論文・報告

A Data-Driven Method for Developing Custom Customer-Based Duty Cycles from Fleet Data for Vehicle Testing and Validation

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Abstract

Fleet data provides Automotive manufacturers with a practical method to understand how vehicles are used by customers in real-world operation., This customer data is especially critical because vehicle operation varies significantly by vocation, payload, location, driver usage, and most importantly emission regulations. These characteristics provide a quantitative basis for, customer usage-pattern analysis, real-world product performance assessment, duty-cycle development, validation, and prioritization of future technology investments. This paper presents a data-driven approach for converting the resulting insights to create a direct link between field usage and OEM decision-making by using a case study in which customer data is used to classify customers from a pool of fleet data to develop a High-Demand In-Use Testing cycle.

要　旨

大手流通企業が保有する車両の情報は、実際にどのように車が使われているか知るうえでとても有用である。車両開発において市場での運用を想定した試験を行うが、顧客の運用に近いテストパターンが望ましい。本稿では、これらの車両から得られたデータを元に高負荷な市場での車両運用のテストパターンを作る取り組みを紹介する。

1 Introduction

Future commercial vehicle development is increasingly influenced by the need to match product capability with actual customer operation. Traditional development programs use regulatory cycles, proving-ground procedures, engineering assumptions, and limited customer feedback. While these legacy inputs remain necessary to establish baseline structural and emissions performance, they operate as highly controlled environments. Consequently, they fail to fully capture the stochastic, wide-ranging real-world boundary conditions created by highly variable route topography, shifting payload distributions, ambient climates, urban-to-highway traffic congestion, specialized vocational applications, and erratic operator habits[1][3][5].

Fleet data can close this gap by providing direct evidence of how vehicles are used in the market. By analyzing customer operation across a fleet, an Original Equipment Manufacturer (OEM) can identify usage clusters, severe applications, route demands, thermal exposure, idle behavior, energy consumption, and real-world performance trends. For instance, proactively integrating real-world profiles allows OEMs to mitigate compliance risks for mandatory, post-production audits like the Heavy-Duty In-Use Testing (HDIUT) program, as well as global standards like Real Driving Emissions (RDE) testing. OEM's Product planning teams can leverage these data-driven insights to strategically prioritize future Research and Development (R&D) pipelines, balance technology investment portfolios, and align next-generation architectures with actual customer applications. Concurrently, engineering teams can use the exact same fleet-derived datasets to establish rigorous development targets, apply precise engineering judgment, define highly accelerated validation cycles, and objectively evaluate whether

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future component designs truly mirror the real-world customer operation[3][5][6][9].

2 Strategic value of fleet data

Product planning and engineering decisions require evidence about customer needs, operating severity, technology suitability, and market opportunity. Fleet data provides this evidence by showing real-world operation across applications, regions, routes, and vehicle configurations. Planning teams can use it to identify priority markets and future investments, while engineering teams can use it to distinguish representative and severe-use operation, apply engineering judgment, and define validation targets for future vehicle programs[3][5]. As outlined in **Table 1**, the fleet data applications span across multiple powertrain architecture directly enabling targeted engineering decisions. For any OEM the value of this approach is the ability to convert customer operation into quantified planning/validating inputs which creates a stronger link between field evidence, future project development plans, and business decisions.

Table 1 Examples of fleet-data applications across powertrain types and planning purposes

Powertrain or program	Fleet-data insight	Planning decision enabled	Example output
ICE and aftertreatment	Cold start frequency, high-load operation, idle ratio, fuel economy, SCR thermal exposure	Aftertreatment robustness, heater strategy, calibration margin, durability target	Cold-start/high-load HDIUT cycle
BEV	Daily distance, speed distribution, stop frequency, energy demand, ambient and thermal exposure	Battery capacity, range target, charging strategy, route suitability	Customer-derived range and charge plan
Hybrid	Urban/highway mix, idle time, acceleration demand, load variation, energy recovery opportunity	Hybrid system sizing, battery capacity, control strategy, engine-electric balance	Hybrid duty-cycle library
Fuel cell	Route length, continuous load, refueling opportunity, thermal exposure, downtime patterns	Hydrogen storage size, fuel-cell power rating, infrastructure and route strategy	Fuel-cell application suitability map
All powertrains	Customer segmentation, route severity, real-world product performance, field reliability signals	Project prioritization, investment planning, validation conditions, target setting	Market-specific development plan

