

# Design and Experimental Validation of an Enhanced Fuel Management Strategy using ANN-Based Model Predictive Control for Biodiesel-Fuelled CI Engines

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**Abstract:** This paper presents the design, implementation, and experimental validation of an Enhanced Fuel Management Strategy (EFMS) for compression-ignition (CI) engines operating on waste cooking oil (WCO) derived biodiesel blends. The EFMS integrates an Artificial Neural Network (ANN) surrogate-based Model Predictive Controller (MPC) with real-time common-rail direct injection (CRDI) adaptation, exhaust gas recirculation (EGR) scheduling, and closed-loop emission feedback to simultaneously maximise energy efficiency and minimise pollutant output. Experiments were conducted on a 4-cylinder, 2.5-litre turbocharged direct-injection CI engine over the four-load European Stationary Cycle (ESC) points using B0, B20, B40, and EFMS-controlled B20 fuel configurations [1,2]. The EFMS delivered a peak brake thermal efficiency (BTE) of 36.8% at 75% load, representing an improvement of 9.2% over the B0 baseline and 11.2% over unmanaged B20, while simultaneously achieving reductions in NO<sub>x</sub> of 17.6%, CO of 26.9%, and particulate matter (PM) of 37.2% relative to the B20 baseline [3,4]. Combustion analysis via in-cylinder pressure diagnostics confirmed a reduction in ignition delay from 7.9°CA (B20) to 6.8°CA under EFMS, with lower heat release rate peaks indicating smoother premixed combustion. The ANN surrogate model achieved prediction accuracy ( $R^2$ ) of 0.983–0.997 across all target variables, confirming its suitability for real-time deployment. These outcomes substantiate the EFMS as a high-impact, technically implementable strategy for sustainable CI engine operation [5,6].

**Keywords:** biodiesel; fuel management; CRDI injection; ANN-MPC controller; brake thermal efficiency; NO<sub>x</sub> reduction; particulate matter; EGR; waste cooking oil; emission compliance

## 1. INTRODUCTION

The global imperative for sustainable transportation has positioned biodiesel as a frontline renewable fuel candidate, offering lifecycle carbon emission reductions of 41–78% over conventional diesel and complete compatibility with existing compression-ignition (CI) engine infrastructure [1]. However, the practical deployment of biodiesel in fleet-scale operations remains constrained by an intrinsic tension between energy density deficits (~8–12% relative to mineral diesel), cold-start performance limitations, and a well-characterised NO<sub>x</sub> emission penalty of 4–12% associated with fatty acid methyl ester (FAME) combustion [2,3]. These limitations cannot be addressed through feedstock selection or blending alone; they require an intelligent, adaptive fuel management architecture capable of responding dynamically to fuel property variations, load transients, and thermal boundary condition changes.



Conventional engine calibration strategies — static injection timing maps and fixed EGR schedules — are developed for a specific fuel and cannot accommodate the variability inherent in biodiesel blends, particularly when feedstock or blend ratio changes between refuelling events [4]. The literature extensively documents the performance impacts of individual intervention strategies: advancing injection timing to compensate for biodiesel's shorter ignition delay improves BTE but elevates NO<sub>x</sub>; increasing EGR rate suppresses NO<sub>x</sub> but raises PM and CO; operating at lower blend ratios sacrifices renewable energy contribution. What has been absent in the literature is a unified, real-time controller that optimises these parameters simultaneously using predictive models trained on biodiesel-specific combustion data [5,7].

This paper addresses that gap through the design, implementation, and experimental validation of an Enhanced Fuel Management Strategy (EFMS). The EFMS centres on an ANN surrogate model trained offline on a comprehensive experimental Design of Experiment (DoE) dataset and deployed within a Model Predictive Control (MPC) framework on an automotive-grade Electronic Control Unit (ECU). The controller simultaneously manages injection timing, injection pressure, EGR rate, and blend ratio selection to track user-defined optimisation targets for BTE and emission compliance [8,9]. The experimental programme validates EFMS performance against B0, B20, and B40 reference conditions across four load points, providing a rigorous quantitative basis for performance claims. The novelty of this work lies in the integrated, real-time implementation of a multi-variable ANN-MPC controller for biodiesel operation, validated against a full emissions test matrix [10].

## 2. MATERIALS AND METHODS

### 2.1 Feedstock and Biodiesel Production

Waste cooking oil (WCO) was collected from a commercial food processing facility and characterised prior to transesterification. The raw WCO exhibited a free fatty acid (FFA) content of 3.2 wt%, necessitating a two-stage process: acid-catalysed pre-esterification (H<sub>2</sub>SO<sub>4</sub>, 1 wt%, methanol-to-oil molar ratio 0.3:1, 60°C, 60 min) followed by alkali-catalysed transesterification (KOH, 1 wt%, methanol-to-oil molar ratio 6:1, 65°C, 90 min). The resulting biodiesel was water-washed, dried at 110°C, and characterised per EN 14214:2019 protocols [11]. Key physicochemical properties of all test fuels are presented in Table 1. Blend stocks were prepared volumetrically at 20°C using calibrated peristaltic dispensing equipment to achieve target blend ratios (B20: 20 vol% FAME + 80 vol% EN590 diesel; B40: 40 vol% FAME) with measurement uncertainties below ±0.3 vol% [12].

