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

Booklet of PhD Theses

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1. INTRODUCTION

Marine diesel engines serve as the cornerstone of international shipping, dominating propulsion systems across the global 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 high power density with durability and reliability [3].

Implementing robust performance monitoring and predictive maintenance remains constrained by harsh operating conditions, sensing and data limitations and economic and organizational pressures, which collectively reduce data reliability and diagnostic accuracy [4].

Recent technological advances partially mitigate these limitations. Simulation platforms enable virtual replication of engine behavior under varying conditions and provide contextual baselines for anomaly detection, reducing false alarms by up to 40% in field applications [4].

Within this context, the key research gap addressed in this work is the development of a surrogate-assisted, physics-informed and uncertainty-aware decision support system that balances accuracy, computational efficiency and shipboard applicability. The proposed approach integrates Diesel-RK simulation baselines with Neural Network surrogates, fuzzy operator-defined weighting and Multi-Criteria Decision-Making (MCDM) to translate competing objectives: Specific Fuel Consumption (*SFC*), Nitrogen Oxides Emissions Index (*NO_x*), Particulate Matter (*PM*) and operational constraints into a single optimal operating recommendation. In addition, an Expert System based maintenance module converts detected abnormalities into transparent diagnostics and predictive, cost-aware interventions, enabling robust and generalizable performance management under harsh, dynamic and data-limited maritime conditions.

2. OVERVIEW OF METHODOLOGY AND RESULTS

This section presents the development and validation of the main computational modules of a novel Decision Support System for large two-stroke marine diesel engines. The framework begins with 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 balancing Specific Fuel Consumption (*SFC*), Nitrogen Oxides Emissions Index (*NO_x*) and Particulate Matter (*PM*).

Subsequently, the decision-making process is established by benchmarking and selecting robust Multi-Criteria Decision-Making (MCDM) methods to translate the Pareto set into actionable rankings. This is further enhanced through an operator-defined fuzzy weighting module, enabling adaptive, preference-driven adjustment of criterion importance under varying operational priorities. Finally, a knowledge-based Expert System is developed for fault diagnosis and predictive maintenance, providing a health-aware supervisory layer.

While each module is independently validated, the primary contribution lies as well in their integration into a unified, closed-loop Decision Support System (DSS). This integration defines the data flow, interfaces and gating mechanisms through which outputs from each module constrain and enable subsequent processes. The focus is therefore on the interconnection logic rather than re-calculation of individual methodologies.

A key methodological challenge is the high computational cost of evaluating a detailed thermodynamic model of a two-stroke marine diesel engine. To address this, a data-driven NN surrogate is developed to emulate the high-fidelity simulation software. Trained on a systematically generated dataset, the surrogate approximates engine responses to control

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

parameters with significantly reduced computational effort. The validated surrogate is then embedded within the NSGA-II algorithm to perform constrained multi-objective optimization, generating Pareto fronts that capture trade-offs between *SFC*, *NO_x* and *PM* under operational and regulatory constraints.

The integrated DSS architecture combines surrogate-based optimization, fuzzy-weighted MCDM and a rule-based Expert System within a unified supervisory framework. A central gating mechanism directs system operation based on real-time engine condition assessment. The workflow begins with classification of the engine state as Normal or Abnormal using sensor data evaluated against predefined thresholds and a knowledge base. This classification determines whether the system proceeds with performance optimization (normal operation) or maintenance-oriented diagnostics and corrective planning (abnormal operation), as illustrated in Figure 1.

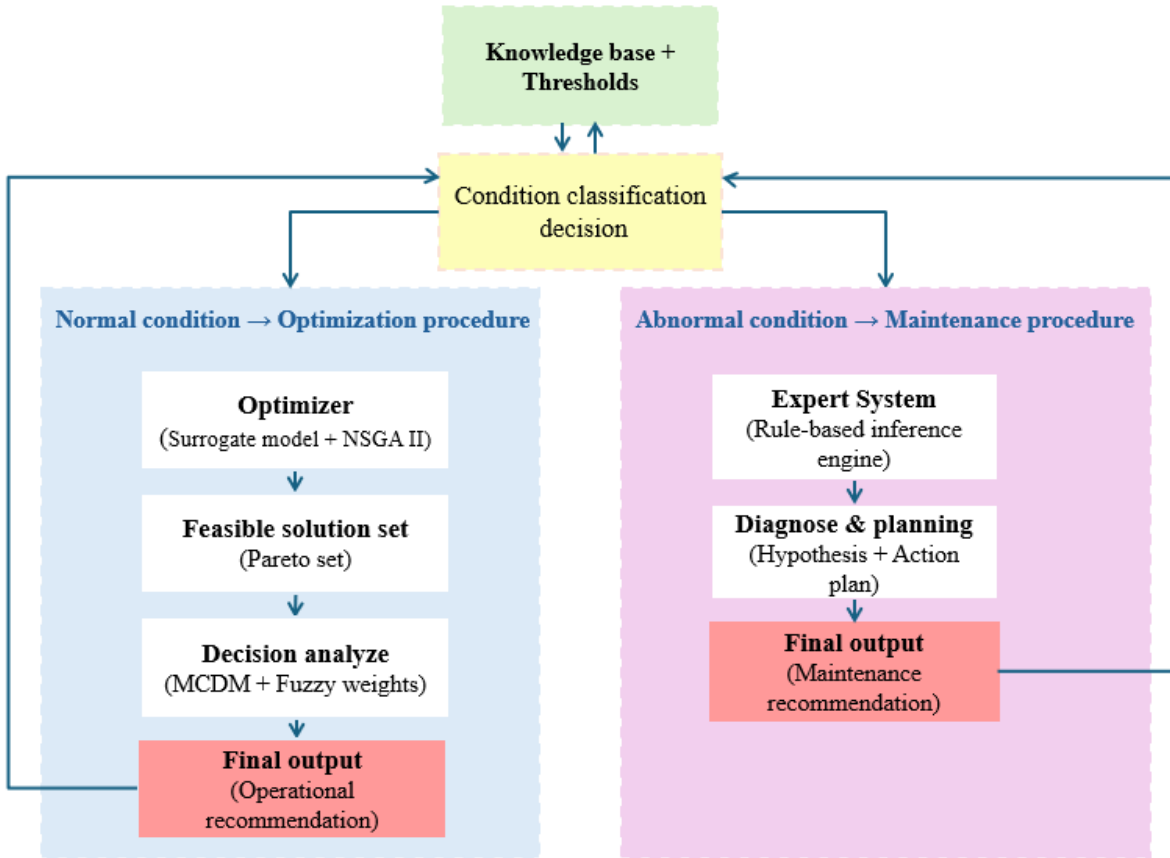


Figure 1. Integrated framework architecture of the elaborated Decision Support System

Figure 2 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 NN 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 process focuses on identifying robust MCDM methods using the Diesel-RK baseline decision matrix.

