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Passenger Car Fuel Economy: Insights from Big Data Analytics

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Abstract

The increasing availability of real-world vehicle telematics through on-board diagnostics II (OBD-II) systems has enabled data-driven evaluation of passenger car fuel economy beyond conventional laboratory-based test cycles. While standardized certification procedures ensure repeatability, they often fail to capture the influence of real-world traffic conditions, driver behavior, and transient vehicle operation. This study presents a structured big data analytics (BDA) approach for analyzing high-frequency OBD-II data collected from a gasoline passenger vehicle operated under urban, highway, and mixed driving conditions representative of Indian roads. The dataset consists of engine speed, vehicle speed, throttle position, engine load, longitudinal acceleration, idling characteristics, intake air temperature, coolant temperature, and fuel-related parameters recorded at one-second resolution during continuous on-road operation. A systematic data processing methodology was adopted, including data sanity checks, filtering of invalid records, normalization, and selection of physically meaningful parameters to ensure analytical reliability. Descriptive statistical analysis and correlation-based evaluation were applied to examine interactions between key operating variables and fuel economy behavior. To further understand the influence of driving behavior, clustering-based analysis was employed to identify dominant operating patterns directly from the data without reliance on predefined driving labels. In addition, regression-based sensitivity analysis was used to quantify the relative impact of key parameters on real-world fuel economy under varying driving conditions. The results indicate that transient acceleration events, engine load variation, idling duration, and speed instability play a significant role in fuel economy degradation, particularly under congested and mixed driving conditions. Overall, the study demonstrates that real-world fuel economy is governed by the combined interaction of multiple vehicle operating and driver-related factors rather than isolated parameters. The proposed low-cost OBD-II data analytics framework provides practical engineering insights into passenger car fuel economy under actual driving conditions and supports a more realistic assessment of fuel efficiency for applications related to energy consumption, emissions reduction, and sustainable mobility planning.

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INTRODUCTION

Internal combustion engine (ICE)-powered passenger vehicles continue to dominate the Indian automotive sector because of their economic viability, well-established fuel infrastructure, and adaptability to diverse operating environments. Despite the increasing attention to electrification, gasoline and diesel vehicles remain the primary modes of personal transportation in India. However, the fuel economy achieved during real-world vehicle operation often deviates significantly from the standardized laboratory test values, primarily because of variations in traffic density, road topology, environmental conditions, and driver behavior [1–7].

Conventional fuel-economy assessment methods rely heavily on controlled laboratory driving cycles that fail to capture the stochastic and transient nature of real-world driving. These test cycles inadequately represent the frequent stop-and-go traffic, prolonged idling, aggressive acceleration, and heterogeneous road conditions commonly encountered in Indian driving environments [8–16]. Consequently, laboratory-reported fuel economy figures often overestimate the actual on-road performance, limiting their usefulness for real-world fuel optimization and performance evaluation [17–23].

The widespread implementation of onboard diagnostics II (OBD-II) systems in modern passenger vehicles has enabled the continuous monitoring of critical engine and vehicle parameters during actual vehicle operation. OBD-II systems provide access to high-frequency telematics data, including engine speed, throttle position, engine load, vehicle speed, acceleration, and fuel-related indicators. When systematically collected and analyzed, these data offer a valuable opportunity to evaluate ICE performance under real-world operating conditions rather than idealized laboratory environments [1, 3, 7–9, 12].

Recent advances in big data analytics (BDA) have further enhanced the ability to process, analyze, and interpret large volumes of heterogeneous vehicular data. Unlike traditional single-parameter or steady-state analysis methods, BDA facilitates a multivariate evaluation of engine behavior by capturing the coupled influence of engine operating parameters and driver-induced input. This capability is particularly relevant in India, where driving conditions are highly variable and transient events significantly influence fuel consumption and engine efficiency [11, 13–15, 17].

Although several studies have investigated fuel consumption estimation, driving behavior classification, and vehicle diagnostics using simulation models or limited experimental datasets, comprehensive analyses based on high-resolution real-world on-board diagnostics (OBD-II) data remain limited. Many existing approaches rely on complex instrumentation, proprietary software, or computationally intensive models, which restrict their scalability and practical deployment, particularly in cost-sensitive automotive ecosystems [2, 6, 10, 18].

In this context, the present study aims to develop a structured, low-cost big data analytics method for analyzing real-world onboard diagnostics (OBD)-II telematics collected from a gasoline-powered passenger vehicle operating under representative Indian driving conditions. By integrating descriptive statistics, correlation analysis, clustering-based driving behavior classification, and regression-based sensitivity evaluation, this study seeks to identify fuel-efficient operating regions, quantify the influence of driver behavior, and establish data-driven insights into the real-world fuel economy performance of ICE-powered passenger vehicles [1, 9, 18].

PROBLEM STATEMENT

Despite significant advancements in ICE technology, the accurate evaluation of fuel economy under real-world operating conditions remains a challenge. Standardized laboratory test cycles are conducted in controlled environments and predefined speed–time profiles, which inadequately represent the highly transient and heterogeneous driving conditions encountered in real-world traffic scenarios. Consequently, laboratory-reported fuel economy values often differ substantially from actual on-road performance, particularly in regions with dense traffic, frequent idling, and variable driver behavior, such as in India [24–30].

