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Fuel Level Estimation in Tank of Truck in Motion

Pawel Biernacki and Urszula Libal

***Abstract*—The paper presents the results of a case study on estimating the fuel level in the tank of a motor vehicle. A method based on the concept of particle filtering of noisy measurement data is proposed. The algorithm designed using the Sequential Monte Carlo method with Sequential Importance Sampling is combined with classical digital filters used for signal filtering. In the simulations, real data obtained by measuring fuel levels in the tanks of TIR heavy trucks from one of the Polish trucking companies are used. The performance of the applied method was considered in various measurement situations, such as refueling, driving on an uneven road surface, driving on steep roads, and fading of the measurement signals.**

***Keywords*—automotive sensors; particle filter; Sequential Monte Carlo; fuel level; heavy truck; vehicle in motion**

I. INTRODUCTION

IT is crucial for drivers to accurately know the fuel level in a vehicle's tank, as this information is vital for predicting the remaining driving distance and planning routes effectively. Accurate fuel level readings help to plan trips, determine optimal fuel fuel times, and adjust driving strategies. Inconsistent or inaccurate fuel level measurements can complicate trip planning and lead to inefficiencies. For motor carriers, accurately determining the fuel consumption of their fleet of vehicles is a major concern for both economic and operational reasons [1]. Monitoring actual fuel consumption is essential for calculating the true costs of operations, maintaining the technical condition of vehicles, and identifying potential instances of fuel theft.

In the literature, various algorithms have been developed to estimate fuel consumption [2] [3] [4] [5]. However, real-time implementation of these algorithms has received limited attention. During the past decade, numerous fuel estimation algorithms have been proposed. For example, the authors of [6] developed an algorithm based on a power-based model, which requires instantaneous values for acceleration and speed; therefore, it is not suitable for eco-routing applications. The author of [2] proposed a non-iterative fuel estimation model. The technique presented in [7] to address the vehicle routing problem (VRP) utilizes the Comprehensive Modal Emission Model (CMEM), which also requires speed and acceleration data to estimate fuel consumption. Furthermore, the authors of [4] proposed an algorithm based on RPM and designed a hardware architecture using floating-point arithmetic to implement the fuel estimation algorithm.

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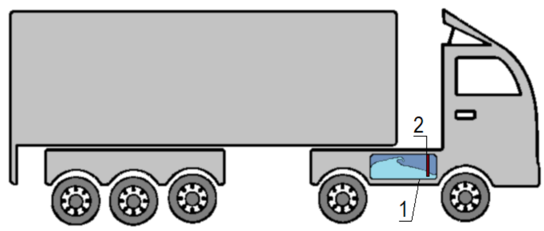

Fig. 1. TIR heavy truck with: 1) fuel tank and 2) measuring probe.

In the literature, model-based filters, such as the Kalman filter [8], the H∞ filter [9] [10], and the RLS filter [11] [12], are optimal as long as the following criteria are met:

- The system dynamics are linear,
- Process noise and measurement noise are un-correlated and zero-mean white noise,
- The system dynamics are observable and detectable.

In this paper, methods based on the Sequential Monte Carlo algorithm combined with digital filters are discussed and compared. Particle filtering [13] [14] [15] [16] [17] [18] with Monte Carlo resampling has the ability to estimate highly nonlinear systems under the right circumstances. It approximates the distribution of a variable using particles as a model. For the measurement of fuel level, which represents a non-linear system, such a solution seems promising and should be an effective way to estimate the amount of fuel in the tank of a vehicle in motion.

II. PROBLEMS RELATED TO FUEL LEVEL MEASUREMENT

The fuel level data recorded by the probe placed in the vehicle tank is not directly interpretable. This is due to the constant motion of liquid gasoline caused by the movement of the vehicle (Fig. 1):

There are sources of disturbances and uncertainties that affect the precision and accuracy of measured fuel levels. Mechanical disturbances or process noise affect the measured fuel levels. The liquid in the tank may cause a sloshing phenomenon in the tank as the car accelerates or decelerates. The angular orientation of the car also changes the displacement of the fluid in the tank (Fig. 2). The motion of the fluid and its displacement in the tank will be influenced by the actual

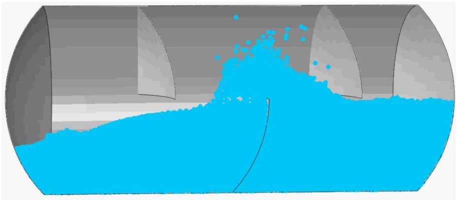

Fig. 2. Model of sloshing phenomenon with fuel fluctuating in a tank.

volume of the fluid. The sensor itself may also be noisy, which is yet another factor that influences fuel level readings.

