the essential input for the subsequent decision-making components of this dissertation, specifically the multi-criteria ranking and fuzzy preference adaptation modules developed in later chapters.

Figure 3.1. summarizes the workflow used to construct the Pareto front, from Diesel-RK dataset generation to NN surrogate training and validation. The trained surrogate is then embedded in NSGA-II to obtain the non-dominated Pareto front solutions.

The chapter is organized into five sections. Section 3.1. introduces the representative low-speed two-stroke marine diesel engine, defines the six key controllable parameters and summarizes the Diesel-RK high-fidelity thermodynamic and emission software used in this work. Section 3.2. details the construction of the design space, the Latin Hypercube sampling and subsequent full-factorial refinement in Diesel-RK software to obtain the final dataset for surrogate training. Section 3.3. presents the Neural Network surrogate, including its structure, data partitioning and training procedure. Section 3.4. formulates the constrained multi-objective optimization problem and specifies the NSGA-II configuration and workflow employed to search the six-dimensional control space. Finally, Section 3.5. reports the case-study results, including quantitative validation of the surrogate model and analysis of the NSGA-II Pareto front, from which representative operating strategies are derived for use in the subsequent decision support chapters.

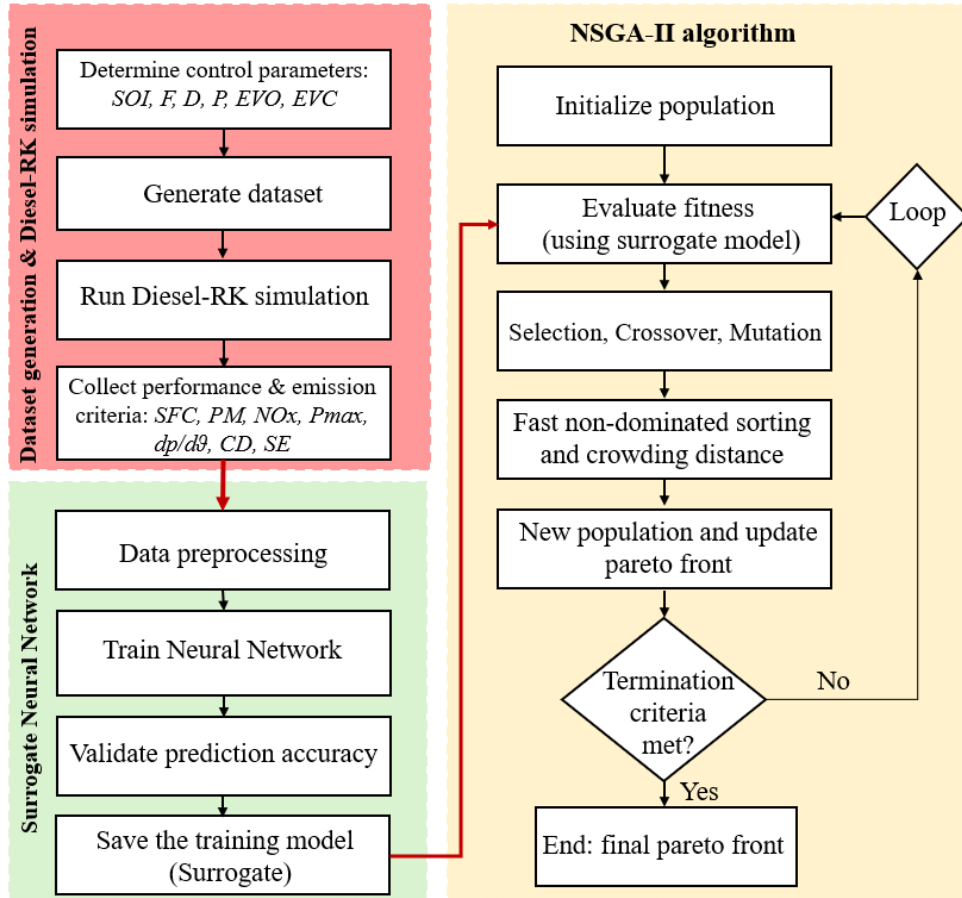


Figure 3.1. Flowchart of surrogate NN multi-objective optimization

3.1. Identifying key controllable parameters of marine diesel engine and Diesel-RK simulation design space

The study investigates a two-stroke, low-speed marine diesel engine using a virtual S60-class model calibrated on S60MC-C8.8 reference data and used as a proxy for the MAN B&W S60-MC-C8-8 series. This engine is a benchmark design for ocean vessels due to its combination of high efficiency, operational flexibility and suitability for advanced research. The key characteristics of the selected low-speed two-stroke engine include:

1. High thermal efficiency: exceeding 50% at optimal load, which is crucial for reducing fuel consumption and operational costs.
2. Superior scavenging control: the uniflow scavenging process offers improved gas exchange efficiency and controllability compared to other methods (e.g. loop scavenging), leading to better cylinder charging and lower emissions.
3. Fuel flexibility: compatibility with a wide range of fuels, including Heavy Fuel Oil (HFO), Marine Diesel Oil (MDO) and Liquefied Natural Gas (LNG) in diesel dual-fuel modes, allowing for adaptation to fuel availability and environmental regulations.
4. Advanced combustion control: the integration of electronically controlled, common rail fuel injection and low-speed operation (85–105 RPM) provides a stable and extended time window for combustion, making this engine an ideal platform for parametric studies. Specifically, allowing for detailed investigation of:

- fuel injection strategies, such as timing, pressure and split injections, which are critical for optimizing performance and meeting emission standards;
- exhaust valve timing, including the impact of valves opening and closing on scavenging efficiency, combustion phasing and pollutant formation.

3.1.1. Selection and definition of controllable engine parameters for the studied marine engine

The elaborated module targets control-oriented optimization rather than hardware redesign. Consequently, the control parameters varied within the simulations were selected based on their practical adjustability in real engine operation. Accordingly, the following six parameters were selected and varied within the simulation space:

1. **Start of Injection (*SOI*)**: measured in Crank Angle Degrees Before Top Dead Center [$^{\circ}\text{CA-BTDC}$], it defines when fuel injection begins during the engine cycle. Advancing or delaying *SOI* influences ignition delay and the degree of premixed combustion, which in turn affects NO_x emissions.
2. **Fuel Mass Fraction (*F*)**: this parameter defines the proportion of fuel allocated to the pilot injection event, measured in percentage of the full injected fuel [%]. It was varied to study how splitting the fuel dose between a small pilot and a larger main injection impacts combustion characteristics, including the formation of *PM* and NO_x .
3. **Dwell Time (*D*)**: this is the time interval between the pilot and main injection events, measured in Crank Angle degrees [$^{\circ}\text{CA}$].
4. **Common-Rail Fuel Pressure (P_{fuel})**: this parameter controls how forcefully fuel is injected into the combustion chamber, measured in bar. Higher pressures improve atomization (breaking the fuel into finer droplets), which enhances combustion efficiency and reduces particulate formation.
5. **Exhaust Valve Opening (*EVO*)**: measured in Crank Angle Degrees relative to Bottom Dead Center [$^{\circ}\text{CA-BBDC}$].
6. **Exhaust Valve Closing (*EVC*)**: measured in Crank Angle Degrees relative to Bottom Dead Center [$^{\circ}\text{CA-ABDC}$]. Adjusting the values timing changes the effective compression ratio and the engine's scavenging efficiency, affecting residual gas levels and emission behavior.

These six variables provide an expressive and practical control space, capturing the principal mechanisms governing efficiency and emissions while being directly accessible via modern engine control systems.

The parameter limits for the surrogate based optimization was rigorously defined through a synthesis of engineering specifications and regulatory frameworks. The limits were set using:

- manufacturer's operational limits: primarily from MAN Diesel technical documentation and Diesel-RK guidelines, which constrain peak cylinder pressure (P_{max}), maximum pressure-rise rate ($dp/d\theta$) and allowable injection and valve timings (*EVO/EVC*) [11, 13, 33, 84];
- regulatory emission limits, in particular the IMO MARPOL Annex VI Tier III requirements on emissions limits Nitrogen oxides (NO_x) and typical research-level limits on Particulate Matter (*PM*) [85];
- prior experimental and simulation studies on similar low-speed marine engines provide realistic envelopes for injection fraction (*F*), Common-Rail Fuel Pressure (P_{fuel}) [86].

Within these limits, the design space is constructed by varying the before mentioned six key engine control parameters. Each parameter is discretized on a uniform grid that reflects both realistic actuator resolution and simulation feasibility. The extracted ranges and discretization are summarized in Table 3.1.

Table 3.1. Design space for engine simulation and surrogate-based optimization

Parameters	Range	Unit	Step size	Number of steps
Start of Injection (SOI)	1° to 8°	[°CA-BTDC]	1°	8
Fraction per Injection Event (F)	1 to 12	[%]	1	12
Dwell Time (D)	1° to 5°	[°CA]	1°	5
Common-Rail Fuel Pressure (P_{fuel})	600 to 1000	[bar]	50	9
Exhaust Valve Opening (EVO)	60° to 74°	[°CA-BBDC]	2°	8
Exhaust Valve Closing (EVC)	100° to 130°	[°CA-ABDC]	5°	7

A full factorial exploration of this design space yields **241,920** unique input configurations, computed as $(8 \cdot 12 \cdot 5 \cdot 9 \cdot 8 \cdot 7 = 241,920)$ distinct engine configuration cases.

A full exploration of the design space **241,920** engine configuration of input parameters, presenting a significant computational demand. To thoroughly but efficiently explore the design space, I used the Latin Hypercube Sampling (LHS) method, generating 500 representative cases. Unlike random sampling, LHS is a statistical method that ensures balanced coverage by dividing each parameter into equal intervals and selecting one sample per interval [93]. This approach minimizes the uneven sampling density and captures the full range of possible scenarios, making our analysis both computationally efficient and statistically robust [93].

Mathematically, the input range of each control parameter is divided into N non-overlapping intervals of equal probability. One value is randomly selected from each interval. The applied LHS method reduces variance and improves coverage efficiency. The sampled 500 configuration results were analyzed in alignment with a set of regulatory, operational and combustion stability limits, which are as follows:

1. **Specific Fuel Consumption (SFC):** Specific Fuel Consumption is the fuel mass required to deliver a unit of useful mechanical energy output. Equivalently, it is the fuel mass flow rate normalized by delivered mechanical power output, commonly reported in [kg/kWh] or [g/kWh].

$$SFC \leq 0.2 \text{ [kg/kWh]}$$

2. **NO_x Emissions Index:** The NO_x Emissions Index is the mass of total nitrogen oxides emitted per unit useful mechanical energy output, expressed in [g/kWh]. In marine compliance terminology, " NO_x emissions" are defined as the total emission of nitrogen oxides, calculated as a total weighted emission expressed as NO_2 equivalent, determined using prescribed test cycles and measurement methods.

IMO MARPOL Annex VI Regulation 13 Tier III for engines with rated speed less than 130 [rpm]:

$$NO_x \leq 3.4 \text{ [g/kWh]}$$

3. **Particulate Matter (PM) Emissions:** PM Emissions are the mass of particulate matter in the exhaust per unit useful mechanical energy output, expressed in [g/kWh].

$$PM \leq 0.15 \text{ [g/kWh]}$$

In addition, to ensure physically realistic and mechanically safe operating conditions, the following limits are imposed:

4. **Combustion Duration (CD):** Combustion Duration is the crank-angle interval over which the main fraction of fuel energy is released. Setting limits to CD prevents unrealistically slow/late combustion (efficiency loss, higher exhaust temperatures) and unrealistically fast combustion (noise/harshness), keeping the optimization results within a stable combustion.

$$35 \leq CD \leq 45 \text{ [°CA]}$$

5. **Peak Cylinder Pressure (P_{max}):** Peak Cylinder Pressure is the maximum instantaneous in-cylinder pressure reached over the engine cycle.

$$P_{max} \leq 170 \text{ [bar]}$$

6. **Maximum Pressure Rise Rate ($dp/d\theta$):** Pressure Rise Rate is the rate of change of in-cylinder pressure with crank angle.

$$dp/d\theta \leq 4 \text{ [bar/°CA]}$$

7. **Synthetic Emission Index (SE):** Synthetic Emission Index is a composite emissions objective used to represent the NO_x –PM trade-off (and in some formulations also fuel consumption) by normalizing pollutants by reference/target values and combining them with weights/exponents. SE value is added via Diesel-RK's internal formulation to capture the NO_x –PM trade-off during combustion [94]. The detailed formulation of SE used in Diesel-RK software is provided in Section 3.4.3, see Equation (3.6).

The feasible cases were analyzed following the initial simulation to identify refined parameter ranges that maintained engineering relevance and regulatory compliance while reducing the decision space for subsequent high-resolution optimization within the MCDM framework.

Table 3.2. summarizes the new ranges of the control parameters used in this dissertation. The ranges were adjusted to ensure regulatory compliance, combustion stability and physical realism within a two-stroke marine diesel engine context. The adjustments were guided by the above-mentioned set of regulatory, operational and combustion stability limits. In addition to specific constraints, such as avoiding excessive peak cylinder pressure (P_{max}), maintaining efficient scavenging and minimizing emissions (NO_x , PM).

Table 3.2. Control parameter new ranges

Parameters	Unit	Original range	New adjusted ranges	Step size	New number of steps
Start of Injection (SOI)	[°CA-BTDC]	1° to 8°	1° to 5°	1°	8
Fraction per Injection Event (F)	[%]	1 to 12	1 to 8	1	12
Dwell Time (D)	[°CA]	1° to 5°	2° to 5°	1°	5
Common-Rail Fuel Pressure (P_{fuel})	[bar]	600 to 1000	700–950	50	9
Exhaust Valve Opening (EVO)	[°CA-BBDC]	60° to 74°	62° to 68°	2°	8
Exhaust Valve Closing (EVC)	[°CA-ABDC]	100° to 130°	110° to 125°	5°	7

A subsequent full-factorial Diesel-RK campaign over the adjusted ranges in Table 3.2. yielded **15,360** simulated operating points ($5 \cdot 8 \cdot 4 \cdot 6 \cdot 4 \cdot 4$). All cases satisfying the above physical and regulatory constraints were retained, forming the final dataset for surrogate training. The refined dataset of 15,360 feasible cases was retained for training the surrogate model. This dataset captures the nonlinear interactions between control parameters and engine performance outputs, forming the foundation for subsequent machine learning and optimization stages.

Practical surrogate model training not only depends on architecture selection but also on the quality and representativeness of the processed dataset. Transitioning from large, raw simulation datasets to more refined, "smart" data through normalization and feature scaling ensures balanced learning and prevents bias toward variables of higher magnitude. Similar concepts are emphasized in recent work on gradient-based optimization approaches for machine learning, which highlight the role of structured data preparation and tailored optimization strategies in improving convergence and model generalization [95].

3.1.2. Application of the Diesel-RK simulation software for the studied marine engine

The high-fidelity thermodynamic engine model used in the dissertation is constructed using the Diesel-RK software, version v4.189, a dedicated simulation tool for internal combustion engines [94]. Its application is justified by its ability to resolve the coupled physics of in-cylinder thermodynamics, gas exchange processes and emission formation, which are critical for the selected low-speed two-stroke marine diesel engine. This section outlines the key physical sub-models within Diesel-RK to establish a clear understanding of the simulated performance indicators and inherent limitations, thereby providing context for the subsequent surrogate modeling and optimization.

The combustion model in Diesel-RK employs a quasi-dimensional, multi-zone approach. Each fuel spray is discretized into a set of distinct zones that evolve along their penetration paths. This framework simulates the transient processes of liquid fuel injection, primary and secondary breakup, droplet evaporation and turbulent mixing via semi-empirical correlations calibrated for high-pressure marine diesel sprays. Ignition delay is calculated using an Arrhenius-type correlation dependent on local temperature and pressure conditions. The subsequent heat release rate is computed as a combined contribution from an initial premixed combustion phase and a subsequent diffusion-controlled burning phase. A Woschni-type model governs convective heat transfer between the combustion zones and the cylinder walls. At the same time, the thermodynamic state of each zone is advanced by applying the first law of thermodynamics. Crucially, by resolving individual spray plumes instead of assuming a perfectly homogeneous charge, this approach captures the sensitivity of critical parameters (such as peak cylinder pressure, pressure-rise rate and NO_x formation) to control variables (such as injection timing, rail pressure and fuel-splitting strategies).

For the gas exchange process, Diesel-RK represents the engine's air-path as an integrated network of control volumes (e.g. cylinder, scavenge and exhaust receivers, turbocharger) connected by flow restrictions.

For the uniflow-scavenged two-stroke engine under study, the opening and closing of the scavenge ports and the exhaust valve are modeled using effective flow areas and discharge coefficients, which allows for the computation of instantaneous mass flow rates as a function of instantaneous pressure differential and crank angle.

The turbocharger is modeled using performance maps for the compressor and turbine, which are dynamically coupled to the engine cylinders through the gas receivers. This integrated approach enables a self-consistent prediction of boost pressure, air-fuel ratio and exhaust gas temperature for each simulated operating point.

For emissions, Diesel-RK software incorporates dedicated phenomenological sub-models for predicting key emissions. NO_x formation is primarily computed via the extended Zeldovich mechanism [94], applied to the high-temperature burned gas zones identified by the combustion model.

For PM , a semi-empirical formation-oxidation model is employed [94]. In this model, the net soot mass is determined by the competing rates of soot production (dependent on local equivalence ratio and temperature in fuel-rich regions) and soot oxidation (dependent on temperature and residence time in the diffusion flame). While Diesel-RK offers multiple soot model parameterizations, the present work employs a single, fixed formulation across all simulations. This ensures that any relative change in predicted PM emissions can be connected to the variations in the controllable input parameters.

Diesel-RK high-fidelity results serve a dual purpose in the dissertation: it constitutes the target data for training the neural network surrogate model and define the objective functions and constraints for the subsequent multi-objective optimization.

3.2. Dataset generation for the studied marine diesel engine using Diesel-RK

Diesel-RK has been widely applied and validated in academic and engineering contexts for evaluating diesel engine performance and emissions, offering high predictions under various fuel types and operating conditions [87-91].

Figure 3.2. shows representative some of Diesel-RK setup windows used to define the operating mode and boundary conditions, configure and calibrate the different sub-systems.

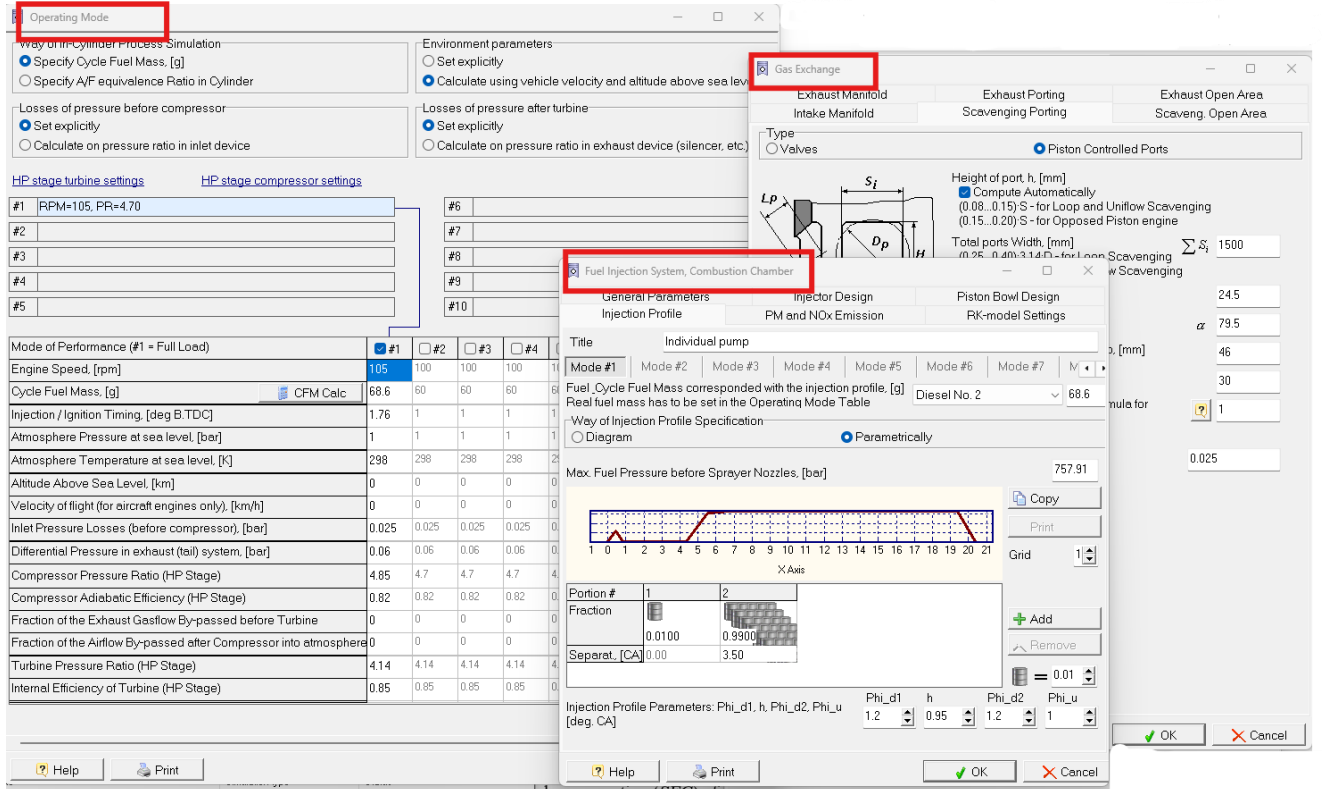


Figure 3.2. Diesel-RK interfaces for operating modes, gas exchange and fuel system calibration

To accurately characterize and optimize the operational performance of a two-stroke marine diesel engine. The simulation setup was calibrated to full-load conditions, producing a piston engine power

of 19,003 kW at 105 rpm, with a brake mean effective pressure (P_{mep}) of 20 bar and Specific Fuel consumption (SFC) of 0.1819 kg/kWh.

To represent the fuel injection process in this simulation, an approximate injection profile was created by combining data from three prototype injector systems, labeled System A, B and C in Figure 3.3. These three injector systems are used to approximate realistic injection behavior. The resulting experimental diagram is typical and it was used in combustion model calibration in the simulation of spatial interaction of fuel sprays in a combustion chamber of a two-stroke marine diesel engine [92]. As shown in Figure 3.1. the graph plots the fuel injection rate [mg/°CA] with the crankshaft rotation angle [°CA]. The injection event occurs around Top Dead Center (TDC), which is the point of maximum piston compression. Each colored line shows how a single injector delivers fuel over time (A, B, C), which is used to approximate realistic injector behavior. The variations between them represent differences in injector design, such as nozzle hole size or hydraulic flow characteristics. The black line (Sum) combines the effects of all three injectors and represents the total injection profile used in my simulation.

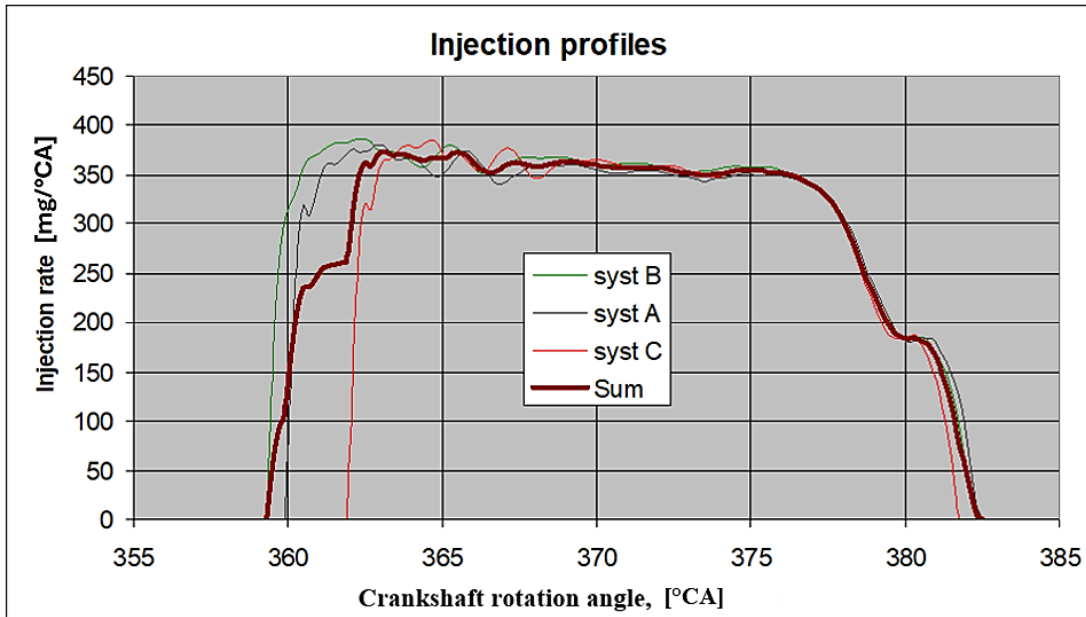


Figure 3.3. Injection profile [own]

While this composite profile was created to mimic a complex, real-world injection event that might involve multiple pilot or main injections, it introduces some margin of error in key simulation outputs, as it can slightly distort the prediction of the Heat Release Rate (HRR) peak. Despite these limitations, the approximation is sufficiently accurate for comparative studies. The use of a consistent, though approximated, injection profile across all simulations is crucial. It ensures that the performance differences between the alternatives are due to the changes in the control parameters and not from random variation in the injection model.

3.3. The elaborated surrogate neural network module for the studied marine engine model

The NN surrogate module was trained using the refined dataset of 15,360 feasible cases (Section 3.1.1.). The dataset was divided into 70% for training (10,639 samples), 10% for validation (1,681 samples) and 20% for testing (3,040 samples). Before training, all six input parameters and seven output metrics were scaled to a common numerical range of $[-1$ to $1]$ using the StandardScaler technique. This step ensures that variables with different units and magnitudes contribute equally to the learning process, preventing the neural network from becoming biased toward features with larger numerical values. The surrogate model itself is a feedforward neural network with 97,863 trainable parameters (weights), meaning it has nearly one hundred thousand adjustable connections that are iteratively optimized during training to accurately map the relationship between engine control settings and performance outcomes. This large number of parameters allows the model to capture complex, nonlinear behaviors of marine diesel engines while maintaining sufficient flexibility to generalize to unseen operating conditions.

Figure 3.4. illustrates the NN architecture for the marine engine surrogate model. The model receives the six control parameters as inputs and processes them through two shared fully connected layers (256 and 128 neurons), each followed by Batch Normalization, ReLU activation and Dropout (0.2). From the shared backbone, seven output heads branch out, each consisting of a hidden layer (32, 32, 64, 32, 64, 128 and 128 neurons) and a final output neuron predicting one of the seven performance metrics.

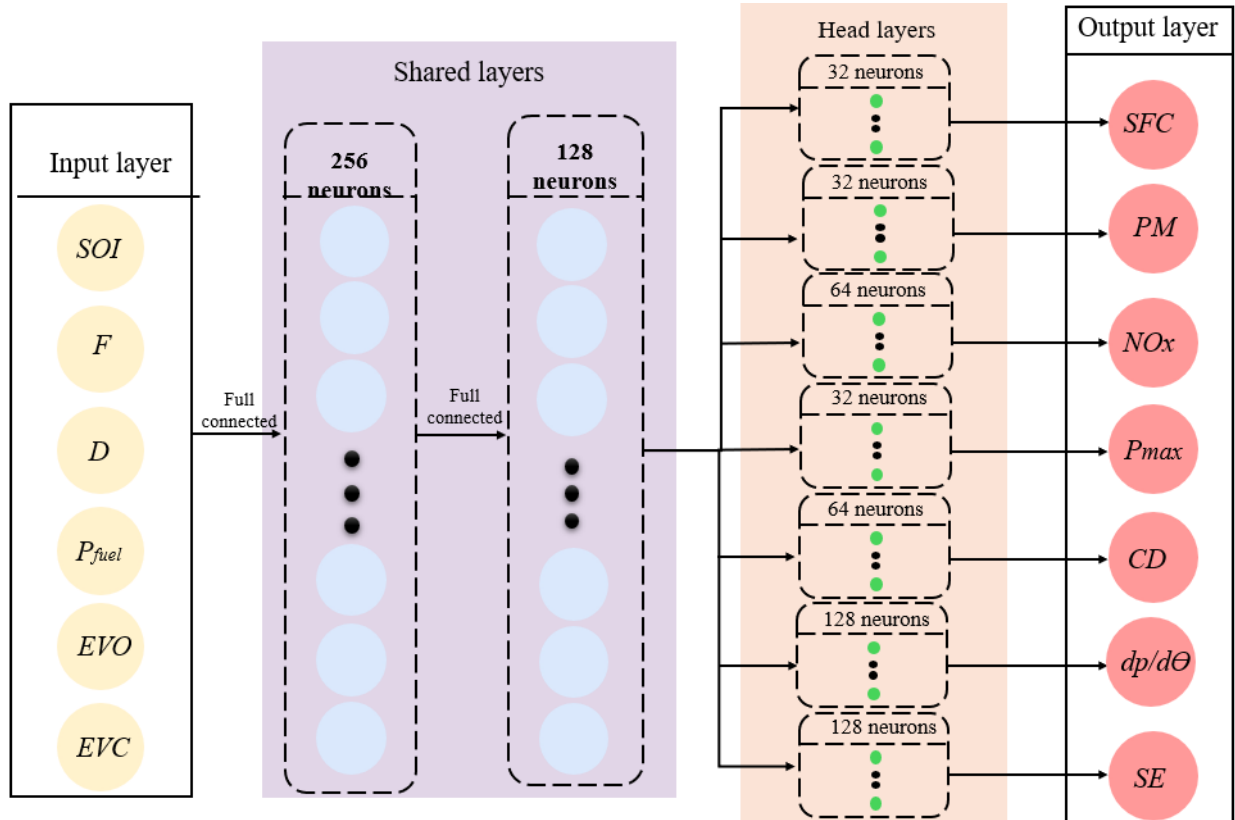


Figure 3.4. Neural Network architecture for marine engine surrogate model

The NN surrogate model was trained for up to 422 epochs (one epoch equals one full pass through the training set) using a batch size of 32, employing the AdamW optimizer (weight decay = $1 \cdot 10^{-4}$, i.e. a small regularization term discouraging overly large weights) with learning rates of 0.001 for

shared layers and 0.0005 for the head layers. The Mean Squared Error (MSE) loss function guided optimization and early stopping (patience = 50) was used, training stopped if the validation MSE did not improve for 50 consecutive epochs.