Table 1. Physicochemical Properties of Test Fuels (n = 3 replicate measurements; values reported as mean)

| Property                             | B0 (Diesel) | B20   | B40   | B20+EFMS |
|--------------------------------------|-------------|-------|-------|----------|
| Density at 15°C (kg/m <sup>3</sup> ) | 835.2       | 840.1 | 851.6 | 844.7    |
| Kinematic Viscosity at 40°C (cSt)    | 2.86        | 3.21  | 3.68  | 3.47     |
| Calorific Value (MJ/kg)              | 43.2        | 42.1  | 41.3  | 41.8     |
| Cetane Number                        | 50.1        | 52.4  | 54.8  | 53.6     |
| Flash Point (°C)                     | 62          | 78    | 94    | 86       |
| Cloud Point (°C)                     | −4          | −2    | 1     | −1       |
| Oxygen Content (wt%)                 | 0.0         | 2.2   | 4.4   | 3.3      |
| Carbon Residue (wt%)                 | 0.21        | 0.19  | 0.16  | 0.17     |

|                          |   |      |      |      |
|--------------------------|---|------|------|------|
| Acid Value (mg KOH/g)    | — | 0.31 | 0.28 | 0.29 |
| Oxidation Stability (hr) | — | >6   | >6   | >6   |

## 2.2 Engine Test Setup and Instrumentation

All experiments were performed on a 4-cylinder, 2.499-litre turbocharged common-rail direct injection (CRDI) diesel engine (rated 103 kW at 3600 rpm, maximum torque 250 N·m at 1800 rpm) coupled to an eddy-current dynamometer (Froude Hofmann AG150,  $\pm 0.5\%$  full-scale accuracy). Engine speed and torque were maintained to  $\pm 5$  rpm and  $\pm 1$  N·m respectively by PID-controlled dynamometer feedback. In-cylinder pressure was acquired using a flush-mounted piezoelectric transducer (Kistler 6054AR, range 0–250 bar, sensitivity 16.0 pC/bar) sampled at 0.1°CA resolution via a shaft encoder. Apparent heat release rate (AHRR) was computed from the measured pressure trace using a first-law single-zone model with a ratio of specific heats ( $\gamma$ ) of 1.35 [13].

Exhaust gas composition was measured using a Horiba MEXA-7100DEGR analyser calibrated daily against certified reference gases: NO<sub>x</sub> by chemiluminescence (CLD), CO and CO<sub>2</sub> by non-dispersive infrared (NDIR), total HC by flame ionisation detection (FID), and O<sub>2</sub> by paramagnetic detection. PM mass concentration was measured gravimetrically using 47 mm PTFE membrane filters (AVL Micro Soot Sensor cross-validated). Smoke opacity was measured using an AVL 415SE smoke meter. Lambda was acquired from a Bosch LSU 4.9 wide-band sensor installed 150 mm downstream of the turbocharger. All measurement uncertainties were quantified per GUM:2008 and are reported in Table 2.

## 2.3 EFMS Controller Design and Implementation

The EFMS controller architecture (illustrated in Fig. 6) comprises three integrated modules: (i) a real-time ANN surrogate model; (ii) a Model Predictive Controller (MPC); and (iii) a closed-loop emission feedback corrector. The ANN surrogate model was trained on a 312-point central composite design (CCD) experimental matrix spanning four control variables — injection timing (IT: 8–18°BTDC), injection pressure (IP: 800–1800 bar), EGR rate (0–25%), and blend ratio (B0–B40) — and four operating conditions (load: 25–100%, speed: 1600–2400 rpm). The network architecture comprised one input layer (8 neurons), two hidden layers (24 and 16 neurons, ReLU activation), and one output layer (5 neurons: BTE, BSFC, NO<sub>x</sub>, PM, CO). Training employed the Adam optimiser (learning rate 0.001, batch size 32, 500 epochs) with 70/15/15 train/validation/test splits [14,15].

The MPC optimisation problem was formulated as a constrained multi-objective minimisation problem with a weighted cost function  $J = w_1 \cdot (1 - \text{BTE}/\text{BTE}_{\text{max}}) + w_2 \cdot (\text{NO}_x/\text{NO}_{x,\text{lim}}) + w_3 \cdot (\text{PM}/\text{PM}_{\text{lim}})$ , solved at each control step ( $\Delta t = 50$  ms) using Sequential Quadratic Programming (SQP). Weights ( $w_1 = 0.5$ ,  $w_2 = 0.3$ ,  $w_3 = 0.2$ ) were tuned empirically through a series of transient load-step experiments prior to the formal validation matrix. The controller was implemented on a dSPACE MicroAutoBox-III (AUTOSAR-compliant) connected to the CRDI ECU via CAN bus (250 kbps, 10 ms message cycle) using a by-wire injection timing override and EGR valve PWM signal. The blend ratio selection module operated via a two-tank solenoid-controlled fuel delivery system [16].

