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Sustainable Urban Mobility for Road Information Discovery-Based Cloud Collaboration and Gaussian Processes

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Abstract: A novel cloud-based collaborative estimation framework for traffic management, utilizing a Gaussian Process Regression approach is introduced in this work. Central to addressing contemporary challenges in sustainable transportation, the framework is engineered to enhance traffic flow efficiency, reduce vehicular emissions, and support the maintenance of urban infrastructure. By leveraging real-time data from Priority Vehicles (PVs), the system optimizes road usage and condition assessments, contributing significantly to environmental sustainability in urban transport. The adoption of advanced data analysis techniques not only improves accuracy in traffic and road condition predictions but also aligns with global efforts to transition towards more eco-friendly transportation systems. This research, therefore, provides a pivotal step towards realizing efficient, sustainable urban mobility solutions.

Keywords: sustainable urban mobility; cloud-based collaboration; road information discovery; Kalman Filter; Gaussian process

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1. Introduction

The quest for sustainable urban mobility has become increasingly vital as cities evolve into smarter, more integrated environments. This movement seeks to harmonize urban development with environmental stewardship and safety enhancements in transportation systems. Our research builds upon the foundation laid by recent seminal works, which collectively advance our understanding and application of sustainable mobility solutions. In [1], the authors emphasize the importance of sustainable development and urban planning, particularly in the context of port cities, where the environmental impact of port activities is substantial. Their work focuses on the integration of Sustainable Urban Mobility Planning (SUMP) approaches to improve mobility and transportation sustainability in port areas. A case study at the Port of Bar in Montenegro showcases the practical application of their methodology, resulting in the implementation of a hybrid bus system for port employee transportation. This study highlights the need for tailored mobility solutions that cater to the unique characteristics of each port area. Expanding on this notion of tailored solutions, in [2] the author discusses the vital role of Intelligent Transport Systems (ITS) in enhancing traffic safety and aligning with sustainable transport principles. The paper reviews the impact of real-time information systems on driver behavior and the effectiveness of various detection and communication technologies. Despite numerous advances, Tonec notes the gap in deploying these solutions across multimodal environments, particularly due to the infrastructural requirements not met in many parts of the world. A framework for a universally accessible system is proposed, leveraging widely available technologies to benefit diverse users. Furthering the discussion on technological advancements, the author in [3] investigates machine learning applications for predicting traffic flow, which is instrumental in managing urban transportation sustainably. Utilizing data from the Hong Kong Transport Department, Tao proposes various machine learning methodologies to predict traffic, thus allowing for proactive congestion management strategies. This research underscores the potential of machine learning to facilitate decision-making processes that can enhance the sustainability of urban transport systems. Complementing these studies, the authors in [1] propose an integrated approach combining GIS and Data Mining methods to analyze urban traffic accidents in Hanoi, Vietnam. This study segments accident data into clusters to examine correlations between causes and accidents and identifies hotspots using GIS techniques. Their findings offer a nuanced understanding of accident patterns, contributing to efforts to improve traffic safety and infrastructure sustainability. This comprehensive approach has implications for urban planners and policymakers seeking to mitigate traffic accidents and enhance the efficiency of transportation systems. Together, these studies contribute to a growing body of work that seeks to reconcile the need for urban development with environmental and safety concerns, advancing our understanding of sustainable urban mobility.

The advent of intelligent transportation systems, particularly those incorporating real-time road data, signifies a crucial advancement in urban sustainability. These systems, emerging as a pivotal solution for modern cities, aim to address the pressing environmental challenges of our time. Their role extends beyond enhancing driver and passenger safety; they are also instrumental in shaping sustainable urban environments [4]. By optimizing fuel consumption and improving overall traffic flow, these systems substantially reduce the carbon footprint of urban transportation. The sustainable management of urban infrastructure is intricately linked with the efficient monitoring of road conditions. Government agencies, now more than ever, rely on real-time data for planning eco-friendly road maintenance strategies. The advent of Priority Vehicles (PVs) equipped with state-of-the-art sensing and networking capabilities marks a significant shift in how road data is gathered. This transition not only enhances the accuracy of traffic management but also promotes environmental conservation by reducing the need for extensive physical infrastructure [5,6]. Recognizing the urgent need for sustainable urban mobility solutions, our research introduces a cloud-based collaborative estimating framework. Inspired by previous studies [7,8], this framework utilizes a fleet of PVs, optimizing the accuracy and resilience of road information systems. The integration of cloud computing and Gaussian processes [9], along with data analysis advancements like the Kalman Filter [10], provides a robust approach to managing urban traffic and road conditions. Central to this framework is the Noisy Input Gaussian Process (NIGP) [11], which addresses GPS uncertainties, enhancing the reliability and precision of the traffic management systems. This accuracy is vital for reducing traffic congestion, minimizing vehicular emissions, and contributing to the global effort towards sustainable urban development [12]. By improving route planning and traffic flow, our methodology supports the transition to more sustainable, efficient urban transportation networks. The study by [13] introduces a cloud-assisted collaborative estimating system for on-road sensors, aiming to enhance the safety, efficiency, and comfort of next-generation automobiles while promoting sustainability. The system iteratively improves estimate accuracy by combining onboard measurements with pseudomeasurements from previous vehicles, utilizing a Noisy Input Gaussian Process (NIGP) approach to manage uncertainties. Extensive simulations and tests demonstrate that the proposed system significantly improves onboard performance, reduces variance, and minimizes uncertainty, especially when using NIGP pseudomeasurements. This approach not only enhances vehicle safety and comfort but also contributes to sustainability by optimizing sensor data accuracy, reducing energy consumption, and improving overall transportation efficiency. Future research will focus on developing more data-efficient algorithms for real-world implementation. Additionally, another study [14] addresses sustainability challenges in transportation networks, specifically focusing on conflicts between trams and Connected Vehicles (CVs) at intersections. They propose a Transit Signal Priority (TSP) system aimed at reducing delays, minimizing energy consumption, and enhancing passenger comfort. Through collaborative optimization and an improved genetic algorithm, the TSP system significantly reduces transit times for trams (45.8%) and overall transit times for trams and CVs (17.1%). It also achieves a substantial reduction in energy consumption (34.7%) and discomfort levels (25.8%). This research plays a vital role in promoting sustainable urban mobility by optimizing transportation systems for efficiency, reduced emissions, and improved passenger experience. Moreover, this research draws inspiration from recent studies that aim to enhance road safety while promoting sustainability in transportation networks [14]. The proposed framework is designed to minimize delays and energy consumption, further contributing to the sustainability of urban mobility. By addressing conflicts between different modes of transportation, it aligns with the goal of reducing emissions and optimizing travel times. This work is not just a technical contribution to traffic management and road safety; it is a significant step towards achieving sustainable urban mobility. The proposed framework underscores the importance of integrating environmental considerations into transportation planning and management. It highlights how technological innovations can be harnessed to meet sustainability goals, paving the way for a more environmentally friendly and efficient future in urban transportation. In embracing this sustainable approach, the research contributes to the broader goal of creating greener, more livable cities for future generations.

