International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 10 October 2026
Page No: 5661 - 5677
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0738

Digital Twins for Biofuel Integration and Optimization in Internal Combustion Engines: A Critical Review and Research Roadmap

Gundumalla Krishna[1], Dr.C. Sivarajan[2]
[1]Research Scholor, Mechanical Engineering, Annamalai University, Annamalai Nagar, Chidambaram, Tamilnadu, India-608002
[2]Associate Professor, Mechanical Engineering, Annamalai University, Annamalai Nagar, Chidambaram, Tamilnadu,India -608002
Emails: *krishnaphd1995@gmail.com[1], csrajan18au@rediffmail.com[2]*

Abstract
Digital twins (DTs) are increasingly proposed as a bridge between high-fidelity engine physics, real-time sensing, artificial intelligence (AI), and closed-loop optimization, yet their role in biofuel-powered internal combustion engines (ICEs) remains fragmented. This critical review evaluates how condition monitoring, AI-based diagnostics, fast-running engine models, and DT implementations can be integrated into a fuel-aware framework for biofuel ICEs. A structured search of original research was conducted across major publisher databases and scholarly discovery services, including ScienceDirect, Springer Nature, Wiley/IET, SAE Mobilus, RSC Publishing and MDPI, with the search updated to 19 August 2026. Review-only papers were excluded from the evidential corpus; the synthesis therefore relies on primary experimental, computational, or validated digital-twin studies. Three contributions distinguish this review. First, a five-layer taxonomy is proposed that separates sensing, state estimation, twin-model fidelity, intelligence, and actuation, allowing DT maturity to be compared independently of terminology. Second, conventional-fuel and biofuel deployments are compared through a fuel-to-fault pathway linking viscosity, volatility, oxygen content, ignition quality, oxidation stability and material compatibility to measurable signatures, degradations and control actions. Third, a BioTwin-ICE architecture is proposed in which a physics core is continuously corrected by data-driven residual models and uncertainty-aware parameter adaptation. The literature shows that engine DTs have progressed from real-time 0D/1D virtual engines to hybrid combustion prediction, fault isolation and optimization, whereas direct biofuel-specific DT demonstrations remain limited. The principal research opportunity is therefore not another generic engine surrogate, but validated fuel-aware twins that remain accurate under feedstock variation, ageing, transient operation and component degradation while satisfying real-time and safety constraints. Actionable research questions and validation metrics are provided to guide this transition.

Keywords: *biofuels; condition monitoring; digital twin; fault diagnosis; hybrid physics–AI; internal combustion engine; predictive maintenance*

1. Introduction
Internal combustion engines remain indispensable in heavy-duty road transport, marine propulsion, distributed power generation, agriculture and other duty cycles in which energy density, infrastructure availability and rapid refuelling remain decisive. Their continuing role is now coupled to a strong requirement for lower lifecycle carbon emissions, lower criteria pollutants and higher operational availability. Bio-derived fuels—including biodiesel, renewable oxygenates and blended low-carbon fuels—can reduce fossil-carbon dependence without requiring a complete replacement of the installed engine platform. However, they also expand the operating envelope that the engine-management and health-monitoring system must understand. The result is a control and diagnostic problem in which fuel composition, combustion behaviour, emissions, ageing and component condition become tightly coupled rather than separable engineering tasks. Conventional condition monitoring provides valuable information but is usually organized around isolated signals or predefined thresholds.

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 10 October 2026
Page No: 5661 - 5677
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0738

Experimental studies have shown that misfire and valve-clearance faults can be detected from multi-sensor vibration features [16], while combined rule-based and probabilistic/neural methods can extend diagnosis across engine speeds [17]. More recent convolutional architectures can operate directly on measured vibration or crank-angle-domain signals and achieve high classification accuracy under noise [18–21]. These studies establish the diagnostic value of data-driven methods, but a classifier alone does not constitute a digital twin: it typically lacks an explicit representation of engine state, bidirectional synchronization with the physical engine, causal simulation of unobserved operating scenarios, and a mechanism for translating diagnosis into a constrained control or maintenance action. The distinction matters because engine digital twins are already moving beyond static simulation. Bondarenko and Fukuda developed a real-time diesel-engine twin that combined a cycle-mean model with crank-angle-resolved phenomenological combustion [1]. Guan et al. coupled calibrated engine models with multi-objective optimization to form a digital-twin optimization platform [2], while Söderäng et al. demonstrated a physics-based fast-running engine model coupled to a complete power-plant model and validated against measurements [3]. Digital-twin frameworks have also been used to support diesel-engine fault diagnosis [4,6], marine engine condition assessment [5], data-driven in-cylinder combustion reconstruction [7], real-world emissions prediction [9,10], and embedded or ultra-fast engine modelling [11,12]. Collectively, these studies demonstrate that a DT is best treated as an operational architecture rather than as a single model. Biofuels make the DT problem harder. Controlled experiments show that oxygenated biofuel combinations can materially shift ignition delay, heat-release phasing, efficiency and the NOx–soot trade-off [26], while second-generation biodiesel blends alter ignition and flame development in ways that depend on blend fraction and operating condition [27]. Long-duration studies additionally report injector deposits, lubricant changes, component wear and fuel-system compatibility effects for biodiesel blends [28–32]. Thus, a biofuel-capable DT must capture not only instantaneous combustion performance but also fuel-property uncertainty and degradation pathways that evolve over hours, months and seasons. A model calibrated to one biodiesel feedstock, one blend ratio or fresh fuel may therefore become systematically biased when viscosity, oxidation state, cetane behaviour or composition changes. The key gap in the present literature is consequently one of integration. Engine condition-monitoring papers often stop at classification; AI studies often stop at prediction; engine-model studies frequently optimize performance under a fixed fuel definition; and biofuel studies commonly characterize physical behaviour without embedding those effects in an online virtual representation. A small but important group of recent studies is beginning to bridge this divide. For example, hybrid physics–neural models have been developed for real-time combustion variables [24], and a 2026 physics-encoded multi-task learning study used biodiesel-engine experiments to construct a thermodynamically constrained predictive framework explicitly described as a digital twin [15]. These developments suggest that fuel-aware hybridization is a technically plausible route, but they do not yet establish a standardized, transferable or fleet-ready solution. This review therefore addresses five questions: (i) what capabilities differentiate traditional monitoring, AI diagnostics and a true engine DT; (ii) which engine-DT architectures have been experimentally or computationally validated; (iii) which biofuel properties must become explicit twin states or exogenous inputs; (iv) how should physics-based and data-driven models be coupled to preserve real-time capability without sacrificing generalization; and (v) what validation evidence is required before a biofuel DT can be trusted for closed-loop control or predictive maintenance? The novelty of this work lies in a five-layer DT taxonomy, a fuel-to-fault mapping specific to biofuel ICEs, a cross-comparison of conventional and biofuel-oriented implementations, and the proposed BioTwin-ICE architecture and research roadmap. The objective is not to introduce another broad definition of a digital twin, but to establish a technically testable framework that can guide future experiments and implementations.

