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Diagnostic analysis of exhaust gas with a rapidly changing temperature from a marine diesel engine: interaction analysis

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This article presents the next stage of research aimed at identifying the impact of input parameters, defined as changes in the design parameters of a marine diesel engine, on selected output parameters treated as diagnostic indicators derived from the rapidly varying exhaust gas temperature signal. In relation to earlier analyses of the individual and simultaneous impact of design parameters and engine load, the novelty of this study lies in assessing and quantifying the effects of interaction between these input factors using the interaction coefficient of significance. Three design parameters were analyzed: the active section area of the intake air duct, Ain; the injector opening pressure, p_{inj}; and the compression ratio, ε. Based on the rapidly varying exhaust gas temperature, three diagnostic indicators were defined for a single operating cycle of a four-stroke engine: h_{av}, ΔT_{av} and $(\Delta T/\Delta\tau\uparrow)_{av}$. The statistical analysis revealed that the strongest coupled interaction occurs between engine load P and intake air duct area Ain for the average specific enthalpy h_{av}, reaching a positive interaction coefficient of $\Delta F_i = +39.40$. In contrast, dynamic indicators (ΔT_{av} and $(\Delta T/\Delta\tau\uparrow)_{av}$) exhibited additive behavior for intake area changes ($\Delta F_i = -1.124$). However, significant positive interactions with injector pressure p_{inj} ($\Delta F_i = +4.12$ for ΔT_{av}) and compression ratio ε ($\Delta F_i = +2.28$ for both dynamic metrics). The results enabled the formulation of conclusions and a criterion for selecting an appropriate diagnostic indicator, depending on the functional system under analysis in the diesel engine.

Key words: *marine diesel engine, fossil fuels, exhaust gas temperature, diagnostic information, F-statistic of Fisher-Snedecor distribution*

1. Introduction

Reliable identification of fault-related changes in marine diesel engines requires quantitative evaluation of how structural parameters affect diagnostic signals. In recent years, researchers have extensively investigated exhaust gas temperature analysis as a non-invasive tool for assessing the thermal and operational condition of internal combustion engines. For instance, Zhou et al. [22] demonstrated that exhaust gas temperature profiles exhibit strong nonlinear behavior across varying engine operating regimes, underscoring the need for advanced dynamic signal processing. Similarly, Li et al. [11] used thermodynamic simulation models coupled with data-driven algorithms to evaluate the effects of localized defects in combustion chamber components on downstream thermal parameters. While these studies highlight the high diagnostic value of exhaust gas temperature [23], most available approaches focus either on steady-state thermal parameters or isolated fault conditions, often neglecting the complex cross-factor interactions that occur in real-world marine operation.

In earlier work, this problem was addressed using a single-factor statistical analysis of diagnostic indicators derived from rapidly varying exhaust-gas temperature signals [18]. This stage enabled the identification of statistically insignificant variables and the reduction of the dataset under analysis. It was found that a decrease in injector opening pressure p_{inj} did not produce a statistically significant effect on the average specific enthalpy of exhaust gas h_{av} under selected operating conditions.

Subsequent studies extended the analytical framework to a two-factor approach, allowing simultaneous evaluation of structural parameters under varying engine load conditions [17]. This approach made it possible to determine both the combined influence of input variables and the relative importance of each parameter.

The present study focuses on the analysis of interaction effects between input parameters. Interaction occurs when the response of a diagnostic indicator to one input parameter depends on the level of another parameter. Identification of such relationships is essential in complex thermodynamic systems, where multiple factors simultaneously influence the observed output. The applied statistical tools allow detection and quantitative evaluation of interaction effects [1].

The analysis was based on the same experimental signals obtained during earlier investigations carried out at the same laboratory test stand. Diagnostic indicators were determined for a single operating cycle of a four-stroke marine engine and included: the average specific enthalpy h_{av}, the average interpeak value ΔT_{av}, and the average rate of temperature change $(\Delta T/\Delta\tau\uparrow)_{av}$ of the rapidly varying exhaust gas temperature signal.

Interaction between variables represents a non-additive relationship in which the level of one variable influences the effect of another input parameter on a dependent variable. In such cases, independent analysis of individual variables is insufficient to describe system behavior fully. The combined influence of interacting parameters differs from the sum of their individual effects, a characteristic of complex processes in internal combustion engines.