3.4. Formulation of the surrogate-based multi-objective optimization problem

The surrogate-based optimization module presented in this dissertation is designed to identify operating strategies that simultaneously optimize fuel efficiency and emission characteristics for large-bore two-stroke marine diesel engines. The framework employs the trained Neural Network surrogate as a fast evaluator of engine performance and emissions. The resulting optimization problem is inherently multi-objective: SFC , PM and NO_x should all be minimized, but improvements in one objective typically degrade at least one of the others. This leads naturally to a Pareto-based formulation in which the goal is not the identification of a single "optimal" solution, but rather the construction of a comprehensive set of non-dominated operating points that represent the complete spectrum of optimal trade-offs among the competing performance criteria.

The optimization uses NSGA-II algorithm's ability to handle multiple conflicting objectives directly, without resorting to weighted sums. Furthermore, its elitist non-dominated sorting and crowding-distance diversity control ensure a well-distributed Pareto front, which is a critical feature for the complex, nonlinear search spaces in engine calibration. Coupled with a fast NN surrogate for objective evaluation, this approach allows for the efficient exploration of a large number of candidate points to build a substantial trade-off set within the constraints, such as simultaneously minimizing fuel consumption and emissions while maintaining engine performance [96].

The novelty of the elaborated methodology lies in how surrogate modeling and Pareto optimization are operationalized for large-bore two-stroke marine diesel engines. Instead of performing computationally expensive simulation-based optimization directly, a multi-output NN surrogate is trained to emulate the engine response. The surrogate is then embedded as the objective evaluator within a Pareto-based NSGA-II algorithm, enabling construction of a high-resolution set of non-dominated operating solutions that simultaneously minimize SFC , NO_x and PM under realistic operating constraints. The proposed workflow is explicitly structured to produce a decision-ready trade-off library that can be carried forward to the subsequent decision stage (MCDM/weighting) of the full overall framework.

3.4.1. Objective functions

The optimization problem involves three objective functions SFC , NO_x and PM , which cannot be expressed as closed-form equations of the control parameters (SOI , F , D , P_{fuel} , EVO , EVC), which is a fundamental feature of engine calibration, where outputs arise from tightly coupled, nonlinear thermo-fluid processes [154]. Consequently, these objectives are inherently evaluation-based and treated as black-box mappings derived from high-fidelity simulation or experiment rather than from explicit analytical formulas (see references [60-64]). In this research, the high-fidelity Diesel-RK simulation software provides this mapping. To enable efficient multi-objective optimization, the model then represented by a trained neural network surrogate, which preserves the precise input-output definitions. Literature-based semi-empirical emission correlations are typically engine and dataset-specific and require fitted calibration constants, limiting their transferability; therefore, cited here to contextualize observed trends [154-156], while the optimization itself in my dissertation relies on the Diesel-RK/NN mapping.

The three objective functions (F_1 , F_2 , F_3) that collectively characterize the operational quality of the marine diesel engine from both economic and environmental perspectives are formulated as a multi-objective optimization problem in the following section.

Each objective function is defined as a minimization of the corresponding emission or consumption parameter, reflecting the practical imperative to reduce both fuel expenditure and environmental impact during engine operation.

➤ **Minimize the Specific Fuel Consumption (*SFC*)**

$$F_1 = SFC(SOI, F, D, P_{fuel}, EVO, EVC) \quad [\text{kg/kWh}] \quad (3.1)$$

This first objective function targets fuel economy, a primary operational-cost driver for ship operators because it directly affects voyage fuel expenditure and overall operating costs [54, 68]. *SFC* directly quantifies fuel-to-work conversion efficiency and is therefore a compact, comparable indicator of operating economy across control settings.

➤ **Minimize engine Particulate Matter (*PM*) emissions**

$$F_2 = PM(SOI, F, D, P_{fuel}, EVO, EVC) \quad [\text{g/kWh}] \quad (3.2)$$

The second objective function concerns particulate matter emissions, which are a key ship-exhaust pollutant and a major air-quality concern, particularly in coastal and port regions, due to their documented links to adverse health outcomes and atmospheric pollution [26, 28]. *PM* is a key indicator of soot/smoke propensity, combustion quality, environmental impact and energy-normalized *PM* is standard-compatible and comparable across operating points.

➤ **Minimize engine Nitrogen Oxides (*NO_x*) emissions**

$$F_3 = NO_x(SOI, F, D, P_{fuel}, EVO, EVC) \quad [\text{g/kWh}] \quad (3.3)$$

The third objective function addresses nitrogen oxides emissions, which are a regulated pollutant in marine propulsion and a key compliance driver under MARPOL Annex VI [27,85]. *NO_x* is tightly coupled to combustion temperature/oxygen availability, so reducing *NO_x* can systematically worsen *SFC* and/or *PM*, making multi-objective treatment necessary.

The absence of explicit, universal mathematical equations for the objectives and a link to the control parameters is not available as a tractable closed-form function. The reason is arises from the fundamental nature of internal combustion physics. The relationships between control parameters (e.g. injection timing, pressure) and the objective functions are governed by a complex system of non-linear, coupled and time-dependent partial differential equations describing turbulence, spray dynamics, chemical kinetics and heat transfer. Deriving a simplified, accurate and generally applicable analytical expression from these first principles is unmanageable for practical engine calibration. Consequently, the research community and industry rely on two primary pathways: 1.) high-fidelity physics-based simulation tools that numerically solve the governing relations, or 2.) data-driven surrogate models trained on experimental or simulation data. This research adopts the latter approach, using the high-fidelity Diesel-RK software to generate the essential mapping, which is then approximated by a neural network surrogate to enable efficient optimization. While semi-empirical correlations exist in the literature, it often derived for specific engine architectures and operating regimes, requiring fitted constants that limit its generalizability.

The before mentioned three objective functions are not independent but are coupled through the underlying combustion physics governing diesel engine operation. Specifically, operating conditions that favor reduced NO_x emissions through lower combustion temperatures typically result in incomplete fuel oxidation and elevated PM formation, while strategies aimed at minimizing PM emissions through elevated temperatures and extended combustion durations tend to increase NO_x production. The inherent trade-off structure validates the multi-objective formulation and underscores the necessity of generating a comprehensive Pareto front rather than pursuing a single objective optimization.

3.4.2. Design variables

The selection of design variables (also termed decision variables or control parameters) is a critical aspect of the optimization problem formulation, as these variables define the searchable decision space, which the algorithm seeks optimal solutions. For the present investigation, six operational parameters (SOI , F , D , P_{fuel} , EVO , EVC) were identified as the primary control variables governing the engine performance and emission characteristics. These parameters represent the adjustable operating conditions that can be manipulated in practice through engine control systems, fuel injection equipment, or operational procedures without requiring hardware modifications to the engine structure.

The design variables to be optimized are the following:

- SOI Start of Injection [$^{\circ}CA$ -BTDC];
- F Pilot injection fuel mass fraction [%];
- D Injection dwell time between pilot and main injections [$^{\circ}CA$];
- P_{fuel} Common-rail fuel pressure [bar];
- EVO Exhaust Valve Opening timing [$^{\circ}CA$ -BBDC];
- EVC Exhaust Valve Closing timing [$^{\circ}CA$ -ABDC].

The lower and upper limits for these variables are derived from manufacturer technical guides, prior calibration studies and simulation feasibility considerations and have been specified in Section 3.1.1.

3.4.3. Design constraints

The optimization problem is subject to a comprehensive set of constraints derived from regulatory requirements, engine operational limitations and combustion stability considerations. These constraints serve to restrict the search to feasible operating regions where the identified solutions can be practically implemented while ensuring compliance with applicable emission standards and maintaining safe engine operation. The constraints are categorized into emission-based constraints, which enforce regulatory compliance and mechanical-thermal constraints, which ensure physically realistic and mechanically safe operating conditions.

The emission-based constraints enforce compliance with the International Maritime Organization (IMO) Tier III regulations [85], which establish maximum permissible emission levels for marine diesel engines operating in Emission Control Areas (ECAs). These regulatory limits are specified as follows:

- Specific Fuel Consumption (SFC): $SFC \leq 0.2$ [kg/kWh],
- NO_x Emissions Index: $NO_x \leq 3.4$ [g/kWh],
- Particulate Matter (PM) Emissions: $PM \leq 0.15$ [g/kWh].

(3.4)

To ensure physically realistic and mechanically safe operating conditions, the following additional constraints are imposed on the combustion and mechanical parameters. These limits are specified as follows:

- Combustion Duration (CD): must remain within 35° to 45° crank angle [$^\circ CA$],
- Peak Cylinder Pressure (P_{max}): $P_{max} \leq 170$ [bar],
- Maximum Pressure Rise Rate ($dp/d\theta$): $dp/d\theta \leq 4$ [bar/ $^\circ CA$],
- Synthetic Emission Index (SE): computed value using Diesel-RK's internal formulation to capture the NO_x – PM trade-off during combustion [94]. SE can be calculated by the following formulation:

$$SE = \max\left(1, \frac{NO_x}{NO_{x0}}\right)^{m_1} + \max\left(1, \frac{PM}{PM_0}\right)^{m_2} + \frac{SFC}{SFC_0} \quad (3.6)$$

where:

- NO_x : Simulated nitrogen oxide emission index [g/kWh],
- NO_{x0} : Target (reference) NO_x emission index [g/kWh],
- PM : Simulated particulate matter emission level [g/kWh],
- PM_0 : Target (reference) PM emission index [g/kWh],
- m_1 : Exponent controlling the weight of NO_x penalty,
- m_2 : Exponent controlling the weight of PM penalty,
- SFC : Simulated specific fuel consumption [kg/kWh],
- SFC_0 : Reference average or target SFC [kg/kWh].

In this equation (3.6) the $\max(1, \dots)$ function is applied only to NO_x and PM to act as penalty functions. This ensures that if emissions are below their targets, they do not reduce the overall SE value. The penalty activates only when emissions exceed the targets, increasing nonlinearly based on the exponents m_1 and m_2 .

SFC is not placed inside a $\max()$ function because it contributes to the index linearly regardless of its value. Fuel consumption is always considered in the SE , even if it is better than the reference level, which aligns with operational goals that continuously prefer lower SFC values and only consider PM and NO_x when they are over compliance.

3.4.4. NSGA-II based optimization algorithm

NSGA-II algorithm is an elitist multi-objective evolutionary algorithm that seeks both convergence and diversity along the Pareto optimal set. Its principal mechanisms are as follows:

- 1.) fast non-dominated sorting for solution ranking,
- 2.) elitist retention through parent–offspring population merging and
- 3.) diversity preservation using the crowding-distance criterion [42, 48].

Selection of candidate solutions (engine configuration) is performed via a crowded-comparison operator that prefers solutions with lower non-dominance rank and larger crowding distance. This selection strategy is coupled with real-coded variation operators (Simulated Binary Crossover and polynomial mutation) to generate new candidate solutions. Together, these mechanisms provide a practical balance between convergence toward the Pareto optimal set and uniform coverage of the trade-off surface.

Figure 3.5 summarizes the same evolutionary cycle in flowchart form, while the full NSGA-II pseudocode is provided in Appendix 1 [96].

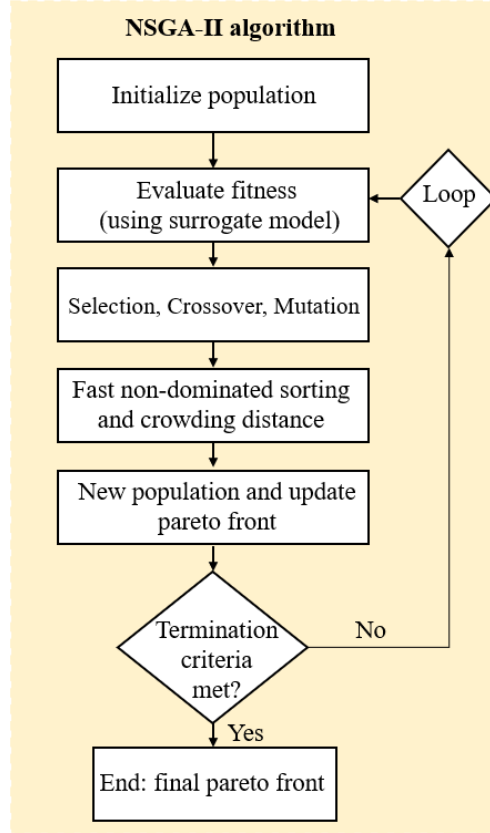


Figure 3.5. NSGA-II based optimization algorithm [96]

The optimization process using NSGA-II algorithm proceeds through the following stages:

1. Population initialization: the search begins by generating a diverse set of 1,000 candidate solutions. Latin Hypercube Sampling (LHS) is employed to systematically sample the six-dimensional decision space, ensuring uniform coverage and avoiding initial clustering that could bias the search.
2. Fitness evaluation: for each individual solution, the trained neural network surrogate model rapidly predicts the engine's seven key performance parameters (SFC , PM , NO_x , D , P_{fuel} , $dp/d\theta$, SE). These predictions are used to compute the three objective functions (minimizing SFC , PM and NO_x) while checking for constraint violations related to pressure limits, emission thresholds and combustion duration.
3. Selection via non-dominated sorting: solutions are ranked into Pareto fronts based on the principle of non-dominance, where a solution is considered superior if it is no worse in all objectives and strictly better in at least one. A crowding distance metric is applied within each front to maintain population diversity, ensuring that candidate solutions are well-spread along the trade-off surface.
4. Reproduction (crossover and mutation): using Simulated Binary Crossover (SBX) with a probability of 0.9 and polynomial mutation, parent solutions exchange genetic information to

produce offspring. SBX explores new regions by recombining parental traits, while Polynomial Mutation introduces minor variations that enable fine-grained search and prevent premature convergence.

5. Survivor selection and iteration: the combined parent-offspring population is evaluated, ranked and truncated to the top 1,000 individuals for the next generation. Duplicate elimination ensures genetic diversity is preserved throughout evolution.
6. Termination and Pareto front extraction: in order to increase the number of solutions on the Pareto optimal front this evolutionary cycle was repeated for 200 generations, progressively refining the population. The algorithm converges to a Pareto optimal front, representing a set of non-dominated solutions that balance fuel efficiency and emissions under operational constraints.

3.5. Optimization results for the marine diesel engine – case study

The validation of the elaborated surrogate NN model and multi-objective optimization framework on the studied two-stroke marine diesel engine is demonstrating how the developed neural network model, integrated in NSGA-II algorithm, effectively identifies operating conditions that minimize fuel consumption and pollutant emissions while adhering to IMO Tier III constraints.

3.5.1. Results of the developed surrogate neural network model for the studied marine engine (Accuracy analysis)

The elaborated NN surrogate model was developed to emulate the behavior of a two-stroke marine diesel engine under varying injection and valve timing configurations. The NN model, comprising 97,863 trainable parameters, was trained on a simulation dataset generated using Diesel-RK software. Figure 3.6. illustrates the evolution of training and validation loss, demonstrating consistent learning progression and generalization capability throughout training. The model was trained for 422 epochs with early stopping, achieving stable convergence without overfitting.

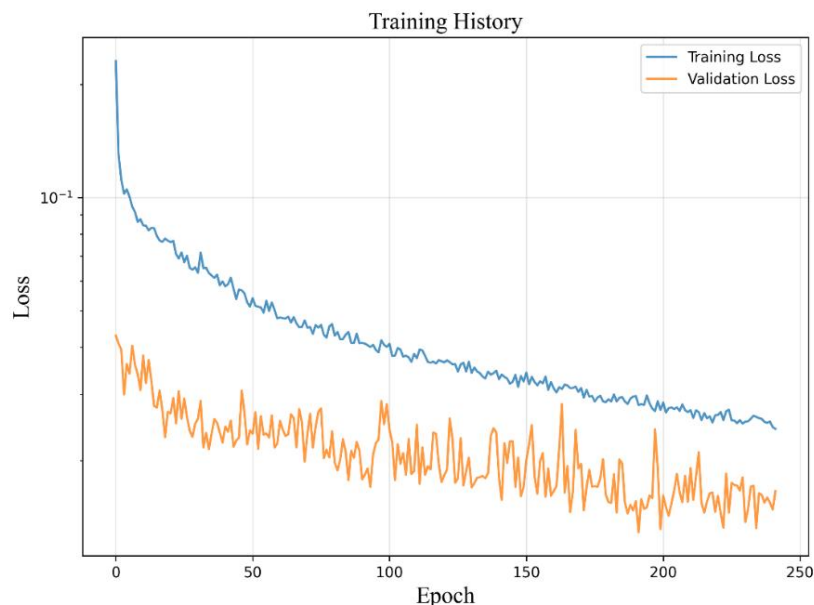


Figure 3.6. Training and validation loss

On the test dataset (see Section 3.3.), the surrogate achieved a final overall coefficient determination of $R^2=0.9833$ and mean squared error (MSE) of 0.2935 on the test dataset. Table 3.3. summarizes the individual predictive accuracy metrics for each output, including root mean square error ($RMSE$), mean absolute error (MAE) and mean absolute percentage error ($MAPE$).

Table 3.3. Predictive metrics for each output

Outputs	R^2	$RMSE$	MAE	$MAPE$
SFC	0.9946	0.0004	0.0003	0.17%
NO_x	0.9784	0.0545	0.0287	1.11%
PM	0.9849	0.0023	0.0017	1.79%
P_{max}	0.9950	1.3090	1.0349	0.70%
$dp/d\theta$	0.9678	0.0941	0.0499	1.39%
CD	0.9863	0.5673	0.4088	0.89%
SE	0.9759	0.0835	0.0458	1.28%

Across all performance indicators, the NN surrogate model demonstrates high predictive fidelity, with R^2 values exceeding 0.970 and percentage errors typically below 2%. The accuracy is particularly notable for SFC and P_{max} , both achieving $R^2 > 0.995$, indicating near-perfect reproduction of the simulated combustion dynamics.

Scatter plots comparing predicted versus true values (Diesel-RK simulation outputs) for each target variable, Figure 3.7. provide comprehensive visual validation of the surrogate model's predictive capability. Across all seven outputs (SFC , NO_x , PM , P_{max} , $dp/d\theta$, CD , SE), the data points align closely with the 45° reference line, indicating near-perfect prediction accuracy. The details of Figure 3.7 are as follows:

- SFC (Figure 3.7. a): Predictions exhibit an almost one-to-one correspondence with true values ($R^2 = 0.995$), showing negligible difference across the entire operating range.
- NO_x (Figure 3.7. b): The model accurately captures NO_x formation trends ($R^2 = 0.978$), reflecting its ability to reproduce complex thermochemical pathways.
- PM (Figure 3.7. c): Particulate emissions are predicted with strong agreement ($R^2 = 0.985$), with only minor differences at lower PM levels.
- P_{max} (Figure 3.7. d): The model accurately captures peak combustion pressures ($R^2 = 0.995$), with no noticeable bias or systematic error.
- $dp/d\theta$ (Figure 3.7. e): Despite rapid transient behavior in pressure rise rates, the surrogate maintains high fidelity ($R^2 = 0.968$).
- CD (Figure 3.7. f): Predictions remain tightly clustered around the true values ($R^2 = 0.986$), ensuring reliable combustion phasing representation.
- SE (Figure 3.7. g): The synthetic emission index shows excellent correlation ($R^2 = 0.976$), validating its utility for multi-criteria optimization.

Overall, these plots confirm that the neural network surrogate not only reproduces individual performance metrics with high accuracy but also preserves the underlying thermodynamic and emission dynamics essential for reliable optimization and decision-making. This level of predictive fidelity ensures that subsequent NSGA-II optimization operates on a surrogate with nearly indistinguishable accuracy from the original Diesel-RK simulator.

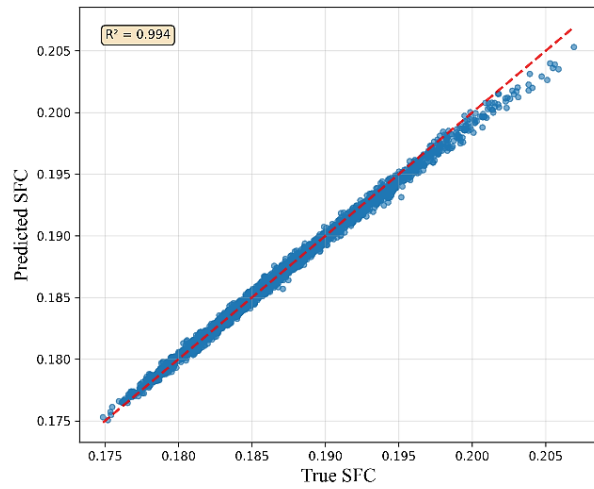


Figure 3.7. a

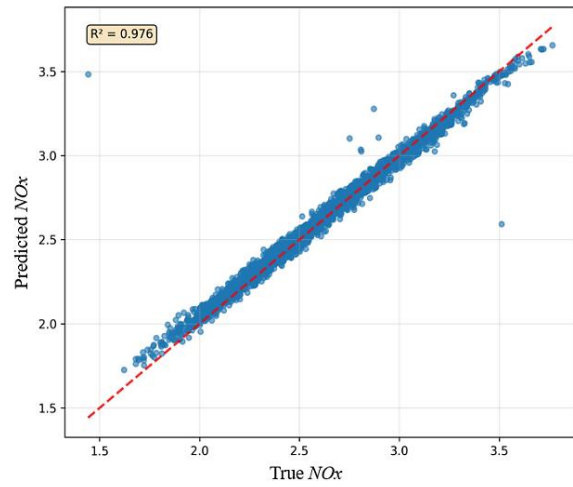


Figure 3.7. b

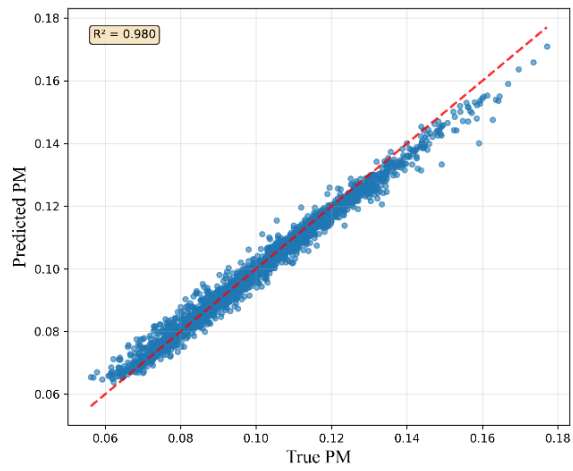


Figure 3.7. c

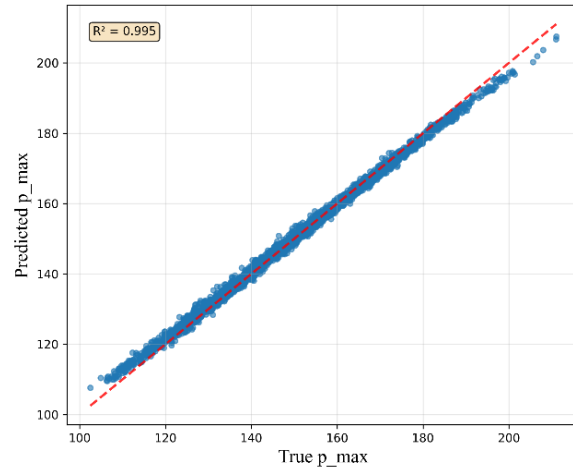


Figure 3.7. d

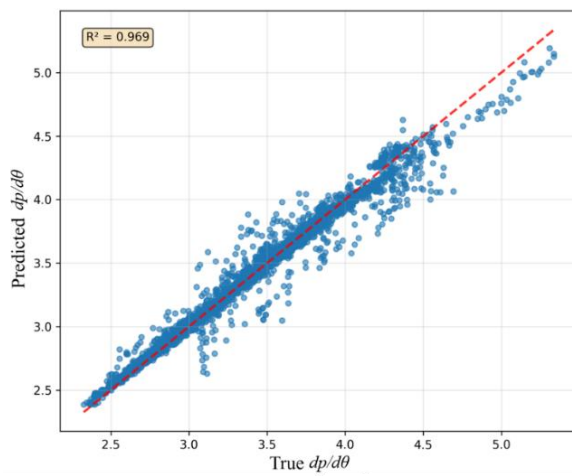


Figure 3.7. e

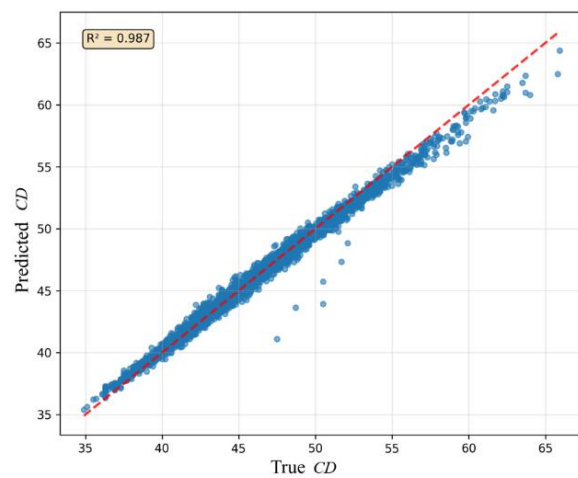


Figure 3.7. f

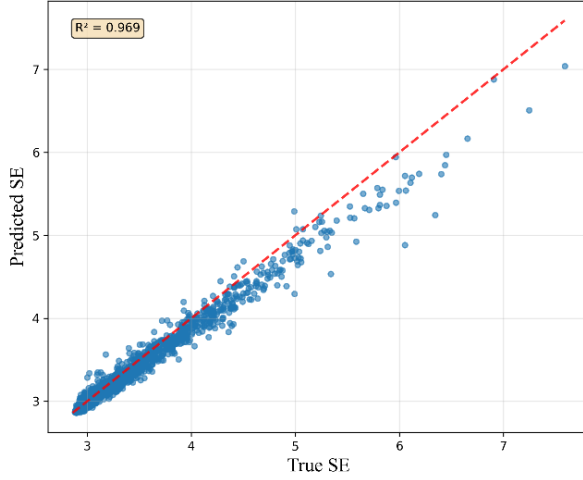


Figure 3.7. g

Figure 3.7. Predicted vs. true values for marine engine performance parameters

The high-accuracy predictions across fuel consumption, combustion characteristics and emissions validate the suitability of the developed surrogate for integration into computationally intensive optimization workflows. Specifically, its deployment within the NSGA-II evolutionary framework enables rapid exploration of the six-dimensional control parameter space (SOI , F , D , P_{fuel} , EVO , EVC), facilitating efficient generation of Pareto optimal trade-offs between fuel efficiency and combustion stability (NO_x , PM).

3.5.2. Results of NSGA-II-based multi-objective optimization

The trained NN surrogate model was integrated into an NSGA-II multi-objective optimization algorithm to minimize SFC , PM and NO_x . The resulting Pareto front (Figure 3.8.) represents the non-dominated trade-off surface among SFC , PM and NO_x objectives. A well-defined convex front is observed, indicating the presence of distinct operating regimes where improving fuel efficiency inevitably increases PM or NO_x emissions, reflecting the well-known NO_x – PM trade-off in diesel combustion physics and confirms that the optimizer has identified meaningful performance boundaries.

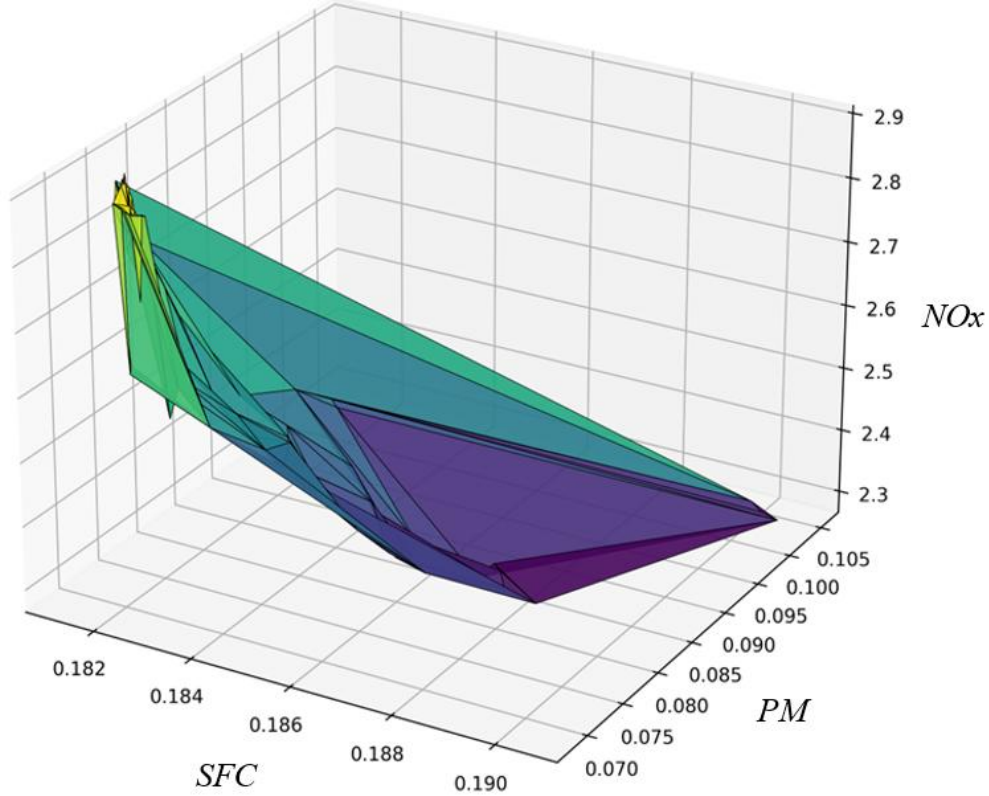


Figure 3.8. Pareto optimal showing the trade-off surface among SFC , PM and NO_x objectives

Figure 3.8. illustrates the three-dimensional Pareto surface obtained from the NSGA-II algorithm, where each point represents a non-dominated solution. The color gradient indicates NO_x emission levels, allowing visual identification of operating regions that present fuel efficiency versus emission reduction. The Pareto front shows a convex trade-off surface, meaning that significant improvements in SFC typically lead to higher NO_x emissions index, reflecting the intrinsic thermodynamic trade-off in diesel combustion.

