DEVELOPMENT OF AN AI-DRIVEN PREDICTIVE MODEL FOR VEHICLE FEATURE OPTIMIZATION & DIAGNOSTIC TUNING USING AN EXTENDED KALMAN FILTER (EKF) STATE ESTIMATOR

by

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To my parents, my family, my wife, and my son Elias—thank you for your endless love, strength, and encouragement that carried me through every step of this journey.

PREFACE

This dissertation emerged from my professional and research experience working at the intersection of connected vehicle systems, fleet analytics, and intelligent diagnostics. Through both industry practice and academic investigation, I observed persistent limitations in traditional diagnostic frameworks that rely on static thresholds and model assumptions that do not adapt to evolving vehicle behavior, environmental variability, or system-specific differences that arise across platforms, configurations, and operating conditions. These observations motivated the development of a hybrid estimation and learning framework capable of improving diagnostic consistency and predictive capability across heterogeneous vehicle environments.

The research presented in this work explores the integration of physics-based state estimation with data-driven learning methods to address challenges related to signal uncertainty, platform-level variability, and long-term system drift in modern connected and automated vehicles. By combining Extended Kalman Filter (EKF) estimation with artificial intelligence techniques, this dissertation proposes an adaptive architecture that supports more reliable feature estimation, predictive maintenance strategies, and scalable diagnostic tuning for next-generation mobility systems.

This work reflects both academic research and practical engineering experience with real-world telemetry, autonomous mobility platforms, and large-scale fleet systems. While focused on modern vehicles, the proposed methods apply broadly to adaptive perception and prediction in complex cyber-physical systems.

ABSTRACT

DEVELOPMENT OF AN AI-DRIVEN PREDICTIVE MODEL FOR VEHICLE FEATURE OPTIMIZATION & DIAGNOSTIC TUNING USING AN EXTENDED KALMAN FILTER (EKF) STATE ESTIMATOR

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Adviser: Mohamed A. Zohdy, Ph.D.

Modern connected and automated vehicles rely on increasingly complex sensing, perception, and estimation architectures to infer internal system states and predict future behavior from high-volume, noisy, and nonlinear sensor data. Similar challenges arise across a broad class of engineered systems and intelligent devices, including robotic and autonomous platforms, where accurate perception and prediction under uncertainty are essential for safe, reliable, and sustained operation. As these systems age or operate across diverse environments and usage conditions, discrepancies emerge between modeled dynamics and observed measurements due to sensor drift, component degradation, environmental variability, and unmodeled nonlinear effects.

These discrepancies degrade state estimation accuracy, destabilize diagnostic interpretations, and reduce the reliability of perception-driven and prediction-driven decision-making.

This dissertation develops an adaptive perception and prediction framework that integrates nonlinear state estimation with data-driven learning to support continuous

system understanding under uncertainty. The proposed approach combines a model-based estimation layer that captures nominal system dynamics and enforces physical consistency with a learning-based predictive layer that models residual nonlinearities, long-term signal drift, and cross-sensor dependencies that are difficult to represent analytically. Through recursive estimation and forward prediction, the framework enables simultaneous inference of latent system states and anticipation of future system behavior. An adaptive tuning mechanism further refines perception and diagnostic interpretations by dynamically adjusting internal thresholds and confidence bounds based on predicted behavior, operational context, historical system performance, and evolving system characteristics.

The framework is evaluated using both real-world and simulated datasets representative of connected vehicle networks and autonomous sensing systems. The evaluation demonstrates accurate estimation and prediction of motion states, actuation responses, thermal behavior, and system health indicators under varying operating conditions. Experimental results show improved estimation accuracy, enhanced predictive stability, faster convergence, and increased robustness to noise and sensor degradation when compared to conventional model-based estimators, standalone learning-based approaches, and static diagnostic frameworks. The proposed methodology further enables more consistent perception and diagnostic interpretation across heterogeneous systems, devices, and operating environments.

This research contributes a scalable and generalizable methodology for integrated perception and prediction in modern connected vehicles and autonomous systems. By enabling estimation and diagnostic models to continuously learn, adapt, and recalibrate over time, the proposed framework supports long-term autonomy, resilience, and reliability in complex cyber-physical systems operating under uncertainty, change, and degradation. The proposed framework supports next-generation predictive maintenance strategies in connected fleets and contributes to the realization of adaptive, self-calibrating diagnostic systems for intelligent vehicles.

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LIST OF ABBREVIATIONS

ABS	Anti-lock Braking System
ADAS	Advanced Driver Assistance Systems
AI	Artificial Intelligence
APP	Accelerator Pedal Position
CAN	Controller Area Network
CAN-FD	Controller Area Network – Flexible Data Rate
CBM	Condition-Based Maintenance
DTC	Diagnostic Trouble Code
ECU	Electronic Control Unit
EKF	Extended Kalman Filter
EV	Electric Vehicle
GPS	Global Positioning System
KPI	Key Performance Indicator
LSTM	Long Short-Term Memory

MAPE	Mean Absolute Percentage Error
ML	Machine Learning
OEM	Original Equipment Manufacturer
OTA	Over-the-Air
PHM	Prognostics and Health Management
RMSE	Root Mean Square Error
RPM	Revolutions Per Minute
SOC	State of Charge
SOH	State of Health
TCU	Telematics Control Unit
UKF	Unscented Kalman Filter
VIN	Vehicle Identification Number
V2V	Vehicle-to-Vehicle Communication
IoT	Internet of Things
RVCI	Route–Vehicle Compatibility Index

CHAPTER 1 – INTRODUCTION

1.1 Background and Motivation

The rapid evolution of modern vehicles into highly instrumented, intelligent, and increasingly autonomous systems has transformed the way diagnostics, state estimation, and predictive maintenance are performed. Today's connected and intelligent vehicles are equipped with dozens of electronic control units (ECUs), advanced driver-assistance systems (ADAS), real-time communication modules, and extensive sensing capabilities. The growth of autonomous mobility platforms, connected fleets, electrified powertrains, and data-driven automotive ecosystems has intensified the need for accurate and adaptive diagnostic frameworks. Fleet operations such as police patrol vehicles, commercial delivery fleets, ride-share platforms, and autonomous shuttles rely heavily on consistent and reliable diagnostic performance across large populations of vehicles. These environments introduce significant variability due to differences in VIN configurations, operating conditions, mileage accumulation, and driving styles, making traditional static diagnostics inadequate.

Simultaneously, the importance of accurate diagnostics has never been greater. Diagnostic systems ensure safe operation, reduce unexpected failures, and support efficient maintenance strategies. Incorrect diagnostics can result in false alarms, unnecessary service events, reduced vehicle availability, and customer dissatisfaction. More critically, undetected component degradation or behavior drift can compromise safety, lead to poor fuel efficiency, increase emissions, and impair the performance of advanced safety systems. System diagnostic thresholds often become misaligned after component upgrades, module replacements, or software updates, because the calibration values remain based on historical conditions rather than the vehicle's present state. This makes it clear that conventional rule-based and lookup-table diagnostics are no longer sufficient for modern intelligent vehicles.

Adding to this challenge is the rising complexity of vehicle signals. Modern vehicles continuously generate high-frequency, nonlinear, and noisy data across CAN buses, sensor networks, and subsystem interfaces. Signals such as engine speed, torque, accelerator pedal position, brake pressure, steering angle, thermal states, and battery health vary widely between vehicles and degrade over time. Each of these signals is influenced by numerous interacting factors including environmental conditions, driver behavior, mechanical wear, and software changes. The nonlinear interactions among these signals create a complexity that traditional diagnostic thresholds and simple filtering techniques cannot adequately handle. Traditional filters struggle to estimate underlying states when signals contain drift, hysteresis, sensor degradation, or mode-dependent behavior.

For these reasons, the combination of advanced estimation techniques and artificial intelligence has emerged as a critical direction for next-generation diagnostics. The Extended Kalman Filter (EKF) remains one of the most widely used methods for real-time state estimation in nonlinear systems, offering mathematically grounded prediction, smoothing, and noise suppression. However, EKF alone is insufficient to model long-term drift, VIN-specific variation, or complex nonlinear behaviors. Machine learning and AI techniques excel in capturing patterns, correlations, and nonlinearities that analytical models cannot. Integrating AI with EKF enables a hybrid approach that compensates for model limitations, learns from historical data, predicts future behavior, and adapts diagnostic thresholds dynamically.

Therefore, the motivation for this dissertation arises from the convergence of three forces:

(1) the expansion of intelligent and autonomous vehicles requiring adaptive and consistent diagnostics;

(2) the critical importance of accurate, real-time diagnostic insight for safety, reliability, and fleet operations; and

(3) the increasing complexity and variability of vehicle signals, which demands a more intelligent, adaptive, and predictive diagnostic model.

These challenges form the foundation for the development of an AI-Integrated Extended Kalman Filter prediction model for vehicle feature estimation and adaptive diagnostic tuning, as explored throughout this dissertation.

These challenges position vehicle diagnostics as a perception problem, where latent system states must be inferred and predicted under uncertainty using recursive estimation techniques rather than directly measured [2].

1.1.1 Perception and Prediction in Modern Systems

Modern connected and automated vehicles and systems increasingly operate as perception-driven cyber-physical systems. Rather than relying solely on direct sensor measurements, these vehicles continuously infer latent internal states—such as motion, intent, health, and system readiness—from noisy, partial, and delayed observations. from noisy, partial, and delayed observations through probabilistic multi-sensor fusion techniques [83]. This process of perception extends beyond environmental sensing and includes the estimation of internal vehicle states that are not directly measurable but are critical for control, safety, diagnostics, and autonomy.

Perception in this context is inherently predictive. Estimation frameworks must not only interpret current sensor measurements but also forecast near-future system behavior to enable stable control, early fault detection, and robust decision-making. Recursive estimation techniques based on probabilistic state-space modeling provide a principled mechanism for combining prior system knowledge with incoming observations, allowing vehicles to continuously update their internal belief of system state under uncertainty [3].

In both automotive and robotic systems, Kalman filtering and its nonlinear extensions have become foundational tools for perception and prediction. These methods enable a prediction–correction cycle in which system dynamics are used to anticipate future states, while sensor measurements are incorporated to correct estimation error.

This paradigm is widely used in navigation, localization, sensor fusion, and robotic perception, and forms the backbone of many autonomous systems.

However, real-world vehicle perception challenges extend beyond the assumptions of classical estimation theory. Sensor drift, component aging, environmental variability, and long-term behavioral changes introduce nonstationary effects that degrade estimation performance over time. As a result, perception models that rely solely on fixed dynamics and static noise assumptions struggle to maintain accuracy throughout a vehicle's operational life. These challenges motivate the integration of adaptive and learning-based methods into traditional estimation frameworks.

This dissertation builds upon the perception–prediction foundations of recursive state estimation by introducing an adaptive, learning-enhanced framework capable of evolving with system behavior over time. While modern vehicles serve as the primary application domain, the proposed methodology generalizes to other intelligent systems, including robotic platforms and autonomous devices, where long-term perception reliability is essential.

1.2 Problem Statement

Modern automotive platforms exhibit growing variability across trims, powertrains, software versions, and operational modes. Although these vehicles share a common diagnostic architecture, their physical behavior diverges significantly due to sensor aging, firmware updates, and driveline configuration differences. There are three foundational challenges this dissertation addresses:

(1) diagnostic thresholds vary across vehicles with identical hardware;

(2) thresholds do not adapt as systems age or as components are replaced; and

(3) there is no secure mechanism to track, validate, or synchronize diagnostic updates across distributed fleets. Prior system-level methods for evaluating vehicle diagnostic parameters and managing distributed diagnostic behavior in connected vehicle environments have been proposed in earlier patented architectures [80]. These three factors create persistent inconsistency in diagnostic outcomes and justify the need for an adaptive, VIN-aware, and tamper-resistant diagnostic framework.

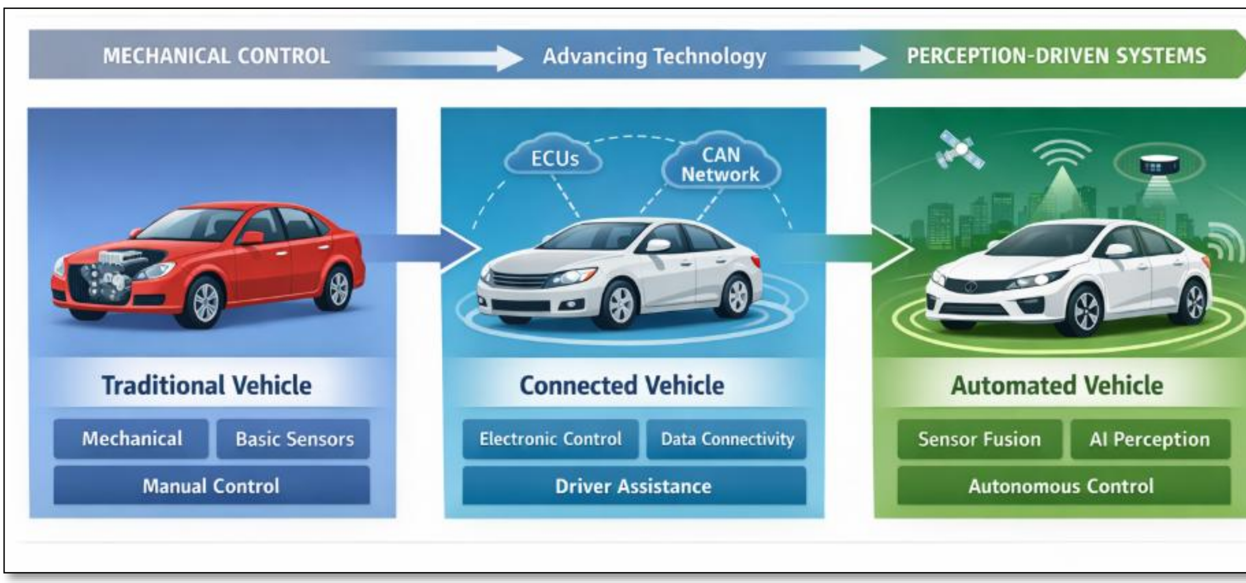


Figure 1.0: Evolution of Vehicle Architectures

The increasing intelligence and connectivity of modern vehicles has amplified the need for reliable, adaptive, and context-aware diagnostic systems. While traditional diagnostics depend heavily on static calibration tables and manufacturer-defined thresholds, these values are typically generated under controlled laboratory conditions and do not accurately reflect the dynamic operational environments experienced by vehicles in real-world usage. As vehicles age, undergo part replacements, receive software updates, or operate under varying environmental and load conditions, the underlying diagnostic parameters drift from their original calibration. This drift leads to degraded diagnostic accuracy, inconsistent fault detection behavior, and diminished reliability in safety-critical decisions.

At the same time, the complexity of the signals used in diagnostic decision-making has increased dramatically. CAN bus data, which forms the backbone of in-vehicle communication, contains high-frequency, nonlinear, and interdependent signals such as engine torque, RPM, throttle position, brake pressure, temperature sensors, steering dynamics, and battery state-of-health indicators. These signals are influenced by multiple sources of variability including driver behavior, vehicle aging, VIN-specific configurations, firmware changes, and component degradation which makes it increasingly difficult to maintain stable diagnostic performance using static, rule-based approaches.

Current diagnostic methods also lack the ability to generalize across vehicles. Two vehicles of the same model, and year can exhibit different signal signatures due to VIN-specific tolerances, driving style differences, load conditions, and history of maintenance or component replacement. When diagnostic thresholds are uniform across all vehicles, this VIN-level variability often leads to false positives in some vehicles and missed detections in others. In fleets, where dozens or hundreds of vehicles operate under diverse conditions, this inconsistency results in unreliable fleet analytics, confusing cross-vehicle comparisons, and increased operational costs from unnecessary service events.

Furthermore, traditional model-based estimation techniques such as the Kalman Filter and its nonlinear variant, the Extended Kalman Filter (EKF), although powerful in real-time estimation, still rely heavily on analytical modeling assumptions. These models require accurate noise characterization, correct system dynamics, and strong assumptions about the relationships between variables. In real-world vehicles, however, nonlinearities, delays, seasonal trends, and long-term drift often violate these assumptions. As a result, the EKF alone cannot fully capture the complexity and evolution of vehicle behavior over time.

Conversely, machine learning and artificial intelligence (AI) techniques excel at extracting nonlinear patterns, learning from historical data, and identifying hidden relationships among signals. However, pure data-driven models lack the physical grounding and real-time filtering capabilities required for safety-critical automotive diagnostics. They may generalize poorly outside of training conditions, require substantial labeled datasets, and fail to enforce physical or safety constraints.

Thus, the central problem addressed in this dissertation is the lack of a unified, adaptive, AI-enhanced diagnostic framework capable of:

- estimating vehicle features accurately in real-time,

- adapting diagnostic thresholds dynamically as vehicle behavior changes,
- correcting for sensor drift, environmental and component variation,
- harmonizing diagnostic parameters across heterogeneous fleets,
- learning from historical and real-world operational data,
- preserving physical plausibility while leveraging predictive power of AI.

Also, this dissertation addresses this gap by developing an AI-Integrated Extended Kalman Filter prediction model designed to provide accurate state estimation, robust feature extraction, and adaptive diagnostic threshold tuning, all while accommodating VIN-specific behaviors and fleet-level variability. The problem is thus defined as the challenge of creating a hybrid EKF–AI system that learns continuously, adapts dynamically, and ensures long-term diagnostic consistency across diverse vehicles and operational conditions.

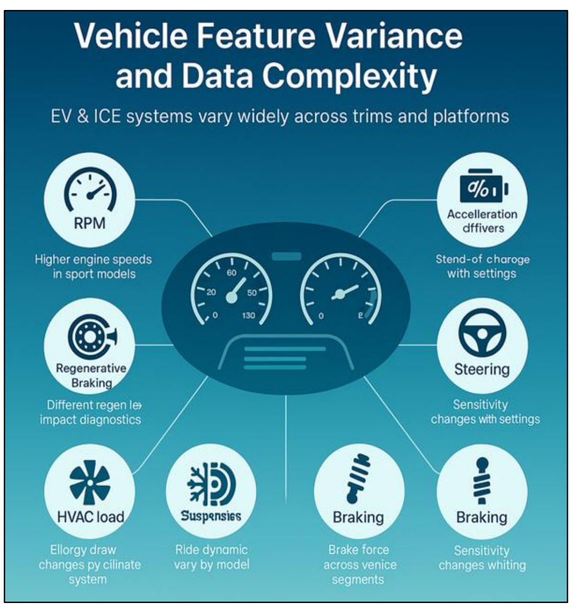


Figure 1.1: Vehicle Variance & Complexity

This figure illustrates the variability of vehicle features and operational data across different platforms, and propulsion types (EV and Engine). It highlights how core subsystems RPM behavior, acceleration response, regenerative braking, steering sensitivity, braking dynamics, suspension characteristics, and HVAC load—exhibit differing performance signatures. These variations introduce significant complexity for diagnostics, analytics, and predictive modeling, as each subsystem may respond differently depending on drive modes, climate conditions, & charge states.

From a perception standpoint, this inconsistency reflects a failure to maintain accurate internal state belief over time

At fleet scale, this inconsistency leads to unnecessary service interventions, reduced vehicle availability, increased warranty expenditure, and diminished confidence in diagnostic interpretation across heterogeneous vehicle populations.

1.3 Research Gaps

Modern vehicle diagnostics and feature estimation rely on a combination of static calibration tables, rule-based fault detection systems, and limited model-based estimation methods. While these approaches have been historically sufficient for traditional vehicles operating under predictable conditions, they are increasingly inadequate for intelligent, connected, and autonomous vehicle platforms. A thorough analysis of existing literature reveals several critical research gaps that motivate the development of an AI-Integrated Extended Kalman Filter (EKF) prediction model.

1.3.1 Lack of Adaptive Diagnostic Thresholds

Most OEM diagnostic systems are built around static thresholds, defined during early development stages through controlled dynamometer tests, calibration sessions, and pre-production bench validation. These thresholds do not evolve with vehicle aging, environmental exposure, or long-term component degradation.

After module replacements, software upgrades, or hardware changes (e.g., turbocharger replacements, firmware changes, TCU updates), the vehicle continues to rely on outdated diagnostic tables, resulting in:

- False-positive diagnostic trouble codes (DTCs),
- Undetected degradations,
- Incorrect feature interpretation,
- And inconsistent customer experience.

No current OEM framework provides continuous self-adjustment of diagnostic parameters based on real behavior.

1.3.2 Insufficient Handling of VIN-to-VIN Variation

Vehicles with the same make, model, and year can still exhibit significant VIN-specific variation due to manufacturing tolerances, firmware differences, module revisions, wear histories, and driver behavior.

Existing diagnostic systems poorly handle this variation because:

- thresholds are globally applied, not VIN-adaptive,
- signal patterns vary across vehicles,
- OEM tunings do not reflect individual vehicle aging,
- post-upgrade thresholds are not recalculated.

Research has yet to produce a systematic, data-driven method for generating VIN-specific or vehicle-specific adaptive thresholds.

1.3.3 Limitations of Traditional EKF in Real-World Nonlinear Environments

Although the EKF is widely used in automotive state estimation, it suffers from several constraints:

- It requires accurate system models.
- Linearization introduces estimation errors for highly nonlinear systems.
- Noise assumptions may be invalid in real-world nonlinear vehicle environments due to unmodeled disturbances and sensor degradation [5].
- It cannot model long-term behavioral drift.
- It struggles with mode switching (e.g., towing mode, sport mode).

Vehicle behavior often exhibits nonlinear patterns, hysteresis, aging effects, and complex cross-correlations in CAN signals that linearization-based EKF approaches may fail to accurately capture [7][8], hysteresis, aging effects, intermittent faults, and complex cross-correlations in CAN signals that the EKF alone cannot fully capture.

Thus, a hybrid EKF + AI approach is needed to combine model-based physical rigor with data-driven adaptability.

1.3.4 Lack of Predictive Capability in OEM Diagnostics

Current diagnostic techniques are reactive, not predictive. They signal faults after thresholds are exceeded, rather than forecasting future deviations.

Gaps include:

- no forecasting of upcoming component degradation,
- no prediction of threshold drift based on historical data,
- no estimation of future sensor behavior or instability,
- no early warning for fleet operations.

Literature lacks integrated predictive models that combine estimation, learning, and threshold evolution.

1.3.5 Absence of Fleet-Wide Parameter Normalization

Fleet operators require cross-vehicle comparison to assess:

- vehicle health,
- driver performance,
- operational stress,
- component failures,
- fleet-level optimization.

However, variability across vehicles (VIN, age, firmware, modes) makes cross-fleet analytics inconsistent.

This paper proposes a groundbreaking concept:

- using fleet behavior to inform vehicle behavior,
- normalizing thresholds across the fleet,
- using a distributed/secure approach (blockchain mentioned).

No existing research provides a mathematical framework for normalizing diagnostic parameters across connected fleets.

1.3.6 Limited Integration of AI with Real-Time State Estimation

AI models excel at learning nonlinearities, while EKF excels at real-time filtering. Yet the two remain rarely integrated in published vehicle diagnostics research.

Gaps include:

- no unified EKF–AI loop,
- no AI-driven covariance tuning,
- no ML-driven residual correction,
- no hybrid architecture for adaptive diagnostics,
- no continuous-learning mechanism integrated with state estimation

This dissertation addresses a critical set of gaps:

- No adaptive diagnostic thresholding system.
- No VIN-specific and vehicle-specific tuning mechanism.
- No EKF-based predictor that handles nonlinearities and drift.
- No predictive diagnostic framework combining history + estimation.
- No fleet-wide normalization method for consistent thresholds.
- No integrated EKF–AI hybrid model in automotive diagnostics.
- No unified architecture featuring estimation with threshold tuning.

These gaps form the foundation and justification for AI-Integrated EKF Prediction Model.

1.4 Research Objectives

The overarching goal of this dissertation is to design, develop, and evaluate an AI-Integrated Extended Kalman Filter (EKF) prediction model capable of robust vehicle feature estimation and adaptive diagnostic threshold tuning across connected and heterogeneous fleets. This goal is driven by the increasing complexity of modern vehicle systems, the limitations of traditional diagnostic methodologies, and the growing demand for predictive intelligence in real-time automotive applications.