The primary novelty and main contribution of this work lie in the transition from decoupled single- and dual-factor evaluations to a comprehensive quantification of the significance of cross-factor interactions using the interaction coefficient ΔF_i. By isolating pure structural fault responses from load-induced signal modulation, this study provides a novel, practical selection criterion for dynamic diagnostic indicators, establishing a robust framework for real-time diagnostics and condition-based maintenance in marine energy systems.

2. The importance of rapidly varying exhaust gas temperature in the parametric diagnostics

Parametric diagnostics of marine engines play a key role in ensuring reliable and safe operation, especially under long-term operation and variable loads. It enables early detection of malfunctions in the engine's functional systems by analyzing changes in measured operating parameters before damage occurs [7, 8]. Parametric diagnostics are also essential for meeting classification society requirements and protecting the marine environment.

Exhaust gas temperature measurement is one of the data sources in parametric diagnostics of marine engines, although average values are usually analyzed. Changes in the rapidly varying exhaust gas temperature within a single operating cycle reflect processes occurring in the cylinder, particularly the quality of combustion and the condition of the engine's functional systems. Exhaust gas temperature analysis, especially in its dynamic form, enables the detection of deviations from nominal operating conditions and early signs of wear or damage to engine components.

However, due to the high dynamics of exhaust gas temperature changes, direct interpretation of the signal is difficult. To obtain the maximum amount of diagnostic information, the rapidly varying signal must be appropriately processed using mathematical and statistical tools [18]. Therefore, appropriate tools are being sought that are tailored to the rapidly varying signals produced by diagnostic tests. One of them is the F-statistic from the Fisher-Snedecor distribution in variance analysis, which provides a lot of information [2].

3. F-statistic as a tool to determine interactions between factors

In the analysis performed, the statistical significance of both main effects and interaction terms was evaluated using a two-factor F-statistic. Particular attention was given to interaction terms, which indicate non-additive relationships between input variables. The presence of an interaction effect indicates that the influence of one input factor on the dependent variable depends on the level of another input factor. Consequently, the combined effect of the factors cannot be interpreted solely based on their individual effects. In the analyzed system, interaction is identified when the response of a dependent variable to one input factor varies with the level of another input factor [2, 13]. The validity of the applied F-test was based on the assumptions of independence of observations, homogeneity of variances, and approximate normality of residuals. The value of the statistic for the interaction between the input variables considered in the two-factor statistical analysis $F_{cal\_interaction}$ (F_{cali}) was calculated as the ratio of the variance of the interactions to the within-group variance (error component), according to the following relationship:

$$F_{cal\_interaction} = F_{cali} = \frac{S_{IN}}{S_R} \cdot \frac{(p-1)\cdot(q-1)}{p\cdot q\cdot(r-1)} \quad (1)$$

where r – number of groups.

The interaction mean square was determined using the interaction degrees of freedom equal to (p−1)(q−1) and the calculated sums of squares associated with the interaction effect and the residual error S_R [17]. If several measurements are available in each group (at each intersection of a row and a column), the intergroup sum of squares of deviations is determined from the following relationship:

$$S_M = \sum_{i=1}^{p}\sum_{j=1}^{q}\sum_{k=1}^{r} h_{ijk}^2 - p\cdot q\cdot \bar{h}^2 \quad (2)$$

where k – measurement number in the group.

Then, the interactive sum of squares of deviations in the analysis of variance of double classification is understood as the relationship:

$$S_{IN} = S_M - S_I - S_{II} \quad (3)$$

The presence of interaction between the input factors was evaluated using the calculated F-statistic for the interaction effect (F_{cal}). The obtained value was compared with the critical value (F_{cri}) corresponding to the adopted significance level and the appropriate degrees of freedom. If F_{cal} exceeded F_{cri}, the interaction effect was considered statistically significant, indicating that the influence of one input factor depended on the level of the other factor. In such a case, the combined effect of the factors differed from the sum of their individual effects.

Conversely, when F_{cal} was lower than or equal to F_{cri}, no statistically significant interaction was identified, and the factors were considered additive. This implies that each factor affected the response variable independently, without altering the other factor's effect.

A statistically significant interaction indicates that the response observed at a given level of one factor depends on the level of the second factor. In contrast, in the absence of a significant interaction effect, the influence of each factor can be interpreted independently [2, 13].