To ensure full transparency and reproducibility, the complete numerical definition of the final Pareto optimal set is reported in Appendix 2. The appendix provides descriptive statistics and the full list of the 163 non-dominated operating points with their corresponding objective values (SFC , PM and NO_x).

Pattern analysis of the Pareto optimal solutions further identified three operational regimes:

1. Fuel efficiency dominated cluster, minimizing SFC with moderate PM and elevated NO_x .
2. NO_x controlled cluster, minimized NO_x at the cost of increased fuel consumption.
3. PM controlled cluster, lowest soot emissions with balanced NO_x and moderate SFC .

To complement the 3D view of the Pareto optimal, Figure 3.9. presents pairwise objective plots (SFC vs. PM , SFC vs. NO_x and PM vs. NO_x). The following correlations were observed:

1. A strong negative correlation between SFC and NO_x , indicates that aggressive fuel-saving strategies increase NO_x formation due to advanced combustion phasing and higher in-cylinder temperatures.
2. A negative correlation between PM and NO_x , highlighting the classical diesel trade-off where measures to reduce soot often increase thermal NO_x formation.
3. A mild positive correlation between SFC and PM suggests that particulate reduction aligns moderately with fuel savings but becomes less effective when pushing for minimum fuel consumption.

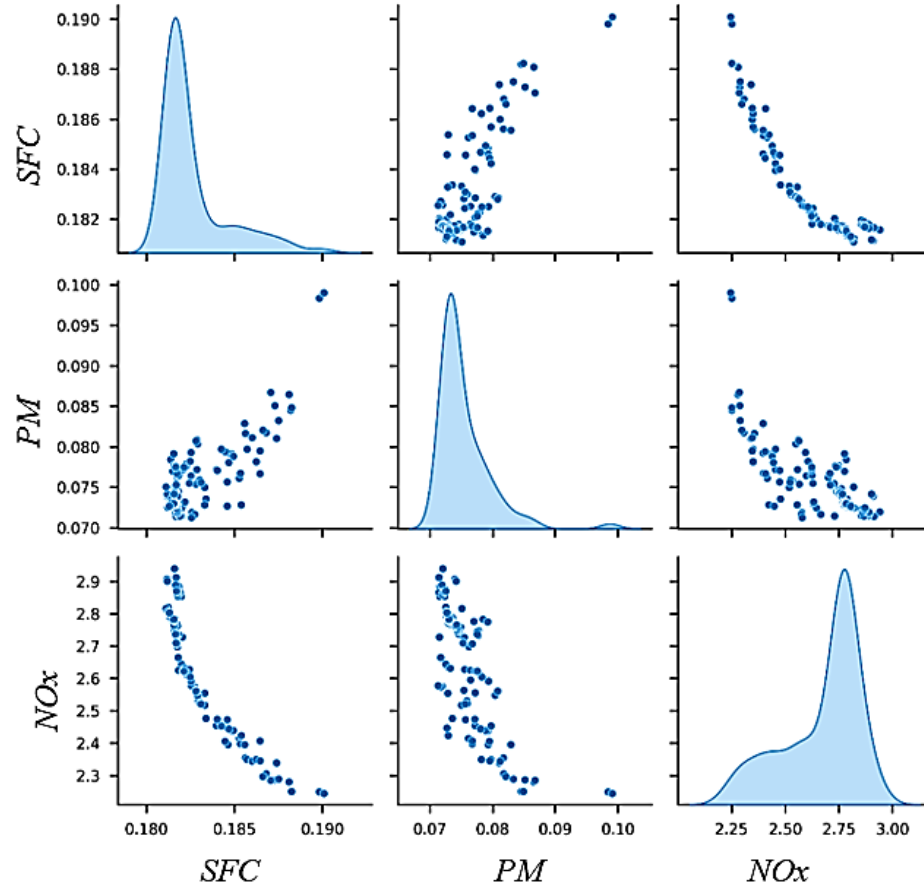


Figure 3.9. Pairwise relationships among objectives (SFC , PM , NO_x) for Pareto optimal solutions, illustrating correlations and dominance regions

These visualizations are intended to interpret the structure of the Pareto optimal (i.e. how improvements in SFC are traded against NO_x and PM) rather than a single operating point. The outcome of Chapter 3 is therefore a decision-ready library of non-dominated operating strategies that spans the feasible trade-off space under the imposed engine constraints.

4. MULTI-CRITERIA DECISION-MAKING METHODS SELECTION AND SURROGATE VALIDATION FOR PARETO OPTIMAL SET IN MARINE ENGINES

This chapter establishes the multi-criteria decision step of the management support framework and tests whether the surrogate-based optimization developed in Chapter 3 preserves decision-consistent recommendations to those obtained using Diesel-RK software. Chapter 3 showed that a neural network surrogate, integrated into NSGA-II, can generate a big Pareto optimal set of non-dominated operating strategies that balance *SFC*, *NO_x* and *PM* outcome under Tier III and mechanical constraints. In practice, however, ship operators and automated controllers cannot act on a big set of Pareto optimal points; they require a small number of recommended settings tailored to the current operating context. Selecting one (or top) implementable solution from a Pareto optimal set requires an MCDM framework to formalize operator preferences and resolve the non-dominated trade-offs.

To address this problem, Chapter 4 systematically evaluates fourteen MCDM methods, grouped into scoring based, distance based, pairwise comparison, outranking and hybrid methods categories to identify the approach(es) that deliver stable, interpretable and preference consistent rankings of the Pareto optimal operating points.

A baseline Diesel-RK decision matrix is constructed to provide a single, consistent input to all candidate MCDM methods. In this context, the decision matrix is the tabular representation of the problem where each row is one feasible engine operating alternative (*SOI*, *F*, *D*, *P_{fuel}*, *EVO*, *EVC*) and each column is a decision criterion (*SFC*, *NO_x*, *PM*), containing the corresponding simulated performance value. This "alternatives vs. criteria" layout is the standard way of MCDM methods to compare options. By using the Diesel-RK decision matrix, the chapter evaluates MCDM methods' behavior in terms of: 1.) rank stability under changes, 2.) cross-method consensus and 3.) sensitivity to MCDM methods modelling differences as a robustness check. The NN-NSGA-II Pareto set is then used for decision-consistency validation. Decision consistency is quantified using compact, decision-relevant indicators.

In the MCDM step, the surrogate is considered adequate not only when it achieves low prediction error, but when it preserves the decisions implied by the high-fidelity model.

The chapter is organized as follows: Section 4.1. clarifies the role of MCDM in the integrated decision support framework and why ranking is required on top of Pareto optimal set. Section 4.2. summarizes the fourteen candidate algorithms. Section 4.3. formulates the Diesel-RK baseline decision matrix and the surrogate Pareto validation set in a unified MCDM structure. Section 4.4. presents the Diesel-RK-based algorithm-selection results and identifies the recommended robust methods. Section 4.5. provides the surrogate decision-consistency validation.

4.1. Role of multi-criteria decision-making in the integrated framework

The dissertation implements a fully integrated Decision Support System in which Diesel-RK software provides the high-fidelity reference data, a neural network surrogate enables rapid evaluation, NSGA-II algorithm generates a feasible Pareto optimal set and an MCDM step for final decision recommendation.

Figure 4.1. summarizes the performance optimization procedure. Diesel-RK simulations are first used to generate a dataset across six controllable parameters, which is then used to train the neural network surrogate for rapid prediction of key performance and emission indicators. The surrogate replaces the high-fidelity simulator within NSGA-II algorithm to produce a Pareto optimal set of non-

dominated operating configurations balancing SFC , NO_x and PM outcomes under Tier III and mechanical constraints.

Within this optimization procedure, MCDM provides the decision interface between the optimization output and implementation: it converts the Pareto optimal set into a small number of preference-consistent and operationally actionable control recommendations. This chapter focuses on identifying robust MCDM methods using the Diesel-RK baseline decision matrix.

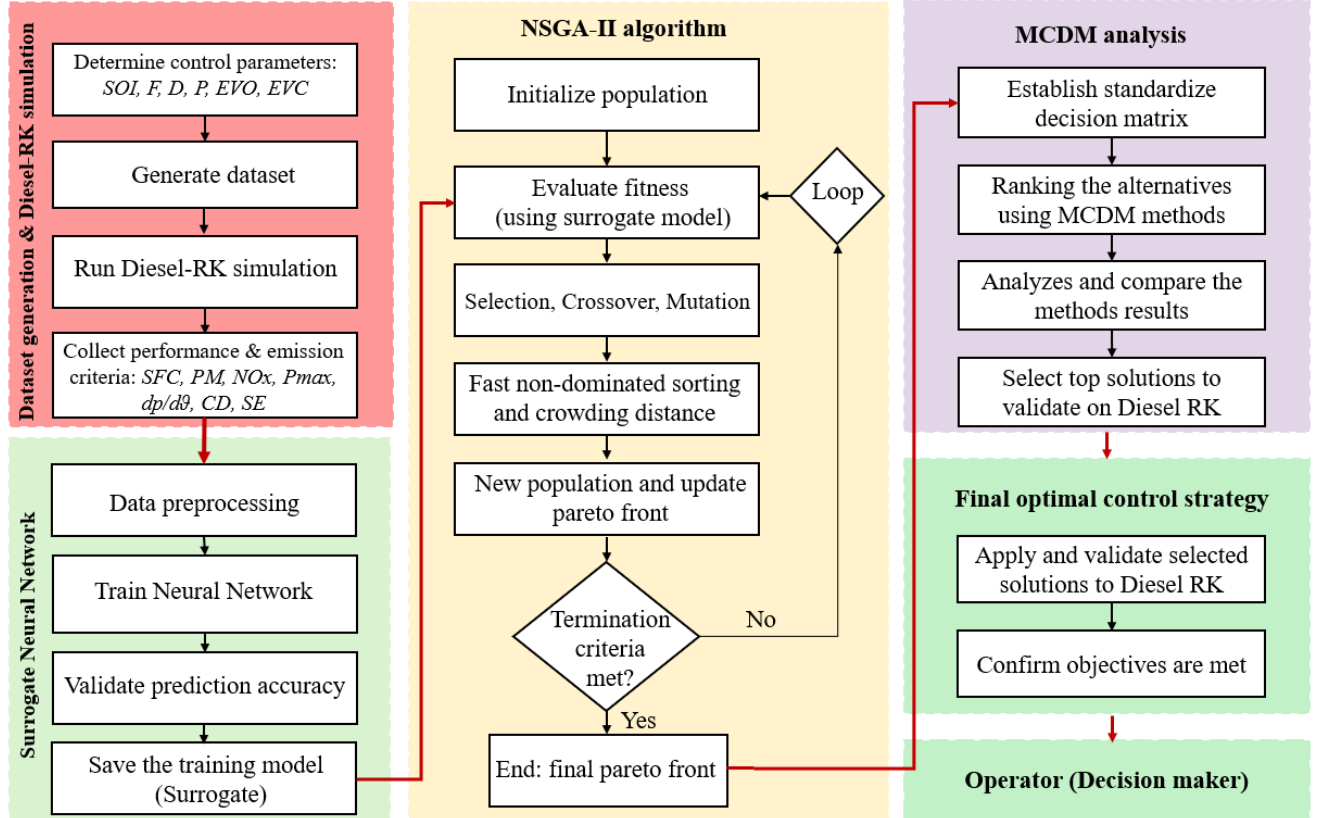


Figure 4.1. Flowchart of the performance optimization procedure

4.2. Multi-Criteria Decision-Making methods: overview

The primary objective of this chapter is to identify the most suitable MCDM methods for marine applications, focusing on enhancing the performance of two-stroke marine diesel engines through optimal control parameter selection. Given the complexity of marine engine optimization, which involves balancing multiple, often conflicting, performance indicators such as SFC , NO_x and PM , a structured decision-making framework is essential to support reliable operation.

The study systematically evaluates representative MCDM methods across the major methodological categories identified in the literature [97-103]:

1. Scoring-Based methods,
2. Distance-Based methods,
3. Pairwise Comparison-Based methods,
4. Outranking methods,
5. Hybrid or Intelligent Systems-Based methods.

Each category offers distinct strengths and operational characteristics. For example, Scoring-Based methods such as SAW and WASPAS are computationally simple and suitable for real-time decision loops. Distance-Based methods like TOPSIS and VIKOR handle trade-offs in performance-versus-emission scenarios with geometric clarity. Pairwise Comparison-Based methods enable expert-driven decisions based on hierarchical structures or network dependencies. Outranking methods like PROMETHEE II build preference functions and use outranking flows. Hybrid methods, such as TriMetric Fusion (TMF) [61], integrate complementary mathematical strategies to enhance ranking robustness. These methods draw upon recent trends in combining optimization, machine learning and hierarchical logic to improve decision accuracy in engineering systems [104-106].

Different representative methods from each MCDM category were implemented and benchmarked against each other by applying them to the same Diesel-RK decision matrix and comparing the MCDM methods' outputs.

My research aims to observe each algorithm's consistency and ranking behavior and evaluate its practicality for onboard integration or automated control environments in marine applications.

The before mentioned five categories of methods differ in their mathematical foundations, assumptions and practical implications for decision-making [97-103]. The following overview outlines each method's core principle and mathematical foundation, forming the basis for comparative evaluation in later sections.

Table 4.1. provides a structured overview of the examined MCDM methods, grouped by their methodological category. The logical and core mathematical formulation for each method is briefly summarized. This categorization clarifies the diversity of approaches within the MCDM landscape. It lays the foundation for comparative analysis regarding ranking behavior, sensitivity to weighting and normalization and robustness across scenarios.

Table 4.1. Categorization of the implemented fourteen MCDM methods with mathematical justification

Category	Method	Logical and mathematical justification	Contributor
Scoring-Based Methods	SAW Simple Additive Weighting	Classic linear function: $S_i = \sum w_j \cdot x_{ij}$ Each alternative is scored by summing the products of criterion weights (w_j) and normalized performance values (x_{ij}). Higher scores indicate better performance.	Kenneth R. McCrimmon [107]
	MARCOS Measurement of Alternatives and Ranking according to Compromise Solution	Derives utility function $K_i = S_i/S_{ref}$; where S_i is the weighted normalized score of an alternative and S_{ref} is a reference score (ideal or not ideal). It evaluates how close each option is to the reference.	Željko Stević, Dragan Pamučar, Adis Puška, Prasenjit Chatterjee [108]
	WASPAS Weighted Aggregated Sum Product Assessment	Combines additive and multiplicative utility: $Q_i = \lambda \cdot \sum w_j \cdot x_{ij} + (1 - \lambda) \cdot \prod (x_{ij})^{w_j}$; where it combines the additive (SAW) and multiplicative models for more flexibility. λ is a balance factor between 0 and 1.	Edmundas Kazimieras Zavadskas, Zenonas Turskis, Jurgita Antucheviciene, Algimantas Zakarevičius [109]
	MAIRCA Multi-Attribute Ideal-Real Comparative Analysis	Calculates theoretical vs. real preference difference: $D_i = \sum T_{ij} - R_{ij} $; where D_i measures deviation between theoretical preferences (T_{ij}) and actual ratings (R_{ij}). Lower D_i means a better match to the ideal.	Gigović, Ljubomir, Dragan Pamučar, Zoran Bajić and Milić Milićević [110]

	MARA Magnitude of the Area for the Ranking of Alternatives	Calculates the geometric area formed by their normalized criteria values, interpreting each as a point in n -dimensional space. The larger the enclosed area (via polygon or hypervolume formulas), the better the overall, balanced performance.	Gligorić, Miloš, Zoran Gligorić, Suzana Lutovac, Milanka Negovanović and Zlatko Langović [111]
	ORESTE (Organisation Rangement Et SynThèse de données relationnelles)	Uses ordinal regression and pseudo-criteria to translate qualitative ranks into utility scores.	Marc Roubens [112]
Distance- Based Methods	TOPSIS Technique for Order Preference by Similarity to Ideal Solution	Uses Euclidean distances to ideal/anti-ideal solutions: $C_i = D^- / (D^+ + D^-)$; calculates closeness to the ideal solution (D^+) and distance from the worst (D^-) using Euclidean distance.	Ching-Lai Hwang and Kwang Yoon [113]
	MABAC Multi-Attributive Border Approximation Area Comparison	Calculates how far each alternative is from a neutral or border zone; larger deviations from the border (toward ideal) are better.	Dragan Pamučar and Goran Čirović [114]
	OCRA Operational Competitiveness Rating Analysis	Constructs a weighted normalized matrix and calculates performance based on deviation from a reference vector.	Celik Parkan [115]
	VIKOR VIseKriterijumska Optimizacija Kompromisno Resenje	$Q_i = v \cdot (S_i - S^*) / (S^- - S^*) + (1-v) \cdot (R_i - R^*) / (R^- - R^*)$; where S_i is the total gap of alternative i from the ideal (group utility). R_i is the worst Performance of alternative i among all criteria (individual regret). S^* and S^- are the best and worst values of S among all alternatives. R^* and R^- are the best and worst values of R among all alternatives. v is weight, indicating the importance of group utility vs. individual regret.	Serafim Opricović [116]
Pairwise Comparison Methods	PIV Proximity Indexed Value	PIV ranks alternatives based on their relative closeness to both the ideal and anti-ideal solutions. $PIV_i = D^- / (D^+ + D^-)$; where D^+ is the distance to the ideal solution and D^- is the distance to the worst (anti-ideal) solution.	Sameera Mufazzal and Sayed Mohammed Muzakkir [117]
	WISP Integrated Simple Weighted Sum Product	WISP is a hybrid method that integrates both weighted sum (SAW) and weighted product (WPM) techniques. $WISP_i = \lambda \cdot \sum (w_j \cdot x_{ij}) + (1 - \lambda) \cdot \prod (x_{ij})^{w_j}$; where $\lambda \in [0, 1]$ is the control parameter that adjusts the influence of SAW vs. WPM.	Stanujkic, Dragisa, Gabrijela Popovic, Darjan Karabasevic, Ieva Meidute- Kavaliauskiene and Alptekin Ulutaş [118]

Outranking Method	PROMETHEE II Preference Ranking Organization METHod for Enrichment of Evaluations	Uses preference flows to compare alternatives on how much they outrank or are outranked by others.	Jean-Pierre Brans & Bertrand Mareschal [119]
Hybrid Method	Tri Metric Fusion	CAWI (Criteria Aggregated Weighted Index), BECI (Balanced Extreme Criteria Index) and Euclidean distance to synthesize rankings with high robustness and low sensitivity.	Hammoud [61]

MCDM methods offer a mathematically structured means of navigating complex decision environments. MCDM methods does not seek to produce a single "correct" answer. Instead, it provides a formal structure for aggregating diverse economic, environmental and operational criteria while acknowledging that preferences, trade-offs and uncertainties must be explicitly modeled rather than assumed. However, the multiplicity of available MCDM methods introduces a practical challenge: different methods can lead to different rankings for the same dataset. This divergence is not due to computational error but from each method's underlying assumptions regarding distance metrics, normalization, compensatory behavior and preference aggregation. As such, method selection must be aligned with the structure of the decision environment and the nature of the trade-offs involved.

The primary research focus in this chapter is the systematic evaluation and comparison of the examined fourteen MCDM methods for selecting control strategies for two-stroke marine diesel engines under emission and performance limits.

4.3. Decision matrix formulation for MCDM evaluation

In MCDM, the decision matrix is the foundational framework for evaluating and comparing control parameters against multiple, often conflicting, criteria. This structured representation enables systematic decision analysis where trade-offs between performance, emissions and efficiency must be carefully balanced.

In the general MCDM setting, the decision problem is represented by the decision matrix [97]:

$$\underline{\underline{X}} = [x_{ij}] = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{k1} & x_{k2} & \cdots & x_{km} \end{pmatrix} \quad (4.1)$$

where: each element x_{ij} in the matrix quantifies the value of the alternative A_i to criterion C_j .

The main elements of MCDM are:

1. Decision alternatives ($A_1, A_2, \dots, A_k$) represent the different options of control parameters available for evaluation. Each alternative is assessed based on how it meets the various objective criteria.
2. Evaluation criteria ($C_1, C_2, \dots, C_m$) are the factors that must be considered when making the optimal decision. Each criterion can be quantitative or qualitative.

The decision-making problem is structured using Diesel-RK simulations data. This matrix systematically captures the performance of each alternative against each criterion. To assess decision consistency and robustness against the underlying physics-based model, the decision matrix is constructed from the full Diesel-RK simulations introduced in Chapter 3. The six controllable input

parameters (SOI , F , D , P_{fuel} , EVO , EVC), were initially defined over broad engineering ranges and then refined to a narrower, physically realistic and regulation-compliant design space (Section 3.1.1.).

The total number of possible combinations of input parameters, as mentioned in Section 3.1.1. is 15,360 feasible cases, which reflects the design space and after applying the limitation conditions (Section 3.4.) to the latest simulation results, the total number of possible combinations of input parameters becomes 4,454 feasible cases.

Table 4.2. presents the decision matrix constructed by Diesel-RK simulation results for the 4,454 feasible cases. Each row represents a distinct alternative (i.e. a unique combination of control parameters), while the columns correspond to either an input variable or an output performance criterion. The decision variables include (SOI , F , D , P_{fuel} , EVO , EVC). These were varied systematically to generate representative engine operating scenarios within the refined parameter space.

The input parameters SFC , PM and NO_x serve as the decision criteria (C_j) for subsequent MCDM analysis. The dataset captures the multi-objective trade-offs inherent to marine diesel engine operation, where improvements in fuel efficiency often compete with stricter emission constraints. This matrix forms the quantitative foundation upon which various MCDM methods (e.g. SAW, TOPSIS, TMF) are applied to rank and identify optimal set configurations.

Table 4.2. Diesel-RK Decision matrix

Alternative A_i	SOI [°CA- BTDC]	F [%]	D [°CA]	P_{fuel} [bar]	EVO [°CA- BBDC]	EVC [°CA- ABDC]	Criterion C_j		
							SFC [kg/kWh]	PM [g/kWh]	NO_x [g/kWh]
1	1	1	2	700	62	110	0.185	0.079	2.521
2	2	1	2	700	62	110	0.183	0.075	2.600
3	4	3	3	800	64	115	0.181	0.077	2.829
4	5	8	3	850	64	115	0.181	0.095	3.349
5	1	8	3	950	64	115	0.187	0.111	2.688
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
4,454	.	.	.	.	.	.	.	.	.

4.4. Evaluation results of MCDM methods for the studied marine diesel engine

This section reports the benchmarking (comparative evaluation) of fourteen MCDM methods on the 4,454 feasible Diesel-RK simulation results for two-stroke marine diesel engine optimization. Each alternative configuration corresponds to a distinct engine operating strategy (calibration) defined by the selected controllable settings (SOI , F , D , P_{fuel} , EVO , EVC) and characterized by the resulting performance/emission indicators SFC , NO_x and PM in addition to any indicators retained in the final decision model relating to engine performance monitoring.

In this dissertation, the MCDM evaluation does not seek a single "true" ranking. Instead, it aims to identify methods that produce reliable decision outputs when applied to a large two-stroke marine diesel engine. Given that MCDM outputs are inherently rank-based (i.e. it recommends which alternative should be preferred), the evaluation is deliberately rank-based and focuses on two complementary properties: cross-method consensus and ranking similarity [120].

First, consensus analysis reduces reliance on any single method's logic by identifying alternatives that are consistently preferred across multiple ranking models. Rank aggregation via Borda Count method provides a transparent, widely accepted mechanism for harmonizing multiple ordered lists into a single consensus order, thereby highlighting each engine alternative configuration that remains competitive under different MCDM methods.

Second, stability (sensitivity) analysis is applied because MCDM rankings can shift with reasonable variations in method choices, most notably criterion weights and normalization assumptions. As a standard robustness tool in MCDM, sensitivity analysis assesses whether conclusions hold under plausible perturbations in preference parameters and methodological assumptions [121].

4.4.1. Results of the consensus analysis of the MCDM methods

To harmonize the diverse rankings produced by the 14 individual MCDM methods, I employed the Borda Count method [122]. The Borda Count is a consensus-based voting procedure used to generate a single, aggregate ranking from a set of multiple ordered lists. Its primary advantage is its ability to identify alternatives that are broadly favored across different evaluation perspectives, thereby producing a more robust and less biased final ranking [122].

In this research, the application of the Borda Count was performed as follows:

1. Rank assignment: each of the 14 MCDM methods provided a complete ranking of the 4,454 alternative configurations of the selected controllable settings (SOI , F , D , P_{fuel} , EVO , EVC) based on each method's preference ranking mechanism.
2. Point allocation: for each of these 14 methods, each alternative received points equal to its rank; for example, an alternative ranked 1st by an algorithm received 1 point, an alternative ranked 10th received 10 points and an alternative ranked last (4,454th) received 4,454 points.
3. Score aggregation: for each of the 4,454 alternatives, the points from all 14 MCDM methods were summed and the sum is the alternative's final Borda Score.
4. Final ranking: the alternatives were then ranked based on their Borda Scores, from lowest to highest; a lower Borda Score signifies a more preferable alternative configuration, as it indicates a consistently higher existence across the majority of the MCDM methods.

The Borda Count method effectively identifies the engine configurations that represent the best compromise solution, mitigating the risk of selecting an alternative that performs exceptionally well by one method's logic but poorly by others.

Figure 4.2. provides a comparative visualization of the top 15 ranked alternatives across the 14 selected MCDM methods. The color scale ranges from green (most consistent) to red (least consistent), where alternatives closer to green indicate higher agreement among the 14 sets of results. The lines in the figure represent top 15 alternative configuration, showing the control parameters SOI , F , D , P_{fuel} , EVO , EVC and SE value. The columns in the figures show the configuration rank at each MCDM method.

The comparative analysis revealed clear variation in method agreement, as visually captured in the consistency matrix (Figure 4.2.). Alternatives exhibiting green-coded consensus reflect strong method convergence and are thus ideal candidates for real-world implementation or further validation. Conversely, red-coded rankings signaled greater instability, suggesting sensitivity to the choice of decision-making methodology.

This analysis approach mitigates the limitations inherent in relying on a single MCDM method and reinforces the importance of ensemble evaluation in complex engineering decision contexts. By

emphasizing consensus and stability, this procedure supports the development of a more transparent engine performance optimization strategy.

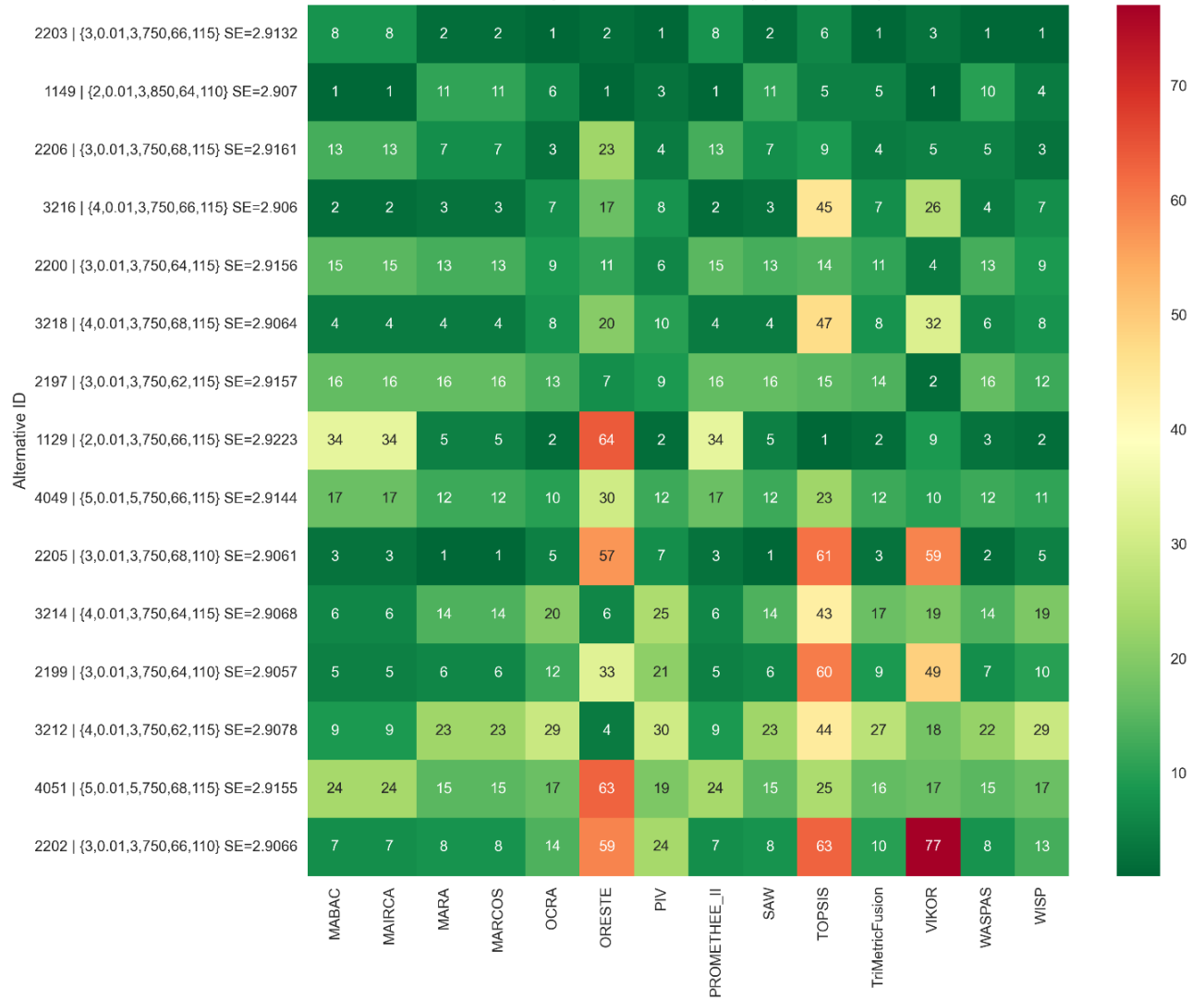


Figure 4.2. Ranking of the top 15 alternative configurations (by Borda Count method)

The results reveal clear differences in cross-method agreement. Alternatives with predominantly green-coded ranks indicate strong method convergence and therefore represent robust candidates for implementation or follow-up validation. Conversely, alternatives showing red-coded dispersion indicate disagreement among methods, suggesting a higher sensitivity of the decision outcome to the selected MCDM formulation.

