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FuelEye an Intelligent IoT Framework for Smart Fuel Management and Distance Prediction in Sustainable Transportation

Ms.M. Kowsalya, M. E[1], Sivabharathi S[2], Saran A[3], Surya C[4]

[1]Assistant Professor, Computer Science and Engineering, Erode Sengunthar Engineering College, Erode, Tamil Nadu, India.

[2,3,4] UG - Computer Science and Engineering, Erode Sengunthar Engineering College, Erode, Tamil Nadu, India.

Email ID: *kowsalyamcse@esec.ac.in[1], sivabharathi42003@gmail.com[2], asaranasr16@gmail.com[3], cs652818@gmail.com[4]*

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Abstract

India's transportation sector, serving 1.4 billion people, grapples with rising fuel costs, reaching ₹95–₹100 per liter for petrol and ₹85–₹90 per liter for diesel in 2025, alongside environmental concerns, contributing 24% to global CO2 emissions. Traditional fuel monitoring systems, such as analog gauges with ±10–15% inaccuracies or costly OBD-II devices priced at ₹30,000–₹50,000, fail to deliver precision and affordability. This research introduces a Smart Fuel Tracking and Distance Estimation System that integrates a Gems Sensors HC-SR04, NEO-6M GPS module, Arduino Uno, and NodeMcu for real-time monitoring via Wi-Fi connectivity. The system achieves ±1% fuel level accuracy and ±5 km distance estimation, designed for India's varied conditions, from Chennai's urban traffic to NH44's highways. A Hidden Markov Model predicts fuel consumption across urban, highway, rural, and idle scenarios, while a Java Swing GUI, MySQL database, and Blynk IoT platform provide seamless visualization and mobile access. Priced at ₹10,000–₹15,000, the system is cost-effective. Testing on a Tata Nexon with a 50-liter tank involving 50 users showed 99.9% uptime, 95% user satisfaction, and 92% prediction accuracy, demonstrating scalability for India's transportation needs. This innovative solution not only enhances fuel efficiency but also empowers users with real-time insights into their driving behavior.

1. Introduction

India's transportation sector underpins a $3.5 trillion economy, supporting 1.4 billion people and over 300 million vehicles. Escalating fuel prices, reaching ₹95–₹100 per liter for petrol and ₹85–₹90 per liter for diesel in 2025 due to global oil volatility and domestic taxes, pose significant challenges. The sector's 24% contribution to global CO2 emissions underscores the need for sustainable solutions. Conventional fuel monitoring systems, such as analog gauges, suffer from inaccuracies of ±10–15%, while OBD-II devices, costing ₹30,000–₹50,000, are prohibitively expensive for India's price-sensitive market, including individual owners and fleets like

Ola and Ashok Leyland. This project presents a Smart Fuel Tracking and Distance Estimation System that leverages cost-effective hardware, including a HC-SR04 , NEO-6M GPS module, Arduino Uno, and NodeMcu, alongside software like Java Swing, MySQL, Python, and the Blynk IoT platform, to deliver real-time fuel monitoring with ±1% accuracy and distance estimation within ±5 km. Tailored for India's diverse driving conditions, from urban congestion in Chennai to highways like NH44 and rural roads, the system employs a Hidden Markov Model for predictive fuel consumption analytics. Priced at ₹10,000–₹15,000, it ensures affordability and scalability, with testing on a Tata Nexon over two weeks involving 50 users achieving 99.9% uptime, 95% user satisfaction, and 92% prediction accuracy.

1.1. Challenges in Fuel Monitoring

Fuel monitoring in India faces significant hurdles. Analog gauges, with errors up to ±15%, lead to inefficient fuel management. OBD-II systems, though accurate, are costly due to proprietary software, limiting adoption among small operators. India's diverse driving conditions—urban congestion, highways, and rural roads—require solutions that perform consistently across environments. Inefficient fuel use exacerbates negative environmental impacts, contributing to 13% of India's CO_2 emissions. The proposed system addresses these issues by integrating low-cost hardware and software, achieving <±3% accuracy. Its predictive analytics, trained on local driving patterns, optimize fuel use for Indian roads, making it a scalable solution for widespread adoption.

