MANAGING FUEL CONSUMPTION AND EMISSIONS FOR HYBRID ELECTRIC VEHICLES THROUGH OPTIMIZATION OF ENGINE OPERATION

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This paper presents a multi-objective optimization framework for improving internal combustion engine performance in hybrid electric vehicles, specifically targeting the minimization of fuel consumption and emissions (CO, NOx, HC, PM). The proposed method integrates normalized objective functions with weighted factors to develop a unified performance index, facilitating the simultaneous optimization of multiple conflicting objectives. Utilizing the NSGA-II algorithm, a diverse set of Pareto optimal points is generated, each representing different trade-offs between the objectives. The study's results demonstrate significant improvements in engine performance through the application of the unified ICE operation map, showcasing a notable reduction in emissions with only a slight increase in fuel consumption. The methodology was validated via MATLAB simulations on two case studies involving parallel and series hybrid electric vehicles, employing a custom synthesized drive cycle for energy management strategy evaluation. The unified map enabled real-time control and efficiency improvements by balancing different emission parameters, thus optimizing ICE operation across various conditions.

Key words*: internal combustion engine; engine optimization; hybrid electric vehicle; multi-objective optimization; fuel economy; pollutant emission*

1. Introduction

Pollutant emissions from traffic are a growing environmental concern. The transportation sector accounts for approximately 20% of global energy consumption and is responsible for nearly 25% of global energy-related CO_2 emissions, with 75% of these emissions coming from road transport [1,2]. This trend is escalating due to economic and population growth. Concurrently, exposure to poor air quality remains a significant public health concern worldwide [3].

Various initiatives have aimed to enhance fuel efficiency and curb emissions from vehicles, including the implementation of more stringent automotive emission standards [4]. As demand for fuel rises and environmental regulations on exhaust emissions become more stringent, innovative solutions in transportation are imperative. These solutions include advancements in engine and vehicle technologies, improved fuel quality, and the adoption of renewable fuels. One prominent innovation in transportation systems is hybrid electric vehicles (HEVs), offering a blend of internal combustion engine (ICE) and electric vehicle (EV) characteristics, providing the potential to incorporate the best design features of both technologies while significantly improving fuel consumption [5–7]. While

HEVs do combine the benefits of both ICE vehicles and EVs, the complexity of their powertrain necessitates sophisticated power control strategies. These strategies aim to enhance operational efficiency, fuel economy, and reduce exhaust emissions. To fully leverage the advantages of HEVs, effective energy management strategies (EMS) must be developed and implemented which poses a significant challenge [8,9].

Although the environmental issues have received substantial attention, much of the existing literature on EMS predominantly focuses on minimizing fuel consumption while overlooking emissions [10–16]. Only a few studies address exhaust emissions directly. For instance, in Ref. [17], an optimization framework was developed with two objective functions: drivetrain cost as the primary objective and a weighted combination of equivalent fuel consumption and exhaust emissions as the secondary objective. This formulation included separate components for fuel consumption, CO emissions, and NOx and HC emissions. A fuzzy logic algorithm was employed for effective EMS, using simulation with the ADVISOR software. Similarly, in Ref. [18] a fuzzy logic controller was utilized, optimized by a genetic algorithm, to minimize fuel consumption and emissions in a predefined HEV configuration. In Ref. [19] ICE torque is parameterized as a sum of radial basis functions, enabling smooth input signals while analytically capturing transient dynamics to minimize fuel consumption and pollutant emissions efficiently. Meanwhile, Refs. [20] and [21] applied particle swarm optimization methods for component sizing, considering both fuel economy and exhaust emissions. In Ref. [22], a Pareto-based analysis was conducted to assess the impact of motor/generator and battery size on fuel consumption and CO2 emissions. Additionally, Ref. [23] proposed an energy flow control strategy based on genetic algorithm theory to minimize a weighted objective function, effectively reducing exhaust pollutants. In Ref. [24] a hybrid EMS for a series-parallel PHEV was introduced, combining a rule-based control strategy with genetic algorithm based optimization to enhance fuel economy, reduce HC and NOx emissions, and address battery limitations. Using a mathematical model verified through simulation in the MATLAB/Simulink environment, the proposed method achieved significant performance improvements.

Despite the pressing nature of pollutant emissions calls for environmental protection, a limited number of studies have focused on reducing exhaust emissions. Those that did often concentrated on specific emissions like CO_2 [22] or on component sizing without deeper analysis of ICE operation, which is the primary source of fuel consumption and exhaust emissions. These studies missed the opportunity offered by HEVs to downsize ICE while maintaining adequate power at the wheels [25], as well as optimizing engine operation by ensuring it runs within efficient regions with support from the electric motor. Research indicates that optimizing engine operation is crucial for reducing emissions and fuel consumption, as ICE parameters have the most significant impact on overall powertrain efficiency [26,27]. Failure to deeply analyze engine operation can lead to sub-optimal results, especially taking into account that research has shown that HEVs showed no reduction in HC emissions and consistently higher CO emissions compared to the conventional ICE vehicles [5]. Additionally, studies have shown that achieving lower emissions and consumption often results in higher powertrain costs [17], underscoring the need to address both fuel consumption and exhaust emissions in predefined hybrid powertrain configurations to optimize performance cost-effectively.

Based on these considerations, the motivation for this research stems from the critical need to develop an EMS that minimizes a cost function considering both fuel consumption and emissions across various torque and speed values. This approach aims to establish a unified ICE operating map and an optimal operating line (OOL) to guide efficient vehicle operation in a computationally efficient and real-time implementable manner. This can be applied to any predefined HEV configuration or existing EMS, optimizing engine operation without the need to redesign or resize components in the powertrain.

In this research, a unified ICE map was developed and applied to enhance the performance of HEVs across two case studies, illustrating the algorithm's effectiveness. For a selected Pareto solution, when implemented in existing EMSs, a significant reduction in pollutant emissions of approximately 30% was achieved, with a corresponding slight increase in fuel consumption of around 3% to 5%. Other Pareto solutions can be chosen based on individual criteria, allowing for different outcomes in fuel consumption while maintaining balanced trade-offs.

2. ICE unified map and optimal operation line derivation

HEVs have a complex powertrain consisting of at least one electric motor in addition to the ICE. Different configurations of HEV powertrains, offer varying degrees of flexibility in adjusting the operating point of the ICE.