4.4.2. Results of the stability analysis of the MCDM methods

To ensure that the recommended engine controllable settings are not just high-performing but also reliable, a stability analysis was conducted. This means the consistency of each engine configuration was ranked across all 14 MCDM methods.

For every engine configuration, the following calculations have been done:

1. Standard deviation (σ): shows how much the rankings for a given configuration varied across the 14 methods, a lower σ means the configuration was ranked similarly (and consistently) by most methods.
2. Range: shows the difference between the highest and lowest ranks that a configuration received, a smaller range means the rankings were closely grouped.

The top five most stable alternative configurations, which exhibit the lowest standard deviation in their ranks across all MCDM methods, are the following:

- **Configuration 2203** | {3, 1, 3, 750, 66, 115}, **SE = 2.9132**: $\sigma = 2.87$, range = 7
- **Configuration 2200** | {3, 1, 3, 750, 64, 115}, **SE = 2.9156**: $\sigma = 3.41$, range = 11
- **Configuration 1149** | {2, 1, 3, 850, 64, 110}, **SE = 2.907**: $\sigma = 4.10$, range = 10
- **Configuration 2197** | {3, 1, 3, 750, 62, 115}, **SE = 2.9157**: $\sigma = 4.31$, range = 14
- **Configuration 2206** | {3, 1, 3, 750, 68, 115}, **SE = 2.9161**: $\sigma = 5.57$, range = 20

Among all configurations, configuration 2203 ($SOI = 3$, Fraction = 1, $D = 3$, $P_{fuel} = 750$, $EVO = 66$, $EVC = 115$, $SE = 2.9132$) emerged as the most stable, with the lowest standard deviation ($\sigma = 2.87$), while also achieving 100% consensus. This strong convergence across methods affirms its reliability and resilience to ranking bias. Notably, it was ranked within first WASPAS, WISP, PIV and TMF.

In Addition to the above two analyses results, we can notice that the absolute best SE value was observed in **Configuration 2199** (this configuration is out of the top 5), with $SE = 2.905$. Although marginally better in the SE index, this alternative exhibited lower consensus and stability across methods. The methods that ranked this configuration highest were PROMETHEE II, MABAC and MAIRCA.

4.4.3. Recommended MCDM methods for marine diesel engine applications

The results analysis reveals a critical insight: Alternative configurations 2203 and 2200, demonstrated exceptional ranking stability and appeared in the top ranks across all 14 methods, achieving high consensus as well. These results highlight that method consensus and ranking stability are critical robust indicators. For real-world applications such as marine engine tuning, where consistent and reliable decision-making is essential, this stability is arguably as important as the raw performance metric itself.

Notably, alternative with the lowest SE value does not necessarily represent the most robust or widely supported choice. This is clearly demonstrated by the case of configuration 2199, which, despite achieving the lowest SE index (2.905) across all 4,454 simulated alternatives, exhibited poor ranking stability ($\sigma = 12.19$). Its significant fluctuation across the different MCDM methods suggests that its top performance is highly sensitive to the specific weighting and calculation method used, thereby limiting its reliability.

This divergence proves that no single MCDM method should be treated as universally optimal for marine applications. Therefore, the most dependable foundation for optimization in such complex, regulation-bound environments is provided by methods that successfully balance performance with stability, namely the WISP, PIV and TMF methods.

Thus, while multiple alternatives exhibit strong performance, WISP, PIV and TMF methods stand out for its high alignment with consensus rankings, low variability and ability to identify stable and optimal SE configurations. These three algorithms offer the best overall balance of ranking accuracy

based on both results analyses, consensus alignment and discriminatory sensitivity, making them the most suitable MCDM methods for marine engine support systems under complex multi-criteria trade-offs.

These findings carry substantial practical relevance for marine engine operators, regulators and control system developers. In real-world applications, consistency and robustness across decision-making frameworks are critical to ensure safe and optimized performance under varying operating conditions. By identifying alternatives that are both high-performing (in terms of emission index SE) and stable across diverse MCDM rankings, the results supports data-driven tuning of engine parameters, a valuable contribution to engine onboard decision support systems and IMO compliance strategies. Notably, the demonstrated effectiveness of WISP, PIV and TMF methods in isolating both optimal and stable configurations offer a blueprint for real-time engine control systems where algorithmic consensus is essential to avoid oscillatory behavior or sub-optimal tuning.

4.5. Pareto optimal solutions validation using MCDM methods

Sections 4.3-4.4 compare and evaluate the MCDM methods using the Diesel-RK decision matrix, so that method selection was grounded in the high-fidelity physics model and not confounded by surrogate approximation effects. However, in the fully integrated decision-support system, the NN surrogate replaces Diesel-RK during optimization to enable wide NSGA-II search and rapid generation of a Pareto optimal set. For this reason, it is necessary to "close the loop" and verify that the decision step remains reliable when implemented on surrogate-generated alternatives.

The NSGA-II algorithm uses the Pareto optimal set of 163 non-dominated operating strategies satisfying Tier III and mechanical constraints (see Appendix 2). This set represents the operational candidates' configuration settings that the onboard decision support system would rank in real time.

To select the most operationally viable engine configuration from the Pareto optimal set, three distinct MCDM methods were applied: PIV, WISP and TMF.

Table 4.3. presents the rankings obtained from each MCDM method. Notably, all three methods produced identical top 5 rankings, indicating a high degree of stability and decision consensus. Such agreements strengthens confidence in the selected solutions and demonstrate that the optimization space is well-structured with clear dominance relationships among alternatives.

Table 4.3. Rankings of the top 5 Pareto optimal solutions using PIV, WISP and TMF methods

Solutions	SOI	F	D	P_{fuel}	EVO	EVC	SFC	PM	NO_x
S1	1.760	1.1	3.396	757.910	67.970	114.343	0.185	0.072	2.423
S2	2.248	1.0	2.931	798.053	67.236	115.076	0.184	0.072	2.447
S3	2.717	1.0	2.657	763.661	63.445	114.043	0.183	0.073	2.476
S4	2.688	1.2	2.970	797.741	65.236	115.305	0.182	0.071	2.577
S5	2.774	1.3	3.213	790.899	67.752	115.773	0.182	0.070	2.573

The consensus identifies solution **S1** as the most robust configuration, offering the best trade-off between fuel efficiency and emissions under regulatory constraints. The consensus identifies solution S1 as the most robust configuration, as it consistently ranked at the top 1 across all three MCDM methods (PIV, WISP and TMF), demonstrating independence from method-specific biases. **S1** offers a balanced compromise by simultaneously minimizing SFC , NO_x and PM within IMO Tier III constraints, whereas alternative solutions (**S2-S5**) prioritize one objective at the expense of others. Furthermore, Diesel-RK revalidation confirmed minimal difference from surrogate predictions,

underscoring the physical reliability of **S1** as the best trade-off configuration. The other four solutions (**S2**, **S3**, **S4**, **S5**) provide slightly different operational balances but remain close to **S1** in terms of objective values, offering fallback options for varying voyage conditions or Emission Control Areas. Beyond the solution **S5**, the three methods show slight divergences in rankings. This behavior is expected because solutions outside the top-5 are closer in aggregated scores, making it more sensitive to method-specific weighting and normalization approaches.

To ensure complete physical fidelity and validate the surrogate-based optimization, the top-ranked Solution **S1** was re-evaluated using Diesel-RK simulations (Table 4. 4.). The convergence of all three MCDM methods (PIV, WISP and TMF), coupled with Diesel-RK software validation, confirms that the final operation recommendation is not only computationally consistent but also grounded in accurate thermodynamic and emissions modeling.

Table 4.4. Re-evaluated the top-1 solution using Diesel-RK simulations

Solution S1	<i>SFC</i> [kg/kWh]	<i>PM</i> [g/kWh]	<i>NO_x</i> [g/kWh]
Diesel-RK software	0.186	0.082	2.489
NN surrogate model	0.185	0.072	2.423
Difference	0.001	0.010	0.066

The re-evaluated results in Table 4.4. demonstrate that the differences between the surrogate predictions and Diesel-RK simulations are minimal. These differences correspond to errors: *SFC* deviation is ~1%; *NO_x* deviation is ~3%; *PM* deviation is higher (~10–15%) but remains small in absolute magnitude (0.01 g/kWh) and does not change the top-k decision region and confirms that the surrogate model preserves the physical fidelity of the high-fidelity simulator. This close agreement underscores the reliability of **S1** solution as the final optimized configuration, ensuring that the selected solution is both computationally consistent and thermodynamically accurate for practical implementation.

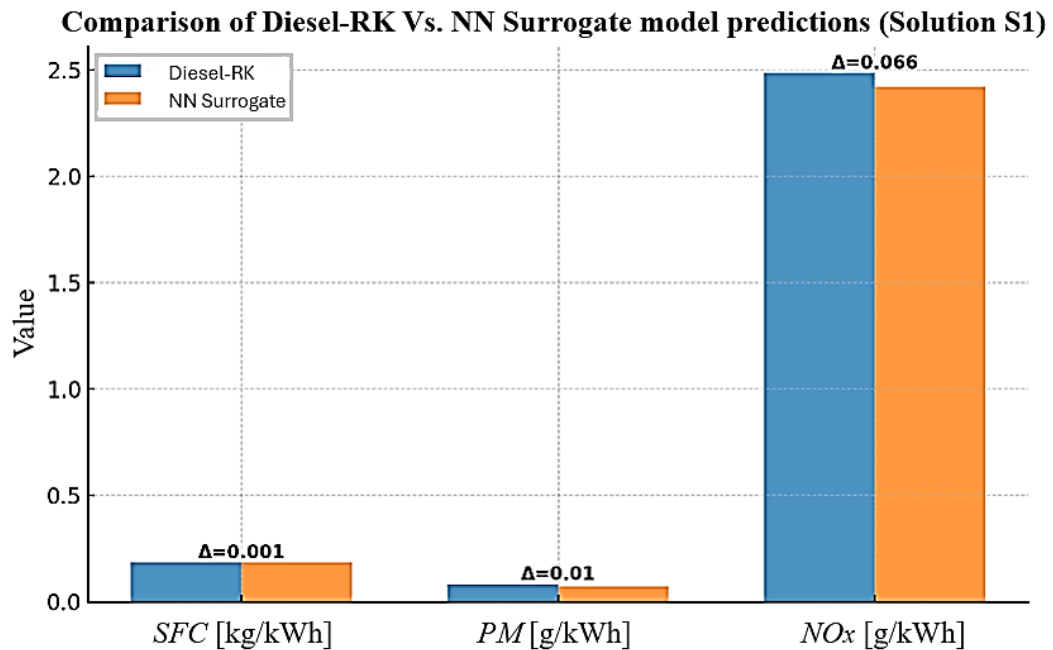


Figure 4.3. Differences between Diesel-RK vs. NN surrogate predictions

Figure 4.3. shows the comparison of Diesel-RK and NN surrogate model predictions for the top-ranked solution S1. The surrogate model closely reproduces the high-fidelity simulator outputs, with differences of $\Delta SFC = 0.001$ kg/kWh, $\Delta PM = 0.01$ g/kWh and $\Delta NO = 0.066$ g/kWh. The negligible differences (<2%) confirm the physical fidelity of the surrogate and validate its reliability for integration into multi-objective optimization and decision-making workflows.

Accordingly, **solution S1** ($SOI = 1.76^\circ$, $F = 1.12$, $D = 3.40^\circ$, $P_{fuel} = 757.91$ bar, $EVO = 67.97^\circ$, $EVC = 114.34^\circ$) is selected as the **final optimized configuration, offering the best trade-off, in full compliance with IMO Tier III regulations.**

In summary, the integrated NSGA-II and MCDM framework successfully identified engine control strategies that **meet both fuel efficiency and emission reduction goals** under IMO Tier III regulations. Among the Pareto optimal candidates, five solutions consistently ranked highest across all three MCDM methods (PIV, WISP and TMF), confirming the robustness of the optimization process. Solution S1 emerged as the most balanced configuration, achieving $SFC = 0.185$ kg/kWh, $PM = 0.072$ g/kWh and $NO_x = 2.423$ g/kWh, all within the defined constraints. Its re-evaluation using Diesel-RK simulations showed minimal difference (e.g. $\Delta SFC = 0.001$), validating the surrogate model's accuracy. Compared to other top solutions, S1 maintains superior emission control with only a marginal difference in fuel consumption, making it the most practical and regulatory-compliant choice.

These findings demonstrate the procedure's capability to deliver actionable, data-driven decisions for marine engine performance optimization in real-world scenarios.

5. OPERATOR-DEFINED FUZZY WEIGHT ADAPTATION FOR MULTI-CRITERIA RANKING

This chapter introduces the operator-defined fuzzy weighting procedure of the elaborated marine engine decision support framework. Chapter 3 established a surrogate-assisted optimization procedure capable of generating a constrained Pareto optimal set of feasible, non-dominated operating strategies for a two-stroke marine diesel engine. Chapter 4 then established the multi-criteria decision procedure by benchmarking candidate MCDM methods on a physics-based Diesel-RK simulation data and validating that the selected robust methods remain decision-consistent when applied to the surrogate-derived Pareto set. Moreover, the practical deployment challenge is not only which MCDM method is sufficiently stable, but also how the criterion weights are defined in a real shipboard context. In operation, preference decisions are non-stationary: fuel-cost pressure, schedule constraints and Emission Control Area compliance can legitimately shift the relative importance of fuel consumption and emissions. In many MCDM applications, criterion weights are treated as fixed and precisely specified. In a shipboard decision-support context, this assumption becomes a system limitation because it offers a single, static preference in the ranking, despite the fact that operational priorities are inherently time-varying, especially in marine applications. To address this mismatch, Chapter 5 introduces an operator-defined fuzzy weight adaptation procedure that translates intuitive importance statements into a consistent, normalized weight vector without requiring unrealistic numerical exactness. Using an interpretable Mamdani-type inference structure grounded in fuzzy set theory, the fuzzy weighting module maps operator ratings of the objectives *SFC*, *NO_x* and *PM* into weights that can be directly coupled to the robust MCDM ranking methods selected in Chapter 4.

To formalize imprecise and linguistic operator preferences without requiring unrealistic numerical exactness, this chapter adopts fuzzy set theory as the weighting mechanism. Fuzzy sets provide a mathematically rigorous representation of graded truth and linguistic concepts (e.g. "low", "high"). Building on classical Mamdani-type inference (one of the most widely used, interpretable fuzzy control paradigms) [123], this chapter develops a dedicated Fuzzy Logic Module (FLM) that maps operator importance ratings for the three core criteria (*SFC*, *NO_x*, *PM*) on a continuous 0-10 scale into a crisp, normalized weight vector suitable for MCDM ranking. The FLM produces weights that can be coupled to any ranking algorithm. In addition, in this dissertation, it is integrated with the robust MCDM methods selected in Chapter 4 to ensure that preference adaptation does not reintroduce instability through the choice of ranking method.

The chapter demonstrates the full procedure from operator preference to a final recommended operating point, as shown in Figure 5.1: 1.) fuzzification of the operator's stated importance ratings, 2.) rule-based inference to mediate trade-offs when multiple criteria are simultaneously prioritized, 3.) defuzzification and normalization to obtain usable weights and 4.) re-ranking of the fixed Pareto decision matrix using the selected MCDM methods to identify a small number of context-appropriate recommendations.

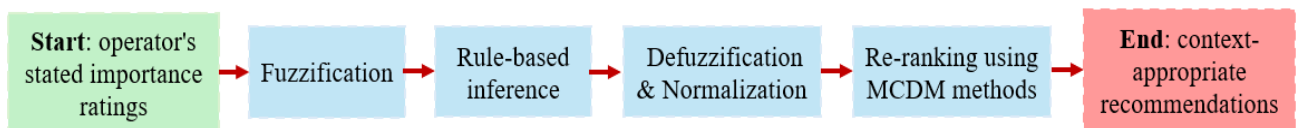


Figure 5.1. Full procedure flowchart of the operator preference integration process

The chapter is organized as follows: Section 5.1. presents the architecture of the FLM and its integration point within the MCDM procedure. Section 5.2. define the fuzzification design (linguistic partition and membership functions), the rule base and inference principles and the defuzzification/normalization steps that yield crisp MCDM weights. Section 5.3. details the coupling of the fuzzy-derived weights with the selected MCDM core for ranking. Finally, Section 5.4. presents the case study on the Pareto front, including operator-priority scenarios, response-surface interpretation, ranking outcomes and robustness/sensitivity analysis.

5.1. Architecture and methodology of the newly elaborated Fuzzy Logic Module

The core of the elaborated methodology is a Mamdani-type Fuzzy Logic Module [123-125]. The FLM was designed to function as a dedicated module that translates imprecise operator preferences into a set of crisp, normalized weights for MCDM. The primary objective is to bridge the gap between the operator's judgment and the quantitative data required by MCDM methods. The overall workflow, encompassing fuzzification, inference and defuzzification, is illustrated in Figure 5.2.

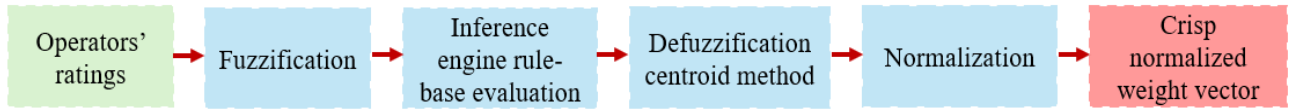


Figure 5.2. Flowchart of the Fuzzy Logic Module for MCDM weighting

Figure 5.2. illustrates the full workflow of the fuzzy logic module. These ratings are fuzzified and processed through a rule-based inference mechanism; the resulting crisp weights are then passed to the selected MCDM method, which ranks the fixed set of feasible alternatives (e.g. Pareto optimal operating points).

The fuzzy logic module uses three input variables to capture operator preferences:

1. *SFC* importance (x_{SFC}),
2. *NO_x* importance (x_{NOx}),
3. *PM* importance (x_{PM}).

The corresponding output variables produced:

1. *SFC* weight (w_{SFC}),
2. *NO_x* weight (w_{NOx}),
3. *PM* weight (w_{PM}).

5.2. Fuzzy weighting design: fuzzification, rule base and defuzzification

As introduced in Figure 5.1. the system's process begins with the fuzzification of operator-defined importance ratings. The FLM takes as input three operator-defined importance ratings on a continuous [0,10] scale, corresponding to the three minimized criteria used throughout the dissertation: *SFC*, *NO_x* and *PM*. The outputs are three weights w_{SFC} , w_{NOx} , w_{PM} , which are directly compatible with weighted MCDM ranking.

All variables share a continuous universe of discourse [0, 10], representing the full scale of importance from negligible importance to maximum importance. Each input variable is divided into five linguistic terms: Very Low (VL), Low (L), Medium (M), High (H) and Very High (VH). The Triangular Membership Functions (MFs) were selected for their computational efficiency,

interpretability and robustness [126, 127]. The mathematical definition of a triangular MF for a term with parameters (a, b, c) is the following [128]:

$$\mu(x; a, b, c) = \max(0, \min(\frac{x-a}{b-a}, \frac{c-x}{c-b})) \quad (5.1)$$

where:

- μ : The membership grade, a real number in the interval $[0, 1]$. It quantifies the degree of truth or the extent to which the crisp input x belongs to the fuzzy set defined by the linguistic term (e.g. "High").
- x : The crisp input value on the universe of discourse, representing a specific numerical importance rating provided by the operator within the range $[0, 10]$.
- a : The lower boundary parameter defines the left foot of the triangle where the membership grade begins to increase from zero.
- b : The peak parameter, defining the vertex of the triangle where the membership grade reaches its maximum value.
- c : The upper boundary parameter, defining the right foot of the triangle where the membership grade returns to zero.

The symmetric and overlapping parameters adopted in this research are summarized in Table 5.1. and illustrated in Figure 5.3.

Table 5.1. Triangular membership function parameters

Linguistic Term	Parameters (a, b, c)
1. Very Low (VL)	(0, 0, 2.5)
2. Low (L)	(0, 2.5, 5.0)
3. Medium (M)	(2.5, 5.0, 7.5)
4. High (H)	(5.0, 7.5, 10.0)
5. Very High (VH)	(7.5, 10.0, 10.0)

The input to the FLM is a direct $[0-10]$ rating from the operator for criterion importance, where 0 and 10 represent the "not important at all" and "extremely important" extremes and 5 is the natural neutral midpoint. To cover this universe with five linguistic terms (Very Low, Low, Medium, High, Very High), I adopt a symmetric, equally spaced partition of the $[0, 10]$ interval with breakpoints at 0, 2.5, 5, 7.5 and 10. In this mapping, the cores of the five triangular membership functions are centered at these points (0, 2.5, 5, 7.5 and 10), ensuring that "Medium" is centered at 5, "Low" and "High" are placed at equal distance from the center and "Very Low" and "Very High" occupy the extremes. This symmetric, 2.5 unit spacing preserves interpretability for the operator, avoids bias toward either end of the scale and yields smoothly overlapping triangular sets that are standard in Mamdani-type fuzzy controllers, while keeping the parametrization transparent and straightforward.

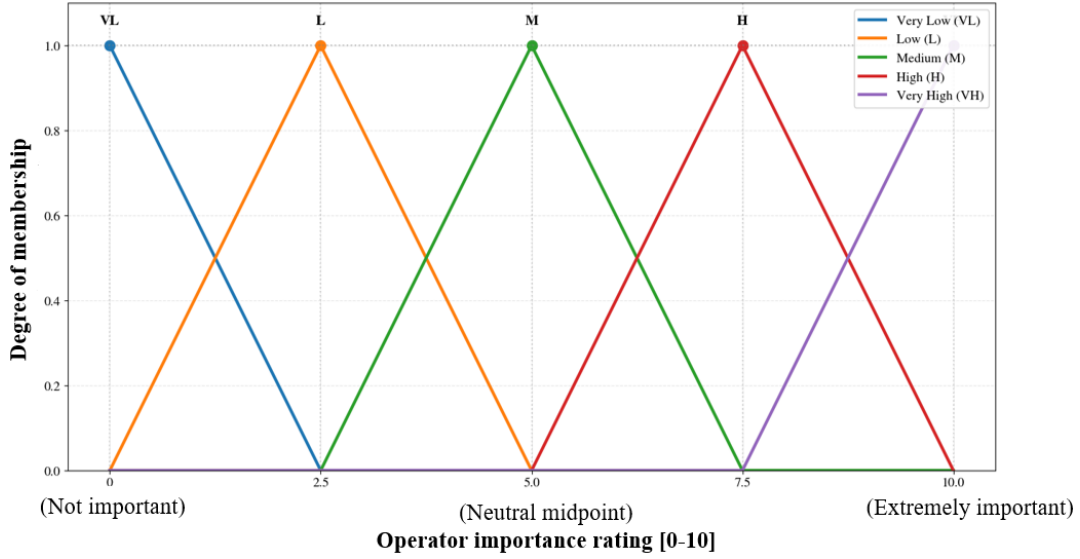


Figure 5.3. Triangular membership functions for operator importance rating

In this research, the triangular membership functions on the [0-10] importance scale are fixed to a symmetric, equally spaced partition (0-2.5-5-7.5-10) for interpretability and no further tuning of these parameters is performed. Although the exact MF boundaries are not tuned in this study, the overlapping structure and consistent rule base imply that small shifts of the internal breakpoints would change the derived weights gradually; I therefore expect the identity of the most preferred region of the Pareto surface to remain stable under moderate perturbations of the MF boundaries, even if the detailed ordering of very similar alternatives may vary.

The core of the FLM is a complete Mamdani rule base ($5 \cdot 5 \cdot 5 = 125$ IF-THEN rules) that I generated automatically to ensure coverage of the above triangular functions and to formalize expert knowledge through four hierarchical principles.

The hierarchical principles of Mamdani inference for weight synthesis are the following [129-131]:

1. Competitive Mediation (Trade-off): when two or more conflicting criteria are rated (Very High), their outputs are downgraded to (High), preventing unrealistic dominance in multi-critical scenarios.
2. Uncontested Dominance: if one criterion is (Very High) and the others are (Medium) or (Lower), the dominant criterion retains its (Very High) consequent.
3. Symmetry: equal input importance ratings must yield equal output weights, ensuring fairness.
4. Baseline Principle: for all other combinations, outputs mirror the inputs directly.

The principles are applied in a lexicographic (hierarchical) order: first competitive mediation, then uncontested dominance, then symmetry and finally the baseline rule. For each discrete combination of input linguistic levels (VL, L, M, H, VH) across the three criteria, exactly one rule is generated by checking these principles in that sequence. This guarantees that there is no pair of rules with identical antecedents but different consequents, i.e. no logical contradictions at the rule level. For example, the limiting case (VH, VH, VH) is handled uniquely by the competitive-mediation principle, which downgrades all three outputs to (H, H, H) while remaining consistent with symmetry (all inputs and outputs remain equal). The combination (VH, M, L) is uniquely governed by uncontested dominance, producing (VH, M, L) and (M, M, M) is consistent with both symmetry and the baseline principle, since both prescribe (M, M, M); in the hierarchy, this produces a single, non-conflicting rule. By construction, therefore, the 5^3 -rule base has a one-to-one mapping between each linguistic input triplet and its consequent triple and the limiting cases do not induce contradictory rules.

The rule base follows a complete 5^3 structure over the three linguistic inputs (*SFC* importance, NO_x importance, *PM* importance), each described by the terms Very Low (VL), Low (L), Medium (M), High (H) and Very High (VH). Each rule takes the following form:

IF *SFC* importance is A and NO_x importance is B and *PM* importance is C,
THEN *SFC* weight is w_{SFC} and NO_x weight is w_{NO_x} and *PM* weight is w_{PM} .

For example, one concrete rule from the "competitive mediation" region has the following form:

IF *SFC* importance is Very High and NO_x importance is Medium and *PM* importance is Low, THEN
SFC weight is Very High and NO_x weight is Medium and *PM* weight is Low.

In this way, all 125 rules are generated by systematically combining the five linguistic levels on each input and assigning consequents that respect the four design principles (competitive mediation, uncontested dominance, symmetry, baseline).

The approach provides comprehensive coverage of input cases while keeping the rule base logically consistent.

In this context, "conflicting criteria" are understood in the standard multi-objective sense: *SFC*, NO_x and *PM* are all minimized simultaneously on a Pareto front, so an improvement in one dimension typically requires deterioration in at least one of the others. Operationally, the Competitive Mediation principle is therefore triggered whenever two or more important ratings fall into the Very High (VH) linguistic level, regardless of the specific pair and not based on a numerical conflict index such as correlation or covariance. This threshold-based definition keeps the rule base transparent and straightforward for operators while remaining consistent with the trade-off structure observed in the Pareto optimal dataset.

The aggregated fuzzy sets are transformed into crisp outputs via the Centroid of Area (CoA) method [132-135]:

$$z^* = \frac{\int z \cdot \mu(z) dz}{\int \mu(z) dz} \quad (5.2)$$

where:

z^* : the centroid (defuzzified crisp output) of the aggregated output fuzzy set;

z : the output variable of the FLM (here, the pre-normalized weight for a given criterion);

$\mu(z)$: the aggregated membership function of the output fuzzy set after rule firing and aggregation.

Which results in three preliminary (unnormalized) weights: w'_{SFC} , w'_{NO_x} , w'_{PM} . To ensure comparability across criteria, these are normalized as follows:

$$\begin{aligned} w_{SFC} &= \frac{w'_{SFC}}{w'_{SFC} + w'_{NO_x} + w'_{PM}} \\ w_{NO_x} &= \frac{w'_{NO_x}}{w'_{SFC} + w'_{NO_x} + w'_{PM}} \\ w_{PM} &= \frac{w'_{PM}}{w'_{SFC} + w'_{NO_x} + w'_{PM}} \end{aligned} \quad (5.3)$$

where:

w'_{SFC} , w'_{NO_x} , w'_{PM} : The pre-normalized (raw) outputs of the FLM after defuzzification (CoA).