3 Fleet data analytics framework

To systematically translate raw vehicle telematics into actionable engineering metrics and strategic planning decisions, a structured, sequential workflow is required. **Figure 1** illustrates the proposed Fleet Data Analytics Framework, which maps the end-to-end pipeline from initial edge data acquisition to final downstream product deployment. This linear progression ensures that data is rigorously conditioned, contextually analyzed, and translated into high-utility validation targets Unlike conventional architectures that process heavy, continuous raw time-series streams, this specialized framework ingests aggregated MIMAMORI*1 Controller unit (MMU) data. **Figure 2** shows process flow of how MMU-based approach uses aggregated, pre-processed vehicle data to quickly identify customer operation across fleets with lower processing effort and minimal test instrumentation, compared with conventional raw time-series data analysis.

By transforming these pre-compiled, vehicle-processed health and operational summaries into targeted inputs, the framework effectively bridges commercial fleet tracking with engineering validation [3][5].

*1 MIMAMORI (Fleet operation data source used in the ISUZU N-SERIES case study.)

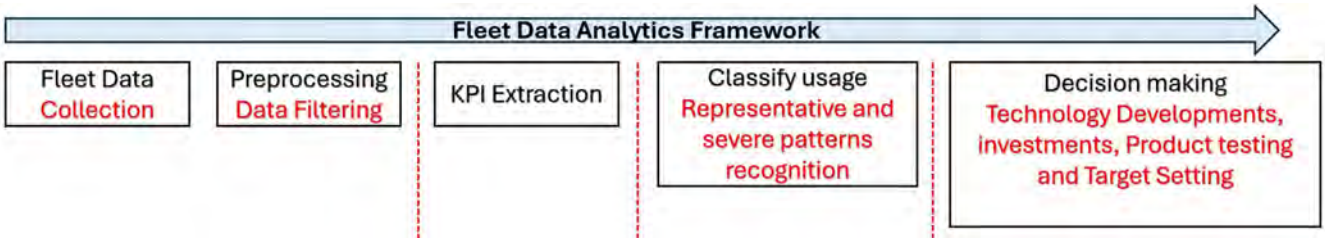


Figure 1　Fleet-data analytics framework

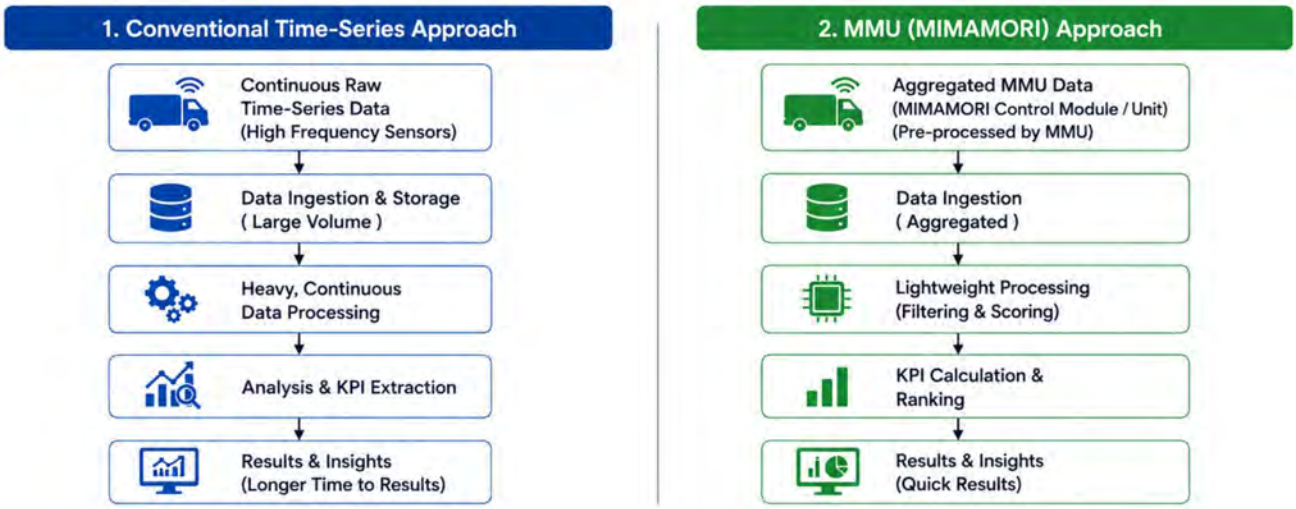


Figure 2　Time series vs MMU data process flow comparison

3.1 Fleet data preparation and quality filtering

The framework initiates by aggregating an expansive, statistically significant MMU dataset across a diverse, geographically distributed customer operational fleet. This data is further filtered to ensure data integrity and quality control by eliminating anomalies or parameters.

3.2 KPI extraction

The second step is to convert raw operation data into KPIs that describe customer usage. The exact Key Performance Indicators (KPIs) depend on the purpose/objective of the analysis. For example, an aftertreatment study may emphasize cold operation. A Battery Electric Vehicle (BEV) study may emphasize route length, speed distribution, energy demand. A Fuel-Cell (FC) study may emphasize hydrogen storage requirement and refueling availability[6][7].

3.3 Usage Classification and Severity Scoring