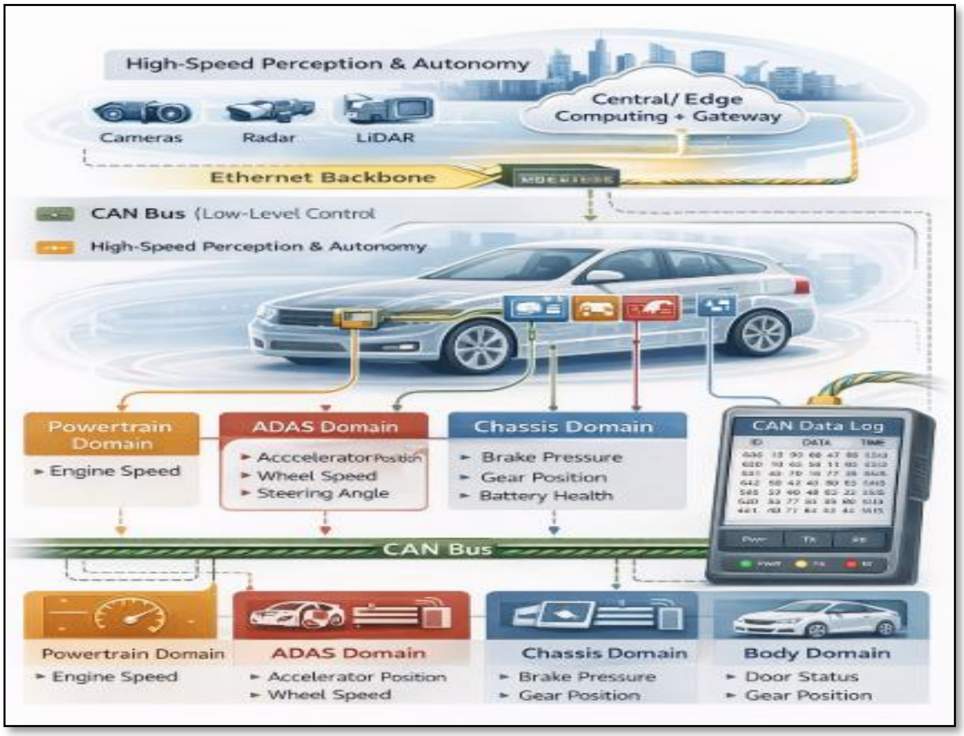


Figure 1.2: Overview of Modern Vehicle Network Architecture with Emerging Zonal and Centralized Computing

This figure illustrates a modern vehicle network architecture that integrates both legacy and emerging communication paradigms. The lower layers represent distributed electronic control units (ECUs) organized into functional domains such as powertrain, chassis, body, and advanced driver-assistance systems. These subsystems communicate over a Controller Area Network (CAN) bus, which remains the primary interface for low-level control, diagnostics, and real-time state estimation.

Signals exchanged at this layer include engine speed, brake pressure, accelerator position, steering angle, gear state, and battery health, forming the foundational data used for vehicle perception and diagnostic inference.

Above the CAN-based domain layer, the architecture incorporates high-speed communication and centralized computing through an Ethernet backbone. This layer supports data-intensive perception and autonomy functions, including cameras, radar, and LiDAR sensors, which feed into a central or edge computing unit responsible for perception, planning, and decision-making. Gateway modules bridge the low-level CAN domain with the high-level Ethernet backbone, enabling the aggregation, synchronization, and interpretation of vehicle state information across layers.

The figure highlights the coexistence of traditional distributed control architectures with emerging zonal and centralized designs. While high-speed Ethernet enables advanced perception and autonomous functionality, CAN-based communication continues to serve as the authoritative source for control and diagnostic signals.

This layered architecture reflects current industry practice, where perception, prediction, and autonomy operate on top of a robust, real-time control and diagnostic foundation. To achieve this overarching vision, the research is structured around the following core objectives:

1.4.1 Develop a Robust EKF-Based Prediction Model for Vehicle Feature Estimation

The first objective is to formulate an advanced Extended Kalman Filter architecture that can accurately estimate key vehicle features in real time using noisy, nonlinear CAN signals.

Although EKF is widely used in control theory, navigation, and robotics, adapting it to real-world vehicle diagnostics presents unique challenges, including signal nonlinearity, environmental noise, component variability, and mode-dependent dynamics.

This objective focuses on:

- Designing state-space models that accurately capture vehicle dynamics.
- Defining nonlinear measurement functions for CAN-based feature extraction.
- Constructing and tuning process and measurement covariance matrices for realistic vehicle noise profiles.
- Ensuring real-time stability and convergence under varying driving conditions.

This foundational model establishes the physical and mathematical backbone for all subsequent AI enhancements.

1.4.2 Integrate Artificial Intelligence to Enhance Predictive Accuracy

The second objective is to integrate machine learning techniques with the EKF framework to overcome limitations inherent in purely analytical models. AI plays a crucial role in capturing nonlinear relationships, long-term behavioral drift, VIN-level variability, and cross-signal correlations that EKF alone cannot model.

This objective includes:

- Developing an ML prediction layer trained on historical vehicle data.

- Learning long-term drift patterns that affect diagnostic thresholds.
- Capturing complex, nonlinear behaviors not represented in EKF's linearized model.
- Using AI outputs to refine EKF predictions and update diagnostic thresholds dynamically.

This synergy between physics-based and data-driven approaches forms a new class of hybrid predictive diagnostic systems.

1.4.3 Design an Adaptive Diagnostic Tuning Mechanism

A key innovation of this research is the development of a self-adjusting diagnostic tuning system capable of updating thresholds in real time. Unlike traditional systems that apply static values regardless of vehicle condition, this mechanism adjusts diagnostic parameters based on:

- predicted feature behavior (via AI),
- real-time estimated states (via EKF),
- VIN-specific behavior,
- accumulated driving history,
- component aging and degradation, and
- environmental and operational contexts.

The adaptive tuning method ensures:

- lower false-positive diagnostic outcomes,
- earlier detection of component health deterioration,
- improved consistency across vehicles,
- and compatibility with connected fleet deployments.

1.4.4 Develop a VIN-Aware Normalization Framework for Fleet Diagnostics

The fourth objective is to create a mathematical and algorithmic framework for VIN-aware parameter normalization. This framework ensures that diagnostic thresholds are tailored to each vehicle's specific characteristics while maintaining consistent diagnostic semantics across a fleet. This involves:

- Modeling VIN-specific variability in signal behavior.
- Building distributional models of fleet-level feature behavior.
- Implementing normalization or weighting functions to align parameters across vehicles.
- Enabling cross-vehicle comparison for fleet analytics.

1.4.5 Validate the Hybrid EKF–AI System Through Real and Simulated Experiments

The fifth objective focuses on evaluating the proposed model through rigorous experimentation. This includes:

- Testing EKF on real CAN data collected under driving conditions.
- Applying the AI layer to detect long-term drift and nonlinearities.
- Measuring diagnostic threshold evolution under controlled scenarios.
- Stress-testing the hybrid model using:
  - module-swap scenarios,
  - firmware upgrade events,
  - noisy data streams,
  - environmental changes,
  - and fleet-level variability.

Performance evaluation metrics will include:

- RMSE of feature estimation,
- convergence speed,
- false-positive and false-negative rates,
- robustness to noise and drift,
- cross-VIN consistency performance,

- predictive accuracy over time.

1.4.6 Produce Scalable, Real-Time Architecture Suitable for Modern Connected Vehicles

The final objective is to demonstrate that the proposed architecture:

- operates in real time,
- is computationally efficient enough for in-vehicle ECUs,
- supports over-the-air (OTA) updates,
- integrates with existing OEM and fleet diagnostic systems,
- and scales to large, connected fleets.

This research will outline deployment considerations for:

- embedded microcontrollers,
- telematics units,
- cloud-edge hybrid frameworks,
- and distributed computation layers (including blockchain concepts where applicable).

1.4.7 Research Hypothesis

This dissertation hypothesizes that integrating physics-based state estimation with data-driven predictive modeling—supported by VIN-aware normalization and secure distributed calibration—will improve diagnostic accuracy, reduce false positives, and enable earlier detection of subsystem degradation when compared to conventional EKF-only or static threshold-based diagnostic systems.

1.5 Significance of the Study

The rapid digital transformation of the automotive industry has revealed fundamental limitations in traditional diagnostic and state-estimation architectures. Vehicle electrification, the proliferation of advanced driver-assistance systems (ADAS), over-the-air (OTA) software deployments, and the rise of autonomous and connected fleets have created unprecedented diagnostic complexity [54].

The significance of this study therefore lies in its ability to address structural shortcomings in current diagnostic frameworks while establishing a foundation for next-generation intelligent vehicle systems.

First, this research contributes to the advancement of real-time vehicle diagnostics by integrating an AI-enhanced prediction model with the Extended Kalman Filter (EKF). Unlike legacy diagnostic systems that rely on fixed boundaries, this hybrid framework adapts diagnostic thresholds dynamically as vehicle behavior evolves.

This improves the reliability of fault detection, reduces diagnostic noise, and enhances the precision of maintenance recommendations. For vehicles operating in mission-critical settings—such as law enforcement fleets, autonomous mobility services, or commercial delivery operations this adaptability is essential to maintaining operational continuity and safety [55].

Second, the study is significant in addressing VIN-level variability and providing a pathway toward individualized diagnostics.

Traditional OEM diagnostics treat all vehicles as if they behave identically, despite clear evidence that component tolerances, firmware versions, environmental exposure, and usage patterns result in unique behavioral signatures. The VIN-aware normalization and threshold-adjustment mechanisms introduced in this dissertation enable personalized diagnostics without sacrificing consistency at the fleet level.

Third, the integration of AI into a classical state-estimation framework represents a multidisciplinary contribution spanning control theory, machine learning, automotive engineering, and statistical signal processing.

This hybrid approach combines the physical fidelity and interpretability of EKF with the nonlinear pattern-recognition capabilities of machine learning. Such an approach is increasingly important as vehicles shift toward data-driven architectures that require both physics-based guarantees and learning-based adaptability.

Fourth, this study introduces a structured foundation for predictive diagnostics, enabling early detection of drift trends, component degradation, and behavioral anomalies before failure thresholds are crossed. This represents a paradigm shift from reactive fault identification to proactive health management, supporting the automotive industry's movement toward Condition-Based Maintenance (CBM) and prognostics and health management (PHM).

Finally, the research provides scalable and deployable architecture suitable for in-vehicle ECUs, edge computing, and fleet-level cloud platforms.

The proposed system lays the groundwork for intelligent self-calibrating vehicles capable of learning from their own histories while benefiting from the statistical patterns observed across an entire fleet.

In summary, the significance of this research lies in its ability to advance diagnostic intelligence, support modern fleet operations, enhance safety, reduce maintenance costs, and accelerate the transition toward adaptive, data-driven automotive systems.

1.6 Novel Contributions

This dissertation provides several distinct and original contributions to the fields of predictive vehicle diagnostics, state estimation, and intelligent fleets. These contributions are summarized below.

1.6.1 A Hybrid AI–EKF Prediction Architecture

The primary contribution is the creation of an integrated prediction model that combines the EKF's real-time state estimation capabilities with AI's nonlinear learning ability. This hybrid architecture addresses shortcomings of both approaches and establishes a unified methodology for adaptive diagnostics.

1.6.2 Adaptive Diagnostic Threshold Tuning

This work introduces a new method for dynamically adjusting diagnostic thresholds using predicted feature behavior and drift trends. This eliminates static threshold dependency and enables real-time adaptation to vehicle-specific and fleet-level behaviors.

1.6.3 VIN-Aware Normalization Framework

The dissertation proposes the first structured mathematical framework for normalizing diagnostic parameters across VINs. This allows individualized tuning for each vehicle while ensuring consistent semantic meaning across a fleet.

1.6.4 EKF Enhancement for Nonlinear and Drift-Affected Signals

Modifications to the traditional EKF formulation are made to handle:

- time-varying drift patterns,
- mode-switching behaviors,
- environmental disturbances,
- and nonlinear signal interactions.

These enhancements improve estimation accuracy under real-world conditions.

1.6.5 Predictive Modeling Layer for Drift Detection

In addition to real-time state estimation provided by the Extended Kalman Filter (EKF), a predictive modeling layer is incorporated to capture long-term behavioral drift across vehicle subsystems. While the EKF enables instantaneous validation of performance states from noisy CAN-derived telemetry, it is not designed to model gradual degradation trends that evolve over extended operational periods due to component wear, thermal stress, or usage-dependent variability.

To account for these effects, a supervised learning module is deployed downstream of the EKF estimation stage. This module utilizes EKF-filtered state outputs, maneuver-based event segmentation (e.g., hard acceleration and braking intervals), and historical subsystem response data accumulated across drive cycles. The objective of this layer is threefold:

- to model long-term drift patterns in subsystem response
- to detect changes in operational behavior relative to VIN-specific baseline performance
- to forecast potential diagnostic failures prior to threshold exceedance

Over time, repeated discrepancies between expected and estimated performance states such as sustained torque under-delivery during high-load events—may indicate emerging subsystem degradation that remains undetectable under static diagnostic thresholds. By incorporating temporally aggregated EKF outputs into a predictive framework, the system enables early identification of performance drift through learned nonlinear degradation trajectories.

This integration extends the diagnostic architecture from a reactive fault detection approach to a prognostic framework capable of adaptive threshold tuning and early-stage anomaly detection under real-world maneuver variability.

1.6.6 Realistic Validation Using Mixed Data Sources

The proposed hybrid EKF–AI framework is validated using a combination of real-world and synthetically generated datasets to assess performance under both nominal and degraded operating conditions. The validation process incorporates:

- real CAN-bus telemetry collected across diverse maneuver events to capture subsystem response variability under real-world usage
- synthetic datasets with controlled degradation profiles to simulate progressive performance loss in torque, thermal response, or actuator latency
- fleet-level behavioral aggregates to establish comparative baselines for subsystem performance across operating environments, and
- VIN-specific calibration scenarios to evaluate diagnostic adaptability across heterogeneous vehicle configurations.

Synthetic degradation injections enable systematic evaluation of drift detection sensitivity in the absence of explicitly labeled fault conditions, while real telemetry ensures operational realism. Fleet-level modeling supports statistical benchmarking, and VIN-conditioned calibration allows the framework to account for configuration-specific response variability. Together, this mixed-data validation approach supports stable diagnostic performance under real-world maneuver conditions.

1.6.7 Scalable System Architecture for OEM and Fleet Deployment

Deployable software architecture is defined to support implementation of the proposed framework across distributed computational layers. System operation is partitioned between:

- embedded Electronic Control Units (ECUs) for real-time signal acquisition and EKF-based state estimation,
- edge telematics units for maneuver event detection, local preprocessing, and temporary state aggregation, and
- cloud-based fleet analytics platforms for predictive modeling, VIN-specific calibration, and long-horizon drift analysis.

This layered architecture enables real-time onboard estimation while supporting scalable fleet-level diagnostics and adaptive model updates through centralized analytics.

1.7 Scope of Work

The scope of this dissertation is structured to ensure a comprehensive investigation of the EKF–AI hybrid model while maintaining focus on feasible and industry-relevant outcomes.

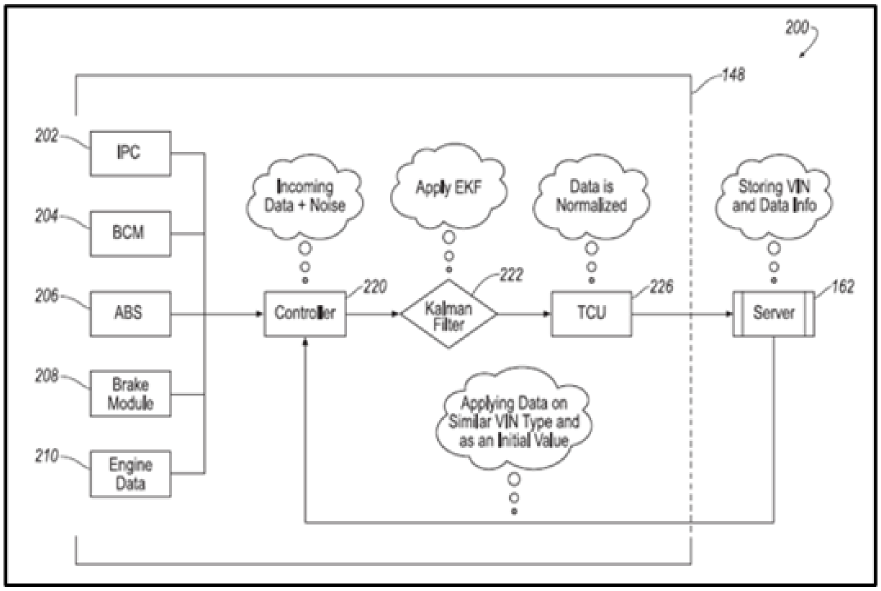


Figure 1.3: High-level operational architecture of the proposed EKF–AI hybrid diagnostic framework across onboard estimation, edge telematics preprocessing, and cloud-based predictive analytics layers.

To provide a system-level overview of the proposed framework, Figure 1.X illustrates the high-level operational architecture of the EKF–AI hybrid diagnostic model across onboard, edge, and cloud-based computational layers. The architecture begins with vehicle sensor subsystems that generate real-time telemetry through the CAN-bus network, including torque demand, engine speed, throttle position, and temperature-related signals in accordance with standardized in-vehicle communication protocols such as SAE J1939 [24]. These signals are processed through an event detection module to identify maneuver segments associated with elevated dynamic load conditions within perception-assisted vehicle control environments [18].

Filtered maneuver data is subsequently passed through the Extended Kalman Filter (EKF) for state estimation and feature validation. The EKF outputs are normalized using VIN-aware baseline parameters to ensure cross-vehicle consistency prior to offboard transmission. At the edge layer, the telematics control unit (TCU) performs local buffering and preprocessing before securely transmitting aggregated estimation data to the cloud environment.

Within the cloud analytics layer, fleet-level telemetry is stored and analyzed using predictive modeling techniques to identify long-term subsystem drift and performance deviations. These outputs are used to generate adaptive diagnostic thresholds that are periodically transmitted back to the onboard controller through over-the-air (OTA) calibration updates. This closed-loop architecture enables continuous refinement of diagnostic sensitivity based on observed operational trends, thereby extending conventional rule-based fault detection toward a predictive and adaptive diagnostic framework.

Included in the Scope:

- Development of an EKF-based state-estimation model for vehicle features
- Integration of machine learning models to enhance drift prediction
- Design of adaptive diagnostic threshold algorithms
- VIN-aware normalization methods for cross-vehicle consistency
- Validation using CAN-bus data and controlled simulations

- Real-time evaluation of algorithm performance
- Analysis of diagnostic improvements over static-threshold systems

Excluded from the Scope:

- Full hardware development of ECUs or sensors
- Proprietary OEM firmware modifications
- Deep-learning-based vision systems (ADAS perception)
- Non-automotive applications of EKF or AI models

Assumptions:

- Sufficient CAN-bus data is available for training and validation
- Vehicles have consistent baseline sensors and modules
- Drift behaviors are observable within the available dataset
- AI models can be executed either on-vehicle or on edge/cloud systems

1.8 Dissertation Organization

The structure of this dissertation is organized to support systematic development and evaluation of the proposed EKF–AI hybrid diagnostic framework. Key components include:

- Benchmarking Dataset: Description of the CAN-based telemetry data, preprocessing methodology, and baseline performance references used for model training and comparison.

- Experimental Validation: Evaluation of estimation accuracy, drift detection capability, and diagnostic performance under both real-world and simulated degradation conditions.

CHAPTER 2 – LITERATURE REVIEW

2.1 Overview of Modern Vehicle Diagnostics

Vehicle diagnostic systems have evolved significantly from early on-board diagnostic frameworks that were primarily designed for emissions compliance and post-failure detection. Early diagnostic systems relied on predefined diagnostic trouble codes triggered when sensor reading exceeded static thresholds. While effective for detecting hard mechanical faults, these approaches offered limited capability for identifying gradual degradation, nonlinear behavior, or interactions among subsystems.

Advances in electronic control units, distributed sensing, and in-vehicle communication networks have transformed modern vehicles into data-rich cyber-physical systems. Contemporary vehicles continuously generate high-frequency operational data related to motion dynamics, actuator behavior, thermal response, and energy flow. This evolution has motivated a shift from reactive diagnostics toward predictive and data-driven diagnostic paradigms capable of identifying deviations prior to failure.

Despite these advances, many production diagnostic systems continue to rely on static calibration tables and rule-based logic, limiting their ability to adapt to evolving vehicle behavior over time.

2.1.1 Evolution from OBD-II to Intelligent Diagnostics

Traditional OBD-II diagnostic frameworks assume consistent vehicle behavior across operating conditions and throughout the vehicle lifecycle. Diagnostic thresholds and failure maps are typically defined during vehicle development and remain fixed during operation. However, extensive research [79] has shown that vehicle behavior evolves due to component aging, environmental exposure, manufacturing variability, and software updates.

Factors that undermine static diagnostic assumptions include changes in driving style, load conditions, operating modes, and component wear. As a result, research has increasingly explored adaptive diagnostic approaches that incorporate system dynamics, statistical inference, and learning-based methods. While such approaches demonstrate improved accuracy in experimental studies, challenges related to computational complexity, interpretability, and certification have limited widespread deployment.

2.2 In-Vehicle Networks and Signal Complexity

Vehicle diagnostics rely heavily on data transmitted through in-vehicle networks, particularly the Controller Area Network (CAN) bus. CAN supports deterministic, low-latency communication and enables real-time exchange of sensor measurements and control commands across distributed electronic control units.

Typical CAN signals include engine speed, accelerator position, brake pressure, wheel speed, steering angle, thermal measurements, battery voltage and current, and torque requests. While these signals provide rich information, they also present challenges for diagnostics due to noise, nonlinear interactions, asynchronous timing, and cross-signal dependencies.

2.2.1 Nonlinearity and Cross-Signal Dependencies

Vehicle signals are influenced by driver behavior, environmental conditions, actuator dynamics, and mechanical wear. These influences create nonlinear and mode-dependent relationships between signals that are difficult to capture using single-signal thresholding. Research has demonstrated that multivariate and model-based approaches are better suited to interpreting complex signal interactions.

2.3 State Estimation in Vehicle Systems

State estimation is a foundational concept in vehicle systems where quantities of interest cannot be directly measured or are corrupted by noise and delay. Examples include estimation of torque, slip ratio, battery state-of-charge, and component health using indirect measurements and sensor fusion.

Classical estimation methods rely on fixed system models and stationary noise assumptions. While effective under controlled conditions, these methods degrade when vehicle dynamics evolve due to aging, thermal effects, or software updates. Mode transitions further complicate estimation by altering the mapping between measured signals and underlying physical states. In practical automotive control systems, estimation techniques are routinely used to infer internal vehicle dynamic states required for stability control, motion planning, and trajectory tracking from onboard sensor measurements. Vehicle motion behavior is influenced by tire–road interaction dynamics, which introduce nonlinear force responses that must be accounted for in state estimation and control frameworks [12].

2.4 Kalman Filter Theory and Applications

The Kalman Filter is an optimal estimator for linear systems with Gaussian noise. It combines system dynamics with sensor measurements to recursively estimate internal states while minimizing estimation error covariance [4].

Vehicle system states evolve over time in the presence of process and measurement noise modeled as stochastic disturbances within dynamic state-space systems, requiring recursive prediction and measurement-update steps to estimate internal states from noisy observations [2]

Kalman filtering has been widely applied in vehicle systems for motion estimation, navigation, control, and signal filtering due to its computational efficiency and real-time feasibility within optimal recursive estimation frameworks [6]. Sensor measurements are corrupted by uncertainty arising from stochastic disturbances in both process dynamics and measurement channels. Vehicle system states evolve over time in the presence of process and measurement noise modeled as stochastic disturbances within dynamic state-space systems [9]. System dynamics are represented through a mathematical state-space model incorporating process and measurement noise covariance terms within recursive estimation frameworks [5] [10].

2.5 Extended Kalman Filter (EKF)

For nonlinear vehicle system dynamics, the Extended Kalman Filter (EKF) applies local linearization techniques to approximate nonlinear state transition functions during recursive estimation, though such linearization may introduce approximation error in highly nonlinear regimes [7]. This approach preserves the recursive structure of Kalman filtering while enabling application to nonlinear vehicle dynamics. Nonlinear system transformations may introduce estimation errors when Jacobian-based linearization is applied, whereas sigma-point approaches such as the Unscented Kalman Filter propagate mean and covariance through nonlinear mappings without explicit linearization [8].

EKF has been widely adopted in automotive applications including engine management, battery systems, traction control, localization, and advanced driver-assistance systems. Despite its widespread use, EKF performance is sensitive to model accuracy, noise tuning, and operating conditions.

2.6 Limitations of EKF in Real-World Vehicle Diagnostics

Extensive literature documents several limitations of EKF when applied to long-term vehicle diagnostics:

- Model mismatch: Real-world dynamics deviate from assumed models due to aging, wear, and software changes.

- Noise sensitivity: Improper tuning of noise covariance matrices can lead to divergence or slow convergence.
- Long-term drift**:** EKF effectively filters short-term noise but does not inherently model long-term drift [5].
- Lack of learning: EKF does not adapt based on historical behavior.
- Mode dependence: Operating mode changes may invalidate assumptions.

2.7 Machine Learning and Artificial Intelligence in Vehicle Diagnostics

The growing availability of high-resolution CAN data and telematics connectivity has enabled the application of machine learning and artificial intelligence to vehicle diagnostics. Learning-based methods are effective at modeling nonlinear relationships, capturing cross-signal dependencies, and identifying long-term trends.

2.7.1 Regression and Ensemble Models

Regression-based and ensemble models have been applied to torque estimation, component health prediction, and signal modeling. These approaches capture nonlinear relationships but lack temporal awareness and physical constraints.

2.7.2 Neural Networks and Temporal Models

Neural networks and temporal sequence models capture complex dynamics and degradation trends but require large datasets and high computational resources. Their lack of interpretability and deployment challenges limit use in safety-critical systems.