These values are non-negative, expressed on an arbitrary scale and do not necessarily sum to 1.

w_{SFC} , w_{NOx} , w_{PM} : The normalized weights used by the MCDM method. They are dimensionless proportions in $[0,1]$ that sum to 1 ($\sum w_i = 1$). They represent the final, comparable importance shares of the criteria.

The result is a normalized weight ready for integration into MCDM ranking methods such as the selected PIV, WISP and TMF.

5.3. Ranking implementation: applying FLM weights in one of the selected MCDM methods

To translate the fuzzy-derived weight vector into an implementable operating recommendation, the Pareto optimal alternatives established in Chapter 3 are ranked using the TriMetric Fusion (TMF) method. TMF was selected based on the method selection and robustness evaluation reported in Chapter 4, where TMF (together with PIV and WISP) exhibited high stability and strong consensus alignment across two-stroke marine diesel decision matrices [136]. Accordingly, the present section employs it as a representative robust MCDM method to evaluate the effect of the operator-defined fuzzy weighting module on the final ranking outcomes.

TMF is an advanced MCDM method designed to enhance ranking robustness by synthesizing three distinct, complementary decision metrics into a single consensus index [61]:

1. Criteria Aggregated Weighted Index (CAWI): A linear weighted-sum score that estimates each alternative's overall utility across all criteria; it rewards consistent overall performance.

$$CAWI_i = \sum_{j=1}^n w_j \cdot x'_{ij} \quad (5.4)$$

where: w_j is the weight of the criterion j and x'_{ij} is the normalized value of the alternative i on criterion j .

2. Balanced Extreme Criteria Index (BECI): A non-linear index that penalizes extreme imbalances across criteria, ensuring that strength in one dimension does not mask critical weakness in another; it promotes balanced solutions.

$$BECI_i = \alpha \cdot \max_j (w_j \cdot x'_{ij}) + (1 - \alpha) \cdot \min_j (w_j \cdot x'_{ij}) \quad (5.5)$$

where: $\alpha \in [0,1]$ is a weighting parameter (default: 0.5), enables flexible control over the influence of best and worst criteria.

3. Euclidean Distance Metric (DIS): A geometric measure of proximity to a hypothetical ideal point in the multi-criteria space; a smaller distance indicates a better alternative.

$$DIS_i = \sqrt{\sum_{j=1}^n (w_j \cdot x'_{ij} - 1)^2} \quad (5.6)$$

The three metrics are aggregated using a TOPSIS approach [38]:

$$SI_i = \frac{s_i^-}{s_i^+ + s_i^-} \quad (5.7)$$

where: S_i^+ and S_i^- are distances to positive and negative ideal points in the (CAWI, BECI, DIS) metric space.

The fusion of these three perspectives, global utility, balance and geometric proximity, mitigates the inherent biases of any single metric. This makes TMF highly robust against rank reversals and sensitive to the nuanced trade-offs present in the Pareto front set [40]. This robustness is crucial when handling the weights produced by the fuzzy module, ensuring that the final ranking is stable and reflective of the operator's complex priorities.

Figure 5.4. shows the full path from operator priorities to a final decision: fuzzy logic produces the weight vector $\mathbf{w}$, TMF scores and ranks the Pareto candidates and the top-ranked alternative is selected as the final decision.

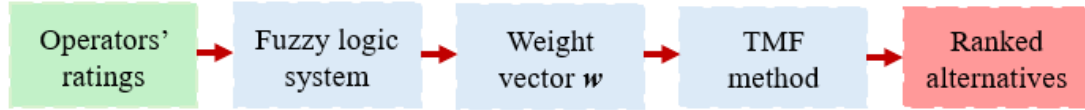


Figure 5.4. Full procedure from operator priorities to the final decision via fuzzy weights $\mathbf{w}$ and TriMetric Fusion method

From an implementation point of view, the FLM has three input variables (SFC , NO_x , PM), each described by five triangular membership functions, which yield a complete Mamdani rule base of $5^3 = 125$ rules. Evaluating one set of operator importance ratings requires: 1.) computing the membership degrees of the three inputs, 2.) firing the 125 rules and 3.) performing centroid defuzzification of a single output. In addition, the FLM will not be executed at engine-cycle frequency: it is used only when the operator adjusts the importance ratings or when a new Pareto front is loaded, i.e. on a decision-support time scale of seconds or minutes rather than milliseconds. Although a fully populated Mamdani rule-based scale as 5^n with the number of criteria and would become impractical if many additional criteria were introduced, the present design is intentionally restricted to three core engine performance criteria (SFC , NO_x , PM), for which 125 rules remain fully tractable. Any future extension to more indicators would not simply extend the rule base to 5^4 or 5^5 , but would use aggregated bundled criteria, fewer linguistic terms, or sparse/hierarchical rule bases to avoid combinatorial growth.

5.4. Demonstration on the Pareto set: scenarios, ranking shifts and robustness

The newly elaborated fuzzy weighting methodology was demonstrated on the Pareto front generated using NSGA-II algorithm in Chapter 3, which reflects the balance of the three conflicting criteria (SFC , NO_x , PM), all of which are minimized.

The values of the three criteria are structured into the Pareto front decision matrix $\underline{\underline{D}}$:

$$\underline{\underline{D}} = \begin{bmatrix} SFC_1 & NOx_1 & PM_1 \\ SFC_2 & NOx_2 & PM_2 \\ \vdots & \vdots & \vdots \\ SFC_m & NOx_m & PM_m \end{bmatrix} \quad (5.8)$$

The 163 Pareto optimal alternatives are reported in (Appendix 2). Across the set, SFC has a mean value of 0.1826 with a standard deviation of 0.0019 and a range of [0.1811 – 0.1901], PM has a mean

of 0.0754 with a standard deviation of 0.0042 and a range of [0.0713 - 0.0990], while NO_x has a mean of 2.6732 with a standard deviation of 0.1756 and a range of [2.2447 - 2.9392].

5.4.1. Operator-priority scenarios and fuzzy weight generation

The validation of the elaborated fuzzy weighting module was evaluated across four representative operational scenario-based. These scenarios capture a range of realistic operator priorities, from focused single-objective emphasis to complex multi-criteria trade-offs. For each operator, priorities are provided as importance ratings (for SFC , NO_x and PM) on a [0-10] scale. And converted by the fuzzy module into a valid normalized weight vector $\mathbf{w} = [w_{SFC}, w_{NO_x}, w_{PM}]$ with $\sum w_i = 1$, to use by the MCDM ranking procedure.

The four tested scenarios are the following:

1. Fuel-Economy Priority: Simulate open-sea operation, where fuel cost is paramount. Inputs reflect a high priority for SFC (7.0) with moderate concern for NO_x (5.0) and lower priority for PM (3.0).
2. Strict Environmental Compliance: The ship's entry into an Emission Control Area (ECA), where emissions limits are critical. Inputs show low priority for SFC (2.5) and very high priorities for both NO_x (8.5) and PM (8.0).
3. Balanced Performance: This represents neutral conditions or a general operational philosophy, with all three criteria given equal importance (5.0, 5.0, 5.0).
4. High Competition (Trade-off): The challenges the system faces with two simultaneously dominant criteria (SFC and NO_x at 9.0) and one neglected criterion, PM (2.0), testing the module's ability to mediate competing priorities.

It should be noted that, in this research, the four scenarios are used as conceptual operator archetypes rather than empirically elicited preference distributions; they are intended to span typical extremes in practice (fuel-cost driven operation, strict emission constraints, neutral conditions, intense commercial pressure) and to test the behavior of the fuzzy weighting module under clearly differentiated priority settings. The resulting normalized fuzzy-derived weights for each scenario are presented in Table 5.2.

Table 5.2. Operator priority inputs and corresponding normalized fuzzy-derived weights

Scenarios	Input Importance ($x_{SFC}, x_{NO_x}, x_{PM}$)	Output Weights ($w_{SFC}, w_{NO_x}, w_{PM}$)
1. Fuel Economy Priority	(7.0, 5.0, 3.0)	(0.460, 0.333, 0.207)
2. Strict Environmental Compliance	(2.5, 8.5, 6.0)	(0.154, 0.474, 0.373)
3. Balanced Performance	(5.0, 5.0, 5.0)	(0.333, 0.333, 0.333)
4. High Competition (Trade-off)	(9.0, 9.0, 2.0)	(0.422, 0.422, 0.155)

Table 5.2 summarizes the output of the FLM under four representative operator-priority scenarios. Overall, the results confirm that the FLM translates qualitative operator preferences into consistent, normalized and operationally sensible weight vectors, while enforcing the intended mediation logic embedded in the Mamdani rule base. The key observations are as follows:

1. In Scenario 1, the high input for SFC is correctly translated into the most significant weight (0.459), ensuring it will be the dominant factor in the final MCDM ranking.

2. Scenario 2 shows a decisive shift in emphasis towards the emission criteria, which together account for over 84% of the total weight ($0.474 + 0.373$), effectively aligning the system with ECAs compliance requirements.
3. As expected, Scenario 3 yields perfectly uniform weights, providing a neutral baseline for comparison.
4. Most importantly, Scenario 4 clearly illustrates the action of the fuzzy rule base's trade-off mediation principle. Although both *SFC* and *NO_x* were given identical, very high input importance (9.0), the system did not assign them disproportionately high weights. Instead, it balanced them at 0.422 each, preventing a single criterion from unrealistically dominating the decision. This demonstrates the module's ability to generate rational and balanced weights even under conflicting, high-stakes priorities, a significant advantage over simple linear normalization.

In all cases, the underlying propulsion configuration remains the same; only the operator's prioritization of *SFC*, *NO_x* and *PM* changes.

It is worth noting that, when the same Pareto optimal is weighted using objective (data-driven) weighting methods, as the Entropy and CRITIC methods [63, 75], almost all importance is on *NO_x*. In contrast, the FLM correctly reproduces a neutral operator stance (5-5-5) as equal weights.

Table 5.3. Comparison of FLM (Balanced Performance) and objective weighting methods for the three criteria (*SFC*, *PM*, *NO_x*)

Methods	<i>SFC</i>	<i>PM</i>	<i>NO_x</i>
FLM	0.333	0.333	0.333
Entropy	0.014	0.293	0.691
CRITIC	0.273	0.322	0.403

The results in Table 5.3. show that, for the same three criteria and underlying Pareto front, objective methods assign extremely imbalanced importance. Entropy and especially CRITIC method concentrate almost all weight on *NO_x* due to its larger variance and strong negative correlation with *SFC* and *PM*. In contrast, when the operator declares "balanced" importance (5-5-5), the FLM returns equal weights, which are fully transparent and directly interpretable as a neutral status between *SFC*, *NO_x* and *PM*.

5.4.2. Fuzzy system behavior and trade-off analysis

To further validate the logical consistency of the fuzzy rule base and provide intuitive insight into its decision-making process, I analyzed the system's response surface. Figure 5.5. illustrates *SFC* weight as a function of both *SFC* importance and *NO_x* importance, while *PM* importance is constant at a neutral value of 5.0.

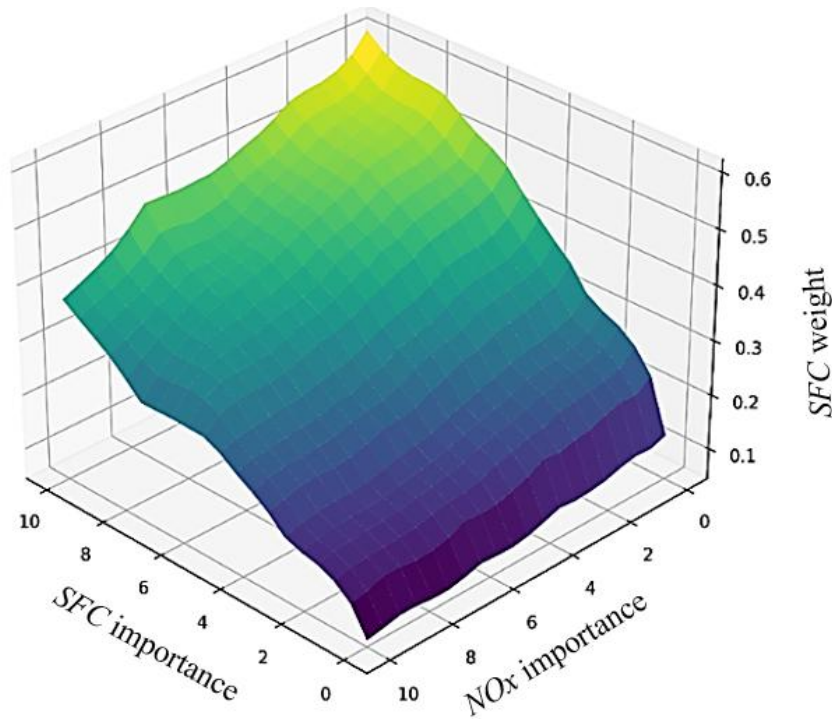


Figure 5.5. Fuzzy logic response: *SFC* weight as a function of *SFC* and *NO_x* importance

The response surface reveals several key behaviors of the proposed weighting module, summarized as follows:

1. The surface demonstrates that *SFC* weight increases most significantly (reaching approximately 0.55-0.60) when *SFC* importance is high (8-10) while *NO_x* importance is low (0-3). This region represents scenarios where fuel economy is the priority and the system correctly reflects the *SFC* weighting accordingly.
2. Most importantly, the surface clearly visualizes the "Competitive Mediation" principle encoded in the rule base. When both *SFC* and *NO_x* importance are simultaneously high, the system actively suppresses their individual weights to prevent either criterion from dominating unrealistically. Instead of reaching extreme values (>0.7), the *SFC* weight plateaus at approximately 0.35-0.45, ensuring balanced consideration of both competing priorities.
3. The surface varies gradually without abrupt jumps: small changes in importance ratings lead to only small changes in the resulting weights. This behavior indicates that the rule base and membership functions interact coherently and produce stable, predictable outputs, which is important for operators in the decision-support system.

The fuzzy weighting module translated imprecise operator preferences into mathematically sound weights that reflect both individual criterion importance and the necessary compromises between competing objectives.

5.4.3. Impact of fuzzy weights on MCDM ranking

The most crucial test of the fuzzy weighting module is its ability to drive the MCDM process to select distinct, context-appropriate operating points from the Pareto front set. Using TMF method with the fuzzy-derived weights from Section 5.4.1., the engine configurations were ranked for each operational scenario. The top-ranked alternatives and their performance values are presented in Table 5.4., which provides a direct, quantitative view of the trade-offs being made.

Table 5.4. Top-ranked alternatives under different operator-priority scenarios

Ranking	Scenario 1 Fuel Economy Priority $w = [0.460, 0.333, 0.207]$	Scenario 2 Strict Environmental Compliance $w = [0.154, 0.474, 0.373]$	Scenario 3 Balanced Performance $w = [0.333, 0.333, 0.333]$	Scenario 4 High Competition $w = [0.422, 0.422, 0.155]$
1 st	Alternative 27	Alternative 4	Alternative 4	Alternative 4
2 nd	Alternative 4	Alternative 27	Alternative 27	Alternative 27
3 rd	Alternative 10	Alternative 38	Alternative 10	Alternative 25
4 th	Alternative 18	Alternative 10	Alternative 18	Alternative 30
5 th	Alternative 15	Alternative 2	Alternative 15	Alternative 38

The results in Table 5.4. demonstrate that the fuzzy-derived weights effectively reconfigure the TMF ranking by altering the valuation of the inherent performance trade-offs between alternatives, leading to distinct, priority-driven selections. The key outcomes of this preference-driven re-ranking are summarized as follows:

1. **Fuel Economy Priority:** The high *SFC* weight (0.460) made in **Alternative 27's** superior fuel economy the dominant factor. The TMF algorithm prioritized this alternative because its key strength aligned perfectly with the primary operator objective, accepting its higher emissions as a trade-off for significant cost savings.
2. **Strict Environmental Compliance:** The high emission weights ($w_{NO_x} + w_{PM} = 0.847$) caused a fundamental shift, making low emissions the critical determinant. **Alternative 4** rose to the top as its excellent low-*NO_x* and low-*PM* performance became the most valuable asset. Conversely, **Alternative 27** was penalized because its high emissions became a severe liability under this priority, despite its fuel efficiency.
3. **Balanced Performance:** Under equal weights, the TMF algorithm identified **Alternative 4** as the most robust compromise TMF identified **Alternative 4** as the most robust compromise. While this alternative excels in emissions reduction, its selection under balanced weights suggests TMF prioritizes avoiding severe performance deficits in any criterion, making it the least risky choice despite its fuel economy trade-off.
4. **High Competition (Trade-off):** This scenario highlights the fuzzy system's mediation. Despite *SFC* and *NO_x* having equal, high importance, **Alternative 4** was selected over **Alternative 27**. This outcome demonstrates that the cost of high *NO_x* emissions was deemed unacceptable relative to its *SFC* benefit. The system effectively prevented a single criterion from dominating, with TMF favoring the alternative that, while less fuel-efficient, avoids a critical failure in the equally weighted *NO_x* criterion.

To quantify the structural divergence in rankings introduced by the four operator-priority scenarios, Spearman's rank correlation coefficient (ρ) was computed for all scenario pairs (Table 5.5.). For the 163 Pareto optimal alternatives, the resulting coefficients range from $\rho = 0.824$ to $\rho = 0.983$, indicating strong monotonic agreement between the scenario-specific TMF rankings.

Spearman's rank correlation coefficient (ρ) [137, 138] is a measure of how similar two rankings are. It compares the order of items (here: the 163 Pareto alternatives) under two different scenarios and returns a value between -1 and $+1$:

- $\rho = +1$: the two scenarios produce **exactly the same ranking order**,
- $\rho \approx 0$: the two rankings are **unrelated**,
- $\rho = -1$: one ranking is the exact opposite of the other.

In this dissertation, ρ is used as a ranking-stability indicator: it quantifies how much the MCDM ranking of the 163 Pareto alternatives changes when the weighting scenario changes.

Table 5.5. Spearman's rank correlation analysis

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Scenario 1	1	0.8670	0.9830	0.8239
Scenario 2	0.8670	1	0.8738	0.9834
Scenario 3	0.9830	0.8738	1	0.8287
Scenario 4	0.8239	0.9834	0.8287	1

The strong correlations between scenario-specific rankings are expected because the candidate solutions are drawn from a non-dominated Pareto front. Since all alternatives are non-dominated, each represents an optimal trade-off. Consequently, significant shifts in criterion weights are required to cause a substantial re-ordering of the top-ranked alternatives. The high correlations between specific scenarios indicate that their respective fuzzy weight sets were not sufficiently distinct to overcome the inherent "good quality" of all solutions on the front. Furthermore, the analysis reveals a clear, strong correlation between Scenario 1 (Fuel Economy) with Scenario 3 (Balanced) and Scenario 2 (Strict Compliance) with Scenario 4 (High Competition). This indicates that these paired scenarios share a high similarity, producing near rankings. Most importantly, the weakest correlations (e.g. $\rho \approx 0.82$) occur between Scenario 1 (Fuel Economy) and Scenario 4 (High Competition). This demonstrates that the fuzzy weighting module is indeed capable of generating weight sets distinct to drive a fundamental re-ranking, effectively segmenting the Pareto front into different preference-based groups despite the inherent similarity of the non-dominated alternatives.

In addition, Table 5.6. shows that, for all four operator-priority scenarios, the TMF rankings produced under FLM weights are strongly correlated with those obtained from Entropy and CRITIC weights, with Spearman's ρ ranging from 0.708 to 0.973. This confirms that the overall ordering of Pareto optimal operating points is robust across weighting philosophies, even when the underlying weights are defined either by operator-driven fuzzy ratings or by purely objective entropy/contrast measures, the resulting rankings remain very similar. The added value of the elaborated FLM module is therefore not in creating radically different rankings, but in providing a transparent and interpretable interface for formalizing operator preferences, while still delivering rankings that are consistent with established objective weighting schemes.

Table 5.6. Spearman's rank correlation (ρ) between TMF rankings obtained with FLM weights and objective weights (Entropy, CRITIC) for each operator-priority scenario

	ρ (FLM vs. Entropy)	ρ (FLM vs. CRITIC)
Scenario 1	0.708	0.912
Scenario 2	0.927	0.973
Scenario 3	0.713	0.918
Scenario 4	0.964	0.948

From an implementation perspective, the FLM and TMF ranking module was implemented in a Python 3.13 environment with standard scientific libraries such as NumPy and scikit-fuzzy (a.k.a. skfuzzy).

6. NEWLY DEVELOPED KNOWLEDGE BASED EXPERT SYSTEM FOR PREDICTIVE MAINTENANCE AND FAULT DIAGNOSIS IN LARGE TWO-STROKE MARINE DIESEL ENGINES

The preceding Chapters 3–5 developed a multi-objective optimization framework for marine diesel engine operation; its recommendations are predicated on the engine remaining in a normally healthy state. In practice, operational decisions must be conditioned on the engine's technical condition, because rising faults can invalidate optimality by reducing efficiency, compromising safety margins, or accelerating physical damage. This chapter addresses this limitation by introducing a diagnostic and maintenance step that supervises the optimization workflow and enforces health-aware operating constraints.

Marine diesel engines are complex systems whose operational cost and risk exposure are strongly coupled with technical state; inadequate maintenance decisions increase unnecessary interventions, while delayed diagnosis increases the probability of critical and costly damage.

The core contribution in this chapter is a newly developed Knowledge Based Expert System (KBES) that performs real-time fault diagnosis and prescribes maintenance actions. It adopts the dissertation's overarching philosophy: 1.) reduce a complex, high-dimensional problem (engine health monitoring) to a structured decision object (a set of subsystem-specific rules) and 2.) implement a transparent, operable decision mechanism. The new KBES translates streams of sensor data into explicit fault hypotheses and ordered action plans, mirroring the systematic troubleshooting of a chief engineer. Its outputs are then formalized as constraints for the optimization (surrogate → NSGA-II → MCDM) loop introduced in Chapters 3–5, ensuring that any performance-improvement recommendations remain consistent with the engine's current health condition.

This integration aligns with the maritime industry's shift toward Condition-Based Maintenance and Predictive Maintenance, moving from periodic to need-based interventions. This chapter is structured as follows: Section 6.1. establishes the diagnostic foundation through functional decomposition and parameter selection. Section 6.2. details of the KBES conception, including knowledge representation and inference. Section 6.3. formalizes the Expert System outputs by mapping abnormal parameter states to subsystem-level fault classes, ordered operational responses and clarifies how these outputs are exposed as health-state constraints that supervise the optimization and MCDM recommendations developed in Chapters 3–5.

6.1. Diagnostic foundation: subsystems, failure modes and parameter selection

Marine diesel engines are interconnected systems where a fault in one subsystem spreads, causing secondary symptoms and performance degradation. Effective diagnosis requires a systematic, localized approach. I adopt a functional decomposition into the five core subsystems, each characterized by distinct failure modes, measurable signatures and corrective action pathways:

1. **Fuel subsystem** (feeding + injection): faults in supply pressure, filtration, viscosity control, or injection directly affect combustion. Primary indicators are thus combustion pressure, injection pressure and fuel supply pressure.

2. **Lubrication subsystem:** critical for safety and wear. Key parameters (oil pump pressure, oil pressure, oil temperature, oil level) are sensitive to both supply-side issues (pump/regulating valve, plugged lines) and degradation/contamination indicators (oil cooler performance, polluted oil, leaks).
3. **Cooling subsystem:** provides diagnostic evidence for heat rejection faults. Coolant pressure and jacket water outlet temperature are primary signals for detecting restrictions, pump failures, or coolant loss.
4. **Air supply subsystem** (turbocharging + charge-air cooling): includes turbocharging and charge-air cooling. Failures here (e.g. filter blockage, compressor fouling, cooler blockage) reduce air mass flow and excess air ratio. Critical parameters are charge-air pressure and temperature after the cooler.
5. **Exhaust subsystem:** offers aggregated insight into combustion quality and gas exchange. Exhaust Gas Temperature (EGT) per cylinder and exhaust color are key diagnostic variables.

Increasing diagnosing parameters does not linearly improve diagnosability and can overload operators. Therefore, selection criteria were established to guide the diagnosing parameter-selection process, these criteria are as follows:

1. High-Information: Sensitive to multiple failures within their subsystem.
2. Practically Available: Commonly measured on modern engine monitoring systems.
3. Actionable: Directly map to specific inspection or maintenance tasks.

The diagnostic procedure developed in this research is structured around a carefully selected set of diagnostic parameters mapped to five critical marine diesel engine subsystems: fuel, lubrication, cooling, air supply and exhaust subsystems. Parameter selection was conducted through a literature search, evidence-based approach, combining expert opinions with published statistical analyses, experimental/field validations and simulation-based verification reported by prior studies. No new experimental testing or fault simulations were performed within this dissertation; rather, the cited evidence was consolidated and operationalized into a coherent subsystem-level diagnostic framework suitable for shipboard conditions.

Specifically, each diagnosing parameter was retained based on at least one of the following literature-derived evidence:

1. Failure-mode relevance and subsystem information reported in literature and in reliability analyses.
2. Expert practice as documented in technical guidance (e.g. commonly monitored variables and diagnostic conventions reported by practitioners and industry sources).
3. Published statistics (e.g. correlation/trend/feature selection results reported in prior studies) demonstrating for abnormal states.
4. Published experimental/field evidence and simulation/fault studies reporting consistent symptom response and maintenance actions.

The methods cited in Table 6.1. refers to supporting evidence reported in the referenced sources, not additional testing performed within this dissertation. Table 6.1. lists the final parameter set and the corresponding evidence basis for each parameter in the KBES knowledge base.

Table 6.1. Diagnostic parameter set and selection evidence of marine diesel engine subsystem

	Parameters	Method	References
Fuel Subsystem	Pressure after feeding pump	Experts' opinion. Statistical data analyses. Experimental validation. Marine diesel engine failure simulator.	[139] [140] [141] [142]
	Injection pressure		
	Combustion pressure		
Lubrication Subsystem	Oil pump pressure	Experimental Validation. Marine diesel engine failure simulator.	[141] [143] [144] [146]
	Oil temperature		
	Oil pressure		
	Oil level		
	Cylinder oil parameters		
	System oil parameters		
Cooling Subsystem	Coolant pressure	Experimental Validation. Marine diesel engine failure simulator.	[141] [146] [145]
	Jacket water temperature		
	Cooling water quality		
	Deaerating tank condition		
Air Supply Subsystem	Pressure after turbocharger	Experts' opinion. Statistical Data Analyses. Marine diesel engine failure simulator	[140] [141] [22] [147]
	Temperature after cooler		
	Turbocharger condition		
Exhaust Subsystem	Exhaust gas temperature	Experts' opinion. Statistical data analyses. Thermal failure simulation of diesel engine.	[140] [148] [149] [150] [151] [152]
	Exhaust gas color		
	Exhaust valve condition		
	Scavenge box condition		

This selection of diagnosing parameters is intentionally compatible with shipboard practice: it prioritizes signals that are commonly measured (or observable), interpretable by operators and suitable for mapping to action-oriented maintenance guidance.

6.2. Knowledge Based Expert System conception and implementation

The elaborated Knowledge Based Expert System (KBES) adopts a modular production-rule (IF/THEN) architecture to transform real-time engine monitoring data into fault hypotheses and recommended actions. Conceptually, the KBES is organized around two distinguished parts: 1.) diagnostic parameter processing and 2.) a forward-chaining inference engine operating over a fact base and a rule base.

1. Diagnostic parameter processing: sensor signals acquired from the engine monitoring system are mapped into diagnostic parameters (e.g. pressures, temperatures, etc.). Each parameter is evaluated against configurable normal ranges/thresholds and categorized into a qualitative state (e.g. Normal/Abnormal). These categories are then asserted as facts in the KBES fact base (working memory), representing the current engine condition in a machine-interpretable form.
2. Forward-chaining inference engine: the KBES reasoning mechanism is implemented as a forward-chaining inference engine that evaluates the current fact base against a modular rule base (knowledge base). The rule base contains subsystem-oriented IF/THEN rules that contain recognizable parameter-state patterns and their implications for the fuel, lubrication, cooling, air supply, exhaust subsystems. During execution, the inference engine repeatedly performs a match,

select and fire cycle, in order to match current facts to rules, identify the set of satisfied rules and fires the applicable rule to produce maintenance recommendations and actions.

The fired rules generate the KBES outputs in the form of 1.) fault hypothesis candidates and 2.) action recommendations, which are presented to the operator.

If no abnormal parameter states are present in the evidence, the KBES returns a normal/no-action outcome; otherwise, the forward-chaining inference cycle is executed to generate fault hypotheses and recommended actions. Figure 6.1. provides an overview of the KBES workflow.

