

Article

A Digital Twin Framework for Monitoring and Fault Identification of Marine Internal Combustion Engines

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Abstract

Monitoring the current technical condition of a marine internal combustion engine and diagnosing the causes of deviations of its operating parameters from reference values are important tasks for ensuring the efficient and safe operation of marine power plants and vessels in general. This study develops a digital twin framework for marine engine diagnostics and demonstrates its integration with the DEPAS 5.0W diagnostic system. The framework combines a calibrated 0D–1D engine-process model, sensor-based identification of the current operating mode, reference-state generation, and inverse identification of physical factors responsible for deviations from expected engine behavior. The mathematical model is adapted for digital twin operation through operating-mode-dependent parameterization, including a modified fuel-injection approximation. A four-factor constrained factorial numerical experiment with second-order response-surface models is used to investigate the inverse diagnostic problem. The approach is demonstrated first using virtual marine engines and subsequently using experimentally acquired data from a Weichai WP4 diesel generator with a controlled intake restriction introduced by a throttle valve. The results demonstrate that the proposed framework supports the identification of the most probable physical cause of the observed deviation when multiple potential fault factors are considered. At the same time, the results reveal the practical non-uniqueness of the inverse problem, as different factor combinations may produce similar observable engine responses. The Mahalanobis distance is shown to provide improved fault discrimination in the investigated case compared with individual pressure-based objective functions. The proposed architecture provides a basis for further development of automated digital twin-assisted diagnostics, including systematic uncertainty and identifiability analysis and validation under controlled faults.



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Keywords: fault diagnostics; marine internal combustion engine; digital twin; design of experiments; objective function; condition monitoring

1. Introduction

Internal combustion engines (ICE) are key components of a ship power plant, and their reliable operation directly affects the economic efficiency of vessel operation, navigation safety, and the level of environmental impact. Therefore, continuous efforts are being devoted to improving engine design, optimizing engine operating processes and operational methods [1], as well as adapting engines to new fuels and regulatory requirements [2].

One of the major directions contributing to the improvement of marine ICE operation efficiency is the implementation of modern digital technologies for continuous technical

condition monitoring, automation of engine control, and development of onboard self-diagnostic systems capable of assessing the current engine condition during operation. The development of this field has led to the emergence and practical implementation of digital twin (DT) technologies [3,4].

Manufacturers of modern marine engines already offer commercial services based on DT technologies. Everllence provides the PrimeServ Assist platform for real-time monitoring and AI-based diagnostics [5]. Wärtsilä offers the Operational Performance Improvement & Monitoring (Operim) system, which integrates a virtual twin for comparison between actual and expected engine performance [6]. WinGD developed the WinGD Integrated Digital Expert (WiDE) platform, which utilizes a customized DT model based on factory test data to provide actionable engine health assessment [7,8]. Nevertheless, further improvement of this technology remains an important research task.

A digital twin can be defined as a virtual representation of an internal combustion engine that reproduces selected aspects of its operation and behavior. It is not simply a physics-based mathematical model but an integrated computational representation linked to a specific physical engine through measurement, data processing, communication, and model-update mechanisms. The distinction is important for diagnostic applications: a calibrated simulation model can predict engine behavior for prescribed inputs, whereas a DT additionally receives information from the physical asset, adapts its computational inputs to the current operating condition, and returns model-derived information to support assessment of the physical asset. Depending on its intended purpose, a DT should provide the most reliable possible prediction of variations in engine and subsystem parameters under different operating conditions. Digital twins of ICE may serve different purposes and can be classified as follows.

By purpose:

- Engine control;
- Engine diagnostics and condition monitoring;
- Engine repair and maintenance;
- Engine design and optimization;
- Personnel training and teaching;

By primary focus:

- Engine operating process;
- Wear, lubrication, and cooling processes;
- Thermal and mechanical stresses;
- Engine component design and assembly.

By deployment architecture:

- Embedded into the engine ECU;
- Remotely accessible cloud-based systems;
- Standalone PC-based installations.

The classifications presented above describe possible application domains of digital twins rather than mutually exclusive categories. A single DT architecture may support several functions during the engine lifecycle. In the present study, the proposed DT is primarily classified as a diagnostic and condition-monitoring DT because the investigated data flow, model functions, and algorithms are specifically designed to identify deviations in engine operation and their probable physical causes. Some of the underlying modeling and operating-state identification procedures may also be applicable to other DT functions, such as control or performance optimization; however, these applications are outside the scope of the present study.

Digital twins have potential for application during the whole engine lifecycle, starting from its design and production [9]. The most challenging task in terms of achieving both high computational speed and high prediction accuracy is the development of DT intended for real-time engine control [10]. Such DTs may operate as “shadow models” running in parallel with real ECUs to validate control actions or predict engine behavior before actual actuation. DTs could be an effective and cost-saving instrument for educational and training purposes [11].

One of the promising applications of digital twins for marine ICE is technical condition diagnostics and condition monitoring. Intensive research efforts in this area are aimed both at improving mathematical models specifically adapted for DT applications [12,13] and at enhancing interaction between the digital twin and the real engine through sensor systems [14], including integration into comprehensive ship power plant diagnostic systems [15,16]. Particular attention should also be paid to the growing application of machine learning techniques in systems employing digital twins [17–21].

Despite the significant progress achieved in this field, the effective application of DT for diagnostics and condition monitoring of marine ICE still requires overcoming several important challenges. First, it is necessary to ensure an appropriate balance between the level of detail of the DT mathematical model and computational speed, especially for online monitoring applications or when diagnostic conclusions must be obtained during real-time engine operation [22]. Second, reliable identification of the current engine operating mode by the digital twin must be ensured, which requires determination of the necessary sensor set and appropriate methods for sensor data processing [23,24]. Finally, robust methods for fault identification and technical condition assessment using digital twins should be developed to ensure acceptable diagnostic reliability, support automation, and provide unambiguous diagnostic conclusions. Therefore, the objective of this study is to develop and demonstrate a framework for integrating a physics-based digital twin of a marine internal combustion engine with an experimental diagnostic system. The proposed approach combines experimental identification of the engine operating state, physics-based simulation, and inverse analysis of deviations between measured and simulated parameters. The working hypothesis is that such integration can provide additional diagnostic information that cannot be obtained from the measured parameters alone and can be used to identify the most probable factors responsible for deviations in the engine operating process.

The digital twin framework developed in this study combines an engine-specific 0D–1D thermodynamic model with the DEPAS 5.0W diagnostic system and the associated data-processing and communication infrastructure.

Unlike our previous studies, which focused primarily on simulation-based diagnostics, measurement diagnostics, real-time parametric diagnostics, or experimental evaluation of DT components, the present study addresses their integration into a unified diagnostic workflow in which the physics-based DT is directly connected to experimentally measured engine-process data.

The principal methodological contribution of this study is the development of an engine-specific digital twin framework in which a calibrated physics-based engine model is coupled with experimental sensor data and an inverse diagnostic procedure for identification of probable fault-related parameters. A second contribution is the formulation of requirements for adapting the underlying physics-based model to diagnostic digital twin applications. In particular, model parameters should have a physical interpretation, correspond to potentially diagnosable engine conditions, and provide sufficient sensitivity to the considered faults. Therefore, the modification of the fuel-injection submodel presented in this study is considered an example of such adaptation. For inverse fault identification, established design-of-experiments, response-surface, and optimization techniques are

employed. The proposed architecture is algorithm-independent and may subsequently accommodate alternative inverse-modeling, state-estimation, or optimization approaches.

2. Definitions

Although the application of mathematical modeling to the diagnosis of the technical condition of ICE is a widespread practice, the theoretical foundations and methodological approaches to the application of DT for technical condition diagnostics remain insufficiently systematized. In particular, the application of DT for representing engine operating processes requires the development of algorithms for automated simulation and extraction of diagnostic features capable of indicating deviations in engine technical condition.

Consider several definitions. An engine **operating mode** is defined as the set of operational engine parameters that characterize the current load and control state of the engine without considering its technical degradation. An engine possesses a set of operating modes $\mathcal{O}$, while each individual operating mode $\bar{O}$ belongs to this set:

$$\bar{O} \in \mathcal{O}; \bar{O} = (n_{crank}, P_b, p_i, b_b, \dots, t_t), \quad (1)$$

A **technical condition** of the engine is defined as the set of parameters describing the technical properties and degradation state of the engine and its subsystems. For the set of technical conditions $\mathcal{H}$, each particular technical condition $\bar{H}$ is considered as

$$\bar{H} \in \mathcal{H}; \bar{H} = (p_{compr}, b_b, b_{oil}, P_{b,max}, \dots, p_{max}), \quad (2)$$

The reference technical condition $\bar{H}_{etalon} \in \mathcal{H}$ is defined as the factory condition of the engine or as its optimal technical condition.

Monitoring of the engine operating process is defined as the observation, analysis, and statistical processing of a set of measurable engine parameters under given operating conditions. For the space of observable parameters $\mathcal{Y}$, a particular available vector of the monitored parameters may be denoted as $\bar{Y}$:

$$\bar{Y} \in \mathcal{Y}; \bar{Y} = (p_{oil}, t_{w1}, n_{crank}, \dots, p_s). \quad (3)$$

Figure 1 shows the interaction of vectors schematically $\bar{O}$, $\bar{H}$, and $\bar{Y}$ as constituents of their sets for a given engine under given conditions of operation. Although some of the parameters are common for all three vectors, others are specific to each. However, it is intended as a conceptual illustration of the relationships between the considered sets rather than as a formal mathematical representation. For example, the exhaust gas temperature of individual engine cylinders can simultaneously belong to all three categories: it characterizes the current engine operating mode, provides information about the engine technical condition, and represents a practically measurable parameter available for monitoring. In contrast, engine rotational speed primarily defines the operating mode and is also a directly monitored parameter, whereas the cylinder wear parameter belongs to the set of technical-condition parameters and is generally not directly measurable during normal engine operation. Such relationships illustrate the meaning of the intersections between the sets shown in Figure 1 and explain why different types of parameters may simultaneously contribute to operating-mode identification, technical-condition assessment, and fault diagnosis.

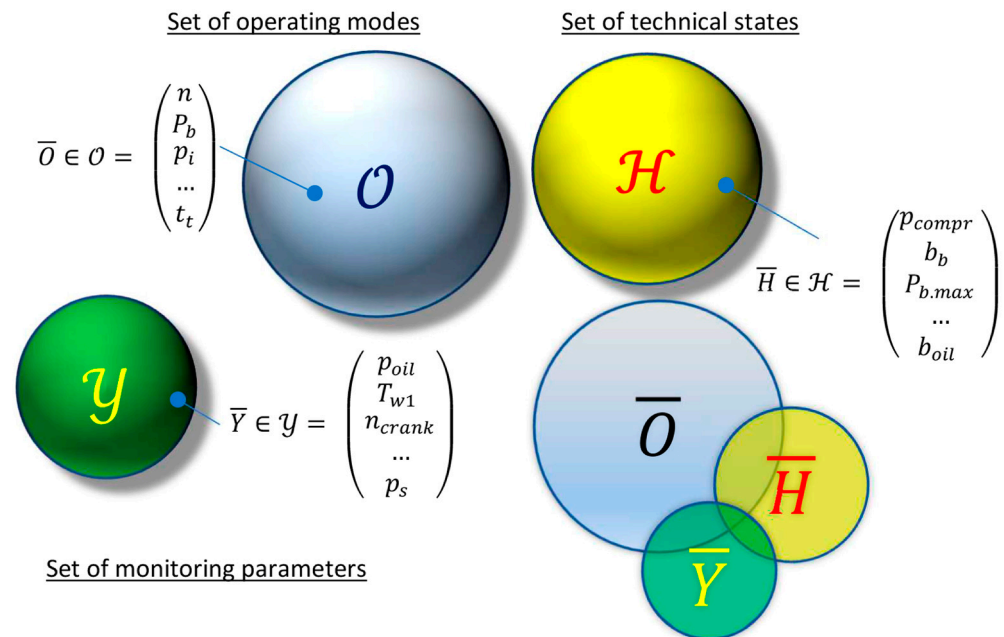


Figure 1. Sets of operating modes, technical conditions, and monitoring parameters and their interrelation.

The mathematical model of an engine operating process may be represented in the following general form:

$$\bar{R} = f(\bar{I}, \bar{C}, \bar{O}, \bar{H}); \bar{R} = \begin{pmatrix} P_b \\ b_b \\ \dots \\ t_t \end{pmatrix}; \bar{I} = \begin{pmatrix} D_{cyl} \\ S_{pist} \\ \dots \\ \Phi_{inj} \end{pmatrix}; \bar{C} = \begin{pmatrix} p'_{max} \\ p'_i \\ \dots \\ p'_s \end{pmatrix}, \quad (4)$$

where the resulting vector $\bar{R}$ is a function of the input parameter vector $\bar{I}$, the calculation control vector $\bar{C}$, the engine operating mode vector $\bar{O}$, and the technical condition vector $\bar{H}$.

The vector $\bar{R}$ contains the simulation results, including engine operating process parameters and corresponding process diagrams. The vector $\bar{I}$ represents the input data used for calculations. This vector may be divided into two components: the vector of constant parameters $\bar{I}_{const}$, which remains unchanged between calculations for a given digital twin application scenario, and the vector of variable parameters $\bar{I}_{var}$, whose values change depending on the engine operating mode:

$$\bar{I} = (\bar{I}_{const}, \bar{I}_{var}). \quad (5)$$

The constant parameters may include, for example, the geometric dimensions of the cylinder–piston group, the number of cylinders, and fuel injector characteristics. It should be noted that the set of constant parameters is specific to each engine and depends on the particular digital twin application scenario. The most commonly used variable parameters include crankshaft rotational speed, fuel injection timing, injection duration, boost pressure, and similar operating variables.

The vector $\bar{I}_{var}$ may also be divided into two components: parameters available from sensor measurements and parameters that remain unknown due to the absence of corresponding sensors or the impossibility of direct measurement. Determination of the latter component represents a significant challenge and may influence the selection and configuration of the vector $\bar{C}$.

The vector $\bar{C}$ may be interpreted as a set of parameters defining the calculation strategy or computational mode. For example, calculations may be performed with balancing of turbine and compressor power within the turbocharging system and determination of boost pressure, or alternatively with prescribed boost pressure values. Similarly, calculations may involve determination of the fuel injection timing required to achieve a specified maximum cylinder pressure, or may be carried out with fixed injection timing values.

3. Digital Twin Framework

In this study, the digital twin (DT) is defined as a fit-for-purpose digital representation of a specific marine diesel engine, maintained through the acquisition and exchange of relevant information from the corresponding physical asset. This interpretation follows the general principles of the ISO 23247 series while adapting its terminology to the marine-engine diagnostic context. ISO 23247-1:2021 provides terminology and general principles for digital twin frameworks, whereas ISO 23247-2:2021 defines a reference architecture separating the observable physical domain, data collection and device communication functions, the digital twin domain, and user/application functions [25,26].