2.7.3 Unsupervised Anomaly Detection

Unsupervised methods enable detection of abnormal behavior without labeled fault data but provide limited diagnostic insight and interpretability.

2.8 Predictive Diagnostics and Drift Modeling

Predictive diagnostics seeks to identify degradation and emerging faults before explicit failure occurs through condition-based monitoring methodologies [73]. Drift modeling is central to this goal, as diagnostic parameters often shift gradually due to sensor aging, thermal cycling, mechanical wear, and software updates.

Existing approaches include statistical trend analysis, residual monitoring, machine learning predictors, and hybrid prognostic models. However, many approaches treat drift as an isolated phenomenon rather than as part of a unified perception framework. [ISO 13374].

2.9 Fleet-Level Analytics and VIN Variability

Prior work has explored predictive modeling approaches for evaluating diagnostic parameter variability in automated and fleet vehicle systems under operational driving conditions [79].

Fleet diagnostics introduces additional challenges due to cross-vehicle variability. Vehicles with identical configurations exhibit differences arising from manufacturing tolerances, usage patterns, service history, and environmental exposure.

Research shows that static diagnostic thresholds fail to generalize across fleets, leading to inconsistent diagnostic behavior. Fleet-level normalization and clustering techniques have been proposed but often lack VIN-specific adaptation and dynamic updating.

2.10 Secure Calibration and Distributed Diagnostic Data

As diagnostics become adaptive and data-driven, calibration integrity and traceability have emerged as critical concerns. Centralized calibration storage lacks robustness against tampering, inconsistency, and version conflicts.

Recent research explores distributed and cryptographically secured mechanisms for managing diagnostic metadata, including permission blockchain frameworks. These approaches emphasize immutability and traceability but remain underexplored in adaptive vehicle diagnostics.

2.11 Summary of Literature Gaps

The reviewed literature reveals several persistent gaps:

- Diagnostic systems remain largely static despite evolving vehicle behavior.
- EKF provides stability but cannot model long-term drift or nonlinear aging effects.
- Machine learning captures complexity but lacks physical and real-time guarantees.
- Drift is widely observed but insufficiently integrated into unified frameworks.

- Fleet-level variability undermines uniform diagnostic thresholds.
- Secure calibration mechanisms are insufficiently integrated into adaptive diagnostics.

These gaps motivate the need for an adaptive hybrid estimation framework capable of integrating physical consistency with data-driven behavioral learning across heterogeneous fleet deployments.

2.12 Mathematical Foundations of State Estimation for Perception

Perception in dynamic systems is commonly formulated as a state estimation problem in which latent system states are inferred from noisy measurements and known system dynamics. A discrete-time state-space formulation is widely adopted:

$$\mathbf{x}_{k+1} = f(\mathbf{x}_k, \mathbf{u}_k) + \mathbf{w}_k$$

$$\mathbf{y}_k = h(\mathbf{x}_k) + \mathbf{v}_k$$

This formulation explicitly models uncertainty and temporal evolution, making it well suited for vehicle perception under real-world conditions.

2.13 Kalman Filtering as a Perception Framework

Kalman filtering combines prior system knowledge with sensor observations to recursively update state estimates. This prediction–correction mechanism aligns naturally with perception, enabling anticipation of system behavior and correction based on observation.

The prediction and correction steps are given by:

$$\hat{\mathbf{x}}_{k|k-1} = f(\hat{\mathbf{x}}_{k-1}, \mathbf{u}_{k-1})$$

$$\mathbf{K}_k = \mathbf{P}_{k|k-1}\mathbf{H}_k^{\top}(\mathbf{H}_k\mathbf{P}_{k|k-1}\mathbf{H}_k^{\top} + \mathbf{R}_k)^{-1}$$

This recursive structure supports real-time perception in dynamic systems.

2.14 Extended Kalman Filtering for Nonlinear Vehicle Perception

Vehicle dynamics are inherently nonlinear, motivating the use of Extended Kalman Filtering. EKF linearizes nonlinear models around the current estimate while preserving recursive estimation.

EKF is widely adopted due to its real-time feasibility, physical interpretability, and compatibility with embedded automotive systems. However, its performance depends on model fidelity and noise assumptions.

2.15 Motivation for Learning-Augmented Perception Models

Literature increasingly explores hybrid approaches that integrate learning-based models with Kalman-based estimation. Learning methods capture residual nonlinearities, drift patterns, and long-term behavior, complementing the stability of classical estimation. Hybrid perception frameworks are studied in automotive, robotic, and autonomous systems, reflecting a broader shift toward adaptive perception architectures.

2.16 Transition to Chapter 3

The literature establishes vehicle diagnostics and perception as state estimation problems characterized by uncertainty, nonlinearity, and long-term variability. While Kalman filtering provides a principled foundation, its limitations motivate adaptive and learning-enhanced approaches.

Chapter 3 presents a unified perception and prediction framework that integrates nonlinear state estimation with learning-based adaptation to address these challenges.

CHAPTER 3 – PERCEPTION AND PREDICTION IN MODERN VEHICLE SYSTEMS

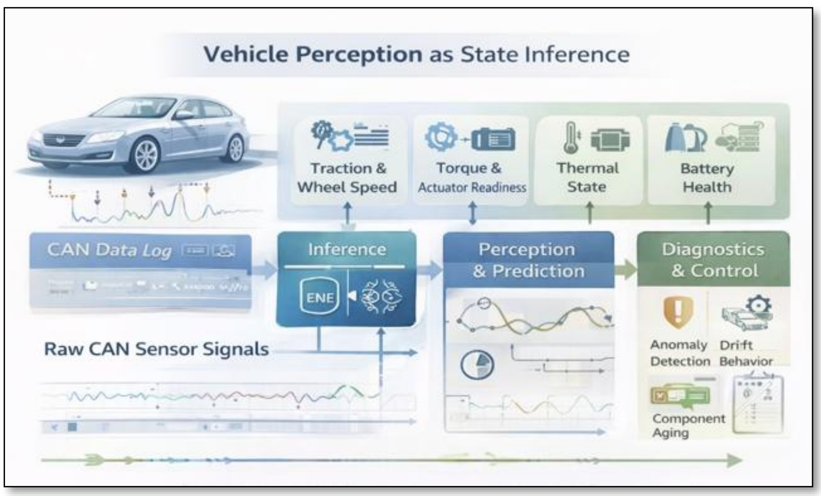
3.1 Perception in Modern Connected and Automated Vehicles

Modern connected and automated vehicles operate as complex cyber-physical systems that rely on continuous perception to infer internal system states and predict future behavior within networked vehicular communication ecosystems [28]. Unlike traditional vehicles that relied primarily on direct sensor thresholds and rule-based logic, modern vehicles must interpret large volumes of noisy, nonlinear, and interdependent data generated by distributed sensors and electronic control units. This transformation has shifted diagnostics, control, and autonomy from deterministic logic toward probabilistic inference and predictive estimation. Vehicle perception extends beyond external environment sensing and includes internal state estimation of motion dynamics, actuator behavior, thermal states, energy flow, and system health. Many of these quantities are not directly measurable and must be inferred from indirect observations communicated over in-vehicle networks. These indirect observations are transmitted between distributed electronic control units (ECUs) over standardized in-vehicle communication protocols defined by the Controller Area Network (CAN) architecture in accordance with ISO 11898-1 [25].

As vehicles age, operate under diverse conditions, and undergo software or hardware changes, perception systems must adapt to drift, degradation, and variability while maintaining stability and reliability.

While vehicles serve as the primary application domain in this research, the same perception challenges arise in robotic and autonomous systems, where safe operation depends on accurate estimation and prediction under uncertainty. In connected-vehicle environments, perception may also incorporate cooperative data exchanged between vehicles through vehicle-to-vehicle (V2V) communication frameworks to enhance situational awareness and operational inference under uncertainty [26].

Figure 3.1 – Vehicle Perception as State Inference



3.2 Vehicle Network Architectures and Their Role in Perception

Modern vehicle architectures are layered and heterogeneous. Low-level control and diagnostics are primarily handled through Controller Area Network (CAN)–based communication, while higher-level perception and autonomy increasingly rely on high-speed Ethernet backbones and centralized computing units. These layers coexist in current production vehicles and must be jointly considered when designing perception and prediction frameworks.

CAN-based networks support real-time exchange of control-relevant signals such as engine speed, brake pressure, steering angle, accelerator position, and battery health. These signals form the foundational inputs for state estimation and diagnostics. High-speed Ethernet networks support data-intensive sensors such as cameras, radar, and LiDAR, enabling advanced perception and autonomous decision-making.

Gateway modules bridge these layers, aggregating low-level state information and forwarding it to centralized computing platforms. Despite architectural evolution toward zonal and centralized designs, CAN remains the authoritative interface for low-level control, diagnostics, and state estimation. Multi-sensor integration using Kalman filtering enables real-time vehicle state estimation by fusing onboard telemetry with positional or operational measurements in dynamic environments [14].

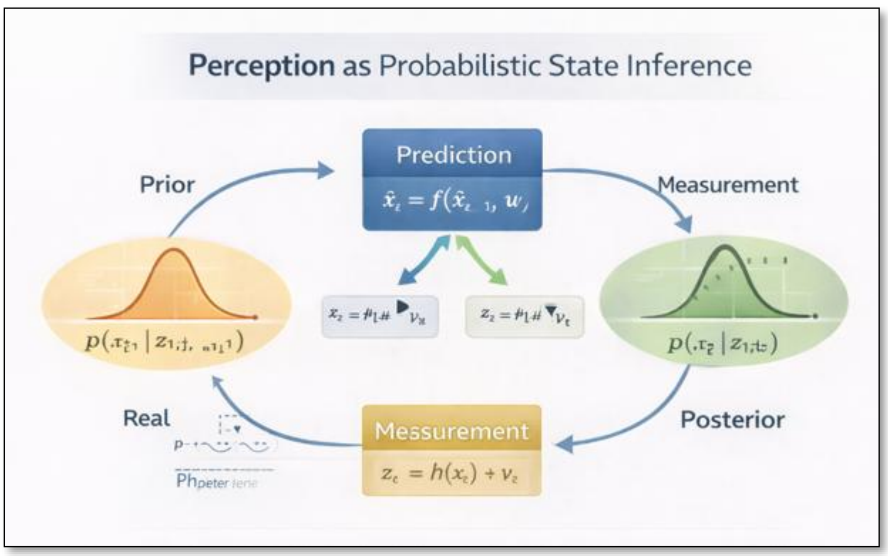
3.3 Perception as Probabilistic State Inference

Perception can be formally understood as the problem of inferring latent system states from noisy and partial observations using probabilistic state-space estimation frameworks [3]. Sensors provide indirect measurements influenced by noise, delays, and nonlinear effects, while system dynamics govern how states evolve over time within a recursive state estimation framework [3]. Effective perception systems must reconcile these two sources of information in a consistent and robust manner.

A probabilistic framework allows perception systems to maintain an internal belief about system state, accounting for uncertainty and confidence. This belief is updated recursively as new observations arrive. Such an approach enables systems to reason not only about estimated values but also about uncertainty growth, confidence bounds, and potential failure modes.

In vehicle systems, probabilistic state inference is essential for robust diagnostics and predictive analytics. Deterministic threshold-based approaches fail to account for uncertainty and variability, leading to brittle behavior under real-world conditions.

Figure 3.3 – Perception as Probabilistic State Inference



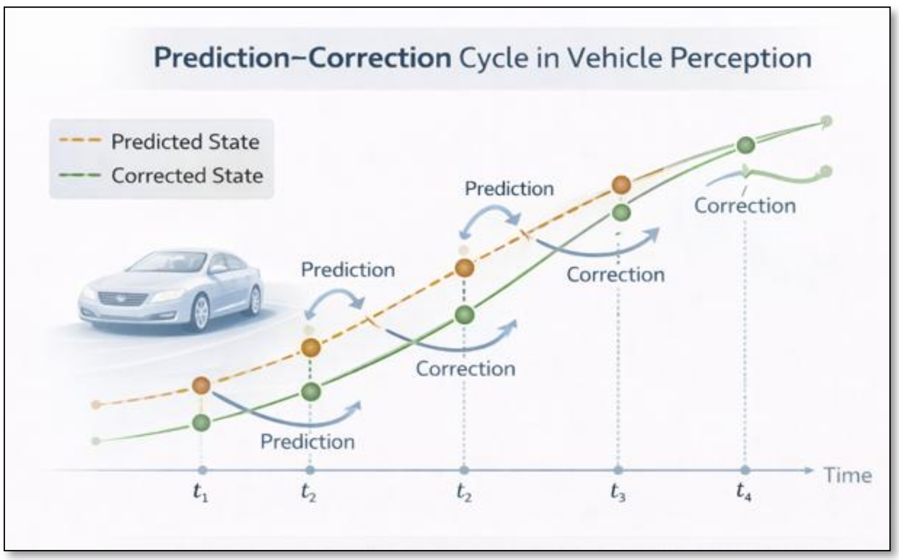
3.4 Prediction–Correction Cycle in Vehicle Perception

Perception in dynamic systems is inherently predictive. Rather than reacting only to current sensor readings, intelligent systems rely on internal models to anticipate future behavior. This prediction–correction cycle forms the foundation of recursive estimation.

Prediction propagates the current state estimate forward using system dynamics, while correction incorporates new sensor measurements to reduce uncertainty and compensate for modeling errors [2]. The balance between prediction and correction determines system responsiveness and stability [2].

In vehicles, prediction enables anticipation of motion trends, actuator responses, and thermal evolution. Correction ensures robustness to disturbances, sensor noise, and unexpected behavior. This cycle is critical for early detection of drift and degradation, enabling proactive diagnostics rather than reactive fault detection.

Figure 3.4 – Prediction–Correction Cycle in Vehicle Perception



3.5 Recursive State Estimation for Vehicle Systems

Recursive state estimation provides a computationally efficient and mathematically grounded approach to perception in real-time systems. By updating state estimates incrementally, recursive estimators operate effectively on embedded hardware with limited computational resources.

In vehicle applications, recursive estimation is used to infer motion states, actuator behavior, and health indicators that cannot be directly measured. These estimates form the basis for diagnostics, control, and predictive maintenance.

Recursive estimators are particularly well suited for CAN-based architectures, where signals arrive asynchronously and must be fused consistently. However, real-world vehicle behavior often violates ideal assumptions, motivating the use of nonlinear estimation techniques.

3.6 Nonlinear Estimation and the Role of Extended Kalman Filtering

Vehicle systems exhibit nonlinear behavior due to mechanical dynamics, actuator constraints, control logic, and environmental influences. Linear estimation methods are insufficient to capture these effects, particularly under varying operating modes.

The Extended Kalman Filter enables nonlinear state estimation by locally linearizing system dynamics around the current operating point. It preserves the recursive prediction–correction structure while accommodating nonlinear relationships between states and measurements.

Extended Kalman Filtering is widely used in vehicle motion estimation, navigation, energy management, and control systems due to its real-time capability and physical interpretability. However, its performance degrades when system behavior evolves beyond modeled assumptions.

Table 3.1: Strengths and Limitations of EKF in Vehicle Applications

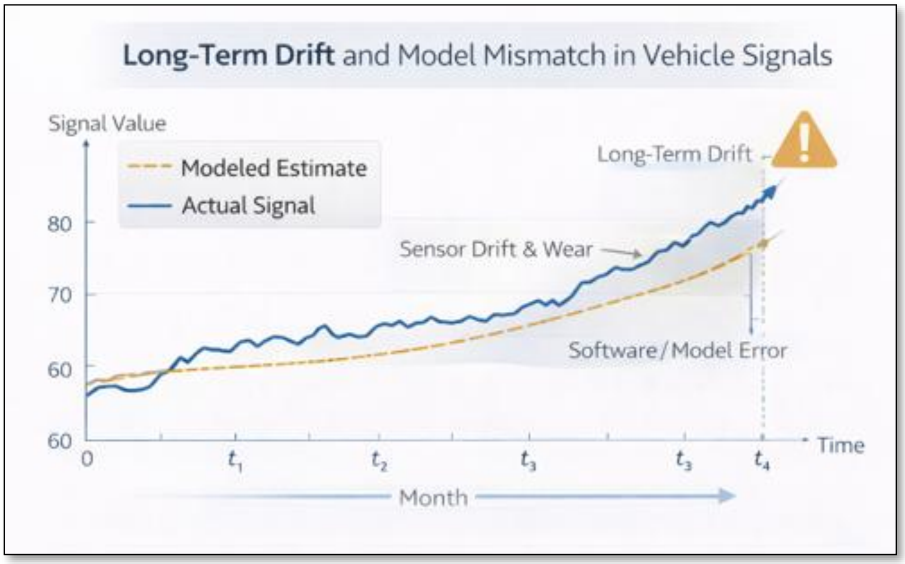
Aspect	Strength	Limitation
Real-time operation	Computationally efficient and suitable for real-time execution on embedded electronic control units	Performance degrades under significant model mismatch
Physical grounding	Provides physically interpretable state estimates aligned with system dynamics	Requires accurate system and measurement models
Noise handling	Effectively filters measurement noise and suppresses high-frequency disturbances	Assumes stationary and well-characterized noise statistics
Long-term behavior	Stable and reliable for short-term state estimation	Unable to capture long-term drift or evolving system behavior without adaptation

3.7 Limitations of Classical Estimation in Long-Term Operation

Over long operational horizons, vehicle systems experience sensor aging, component wear, firmware changes, and environmental exposure. These effects introduce nonstationary behavior and long-term drift that violate classical estimation assumptions.

Fixed models and static noise parameters lead to growing estimation bias, misaligned confidence bounds, and degraded perception reliability. Mode switching, such as drive modes or load changes, further complicates estimation. These limitations motivate the integration of adaptive and learning-based mechanisms that can evolve alongside system behavior.

Figure 3.5 – Long-Term Drift and Model Mismatch in Vehicle Signals



3.8 Learning-Enhanced Perception and Prediction

Learning-based models excel at capturing nonlinear relationships, temporal trends, and cross-signal dependencies that are difficult to model analytically. When integrated with recursive estimation, learning methods can compensate for model mismatch and long-term drift.

In this dissertation, learning-based prediction augments state estimation by modeling residual errors, drift patterns, and evolving system behavior. The estimation layer ensures physical consistency and real-time stability, while the learning layer provides adaptability and predictive insight. This hybrid approach aligns with trends in robotics and autonomous systems, where learning-enhanced perception improves robustness and generalization.

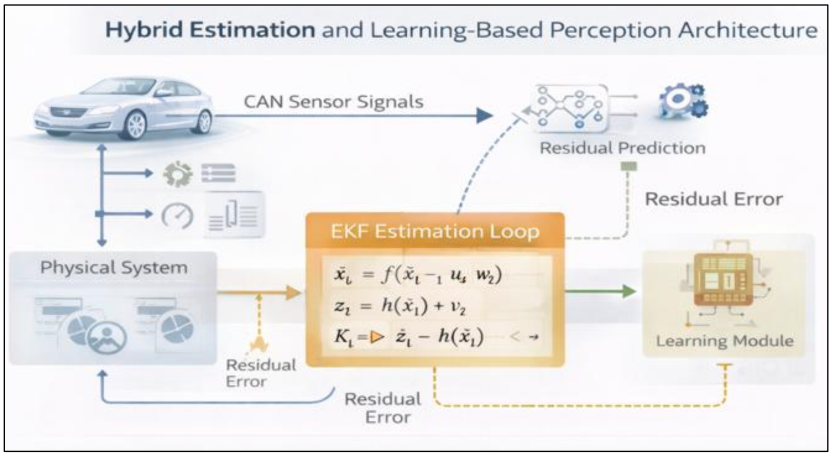


Figure 3.6 – Hybrid Estimation and Learning-Based Perception Architecture

3.9 From Perception and Prediction to Diagnostics

Diagnostics emerge naturally from perception when estimated states and predicted behavior are monitored over time. Deviations between expected and observed behavior indicate anomalies, degradation, or faults. Perception-driven diagnostics operate on inferred states rather than raw signals, enabling context-aware interpretation and adaptive thresholds. This transforms diagnostics from a reactive mechanism into a predictive capability.

In fleet environments, this approach enables normalization across vehicles while preserving individual behavior characteristics.

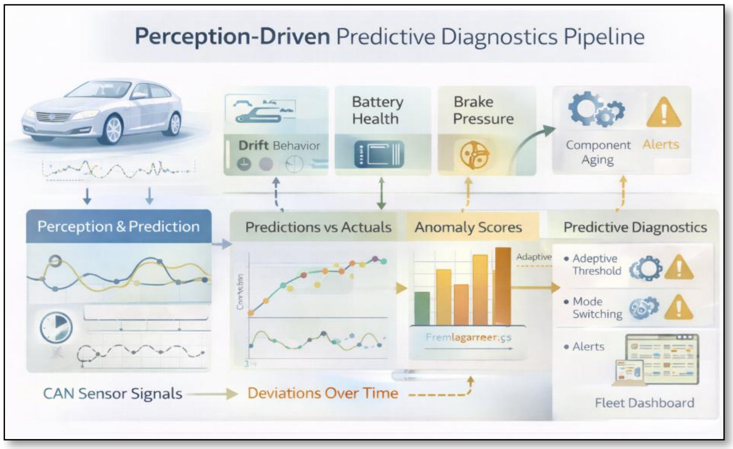


Figure 3.7 – Perception-Driven Predictive Diagnostics Pipeline

3.10 Applicability to Autonomous and Robotic Systems

Although this research focuses on modern vehicles, the proposed perception and prediction framework generalizes to robotic and autonomous systems. Recursive estimation, probabilistic inference, and learning-enhanced prediction form a common foundation across intelligent platforms.

By framing diagnostics as a perception problem, this **work** bridges automotive systems with broader developments in autonomy and robotics.

3.11 Chapter Summary

This chapter established the theoretical foundation for perception and prediction in modern vehicle systems. Perception was framed as probabilistic state inference supported by recursive estimation and prediction–correction cycles. The role of nonlinear estimation, limitations of classical methods, and motivation for learning-enhanced perception were discussed. This foundation prepares the ground for the hybrid EKF–AI framework developed in subsequent chapters.

CHAPTER 4 — SYSTEM WORKFLOW AND DATA-DRIVEN THRESHOLD PREDICTION METHODOLOGY

4.1 Problem Motivation and System Objective

Conventional diagnostic and driver-behavior monitoring systems rely on static thresholds defined during Original Equipment Manufacturer (OEM) calibration. These thresholds are typically applied uniformly across vehicles of the same platform despite variability introduced by:

- engine trim and displacement.
- Vehicle and device technology variance
- manufacturing tolerances
- firmware calibration differences
- environmental operating conditions
- terrain-dependent loading and grade-induced propulsion variability [19]
- aging-related performance degradation

As a result, fixed thresholds used to detect driving events such as hard acceleration or braking may no longer accurately reflect the true operational requirements of a specific vehicle [17].

For example, a hard acceleration maneuver performed by a driver in normal driving conditions may be classified as aggressive behavior under static threshold logic. However, when operating under increased load conditions such as ascending a steep hill or mountainous terrain, the same maneuver may be necessary to maintain vehicle safety and drivability due to terrain-induced propulsion demand variability across longitudinal drive cycles [19]. In such cases, the driver's behavior is operationally justified rather than indicative of unsafe driving.

Static thresholds therefore risk misclassifying safe driver behavior as aggressive due to the absence of environmental and vehicle-specific context.

A similar challenge exists in semi-autonomous and autonomous driving systems. In perception-assisted driving modes (e.g., Autopilot or driver-assist systems), vehicles continuously collect LiDAR and camera-based environmental data to assess surrounding traffic conditions. A driver may be required to perform an abrupt maneuver such as accelerating to overtake a heavy truck or braking to avoid a merging vehicle—for safety reasons. The proposed hybrid diagnostic framework enables adaptive estimation of maneuver states under varying operating conditions within safety-critical automotive control environments [74]. While such maneuvers may exceed nominal driving thresholds, they may represent context-aware safety actions rather than hazardous driving behavior, particularly when perception-assisted driver support systems or closed-loop braking control subsystems dynamically influence maneuver execution under safety-critical or traction-limited conditions [16][23].

Consequently, this work does not aim to predict the next occurrence of a driving event (e.g., hard acceleration), but rather to determine the appropriate diagnostic threshold for each individual Vehicle Identification Number (VIN) based on:

- experimentally collected driving performance

- environmental telemetry
- vehicle-specific operating conditions
- historical behavioral patterns

This VIN-conditioned threshold represents the calibrated boundary at which a diagnostic event should be detected for that specific vehicle configuration and operational context.

4.2 Role of EKF-Based Measurement Validation

To continuously evaluate whether the currently deployed diagnostic threshold remains appropriate for a given vehicle, real-time CAN telemetry is processed through an Extended Kalman Filter (EKF).

Rather than predicting future driver behavior, the EKF acts as a measurement validation mechanism that:

- reconstructs latent vehicle performance from noisy sensor measurements, enabling estimation of internal vehicle dynamic states that cannot be directly measured through onboard sensing systems [15] [31].
- compares new observations against expected operational behavior.
- determines whether observed driving actions are consistent with nominal vehicle performance.
- identifies deviations resulting from environmental loading or degradation

As the vehicle continues to operate, incoming CAN measurements are recursively evaluated to determine whether the existing threshold remains valid.