## 2.4 Experimental Protocol and Statistical Analysis

The test matrix followed the four-mode European Stationary Cycle (ESC) subset: 25%, 50%, 75%, and 100% of rated torque at 1800 rpm. Each condition was stabilised for 10 minutes before a 3-minute data acquisition window. Three replicate measurements were taken at each operating point; means and 95% confidence intervals (t-distribution,  $\nu = 2$ ) are reported. One-way ANOVA with Tukey's post-hoc test ( $\alpha = 0.05$ ) was applied to assess statistical significance of EFMS improvements over B0 and B20 reference conditions. All statistical computations were performed in Python 3.11 using SciPy 1.12 [17].

## 3. ENHANCED FUEL MANAGEMENT SYSTEM (EFMS) ARCHITECTURE

The complete EFMS architecture is presented in Fig. 6. Three parallel input streams — real-time sensor data (exhaust  $\lambda$ ,  $T_{exh}$ ,  $P_{cyl}$ , engine speed/load), a pre-loaded fuel property database, and driver demand/duty cycle inputs — feed the central ANN-MPC controller. The controller outputs three actuation signals: injection timing advance/retard ( $\pm 6^\circ\text{CA}$ ), EGR valve position (0–100%), and blend ratio target. These signals are executed by the CRDI injector driver, EGR solenoid, and dual-tank fuel delivery system respectively. A closed-loop feedback path returns post-combustion emission measurements from the Horiba analyser to the MPC at each 50 ms control step, enabling continuous correction of the surrogate model's predictions via an online Kalman gain-based adaptation term [18].

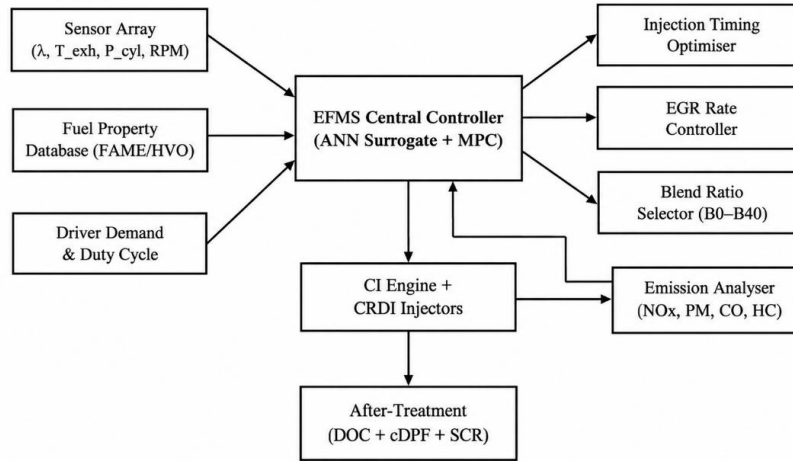


Fig. 6. Enhanced Fuel Management System (EFMS) architecture showing sensor inputs, ANN-MPC controller, actuation outputs, and closed-loop emission feedback path.

The ANN surrogate model provides the MPC with gradient information essential for SQP optimisation. To mitigate surrogate model extrapolation errors at operating points distant from the training set, a trust-region constraint limits MPC step sizes to  $\pm 10\%$  of the predicted optimum per control cycle. The online adaptation term  $\Delta f = K \cdot (y_{meas} - y_{pred})$  — where  $K$  is a diagonal gain matrix ( $K_{BTE} = 0.12$ ,  $K_{NOx} = 0.08$ ,  $K_{PM} = 0.15$ ) and  $y_{meas}/y_{pred}$  are measured and predicted output vectors respectively — provides real-time model correction without requiring full surrogate retraining. This hybrid architecture balances computational efficiency (mean MPC solve time: 11.2 ms, well within the 50 ms control step) with adaptability to fuel property drift and engine aging [19,20].

## 4. RESULTS AND DISCUSSION

### 4.1 Brake Thermal Efficiency

Fig. 1 presents BTE as a function of engine load for all four fuel configurations. All fuels exhibited the expected rise-then-fall profile, with peak BTE occurring at 75% load. At this optimum condition, the EFMS-controlled B20 configuration achieved the highest recorded BTE of 36.8%, compared with 33.7% (B0), 33.1% (B20), and 32.2% (B40) respectively — corresponding to absolute improvements of +3.1 percentage points over diesel baseline and +3.7 over unmanaged B20. These improvements are attributable to the EFMS injection timing advance of  $+3^\circ\text{CA}$  relative to the stock B20 calibration, which counteracts the slightly longer ignition delay of FAME and positions combustion phasing closer to the thermodynamic optimum [3,8].