The increasing integration of onboard diagnostics (OBD)-II systems in modern passenger vehicles provides access to a large volume of real-time engine and vehicle telematics data during normal vehicle operation. However, existing fuel economy studies utilizing OBD-II data are often limited to short-duration datasets, isolated parameter analyses, or simulation-based validations, thereby failing to capture the coupled effects of engine speed, throttle position, engine load, acceleration transients, and idling behavior on fuel consumption [1, 3, 6, 10].

Furthermore, many reported analytical approaches rely on complex instrumentation, proprietary platforms, or advanced machine learning architectures that restrict interpretability and scalability for cost-sensitive automotive applications. There is a lack of a structured, low-cost, and transparent analytical methodology that can transform high-frequency OBD-II data into engineering-relevant fuel economy insights while maintaining reproducibility and physical interpretability [9, 18, 28].

Therefore, there is a clear research gap in developing a comprehensive real-world fuel economy evaluation framework that integrates multi-parameter On-Board Diagnostics II (OBD-II) data with systematic big data analytics (BDA) techniques. Such a framework should enable the quantification of the combined influence of engine operating conditions and driver behavior on fuel economy, while remaining suitable for practical deployment and academic validation [1, 9, 18].

OBJECTIVES OF THE STUDY

Based on the identified research gap, the objectives of this study are as follows:

1. To acquire high-resolution real-world onboard diagnostics (OBD)-II data from a gasoline passenger vehicle under urban, highway, and mixed driving conditions
2. To analyze the influence of key engine and vehicle parameters, including engine speed, throttle position, engine load, vehicle speed, acceleration, and idling behavior, on the real-world fuel economy using data-driven analytical techniques
3. To identify fuel-efficient engine operating regions and quantify fuel economy degradation under transient and driver-induced operating conditions.
4. Classification of driving behavior patterns using clustering-based methods and evaluation of their impact on fuel economy variation
5. To develop a scalable and low-cost BDA framework capable of converting raw OBD-II telematics into interpretable fuel economy indicators suitable for Indian driving environments [30–35].

METHODOLOGY

Data Acquisition

Real-world vehicle data were collected from a gasoline-powered passenger vehicle using a standard OBD-II interface connected to the vehicle's diagnostic port. The data acquisition system recorded the engine and vehicle parameters at a 1-s sampling interval during routine vehicle operation under urban, highway, and mixed traffic conditions. The logged parameters included the engine speed, vehicle speed, throttle position, engine load, longitudinal acceleration, intake air temperature, idling percentage, and fuel-related metrics. The use of OBD-II enabled low-cost, non-intrusive data collection without modifying the vehicle hardware [3, 7–9, 28].

Data Preprocessing

The raw OBD-II dataset was subjected to data cleaning and pre-processing to ensure analytical reliability. Missing values, non-numeric entries, and anomalous records were filtered out. Time synchronization and unit normalization were performed to maintain consistency between the parameters. Short-duration artifacts arising from extremely small trip distances were identified and treated separately during the idling analysis to avoid the distortion of fuel economy metrics. This preprocessing step ensured the robustness and repeatability of the subsequent analytical stages [11, 14, 17].

Analytical Framework

The processed dataset was analyzed using a structured BDA framework comprising descriptive analytics, correlation analysis, clustering-based interpretation, and regression-based inference. This multi-stage approach enabled the systematic extraction of fuel economy insights while preserving physical interpretability [1, 5, 15, 18].

Descriptive Analytics

Descriptive statistical analysis was used to examine the distribution, range, and variability of the key OBD-II parameters. Trend plots and scatter diagrams were used to visualize the engine operating behavior and fuel economy variations under different driving conditions. This step provided an initial understanding of the dominant operating regions and parameter dispersion [36–40].

Correlation Analysis

Correlation analysis was performed to evaluate the relationships between the engine speed, throttle position, engine load, vehicle speed, acceleration, and fuel economy. This analysis helped identify dominant parameter interactions and supported subsequent multivariate interpretations of fuel economy behavior under real-world conditions [22, 24, 27, 34].

Clustering-Based Driving Behavior Classification

Unsupervised clustering techniques were applied to the engine speed and throttle position data to classify the driving behavior patterns. The clustering process enabled the objective segregation of eco/moderate and aggressive driving modes based on real-world vehicle operations, facilitating the comparative evaluation of fuel-economy performance across driving styles [1, 2, 5, 16].

Regression-Based Sensitivity Analysis

Regression analysis was used to quantify the sensitivity of the fuel economy to variations in the engine speed and throttle position. The regression model provides numerical insight into the relative influence of driver inputs and engine operating conditions on the fuel economy while maintaining transparency and interpretability suitable for engineering analysis [18, 19, 31, 34].