2. Review Methodology

2.1.Review design and information sources

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 10 October 2026
Page No: 5661 - 5677
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0738

The manuscript was revised as a structured critical review rather than a purely narrative overview. Searches were performed through publisher databases and scholarly discovery services that directly expose peer-reviewed engineering literature: ScienceDirect, Springer Nature, Wiley/IET, SAE Mobilus, RSC Publishing and MDPI. Searches were last updated on 19 August 2026. Because the purpose of the review is technological synthesis rather than bibliometric ranking, the evidence base was deliberately restricted to original research used to support technical claims; review articles were not used as evidential citations in the revised manuscript. Search strings were combined iteratively around four concept blocks: (1) 'digital twin' AND ('diesel engine' OR 'internal combustion engine' OR 'combustion engine'); (2) ('fault diagnosis' OR 'condition monitoring' OR 'misfire') AND ('diesel engine' OR 'internal combustion engine') AND ('vibration' OR 'CNN' OR 'machine learning'); (3) ('biodiesel' OR 'biofuel' OR 'oxygenated fuel') AND ('engine' OR 'injector') AND ('combustion' OR 'emissions' OR 'durability' OR 'deposit'); and (4) ('hybrid model' OR 'physics-based' OR 'physics-informed') AND ('machine learning' OR 'neural network') AND ('engine' OR 'combustion'). Backward and forward title-based searching was then used to identify closely related original studies when they directly addressed the comparison dimensions of this review.

2.2.Eligibility, extraction and synthesis

Studies were included when they reported original experimental measurements, validated numerical models, real-time/fast-running engine models, engine fault-diagnosis experiments, model-in-the-loop or hardware-in-the-loop demonstrations, or explicitly constructed digital twins relevant to ICE operation. Studies were excluded when they were review-only articles, duplicated reports, non-engine digital-twin applications without a transferable engine modelling contribution, conceptual papers without validation, or abstract-only records that did not provide sufficient methodological information. Biofuel evidence was included when it quantified fuel-induced changes in combustion, emissions, spray behaviour, deposits, corrosion, wear or data-driven engine prediction that must be represented by a future DT. For each included study, the following fields were extracted where available: engine and fuel, measurement channels, modelling class, physical-model content, data-driven content, synchronization or online update mechanism, target variables, validation basis, execution-time claim, diagnostic/optimization output and principal limitation. The synthesis was organized around capability rather than publication chronology. This approach makes it possible to compare, for example, a fast-running 1D model and a CNN fault classifier according to the distinct roles they would occupy inside a DT, rather than treating them as competing technologies. As shown in Figure 1 Structured critical-review workflow used for evidence selection, extraction and synthesis

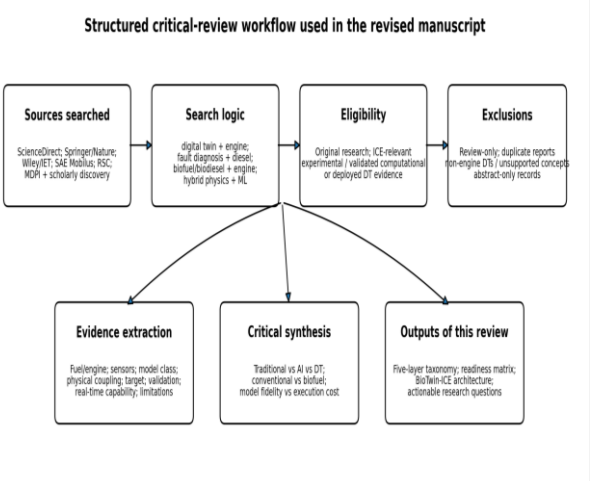


Figure 1 Structured critical-review workflow used for evidence selection, extraction and synthesis

3. From Condition Monitoring to Digital-Twin Capability

3.1.Signal-based monitoring and physical observability

ICE condition monitoring begins with observability: faults must produce measurable changes before they can be inferred. Mechanical and combustion faults alter cylinder-head vibration, crankshaft speed fluctuation, acoustic radiation, pressure development, exhaust composition, temperature and flow. Multi-sensor vibration experiments have demonstrated that misfire and valve-clearance conditions can be separated when feature extraction and statistical selection are matched to the engine operating state

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 10 October 2026
Page No: 5661 - 5677
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0738

[16]. Rule-based preprocessing combined with Bayesian networks or back-propagation neural networks has likewise been shown to identify multiple diesel-engine faults over a range of speeds using experimentally acquired vibration signals [17]. These results support the use of vibration as a low-cost state indicator but also reveal a recurring limitation: the measured feature is an indirect projection of several coupled physical processes. For a DT, condition-monitoring signals should therefore be classified by the state they constrain. Cylinder pressure and crank-angle-resolved speed constrain combustion phasing and torque production; manifold pressure and temperature constrain air-path state; vibration constrains mechanically induced events; exhaust NOx, oxygen and particulate proxies constrain combustion and aftertreatment state; and fuel-quality descriptors constrain the boundary conditions of spray, ignition and oxidation. A diagnostic system that fuses these channels can distinguish a sensor anomaly, a combustion shift and a mechanical degradation more reliably than a single-modality threshold, particularly when the model can test counterfactual explanations.

3.2.AI diagnostics: strength, failure modes and role inside a twin

AI substantially improves feature extraction and classification in non-stationary engine signals. Random convolutional ensembles have been validated on measured diesel-engine vibration data [18]. Multi-domain twin-CNN inputs improved misfire detection under strong noise and changing working conditions [19], and a multi-scale CNN-LSTM with an explicit denoising module retained high accuracy across severe noise levels and cross-noise generalization tasks [20]. A shallow CNN using crank-angle-domain information has also been demonstrated for real-time abnormality detection and classification [21], while transfer-learning approaches show how pretrained convolutional features can reduce data requirements for diesel-engine fault recognition [22]. These studies show that deep models can learn representations that are more robust than manually engineered feature sets. The limitation is epistemic rather than purely statistical. High classification accuracy within an experimental fault library does not guarantee correct diagnosis of an unseen fuel, a slowly drifting sensor, a compound fault or a new hardware configuration. Data-driven models can also confound correlated causes: for example, an apparent combustion anomaly may arise from altered fuel ignition quality, injector deposit growth, rail-pressure deviation or air-path error. A DT should use AI as one layer of evidence, not as an unconstrained substitute for the physical system. Physics-anchored residual models, model-based virtual sensors and uncertainty estimates are especially valuable when operation extends beyond the training domain. As shown in Table 1 Critical comparison of traditional monitoring, AI-based diagnostics and digital-twin approaches.