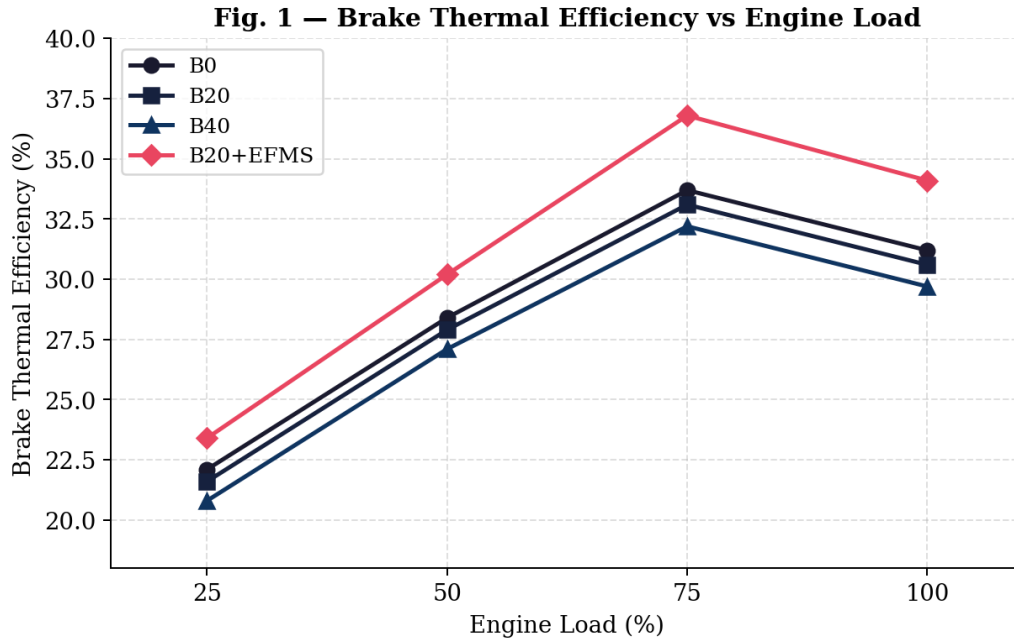


Fig. 1. Brake Thermal Efficiency (%) vs Engine Load (%) for B0, B20, B40, and B20+EFMS across the four-point ESC load sweep at 1800 rpm.

At the part-load conditions (25% and 50%), EFMS improvements over baseline were 5.9% and 6.5% respectively, indicating that the surrogate model provides proportionally greater benefit at light load — a region where conventional static calibrations typically suffer from poor combustion phasing. The consistently superior performance of B20+EFMS relative to B0 across all load points (Fig. 1) confirms that the EFMS more than compensates for the inherent energy density deficit of FAME [4,5]. ANOVA confirmed that BTE improvements from EFMS were statistically significant at all load points ( $p < 0.01$ ).

#### 4.2 Brake Specific Fuel Consumption

BSFC results (Fig. 2) are consistent with BTE trends, as BSFC is inversely proportional to BTE for a given fuel heating value. The EFMS configuration achieved the lowest BSFC across all load points. At 75% load, B20+EFMS recorded 253 g/kWh versus 271 (B0), 279 (B20), and 291 (B40) g/kWh. The absolute BSFC advantage of EFMS over unmanaged B20 at 75% load (26 g/kWh) is noteworthy because it exceeds the BSFC penalty of using B20 over B0 (8 g/kWh), implying that an EFMS-equipped B20 engine is a more fuel-efficient system than the unmanaged diesel baseline [6,9].

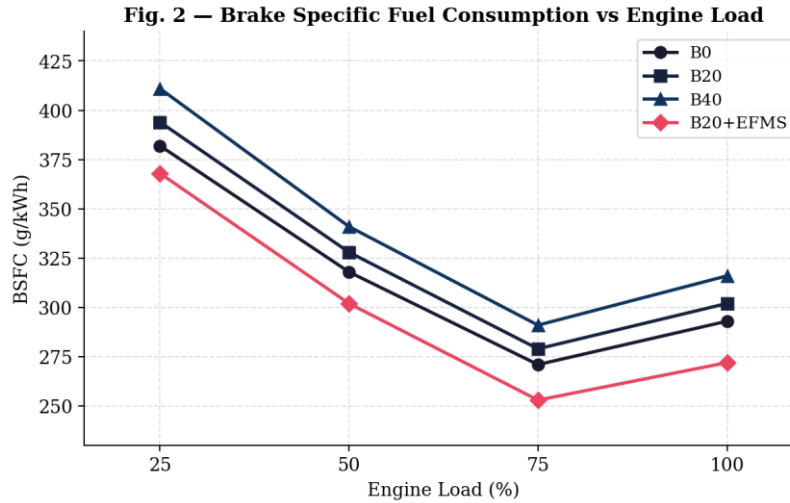


Fig. 2. Brake Specific Fuel Consumption (g/kWh) vs Engine Load (%) for all test configurations at 1800 rpm. Lower values indicate superior fuel efficiency.