In accordance with this concept, the physical engine is considered the physical asset represented by the DT rather than a component of the digital twin itself, as shown in Figure 2. The measurement and communication infrastructure provides the interface between the physical and digital domains. In the present study, this infrastructure is implemented using the DEPAS 5.0W diagnostic system, which acquires experimental data from the Weichai WP4 marine diesel generator (Weichai Power Co., Ltd., Weifang, China), including in-cylinder pressure and vibration signals, together with other available operating parameters. The acquired signals are processed locally and transmitted to the user interface and the computational environment through the available communication infrastructure. The DEPAS 5.0W diagnostic system is designed as a portable system for marine diesel engine diagnostics, so the Weichai-based test bench could be considered as an example and replaced with a ship-based engine.

The DT domain contains the digital representation of the investigated engine and its computational representation of the relevant engine processes. In the present implementation, the physics-based 0D–1D thermodynamic engine model implemented in the Blitz-PRO simulation service constitutes the computational core of the digital twin. The model is calibrated for the corresponding physical engine using experimental and documentation data and is used to reproduce the engine operating process for specified operating conditions and parameter values.

The proposed digital twin-based diagnostic system comprises the DT together with the data-acquisition and communication infrastructure and the diagnostic application. The latter provides functions for comparing measured and simulated parameters, evaluating objective functions, testing alternative fault hypotheses, and generating diagnostic indicators. Thus, the DT and the broader diagnostic system are distinguished conceptually, although they operate as an integrated architecture in the proposed implementation.

During operation, DEPAS performs online acquisition and processing of the engine measurements. Selected measurement data are transferred to the digital domain, where the corresponding operating condition is specified for the physics-based model. The model can then be executed through the Blitz-PRO service, and the simulated parameters and process diagrams can be compared with the experimentally obtained data. The resulting deviations are used to calculate diagnostic indicators and evaluate alternative technical-condition hypotheses.

In the present implementation, online data acquisition should not be interpreted as continuous real-time synchronization of the digital twin. The DEPAS measurement system operates continuously during the diagnostic measurement procedure, whereas execution of the Blitz-PRO model is initiated according to the diagnostic workflow using the selected operating condition and measured parameters. Therefore, the present study demonstrates an online data-connected, model-based diagnostic architecture rather than an autonomous continuously synchronized DT with a fixed update frequency. Continuous automatic synchronization and automated online fault identification are considered directions for further development.

According to the conceptual diagram presented in Figure 2, the application of a DT for diagnostics purposes involves several functional stages:

1. Calibration of the physics-based mathematical model of the investigated engine using available experimental and documentation data.
2. Determination of the sensor set through which the DT receives information about the current engine operating mode and its parameters.
3. Determination of objective and constraint parameters, as well as parameters carrying diagnostic information regarding the engine technical condition.
4. Definition of fault hypotheses and the corresponding healthy technical condition/reference state against which deviations are evaluated.

Therefore, calibration of the mathematical model for a digital twin involves not only performing simulations, but also comparing the obtained results with documentation and experimental data. Such comparison is performed for a subset of analyzed operating modes:

$$\mathcal{O}_{cal} \subset \mathcal{O}; \bar{O}_k \in \mathcal{O}_{cal}, k = 1, 2, \dots, N. \quad (6)$$

For each operating mode $\bar{O}_k$, a discrepancy vector $\bar{\delta R}_k$ is determined:

$$\bar{\delta R}_k = g(\bar{R}_{etalon}(\bar{O}_k) - \bar{R}_{model}(\bar{O}_k)), \quad (7)$$

$$\bar{\delta R} = \begin{pmatrix} \delta p_{max} \\ \delta p_i \\ \dots \\ \delta p_s \end{pmatrix}; \bar{R}_{etalon} = \begin{pmatrix} p'_{max} \\ p'_i \\ \dots \\ p'_s \end{pmatrix}; \bar{R}_{model} = \begin{pmatrix} p_{max} \\ p_i \\ \dots \\ p_s \end{pmatrix}, \quad (8)$$

In this formulation, the vector $\bar{\delta R}_k$ may be interpreted as a vector of relative deviations between the simulation results and the available literature or experimental data.

The calibration process of the mathematical model may therefore be represented as an optimization problem aimed at minimizing the following functional:

$$\min \sum_{\bar{O}_k \in \mathcal{O}_{cal}} \|\bar{R}_{etalon}(\bar{O}_k) - f(\bar{I}, \bar{C}, \bar{O}_k, \bar{\delta R}_k)\|^2. \quad (9)$$

An important stage in the application of a DT is the identification of the current engine operating mode using the available (often highly limited) data obtained from sensors installed on the engine. These data may be represented by the observation vector $\bar{Y}_{sensor} \in \bar{R}_{actual}$. For this reason, preliminary calibration and tuning of the mathematical model are essential. The process of engine operating mode identification may also be represented as the following optimization problem:

$$\min_{\bar{\delta R}} \|\bar{Y}_{sensor} - f(\bar{I}, \bar{C}, \bar{\delta R})\|. \quad (10)$$

The application of a DT for diagnostic purposes must solve the principal problem not merely of performing parallel simulation of engine operating processes during diagnostic analysis, but also of developing algorithms capable of producing additional diagnostic criteria or indicators characterizing the technical condition of the engine. This may be formulated as the determination of the engine technical condition deviation vector $\overline{\delta H}$, which contains deviations between a selected set of characteristic engine parameters and their corresponding reference (desired) values:

$$\overline{\delta H} = h(\overline{H}_{actual} - \overline{H}_{etalon}); \quad (11)$$

$$\overline{\delta H} = \begin{pmatrix} \delta P_b \\ \delta b_b \\ \dots \\ \delta g_{NOx} \end{pmatrix}; \overline{H}_{actual} = \begin{pmatrix} P'_b \\ b'_b \\ \dots \\ g'_{NOx} \end{pmatrix}; \overline{H}_{etalon} = \begin{pmatrix} P_b \\ b_b \\ \dots \\ g_{NOx} \end{pmatrix}. \quad (12)$$

Importantly, the values of the vectors $\overline{H}_{actual}$ and $\overline{H}_{etalon}$ may be obtained either experimentally, through simulation, or by a combination of both approaches, which introduces additional variability into digital twin applications. In this paper, $\overline{H}_{etalon}$ denotes the set of engine parameters simulated by the DT for the identified operating mode, whereas $\overline{H}_{actual}$ represents the corresponding set of parameters obtained from direct diagnostic measurements. Both vectors therefore have the same dimensionality and contain corresponding physically comparable parameters, which enables their component-wise comparison.

From this perspective, minimization of the vector $\overline{\delta H}$, or the objective functions, calculated on its basis, may be considered a formal representation of the diagnostic fault identification process, particularly when a set of parameters used for such minimization can be specified:

$$\min_{\overline{\delta H}} \|\overline{H}_{actual} - f(\overline{I}, \overline{C}, \overline{\delta H})\|. \quad (13)$$

It may therefore be stated that the vector $\overline{C}$ activates specific DT algorithms aimed at reliable identification of a particular fault.

Thus, the operation of a marine engine DT may be formally represented as an optimization problem whose solution consists of identifying the factors (parameters governing engine operation) responsible for the actual deviation of engine operating parameters from their reference or expected values. Analysis of these parameters and their values constitutes the diagnostic feature indicating a particular fault condition.

The development of effective methods and algorithms for solving this optimization problem therefore remains an important research problem.

4. Configuring the Digital Twin

The application of digital twins for solving problems related to diagnostics of the technical condition of internal combustion engines may be implemented according to various schemes and principles. One possible approach is considered below using the laboratory test-bench of Odesa National Maritime University based on a Weichai WP4 marine diesel generator [27]. The underlying mathematical model of the DT is based on the on-line service Blitz-PRO, which provides simulations of static and transient ICE operations using 0D–1D thermodynamic models [28,29]. The model enables the simulation of working processes in diesel, spark-ignition, and dual-fuel engines, employing the advanced Razleitsev combustion model, prediction of toxic emissions, and turbocharger performance maps to achieve a closed simulation loop.

According to the scheme presented in Figure 2, the main stages include calibration of the digital twin mathematical model, identification of the current engine operating mode, and diagnostics of the engine technical condition.

4.1. Mathematical Model Calibration

At the first stage, calibration of the mathematical model is performed considering the operating mode space $\mathcal{O}_{cal} \subset \mathcal{O}$. For the investigated engine, this space is restricted to the neighborhood of a few fixed operating modes: the Weichai WP4 test-bench operates at a constant rotational speed while the electrical load is varied through three available resistance-load levels, as shown in Table 1.

Table 1. Set of operating modes $\mathcal{O}_{cal}$ used for mathematical model setup.

Nº	Designation	P_b , kW	n_{crank} , rpm
1	$\bar{O}_1$	0	670
2	$\bar{O}_2$	0	1500
3	$\bar{O}_3$	18	1500
4	$\bar{O}_4$	36	1500

To determine the mathematical model calibration parameters, i.e., to obtain the array of vector values $\bar{R}_{etalon}(\bar{O}_k)$, both the literature data and experimental engine test data were used. Such experiments should preferably be carried out according to classical experimental procedures, namely:

- Ensuring steady-state engine operation with stabilization of all controlled parameters, primarily temperatures of cooling media and exhaust gases;
- Applying averaging procedures over a sample of 50–100 consecutive engine cycles in order to reduce the influence of cycle-to-cycle variability of the engine operating process.

Such experiments require specialized equipment and laboratory test-bench conditions; however, they provide the most reliable information regarding engine operating processes. Table 2 and Figure 3 present examples of experimental data obtained in accordance with the above-mentioned principles.

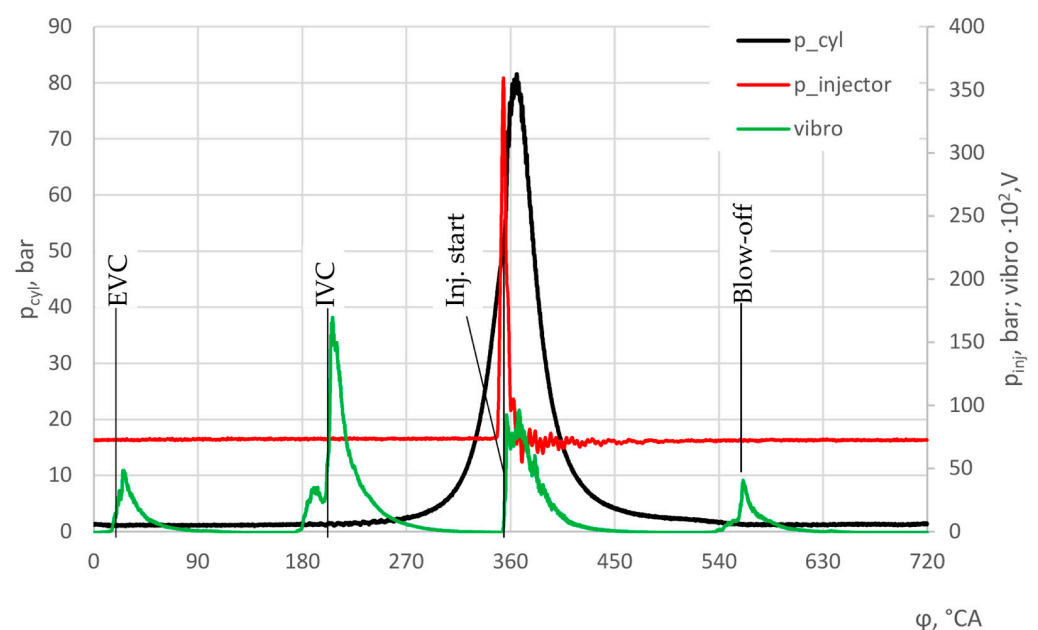


Figure 3. Averaged and normalized experimental data for the test engine at $\bar{O}_3$ ($P_b = 18$ kW at 1500 rpm) as a result of 72 consecutive cycles being processed.

Table 2. Example of the vector $\bar{R}_{etalon}$ for the operating mode $\bar{O}_3 = (P_b = 18 \text{ kW}, n = 1500 \text{ rpm})$.

Nº	Parameter	Units	Value	Accuracy
Parameters of the operating mode				
1	P_b	kW	18.5	± 0.1
2	n_{crank}	rpm	1509.3	± 0.1
3	p_0	bar	1.01	± 0.01
4	t_0	$^{\circ}\text{C}$	10	± 0.1
5	t_{w1}	$^{\circ}\text{C}$	80	± 0.5
6	t_{oil1}	$^{\circ}\text{C}$	75	± 0.5
Experimental data				
7	$p_{cyl} = f(\varphi)$	bar	Arrays of data, visualization as diagrams (see Figure 3 for example)	1%
8	$p_{inj} = f(\varphi)$	bar		1%
9	$p_{pump} = f(\varphi)$	bar		1%
10	flywheel = $f(\varphi)$	V		-
11	$V_{vibro} = f(\varphi)$	V		-
12	p_s	bar	1.15	± 0.01
13	t_s	$^{\circ}\text{C}$	43.3	± 0.1
14	G_{air}	kg/s	4.62	± 0.005
15	G_{fuel}	kg/h		± 0.005
16	t_t/t_2	$^{\circ}\text{C}$	281.5/258.3	± 0.5
17	$t_{t.cyl1}, t_{t.cyl2}, t_{t.cyl3},$ $t_{t.cyl4}$	$^{\circ}\text{C}$	267.3, 252.5, 279.3, 235.5	± 0.5
18	[CO]	ppm	80.4	2%
19	[NO _x]	ppm	1230	2%
20	[O ₂]	%	15.4	2%
Manufacturer data				
21	ε	-	18	-
22	b_b	g/(kW·h)	-	-
23	φ_{IVC}	$^{\circ}\text{CA}$ after BDC	20	-
24	φ_{IVO}	$^{\circ}\text{CA}$ before TDC	9	-
25	φ_{EVC}	$^{\circ}\text{CA}$ after TDC	18	-
26	φ_{EV0}	$^{\circ}\text{CA}$ before BDC	42	-
Outcome of experimental data processing				
27	p_i	bar	3.97	± 0.01
28	b_i	g/(kW·h)	173.8	± 0.5
29	p_{max}	bar	79.4	± 0.5
30	p_c	bar	57	± 0.5
31	p_{ign}	bar	52.8	± 0.5
32	φ_{IVC}	$^{\circ}\text{CA}$ after BDC	20.2	± 0.5
33	φ_{IVO}	$^{\circ}\text{CA}$ before TDC	-	
34	φ_{EVC}	$^{\circ}\text{CA}$ after TDC	19.8	± 0.5
35	φ_{EV0}	$^{\circ}\text{CA}$ before BDC	-	
36	φ_{ign}	$^{\circ}\text{CA}$ before TDC	5.7	± 0.5
37	$\varphi_{inj.start}$	$^{\circ}\text{CA}$ before TDC	9	± 0.5
38	φ_{inj}	$^{\circ}\text{CA}$	8	± 0.5
39	$d\sigma/d\varphi = f(\varphi)$	-		
40	$dx/d\varphi = f(\varphi)$	-		

A separate important problem is the processing of experimental data, during which several tasks must be solved:

- Reliable determination of the top dead center (TDC) position;
- Accounting for the influence of crankshaft angular velocity irregularity;
- Averaging of sequential cycle data;
- Determination of fuel injection timing and injection duration;
- Determination of fuel ignition timing;

- Calculation of fuel injection characteristics and heat release characteristics.