Possible, but not the only, situations that interfere with the correct measurement of fuel levels are:

- Driving on uneven pavement,
- Rapid braking or acceleration,
- Torsion,
- No measurement signal.

Taking into account the requirements of motor carriers, the system for determining the actual fuel burn should correctly determine the moment of refueling and its value, correctly estimate the current fuel burn, and detect with some assumed accuracy the possible fuel spillage from the tank.

III. Measurements

All data were collected using pressure probes fitted into truck tanks that traveled all over Europe. Various road conditions were considered:

- highway driving,
- driving in the mountains,
- refueling,
- accelerating and decelerating

Fig. 3. Pressure probe.

The pressure probe used (Fig. 3) is designed to measure the fuel levels in the tanks of motor vehicles, work machines, and locomotives. The fuel level is measured by comparing the height of the liquid column and resulting from it, hydrostatic pressure. The probe consists of two parts: a sensing part in a steel tube and an electronic part in an aluminum housing that can be sealed. The measuring element is a piezoresistive sensor separated from the medium by a diaphragm. The pressure is measured at the diaphragm level of the immersed probe (5 mm above the tank bottom). Depending on the type of tank (non-pressurized or pressurized), pressure measurement is related to atmospheric pressure or pressure inside the tank. An example of a raw reading from the measuring probe is shown in (Fig. 4). A sudden increase in fuel level at the beginning of the graph corresponds to the time when the vehicle is refueled.

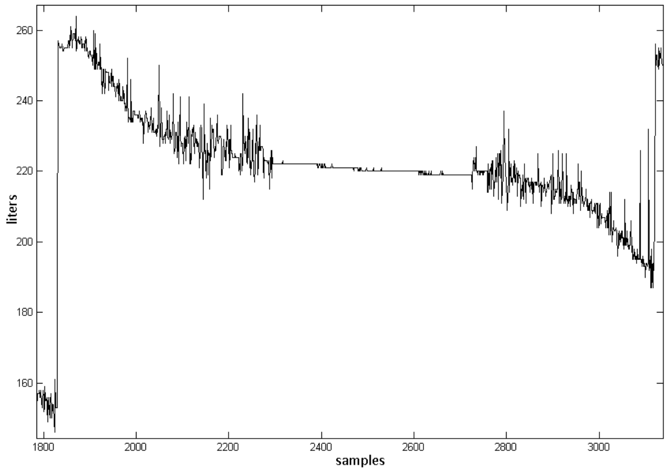

Fig. 4. Signal from the measuring probe.

IV. Assumptions

Digital averaging (low-pass) filters were used for fuel level estimation, which was also confronted with the averaging of measurement data by the particle method. As the tests showed, the use of only the low-pass filter (averaging) or the particle method does not allow the correct determination of the fuel level. It is clear that handling some situations that disturb the measurement (mentioned above) requires the use of intelligent procedures for their recognition and processing in the estimation system. Particularly critical is the moment of refueling. Determining its beginning, end, and value gives the opportunity to detect possible fuel spills (most gasoline thefts take place during refueling), is the starting point for determining combustion, and is the basis for verifying the correctness of the operation of the measuring and estimating system. The accuracy of the measuring system can be verified on the basis of fuel purchase invoices flowing to the carrier. Fig. 2) shows an example of probe indications during the refueling process. In addition to the readings of the measuring probe placed in the vehicle tank, the estimation system also uses data on vehicle speed, vehicle distance traveled, and the elapsed time between successive readings of the probe. This data greatly facilitates the correct determination of the fuel level in the tank. Taking into account the above discussion, the following estimation system is proposed.

1) While the vehicle is at a standstill (zero speed, distance traveled almost zero) – the check whether a refueling moment has occurred.

2) While driving – the use of an averaging filter to determine the current fuel level.

The moment of refueling is determined by the cumulative incident:

- Stopping time longer than t_1 seconds (refueling takes at least a minute),
- Distance traveled less than s_1 meters (measuring the position of a standing vehicle with a GPS system does

not always give the same result),

- An increase in the fuel level in the tank by m_1 liters.