Additionally, the value of the interaction coefficient of significance ΔF_i was determined as the difference between the calculated value of the statistic for the F_{cali} interaction and the critical value read from the F_{cri} tables, according to the following relationship:

$$\Delta F_i = F_{cali} - F_{cri} \quad (4)$$

To obtain the value of the F_{cal} statistic and the confidence coefficient ΔF, and thus answer the key question concerning the significance of the impact of selected input factors – engine structure parameters – on defined diagnostic indicators, it was necessary to follow the developed statistical testing scheme shown in Fig. 1 [19]. It must be explicitly emphasized that the rapidly varying exhaust-gas temperature stream is the primary diagnostic signal in this analytical framework. Initial diagnostic signal conditioning involved mathematical processing to filter out measurement-system noise and anomalies.

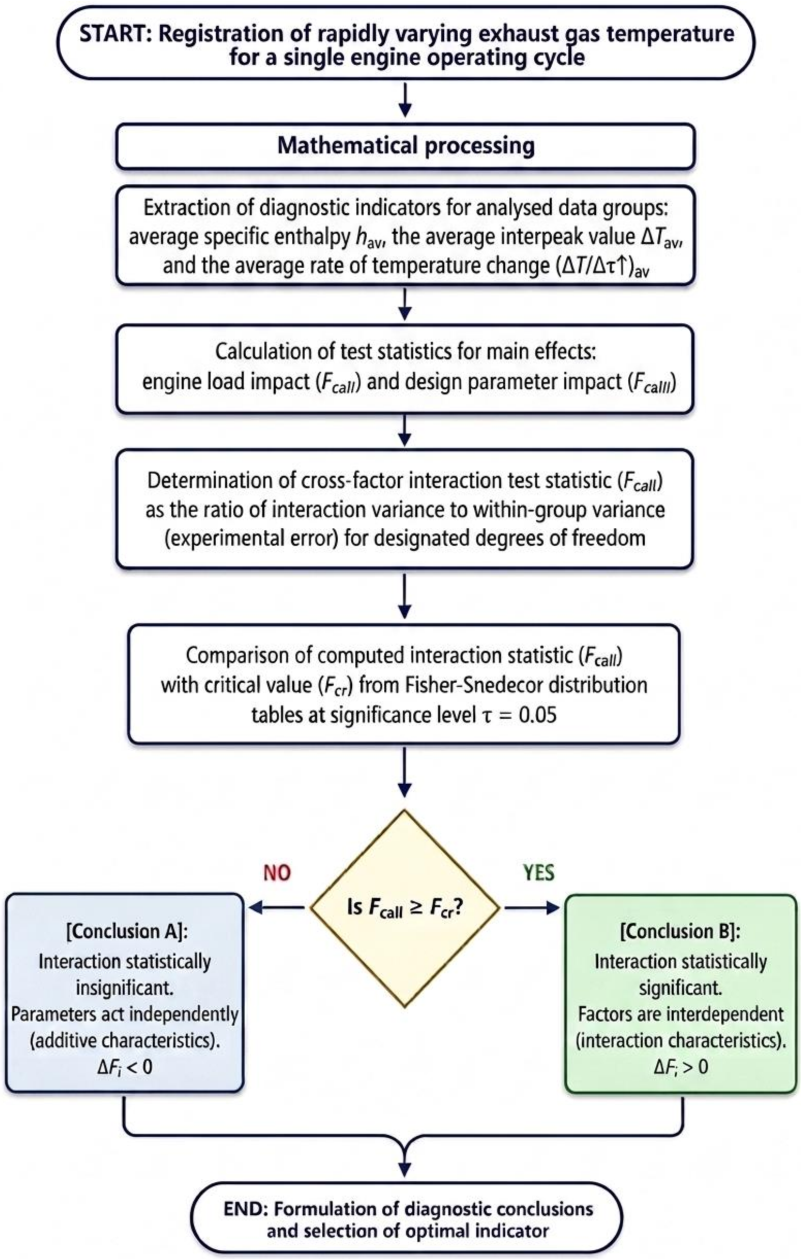

Fig. 1. Flowchart of the statistical procedure for evaluating interaction effects and selecting diagnostic indicators based on rapidly varying exhaust gas temperature measurements

High-frequency measurement noise was attenuated using a polynomial smoothing filter based on the least squares method (Savitzky-Golay approach) applied to cycle-by-cycle temperature profiles.

