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A telematics platform for enhancing green energy efficiency in logistics

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Abstract. The transport logistics sector remains a significant contributor to global greenhouse gas emissions, primarily CO2, demanding an urgent transition towards green energy and enhanced operational efficiency. While fleet monitoring is common, effective management necessitates granular analysis of both fleet performance and specific driver behaviours. This paper presents the development and implementation of a novel Internet of Things (IoT) platform, designed to capture and analyse real-time telematics data from transport vehicles. The primary innovation of this platform lies in its methodological framework, which moves beyond conventional GPS tracking to perform granular CO2 quantification. It achieves this by programmatically disaggregating telematics data into distinct operational states, notably 'engine idling' versus 'vehicle running'. This disaggregation enables the precise calculation of emissions from high-waste activities. By correlating this granular emissions data with driver-specific behaviours and route patterns, the system provides logistics managers with high-value, actionable insights to reduce energy consumption. The objectives are twofold: to facilitate targeted driver feedback for modifying inefficient practices and to identify opportunities for route optimization. This contributes directly to green energy adoption through measurable fuel savings and emission reductions, offering a scalable solution for sustainable logistics.

1 Introduction

The transport logistics sector remains a significant contributor to global greenhouse gas emissions, primarily CO2, demanding an urgent transition towards green energy and enhanced operational efficiency. While fleet monitoring is common, effective management necessitates granular analysis of both fleet performance and specific driver behaviours. This paper presents the development and implementation of a novel Internet of Things (IoT) platform, designed to capture and analyse real-time telematics data from transport vehicles.
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2 Related Work

The advancement of green logistics has been investigated through diverse technological and methodological approaches. Kumar [1] addresses the persistent challenges of traffic congestion and road safety that conventional, fixed-timing traffic signal systems fail to resolve. They propose that IoT offers a promising solution by enabling real-time monitoring, analysis, and adaptive control of traffic systems. Efimova and Saini (2023) [2] demonstrated that automated RFID monitoring systems could achieve substantial reductions in transit times and associated carbon emissions within container logistics. Their study employed a mathematical framework establishing a direct correlation between transit duration, fuel consumption, and emission outputs. Complementing this, Kalwar (2024) [3] emphasized the role of integrated Information and Communication Technologies (ICT) encompassing GPS, IoT, and cloud computing in enhancing vehicle utilisation efficiency and minimizing CO2 emissions via real-time route optimization. The author concurrently cautioned that suboptimal infrastructure could undermine these advantages, potentially exacerbating fossil fuel consumption. Empirical evidence from a logistics case study (2022) [4] highlights that technical vehicle improvements must be paired with human-centric behavioural changes to achieve meaningful sustainability goals in logistics. Parthasarathy (2024) [5] proposed an AI-driven framework for carbon footprint tracking across logistics networks, utilizing predictive analytics to forecast emissions and recommend low-carbon routes, thus highlighting the shift from reactive to proactive management.

Wei et al. (2020) [6] developed an optimized Road Freight Transportation Routing Strategy (RFTRS) that harmonizes emission reduction targets with economic and regulatory constraints, underscoring the significant influence of speed on fuel efficiency per meter. Contemporary research on telematics (2025) [7] by implementing a telematics-based monitoring and coaching program across a 500-vehicle fleet, the company tracked metrics including speed, idling duration, and acceleration patterns. Performance scorecards facilitated structured feedback and training, culminating in a 12% reduction in fuel consumption, a 30% decrease in harsh braking incidents, and a measurable decline in emissions. This approach also engendered a cultural shift towards fuel-conscious driving among participants. The strategic dimension of route planning has been identified as another critical lever. At a granular level, Zhang et al. (2022) [8] advanced the evaluation of eco-driving by establishing vehicle-specific power (VSP) distribution baselines, revealing that driving style can account for fuel consumption variations of 15-25% for internal combustion engines and up to 50% for hybrid vehicles. Qian et al. (2025) [9] further decomposed energy consumption patterns, identifying acceleration (38%) and cruising (35%) as the predominant modes under urban conditions, with idling contributing 19%. While this amount of research validates the significance of monitoring, behavioural, and routing interventions, a notable gap persists in their holistic integration. Wickramanayake et al.[10] proposes a novel, machine learning-driven framework to enhance vehicle fuel efficiency by specifically targeting and modifying driver behaviour in real time. The authors argue that substantial fuel savings (up to 20%) can be achieved through better driving practices, even more than engine

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design alone. Existing systems often specialise in isolated aspects or necessitate complex hardware. The principal innovation of our platform lies in its capacity to derive granular, actionable emission intelligence, specifically differentiating between idling and running states from standard GPS telematics data, thereby offering a pragmatically deployable yet analytically sophisticated tool for fleet sustainability management.