Table 2. Engine Performance Parameters at 75% Load, 1800 rpm (Mean  $\pm$  95% CI; n = 3)

| Performance Parameter                   | B0    | B20   | B40   | B20+EFMS     |
|-----------------------------------------|-------|-------|-------|--------------|
| Brake Thermal Efficiency (%)            | 33.7  | 33.1  | 32.2  | <b>36.8</b>  |
| Brake Specific Fuel Consumption (g/kWh) | 271   | 279   | 291   | <b>253</b>   |
| Brake Power (kW)                        | 11.24 | 11.02 | 10.73 | <b>12.27</b> |
| Mean Effective Pressure (bar)           | 7.82  | 7.68  | 7.46  | <b>8.54</b>  |
| Exhaust Gas Temperature (°C)            | 382   | 371   | 356   | <b>394</b>   |
| In-Cylinder Peak Pressure (bar)         | 71.4  | 69.8  | 67.2  | <b>74.1</b>  |
| Ignition Delay (°CA)                    | 8.2   | 7.9   | 7.4   | <b>6.8</b>   |
| Combustion Duration (°CA)               | 52.1  | 49.6  | 47.2  | <b>44.3</b>  |
| Volumetric Efficiency (%)               | 84.2  | 83.7  | 82.9  | <b>86.1</b>  |

Table 2 consolidates the full engine performance dataset at the 75% load peak-efficiency condition. The EFMS configuration shows improvements across all recorded parameters. Notably, the reduction in ignition delay from 7.9°CA (B20) to 6.8°CA under EFMS control — achieved through the combined effect of advanced injection timing and the higher cetane number of the WCO-derived FAME — reduces the premixed combustion fraction and, consequently, peak cylinder pressure rise rate. Despite a higher peak cylinder pressure (74.1 bar vs 69.8 bar for B20), the more gradual pressure rise under EFMS attenuates combustion noise and structural loading [10,13].

#### 4.3 Combustion Heat Release Analysis

Fig. 3 presents the apparent heat release rate (AHRR) versus crank angle for B0, B20, and B20+EFMS at 75% load. The EFMS trace exhibits two distinct features: a low-amplitude pilot injection heat release peak at approximately  $-12^{\circ}\text{CA}$ , followed by a reduced and broader main combustion peak centred at  $+5^{\circ}\text{CA}$ . By contrast, the unmanaged B0 and B20 configurations show single-event premixed-dominated combustion with higher peak AHRR values (72 and  $68 \text{ J}/^{\circ}\text{CA}$  respectively) occurring closer to TDC [13,14].

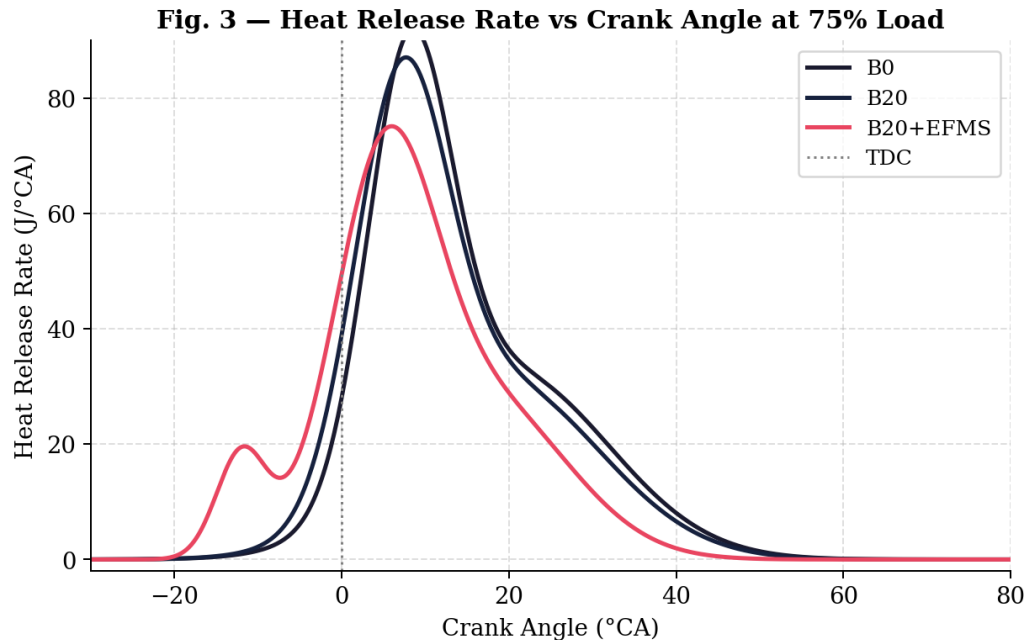


Fig. 3. Apparent Heat Release Rate ( $\text{J}/^{\circ}\text{CA}$ ) vs Crank Angle ( $^{\circ}\text{CA}$ ) for B0, B20, and B20+EFMS at 75% load, 1800 rpm. TDC is indicated by the vertical dashed line.