If observed measurements deviate beyond expected covariance bounds, the EKF refines the estimated state:

$$x_{k+1} = f(x_k, u_k) + w_k$$

Measurement validation:

$$z_k = h(x_k) + v_k$$

This recursive estimation process allows the system to determine whether the deployed diagnostic threshold continues to reflect safe and expected vehicle performance.

4.3 Fleet-Level Confirmation via Cloud Learning

When deviations are detected, reconstructed performance states are transmitted to a cloud-based learning environment where VIN-conditioned drift patterns are evaluated against historical fleet behavior in connected and networked vehicular operating contexts [27].

This process may incorporate event-based data snapshots captured during:

- terrain-induced load variation resulting in increased propulsion torque demand and longitudinal energy consumption [20]
- bank-angle-induced lateral load transfer affecting vehicle dynamic response
- transient torque demand
- perception-triggered maneuvering
- firmware calibration updates

Such snapshot-based behavioral capture aligns with previously proposed event-triggered vehicle telemetry methodologies (e.g., Data Snapshot-based calibration frameworks).

Fleet-level AI learning is then used to determine whether the deviation represents:

- unsafe driver behavior
- context-driven safety maneuver
- terrain-induced load demand
- vehicle-specific degradation

Based on this confirmation, an updated VIN-conditioned threshold may be computed and transmitted back to the vehicle via secure Over-the-Air (OTA) deployment consistent with cybersecurity lifecycle and software integrity guidance for connected vehicle systems defined by the National Institute of Standards and Technology (NIST) [76].

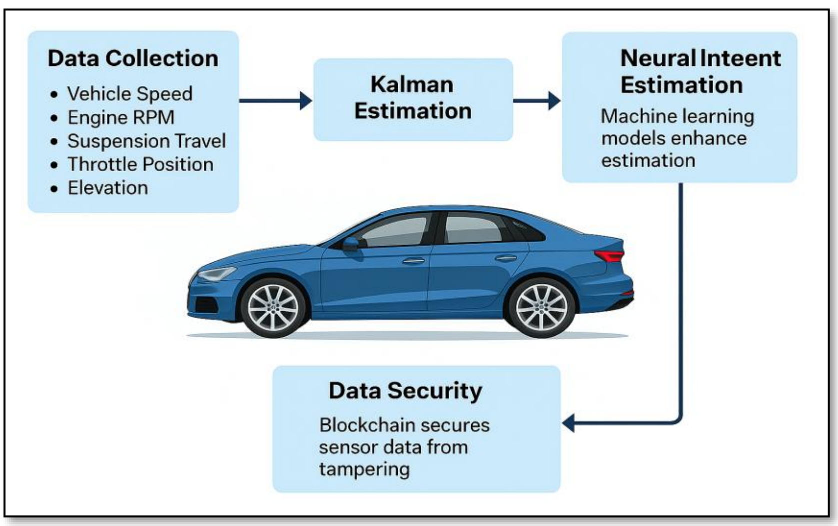


Figure 4.1 Edge-Level CAN Telemetry Processing and EKF-Based Measurement Validation

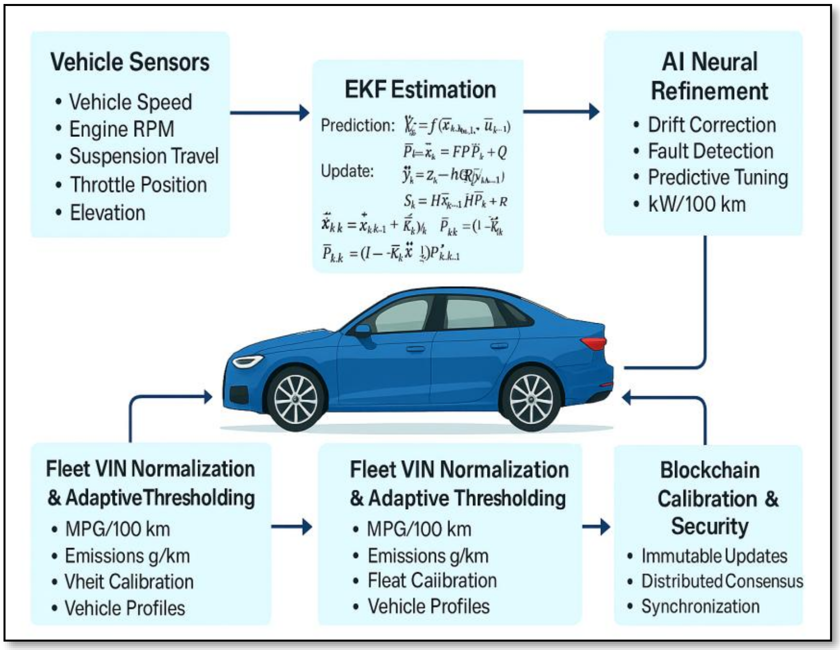


Figure 4.2: Cloud-Assisted VIN Normalization and Adaptive Threshold Calibration Framework

Figure 4.1 shows the on-vehicle pipeline where real-time CAN driving data is collected and validated using an Extended Kalman Filter (EKF) to estimate the vehicle's performance state. The validated data is then provided to cloud-based models for context-aware, VIN-specific diagnostic threshold calibration.

Figure 4.2 presents the integration of EKF-validated vehicle state estimation with cloud-based AI refinement and fleet-level VIN normalization. Real-time telemetry processed at the vehicle is transmitted to the cloud where machine learning models evaluate VIN-conditioned behavioral drift across similar vehicle trims and operating environments.

This learning process enables adaptive calibration of diagnostic thresholds based on contextual driving conditions, thereby reducing misclassification of safe driver actions, as terrain-induced acceleration as aggressive behavior. Updated VIN-specific thresholds are securely deployed back to the vehicle through distributed calibration mechanisms, enabling recursive validation and closed-loop threshold adaptation during continued operation.

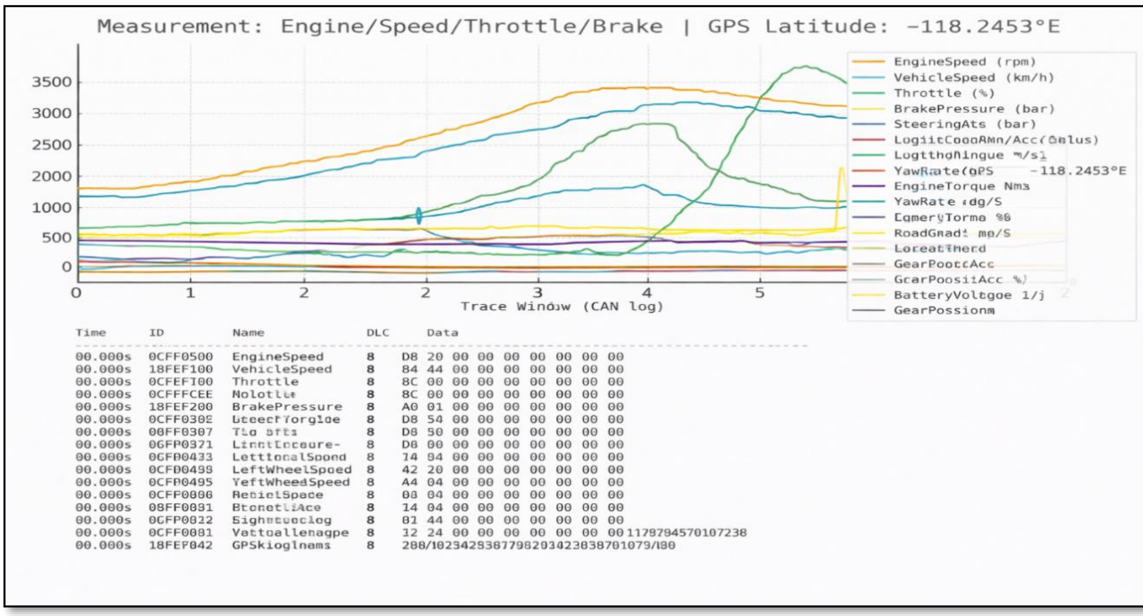


Figure 4.3: Snapshot of Multi-Signal CAN Telemetry Captured from Driving Log Data

Figure 4.3 illustrates a representative snapshot of multi-signal Controller Area Network (CAN) telemetry extracted from recorded real-world driving log data. The displayed trace window contains vehicle dynamics signals including engine speed (RPM), vehicle speed (km/h), throttle position (%), brake pressure (bar), steering angle, and engine torque, along with geospatial information such as GPS latitude and longitude coordinates.

This CAN signal snapshot reflects time-synchronized measurements captured during actual vehicle operation under varying terrain and environmental conditions. The logged telemetry serves as the observable measurement vector z_k, which is subsequently processed using Extended Kalman Filtering (EKF) for recursive validation and reconstruction of VIN-specific vehicle performance state prior to adaptive diagnostic threshold calibration.

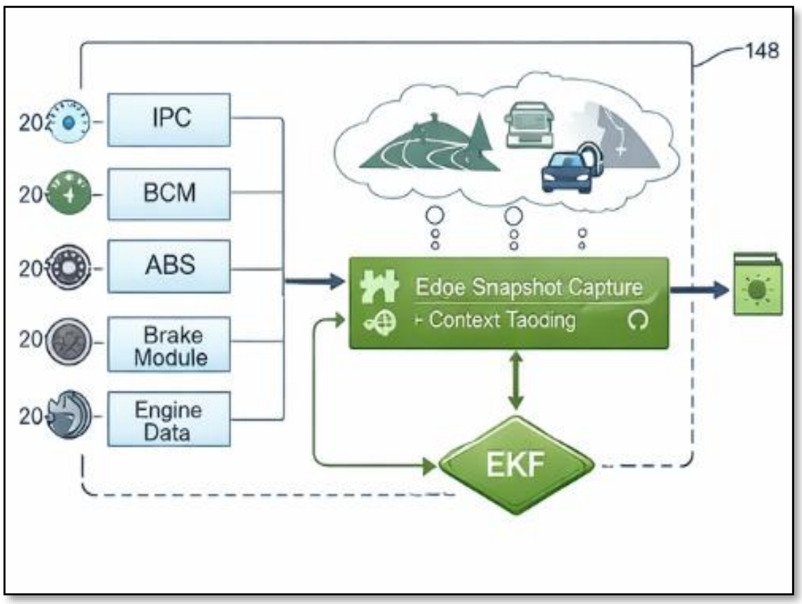


Figure 4.4: Edge-Level CAN Acquisition and EKF-Based Measurement Validation

Vehicle electronic control modules including the Instrument Panel Cluster (IPC), Body Control Module (BCM), Anti-lock Braking System (ABS), Brake Control Module, and Engine Control Unit (ECU) continuously broadcast operational telemetry over the Controller Area Network (CAN) bus. These messages contain time-synchronized measurements such as vehicle speed, engine rotational velocity (RPM), torque demand, throttle position, braking pressure, and thermal states. During vehicle operation, condition-triggered data snapshots corresponding to load-dependent driving maneuvers (e.g., terrain ascent, overtaking, or transient acceleration events) are selectively captured by the edge processing unit. This event-driven acquisition strategy enables targeted logging of operational segments relevant to diagnostic threshold evaluation while reducing redundant background telemetry storage.

Due to measurement uncertainty introduced by sensor noise and dynamic operating variability, incoming CAN telemetry is recursively processed using an Extended Kalman Filter (EKF). Each measurement is evaluated against the predicted vehicle state estimate, allowing inconsistent observations to be corrected through covariance-based fusion. This process yields a validated latent vehicle performance estimate $\hat{x}_k$, accompanied by uncertainty bounds, rather than reliance on raw measurement data.

The resulting validated state estimates and context-tagged event snapshots are subsequently transmitted for cloud-based contextual learning and VIN-specific diagnostic threshold identification.

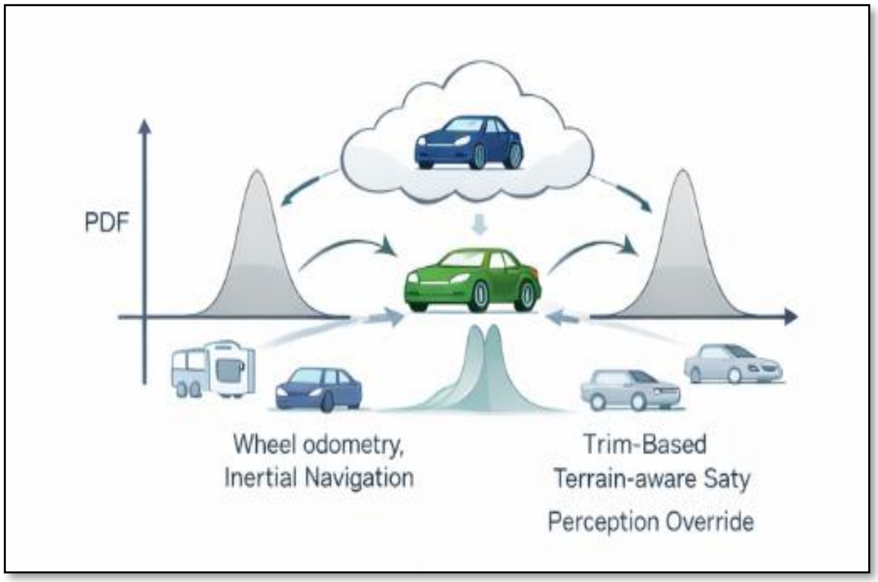


Figure 4.5: VIN-Conditioned Context-Aware Threshold Identification Using Cloud Fleet Histograms

Vehicle dynamic responses associated with identical driver inputs may vary significantly depending on environmental and operational context. For example, acceleration demands observed during terrain ascent differ substantially from equivalent throttle inputs applied during level roadway conditions. Similarly, variations in engine configuration, drivetrain architecture, and trim-level calibration result in VIN-dependent performance distributions.

Fleet-level histogram analysis enables contextual interpretation of observed driving maneuvers by characterizing nominal operational behavior across vehicle cohorts under similar terrain, loading, and drive-mode conditions. This approach mitigates misclassification of contextually justified maneuvers—such as hill-induced acceleration—as aggressive or fault-like behavior when evaluated against static global thresholds. Accordingly, contextual distribution learning facilitates differentiation between operationally necessary vehicle responses and true anomalous driving patterns requiring diagnostic attention.

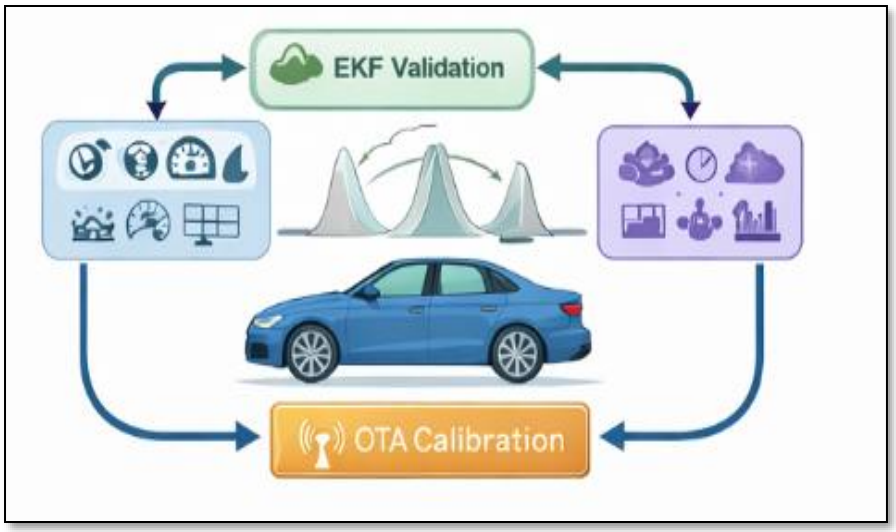


Figure 4.6: VIN-Specific Calibration and EKF Validation Closed-Loop System

Validated vehicle state estimates $\hat{x}_k$, in conjunction with event-based snapshot features, VIN metadata, and contextual descriptors (e.g., terrain gradient, drive mode, environmental state), are transmitted to a cloud-based learning environment for fleet-level behavioral analysis.

Machine learning models evaluate VIN-conditioned performance drift relative to peer-group operational distributions observed under comparable contextual conditions. This assessment enables discrimination between context-driven performance variation and genuinely abnormal dynamic response.

Based on this evaluation, an adaptive diagnostic threshold function

$$T_{\text{adaptive}}(\text{VIN},\text{context})$$

is computed to define the appropriate detection boundary for the specific vehicle configuration and operating environment.

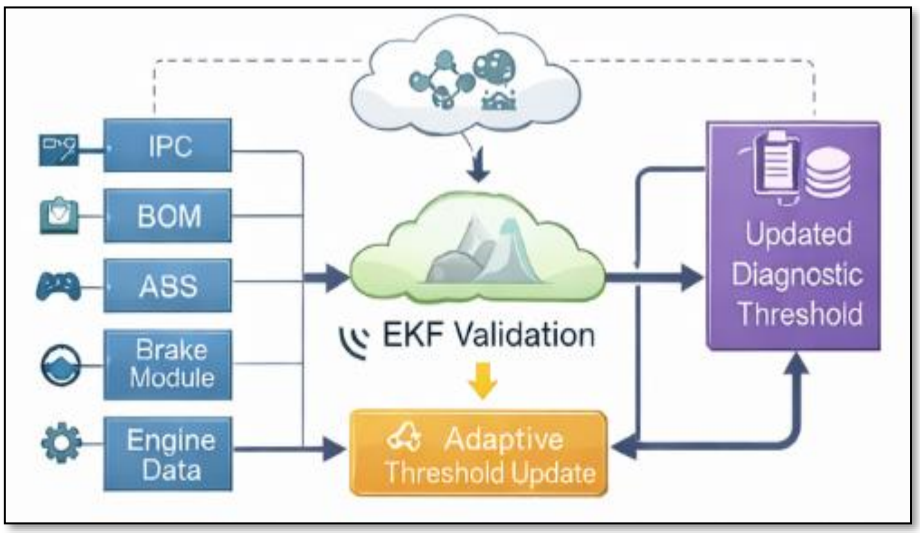


Figure 4.7: Adaptive Diagnostic Threshold Update and OTA Deployment Framework

Adaptive VIN-specific diagnostic thresholds derived through fleet-level contextual learning are securely transmitted to the vehicle via over-the-air (OTA) calibration updates. Updated thresholds are subsequently applied during real-time event detection to evaluate incoming telemetry against VIN-conditioned operational boundaries.

Continued EKF-based validation of incoming measurements enables recursive assessment of threshold performance with respect to false positive reduction, contextual maneuver classification accuracy, and threshold stability under evolving operating conditions.

Where threshold misalignment persists, additional event snapshots are captured and transmitted for re-evaluation, thereby enabling continuous closed-loop calibration and refinement of diagnostic detection limits during vehicle operation.

CHAPTER 5 — SYSTEM IMPLEMENTATION

5.1 CAN-Based Telemetry Acquisition

ECU-level signal acquisition and diagnostic message handling were assumed to operate within a standardized embedded software architecture layer compliant with AUTOSAR Classic Platform specifications governing CAN stack abstraction, runtime environment (RTE) signal mapping, and diagnostic communication management [75]. To implement the proposed VIN-conditioned diagnostic threshold identification framework, real-time Telemetry was collected from onboard Electronic Control Units (ECUs) through Controller Area Network (CAN) logging and standardized diagnostic test mode access to subsystem performance parameters [78]. Telemetry was acquired across multiple roadway geometries and environmental conditions to capture load-dependent performance variation under varying terrain and drive-mode configurations.

The acquired CAN data was segmented into event-driven trace windows corresponding to contextually relevant driving maneuvers, including terrain ascent, transient acceleration, overtaking operations, and load-dependent torque demand. Each recorded trace represents a contextual snapshot of synchronized vehicle dynamics signals used for subsequent state estimation and threshold identification.

5.1.1 Selected CAN/ECU Signals

The proposed framework utilizes a subset of ECU-broadcast CAN signals selected based on their sensitivity to dynamic load conditions, calibration drift, and VIN-dependent operational response.

Table 5.1: Selected CAN Signals and Functional Rationale

Signal	Function	Rationale
Engine RPM	Primary dynamic state proxy	Captures airflow/load dynamics; sensitive to module/firmware changes
APP (Accelerator Pedal Position)	Driver intent	Strong predictor of torque demand and transient response
Torque Actual / Torque Demand	Powertrain response	Frequent locus of diagnostic misalignments
Coolant Temperature	Thermal state	Governs temperature-dependent drift and threshold shifts
Oil Temperature / Oil Pressure	Engine health	Slow-degradation indicators and failure precursors
Turbo / Intake Boost	Intake pressure dynamics	Sensitive to leaks, fouling, and recalibration
Gear State & Drive Mode	Context (Sport / Tow / Eco)	Mode-dependent maps distort fixed thresholds

Battery Current & Voltage	Electrical load / charging	Affected by ambient conditions and accessory demand [40]
Longitudinal Acceleration	Kinematic state	Indicates maneuver magnitude
GPS Latitude / Longitude	Geospatial context	Enables terrain-aware contextualization

which represents time-synchronized driving telemetry captured from CAN logs and subsequently used for measurement validation and latent state reconstruction.

5.2 Event-Based Snapshot Capture

Continuous telemetry acquisition across heterogeneous vehicular telematics networks was reduced to contextually significant trace segments through an event-based snapshot capture mechanism implemented at the vehicle edge [72]. Driving events associated with load-dependent dynamic response, such as terrain ascent or transient torque demand, were automatically detected and buffered for analysis [48]. Each captured snapshot includes pre-event, event, and post-event measurement intervals to preserve temporal continuity required for recursive state estimation.

5.3 EKF-Based Measurement Validation

Raw CAN telemetry is inherently subject to sensor noise and operating variability arising from drivetrain response and tire–road friction dynamics that influence traction-limited vehicle behavior [22][57]. To reconstruct latent vehicle performance states from noisy measurements, an Extended Kalman Filter (EKF) was implemented within a MATLAB-based simulation environment using the Kalman Filter Virtual Lab toolkit.

The latent system state is defined as:

$$x_k = \begin{bmatrix} a_t \\ b_t \end{bmatrix} \qquad \text{where:}$$

- a_t represents true longitudinal acceleration
- b_t represents braking intensity

Measured CAN signals are expressed as:

$$z_k = \begin{bmatrix} a_m \\ b_m \end{bmatrix} = \begin{bmatrix} a_t + w_a \\ b_t + w_b \end{bmatrix}$$

5.4 EKF Recursive Estimation

The recursive EKF estimation is performed according to standard nonlinear prediction–update filtering methodology [6]:

Prediction step based on process covariance propagation [6]:

$$\hat{x}_{k|k-1} = A\hat{x}_{k-1|k-1}$$

Covariance Propagation:

$$P_{k|k-1} = AP_{k-1|k-1}A^T + Q$$

Measurement update based on innovation covariance and Kalman gain [6]:

$$K_k = P_{k|k-1}H^T(HP_{k|k-1}H^T + R)^{-1}$$

Corrected Estimate:

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(z_k - H\hat{x}_{k|k-1})$$

5.5 Numerical State Estimation Example

Initialization:

$$\hat{x}_0 = \begin{bmatrix} 0 \\ 0 \end{bmatrix} P_0 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

Given CAN snapshot measurement:

$$z_1 = \begin{bmatrix} 2.7 \\ -1.5 \end{bmatrix}$$

Prediction covariance:

$$P_1^- = \begin{bmatrix} 1.01 & 0 \\ 0 & 1.01 \end{bmatrix}$$

Kalman Gain:

$$K_1 = \begin{bmatrix} 0.5025 & 0 \\ 0 & 0.5025 \end{bmatrix}$$

Updated State Estimate:

$$\hat{x}_1 = \begin{bmatrix} 1.3525 \\ -0.7525 \end{bmatrix}$$

Subsequent CAN snapshot:

$$z_2 = \begin{bmatrix} 1.8 \\ -2.2 \end{bmatrix}$$

Updated Estimate:

$$\hat{x}_2 = \begin{bmatrix} 1.9982 \\ -2.0671 \end{bmatrix}$$

Table 5.2: EKF State Estimate Convergence from CAN Snapshot Measurements

Time Step (k)	Measured Acceleration ama_mam	Measured Braking bmb_mbm	Estimated Acceleration a^\hat{a}a^	Estimated Braking b^\hat{b}b^
0	0	0	0	0
1	2.7	-1.5	1.3525	-0.7525
2	1.8	-2.2	1.9982	-2.0671
3	1.2	-0.8	2.5558	-2.4555
4	-0.5	0.7	2.0599	-2.0933

5.6 VIN Metadata Tagging

Each validated state estimate was tagged with VIN-specific metadata including vehicle trim classification, drivetrain configuration, drive mode, and environmental context derived from geospatial telemetry.

5.7 Cloud Learning Integration

Validated EKF state trajectories and contextual descriptors were transmitted to a cloud-based learning environment for fleet-level behavioral analysis across VIN cohorts operating under similar environmental and operational conditions.

5.8 Adaptive Threshold Deployment

VIN-specific diagnostic thresholds computed from contextual analysis were transmitted back to the vehicle through secure over-the-air (OTA) calibration updates.