3 Platform Architecture

The platform is designed as a cloud-based system that integrates data acquisition, processing, analysis, and visualization to support green energy goals in Fig.1.

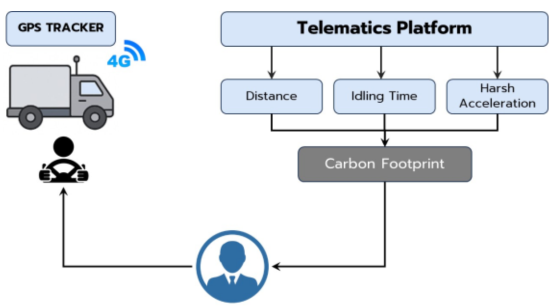

Fig. 1. Platform Architecture.

The architecture consists of three primary layers. The process begins with data acquisition, where a GPS Tracker installed on a vehicle, which is operated by a driver, transmits raw data via a 4G connection to the central Telematics Platform. These devices are responsible for data processing, where it extracts and quantifies key performance metrics indicative of operational efficiency and driver behaviour, specifically GPS coordinates, timestamps , distance travelled, idling time, vehicle speed, engine status (on/off), fuel consumption rates. These quantified metrics are then used to calculate the vehicle's overall carbon footprint. The diagram concludes with a crucial feedback loop: the calculated carbon footprint data is provided to a Logistics Manager, who then uses this specific, actionable intelligence to provide targeted coaching and feedback directly back to the driver, ultimately aiming to modify inefficient driving practices and reduce emissions. To accurately model CO2 emissions, the platform first categorises the vehicle's state into two main categories derived from the GPS data: 'Idling' (engine on, speed = 0) and 'Running' (engine on, speed > 0). This distinction is critical, as emission factors differ significantly between these states. The total CO2 emission (in kgCO2e) is calculated as the sum of emissions from idling and running, as shown in equation (1).

$$\text{Energy}_{\text{total}} = \text{Energy}_{\text{idling}} + \text{Energy}_{\text{running}} \qquad (1)$$

Where $\text{Energy}_{\text{idling}}$ is calculated by multiplying the total idling time (in hours) by a vehicle-specific idling fuel consumption rate and a standard CO2 emission factor per liter of fuel. $\text{Energy}_{\text{running}}$ is calculated using distance-based or fuel-based models correlated with vehicle speed and specifications. The platform was deployed in a pilot study with a local logistics company. We tracked 16 vehicles over a year period.

4 Results

The platform's efficacy was validated through a 1-year pilot study with a local logistics partner, monitoring a fleet of 16 vehicles. The platform dashboard in Fig. 2 provided managers with both fleet-wide summaries and granular per-trip analytics, highlighting key energy performance indicators. This dashboard illustrates a real-time truck tracking map, that shows the GPS locations of the 16 vehicles in the fleet. A fleet summary list details each vehicle's status, name, and the time of its last data transmission. This integrated design enables managers to monitor real-time operations while simultaneously accessing the key energy performance indicators generated by the platform.

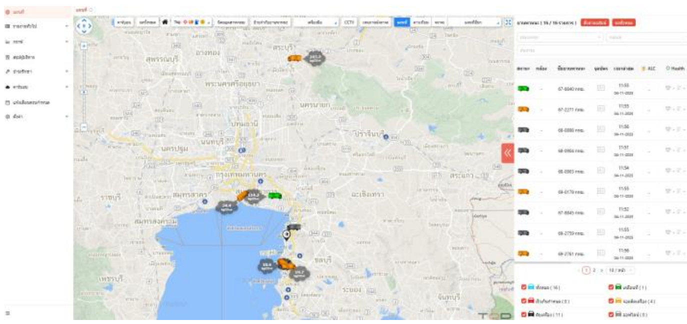

Fig. 2. Real-time Tracking and Energy/Emissions Dashboard.

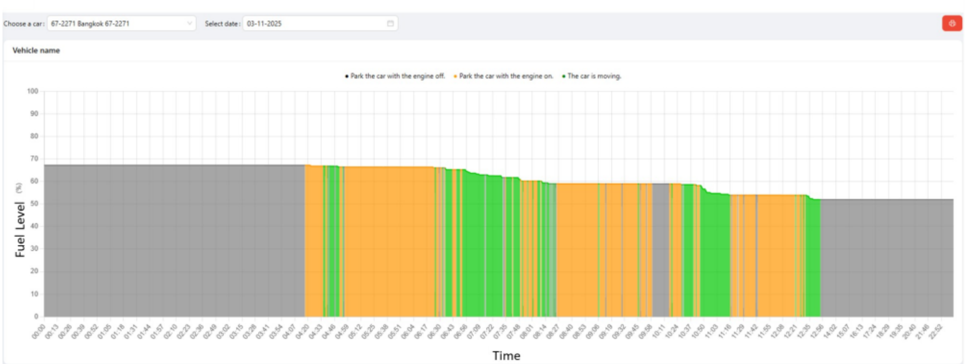

Fig.3 Vehicle-Specific Energy and Emissions Profile.