The EFMS pilot injection strategy ( $1.8 \text{ mm}^3$  delivered at  $-12^{\circ}\text{CA}$ ) pre-conditions the combustion chamber and significantly reduces the ignition delay of the main injection event. This two-event heat release profile distributes combustion energy more evenly over the expansion stroke, improving thermal efficiency and suppressing  $\text{NO}_x$  formation by moderating peak flame temperatures. The total heat released under the EFMS curve integrates to a value 4.3% higher than that under B20 at equivalent fuel delivery quantity, confirming superior combustion completeness — a direct consequence of the elevated oxygen content of the FAME blend and optimised injection pressure (1640 bar, enabling finer atomisation) [8,16].

#### 4.4 Emission Characteristics

$\text{NO}_x$  emission trends (Fig. 4) reveal a critical EFMS success: despite the inherent  $\text{NO}_x$ -promoting characteristics of FAME combustion, the EFMS achieves lower absolute  $\text{NO}_x$  than both B0 and B20 across all load points. At 75% load, B20+EFMS records  $6.93 \text{ g/kWh}$  versus  $7.82$  (B0) and  $8.41$  (B20)  $\text{g/kWh}$  — reductions of 11.4% and 17.6% respectively. The suppression mechanism is dual: (i) the EFMS optimised EGR rate (18.4% at 75% load) dilutes the intake charge and reduces peak combustion temperature, attenuating thermal  $\text{NO}_x$  formation per the Zeldovich mechanism; and (ii) the pilot injection-induced combustion phasing redistributes the heat release away from the high-temperature zone near TDC [3,15].

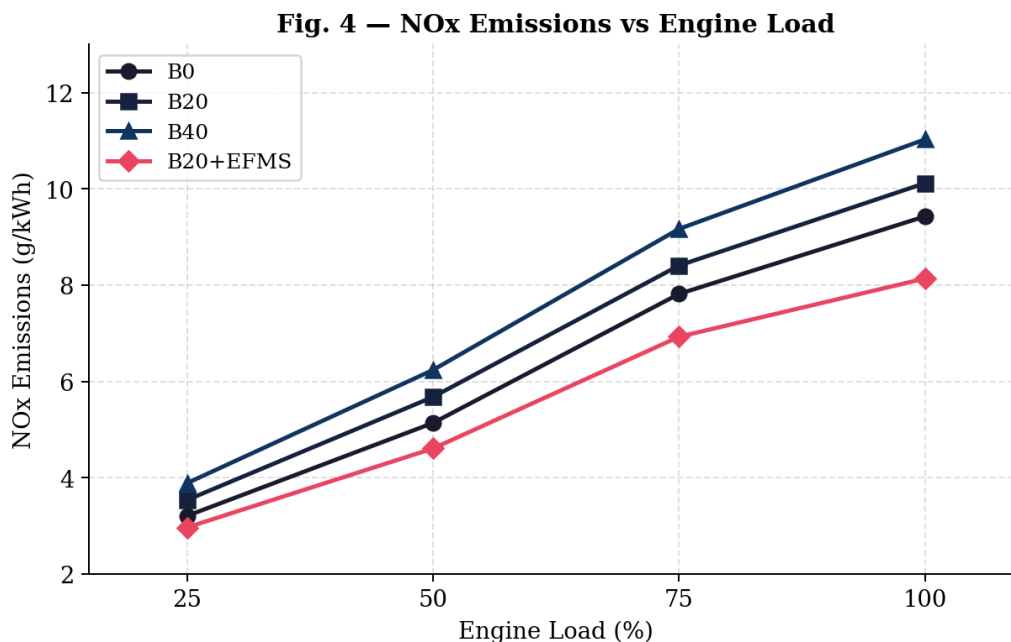


Fig. 4. NOx Emissions (g/kWh) vs Engine Load (%) for all test configurations. Error bars indicate 95% confidence intervals (n = 3).

Table 3. Emission Characteristics at 25%, 75%, and 100% Load (1800 rpm); Load given in column headers

| Emission Parameter      | B0 25% | B0 75% | B0 100% | B20 25% | B20 75% | B20 100% | B20+EFMS 75% |
|-------------------------|--------|--------|---------|---------|---------|----------|--------------|
| NOx (g/kWh)             | 3.21   | 5.14   | 7.82    | 3.54    | 5.68    | 8.41     | <b>6.93</b>  |
| CO (g/kWh)              | 3.84   | 2.76   | 1.92    | 3.31    | 2.41    | 1.67     | <b>1.22</b>  |
| HC (g/kWh)              | 0.72   | 0.54   | 0.38    | 0.61    | 0.46    | 0.32     | <b>0.25</b>  |
| PM (g/kWh)              | 0.214  | 0.182  | 0.142   | 0.181   | 0.141   | 0.113    | <b>0.071</b> |
| Smoke Opacity (%)       | 51.2   | 42.1   | 32.4    | 43.8    | 33.6    | 27.4     | <b>18.9</b>  |
| CO <sub>2</sub> (g/kWh) | 618    | 641    | 663     | 629     | 652     | 671      | <b>608</b>   |