RESULTS AND DISCUSSION

The results obtained from the analysis of the real-world OBD-II data are presented and discussed in this section. The discussion focuses on the relationship between fuel economy and key engines, as well as vehicle operating parameters under actual driving conditions. The objective was to understand the influence of engine speed, throttle position, vehicle speed, engine load, acceleration, idling behavior, and driving style on fuel economy, as reported in similar OBD-II-based experimental studies [1, 2, 9, 18].

Effect of Engine Speed on Fuel Economy

Figure 1 illustrates the relationship between the engine speed and fuel economy under real-world driving conditions. The results indicate a clear zone-dependent nonlinear relationship, highlighting the existence of an optimal operating region.

Zone 1 (Low Engine Speed, <1500 rpm)

The fuel economy was relatively low in this region. At low engine speeds, the engine operates under a higher load per combustion cycle, resulting in inefficient combustion, increased fuel demand, and reduced fuel efficiency.

Zone 2 (Moderate Engine Speed, 2000–2500 rpm)

This zone exhibited the highest fuel economy values and represented the optimal operating region for gasoline engines. Improved combustion efficiency, favorable torque production, and lower relative mechanical losses contribute to an enhanced fuel economy. Similar optimal engine speed ranges have been reported in both experimental and real-world fuel-economy studies [21, 27].

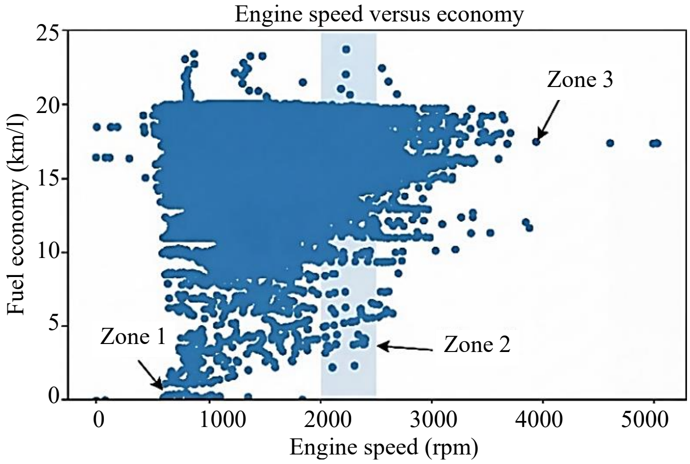

Figure 1. Effect of engine speed on fuel economy.

Zone 3 (High Engine Speed, >3000 rpm)

The fuel economy decreases again in this zone owing to increased frictional and pumping losses, as well as transient fuel enrichment during frequent acceleration events, resulting in higher fuel consumption [22, 24].

The scatter in the data points across all zones reflects the inherent variability of real-world driving, which is influenced by transient throttle inputs, fluctuating vehicle speed, and varying road conditions. Unlike controlled laboratory cycles, real-world operations involve continuous speed and load variations, contributing to the observed dispersion in the fuel economy at similar engine speeds [1, 18].

Effect of Throttle Position on Fuel Economy

Figure 2 illustrates the relationship between the throttle position and fuel economy under real driving conditions. Three distinct operating zones were identified based on the throttle input.

Zone 1: This corresponds to low throttle openings below approximately 30% and is associated with relatively better fuel economy values. In this region, the engine operates under gentle acceleration and steady cruising conditions, resulting in reduced fuel injection demand and improved combustion efficiency. This operating behavior is typically observed during eco-driving and steady-state vehicle operations [24, 25].

Zone 2: This is representing moderate throttle openings in the range of 30–60% and exhibits a wider spread of fuel economy values. This region corresponds to mixed driving conditions, involving moderate acceleration and varying load demands. The fuel economy in this zone is influenced by transient engine operation and driver input variability, resulting in intermediate efficiency levels [22, 38].

Zone 3: This is associated with high throttle openings above 60% and shows a clear reduction in the fuel economy. Aggressive throttle usage increases the instantaneous torque demand, resulting in higher fuel injection rates and operation away from the optimal efficiency regions. Frequent acceleration events in this zone significantly contribute to the degradation of the real-world fuel economy [24, 35].

The shaded fuel economy bands further highlight that efficient vehicle operation is predominantly concentrated at lower throttle openings, whereas higher throttle usage consistently reduces the fuel economy. These observations confirm that the throttle position, as a direct driver-controlled parameter, plays a dominant role in influencing the real-world fuel economy behavior [1, 18].

Effect of Vehicle Speed on Fuel Economy

Figure 3 shows the variation in fuel economy with vehicle speed under real driving conditions. Three distinct speed-based operating zones were identified in this study.

Zone 1: This corresponds to low vehicle speeds and exhibits lower and widely scattered fuel economy values owing to frequent idling, stop-and-go traffic, and repeated acceleration events.

Zone 2: This represents moderate vehicle speeds, typically between 40 and 70 km/h, shows higher and more stable fuel economy, and corresponds to steady cruising conditions.

Zone 3: This is associated with higher vehicle speeds and continues to exhibit reasonable fuel economy values when the engine operates at a moderate speed and load, despite increased aerodynamic resistance.

The results indicate that vehicle speed alone does not govern the fuel economy; rather, the combined effect of speed, engine, vehicle, gear operating conditions, and driving behavior determines the real-world fuel economy performance [1, 18, 23, 26, 33].