Outliers and operational anomalies were identified using statistical criteria (evaluating residuals exceeding 3 standard deviations (±3σ) from the group mean) as well as physical boundaries dictated by the thermodynamic limits of the single-cylinder test engine. A critical phase in evaluating the thermocouple's dynamic characteristics requires determining its specific response to sinusoidal thermal excitation generated within the CI test engine stream. This procedure quantifies both the phase shift and the thermal amplitude attenuation captured by the sensor relative to the actual, induced fluctuations in the exhaust gas temperature [19]. Diagnostic indicators were determined from the waveform obtained for the actual, interference-free rapidly varying exhaust gas temperature. The randomized complete block design was employed to reduce the influence of nuisance variables and improve the precision of the estimated effects [18]. The process continues with the evaluation of main effects, which involves calculating the test statistics to determine the individual impact of the engine load and design parameters. To explore how these variables influence each other, a cross-factor interaction test statistic is computed by analyzing the ratio of interaction variance to the internal experimental error, with the degrees of freedom specified. This calculated interaction value is then validated by comparing it with the theoretical critical value from the Fisher-Snedecor distribution at the 0.05 significance level. This comparison provides the basis for assessing the statistical significance of the interaction effect. Ultimately, the obtained statistical criteria support the selection of the most appropriate diagnostic indicator.

4. Research data for statistical analysis

In the first step, the impact of changes in design parameters was analyzed using the DIESEL-RK program on selected engine operating parameters to identify and analyze diagnostic parameters at no cost [10, 16]. An extensive literature review was also conducted on the most common conditions of functional engine system failure [21]. On this basis, the functional systems considered most unreliable in a marine IC engine were selected for testing: the fuel supply system [6, 20], the air intake duct [9, 12], and the structural elements that limit the combustion chamber [3, 15, 19]. The tests were then conducted in accordance with the data in Table 1 and the regulatory characteristics of engine operation [4]. Empirical testing was conducted on a specialized laboratory installation equipped with a Farymann Diesel D10 marine engine operating in a generator configuration to supply an electric heating load. The primary technical specifications of the tested engine are as follows:

- Engine type: four-stroke, single-cylinder, naturally aspirated, indirect injection with a vortex pre-combustion chamber
- Nominal power: 6 kW at a nominal rotational speed of 1500 min^{-1}
- Nominal torque: 38 Nm
- Cylinder bore/piston stroke: 90/120 mm
- Connecting rod length: 225 mm
- Displacement volume: 765 cm^3
- Nominal injector opening pressure: 12 MPa.

Transient thermal monitoring of the exhaust stream used an Inconel-sheathed, grounded Type K thermocouple with a 0.5 mm outer-diameter junction. This sensor configuration possessed a characteristic time constant of 65 ms, with the underlying data acquisition system operating at a sampling frequency of approximately 7000 Hz. According to IEC 60584-2 Class 1 standards, the Type K thermocouple features an intrinsic measurement accuracy of $\pm1.5^{o}C$ across the operating temperature range. Accounting for the entire signal acquisition channel (including signal-conditioning modules and A/D conversion), the expanded measurement uncertainty for the exhaust gas temperature was evaluated as U(t) = ±2.1°C at a 95% confidence level (k = 2).

5. Diagnostic interaction analysis using dynamic exhaust gas temperature indicators

Methodological foundations and interactive hypotheses

To clarify, the rapidly varying exhaust gas temperature $t_{exh}(\tau)$ is the primary physical signal measured on the engine. The average specific enthalpy h_{av} is a derived thermodynamic indicator calculated directly from this temperature signal and the temperature-dependent specific heat of the exhaust gas over one operating cycle. Together with ΔT_{av} and $(\Delta T/\Delta\tau\uparrow)_{av}$, it forms a set of three diagnostic indicators calculated from the same temperature waveform.

A preliminary single-factor statistical verification clearly demonstrated that the injector opening pressure p_{inj} exerts no meaningful influence on the average specific enthalpy h_{av} under engine operating loads 1 and 2 according to the specified control characteristics. Under operating load condition 3, however, the statistical impact of this structural parameter proved significant. Yet, it remained lower (ΔF = 9.06) than its concurrent influence on the other two diagnostic indicators, where the computed confidence coefficients reached orders of magnitude in the dozens or even hundreds. For this reason, it was found that the injector opening pressure p_{inj} would be excluded as a variable influencing the average specific enthalpy h_{av} during subsequent multi-parameter evaluation phases [17, 18].