Once the distinct KPIs are extracted, individual fleet vehicles are categorized into specific commercial vocations that isolate their primary operating signatures. These classifications typically distinguish between high-speed long-haul highway transit, urban stop-and-go delivery routing, high-idle municipal or vocational operations, extreme cold-region deployments, and severe high-energy demand applications. **Figure 3** illustrates these distinct commercial vehicle vocations alongside their respective real-world usage distributions.

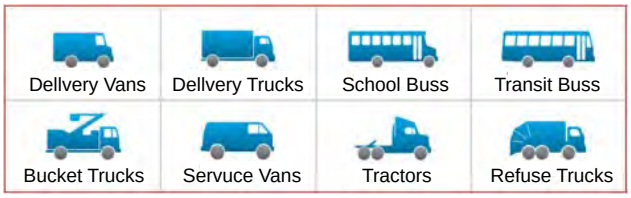


Figure 3　Different vocation of commercial vehicle

For planning purposes, classification should identify both representative use and severe use. Representative use supports mainstream target setting, while severe use supports robustness, durability, emissions, and worst-case validation planning.

To synthesize multi-dimensional KPIs featuring disparate physical units into a singular, cohesive assessment tool, a standardized severity index is implemented. For any individual metric where a higher numerical value directly correlates with elevated component stress, the normalized rating is calculated using a linear min-max feature scaling approach shown in **Equation (1)**.

$$x_{norm} = (x - x_{min}) \,/\, (x_{max} - x_{min}) \quad \cdots(1)$$

The resulting normalized KPI ratings are subsequently aggregated through weighted distribution, and the final composite score is normalized a second time to ensure scale consistency. The assignment of specific weighting factors is directly governed by the downstream engineering target. As in the HDIUT cases study showcased in the later part of this paper, a cold-start emissions optimization study will heavily penalize lower non idling states and cold thermal states.

3.4 Decision making

The final block is where the recognized operational patterns are translated into actual decisions, technology developments, investments, vehicle testing, and target setting. The synthesized duty cycles and severe-use profiles are deployed multi-functionally across the organization:

- Product Testing & Validation: Directly generates localized, real-world testing procedures, such as custom HDIUT or RDE compliance cycles for laboratory dynamometer and Portable Emissions Measurement System (PEMS) evaluation.
- Target Setting: Establishes rigorous, data-justified reliability and durability targets for next-generation vehicles based on actual customer boundaries.
- Technology Investments & Development: Informs R&D teams where to allocate capital–such as optimizing battery capacities for specific BEV routes or refining Selective Catalytic Reduction aftertreatment system (SCR) heater strategies for high-frequency cold-start profiles.