In series-parallel configurations, optimal working point strategies leverage electric motor (EM) to provide additional power, taking advantage of the favorable torque-speed characteristics of the EM while ensuring that the ICE operates at its optimal point [6]. The engine optimal operation line strategy employs a power-following approach, where the ICE consistently operates along its optimal operation line unless the required current exceeds battery or EM limits [28]. Another approach, known as the engine optimal efficiency approach, focusing on maintaining the ICE within its optimal efficiency region while concurrently maximizing transmission efficiency. This strategy aims to achieve a system optimal operation by harmonizing the performance of the ICE with transmission efficiency considerations [29].

In the context of series hybrid configurations, two EMSs have been proposed for hybrid electric bulldozers. In Ref. [30] an adaptive smooth power following control strategy based on an optimal efficiency map was introduced. This strategy employs a fuzzy logic controller to automatically adjust output power, optimizing state of charge (SOC) within a permissive range, outperforming typical power-follower control strategies. Additionaly, an engine multipoint speed switching control strategy for hybrid electric tracked bulldozers was proposed in Ref. [31]. This strategy dynamically selects predefined operating points for the engine based on demand power, enhancing efficiency and performance in practical applications which is validated with the hardware-in-the-loop test bench. In parallel configurations, the electric assist control strategy stands out as a commonly used rule-based approach aimed at improving engine efficiency through a power-following mechanism [13,18,32,33]. Notably, there is limited published research on alternative strategies in this context. One notable exception is a study employing torque leveling, albeit specifically for a through-the-road HEV [34].

None of these papers, with the exception of Refs. [33] and [32], have included emissions as a metric of their EMS success, focusing solely on fuel consumption. Furthermore, both of these studies concentrate on the optimization of EMS, which is questionable from the standpoint of real-time implementation due to the complexity of multi-objective optimization. Additionally, Ref. [32] clearly notes that the choice of weighting factors significantly influences the optimization results, as the objectives of fuel consumption and emissions are inherently different and not easily scalable against each other.

For these reasons, this paper adopts a different approach to optimization. The optimization is conducted offline by analyzing and creating a unified optimal ICE map and then deriving the optimal operating line. This line is subsequently fed to the EMS as a control map, which has been proven to be a fast and easily implementable real-time solution [35].

2.1. Problem description

As previously noted, existing research has primarily emphasized improving fuel economy rather than addressing emissions. However, operating the ICE in the fuel-optimal area does not necessarily ensure low emissions, and vice versa. Depending on the observed ICE, optimal performance maps may exhibit distinct sections highlighting trade-offs between fuel consumption (FC) and emissions such as carbon monoxide (CO), nitrogen oxides (NOx), hydrocarbons (HC) and particulate matter (PM). For example, Figure 1 and Figure 2 illustrate the fuel and emission maps for a Caterpillar 3126E Turbo Diesel Engine, with detailed measurement data obtained from ADVISOR [36].

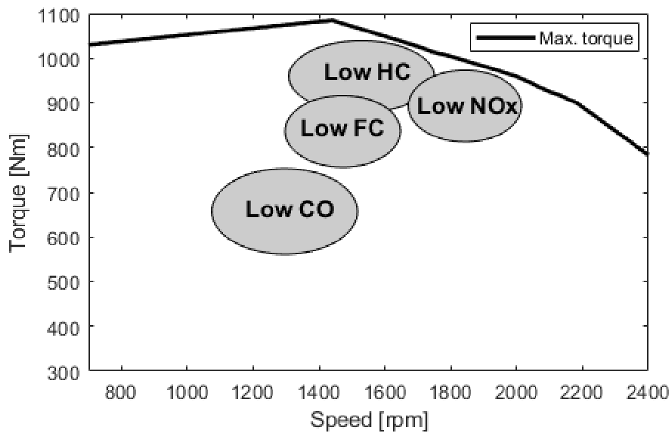


Figure 1. Trade-off between fuel economy and emissions

The data for this ICE was obtained from the Caterpillar 3126E engine specification sheet and through testing conducted using the European Stationary Cycle (ESC). This data includes fuel consumption and emissions metrics (NOx, CO, and HC) across 13 operating points. The data are fully available in ADVISOR and have been selected as a benchmark case study for optimization and presentation in this paper. Key ICE parameters are listed in Table 1.

Table 1. Overview of key parameters of Caterpillar 3126E ICE

Parameter	Value
Maximum power	205 kW @ 2200 rpm
Maximum torque	1085 Nm
Displacement	7.2 l
Bore	110 mm
Stroke	127 mm

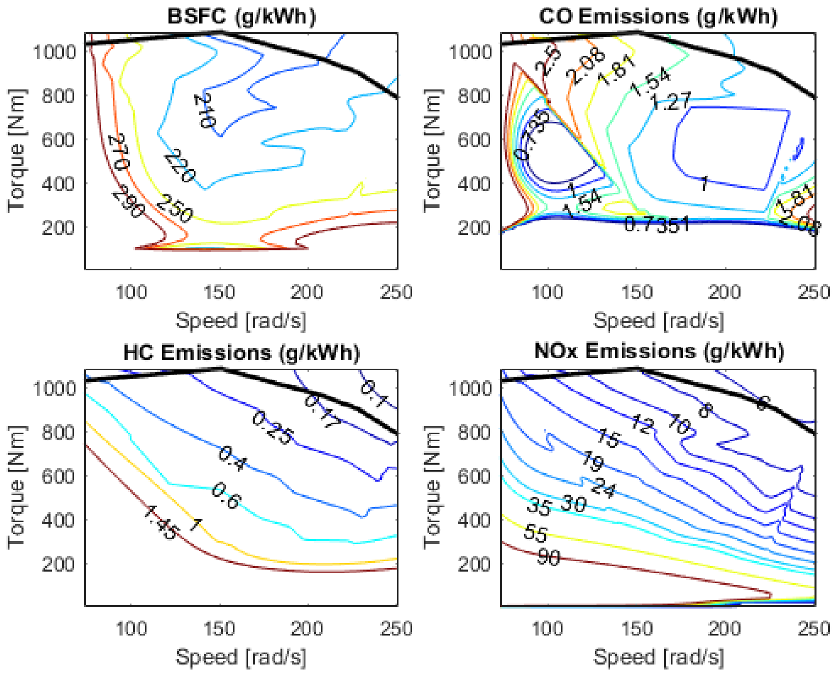


Figure 2. Hot (90° of coolant), steady-state maps of the ICE

This unified map can be visualized as a grid with respect to ICE speed and torque, as illustrated in Figure 3. Each *(i, j)* pair in the unified ICE operating map is associated with multiple objectives, each representing a distinct aspect of engine performance such as fuel consumption and emissions of CO, HC, and NOx. These objectives are combined into a single performance metric named ICE performance index (PI). The way to conduct this is to derive a single-objective function from multiple objectives by introducing weighting factors. Before initiating optimization, the objective functions are normalized to a common non-dimensional scale in the range between 0 and 1 using the following expression:

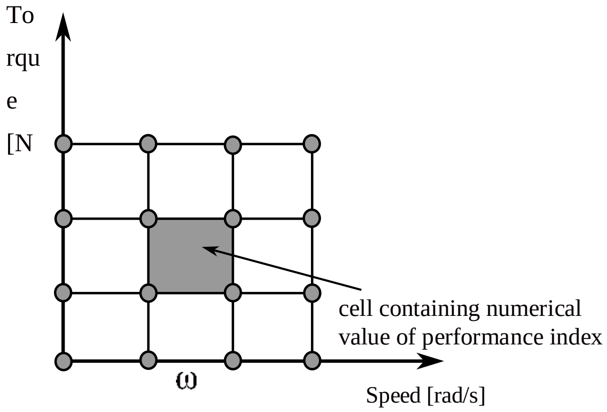


Figure 3. Unified ICE map grid

$$\overline{m}_k = \frac{m_k - \min(m_k)}{\max(m_k) - \min(m_k)} \qquad (1)$$

where $\overline{m}_k$ and m_k are normalized map and original map respectively, and $k = [FC, CO, HC, NO_x]$. This normalization step ensures that all objectives are placed on a comparable scale, preventing any single objective from dominating the optimization process due to differences in scale. After implementing weight factors, the PI is derived as:

$$PI(i,j) = \omega_1 \cdot \overline{m}_{FC,ij} + \omega_2 \cdot \overline{m}_{CO,ij} + \omega_3 \cdot \overline{m}_{HC,ij} + \omega_4 \cdot \overline{m}_{NO_x,ij} \qquad (2)$$

where $\overline{m}_{fuel}$, $\overline{m}_{CO}$, $\overline{m}_{HC}$, and $\overline{m}_{NO_x}$ are normalized ICE fuel consumption and emissions respectively, while and $\omega_{1,\dots,4}$ are corresponding weight factors.

Note that additional ICE objectives, such as PM emissions or other, can also be included in the PI derivation without any change in the optimization procedure. Obviously, this method involves the sum of weighted functions approach to determine the optimum operation point of the ICE, a technique often used due to its simplicity and ease of implementation. However, it has been shown that this method does not provide satisfactory results, especially in non-convex spaces, and the outcome is highly sensitive to the chosen weights [33,37]. This issue is further emphasized in this paper, as the normalized parameters are summed at their corresponding positions in the ICE map grid *(i,j)*, where the singular numerical value of each parameter is constant. The only variable is the weighting factor, and optimizing this is the core of the problem. Therefore, it is not viable to randomly select weights or to choose them based on previous experience or knowledge. Additionally, this approach may result in one solution dominating over others. Although normalization achieves the same scale, the parameters remain incommensurable, and this approach does not account for the distribution and grouping of values on that scale. For example, 90% of the values of one parameter may be grouped in the [0, 0.05] region of the scale, while another parameter has 90% of its values in the [0.8, 0.9] region. To address this issue, the concept of Pareto optimal solutions is employed in multi-objective optimization. Using this method, a set of Pareto optimal points is obtained, where any improvement in one objective inevitably leads to deterioration in at least one other objective, as illustrated in Figure 4. The problem is formulated as a multi-objective optimization task, seeking to identify a set of weights (or decisions) that optimize multiple conflicting objectives concurrently. To achieve this, an objective vector is defined to represent the different performance measures or criteria that are intended to be optimized simultaneously. This objective vector can be expressed as:

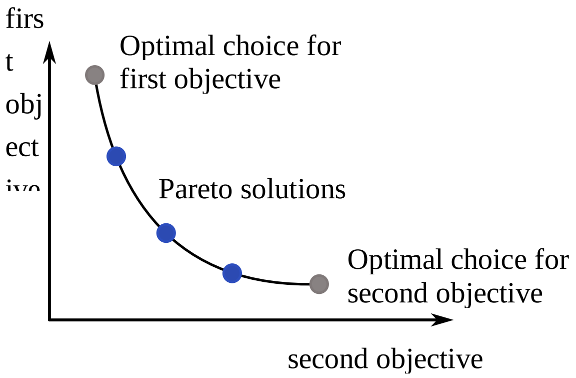


Figure 4. Pareto frontier illustration

$$J = \left[\omega_1 \cdot \overline{m}_{FC} \quad \omega_2 \cdot \overline{m}_{CO} \quad \omega_3 \cdot \overline{m}_{HC} \quad \omega_4 \cdot \overline{m}_{NO_x}\right]$$
$$subject\ to: \sum_{p=1}^{4} \omega_p = 1 \ \ and \tag{3}$$
$$0 \le \omega_p \le 1 \ \forall p$$

The aim is not to combine objectives into a single metric but to explore the trade-offs between them, as improving one objective might lead to degradation in others. In this context weights are used in auxiliary capacity, using them to transform the multi-objective problem into a series of single-objective problems. By assigning different weights to each objective, a set of solutions is generated that span the trade-off space. This optimization approach approximates a Pareto front by progressively increasing the number of solutions, allowing it to incrementally 'learn' the shape of the Pareto front and concentrate computational effort where new information can be most effectively obtained. By adaptively determining where to refine further, this approach produces well-distributed solutions.

Specifically, for each position in the engine map grid, the approach optimizes the objective vector, seeking a single set of weights that delivers the optimal engine operation across the entire grid. Secondly, the use of weights enables parameter sensitivity analysis, allowing for the assessment of how changes in one parameter affect others. This approach facilitates the exploration of different regions within the objective space and the evaluation of trade-offs among conflicting objectives. Different combinations of weights yield distinct sets of Pareto-optimal solutions, providing insights into trade-offs and supporting informed decision-making in the EMS design process. Ultimately, these weighted objectives offer a means to prioritize goals and navigate the complex landscape of performance metrics, assisting in the identification of solutions that best align with desired preferences and constraints. This approach enables engineers to make informed choices and optimize engine management strategies effectively.