Two-factor statistical analysis was applied to the collected data. This approach enabled the identification of the main effects associated with each input parameter. Additionally, it enabled verification of statistically significant interactions between variables. This capability is achieved by verifying, alongside the baseline single-variable criteria, an additional interactive null hypothesis:

H0: There is no interaction between the engine operating load and the tested structural parameter

Research questions:

1. Does the structural configuration parameter (active section area of the intake air duct A_{in}, injector opening pressure p_{inj}, or compression ratio ε) actively determine the defined diagnostic indicators (average specific enthalpy h_{av}, average interpeak value ΔT_{av} or the average rate of temperature change $(\Delta T/\Delta\tau\uparrow)_{av}$, independently of the engine operating load?
2. Does the engine operating load P significantly alter the designated diagnostic parameters, independently of the structural design modifications?
3. Do the selected structural design variable and the engine operating load affect the values of the determined diagnostic indicators?
4. If the interactive null hypothesis H0 cannot be rejected - meaning the statistical evaluation provides a negative response to the third question – the independent variables are mathematically confirmed to be additive. Under an additive configuration, the input components do not jointly determine the variance of the diagnostic signal but instead independently modulate the mean of the target output factor.

Table 1. Engine load values and design parameters, which are input factors in diagnostic tests [18]

Structural parameter (input factor)	Symbol	Unit	Reference value	Related changes
Engine load	P	W	1200 (0.2 P_{NOM})	768 (0.64·P_{REF}) 432 (0.36·P_{REF})
Active section area of the intake air duct	A_{in}	mm^2 (%)	804 (100%)	603 (0.75·A_{REF}) 401 (0.5·A_{REF})
Injector opening pressure	p_{inj}	MPa	12	10
Compression ratio	ε	–	22:1	21:1

The two-factor analysis of variance was executed using a fully balanced experimental design with equal sample sizes across all factor combinations. This balanced structure provides inherent robustness to mild departures from strict parametric assumptions, ensuring reliable hypothesis testing for temperature measurements acquired under stabilized engine operating conditions.

Evaluation of empirical outputs and factor interactions

To develop a comprehensive understanding of these operational dependencies across the multi-variable testing matrix, a systematic evaluation was executed based on the empirical results consolidated in the single, unified Table 2. Measurements were recorded continuously at a sampling frequency of 7000 Hz under stabilized engine operating points defined by discrete combinations of engine load and structural parameter variations. From these continuous, rapid temperature waveforms, dynamic diagnostic indicators were evaluated for discrete operating cycles. To maintain a concise analytical focus and avoid redundant signal-plot depictions, the raw dynamic waveforms were processed into representative averaged indicators across N = 18 (or N = 8) independent test cycles per group, serving as the empirical input for the Snedecor-Fisher evaluation.

The first analytical block isolates the cross-effects generated between the engine operating load P and the active section area of the intake air duct A_{in}. For the mathematical model evaluating the average specific enthalpy h_{av}, the interaction term had 4 degrees of freedom, with both independent variables operating at the same number of variability levels ($p = q = 3$). Analyzing 18 distinct measurement samples within each factor group established an overall total number of degrees of freedom of 53, leaving 45 degrees of freedom assigned to the within-group error matrix. Under these statistical constraints and at a pre-defined significance level of $\alpha = 0.05$, the theoretical critical threshold extracted from the statistical distribution tables was $F_{cr(0.05;\,4;\,45)} = 2.57874$ for a right-sided critical region [5].

The results summarized in Table 2 demonstrate that engine operating load P is the dominant factor influencing the average specific enthalpy h_{av} ($\Delta F_I = 1011.55$). This effect significantly exceeds the contribution of the remaining variables. Concurrently, the active section area of the intake air duct A_{in} also exhibits a statistically meaningful influence on this dynamic metric, yielding a confidence factor of $\Delta F_{II} = 559.8$. A statistically significant interaction between the analyzed factors was observed, indicated by a positive interaction coefficient with a significance level of $\Delta F_i = 39.4$.

The calculated interaction significance metric reflects both the statistical validity and the relative strength of the impact of the coupled factors. All factor pairings evaluated as statistically interactive exceeded the theoretical critical threshold at the predefined significance level, and the relative magnitudes of the test statistics indicated the overall effect size within the testing matrix.