Each of the above-mentioned tasks requires the development of efficient computational algorithms and their implementation in software. For example, accurate determination of the TDC position is performed using both the crankshaft position sensor signal and analysis of the compression curve of the experimental indicator diagram using methods proposed in [30–32]. These methods are implemented in the DEPAS 5.0W diagnostic system and have proven their reliability. Compensation for errors associated with crankshaft rotational speed irregularity is achieved using both direct signal acquisition from the flywheel toothed ring and analytical methods based on calculation of the resultant tangential force. FFT-based filtering algorithms are applied for determination of fuel ignition timing and the calculation of heat release characteristics as it is shown in Figure 4.

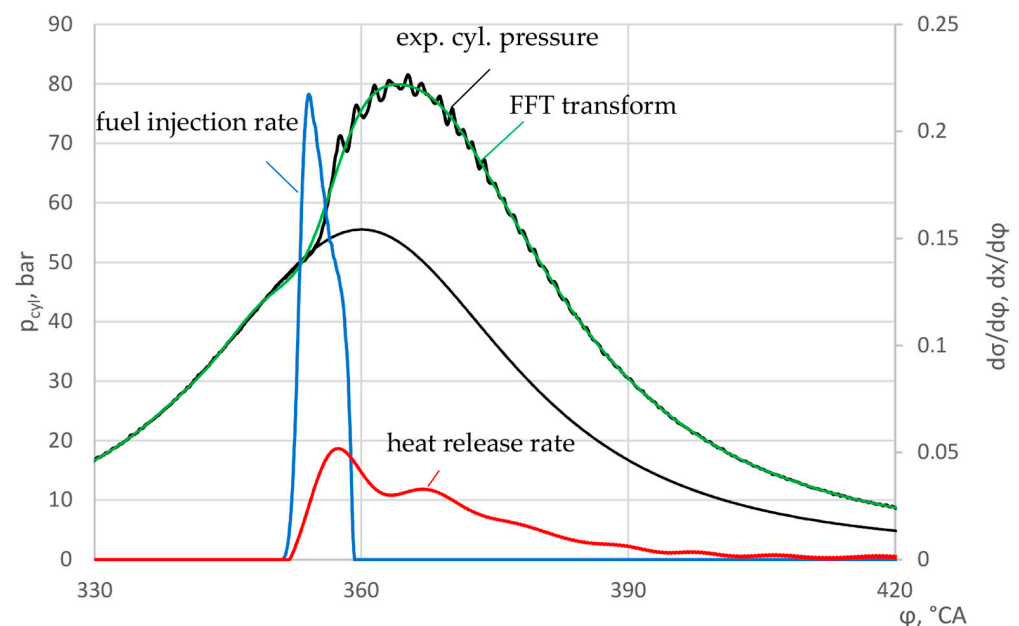


Figure 4. Experimental cylinder pressure diagram superimposed with the calculated fuel injection rate diagrams and heat release rate diagrams for a test engine at mode $\overline{O}_3$ ($P_b = 18$ kW at 1500 rpm).

The following criteria were used for calibration of the mathematical model. For integral parameters averaged over the engine cycle, such as boost pressure, fuel consumption rate, and similar quantities, the objective function δ_{int} is proposed:

$$\delta_{int} = \sqrt{\frac{1}{N} \sum_{i=1}^N \left(\frac{y_i^{exp} - y_i^{sim}}{y_i^{exp}} \right)^2} \cdot 100\% \quad (14)$$

where N is the number of selected parameters, y_i^{exp} is the experimentally measured value, and y_i^{sim} is the corresponding simulated value.

For the in-cylinder pressure diagram (indicator diagram), it is reasonable to use the parameter Δp_{RMS} , defined as the root-mean-square deviation between the simulated and experimental pressure traces over the engine cycle:

$$\Delta p_{RMS} = \sqrt{\frac{1}{L} \sum_{j=1}^L (p_j^{exp} - p_j^{sim})^2} \quad (15)$$

where L is the number of measurement points in the experimental indicator diagram.

The results of mathematical model calibration for three reference engine operating modes are presented in Figure 5 and Table 3.

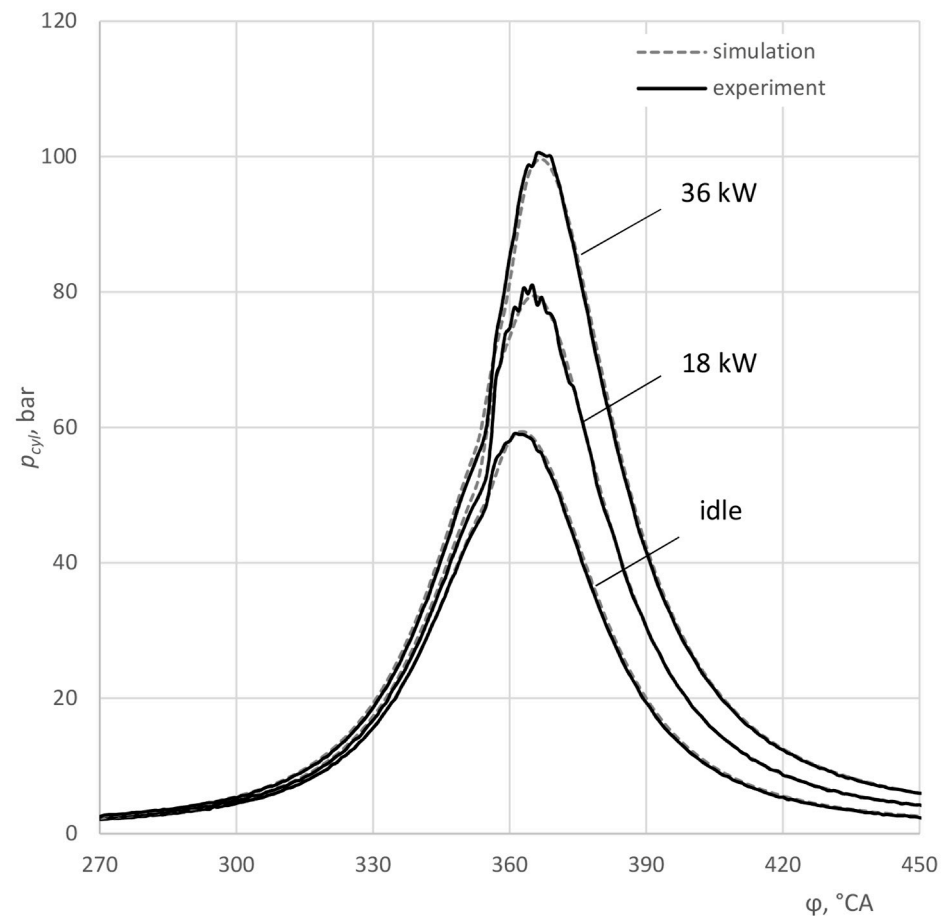


Figure 5. Simulated and experimental indicated diagrams after mathematical model calibration.

Table 3. Mathematical model calibration accuracy.

Operating Mode	Engine Power	δ_{int} , %	Δp_{RMS} , bar
$\bar{O}_2$	0	1.26	0.059
$\bar{O}_3$	18	1.13	0.216
$\bar{O}_4$	36	1.52	0.235

4.2. Operating Mode Identification

From the perspective of mathematical modeling, the problem of identifying the current engine operating mode using sensor data requires accurate synthesis of fuel injection characteristics, fuel combustion characteristics, and proper determination of turbocharger turbomachinery parameters.

An important requirement is the automatic adjustment of the corresponding model calibration parameters based on the calibration data obtained at the reference operating points. As an example of such model adaptation, consider the fuel injection characteristics. Figure 6 presents the experimentally and computationally determined injection rate profiles for three reference operating modes of the investigated diesel generator set: $\bar{O}_2$, $\bar{O}_3$, and $\bar{O}_4$.

The obtained injection characteristics may be directly utilized within the digital twin; however, they remain valid only for the operating conditions under which they were determined. Therefore, the digital twin must be capable of modifying the fuel injection characteristics according to changes in the engine operating mode. In the case of a diesel

generator set, the parameter that primarily characterizes operating mode variations from the perspective of fuel injection is the injection duration, which can be experimentally determined through analysis of a vibroacoustic sensor signal.

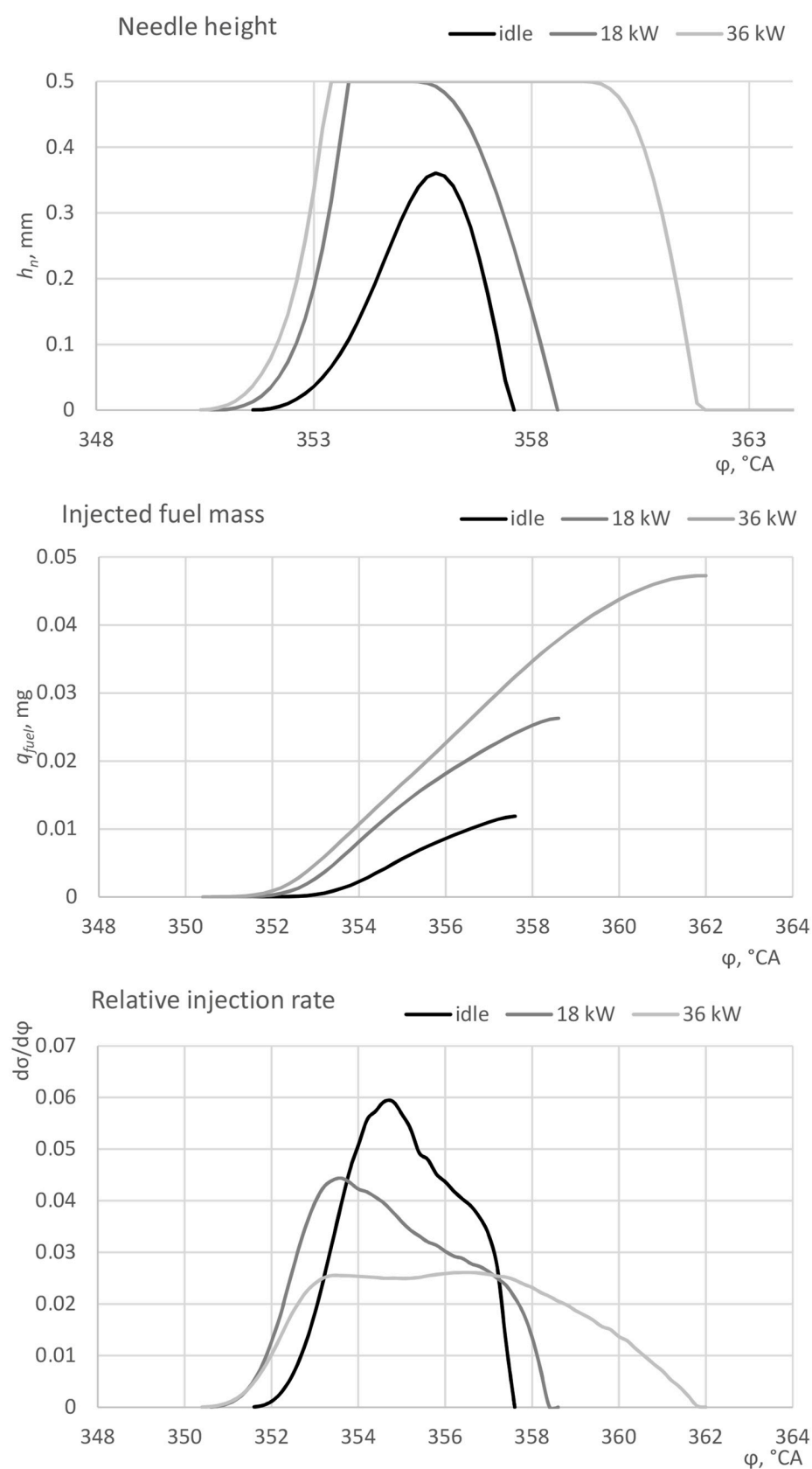


Figure 6. Fuel-injection diagrams for three operating modes at 1500 rpm.

In his work, Razleitsev [33] proposed approximating fuel injection characteristics using the sum of two parabola-type functions:

$$\frac{d\sigma}{d\bar{\varphi}} = \left(\frac{d\sigma}{d\bar{\varphi}}\right)_1 + \left(\frac{d\sigma}{d\bar{\varphi}}\right)_2; \quad (16)$$

$$\frac{d\sigma}{d\bar{\varphi}} = \left[a \cdot (\bar{\varphi}^{m_1-1} - b \cdot \bar{\varphi}^{m_2-1}) \right]_{\bar{\varphi}=0}^{\bar{\varphi}=\Phi_{inj1}} + c \cdot (\bar{\varphi}^{m_3-1} - \bar{\varphi}^{m_4-1})_{\bar{\varphi}=0}^{\bar{\varphi}=1}, \quad (17)$$

where $\bar{\varphi} = \varphi / \varphi_{inj}$ is the normalized injection angle, Φ_{inj1} is the relative duration of application of the first approximation function, and a , b , c , m_1 , m_2 , m_3 , and m_4 are calibration coefficients.

Figure 6 shows the experimentally and computationally derived injection characteristics plotted as a function of the normalized injection angle $\bar{\varphi}$. A common feature of all obtained curves can be observed during the initial injection phase, namely a gradual increase in the injection rate that closely follows an exponential trend.

Such behavior cannot be adequately represented by the original Razleitsev equations. However, satisfactory approximation can be achieved through a minor modification of the model:

$$\frac{d\sigma}{d\bar{\varphi}} = \left[a \cdot (\bar{\varphi}^{m_1-1} - b \cdot \bar{\varphi}^{m_2-1}) \right]_{\bar{\varphi}=0}^{\bar{\varphi}=\Phi_{inj1}} + c \cdot (\bar{\varphi}^{m_3-1} - \bar{\varphi}^{m_4-1})_{\bar{\varphi}=\Phi_{inj2}}^{\bar{\varphi}=1} \quad (18)$$

where Φ_{inj2} denotes the relative start point of application of the second approximation function.

When $\Phi_{inj2} = 0$, the original Razleitsev formulation is recovered. Appropriate selection of Φ_{inj1} and Φ_{inj2} enables satisfactory approximation of the initial stage of fuel injection.

When the injection duration changes, the calibration parameters a , b , c , m_1 , m_2 , m_3 , m_4 , Φ_{inj1} , and Φ_{inj2} must also change. However, for practical implementation within a digital twin, it is desirable to minimize the number of variable parameters. In the present case, satisfactory representation of the injection characteristics over the investigated operating range can be achieved by varying only three parameters: m_4 , Φ_{inj1} , and Φ_{inj2} .