Going into the optimization, the following assumptions have been made:

- Data Normalization: It is assumed that the engine map data (fuel consumption, CO, HC, and NOx emissions) is provided in a consistent format and has already been cleaned and pre-processed. The data is normalized to the range [0, 1] for each objective to ensure comparability across different units and scales.
- Fixed Engine Map Dimensions: The engine maps used in the optimization are assumed to have fixed dimensions. This structure is consistent across all objectives.
- Linear Combination of Objectives: It is assumed that the weighted sum of the normalized objective maps is a reasonable representation of the combined impact of these objectives on engine operation. The optimization assumes that the weights directly influence the combined emissions and fuel consumption.
- Uniform Weighting: The weights for the objectives are assumed to be bounded between 0 and 1, and they must sum to 1. This assumption ensures that the total contribution of all objectives remains consistent during the optimization.

2.2. Optimization algorithm

For solving the optimization problem, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) is used. NSGA-II is a popular evolutionary algorithm designed to explore and identify Pareto-optimal solutions efficiently. It is versatile and can be applied to a range of problems, including the optimization of ICE operation [38]. It operates by maintaining a population of candidate solutions, referred to as individuals, and iteratively evolves this population through genetic operations including selection, crossover, and mutation. The entire optimization procedure, incorporating this evolutionary process, is depicted in Figure 5. The NSGA-II algorithm places a strong emphasis on maintaining diversity among solutions within the population. It ranks these solutions based on dominance relationships, aiming to approximate the Pareto front - the set of non-dominated solutions representing optimal trade-offs between conflicting objectives.

Through this approach, a Pareto front was identified, illustrating the trade-off surface where improving one objective results in the deterioration of at least one other objective (see Figure 4). The Pareto front showcases a range of optimal compromises, offering valuable insights for selecting among trade-offs based on preferences and priorities. Given that multiple Pareto solutions are generated, it becomes necessary to choose an optimal solution for further analysis. In this study, the selection of a Pareto optimal solution is based on its distance from the origin (0,0,0,0) in the 4D objective space:

$$d = \sqrt{x_1 + x_2 + x_3 + x_4} \quad (4)$$

where d is the Euclidean distance from the origin, while x_1, x_2, x_3, and x_4 are the respective objective values in the 4D space.

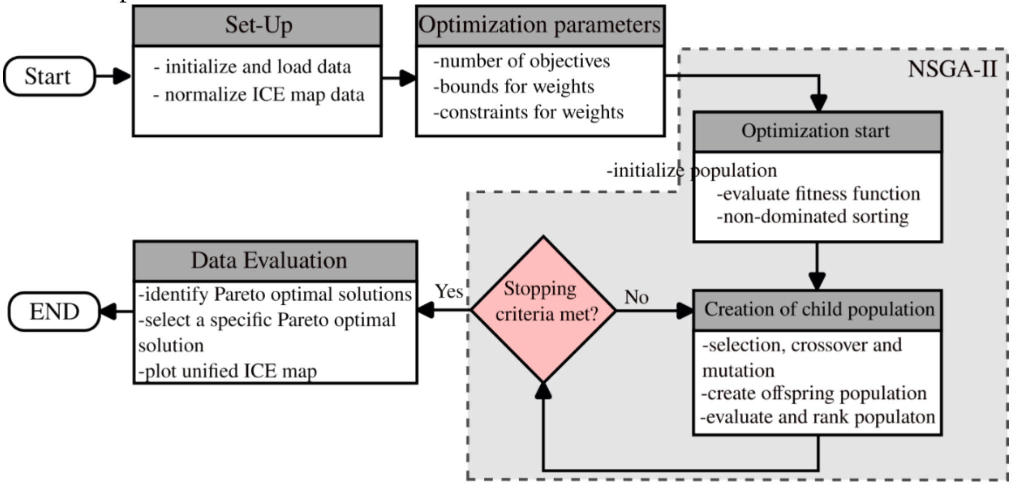


Figure 5. Flowchart of the optimization procedure for creation of unified ICE map

By calculating the Euclidean distance from the origin for each Pareto solution, the aim is to identify a solution that is relatively close to the origin, indicating a balanced compromise across all objectives. Consequently, the solution with the smallest distance to the origin is selected, representing a favorable balance among all objectives. This selected Pareto solution for the Caterpillar 3126E diesel engine is highlighted in red in Figure 6, illustrating its position in the multi-dimensional objective space and its proximity to the origin as an indicator of balance across the objectives.

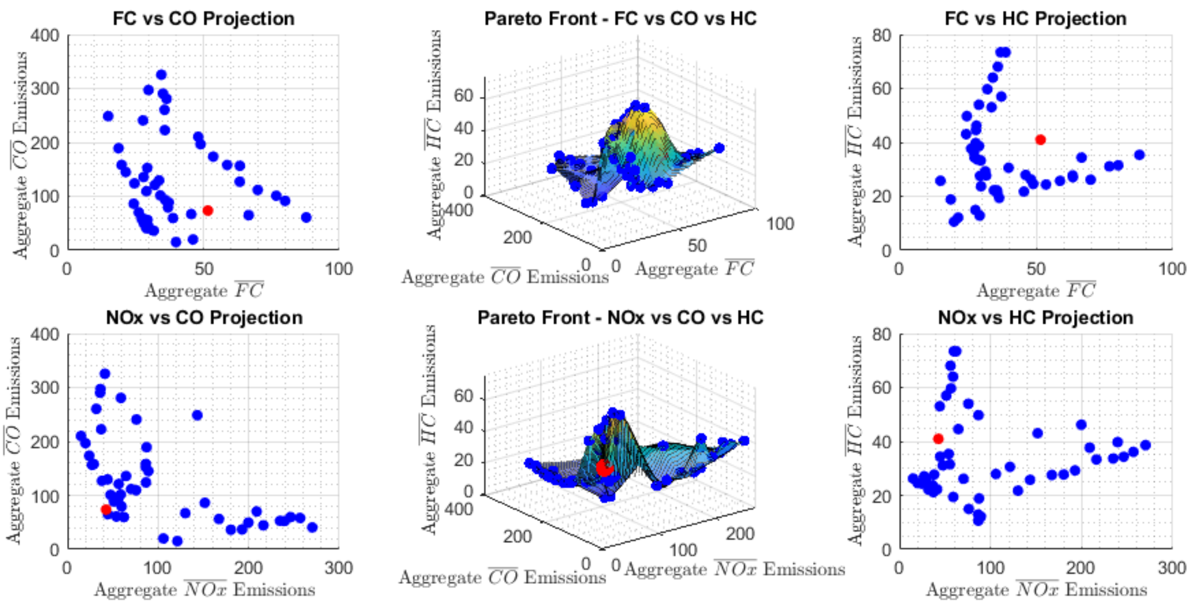


Figure 6. Plots of the Pareto front in 3D (middle) and 2D projections (views of the Pareto front when rotated around the relevance-axis with two different viewing angles in both columns)