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

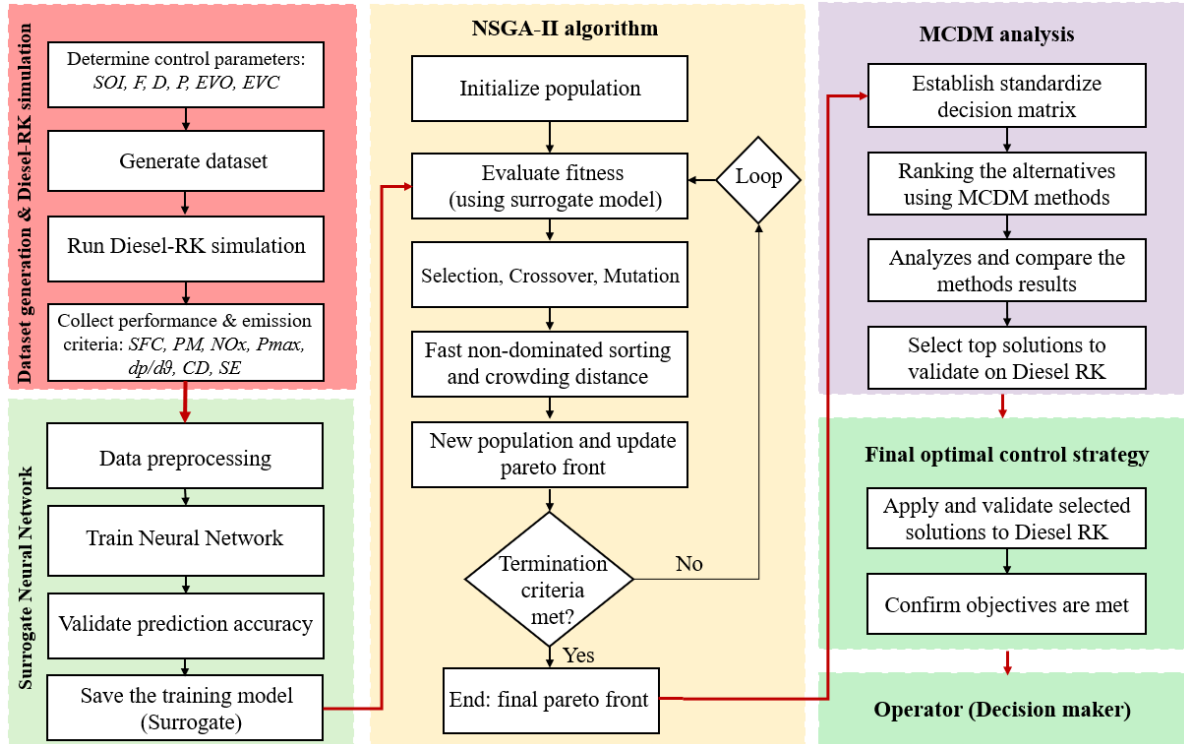


Figure 2. Flowchart of the performance optimization procedure

The six control variables define a practical and expressive design space, capturing key mechanisms governing efficiency and emissions while remaining accessible through modern engine control systems.

The parameter limits for surrogate-based optimization are defined through a synthesis of engineering specifications and regulatory requirements, including:

- manufacturer's operational limits [5-8];
- regulatory emission limits [9];
- prior experimental and simulation studies [10].

Following initial simulations, feasible cases are analyzed to refine parameter ranges, ensuring compliance, combustion stability and reduced decision space for high-resolution optimization within the MCDM stage.

Table 1. summarizes the parameter ranges used in this study. These ranges ensure regulatory compliance, physical realism and stable combustion, while avoiding excessive P_{max} , maintaining effective scavenging and minimizing emissions.

Table 1. Design space for engine simulation and surrogate-based optimization

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

A full-factorial Diesel-RK campaign over the ranges in Table 1. yielded **15,360** simulated operating points ($5 \cdot 8 \cdot 4 \cdot 6 \cdot 4 \cdot 4$). All Cases satisfying physical and regulatory constraints

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

were retained, forming the final dataset for surrogate training. This dataset captures nonlinear interactions between control parameters and engine performance outputs, providing the foundation for subsequent machine learning and optimization stages.

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

The high-fidelity thermodynamic engine model used in this work is developed using Diesel-RK (v4.189), a specialized simulation tool for internal combustion engines [11]. Its selection is based on its capability to resolve coupled in-cylinder thermodynamics, gas exchange processes and emission formation, which are critical for modeling low-speed two-stroke marine diesel engines. Diesel-RK has been extensively validated in academic and engineering applications for predicting diesel engine performance and emissions across various fuels and operating conditions [12-16].

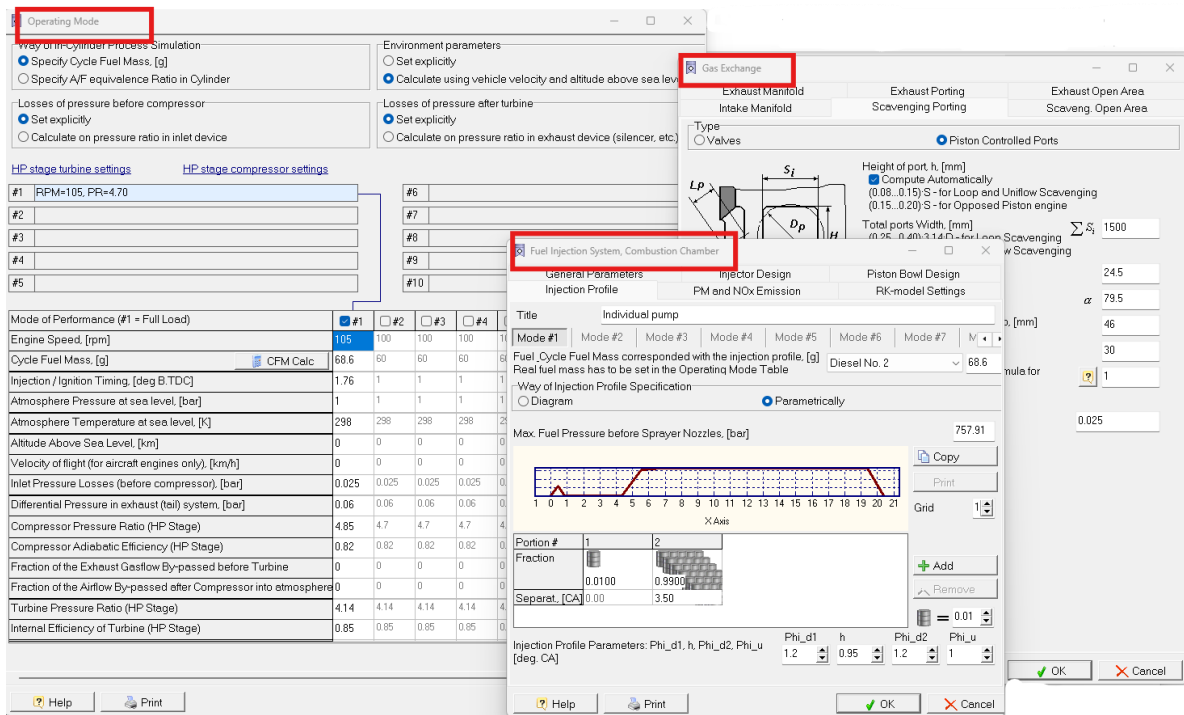


Figure 3. Diesel-RK interfaces for operating modes, gas exchange and fuel system calibration

The simulation setup is calibrated to full-load operation, yielding a piston engine power of 19,003 kW at 105 rpm, with a brake mean effective pressure (P_{mep}) of 20 bar and a specific fuel consumption (SFC) of 0.1819 kg/kWh.

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

The NN surrogate module was trained using a refined dataset of 15,360 feasible cases, split into 70% training (10,639 samples), 10% validation (1,681 samples) and 20% testing (3,040 samples). Prior to training, all six input parameters and seven output metrics were scaled to the range $[-1, 1]$ using StandardScaler to ensure balanced feature contribution and avoid bias from differing magnitudes. The surrogate is a feedforward neural network with 97,863 trainable parameters, enabling accurate mapping between engine control settings and performance

outputs. Figure 4. illustrates the network architecture. The model accepts six control parameters as inputs, processed through two shared fully connected layers (256 and 128 neurons) with Batch Normalization, ReLU activation and Dropout (0.2). From this shared backbone, seven output heads branch out, each comprising a hidden layer (32, 32, 64, 32, 64, 128 and 128 neurons) and a final neuron predicting one performance metrics.

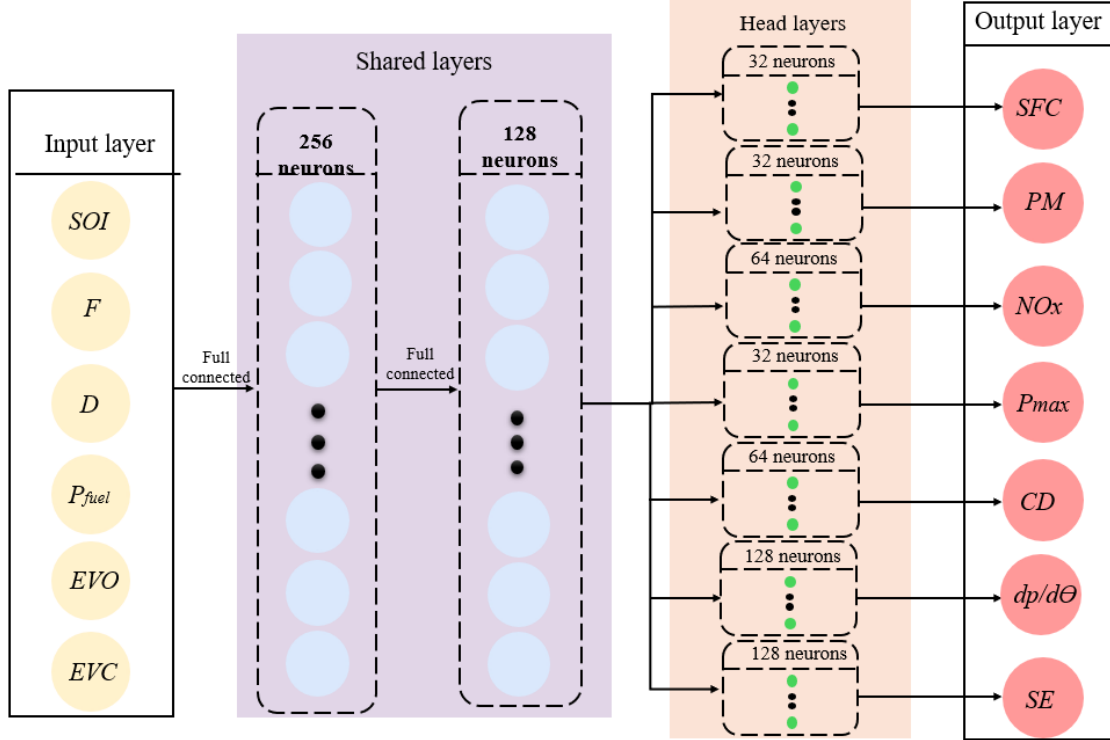


Figure 4. Neural Network architecture for marine engine surrogate model

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.