Table 1 Critical comparison of traditional monitoring, AI-based diagnostics and digital-twin approaches.

Dimension	Traditional / signal based	AI / data driven	Digital twin
Primary representation	Thresholds, signal features, rule sets	Statistical or neural mapping from measurements to classes/targets	Synchronized virtual engine state combining physics, data and operational context
Typical inputs	OBD codes, vibration, temperature, pressure	Raw or transformed multi-sensor data	Sensors + actuator commands + fuel descriptors + physics states + history

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 10 October 2026
Page No: 5661 - 5677
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0738

Main strength	Simple, interpretable, low compute	High nonlinear discrimination and automated feature learning	Counterfactual simulation, state estimation, diagnosis, prognosis and optimization in one loop
Principal weakness	Reactive and operating-point dependent	Training-domain dependence; weak causality; data hunger	Model calibration, synchronization, compute cost, uncertainty and interface complexity
Response to new fuel	Threshold recalibration	Retraining/domain adaptation often required	Fuel properties can enter as states/parameters with online adaptation
Fault isolation	Pattern/limit based	Probabilistic/classification based	Model mismatch + AI classification + virtual fault reproduction
Control integration	Usually indirect	Possible but may lack physical constraints	Native closed-loop what-if evaluation and constrained optimization
Evidence in ICEs	Established diagnostic practice	Strong experimental evidence [16–21]	Growing validated evidence [1–13] but heterogeneous maturity

4. Digital-Twin Implementations for Internal Combustion Engines

4.1.A five-layer taxonomy for engine digital twins

Terminology is inconsistent across the engine literature: 'virtual engine', 'digital twin', 'surrogate', 'fast-running model' and 'AI engine model' are sometimes used for overlapping capabilities. To make studies comparable, this review proposes five orthogonal layers. Layer 1 is sensing and synchronization: the extent to which the virtual representation receives time-aligned operational data. Layer 2 is state estimation: whether unmeasured engine states and parameters are inferred rather than merely replayed. Layer 3 is model fidelity: 0D/mean-value, 1D gas dynamics, crank-angle-resolved phenomenology, 3D/CFD-derived reduced order, or hybrid. Layer 4 is intelligence: classification, residual learning, parameter adaptation, prognosis or optimization. Layer 5 is actuation: whether twin outputs influence calibration, maintenance or closed-loop control. A model can therefore be high fidelity but low maturity as a DT if it lacks synchronization and actuation; conversely, a compact hybrid model can be highly mature if it is validated online and closes the decision loop.

4.2.Physics-based and fast-running twins

Physics-based engine twins have the advantage of causal structure. Bondarenko and Fukuda combined a cycle-mean model with a phenomenological crank-angle combustion model and reformulated the governing relationships for fast execution, explicitly targeting real-time propulsion-system prediction [1]. Guan et al. used experimentally validated 1D and 3D models to form a DT optimization platform for a variable-compression-ratio engine and coupled it with NSGA-II multi-objective optimization [2]. Söderäng et al. reduced a crank-angle-resolved large-

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 10 October 2026
Page No: 5661 - 5677
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0738

bore engine model into a fast-running form and coupled it with generator, battery and grid models, with measured-data validation and real-time execution analysis [3]. These studies establish a central DT design trade-off: a physical model must retain the states required for diagnosis and control while eliminating detail that prevents real-time computation. Real-time virtual-engine work outside papers explicitly labelled as DT is also directly relevant. Early real-time diesel simulation and hardware-in-the-loop studies established the execution-time discipline that modern twins inherit [23,25]. Duraiarasan et al. developed embedded models for a heavy-duty diesel engine and aftertreatment system to predict fuel consumption and tailpipe emissions under transient operation [11]. Such models provide the physics layer needed by a DT even if the original application is model-based control. More recent work has accelerated the virtual engine further by replacing parts of a calibrated 1D engine model with modular LSTM-based networks, reporting approximately 300-fold faster prediction while retaining most of the reference-model accuracy [12]. A 2026 hybrid symbolic-regression framework further demonstrated a compact, interpretable, control-oriented digital twin for a gas internal-combustion engine, highlighting the value of recursive low-order identification for transient deployment [13]. This progression—from physics to hybrid surrogates—shows why fidelity should be selected according to the time scale of the decision rather than maximized indiscriminately.

4.3.Data-assisted and diagnostic twins

For diagnosis, the twin must reproduce the fault mechanism rather than only label it. Jiang et al. integrated physical-model information with an adaptive sparse attention network for diesel-engine valve-fault diagnosis, using the attention distribution to improve interpretability [4]. Bo et al. proposed a three-stage digital-twin-driven diagnostic process—classification, virtual fault reproduction and maintenance decision—and used an optimization–simulation calculation to reduce dependence on exhaustive fault-degree databases [6]. Minchev et al. implemented a performance DT on a marine diesel-generator test bench, transmitting sensor data to a server and calibrating the engine-cycle model over 27 operating modes [5]. These studies are especially important because they connect data-driven classification to model-based explanation. Combustion-focused twins are developing in parallel. Hu et al. combined a double-Wiebe combustion representation with a snake-optimizer-tuned CNN–Bi-LSTM parameter model to reconstruct and predict in-cylinder combustion across operating conditions [7]. A hybrid physics-based and stochastic neural framework reported by Ankobea-Ansah and Hall used neural prediction of combustion descriptors inside a 0D Wiebe structure, providing a representative example of how a mechanistic scaffold can be retained while data-driven components learn difficult mappings [24]. Such structures are directly transferable to fuel-aware DTs because fuel properties can be introduced into the learned parameter layer without discarding thermodynamic consistency.

4.4.Empirical powertrain twins and real-world emissions

Empirical twins can be effective when the target is system-level performance rather than detailed combustion causality. Roberts and co-workers used transient test data and dynamic design-of-experiments methods to construct validated powertrain twins for rapid characterization of performance and emissions under virtual driving and environmental conditions [9,10]. The same empirical-twin philosophy has been extended to prediction over synthetic machine-handling cycles, demonstrating portability of transient powertrain surrogates beyond conventional regulatory cycles [14]. Saurabh and Sureka used a 0D–1D simulation-based DT to rank unhealthy engine-part hypotheses against real truck data [8]. These approaches are attractive for calibration and service because they reduce physical testing, but their robustness depends on whether the training campaign covers the environmental, fuel and degradation space encountered in service. As shown in Table 2. Representative original digital-twin and twin-enabling implementations for ICEs.

