

Using Ultrasonic Sensor for Fuel Measurement in Diesel Locomotives

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Abstract: This paper explores how ultrasonic sensors can be used to measure fuel volume in diesel locomotives. We will look at a real-world example in which we will see how the sensor can be installed. We will also see how it is calibrated to give accurate results.

Keywords: Ultrasonic Sensors, Diesel Locomotives, IoT, Cloud, Microcontroller

I. INTRODUCTION

Many vehicles these days use very sophisticated fuel measurement systems. These systems provide an accurate reading of the instantaneous fuel capacity [1]. This makes it easy to calculate fuel consumption and thus narrowing down problems encountered, if any.

However, this is not the case with heavier vehicles such as trucks, diesel locomotives, marine vessels etc. These vehicles use older methods and traditional techniques. It is also worth noting that these vehicles carry a considerably large volume of fuel at any given time. Combine the aforementioned factors and we have a grave problem that requires immediate attention. Due to the inefficiencies many problems arise such as fuel theft, unexpected shortage and increased costs. We are going to be focussing on how these problems can be mitigated using ultrasonic sensors.

II. ULTRASONIC SENSORS FOR FUEL MEASUREMENT

The ultrasonic sensors are suited for fuel measurement for the following reasons [2]:

A. *Relatively Inexpensive*

Ultrasonic sensors are sufficiently accurate for fuel measurement at a relatively cheaper price as compared to capacitive sensors of similar specifications. Even float-type sensors are expensive.

B. *Hassle-free Installation*

Ultrasonic sensors are easy to install. Generally, any opening above the tank, such as the vent pipe can accommodate these sensors. This means that the tank need not be modified, by drilling holes, just for a sensor installation. Modification has to be made in order to install capacitive or float-type sensors.

C. *Contactless*

Ultrasonic sensors, unlike their capacitive or float-type counterparts, need not be in contact with the fuel being measured. This means they work efficiently even in corrosive environments.

III. INSTALLATION ON DIESEL LOCOMOTIVES

As mentioned earlier, ultrasonic sensor installation is easier than others. We will demonstrate this by explaining how it can be installed on a locomotive tank.

All diesel locomotive tanks, especially in India, have a maximum fuel carrying capacity of 5000 litres [3]. In order to accommodate the vapours, a special opening is given at one of the edges. A vent pipe is attached to this opening. This vent pipe is fully detachable for maintenance. The idea is to install a small ultrasonic sensor, such as the HC-SR04[4], in between the vent pipe and the fuel tank opening.

The HC-SR04 is small enough to not obstruct the opening and allows the vapours to pass. The microcontroller, which is used to control this sensor, is installed separately in the grill provided near the fuel tank. In this way both these components are installed and concealed.



IV. CALIBRATION OF THE SENSOR

An ultrasonic sensor works by measuring the distance between itself and a plane surface or an obstacle. In our case, the plane surface is the top surface of the diesel in the tank. The HC-SR04 ultrasonic sensor is composed of a transmitter, marked T and a receiver, marked R. Whenever distance is to be measured, the microcontroller sends a trigger signal, which in turn makes the transmitter emit an ultrasonic pulse. This pulse hits the surface in question, reflects and returns back. The receiver on the sensor picks up this pulse and reports it to the microcontroller. The microcontroller keeps track of the time it takes for the above process to complete and then calculates the distance using the formula [5]:

$$Distance = \frac{Time \times Speed\ of\ Sound}{2}$$

Since ultrasonic sensors only give us distance, we must transform it into other parameters, such as fuel volume in our case. In order to achieve successful measurement, calibration must be performed. We will now see how to calibrate the HC-SR04 installed on the locomotive fuel tank. It is to be noted that, we have performed and documented everything on a real Indian Railways WDM2 locomotive [6]. We begin with an empty tank and take the initial reading of the sensor. We then fill the tank with the fuel, diesel here, in constant successive increments and note the readings. We chose this increment to be 50 litres as it was feasible at the time. The collected data can be seen in Table I.