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

The trained NN surrogate is used as a fast evaluator of engine performance and emissions. The problem is inherently multi-objective: Specific Fuel Consumption (SFC), Particulate Matter (PM) and Nitrogen Oxides (NO_x) must be minimized, although improvements in one objective typically degrade others. Accordingly, a Pareto-based formulation is adopted, constructing a set of non-dominated solutions representing optimal trade-offs rather than a single optimum. The optimization employs the NSGA-II algorithm, which handles conflicting objectives without weighted aggregation. Its elitist non-dominated sorting and crowding-distance mechanisms ensure convergence and diversity of the Pareto front, which is essential for nonlinear engine calibration problems. Coupled with the NN surrogate, this enables efficient exploration of large design spaces under operational and regulatory constraints [17]. The methodological novelty lies in embedding a multi-output NN surrogate within the NSGA-II framework, replacing computationally expensive direct simulations. This enables generation of

a high-resolution, decision-ready Pareto set minimizing SFC , NO_x and PM under realistic constraints, which is subsequently used in the MCDM-based decision stage.

2.4.1. Objective functions

The optimization considers three objectives, which cannot be expressed in closed form due to the coupled nonlinear thermo-fluid processes governing engine behavior [154]:

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

$$F_1 = SFC(SOI, F, D, P_{fuel}, EVO, EVC) \quad [\text{kg/kWh}] \quad (1)$$

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

$$F_2 = PM(SOI, F, D, P_{fuel}, EVO, EVC) \quad [\text{g/kWh}] \quad (2)$$

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

$$F_3 = NO_x(SOI, F, D, P_{fuel}, EVO, EVC) \quad [\text{g/kWh}] \quad (3)$$

2.4.2. Design variables

The design variables to be optimized are the following:

SOI Start of Injection [$^{\circ}\text{CA-BTDC}$];

F Pilot injection fuel mass fraction [%];

D Injection dwell time between pilot and main injections [$^{\circ}\text{CA}$];

P_{fuel} Common-rail fuel pressure [bar];

EVO Exhaust Valve Opening timing [$^{\circ}\text{CA-BBDC}$];

EVC Exhaust Valve Closing timing [$^{\circ}\text{CA-ABDC}$].

2.4.3. Design constraints

The optimization is subject to regulatory and physical constraints, including:

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

(4)

- Particulate Matter (PM) Emissions: $PM \leq 0.15$ [g/kWh].

- Combustion Duration (CD): must remain within 35° to 45° crank angle [$^{\circ}\text{CA}$],

- Peak Cylinder Pressure (P_{max}): $P_{max} \leq 170$ [bar],

(5)

- Maximum Pressure Rise Rate ($dp/d\theta$): $dp/d\theta \leq 4$ [bar/ $^{\circ}\text{CA}$],

- 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:

$$SE = \max\left(1, \frac{NO_x}{NO_{x0}}\right)^{m_1} + \max\left(1, \frac{PM}{PM_0}\right)^{m_2} + \frac{SFC}{SFC_0} \quad (6)$$

where: NO_x, PM, SFC are simulated values, NO_{x0}, PM_0, SFC_0 are reference targets and m_1, m_2 are weighting exponents.

2.4.4. 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 [18, 19].

Candidate solutions are selected using a crowded-comparison operator favoring lower rank and higher diversity. Variation is introduced via simulated binary crossover and polynomial mutation, balancing convergence toward the Pareto front with uniform coverage of the solution space. Figure 5. NSGA-II based optimization algorithm [17].

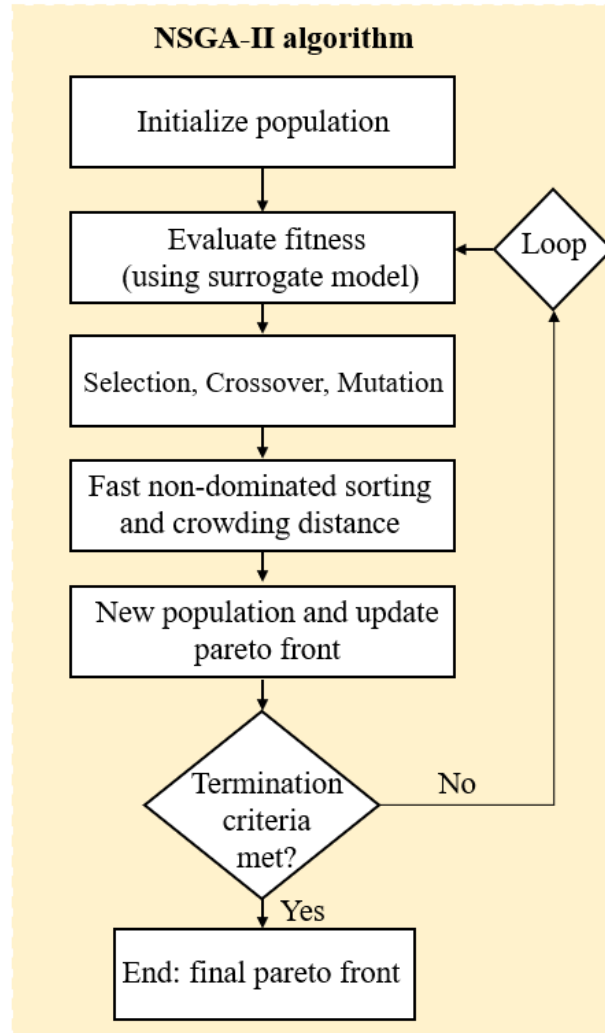


Figure 5. NSGA-II based optimization algorithm [17]

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

Figure 6. shows the evolution of training and validation loss, indicating stable convergence and good generalization without overfitting after 422 epochs with early stopping.

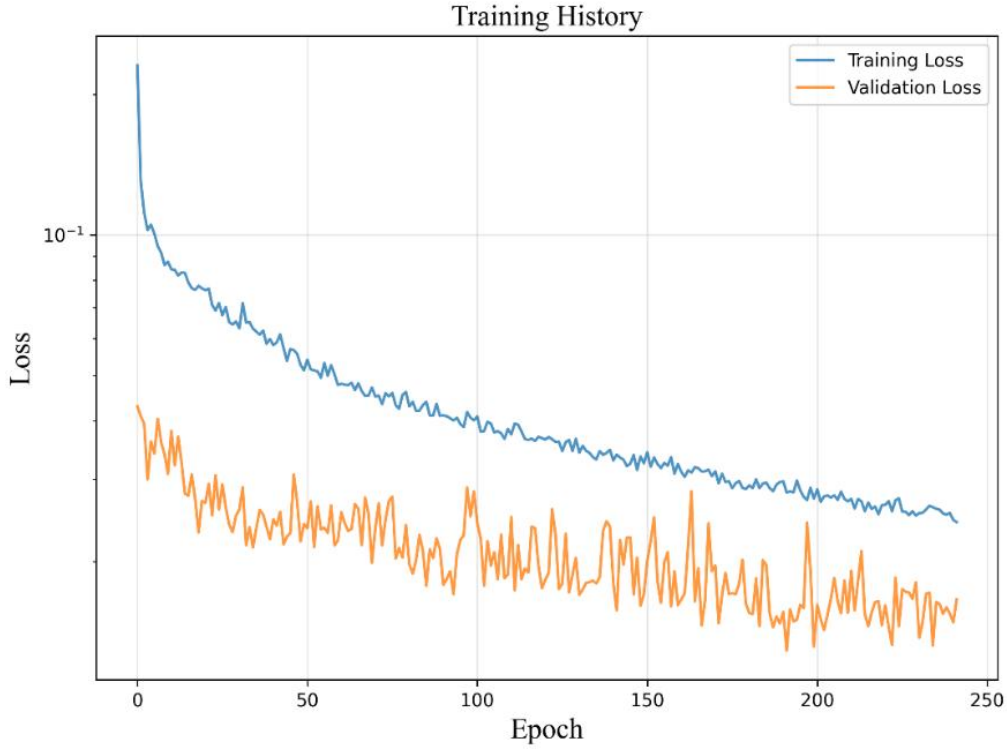


Figure 6. Training and validation loss

On the test dataset, 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 2. 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 2. 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 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.