4 Case Study: HDIUT cycle generation using ISUZU N-SERIES MIMAMORI data

The HDIUT case study demonstrates how the proposed data driven framework can be applied to a specific research and development need. As mentioned in the introduction section with post-production audits in scope, the team planned to investigate customer data and understand customer usage patterns that can be used to create a drive cycle that can be used to generate similar results at development phases.

The scenario of interest includes repeated cold starts, high-load driving, engine shutdown, soak time, and repeated operation during a work shift. This operating pattern is important because aftertreatment systems such as SCR may have reduced effectiveness before reaching sufficient thermal temperature, and repeated cold operation can increase emissions risk. Fleet data provides a practical way to evaluate whether this type of severe-use condition exists in the field and how frequently it occurs within customer operation[2][4].

For the HDIUT example in this paper, a minimum mileage threshold of 500km is considered to avoid making decisions based on very small sample exposure.

For this case study, ISUZU N-SERIES MIMAMORI data is used to identify customer vehicles with operation patterns that may represent a realistic high-demand condition. The objective is not only to create a test cycle, but to demonstrate how fleet data can be transformed into evidence for planning and development decisions (**Figure 4**).

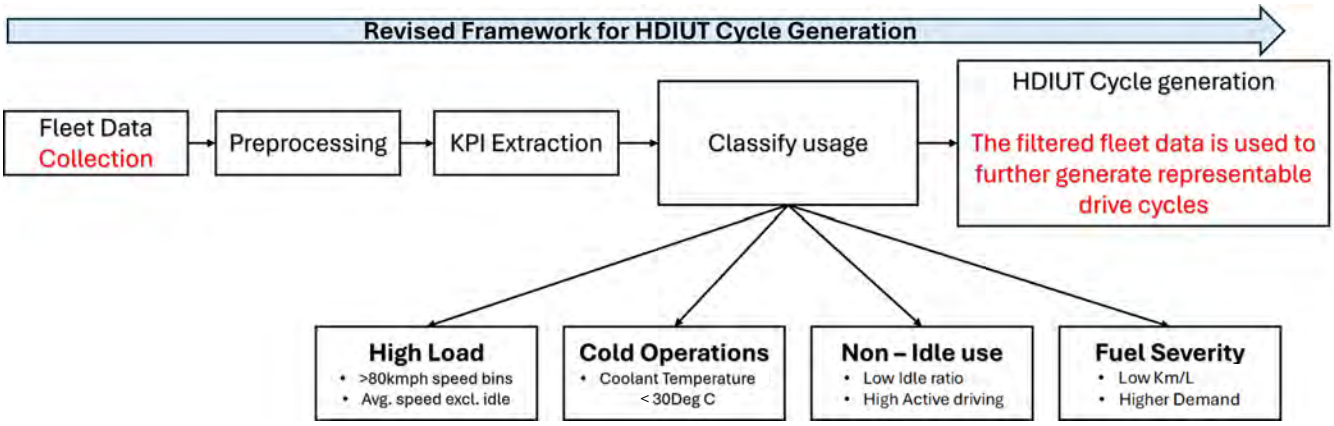


Figure 4 Revised framework for HDIUT cycle generation from fleet data

4.1 KPI logic for HDIUT identification

For HDIUT identification, KPI logic focuses on four customer-operation characteristics: high-load driving, cold operation, non-idle operation, and fuel-consumption severity. These characteristics were selected because they represent the combination of operation that can challenge thermal management and emissions control while still being based on actual customer field data.

4.2 Rating calculation

The ISUZU N-SERIES fleet data analysis converts each raw operating metric into a normalized KPI rating so that parameters with different units can be compared on a common 0 - 1 scale. For KPIs where a higher raw value indicates greater severity, such as average speed or high-speed exposure, min–max normalization is applied directly. For KPIs where a lower raw value indicates greater severity, such as idle ratio or fuel economy, inverse normalization is applied. This allows each KPI to be evaluated individually or combined with other KPIs based on the objective of the analysis.

The final severity score is calculated from the selected KPI set using a normalized weighted combination with higher priority given to non-idle operation and cold operation as shown in **Equation (2)**.

$$Final\ Score = [(3 * Non - Idle) + (2 * Cold\ Operations) + (1 * High\ speed) + (1 * High\ Fuel) \quad \cdots(2)$$

The initial demonstration uses equal KPI contribution, but the method is intentionally expandable. Depending on the research or validation requirement, different KPIs can be added, removed, weighted, or evaluated separately.