Selecting the Pareto solution closest to the origin provides a mathematically objective and balanced method for identifying a compromise among all objectives. However, since the optimization is conducted offline, each Pareto solution can be examined individually. This allows for a more detailed evaluation of fuel consumption and emissions, facilitating the selection of the Pareto solution that best meets the desired criteria or outcomes.

2.3. Optimal operating line

After obtaining weights values from the pareto solutions, a unified ICE operation map can be obtained with a unique unified performance index, as illustrated in the Figure 7. With the unified ICE operation map constructed, the OOL can now be devised. The OOL can be established depending on the desired control input. If torque is the control input, the OOL is devised such that, for each speed in the ICE map grid, it connects grid points with the lowest PI. Conversely, if speed is the control input, the process is reversed. However, if ICE power is the control input, an isopower curve is determined within the bounds of the grid, and then the point with the minimum PI for all points on the grid can be easily obtained. These OOLs, obtained in these ways, are illustrated in Figure 8. The unified ICE map and the devised optimal operating lines can further aid in designing EMS. These can be used in rule-based strategies to guide the placement of the engine operating point for various driving conditions or in efficiency maximization strategies using maps [35]. Notably, the unified engine operation map is entirely precalculated and readily available, making it easy to read and implement in real time. This unified map enables real-time control and efficiency improvements by balancing different emission parameters, as demonstrated in the next section.

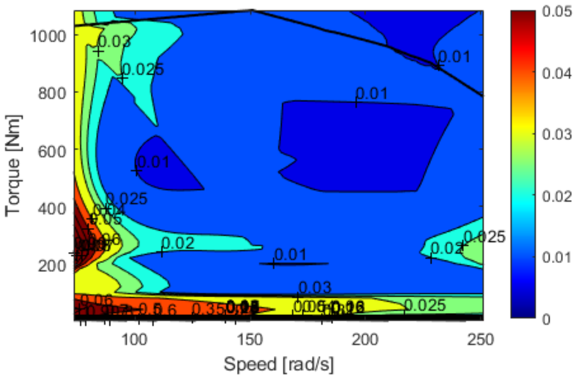


Figure 7. Unified ICE operation map

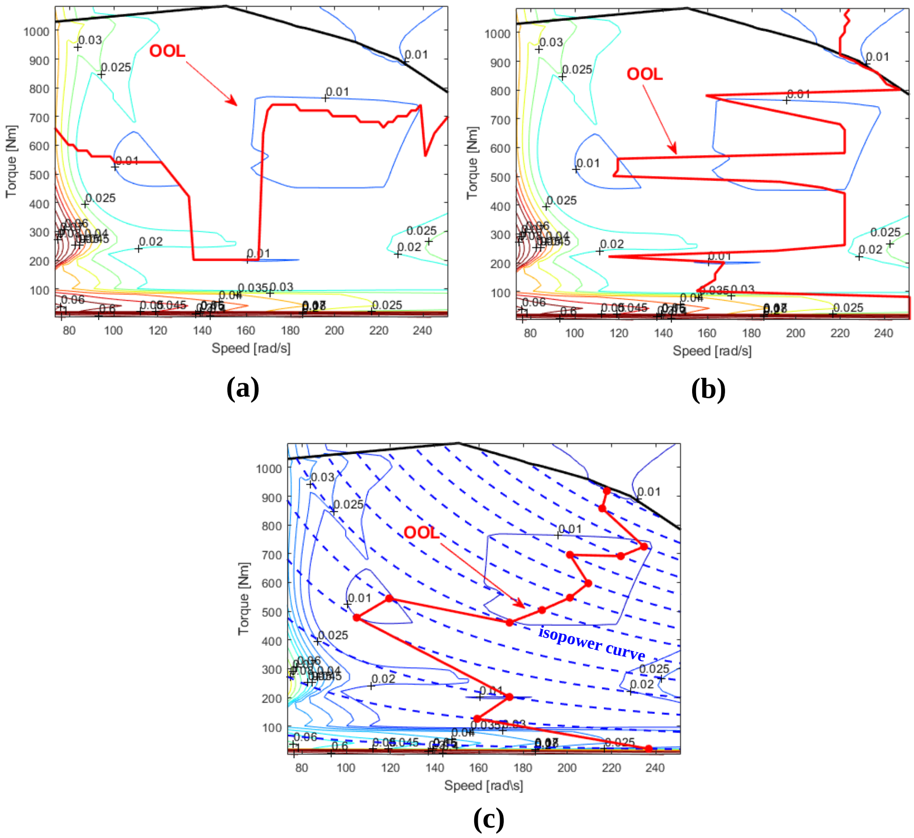


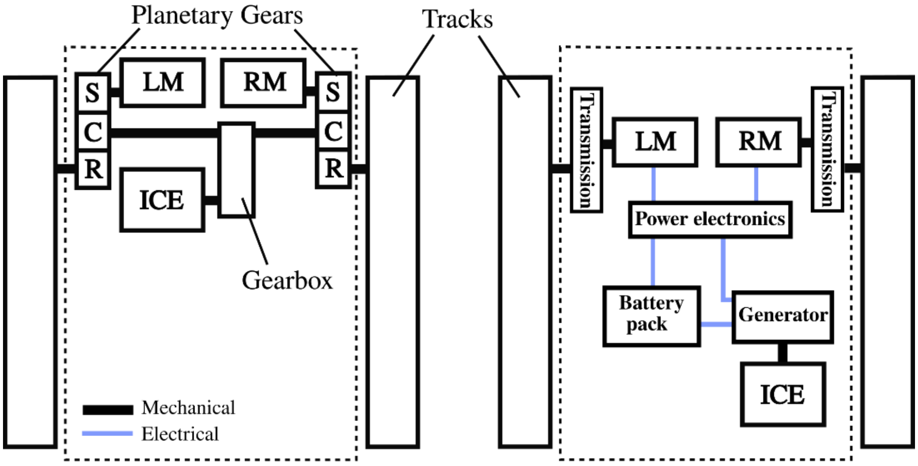
Figure 8. Optimal operation line (a) for speed input, (b) for torque input and (c) for power input