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.

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

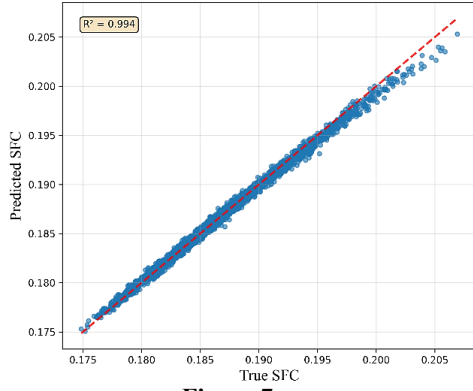


Figure 7. a

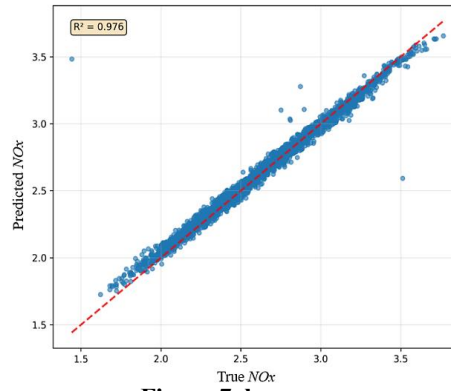


Figure 7. b

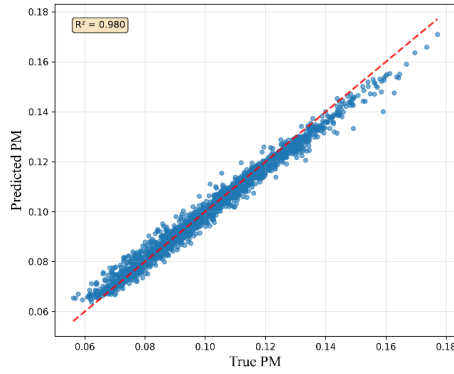


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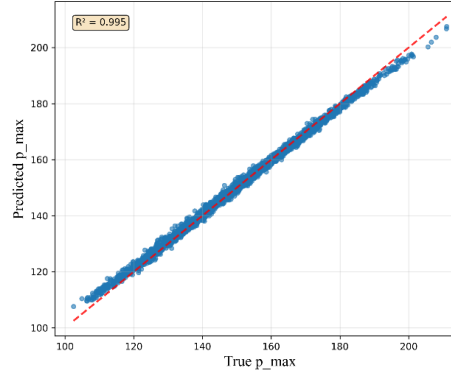


Figure 7. d

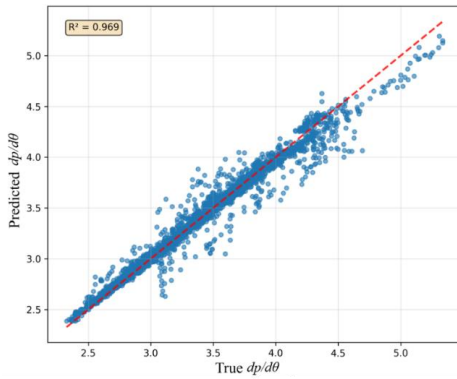


Figure 7. e

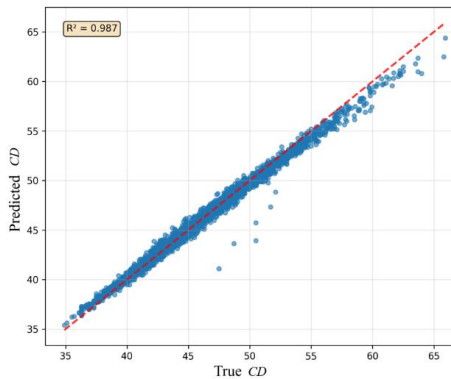


Figure 7. f

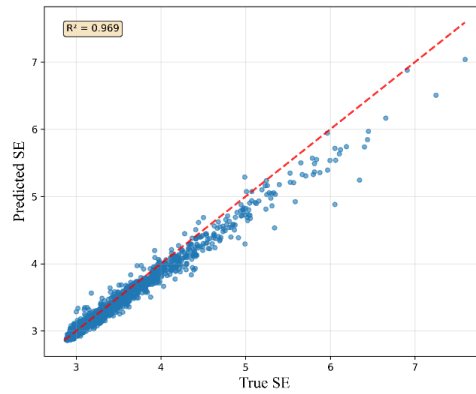


Figure 7. g

Figure 7. Predicted vs. true values for marine engine performance parameters

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

The trained NN surrogate was integrated into the NSGA-II algorithm to minimize SFC , PM and NO_x . The resulting Pareto front (Figure 8) defines the non-dominated trade-off surface among these objectives. A convex front is observed, indicating distinct operating regimes where improvements in fuel efficiency led to increased emissions, reflecting the inherent NO_x – PM trade-off in diesel combustion and confirming that the optimizer identifies meaningful performance boundaries.

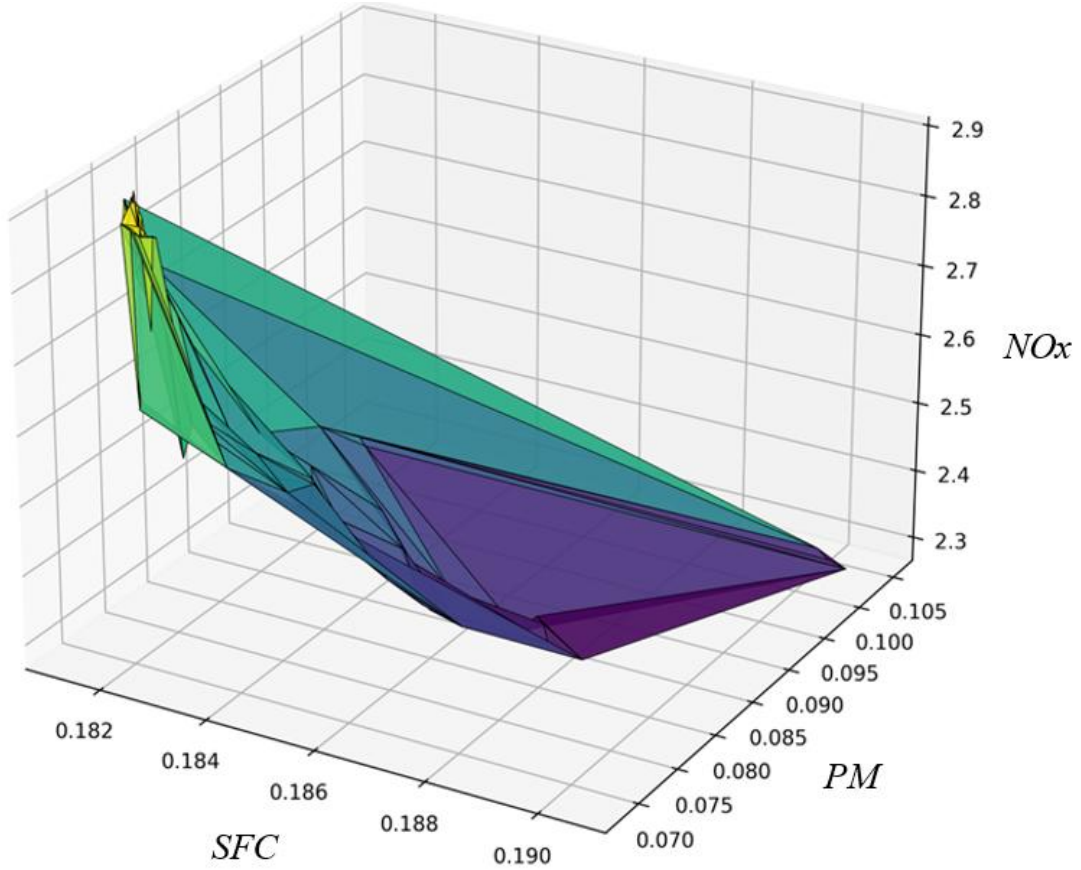


Figure 8. Pareto optimal showing the trade-off surface among SFC , PM and NO_x objectives

The three-dimensional Pareto surface shows each non-dominated solution, with color gradients representing NO_x levels. This visualization highlights regions balancing fuel efficiency and emission reduction, demonstrating that improvements in SFC are generally associated with higher NO_x , consistent with thermodynamic constraints.