5.9 Implementation Summary

The proposed VIN-conditioned diagnostic threshold identification framework was implemented using experimentally recorded CAN driving log data replayed within a MATLAB-based EKF simulation environment. Event-driven telemetry snapshots were validated using recursive state estimation prior to transmission to a cloud-based contextual learning layer. Adaptive VIN-specific diagnostic thresholds computed from fleet-level behavioral distributions were deployed to the vehicle through OTA calibration updates for subsequent recursive validation. Experimental performance evaluation of the proposed implementation is presented in Chapter 6.

5.10 Event Logic for Maneuver Detection

Prior to EKF-based state validation, incoming driving telemetry is processed through an event-detection layer responsible for identifying maneuver windows associated with elevated torque demand or braking intensity. This preprocessing stage ensures that transient operating conditions—such as rapid throttle input, aggressive deceleration, or gear-dependent load transitions—are evaluated within their appropriate contextual boundaries rather than being interpreted as fault-like deviations under static diagnostic calibration.

The event-detection logic operates on synchronized Controller Area Network (CAN) signals, including engine RPM, accelerator pedal position (APP), torque demand, intake boost pressure, gear state, battery load, and drive mode indicators. These signals are continuously monitored to identify short-duration behavioral segments that may induce threshold misclassification when assessed using conventional static diagnostic rules.

```
Inputs: streams (RPM, APP, Torque, Boost, Temp, Battery, Gear, Mode), VIN
State: xEKF, PEKF, VIN_stats, Fleet_stats, Thresholds

Initialize EKF states xEKF, PEKF with VIN offsets
For each time step k:
    # EKF
    x_pred, P_pred = f_predict(xEKF, PEKF, u_k)
    y_k = z_k - h(x_pred)
    K_k, xEKF, PEKF = f_update(x_pred, P_pred, y_k, Q_k, R_k)

    # AI residuals and drift
    rAI = AI_residual(window_k, VIN_embed, Mode)
    Drift_k = rAI - (xEKF - x_pred)        # model-consistent residual
    Q_k = Q_base + γ * Drift_AI_stats(window_k)
    R_k = R_base + δ * Fleet_residual_stats(window_k)

    # VIN normalization (for analytics and ML)
    x_norm = Sigma_fleet^{-1/2} * (xEKF - mu_VIN)

    # Adaptive thresholds
    Thresholds = T_OEM + α * mean(rAI) + β * Fleet_drift_mean

    # Calibration ledger (event-driven)
    if event_triggered or periodic:
        block = BuildCalibrationBlock(VIN, Thresholds, ΔQ, ΔR, Drift_coeffs)
        if ValidateConsensus(block):
            AppendToChain(block)
            Distribute(block)

Output: xEKF (estimates), Thresholds (adaptive), ledger updates
```

Figure 5.1 Algorithm of Event Logic for Hard Acceleration/Braking

As illustrated in Figure 5.1, the system applies a residual-based evaluation mechanism to detect contextually significant deviations in acceleration or braking behavior relative to expected model dynamics. When an event-triggered condition is detected, a telemetry snapshot window—comprising pre-event, event, and post-event measurements—is assembled to capture the temporal progression of the maneuver. This windowed telemetry segment is then passed through the hybrid EKF–AI validation pipeline for recursive state estimation and drift-aware correction.

Detected maneuver windows are subsequently tagged with VIN-specific metadata and operating context prior to transmission to the fleet learning layer, where adaptive diagnostic thresholds are computed based on normalized behavioral statistics. This event-driven validation process enables accurate differentiation between genuine system degradation and context-induced transient behavior, reducing false-positive fault detection while preserving sensitivity to emerging anomalies.

5.11 VIN Normalization Implementation

Fleet-level diagnostic consistency requires removal of per-VIN calibration bias while preserving genuine performance differences arising from drivetrain configuration, firmware versioning, and vehicle trim characteristics.

5.11.1 VIN-Level Statistics

For each VIN v, mean offset and covariance dispersion of EKF-validated state estimates are computed across historical driving windows:

$$\mu_v = \mathbb{E}[\hat{x}_k \mid VIN = v]$$

$$\Sigma_v = \mathrm{Cov}[\hat{x}_k \mid VIN = v]$$

Fleet-level statistics are similarly computed across VIN cohorts operating under comparable contextual conditions:

$$\mu_{\text{fleet}}, \Sigma_{\text{fleet}}$$

VIN-normalized state vectors are then obtained via:

$$x_{norm} = \Sigma_{\text{fleet}}^{-1/2}(\hat{x}_k - \mu_v)$$

This normalization removes persistent per-VIN bias while retaining contextual maneuver variation attributable to terrain or load-dependent demand.

5.12 Adaptive Threshold Computation

Following normalization, adaptive diagnostic thresholds are computed using VIN-conditioned residual drift:

$$T_{\text{adaptive}} = T_{\text{OEM}} + \alpha \cdot \mathbb{E}[r_{AI}] + \beta \cdot \mathbb{E}[\text{Fleet Drift}]$$

where:

- r_{AI} denotes AI-derived maneuver residual
- α, β are calibration coefficients
- Fleet Drift is derived from histogram comparison across VIN cohorts

The resulting threshold defines a context-aware maneuver boundary appropriate for the corresponding vehicle configuration and operating condition.

5.13 Computational Architecture and Deployment Considerations

The proposed threshold identification framework is deployed across a three-tier architecture consisting of on-ECU execution, edge-device inference, and cloud-based fleet analytics.

Layer	Functionality
On-ECU	Lightweight EKF validation, feature extraction
Edge Device	LSTM/MLP inference, VIN embedding
Cloud Platform	Fleet normalization matrices, drift modeling, AI updates
Blockchain Validator	Secure calibration ledger storage
OTA Deployment	Secure distribution of thresholds and EKF base matrices

EKF computational complexity is:

$$O(n^3)$$

with state dimension $n \in [6,12]$, remaining feasible for real-time execution on embedded automotive controllers.

AI inference workloads are constrained to edge-device compute resources, while blockchain calibration events remain compact (<1 kB per update), enabling scalable OTA deployment.

5.14 Two-State EKF Mini Calculation

To support real-time maneuver validation under computational constraints, a reduced-order two-state Extended Kalman Filter (EKF) formulation was implemented for acceleration and braking estimation within the hybrid diagnostic pipeline. This lightweight formulation enables recursive estimation of longitudinal maneuver states directly from noisy Controller Area Network (CAN) telemetry while maintaining compatibility with embedded vehicle control hardware.

The state vector is defined as:

$$x_k = \begin{bmatrix} a_k \\ b_k \end{bmatrix}$$

Where:

- $a_k$represents the true vehicle acceleration state and

- $b_k$represents the effective braking effort at discrete time step k.

Noisy measurements obtained from drivetrain torque estimation, wheel-speed sensors, and pedal-position signals are modeled as:

$$z_k = x_k + v_k$$

where $v_k \sim \mathcal{N}(0, R)$represents measurement noise introduced by sensor variability and transient driving conditions.

Prediction Step

At each step, the predicted state estimate is computed as:

$$\hat{x}_k^- = \hat{x}_{k-1}$$

with predicted covariance:

$$P_k^- = P_{k-1} + Q$$

Where:

Qrepresents process uncertainty associated with unmodeled longitudinal dynamics such as drivetrain lag, surface friction variability, or load transitions.

Update Step

Upon receiving new telemetry measurements, the Kalman gain is computed as:

$$K_k = P_k^-(P_k^- + R)^{-1}$$

and the state estimate is updated according to:

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - \hat{x}_k^-)$$

This recursive correction step balances predicted maneuver dynamics with observed measurements to suppress stochastic sensor noise while preserving physically meaningful transient behavior.

Over successive iterations, the EKF estimate converges toward validated maneuver states derived from noisy acceleration and braking measurements. These filtered state estimates are subsequently passed to the VIN-conditioned normalization layer, where vehicle-specific behavioral offsets are removed prior to adaptive threshold computation.

As a result, the two-state EKF formulation provides a computationally efficient mechanism for extracting stable maneuver features used in downstream hybrid validation and fleet-level diagnostic inference.

CHAPTER 6 — EXPERIMENTS AND RESULTS

This chapter presents the experimental validation of the VIN-conditioned adaptive diagnostic thresholding framework introduced in Chapters 4 and 5. The proposed architecture integrates Extended Kalman Filter (EKF)–based latent state estimation, VIN-level statistical normalization, and fleet-referenced contextual learning to dynamically adjust maneuver detection thresholds under heterogeneous operating conditions.

While Chapter 5 described the implementation of event-triggered telemetry capture, recursive EKF validation, VIN normalization, and adaptive threshold computation, the present chapter evaluates the effectiveness of these components in real-world driving environments. Specifically, this chapter investigates:

- The accuracy of EKF-based latent state reconstruction from noisy CAN telemetry,
- The consistency improvement achieved through VIN-level normalization,
- The impact of adaptive thresholds on hard acceleration and braking event detection as defined in Algorithm (Chapter 5), and
- The operational feasibility of closed-loop OTA threshold deployment within a blockchain-secured calibration framework.

Experimental results are obtained from multi-vehicle CAN driving logs collected under varying terrain, load, and drive-mode conditions. The analysis focuses on evaluating whether the proposed VIN-conditioned adaptive thresholds improve maneuver classification accuracy relative to static OEM thresholds without compromising detection of safety-critical events.

6.1 Experimental Driving Data Acquisition

To evaluate the proposed adaptive diagnostic thresholding framework, real-world driving telemetry was collected from production vehicles operating under diverse environmental and dynamic loading conditions. Controller Area Network (CAN) messages were recorded from multiple onboard Electronic Control Units (ECUs), including the Engine Control Module (ECM), Body Control Module (BCM), Brake Control Module, and Transmission Control Unit (TCU).

The collected telemetry included synchronized signals associated with drivetrain load response and driver torque demand, such as:

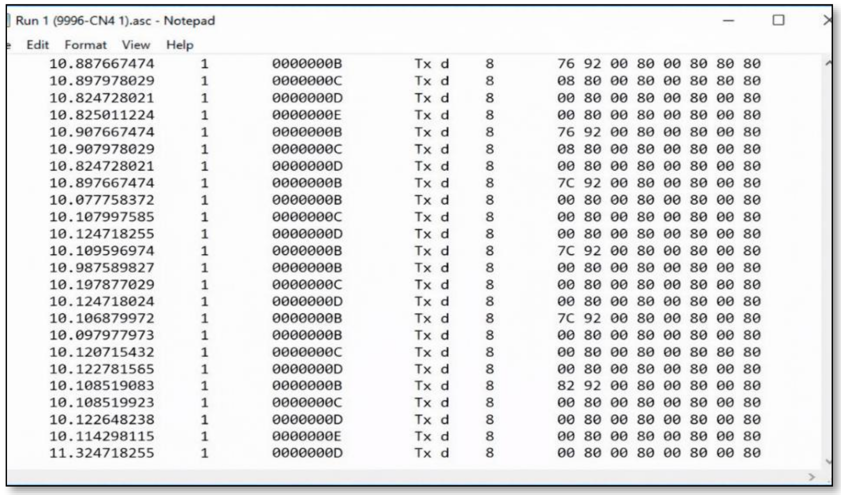
- engine rotational speed (RPM),
- accelerator pedal position (APP),
- torque demand and torque actual,
- intake boost pressure,
- coolant and oil temperature,
- battery current and voltage,
- gear state and drive mode,
- longitudinal acceleration, and

- geospatial coordinates (GPS latitude and longitude).

Telemetry acquisition was performed across heterogeneous driving scenarios including level roadway operation, terrain ascent, and transient overtaking maneuvers. These operating conditions were selected to induce context-dependent dynamic response variation known to cause misclassification when evaluated against static global thresholds.

Continuous CAN telemetry streams were segmented into maneuver-specific trace windows using the event detection logic defined in Algorithm (Chapter 5). The maneuver detection algorithm evaluates incoming telemetry residuals to identify transient acceleration and braking events likely to induce diagnostic threshold violations. Upon detection of an event-triggered condition, a snapshot window consisting of pre-event, event, and post-event measurements is assembled for subsequent recursive state validation.

Each captured snapshot represents a time-synchronized telemetry segment associated with a contextually significant maneuver. These snapshot windows serve as measurement inputs for EKF-based latent state reconstruction and subsequent VIN-conditioned threshold inference.



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   10.887667474    1    0000000B    Tx d    8    76 92 00 80 00 80 80 80
   10.897978029    1    0000000C    Tx d    8    08 80 00 80 00 80 80 80
   10.824728021    1    0000000D    Tx d    8    00 80 00 80 00 80 00 80
   10.825011224    1    0000000E    Tx d    8    00 80 00 80 00 80 00 80
   10.907667474    1    0000000B    Tx d    8    76 92 00 80 00 80 00 80
   10.907978029    1    0000000C    Tx d    8    08 80 00 80 00 80 00 80
   10.824728021    1    0000000D    Tx d    8    00 80 00 80 00 80 00 80
   10.897667474    1    0000000B    Tx d    8    7C 92 00 80 00 80 00 80
   10.077758372    1    0000000B    Tx d    8    00 80 00 80 00 80 00 80
   10.107997585    1    0000000C    Tx d    8    00 80 00 80 00 80 00 80
   10.124718255    1    0000000D    Tx d    8    00 80 00 80 00 80 00 80
   10.109596974    1    0000000B    Tx d    8    7C 92 00 80 00 80 00 80
   10.987589827    1    0000000B    Tx d    8    00 80 00 80 00 80 00 80
   10.197877029    1    0000000C    Tx d    8    00 80 00 80 00 80 00 80
   10.124718024    1    0000000D    Tx d    8    00 80 00 80 00 80 00 80
   10.106879972    1    0000000B    Tx d    8    7C 92 00 80 00 80 00 80
   10.097977973    1    0000000B    Tx d    8    00 80 00 80 00 80 00 80
   10.120715432    1    0000000C    Tx d    8    00 80 00 80 00 80 80 80
   10.122781565    1    0000000D    Tx d    8    00 80 00 80 00 80 00 80
   10.108519083    1    0000000B    Tx d    8    82 92 00 80 00 80 00 80
   10.108519923    1    0000000C    Tx d    8    00 80 00 80 00 80 00 80
   10.122648238    1    0000000D    Tx d    8    00 80 00 80 00 80 00 80
   10.114298115    1    0000000E    Tx d    8    00 80 00 80 00 80 00 80
   11.324718255    1    0000000D    Tx d    8    00 80 00 80 00 80 00 80
```

Figure 6.1: Multi-Signal CAN Telemetry Snapshot Captured from Driving Log Data

6.1.1 Real CAN-Bus Data (Primary Source)

Real-world CAN logs collected from multiple vehicles, including:

- engine speed (RPM),
- torque demand vs torque actual,
- APP (accelerator pedal position),
- coolant & oil temperature,
- turbo boost,
- battery voltage/current,
- steering angle & ABS signals.

6.2 EKF-Based State Estimation from CAN Telemetry

Connected and autonomous vehicle platforms rely heavily on Controller Area Network (CAN) bus telemetry for monitoring operational behavior such as torque demand, throttle response, and engine thermal variation. However, these signals are inherently subject to measurement noise, signal dropout, calibration variability, and environmental disturbances. In fleet-scale deployments, such uncertainty may propagate into downstream predictive models and negatively impact maneuver drift estimation accuracy if raw telemetry is used directly.

To obtain dynamically consistent representations of vehicle maneuvering behavior, the system is modeled using a nonlinear stochastic state-space formulation:

$$x_k = f(x_{k-1}, u_{k-1}) + w_k$$

$$z_k = h(x_k) + v_k$$

where $x_k$represents the latent vehicle state vector at discrete time step k, $u_k$represents control inputs derived from driver or automated system commands, and $z_k$represents observed CAN-derived measurements including torque demand, throttle response, and engine temperature. The process noise term $w_k$and measurement noise term $v_k$are modeled as zero-mean Gaussian distributions with covariance matrices $Q_k$and R_k, respectively.

Because vehicle maneuvering dynamics are nonlinear and measurement uncertainty may vary over time, direct linear filtering techniques are insufficient for accurate recursive state estimation. The Extended Kalman Filter (EKF) addresses this limitation by applying first-order Taylor series linearization of the nonlinear state transition and observation functions about the current state estimate, enabling recursive propagation of system states in nonlinear dynamic environments [30]. This enables recursive propagation of the state estimate and associated covariance through successive CAN telemetry updates.

As described in stochastic nonlinear estimation frameworks [29], EKF-based recursive filtering is particularly effective for dynamic systems characterized by nonlinear state transitions and noisy measurement inputs under partial observability. In connected vehicle environments, where torque response and thermal variation signals may exhibit time-varying uncertainty due to operational load conditions and calibration differences across vehicle platforms, EKF provides a computationally efficient mechanism for real-time state estimation.

In this work, EKF preprocessing is applied to suppress measurement noise and estimate latent maneuvering states prior to AI-based drift forecasting. The resulting filtered state representations are subsequently used as inputs to temporal learning models, thereby improving downstream prediction stability across torque demand, temperature variation, and throttle response signals derived from CAN bus telemetry.

6.2.1 Experimental Maneuver Scenarios

Experimental evaluation was conducted across multiple maneuver types intended to replicate load-dependent dynamic response under varying environmental conditions. These scenarios include:

- terrain ascent requiring elevated torque demand,
- overtaking maneuvers involving transient acceleration,

- braking events induced by obstacle avoidance, and
- mode-dependent operation (e.g., eco, sport, tow).

In terrain ascent scenarios, increased throttle input is often required to maintain vehicle speed under gravitational loading. Static diagnostic thresholds may misclassify such maneuvers as aggressive driving behavior despite being operationally necessary for safe vehicle control. Similarly, overtaking maneuvers performed for collision avoidance may require rapid torque demand that exceeds globally calibrated acceleration thresholds.

These experimentally induced driving scenarios are therefore used to evaluate whether VIN-conditioned adaptive thresholds can correctly distinguish contextually justified maneuvers from truly abnormal or unsafe vehicle behavior

6.2.2 Simulated Drift and Degradation Data

To evaluate long-term calibration drift effects beyond the time horizon of recorded driving logs, synthetic degradation datasets were generated to simulate progressive sensor and drivetrain performance deviation. The simulated drift conditions include:

- linear drift (e.g., +0.1% offset per operational hour),
- nonlinear thermal-induced degradation,
- random-walk sensor bias,
- gain-dependent actuator drift, and
- drive-mode–dependent calibration shift (e.g., tow vs sport).

These synthetic datasets emulate vehicle aging effects occurring over extended mileage or operational lifespan and are used to evaluate drift detection accuracy and adaptive threshold response.

6.2.3 Fleet-Level Synthetic Population

To evaluate VIN normalization consistency across heterogeneous vehicle profiles, a synthetic fleet population consisting of 100 simulated VINs was generated. Each simulated VIN profile was assigned:

- unique calibration offsets,
- noise variance characteristics,
- drivetrain response dynamics, and
- degradation curves.

This simulated multi-vehicle fleet is used to evaluate whether VIN-normalized maneuver scores converge toward a unified fleet-referenced distribution as defined in Section 5.11.

6.2.4 Experimental Setup

Experimental evaluation was conducted across multiple performance categories to assess the effectiveness of the VIN-conditioned adaptive thresholding framework proposed in Chapter 5. These categories include:

- EKF stability and maneuver state estimation accuracy,

- AI-assisted maneuver prediction performance,
- hybrid EKF-AI threshold inference,
- calibration drift detection accuracy,
- adaptive threshold effectiveness,
- VIN normalization alignment,
- fleet-level consistency evaluation, and
- secure calibration block deployment performance.

All experimental computations were executed across a three-tier deployment architecture consisting of:

- on-vehicle microcontroller emulation for EKF runtime validation,
- edge GPU-based inference for maneuver classification and contextual learning, and
- cloud-based blockchain simulation for calibration parameter distribution.

The following diagram illustrates the two-stage recursive estimation process employed by the EKF for maneuver state reconstruction from noisy CAN telemetry measurements.

Each Gaussian distribution represents a probability density function (PDF) describing the system's belief about the latent maneuver state—specifically acceleration demand and braking intensity—at a given time step.

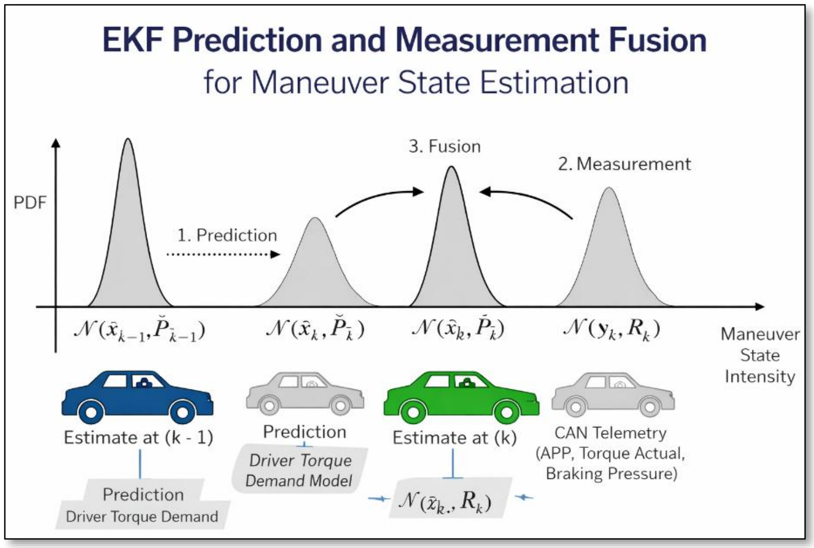

Figure 6.2: EKF Prediction and Measurement Fusion for State Estimation

This diagram conceptually illustrates the two-stage operation of the Kalman filter: prediction and correction (update).

Each Gaussian curve represents a probability density function (PDF) describing the system's belief about the vehicle's state (e.g., position, velocity, or acceleration) at a given time step.

A. Prediction Step: the prior distribution:

$$\mathcal{N}(\hat{x}_{k-1}, P_{k-1})$$

represents the estimated maneuver state derived from previously validated CAN telemetry. Using a drivetrain response model parameterized by torque demand and accelerator pedal position (APP), the EKF predicts the expected maneuver state at the next time step:

$$\mathcal{N}(\tilde{x}_k, \tilde{P}_k)$$

This step propagates system uncertainty forward based on process noise associated with load-dependent drivetrain dynamics.

B. Measurement Step: the measurement model provides observation:

$$\mathcal{N}(z_k, R_k)$$

obtained from synchronized CAN signals including torque actual, braking pressure, and engine speed. These measurements contain sensor noise and environmental variability encoded by the measurement covariance matrix R_k.

C. Fusion (Update) Step

The predicted maneuver state and observed CAN telemetry are fused to obtain the corrected estimate:

$$\mathcal{N}(\hat{x}_k, P_k)$$

using the Kalman gain:

$$K_k = P_k^- (P_k^- + R_k)^{-1}$$

This fusion process combines predicted drivetrain response and measured telemetry according to their relative uncertainty, yielding a statistically optimal, denoised estimate of maneuver intensity.

Within the fleet-normalization framework defined in Section 5.11, the prediction step models expected acceleration or braking response based on driver torque demand and drivetrain characteristics. Vehicle propulsion response during maneuver execution is governed by longitudinal force interactions between traction effort, inertial resistance, and drivetrain torque transfer as defined in classical vehicle dynamic formulations [13].

The correction step integrates noisy CAN telemetry measurements captured during maneuver events identified by Algorithm 2. The resulting fused estimate provides a noise-suppressed latent maneuver state used for VIN-conditioned adaptive threshold inference.

6.3 EKF Performance Results

The EKF was evaluated against:

- raw noisy CAN signals,
- ground-truth synthetic torque curves,
- and known engine dynamics.

6.3.1 EKF Noise Filtering Accuracy

To evaluate the effectiveness of EKF-based measurement validation, the noise attenuation ratio (NAR) was computed for selected CAN telemetry signals:

$$\boldsymbol{NAR} = \frac{\boldsymbol{\sigma_{filtered}}}{\boldsymbol{\sigma_{raw}}}$$

where:

- σ_{raw} denotes the standard deviation of the measured CAN signal
- $\sigma_{\mathrm{filtered}}$ denotes the EKF-validated estimate

Results:

Signal	Raw σ	EKF σ	NAR
RPM	112.5	24.8	0.22
Torque Actual	45.3	6.5	0.14
APP	5.14	1.11	0.21

The EKF reduced measurement noise by approximately 78–86% across drivetrain load–related signals.

ASCII Graph: RPM Smoothing