Figure 7 presents the regression relationships obtained for these parameters as functions of the injection duration φ_{inj} . Application of the proposed fuel injection model to both the reference operating modes and an arbitrary intermediate operating mode is illustrated in Figure 8. The results demonstrate that the modified equations provide a sufficiently accurate approximation of the experimental injection characteristics, including the critical initial stage of fuel injection.

4.3. Fault Identification

To employ a digital twin for engine condition diagnostics, an optimization problem must be solved. One potentially effective approach is the application of Design of Experiments (DoE) methodology and statistical response surface analysis.

In particular, the following approach may be proposed. The engine is considered as a collection of interconnected systems and mechanisms, including the fuel injection system, air supply system, valve timing mechanism, cylinder–piston assembly, and others. For each system or mechanism, a set of parameters can be identified that reflects specific fault conditions and can be incorporated into the engine process simulation.

For the fuel injection system, such parameters may include the fuel injection timing, injection duration, injector nozzle hole diameter, and fuel density and viscosity. For the valve timing mechanism, the relevant parameters include intake and exhaust valve opening and closing timings. For the air supply system, characteristic parameters include charge-air cooler resistance and effectiveness, compressor and turbine adiabatic efficiencies, turbine

flow capacity, exhaust system resistance, and similar quantities. The selection of parameters depends on the specific engine under investigation.

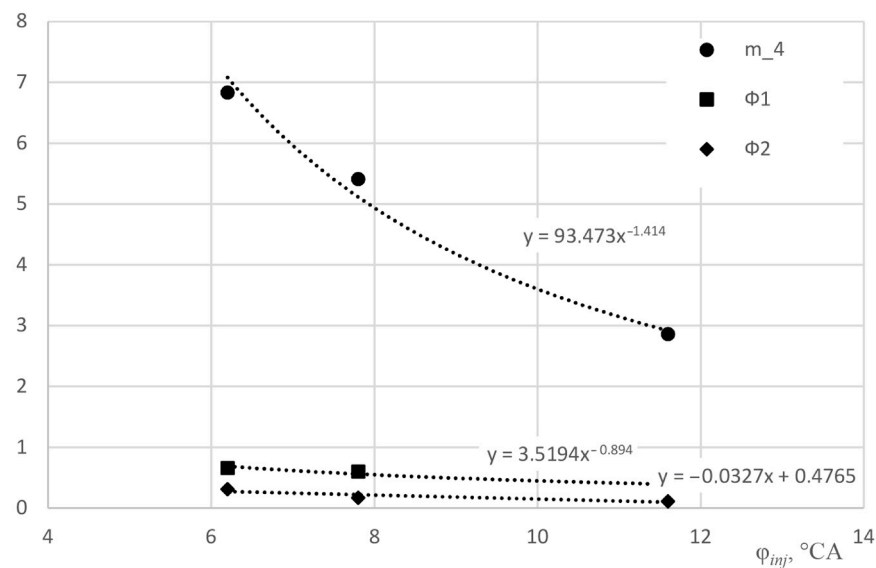


Figure 7. Regressions for chosen coefficients of injection characteristics prediction.

The fault identification procedure may be formulated as a sequential analysis of each selected engine subsystem. For this purpose, a numerical experiment is performed using either a full-factorial experimental design matrix or an appropriate constrained factorial design. For each parameter representing a potential fault, a baseline level and variation interval are specified. The objective functions are selected to quantify deviations between simulation results and diagnostic or monitoring data obtained from the actual engine.

For integral engine performance parameters, the objective function δ_{int} defined by Equation (14) is employed. For indicator diagrams, which remain one of the most informative diagnostic tools in marine engine practice, the following objective function is proposed:

$$\Delta p_{ID} = \sqrt{\Delta p_{RMS} \cdot \Delta p_{max}} \quad (19)$$

where Δp_{RMS} and Δp_{max} denote the root-mean-square deviation (defined according to Equation (15)) and the maximum deviation between experimental and simulated indicator diagrams, respectively.

For a more detailed analysis of indicator diagram discrepancies, logarithmic objective functions may also be introduced:

$$\Delta \ln(\bar{p})_{ID} = \sqrt{\Delta \ln(\bar{p})_{RMS} \cdot \Delta \ln(\bar{p})_{max}}, \quad (20)$$

$$\Delta \ln(\bar{p})_{RMS} = \sqrt{\frac{1}{L} \sum_{j=1}^L \left(\ln(\bar{p})_j^{exp} - \ln(\bar{p})_j^{sim} \right)^2}, \quad (21)$$

where $\bar{p} = p/p_{ref}$ —the dimensionless ratio between pressure and reference pressure (for the current study, $p_{ref} = 1$ bar).

The logarithmic representation normalizes deviations across different phases of the engine cycle, particularly during combustion and gas-exchange processes. This feature is important when diagnosing faults originating from different engine subsystems. Figure 9 illustrates the simulation results obtained for a prototype engine, selected as the MAN B&W 8S50ME-B8 operating at 75% MCR along the propeller characteristic. A combined

fault condition involving cylinder wear and exhaust valve malfunction was artificially introduced. It can be observed that the $\ln(p) = f(\varphi)$ diagram provides substantially better visualization of deviations during both combustion and gas-exchange phases than the conventional $p = f(\varphi)$ indicator diagram.

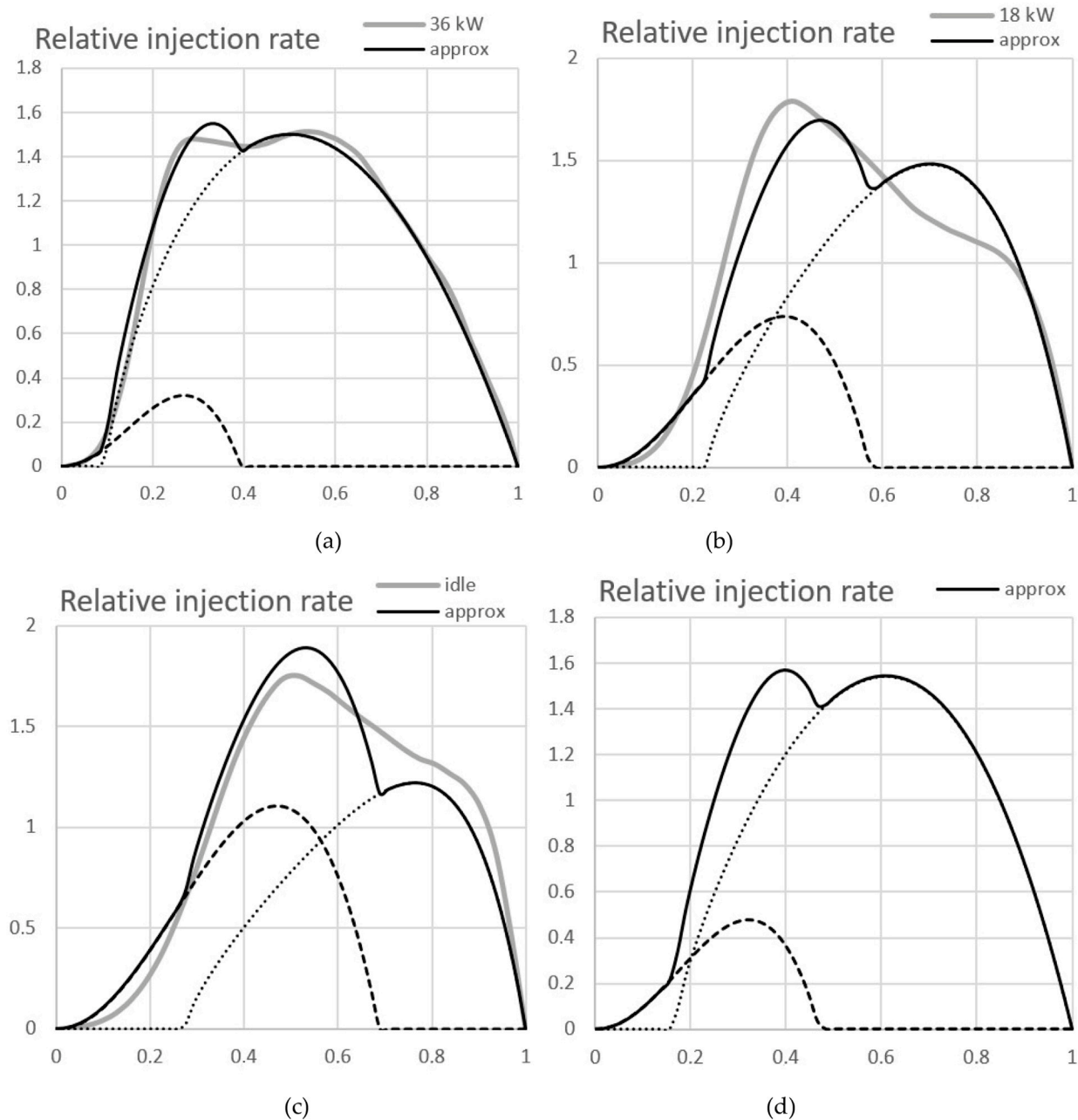


Figure 8. Experimental (gray) and simulated (black) fuel injection diagrams: (a) 36 kW, (b) 18 kW, (c) idle, (d) for intermediate point demonstration ($\varphi_{inj} = 10^\circ \text{CA}$).

Before demonstrating the application of the proposed DoE methodology for the research Weichai WP4 test-bench, consider the synthetic (simulated) case for the MAN B&W 6S80ME-C7 low-speed marine diesel engine prototype. A mathematical model setup was developed within the Blitz-PRO simulation environment based on manufacturer and sea-trial data for this engine. A fault associated with the fuel injection system was simulated for one of the six cylinders while operating at 75% MCR along the propeller characteristic.

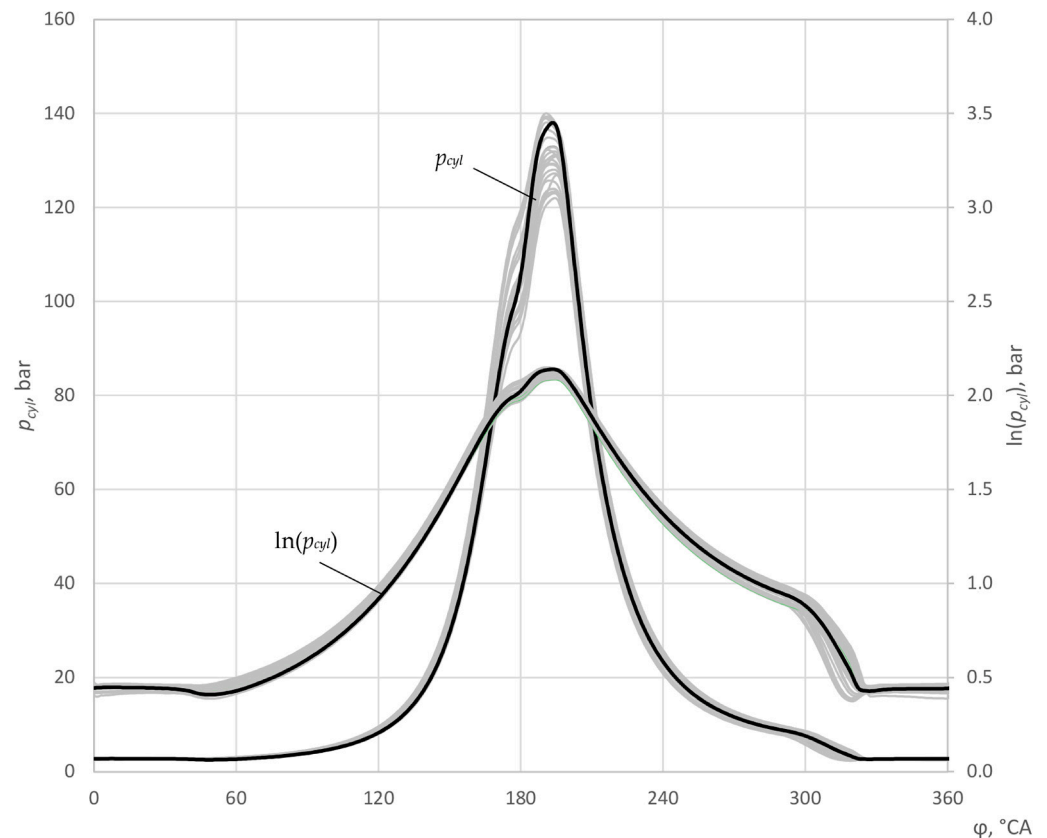


Figure 9. Constrained factorial experiment simulation diagrams for MAN B&W 8S50ME-B8 at valve-train system and cylinder wear malfunction. Black lines—target diagrams, gray lines—24 variants of the constrained experiment.

The input dataset available for fault detection consisted of measurements obtainable using standard engine instrumentation, as summarized in Table 4, together with the indicator diagram of the affected cylinder. Furthermore, it was assumed that the faulty subsystem was known in advance and that only two fault-related parameters deviated simultaneously from their healthy values, which was considered at the stage of experiment design. It was additionally assumed that the faulty subsystem was known in advance and that only two fault-related parameters deviated simultaneously from their healthy reference values. This assumption was incorporated into the design of the numerical experiment. For four factors with three levels each, the complete factorial space contains ($3^4 = 81$) factor combinations. However, under the imposed constraint that only two factors may deviate simultaneously from their reference values, the number of investigated combinations is reduced to 24. Thus, the numerical experiment was based on a constrained factorial design. Other assumptions concerning the number of simultaneously deviating factors, the number of factor levels, and additional physical constraints would result in a different experimental design matrix.

All simulations were performed using a constant cycle fuel delivery of $q_f = 135.4$ g/cycle. The following diagnostic factors were investigated:

- Injection timing $\varphi_{start.inj}$, characterizing fuel pump adjustment quality and high-pressure fuel pump valve condition;
- Injection duration φ_{inj} , characterizing wear of fuel equipment and injector adjustment;
- Injector nozzle hole diameter $d_{inj.holes}$, characterizing nozzle wear;
- Coefficient E_c in the fuel spray mean diameter correlation, characterizing deterioration of the injector needle valve.

Table 4. Set of data from sensors for a 75% MCR propeller load operation of the virtual engine MAN B&W 6S80ME-C7.

Parameter	Units	Etalon	Malfunction
Indicated mean effective pressure, IMEP	bar	16.66	15.99
Maximum pressure, p_{max}	bar	120.3	111.3
Compression pressure, p_{comp}	bar	107.5	105.7
Exhaust gas temperature after exhaust valve, t_{exh}	°C	376.5	405
Scavenge air receiver pressure, p_s	bar	2.94	2.93
Scavenge air cooler air inlet temperature, t_k	°C	142	140.8
Air pressure drop across scavenge air cooler, Δp_{CAC}	bar	0.02	0.02
Air pressure drop across air intake filter, Δp_{int}	bar	0.01	0.01
Scavenge air receiver temperature, t_s	°C	46.4	46.5
T/C air intake temperature, t_{int}	°C	20	20

Table 5 summarizes the baseline factor levels, variation intervals, and parameter values corresponding to both healthy (etalon) and faulty (malfunction) operating conditions.