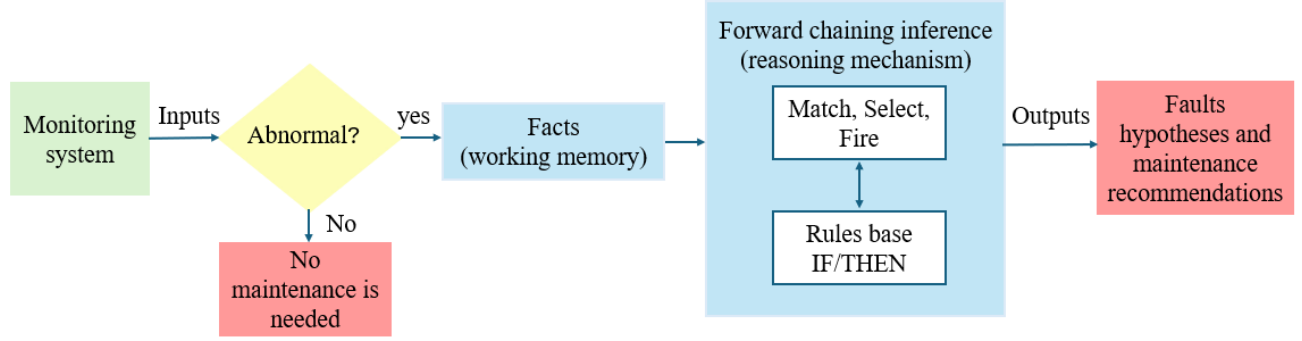


Figure 6.1. Knowledge Based Expert System flow

6.2.1. Knowledge representation: Facts and Rules

The KBES represents diagnostic knowledge in two parts, where the current engine condition is stored as facts (working memory/fact base) and the knowledge is stored as a rule base (IF/THEN rules). The two parts are represented as follows:

1. Fact Base: contains the classifications about the current state. Each diagnostic parameter p_i has a fact derived by comparing the parameter value to the engine-specific normal range $[L_i, H_i]$:

$$\text{Condition}(p_i) = \begin{cases} \text{Normal,} & \text{if } L_i \leq p_i(t) \leq H_i \\ \text{Low,} & \text{if } p_i(t) < L_i \\ \text{High,} & \text{if } p_i(t) > H_i \end{cases} \quad (6.1)$$

where:

- p_i : value of diagnostic parameter i at time t ,
- L_i : lower normal limits for parameter,
- H_i : upper normal limits for parameter,
- i : index represents the selected diagnostic parameter set.

2. Rule Base: includes knowledge as IF/THEN rules, has the following structure:

IF Condition(s) on Facts, THEN Assert recommendation action.

6.2.2. Inference mechanism and reasoning strategy of the Knowledge Based Expert System

The KBES system uses a data-driven, forward-chaining inference strategy, ideal for continuous monitoring of diesel engines. The process, formalized in Figure 6.2. is triggered by a significant parameter deviation from defined normal operation. To illustrate this reasoning procedure, Figure 6.2. presents the forward-chaining inference workflow implemented in the new KBES. It shows how incoming sensor values are first evaluated against configurable thresholds to produce real-time diagnostic facts. These facts are processed by the inference engine, which selects and fires applicable rules to generate both fault diagnoses and ranked maintenance actions. This diagram makes the expert system's internal logic transparent and highlights the dynamic nature of fault detection as a real-time, iterative process integrated with onboard decision-making.

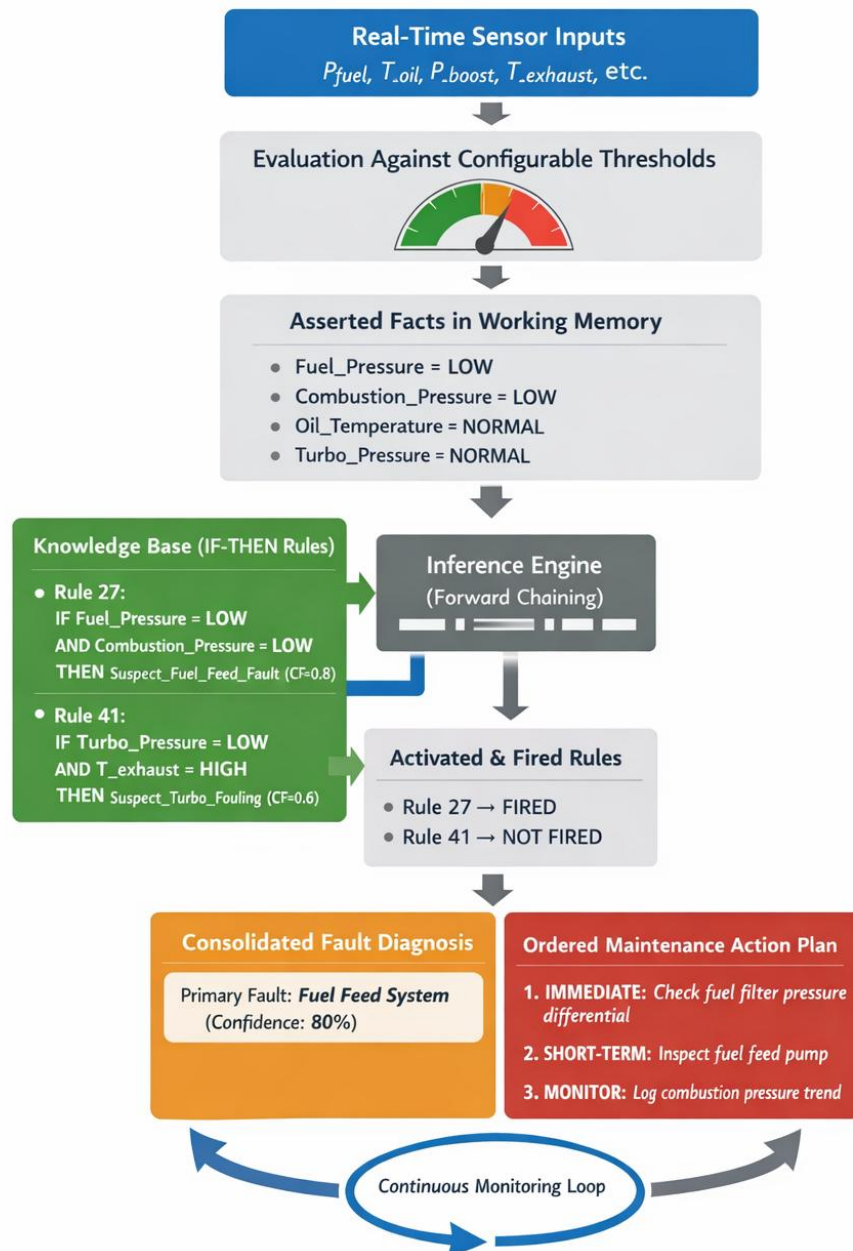


Figure 6.2. Forward-chaining inference workflow of the new Knowledge Base Expert System [own]

In summary, the reasoning strategy is a forward-chaining, data-driven approach that exhaustively infers all supported diagnoses from the given sensor data, while using priority and confidence measures to manage concurrent rule firings. This ensures that the Expert System replicates the thought process of a human expert as closely as possible, checking all indicators, considering multiple hypotheses and weighing them, but at the speed of an automated system. The result is a robust inference step that can swiftly identify abnormal conditions and propose actionable guidance, forming the basis for timely and informed maintenance decisions.

6.2.3. Integration of the Knowledge Based Expert System with the shipboard monitoring system

A distinguishing feature of the Expert System is its integration into the operational environment of the marine engine and its connection with the optimization procedure described in previous chapters.

On the input side, the Expert System is developed to harmonize with the ship's engine monitoring and data acquisition systems. All the diagnostic parameters utilized by the knowledge base correspond to sensor outputs that are typically available on modern marine diesel engines. On the output side, the Expert System's diagnoses and recommendations completeness initiate the optimization procedure of the decision support system. The role of the Expert System output is to constrain and condition the optimization processes based on the actual health state of the engine, which aligns with the idea that efficient operation and maintenance decisions must be made with full awareness of current condition.

It is important to note that this supervisory logic procedure (the Expert System), along with the optimization procedure, runs in parallel to the existing engine control systems, monitoring and advising, which makes retrofitting it to existing ships feasible. The outputs can be presented to human decision-makers on the ship's monitoring displays or fed into higher-level ship management software.

6.3. Fault classification and operational responses derived from the Expert System

This section formalizes the actionable outputs of the knowledge based module by converting monitored diagnostic parameters into 1.) fault classes at the subsystem level and 2.) operational responses ranging from monitoring recommendations to immediate protective actions. The knowledge is presented as a set of subsystem-specific diagnostic tables that can be implemented directly as rule sets within the Expert System and interpreted consistently by the ship crew.

The diagnostic logic is grounded in two complementary evidence streams: 1.) industry recommendations that define lubrication concepts, oil analysis expectations and typical degradation pathways for two-stroke crosshead engines; furthermore, 2.) technical documentation that specifies system architecture constraints, alarm philosophies and troubleshooting practices for electronically controlled two-stroke engines [153]. In addition, the collected information adopts established principles from the research literature on Knowledge Based and Expert System fault diagnosis for marine diesel engines, where interpretability and operational usability are treated as primary development requirements [33].

Table 6.2. consolidates **Fuel Subsystem diagnostics** across fuel supply/conditioning, injection event quality and the resulting combustion-pressure response. The intent is to separate "upstream" faults (temperature/viscosity/filters/feed pressure stability) from "downstream" injections and combustion signals, using data where available. For low-speed two-stroke engines, ME/ME-C denotes the electronically controlled engines (servo-hydraulic actuation commanded by the control system), whereas MC/MC-C denotes the conventional camshaft-controlled engines; the suffix "-C" indicates

the compact variant. Therefore, on ME/ME-C engines, electronic actuation checks are treated separately from the mechanical timing/actuation checks relevant to MC/MC-C engines [139-142].

Table 6.2. Fuel Subsystem – Diagnostic parameters, conditions and experts' opinions

Parameter	Condition	Diagnosis, Action
Pressure after feeding pump	Higher than normal range	1. Filters on the input line (check). 2. Fuel has a low temperature (mis-heating). 3. Circulation valve (wrong calibration). 4. Problem with the viscosity regulator. 5. Problem in feeding pump (confirm with sounds): - a.) calibration of suction inlet or ejection outlet (less likely); - b.) relief valve.
	Lower than normal range	1. Fuel has a high temperature. 2. Fuel level at daily service tank. 3. Polluted service tank\Blockage in the inlet pipe. 4. Check filters on the input line. 5. Leak from input line\ pressure sensors. 6. Problem in feeding pump (confirm with sounds). 7. Relief valve. 8. Check circulation line. 9. Measurement error (check with sight).
Injection pressure	Higher than normal value plus tolerance	1. Verify injection event timing using indicator card or in-cylinder pressure sensor (possible injector sticking or late actuation). 2. Check the operation of the fuel injection valve actuation (conduct Cylinder Loop Test). 3. Wrong calibration (late injecting), it should accompany low compressing pressure and an increase in temperature of exhaust gases. Note: In common rail systems, verify rail pressure sensor and fuel pump delivery.
	Lower than normal value minus tolerance	1. Expansion in injection nozzle (chemical ingredients in fuel), check treatment process. 2. Spring elasticity. Both lead to early injections, accompanied by the decrease in the temperature of exhaust gases.
Combustion pressure	Higher than normal range	1. Fuel pump actuator malfunction or timing error (confirm with indicator diagram or electronic control log). 2. Injector (confirm via indicator card pressure trace, injector leak-off/return trend and cylinder-to-cylinder Exhaust Gas Temperature (EGT) deviation). 3. Feeding pump (confirm via pressure pulsation trend and fuel temperature/viscosity log). 4. Verify actuator control / command-response mismatch (ME/ME-C: FIVA + control oil pressure, MC/MC-C: pump rack/timing). 5. Check exhaust valve timing (hydraulically actuated).

	Lower than normal range	1. investigate actuator timing and injection duration. 2. Excessive clearance in the high-pressure pump (MC/MC-C only). 3. Injector (confirm with sounds). 4. Feeding pump (confirm with sounds). 5. Actuator misfire, hydraulic system fault (confirm via pressure trace and fuel rail command log). 6. Delayed exhaust valve opening or insufficient scavenge air pressure. 7. Check FIVA valve (ME/ME-C only) and exhaust valve air spring pressure.
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Table 6.3 structures **lubrication Subsystem diagnostics** according to the multi-lubrication nature of two-stroke crosshead engines (system oil, cylinder oil and, where applicable, piston cooling oil). The actions prioritize safety-critical conditions (pressure loss, overheating, contamination) and incorporate oil-analysis logic (Base Number/ Total Acid Number/viscosity) where this provides earlier fault discrimination than alarms alone [141, 143, 144, 146].

Table 6.3. Lubrication Subsystem – Diagnosis parameters, conditions and experts' opinions

Parameter	Condition	Diagnosis, Action
Oil pump pressure	Higher than normal range	1. Cold oil (check oil temperature). 2. Pressure regulating valve on the oil pump. 3. Verify whether the abnormal pressure is in the system oil circuit (main bearings/crosshead) or the piston cooling oil circuit (if separated) and confirm regulator valve position. 4. Plugged pipes (less likely to happen).
	Lower than normal range	1. Critical: Unsealed bearing (main, crosshead, or crankpin). 2. Increase in clearances due to wear. 3. Pump wear or internal leakage. 4. Relief valve setting.
Oil temperature	Higher than normal range	1. Oil cooler. 2. Solid bearing (check heat sensor). 3. Elevated piston cooling oil temperature indicates cooling system malfunction.
	Lower than normal range	1. Cold engine. 2. Mis-cooling. 3. Polluted oil. 4. Leak from heat regulator. 5. Oil filters problem. 6. Check preheater operation.
Oil pressure	Higher than normal range	1. Critical: Blockage in oil holes (accompanied by increase in temperature). 2. Verify pressure regulation valve operation.

	Lower than normal range	External: leak in the oil lines (diagnosed with sight and excessive heat). Internal leakage: 1. Confirm whether pressure loss is in main bearing circuit, piston cooling circuit, or cylinder lubrication system. 2. Use cylinder oil consumption logs, scavenge drain analysis and oil mist detector. 3. Check crosshead bearing and piston cooling circuit for leakage.
Oil level	Higher than normal range	Distinguish whether level is in main sump or piston cooling tank (if separated). In two-strokes, piston cooling oil leaks can also affect expansion tank readings. 1. Water ingress (confirm via water-in-oil sensor, LO separator alarms and lab trend: Na/K, water %, TAN). 2. Fuel leak (viscosity test). 3. Cylinder oil contamination from stuffing box drain.
	Lower than normal range	1. Critical: Oil leakage (check for blue smoke). 2. In case of external leaks, check with sight. Note: Elevated cylinder oil consumption indicates cylinder lubrication system fault.
Cylinder oil parameters	High consumption	1. Worn piston rings or liners. 2. Incorrect cylinder oil feed rate. 3. Poor piston ring seating. Note: Verify quill position and lubrication timing.
	BN depletion	1. High sulfur fuel operation. 2. Insufficient feed rate. 3. Contamination from system oil. Note: Monitor drain oil analysis for BN trend.
System oil parameters	Contamination	1. Cylinder oil contamination (check compatibility). 2. Water ingress (check water separability). 3. Fuel dilution (check flash point). 4. Particulate accumulation (check filter differential).
	Degradation	1. Oxidation (check TAN increase). 2. Thermal degradation (check viscosity at 100°C). 3. Additive depletion (check BN). Note: Piston cooling oil requires enhanced oxidation stability.

Table 6.4 captures **cooling Subsystem diagnostics** with emphasis on pressure/level behavior (restriction vs. leakage) and temperature-control malfunctions (thermostatic regulation and flow adequacy). The expansion-tank static head requirement is treated as a design/installation constraint because it directly conditions alarm validity and cavitation margin in high-temperature jacket-water circuits for two-stroke engines [141, 145, 146].

Table 6.4. Cooling Subsystem – Diagnosis parameters, conditions and experts' opinions

Parameter	Condition	Diagnosis, Action
Water pressure	Higher than normal range	1. Blockage in water lines (problem in water treatment or calcareous sediments), less likely to happen. 2. Problem with regulator valve (accompanied with temperature change). Note: Verify expansion tank location provides adequate static head (minimum 15m above exhaust valves).
	Lower than normal range	Before the engine: 1. If not accompanied by abnormal decrease in water level at expansion tank, then it is pump problem (confirm with sounds). 2. If it is accompanied by a slow and gradual decrease in water level, then it is an increase in wear at pump body (water mistreatment). 3. If accompanied by a fast and sudden water level decrease, then pump collapses.
		After the engine: The possible problem is accompanied by an abnormal decrease in the expansion tank and may be: 1. Leakage problem: Internal: check exhaust gases' color and temperature. External: check pipes and joint points. 2. Measurement device error.
Jacket water temperature	Higher than normal range	1. Thermostatic valve malfunction. 2. Insufficient cooling water flow. 3. Fouled jacket water cooler. Note: Minimum 50°C required before normal engine start.
	Lower than normal range	1. Excessive thermostatic opening. 2. High load on auxiliary engines. Note: Below 50°C start temperature increases cold corrosion risk during low-load operation.
Cooling water quality	Corrosion indicators	1. Check inhibitor concentration (nitrite-borate based recommended). 2. Weekly visual inspection during running. 3. Quarterly laboratory analysis. 4. Annual system flush and inhibitor replenishment.
Deaerating tank condition	Gas accumulation	1. Critical: Cylinder liner rupture suspected. 2. Check combustion gas detection. 3. Verify expansion tank level correlation. Immediate investigation required.

Table 6.5 frames the **Air Supply Subsystem diagnosis** around scavenge receiver pressure and charge-air temperature as the primary indicators governing excess-air ratio and combustion stability in loop-scavenged two-stroke operation. The rules distinguish surge-related conditions from non-surge performance degradation and include cross-checks against turbocharger speed trends and cylinder power balance (indicator cards) where available [22, 140, 141, 147].

Table 6.5. Air Supply Subsystem – Diagnosis parameters, conditions and experts' opinions

Parameter	Condition	Diagnosis, Action
Scavenge Air Receiver Pressure	Higher than normal range	1. High backpressure. 2. Sensor drift / control mismatch: verify scavenge receiver pressure sensor calibration and compare with turbo speed/compressor map trend. 3. Partial blockage in air pass (rarely happens). 4. Verify economizer condition (if fitted). Immediate action: diagnose at steady load; reduce load only if accompanied by surging, abnormal EGT, or compressor instability.
	Lower than normal range	Turbocharger surge: In two-stroke constant-pressure turbocharging systems, surging is less frequent but still possible. Monitor scavenge air pressure fluctuations and turbo rpm deviation. Possible reasons: 1. Air filter plugging (remove and clean). 2. Polluted turbo (check if the compressor and the turbine had cleaned regularly). 3. Unsteady shaft/Wear damage. 4. Air cooler fouling (accompanied by high temperature). 5. Scavenge fire (check scavenge box relief). 6. Uneven power distribution between cylinders (check indicator cards). Immediate action: reduce speed to load at which surging stops; If necessary open the air cooler inspection hole to stop surging.
		The turbocharger does not surge: 1. Unsealed joints before engine (check). 2. Turbocharger calibration (check). 3. Excessive clearance (maintenance). 4. Auxiliary blower failure (check activation at low load). Immediate action: Reduce speed to load at which surging stops; If necessary open air cooler inspection hole to stop surging.
Temperature after cooler	Higher than normal range	1. Blockage in water tubes (sediments). 2. Blockage in air tubes (accompanied by surging in turbocharger). 3. Water mist catcher fouling. 4. Insufficient cooling water flow.
	Lower than normal range	Overcooling (modify thermostatic setting). Note: Excessive cooling reduces combustion efficiency and promotes cold corrosion.
Turbocharger condition	Abnormal sound	1. Bearing wear (howling/whining). 2. Blade damage (knocking/banging). 3. Surge condition. Action: Verify wastegate or bypass valve operation.

	Speed deviation	1. Turbine restriction (fouled nozzles/blades). 2. Compressor restriction (fouled air passages). 3. Insufficient exhaust energy. Action: Take indicator cards for power distribution analysis.
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Table 6.6 treats the **Exhaust Subsystem** side as an aggregated symptom channel that couple combustion quality, scavenge efficiency and exhaust valve behavior. Rules are therefore split between single-cylinder deviations (injector/exhaust valve/local cooling leak) and all-cylinder shifts (air supply degradation, fuel quality/viscosity issues) and they retain smoke-color logic as an operator-validated symptom stream [148-152, 140].

Table 6.6. Exhaust Subsystem – Diagnosis parameters, conditions and experts' opinions

Parameter	Condition	Diagnosis, Action
Exhaust gas temperature	Higher than normal range	One unit: 1. Injector (wrong modification), 75% probability and accompanied with black smoke. 2. Exhaust valve leakage / poor seating or actuation fault (verify hydraulic actuation pressure, air spring and valve stroke feedback). 3. High-pressure pump problem (less likely to happen and accompanied by a change in compressing- pressure). 4. Exhaust valve malfunction (check hydraulic actuation and air spring).
		All units: 1. Over-loaded turbocharger (check air temperature and indicator card). 2. Fuel problem (check viscosity regulator). 3. Verify scavenge air pressure and temperature. Note: Typical operational guidance limits cylinder-to-cylinder deviation; confirm the alarm threshold in the engine monitoring system.
	Lower than normal range	One unit: 1. Unsealed cylinder jacket. 2. Unsealed valves. 3. Exhaust valves not opening fully (check stroke).
		All units: 1. Possible problem is air temperature (overcooling). 2. Check auxiliary blower operation at low load.
Exhaust gas color	Black	1. Small air amount (wrong calibration/leakage). 2. Fuel components (appear in first use). 3. Fuel parameter (temperature-viscosity); check viscosity regulator. 4. Injectors (wrong calibration); check indicator card. 5. Pumps (wrong calibration); check indicator card. 6. Check turbocharger compressor efficiency.

	White	1. Economizer (check by reducing load or conversing mechanism). 2. Check the temperature after all units (define the leaking unit) and (confirm from the water expansion tank). 3. Leak from piston cooling tubes (typically in crosshead 2-stroke engines using water-cooled pistons). 4. Leak from cylinder jacket. 5. Steam in the air. 6. Check stuffing box drain for cooling medium.
	Blue	Excess oil burning, possible causes: 1. Oil specifications (in case the oil is being used for the first time). 2. Piston oil rings corrosion. 3. Collapse in the fire valve lubrication system (wrong calibration). 4. Increasing cylinder jacket lubrication (wrong calibration). Immediate action: 1. Reducing oil amount to minimize leakage. 2. Distinguish cylinder oil (high BN, once-through) vs. system oil (low BN, circulated) source.
	Yellow	The possible problem is a fuel problem (in case of first use) has increase in sulfur amount. Note: During fuel changeover, monitor cold corrosion risk at low load; adjust cylinder oil BN if necessary.
Exhaust valve condition	Abnormal operation	1. Check exhaust valve stroke (supervision alarm). 2. Verify air spring vent hole condition. 3. Check hydraulic actuation pressure. 4. Listen to valve knocking or noise. 5. Exhaust valve malfunction affects scavenging and cylinder pressure.
Scavenge box condition	Fire indicators	1. Smoke from the scavenge box relief valves. 2. Elevated scavenge space temperature. 3. Rapid pressure fluctuations. 4. Causes include excessive cylinder lubrication, worn rings, or carbon accumulation. Immediate action: Reduce load, activate fire suppression if necessary.

Collectively, Tables 6.2.–6.6. implement a fault-to-action translation procedure that is directly usable by the Expert System: measured parameters are first classified into abnormal states, then mapped into fault hypotheses and finally converted into an ordered operational response (monitor → inspect → correct → protect/shutdown).

The diagnostic procedure provides two concrete outputs required by the decision support system framework: 1.) a diagnosis and maintenance advisory and 2.) explicit health-state constraints that can gate the real-time optimization recommendations, ensuring that "optimal" settings are only proposed when consistent with current machinery condition. Two practical constraints should be noted. First, threshold values and alarm interpretations remain engine- and installation-specific (OEM setpoints, sensor locations and operating mode), so the Tables 6.2.–6.6. should be deployed with configurable

ranges rather than fixed constants. Second, knowledge based rules provide high interpretability and immediate deployability but may not capture all interacting fault combinations; therefore, the rule base is best treated as a supervisory, safety-oriented diagnostic core that can later be augmented by probabilistic or data-driven module when sufficient fault history becomes available. The full diagnostic procedure is presented in Chapters 7 and 8 (both as a standalone module and in closed-loop interaction with the surrogate-assisted optimization procedure) as part of the holistic Decision Support System architecture and numerical example.

6.4. Summary and remarks: Knowledge Based Expert System outcomes and role in the integrated Decision Support System

This chapter introduced a Knowledge Based Expert System that closes a critical gap in the dissertation workflow: while Chapters 3–5 generate Pareto optimal operating recommendations (Surrogate NN → NSGA-II → MCDM), those recommendations are only meaningful when the engine is in a normal technical condition. The KBES therefore serves as a health-supervisory diagnostic procedure that 1.) interprets the monitoring evidence, 2.) outputs a prioritized, action-oriented maintenance plan and 3.) converts the diagnosed abnormal condition into normal operation condition that leads to proper implementation for the optimization procedure. The key results of the KBES diagnostic procedure are summarized as follows:

1. Operationally compatible diagnostic parameter set and subsystem decomposition.

The chapter operationalized diagnosis via a compact, ship-practical set of parameters mapped to five subsystems (fuel, lubrication, cooling, air supply, exhaust), emphasizing signals that are high-information, commonly available in ship monitoring systems and directly actionable.

2. A transparent rule-based inference mechanism suitable for continuous monitoring.

The KBES implements a forward-chaining reasoning strategy to generate diagnoses and responses. The operator-defined normal ranges are vital to establish the expert logic under varying engine types and operating contexts. In addition, the KBES is not a black box; it generates traceable IF/THEN explanations consistent with shipboard troubleshooting practice.

3. Direct fault-to-action translation in a form usable onboard.

Tables 6.2–6.6 implement the KBES's core deliverable: a structured mapping from abnormal parameter states → fault hypotheses → ordered inspection/correction/protection actions. The action-plan orientation reflects a ranked troubleshooting sequence rather than a single ambiguous instruction.

4. Health-aware overview of optimization and decision-making.

The result of this chapter is the diagnostic health-aware procedure to separate the two different work environments, which are:

- Normal health: the KBES outputs become constraints that define an admissible operating region for the optimizer/MCDM modules.
- Abnormal/unsafe health: the KBES outputs shift to protective and maintenance actions until the state returns to acceptable limits.

This condition separation resolves a practical failure mode of the optimization procedure: recommending "optimal" settings when the engine is drifting into faults (e.g. degraded air supply, abnormal lubrication pressures, cooling restrictions) and the optimization can become physically invalid or safety-compromising.

The knowledge base is deliberately modular, enabling incremental extension (additional rules, additional parameters, engine-type adaptation) without redesigning the inference mechanism.

Chapter 6 delivers the missing health-supervision step needed to strengthen the dissertation's optimization procedure in real marine contexts. It transforms raw monitoring evidence into diagnostic actions and it provides the formal mechanism to gate the optimization and MCDM recommendations. Chapters 7 and 8 build directly on this foundation by implementing the integrated architecture and demonstrating, through numerical examples, how the KBES interacts in closed-loop with the surrogate-assisted optimization procedure to produce health-consistent operating recommendations and maintenance-aware decision support.

7. THE INTEGRATED DECISION SUPPORT SYSTEM: ARCHITECTURE AND WORKFLOW

Chapters 3 through 6 have systematically developed and validated the main computational modules of a novel decision support framework for large two-stroke marine diesel engines. Chapter 3 established a surrogate-assisted multi-objective optimization core, coupling a high-fidelity neural network surrogate with the NSGA-II algorithm to generate a Pareto optimal set of engine operating strategies that balance Specific Fuel Consumption (*SFC*), Nitrogen Oxides Emissions Index (*NO_x*) and Particulate Matter (*PM*) emissions. Chapter 4 introduced the decision process, benchmarking and selecting robust Multi-Criteria Decision-Making (MCDM) algorithms to translate the Pareto set into actionable rankings. Chapter 5 enhanced the process with an operator-defined fuzzy weighting module, enabling dynamic, preference-aware adaptation of criterion importance in response to shifting operational priorities. Finally, Chapter 6 developed a knowledge based Expert System for fault diagnosis and predictive maintenance, providing a health-aware supervisory procedure. While each step functions effectively in isolation, the ultimate value of the proposed framework lies in its integration into a single, coherent and closed-loop Decision Support System (DSS). The standalone validation of each step, while necessary, does not demonstrate how the DSS operates as a whole, how data flows, how outputs from one step constrain or enable another and how the integrated system performs under realistic, operational scenarios. Therefore, the purpose of Chapter 7 is to define and illustrate the holistic integration of all previous steps. The focus is not on re-deriving the internal mathematics of each step but on clarifying their interlocking logic: the interfaces, data exchanges and gating mechanisms that unify surrogate-based optimization, MCDM ranking, fuzzy preference adaptation and Expert System diagnostics into a single operational workflow. This chapter presents the final, integrated system architecture and performance.

The chapter is organized as follows: Section 7.1. presents the integrated DSS architecture, clarifying the connections and control flow between the surrogate based optimization procedure, the fuzzy-weighted MCDM decision step and the Knowledge Based Expert System. Section 7.2. describes the programming environment and the main operator interfaces used to execute the integrated workflow.

7.1. Architecture of the elaborated Decision Support System including MCDM, Surrogate Optimization, Fuzzy Logic and Expert System

The integrated framework synthesizes the independently validated steps developed in Chapters 3 to 6 into a unified, closed-loop decision-support system. This architecture is designed to operate dynamically, responding to both operational objectives and engine health states. It merges surrogate-assisted multi-objective optimization, fuzzy-weighted MCDM and a rule-based Expert System within a single supervisory logic, governed by a gating mechanism that led to the appropriate computational pathway. The system's logic is illustrated in Figure 7.1. The workflow begins with a triggered evaluation of the engine's condition, classified as either Normal or Abnormal based on real-time data evaluated against a pre-defined knowledge base and thresholds. This binary classification acts as the primary gate, determining whether the action is directed toward the performance optimization procedure (optimization of normal operations) or the maintenance procedure (fault diagnosis and corrective planning of abnormal operation).