To further interpret these relationships, Figure 9. presents pairwise objective plots:

1. A strong negative correlation between SFC and NO_x ,
2. A negative correlation between PM and NO_x ,
3. A mild positive correlation between SFC and PM .

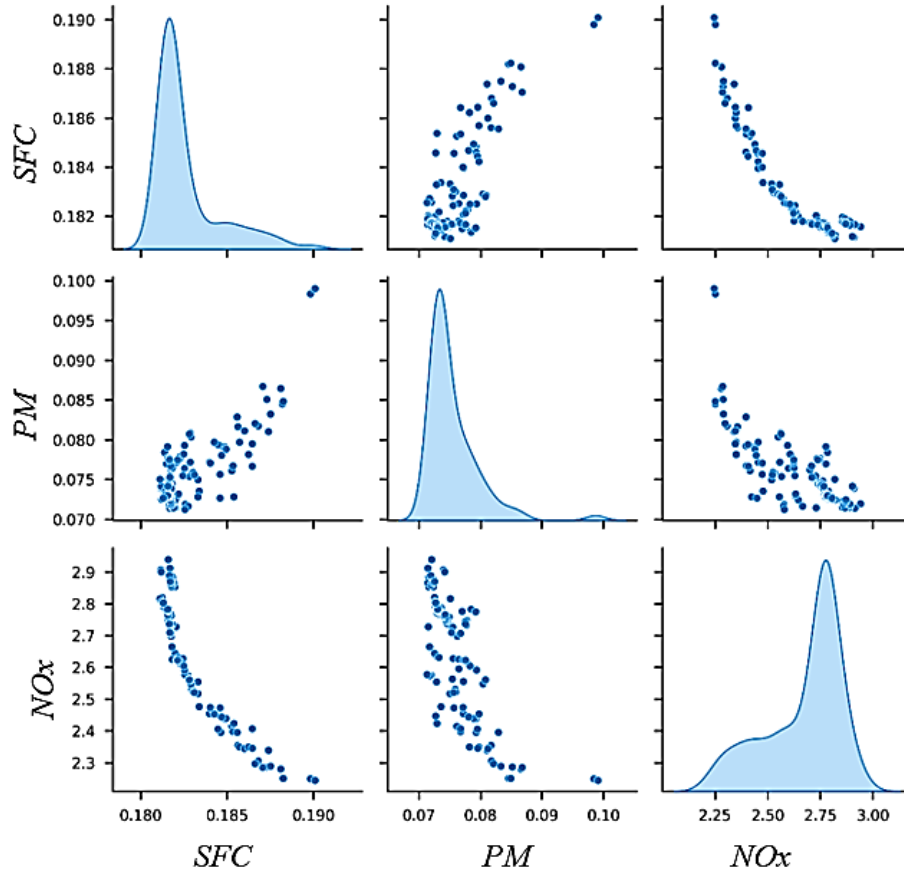


Figure 9. Pairwise relationships among objectives (SFC , PM , NO_x) for Pareto optimal solutions, illustrating correlations and dominance regions

These results characterize the structure of the Pareto set rather than a single operating point. The outcome is a decision-ready library of non-dominated operating strategies spanning the feasible trade-off space under the defined constraints.

2.7. Multi-Criteria Decision-Making implementation

This section identifies suitable MCDM methods for marine applications, focusing on optimal control selection for two-stroke marine diesel engines. Given the inherently conflicting objectives (SFC , NO_x , PM), a structured decision framework is required to ensure robust operational decisions. The study evaluates 14 representative MCDM methods across major methodological classes, focusing on ranking consistency, sensitivity to weighting, normalization, and suitability for onboard or automated marine implementation. Table 3. summarizes the methods grouped by category, providing a basis for comparative analysis of ranking behavior and robustness.

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

Table 3. Categorization of the implemented fourteen MCDM methods

Category	Method	
1. Scoring-Based Methods	SAW	Simple Additive Weighting
	MARCOS	Measurement of Alternatives and Ranking according to Compromise Solution
	WASPAS	Weighted Aggregated Sum Product Assessment
	MAIRCA	Multi-Attribute Ideal-Real Comparative Analysis
	MARA	Magnitude of the Area for the Ranking of Alternatives
	ORESTE	(Organisation Rangement Et SynThèse de données relationnelles)
2. Distance-Based Methods	TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
	MABAC	Multi-Attributive Border Approximation Area Comparison
	OCRA	Operational Competitiveness Rating Analysis
	VIKOR	Vlsekriterijumska Optimizacija Kompromisno Resenje
3. Pairwise Comparison Methods	PIV	Proximity Indexed Value
	WISP	Integrated Simple Weighted Sum Product
4. Outranking Method	PROMETHEE II	Preference Ranking Organization METHod for Enrichment of Evaluations
5. 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.

MCDM methods provide a structured framework for aggregating multiple conflicting criteria without enforcing a single “true” solution. However, different methods may yield different rankings due to differences in normalization, distance metrics and aggregation logic. Therefore, method selection must reflect the structure of the decision environment and trade-off characteristics

To analyze the ranking differences across the 14 methods, the Borda Count method was applied to generate a consensus ranking [20]. This approach identifies alternatives consistently favored across methods, improving robustness and reducing bias.

The consistency matrix (Figure 10) shows clear variation in agreement. Green-coded alternatives indicate strong convergence across methods and represent robust candidates for implementation, while red-coded cases indicate instability and sensitivity to the MCDM formulation. Overall, this ensemble approach mitigates reliance on any single MCDM method and improves decision robustness in complex engine optimization contexts.

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



Figure 10. Ranking of the top 15 alternative configurations (by Borda Count method)

2.7.1. Results of the stability analysis of MCDM methods

A stability analysis was performed to evaluate ranking consistency across all 14 methods. For each configuration, two indicators were computed:

1. Standard deviation (σ): measures ranking dispersion across methods
2. Range: difference between best and worst ranks

Lower values indicate higher robustness and method agreement.

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

Configuration 2203 is the most stable ($\sigma = 2.87$) and achieved full consensus, consistently ranking highly across WASPAS, WISP, PIV and TMF, confirming robustness against method bias.

From the comparative analysis, the recommended MCDM methods for marine diesel engine applications shows:

1. Configurations 2203 and 2200 show highest stability and consistent top rankings.
2. Lowest *SE* does not guarantee robustness (e.g. 2199).

3. WISP, PIV and TMF demonstrate strongest alignment with consensus rankings and stability.

2.7.2. Pareto optimal solutions validation using MCDM methods

To ensure robustness of surrogate-based optimization, the Pareto set generated by NSGA-II (163 solutions) is evaluated using selected MCDM methods (PIV, WISP, TMF). This step verifies consistency between surrogate-driven optimization and decision-making. Table 4. shows identical top-5 rankings across all three methods, indicating strong consensus and a well-structured Pareto space.

Table 4. Rankings of the top 5 Pareto optimal solutions using PIV, WISP and TMF methods

Solutions	<i>SOI</i>	<i>F</i>	<i>D</i>	<i>P_{fuel}</i>	<i>EVO</i>	<i>EVC</i>	<i>SFC</i>	<i>PM</i>	<i>NO_x</i>
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

Solution **S1** is consistently ranked first across all methods, indicating strong robustness and minimal method bias. It achieves a balanced trade-off between *SFC*, *NO_x* and *PM* under Tier III constraints, while **S2–S5** represent alternative operating compromises. S1 was re-evaluated using Diesel-RK (Table 5), confirming close agreement with surrogate predictions.

Table 5. 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

These differences are small and do not affect decision ranking, confirming physical consistency of the surrogate.