Table 5. Values of variable factors.

Parameter	Units	Base Level	Interval of Variation	Etalon Value	Malfunction Value
$\varphi_{start.inj}$	°CA	2	3	2	2
φ_{inj}	°CA	23	3	20	24
$d_{inj.holes}$	mm	1.3	0.1	1.2	1.35
E_c	-	1.2	0.05	1.15	1.15

Table 6 presents the constrained factorial design matrix together with the corresponding values of the three objective functions δ_{int} , Δp_{ID} , and $\Delta \ln(p)_{ID}$. The same table also contains the calculated response surfaces obtained using second-order polynomial regression models. To assess the adequacy of the second-order response surface models used for inverse fault identification, additional statistical indicators were calculated for each regression function, including the coefficient of determination (R^2), adjusted coefficient of determination (adjusted R^2), and the root mean square error (RMSE). The obtained response surfaces demonstrated high approximation quality, with R^2 values ranging from 0.947 to 0.978 and adjusted R^2 values ranging from 0.864 to 0.943. The logarithmic pressure objective function exhibited the lowest adjusted R^2 , indicating that this response is more difficult to approximate because it is particularly sensitive to deviations during the gas-exchange process. Figure 10 presents the synthesized indicator diagrams corresponding to different factor combinations.

Table 6. Constrained factorial design matrix for the controlled parameters.

№	Factors				Target Functions			Regression		
	$\varphi_{start.inj}$	φ_{inj}	$d_{inj.holes}$	E_c	δ_{int}	Δp_{ID}	$\Delta \ln(p)_{ID}$	δ'_{int}	$\Delta p'_{ID}$	$\Delta \ln(p)_{ID}$
	°CA	°CA	mm	-	%	bar	-	%	bar	-
1	2	20	1.4	1.25	1.37	2.64	0.0114	1.58	3.14	0.0159
2	2	20	1.3	1.25	3.28	5.54	0.0223	2.91	4.91	0.0197
3	2	26	1.2	1.25	0.64	0.99	0.0059	1.01	1.32	0.0047
4	2	23	1.2	1.25	3.05	4.30	0.0190	2.44	3.26	0.0209
5	5	20	1.2	1.25	9.54	17.34	0.0671	9.61	17.50	0.0651
6	−1	20	1.2	1.25	2.47	3.98	0.0537	2.80	4.65	0.0531
7	2	20	1.4	1.2	1.59	3.54	0.0141	1.90	3.64	0.0108
8	2	20	1.3	1.2	4.18	6.62	0.0265	3.45	5.66	0.0204

Table 6. Cont.

№	Factors				Target Functions			Regression		
	$\varphi_{start.inj}$	φ_{inj}	$d_{inj.holes}$	E_c	δ_{int}	Δp_{ID}	$\Delta \ln(p)_{ID}$	δ'_{int}	$\Delta p'_{ID}$	$\Delta \ln(p)_{ID}$
	°CA	°CA	mm	-	%	bar	-	%	bar	-
9	2	26	1.2	1.2	1.28	1.48	0.0080	1.46	2.31	0.0070
10	2	23	1.2	1.2	3.66	5.15	0.0222	3.04	4.26	0.0254
11	5	20	1.2	1.2	10.09	18.51	0.0704	10.77	19.48	0.0756
12	−1	20	1.2	1.2	2.96	4.72	0.0538	3.15	4.67	0.0559
13	2	26	1.4	1.15	3.54	5.27	0.0238	2.34	3.61	0.0193
14	2	23	1.4	1.15	0.51	0.69	0.0044	1.69	2.45	0.0118
15	5	20	1.4	1.15	6.15	12.26	0.0455	6.01	11.95	0.0474
16	−1	20	1.4	1.15	1.10	2.74	0.0115	0.73	2.37	0.0055
17	2	26	1.3	1.15	0.58	1.29	0.0055	1.72	2.78	0.0069
18	2	23	1.3	1.15	2.12	3.00	0.0129	2.26	3.17	0.0134
19	5	20	1.3	1.15	8.88	16.13	0.0640	8.56	16.03	0.0594
20	−1	20	1.3	1.15	1.58	2.82	0.0133	1.71	2.85	0.0247
21	5	26	1.2	1.15	5.35	9.15	0.0357	5.11	8.89	0.0351
22	−1	26	1.2	1.15	1.26	4.50	0.0193	1.00	3.79	0.0253
23	5	23	1.2	1.15	7.98	14.20	0.0600	7.93	13.75	0.0601
24	−1	23	1.2	1.15	1.68	2.37	0.0544	1.66	2.82	0.0414
							R^2	0.966	0.978	0.947
							R^2_{adj}	0.912	0.943	0.864
							RMSE	0.875	1.291	0.008

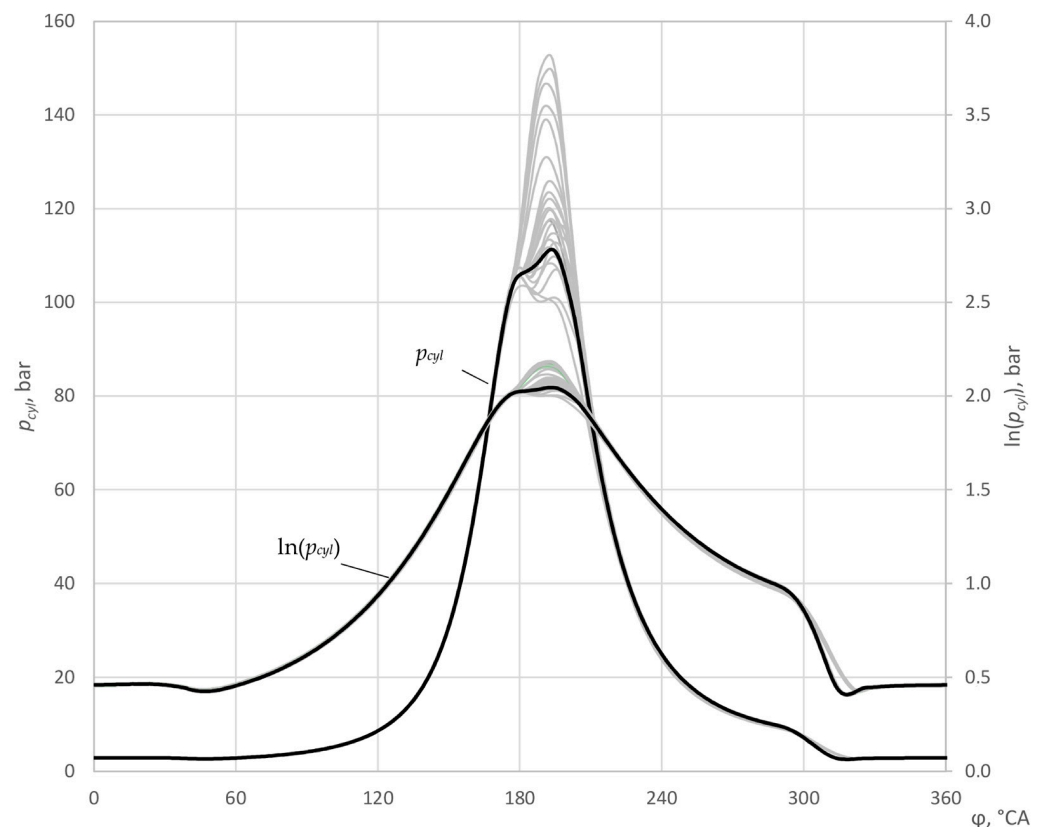


Figure 10. Constrained factorial experiment simulation diagrams for MAN B&W 6S80ME-C7 at fuel-injection system malfunction. Black lines—target diagrams, gray lines—24 variants of the constrained experiment.

The response functions were approximated using second-order polynomial regression equations of the form:

$$g(x_1, x_2, x_3, x_4) = a_0 + a_1 \cdot x_1 + a_2 \cdot x_2 + a_3 \cdot x_3 + a_4 \cdot x_4 + a_5 \cdot x_1 \cdot x_2 + a_6 \cdot x_1 \cdot x_3 + a_7 \cdot x_1 \cdot x_4 + a_8 \cdot x_2 \cdot x_3 + a_9 \cdot x_2 \cdot x_4 + a_{10} \cdot x_3 \cdot x_4 + a_{11} \cdot x_1^2 + a_{12} \cdot x_2^2 + a_{13} \cdot x_3^2 + a_{14} \cdot x_4^2 \quad (22)$$

The coefficients a_i for the three objective functions are provided in Table 7.

Table 7. Coefficients of regression equations for selected target functions.

	a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7
δ_{int}	-9.57×10^1	9.07×10^{00}	-6.82×10^{00}	-1.16×10^2	4.08×10^2	-1.20×10^{-1}	-2.62×10^{00}	-2.68×10^{00}
Δp_{ID}	-1.59×10^2	2.20×10^1	-1.01×10^1	-1.66×10^2	6.20×10^2	-3.24×10^{-1}	-6.00×10^{00}	-6.55×10^{00}
$\Delta \ln(p)_{ID}$	-1.14×10^{00}	1.40×10^{-2}	-4.26×10^{-2}	-2.53×10^{00}	5.25×10^{00}	-4.89×10^{-4}	1.21×10^{-2}	-2.59×10^{-2}
	a_8	a_9	a_{10}	a_{11}	a_{12}	a_{13}	a_{14}	
δ_{int}	3.99×10^{00}	1.04×10^{00}	4.40×10^1	2.40×10^{-1}	1.00×10^{-2}	-9.90×10^{00}	-2.01×10^2	
Δp_{ID}	5.18×10^{00}	9.32×10^{-3}	5.05×10^1	4.92×10^{-1}	7.99×10^{-2}	-2.20×10^{00}	-2.81×10^2	
$\Delta \ln(p)_{ID}$	4.66×10^{-2}	1.45×10^{-2}	1.18×10^{00}	3.92×10^{-3}	-7.32×10^{-4}	2.16×10^{-2}	-2.87×10^{00}	

As an additional assessment of the regression response surfaces, six intermediate factor combinations within the investigated factor space were considered. The same constraint used in the design of the numerical experiment was applied when selecting these points: only two fault-related factors were allowed to deviate simultaneously from their reference values. This ensured that the intermediate-point assessment remained consistent with the assumed diagnostic scenario.

For each factor combination, the objective-function values obtained from the physical engine-process simulation were compared with the corresponding values calculated using the polynomial regression equations (Table 8). The comparison shows that the agreement between the simulation and regression results at the intermediate points is generally poorer than that observed at the design points. Nevertheless, the response surfaces may still be useful for preliminary localization of the objective-function extrema and for conducting inverse optimization within the investigated parameter space. However, the resulting extrema should be verified using the full engine-process simulation model.

Table 8. Intermediate-point assessment of the regression response surfaces.

№	Factors				Target Functions			Regression		
	$\Phi_{start.inj}$	Φ_{inj}	$d_{inj.holes}$	E_c	δ_{int}	Δp_{ID}	$\Delta \ln(p)_{ID}$	δ'_{int}	$\Delta p'_{ID}$	$\Delta \ln(p)_{ID}$
	°CA	°CA	mm	-	%	bar	-	%	bar	-
1	3	22.5	1.2	1.15	5.99	9.67	0.0548	4.29	6.80	0.0249
2	2	25	1.2	1.23	1.66	2.05	0.0102	1.79	2.73	0.0145
3	1.5	20	1.25	1.15	3.21	5.00	0.0132	5.49	8.54	0.0139
4	4	20	1.2	1.19	8.90	15.80	0.0624	8.38	14.72	0.0529
5	-0.8	20	1.37	1.15	0.45	2.01	0.0085	0.96	2.30	0.008
6	2	23.5	1.33	1.15	0.93	1.32	0.006	2.07	2.87	0.0134
R ²								0.828	0.854	0.675
RMSE								1.285	2.021	0.013

The obtained regression models were subsequently analyzed to locate their extrema and determine the factor combinations corresponding to the minimum objective function values. The results are presented in Table 9.

As can be seen, the analysis successfully identified the nature of the simulated malfunction, namely prolonged fuel injection (a possible consequence of leakage within the high-pressure fuel pump) combined with deteriorated fuel atomization (a possible consequence of injector nozzle wear). However, the exact numerical values of the fault-related parameters were not estimated accurately.

Table 9. Estimation of factor values by regression functions extremum analysis.

Parameter	Units	From Functions Extremums			Actual Values
		δ'_{int}	$\Delta p'_{ID}$	$\Delta \ln(p)'_{ID}$	
$\varphi_{start.inj}$	°CA	0.2	2	2	2
φ_{inj}	°CA	20	26	26	24
$d_{inj.holes}$	mm	1.4	1.2	1.2	1.35
E_c	-	1.15	1.25	1.25	1.15

$$d_{32} = 10^6 E_c d_{inj.holes} \frac{M^{0.0733}}{(\bar{\rho} We)^{0.266}}; \quad (23)$$

$$M = \frac{\mu_{fuel}^2}{d_{inj.holes} \rho_{fuel} \sigma_{fuel}}; \bar{\rho} = \frac{\rho_c}{\rho_{fuel}}; We = \frac{u_{inj}^2 d_{inj.holes} \rho_{fuel}}{\sigma_{fuel}} \quad (24)$$

Consequently, the results demonstrate the importance of selecting factors with sufficiently independent physical effects when constructing the diagnostic experiment.

It is also informative to compare the optimized parameter values with the actual values used to simulate the malfunction. Such a comparison is presented in Figure 11a. The results indicate that the parameter combinations identified through optimization reproduce the actual engine process with satisfactory accuracy, particularly for parameter set (3) shown in Figure 11.

The obtained results for this case also reveal an important limitation of the inverse diagnostic problem. Different combinations of physically meaningful model parameters may produce very similar engine responses. Therefore, a good agreement between a simulated and measured pressure trace does not necessarily imply unique identification of the underlying fault parameters. This behavior is related to the physical meaning of the investigated factors and their influence on the engine working process. For example, a reduction in the injection advance angle may decrease the maximum combustion pressure and increase the exhaust-gas temperature upstream of the turbocharger turbine. A similar effect may result from an increase in the injection duration or the nozzle-hole diameter. Consequently, deterioration of the fuel injection system, resulting, for example, from an increased injection duration, may be partially compensated for by advancing the start of fuel injection. Such compensating effects can lead to closer objective function responses for different combinations of model parameters. Figure 11b illustrates this phenomenon using the dependence of the δ_{int} on the injection advance angle, $\varphi_{start.inj}$. The solid curve corresponds to a constant injection duration of $\varphi_{inj} = 24$ °CA, and the dashed curve was obtained by adjusting φ_{inj} for each value of $\varphi_{start.inj}$ to achieve the lowest attainable value of δ_{int} . The two other factors— $d_{inj.holes} = 1.35$ mm and $E_c = 1.15$ were kept constant. The results demonstrate that the compensating influence of one factor can reduce the distinctness of the extremum associated with another factor. Consequently, the location of the minimum may become more difficult to determine unambiguously, which complicates the inverse identification of the individual parameter values. The complexity of the inverse problem may increase further when the number of investigated factors is expanded. Additional factors can introduce new compensating effects and interactions, resulting in several parameter combinations with similar objective-function values, as well as flatter or less pronounced extrema.