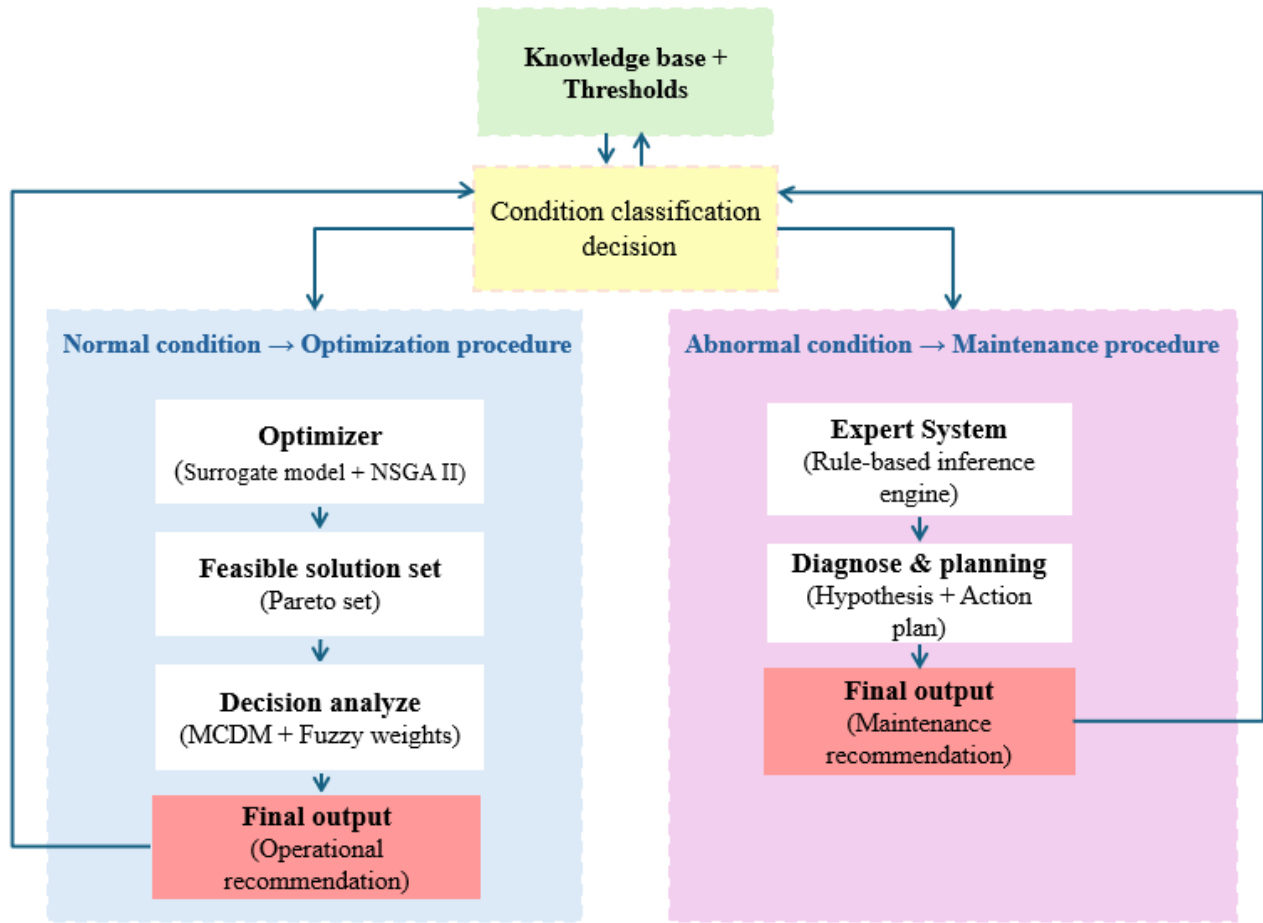


Figure 7.1. Integrated framework architecture of the elaborated Decision Support System

The integrated architecture can be conceptualized through two complementary perspectives: 1.) the sequential workflow illustrated in Figure 7.1, which emphasizes process flow and decision gates and 2.) the functional decomposition detailed in Table 7.1, which specifies the inputs, outputs and role of each constituent component. Together, these representations provide a complete view of the DSS structure and operational logic. Table 7.1 shows the key steps of the integrated DSS, detailing the inputs, outputs and interdependencies. This table representation clarifies the data interfaces and functional responsibilities at each stage of the decision procedure.

Table 7.1. Functional decomposition of the integrated decision support system

Step	Input	Output	Role
Health condition classification	Knowledgebase and thresholds	Current condition label (Normal / Abnormal)	Primary selection step: performance optimization vs. maintenance
Surrogate NN model	Operating context (load/speed, boundary conditions)	Predicted objectives (<i>SFC</i> , <i>NO_x</i> , <i>PM</i>)	Fast objective/constraint evaluation for search and screening

NSGA-II (surrogate-based) algorithm	Surrogate objective and constraint predictions	Pareto optimal set (feasible solutions)	Generates trade-off alternatives for the decision step
Fuzzy preference module (operator weights)	Operator preference inputs	Normalized weights vector	Calculate preference weights for the objectives
MCDM ranking method	Feasible set, criteria normalization and weights	Ranked alternatives and top-K recommendations	Converts Pareto set into an actionable shortlist
Operational recommendation (advisory procedure)	Top-K ranked candidates	Implementable setpoint + expected performance improvement	Provides the final recommended operating choice(s)
Expert System inference (abnormal/ maintenance gate)	Evidence (alarms, trends, deviations), knowledge base, and thresholds	Fault hypothesis set (ranked) + explanation	Interpretable diagnosis and action generation
Maintenance action planning	Fault hypotheses, severity/operability constraints and maintenance context	Maintenance recommendation (actions + prioritization)	Converts diagnosis into an actionable plan
Logging and Updates	Inputs, decisions, outcomes, operational feedback	Updated logs, threshold refinement, model update triggers (where applicable)	Supports refinement of thresholds and model update decisions

Table 7.1. highlights that the DSS integration is not a serial process; rather, it is a supervised decision loop with explicit health awareness and well-defined key methods. The health classification step functions as a safety-critical identifier: in normal conditions, it supports performance optimization and ranking, while in abnormal conditions, it supports computation toward interpretable diagnosis and maintenance action planning. The two procedures operate on structured data flow, predicted criteria, Pareto feasible sets, weights and ranked alternatives, ensuring that each implemented step is clear and traceable.

As shown in both Figure 7.1. and Table 7.1. the integrated DSS is governed by a condition classification and decision that selects between two operational modes: a performance optimization procedure executed in normal conditions and a maintenance procedure executed when the condition is flagged as abnormal. These two procedures are intentional design choices. First, it recommends diagnosis and maintenance when conditions are unsafe or diagnostically uncertain. Second, it ensures that abnormal operation is addressed using interpretable, knowledge-driven reasoning. The reasoning follows a classical Expert System architecture, including a knowledge base, an inference engine, and an explanation capability.

The operation of the integrated DSS can be described in two procedures (Figure 7.1.), as follows:

- 1. Performance optimization (Normal Condition):** when the DSS system classifies the engine condition as Normal, the performance optimization procedure starts. The surrogate

model (Chapter 3) serves as a computationally efficient emulator of the high-fidelity engine model, predicting the defined key performance indicators (e.g. *SFC*, *NO_x* and *PM*) for any given set of control parameters. This surrogate is coupled with the NSGA-II algorithm to explore the multi-objective design space, generating a Pareto optimal set of feasible operating points that maps the trade-offs between the key performance indicators. The resulting Pareto set is passed to the decision step (Chapters 4 and 5). In this step, the Fuzzy Weighting module translates often-imprecise operator preferences into normalized weights using fuzzy set theory. This weight vector is then utilized by a selected MCDM method (e.g. TMF, PIV, etc.) to rank the Pareto set alternatives, transforming a set of trade-off solutions into a single, context-aware operational recommendation. This closed-loop performance procedure enables adaptive, preference-driven optimization without requiring direct human involvement in the numerical search process.

2. **Maintenance (Abnormal Condition):** if the condition classification triggers an Abnormal condition, control is diverted to the elaborated Knowledge Based Expert System (Chapter 6). This system employs a rule-based inference engine, which matches fault signals against a structured knowledge base of failure modes, diagnostic rules and symptom-fault relationships. The output is a diagnostic hypothesis. Subsequently, maintenance planning with procedural knowledge is used to generate a prioritized action plan, specifying recommended inspections, parts replacements or adjustments. This procedure ensures that fault conditions are addressed with consistent, knowledge-driven responses, reducing reliance on individual operator experience.

The two procedures are not isolated; they interact through shared data structures and a supervisory logic. Furthermore, the condition classification itself can be refined over time based on historical fault data and operator feedback, creating an adaptive knowledge loop.

Overall, the novelty of the proposed DSS lies in the explicit supervisory integration of predictive performance optimization and interpretable maintenance reasoning within one coherent workflow, so the DSS system can recommend optimal operating settings under normal conditions while remaining health-aware and procedurally conservative under abnormal conditions.

7.2. Programming environment and main operator interfaces of the Decision Support System

To support integration of the computational modules developed in Chapters 3 – 6 into a single holistic Decision Support System, the elaborated DSS was implemented as a modular software. This section documents: 1.) the programming environment and software structure used to integrate the surrogate optimization, MCDM decision module component, fuzzy preference module and KBES reasoning module component and 2.) the two main operator interfaces through which the DSS is executed. Detailed scenario-level runs and results obtained using these interfaces are presented in Chapter 8.

1. Programming environment and software structure: the integrated decision support system was developed in a Python 3.13 environment and structured as modular components with clearly defined inputs and outputs. The implementation relies on a combination of standard and specialized scientific Python libraries, including:
 - a) *numpy*: for efficient numerical computations and handling of multidimensional arrays,
 - b) *pandas*: for data manipulation, cleaning and analysis using dataframe structures,
 - c) *matplotlib*: for creating static, interactive and publication-quality visualizations and plots,

- d) pytorch: for building and training machine learning / deep learning models, enabling flexible tensor computations and automatic differentiation (for surrogate model implementation),
- e) pymoo: for multi-objective optimization, providing state-of-the-art algorithms to solve complex problems with multiple conflicting objectives (for applying NSGA-II algorithm),
- f) scikit-fuzzy (commonly imported as skfuzzy): for implementing fuzzy logic and fuzzy inference systems, supporting uncertainty modeling and approximate reasoning (for FLM implementation),
- g) pyside6: for developing the cross-platform Graphical User Interface (GUI), leveraging the Qt framework to create intuitive and responsive desktop applications.

This selection of libraries enables efficient data processing, advanced modeling (including optimization under uncertainty), machine learning capabilities and a professional user interface within a single cohesive Python-based application.

2. Main operator interfaces of the elaborated DSS: the integrated DSS is accessed through two operator interfaces aligned with the workflow in Figure 7.1. The performance optimization interface (Normal-condition procedure), shown in Figure 7.2., provides access to the performance optimization procedure. The maintenance diagnosis interface (Abnormal-condition procedure), shown in Figure 7.3., provides access to the KBES-based maintenance diagnosis procedure. These interfaces introduce the integrated DSS logic by maintaining a clear separation between normal condition performance and abnormal condition diagnostic recommendations.

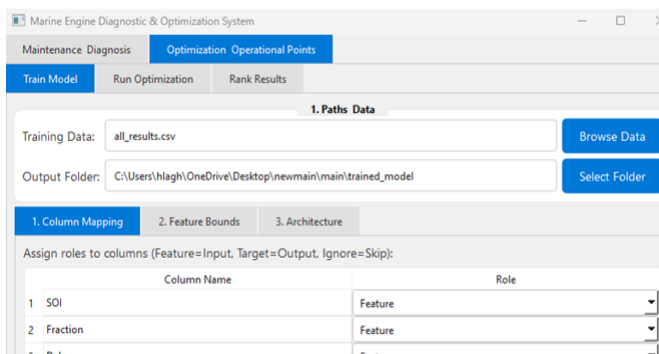


Figure 7.2. The elaborated DSS system:
performance optimization interface

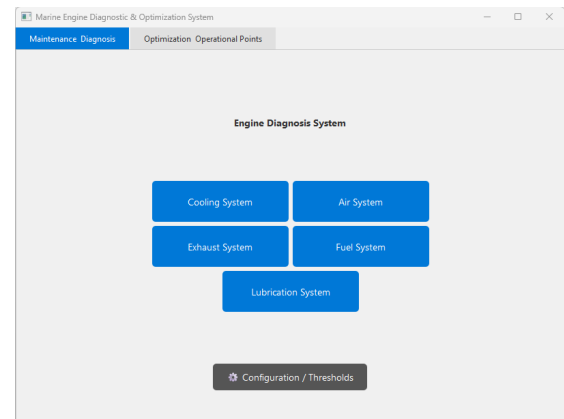


Figure 7.3. The elaborated DSS system:
maintenance diagnosis interface

8. APPLICATION OF THE NEWLY DEVELOPED DECISION SUPPORT SYSTEM

This chapter demonstrates the practical application of the newly developed Decision Support System (DSS) for large two-stroke marine diesel engines. Building upon the methodological developments and validations presented in Chapters 3 – 6, this chapter illustrates how the integrated framework operates as a supervisory management support system under both Normal and Abnormal engine conditions. This chapter is structured as follows: Section 8.1. presents a detailed numerical example of a surrogate-assisted, MCDM driven and performance optimization procedure, set in a representative operational scenario. The following example illustrates how multi-objective trade-offs are transformed into implementable operating strategies and a single, context-aware recommendation. Section 8.2. provides a complementary numerical example focusing on predictive maintenance and fault handling, demonstrating the operation of the Knowledge Based Expert System under abnormal conditions. Finally, Section 8.3. synthesizes the two operation procedures in a system-level evaluation, demonstrating the added value of integrating optimization, decision-making and diagnostics into a holistic management support system.

8.1. Numerical example 1: Surrogate-assisted MCDM driven performance optimization

This numerical example demonstrates the normal condition performance procedure of the integrated DSS, starting from surrogate-based objective prediction and NSGA-II Pareto generation to fuzzy-weighted MCDM ranking and an operational recommendation. The numerical example is formulated using the same S60-class low-speed two-stroke engine model adopted throughout the dissertation. The aim is to show how the DSS converts a multi-objective trade-off surface into a small set of implementable operating strategies and a single context-aware recommendation, while maintaining feasibility and fulfillment to mechanical and emissions constraints.

The performance pathway is executed when the health condition of the engine is classified as **Normal**, meaning that monitored indicators remain within the configured normal operation limits. Under this condition, the operator starts the optimization procedure, which is implemented in the "**Optimization Operational Points**" module of the software. The workflow is executed in three sequential steps reflected by the user-interface tabs: 1.) Train Model, 2.) Run Optimization and 3.) Rank Results, as shown in Figure 8.1.

Figure 8.1. shows the interface used to load the training dataset and define the feature/target mapping required by the surrogate model. The input variables are assigned as Features (SOI , F , D , P_{fuel} , EVO , EVC), while key performance and constraint-related outputs are assigned as targets (SFC , P_{max} , dp/dCA , CD , PM , NO_x and SE). This mapping ensures that the surrogate supports both 1.) multi-objective optimization and 2.) early constraint evaluation through constraint predictions. The interface also offers the flexibility to set the training hyperparameters (e.g. epochs, batch size, learning rates, dropout, patience, seed), allowing controlled and repeatable training consistent with the validated surrogate methodology established in Chapter 3.

Marine Engine Diagnostic & Optimization System

Maintenance

Diagnosis

Optimization

Operational Points

Train Model

Run Optimization

Rank Results

1. Paths Data

Training Data: all_results.csv

Browse Data

Output Folder: C:\Users\hlagh\OneDrive\Desktop\newmain\main\trained_model

Select Folder

1. Column Mapping

2. Feature Bounds

3. Architecture

Assign roles to columns (Feature=Input, Target=Output, Ignore=Skip):

	Column Name	Role
1	SOI	Feature
2	Fraction	Feature
3	Delay	Feature
4	Pressure	Feature
5	EVO	Feature
6	EVC	Feature
7	SFC	Target
8	p_max	Target
9	dp/dCA	Target
10	duration	Target
11	PM	Target
12	NOx	Target
13	SE	Target

Update Downstream Tables

Training Hyperparameters

Epochs: 800

Batch Size: 32

LR (Shared): 0.00100

LR (Head): 0.00050

Patience: 50

Dropout: 0.20

Seed: 42

Training Model

View Metrics

Loaded 13 columns. Please verify mappings.

Figure 8.1. The elaborated DSS system: surrogate preparation interface (Train Model)

Figure 8.2. shows the optimization configuration and execution interface. The operator first selects the optimization objectives (minimize SFC , PM and NO_x), then defines admissible decision-variable boundaries for the studied engine control parameters (SOI , F , D , P_{fuel} , EVO , EVC). Next, feasibility is enforced by specifying constraint limits consistent with safe/acceptable operation, including a P_{max} , $dp/d\theta$, CD , PM , NO_x and SE . The optimization module then executes the NSGA-II algorithm using the trained surrogate as the fast evaluator, generating a Pareto optimal set of feasible operating points.

Finally, the interface includes NSGA-II settings: population size and generation number, thereby reducing the likelihood of recommending borderline solutions when prediction uncertainty or operational disturbances exist.

Marine Engine Diagnostic & Optimization System

Maintenance Diagnosis **Optimization** Operational Points

Train Model **Run Optimization** Rank Results

0. Paths Config

Model Directory: C:/Users/hlagh/OneDrive/Desktop/newmain/main/trained_model Select Model Dir

Results Directory: C:/Users/hlagh/OneDrive/Desktop/newmain/main/results Select Results Dir

1. Select Optimization Objectives

- ☒ Minimize SFC (Fuel Consumption)
- ☒ Minimize PM (Particulate Matter)
- ☒ Minimize NOx (Nitrogen Oxides)

2. Set Parameter Bounds

Parameter	Min	Max
Start of Injection:	1.00	5.00
Injection Fraction:	0.01	0.08
Injection Delay:	2.00	5.00
Injection Pressure:	700.00	950.00
Exhaust Valve Opening:	62.00	68.00
Exhaust Valve Closing:	110.00	125.00

3. Set Constraint Limits

Max Pressure [bar]:	170.00
Max Pressure Rise Rate [bar/CA]:	4.00
Min Combustion Duration [CA]:	35.00
Max Combustion Duration [CA]:	45.00
Max PM [g/kWh]:	0.15
Max NOx [g/kWh]:	3.40
Max Emission Index:	3.50

4. NSGA-II Settings

Population Size: 1000

Max Generations: 800

Run Optimization

Optimization completed! 100%

Figure 8.2. The elaborated DSS system: surrogate-assisted NSGA-II execution interface (Run Optimization)

Once the Pareto solutions are generated, the DSS transitions from "Pareto optimal" to "Random results" based on operator preferences. Figure 8.3. shows the ranking interface, where the Pareto solution file is loaded and the criterion importance is specified on a simple [0–10] scale (*SFC*, *PM*, *NO_x*). These importance inputs are converted into a normalized weight vector by the fuzzy preference module (Chapter 5) and the selected MCDM ranking logic (Chapter 4) produces a complete ordering of feasible Pareto solutions. The ranked list is displayed directly within the interface and can be exported for traceability and reporting.

In this way, the decision module resolves the multi-objective trade-off into 1.) a ranked short list (Top-K) and 2.) a single best compromise operating point under the specified preference setting, providing an operationally actionable recommendation rather than an unfiltered Pareto surface.

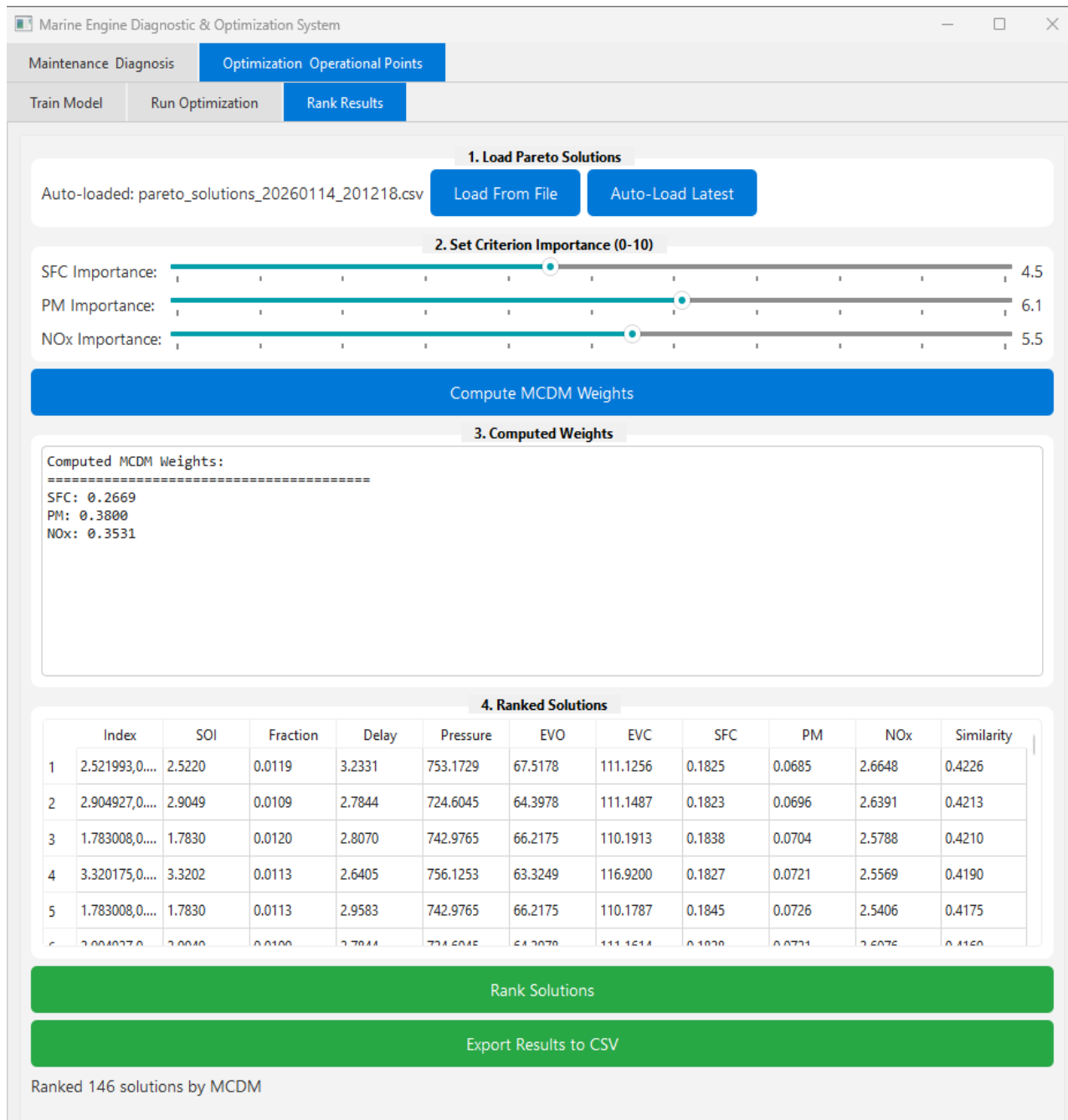


Figure 8.3. The elaborated DSS system: ranking interface (Rank Results)

8.2. Numerical example 2: Predictive maintenance and fault handling via the elaborated Knowledge Based Expert System

This numerical example illustrates the procedure of the abnormal condition in the integrated DSS, using the same S60-class two-stroke engine model adopted throughout the dissertation. The objective is to show how condition-monitoring evidence (alarms, trend and deviations) is transformed into 1.) an interpretable fault hypothesis set and 2.) a prioritized maintenance action plan, while ensuring that the performance optimization procedure is not executed under diagnostically uncertain or potentially unsafe conditions. The diagnostic logic follows the Expert System structure developed in Chapter 6 (knowledge base, inference engine and explanation capability) and uses the subsystem-oriented parameterization defined in Section 6.3. for Fuel, Lubrication, Cooling, Air Supply and Exhaust subsystems.

The engine is assumed to operate under the same representative operation regime used for the performance example (Section 8.1.), i.e. within the low-speed two-stroke envelope ($\approx 85\text{--}105$ rpm) for which the virtual S60-class model was calibrated.

Figure 8.4. is the entry dashboard of the elaborated DSS maintenance module. It serves as the initial operator interface for diagnosis, providing direct access to subsystem-specific diagnostic screens (Cooling, Air, Exhaust, Fuel and Lubrication) and to the parameterization interface used to set the diagnostic thresholds. In particular, the "Configuration/Thresholds" option on this dashboard links to the threshold configuration interface shown in Figure 8.4. where the Normal-operation limits are defined.

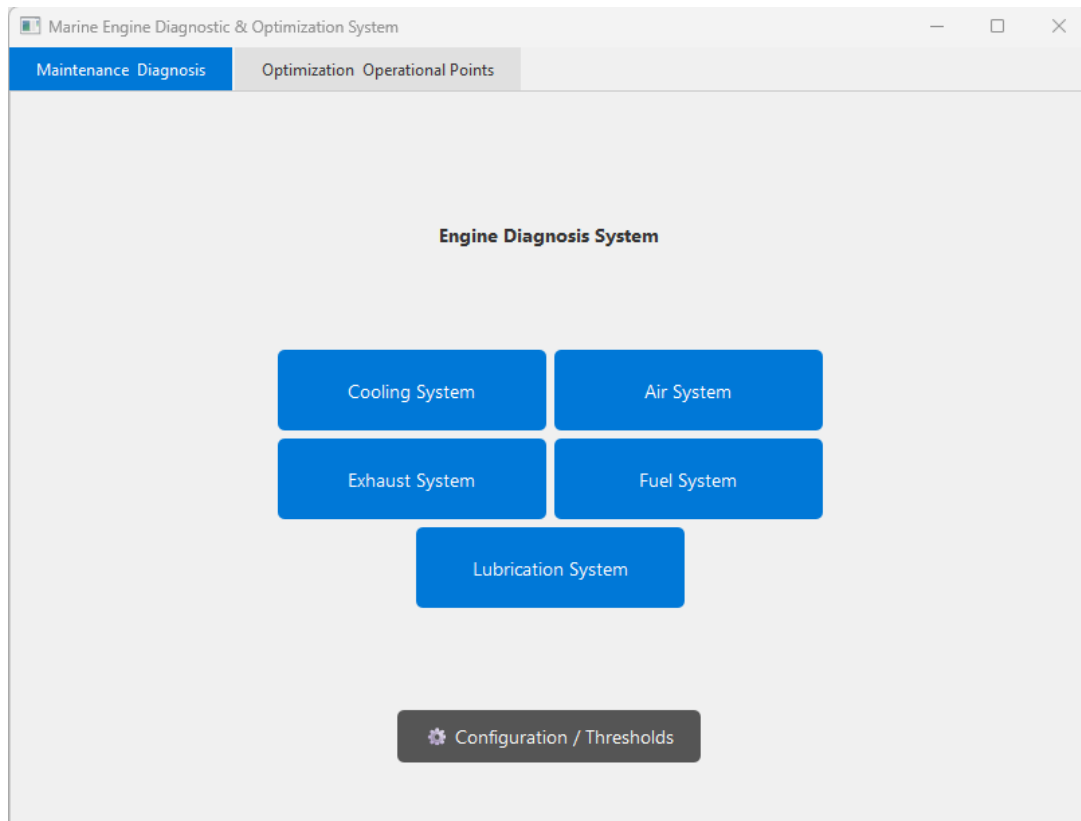


Figure 8.4. The elaborated DSS system: maintenance diagnosis interface

In the configuration interface (Figure 8.5.), the operator defines the normal-operation limits by specifying admissible boundaries for the key condition-monitoring indicators and, where required, time-based confirmation rules. These settings constitute the threshold knowledge base against which measurements and trends are evaluated.

Figure 8.5. illustrates the threshold configuration interface through which the Normal-operation limits are defined. To ensure reproducibility of the abnormality trigger in this case study, the corresponding numeric settings adopted for the studied S60-class engine are summarized in Table 8.1. including the configured limits, dimensions and the measurement basis for each parameter.

The screenshot shows a web-based configuration interface for a marine engine diagnostic system. The title bar reads 'Marine Engine Diagnostic & Optimization System'. Below the title bar, there are four tabs: 'Maintenance', 'Diagnosis' (which is active and highlighted in blue), 'Optimization', and 'Operational Points'. The main content area is titled 'System Configuration (Thresholds)' and features a 'Back' button on the left and a 'Save Parameters' button on the right. The interface contains a list of 18 parameters, each with a label and a corresponding numeric input field. The parameters and their values are as follows:

Parameter	Value
Fuel Pressure Low:	6.5
Fuel Pressure High:	9.0
Fuel Comb. Press Low:	125
Fuel Comb. Press High:	165
Fuel Inj. Ideal:	800
Fuel Inj. Allowance:	20
Scavenge Air Receiver Press Low:	3.4
Scavenge Air Receiver Press High:	4.3
Air Temp After Cooler Low:	40
Air Temp After Cooler High:	60
Smoke Temp Low:	340
Smoke Temp High:	430
Oil Pump Press Low:	3.5
Oil Pump Press High:	5.2
Oil Temp Low:	38
Oil Temp High:	50
Oil Level Low:	30
Oil Level High:	80
Oil Reg. Press Low:	180
Oil Reg. Press High:	260

Figure 8.5. The elaborated DSS system: configuration (thresholds) interface

Table 8.1. provides the configured Normal-operation limits needed for the health-condition evaluation for the numerical example scenario.