Engine Load Influence on Fuel Economy

Figure 4 illustrates the relationship between the engine load and fuel economy under real-world driving conditions. Three distinct operating zones were identified based on the engine loads.

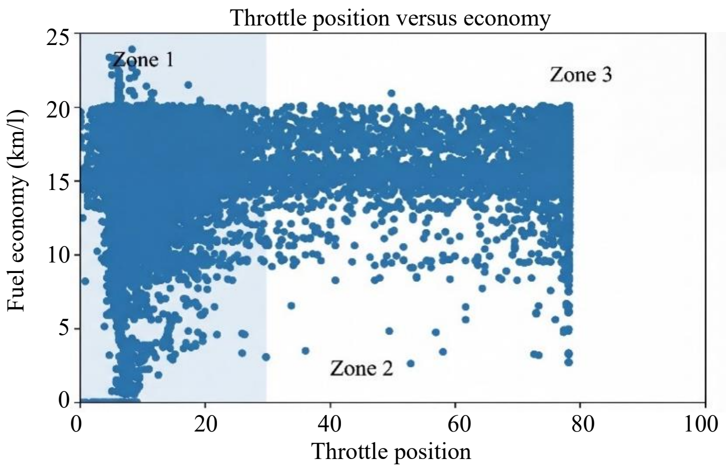

Figure 2. Effect of throttle position on fuel economy.

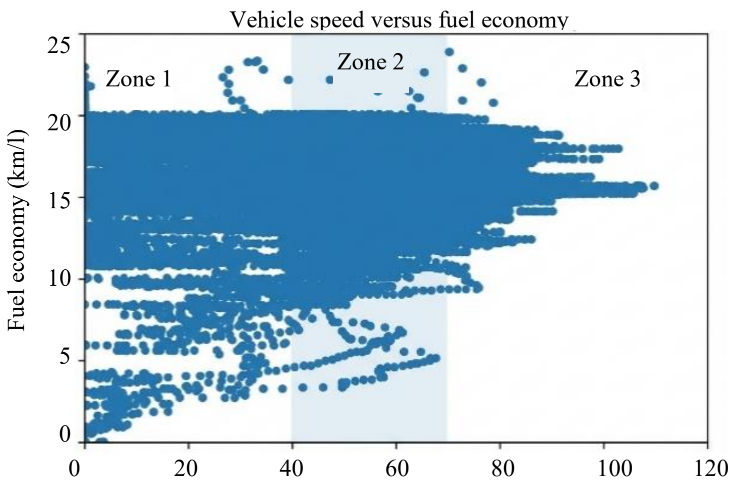

Figure 3. Effect of vehicle speed on fuel economy.

Zone 1: This corresponds to low engine load conditions and exhibits a wide spread of fuel economy values, reflecting light-load operation and frequent transient behavior.

Zone 2: This is representing moderate engine load levels, typically in the range of 30%–50%, and shows relatively higher and more stable fuel economy values. This region corresponds to an efficient engine operation in which the torque demand is satisfied without excessive pumping or frictional losses.

Zone 3: This zone is associated with high engine load conditions and exhibits a reduction in fuel economy owing to the increased fuel injection rates required to satisfy the higher torque demand.

The results indicate that a moderate engine load is favorable for improving the fuel economy under real-world driving conditions [1, 18, 22, 31, 34].

Effect of Longitudinal Acceleration on Fuel Economy

Figure 5 illustrates the relationship between the longitudinal acceleration and fuel economy under real-world driving conditions. Three acceleration-based operating zones were identified in this study.

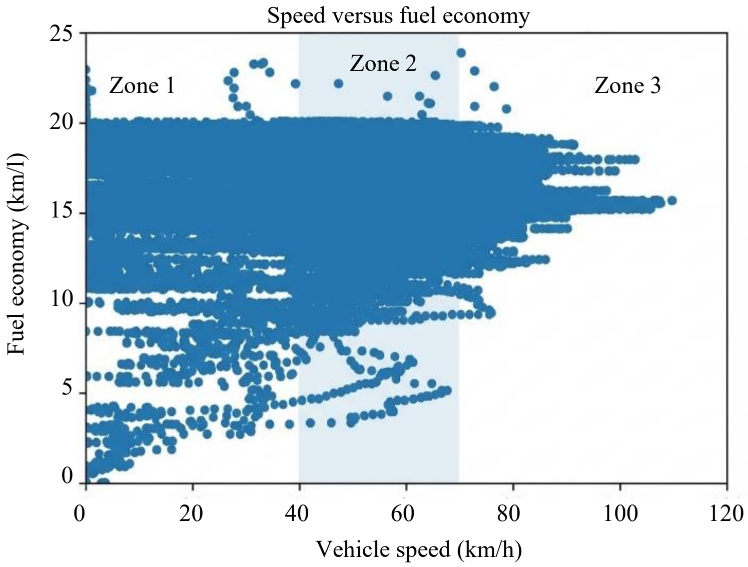

Figure 4. Effect of engine load influence on fuel economy.