A separate analytical pattern emerges when shifting the focus to the other two rapidly varying diagnostic indicators: the average interpeak value ΔT_{av} of rapidly varying exhaust gas temperature and the average rate of temperature change $(\Delta T/\Delta\tau\uparrow)_{av}$. Because these parameters use the same underlying experimental dataset, all initial statistical assumptions, group sizes, and degrees of freedom remain identical to those in the previous calculations. However, as detailed in Table 2, the interaction analysis mathematically excludes any significant coupled dependency between the engine operating load P and the active section area of the intake air duct A_{in} for these specific time-varying features. The computed interaction coefficient of significance, ΔF_i, is negative and equals –1.124. This negative value confirms that for both the average interpeak value and the average rate of temperature change, the input variables exhibit an additive character, meaning a simultaneous cross-factor impact on these dependent diagnostic measures is statistically rejected.

Table 2. Consolidated test statistics of the Snedecor-Fisher distribution and interaction significance coefficients (ΔF_i) for diagnostic indicators derived from rapidly varying exhaust gas temperature signals

Input factor pair (engine load P × structural parameter)	Evaluated diagnostic indicator	Test statistic F_{calI} (engine load effect)	Test statistic F_{calII} (structural effect)	Interaction test statistic F_{cali}	Interaction coefficient of significance ΔF_i	Type of relationship
Engine load (P) × intake air duct area (A_{in}) $F_{cri} = 2.58$	h_{av}	1014.76	563.01	41.98	+39.40	Interactive (strong)
	ΔT_{av}	0.014	56.77	1.456	–1.123	Additive
	$(\Delta T/\Delta\tau\uparrow)_{av}$	0.014	56.78	1.455	–1.124	Additive
Engine load (P) × injection pressure (p_{inj}) $F_{cri} = 3.55$	ΔT_{av}	16.367	491.07	7.67	+4.12	Interactive
	$(\Delta T/\Delta\tau\uparrow)_{av}$	5.203	314.14	3.47	–0.084	Additive
Engine load (P) × compression ratio (ε) $F_{cri} = 3.55$	h_{av}	436.08	70.24	0.74	–2.814	Additive
	ΔT_{av}	12.31	278.25	5.84	+2.28	Interactive
	$(\Delta T/\Delta\tau\uparrow)_{av}$	12.31	278.71	5.84	+2.28	Interactive

Subsequently, the analytical procedure was extended to evaluate the cross-effects between the engine operating load P and the remaining structural parameters, namely the injector opening pressure p_{inj} and the compression ratio ε, following the specific algorithmic framework detailed in [17, 18]. For these specific factor pairings, the statistical parameters were configured with an interactive degrees-of-freedom count of 2, reflecting individual factor variability levels of p = 3 and q = 2. Based on a sample size of 8 independent measurements per group, the total number of degrees of freedom was 23, with 18 degrees of freedom remaining within the error matrix. These conditions yielded a theoretical critical threshold value of $F_{cr(0.05;2;18)} = 3.55456$ under an identical right-sided critical zone definition at $\alpha = 0.05$.

Regarding the pairing of engine operating load P and injector opening pressure p_{inj}, the results summarized in Table 2 indicate that p_{inj} influences the average interpeak value ΔT_{av} of rapidly varying exhaust gas temperature, with a confidence factor of $\Delta F_{II} = 486.66$. Shifting the engine operating load P also produces a statistically valid, though markedly smaller, alteration in this indicator ($\Delta F_I = 12.81$). Furthermore, the mathematical verification confirms a genuine coupled dependency between the engine operating load P and the injector opening pressure p_{inj}, tracking a positive interaction coefficient of significance of $\Delta F_i = 4.12$.

When observing the average rate of temperature change $(\Delta T/\Delta\tau\uparrow)_{av}$, the injector opening pressure p_{inj} retains its strong statistical dominance with a confidence factor of $\Delta F_{II} = 309.73$. In contrast, the engine operating load P shows a minimal but still significant contribution ($\Delta F_I = 1.65$). However, no coupled dependency is detected for this dynamic diagnostic indicator, as the interaction coefficient of significance, ΔF_i, drops to –0.08. For the average specific enthalpy h_{av}, a two-factor verification indicates that, while both independent inputs significantly affect the metric, they do not interact and follow a purely additive model. Regarding the role of the injector opening pressure, single-factor verification showed that its impact on the average specific enthalpy remains minor across the operating range. While dynamic temperature indicators show extreme sensitivity to injection pressure drops, the cycle-average specific enthalpy is primarily governed by engine load and intake air-flow restrictions, making injection pressure diagnostically secondary in enthalpy-based evaluations.