2. Problem Definition

PVs are crucial to sustainable urban mobility, acting as mobile sensors for real-time road data collection, which is pivotal for intelligent transportation systems. These data aid in traffic optimization, safety improvements, and environmental impact reduction. PVs' roles span from road condition monitoring to aiding emergency responses, signifying a move towards adaptive, resilient urban transport networks. Their deployment facilitates a shift from reactive to proactive management, enabling informed urban planning and traffic management that align with sustainability goals. PVs are thus integral to developing smarter, eco-friendlier cities.

In this work, communication protocols include standard vehicular communication technologies, i.e., Dedicated Short-Range Communications (DSRC), to transmit the data to a cloud platform. The cloud architecture acts as a central platform to aggregate data from multiple PVs. These data are used to update a Gaussian Process model, which then sends "pseudomeasurements" back to the PVs to refine their onboard estimations. Pseudomeasurements are generated from the aggregated data using Gaussian Process Regression. These are then used as additional inputs to the local estimators (KF) to improve the accuracy of the road information estimates provided by each PV.

The primary objective of this study is to advance sustainable urban transportation by developing a system that leverages PVs for the collection and aggregation of traffic data. Envision a scenario where a PV navigates a specific road segment, as shown in Figure 1. This segment, demarcated by road markers, is crucial for understanding the road's profile and condition, which directly impacts sustainable traffic management. The PV utilizes a range of sensors, including accelerometers and GPS, to gather comprehensive road data.

Key parameters for analyzing the interaction between the road and a PV are identified, encompassing:

- The system's current state;
- Control inputs;
- Road profile;
- Inherent system process noise;
- System matrices of suitable dimensions.

This research aligns with the model proposed in [15], focusing on parameters that characterize road conditions from a sustainability perspective. Each PV employs a state estimator, such as a KF [16], to integrate road data with the vehicle's state, enhancing the accuracy of sustainable traffic flow and road maintenance strategies.

The central aim is to establish a cloud-based collaborative estimation framework to increase the precision of road information estimates. This framework, crucial for sustainable urban mobility, employs a fleet of PVs and a central cloud system for crowdsourcing road information using Gaussian Process Regression. The regressed model, serving as an initial measurement set, refines local estimators. Incorporating both Kalman Filter and Gaussian Process Regression, our framework underpins a sustainable approach to urban traffic management.

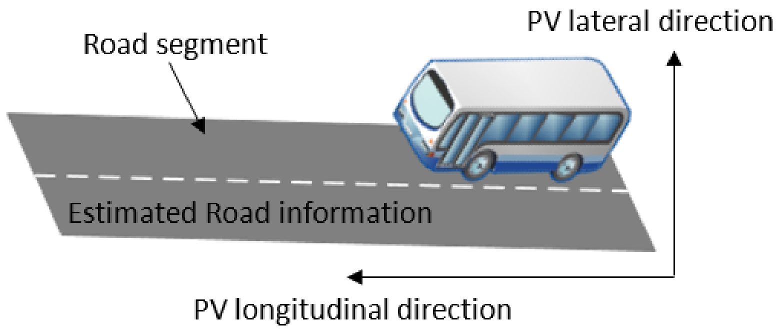

Figure 1. Road information estimation on a road segment.

3. Modeling and Presumptions

This section expands the conceptual framework and key assumptions of our traffic state estimator, emphasizing sustainable urban mobility. The estimator utilizes the KF and Gaussian Process methodologies, integral to developing environmentally conscious transportation systems. The KF, celebrated for its precision in predicting unknown variables, plays a vital role in sustainable traffic management. By analyzing time-series measurements, the KF allows for efficient route planning and congestion mitigation, directly contributing to reduced emissions and fuel consumption [17].

The KF states include the vehicle's kinematic state which includes the vehicle's position in both longitudinal and lateral directions, velocity, and acceleration. These states are fundamental for predicting the vehicle's future location and for adjusting speed in response to traffic conditions. In addition, KF states include traffic flow state which represents the rate at which vehicles are passing a particular section of the road, which is critical for understanding and managing congestion. Furthermore, KF states include traffic density state which measures the number of vehicles within a certain segment of the road, providing an estimation of vehicular congestion levels. The last KF state includes the environmental state which includes variables such as road friction and weather conditions that can influence vehicle performance and traffic flow. The KF operates in two critical phases:

1. Prediction Phase: Also referred to as "propagation", this phase involves forecasting the future state of the variables based on current estimates.
2. Updating Phase: Often called "correction", this stage involves refining the predictions with actual measurements to minimize errors.

The objective is to attain accurate state estimates, which in turn facilitate informed decisions in urban traffic management, crucial for sustainable city planning. The detailed algorithm and its implementation in our study are illustrated in Figures 2 and 3. The provided figures depict the operational framework of the Kalman Filter (KF) Algorithm, a critical tool in the estimation of traffic states for sustainable urban mobility. Figure 2 presents an overview of the Kalman Filter Algorithm, illustrating its systematic approach to refining traffic estimates:

1. Initial Estimate: The process starts with initial estimations of key parameters such as vehicle stops, road speed, and road delay, along with their associated error covariance.
2. Prediction Time Update: This phase projects the state and the error covariance ahead in time, preparing for the upcoming measurements.
3. Observation and Update: Upon receiving new data, the algorithm computes the Kalman Gain and updates both the estimate and the error covariance to improve accuracy.