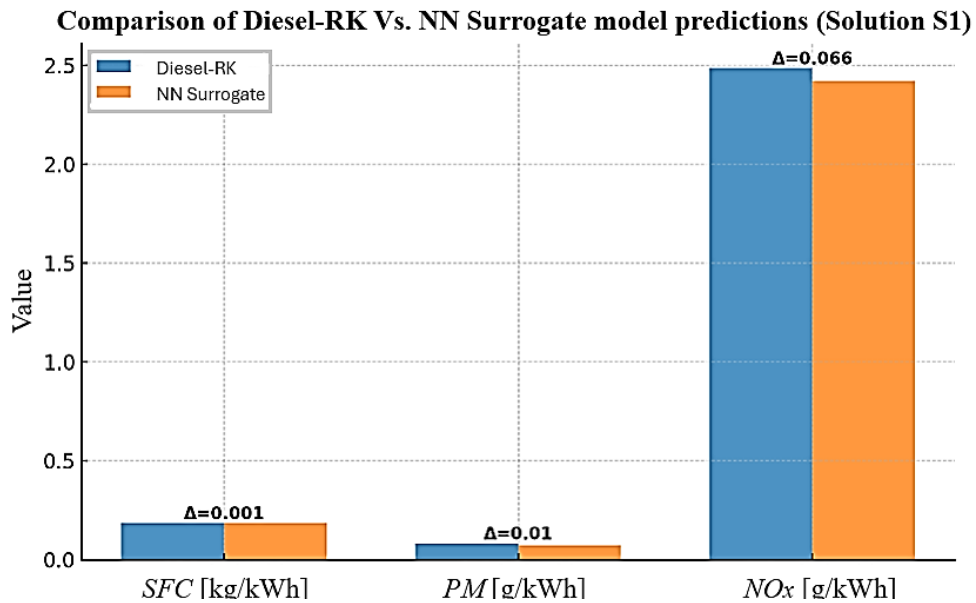


Figure 11. Differences between Diesel-RK vs. NN surrogate predictions

The surrogate closely reproduces Diesel-RK outputs, validating its suitability for optimization and decision-making. 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 optimal configuration. It satisfies IMO Tier III constraints and provides the best overall trade-off between fuel efficiency and emissions.

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

The core of the elaborated methodology is a Mamdani-type Fuzzy Logic Module (FLM) [21-23]. The FLM is designed to translate imprecise operator preferences into crisp, normalized weights for MCDM. Its main purpose is to bridge qualitative operator judgment and quantitative decision inputs required by MCDM methods. The full workflow is shown in Figure 12.

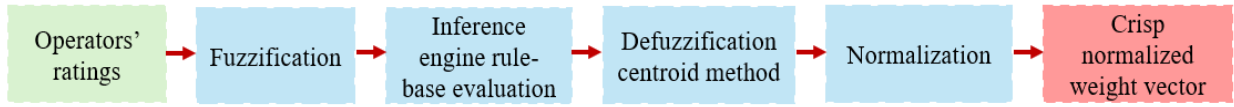


Figure 12. Flowchart of the Fuzzy Logic Module for MCDM weighting

The fuzzy logic module processes operator preferences, applies rule-based inference and outputs normalized weights used by the selected MCDM method to rank 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_{NO_x}),
3. PM importance (x_{PM}).

The corresponding output variables produced:

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

The FLM was validated using four representative operational scenarios capturing realistic marine operating priorities. Inputs are expressed on a [0–10] scale and mapped to normalized weights satisfying $\sum w_i = 1$, used in MCDM ranking. The scenarios are:

1. Fuel-Economy Priority: High SFC importance (7.0), moderate NO_x (5.0), low PM (3.0), representing open-sea operation.
2. Strict Environmental Compliance: Low SFC (2.5), high NO_x (8.5) and PM (6.0), representing ECA operation.
3. Balanced Performance: Equal importance for all criteria (5.0, 5.0, 5.0).
4. High Competition (Trade-off): High SFC and NO_x (9.0, 9.0), low PM (2.0), representing conflicting commercial priorities.

These scenarios are conceptual operator archetypes designed to span typical operational extremes rather than empirically derived distributions.

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

Table 6. Operator priority inputs and corresponding normalized fuzzy-derived weights

Scenarios	Input Importance (x_{SFC}, x_{NOx}, x_{PM})	Output Weights (w_{SFC}, w_{NOx}, 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)

The results confirm that the FLM consistently converts qualitative preferences into stable and normalized weight vectors:

1. **Scenario 1:** SFC becomes dominant (≈ 0.46), correctly prioritizing fuel economy.
2. **Scenario 2:** Emission criteria dominate ($>84\%$ combined weight), aligning with ECA compliance.
3. **Scenario 3:** Equal inputs yield uniform weights, forming a neutral baseline.
4. **Scenario 4:** Despite identical high importance for SFC and NOx (9.0), the module prevents dominance and balances both at 0.422 each, demonstrating controlled trade-off mediation.

This behavior highlights the advantage of fuzzy inference over linear normalization, particularly under conflicting high-priority inputs. The engine configuration remains unchanged; only the preference structure varies. To validate internal consistency, the response surface of the FLM was analyzed. Figure 13. shows *SFC* weight as a function of *SFC* and *NO_x* importance, with *PM* fixed at 5.0.

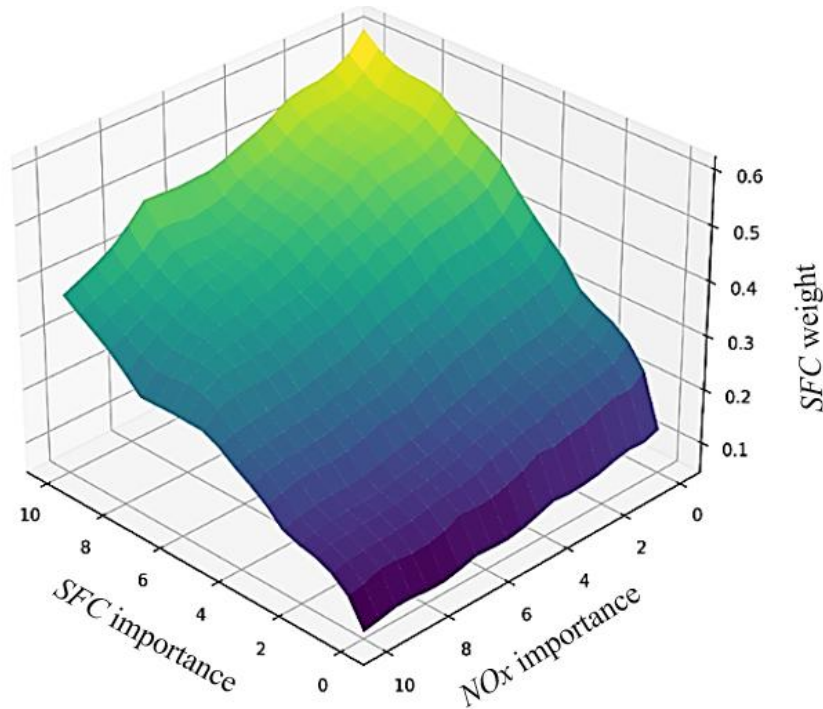


Figure 13. Fuzzy logic response: *SFC* weight as a function of *SFC* and *NO_x* importance

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

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

1. *SFC* weight increases with *SFC* importance, reaching ~0.55–0.60 when *SFC* is high and *NO_x* is low, reflecting correct prioritization of fuel economy.
2. Under simultaneous high *SFC* and *NO_x* importance, the system suppresses extreme weighting, stabilizing *SFC* weight around 0.35–0.45. This demonstrates the embedded “competitive mediation” rule.
3. The response surface is smooth and continuous, indicating stable inference behavior without abrupt transitions.

Overall, the FLM produces consistent and physically interpretable weights while preserving trade-off awareness between conflicting objectives.

The final validation evaluates whether fuzzy-derived weights meaningfully influence MCDM ranking outcomes. Using the TMF method, Pareto alternatives were ranked under each scenario.

Table 7. 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 7. 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.

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

Marine diesel engines are tightly coupled systems where a fault in one subsystem propagates and induces secondary symptoms. Effective diagnosis therefore requires a structured functional decomposition into five subsystems, each associated with specific failure modes, measurable indicators and corrective actions:

1. Fuel subsystem (feeding + injection): faults in supply pressure, filtration, viscosity or injection directly affect combustion. Key indicators include combustion pressure, injection pressure and fuel supply pressure.
2. Lubrication subsystem: critical for wear prevention and safety. Oil pump pressure, oil pressure, oil temperature and oil level reflect supply faults, degradation, contamination and leakage conditions.
3. Cooling subsystem: diagnosis is based on heat rejection behavior. Coolant pressure and jacket water outlet temperature indicate pump faults, restrictions or coolant loss.
4. Air supply subsystem (turbocharging + charge-air cooling): failures such as filter blockage or compressor/cooler fouling reduce air mass flow and excess air ratio. Key indicators are charge-air pressure and post-cooler temperature.
5. Exhaust subsystem: provides aggregated combustion health signals. Exhaust gas temperature (EGT) per cylinder and exhaust color are primary diagnostic variables.