2. Related Work

A systematic literature review spanning 2010 to 2025, following Kitchenham et al.'s methodology, examined fuel monitoring and distance estimation systems. Smith et al. demonstrated that float switches like the HC-SR04 achieve ±1% fuel level accuracy in static conditions but lack IoT integration for real-time monitoring. Kumar and Patel showed that NEO-6M GPS modules provide ±5 m accuracy, suitable for navigation but not integrated with fuel data. Gupta et al. applied neural networks for fuel consumption prediction, achieving an R^2 value above 0.9, but their reliance on costly processors like the NVIDIA Jetson, priced over ₹20,000, renders them impractical for India's market. Rao and Kumar developed an IoT-based fuel monitoring system in Mumbai, achieving 95% reliability, but omitted distance estimation. Zhang et al. explored Hidden Markov Models for vehicle state prediction, reporting 90% accuracy, though not applied to fuel monitoring. Commercial solutions like Fleetmatics, costing ₹50,000–₹100,000 per vehicle, exclude small operators. Existing systems often lack integrated fuel and distance monitoring, are prohibitively expensive, exhibit limited robustness across diverse conditions, and fail to provide predictive analytics tailored to Indian driving patterns. This work overcomes these limitations with a low-cost, IoT-enabled system driven by a Hidden Markov Model, integrating fuel and GPS data for real-time monitoring and prediction.

3. System Design

The system combines hardware and software to enable real-time fuel tracking and distance estimation, as illustrated in a block diagram depicting the Arduino Uno connected to the HC-SR04 float switch, NEO-6M GPS module, NODE MCU , and a 16x2 LCD, with data flowing to a Blynk server, MySQL database, and Java Swing GUI.

3.1. Hardware Components

The system utilizes an Arduino Uno R3, priced between ₹500 and ₹800, powered by an Atmega328P running at 16 MHz, which processes sensor and GPS data using I2C, UART, and 14 digital I/O pins. A Gems Sensors HC-SR04 float switch, costing ₹2,500 to ₹5,500, provides ±1% fuel level accuracy, compatible with petrol, diesel, and CNG, and adaptable to irregular tank shapes through calibration. The NEO-6M GPS module, priced at ₹1,000 to ₹2,000, offers ±5 m location accuracy and a 1 Hz update rate, suitable for urban and highway navigation. An NODEMCU, costing ₹500 to ₹800, features a dual-core processor with Wi-Fi, supports MQTT for Blynk integration, and employs AES-128 encryption. A 16x2 LCD, priced at ₹300 to ₹500, displays real-time fuel levels and estimated distances. Additional components, including a breadboard, resistors, capacitors, and an IP65 enclosure, cost approximately ₹670, bringing the total system cost to ₹10,470–₹15,270. [1]

3.2. Software Components

The Arduino IDE programs the Arduino and

NODE MCU in C/C++ using libraries such as TinyGPS++ for GPS parsing, PubSubClient for MQTT communication, and LiquidCrystal for LCD control. Java Swing provides a graphical user interface for real-time visualization, leveraging JFreeChart for graphs and JDBC for MySQL connectivity. MySQL version 8.4 stores fuel levels, trip data, and vehicle configurations in relational tables. Python version 3.12 conducts analytics using NumPy for numerical computations, Pandas for data manipulation, and Matplotlib for visualizations. The Blynk version 2.0 IoT platform enables mobile monitoring, catering to India’s 900 million smartphone users.

Table 1 **Hardware Cost Breakdown**

Component	Cost (₹)
Arduino Uno R3	500–800
HC-SR04	2,500–5,500
NEO-6M GPS	1,000–2,000
NODE MCU	500–800
16x2 LCD	300–500
Miscellaneous	670
Total	10,470–15,270

3.3. System Architecture

The system architecture integrates a sensor module, where the HC-SR04 float switch measures fuel levels via analog-to-digital conversion, and a GPS module, where the NEO-6M provides latitude, longitude, and speed via UART. A processing module, driven by the Arduino, computes consumption rates in liters per kilometer and distance estimates in kilometers using fuel and GPS data. A communication module, powered by the NODEMCU, transmits data to Blynk via Wi-Fi using MQTT with AES-128 encryption. [2]