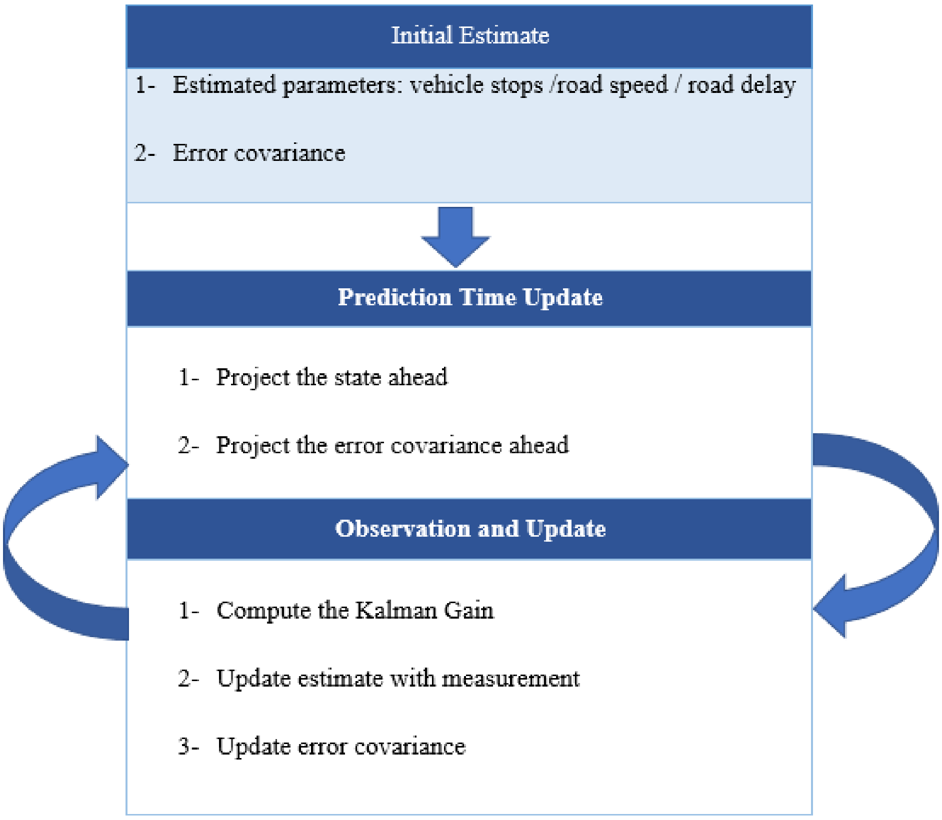

Figure 2. Overview of Kalman Filter Algorithm.

Figure 3 offers a more detailed look at the steps involved in the Kalman Filter Algorithm:

1. Start: The algorithm initializes by reading the initial road state estimate.
2. Calculate Covariance: It calculates the initial error covariance.
3. Calculate State Ahead: At each time step t, the algorithm predicts the state at the next time step $t+1$.
4. Calculate Error Covariance Ahead: It also projects the error covariance forward.
5. Kalman Gain and Correction: Using the new measurements, the Kalman Gain is computed to adjust the state estimate.
6. Recover Information: Finally, the road information is updated, and the process repeats, incorporating the new augmented state estimate into subsequent predictions.

These figures align with the KF's two-phase operation—prediction and updating—described in the text. The KF's ability to adaptively process time-series measurements ensures efficient route planning and congestion management, leading to sustainable outcomes like reduced emissions and fuel consumption. In addition to the KF, the Gaussian Process (GP) Regression is employed to model road information as a spatial function. The GP's strength lies in its Gaussian functions and adaptively trained weight vector, which collectively improve the prediction of traffic patterns and road maintenance needs. Its kernel function, defined by critical hyperparameters, is essential for evaluating the environmental impacts of road conditions. By effectively crowdsourcing and estimating data from PVs, the GP substantially supports the sustainable management of traffic systems.

In the context of sustainability, road information is modeled as a spatial distance function using Gaussian Process (GP) Regression. This approach not only predicts traffic patterns but also assists in identifying areas requiring maintenance, thus aiding sustainable road infrastructure management.

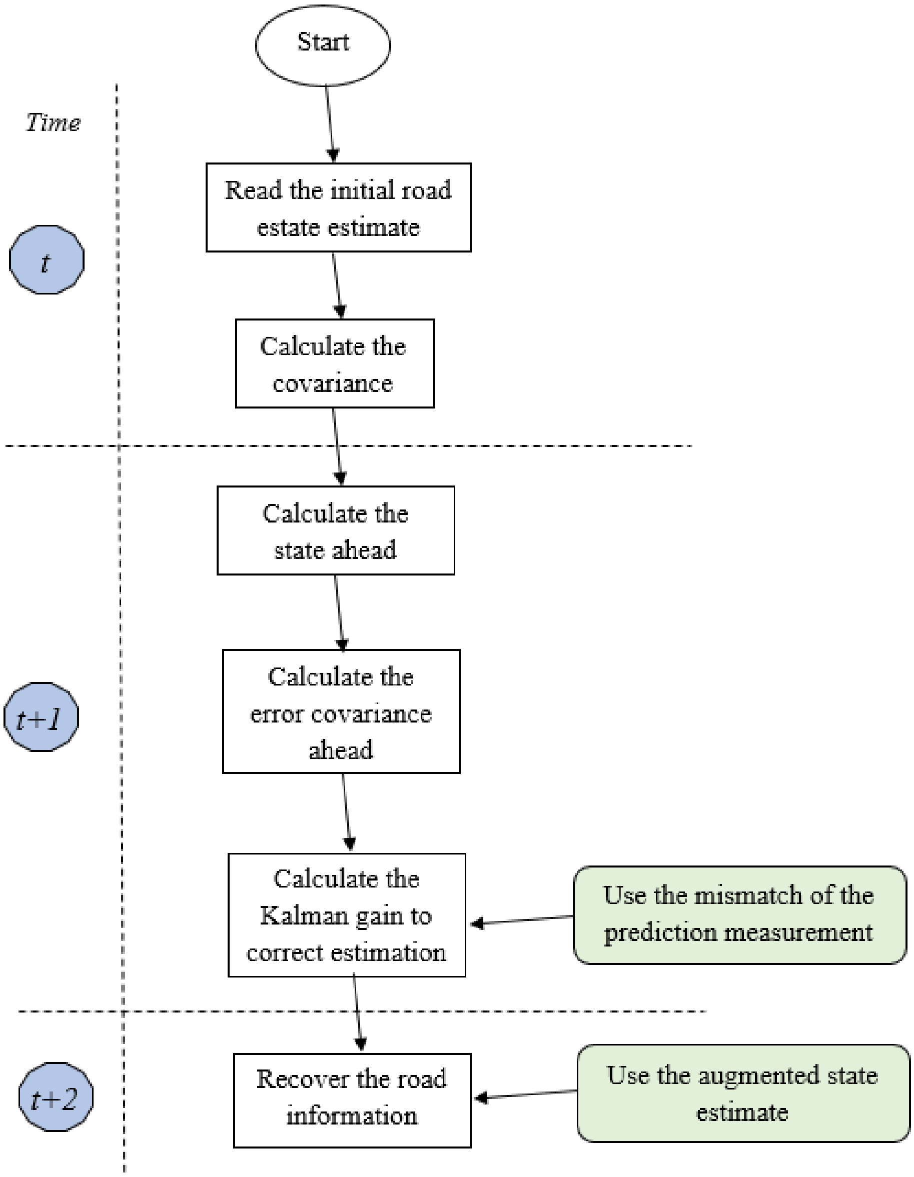

Figure 3. Detailed steps of Kalman Filter Algorithm.