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

Increasing the number of diagnostic parameters does not necessarily improve diagnosability and may overload operators. Therefore, parameter selection is guided by three criteria:

1. High information content: sensitivity to multiple failure modes
2. Practical availability: commonly measured in marine monitoring systems
3. Actionability: directly linked to maintenance actions

The diagnostic framework is based on a carefully selected parameter set mapped to the five subsystems. Selection was conducted through a literature-based evidence approach combining expert knowledge, statistical analyses, experimental/field validation and simulation studies. No new experiments were performed; instead, existing validated evidence was consolidated into a shipboard-relevant diagnostic structure. Each parameter was included based on at least one of the following evidence types:

1. Failure-mode relevance reported in reliability and diagnostic studies .
2. Expert practice with technical and industrial guidelines.
3. Statistical studies demonstrating correlation with abnormal states.
4. Experimental or simulation-based validation of fault signatures.

The methods in Table 8. refer to external evidence, not new experiments conducted in this dissertation.

Table 8. Diagnostic parameter set and selection evidence of marine diesel engine subsystem

	Parameters	Method
Fuel Subsystem	Pressure after feeding pump	Experts' opinion. Statistical data analyses. Experimental validation. Marine diesel engine failure simulator.
	Injection pressure	
	Combustion pressure	
Lubrication Subsystem	Oil pump pressure	Experimental Validation. Marine diesel engine failure simulator.
	Oil temperature	
	Oil pressure	
	Oil level	
	Cylinder oil parameters	
	System oil parameters	
Cooling Subsystem	Coolant pressure	Experimental Validation. Marine diesel engine failure simulator.
	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
	Temperature after cooler	
	Turbocharger condition	
Exhaust Subsystem	Exhaust gas temperature	Experts' opinion. Statistical data analyses. Thermal failure simulation of diesel engine.
	Exhaust gas color	
	Exhaust valve condition	
	Scavenge box condition	

This parameter set is intentionally aligned with shipboard operation, prioritizing measurable, interpretable and action-oriented variables.

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.

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

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 14. provides an overview of the KBES workflow.

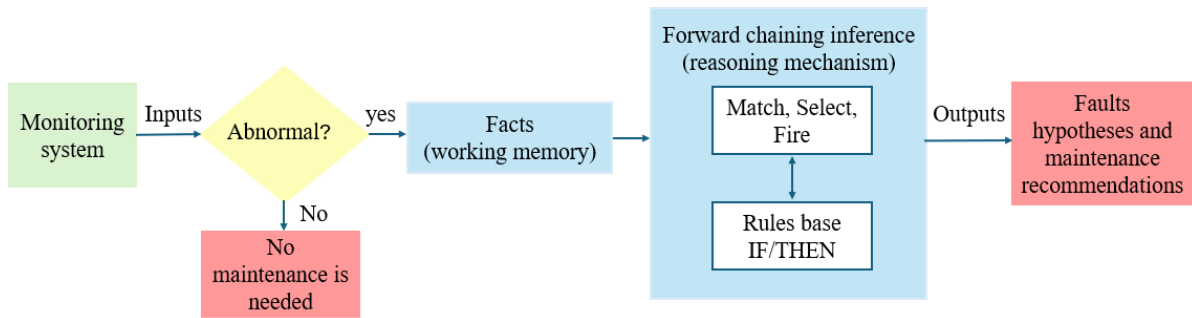


Figure 14. Knowledge Based Expert System flow

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

This example demonstrates the Normal-condition pathway of the DSS, from surrogate-based prediction and NSGA-II optimization to fuzzy-weighted MCDM ranking. The case uses the S60-class two-stroke engine model to illustrate how a multi-objective Pareto set is converted into a ranked and implementable operating strategy. When the engine is classified as Normal, the optimization module is activated through three steps (Figure 15): model training, optimization execution, and result ranking.

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

1. Paths Data

Training Data: all_results.csv
Output Folder: C:\Users\hgh\OneDrive\Desktop\newmain\main\trained_model

1. Column Mapping

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

Training Hyperparameters

Epochs: 800
LR (Shared): 0.00100
Patience: 50
Seed: 42

Batch Size: 32
LR (Head): 0.00050
Dropout: 0.20

0. Paths Config

Model Directory: C:\Users\hgh\OneDrive\Desktop\newmain\main\trained_model
Results Directory: C:\Users\hgh\OneDrive\Desktop\newmain\main\results

1. Select Optimization Objectives

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

2. Set Parameter Bounds

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

Figure 15. The elaborated DSS system: optimization procedure

Figure 16. shows the ranking stage, where operator preferences (0–10 scale) are transformed into fuzzy weights and used by MCDM methods to rank solutions. The output is a Top-K list and a single recommended operating point.

1. Load Pareto Solutions

Auto-loaded: pareto_solutions_20260114_201218.csv

2. Set Criterion Importance (0-10)

SFC Importance: 4.5
PM Importance: 6.1
NOx Importance: 5.5

3. Computed Weights

Computed MCDM Weights:
SFC: 0.2669
PM: 0.3800
NOx: 0.3531

4. Ranked Solutions

Index	SOI	Fraction	Delay	Pressure	EVO	EVC	SFC	PM	NOx	Similarity
1	2.521993,0...	2.5220	0.0119	3.2331	753.1729	67.5178	0.1825	0.0685	2.6648	0.4226
2	2.904927,0...	2.9049	0.0109	2.7844	724.6045	64.3978	0.1823	0.0696	2.6391	0.4213
3	1.783008,0...	1.7830	0.0120	2.8070	742.9765	66.2175	0.1838	0.0704	2.5788	0.4210
4	3.320175,0...	3.3202	0.0113	2.6405	756.1253	63.3249	0.1827	0.0721	2.5569	0.4190
5	1.783008,0...	1.7830	0.0113	2.9583	742.9765	66.2175	0.1845	0.0726	2.5406	0.4175

Rank Solutions

Export Results to CSV

Ranked 146 solutions by MCDM

Figure 16. The elaborated DSS system: ranking interface (Rank Results)

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

This example illustrates the Abnormal-condition pathway using the same S60-class engine. The objective is to convert monitoring signals into fault hypotheses and maintenance actions while preventing unsafe operation and bypassing performance optimization.

The diagnostic system follows the Expert System structure and subsystem-based parameterization (fuel, lubrication, cooling, air, exhaust).

Figure 17 provides the maintenance dashboard, while defines threshold configuration for normal operation limits. Abnormality is demonstrated using the Air Supply subsystem:

- Scavenge pressure below threshold
- Charge-air temperature above threshold

These deviations trigger an Abnormal classification.

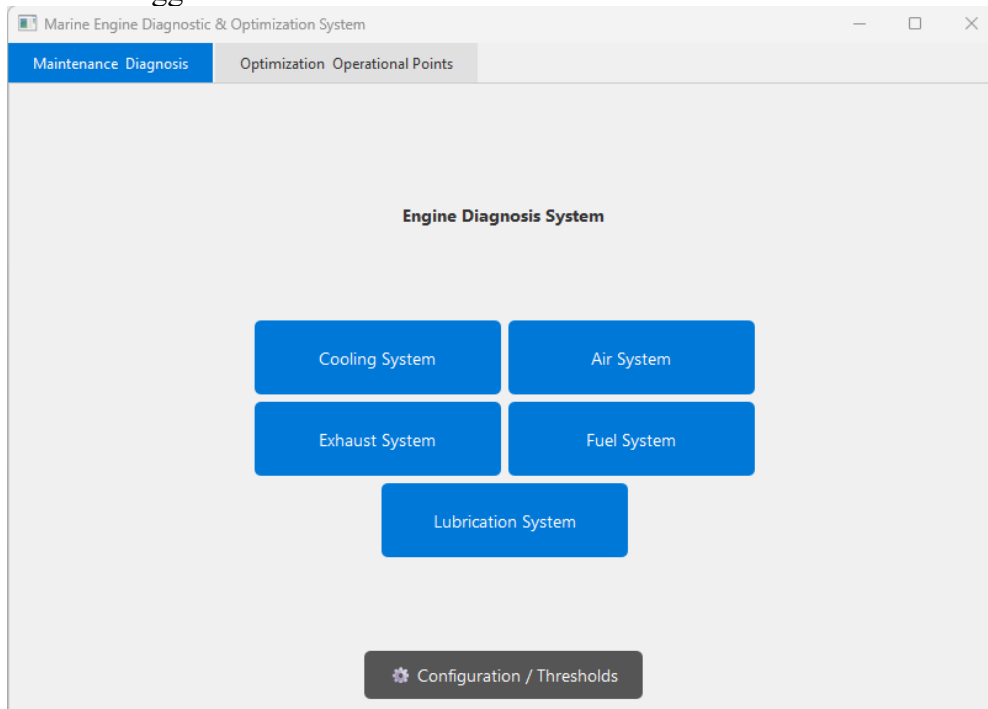


Figure 17. The elaborated DSS system: maintenance diagnosis interface

Once triggered, the inference engine processes input data based on the air-path diagnostic parameter set. The system evaluates conditions using the rule base and generates:

- Fault hypothesis
- Maintenance actions

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

System Configuration (Thresholds)

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

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 18. The elaborated DSS system: Air subsystem diagnosis

2. NEW SCIENTIFIC RESULTS – THESES

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.