For example, a cold-start emissions study may assign higher weight to coolant temperature and soak-related indicators, while a highway-load validation study may prioritize high-speed exposure and non-idle operation.

This data-driven structure allows KPI selection, threshold definition, and scoring logic to be quantified according to the specific engineering or product-planning objective, rather than forcing one fixed interpretation of fleet data.

4.3 Sample ISUZU N-SERIES MIMAMORI results

Five sample vehicles from the ISUZU N-SERIES MIMAMORI dataset were considered for this analysis. Actual Vehicle Identification Numbers (VINs)*2 are not disclosed to protect intellectual property and maintain data privacy. Within each VIN, the KPI that are associated with HDIUT cycle characteristics are chosen as shown in **Table 2**.

*2 VIN (anonymized in this paper for publication readiness)

Table 2 Sample ISUZU N-SERIES MIMAMORI vehicles used for HDIUT screening

Sample	Mileage (km)	Avg speed excl. idle (km/h)	>80 exposure (%)	Idle ratio (%)	Avg fuel economy (km/L)
VIN-A	3,478	92.25	83.03	9.2	4.38
VIN-B	17,177	81.96	67.66	8.2	5.4
VIN-C	18,340	91.8	74.23	8.8	4.3
VIN-D	2,572	19.59	0	56.8	3.51
VIN-E	1,282	12.85	0.14	45.7	2.91

The values show that VIN-A, VIN-B, and VIN-C operate with high vehicle speed with respect to avg speed, velocity bins, and low idle ratio. These vehicles are therefore strong candidates for high-load HDIUT cycle generation. VIN-D and VIN-E show low speed and high idle ratio, so they are not HDIUT candidates, although they may be useful for other product-planning studies such as urban-idle operation or stop-and-go route evaluation.

Figure 5 compares the cumulative operating hours for each VIN across low coolant temperature bins below 30°C. Operation in these temperature ranges is important because it represents periods where the engine and after-treatment system may not yet be fully warmed up, which can increase emissions sensitivity during repeated cold-start, low idle and high-load operation.

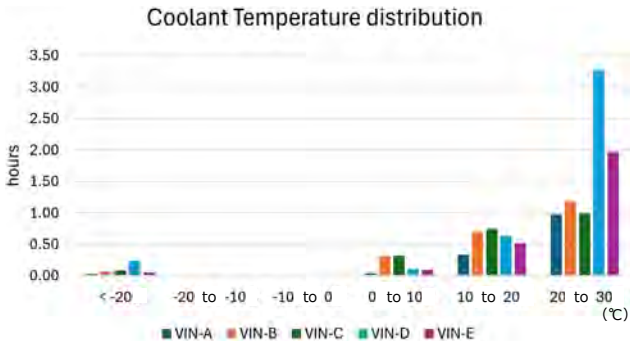


Figure 5 Coolant temperature distribution for anonymized VINs used in HDIUT cold-operation screening

The proportion of operational time spent in each velocity bin for five anonymized VINs is compared in **Figure 6**. When paired with cold-operation exposure, low idle ratio, and high fuel-consumption severity, higher exposure in the 80 km/h and above speed range implies stronger high-speed operation and is therefore thought to be more significant for HDIUT candidate selection. (The engineering assessment may once more be used to modify the 80 km/h limitation).

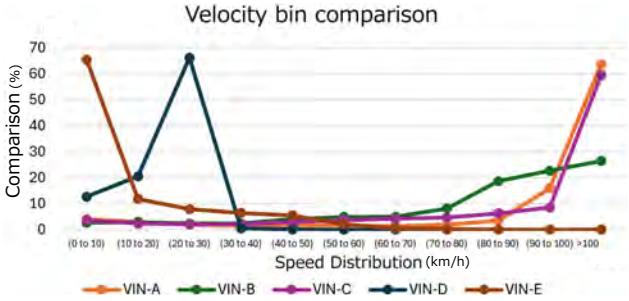


Figure 6 Velocity bin comparison for anonymized VINs used in HDIUT high-load operation screening

For HDIUT candidate selection, lower idle ratio is preferred because it indicates that a larger portion of engine running time is associated with active driving rather than stationary operation. **Figure 7** compares vehicle running time, engine running time, and total idle time for the anonymized VINs. The idle ratio is calculated as total idle time divided by engine running time.