Central to the GP model are:

- Gaussian Functions: Essential for the GP's predictive capabilities.
- Weight Vector: Adaptively trained from data to enhance accuracy and sustainability insights.

The GP also uses a kernel function with key hyperparameters (standard deviation and lengthscale) to define spatial covariances, crucial for assessing environmental impacts of road conditions. This model, by accurately estimating mean function values and kernel uncertainties, effectively crowdsources data from PVs, bolstering sustainable traffic management. To further align our modeling approach with sustainability goals, we introduce the following mathematical formulations:

- Fuel Consumption Model:

$$\text{Fuel Consumption} = f(\text{Traffic Speed}, \text{Traffic Density}) \quad (1)$$

Equation (1) models how traffic speed and density, estimated by the KF, impact fuel consumption, a key sustainability metric.

- Emission Estimation:

$$\text{Emissions} = g(\text{Traffic Speed}, \text{Traffic Density}, \text{Vehicle Type}) \quad (2)$$

In Equation (2), g calculates emissions based on traffic conditions and vehicle types, which are integral for assessing and reducing environmental impact.

- Road Wear Impact:

$$\text{Road Wear} = h(\text{Traffic Load}, \text{Road Condition}) \quad (3)$$

In Equation (3), h models the impact of traffic on road wear, informing sustainable road maintenance practices.

These equations, embedded within our traffic estimation framework, provide a quantitative basis for assessing and enhancing the sustainability of urban transportation systems.

4. Road Information Discovery through Cloud Computing and Gaussian Processes

This section delves into the intricacies of our innovative cloud-based estimation framework, which integrates the Kalman Filter (KF) and Gaussian Process (GP) to advance sustainable traffic management and urban planning practices.

4.1. Synergistic Cloud-Based Estimation for Sustainable Mobility

Our framework capitalizes on the strengths of the KF applied on the Passenger Vehicle (PV) side and the GP utilized within the cloud infrastructure. This synergy creates a robust system for estimating road conditions, crucial for eco-friendly urban development. PVs harness GP models from the cloud, refined using aggregated data from multiple PVs, to boost predictive capabilities for both environmental and traffic conditions.

The GP model plays a central role in providing a nuanced assessment of road conditions, pivotal for eco-conscious urban development. It outputs detailed estimates through its mean function, while its kernel function quantifies the inherent uncertainties. These estimates, termed "pseudomeasurements", are key to developing an Augmented Output (AO) that enriches onboard measurements with critical sustainability metrics.

By amalgamating this AO with the KF, the framework is designed to simultaneously estimate the state of the road conditions and the PV's own state, leading to an optimized traffic flow and a diminished environmental footprint. This dual estimation process results in an augmented state vector, which informs an output matrix and a measurement noise covariance matrix, both dependent on the GP's predictive accuracy to achieve sustainable outcomes. The approach aims to minimize the Minimum Mean Square Error (MMSE), a vital goal for achieving precision in sustainable urban traffic systems. MMSE refers to the smallest possible average of the squared differences between an estimator's predictions and the actual values of the parameter being estimated. It is a statistical measure used to gauge the accuracy of an estimator by quantifying how close its predictions are to the true values, with the MMSE estimator being the one that minimizes this error. In the context of the KF, MMSE is crucial as the filter seeks to provide the most accurate state estimates by minimizing the MSE within the given data and system noise constraints. Figure 4 depicts our cloud collaborative estimation framework, illustrating the interaction between the PVs and the cloud-based GP model.

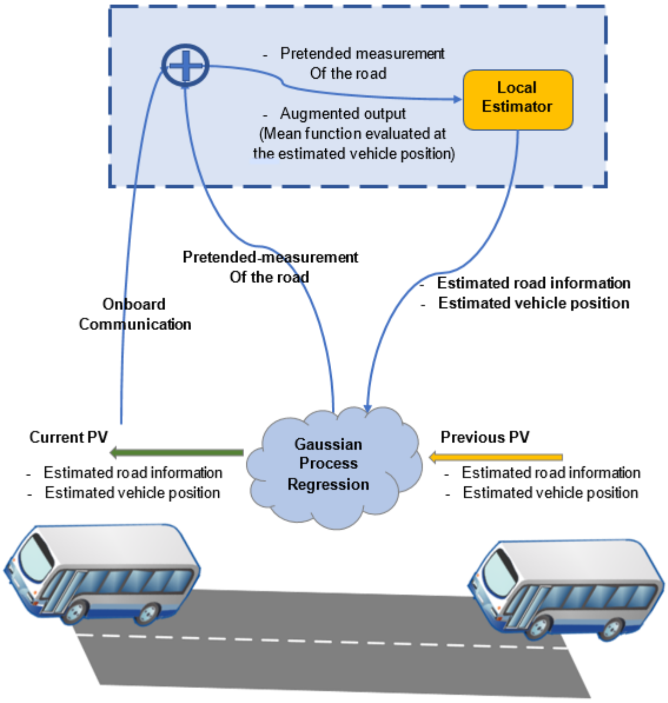

Figure 4. Cloud collaborative estimation-based "pretended-measurement" (crowdsourced GP).

4.2. Utilizing Gaussian Process Pseudomeasurements for Enhanced Estimation

The introduction of GP pseudomeasurements marks a significant improvement in the KF's performance, particularly from a sustainability standpoint. The Mean Square Error (MSE) serves as a benchmark for assessing the estimator's effectiveness in managing traffic sustainably. The KF is meticulously optimized to minimize MSE by integrating environmental factors along with the GP and measurement noises.

To facilitate this, each PV is equipped with a set of sensors tailored for sustainability:

1. Traditional sensors gather onboard environmental and traffic data.
2. Innovative GP-based sensors produce pseudomeasurements, enriching sustainable traffic management insights.

These sensors collect data that feed into the KF to generate estimates that reflect both environmental conditions and measurement uncertainty. This design underscores the value of GP pseudomeasurements in achieving precise and eco-friendly road condition estimations.

4.3. Applying Sustainable Fixed Interval Smoothing for Accurate Road Condition Analysis

The Fixed Interval Smoothing (FIS) technique [18], a retrospective KF method, is employed to refine past estimates of road conditions using current measurements. By enhancing the accuracy of these estimates, FIS contributes to sustainable traffic management by allowing for more precise and timely road maintenance decisions. This process not only ensures smoother traffic flow but also diminishes the environmental impact by reducing the frequency and scale of road repairs.

4.4. Cultivating a Sustainable Cloud Ecosystem via GP Crowdsourcing

Post-FIS, the PVs contribute to a shared pool of smoothed state information that benefits both the immediate estimation of road conditions and long-term urban infrastructure maintenance. In the cloud, a GP model is trained with these updated estimates, perfecting the model's hyperparameters to yield even more accurate predictions of environmental impacts.