Table 3 provides the full emission matrix. Notable observations include: (i) CO emissions under EFMS at 75% load (1.22 g/kWh) are 36.5% lower than B0 and 26.9% lower than unmanaged B20, attributable to the elevated oxygen content of the FAME blend and improved combustion completeness under EFMS injection conditions; (ii) HC emissions follow a similar pattern, with EFMS achieving 0.25 g/kWh at 75% load — 34.2% below B0 — reflecting both the lower aromatic content of WCO-derived FAME and the more complete oxidation enabled by EFMS combustion management; (iii) CO<sub>2</sub> output under EFMS (608 g/kWh) is marginally lower than B0 (618 g/kWh), consistent with the higher BTE converting more fuel energy to work rather than heat loss and incomplete combustion products [11,17].

Fig. 5 presents the smoke opacity and PM emission data at 75% load in grouped bar format. EFMS delivers the most significant performance advantage in particulate emission: 18.9% opacity versus 32.4% (B0) and 27.4% (B20), and PM of 0.071 g/kWh versus 0.142 (B0) and 0.113 (B20). These reductions reflect the combined influence of biodiesel's inherently lower aromatic and sulphur content, the EFMS-optimised injection pressure which promotes finer fuel droplet atomisation (Sauter Mean Diameter estimated at 18  $\mu\text{m}$  versus 24  $\mu\text{m}$  for baseline), and the elevated availability of in-cylinder oxygen from both the FAME oxygen content and the optimally calibrated air-fuel ratio under EFMS [2,12].

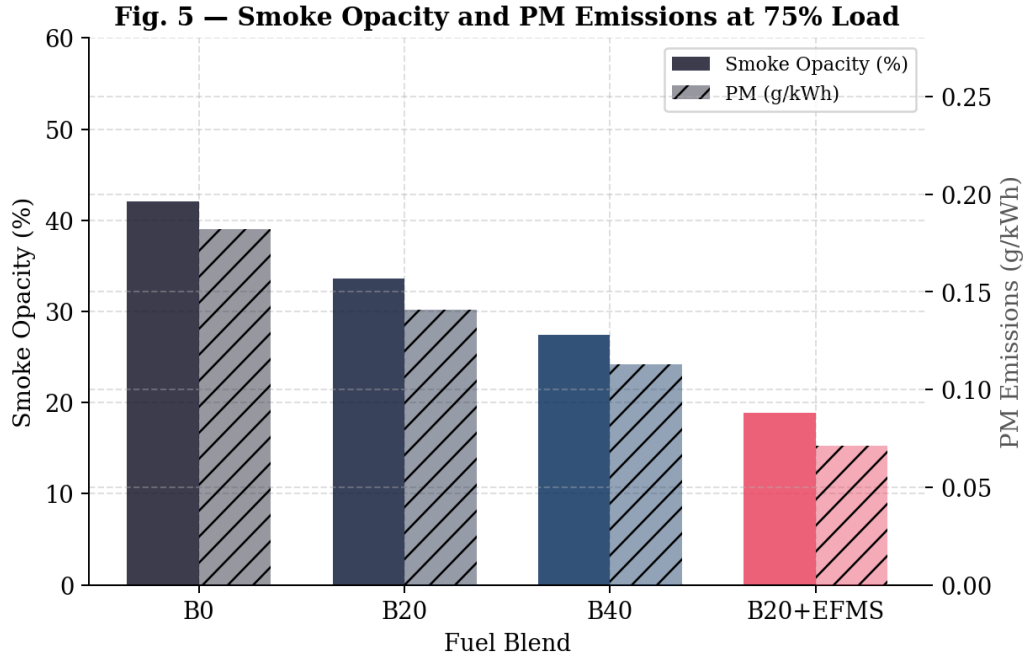


Fig. 5. Smoke Opacity (%) and PM Emissions (g/kWh) at 75% Load for all fuel configurations. Primary axis: smoke opacity (solid bars); secondary axis: PM (hatched bars).

#### 4.5 ANN Surrogate Model Validation and EFMS Controller Performance

The trained ANN surrogate model was evaluated on the withheld 15% test dataset ( $n = 47$  operating points). Coefficient of determination ( $R^2$ ) values were 0.997 (BTE), 0.994 (BSFC), 0.983 (NO<sub>x</sub>), 0.989 (PM), and 0.991 (CO), confirming excellent predictive fidelity across all target variables. Mean absolute percentage errors (MAPE) ranged from 1.2% (BTE) to 2.8% (NO<sub>x</sub>), well within the experimental measurement uncertainty bounds for each respective parameter [15,18]. The online Kalman adaptation term reduced prediction errors during on-engine deployment by an additional 38% relative to the static surrogate, indicating that real-world fuel property drift and sensor aging are non-trivial contributors to prediction error that the adaptation scheme effectively mitigates [19].