Table 8.1. Configured Normal-operation limits (thresholds) used for the numerical example

Engine subsystems	User interface (Threshold)	Value	Dimensions	Measurement basis/note
Fuel subsystem	Fuel pressure Lower limit	6.5	bar	Fuel supply at the engine (pump level).
	Fuel pressure Upper limit	9.0		
	Fuel combustion pressure Lower limit	125	bar	Peak firing / max cycle pressure indicator (use your Chapter 3 constraint logic if different).
	Fuel combustion pressure Upper limit	165	bar	
	Ideal fuel injection	800	bar	Injection pressure target (ME booster), load-dependent. Allowance interpreted as $\pm\%$ around "Ideal" $\rightarrow$ implied range $\approx [640,960]$ bar.
	Fuel injection allowance	20	%	
Air Supply subsystem	Scavenge air receiver pressure Lower limit	3.4	bar	Scavenge/receiver pressure is treated as absolute in engine data.
	Scavenge air receiver pressure Upper limit	4.3	bar	
	Air temperature after the cooler Lower limit	40	$^{\circ}\text{C}$	Charge-air cooler outlet (scavenge air after cooler).
	Air temperature after the cooler Upper limit	60	$^{\circ}\text{C}$	
Exhaust subsystem	Smoke temperature Lower limit (post-turbo)	210	$^{\circ}\text{C}$	Option A (post-turbo / stack): typical after turbo.
	Smoke temperature Upper limit (post-turbo)	280	$^{\circ}\text{C}$	
	Smoke temperature Lower limit (pre-turbo)	340	$^{\circ}\text{C}$	Option B (pre-turbo / turbine inlet): if the sensor is upstream of the turbocharger.
	Smoke temperature Upper limit (pre-turbo)	430	$^{\circ}\text{C}$	

Lubrication subsystem	Oil pump pressure Lower limit	3.5	bar	Main lubricating oil supply.
	Oil pump pressure Upper limit	5.2	bar	
	Oil temperature Lower limit	38	°C	At the inlet of the engine (after cooler).
	Oil temperature Upper limit	50	°C	
	Oil Level Lower limit	30	%	Prefer % tank level (instrumentation-dependent).
	Oil Level Upper limit	80	%	
	Oil regulating pressure Lower limit	180	bar	Hydraulic/servo oil supply (ME HPS class).
	Oil regulating pressure Upper limit	260	bar	
Cooling subsystem	Water pressure Lower limit	2.0	bar	Jacket water (HT FW) pressure at engine inlet/header.
	Water pressure Upper limit	4.0	bar	
	Jacket Water temperature Lower limit	75	°C	Jacket water outlet controlled by a thermostatic valve.
	Jacket Water temperature Upper limit	90	°C	

In this numerical example, the **Abnormal** trigger is illustrated using a scenario related to the **Air Supply subsystem**. Therefore, the abnormality condition is evaluated primarily using the scavenge receiver pressure and charge-air temperature after the cooler. The deviation pattern affecting the Air system is expressed as follows:

1. Scavenge receiver pressure trending **below** its normal boundary (e.g. **3.2** [bar]).
2. Charge-air temperature after the cooler is trending **above** its normal boundary (e.g. **65** [°C]).

In the DSS, these deviations are evaluated against the pre-defined threshold knowledge base by the operator (**Table 8.1.**) and the engine condition is labeled "**Abnormal**".

8.2.1. Input data and interface to the Expert System

Once the abnormal diagnosis is started, the DSS uses the available input in the inference engine, enabling transparent rule firing and explanation generation, consistent with interpretable Expert System principles used in marine engine diagnosis that is compatible with the Chapter 6 knowledge base. The minimum evidence required for air-path diagnosis follows the parameter set summarized in the air-supply diagnostic mentioned in Table 6.5. for scavenge receiver pressure, temperature after cooler and turbocharger condition indicators.

Figure 8.6. illustrates the corresponding air-system diagnosis interface used to enter and evaluate the input data within the elaborated DSS.

Marine Engine Diagnostic & Optimization System

Maintenance Diagnosis Optimization Operational Points

← Back Air System Diagnosis

Inputs

Scavenge Air Receiver Pressure: 3.0

Temperature after cooler: 70

TurboCharger Condition?: None

Run Diagnosis

Expert System Findings

Start the diagnosis as follows :

Turbocharger surge:

In two-stroke constant-pressure turbocharging systems, surging is less frequent but still possible. Monitor scavenge air pressure fluctuations and turbo rpm deviation. Possible reasons:

1. Air filter plugging (remove and clean).
2. Polluted turbo (check if the compressor and the turbine had cleaned regularly).
3. Unsteady shaft/Wear damage.
4. Air cooler fouling (accompanied by high temperature).
5. Scavenge fire (check scavenge box relief).
6. Uneven power distribution between cylinders (check indicator cards).

Immediate action: reduce speed to load at which surging stops; If necessary open the air cooler inspection hole to stop surging.

The turbocharger does not surge:

1. Unsealed joints before engine (check).
2. Turbocharger calibration (check).
3. Excessive clearance (maintenance).
4. Auxiliary blower failure (check activation at low load).

Immediate action: Reduce speed to load at which surging stops; If necessary open air cooler inspection hole to stop surging.

Start the diagnosis as follows :

1. Blockage in water tubes (sediments).
2. Blockage in air tubes (accompanied by surging in turbocharger).
3. Water mist catcher fouling.
4. Insufficient cooling water flow.

Figure 8.6. The elaborated DSS system: Air subsystem diagnosis interface

8.2.2. Maintenance diagnostic procedure and fault recommendations set

Using the Chapter 6 Air Supply subsystem rules (Table 6.5.), the Expert System begins by classifying the low scavenge-pressure condition into two cases: **1.) turbocharger surge**, where the compressor becomes aerodynamically unstable and **2.) non-surge air-path degradation**, where the turbocharger remains stable, but the delivered air is reduced. This separation is essential because the operational risk and the required operator response differ substantially between surging and stable turbocharger operation.

Surge-related case (if detected)

If the monitoring evidence indicates scavenging air pressure fluctuations together with a turbocharger speed deviation, the Expert System suggests Turbocharger surge and reports the most likely causes to be checked, as follows:

1. Air filter plugging (remove and clean),
2. Turbocharger contamination (verify compressor/turbine cleaning intervals),
3. Unsteady shaft/wear damage,
4. Air cooler fouling (typically accompanied by elevated charge-air temperature),
5. Scavenge fire (inspect scavenge box relief arrangements),
6. Uneven cylinder power distribution (check indicator cards/cylinder balance).

Immediate action. The system recommends reducing speed/load to the level at which surging ceases; if necessary, it advises opening the air cooler inspection hole to stop surging.

Non-surge case (illustrative in this scenario)

If the turbocharger is evaluated as **not surging**, the Expert System proceeds with the non-surge branch and prioritizes air-path leakage, calibration/clearance issues and low-load blower support. The reported hypotheses are:

1. Unsealed joints before the engine (inspect for leakage),
2. Turbocharger calibration issue (check),
3. Excessive clearance (maintenance intervention),
4. Auxiliary blower failure or non-activation at low load (verify activation logic and operation).

Although the primary non-surge list above captures mechanical/operational contributors, the Expert System also evaluates charge-air cooler-related restrictions when the evidence includes elevated charge-air temperature after the cooler. In that case, the diagnosis is extended by checking the cooler and associated components, starting with:

1. Blockage in water tubes (sediments),
2. Blockage in air tubes (noted by the system as potentially accompanied by turbocharger surging),
3. Water mist catcher fouling,
4. Insufficient cooling-water flow.

This structure ensures that the diagnosis remains consistent with the system's implemented rule sequencing: surge detection is handled first for safety, followed by non-surge leakage, calibration, clearance, blower checks and then cooler-side restrictions when temperature evidence indicates degraded cooler effectiveness.

8.3. The evaluation and benefits of the elaborated DSS system

This section evaluates the elaborated DSS as a unified, closed-loop framework by synthesizing the results of the Normal-condition performance optimization procedure (Section 8.1.) and the Abnormal-condition maintenance procedure (Section 8.2.). The objective of the evaluation is not to re-evaluate each standalone module, already validated in Chapters 3 – 6, but to verify that their integration yields system-level benefits: 1.) safe and coherent decision process through the health-condition evaluation, 2.) operationally actionable recommendations under shifting priorities and 3.) transparent, traceable reasoning suitable for engineering supervision and post-event analysis. This system-level emphasis is consistent with condition monitoring and diagnostic system requirements that necessitates

structured processing/presentation of health and advisory information and systematic reliability/maintenance data handling across the engine components lifecycle.

Three system-level outcomes of integration are considered to isolate the benefits of different modules' integration, as follows:

1. A **Health-evaluation** requirement is that optimization and ranking are executed only under Normal conditions, while Abnormal conditions trigger diagnosis and maintenance planning. The numerical example in Section 8.1 demonstrates this behavior. Deviations in scavenge receiver pressure and supply air temperature trigger an Abnormal label. The workflow is then directed to the Expert System. This Abnormal condition prevents performance optimization from being executed under potentially unsafe or diagnostically uncertain conditions. The principle is to obtain a safety-preserving supervisory logic. Performance improvements are pursued only when the engine condition is normal and stable. When the engine condition is abnormal, the DSS system switches to interpretable rule-based inference and the DSS system prioritized corrective actions. The importance of configurable thresholds, explicit rule firing and update capability is consistent with established knowledge based diagnostic practice in marine engines.
2. For **Normal operation** (Section 8.1.), the DSS transforms a Pareto set of feasible alternatives into an implementable recommendation through two integration steps: 1.) operator preference translated to fuzzy weights and 2.) robust ranking via the selected MCDM method. In comparative terms, the expected added value of the integrated optimization procedure is not merely a different "best point", but a decision interface that 1.) reduces operator workload by returning a ranked list and a recommended setpoint. 2.) enables systematic adaptation of criterion importance to context (e.g. fuel economy priority versus emissions priority, including operation under regulated zones where NO_x constraints become critical).
3. For **Abnormal operation** (Section 8.2.), the integrated DSS converts monitoring evidence into a ranked fault hypothesis set and an actionable maintenance plan, while generating a recommended maintenance plan. Compared with only alarm systems, the added value of the maintenance diagnostic procedure is a reduction in ambiguity: rather than presenting multiple unprioritized alarms, the DSS provides a structured diagnostic sequence (e.g. surge detection first, then leakage/clearance/blower checks, then cooler-side restrictions) and a prioritized intervention set. This design also supports continuous improvement through logging and rule/threshold refinement, a key practical requirement for ship-specific adaptation of expert knowledge.

The presented evaluation of the DSS system is conducted at conceptual scenarios using a calibrated virtual engine model and rule-based diagnostic logic. While this approach is appropriate for demonstrating the elaborated workflow feasibility and decision logic, broader field validation remains a future step, requiring 1.) larger sets of real fault histories, 2.) ship-specific sensor availability and data quality assessment; furthermore, 3.) long-horizon evaluation of retraining/refinement triggers. These limitations do not reduce the architectural contribution of the DSS, but it defines the pathway for deployment-oriented research and industrial collaboration.

Chapter 8 illustrated that the newly developed DSS is not a collection of isolated methods but a coherent supervisory framework that unifies optimization, preference-aware decision-making and interpretable diagnostics under a safety-preserving evaluation. This integrated evaluation establishes the operational logic and practical value of the DSS framework, thereby positioning the dissertation's final conclusions and future work toward deployment, expanded fault coverage and long-term learning from ships' onboard logs.

9. THESIS - NEW SCIENTIFIC RESULTS

T1. A new Neural Network (NN) surrogate model was developed for computationally efficient multi-objective optimization of marine engine performance and emissions.

1. A multi-output Neural Network model was elaborated, trained on a comprehensive dataset generated from the Diesel-RK software-based simulations. The NN model connects six control parameters (SOI , F , D , P_{fuel} , EVO , EVC) of marine diesel engines to seven key performance and emission outputs (SFC , NO_x , PM , P_{max} , $dp/d\theta$, CD , SE) of the engine combustion process.
2. The developed NN surrogate model demonstrated high predictive accuracy, achieving an overall coefficient of determination R^2 of 0.9833 on test data. Mean Absolute Percentage Errors ($MAPE$) for the primary objectives SFC , NO_x and PM were below 2%.
3. The NN surrogate model's fidelity was validated by comparing its predictions for the Pareto optimal solutions by direct Diesel-RK simulations. The differences were minimal (e.g. $\Delta SFC \approx 0.001$ kg/kWh), confirming its reliability as a fast and physically consistent for optimization.

Published articles relating to T1: P11, P4, P5.

T2. A new surrogate-based multi-objective optimization procedure was elaborated for two-stroke marine diesel engines to identify Pareto optimal operating strategies.

1. The multi-objective optimization problem was formulated to minimize Specific Fuel Consumption (SFC), Nitrogen Oxides Emissions Index (NO_x) and Particulate Matter Emissions (PM) of marine diesel engines. Six control parameters (SOI , F , D , P_{fuel} , EVO , EVC) of the engine act as design variables, in addition to constraints specified by IMO organization Tier III compliance and mechanical limits.
2. An initial optimization procedure was developed, combining the validated NN surrogate model with the NSGA-II optimization algorithm. This procedure efficiently generated a Pareto optimal front of non-dominated optimal solutions, explicitly demonstrating the trade-offs between fuel efficiency and emissions of two-stroke marine diesel engines.
3. The effectiveness of the surrogate-based optimization procedure was validated by re-evaluating the top-ranked Pareto solutions using the high-fidelity Diesel-RK software, which showed close agreement between the predictions of the NN surrogate-based optimization and the simulation results.

Published articles relating to T2: P11.

T3. A new systematic selection and adaptation of the Multi-Criteria Decision-Making (MCDM) methods was developed for marine diesel engine applications in order to support final decision-making for the engine performance optimization.

1. A structured benchmarking of fourteen MCDM methods was conducted using a Diesel-RK-derived decision matrix. The evaluation of the MCDM methods was based on rank stability analysis and consensus analysis to identify the most robust methods for engine trade-off problems.
2. The Proximity Indexed Value (PIV), Integrated Simple Weighted Sum Product (WISP) and TriMetric Fusion (TMF) methods were identified as generating the most stable and consensus-aligned rankings for the studied marine engine optimization problem.

3. The selected robust MCDM methods were successfully applied to rank the Pareto optimal set. The consistent identification of top optimal solutions confirmed the suitability in translating a set of optimal trade-offs into actionable shortlist recommendations in order to support the decision-making process by the engine operator.

Published articles relating to T3: P9.

T4. A complex performance optimization procedure was elaborated for the two-stroke marine diesel engines, integrating the Neural Network surrogate model, the NSGA-II multi-objective optimization algorithm, the MCDM ranking method and a newly developed Fuzzy Logic Module (FLM).

1. A new operator-defined Fuzzy Logic Module was elaborated for dynamic weighting in Multi-Criteria Decision-Making, implemented as a Mamdani-type fuzzy inference system that captures the operator's qualitative importance ratings (on a 0 to 10 scale for *SFC*, *NO_x*, *PM*) into normalized criterion weights for use in the complex optimization procedure.
2. The FLM was integrated as a weighting mechanism within the MCDM ranking method, enabling dynamic, preference-driven re-ranking of the fixed Pareto optimal set without re-optimization. The FLM effectiveness was demonstrated through conceptual scenarios, where the FLM produced distinct, logical weights that led to significant and appropriate changes in the top-ranked engine optimal operating points.
3. A new dedicated Decision Support System (DSS) software application was developed, integrating the NN surrogate model, the NSGA-II algorithm, the MCDM methods and the FLM into a unified graphical user interface. The software's functionality was validated by successfully reproducing the Pareto fronts and FLM-driven rankings from the individual validation optimization steps, thereby confirming the correctness and practical applicability of the elaborated complex optimization procedure for marine diesel engine decision support.

Published articles relating to T4: P10, P7.

T5. A new Knowledge Based Expert System (KBES) was also developed for predictive maintenance and fault diagnosis of marine diesel engines, providing interpretable fault hypotheses and prioritized response actions.

1. The KBES contains a set of diagnostic parameters that was selected based on their sensitivity to common faults, availability via standard engine sensors and consistent with condition monitoring architectures that emphasize structured diagnostic information flows.
2. A forward-chaining inference engine was implemented to process monitoring data using a knowledge base of fault rules. The KBES system outputs are interpretable fault hypotheses and prioritized maintenance recommendations for a proactive marine diesel engine maintenance.
3. The KBES was integrated as the health-state supervisor for the developed Decision Support System (DSS). Its primary function is to classify the engine condition as "Normal" or "Abnormal", thereby identifying the DSS function between the performance optimization procedure and the maintenance diagnosis procedure.

Published articles relating to T5: P1, P2, P3.

LIST OF OWN PUBLICATIONS RELATED TO THE TOPIC OF THE RESEARCH FIELD

- P1:** H. Gharib, G. Kovács, *Development of a new expert system for diagnosing of marine diesel engines based on real-time diagnostic parameters*, **Strojniski Vestnik-Journal of Mechanical Engineering** **2022**, vol. 68, no. 10, pp. 642-655, doi: 10.5545/sv-jme.2022.298 (**Q3, WoS, Scopus, IF: 1.554**)
- P2:** H. Gharib, G. Kovács, *Diagnostic and prognostic strategies for monitoring of diesel engines' technical conditions*, **Lecture Notes in Mechanical Engineering** **2022**, vol. 4, pp. 190-199, doi: 10.1007/978-3-031-15211-5_17 (**Q4, Scopus**)
- P3:** H. Gharib, G. Kovács, *Development of a knowledge-based system for diagnosing of diesel engines*, **Lecture Notes in Mechanical Engineering** **2022**, vol. 4, pp. 200-211, doi: 10.1007/978-3-031-15211-5_18 (**Q4, Scopus**)
- P4:** Gharib, H.; Kovács, G. *Decision support systems for marine diesel engines' operations and maintenance*. In: **Fiatalok a Tudományért 2023**, Miskolci Egyetem, Tudományos Diákköri Konferenciája, Miskolc, Hungary, 9 Nov 2023, pp. 1–8.
- P5:** Gharib, H.; Kovács, G. *A review of prognostic and health management (PHM) methods and limitations for marine diesel engines: new research directions*. **Machines** **2023**, 11, 695, pp. 1-22, doi: 10.3390/machines11070695 (**Q2, WoS, Scopus, IF: 2.6**)
- P6:** Gharib, H.; Kovács, G. *Reliability analysis of marine diesel engines vs. industrial diesel engines: a comparative approach*. **Acta Logistica** **2024**, Vol. 11, No. 2, pp. 325–337, doi: 10.22306/al.v11i2.516 (**Q3, Scopus, IF: 1.35**)
- P7:** Gharib, H.; Kovács, G. *Implementation and possibilities of Fuzzy Logic for optimal operation and maintenance of marine diesel engines*. **Machines** **2024**, 12, 425, pp. 1-16, doi: 10.3390/machines12060425 (**Q2, WoS, Scopus, IF: 2.6**)
- P8:** H. Gharib, G. Kovács, *Maintenance strategies of machines supported by Knowledge-based systems*, **The Annals of the University of Petrosani, Mechanical Engineering Journal** **2021**, vol. 23, pp 20-31.
- P9:** Gharib, H.; Kovács, G. *Multi-Criteria Decision-Making algorithm selection and adaptation for performance improvement of two stroke marine diesel engines*. **Journal of Marine Science and Engineering** **2025**, 13, 1916, pp. 1-20, doi: 10.3390/jmse13101916 (**Q2, WoS, Scopus, IF: 2.8**)
- P10:** Gharib, H.; Kovács, G. *Operator-defined fuzzy weighting in multi-criteria performance optimization of marine diesel engines*. **Eng** **2026**, 7, 21, pp. 1-23, doi: 10.3390/eng7010021 (**Q2, WoS, Scopus, IF: 2.4**)
- P11:** Gharib, H.; Kovács, G. *Performance optimization of marine engine using Neural Network, Genetic Algorithm and Multi-Criteria Decision-Making*. **Alexandria Engineering, Under review** (**Q1, WoS, Scopus, IF: 7.088**)

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APPENDICES

Appendix 1

Pseudocode of the NSGA-II algorithm:

```

procedure NSGA-II ( $N, N_A$ )
   $t \leftarrow 0$ 
   $P_t \leftarrow \text{new\_population}(N)$ 
   $Q_t \leftarrow \emptyset$ 
   $A \leftarrow \text{non\_dominated}(P_t)$ 
  while not stop-criterion do
     $R_t \leftarrow P_t \cup Q_t$ 
     $\mathcal{F} \leftarrow \text{fast\_non\_dominated\_sorting}(R_t)$ 
     $P_{t+1} \leftarrow \emptyset$ 
     $i \leftarrow 1$ 
    while  $|P_{t+1}| + |\mathcal{F}_i| \leq N$  do
       $C_i \leftarrow \text{crowding\_distance\_assignment}(\mathcal{F}_i)$ 
       $P_{t+1} \leftarrow P_{t+1} \cup \mathcal{F}_i$ 
       $i \leftarrow i + 1$ 
    end while
     $\mathcal{F}_i \leftarrow \text{sort}(\mathcal{F}_i, C_i, \text{'descending'})$ 
     $P_{t+1} \leftarrow P_{t+1} \cup \mathcal{F}_i[1: (N - |P_{t+1}|)]$ 
     $Q_{t+1} \leftarrow \text{selection}(P_{t+1}, N)$ 
     $Q_{t+1} \leftarrow \text{crossover}(Q_{t+1})$ 
     $Q_{t+1} \leftarrow \text{mutation}(Q_{t+1})$ 
     $t \leftarrow t + 1$ 
     $A \leftarrow \text{non\_dominated}(A \cup Q_t)$ 
  end while
end procedure

```

Inputs and notation:

- N : population size (number of candidate solutions per generation),
- t : generation index (iteration counter),
- P_t : parent population at generation t , with $|P_t| = N$,
- Q_t : offspring population at generation t , typically $|Q_t| = N$,
- $R_t = P_t \cup Q_t$: merged population used for elitist environmental selection, $|R_t| = 2N$,
- $\mathcal{F} = \{F_1, F_2, \dots\}$: ordered set of nondominated fronts produced by fast nondominated sorting, where F_1 is the best (rank 1) front,
- C_i : crowding-distance values computed for solutions in front F_i ; larger values indicate solutions in less crowded regions (preferred for diversity),
- A : an external archive of nondominated solutions found so far.

Appendix 2

Table 1. Detailed descriptive statistics of the 163 Pareto optimal set

Statistic	Definition	<i>SFC</i>	<i>PM</i>	<i>NO_x</i>
count	The total number of solutions in the Pareto optimal set.	163.0	163.0	163.0
mean	The average value of all solutions for the objective.	0.182	0.075	2.673
std	Standard Deviation: measures the typical spread or variability of the solutions around the mean. A low value means the solutions are tightly clustered.	0.001	0.004	0.175
min	The minimum value achieved for that objective within the optimal set.	0.181	0.071	2.244
25%	First Quartile: the value below which 25% of the solutions fall. Represents the lower-range performance.	0.181	0.072	2.562
50%	Median: the middle value. Half of the solutions are better, half are worse, for this objective.	0.181	0.074	2.760
75%	Third Quartile: the value below which 75% of the solutions fall. Represents the upper-range performance.	0.182	0.077	2.785
max	The maximum value present for that objective within the optimal set.	0.190	0.099	2.939

Table 2. Pareto front for $m=163$ non-dominated objective values

Alternative	<i>SFC</i>	<i>PM</i>	<i>NO_x</i>	Alternative	<i>SFC</i>	<i>PM</i>	<i>NO_x</i>
1	0.185261	0.076127	2.415344	90	0.181498	0.072857	2.786983
2	0.185346	0.076742	2.397784	91	0.181566	0.072918	2.785491
3	0.184846	0.079177	2.438279	92	0.181676	0.072965	2.77659
4	0.185388	0.072859	2.423743	93	0.181504	0.072876	2.786606
5	0.182528	0.07645	2.596486	94	0.181348	0.072897	2.793154
6	0.182101	0.072857	2.633712	95	0.18131	0.072647	2.79598
7	0.182863	0.077185	2.555569	96	0.181463	0.073154	2.78723
8	0.183959	0.077215	2.454673	97	0.181742	0.072241	2.867576
9	0.182959	0.075885	2.532149	98	0.181485	0.073311	2.785091
10	0.183367	0.07355	2.476281	99	0.181575	0.073055	2.779557
11	0.186802	0.081789	2.305897	100	0.181412	0.072637	2.791493
12	0.185615	0.081677	2.355149	101	0.181587	0.073078	2.777389
13	0.182581	0.07195	2.575722	102	0.181405	0.072903	2.791214
14	0.188087	0.086503	2.279731	103	0.181561	0.07343	2.773906
15	0.182735	0.071688	2.573977	104	0.181565	0.073284	2.773174
16	0.182028	0.071484	2.728017	105	0.18138	0.072881	2.792757

17	0.186604	0.082069	2.296446	106	0.18149	0.07319	2.786009
18	0.182554	0.071269	2.577823	107	0.181465	0.073093	2.78694
19	0.187395	0.081044	2.339714	108	0.181156	0.073919	2.907929
20	0.184625	0.079241	2.396006	109	0.181237	0.072487	2.820623
21	0.183018	0.075926	2.523082	110	0.182493	0.078212	2.604206
22	0.185701	0.079714	2.349159	111	0.182123	0.077529	2.622829
23	0.187286	0.085114	2.286972	112	0.181176	0.07408	2.900837
24	0.183297	0.072825	2.555212	113	0.18118	0.074161	2.900645
25	0.188199	0.084557	2.251255	114	0.181104	0.075033	2.816837
26	0.184935	0.078869	2.43899	115	0.181389	0.073022	2.788789
27	0.18458	0.072673	2.447571	116	0.181662	0.077489	2.744901
28	0.181982	0.072463	2.645194	117	0.181666	0.077643	2.732663
29	0.184681	0.078072	2.44494	118	0.181597	0.072998	2.781867
30	0.188232	0.084871	2.250707	119	0.18172	0.073099	2.770503
31	0.184455	0.079431	2.406035	120	0.181578	0.074324	2.760052
32	0.187508	0.083254	2.288869	121	0.181766	0.073236	2.767581
33	0.185995	0.081172	2.344948	122	0.181527	0.07325	2.78208
34	0.182182	0.073212	2.63141	123	0.181214	0.072538	2.806725
35	0.182821	0.075412	2.563719	124	0.181675	0.073357	2.766727
36	0.184246	0.079716	2.45304	125	0.181751	0.073788	2.765443
37	0.183318	0.075011	2.517402	126	0.181585	0.074376	2.758209
38	0.186235	0.078195	2.349648	127	0.181665	0.073683	2.767392
39	0.186438	0.079514	2.345616	128	0.189809	0.0984	2.249929
40	0.181791	0.071663	2.6655	129	0.190087	0.09903	2.244728
41	0.182445	0.075538	2.627881	130	0.181377	0.07281	2.794099
42	0.183097	0.075619	2.52207	131	0.181437	0.073387	2.779205
43	0.186432	0.076692	2.406682	132	0.181327	0.073089	2.789503
44	0.184574	0.075648	2.472771	133	0.181423	0.073557	2.787626
45	0.185572	0.0829111	2.395261	134	0.181546	0.073174	2.782413
46	0.181744	0.076219	2.699092	135	0.181501	0.072959	2.785918
47	0.187052	0.086739	2.285875	136	0.181301	0.072908	2.801513
48	0.181366	0.078462	2.78352	137	0.181492	0.073119	2.784323
49	0.182519	0.079322	2.592473	138	0.181701	0.072473	2.869812
50	0.181724	0.074306	2.747197	139	0.181648	0.073012	2.773553
51	0.181958	0.071534	2.854308	140	0.181601	0.073125	2.774529
52	0.181608	0.074253	2.753425	141	0.181673	0.074046	2.766076
53	0.181588	0.074155	2.765754	142	0.181649	0.072918	2.77813
54	0.181628	0.074103	2.768218	143	0.181727	0.076749	2.707156
55	0.181677	0.074317	2.749674	144	0.181754	0.073899	2.764108
56	0.18159	0.074189	2.762279	145	0.181531	0.073007	2.784498
57	0.182911	0.080393	2.548923	146	0.18142	0.072954	2.789252
58	0.181783	0.074085	2.762665	147	0.181277	0.072755	2.802248
59	0.181563	0.074916	2.757174	148	0.181681	0.075289	2.710276

60	0.181777	0.072266	2.854211	149	0.181604	0.073164	2.768236
61	0.184008	0.077127	2.473509	150	0.181572	0.073125	2.771514
62	0.18159	0.071996	2.939219	151	0.181659	0.077521	2.737181
63	0.181767	0.074642	2.734604	152	0.181574	0.073073	2.777464
64	0.181544	0.074881	2.759287	153	0.181696	0.072873	2.772542
65	0.181791	0.074507	2.738096	154	0.181627	0.072925	2.782998
66	0.181575	0.074865	2.758732	155	0.181573	0.074168	2.766032
67	0.181668	0.071418	2.912806	156	0.181479	0.072877	2.787052
68	0.181601	0.074614	2.745778	157	0.1816	0.072975	2.77737
69	0.181836	0.071538	2.884901	158	0.18149	0.073005	2.786118
70	0.181896	0.071445	2.866887	159	0.181596	0.073	2.780717
71	0.181537	0.079143	2.77569	160	0.181502	0.073014	2.783107
72	0.18167	0.072273	2.877906	161	0.181428	0.07313	2.787575
73	0.181679	0.074378	2.748655	162	0.181541	0.073004	2.783573
74	0.181775	0.071889	2.888445	163	0.18131	0.072697	2.80356
75	0.181567	0.077712	2.748357				
76	0.182855	0.080916	2.561033				
77	0.182812	0.080751	2.56136				
78	0.181586	0.074263	2.76074				
79	0.181688	0.074238	2.750414				
80	0.181823	0.076484	2.625033				
81	0.181653	0.071911	2.889439				
82	0.182278	0.077907	2.612705				
83	0.181493	0.077001	2.77614				
84	0.182238	0.077576	2.619568				
85	0.18167	0.075462	2.726215				
86	0.182073	0.077208	2.622914				
87	0.18175	0.071917	2.860365				
88	0.181623	0.074141	2.767892				
89	0.181684	0.074143	2.757517				

* The bold numbers represent the subset of Pareto solutions that were selected as top-ranked under the operator-priority scenarios reported in Chapter 5 (Table 5.4.).