In this sense, the digital twin should not be regarded as a mechanism that automatically guarantees unique fault identification. Rather, it provides a physics-based environment in which competing fault hypotheses can be generated, compared, and assessed according to their consistency with the available measurements. This distinction is particularly important for practical diagnostics. The diagnostic conclusion may be sufficiently reliable at

the level of a fault mechanism or system, even when the individual physical parameters responsible for the fault cannot be uniquely estimated. For example, the results obtained in the present study allow deterioration of fuel injection and atomization to be identified, while the individual contributions of the nozzle-hole diameter and the spray-model coefficient cannot be uniquely separated. Such practical non-identifiability should therefore be considered an inherent characteristic of the proposed inverse problem rather than an indication that the DT itself is unsuitable for diagnostics.

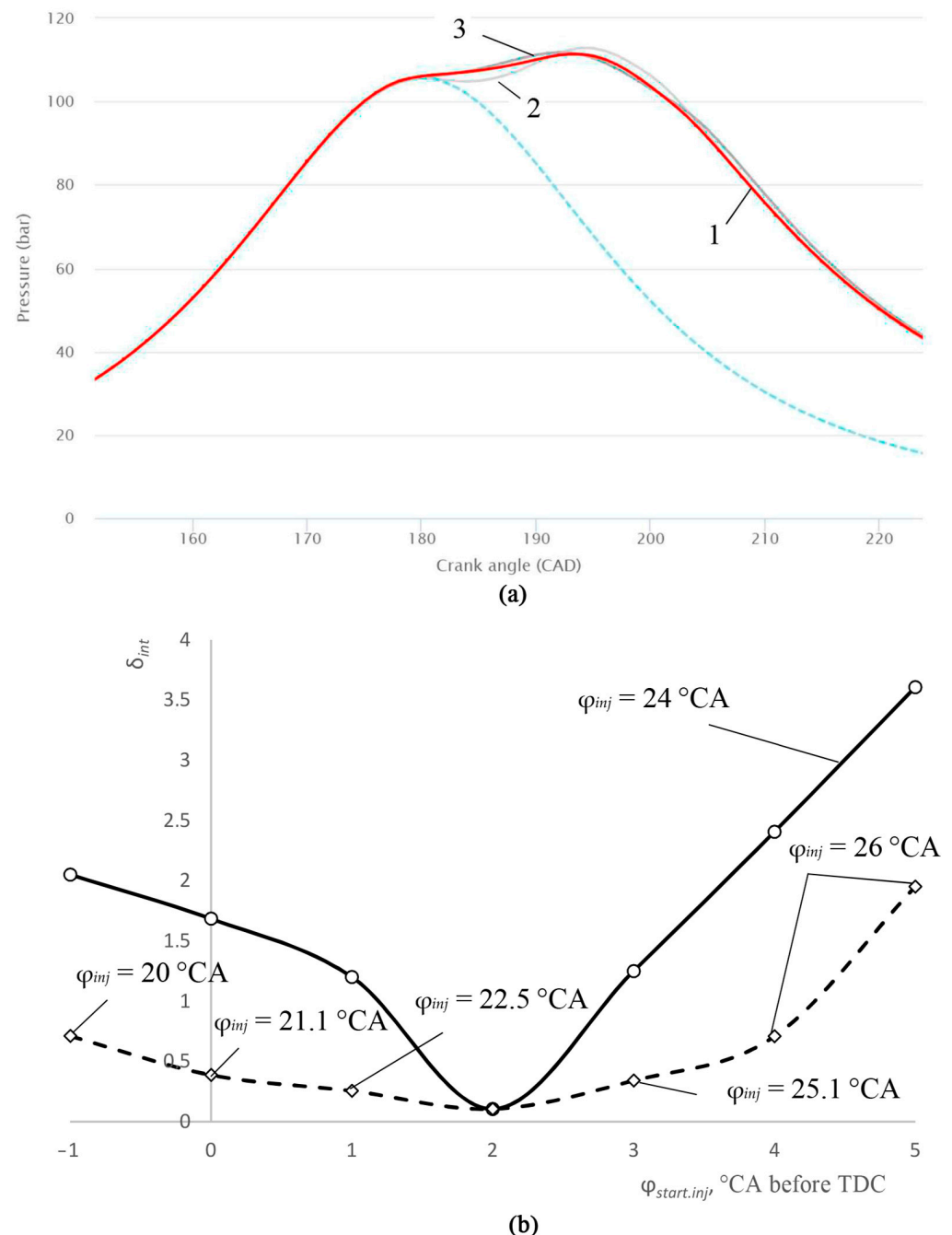


Figure 11. Identifiability problem of optimization: (a) comparison of pressure traces for three sets of varying factors $\varphi_{start.inj}$, φ_{inj} , $d_{inj.holes}$, E_c (output from Blitz-PRO service): (1) 2, 24, 1.35, 1.15; (2) 0.2, 20, 1.4, 1.15; (3) 2, 26, 1.2, 1.25; (b) variation in δ_{int} with the injection advance angle for fixed injection duration $\varphi_{inj} = 24^\circ\text{CA}$ (solid line) and for adjusted injection duration to reach the minimum of δ_{int} (dashed line).

5. Practical Application and Discussion

Following the validation of the methodology using a virtual test case, the next logical step is experimental verification on a research engine. The analysis of the virtual-engine case provides an important methodological implication for the subsequent diagnostic investigation. It demonstrates that the selection of fault-related factors should account not only for their physical relevance to the investigated malfunction but also for their potential interactions and compensating effects. Under real operating conditions, diagnostic procedures become substantially more challenging due to cycle-to-cycle combustion variability and measurement uncertainties affecting both conventional engine parameters and indicator diagrams.

To enable such investigations, controlled modifications of the engine operating process must be introduced experimentally. For example, a throttle valve was installed upstream of the compressor inlet to simulate variations in intake system resistance, as illustrated in Figure 12. An example of the resulting influence on engine performance is shown in Figure 13. Additional factors that may be varied experimentally include fuel delivery parameters, exhaust system resistance, and fuel properties.

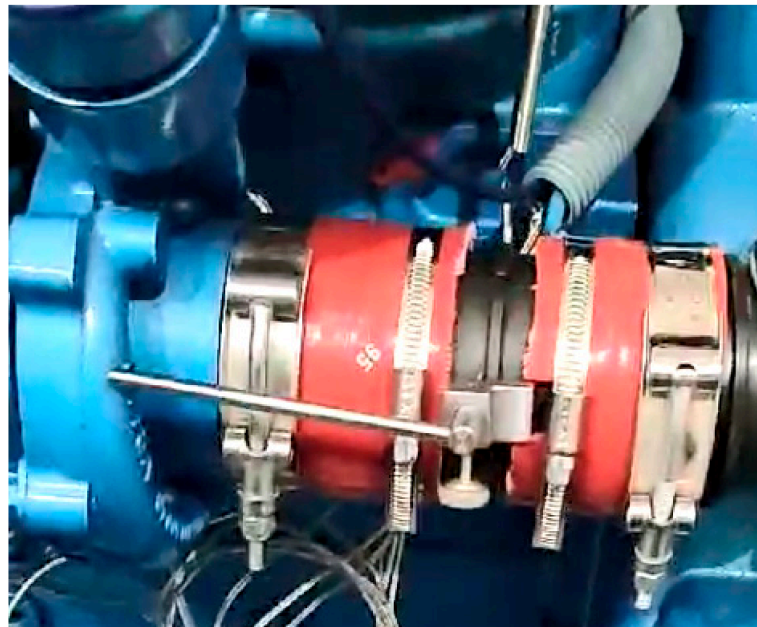


Figure 12. Throttle valve installation on the test engine.

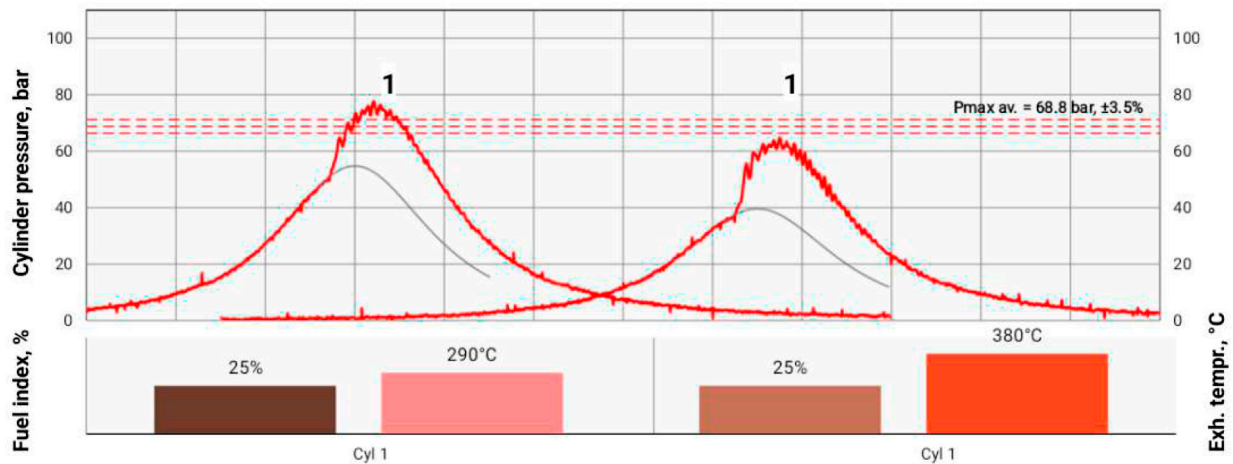
The intake throttle installed on the experimental engine makes it possible to introduce a controlled and reproducible disturbance into the engine operating process. This physical intervention was therefore used to demonstrate the application of the digital twin for identifying the introduced disturbance among several possible fault-related factors.

Four factors were considered: intake restriction upstream of the compressor, Δp_{int} (a physical factor introduced using the intake throttle); exhaust-system restriction Δp_{exh} ; compressor adiabatic efficiency, $\eta_{ad.cmprr}$; and an equivalent cylinder leakage area, μF_{leak} , representing cylinder degradation. All four factors have a substantial influence on the gas-exchange processes and, consequently, on the overall engine operating process. The first factor represents the physically introduced disturbance, whereas the other three were considered as alternative fault hypotheses that could potentially produce similar deviations in the monitored engine parameters.

The operating point selected for the analysis was 18 kW at 1500 rpm, corresponding to the experimental condition presented in Figure 13.

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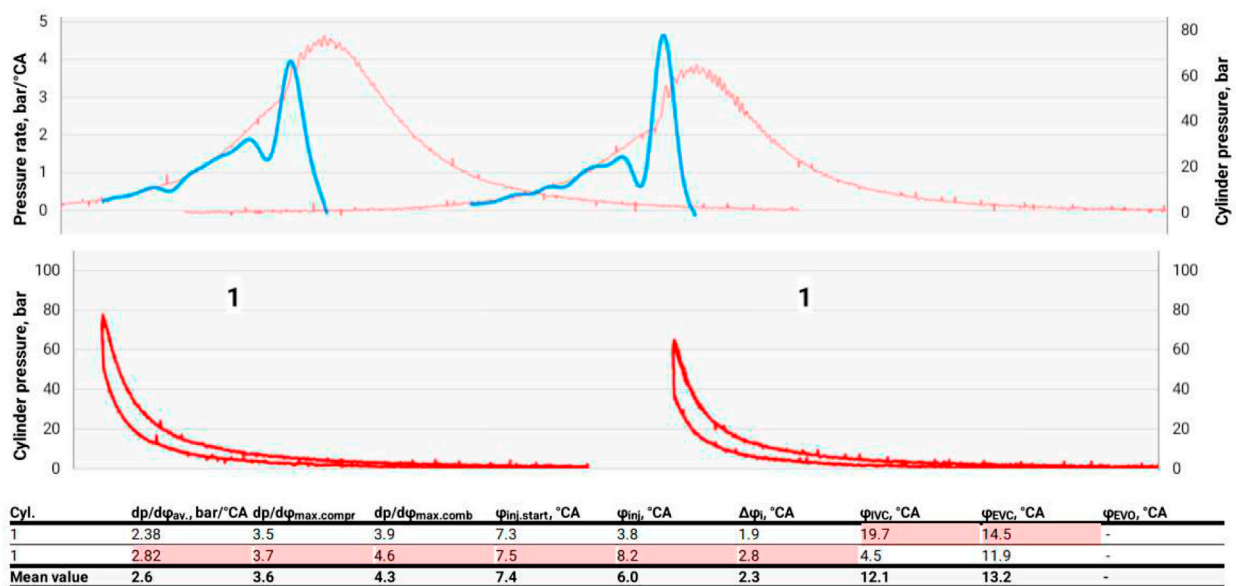
Power Plant: Depas Lab
Engine: Weichai WP4
Details:



Cyl.	n_{crank} , rpm	IMEP, bar	$P_{ind.cyl}$, kW	p_{max} , bar	$\phi_{p,max}$, °CA	p_{ign} , bar	ϕ_{ign} , °CA	p_{compr} , bar
1	1503.8	4.2	5.9	75.1	4.6	51.3	5.4	54.8
1	1502.0	4.0	5.7	62.4	4.0	37.7	4.8	39.6
Mean value	1502.9	4.1	5.8	68.8	4.3	44.5	5.1	47.2

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Power Plant: Depas Lab
Engine: Weichai WP4
Details:



Cyl.	$dp/d\phi_{av}$, bar/°CA	$dp/d\phi_{max.compr}$	$dp/d\phi_{max.comb}$	$\phi_{inj.start}$, °CA	ϕ_{inj} , °CA	$\Delta\phi_i$, °CA	ϕ_{IVC} , °CA	ϕ_{EVC} , °CA	ϕ_{EVO} , °CA
1	2.38	3.5	3.9	7.3	3.8	1.9	19.7	14.5	-
1	2.82	3.7	4.6	7.5	8.2	2.8	4.5	11.9	-
Mean value	2.6	3.6	4.3	7.4	6.0	2.3	12.1	13.2	-

Figure 13. Depas 5.0W diagnostic system report for 18 kW without throttling (left diagrams) and with throttling (right diagrams).

Before selecting the factor levels and variation intervals and constructing the numerical experiment, the individual influence of each factor on the engine operating process was investigated. Particular attention was paid to whether the considered factors produce sufficiently distinguishable effects in the set of parameters that can be practically obtained from engine sensors. The results of this analysis are presented in Table 10 and Figure 14.