Table I WDM2 Locomotive Fuel Tank Calibration Data

Sr. No.	Distance	Volume
1	64.11	1150
2	63.87	1200
3	62.9	1250
4	61.29	1300
5	60.49	1350
6	58.7	1400
7	57.19	1450
8	56.02	1500
9	54.67	1550
10	53.86	1600
11	53.13	1650
12	52.48	1700
13	51.36	1750
14	50.48	1800
15	49.81	1850
16	48.93	1900
17	48.11	1950
18	47.18	2000
19	46.27	2050
20	45.51	2100
21	44.78	2150
22	43.78	2200
23	43.06	2250
24	42.38	2300
25	41.62	2350
26	41.02	2400
27	40.19	2450
28	39.56	2500
29	38.96	2550
30	37.87	2600
31	36.91	2650
32	36.14	2700
33	35.48	2750
34	34.49	2800
35	33.74	2850
36	32.46	2900
37	31.99	2950
38	31.28	3000
39	30.63	3050
40	29.74	3100



Now that we have the data, we can model it. Plotting the data in a distance v/s fuel volume graph we get Figure 1.

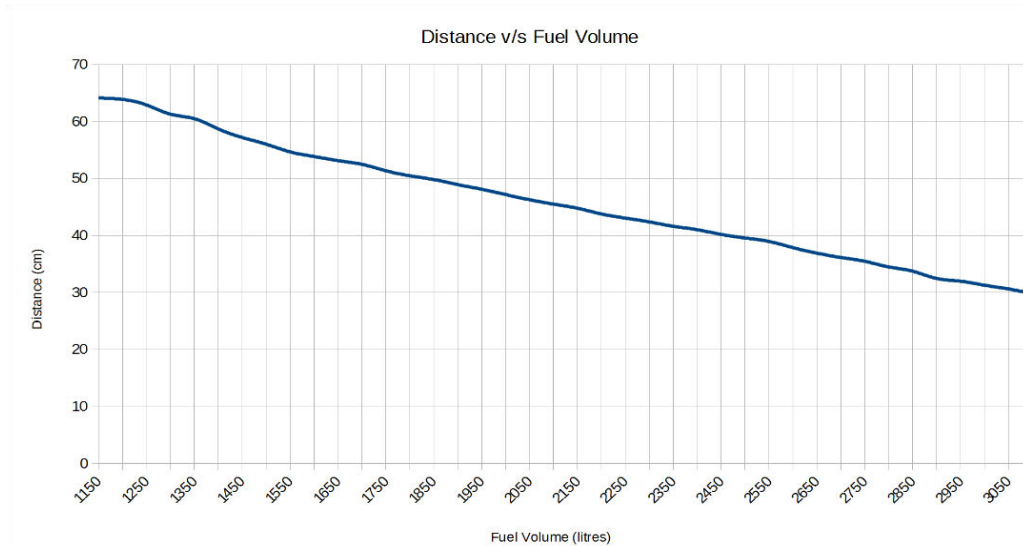


Figure 1. Distance v/s Fuel Volume graph

We can see an almost linear relationship from this graph. To create a model, we find the curve that fits our data using any spreadsheet program such as MS-Excel. First a linear model is evaluated. On plotting a linear trendline through the data, we get Figure 2.