Selecting the values of the parameters t_1, s_1, m_1 is critical for the correct functioning of the estimation system. Wrong values can result in:

1) identification of a refueling event when it is not there, such as sudden vehicle braking, stopping on an incline,
2) the wrong measurement of the amount of fuel fueled,
3) not detecting refueling [2].

When the vehicle is in motion, the selection of parameters and the 'intelligence of operation' of the averaging filters should take into account the inertia of the fuel in the tank, the disappearance of the signal, and the inability of the fuel level in the tank to rise (there is no refueling after all).

V. ESTIMATION OF AVERAGE COMBUSTION BY SEQUENTIAL MONTE CARLO METHOD

In this article, we focus on fuel level estimation using the sequential Monte Carlo method. The approximate measurement data are estimated and smoothed using the particle method [13] [14] [15] [16] [17] [18]. This method seems to be an excellent tool for determining fuel combustion a vehicle in motion due to the fact that one can freely choose the accuracy of averaging depending on the 'noisiness' of the measurement data (Fig. 4)), changing only the number of repetitions (iterations) of the algorithm.

A. State Space Model

A particle filter, also known as a Sequential Monte Carlo (SMC) method [13] [14] [15] [16] [17] [18], is a recursive Bayesian state estimator used to estimate the state of a dynamic system from noisy observations. It is particularly useful in systems where the process and observation models are non-linear or non-Gaussian. The particle filter approximates the posterior distribution of the system's state using a set of random samples called particles, each associated with a weight representing the particle's probability of being the true state. In the problem considered, we are actually dealing with a noisy signal in the form of a certain mapping $y_k = h(x_k, v_k)$ where the input data x_k is the amount of fuel and the output data y_k are associated with certain measurements. The State Space Model is defined as follows:

State Transition Model:

$$x_k = f(x_{k-1}, w_{k-1}), \tag{1}$$

where:
x_k - State at time step k,
f - Function that describes the dynamics of the system.
w_k - process noise.

The particles $\{x_k^{(i)}\}, i = 1, ..., N$ are samples that represent possible states of the system (unknown amount of fuel). The weights $\{w_k^{(i)}, i = 1, ..., N$, represent the likelihood that each particle corresponds to the actual state, based on the observations.

Observation Model:

$$y_k = h(x_k, v_k), \tag{2}$$

where:
y_k - Observation at time step k (signal samples from the sensor),
h - Function related to the state to the observation.
v_k - Observation noise.

B. Particle filter with Sequential Importance Sampling

The particle filter algorithm with Sequential Importance Sampling (SIS) [13] [14] [15] [16] [17] [18] is a technique used to estimate the posterior distribution of a system's state given observations over time. It does so by representing the posterior with a set of weighted samples (particles). The algorithm recursively updates these particles as new observations become available. The particle filter algorithm with sequential importance sampling for the defined in Section 5.1 State Space Model, has the following steps:

1. Initialization:

Generate N particles $\{x_k^{(i)}, i = 1, ..., N\}$, from the initial distribution $p(x_0)$. Assign an initial weight to each particle, typically

$$w_0^{(i)} = \frac{1}{N} \; for \; i = 1, ..., N \tag{3}$$

2. Prediction (Time Update):

Propagate each particle $x_{k-1}^{(i)}$ to the next state using the state transition model:

$$x_k^{(i)} = f(x_{k-1}^{(i)}, w_{k-1}^{(i)}) \tag{4}$$

3. Update (Measurement Update):

Update the weight $w_k^{(i)}$ of each particle based on the likelihood of the observed data given the predicted state:

$$w_k^{(i)} \propto w_{k-1}^{(i)} p(y_k | x_k^{(i)}) \tag{5}$$

In detail, the updated weight is calculated from:

$$w_k^{(i)} = w_{k-1}^{(i)} \frac{p(y_k | x_k^{(i)}) p(x_k^{(i)} | x_{k-1}^{(i)})}{q(x_k^{(i)} | x_{0:k-1}^{(i)}, y_{1:k})} \tag{6}$$