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 10 October 2026
Page No: 5661 - 5677
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0738

Table 2 Representative original digital-twin and twin-enabling implementations for ICEs

Study	Engine / system	Twin model	Primary purpose	Validation basis	Critical limitation / insight
[1] Bondarenko & Fukuda, 2020	Marine diesel	Cycle-mean + crank-angle combustion	Real-time propulsion dynamics	Experimental/model comparison	Strong physical causality; execution/fidelity trade-off
[2] Guan et al., 2021	OPLVCR ICE	1D + 3D validation + NSGA-II	BSFC/NOx optimization	Engine experiments + 3D verification	Optimization-focused; fixed fuel definition
[3] Söderäng et al., 2022	Stationary combustion engine power plant	Fast-running physics model + electrical system	Real-time co-simulation/control	Power-plant measurement data	High physical interpretability; HIL execution still demanding
[4] Jiang et al., 2022	Diesel engine	Physical/data fusion + sparse attention	Valve-fault diagnosis	Engine fault experiment	Improved interpretability; narrow fault domain
[5] Minchev et al., 2023	Marine diesel generator	Cycle model + online data transmission	Condition monitoring / malfunction diagnosis	27 operating modes	Test-bench demonstrated; server-centric implementation
[6] Bo et al., 2024	Diesel engine	Classifier + optimization–simulation model	Fault classification, reproduction, decision	Fuel-injection-system case study	Reduces fault-library burden; computational workflow complex
[7] Hu et al., 2024	High-speed diesel	Wiebe + SO-CNN-Bi-LSTM	Combustion reconstruction/prediction	Bench-test parameters	Strong hybrid concept; fuel generalization not established
[8] Saurabh & Sureka, 2022	Commercial diesel	0D–1D simulation DT	Unhealthy-part ranking	Real customer truck data	Service-oriented; relies on model/failure-mode library
[9] Roberts et al., 2022	Turbocharged diesel	Transient empirical DT + virtual vehicle	RDE/performance prediction	Dynamic DoE test data	Rapid scenario exploration; empirical domain dependence
[10]	Gasoline +	Transient	Real-world	Dynamometer	Scalable

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 10 October 2026
Page No: 5661 - 5677
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0738

Roberts et al., 2024	diesel powertrains	empirical twins	emissions compliance	data + virtual driving	compliance screening; causal detail limited
[11] Duraiarasan et al., 2020	Heavy-duty diesel	Real-time embedded engine/aftertreatment models	Virtual sensing / model-based control	Transient engine validation	Twin-enabling physics; not a full lifecycle DT
[12] Frey et al., 2025	Diesel engine	Modular LSTM surrogate of 1D model	Real-time optimization	Reference 1D model data / validation	Very fast; dependent on surrogate training coverage
[13] Tessaro et al., 2026	Hydrogen SI ICE	Recursive symbolic regression + residual learners	Torque-path DT for control/HIL/fault detection	Experimental WHTC data	Interpretable compact baseline; alternative-fuel transfer evidence

5. Biofuel-Specific Requirements for Engine Digital Twins

5.1. Fuel properties must become dynamic twin inputs

A biofuel DT cannot treat 'fuel type' as a static categorical label. The relevant boundary conditions are continuous and may drift. Viscosity, density, surface tension and volatility influence injection and atomization; cetane behaviour and latent heat influence ignition delay and premixed burn fraction; oxygen content influences soot oxidation and local equivalence ratio; lower heating value changes injected mass for a demanded torque; and oxidation stability, acidity and water affinity influence deposits, corrosion and lubricant degradation. Experiments with biodiesel/oxygenate RCCI combinations demonstrate that fuel properties alter ignition delay, thermal efficiency and emissions even when the engine architecture is unchanged [26]. Optical and engine experiments with second-generation biodiesel blends likewise show blend-dependent ignition and flame-development behaviour [27]. These effects must enter the DT either as measured fuel descriptors, estimated latent variables or adaptive model parameters. This requirement changes the architecture of calibration. In a conventional-fuel twin, a single calibrated combustion map may remain valid over a large fraction of the useful life. For biofuels, calibration should instead be parameterized by measurable or inferable fuel descriptors. When direct fuel sensing is unavailable, the twin can infer effective ignition quality or spray-related parameters from cylinder-pressure residuals, crank-speed response, injection command, exhaust oxygen and emission signatures. The resulting parameter estimates should carry uncertainty bounds because several fuel and hardware effects can produce similar symptoms.

5.2. Fuel-induced degradation must be separated from conventional faults

Long-term biofuel use introduces degradation modes that overlap with conventional diagnostic signatures. Liaquat et al. observed increased injector-tip deposits and wear-metal changes after prolonged operation on PB20 relative to diesel [28], and a related jatropha-biodiesel endurance study reported greater deposits around injector tips and changes in lubricant properties [29]. Matbouei et al. quantified temperature-dependent corrosion of common fuel-system metals exposed to B100 and showed particularly strong interactions for copper-containing materials [30]. A 274-hour CRDI endurance study by Gupta and Agarwal reported changes in deposits,

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 10 October 2026
Page No: 5661 - 5677
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0738

wear and lubricant behaviour under a Karanja-biodiesel blend [31]. Fuel oxidation has also been experimentally linked to fuel-injection-system fouling [32]. These are not isolated material issues: injector deposits alter effective flow area and spray pattern, which then changes combustion phasing, emissions and vibration—exactly the channels that a conventional diagnostic model may interpret as an injector hardware fault. The DT should therefore model a fuel-to-fault pathway. A slow deviation in commanded-to-delivered fuel, accompanied by increasing particulate emissions and a fuel-ageing indicator, should not be treated identically to an abrupt rail-pressure actuator failure. Likewise, a gradual change in friction or compression inferred from crank dynamics should be interpreted alongside lubricant condition and fuel dilution. This is a principal advantage of a state-based DT over a pure classifier: the virtual model can represent multiple competing degradation hypotheses and update their likelihood as additional observations arrive.

5.3.Data-driven biofuel models: useful but not sufficient alone

Primary studies increasingly use machine learning to predict performance and emissions of biodiesel engines. Magesh et al. combined engine experiments with multiple ML algorithms for a pumpkin–maize biodiesel system [33], while Şahin compared ML algorithms for diesel/biodiesel/iso-pentanol performance and emissions prediction [34]. These studies demonstrate the feasibility of compact surrogate models, but most such models are trained on discrete blends, fixed engines and bounded laboratory operating ranges. Their high interpolation accuracy should not be confused with a guarantee of extrapolation to another feedstock or aged fuel. A more DT-like direction is physics-encoded learning. Van Minh et al. developed a physics-encoded multi-task ML framework for a waste-cooking-oil biodiesel system with hydrogen enrichment and explicitly imposed thermodynamic and emission-related constraints, describing the resulting predictor as a digital twin [15]. The significance of this study is architectural: the learning problem is constrained by physical relations rather than being evaluated only by statistical fit. However, the broader literature still lacks independent demonstrations in which the same fuel-aware twin is transferred across feedstocks, blend ratios, engine hardware and long-term degradation. That gap should be considered the central validation challenge for future biofuel DTs. As shown in Table 3 Fuel-to-fault mapping for a biofuel-aware digital twin.