The OOLs are derived by identifying points with the lowest PI for a given input. In practical terms, depending on the configuration and EMS for HEVs, one of these OOLs can be applied. For instance, in a speed-coupled ICE and electric motor system (via a planetary gearset), torque is determined while the ICE speed can vary within the range of the electric motor's speed. In this case, the OOL for speed input can serve as an input for the EMS, allowing the optimal ICE speed to be quickly identified. If this speed is not achievable, the ICE will operate at the closest possible speed. A similar approach applies for torque coupling. When power is the input, such as in series HEVs, an optimal torque-speed pair can be selected based on the pre-calculated OOLs determined for every power value.

These OOLs, presented here, are derived based on the most balanced trade-offs for optimizing ICE operation. The weight of specific objectives can be adjusted as needed to reflect varying priorities. It is important to note that the entire unified ICE operation map can be stored in the EMS; however, depending on the data resolution, this map may prove computationally expensive.

3. Simulation results and analysis

To validate the proposed method for creating a unified ICE operation map, a simulation in MATLAB was conducted for two cases: parallel HEV and series HEV (Figure 9). In both cases, the adopted test vehicle is a hybrid electric tracked vehicle for which the complete vehicle and EMS data are known and have been previously published [13,39,40]. The EMS was adapted from previous work with certain parameter changes due to the adoption of the unified ICE map.



a) b)

Figure 9. Configuration of hybrid electric tracked vehicles used for simulation (a) case study 1, and (b) case study 2 (LM, RM – left and right motor, S – sun, C – carrier, R – ring gear)

Additionally, all vehicle parameters were retained from the previous work except for the engine, which has been downsized in this study The previously used 235 kW engine was replaced with a 205 kW Caterpillar 3126E diesel engine, as detailed experimental data for this engine is available from ADVISOR software [35]. This engine was selected because it offers the closest power value to the original engine while providing the necessary detailed data. The vehicle and simulation data are listed in Table 2, while the custom synthesized drive cycle, specifically designed for EMS evaluation in hybrid electric tracked vehicles [13], is depicted in Figure 10.

It is important to note that the results presented are specific to the Pareto solution closest to the origin, as defined by Eq. (4), and serve as an illustration of the algorithm effectiveness. Given that the optimization is conducted offline, it is possible to evaluate all Pareto solutions and analyze their outcomes. Then, for a specific desired outcome, such as a precise reduction in a particular emission or a maximum allowable increase in fuel consumption, a preference-based selection can be performed to choose the most suitable Pareto solution.

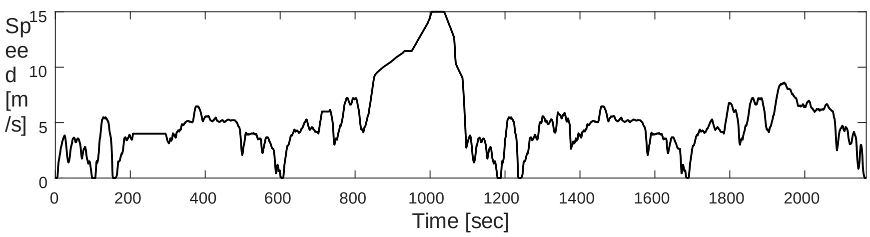


Figure 10. Drive cycle used for simulations

Table 2. Overview of simulation parameters

Parameter	Case study 1	Case study 2
Vehicle mass	13,850 kg	13,850 kg
Track contact length	3.3 m	3.3 m
Vehicle frontal area	5.5 m^2	5.5 m^2
Sprocket radius	0.2577 m	0.2577 m
Vehicle tread	2.526 m	2.526 m
Planetary gear ratio	2.546	-
Rolling resistance coefficient	0.07	0.07
Air density	1.2258 kg/m^3	1.2258 kg/m^3
Drag coefficient	1.1	1.1
ICE	205 kW at 2200 rpm	205 kW at 2200 rpm
EM	2x60 kW, 1800 rpm	2x120 kW, 9000 rpm
Battery	46 kW, 25 kWh	105 kW, 75 kWh

3.1. Case study 1 – parallel HEV

For Case Study 1, vehicle and powertrain specifications were obtained from previous work [13,40] and are listed in Table 2. The multi-mode EMS used for this case study remains the same as in the previous work and operates in five modes:

1. Electric only: where only the electric motors provide traction.
2. ICE only: where only the ICE provides traction.
3. Hybrid mode: where both the ICE and the electric motor provide traction.
4. Traction + Charge: where the ICE provides traction and charges the battery simultaneously.
5. Regenerative braking: where braking energy is recuperated.

In hybrid mode, the EMS selects the speeds of both the EM and the ICE to maintain the operating point of the ICE within the most efficient range at all times, enabled by the speed coupling of the ICE and EM as depicted in Figure 11.

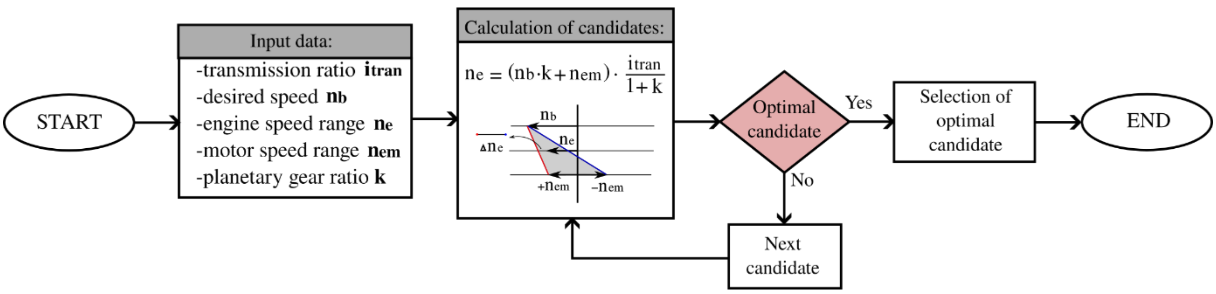


Figure 11. EMS algorithm used in the simulation for case study 1

The EMS explores every possible candidate speed within the EM's range to identify the ICE speed that results in the lowest fuel consumption, using the ICE fuel map. However, this paper introduces a key distinction in the hybrid mode: instead of relying solely on the fuel map for the EM's operating point, the EMS utilizes a unified ICE map. This unified map optimizes the entire ICE operation by balancing fuel consumption and emissions. Simulation results with the new EMS and the unified ICE map indicate a significant reduction in ICE emissions, albeit with a slight increase in fuel consumption, as shown in Figure 12. The proposed EMS with the unified ICE map enabled a reduction of over 32% in emissions at the cost of only a 3.5% increase in fuel consumption.