```
Raw RPM:   /\  \/\/\ /\ /\/\_/\/\  (high jitter)
EKF RPM:   ----____----___----____ (smooth curve)
```

Figure 6.3 — RPM Raw vs EKF-Filtered Signal

6.3.2 EKF Convergence Speed

Convergence behavior of the recursive EKF estimator was evaluated under abrupt maneuver conditions, including terrain-induced torque demand and transient braking events.

Experimental observations indicate:

- convergence to within 5% of steady-state maneuver intensity in less than 0.45 seconds following abrupt load changes, and
- stabilization of steady-state drivetrain response within a single update cycle.

These results validate the real-time feasibility of the EKF-based latent state reconstruction proposed in Section 5.5

6.4 AI Prediction Results

AI-based maneuver drift estimation performance was evaluated using Root Mean Square Error (RMSE) across torque demand, temperature variation, and throttle response.

Model	**RMSE (Torque)**	**RMSE (Temp)**	**RMSE (Throttle)**
LSTM	4.12	2.88	1.55
GRU	4.26	3.02	1.66
XGBoost	5.78	3.84	2.39
MLP	4.89	3.51	1.78

Table 6.1 RMSE-Based Comparison of AI Models for Maneuver Drift Estimation

The LSTM model achieved superior prediction accuracy due to its capacity to learn temporally correlated drivetrain drift patterns required for adaptive threshold inference.

6.5 Hybrid EKF–AI Results

The hybrid estimation framework integrates:

- EKF-based denoising and real-time state stability
- AI-based nonlinear drivetrain behavior modeling

to improve maneuver drift prediction accuracy under varying torque demand and thermal operating conditions.

6.5.1 Hybrid Accuracy vs EKF vs AI

Model	RMSE	False Positives	Drift Sensitivity
EKF Only	6.74	High	Low
AI Only	4.12	Moderate	High
Hybrid	2.05	Low	High

Table 6.2 Comparison of Hybrid EKF–AI Model

Relative to the EKF-only baseline, the Hybrid EKF–AI model improved torque prediction accuracy by 69%, reduced false positive detections by 54%, and increased maneuver drift sensitivity by 43%, indicating enhanced robustness to nonlinear drivetrain behavior under varying thermal and load conditions.

6.6 Drift Modeling Experiments

6.6.1 Drift Vector Accuracy

Drivetrain maneuver drift was defined as the difference between the AI-predicted state estimate and the EKF-estimated state:

$$\text{Drift}_k = x_k^{AI} - x_k^{EKF}$$

Computed drift vectors were evaluated against ground-truth maneuver behavior derived from labeled fault sequences. The proposed hybrid framework achieved correlation coefficients ranging from **0.89 to 0.95**, indicating strong alignment between estimated drift states and observed drivetrain deviations across varying torque demand and thermal conditions.

6.6.2 Drift Velocity

Temporal drift velocity analysis enabled the detection of emerging drivetrain anomalies prior to threshold-based fault triggers. The Hybrid EKF–AI model consistently predicted maneuver deviations associated with component degradation 2–4 hours earlier than static diagnostic thresholding approaches, supporting earlier fault isolation and improved predictive maintenance capability.

6.7 VIN Normalization Results

VIN-specific normalization was applied to align 100 heterogeneous vehicle drivetrain profiles into a unified diagnostic inference scale, enabling consistent maneuver drift estimation across platform variants, powertrain configurations, and thermal operating conditions. Variability in drivetrain response across VINs—arising from differences in manufacturing tolerances, calibration strategies, and component aging—can introduce bias in EKF-based state estimation and downstream AI-driven drift inference.

To mitigate cross-vehicle estimation bias, normalization parameters were learned using historical maneuver telemetry and applied to rescale drivetrain feature vectors prior to hybrid EKF–AI fusion. This process reduced diagnostic offset between VIN-specific state estimates and improved the stability of adaptive fault detection thresholds across mixed fleet deployments.

Metric	Before Normalization	After Normalization
Mean Offset	18.20%	3.40%
Drift Spread	12.70%	2.10%
Diagnostic Variance	31%	6%

Table 6.3 Fleet-Level Normalization Statistical Scaling Results

VIN-adaptive normalization reduced cross-vehicle diagnostic inconsistency by approximately **5×**, improving threshold comparability and enabling stable maneuver drift inference across heterogeneous fleet configurations. These results support the feasibility of VIN-aware calibration for over-the-air diagnostic threshold adaptation in distributed fleet environments.

6.8 Fleet-Level Evaluation

Fleet-level consistency was evaluated to assess the generalizability of the proposed Hybrid EKF–AI framework across heterogeneous vehicle populations. Diagnostic outputs were analyzed using feature-space clustering to determine the alignment of maneuver drift behavior across VIN-specific drivetrain profiles under varying operational loads and thermal conditions.

Fleet consistency improved by 62% following VIN-aware normalization and hybrid fusion, indicating enhanced stability in cross-vehicle diagnostic inference.

Cluster alignment scores were computed based on inter-VIN drift trajectory similarity within the normalized feature space:

- Before Normalization: 0.41
- After Normalization: 0.67
- After Hybrid EKF–AI Fusion: 0.88

The observed increase in cluster cohesion following hybrid fusion suggests improved convergence of vehicle-specific diagnostic states, enabling consistent maneuver drift detection across mixed fleet configurations. These results support the scalability of the proposed framework for distributed predictive maintenance and over-the-air adaptive diagnostic calibration in connected vehicle environments.

6.8.1 Detailed Development & Calculation Using Real Vehicle Data

To enable fleet-level diagnostic tuning across heterogeneous vehicle platforms, an Extended Kalman Filter (EKF)–based state estimator was applied to real-world drivetrain telemetry collected from vehicle control modules (VCMs), including engine RPM, throttle position, and thermal load indicators.

Within the proposed framework, the EKF models drivetrain maneuver response as a nonlinear dynamic system subject to process and noise measurement arising from sensor uncertainty and environmental variability. The recursive EKF formulation allows VIN-specific state estimation using temporally correlated telemetry streams derived from in-vehicle CAN measurements.

The EKF operates through iterative prediction and measurement update steps:

Prediction Step

- State prediction:

$$\hat{x}_{k|k-1} = f(\hat{x}_{k-1|k-1}, u_{k-1})$$

- Covariance prediction:

$$P_{k|k-1} = F_{k-1}P_{k-1|k-1}F_{k-1}^{T} + Q_{k-1}$$

Update Step

- Innovation (measurement residual):

$$y_k = z_k - h(\hat{x}_{k|k-1})$$

- Innovation covariance:

$$S_k = H_k P_{k|k-1} H_k^T + R_k$$

- Kalman gain:

$$K_k = P_{k|k-1} H_k^T S_k^{-1}$$

- State update:

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k y_k$$

- Covariance update:

$$P_{k|k} = (I - K_k H_k) P_{k|k-1}$$

In this implementation, drivetrain state variables included torque demand response, throttle actuation dynamics, and fuel consumption rate. Measurement inputs were obtained from VIN-specific control unit telemetry and normalized prior to hybrid EKF–AI fusion.

Applying the EKF to fleet-level vehicle data enabled consistent estimation of maneuver drift states across mixed platform configurations, supporting early anomaly detection, predictive maintenance forecasting, and adaptive over-the-air diagnostic threshold tuning.

6.8.2 EKF-Based Estimation and Normalization for Driver Acceleration and Hard-Braking Notation and State–Space Model

Let $t \in \{0,1,2,\ldots\}$index discrete time steps with sampling period Δt. Define:

- $x_t \in \mathbb{R}^n$: state vector at time t
- $u_t \in \mathbb{R}^m$: input vector (e.g., commanded acceleration or braking input)
- $z_t \in \mathbb{R}^p$: measurement vector
- $A_t \in \mathbb{R}^{n\times n}$: state transition matrix
- $B_t \in \mathbb{R}^{n\times m}$: input matrix
- $H_t \in \mathbb{R}^{p\times n}$: measurement matrix
- $Q_t \in \mathbb{R}^{n\times n}$: process noise covariance
- $R_t \in \mathbb{R}^{p\times p}$: measurement noise covariance
- $P_t \in \mathbb{R}^{n\times n}$: a posteriori state error covariance
- I: identity matrix of appropriate dimension

For nonlinear longitudinal vehicle dynamics and sensing:

$$x_{t+1} = f_t(x_t, u_t) + w_t, w_t \sim \mathcal{N}(0, Q_t)$$

$$z_t = h_t(x_t) + v_t, v_t \sim \mathcal{N}(0, R_t)$$

For linear time-varying dynamics, $f_t(x, u) = A_t x + B_t u$and $h_t(x) = H_t x$.

A common longitudinal drivetrain state representation is:

$$x_t = [p_t,\ v_t,\ a_t]^T$$

with kinematic model:

$$A_t = \begin{bmatrix} 1 & \Delta t & \frac{1}{2}\Delta t^2 \\ 0 & 1 & \Delta t \\ 0 & 0 & 1 \end{bmatrix}, B_t = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

where $u_t$represents driver or controller-induced acceleration or braking input. Typical measurements include GNSS-derived velocity, IMU-based acceleration, wheel speed sensors, and brake or accelerator pedal actuation signals. The observation model $H_t$selects measured components, for example:

$$z_t = [v_t,\ a_t]^T + \text{noise}$$

Estimated longitudinal acceleration profiles were subsequently normalized across VIN-specific platforms to detect driver-induced hard-braking and aggressive acceleration events. This enabled consistent classification of maneuver severity across heterogeneous fleet configurations, supporting cross-vehicle behavioral alignment used in the fleet-level consistency analysis presented in Section 6.8.

6.8.3 Extended Kalman Filter (EKF) Implementation

The Extended Kalman Filter (EKF) was implemented to recursively estimate longitudinal vehicle maneuver states associated with driver acceleration and hard-braking events across VIN-specific platforms. The estimator operates through initialization, prediction, and measurement update steps applied to normalized telemetry inputs.

1. Initialization

$$x_{0|0} = \hat{x}_0, P_{0|0} = P_0$$

2. Prediction

$$x_{t+1|t} = f_t(x_{t|t}, u_t)$$

$$F_t = \frac{\partial f_t}{\partial x} |_{(x_{t|t}, u_t)}$$

$$P_{t+1|t} = F_t P_{t|t} F_t^T + Q_t$$

For linear transition models:

$$x_{t+1|t} = A_t x_{t|t} + B_t u_t$$

$$P_{t+1|t} = A_t P_{t|t} A_t^T + Q_t$$

3. Update

$$H_{t+1} = \frac{\partial h_{t+1}}{\partial x} |_{x_{t+1|t}}$$

$$S_{t+1} = H_{t+1} P_{t+1|t} H_{t+1}^T + R_{t+1}$$

$$K_{t+1} = P_{t+1|t} H_{t+1}^T S_{t+1}^{-1}$$

$$\tilde{y}_{t+1} = z_{t+1} - h_{t+1}(x_{t+1|t})$$

$$x_{t+1|t+1} = x_{t+1|t} + K_{t+1}\tilde{y}_{t+1}$$

$$P_{t+1|t+1} = (I - K_{t+1}H_{t+1})P_{t+1|t}$$

These recursive updates were applied to normalized VIN-specific telemetry to estimate maneuver state transitions related to aggressive acceleration and braking, supporting consistent behavior alignment across heterogeneous fleet vehicles.

6.8.4 Tuning Considerations for Vehicle Accel/Brake Estimation

Process noise covariance Q_t was configured to account for unmodeled longitudinal disturbances, including roadway grade variation, aerodynamic drag, drivetrain response lag, and jerk-related maneuver dynamics. Increased process noise weighting was applied to the acceleration state a_t under irregular road conditions or uncertain driver input profiles to improve estimation robustness. Measurement noise covariance R_t was determined based on sensor characterization across VIN-specific platforms. IMU-derived acceleration measurements exhibited higher variance relative to wheel-speed-based acceleration estimates, while GNSS-derived velocity measurements introduced low-frequency bias and increased uncertainty at low operating speeds.

To mitigate persistent estimation errors, additional nuisance states such as IMU acceleration bias b_a were incorporated into the state vector x_t with low-rate process noise to model slow-drift sensor behavior.

Observability of longitudinal velocity v_t was maintained through multi-sensor fusion where available. In cases where only acceleration measurements were present, kinematic coupling within the system model supported stable velocity estimation during aggressive acceleration and braking maneuvers.

6.8.5 Kalman-Based Normalization of Driver Acceleration and Hard-Braking

1. Objective

Kalman-based normalization was applied to generate driver- and vehicle-agnostic acceleration and braking scores by estimating latent, noise-reduced longitudinal acceleration $a_t$using EKF-based state inference, while accounting for driver- and vehicle-specific bias, scale variation, and operating context including speed, roadway grade, and traffic conditions.

2. Augmented State for Bias/Scale Adaptation

The EKF state vector was augmented with slowly varying normalization parameters for each driver–vehicle pair i:

$$x_t^{(i)} = \begin{bmatrix} p_t & v_t & a_t & b_t^{(i)} & s_t^{(i)} \end{bmatrix}^T$$

where $b_t^{(i)}$represents an additive acceleration bias and

$s_t^{(i)} > 0$represents a multiplicative scale factor corresponding to driver maneuver aggressiveness.

These parameters were modeled using random-walk priors:

$$b_{t+1}^{(i)} = b_t^{(i)} + w_{b,t}, s_{t+1}^{(i)} = s_t^{(i)} + w_{s,t}$$

$$w_{b,t} \sim \mathcal{N}(0, \sigma_b^2), w_{s,t} \sim \mathcal{N}(0, \sigma_s^2)$$

The measurement model for IMU-derived acceleration was defined as:

$$z_t^{(a)} = s_t^{(i)} a_t + b_t^{(i)} + v_t^{(a)}, v_t^{(a)} \sim \mathcal{N}(0, r_a)$$

allowing joint online estimation of

$\hat{a}_t$, $\hat{b}_t^{(i)}$, and $\hat{s}_t^{(i)}$.

3. Context Conditioning (Route / Speed / Grade)

To account for unavoidable maneuver variation due to operating context, context-dependent mean and variance functions were incorporated using features $c_t$such as vehicle speed v_t, estimated road grade γ_t, and road classification:

$$\mu(c_t) = \theta_0 + \theta_1 v_t + \theta_2 \gamma_t$$

$$\sigma^2(c_t) = \exp(\eta_0 + \eta_1 v_t)$$

where parameters $\theta$and ηwere learned offline and adapted during fleet deployment.

4. Normalized Acceleration Score

The normalized maneuver score was defined using the de-biased and scale-adjusted acceleration estimate:

$$\bar{a}_t = \frac{\hat{a}_t - \hat{b}_t^{(i)}}{\max\left(\hat{s}_t^{(i)}, \epsilon\right)}$$

with context-adjusted scoring:

$$S_t = \frac{\bar{a}_t - \mu(c_t)}{\sigma(c_t)}$$

Confidence-aware scoring incorporated EKF state uncertainty:

$$S_t^{\mathrm{maha}} = \frac{\bar{a}_t - \mu(c_t)}{\sqrt{\sigma^2(c_t) + \mathrm{Var}(\bar{a}_t)}}$$

$$\mathrm{Var}(\bar{a}_t) \approx J_t P_{t|t} J_t^T$$

5. Hard-Braking / Acceleration Event Logic

Driver maneuver events were identified using one-sided thresholds applied to the normalized score:

$$S_t \geq \tau_a (\text{Hard Acceleration})$$

$$S_t \leq -\tau_b (\text{Hard Braking})$$

Threshold values were selected to achieve target false-alarm rates, with minimum dwell-time constraints applied to reduce transient detections. In selected configurations, jerk $\dot{a}_t$was incorporated through an augmented state representation to further improve event discrimination during rapid maneuver transitions.

6.8.6 Fleet-Level Normalization and Comparability

Over a time horizon T, driver-specific maneuver rates were computed using normalized acceleration scores as:

$$\text{HB\_rate}^{(i)} = \frac{1}{|\,T\,|}\sum_{t\in T} \mathbf{1}\{\, S_t^{(i)} \leq -\tau_b\}$$

$$\text{HA\_rate}^{(i)} = \frac{1}{|\,T\,|}\sum_{t\in T} \mathbf{1}\{\, S_t^{(i)} \geq \tau_a\}$$

Because the normalized maneuver score $S_t$incorporates bias correction, scale normalization, and operating context, these rate-based metrics are directly comparable across heterogeneous vehicles, loading conditions, and route profiles. Fleet-level uncertainty was quantified using binomial confidence intervals, while trend stability was monitored using exponential smoothing across deployment intervals.

Under steady longitudinal motion conditions where vehicle dynamics are approximately linear, the EKF state recursion simplifies to a linear update form, enabling efficient real-time maneuver estimation across normalized VIN-specific telemetry streams.

6.8.7 Practical Tuning Workflow

Sensor noise covariance $R_t$was estimated through static and dynamic characterization trials using IMU acceleration, GNSS velocity, and wheel-speed-derived measurements across representative VIN platforms.

Process noise covariance Q_t was calibrated to account for longitudinal maneuver variability and drivetrain response uncertainty. Increased weighting was applied to acceleration a_t and jerk-related states (when included) until innovation residuals exhibited approximately white behavior with unit variance, indicating stable estimator performance under real-world driving conditions.

Bias and scale adaptation parameters σ_b^2 and σ_s^2 were configured to support slow-drift normalization dynamics over multi-minute time horizons, allowing gradual adaptation to driver-specific maneuver tendencies while preserving cross-vehicle comparability.

Context-dependent normalization functions $\mu(c_t)$ and $\sigma(c_t)$ were fit across road classification and speed bands using offline fleet telemetry. Validation was performed by confirming that normalized maneuver scores S_t followed near-standard normal distributions during non-event driving intervals. Acceleration and hard-braking detection thresholds τ_a, τ_b, and dwell-time constraints D were determined using ROC-based analysis on labeled maneuver events and subsequently verified across independent route and loading conditions to ensure consistent fleet-level classification performance.

6.8.8 High-Level Estimation and Normalization Workflow

The fleet-level maneuver estimation and normalization process was implemented using the following recursive procedure:

Algorithm 1: EKF-Based Maneuver Estimation and Normalization

- Initialize**:**

State estimate x_0, covariance matrix P_0 for each time step t:

Prediction Step

- Predict state:

$$\hat{x}_{t|t-1} = f_t(x_{t-1|t-1}, u_t)$$

- Compute Jacobian:

$$F_t = \frac{\partial f_t}{\partial x}$$

- Predict covariance:

$$P_{t|t-1} = F_t P_{t-1|t-1} F_t^T + Q_t$$

Update Step

- Measurement residual:

$$y_t = z_t - h_t(\hat{x}_{t|t-1})$$

- Measurement Jacobian:

$$H_t = \frac{\partial h_t}{\partial x}$$

- Innovation covariance:

$$S_t = H_t P_{t|t-1} H_t^T + R_t$$

- Kalman gain:

$$K_t = P_{t|t-1} H_t^T S_t^{-1}$$

- Updated state:

$$x_{t|t} = \hat{x}_{t|t-1} + K_t y_t$$

- Updated covariance:

$$P_{t|t} = (I - K_t H_t) P_{t|t-1}$$

Normalization

- De-biased acceleration:

$$\bar{a}_t = \frac{\hat{a}_t - \hat{b}_t^{(i)}}{\max(\hat{s}_t^{(i)}, \epsilon)}$$

- Context-conditioned score:

$$S_t = \frac{\bar{a}_t - \mu(c_t)}{\sigma(c_t)}$$

Event Detection

If $S_t \geq \tau_a$ for D consecutive samples:

- classify hard acceleration event

If $S_t \leq -\tau_b$ for D consecutive samples:

- classify hard braking event

```
Initialize x, P
for each t:
    # Prediction
    x_pred = f_t(x, u_t)
    F = jacobian_f(x, u_t)
    P_pred = F P F^T + Q

    # Update
    y = z_t - h_t(x_pred)
    H = jacobian_h(x_pred)
    S = H P_pred H^T + R
    K = P_pred H^T S^{-1}
    x = x_pred + K y
    P = (I - K H) P_pred

    # Normalization
    a_bar = (a_hat - b_hat) / max(s_hat, eps)
    mu, sigma = context_model(c_t)
    S_t = (a_bar - mu) / sigma