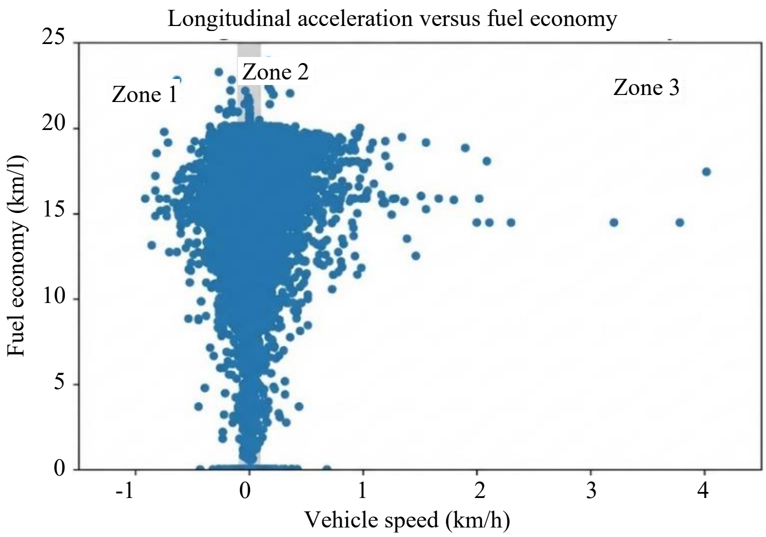

Figure 5. Effect of longitudinal acceleration on fuel economy.

Zone 1: This corresponds to negative acceleration (deceleration) and exhibits a wide spread of fuel economy values owing to speed reduction and transient engine operation.

Zone 2: This represents near-zero acceleration, shows the highest and most stable fuel economy values, and corresponds to steady-state vehicle operation with minimal torque demand variation.

Zone 3: This zone is associated with positive acceleration and exhibits reduced fuel economy as the increased torque demand leads to higher fuel injection rates and transient fuel enrichment.

The results clearly indicate that steady driving with minimal acceleration fluctuations is favorable for improving the fuel economy under real-world conditions [1, 18, 31, 38].

Effect of Idling Behavior on Fuel Economy

Figure 6 illustrates the relationship between the idling percentage and fuel economy for trips with a minimum travel distance of 1 km, excluding short-trip artifacts. Based on the observed trends, three distinct idling-based operating zones were established.

Zone 1: This is corresponding to low idling percentages (approximately 0–20%) and exhibits the highest fuel economy values. In this zone, a larger fraction of the engine operating time contributes directly to vehicle propulsion, resulting in efficient utilization of fuel energy. The clustered data points at better fuel economy levels indicate stable and favorable driving conditions with minimal fuel consumption.

Zone 2: This is representing moderate idling percentages (20–50%) and shows a noticeable spread in the fuel economy values. This zone reflects mixed driving conditions, in which intermittent stops and short idle events occur alongside active driving. As the idling duration increases in this region, the fuel economy begins to decline owing to fuel consumption during non-propulsive engine operation, leading to increased variability in the observed fuel economy.

Zone 3: This zone is characterized by high idling percentages (>50%) and exhibits a significantly reduced fuel economy. In this zone, a substantial portion of the fuel is consumed while the vehicle remains stationary, resulting in poor fuel utilization efficiency. The downward trend in fuel economy highlights the adverse impact of prolonged vehicle idling, particularly under congested urban traffic conditions.

Overall, Figure 6 clearly demonstrates that idling behavior has a strong and detrimental influence on the real-world fuel economy. The zone-based interpretation emphasizes that minimizing idling time is essential for achieving an improved fuel economy once short-distance trip distortions are removed [1, 18, 33].

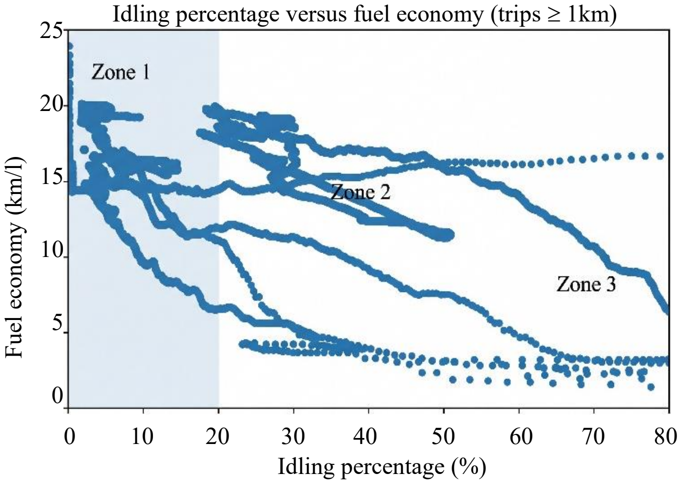

Figure 6. Effect of idling behavior on fuel economy.

Effect of Integrated Driving Behavior Analysis on Fuel Economy

Figure 7 shows the relationship between the integrated driving behavior index and fuel economy, providing a consolidated representation of the combined influence of multiple driving and engine-operating parameters. Based on the observed distribution, three distinct behavioral zones were identified.