The unified ICE map for the 205 kW engine, along with the ICE operating points determined by the EMS, are shown in Figure 13.

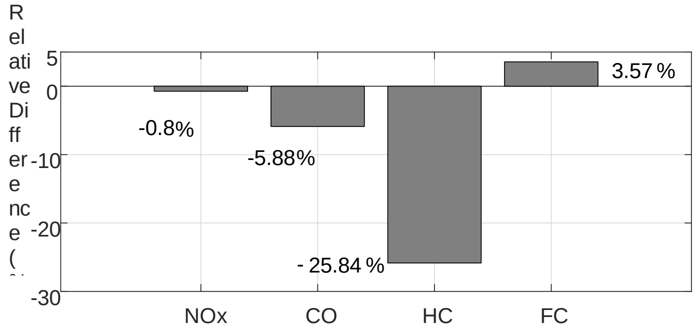


Figure 12. Relative difference of emissions and fuel consumption compared to the baseline EMS

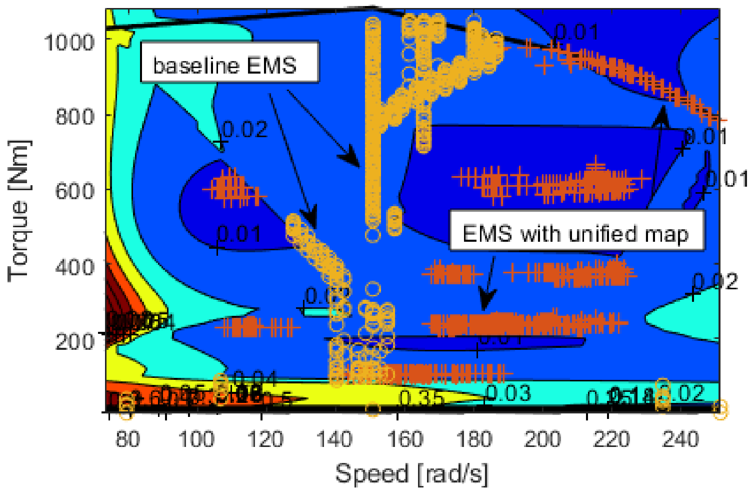


Figure 13. Operating points on the unified ICE map

From Figure 13, it is clear that the EMS works effectively with the unified map and that the operating points are well within the regions of the map with the smallest PI. In the baseline strategy, which was designed exclusively for fuel economy, the operating points were heavily clustered within regions prioritizing minimal fuel consumption. In contrast, the new EMS with the unified map strategically distributes the operating points across broader regions, optimizing for a more general set of parameters, including emissions and overall system efficiency. The unified map facilitated real-time control and efficiency improvements by balancing different emission parameters.

3.2. Case study 2 – series HEV

For Case Study 2, a hybrid electric tracked vehicle with a series configuration was utilized, as illustrated in Figure 9. The baseline EMS used in previous work is the Power Follower Control Strategy (PFCS) [39]. This strategy was selected due to its widespread application in HEVs. PFCS follows a power-following approach, where the ICE power adjusts to meet the load with some deviation to maintain the battery state of charge (SOC). Specifically, the ICE power follows the load when SOC is in predefined range $[SOC_L,\ SOC_U]$, but biases the ICE operation to either charge or discharge the battery when SOC deviates from this predefined range:

$$S(t) = \begin{cases} 0, & \text{if } SOC(t) \geq SOC_U \text{ and } P_L < P_{ICEmin} \\ 1, & \text{if } SOC(t) \leq SOC_U \text{ and } P_L > P_{SSmax} \\ S(t^-), & \text{if } SOC_L < SOC(t) < SOC_U \text{ and } P_L > P_{SSmax} \end{cases} \quad (5)$$

Where $S(t)$ is the ICE control signal, P_L is the power demand, P_{SSmax} is the maximum power of the secondary power source, and P_{ICEmin} is the tunable minimum power of the ICE. When $S(t) = 0$, the ICE power is set to $P_{ICE} = 0$. When $S(t) = 1$, the ICE power is defined as:

$$P_{ICE}(t) = \begin{cases} P_{ICEmin}, & \text{if } SOC(t) \geq SOC_U \\ P_m(t), & \text{if } SOC_L < SOC(t) < SOC_U \\ P_{ICEmax}, & \text{if } SOC(t) \leq SOC_L \end{cases} \quad (6)$$

where P_{ICEmax} is the maximum power of the ICE and $P_m(t)$ is given by:

$$P_m(t) = P_L + P_{ch}\left(\frac{SOC_U + SOC_L}{2} - SOC(t)\right), \quad (6)$$

where P_{ch} is the charging factor, determined iteratively.

In this study, a unified ICE map was incorporated into the PFCS algorithm. Since the output of PFCS is the required ICE power, an OOL of the ICE was developed for every power curve in 5 kW increments and integrated into the PFCS algorithm as a lookup table. This allows the algorithm to select an operating point on the OOL corresponding to each power input. The OOL for the 205 kW ICE used in this simulation, along with the operating points obtained post-simulation, are shown in Figure 14.