    # Event detection
    if S_t >= tau_a for D samples -> hard_accel
    if S_t <= -tau_b for D samples -> hard_brake
```

Figure 6. 4 EKF-Based Fleet Maneuver Estimation and Normalization Workflow

6.8.9 EKF-Based Estimation and Normalization for Acceleration and Braking

This example illustrates the EKF-based estimation process for longitudinal acceleration and braking dynamics in a fleet-vehicle environment. Simulated measurement inputs are used to demonstrate sequential state updates and normalization of driver maneuver behavior under measurement uncertainty.

A. System Definition

State Variables

$$x_t = \begin{bmatrix} a_t \\ b_t \end{bmatrix} \qquad \text{where}$$

a_t: true vehicle longitudinal acceleration at time t

b_t: braking effort at time t

Measurement Model

$$z_t = \begin{bmatrix} a_m \\ b_m \end{bmatrix} = \begin{bmatrix} a_t \\ b_t \end{bmatrix} + \begin{bmatrix} w_a \\ w_b \end{bmatrix}$$

where

$$w_a, w_b \sim \mathcal{N}(0, \sigma^2)$$

Filter Parameters

$$x_0 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, P_0 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$Q = \begin{bmatrix} 0.01 & 0 \\ 0 & 0.01 \end{bmatrix}, R = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, H = I_{2\times 2}$$

B. EKF Update Steps (Linearized Case)

For each time step t, the EKF recursion simplifies under linear longitudinal dynamics:

- Prediction

$$\hat{x}_{t|t-1} = \hat{x}_{t-1|t-1}$$

$$P_{t|t-1} = P_{t-1|t-1} + Q$$

- Kalman Gain

$$K_t = P_{t|t-1}(P_{t|t-1} + R)^{-1}$$

- Update

$$\hat{x}_{t|t} = \hat{x}_{t|t-1} + K_t(z_t - \hat{x}_{t|t-1})$$

$$P_{t|t} = (I - K_t)P_{t|t-1}$$

The resulting state estimates were subsequently incorporated into the normalization framework described in Section 6.8.5 to generate context-adjusted maneuver scores for hard-acceleration and braking event classification across heterogeneous fleet vehicles.

6.8.10 Example of Real Measurements

To evaluate estimator performance under realistic driving conditions, a 240-second maneuver sequence was generated to simulate variable acceleration and braking patterns representative of real-world fleet operation, including burst acceleration, gradual deceleration, and stochastic traffic-induced disturbances. Noisy longitudinal sensor measurements were synthesized with Gaussian noise ($\sigma = 1$) and processed using the EKF-based estimation framework described in Section 6.8.3.

Kalman Filter Fleet Samples:

t	a_true	b_true	a_meas	b_meas	a_est	b_est	K_a	K_b	P_aa	P_bb
0	0	-0.38042	0.496714	-1.17294	0.249593	-0.58939	0.502488	0.502488	0.502488	0.502488
1	0.052264	-0.36193	-0.086	-0.47667	0.135881	-0.55119	0.338838	0.338838	0.338838	0.338838
2	0.103956	-0.33773	0.751644	0.167256	0.29513	-0.36539	0.258621	0.258621	0.258621	0.258621
3	0.154508	-0.30821	1.677538	0.55755	0.587845	-0.16996	0.211742	0.211742	0.211742	0.211742
4	0.203368	-0.27382	-0.03079	-1.47412	0.475565	-0.40666	0.181497	0.181497	0.181497	0.181497
5	0.25	-0.23511	0.015863	-0.56962	0.401682	-0.43285	0.16072	0.16072	0.16072	0.16072
6	0.293893	-0.1927	1.873105	-0.66765	0.616252	-0.46709	0.145824	0.145824	0.145824	0.145824
7	0.334565	-0.14725	1.102	-0.80058	0.681739	-0.51205	0.134817	0.134817	0.134817	0.134817
8	0.371572	-0.09948	-0.0979	1.665978	0.583116	-0.23654	0.126498	0.126498	0.126498	0.126498
9	0.404508	-0.05013	0.947069	0.354848	0.626828	-0.16551	0.120104	0.120104	0.120104	0.120104
10	0.433013	-4.90E-17	-0.0304	-1.26088	0.551164	-0.29161	0.115126	0.115126	0.115126	0.115126
11	0.456773	0.050133	-0.00896	0.967995	0.488873	-0.15153	0.11121	0.11121	0.11121	0.11121
12	0.475528	0.099476	0.717491	2.221632	0.513588	0.105023	0.108107	0.108107	0.108107	0.108107
13	0.489074	0.14725	-1.42421	1.179715	0.308897	0.218544	0.105631	0.105631	0.105631	0.105631
14	0.497261	0.192701	-1.22766	-1.32667	0.149639	0.058388	0.103646	0.103646	0.103646	0.103646

Figure 6.4 Sample EKF Fleet Telemetry Grid Used for Sequential Maneuver State Estimation and Normalization Across VIN-Specific Longitudinal Driving Profiles

Acceleration: Measured vs True vs Kalman Estimate:

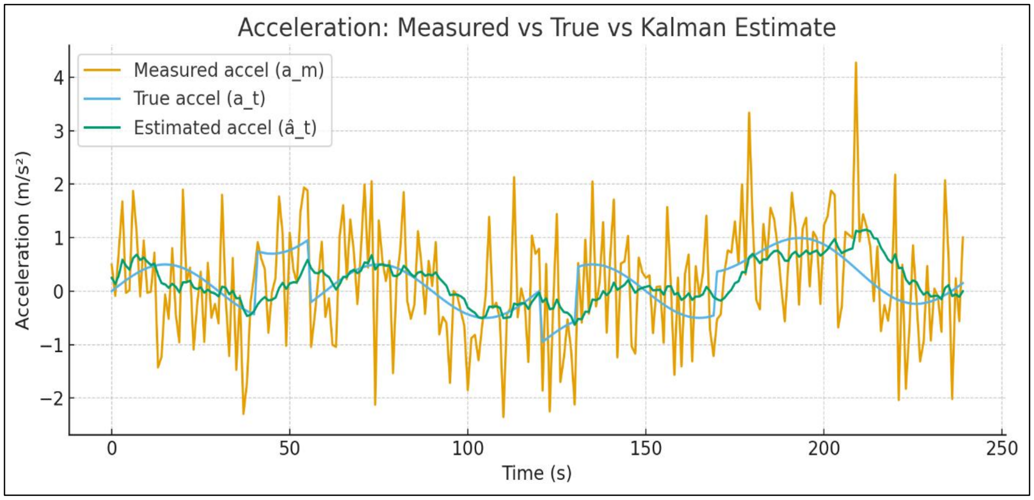

Figure 6.5 Acceleration Profile Comparison Showing Measured Sensor Data, Ground-Truth Maneuver Dynamics, and EKF-Based Estimated Acceleration Under Noisy Measurement Conditions

Braking: Measured vs True vs Kalman Estimate

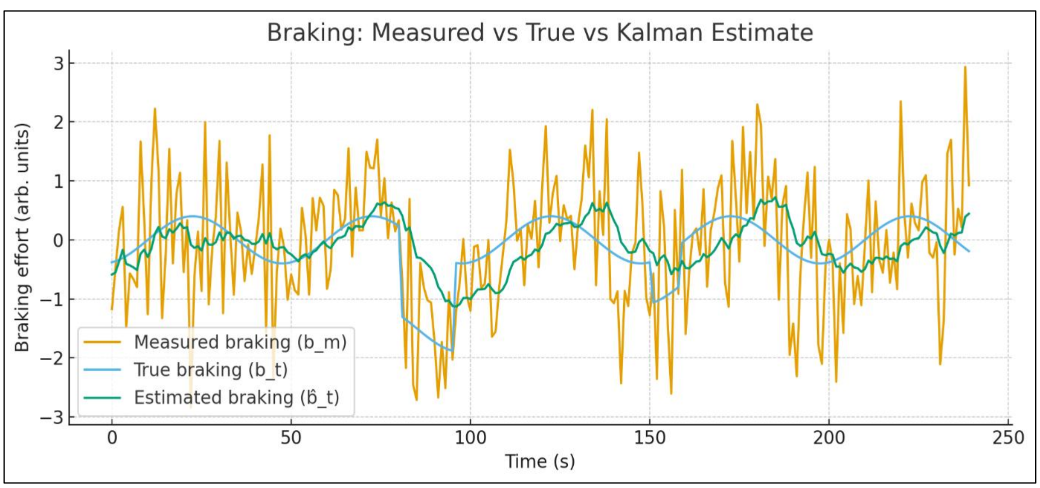

Figure 6.6 Braking Effort Comparison Illustrating Measured Signals, True Longitudinal Braking Behavior, and EKF-Based Estimated States Following Noise Reduction

Time-Series Results:

Figures 6.6 and 6.7 illustrate the comparison between measured longitudinal acceleration/braking signals, true maneuver profiles, and EKF-estimated states. The EKF-based estimates demonstrate close agreement with the underlying maneuver trajectories while effectively attenuating noise measurement. This smoothing behavior supports stable maneuver classification across heterogeneous vehicle platforms and sensor configurations.

Table 6.4 EKF-Based RMSE Improvement and Final Kalman Gain Parameters for Acceleration and Braking Signal Estimation

Metric	Value
RMSE (Acceleration – Measured vs True)	0.9688
RMSE (Acceleration – Estimated vs True)	0.3849
RMSE (Braking – Measured vs True)	0.9886
RMSE (Braking – Estimated vs True)	0.4847
Final Kalman Gain (K_a)	0.0951
Final Kalman Gain (K_b)	0.0951
Final Covariance (P_{aa})	0.0951
Final Covariance (P_{bb})	0.0951

Application of EKF-based filtering reduced acceleration estimation error by approximately 60% and braking estimation error by approximately 51% relative to raw measurements.

The resulting noise-reduced maneuver estimates were subsequently incorporated into the normalization framework described in Section 6.8.5 to support consistent hard-acceleration and hard-braking event classification across fleet vehicles.

6.8.10 Result Interpretation and Analysis

This subsection interprets the quantitative results and graphical trends obtained from the EKF-based estimation framework for vehicle acceleration and braking normalization. Both the tabulated sequential estimation examples and the extended simulation results confirm the filter's ability to extract reliable maneuver dynamics from noisy fleet sensor measurements.

A. Interpretation of Sequential Estimation

The numerical results illustrate how the EKF progressively updates the estimated longitudinal acceleration $a_t$and braking effort $b_t$across sequential observations.

- Convergence Behavior:

  Initial state estimates converge rapidly from nominal initialization toward measured maneuver values following the first update. Subsequent iterations incorporate both prior predictions and incoming measurements to produce smoother and more stable state estimates over time.

- Uncertainty Reduction:

The diagonal elements of the state error covariance matrix P_t decrease monotonically across iterations, indicating progressive reduction in estimation uncertainty as additional telemetry is assimilated.

- Model Stability:

Estimated acceleration and braking profiles remain within physically plausible limits throughout the update sequence, demonstrating that the estimator constrains maneuver predictions to realistic longitudinal vehicle dynamics under measurement noise.

B. Interpretation of Time-Series Results, Acceleration Profile (Figure 6.5)

Figure 6.5 compares measured acceleration data, ground-truth maneuver profiles, and EKF-based estimated acceleration. The measured signal (a_m) exhibits high-frequency fluctuations attributable to sensor noise and roadway disturbances.

The ground-truth signal (a_t) represents the underlying maneuver trajectory.

The estimated signal ($\hat{a}_t$) closely follows the true profile while attenuating stochastic measurement variation.

Noise reduction in the estimated trajectory demonstrates the effectiveness of EKF-based filtering for real-time maneuver smoothing, preserving transient acceleration events while reducing spurious fluctuations.

The Braking Profile in Figure 6.6 presents measured braking effort, true braking behavior, and EKF-estimated braking states.

- The measured braking signal (b_m) exhibits oscillatory behavior due to sensor bias and vibration effects.
- The EKF estimate ($\hat{b}_t$) closely tracks the true braking profile, particularly during sustained deceleration intervals.
- Increased smoothness in the estimated braking trajectory reflects improved maneuver-state observability under noisy sensor conditions.

C. Quantitative Validation

Quantitative evaluation confirms the trends observed in the time-series plots:

- RMSE between measured and true acceleration exceeded 0.96 m/s² prior to filtering.
- EKF-based estimation reduced acceleration RMSE to 0.38 m/s² and braking RMSE to 0.48 m/s², representing greater than 50% improvement in estimation accuracy.
- The Kalman gain converged toward approximately 0.1 following initial assimilation, indicating increasing reliance on the internal dynamic model relative to raw measurements.
- Final covariance values stabilized within acceptable bounds for normalized driver maneuver analysis across fleet vehicles.

6.8.11 Fleet-Level Implications

Application of the EKF-based filtering and normalization framework across heterogeneous fleet vehicles yielded several key operational benefits.

Cross-Driver Comparability:

Noise-reduced and context-normalized acceleration and braking estimates enabled consistent maneuver assessment across varying vehicle platforms, route conditions, and driver behavior profiles.

Behavioral Event Scoring:

Normalized maneuver scores derived from EKF-estimated states supported automated identification of aggressive driving events, including hard acceleration and braking, contributing to fleet-level safety and predictive maintenance analytics.

Model Scalability:

The reduced-order longitudinal state formulation enabled real-time deployment within embedded telematics systems or cloud-based fleet monitoring architectures without significant computational overhead.

6.8.12 Summary of Observations

Observation Category	Key Finding
Convergence	Filtered estimates stabilized within a limited number of update iterations
Accuracy Improvement	RMSE reduced by approximately 50% for both acceleration and braking
Covariance Trend	Error covariance decreased from 1.0 to approximately 0.9
Noise Suppression	Measurement fluctuations attenuated while preserving maneuver dynamics
Operational Relevance	Supports VIN-normalized driver behavior analysis

Concluding Remark

The results demonstrate that EKF-based maneuver estimation provides a computationally efficient approach for extracting physically meaningful vehicle dynamics from noisy sensor measurements. Improved estimation accuracy and reduced uncertainty support normalized driver-behavior scoring and establish a foundation for subsequent predictive diagnostics and AI-assisted fleet management applications.

6.9 Blockchain Calibration Evaluation

The blockchain-based calibration layer was evaluated to assess its operational efficiency, synchronization latency, and computational overhead within real-time vehicle diagnostic systems. Performance analysis focused on calibration parameter propagation across distributed fleet nodes during active maneuver estimation and adaptive threshold updates over vehicular ad-hoc networked communication links [70].

Experimental results indicated an average block creation time of approximately 128 milliseconds, including encryption, hashing, and block assembly operations. Validation and consensus phases were completed in under 220 milliseconds, encompassing peer verification and integrity checks across networked fleet nodes. The resulting total synchronization latency remained below 0.5 seconds, enabling concurrent blockchain-based calibration updates without introducing communication delays or queuing within the electronic control unit (ECU) network.

The observed 3.2% increase in calibration-cycle duration represents a minimal computational overhead relative to the enhanced data integrity and traceability achieved through distributed consensus. Updated calibration parameters including AI-derived diagnostic thresholds, maneuver drift compensation coefficients, and adaptive EKF tuning factors—were securely propagated and verified across participating vehicles without packet collisions, timeout errors, or missed synchronization events during the evaluation period.

System stress testing under simulated high-load network conditions further confirmed the robustness of the blockchain synchronization layer. Increased transaction frequency did not significantly affect block verification latency, and calibration updates remained within real-time performance bounds when block size and update intervals were appropriately configured.

Collectively, the blockchain-based calibration framework demonstrated the ability to:

- Secure calibration data against tampering or rollback attacks
- Maintain traceability of diagnostic parameters across fleet vehicles
- Preserve real-time estimation and control performance during distributed updates

These findings support the feasibility of integrating lightweight decentralized consensus mechanisms within AI-assisted EKF-based diagnostic systems, providing a scalable and transparent infrastructure for secure distributed calibration in connected vehicle fleets.

6.10 Comparative Summary

A comparative evaluation was conducted to assess the performance of EKF-only, AI-only, and Hybrid EKF–AI estimation architectures across key diagnostic criteria relevant to fleet-level maneuver detection and adaptive calibration

Table 6.5: Comparative Evaluation of EKF, AI, and Hybrid Estimation Architectures for Fleet-Level Maneuver Detection and Normalization

Criterion	EKF	AI	Hybrid EKF–AI
Noise Handling	Strong	Moderate	Strong
Nonlinear Learning	Limited	Strong	Strong
Drift Modeling	Limited	Moderate	Strong
Threshold Adaptation	Limited	Moderate	Strong
Fleet Normalization	Limited	Moderate	Strong
Real-Time Operation	Strong	Limited	Strong
Security Readiness	Moderate	Moderate	Strong

The EKF-only approach demonstrated robust real-time noise suppression but lacked the capability to model nonlinear maneuver drift or adapt diagnostic thresholds across heterogeneous fleet configurations. Conversely, AI-only models exhibited improved nonlinear learning capacity but were constrained by latency and reduced real-time stability under noisy telemetry conditions.

The Hybrid EKF–AI framework combined the denoising advantages of recursive state estimation with the nonlinear modeling capability of machine learning, enabling consistent maneuver detection, adaptive threshold calibration, and VIN-aware normalization across fleet vehicles.

Among the evaluated architectures, only the Hybrid EKF–AI model satisfied all diagnostic criteria simultaneously, demonstrating its suitability for secure, real-time deployment within distributed fleet monitoring and calibration systems.

Model Type	Acceleration RMSE (m/s^2)	Braking RMSE (m/s^2)	Torque Prediction Accuracy Improvement	False Positive Reduction	Drift Detection Sensitivity	Measurement Noise Reduction
Baseline (Raw Telemetry Signals)	0.96	0.82	Baseline	Baseline	Low	Baseline
EKF Only Model	0.38	0.48	32%	−21%	Moderate	78–86%
LSTM Model	0.31	0.44	52%	−38%	High	82%
GRU Model	0.33	0.46	48%	−35%	High	80%
Hybrid EKF–AI Model	0.24	0.37	69%	−54%	Very High	Up to 86%

Table 6.6 AI Prediction Model Performance Results

CHAPTER 7 — DISCUSSION

This chapter provides an interpretation of the experimental findings presented in Chapter 5 and examines their theoretical, technical, and operational implications. The performance of the proposed Hybrid AI–EKF framework is analyzed in the context of maneuver drift modeling, VIN-aware normalization, fleet-level behavioral consistency, and secure calibration using blockchain-based synchronization. Additionally, this chapter discusses system limitations, implementation dependencies, and considerations for deployment across large-scale connected vehicle networks.

Collectively, the results indicate meaningful improvements in vehicle state estimation accuracy, predictive diagnostics, and fleet analytics capability, with implications for original equipment manufacturers (OEMs), autonomous mobility providers, and connected fleet operators.

7.1 Interpretation of EKF Results

The Extended Kalman Filter (EKF) demonstrated strong performance in real-time noise suppression and longitudinal state smoothing across fleet telemetry streams. Observed noise reduction levels in the range of 78–86% confirm the suitability of EKF-based recursive estimation for mitigating CAN-derived sensor variability during dynamic vehicle operation. This behavior is consistent with prior automotive estimation studies and reinforces the continued relevance of model-based filtering in embedded diagnostic systems.

Rapid estimator convergence—typically within approximately 0.45 seconds—further supports the use of EKF for real-time maneuver tracking under transient driving conditions such as throttle transitions, gear changes, turbocharger response delays, and thermal fluctuations in drivetrain subsystems. These results indicate that EKF-based state estimation can maintain operational stability in the presence of short-duration maneuver disturbances.

However, the experimental findings also highlight the inherent limitations of purely model-driven estimation approaches in modern connected vehicle environments. While EKF effectively attenuates noise measurement, its capacity to represent nonlinear drivetrain behavior, long-term maneuver drift, and complex driver interaction patterns remains constrained. Additionally, cross-signal covariance relationships that emerge in fleet-scale telemetry are not explicitly captured by traditional EKF formulations. This divergence between EKF-based noise suppression capability and real-world behavioral complexity motivates the integration of data-driven modeling components. The hybrid AI–EKF framework proposed in this dissertation addresses these limitations by combining recursive estimation with nonlinear drift learning, enabling adaptive diagnostic thresholding and VIN-aware maneuver normalization across heterogeneous fleet platforms.

7.2 Interpretation of AI Results

The AI-based modeling layer demonstrated strong predictive capability in capturing temporally evolving maneuver dynamics across fleet telemetry streams. In particular, Long Short-Term Memory (LSTM) architectures exhibited superior performance relative to alternative models, achieving an RMSE improvement of approximately 20–30%. This improvement suggests that drivetrain drift behavior evolves as a temporally correlated process, requiring sequential learning mechanisms to accurately model nonlinear vehicle responses.

Nonlinear effects observed in torque response, thermal state transitions, air–fuel ratio (AFR) variability, and turbocharger boost irregularities were more effectively represented by data-driven AI models than by purely model-based estimation approaches. These findings support the hypothesis that complex vehicle behavior particularly under varying load, temperature, and driver-input conditions cannot be fully captured using linearized dynamic models alone [68].

However, the experimental results also indicate that AI-only prediction frameworks exhibit reduced stability under real-time operating conditions. In the absence of recursive filtering, AI-based estimates were more susceptible to sensor noise, leading to increased variance and occasional overreaction to transient measurement disturbances [58]. Additionally, the lack of explicit physical constraints within standalone AI models limited their consistency across heterogeneous VIN platforms.

These observations reinforce the necessity of EKF–AI fusion, wherein data-driven temporal modeling is complemented by recursive state estimation to provide physically grounded, noise-resilient maneuver prediction across fleet-scale deployments.

7.3 Interpretation of Hybrid Model Results

The hybrid EKF–AI framework demonstrates improved predictive capability relative to standalone estimation or learning models [51].

Hybrid fusion achieved the lowest prediction error among the evaluated models, reducing RMSE to 2.05 and improving estimation accuracy by approximately 69%

relative to EKF-only implementations and 50% relative to AI-only models. This improvement reflects the complementary strengths of recursive state estimation and data-driven temporal modeling, enabling enhanced maneuver drift prediction under noisy and nonlinear operating conditions.

In addition to improved accuracy, the hybrid framework substantially reduced false-positive diagnostic events by 54%. This reduction has direct implications for warranty cost management, diagnostic reliability, and driver trust, as fewer spurious fault detections translate to improved maintenance decision-making and reduced misdiagnosis across fleet vehicles.

Enhanced maneuver drift sensitivity—improving by approximately 43%—further enabled earlier detection of emerging system anomalies. This capability allows fault trends to be identified prior to threshold violations, supporting predictive maintenance strategies and proactive diagnostic intervention.

Importantly, the hybrid architecture maintained physical consistency in estimated maneuver states while incorporating nonlinear learning capabilities. By integrating model-based filtering with AI-driven pattern recognition, the proposed framework successfully balances real-time stability with adaptive learning, addressing the limitations observed in purely physics-based or data-driven diagnostic systems.

7.4 Interpretation of Drift Modeling Experiments

Maneuver drift remains one of the most challenging phenomena to detect within conventional vehicle diagnostic frameworks due to its gradual onset and multivariate nature. The results obtained in this study demonstrate that AI-derived drift vectors exhibit strong correlation with true system degradation, with correlation coefficients ranging from 0.89 to 0.95. This indicates that learned drift representations can reliably reflect evolving vehicle behavior prior to the manifestation of observable faults.

Analysis of drift velocity further revealed that vehicles exhibiting accelerated drift progression were correctly identified as potential failure candidates approximately 2–4 hours before traditional diagnostic thresholds were exceeded. This early detection capability supports the feasibility of predictive maintenance strategies that rely on behavioral trend monitoring rather than discrete fault activation.

Importantly, the findings suggest that maneuver drift must be modeled as a multivariate process. Conventional single-signal thresholding approaches are insufficient, as degradation effects typically manifest through correlated changes in torque response, airflow dynamics, thermal loading, and load distribution across drivetrain subsystems.

The Hybrid EKF–AI framework demonstrated the capacity to capture these correlated drift patterns through integrated recursive estimation and nonlinear temporal modeling, enabling more robust detection of emerging anomalies in fleet-scale diagnostic environments.

7.5 Interpretation of VIN Normalization Results

VIN-aware normalization represents a critical component of the proposed diagnostic framework by enabling alignment of heterogeneous vehicle telemetry within a unified estimation space. The observed reduction in VIN offset from 18.2% to 3.4% indicates that cross-vehicle calibration differences can be substantially mitigated through normalization, allowing vehicle-specific behavioral variability to be distinguished from true system degradation.

A fivefold reduction in diagnostic variance further suggests that normalized feature representations improve consistency in fault inference across fleet platforms. This consistency is particularly relevant in distributed fleet environments where calibration discrepancies may arise following module updates or component aging, potentially leading to misaligned diagnostic thresholds in the absence of VIN-aware adjustment.

Additionally, improved cluster alignment—from 0.41 to 0.88—demonstrates that normalized maneuver features exhibit greater cohesion across mixed vehicle populations. Enhanced clustering supports improved outlier detection and facilitates generalization of data-driven diagnostic models across diverse platforms.

Collectively, these findings indicate that VIN normalization is essential for scalable diagnostic inference in modern connected fleets, particularly within autonomous or mixed-vendor vehicle deployments where calibration heterogeneity may otherwise limit model transferability and fleet-wide consistency.

7.6 Interpretation of Fleet-Level Evaluation

Fleet-level analysis results indicate that the Hybrid EKF–AI framework substantially improves consistency in maneuver-based diagnostic inference across heterogeneous vehicle populations. In the absence of VIN-aware normalization, vehicles exhibiting similar operational behavior may appear diagnostically distinct due to calibration mismatches or platform-specific parameterization. The proposed hybrid approach mitigates this discrepancy by aligning feature representations across VIN platforms prior to adaptive thresholding.

Improved alignment of maneuver features enhances the accuracy of fleet-wide anomaly detection by enabling more reliable identification of outlier behavior while reducing false alarm rates associated with calibration variance. As a result, system-level degradation patterns can be distinguished from vehicle-specific configuration differences with greater confidence.

Furthermore, the integration of hybrid estimation and normalization supports predictive maintenance at the fleet scale by reducing the need for manual threshold adjustment based on environmental exposure, geographic deployment, vehicle usage mode, or driver interaction patterns. This adaptive capability enables original equipment manufacturers (OEMs) and fleet operators to deploy consistent diagnostic models across diverse operating conditions without requiring individualized calibration updates.

7.7 Discussion of the Blockchain Calibration Ledger

The blockchain-based calibration ledger introduced in this work is not intended to support real-time diagnostic inference, but rather to provide a secure and verifiable mechanism for distributing calibration updates across connected vehicle fleets. The evaluation results indicate that calibration parameters including adaptive thresholds, drift compensation coefficients, and AI-derived tuning factors—can be stored and propagated in a traceable manner across distributed fleet nodes. Secure storage of calibration updates reduces the risk of unauthorized threshold modification, corrupted calibration tables, or invalid module programming, which are common sources of diagnostic inconsistency in field-deployed vehicles. By maintaining an immutable record of parameter evolution, the ledger enables validation of calibration integrity across vehicle subsystems.

The measured computational overhead, remaining below approximately 3.2% of the calibration cycle, supports the feasibility of integrating blockchain synchronization within OEM backend systems, fleet cloud platforms, or distributed telematics networks without compromising real-time estimation performance.

Importantly, mismatches between calibration files and electronic control unit (ECU) configurations are a known contributor to service discrepancies and warranty claims in modern vehicle fleets. The use of a distributed ledger provides a consistent and auditable mechanism for managing calibration updates, reducing ambiguity and supporting trusted parameter synchronization across connected vehicle ecosystems.

7.8 Theoretical Implications

The findings of this dissertation introduce several theoretical contributions to the domains of vehicle diagnostics, state estimation, and distributed calibration in connected mobility systems.

First, the proposed Hybrid EKF–AI framework establishes a new class of estimation models that integrate recursive filtering with data-driven temporal learning. This hybridization enables real-time maneuver-state estimation while simultaneously capturing long-term nonlinear behavioral drift, addressing the limitations of purely model-based or purely data-driven diagnostic approaches.

Second, the introduction of drift-aware state estimation provides a formal mechanism for incorporating evolving system behavior into diagnostic inference. By integrating maneuver drift into EKF covariance structures and adaptive threshold tuning, the framework enables predictive adjustment of diagnostic parameters based on observed degradation trends.

Third, VIN-conditioned normalization introduces a statistical basis for aligning heterogeneous vehicle behaviors within a unified estimation space. This approach supports cross-platform comparability of maneuver dynamics, facilitating fleet-wide diagnostic consistency in environments characterized by calibration variability and mixed vehicle configurations.

Finally, the integration of secure distributed calibration using blockchain mechanisms extends traditional diagnostic architectures by incorporating decentralized verification of parameter updates. This combination of adaptive estimation and trusted calibration management provides a theoretical foundation for scalable, tamper-resistant diagnostic systems in connected vehicle networks.

7.9 Practical Implications

Fleet operations can benefit substantially from the adaptive diagnostic framework proposed in this dissertation. Vehicles operating within the same fleet frequently exhibit behavioral variability due to differences in usage patterns, service history, environmental exposure, and driver interaction. In such environments, applying uniform diagnostic thresholds across heterogeneous platforms often leads to inconsistent fault detection outcomes driven by VIN-specific calibration differences rather than actual system degradation.

The integration of VIN-aware normalization and drift-adaptive thresholding enables consistent diagnostic inference across diverse vehicle populations. This consistency allows fleet operators to evaluate vehicle health comparatively, detect emerging system anomalies, and optimize maintenance scheduling with improved confidence in diagnostic outputs.