Finally, the joint actions of the engine operating load P and the compression ratio ε reveal distinct diagnostic behavior across all target variables in Table 2. For the average specific enthalpy h_{av}, the engine operating load P is the dominant source of variance ($\Delta F_I = 432.53$), while the compression ratio ε has a secondary but significant impact ($\Delta F_{II} = 65.83$). The cross-factor interaction between P and ε on the average specific enthalpy h_{av} is statistically excluded, as the interaction coefficient of significance, ΔF_i equals –2.814.

In contrast, evaluating the average interpeak value ΔT_{av} and the average rate of temperature change $(\Delta T/\Delta\tau\uparrow)_{av}$ reveals a clear reversal in the dominance of factors. Here, the structural configuration parameter – the compression ratio ε – governs the signal variance, yielding high confidence coefficients of $\Delta F_{II} = 273.84$ and $\Delta F_{II} = 274.3$, respectively, compared to the minor contributions from the

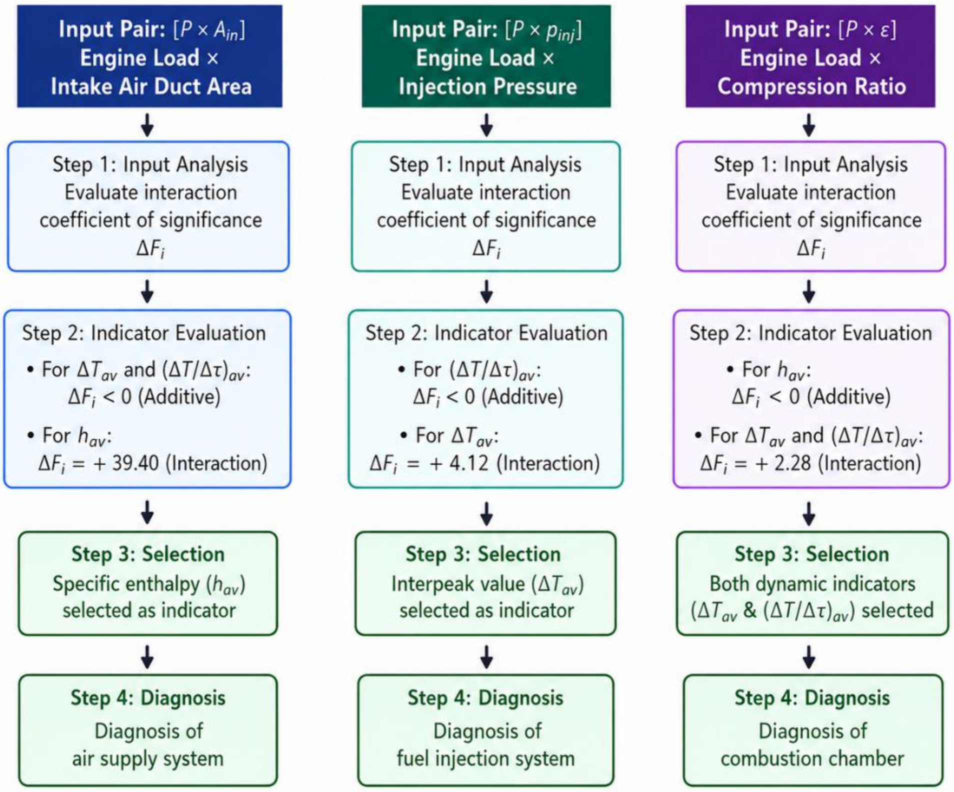

Fig. 2. Interactive matrix for diagnostic indicator selection based on interaction significance coefficient (ΔF_i)

engine operating load P (ΔF_I = 8.75). Crucially, the mathematical model confirms a valid cross-factor interaction for both dynamic metrics, with the interaction coefficient of significance, ΔF_i, reaching a positive value of 2.28 in both cases.

Comparative assessment of structural and operational interactions

Based on the values of the interaction coefficient of significance ΔF_i summarized in Fig. 2, the strongest interaction occurs when the active section area of the intake air duct A_{in} and the engine operating load P influence the average specific enthalpy h_{av} (ΔF_i = 39.4). This high positive value clearly indicates that these two parameters are strongly correlated, meaning that the diagnostic sensitivity of the intake air system varies with engine load.