Table 3 Fuel-to-fault mapping for a biofuel-aware digital twin

Fuel attribute	Physical pathway	Observable signatures	Twin state / parameter	Possible DT action	Primary evidence
Viscosity / density	Injection rate, atomization, penetration	Rail/injection command, pressure response, combustion phasing, smoke proxy	Effective injector flow coefficient; spray/evaporation parameter	Adapt injection pressure/timing; flag injector-flow drift	[26–29]
Cetane / ignition quality	Ignition delay and premixed burn fraction	Cylinder pressure, CA10/CA50, crank acceleration	Ignition-delay / Wiebe-shape parameters	Shift SOI/EGR; update combustion map	[26,27]
Oxygen content / oxygenate fraction	Local equivalence ratio and soot oxidation	NOx, O2, PM/smoke, HRR	Emission-source correction factors	Constrained NOx–soot optimization	[26,27]

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 10 October 2026
Page No: 5661 - 5677
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0738

Heating value	Fuel mass required for torque	Injected quantity, torque/IMEP, exhaust temperature	Fuel-energy scaling factor	Correct torque path and fuel consumption estimate	[26,27,33,34]
Oxidation stability / acidity	Gums, deposits, corrosion	Fuel-age proxy, injector correction, metal/lube indicators	Deposit-growth / corrosion state	Maintenance prognosis; derate or service recommendation	[28–32]
Feedstock / blend variability	Combined shifts in thermochemical properties	Multi-sensor residual pattern	Fuel latent vector with uncertainty	Domain adaptation / online parameter estimation	[15,33,34]

Table 4 Conventional-fuel versus biofuel digital-twin requirements

Dimension	Conventional-fuel DT	Biofuel-aware DT
Fuel definition	Relatively stable specification	Feedstock, blend, oxygenate, ageing and batch variability must be represented
Calibration strategy	Fixed maps plus environmental correction	Fuel-parameterized maps or online parameter adaptation
Combustion model	Speed/load/actuator dependence dominant	Must additionally capture fuel-dependent ignition, evaporation and heat-release shape
Fault library	Hardware and sensor faults dominate	Hardware faults + fuel-quality drift + deposits/corrosion interactions
Training data	Operating envelope coverage	Operating envelope × fuel-property envelope × degradation state
Validation	Steady/transient cycles and environmental conditions	Cross-fuel, cross-batch, aged-fuel, transient and degraded-hardware validation
Optimization	Fuel economy / NOx / PM / torque	Same objectives plus blend constraints, stability, material protection and uncertainty
Update mechanism	Periodic calibration updates	Online/continual adaptation with safeguards against catastrophic forgetting
Trust requirement	Prediction accuracy inside certified fuel domain	Accuracy + physical consistency + calibrated uncertainty under fuel-domain shift

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 10 October 2026
Page No: 5661 - 5677
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0738

6. Proposed Biotwin-Ice Framework

Based on the evidence synthesis, this review proposes BioTwin-ICE as a reference architecture rather than a single algorithm. The architecture is deliberately hybrid: the physics layer provides causal state evolution and enforces mass, energy and actuator constraints; the data-driven layer learns residuals, difficult submodels and degradation mappings; an uncertainty layer determines whether a prediction is sufficiently reliable for automated action; and the actuation layer converts predictions into constrained calibration or maintenance decisions. The design objective is graceful degradation: when data quality declines or the fuel moves outside the learned domain, the twin should widen uncertainty and fall back to conservative physics-based control rather than producing a confident but unsupported optimum.

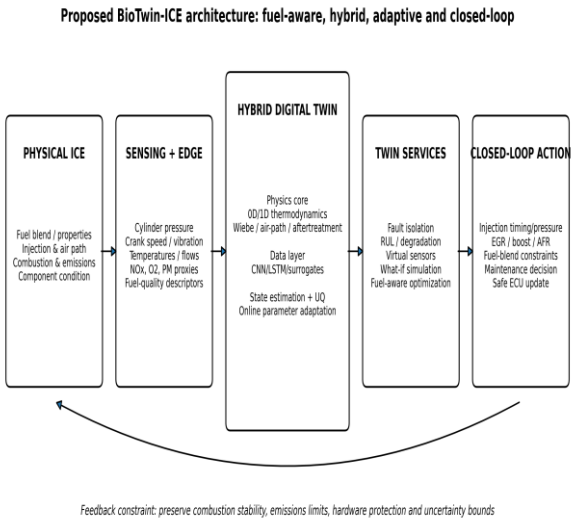


Figure 2 Proposed BioTwin-ICE architecture for fuel-aware monitoring, diagnosis, prognosis and constrained optimization

6.1. Layer A: physical engine and sensing plane

The physical layer should expose the minimum sensor set required to resolve combustion, air-path, emissions and mechanical condition. A practical configuration may combine existing ECU signals with a limited number of higher-information channels such as cylinder-pressure sensing on an instrumented cylinder, crank-speed fluctuation, selected vibration channels, exhaust lambda/NOx and temperature. The twin should also ingest commanded actuator states rather than only measured outputs; without injection timing, rail-pressure command, EGR position and boost command, model mismatch cannot be correctly attributed.

6.2. Layer B: hybrid state and parameter estimation

A fast-running 0D/1D physics core is appropriate for mass-flow, thermodynamic and mean-value states, while a crank-angle combustion submodel can be retained where CA50, pressure rise or emissions are control targets. Neural networks should be used where the mapping is strongly nonlinear or expensive to compute, but preferably as residual or parameter models. The hybrid structures demonstrated in engine combustion studies [7,24] provide a template: the network predicts a compact set of physically meaningful parameters, and the mechanistic model converts them into complete trajectories. This makes the model easier to audit and allows fuel-property adaptation to be expressed through parameters with physical interpretation.

6.3. Layer C: diagnostic and prognostic intelligence

The diagnostic layer should combine discriminative models with virtual fault reproduction. CNN/LSTM methods can rapidly rank fault hypotheses from high-dimensional signals [18–21], while the physics twin tests whether each hypothesis can reproduce the observed torque, pressure, air-path and emissions residuals. A fault is accepted only when both statistical evidence and model-consistency thresholds are satisfied. Slow degradation states—injector flow loss, compression reduction, sensor bias, deposit growth or catalyst/aftertreatment drift—should be estimated recursively and projected forward for maintenance planning.