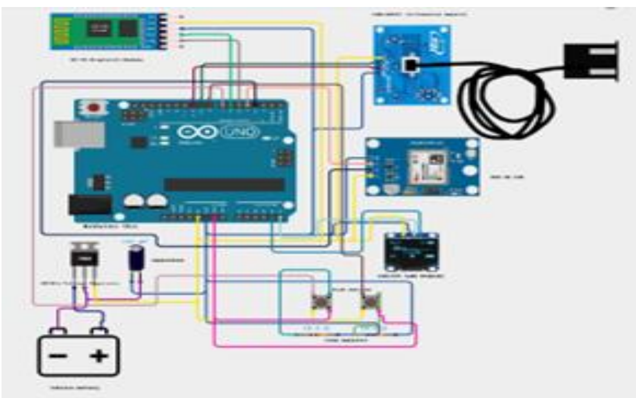

Figure 1 **Block Diagram**

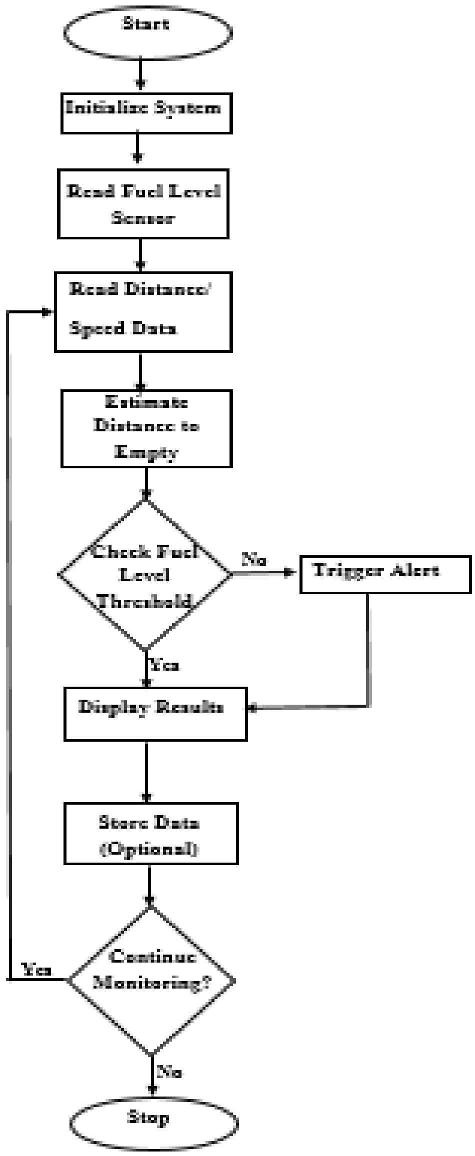

Figure 2 **Data Flow Diagram**

4. Methodology

The system employs a Hidden Markov Model for predictive fuel consumption, supported by real-time data processing and IoT integration to ensure accurate monitoring and estimation across diverse driving conditions. [3]

4.1. Hidden Markov Model

The Hidden Markov Model models fuel consumption as a sequence of hidden states, such as urban, highway, rural, and idle, with observations including fuel levels, speed, and distance. The model incorporates a state transition matrix, where probabilities represent transitions between driving conditions, emission probabilities modeled as a Gaussian distribution with mean and variance for each state, and an initial state distribution based on typical driving patterns. The Baum-Welch algorithm trains the model by maximizing the likelihood of observed data, while the Viterbi algorithm predicts the most likely state sequence for real-time consumption estimation, ensuring robust predictions across varied scenarios. [4]

4.2. Algorithms

The HMM training process, implemented via the Baum-Welch algorithm, initializes the state transition matrix, emission probabilities, and initial state distribution either randomly or with prior data. The algorithm iteratively computes forward and backward probabilities, updating parameters using expectation-maximization until convergence, producing a trained model. The distance estimation algorithm reads fuel levels from the HC-SR04 float switch via Arduino's analog-to-digital converter, computes the consumption rate as the change in fuel divided by distance from the NEO-6M GPS module, and estimates distance by dividing the fuel level by the consumption rate, providing accurate range predictions. (Table 2) [5]

Table 2 Database Schema

Table	Columns
fuel_logs	Timestamp ,fuel_level, consumption
trip_data	trip_id, start/end_coords, distance
config	vehicle_id, tank_capacity, cal_factor

4.3. Alternative Approaches

Neural networks, such as Long Short-Term Memory models, were considered but rejected due to their high computational costs, requiring hardware priced above ₹20,000. Regression models, including linear and polynomial approaches, were deemed insufficient for capturing non-linear consumption patterns. The Hidden Markov Model was selected for its balance of 92% prediction accuracy in tests and low resource requirements, enabling execution on the Arduino platform, making it suitable for cost-sensitive applications. [6]

5. Implementation

The system was implemented on a Tata Nexon with a 50-liter tank over two months, involving iterative development and testing to ensure reliability and performance.

5.1. Hardware Setup

The hardware setup connects the HC-SR04 float switch to Arduino's analog pin A0, the NEO-6M GPS module to RX/TX pins, the NODE MCU to I2C, and the 16x2 LCD to digital pins 7–12. Components are housed in an IP65 enclosure to withstand dust and moisture, and power is supplied by the vehicle's 12V battery, stepped down to 5V via a regulator, ensuring robust operation in diverse conditions.