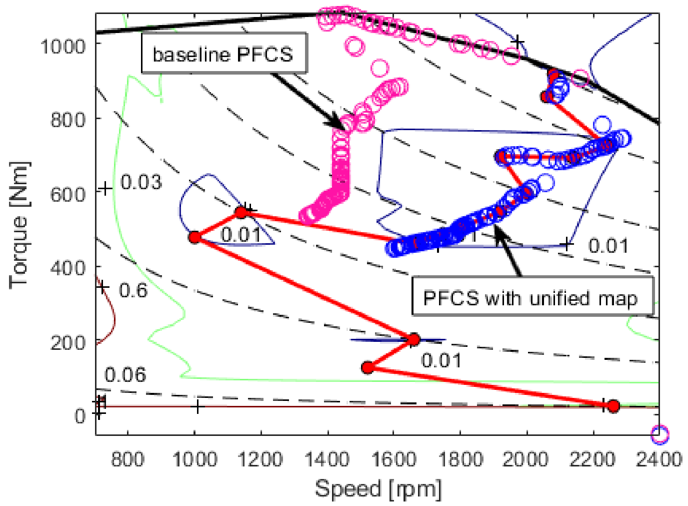


Fig. 14. Comparison of operating points for baseline and modified PFCS (note that the dashed isopower curves are plotted in 30 kW steps for readability)

Figure 14 illustrates that the operating points with the unified ICE map closely match the preset OOL, adhering to the smallest performance index for each input power. Simulation results with the modified PFCS demonstrate a significant reduction in ICE emissions, as depicted in Figure 15. The results indicate that the modified PFCS with the unified ICE map achieved a notable reduction of over 29% in emissions, with a relatively modest increase of 5.94% in fuel consumption. The observed reduction in emissions for series HEVs is somewhat smaller compared to parallel HEVs, which can be attributed to the inherently more efficient operation of the ICE in series configurations. Series HEVs often benefit from their design, which allows the ICE to operate primarily within its efficient regions due to the lack of a direct physical connection to the load. This design choice generally results in better overall efficiency and potentially less room for improvement compared to parallel HEVs.

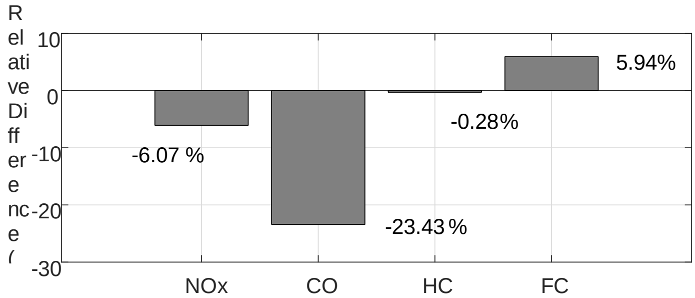


Fig. 15. Relative differences in emissions and fuel consumption compared to the baseline PFCS

3.3. Discussion and analysis

The proposed method for optimizing ICE operation balances conflicting objectives—fuel consumption and emissions—by generating a Pareto front that offers a range of optimal trade-offs rather than a single fixed solution. This approach provides flexibility, enabling engineers to select solutions based on factors such as emission regulations, aftertreatment capabilities, or specific performance targets. Using the NSGA-II algorithm ensures a diverse set of solutions, facilitating offline analysis where each Pareto-optimal point can be evaluated individually.

The selected solution closest to the origin represents a balanced compromise across all objectives, but other points on the Pareto front can be prioritized depending on context. For instance, stricter emission regulations might favor solutions minimizing NOx or HC emissions, even at the expense of slightly higher fuel consumption. Conversely, when fuel efficiency is the priority, another solution may be chosen that minimizes consumption while maintaining acceptable emissions. For example, the most practical solution would be to determine all Pareto solutions which satisfy the environmental regulatory demand for emissions, and then out of that pool of solutions choose the most fuel efficient one. This adaptability aligns with the complex requirements of HEVs, where powertrain flexibility allows for more effective optimization of engine operation. The unified ICE map developed in this study can also be applied to ICE-only configurations by optimizing gearshifting strategies. However, the flexibility of HEVs, where the electric motor assists in managing power demands, allows for significantly greater optimization potential. This makes the combination of HEVs and unified ICE maps the most effective approach for balancing fuel consumption and emissions.

In the case studies, the unified ICE map enabled a substantial reduction in overall emissions by incorporating trade-offs across operating conditions. While the modified EMS, which relied on the unified map instead of traditional fuel consumption maps, resulted in a slight increase in fuel consumption, the environmental benefits were considerable. This demonstrates the value of the unified ICE map as a tool for achieving balanced performance and emissions in modern vehicle powertrains. Notably, the results closely align with previous research [41], which also reported significant emission reductions accompanied by a slight increase in fuel consumption.

4. Conclusion

This paper presents a multi-objective optimization framework for the ICE performance, focusing on minimizing fuel consumption and emissions (CO, NOx and HC). The developed methodology integrates normalized objective functions with weighted factors to derive a unified performance index, enabling the simultaneous optimization of multiple conflicting objectives.

By employing the NSGA-II algorithm, the study successfully generates a diverse set of Pareto optimal points, each representing a different trade-off between the objectives. This approach not only facilitates a better understanding of the trade-offs between various performance metrics but also supports informed decision-making in the design and optimization of EMS. Engineers can explore different solutions along the Pareto front and select the most practical option based on specific demands, such as regulatory requirements, vehicle design constraints, or operational priorities. The application of this optimization strategy to the engine map grid results in significant performance improvements, as evidenced by the possibility of enhancing the already existing EMS such that the considerable reduction in emissions is achieved compared to baseline data. The EMS application of the unified ICE map can be achieved by precalculating the entire ICE map and using it in the EMS, or, if computationally expensive, by deriving OOLs for the specified inputs used in the EMS.

Future work will enhance model scalability to develop high-fidelity scaled models based on the optimized maps. The integration of other powertrain elements, such as battery, motor, and transmission efficiency maps, will be explored to create a comprehensive performance map. This integrated map will aid in deriving a rule-based strategy to maximize overall powertrain efficiency and achieve better fuel economy. Additionally, the selection of weights in the optimization process can be refined based on emission standards or the quality of the exhaust aftertreatment system. The dynamic nature of these maps, influenced by variables like coolant temperature, can be enhanced using mathematical relationships to provide more adaptive and accurate control strategies.

In conclusion, this research has laid a foundation for optimizing ICE operation in HEVs, demonstrating the feasibility and benefits of a unified approach to emission and fuel consumption reduction. Future work will build upon these findings to further refine and expand the applicability of these optimization strategies, contributing to the development of more efficient and environmentally friendly powertrain systems.

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