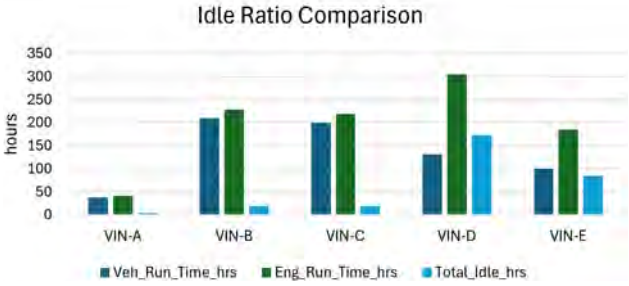


Figure 7 Idle operation comparison foranonymized VINs used in HDIUT non-idle operation screening

The results in **Figure 8** show a clear separation between the candidate and non-candidate vehicles. VIN-A, VIN-C, and VIN-B have final normalized ratings of 1.000, 0.986, and 0.918 respectively. These ratings

are driven primarily by HDIUT case requirements. VIN-D and VIN-E have final ratings close to zero because their operation is dominated by low-speed and high-idle usage.

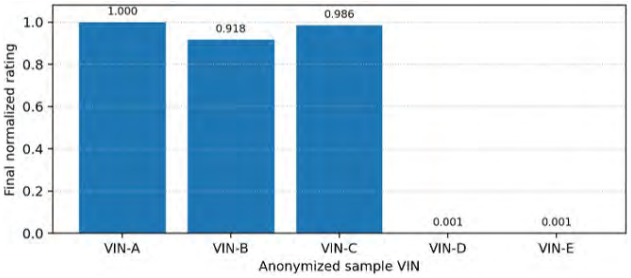


Figure 8 Final normalized HDIUT severity rating for anonymized sample VINs

For this demonstration, the selected VINs were intentionally chosen from the extreme ends of the normalized rating distribution to clearly explain the KPI logic and candidate-selection approach. VINs with ratings close to 1 represent strong alignment with the target HDIUT severe-use condition, while VINs with ratings close to 0 represent low alignment. This contrast helps demonstrate how fleet data can be used to separate high-priority HDIUT candidates from less relevant customer usage patterns.(**Table 3**)

Table 3 Normalized KPI ratings for sample ISUZU N-SERIES MIMAMORI vehicles

Sample	Avg speed rating	High-speed rating	Cold rating	Non-idle rating	Fuel severity rating	Final normalized rating
VIN-A	0.91	0.93	0.03	0.88	0.14	1
VIN-B	0.8	0.76	0.04	1	0.09	0.918
VIN-C	0.91	0.83	0.04	0.93	0.15	0.986
VIN-D	0.1	0	0.08	0.06	0.21	0.001
VIN-E	0.02	0	0.05	0.1	0.28	0.001

4.4 Interpreting the HDIUT candidate vehicles

The candidate vehicles illustrate how aggregate fleet data can identify realistic customer operation that should be considered during future vehicle development. VIN-A and VIN-C combine very high average speed this indicates a strong highway or high-load operating pattern. VIN-B also shows high-speed operation and the strongest non-idle rating among the sample vehicles. These characteristics make the three vehicles suitable starting points for retrieving trips or route segments that can be assembled into a high-demand cycle.

The cold-operation metric in the sample should be interpreted carefully. A vehicle may have cold coolant exposure without also having immediate high-load operation after the cold starts. Even without the timestamp data, aggregate KPIs can still narrow the candidate list, but cycle construction should be confirmed with additional data or targeted instrumentation.