This collaborative phase involves PVs sharing and assimilating road condition data, underpinning a collective effort to thoroughly comprehend the implications of road conditions on sustainability. The cloud refines the GP hyperparameters, which, in conjunction with the mean and kernel functions, equip PVs with the capability to make precise environmental impact predictions. These enhanced predictions are then circulated to subsequent PVs, fostering a continuous loop of sustainable data sharing and analysis, as illustrated in Figure 4. This collaborative feedback mechanism ensures that each PV contributes to, and benefits from, a constantly evolving understanding of road conditions, culminating in a more sustainable and informed urban traffic network.

5. Sustainable Traffic Estimation via Simulation

This section examines the role of the Global Positioning System (GPS) within Priority Vehicles (PVs) from a sustainability perspective. Addressing GPS inaccuracies is vital for environmentally efficient navigation and routing. By leveraging the Noisy Input Gaussian Process (NIGP) regression, as recommended by [11], we can incorporate GPS uncertainty into our models, leading to a reduction in unnecessary fuel consumption through improved positioning and thereby contributing to a reduction in greenhouse gas emissions.

The simulation of our cloud collaboration system is not merely a technical validation but also a demonstration of its potential to bolster sustainable traffic management. By analyzing road segments for PV influence on traffic flow, we can assess and enhance the sustainability of vehicle operations, emphasizing reduced environmental impact and improved energy efficiency.

5.1. Simulation Steps for Sustainable Road Profile Estimation

Our cloud-based collaborative road profile estimation framework, designed with sustainability in mind, follows these steps:

- Step 1: Apply the forward Kalman Filter to PV_1, focusing on estimated road distances and relevant sustainability indicators, such as emissions reduction potential. Road distance includes the geometry and condition of the road surface, which are crucial for assessing the road's impact on vehicle emissions and fuel efficiency. The KF and NIGP use road distance metrics to enhance the accuracy of sustainability indicators and environmental impact predictions in a cloud-based collaborative setting.
- Step 2: Implement backward smoothing for PV_i, refining sustainability metrics alongside road distance estimations.
- Step 3: Perform the NIGP for enhancing the accuracy of environmental impact predictions related to the road distance.
- Step 4: Utilize the NIGP from Step 3 to inform the road information with a focus on reducing environmental variances.
- Step 5: Iterate through PVs from i = 2 to N, integrating sustainability considerations as follows:
  1. Map the road distance to sustainability performance metrics.
  2. Refine the NIGP estimations for these metrics.
  3. Employ the NIGP from PV_{i-1} to inform the Kalman Filter's environmental impact computations.
  4. Update the road sustainability profiles using the calculated Kalman Filter.
  5. Conduct backward smoothing for PV_i, enhancing long-term sustainability estimations.
  6. Increment the index i.
  7. Repeat the process for holistic sustainability enhancement.

Consider a PV equipped with a suspension model that not only describes its interaction with the road but also contributes to a sustainable transportation system. This model accounts for sprung and unsprung mass displacements, as well as sprung mass velocity, and interprets the road profile as an output influenced by white Gaussian noise. The noise model includes factors critical to sustainability, such as road roughness coefficient, vehicle speed, and cutoff frequency, which can affect fuel efficiency and emissions. This sustainability-oriented model underpins the cloud collaborative estimation process detailed in Section 5.

5.2. Sustainable Simulation Setup

The simulation parameters are designed to reflect and enhance the sustainability aspects of the transportation system:

- Road segments are 40 m in length, which represents a typical urban block size conducive to sustainable city designs.
- Ten PVs, each with distinct model parameters, are used to represent a diverse fleet that includes electric and hybrid vehicles.
- Two sensors are utilized for measuring sprung mass and suspension displacements, providing data to optimize vehicle performance and reduce environmental impact.
- The simulation spans 1.5 s with a sampling time of 0.01 s, ensuring timely data for responsive and eco-friendly traffic management.
- Each Kalman Filter processes 151 estimation points to provide high-resolution data for minimizing traffic congestion and emissions.
- A fixed-lag smoother is used for Fixed Interval Smoothing (FIS) to balance computational efficiency with the need for precise, real-time traffic data.
- Zero mean functions are assigned to both the cloud-based NIGP and quadratic kernel to reflect a baseline expectation of optimal environmental performance.
- Training data from all PVs are used for NIGP regression, enhancing the system's ability to learn from a wide range of eco-driving patterns.
- Posterior inferences are made based on the NIGP regression, allowing for continuous improvement in sustainable traffic management practices.

In this work, we claim that the simulations were conducted with manageable computational resources and within reasonable time frames.

5.3. Results of Sustainable Simulation

The framework's effectiveness is evaluated with a focus on sustainability metrics:

5.3.1. Performance of the Onboard Estimation

Each PV's onboard Kalman Filter, incorporating the latest NIGP, is assessed for its contribution to sustainable driving practices. The Root Mean Squared Error (RMSE) is measured for each PV's estimation against the actual road conditions, which includes parameters related to environmental efficiency. The RMSE used in the study measures the accuracy of the Priority PV's onboard KF estimations against actual road conditions and includes parameters related to environmental efficiency. It is not specified as a weighted sum but integrates the effects of various error sources, including the performance of NIGP pseudomeasurements and onboard sensors. The RMSE compares the augmented KF's performance with a benchmark setting without GP pseudomeasurements and includes comparisons with simpler pseudomeasurements for thorough assessment.The use of pseudomeasurements from previous PVs is shown to significantly enhance performance, leading to a more sustainable traffic flow, as evidenced in Figure 5. Referencing Figure 5, it is evident that the integration of pseudomeasurements derived from previous PVs has substantially improved performance. Moreover, the application of NIGP pseudomeasurements has yielded superior results, with the crowd-sourced NIGP providing more consistent pseudomeasurements compared to the KF that depends on a preceding vehicle. Additionally, the iterative implementation of the pseudomeasurement technique has progressively enhanced onboard capabilities, especially when utilizing NIGP pseudomeasurements, despite the initial PV not employing any pseudomeasurements, as depicted in Figure 6.

5.3.2. Performance of the Cloud NIGP

This subsection evaluates the cloud-based GP model's effectiveness. Initially, the model is trained solely on data from a single PV, which, as illustrated in Figure 7, results in inadequate characterization. However, incorporating data from 10 PVs, as detailed in Section 5.2, significantly improves the GP's ability to accurately represent the road profile, as evidenced by the decreased variance presented in Figure 8. A comparative analysis of standard GP regression and NIGP regression against a KF averaging benchmark reveals that both GP and NIGP regressions surpass the KF averaging in performance. Notably, the NIGP achieves superior variance reduction and uncertainty minimization. The percentage of variance reduction is approximately 82.62%.