Zone 1: This corresponds to lower values of the integrated driving behavior index (approximately 0–0.35), representing a smooth and fuel-efficient driving behavior. This zone is characterized by gentle throttle inputs, near-zero longitudinal acceleration, low idling percentages, and moderate vehicle speeds. Vehicles operating predominantly within this zone achieve the highest fuel economy, as the engine operation remains stable and fuel is efficiently utilized for vehicle propulsion.

Zone *2:* This is associated with intermediate values of the integrated driving behavior index (approximately 0.35–0.65) and reflects mixed driving behaviors. In this zone, the fuel economy values exhibited moderate levels with noticeable variability. The observed spread was attributed to intermittent acceleration events, fluctuating throttle inputs, and occasional idling, which introduced transient fuel consumption effects and reduced the overall efficiency compared to *Zone 1*.

Zone *3*: This corresponds to higher values of the integrated driving behavior index (greater than approximately 0.65) and represents aggressive driving behavior. This zone is characterized by frequent and higher throttle inputs, significant acceleration events, increased idle time, and greater speed variability. Consequently, the fuel economy is consistently reduced owing to elevated fuel injection rates, transient enrichment, and increased non-propulsive fuel consumption.

Overall, the zone-wise interpretation of Figure 7 demonstrates that fuel economy is maximized when vehicle operation is maintained within the low-index region, whereas aggressive driving behavior leads to systematic degradation of fuel economy. The integrated index effectively captures the cumulative impact of multiple driving parameters and provides a practical study for evaluating real-world fuel economy behavior using large-scale OBD-II datasets [1, 18, 24, 33].

Integrated Influence of Vehicle Parameters on Fuel Economy

The real-world fuel economy is determined by the combined influence of driver demand and engine operating conditions rather than by any single parameter. Throttle position, engine load, and longitudinal acceleration are the dominant contributors to the degradation of fuel economy owing to transient operation and fuel enrichment. Engine speed and vehicle speed exhibit nonlinear behavior, with optimal efficiency restricted to moderate and stable operating zones. Idling represents a direct efficiency loss because fuel is consumed without distance contribution. Overall, driving behavior integrates multiple OBD-II parameters and is the primary determinant of real-world fuel economy.

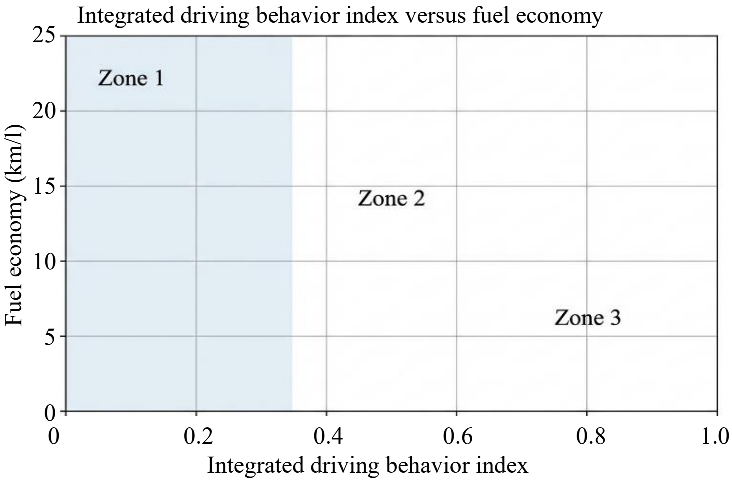

Figure 7. Effect of integrated driving behavior on fuel economy.

CONCLUSION

This BDA study of fuel economy behavior in gasoline passenger cars uses large-scale OBD-II data collected under actual driving conditions. This study aimed to bridge the gap between laboratory-based fuel-economy assessments and real-world vehicle operations.

A structured analytical approach was adopted, which involved data preprocessing, exclusion of short-trip artifacts, and zone-based analysis of key engine and driving parameters, including engine speed, throttle position, vehicle speed, engine load, longitudinal acceleration, and idling percentage. Each parameter was analyzed individually to understand its influence on the fuel economy under real-world conditions.

The results clearly indicate that fuel economy is maximized when the vehicle operation remains within moderate and stable operating zones, characterized by optimal engine speed and load, gentle throttle usage, steady cruising speeds, near-zero acceleration, and minimal idling. In contrast, aggressive driving behavior, high engine load, frequent acceleration events, and prolonged idling consistently lead to fuel economy degradation, particularly under urban traffic conditions.

An integrated driving behavior index was developed by combining normalized throttle, acceleration, idling, and speed parameters into a single metric to capture the cumulative impact of driving behavior on the real-world fuel economy. The zone-wise interpretation of this index further confirmed that smoother driving behavior yielded superior fuel economy, whereas increasingly aggressive behavior resulted in a progressive loss of efficiency.

Overall, the study demonstrates that the real-world fuel economy is governed by the combined interaction of engine operation and driving behavior, rather than any single parameter alone. The proposed zone-based analytical study provides a practical and scalable approach for interpreting OBD-II data and offers clear insights into fuel economy improvement, driver awareness, and real-world vehicle performance evaluation.