6.4. Layer D: optimization and safe actuation

Digital twins add operational value when they influence decisions. Multi-objective engine optimization using a validated virtual engine has already been demonstrated [2], and transient empirical twins have been used to identify problematic operating scenarios before physical testing [9,10]. For biofuels, the optimization problem

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 10 October 2026
Page No: 5661 - 5677
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0738

should minimize fuel/energy consumption, NOx, particulate or smoke indicators and degradation risk subject to constraints on torque tracking, combustion stability, pressure-rise rate, exhaust temperature and uncertainty. A candidate calibration should be deployed only if the prediction interval remains inside a predefined trust region and the action is reversible or independently supervised.

7. Critical Synthesis: What the Literature Demonstrates — and What It Does Not

The engine DT literature now supports four conclusions. First, real-time execution is technically feasible when engine models are reduced around the decision-relevant states [1,3,11,12]. Second, data-driven methods substantially improve diagnosis and nonlinear prediction but require explicit treatment of operating-domain shift [18–21]. Third, hybrid physics–data structures are particularly attractive because they retain interpretable variables while reducing calibration or computational burden [7,24]. Fourth, DT-driven fault reproduction and optimization have moved beyond conceptual discussion into validated case studies [2,4–10]. However, the evidence does not yet justify the claim that a generalized biofuel ICE DT is mature. Most validated DT studies assume a conventional or fixed fuel. Biofuel experiments show that combustion and durability can change as a function of blend chemistry and ageing [26–32], while ML biofuel models are commonly evaluated on bounded laboratory datasets [33,34]. Direct fuel-aware DT evidence is only beginning to appear [15]. Consequently, a high-impact research agenda should prioritize transferability, uncertainty and long-horizon degradation over incremental improvements in within-dataset prediction accuracy. A second limitation is validation fragmentation. Engine-DT papers often report model error but not diagnostic false-alarm rates; AI papers report classification accuracy but not physical consistency; biofuel papers report performance and emissions but not digital-model transfer. Future studies should therefore use a common validation stack: (i) prediction error for physical variables, (ii) real-time factor or inference latency, (iii) fault-detection sensitivity and false-positive rate, (iv) cross-condition and cross-fuel generalization, (v) uncertainty calibration, (vi) optimization regret relative to measured optimum, and (vii) maintenance lead time for progressive degradations. Without this multidimensional validation, two DTs with similar RMSE can have very different operational value.

8. Challenges And Actionable Future Research

8.1. Standardized interfaces and semantic fuel descriptors

The first research priority is a standardized information model for engine twins. Future implementations should define machine-readable variable names, units, timestamps, quality flags and provenance for physical sensors, virtual sensors, actuator commands, fuel descriptors and model states. For biofuels, the interface should not transmit only a blend name. At minimum, the schema should support density, viscosity, lower heating value, ignition-quality descriptor, oxygen fraction, water content or ageing indicator, and uncertainty. The key research question is whether a compact descriptor set can transfer across feedstocks without explicitly modelling full chemical composition.

8.2. Physics-informed and residual hybrid models

The second priority is hybrid modelling with explicit separation between what is known and what is learned. The physics core should carry conservation laws, actuator dynamics and fundamental state relations; the learning component should estimate uncertain combustion parameters, emissions residuals, sensor biases or degradation terms. Experiments should compare black-box, grey-box and residual-learning structures on identical cross-fuel test sets. The central design question is not which architecture gives the lowest training RMSE, but which architecture maintains calibrated uncertainty and physical plausibility during extrapolation.

8.3. Continual learning without loss of safety

A fleet-deployed DT will encounter new batches of fuel and new degradation states. Continual learning is therefore necessary, but uncontrolled online retraining can erase previously learned behaviour or adapt to a faulty sensor. Future systems should use gated updates: a new parameter set is accepted only after residual consistency, physical bounds and independent sensor checks are satisfied. Shadow-mode evaluation should precede active ECU deployment. Research should quantify how much

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 10 October 2026
Page No: 5661 - 5677
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0738

new data are required to adapt to a new biodiesel feedstock and whether parameter-only adaptation is safer than full network retraining.

8.4.Uncertainty quantification and out-of-distribution detection

Closed-loop DT optimization requires uncertainty to become an operational variable. A point prediction with low average error can still be unsafe under a new fuel. Research should therefore combine epistemic uncertainty, measurement uncertainty and model discrepancy. Out-of-distribution detectors should monitor both raw sensor statistics and physically meaningful residuals. The acceptance criterion for automated optimization should be expressed as a probabilistic constraint: the candidate action must remain within thermal, pressure, emissions and hardware-protection limits over the relevant prediction interval.

8.5.Long-horizon fuel–hardware co-degradation

The most underdeveloped area is long-horizon co-degradation. Biodiesel endurance and material studies show injector deposits, lubricant changes and corrosion mechanisms that evolve much more slowly than a combustion cycle [28–32]. Future twin experiments should therefore combine short transient tests with accelerated ageing or long-duration endurance data. A hierarchical twin could use millisecond-to-second combustion states, minute-scale thermal states and hour-to-month degradation states. The research question is whether these time scales can be coupled without making online execution prohibitively expensive.

8.6.Benchmark datasets and validation protocols

Progress will remain difficult to compare without shared benchmarks. An ideal benchmark should contain synchronized raw and ECU signals, known actuator commands, fuel properties, engine operating conditions, induced faults and longitudinal degradation labels for several fuels. At least one fuel or blend should be withheld completely during model development to evaluate true fuel-domain transfer. Model reporting should include inference latency on specified hardware, calibration/uncertainty metrics, cross-fuel performance, and failure cases—not only best-case accuracy. As shown in Table 5 Actionable research roadmap for high-fidelity biofuel engine digital twins.

Table 5 Actionable research roadmap for high-fidelity biofuel engine digital twins

Research question	Recommended experimental/computational design	Key metrics	Design consideration
RQ1: What minimum fuel descriptor set is transferable across feedstocks?	Multi-feedstock engine campaign with measured physicochemical properties	Prediction retained on unseen feedstock; descriptor sensitivity; parameter identifiability	Fuel label alone is insufficient
RQ2: Which hybrid structure best extrapolates?	Benchmark black-box vs residual vs parameter-learning hybrid on identical data	Cross-fuel RMSE; physics-violation rate; uncertainty calibration	Report extrapolation, not only random train/test splits
RQ3: Can the twin distinguish fuel drift from injector degradation?	Factorial ageing/deposit experiments with controlled fuel-property changes	Fault confusion matrix; false alarm rate; identified injector-flow state	Use counterfactual virtual fault reproduction
RQ4: How should online adaptation be gated?	Shadow-mode continual learning under batch changes and sensor bias	Adaptation time; catastrophic-forgetting score; safety violations	Parameter-only update may be safer than full retraining