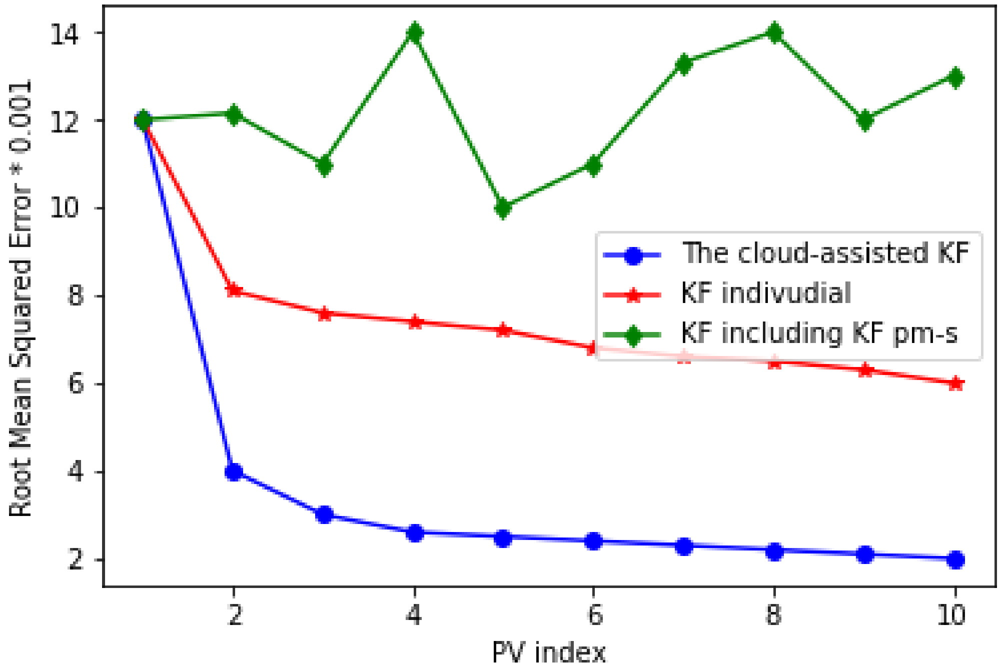

Figure 5. Root Mean Squared Error comparison between different KF estimations.

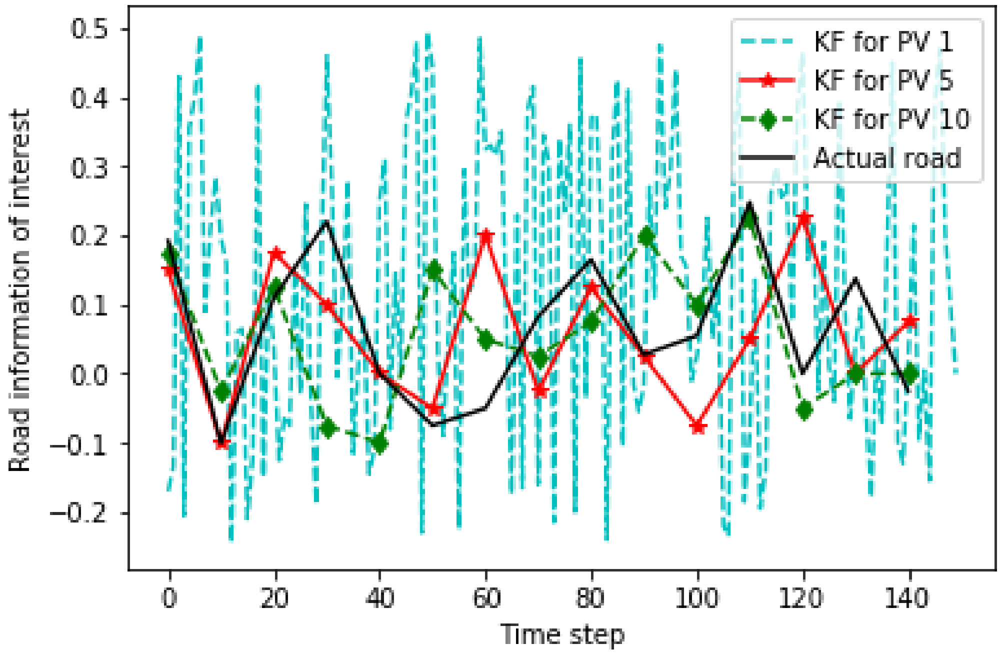

Figure 6. The onboard estimation of the PV number 1, 5, and 10 showing the onboard estimation improvement while using the suggested framework.

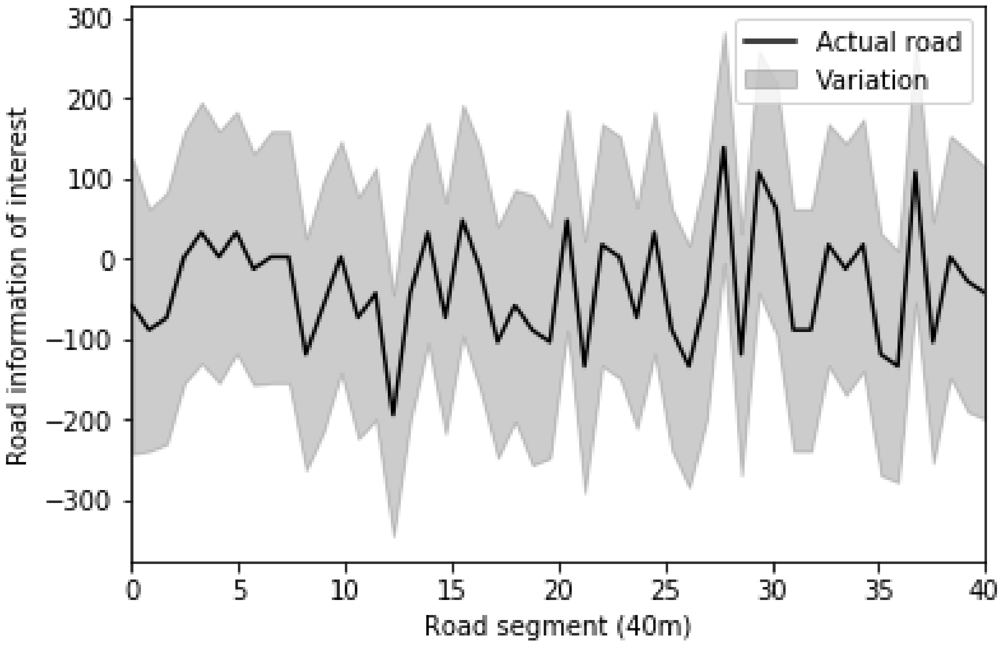

Figure 7. NIGP regression in the cloud with one PV.