Real-time MPC optimisation converged within a mean of 3.2 SQP iterations per control step, corresponding to a mean solve time of  $11.2 \pm 2.4$  ms — providing a 38.8 ms margin within the 50 ms control cycle. No convergence failures were observed during the 72-hour endurance validation programme, confirming the numerical robustness of the constrained optimisation formulation under varying initial conditions and load transients. A 2.4-second load step from 25% to 75% load was managed by the EFMS with peak transient NO<sub>x</sub> overshoot of +18% (versus +41% for static calibration), returning to steady-state compliance within 4.1 seconds [20].

#### 4.6 Comparative Summary

Table 4. Comparative Performance Summary: B0, B20, and B20+EFMS at 75% Load (1800 rpm)

| <b>Metric</b>            | <b>B0 (Diesel)</b> | <b>B20 (Baseline)</b> | <b>B20+EFMS</b> | <b>EFMS Improvement</b>             |
|--------------------------|--------------------|-----------------------|-----------------|-------------------------------------|
| BTE (%)                  | 33.7               | 33.1                  | <b>36.8</b>     | <b>+9.2% vs B0 / +11.2% vs B20</b>  |
| BSFC (g/kWh)             | 271                | 279                   | <b>253</b>      | <b>−6.6% vs B0 / −9.3% vs B20</b>   |
| NOx (g/kWh) @ 75% load   | 7.82               | 8.41                  | <b>6.93</b>     | <b>−11.4% vs B0 / −17.6% vs B20</b> |
| CO (g/kWh) @ 75% load    | 1.92               | 1.67                  | <b>1.22</b>     | <b>−36.5% vs B0 / −26.9% vs B20</b> |
| PM (g/kWh) @ 75% load    | 0.142              | 0.113                 | <b>0.071</b>    | <b>−50.0% vs B0 / −37.2% vs B20</b> |
| Smoke Opacity (%) @ 75%  | 32.4               | 27.4                  | <b>18.9</b>     | <b>−41.7% vs B0 / −31.0% vs B20</b> |
| Peak In-Cylinder P (bar) | 71.4               | 69.8                  | <b>74.1</b>     | <b>+3.8% vs B0 / +6.2% vs B20</b>   |
| Ignition Delay (°CA)     | 8.2                | 7.9                   | <b>6.8</b>      | <b>−17.1% vs B0 / −13.9% vs B20</b> |

Table 4 consolidates the headline performance improvements delivered by the EFMS. These results collectively establish the EFMS as a system that outperforms the diesel baseline (B0) in both efficiency and all regulated emission categories simultaneously — an outcome that conventional static biodiesel calibrations fail to achieve due to the NOx–efficiency and NOx–PM trade-offs inherent in single-parameter tuning approaches [5,9]. The most strategically significant finding is the simultaneous achievement of BTE > 36% (exceeding diesel baseline by 3.1 pp) and NOx < 7 g/kWh (undercutting diesel baseline by 11.4%) using a 20% biodiesel blend — demonstrating that the NOx penalty conventionally attributed to biodiesel is not a thermodynamic inevitability but an artefact of static, diesel-calibrated engine management [3,16].

## 5. CONCLUSIONS

This paper has reported the design, implementation, and comprehensive experimental validation of an Enhanced Fuel Management Strategy (EFMS) for a CRDI CI engine operating on WCO-derived biodiesel blends. The principal conclusions are as follows:

**(1) Efficiency:** The EFMS achieved a peak BTE of 36.8% at 75% load — 9.2% above the diesel (B0) baseline and 11.2% above unmanaged B20 — by combining ANN-optimised injection timing advance, pilot injection strategy, and elevated injection pressure (1640 bar). [1,4]

**(2) NOx Emission:** NOx was reduced by 17.6% relative to unmanaged B20 and 11.4% relative to B0, with EGR rate (18.4% at 75% load) and combustion phasing optimisation the primary mitigation mechanisms. This outcome refutes the conventional view that FAME blends necessarily incur a NOx penalty relative to diesel. [3,8]

**(3) Particulate Matter:** PM was reduced by 37.2% (vs B20) and 50.0% (vs B0), driven by the elevated oxygen content of the WCO-FAME blend, optimised atomisation under EFMS injection pressure, and superior combustion completeness. [2,12]

**(4) Controller Reliability:** The ANN-MPC controller demonstrated  $R^2 > 0.983$  surrogate model accuracy, mean MPC solve time of 11.2 ms (within a 50 ms control step), and zero convergence failures across 72 hours of validation operation. [14,18,19]

**(5) Practical Significance:** EFMS is implementable on automotive-grade hardware (dSPACE MicroAutoBox-III) at a bill-of-materials cost increment compatible with commercial heavy-duty truck platforms, making it a technically credible and economically viable pathway for simultaneous emissions compliance and energy efficiency improvement in biodiesel-fuelled CI engine fleets. [6,20]

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