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 10 October 2026
Page No: 5661 - 5677
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0738

RQ5: What is the real-time fidelity ceiling?	0D, 1D, reduced-order and hybrid models on common hardware	Real-time factor, latency, energy use, accuracy vs state dimension	Choose fidelity by control/diagnostic time scale
RQ6: How should uncertainty constrain optimization?	Closed-loop virtual calibration with OOD fuel cases	Constraint-violation probability; optimization regret; coverage probability	No automated action when uncertainty exceeds trust limit
RQ7: Can degradation be predicted months ahead?	Long endurance test + lubricant/fuel/injector inspection	RUL error; maintenance lead time; degradation-state observability	Couple fast combustion and slow ageing states
RQ8: Can one architecture transfer across engines?	Same twin layer design on two engine platforms	Transfer-learning data requirement; retained physical parameter meaning	Separate platform-independent semantics from engine-specific calibration

Conclusions

Digital-twin technology provides a credible route from reactive engine monitoring to fuel-aware prediction and optimization, but the literature does not support treating every engine model or AI classifier as a digital twin. A mature ICE twin requires synchronized data, state estimation, an executable virtual model, diagnostic or prognostic intelligence, and a pathway from virtual inference to a constrained decision. Original studies now demonstrate each of these capabilities separately and, in several cases, in integrated diesel-engine implementations [1–13]. The strongest emerging direction is hybrid modelling, in which physical equations preserve causality and data-driven models learn difficult parameters, residuals or degradation relationships [7,15,24].

- Traditional vibration, OBD and signal-processing approaches remain valuable for observability but are fundamentally limited when a fault signature changes with operating condition or fuel chemistry. AI models improve discrimination, yet training-domain dependence and causal ambiguity make them insufficient as the sole basis for high-consequence decisions.
- Validated ICE digital twins span real-time physics-based engines, hybrid combustion models, fault-reproduction frameworks, empirical emissions twins and optimization platforms. Their maturity should be judged by sensing, state estimation, model fidelity, intelligence and actuation rather than by the label 'digital twin'.
- Biofuels create a distinct DT requirement because fuel properties and ageing alter ignition, heat release, emissions, deposits, corrosion and wear. Fuel descriptors and fuel-induced degradation states must therefore be explicit twin inputs or estimated latent states rather than hidden disturbances.
- Direct biofuel-specific DT evidence remains limited relative to conventional diesel/gasoline implementations. This gap is a research opportunity: future work should validate twins across feedstocks, blend ratios, aged fuels and progressive hardware degradation instead of reporting only within-dataset accuracy.
- The proposed BioTwin-ICE framework combines a fast physics core, fuel-aware parameter adaptation, data-driven residuals, virtual fault reproduction, uncertainty quantification and constrained optimization.

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 10 October 2026
Page No: 5661 - 5677
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0738

Its central safety principle is that uncertainty must limit actuation: when the fuel or condition is outside the validated domain, the twin should revert to conservative control rather than extrapolate confidently.

- For high-impact future research, standardized data semantics, cross-fuel benchmark datasets, hybrid physics–AI models, continual-learning safeguards and long-horizon fuel–hardware co-degradation experiments are more important than incremental gains in classification accuracy.

In summary, the transition from a generic engine digital twin to a biofuel-aware operational twin is primarily a problem of transferability and trust. The field has sufficient modelling, sensing and AI components to build such systems; the next step is rigorous cross-domain validation that proves they remain physically consistent, computationally real-time and diagnostically reliable when the fuel itself becomes a changing state of the engine system.

References

[1]. Bondarenko O, Fukuda T. Development of a diesel engine's digital twin for predicting propulsion system dynamics. Energy. 2020;196:117126. https://doi.org/10.1016/j.energy.2020.117126.

[2]. Guan J, Li Y, Liu J, Duan X, Shen D, Jia D, Ku C. Experimental and numerical research on the performance characteristics of OPLVCR engine based on the NSGA II algorithm using digital twins. Energy Conversion and Management. 2021;236:114052. https://doi.org/10.1016/j.enconman.2021.114052.

[3]. Söderäng E, Hautala S, Mikulski M, et al. Development of a digital twin for real-time simulation of a combustion engine-based power plant with battery storage and grid coupling. Energy Conversion and Management. 2022;266:115793. https://doi.org/10.1016/j.enconman.2022.115793.

[4]. Jiang J, Li H, Mao Z, Liu F, Zhang J, Jiang Z, Li H. A digital twin auxiliary approach based on adaptive sparse attention network for diesel engine fault diagnosis. Scientific Reports. 2022;12:675. https://doi.org/10.1038/s41598-021-04545-5.

[5]. Minchev D, Varbanets R, Shumylo O, Zalozh V, Aleksandrovska N, Bratchenko P, Truong TH. Digital Twin Test-Bench Performance for Marine Diesel Engine Applications. Polish Maritime Research. 2023;30(4):81–91. https://doi.org/10.2478/pomr-2023-0061.

[6]. Bo Y, Wu H, Che W, Zhang Z, Li X, Myagkov L. Methodology and application of digital twin-driven diesel engine fault diagnosis and virtual fault model acquisition. Engineering Applications of Artificial Intelligence. 2024;131:107853. https://doi.org/10.1016/j.engappai.2024.107853.

[7]. Hu D, Wang H, Yang C, Wang B, Duan B, Wang Y, Li H. Construction of digital twin model of engine in-cylinder combustion based on data-driven. Energy. 2024;293:130543. https://doi.org/10.1016/j.energy.2024.130543.

[8]. Saurabh S, Sureka B. An Evaluation of an Unhealthy Part Identification Using a 0D-1D Diesel Engine Simulation Based Digital Twin. SAE International Journal of Advances and Current Practices in Mobility. 2022. https://doi.org/10.4271/2022-01-0382.

[9]. Roberts P, Bates L, Tabata K, Headley A, et al. RDE Plus - Rapid Characterisation of Vehicle and Powertrain Performance and Emissions using Dynamic Design of Experiments, Digital Twin and Virtual Driving Methodologies. SAE Technical Paper 2022-01-0580. 2022. https://doi.org/10.4271/2022-01-0580.

[10]. Roberts P, Mason A, Headley A, Bates L, et al. Powertrain Digital Twinning for Real-World Emissions Compliance. SAE Technical Paper 2024-01-2602. 2024. https://doi.org/10.4271/2024-01-2602.

[11]. Duraiarasan S, Salehi R, Wang F, Stefanopoulou A, Allain M, Mahesh S. Real-Time Embedded Models for Simulation and

Control of Clean and Fuel-Efficient Heavy-Duty Diesel Engines. SAE Technical Paper 2020-01-0257. 2020. https://doi.org/10.4271/2020-01-0257.