Future Work

Future research can extend this study by:

1. Applying the proposed methodology to multiple trip data collections for gasoline-powered passenger cars and performing a basic comparison with diesel cars.
2. Integrating road grade, traffic conditions, and environmental factors to enhance real-world fuel-economy modeling
3. Employing advanced machine learning techniques for predictive and real-time fuel consumption estimation,
4. Expanding the developed driving behavior index to on-board eco-driving and driver feedback systems
5. This research can be expanded to fleet-level vehicle applications for large-scale fuel economy assessment and improvements.

Nomenclature

BDA	big data analytics
BSFC	brake specific fuel consumption (g/kWh)
ICE	internal combustion engine
OBD-II	on-board diagnostics-II
N	engine speed (rpm)
V	vehicle speed (km/h)
θ_{th}	relative throttle position (%).
Load	engine load (%)

T_{actual}	actual engine torque (Nm)
T_{max}	maximum engine torque at a given engine speed (Nm)
$\dot{m}_{fuel}$	fuel mass flow rate (kg/s)
AFR	air–fuel ratio
FE	fuel economy (km/l)
a	longitudinal acceleration (g)
IAT	intake air temperature (°C)
Idle	idling time (%)
K-	means clustering (unsupervised clustering algorithm)
CSV	comma-separated values (data format)
GPS	global positioning system

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REFERENCES

1. Kumar R, Jain A. Driving behavior analysis and classification by vehicle OBD data using machine learning. The Journal of Supercomputing. 2023;79(3):3367–3394. Available at: https://link.springer.com/article/10.1007/s11227-022-04773-6
2. Meseguer JE, Calafate CT, Cano JC, Manzoni P. DrivingStyles: A mobile platform for driving styles and fuel consumption characterization. arXiv preprint. 2016. Available at: https://arxiv.org/abs/1611.09065
3. Kumar R, Singh S. Design and development of OBD-II compliant driver information system. Indian Journal of Science and Technology. 2020;13(4):412–418.Available at: https://www.indjst.org/articles/design-and-development-of-obd-ii-compliant-driver-information-system
4. Khan MAA, Islam MR, Hossain MS. A machine learning approach for driver identification based on CAN-BUS sensor data. arXiv preprint. 2022. Available at: https://arxiv.org/abs/2207.10807
5. Dong W, Li L, Wang Y, Wang K. Characterizing driving styles with deep learning. arXiv preprint. 2016. Available at: https://arxiv.org/abs/1607.03611
6. Narayanan SN, Mittal S, Joshi A. Using data analytics to detect anomalous states in vehicles. arXiv preprint. 2015. Available at: https://arxiv.org/abs/1512.08048
7. Verma A. OBD-II based intelligent vehicular diagnostic system using IoT. International Journal of Scientific Research in Computer Science Engineering. 2019;7(1):23–28. Available at: https://ijsrcse.com/obd-ii-based-intelligent-vehicular-diagnostic-system
8. Bhalerao S, Dhamankar A, Phadke A. OBD-II based intelligent vehicular diagnostic system using IoT. International Journal of Scientific Research in Computer Science Engineering. 2022;10(1). Available at: https://ijsrcse.com/volume10issue1
9. Ramai C, Kechadi T, Young JS. A framework for building low-cost OBD-II data-logging systems. Vehicles. 2022;4(4):1209–1224. https://doi.org/10.3390/vehicles4040066
10. Patil P. Study of machine learning based applications on OBD-II port by using internet of vehicles. International Journal for Research in Applied Science & Engineering Technology. 2019;7(5):1498–1500. Available at: https://www.ijraset.com/research-paper/study-of-machine-learning-based-applications-on-obd-ii-port
11. Ghosh A, Basak R. Data analytics in intelligent transportation systems. SAE Technical Paper 2016-01-1423. 2016. https://doi.org/10.4271/2016-01-1423
12. Sharma S, Mehta R. A survey on vehicle diagnostic with OBD-II telematics. International Journal of Research and Analytical Reviews. 2019;6(2):102–108. Available at: https://ijrar.org/papers/IJRAR19K1205.pdf