where

$$p(y_k | x_k^{(i)}) \tag{7}$$

is the likelihood of the observation y_k given the state $x_k^{(i)}$ and

$$q(x_k^{(i)} | x_{0:k-1}^{(i)}, y_{1:k}) \tag{8}$$

is the proposal distribution from which the particles are sampled. After calculating all the weights, normalize them so that

$$\sum_{i=1}^{N} w_k^{(i)} = 1 \tag{9}$$

The normalized weights are derived from the equation:

$$\tilde{w}_k^{(i)} = \frac{w_k^{(i)}}{\sum_{j=1}^{N} w_k^{(j)}} \tag{10}$$

4. Resampling:
To address the problem of particle degeneracy (where few particles have significant weights), resample the particles to form a new set. A common criterion for resampling is the effective sample size (ESS):

$$ESS = \frac{1}{\sum_{j=1}^{N} (\tilde{w}_k^{(j)})^2} \tag{11}$$

If ESS falls below a certain threshold, resampling is performed to generate a new set of particles. Particles with high weights are duplicated, while those with low weights are discarded. The weights are then reset to $\frac{1}{N}$.
5. Output estimate:
The current state estimate can be obtained by the weighted mean of the particles or also by selecting the particle with the highest weight. The state estimate derived as the weighted average of the particles is given by:

$$\hat{x}_k = \sum_{i=1}^{N} \tilde{w}_k^{(i)} x_k^{(i)} \tag{12}$$

In summary, the particle filter with Sequential Importance Sampling is a powerful method for tracking and estimating the state of dynamic systems, particularly when dealing with non-linearities and non-Gaussian noise. Its strength lies in its flexibility and ability to approximate complex distributions, although it requires careful implementation to manage computational costs and prevent degeneracy.

VI. SIMULATIONS ON REAL-DATA

The proposed solution was tested using real data. They were taken from the vehicle tank using a sensor (Figure 3) and transmitted over the GSM network to the vehicle fleet monitoring center. There, the data was analyzed by our system. Having the results from the sensors for many vehicles, we were able to check the performance of the system for various parameters of the filters used. We used FIR filters [11] [12] with an order of 5 to 50 and IIR (Butterworth) filters [12] with an order of 2 to 10. The procedure for verifying the accuracy of the system's operation consisted of the following:

1) refuel the vehicle to full,

2) driving in the field,

3) refueling to a full tank.

This approach allowed us to determine the value of the fuel combusted. By comparing this quantity with that estimated by our system, it was possible to determine the accuracy of the system for different values of its parameters.

The Table I shows the average accuracy of the estimate of total fuel burned while driving defined as

$$Q = \frac{1}{T} \sum_{t=1}^{T} \left(1 - \frac{|\mathrm{GT}(t) - \mathrm{EV}(t)|}{\mathrm{GT}(t)}\right) \cdot 100[\%], \tag{13}$$

where T is the number of refueling events, when the ground truth (GT) value could be compared with the estimated value

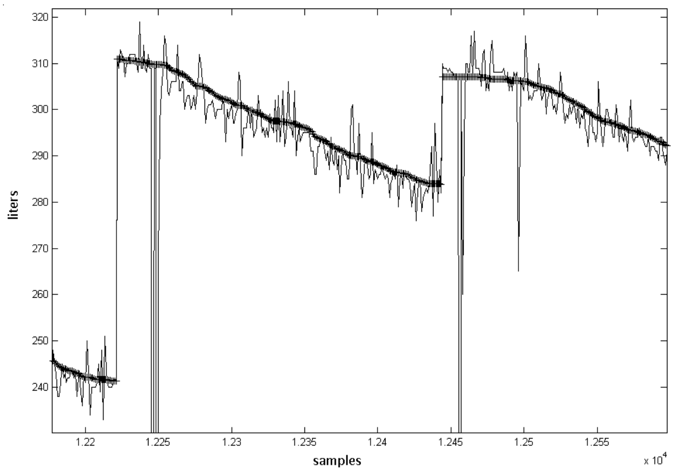

Fig. 5. Fuel measurement for a vehicle in motion - IIR filter of order 5.