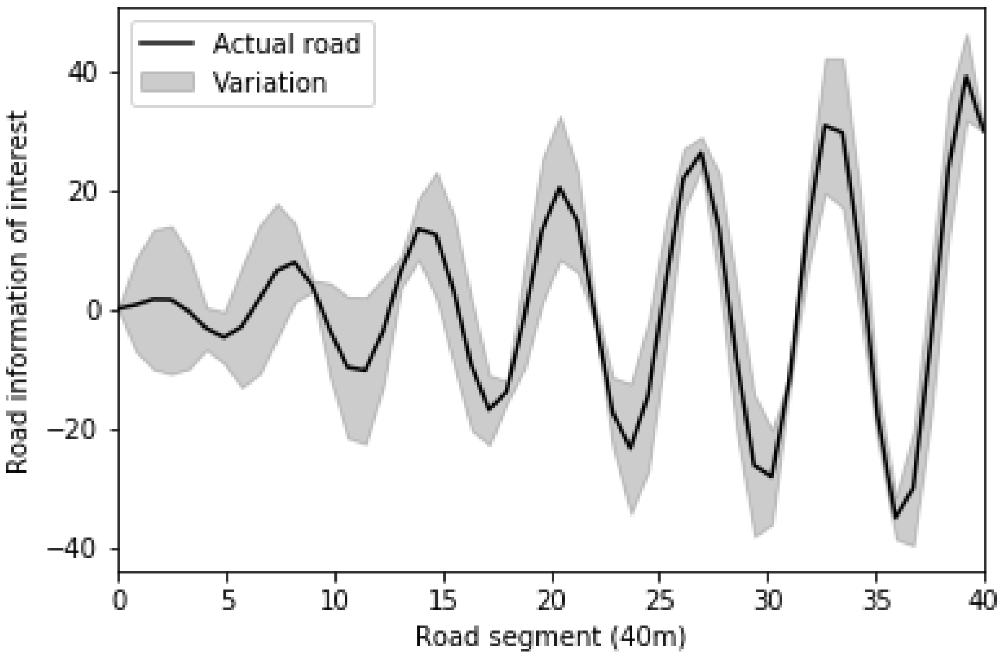

Figure 8. NIGP regression in the cloud with ten PVs.

5.3.3. Sustainability Metrics

In this section, we present the sustainability metrics including Fuel Consumption: 120 units of fuel are consumed. This is a simplified representation based on the traffic speed of 60 km/h and a traffic density of 30 vehicles per km. Emissions: 1800 units of emissions are produced. This calculation assumes the vehicle type has the highest emission factor (type 3, which could represent a gasoline vehicle), along with the given traffic speed and density. Road Wear Impact: 120 units of road wear impact are estimated. This is based on a traffic load of 8000 units (which represent the cumulative weight of vehicles per km) and a road condition factor of 0.7, which indicates relatively good road quality. In the following, we illustrate the RMSE comparison for PV estimations against actual road conditions and the hypothetical environmental impact by vehicle type: Figure 9 illustrates the RMSE comparison for PV Estimations. It compares the actual road conditions with the estimated conditions from three different PVs. The RMSE is calculated for each PV's estimation to measure the accuracy against the actual road conditions. The RMSE values are shown in the legend of the plot. Figure 10 illustrates the Environmental Impact by Vehicle Type. It represents a hypothetical calculation of emissions based on vehicle type, assuming a traffic speed and density. The emissions are calculated using a placeholder function that considers the speed, density, and a factor that represents the vehicle type's emissions efficiency.

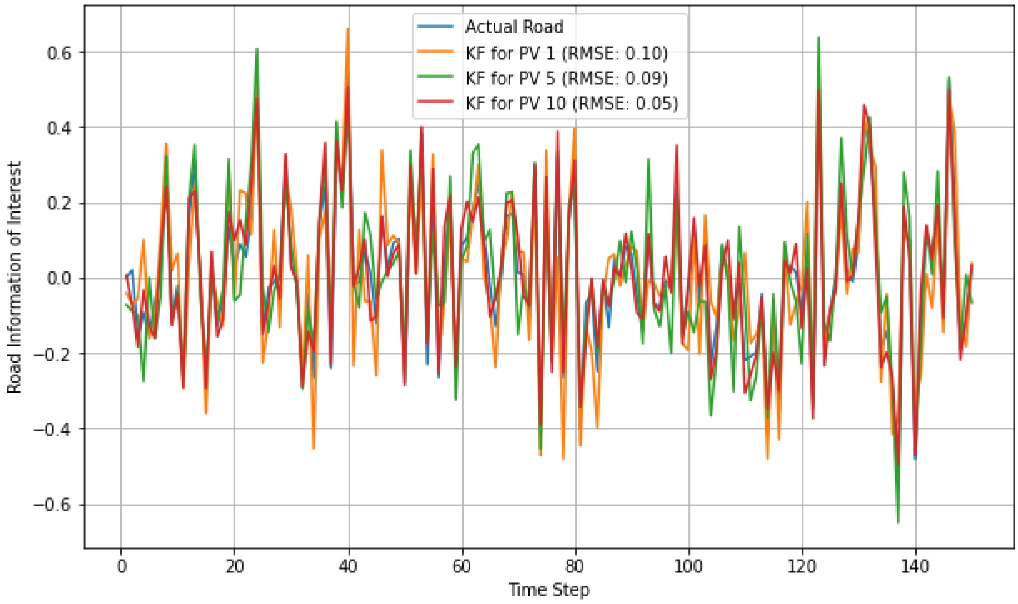

Figure 9. RMSE comparison for PV Estimations.

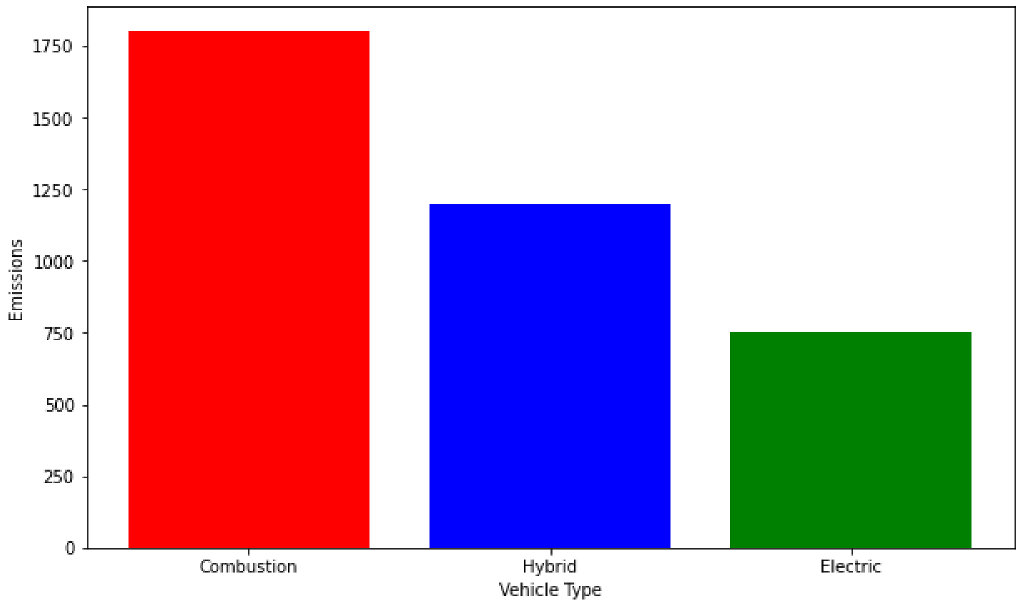

Figure 10. Environmental Impact by Vehicle Type.