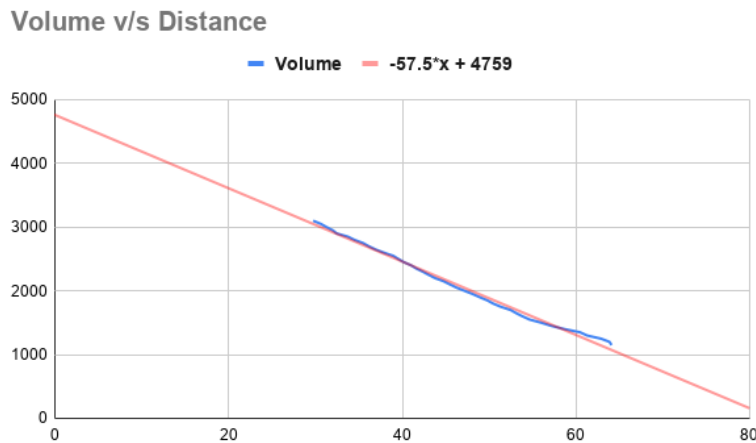


Figure 2. Linear model of the data

We can see that there are significant outliers. To further analyse, we find out what this linear model predicts for the corresponding actual measurement. This analysis can be seen in Table II.

Table II Analysis of Linear Model

Real Values	Prediction by Linear Model	Difference (Prediction - Real)	Absolute Value
1150	1072.675	-77.32	77.32
1200	1086.475	-113.53	113.53
1250	1142.25	-107.75	107.75
1300	1234.825	-65.17	65.17
1350	1280.825	-69.18	69.18
1400	1383.75	-16.25	16.25
1450	1470.575	20.58	20.58
1500	1537.85	37.85	37.85
1550	1615.475	65.48	65.48
1600	1662.05	62.05	62.05
1650	1704.025	54.02	54.02



1700	1741.4	41.4	41.4
1750	1805.8	55.8	55.8
1800	1856.4	56.4	56.4
1850	1894.925	44.92	44.92
1900	1945.525	45.53	45.53
1950	1992.675	42.68	42.68
2000	2046.15	46.15	46.15
2050	2098.475	48.48	48.48
2100	2142.175	42.18	42.18
2150	2184.15	34.15	34.15
2200	2241.65	41.65	41.65
2250	2283.05	33.05	33.05
2300	2322.15	22.15	22.15
2350	2365.85	15.85	15.85
2400	2400.35	0.35	0.35
2450	2448.075	-1.92	1.92
2500	2484.3	-15.7	15.7
2550	2518.8	-31.2	31.2
2600	2581.475	-18.52	18.52
2650	2636.675	-13.32	13.32
2700	2680.95	-19.05	19.05
2750	2718.9	-31.1	31.1
2800	2775.825	-24.18	24.18
2850	2818.95	-31.05	31.05
2900	2892.55	-7.45	7.45
2950	2919.575	-30.43	30.43
3000	2960.4	-39.6	39.6
3050	2997.775	-52.23	52.23
3100	3048.95	-51.05	51.05

Table III Results of Analysis of Linear Model

	Score	Percentage	Verdict
Correct Prediction within error margin	28/40	70%	Unacceptable

We can calculate the score by counting the number of readings that have absolute difference of less than 50. From the analysis we conclude that the linear model is not suitable, since it only gives correct prediction in 70 percent of the readings.

We now test out a quadratic model using a similar approach. Creating a distance v/s fuel volume graph we get Figure 3.

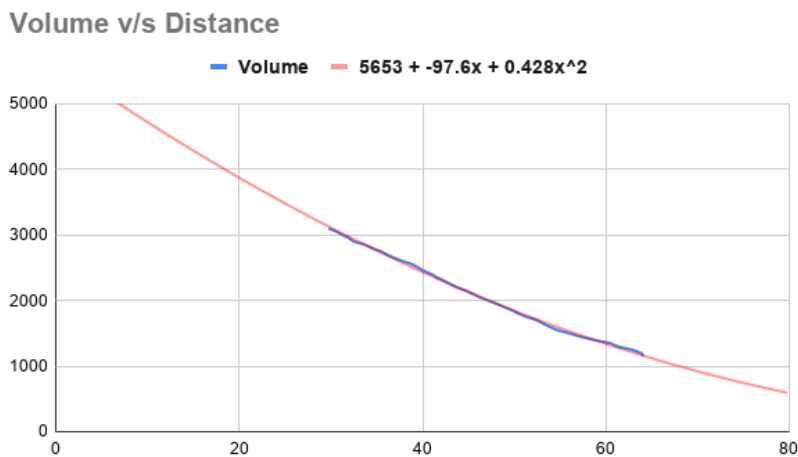


Figure 3. Quadratic model of the data



Here we see a better relationship between the trendline and the actual values. Outliers are also significantly reduced. This is further confirmed by Table IV.