3. LIST OF PUBLICATIONS RELATED TO THE TOPIC OF THE RESEARCH FIELD

- [1] 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)
- [2] 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)
- [3] 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)
- [4] 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.
- [5] 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)
- [6] 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. 32-337, doi: 10.22306/al.v11i2.516 (Q3, Scopus, IF: 1.35)
- [7] 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)
- [8] 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.
- [9] 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)
- [10] 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)
- [11] 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)

3. LITERATURE CITED IN THE THESES BOOKLET

- [1]. IMARC Group Reports, Marine Propulsion Engine Market Size, Share, Trends and Forecast by Engine Type, Power Source, Power Range, Vessel Type and Region, 2025-2033. Report ID: SR112025A3261, <https://www.imarcgroup.com/marine-propulsion-engine-market/> (Accessed on 23rd October 2025).
- [2]. Marine Engine Market Size, Share & Industry Trends. <https://www.marketsandmarkets.com/Market-Reports/marine-engine-market-261640121.html> (Accessed on 23rd October 2025).
- [3]. Addressing Marine Diesel Engine Corrosion & Rust, Marine Diesel Specialists. 2024. <https://marinedieselspecialists.com/engine-corrosion-and-rust.html> (Accessed on 23rd October 2025).
- [4]. Kalafatelis, A. S.; Nomikos, N.; Giannopoulos, A.; Alexandridis, G.; Karditsa, A.; Trakadas, P. Towards predictive maintenance in the maritime industry: A component-based overview. *Journal of Marine Science and Engineering*. Vol. 13, No. 3, p. 1-21, 2025. [doi:10.3390/jmse13030425](https://doi.org/10.3390/jmse13030425).
- [5]. Zhao, H., Ed. *Advanced Direct Injection Combustion Engine Technologies and Development, Volume 2: Diesel Engines*; Woodhead Publishing: Cambridge, UK, 2009. ISBN 9781845697457.
- [6]. Faturachman, D.; Mustafa, S.; Octaviany, F.; Novita, T.D. Failure mode and effects analysis of diesel engine for ship navigation system improvement. *The International Conference on Business Innovation, Entrepreneurship and Engineering*, 6-8th December 2013, Penang, Malaysia.
- [7]. MAN Energy Solutions, PrimeServ Assist, <https://www.man-es.com/services/strategic-expertise/digitalization/primeserv-assist/2> (Accessed on 24th October 2025).
- [8]. Kuleshov, A.S. Multi-zone DI diesel spray combustion model for thermodynamic simulation of engine with PCCI and high EGR level. *SAE International Journal of Engines*, Vol. 2, No. 1, p. 1811-1834, 2009. [doi:10.4271/2009-01-1956](https://doi.org/10.4271/2009-01-1956).
- [9]. International Maritime Organization (IMO), 2021 Revised MARPOL Annex VI, Resolution MEPC.328(76), (adopted June 17, 2021, entered into force November 1, 2022).
- [10]. Seol, J. H., Pham, V.C., Lee, W. J. Effects of the multiple injection strategy on combustion and emission characteristics of a two-stroke marine engine. *Energies*, Vol. 4, No. 20, p. 1-16, 2021. [doi:10.3390/en14206821](https://doi.org/10.3390/en14206821).
- [11]. Diesel-RK is an engine simulation tool <https://diesel-rk.com/Eng/> (Accessed on December 6th, 2025).
- [12]. Noor, C.W.M. and HAFIZUDDIN, M. Analysing the impact of various diesel types on the performance and emissions of marine diesel engines using Diesel-RK software. *University Malaysia Terengganu Journal of Undergraduate Research*, Vol. 7, No. 1, p. 16-26, 2025.
- [13]. Shah, S. and Patel, N. Optimizing diesel engine combustion performance and emissions with Diesel-RK software simulation. *Journal of Mines, Metals & Fuels*, Vol. 73, No. 7, p. 2221-2231, 2025.
- [14]. Al Dawody, M.F. and Bhatti, S.K. Experimental and computational investigations for combustion, performance and emission parameters of a diesel engine fueled with soybean biodiesel-diesel blends. *Energy Procedia*, Vol. 52, No. 1, p. 421-430, 2014. [doi:10.1016/j.egypro.2014.07.094](https://doi.org/10.1016/j.egypro.2014.07.094).
- [15]. Siddique, S.A., Vijaya, K. and Reddy, K. Theoretical investigation on combustion chamber geometry of DI diesel engine to improve the performance by using diesel-RK.

- International Journal of Innovative Technology and Exploring Engineering, Vol. 4, No. 10, p. 2278-3075, 2015.
- [16]. Datta, A. and Mandal, B.K. Impact of alcohol addition to diesel on the performance, combustion and emissions of a compression ignition engine. Applied Thermal Engineering, Vol. 98, No. 1, p. 670-682. 2016. [doi:10.1016/j.applthermaleng.2015.12.047](https://doi.org/10.1016/j.applthermaleng.2015.12.047).
- [17]. Deb, K., Pratap, A., Agarwal, S., Meyarivan, T. A fast and elitist multi-objective genetic algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation, Vol. 6, No. 2, p. 182-197, 2002. [doi:10.1109/4235.996017](https://doi.org/10.1109/4235.996017).
- [18]. Niu, X.; Wang, H.; Hu, S.; Yang, C.; Wang, Y. Multi-objective online optimization of a marine diesel engine using NSGA-II coupled with enhancing trained support vector machine. Applied Thermal Engineering, Vol. 137, No. 1, p. 218-227, 2018. [doi:10.1016/j.applthermaleng.2018.03.080](https://doi.org/10.1016/j.applthermaleng.2018.03.080).
- [19]. Qiao, D.; Mei, H.; Qin, J.; Tang, G.; Lu, L.; Ou, J. Multi-objective optimization for hydrodynamic performance of a semi-submersible FOWT platform based on multi-fidelity surrogate models and NSGA-II algorithms. China Ocean Engineering, Vol. 38, No. 6, p. 932-942, 2024. [doi:10.1007/s13344-024-0075-1](https://doi.org/10.1007/s13344-024-0075-1).
- [20]. Saari, D. G. Selecting a voting method: the case for the Borda count. Constitutional Political Economy, Vol. 34, No. 3, p. 357-366, 2023. [doi:10.1007/s10602-022-09380-y](https://doi.org/10.1007/s10602-022-09380-y).
- [21]. Mohd Adnan, M. R. H.; Sarkheyli, A.; Mohd Zain, A.; Haron, H. Fuzzy logic for modeling machining process: a review. Artificial Intelligence Review, Vol. 43, No. 3, p. 345-379, 2015. [doi:10.1007/s10462-012-9381-8](https://doi.org/10.1007/s10462-012-9381-8).
- [22]. Tang, H. H.; Ahmad, N. S. Fuzzy logic approach for controlling uncertain and nonlinear systems: a comprehensive review of applications and advances. Systems Science & Control Engineering, Vol. 12, No. 1, p. 1-34, 2024. [doi:10.1080/21642583.2024.2394429](https://doi.org/10.1080/21642583.2024.2394429).
- [23]. Bova, S.; Codara, P.; Maccari, D.; Marra, V. A logical analysis of Mamdani-type fuzzy inference, I: theoretical bases. IEEE International Conference on Fuzzy Systems, p. 1-8, 18-23 July 2010. [doi:10.1109/FUZZY.2010.5584830](https://doi.org/10.1109/FUZZY.2010.5584830).