6. Integrating the Framework with Physical Hardware

In this section, we propose integrating the framework with physical hardware, particularly an active suspension testbed, the integration details the following specifics:

1. Hardware Utilized: The Quanser Active Suspension (AS) platform was employed to carry out hardware-in-the-loop experiments. This station simulates a quarter-scale car model and is equipped with an actuator that can be controlled for active suspension purposes. However, for the aim of road profile estimation, the suspension was kept passive.
2. Measurement Tools: Encoders are installed on the suspension station to measure the sprung mass displacement and suspension displacement. These measurements correspond to the C matrix used in the simulation part of the study.
3. Parameter Adjustment: Initially, the model parameters provided in the Quanser User Manual were employed, but due to inaccuracy—potentially caused by wear and tear—the parameters were fine-tuned using the Matlab Parameter Identification toolbox to better fit the experimental setup.
4. Experiment Variability: To mimic a range of vehicle types in the experiment, different sets of parameters were used, and the dynamics of the suspension station were altered by attaching extra masses to the sprung mass.
5. Simulation Reflection: The cloud-assisted collaborative estimation performed during the simulation phase was replicated in the experimental setup to emulate the estimation with multiple vehicles. This included utilizing actual measurements from the suspension station and comparing them with the model outputs.
6. Experiment Duration: Each experiment was conducted for a duration of 4.5 s with a sampling time of 0.03 s, assuming uniform velocity for all vehicles across the road segment.
7. Uncertainty and Variance: The position uncertainty variance was set to mirror the one used in simulation studies, ensuring consistency between simulation and experimental conditions.
8. Performance and Evaluation The actual measurements from the suspension station were compared with model outputs to evaluate performance. Although there was decent performance noted, some mismatch between the identified model and the actual plant was observed.

The specifics provided give insight into the experimental setup and how the computational framework integrates with an actual physical system. It is evident that our collaborative estimation framework was not only tested in simulations but also validated through hands-on experiments, ensuring that the theoretical models hold up when applied to physical hardware.

7. Sustainable Assessment and Limitations

The introduction of a collaborative estimation framework in this study represents a promising advancement towards sustainable traffic management. However, it is crucial to acknowledge the limitations encountered, particularly when integrating the framework with physical hardware components like the Quanser Active Suspension (QAS). The QAS serves as a scaled-down model of a Passenger Vehicle (PV), featuring three primary components: the vehicle's body (sprung mass), the tire's mass (unsprung mass), and the road signal, all crucial for emulating active suspension control that supports eco-friendly vehicle dynamics.

For a comprehensive sustainable assessment, it is imperative to compare the QAS measurements—specifically suspension travel and spring displacement, which are presumed to be captured by encoders—with the simulation outcomes highlighted in Section 5.2. This comparison involves a fleet of 10 heterogeneous vehicles, each characterized by unique parameters that influence their environmental performance.

To ensure an accurate and sustainable evaluation, several steps are proposed:

- Model Tuning and Evaluation: Utilizing tools like the Matlab Parameter-Identification toolbox will be critical for fine-tuning the model parameters. The sustainability impact of the model should then be evaluated against the setup described earlier, focusing on environmental performance metrics.

- Collaborative Estimation with the QAS: Implementing cloud-assisted collaborative estimation for each vehicle configuration within the QAS is vital. This process aims to simulate the interactions among different vehicles and gauge their collective contribution to a sustainable traffic ecosystem, with multiple iterations to guarantee robustness.
- Benchmarking and Sustainability Metrics: A "first run" evaluation is essential to compare the model's predictions with actual hardware data, concentrating on sustainability outcomes like energy efficiency and emission reduction. Maintaining consistent vehicle speed and uncertainty variance from the simulation is crucial to preserve the conditions under which environmental performance was optimized.
- Onboard Estimation Performance: The effectiveness of the onboard estimation can be gauged by comparing the efficiency of the Kalman Filter with and without GP pseudomeasurements. An improvement in the pseudomeasurements' accuracy, as indicated by a lower RMSE, would suggest a more sustainable traffic flow.
- Cloud-Based NIGP Regression Analysis: It is hypothesized that increasing the number of iterations for the cloud-based NIGP regression will enhance the system's sustainability metrics, aligning the mean function more closely with actual road conditions. Therefore, a set of ten runs is recommended to compare the sustainability impact, as measured by RMSE, among GP, NIGP, and average KF estimates.

These evaluations aim to identify the most effective technique—be it GP, NIGP, or averaged KF estimates—for boosting the system's sustainable performance. The insights gained will be instrumental in guiding future enhancements, making the collaborative estimation framework a more effective tool for promoting sustainable urban transportation.

8. Conclusions

In this study, we have developed a unique cloud-based collaborative system for road information discovery that leverages a fleet of heterogeneous vehicles. The system embodies the principles of sustainable urban mobility by crowdsourcing individual vehicle estimations through a Gaussian process. These estimations, utilized as pseudomeasurements, empower subsequent vehicles to refine their local measurements, leading to a more efficient and eco-friendly transportation network. We have demonstrated that our approach significantly enhances local estimation performance, which aligns with the broader goal of reducing environmental impact through improved traffic management. The enhanced local estimates contribute to a continuously evolving cloud-based Gaussian process, fostering a dynamic and responsive system for sustainable urban planning. To address the inherent GPS inaccuracies and their impact on sustainability metrics, we adopted a noisy-input Gaussian process approach that effectively reduced variance and improved the precision of environmental impact assessments. Our extensive simulations and tests underscore the framework's potential to optimize road profile estimation for sustainable outcomes. As we look to the future, our efforts will focus on creating more data-efficient Gaussian processes—which will require fewer data points per road segment. This advancement will further minimize the system's environmental footprint by reducing the computational resources needed for data processing, aligning with the objectives of sustainable smart city initiatives.

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