The simulations demonstrate that each factor produces a specific response in the engine operating parameters. Although all considered disturbances result in an increase in exhaust-gas temperature upstream of the turbine, a reduction in boost pressure, and an increase in brake-specific fuel consumption, their effects differ in several diagnostically

important parameters. An increase in exhaust-system backpressure, for example, results in the preservation or even a slight increase in the maximum cylinder pressure. This effect is primarily associated with the increase in the cyclic fuel dose required to compensate for the increased pumping losses. In contrast, a reduction in compressor adiabatic efficiency, which may be associated with contamination or degradation of the compressor flow path, results in a pronounced decrease in turbocharger speed. A substantially larger reduction in boost pressure is observed when the intake restriction is increased. However, the pressure ratio of the turbocharger compressor changes comparatively little, which is reflected in the relatively small change in turbocharger rotor speed. Cylinder leakage produces another characteristic response, manifested primarily by a pronounced deterioration of the engine efficiency, a substantial increase in fuel consumption, and a significant increase in exhaust-gas temperature upstream of the turbine. These differences indicate that the considered factors can, at least potentially, be discriminated using a combination of measured engine parameters.

Table 10. Estimation of the impact of varying factors on the engine's operating parameters.

Factor	$p_{s, \text{ bar}}$	$t_{s, \text{ }^\circ\text{C}}$	$t_{tr, \text{ }^\circ\text{C}}$	$p_{max, \text{ bar}}$	$p_{ign, \text{ bar}}$	$n_{TC, \text{ rpm}}$	$b_b, \text{ g/(kW}\cdot\text{h)}$
normal operation: $\Delta p_{int.f} = 0.25 \text{ kPa}$; $\Delta p_{exh} = 3 \text{ kPa}$; $\mu_{\eta_{ad.cmpr}} = 1.0$ *	1.145	46.9	244	79.4	50.0	39,005	251.4
$\Delta p_{int.f} = 10 \text{ kPa}$	1.026	46.3	270.9	77.1	44.9	38,156	256.7
$\Delta p_{exh} = 15 \text{ kPa}$	1.129	45.5	259.7	80.6	49.3	37,382	259.1
$\mu_{\eta_{ad.cmpr}} = 0.75$	1.082	46.6	256.8	78.3	47.2	32,364	253.7
$\mu F_{leak} = 10 \text{ mm}^2$	1.081	42.1	476.2	75.1	39.8	32,184	428.4

* $\mu_{\eta_{ad.cmpr}} = \eta_{ad.cmpr} / \eta_{ad.cmpr.ref}$ —multiplier for compressor efficiency map in Blitz-PRO service.

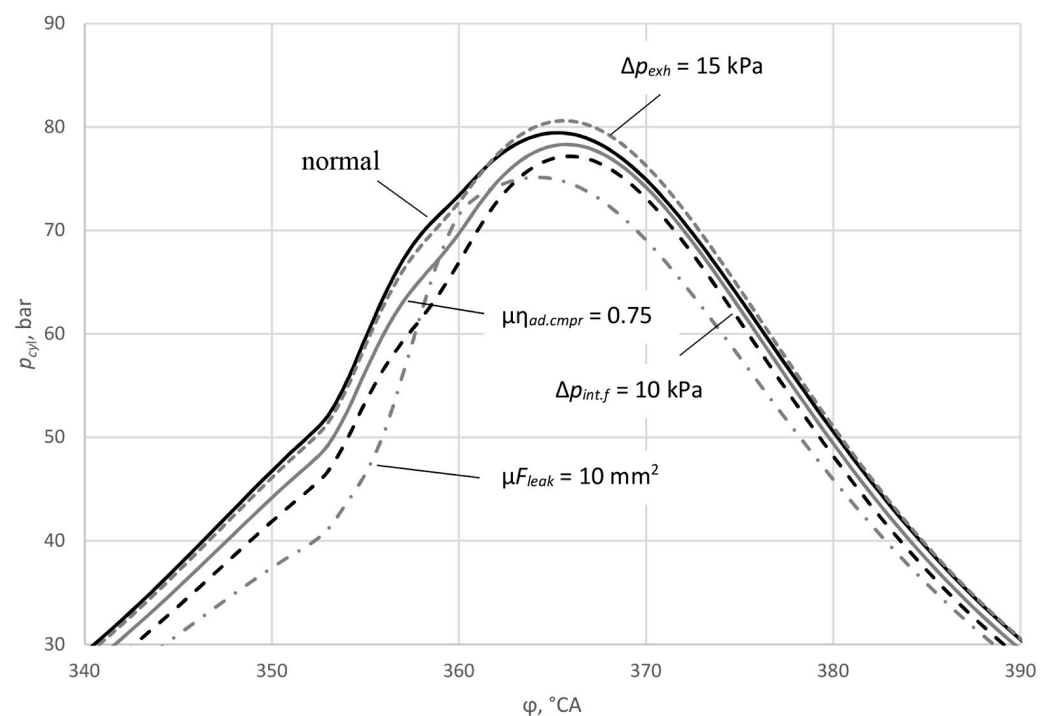


Figure 14. Simulated cylinder pressure traces comparison for normal conditions and for four types of malfunctions: restriction at intake, increased backpressure, lower compressor efficiency, and cylinder leakage.

Based on this preliminary analysis, a constrained factorial experiment was constructed using the four fault-related factors. All calculations were performed for the operating condition $\bar{O}_3 = (P_b = 18 \text{ kW}, n = 1500 \text{ rpm})$. A constant-power operating condition, rather than a constant cyclic fuel dose, was selected because a marine diesel generator must maintain the power demanded by connected consumers. The basic levels and variation intervals of the investigated factors are presented in Table 11.

Table 11. Values of variable factors.

Parameter	Units	Base Level	Interval of Variation	Etalon Value
$\Delta p_{int.f}$	kPa	15	15	0.25
Δp_{exh}	kPa	20	17	3
$\mu\eta_{ad.cmp}$	-	0.8	0.2	1
μF_{leak}	mm ²	5	5	0

In addition to the objective functions introduced above, the Mahalanobis distance, ρ_M , was considered as a multivariate diagnostic objective function:

$$\rho_M = \sqrt{(\bar{Y}^{sim} - \bar{Y}^{exp})^T S^{-1} (\bar{Y}^{sim} - \bar{Y}^{exp})} \quad (25)$$

where $\bar{Y}^{sim}$ and $\bar{Y}^{exp}$ are vectors of sensor-derived parameters obtained from simulation and experiment, respectively, and (S) is the covariance matrix of the corresponding measurement errors.

The use of the Mahalanobis distance provides several advantages in the present diagnostic problem. First, it accounts for differences in the scales and units of the monitored parameters. Second, it allows the expected measurement uncertainty of individual sensors to be incorporated into the diagnostic criterion. Third, the covariance matrix allows correlations between measurement errors to be taken into account. Consequently, the criterion provides a multivariate measure of the discrepancy between the experimentally observed engine conditions and the conditions predicted by the digital twin.

For the construction of the covariance matrix (S), the uncertainties associated with the measured parameters were estimated as follows: $\Delta_1 = \Delta_2 = 500 \text{ kPa}$ for p_{max} and p_{ign} , respectively; $\Delta_3 = 0.2 \text{ }^\circ\text{C}$ for the air receiver temperature t_{res} ; $\Delta_4 = 10 \text{ kPa}$ for the corresponding air receiver pressure p_{res} ; $\Delta_5 = 1 \text{ }^\circ\text{C}$ for the turbine-inlet temperature t_t ; and $\Delta_6 = 100 \text{ rpm}$ for turbocharger speed n_{TC} . Correlations between selected measurement uncertainties were also considered. In particular, a correlation coefficient of ($r = 0.8$) was assumed for p_{max} and p_{ign} , since both quantities are derived from the same in-cylinder pressure signal and may therefore be affected by common sensor, calibration, and signal-processing uncertainties. For the air receiver and turbine-inlet temperatures, a moderate correlation coefficient of ($r = 0.5$) was assumed. This assumption reflects the possibility of common thermal and environmental fluctuations during nominally steady-state operation, while accounting for the different measurement locations and local thermal conditions. The selected correlation coefficients represent physically motivated assumptions rather than estimates obtained from a dedicated repeated-measurement uncertainty study. Therefore, the covariance matrix presented in this study should be regarded as one plausible configuration among several possible alternatives.

The resulting covariance matrix was therefore defined as follows:

$$S = \begin{bmatrix} \Delta_1^2 & 0.8 \cdot \Delta_1 \cdot \Delta_2 & 0 & 0 & 0 & 0 \\ 0.8 \cdot \Delta_1 \cdot \Delta_2 & \Delta_2^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & \Delta_3^2 & 0 & 0.5 \cdot \Delta_3 \cdot \Delta_5 & 0 \\ 0 & 0 & 0 & \Delta_4^2 & 0 & 0 \\ 0 & 0 & 0.5 \cdot \Delta_3 \cdot \Delta_5 & 0 & \Delta_5^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & \Delta_6^2 \end{bmatrix} \quad (26)$$

The constrained factorial numerical experiment, the calculated objective functions, and the corresponding regression models are presented in Table 12. Figure 15 compares the experimentally obtained pressure traces with the cylinder-pressure diagrams synthesized for the different factor combinations defined by the experimental design. The usefulness of logarithmic coordinates for diagnostic analysis is again evident. Compared with the conventional $p = f(\varphi)$ representation, the $\ln(p) = f(\varphi)$ representation provides a more pronounced visual separation of deviations associated with the gas-exchange processes.

Table 12. Constrained factorial design matrix for the controlled parameters.

№	Factors				Target Functions				Regression			
	$\Delta p_{int.f}$	Δp_{exh}	$\mu\eta_{ad.cmp}$	μF_{leak}	δ_{int}	ρ_M	Δp_{ID}	$\Delta \ln(p)_{ID}$	δ'_{int}	ρ'_M	$\Delta p'_{ID}$	$\Delta \ln(p)'_{ID}$
	kPa	kPa	-	mm ²	%		bar	-	%		bar	-
1	0	3	1	10	19.76	159.3	5.46	0.1167	19.91	151.9	5.79	0.1189
2	0	3	0.8	10	20.49	188.9	4.84	0.1074	21.01	176.1	4.66	0.1030
3	0	37	0.6	10	27.26	314.3	4.59	0.1302	27.46	322.5	4.69	0.1301
4	0	20	0.6	10	25.74	270.5	4.25	0.1058	25.03	266.7	3.93	0.1025
5	30	3	0.6	10	35.72	512.4	3.95	0.0877	35.49	513.4	3.55	0.0857
6	15	3	0.6	10	24.55	329.5	1.60	0.0512	24.62	344.2	2.06	0.0589
7	0	3	1	5	23.20	43.4	8.69	0.1291	22.67	66.8	8.45	0.1315
8	0	3	0.8	5	21.72	68.5	7.83	0.1192	21.16	76.7	7.34	0.1145
9	0	37	0.6	5	22.14	143.8	6.48	0.1393	22.74	135.9	6.79	0.1433
10	0	20	0.6	5	22.00	125.5	6.73	0.1151	21.44	116.4	6.33	0.1143
11	30	3	0.6	5	20.58	242.0	2.66	0.0840	20.28	222.9	2.54	0.0776
12	15	3	0.6	5	14.42	137.5	1.97	0.0546	15.79	142.0	2.91	0.0601
13	0	37	1	0	25.58	84.0	9.43	0.1616	24.96	82.9	8.90	0.1582
14	0	20	1	0	25.72	108.5	9.37	0.1487	27.51	110.5	9.93	0.1499
15	30	3	1	0	3.62	8.7	1.67	0.0631	3.91	16.1	1.82	0.0638
16	15	3	1	0	13.63	83.6	5.36	0.0843	12.57	59.2	5.09	0.0813
17	0	37	0.8	0	24.39	89.2	8.85	0.1577	23.56	89.0	9.00	0.1621
18	0	20	0.8	0	24.18	110.8	8.74	0.1401	24.75	111.3	9.44	0.1428
19	30	3	0.8	0	5.89	32.1	1.65	0.0702	6.57	47.2	1.78	0.0715
20	15	3	0.8	0	12.22	83.2	4.84	0.0752	11.84	72.5	4.53	0.0760
21	30	37	0.6	0	13.93	139.7	1.86	0.1295	14.15	131.6	2.21	0.1323
22	15	37	0.6	0	13.54	91.6	4.55	0.1292	13.98	100.7	4.17	0.1217
23	30	20	0.6	0	12.59	106.5	1.89	0.0960	11.93	110.2	1.79	0.0997
24	15	20	0.6	0	13.22	91.7	4.34	0.0937	12.79	98.4	3.89	0.0902
R ²									0.991	0.990	0.977	0.985
R ² _{adj}									0.977	0.975	0.940	0.961
RMSE									1.127	17.83	0.654	0.006

Following the determination of the regression equations, their extrema were investigated to identify the combinations of fault-related factors corresponding to the minimum values of the objective functions. The resulting factor estimates are summarized in Table 13 (full results of simulations are available as Supplementary Material). The reported values represent constrained minima within the investigated factor domain. For the Mahalanobis-distance and $\Delta p'_{ID}$ criteria, the minima occur at the upper boundary of the intake-restriction factor range ($\Delta p_{int.f} = 30$ kPa), while the other factors remain at the corresponding boundary

or reference values. Therefore, these results should be interpreted as boundary solutions within the specified domain rather than as unconstrained extrema.

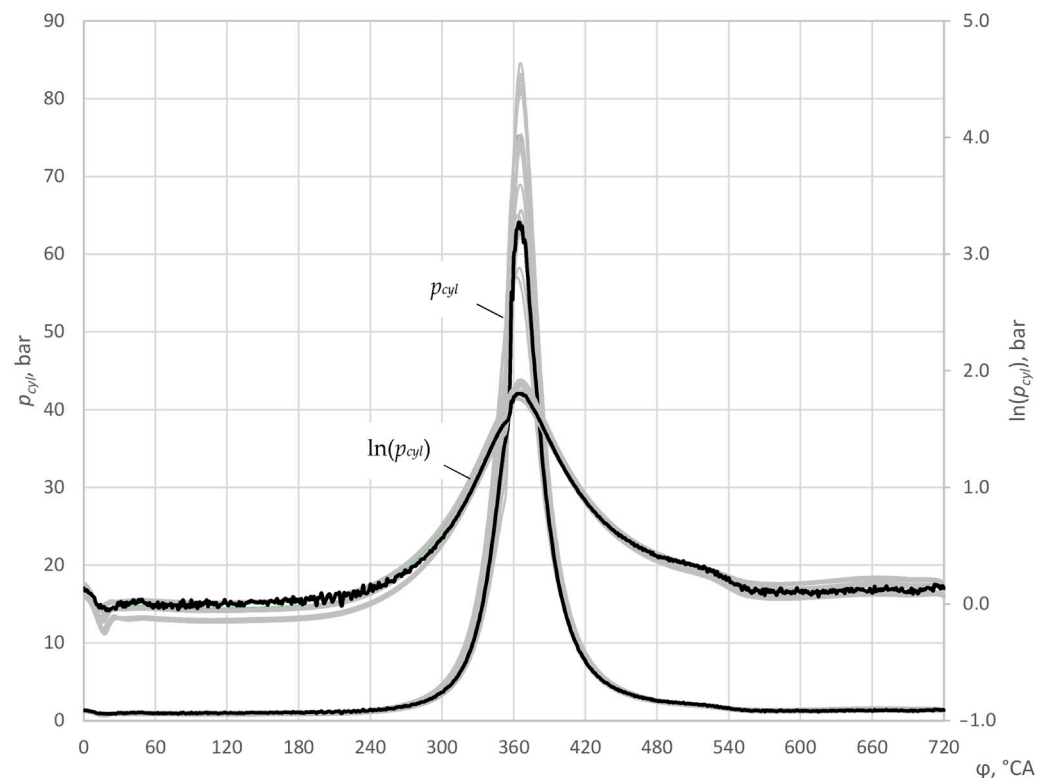


Figure 15. Results of constrained factorial numerical experiment for Weichai WP4 $\bar{O}_3 = (P_b = 18 \text{ kW}, n = 1500 \text{ rpm})$ operating mode. Black lines—experimental diagrams, gray lines—24 variants of the constrained experiment.