Statistical analysis also confirms weaker, but still significant, interactions for the pair of P and ε (influencing both the average rate of temperature change $(\Delta T/\Delta\tau\uparrow)_{av}$ and the average interpeak value ΔT_{av}), as well as for the pair of P and p_{inj} (influencing ΔT_{av}). For these factor pairs, the positive ΔF_i coefficients range from 2.28 to 4.12, meaning that their simultaneous impact on the diagnostic indicators is statistically important. In all other analyzed cases, the interaction coefficients are negative ($\Delta F_i < 0$). This indicates that no statistically significant interaction was detected between these parameters under the evaluated operating conditions, supporting an additive response model.

6. Summary and future research directions

The primary objective of this study was to evaluate the rapidly varying exhaust gas temperature stream as an advanced diagnostic signal and to resolve the problem of load-induced symptom masking through cross-factor interaction analysis. The most significant scientific and practical achievements of this work are as follows:

1. Identification of primary diagnostic metrics: Established that cycle-average specific enthalpy h_{av} is the most sensitive metric for detecting intake duct flow restrictions, whereas dynamic indicators – the average interpeak value ΔT_{av} and average rate of temperature rise $(\Delta T/\Delta\tau\uparrow)_{av}$ – precisely detect injector pressure drops and compression ratio reductions.
2. Resolution of engine load interference: Quantified for the first time, the cross-factor interaction between engine load P and key structural faults. Provided a strong positive interaction (ΔF_i = 39.4) for intake duct restrictions (meaning sensitivity varies with load) and confirmed an additive relationship ($\Delta F_i < 0$) for injection and compression faults, proving these dynamic metrics remain stable regardless of load fluctuations.
3. Establishment of a non-invasive diagnostic key: Developed a minimal-sensor diagnostic matrix that enables accurate fault isolation and technical condition assessment of marine IC engine subsystems without requiring complex multi-sensor installations.

It should be emphasized that while single-cylinder laboratory experiments were crucial for isolating fundamental thermal dependencies without inter-cylinder gas-dynamic interference, practical application to commercial marine power plants requires careful consideration of scale effects and multi-cylinder manifold dynamics.

This investigation marks a major progression in a long-term research program, evolving from baseline single-factor evaluations [17] and dual-factor methods [18] to full cross-factor interaction modeling. By isolating load dependencies, the methodology provides a clear diagnostic key that connects advanced dynamic temperature signal processing with practical marine engineering needs.

Looking forward, the methodology developed in this series of papers can be integrated into next-generation marine IC engine condition monitoring systems across three primary directions:

1. **Development of a Digital Twin of the engine:** The obtained experimental results and the mathematically determined interaction coefficient of significance provide the database necessary to create a digital twin of a marine IC engine. Such a virtual model, supplied with actual, rapidly varying exhaust-gas temperature signals, would enable continuous comparison between the parameters of the actual operating machine and its ideal mathematical baseline [14]. This would enable the detection of the smallest deviations from the nominal state at a very early stage, before they lead to a serious failure in the ship's engine room.
2. **Transition to Condition-Based Maintenance:** The mathematical signal-processing algorithms presented in this work can be implemented in marine monitoring systems to enable real-time parameter analysis [7]. Continuous calculation of the average specific enthalpy of exhaust gas h_{av} and the dynamic indicators (ΔT_{av} and $(\Delta T/\Delta\tau\uparrow)_{av}$) from cycle to cycle will allow ship operators to move away from rigid, calendar-based periodic engine overhauls. Instead, decisions regarding repairs to the injection or intake systems will be made based on their actual wear, significantly reducing ship operating costs and increasing navigation safety.
3. **Scaling the method to multi-cylinder engines:** All studies described in this paper were conducted on a single-cylinder test stand to eliminate gas-dynamic interference between cylinders [17, 18]. The next logical research step is to verify this method on full-scale, multi-cylinder main propulsion engines or auxiliary generator sets. This requires expanding the algorithms to include signal decomposition procedures that precisely isolate and assign the thermal contributions of individual cylinders discharging into a single shared exhaust manifold.

In conclusion, the proposed methodology extends the application of rapidly varying exhaust gas temperature analysis from laboratory conditions towards engineering practice. The developed parameter selection matrix effectively bridges advanced mathematical analysis and the practical needs of shipyard diagnostics, providing a practical tool to improve the reliability of marine energy systems.

Nomenclature

A_{in}	intake air duct area	p_{inj}	opening pressure of injector
F_{cal}	computational statistic	ΔF_i	interaction coefficient of significance
h	specific enthalpy	ΔT	interpeak value
IC	internal combustion	$\Delta T/\Delta\tau$	rate of temperature change
P	load	ε	compression ratio

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