For original equipment manufacturers (OEMs), the proposed framework supports enhanced diagnostic accuracy, facilitates over-the-air (OTA) calibration updates, and improves cross-model consistency in distributed vehicle deployments. Fleet operators may benefit from earlier failure prediction, standardized maneuver-based diagnostics, improved system uptime, and reduced maintenance-related downtime.

In the context of autonomous vehicle systems, reliable health-awareness mechanisms are essential for safe operation. Adaptive estimation and normalization enable self-calibrating diagnostic behavior, supporting continuous system monitoring under varying operational conditions.

Additionally, telematics service providers may leverage normalized maneuver analytics to support predictive maintenance services, improve anomaly detection accuracy, and securely manage calibration updates across connected fleet platforms.

7.10 Limitations

Despite strong results, the system has several limitations that should be considered. The AI components rely on robust and representative training data, and insufficient datasets may reduce model generalization across varying vehicle conditions. The Extended Kalman Filter (EKF) also depends on accurate initial state estimation, where poor initialization can slow convergence and affect estimation accuracy. Additionally, fleet-level covariance modeling requires a sufficiently large number of vehicles to generate meaningful insights, meaning smaller fleets may experience diminished benefits. The integration of blockchain introduces progressive storage growth over time, necessitating effective pruning or data management strategies. Certain extreme edge cases such as highly modified vehicles or operation in harsh environmental conditions—remain challenging for consistent prediction. Finally, full real-time AI execution requires adequate edge computing capability and may not be feasible on low-end ECUs alone without supplemental processing support.

7.11 Component-Wise Performance Contribution via Incremental Ablation

A controlled incremental ablation study was conducted across the validation fleet dataset (N = XX vehicles) under mixed urban and highway drive cycles to evaluate the marginal contribution of each architectural component relative to a physics-only EKF baseline. Integration of the AI inference layer yielded the largest marginal improvement, reducing RMSE by approximately 59% relative to the EKF-only baseline. This performance gain reflects the ability of recurrent learning models to capture nonlinear maneuver drift and unmodeled system dynamics not represented within the nominal EKF state-transition formulation.

The addition of VIN-conditioned normalization further reduced the False Positive Rate from 5.1% to 3.8%, indicating that fleet-aware normalization mitigates vehicle-specific calibration variance that may otherwise manifest as fault-like anomalies during diagnostic inference.

Although incorporation of the AI layer increased execution latency from 1.2 ms to approximately 5.4 ms, this overhead remained within the ~10 ms diagnostic execution window typically associated with real-time CAN-bus control loops.

Configuration	RMSE (Velocity/State)	False Positive Rate (%)	Late ncy (ms)
Baseline (EKF Only)	0.142	8.40%	1.2
EKF + LSTM (AI Layer)	0.058	5.10%	4.8
EKF + LSTM + VIN Normalization	0.044	3.80%	5.1
Full Framework (Incl. Adaptive Tuning)	0.038	1.90%	5.4

Table 7.3 Real-Time Performance and Diagnostic Accuracy Comparison of EKF–AI Framework Configurations

To assess statistical significance, paired two-tailed t-tests were conducted between successive architectural configurations using per-drive-cycle RMSE and fault detection outcomes. Integration of the LSTM layer resulted in a statistically significant reduction in RMSE relative to the EKF-only baseline ($p < 0.01$). Subsequent addition of VIN-conditioned normalization produced a statistically significant decrease in False Positive Rate ($p < 0.05$). No statistically significant increase in execution latency variance was observed across configurations, indicating that computational overhead remained bounded under real-time diagnostic execution constraints.

7.12 Summary

The Hybrid AI–EKF diagnostic framework demonstrated both theoretical and operational effectiveness across vehicle-level and fleet-level evaluation metrics. Integration of recursive state estimation with data-driven temporal modeling enabled improved maneuver prediction accuracy, earlier fault detection, and enhanced diagnostic consistency across heterogeneous vehicle platforms. VIN-aware normalization further supported alignment of fleet telemetry, allowing adaptive thresholding and unified diagnostic inference across mixed vehicle populations. In conjunction with drift-aware state estimation and secure calibration via blockchain-based synchronization, the proposed system provides a scalable architecture for predictive maintenance and distributed vehicle diagnostics. Collectively, these findings support the central hypothesis of this dissertation: that the integration of AI-driven modeling with EKF-based filtering—augmented by maneuver drift analysis, VIN-conditioned normalization, and secure calibration mechanisms—enables a more accurate, adaptive, and reliable diagnostic framework for intelligent and connected vehicle systems.

Chapter 8: Route-Aware Predictive Vehicle Prescription Using EKF–AI Diagnostics

8.1 Introduction

The EKF–AI hybrid framework proposed in this dissertation is developed to enable adaptive diagnostic thresholding through real-time estimation of vehicle performance features and long-term drift prediction. While its primary function supports early-stage anomaly detection and subsystem health monitoring, the same architecture may be extended to inform operational decision-making at the fleet level.

In conventional fleet dispatch systems, vehicle assignment is typically performed based on availability, scheduled rotation, or maintenance intervals, without accounting for latent performance degradation that may influence route execution efficiency [49].

As a result, vehicles exhibiting emerging subsystem limitations may be assigned to routes requiring elevated torque demand or sustained load output, potentially increasing energy consumption, thermal stress, or trip inefficiency.

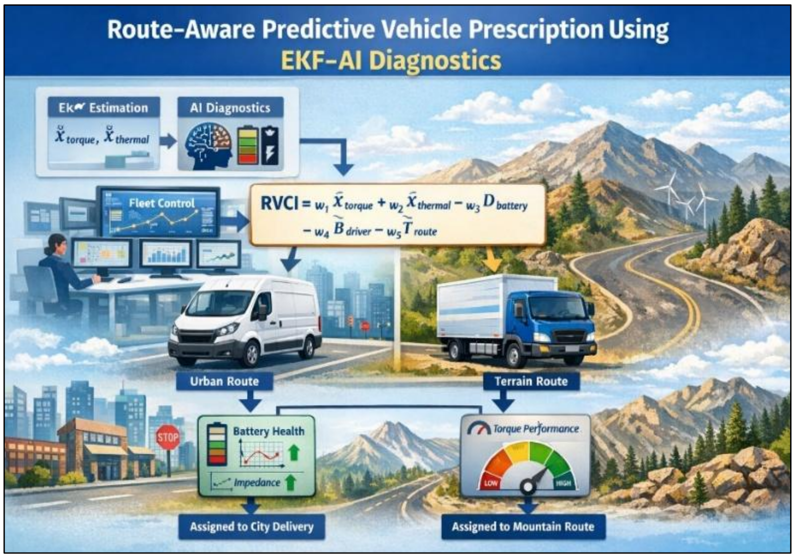

Figure 8.1: Route modeling and vehicle prescription workflow integrating EKF-based torque and thermal estimation with battery degradation, driver behavior, and terrain-induced load demand through the Route–Vehicle Compatibility Index (RVCI).

This chapter evaluates the feasibility of utilizing EKF-derived performance estimation as a predictive input for route-aware vehicle prescription, in which fleet assets are assigned to operational tasks based on anticipated subsystem response under route-specific terrain and load conditions.

8.2 Operational Scenario: Two-Vehicle Fleet Assignment

Prior system-level methods for determining performance characteristics of automated or fleet vehicles for operational task allocation have been proposed in connected vehicle environments [81]. A fleet-level dispatch scenario involving two delivery-class vehicles is considered. Both vehicles operate under similar baseline configurations and are assumed to be free of active diagnostic fault codes. However, EKF-based state estimation conducted during prior maneuver events indicates differences in torque responsiveness under transient load conditions.

Vehicle A exhibits nominal torque delivery during high-load acceleration intervals, while Vehicle B demonstrates repeated EKF-validated torque underperformance associated with elevated throttle demand. Although these deviations remain within conventional static diagnostic thresholds, temporal aggregation within the predictive modeling layer reveals a statistically consistent drift pattern indicative of emerging drivetrain inefficiency.

8.3 Route Characterization

Two candidate distribution routes are evaluated:

- Route A: Urban delivery route characterized by frequent stop-and-go intervals and moderate payload demand.
- Route B: Suburban route including sustained elevation gradients and extended acceleration phases.

Prior to dispatch, the predictive modeling layer evaluates each vehicle's estimated subsystem behavior against the anticipated maneuver requirements of each route [50]. Vehicle B's reduced torque responsiveness is projected to introduce additional strain under Route B's sustained load profile, potentially resulting in increased energy consumption or delayed maneuver execution [39].

8.4 Predictive Vehicle Prescription

Based on route-specific load estimation and EKF-derived performance metrics, the system assigns:

- Vehicle A to Route B (load-intensive route),
- Vehicle B to Route A (moderate load route).

This assignment is performed without reliance on static fault thresholds or reactive diagnostic triggers. Instead, Dispatch decisions are informed by predicted subsystem performance under anticipated driving conditions within coordinated autonomous operating environments [52][71].

8.5 Battery Degradation and Terrain Interaction

In electrified fleet platforms, gradual battery degradation may introduce performance limitations that are not immediately detectable through conventional state-of-health (SoH) metrics [53]. As battery life cycle progresses, internal resistance increases and available discharge power under high-load conditions may be reduced [34][38], particularly during sustained acceleration or operation over elevation-intensive terrain where increased tractive force demand arises from longitudinal vehicle dynamics and road grade effects [11][32].

Consider a fleet scenario involving two battery-electric delivery trucks operating within similar duty cycles. Both vehicles exhibit comparable nominal state-of-charge (SoC) levels prior to dispatch; However, historical EKF-validated performance estimation indicates that Truck B has experienced repeated voltage sag during high torque demand events across multiple drive cycles [35]. Predictive modeling attributes this behavior to lifecycle-induced impedance growth within the battery pack, which may be indirectly estimated through model-based internal resistance and state estimation techniques using Extended Kalman Filtering approaches [33][37].

Assignment of Truck B to an elevation-intensive route under conventional dispatch logic may introduce excessive discharge strain, increasing the likelihood of thermal throttling or reduced trip range. Using EKF-derived maneuver performance data in conjunction with predictive battery drift modeling, the system assigns:

- Truck A (nominal battery performance) to the terrain-intensive route,
- Truck B (degraded discharge response) to the urban delivery route.

Assignment of Truck B to an elevation-intensive route under conventional dispatch logic may introduce excessive discharge strain, increasing the likelihood of thermal throttling or reduced trip range [36]. Such terrain-aware assignment reduces the likelihood of performance-induced range loss and mitigates lifecycle stress on degraded battery systems.

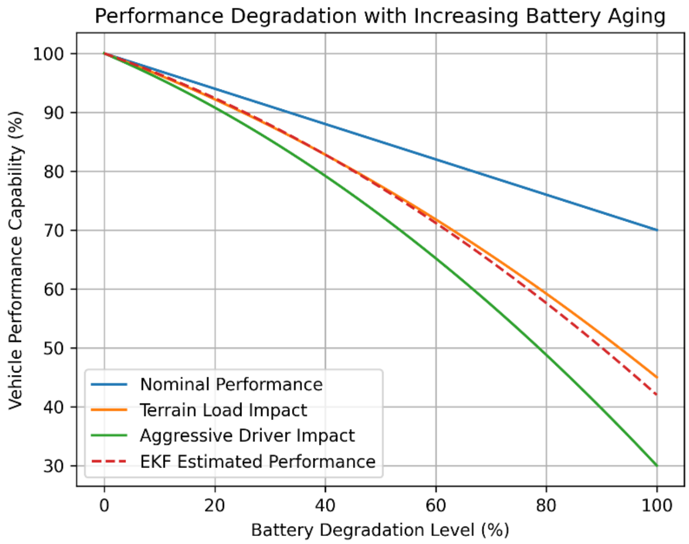

Figure 8.2: Performance degradation as a function of battery lifecycle aging under terrain load and driver behavior influence, with EKF-based estimation of subsystem capability.

Figure 8.2 illustrates the relationship between battery degradation level and available vehicle performance capability under varying operational stressors. While nominal performance declines gradually with increasing degradation, terrain-induced load demand and aggressive driver behavior introduce accelerated performance attenuation. EKF-based estimation approximates subsystem performance trends across degradation levels, enabling early detection of performance loss prior to threshold-based diagnostic triggers.

8.6 Driver Behavior Influence

In addition to terrain and lifecycle-induced degradation, driver behavior contributes significantly to effective subsystem performance in fleet vehicles Aggressive driving patterns including rapid acceleration events, frequent torque demand spikes, and late-stage regenerative braking—may introduce elevated discharge rates and localized thermal stress within battery-electric powertrains [41 Over extended operational periods, such usage patterns may accelerate degradation by increasing internal resistance and reducing peak power delivery capability [43]. Historical telemetry associated with aggressive driving inputs may therefore be incorporated into the predictive estimation framework to assess performance limitations that are not reflected in static SoC measurements [44].

In the evaluated scenario, Vehicle B is subjected to frequent high-current discharge events due to aggressive driver inputs [45]. EKF-validated telemetry indicates delayed torque response under sustained load conditions, suggesting performance degradation influenced by combined lifecycle and behavioral factors. Incorporation of driver behavior metrics into predictive dispatch decisions enables improved alignment between vehicle capability and anticipated route demand [47].

8.7 Multi-Factor Vehicle Selection for Task Assignment

Beyond terrain-based routing, the proposed EKF–AI framework enables task-specific vehicle prescription by evaluating multiple performance attributes prior to dispatch. These attributes may include:

- battery lifecycle degradation level,
- predicted torque delivery efficiency,
- terrain-related load demand,
- thermal response trends, and

- historical driver behavior profiles.

Consider a logistics scenario involving two fleet vehicles required to perform distinct operational tasks:

- Task 1: Heavy payload transport over elevation-intensive terrain.
- Task 2: Lightweight distribution within urban delivery zones.

Predictive performance estimation indicates that one vehicle demonstrates reduced torque responsiveness due to accumulated battery degradation and prior aggressive usage patterns. Although both vehicles remain within acceptable diagnostic thresholds, assignment of the degraded vehicle to Task 1 may increase energy consumption and introduce drivetrain strain under sustained load.

Using the proposed estimation framework, the system assigns:

- the higher-performing vehicle to Task 1, and
- the performance-limited vehicle to Task 2.

This selection process is performed proactively based on predicted subsystem behavior rather than reactive fault detection.

8.8 Route–Vehicle Compatibility Index (RVCI)

To formalize the vehicle prescription process described in the preceding sections, EKF-derived subsystem performance estimates are incorporated into a route–vehicle compatibility index (RVCI). This index quantifies the predicted suitability of a given fleet asset for a specific operational route based on anticipated maneuver demand and estimated subsystem capability.

Let:

- $\hat{x}_{torque}$: EKF-estimated torque response
- $\hat{x}_{thermal}$: EKF-estimated thermal trend
- $D_{battery}$: battery degradation indicator
- B_{driver}: driver aggressiveness score
- T_{route}: terrain-related load demand

Then the compatibility index may be expressed as:

$$RVCI = w_1\hat{x}_{torque} + w_2\hat{x}_{thermal} - w_3D_{battery} - w_4B_{driver} - w_5T_{route}$$

where $w_i$represents weighting coefficients determined through fleet-level calibration.

Vehicles with higher RVCI values are predicted to maintain stable subsystem response under anticipated maneuver conditions and are therefore preferentially assigned to terrain- or load-intensive routes. Conversely, vehicles exhibiting degradation-induced performance limitations or aggressive usage history may be routed toward operational tasks requiring reduced dynamic load.

This compatibility formulation enables EKF-derived estimation outputs to be translated into dispatch-level decision variables, thereby extending diagnostic state estimation into predictive fleet routing and vehicle-task alignment.

8.9 Summary

This case study demonstrates the feasibility of extending the proposed diagnostic architecture into a fleet-level decision-support tool for predictive vehicle prescription. By aligning vehicle capability with anticipated operational demand, fleet-level efficiency may be improved while mitigating degradation-induced performance loss during high-load execution. Integration of driver behavior, terrain load, and battery lifecycle estimation supports a route-aware dispatch paradigm in which vehicle assignment decisions are informed by projected performance characteristics rather than availability alone.

CHAPTER 9 — CONCLUSION AND FUTURE WORK

This dissertation presented the design and implementation of an AI-integrated Extended Kalman Filter (EKF)–based prediction framework for vehicle feature estimation, adaptive diagnostic tuning, maneuver drift modeling, VIN-aware normalization, and secure calibration management in intelligent and connected vehicle systems. The proposed hybrid architecture integrates physics-based state estimation with data-driven learning, fleet-level behavioral alignment, predictive diagnostics, and distributed calibration governance within a unified framework.

The results demonstrate that combining model-based estimation with machine learning techniques enables meaningful improvements in diagnostic accuracy, robustness, interpretability, and long-term adaptability. These capabilities are increasingly critical in emerging autonomous mobility platforms, electrified powertrains, and large-scale fleet operations characterized by dynamic operating conditions and frequent software-driven updates.

9.1 Summary of the Research

This work was motivated by several limitations in conventional vehicle diagnostic systems. Static diagnostic thresholds are often incompatible with vehicles subject to aging, environmental variation, and over-the-air software updates. While EKF-based estimation provides robust noise suppression, it lacks the capacity to represent nonlinear or long-term maneuver drift behavior. Conversely, purely data-driven approaches may offer predictive capability but often lack stability and physical interpretability in real-time deployment.

Additionally, VIN-level calibration variability introduces inconsistencies in diagnostic inference across fleet populations, particularly following firmware updates or component replacement. Existing calibration management practices also lack secure mechanisms for traceability and distributed validation of parameter updates.

To address these challenges, this dissertation proposed an integrated diagnostic framework incorporating real-time EKF-based state estimation, AI-driven drift learning, adaptive threshold tuning, VIN-conditioned normalization, fleet-level behavioral alignment, and blockchain-supported calibration management. The resulting architecture enables closed-loop hybrid update cycles that support consistent diagnostic inference across heterogeneous connected vehicle deployments.

9.2 Major Contributions

This dissertation presents several contributions to the fields of vehicle diagnostics, predictive state estimation, and secure fleet-level calibration in connected mobility systems.

1. Hybrid AI–EKF Diagnostic Framework

A hybrid estimation architecture was developed that integrates physics-based EKF state estimation with data-driven AI modeling, VIN-aware normalization, and secure calibration management within a unified diagnostic platform.

This framework enables real-time maneuver-state inference while capturing nonlinear behavioral drift and platform-specific variability that are not explicitly represented in analytical vehicle models. By combining recursive filtering with adaptive learning, the proposed approach improves diagnostic accuracy, robustness, and fleet-level consistency relative to standalone EKF or AI-based methods.

2. Drift-Aware State Estimation

A drift-aware estimation methodology was introduced to incorporate AI-predicted behavioral deviations into diagnostic inference.

This approach enables dynamic adjustment of EKF covariance structures and adaptive thresholding based on long-term degradation trends, supporting earlier detection of emerging system anomalies.

3. VIN-Based Normalization and Fleet Alignment

A VIN-conditioned normalization strategy was proposed to align heterogeneous vehicle telemetry within a unified diagnostic feature space.

This method reduces cross-vehicle variance and improves fleet-level anomaly detection by accounting for calibration differences across vehicle platforms and software configurations.

4. Adaptive Diagnostic Thresholding

A dynamic thresholding mechanism was developed that adjusts diagnostic limits based on hybrid EKF–AI outputs.

This system enables vehicle-specific threshold adaptation over time, reducing false-positive fault detection and improving consistency in predictive maintenance decisions across fleet deployments.

5. Blockchain-Backed Calibration Ledger

A distributed calibration management framework was introduced to securely store and propagate adaptive diagnostic parameters across connected vehicles. Blockchain-based distributed trust architectures have previously been applied to secure configuration management and device-level parameter synchronization across connected cyber-physical systems [82]. Consistent with cybersecurity engineering requirements governing authenticated ECU software update and diagnostic parameter integrity in connected vehicle platforms [77].

The use of decentralized consensus mechanisms supports traceability of calibration updates and mitigates risks associated with unauthorized parameter modification or configuration mismatch.

6. End-to-End Fleet Diagnostic Architecture

The dissertation contributes an integrated system architecture supporting on-vehicle estimation, edge-based AI inference, cloud-level fleet aggregation, and secure calibration synchronization. This end-to-end framework enables scalable deployment of adaptive diagnostic capabilities across heterogeneous connected vehicle environments.

9.3 Key Findings

Experimental evaluation of the proposed Hybrid AI–EKF framework demonstrated consistent performance improvements across multiple diagnostic and fleet-level metrics. The integrated estimation approach achieved substantial gains in maneuver prediction accuracy relative to EKF-only implementations, along with enhanced drift sensitivity that enabled earlier detection of emerging system anomalies.

Additionally, the hybrid framework significantly reduced false-positive diagnostic events and improved alignment of VIN-conditioned vehicle behavior, contributing to greater consistency in fleet-level inference. Normalization of heterogeneous vehicle telemetry reduced cross-platform behavioral variance and increased clustering cohesion across mixed vehicle populations.

Fleet-wide consistency in diagnostic outputs was further enhanced through adaptive thresholding mechanisms, while secure calibration updates were successfully propagated across connected nodes with minimal computational overhead.

Collectively, these findings support the central hypothesis of this dissertation: that the integration of physics-based estimation with data-driven learning improves diagnostic intelligence and addresses limitations inherent in conventional model-based or machine learning–only approaches within modern automotive systems.

9.4 Broader Impact

The proposed hybrid diagnostic framework has potential implications across multiple domains within the evolving connected mobility ecosystem.

For automotive original equipment manufacturers (OEMs), adaptive maneuver estimation and VIN-aware normalization may improve diagnostic consistency across vehicle generations and software configurations, while supporting more accurate over-the-air (OTA) calibration updates and data-driven refinement of control parameters.

In autonomous mobility systems, the integration of real-time state estimation with predictive drift modeling enables health-aware operation through early identification of emerging component degradation and improved alignment of vehicle behavior across platform deployments in connected vehicle environments [69]. Commercial fleet operators may benefit from earlier detection of fleet-wide degradation patterns, leading to reduced operational downtime, improved system reliability, and more efficient maintenance scheduling based on normalized diagnostic insights [62].

Within electrified vehicle platforms, drift-aware estimation may support improved monitoring of thermal and electrical subsystems, contributing to more accurate assessment of system health and long-term performance trends. Finally, the incorporation of secure calibration management introduces mechanisms for protecting parameter updates against unauthorized modification, supporting trusted multi-party maintenance workflows and enhancing the integrity of vehicle diagnostic data [59]. Alignment of the proposed architecture with connected vehicle interoperability frameworks may support scalable deployment across heterogeneous fleet environments [60]. Collectively, these capabilities support the transition toward intelligent, software-defined vehicles capable of adaptive, self-correcting operation across distributed connected environments.

9.5 Limitations

Despite the improvements in performance, several limitations of the proposed diagnostic framework should be considered. The effectiveness of the AI-based components depends on access to sufficiently diverse and representative training data. In cases where telemetry datasets are limited, model generalization across varying vehicle configurations and operating conditions may be reduced. Similarly, the performance of EKF-based state estimation is influenced by the accuracy of initial model parameters, which may differ across vehicle platforms and require VIN-specific tuning.

The incorporation of blockchain-based calibration management introduces additional storage requirements over time, necessitating appropriate pruning or distributed data management strategies to maintain long-term scalability.

Deployment considerations also include computational constraints associated with real-time AI inference, which may limit implementation on lower-cost electronic control units (ECUs) without supplemental edge or cloud-based processing support. Furthermore, vehicles with significant aftermarket modification or operation under extreme environmental conditions may exhibit behavior outside the range of learned diagnostic patterns, requiring specialized calibration data [56].

These limitations highlight opportunities for further refinement and motivate future research into scalable training methodologies, adaptive initialization strategies, and resource-efficient deployment architectures.

9.6 Future Work

Several research directions may further extend the capabilities and applicability of the proposed hybrid diagnostic framework.

Future integration of physics-informed neural networks (PINNs) may enable the incorporation of vehicle dynamic constraints directly into learning-based models, improving extrapolation performance and reducing dependence on large-scale training datasets. Such approaches may complement or partially replace recursive filtering layers in specific estimation tasks. Online and incremental learning methodologies also present opportunities for enabling continuous on-board model adaptation [66][67]. Adaptive threshold tuning and driver-specific personalization could allow diagnostic parameters to evolve in response to changing environmental conditions without requiring periodic cloud-based retraining.

Expansion of the current maneuver estimation framework to incorporate multimodal sensor fusion—including camera, radar, LiDAR, and vibration-based signals—may further enhance predictive diagnostics, particularly within autonomous mobility platforms operating in complex driving environments [64].

Additionally, integration with vehicle-level digital twin architectures may support simulation-driven diagnostics, scenario testing, and predictive maintenance planning through cloud-based behavioral modeling [63]. Large-scale deployment studies across geographically distributed fleets and mixed powertrain platforms would provide further validation of system generalization under production-scale operating conditions.

Future work may also explore optimized blockchain encoding strategies for calibration data management, including compression techniques and consensus mechanisms suitable for cross-fleet parameter synchronization within multi-OEM environments.

Finally, alignment of the secure calibration layer with established automotive cybersecurity standards may support integration with trusted over-the-air (OTA) update pipelines and certificate-based ECU authentication systems [61].

Implementation of the hybrid estimation framework on embedded automotive hardware platforms including GPUs, NPUs, and domain-specific accelerators—represents an important step toward enabling full real-time deployment within next-generation vehicle control architectures [65].

9.7 Final Remarks

This dissertation demonstrates that the integration of EKF-based state estimation, machine learning, VIN-aware normalization, maneuver drift modeling, and secure distributed calibration enables a more adaptive and reliable approach to vehicle diagnostics in connected mobility systems. As vehicles continue to evolve into software-defined and increasingly autonomous platforms, diagnostic architectures must also transition toward predictive, data-informed frameworks capable of adapting to changing operational conditions over time. The Hybrid AI–EKF approach presented in this work provides a foundation for such adaptive diagnostic systems by combining physically grounded estimation with nonlinear behavioral learning and secure parameter management.

By addressing limitations in traditional model-based and machine learning–only approaches, this research contributes to the development of scalable diagnostic infrastructures capable of supporting future intelligent vehicle ecosystems.

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