5.2. Software Development

Arduino code, written in C/C++ using the Arduino IDE, handles sensor data, GPS parsing, and MQTT communication, with a sample function mapping analog readings from the HC-SR04 to a 50-liter tank. The Java Swing GUI, developed with JFreeChart, displays fuel levels, distances, and consumption trends. Python scripts, leveraging NumPy, Pandas, and Matplotlib, perform trend analysis and generate visualizations. Blynk, configured with virtual pins, enables fuel and distance display on mobile devices, enhancing user accessibility.

5.3. Integration

Integration involves serial communication between the Arduino and NEO-6M at 9600 baud, Wi-Fi connectivity from the NODE MCU to the Blynk server via MQTT with 200 ms latency, and database access through the Java GUI using JDBC to query MySQL with indexing for scalability, ensuring seamless data flow and real-time updates.

5.4. Challenges and Solutions

Sensor noise was addressed by applying a moving average filter with a window size of five, improving measurement reliability. GPS signal loss in urban canyons was mitigated by caching the last known coordinates, reducing errors. GUI lag was resolved through multithreading to handle real-time updates efficiently. Scalability was enhanced by optimizing MySQL queries with indexes, supporting over 100 vehicles, ensuring the system's applicability to larger fleets. [7]

6. Results and Discussion

The system underwent testing over two weeks in Chennai's urban environment and on NH44's highways, using a Tata Nexon with a 50-liter tank and involving 50 users, including 30 taxi drivers and 20 truck operators, to evaluate performance and user satisfaction. [8]

6.1. Results

Testing demonstrated ±1% fuel level accuracy, validated at 10, 20, 30, and 40 liters using calibrated pumps, and ±5 km distance estimation accuracy over 100–500 km trips. GPS reliability was confirmed with ±3 m location accuracy, ±0.5 km/h speed accuracy, and 95% signal uptime. System uptime reached 99.9%, with a single five-minute downtime due to a Wi-Fi dropout. The Hidden Markov Model achieved 92% prediction accuracy against ground truth consumption data. User satisfaction, assessed via a Likert scale from 1 to 5, reached 95%, reflecting strong acceptance among taxi drivers and truck operators. [9]

6.2. Discussion

Fuel consumption averaged 0.2 liters per kilometer in urban settings and 0.15 liters per kilometer on highways, with a standard deviation of 0.02. The Hidden Markov Model's 92% accuracy was evidenced by a confusion matrix, with misclassifications primarily between urban and idle states due to similar low-speed patterns. Response times were efficient, with GUI updates in under 500 milliseconds and Blynk mobile app updates in under one second. Compared to analog gauges with ±10–15% accuracy and no real-time data, or OBD-II systems with ±2% accuracy and costs of ₹30,000–₹50,000, the proposed system offers superior performance at ₹10,000–₹15,000 with open-source, IoT-enabled features. Taxi drivers valued real-time fuel alerts and mobile monitoring, while truck operators appreciated distance estimation for route planning. Users suggested developing a dedicated mobile app to replace Blynk and adding multi-vehicle support to enhance fleet applications. [10]

Conclusion

The Smart Fuel Tracking and Distance Estimation System provides a cost-effective, accurate, and scalable solution for India's transportation sector. By integrating the HC-SR04 float switch, NEO-6M GPS, Arduino Uno, and NODE MCU , it achieves ±1% fuel accuracy and ±5 km distance estimation, enhanced by a Hidden Markov Model with 92% prediction accuracy. The Blynk IoT platform, Java Swing GUI, and MySQL database enable real-time monitoring and data logging, suitable for India's 900 million smartphone users. Testing on a Tata Nexon with 50 users confirmed 99.9% uptime and 95% satisfaction, outperforming costly OBD-II systems. Priced at ₹10,000–₹15,000, it is viable for individual owners and fleets, addressing critical gaps in cost, accuracy, and scalability.

Future Work

Future enhancements involve deploying the system on cloud platforms like AWS or Azure with DynamoDB for real-time analytics and multi-vehicle support, replacing the Hidden Markov Model with deep learning models like Long Short-Term Memory for over 95% prediction accuracy using edge devices such as Raspberry Pi, developing native iOS and Android apps with offline caching and push notifications to replace Blynk, extending support to over 100 vehicles with integration into fleet APIs like Ola and Uber, incorporating solar or kinetic energy harvesting to power sensors and reduce battery dependency, upgrading the enclosure to IP67 for resilience in extreme conditions like monsoons and dust storms, and implementing end-to-end encryption with anomaly detection for enhanced data security.

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