Table IV Analysis of Quadratic Model

Real Values	Prediction by Quadratic Model	Difference (Prediction - Real)	Absolute Value
1150	1154.983	4.98	4.98
1200	1165.261	-34.74	34.74
1250	1207.303	-42.7	42.7
1300	1278.863	-21.14	21.14
1350	1315.245	-34.76	34.76
1400	1398.635	-1.37	1.37
1450	1471.114	21.11	21.11
1500	1528.615	28.62	28.62
1550	1596.418	46.42	46.42
1600	1637.849	37.85	37.85
1650	1675.669	25.67	25.67
1700	1709.728	9.73	9.73
1750	1769.264	19.26	19.26
1800	1816.795	16.8	16.8
1850	1853.427	3.43	3.43
1900	1902.126	2.13	2.13
1950	1948.101	-1.9	1.9
2000	2000.94	0.94	0.94
2050	2053.359	3.36	3.36
2100	2097.681	-2.32	2.32
2150	2140.718	-9.28	9.28
2200	2200.415	0.41	0.41
2250	2243.926	-6.07	6.07
2300	2285.428	-14.57	14.57
2350	2332.28	-17.72	17.72
2400	2369.618	-30.38	30.38
2450	2421.777	-28.22	28.22
2500	2461.761	-38.24	38.24
2550	2500.157	-49.84	49.84
2600	2570.699	-29.3	29.3
2650	2633.669	-16.33	16.33
2700	2684.747	-15.25	15.25
2750	2728.931	-21.07	21.07
2800	2795.908	-4.09	4.09
2850	2847.206	-2.79	2.79
2900	2935.867	35.87	35.87
2950	2968.774	18.77	18.77
3000	3018.844	18.84	18.84
3050	3065.06	15.06	15.06
3100	3128.928	28.93	28.93

Table V Results of Analysis of Quadratic Model

	Score	Percentage	Verdict
Correct Prediction within error margin	40/40	100%	Acceptable

From the analysis we conclude that the quadratic model is suitable, since it gives correct prediction in 100 percent of the readings. Hence, we accept this model and we will use it by programming the trendline equation into the microcontroller.



V. READING FROM THE SENSOR

Now that the sensor is installed and calibrated, it is ready to measure fuel volume. The microcontroller may report the fuel volume readings in the following ways:

- A. *Using an Attached Display:* An inexpensive LCD or OLED screen can be attached to the microcontroller to display the readings locally.
- B. *Using an Attached Computer:* The microcontroller can be attached to a PC, using USB, and the readings can be read on a serial monitor using a terminal emulator such as PuTTY. [7]
- C. *Using Internet of Things (IoT) [8]:* The microcontroller can be attached to a Wi-Fi module. This module will be connected to the Internet and will relay the fuel volume reading to the cloud. The client systems can then connect to the said cloud to access the fuel volume readings. This is by far the most suitable method.

VI. CONCLUSION

We have seen how a relatively inexpensive ultrasonic sensor and microcontroller setup can serve as a reliable and accurate fuel volume measurement device. We also looked at an application of the concept with real-world data. This idea will also be able to accommodate many such heavy vehicles that still use traditional techniques for fuel volume measurement.

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BIOGRAPHIES



Vipul Kushwaha is an ME student and a developer. IoT, sensors and microcontrollers are his areas of interest. He is currently developing an IIoT project for the Indian Railways.



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