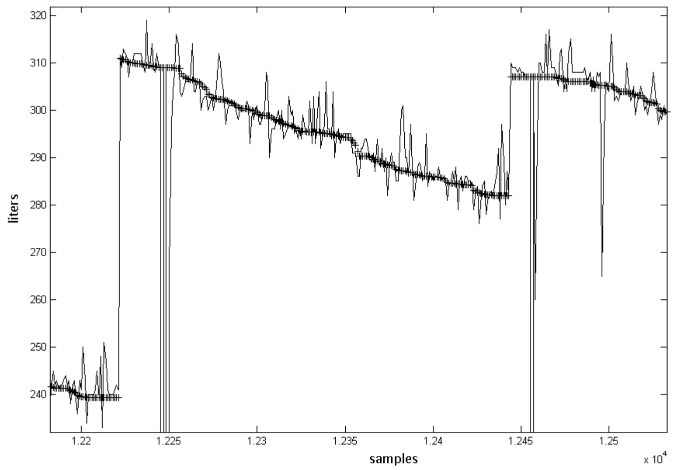

Fig. 6. Measurement for a vehicle in motion - FIR filter (Hamming window) of order 10.

(EV) of the fuel level in a tank of a particular truck. To obtain the ground truth value, the tank was fully refueled and the value estimated directly before the visit at the petrol station as compared with the refueled amount, which was the ground truth at the moment.

TABLE I
AVERAGE COMBUSTION ESTIMATION ACCURACY Q FOR DIFFERENT FILTER TYPES AND ORDERS, AND FUEL LEVEL ESTIMATION MEAN ERROR IN LITERS.

Filter order	Q [%]	Error [liter]
FIR 5	92.02	31.92
FIR 10	94.42	22.32
FIR 30	96.90	12.40
FIR 50	98.13	7.48
IIR 2	92.62	29.52
IIR 5	96.79	12.84
IIR 10	99.03	3.88

Our observations demonstrate that increasing the filter order enhances the accuracy of burned fuel estimation. IIR filters

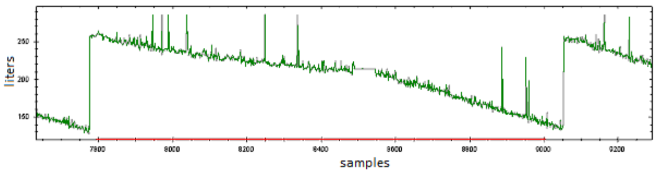

Fig. 7. Particle filter: noised signal before filtration.

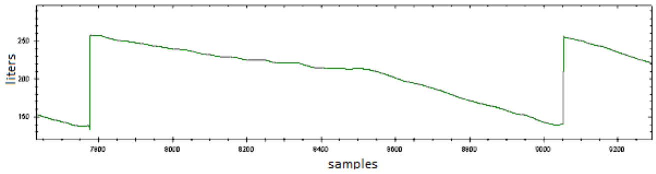

Fig. 8. Particle filter: de-noised signal after filtration.

exhibit superior performance compared to FIR filters in this context. The system achieves a maximum accuracy of approximately 99%. Considering the fuel tank capacity of the surveyed vehicles, which is around 400 liters, the estimation error for burned fuel remains below 4 liters. Simulation studies were conducted and visualized using the MATLAB environment. Representative test results are presented below.

A comparison of Figs. 5 and 6 reveals that the FIR filter exhibits superior tracking performance of the fuel level trajectory. However, this improvement comes at the cost of a higher filter order compared to the IIR filter. Furthermore, given the non-uniform sampling intervals of the probe data, the FIR filter may introduce significant latency, potentially rendering the system unsuitable for real-time online operation.

Within the same order of IIR and FIR filters, the IIR filter generally demonstrates superior performance.

Particle filtering demonstrates high effectiveness in smoothing the signal trajectory, exhibiting competitive performance with the digital filters presented above (compare Figs. 8 and 9). However, achieving a denoised signal as depicted in Fig. 9 requires approximately 200 algorithm iterations, significantly increasing processing time. This computational burden renders particle filtering impractical for real-time systems monitoring numerous vehicles simultaneously.

Fig. 10 shows the moments of the refueling process (the same as in Fig. 4. Selecting the parameters values t_1, s_1, m_1 with the use of an iterative method allowed us to correctly detect the moments of refueling and determine the level of refueling with an accuracy of 5 liters - the results were compared with fuel invoices.