Table 13. Estimation of factor values by regression function extrema analysis.

Parameter	Units	From Functions Extremums			
		δ'_{int}	ρ'_M	$\Delta p'_{ID}$	$\Delta \ln(p)'_{ID}$
$\Delta p_{int.f}$	kPa	28.5	30	30	27
Δp_{exh}	kPa	3	3	32.5	11
$\mu \eta_{ad.cmp}$	-	0.82	1	1	1
μF_{leak}	mm ²	0	0	0	0

All four objective functions consistently identify an increased intake restriction as the dominant factor responsible for the deviation of the engine operating process from the reference condition. At the same time, the individual objective functions provide somewhat different estimates of the factor magnitudes. The δ'_{int} criterion additionally indicates a possible reduction in compressor efficiency, whereas the $\Delta p'_{ID}$ and $\Delta \ln(p)'_{ID}$ criteria indicate a possible increase in exhaust-system restriction. It is important to note that all four response surfaces demonstrated consistently good approximation. The obtained R^2 values ranged from 0.977 to 0.991, while adjusted R^2 ranged from 0.940 to 0.977. These results indicate that the selected 24-run numerical design provides an adequate approximation of the response surfaces within the investigated domain despite the relatively large number of regression coefficients.

The most consistent result is obtained using the Mahalanobis distance as the objective function. In this case, the optimization clearly identifies increased intake restriction while the remaining fault-related factors remain close to their reference values. Thus, the

combined analysis of the available sensor data and the simulated fault hypotheses allows the physically introduced intake restriction to be distinguished from the alternative fault mechanisms. The diagnostic result may depend on the assumed structure of the covariance matrix (S), including the specified measurement uncertainties and correlation coefficients. A more systematic investigation of this influence, including the empirical estimation of the covariance parameters from repeated measurements, is beyond the scope of the present study and represents a direction for further research. As an additional robustness check, the optimization was repeated with all off-diagonal covariance terms set to zero. Although the absolute values of the Mahalanobis distance changed slightly, the resulting diagnostic interpretation remained unchanged, with the intake-restriction factor identified as the dominant fault mechanism.

To provide an initial quantitative assessment of the influence of the considered physical factors on the diagnostic objectives, a normalized sensitivity matrix was calculated from the response surface models:

$$J_{s.n.} = \begin{bmatrix} \left(\frac{\partial \delta'_{int}}{\partial \Delta p_{int.f}} \right)_n & \left(\frac{\partial \delta'_{int}}{\partial \Delta p_{exh}} \right)_n & \left(\frac{\partial \delta'_{int}}{\partial \mu \eta_{ad.cmp}} \right)_n & \left(\frac{\partial \delta'_{int}}{\partial \mu F_{leak}} \right)_n \\ \left(\frac{\partial \rho'_M}{\partial \Delta p_{int.f}} \right)_n & \left(\frac{\partial \rho'_M}{\partial \Delta p_{exh}} \right)_n & \left(\frac{\partial \rho'_M}{\partial \mu \eta_{ad.cmp}} \right)_n & \left(\frac{\partial \rho'_M}{\partial \mu F_{leak}} \right)_n \\ \left(\frac{\partial \Delta p'_{ID}}{\partial \Delta p_{int.f}} \right)_n & \left(\frac{\partial \Delta p'_{ID}}{\partial \Delta p_{exh}} \right)_n & \left(\frac{\partial \Delta p'_{ID}}{\partial \mu \eta_{ad.cmp}} \right)_n & \left(\frac{\partial \Delta p'_{ID}}{\partial \mu F_{leak}} \right)_n \\ \left(\frac{\partial \Delta \ln(p)'_{ID}}{\partial \Delta p_{int.f}} \right)_n & \left(\frac{\partial \Delta \ln(p)'_{ID}}{\partial \Delta p_{exh}} \right)_n & \left(\frac{\partial \Delta \ln(p)'_{ID}}{\partial \mu \eta_{ad.cmp}} \right)_n & \left(\frac{\partial \Delta \ln(p)'_{ID}}{\partial \mu F_{leak}} \right)_n \end{bmatrix} \quad (27)$$

Each matrix element was obtained by normalizing the local partial derivative according to the ratio of the variation range of the corresponding factor to the variation range of the objective function:

$$\left(\frac{\partial y_i}{\partial x_j} \right)_n = \frac{\partial y_i}{\partial x_j} \cdot \frac{\Delta x_j}{\Delta y_i} \quad (28)$$

The calculated sensitivity matrix for the common factor combination point $(\Delta p_{int.f}, \Delta p_{exh}, \mu \eta_{ad.cmp}, \mu F_{leak}) = (30, 3, 1, 0)$ is as follows:

$$J_{s.n.} = \begin{bmatrix} 16.8 & -0.070 & -0.14 & 0.16 \\ 0.37 & 0.155 & -0.142 & 0.22 \\ 26.0 & -0.360 & 0.02 & 0.14 \\ 16.7 & -0.150 & -0.15 & -0.16 \end{bmatrix} \quad (29)$$

The results indicate that the intake restriction parameter $\Delta p_{int.f}$ exhibits the dominant sensitivity for the integral discrepancy δ'_{int} , the indicator-diagram pressure deviation $\Delta p'_{ID}$, and the logarithmic pressure deviation $\Delta \ln(p)'_{ID}$. The corresponding normalized sensitivity coefficients reach 16.8, 26.0, and 16.7, respectively. In contrast, the normalized Mahalanobis distance ρ'_M demonstrates a more balanced sensitivity to intake restriction and cylinder leakage, with coefficients of 0.37 and 0.22, respectively.

The negative coefficients associated with exhaust restriction and compressor efficiency indicate an inverse local response of the corresponding objective functions within the investigated factor ranges. The resulting matrix provides a local, normalized characterization of the objective-function sensitivities at the specified factor combination. It should not be interpreted as a global sensitivity ranking over the entire factor domain or as a complete assessment of parameter identifiability.

It should be emphasized that the numerical values obtained from the optimization should not be interpreted as exact estimates of fault severity. Rather, the results demonstrate the capability of the proposed approach to identify the most probable fault-related factor from a set of competing hypotheses. The remaining differences between the estimated

and physically introduced factor values reflect the non-uniqueness of the inverse problem, the sensitivity of the objective functions to individual parameters, and the influence of measurement uncertainty. Therefore, the present experiment should be considered a demonstration of fault-factor discrimination rather than a complete validation of quantitative fault-severity estimation.

From the practical diagnostic perspective, the result is nevertheless informative: the digital twin indicates the intake path as the primary suspected source of the observed deviation, while indicating the exhaust system and compressor flow path as secondary areas requiring inspection. This demonstrates the potential of integrating a calibrated physics-based engine model with real sensor data and controlled physical disturbances within a digital twin-based diagnostic workflow.

The integration of the digital twin into the DEPAS 5.0W diagnostic system is considered next. In the current implementation, the DT is used for the model-based analysis of previously acquired and stored experimental data rather than for online real-time diagnostic operation. Figure 16 presents examples of the Android application interface for viewing and analyzing diagnostic results.

The user can invoke the digital twin to obtain additional information through mathematical simulation using experimentally measured parameters that define the engine operating condition recorded during a diagnostic session, as shown in Figure 16a. In addition, a reference (expected) operating condition of the engine can be obtained and used for comparison with the actual recorded engine state. This enables further assessment of the engine technical condition using the approaches described above, as illustrated in Figure 16b.

The current workflow therefore represents an offline or post-acquisition diagnostic mode. Online real-time operation would require further optimization of the model execution and data communication, as well as quantitative assessment of the associated computational and communication latency. Such developments may enable the future implementation of a real-time diagnostic configuration, including the possibility of executing a reduced or optimized digital twin model directly on a mobile device. The presented results demonstrate the feasibility of integrating digital twin assistance into an engine diagnostic workflow, while also highlighting several challenges that must be addressed before reliable automated online operation can be implemented in practical marine-engine applications.

Indeed, provided that a properly calibrated digital twin is available, Design of Experiments (DoE) methods can be employed to investigate the influence of various faults and malfunctions within engine systems on the parameters of the operating process. Furthermore, the proposed methodology enables the model-based estimation of fault-related parameters within the investigated parameter space. Such estimates should be interpreted as indicative values supporting fault identification and diagnostic decision-making, rather than as exact measurements of fault severity. Their accuracy depends on the calibration quality of the digital twin, the sensitivity of the selected diagnostic indicators, the availability and quality of measurement data, and the uniqueness of the inverse solution. The obtained estimates can subsequently be compared with the results of engine inspection and maintenance procedures.

An important advantage of the proposed approach is its potential for automation. In the longer term, the proposed architecture could support an automated diagnostic workflow in which engine performance is continuously compared with a reference representation of healthy operation and probable causes of detected deviations are assessed. Such functionality remains a prospective development rather than a demonstrated capability of the current implementation. Its practical realization would require further

investigation of model execution, data communication, uncertainty, and inverse-problem identifiability under real operating conditions.



Figure 16. Screenshots of the DEPAS 5.0W Android application illustrating the implementation of the digital twin for (a) augmenting diagnostic data with digital twin simulation results and (b) optional further analysis for possible malfunctions.

The conducted investigations have also revealed several challenges that require further research:

1. Improvement of numerical experiment design and response surface analysis methods to ensure reliable identification of response function extrema and elimination of physically unrealistic solutions.
2. The digital twin must incorporate physical parameters of engine systems and components that can be directly measured during condition assessment. This requirement

necessitates an adequate level of model detail and adaptation of the mathematical model to the specific engine under consideration.

3. The factors selected to represent potential faults should be physically justified and, where possible, provide distinguishable effects on the engine working process. Their mutual interactions and potential compensating effects should be assessed to reduce the risk of practical non-identifiability.

Therefore, further development of the proposed methodology requires an appropriate level of physical detail within the engine model to represent the most probable fault mechanisms of a specific engine. This will facilitate the selection of diagnostic factors in accordance with the relevant requirements of Design of Experiments theory, including controllability, measurability, compatibility, statistical significance, and reproducibility, while also accounting for factor interactions and the practical identifiability of the inverse problem.

In addition, practical implementation of the proposed approach under real operating conditions must account for cycle-to-cycle variability of the engine operating process and uncertainties associated with measurement systems and sensors.

6. Conclusions

The application of digital twin technology to monitoring and diagnostic systems for marine internal combustion engines represents an important step toward more automated and efficient operation of marine power plants. Early detection of engine faults contributes not only to improved navigational safety and reduced risk of failures, but also to lower fuel and lubricant consumption and reduced environmental impact.

An engine digital twin should provide an adequate level of detail in the simulation of engine operating processes and include, among its input variables, physical parameters describing the principal engine systems and components that may be associated with fault development. Particular importance is attached to the calibration of the mathematical model and to the integration of the digital twin with the actual engine through sensor-based data acquisition.

The digital twin supports the establishment of a reference representation of engine operation based on manufacturer specifications, experimental data, and the calibrated mathematical model. Within the proposed architecture, experimentally acquired diagnostic data can be compared with the corresponding DT predictions for the identified engine operating mode, providing additional information for assessment of the engine technical condition.

From a practical perspective, an important capability of the proposed approach is the identification of probable physical factors responsible for deviations between the observed and reference engine behavior. To address this inverse problem, Design of Experiments and numerical multifactor analysis were employed. The results demonstrate that response-surface models can be used to investigate the relationship between measurable engine deviations and physically meaningful fault-related factors. At the same time, the obtained results demonstrate the practical non-uniqueness of the inverse diagnostic problem: different combinations of factors may produce similar observable responses. Therefore, reliable fault discrimination depends strongly on the selection of diagnostic parameters, objective functions, and fault-related factors whose effects on the monitored engine responses are sufficiently distinguishable.

The experimental case study with the Weichai WP4 engine demonstrates the practical integration of the digital twin with the DEPAS 5.0W diagnostic system. The DT can be accessed from the diagnostic system to supplement experimentally acquired data with model-based information and to provide a reference representation of engine operation. The demonstrated architecture provides a basis for further development toward auto-

mated online fault identification, which has not yet been implemented or validated in the present study.

Further development of the proposed methodology should include independent validation over an extended operating range, systematic parameter-identifiability and sensitivity analysis, consideration of cycle-to-cycle variability and measurement uncertainty, and experimental validation under controlled fault conditions. These developments are necessary to assess the reliability of quantitative fault-parameter estimation and to establish the feasibility and performance requirements of fully automated continuous diagnostic operation.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/asi9100212/s1>: Table S1: Blitz-PRO reports for the constrained experiment for Weichai WP4 case; experimental and Blitz-PRO simulated indicator diagrams for Weichai WP4 case constrained factorial experiment.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

DT	Digital twin
ICE	Internal combustion engine
TDC	Top dead center
BDC	Bottom dead center
EVO	Exhaust valve opening
EVC	Exhaust valve closing
IVO	Intake valve opening
IVC	Intake valve closing
n_{crank}	Engine speed
P_b	Brake power
p_0	Ambient pressure
p_i	Indicator mean effective pressure
p_{max}	Maximum combustion pressure
p_{compr}	Compression pressure
p_{ign}	Pressure at the ignition point
p_s	Charge air pressure
b_b	Brake specific fuel consumption
b_{oil}	Specific lubricating oil consumption

q_{fuel}	Injected fuel mass per cycle
g_{NOx}	Specific NO _x emission
t_0	Ambient temperature
t_s	Charge air temperature after the charge air cooler
t_t	Temperature at turbine inlet
t_{w1}	Cooling water temperature at engine inlet
t_{oil1}	Oil temperature at engine inlet
p_{oil1}	Oil pressure at engine inlet
φ	Crank angle (°CA)

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