[12]. Frey M, Itzen D, Sautter J, Weller L, Hagenbucher T, Yang Q, Grill M, Kulzer AC. Development of Ultra-Fast AI-Driven Diesel Engine Model for Real-Time Optimization. SAE Technical Paper 2025-01-8397. 2025. https://doi.org/10.4271/2025-01-8397.

[13]. Tessaro I, Mariani V, Coelho LDS, Ayala HVH. Hybrid symbolic regression framework for digital twin modeling of gas internal combustion engines. Energy. 2026;344:140035. https://doi.org/10.1016/j.energy.2026.140035.

[14]. Roberts P, Whelan S, Bates L, Maroni C, Leo E, Pezzola ME, Child S. The Prediction of Performance and Emissions for Synthetic Machine Handling Cycles Utilising a Powertrain Empirical Digital Twin. SAE Technical Paper 2024-01-4271. 2024.

[15]. Van Minh N, Jayabal R, Leo GM L, et al. Physics-encoded machine learning for performance and emission prediction of nickel ferrite nanocatalyst and hydrogen-enriched biodiesel in diesel engines. RSC Advances. 2026;16:10798–10821. https://doi.org/10.1039/D5RA09336H.

[16]. Jafarian K, Mobin M, Jafari-Marandi R, Rabiei E. Misfire and valve clearance faults detection in the combustion engines based on a multi-sensor vibration signal monitoring. Measurement. 2018;128:527–536. https://doi.org/10.1016/j.measurement.2018.04.062.

[17]. Cai B, Sun X, Wang J, Yang C, Wang Z, Kong X, Liu Z, Liu Y. Fault detection and diagnostic method of diesel engine by combining rule-based algorithm and BNs/BPNNs. Journal of Manufacturing Systems. 2020;57:148–157. https://doi.org/10.1016/j.jmsy.2020.09.001.

[18]. Wang R, Chen H, Guan C. Random convolutional neural network structure: An intelligent health monitoring scheme for diesel engines. Measurement. 2021;171:108786. https://doi.org/10.1016/j.measurement.2020.108786.

[19]. Qin C, Jin Y, Tao J, Xiao D, Yu H, Liu C, Shi G, Lei J, Liu C. DTCNNMI: A deep twin convolutional neural networks with multi-domain inputs for strongly noisy diesel engine misfire detection. Measurement. 2021;180:109548. https://doi.org/10.1016/j.measurement.2021.109548.

[20]. Qin C, Jin Y, Zhang Z, Yu H, Tao J, Sun H, Liu C. Anti-noise diesel engine misfire diagnosis using a multi-scale CNN-LSTM neural network with denoising module. CAAI Transactions on Intelligence Technology. 2023;8(3):963–986. https://doi.org/10.1049/cit2.12170.

[21]. Shahid SM, Ko S, Kwon S. Real-time abnormality detection and classification in diesel engine operations with convolutional neural network. Expert Systems with Applications. 2022;192:116233. https://doi.org/10.1016/j.eswa.2021.116233.

[22]. Zhang P, et al. Misfire detection of diesel engine based on convolutional neural networks. Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering. 2021;235(8):2148–2165. https://doi.org/10.1177/0954407020987077.

[23]. Shamsi SS. Development of a Real-Time Digital Computer Simulation of a Turbocharged Diesel Engine. SAE Technical Paper 800521. 1980. https://doi.org/10.4271/800521.

[24]. Ankobea-Ansah K, Hall CM. A Hybrid Physics-Based and Stochastic Neural Network Model Structure for Diesel Engine Combustion Events. Vehicles. 2022;4(1):259–296. https://doi.org/10.3390/vehicles4010017.

[25]. Shayler PJ, Allen AJ, Roberts AL. Running Real-Time Engine Model Simulation with Hardware-in-the-Loop for Diesel Engine Development. SAE Technical Paper 2005-01-

0056. 2005. https://doi.org/10.4271/2005-01-0056.

[26]. Zheng Z, Xia M, Liu H, Wang X, Yao M. Experimental study on combustion and emissions of dual fuel RCCI mode fueled with biodiesel/n-butanol, biodiesel/2,5-dimethylfuran and biodiesel/ethanol. Energy. 2018;148:824–838. https://doi.org/10.1016/j.energy.2018.02.015

[27]. Zhong W, Xuan T, He Z, Wang Q, Li D, Xin Z, Huang Y. Experimental study of combustion and emission characteristics of diesel engine with diesel/second-generation biodiesel blending fuels. Energy Conversion and Management. 2016;121:241–250. https://doi.org/10.1016/j.enconman.2016.05.033.

[28]. Liaquat AM, Masjuki HH, Kalam MA, Fazal MA, Khan AF, Fayaz H, Varman M. Impact of palm biodiesel blend on injector deposit formation. Applied Energy. 2013;111:882–893. https://doi.org/10.1016/j.apenergy.2013.06.036.

[29]. Liaquat AM, Masjuki HH, Kalam MA, Rizwanul Fattah IM. Impact of biodiesel blend on injector deposit formation. Energy. 2014;72:813–823. https://doi.org/10.1016/j.energy.2014.06.006

[30]. Matbouei M, Weston DP, Liang X, Hainsworth SV. An investigation of the effect of temperature on the oxidation processes of metallic diesel engine fuel system materials and B100 biodiesel from used cooking oil in exposure testing. Fuel. 2021;285:119063. https://doi.org/10.1016/j.fuel.2020.119063.

[31]. Gupta JG, Agarwal AK. Engine durability and lubricating oil tribology study of a biodiesel fuelled common rail direct injection medium-duty transportation diesel engine. Wear. 2021;486–487:204104. https://doi.org/10.1016/j.wear.2021.204104.

[32]. Ben Amara A, Lecointe B, Jeuland N, Takahashi T, et al. Experimental Study of the Impact of Diesel/Biodiesel Blends Oxidation on the Fuel Injection System. SAE International Journal of Fuels and Lubricants. 2014;7(3):849–860. https://doi.org/10.4271/2014-01-2767.

[33]. Magesh N, Pushparaj T, Vinoth Kannan V, Razak A, Buradi A, Ketema A. Experimental Investigation and Prediction of Performance, Combustion, and Emission Features of a Diesel Engine Fuelled with Pumpkin-Maize Biodiesel using Different Machine Learning Algorithms. Mathematical Problems in Engineering. 2022;2022:9505424. https://doi.org/10.1155/2022/9505424.

[34]. Şahin S. Comparison of machine learning algorithms for predicting diesel/biodiesel/iso-pentanol blend engine performance and emissions. Heliyon. 2023;9(11):e21365. https://doi.org/10.1016/j.heliyon.2023.e21365.