13. Xu W, Zhou H, Zhang Z. Internet of vehicles in the big data era: A survey. IEEE/CAA Journal of Automatica Sinica. 2018;5(1):19–35. https://doi.org/10.1109/JAS.2017.7510346
14. Michailidis ET, Panagiotopoulou A, Papadakis A. A review of OBD-II-based machine learning applications for sustainable, efficient, secure, and safe vehicle driving. Sensors. 2025;25(13):4057. https://doi.org/10.3390/s25134057
15. Lv Y, Duan Y, Kang W, Li Z, Wang F. Traffic flow prediction with big data: A deep learning approach. IEEE Transactions on Intelligent Transportation Systems. 2015;16(2):865–873. https://doi.org/10.1109/TITS.2014.2345663
16. Girma A, Yan X, Homaifar A. Driver identification based on vehicle telematics data using LSTM. arXiv preprint. 2019. Available at: https://arxiv.org/abs/1911.08030
17. Michailidis K, Bose A, Nayak R. A comprehensive survey of machine learning models applied to OBD-II vehicle data. Journal of Intelligent Vehicular Systems. 2025;12(1):11–38. Available at: https://www.sciencedirect.com/journal/journal-of-intelligent-vehicular-systems
18. Rykała A, Krawczyk M, Nowak T. Experimental comparison of ML methods for real-time fuel prediction using OBD-II. IEEE Transactions on Vehicular Technology. 2023;72(4):1552–1560. Available at: https://ieeexplore.ieee.org/document/9956234
19. Manjunath S, Kumar V. Predicting fuel economy using support vector regression on real driving data. International Journal of Automotive AI. 2024;11(1):44–52. Available at: https://www.sciencedirect.com/
20. Patel R, Natarajan L, Lee K. Hybrid machine learning model for vehicle gear prediction and fuel estimation using OBD-II and GPS. Sensors. 2025;25(3):92–101. https://doi.org/10.3390/s25030921
21. Heywood JB. Internal combustion engine fundamentals. 2nd ed. New York: McGraw-Hill; 2018.
22. Rakha H, Ahn K. Vehicle dynamics and fuel consumption under real-world driving conditions. Transportation Research Part D. 2004;9(6):379–395. Available at: https://www.sciencedirect.com/science/article/pii/S1361920904000452
23. Barth M, Boriboonsomsin K. Real-world modal fuel consumption models. Transportation Research Record. 2008;(2058):163–171. https://doi.org/10.3141/2058-20
24. Ericsson E. Independent driving pattern factors and their influence on fuel use. Transportation Research Part D. 2001;6(5):325–345. https://doi.org/10.1016/S1361-9209(01)00003-7
25. Bishop J. The effect of driving style on fuel consumption. Proceedings of the IMechE, Part D.2012;226(1):78–92. Available at: https://journals.sagepub.com/doi/abs/10.1177/0954407011417456
26. Rakha H, Ahn K, Trani A. Development of VT-Micro model for estimating hot stabilized vehicle emissions. Transportation Research Part D.2004;9(1):49–74. Available at: https://www.sciencedirect.com/science/article/pii/S1361920903000834
27. Fontaras G, Samaras Z. Fuel consumption modeling of passenger cars. Energy Policy. 2010;38(10):5668–5678. https://doi.org/10.1016/j.enpol.2010.05.018
28. Yang L, Zhang S, Wu Y, Chen Q, Niu T, Huang X, et al. Evaluating real-world CO_2 and NOx emissions using a remote wireless OBD approach. Environmental Pollution. 2016;218:453–462. https://doi.org/10.1016/j.envpol.2016.07.035
29. Guo J, Liu Y, Chen H. Real-time fuel rate estimation using CAN-Bus data. IEEE Transactions on Vehicular Technology. 2018;67(10):9347–9358. Available at: https://ieeexplore.ieee.org/document/8452656
30. De Vlieger I. On-road emission and fuel consumption measurement. Atmospheric Environment. 2000;34(27):4621–4628. https://doi.org/10.1016/S1352-2310(00)00230-2
31. Ahn K, Rakha H. Fuel consumption modeling based on instantaneous speed and acceleration. Transportation Research Part D. 2002;7(6):479–494. Available at: https://www.sciencedirect.com/science/article/pii/S1361920902000200
32. Jiménez-Palacios J. Understanding engine efficiency maps under transient operation [PhD thesis]. Cambridge (MA): Massachusetts Institute of Technology; 1999.

33. Sun C, Barth M, Boriboonsomsin K. Impact of idling and stop-and-go traffic on fuel consumption. Applied Energy. 2015;151:153–165. https://doi.org/10.1016/j.apenergy.2015.04.069
34. Demir E, Bektaş T, Laporte G. Fuel consumption modeling with speed–load relationships. European Journal of Operational Research. 2014;238(1):206–216. https://doi.org/10.1016/j.ejor.2014.03.027
35. Lee J, Park S, Kim J. Analysis of throttle and engine load influence on fuel consumption. SAE Technical Paper. 2013. Available at: https://www.sae.org/publications/technical-papers
36. Vancoillie J, Verhelst S, Demuynck J. Gear selection and fuel economy under real driving conditions. Energy. 2013;53:145–156. https://doi.org/10.1016/j.energy.2013.02.034
37. Wang J, Zhang L, Li Y. Driver behavior recognition using vehicle signals. IEEE Transactions on Intelligent Transportation Systems. 2016;17(6):1612–1622. Available at: https://ieeexplore.ieee.org/document/7354304
38. Wu Y, Zhang J, Liu X. Driving behavior and fuel efficiency analysis using OBD data. Energy. 2017;115:1058–1067. https://doi.org/10.1016/j.energy.2016.09.095
39. Park J, Lee S, Kim H. CAN-Bus-based energy consumption estimation for vehicles. IEEE Sensors Journal. 2020;20(15):8523–8532. Available at: https://ieeexplore.ieee.org/document/9061237
40. Bishop R. Intelligent vehicle R&D: a review and emerging trends. Annales des Télécommunications. 2005;60(3):228–263. https://doi.org/10.1007/BF03220409