Fig.3 presents the Vehicle-Specific Energy and Emissions Profile dashboard. It is a time-series visualization that correlates a vehicle's Fuel Level (in %) on the y-axis with Time on the x-axis for a specific vehicle on a selected date (03-11-2025). The chart's primary function is to graphically represent the operational status of the vehicle throughout the day by applying colour coding to the background of the fuel level line: grey indicates the car is parked with the engine off; orange signifies the engine is running while the vehicle is stationary (idling); and green denotes the vehicle is moving. This granular visualization of operational states allows for a direct assessment of inefficient practices, such as extended periods of idling (orange segments), which the platform uses as a critical input for quantifying energy waste and emissions.

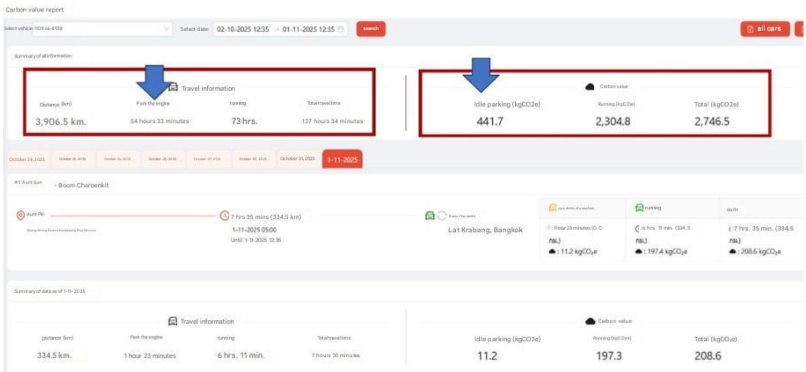

Fig. 4. Platform dashboard showing summary data for travel (distance, idling, running, total time) and carbon emissions (idling, running, total kgCO2e).

The report's focus is on correlating operational activity with quantified carbon emissions over the period from 02-10-2025 to 01-11-2025 in Fig.4. The top summary section, highlighted by red boxes, presents two critical data sets. The Travel Information panel details the fleet's aggregate operational time, showing a total travel distance of 3,906.5 km, with a key finding of 54 hours and 33 minutes of engine idling time ("Park the engine"), 73 hours of running time, and a total engine-on time of 127 hours and 34 minutes. Correspondingly, the Carbon Value panel quantifies the environmental impact: 441.7 kgCO2e attributed to idling, 2,304.8 kgCO2e from running time, and a total emission of 2,746.5 kgCO2e. The data reveals that idling constituted over 42% of the total engine-on time and was directly responsible for approximately 16% of the total carbon emissions1, providing the specific, actionable intelligence required for targeted green energy management.

Fig. 5. Emissions and Idling Time Distribution Across 16 Vehicles.

Fig.5 presents a Summary of Monthly Carbon Emissions for the pilot study. The dashboard component confirms the total size of the monitored fleet, stating a "Total number of cars" of 161. The primary feature is a bar chart that visualizes the distribution of carbon emissions across three months, with the total cumulative emission for the period being 563,470.0kgCO2e2. The data demonstrates a significant variation in emissions between the months: the highest recorded emission was 368,162.0 kgCO2e in August, followed by 102,387. kgCO2e in October, and the lowest was78,839. kgCO2e in September. This chart serves as a high-level performance indicator, enabling logistics managers to track fleet-wide environmental impact over time and identify periods requiring further investigation into operational inefficiencies or changes in workload.

5 Conclusion

This paper demonstrates the successful development and implementation of an IoT platform for monitoring driver behaviour and CO2 emissions, providing a practical tool for advancing green energy in logistics. By distinguishing between running and idling states, the platform provides precise, actionable insights that directly link specific behaviours to carbon emissions and energy inefficiency. The results confirm that such a platform is not merely a monitoring system but an essential enabler for green energy strategies, turning data into actionable intelligence for sustainable fleet management. Future work will integrate with alternative energy vehicles and renewable energy-powered depots to further align logistics operations with the global green energy transition.

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