4.5 From candidate VINs to HDIUT cycle:

The HDIUT cycle-generation process begins by applying the framework to the full fleet dataset and selecting candidate vehicles with high final ratings. Trips or operating windows from those candidate vehicles can then be screened for the target operation sequence. The selected windows are then fed to the in-house developed ISUZU drive cycle tool, that generates representable cycles by interlacing different parts of standard evaluation cycles and generates a time series speed profile that can be used for future vehicle evaluation.[1].

This case study therefore provides an example of how fleet data moves through the complete framework: raw customer data, KPI extraction, severity scoring, candidate identification, route or duty-cycle generation, and final test application. The output is not only a test cycle. It is also evidence that a proposed development scenario is linked to real customer usage.

5 Broader applications of the same approach

The HDIUT case study is an application of a broader fleet-data framework. The same method can be reused to understand customer operation and convert that understanding into future product decisions. The key is to change the KPI set and scoring logic to match the business and engineering question. **Table 4** highlights some of the key outcomes of this framework when used with other powertrain applications.

For route generation, the method can identify actual customer speed profiles, distances, stop patterns, idle events, and thermal conditions[1] Those routes can be converted into simulation inputs, chassis dynamometer cycles, proving-ground schedules, or customer-representative validation plans. For real-world performance and engineering evaluation, the method compares product behavior against actual customer operation, including fuel economy, energy consumption, aftertreatment warm-up, regeneration frequency, range utilization, and thermal limitations. Planning teams can use the results to identify usage clusters that justify investment, while engineering teams can use them to set targets, investigate limitations, and define validation requirements

Table 4 How the same fleet-data approach can support other planning decisions

Planning question	KPI emphasis	Potential decision or output
Which routes are suitable for BEV introduction?	Daily distance, energy demand, charging opportunity, temperature exposure	BEV route suitability and battery/range target
Which customers require hybridization or idle reduction?	Idle ratio, stop frequency, speed distribution, auxiliary load	Hybrid system priority and idle-reduction strategy
Which applications are suitable for fuel cell?	Route length, continuous load, refueling opportunity, payload and climate exposure	Hydrogen storage, fuel-cell power rating, infrastructure plan
Which ICE customers need stronger aftertreatment robustness?	Cold starts, SCR warm-up opportunity, high-load driving, fuel severity	Aftertreatment sizing, heater strategy, calibration margin
Which duty cycles should future vehicles be tested on?	Representative and severe customer clusters from speed, load, idle, thermal, and energy data	Customer-derived validation cycle library
Where should development investment be prioritized?	Fleet population size by severe-usage clusters and technology need	Product roadmap and investment plan

5.1 Limitations and recommended improvements

The case study uses available aggregate MIMAMORI metrics, which are sufficient for identifying candidate vehicles and demonstrating the product-planning and engineering development value of the approach; However, aggregate metrics cannot fully confirm the exact event sequence required for the intended HDIUT condition, such as cold start, transition to high-load driving, repeated operation during a work shift etc. Time series data, where available, should therefore be used as a second-stage confirmation method. This additional step is more time-consuming because it requires trip-level data extraction, time-damp alignment, filtering of large data volumes, and engineering review of candidate segments. Therefore, aggregate KPI analysis is recommended for scalable fleet-level screening, while time-series analysis should be applied selectively to the shortlisted VINs to improve confidence that the selected cycle truly represents the target HDIUT operating condition.

6 Conclusion

This paper presents a fleet-data-driven framework for future powertrain product planning. Its main contribution is positioning fleet data as a strategic planning input, rather than only an engineering diagnostic tool. By translating customer operation into KPIs, usage classifications, and severity ratings, OEMs can better define project targets, technology investments, validation cycles, and customer-segment priorities.

The HDIUT case study demonstrates a practical application. ISUZU N-SERIES MIMAMORI data identified vehicles with cold temperature, low Idle, high average speed, and high normalized severity. Three sample VINs were strong HDIUT candidates, while two represented lower-speed, higher-idle operation better suited to other use-case studies. This demonstrates how fleet data can be converted into customer-derived duty-cycle inputs for vehicle testing and evaluation.

By adjusting KPIs, thresholds, and weighting factors, the same methodology can support other powertrain programs and planning questions, including HDIUT cycle generation, route generation, usage-pattern analysis, real-world performance evaluation, and future Isuzu investment planning.

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