VII. Conclusions

The results obtained from simulation studies of the system for estimating the fuel level in the tank of a motor vehicle allow us to formulate the following conclusions. Identifying the moment of refueling is critical to the effectiveness of the system. The IIR filters, because of their smaller order than FIR filters, appear to be better in a vehicle traffic situation, with the best result of fuel level estimation for IIR filter of order 10 equal approximately 4 liters. The Sequential Monte Carlo method in the form of the particle filter, due to its long processing time, can only be used in off-line systems; where speed and ongoing monitoring of fuel levels are important, digital filters are a better solution. Information on vehicle speed and distance traveled is necessary for the correct determination of the fuel level estimate, the values of the parameters t_1, s_1, m_1 determine the suitability of the estimation system.

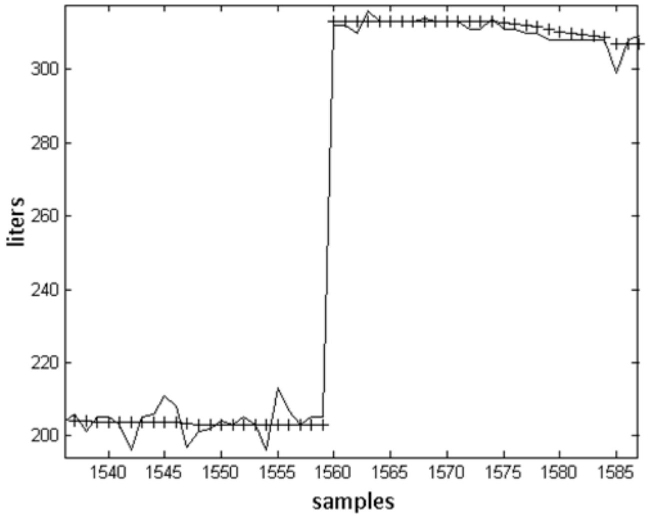

Fig. 9. Vehicle refueling signal (easy case) - IIR filter of order 5.

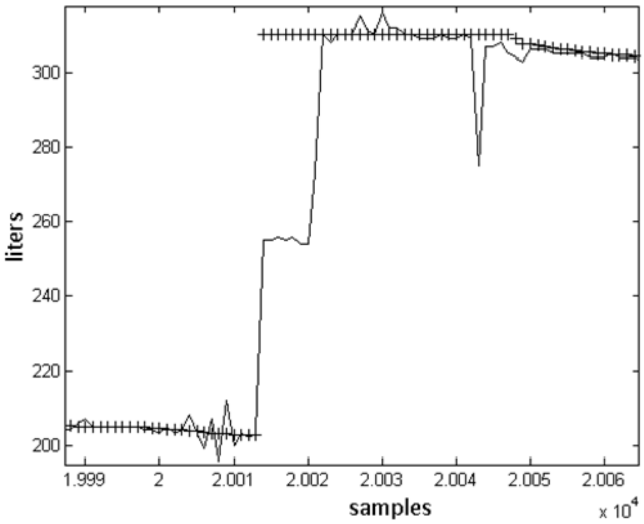

Fig. 10. Vehicle refueling signal (hard case) - IIR filter of order 5.

The conducted tests enabled the estimation of fuel quantity in tanks of truck in motion. However, a limitation lies in obtaining the values of the ground truth, i.e. the values determined after refueling at a petrol station. The validation of the system and the accuracy of the estimates remains a challenging problem.

VIII. Possible Future Improvements

The accuracy of the calculated average fuel level in moving vehicles is deemed satisfactory, albeit with potential for further enhancement. Incorporating additional vehicular data, such as sensor readings, can significantly improve the efficiency of the proposed method.

A valuable addition to the vehicle's instrumentation would be a gyroscope. This device measures the vehicle's inclination. By analyzing gyroscope data, errors in recorded fuel levels, which arise during vehicle movement on inclined surfaces and manifest as abrupt fluctuations in fuel tank content graphs, can be effectively mitigated.

Another module that can enhance algorithm efficiency is a simple thermometer mounted on the fuel tank. This device can detect errors associated with inaccurate fuel level readings from the fuel sensor caused by temperature variations within the fuel container.

To further enhance system capabilities, additional functionalities can be integrated: monitoring driver behavior, satellite tracking, and detecting the presence of the driver and third parties. To achieve this, modules such as a current sensor for the gear, an engine rotation sensor, sensors mounted on the front seats, and a satellite navigation module can be incorporated. Data from these devices, when processed appropriately, can significantly improve fuel consumption estimation in operating vehicles.

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