

## Estimating fuel adulteration in automobiles using robust optical fiber sensors



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### ABSTRACT

The significance of petroleum product consumption in most countries is growing owing to different reasons like urbanization, population increase, development events and life style changes, which in turn leads to prevalent environment pollution. Adulterant refers to the substance that gets added to another and may not be legally allowed in most of the cases. A petroleum fuel is one such case which is vulnerable to adulteration specifically for improving the profit margins. Detection of this petroleum fuels adulteration is challenging as they are naturally present in the compounds already. The compositional variations of these fuels are determined using various physico-chemical properties measurements. For discriminating the adulterated samples from the unaltered ones, the statistical designs along with the data mining help. Monitoring of the quality of fuel is essential at the distribution point for the prevention of adulteration. We propose to use a fuel adulterations setup that is portable, inexpensive and is capable of providing the results in a short time. This includes the use of a light weight optical fiber sensor that gives high performance with low attenuation and there are no fire hazards, as well as they are resistant to harsh environments for testing. The distilled curves along with principal component analysis and support vector machine based classification helps us to build a model that is capable of this adulteration detection.

### 1. Introduction

Adding solvents to the natural fuel is a common practice due to the variance in price among gasoline itself and the solvents. This mixing brings in unpleasant issues to the people living in the society as it emits vapours and other toxic gasses and also makes the automobiles engines to be less durable. Some of the most commonly used solvents include kerosene, toluene, hexane, ethanol, refined petro chemicals etc. Different methods of fuel adulteration estimation methods are available in the literature. A typical fuel adulteration estimation process is detailed in Fig. 1 below:

Adulteration is basically a persistent issue seen all around the world in most countries. Fuels like diesel contaminated with kerosene are very difficult to detect with the regular methods in the market. There is no well-defined method that is accepted universally for adulteration level detection. But, some of the commonly followed methods include evaporation test, density test, concentration test, gas chromatography, compound marker test etc. Adulterated fuel surges different pollutions, as well as condenses the automobile engine performance [1]. With the

help of multivariate classification methods, we can classify the pure and contaminated fuel effectively. In this research, we recommend fleeting wave optical fiber sensor, which is connected with an interface controller in order to identify fuel mixing proportion through refractive index change. We use fiber optic sensors in our method for the process of collecting the data which are then classified accordingly. The fiber optic sensor employed uses optical fibers as a means of transmitting signals to the electronic devices that further process them.

The format of this research paper is organized as follows: Section 2 discusses the methods in the literature relevant to this work, Section 3 details the proposed method, Section 4 deals with experimental data and results while Section 5 concludes the paper with further scope of research related to this topic.

### 2. Related work

The addition of organic solvents in the automobile gasoline is very common and this method weakens the quality of the gasoline along with pollution increase. A simple and low cost, sensitive sensor for detecting

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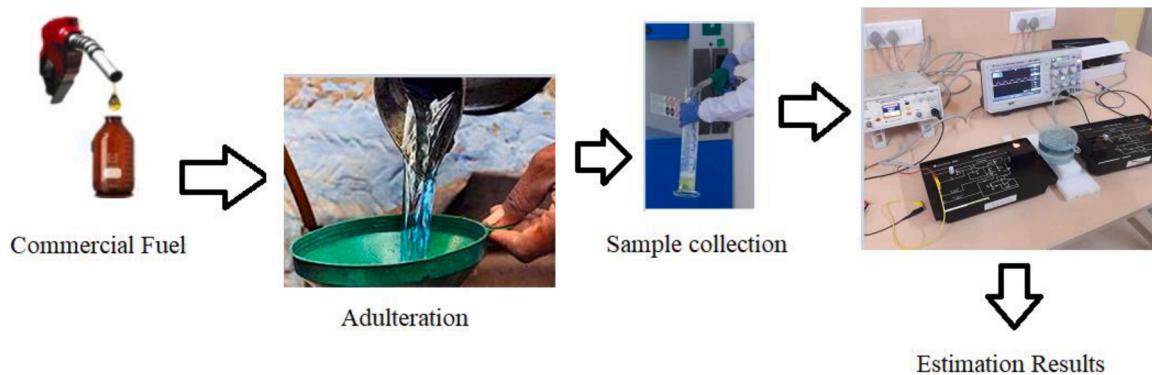


Fig. 1. Fuel adulteration lab setup.

the adulteration in gasoline is the goal of this research work. For this purpose, we started with the literature review of the existing methods used for adulteration detection in the market. There are multiple methods discussed in the literature that helps in the automotive gasoline quality analysis and in this section, we review the most commonly proposed and followed methods in the literature.

L.S. Moreira, D.A. Azevedo and L.A. Avila [2] have discussed about the automotive gasoline quality analysis with the help of gas chromatography technique. They have proposed to use gas chromatography along with mass spectrometry analysis for improving the adulterated gasoline detection. Their results showed that along with adulterated samples, the organic solvent type can also be detected by chromatographic profiles comparison. However, they find that a single GC analysis can find a contaminated gasoline and decline the samples adulterated approved as good quality.

The influence of solvents like white spirit, anhydrous ethanol, diesel and alkylbenzene AB9 on the gasoline was studied by the authors E.V. Takeshita, S.M.A. Guelli, R.V.P. Rezende, and A.A. Ulson de Souza in their work [3]. The mentioned authors have investigated the different parameters like density, distillation curves, reid vapor pressure which showed differential behavior and that is based on the solvent class along with its quantity added to the gasoline. One of the common solvent, ethanol along with hydrocarbons mixture showed a strong effect on the distillation curves and the sudden change in temperature point is a way to detect the adulterations along with its quantity added.

Anita Patil and Vivek Padmakarao Kude has presented a paper [4] in the article that helps in the finding of fuel adulteration using optical fiber sensor and Peripheral Interface Controller in real time. The authors have formulated a fuel sensor sample model and validated the same to identify the adulteration percentage in diesel and petrol by kerosene. The proposed solution is simple in terms of construction, safety handling and real time operation as well. It is capable of detecting up to 5% contamination in the fuel using the evanescent wave absorption

technique. For the purpose of automating the proposed solution, the authors have used PIC along with fuel sensor.

Air pollution is growing day by day and one of the reason is the fast increased use of fossil fuels. R.K. Sharma and Anil Gupta have discussed a novel method [5] for estimating the vehicle fuel adulteration. They feel that it's a world-wide problem that leads to global warming. The main reason for adulteration is the greed fueled by varying tax system in countries for different solvents. So, it is required to observe the fuel value while distributing and also the equipment used for this purpose should be portable. Overall, they discuss the different methods of estimation for fuel adulteration in this paper.

A.K. Pathak and others have presented an intrinsic strength modulated sensor that is used for the purpose of rapid discovery of fuel adulteration [6]. The absorption of evanescent waves is the underlying phenomenon used by the authors in this method. The proposed method uses the intensity difference and detention loss with varying absorptions of the kerosene mixed in petrol are then tested hypothetically with the help of finite element method. The sensor discussed in the proposed method can be beneficial in automotive companies and industries due to its minor size, simple fabrication method, safe with combustible fuels and requires just a trivial amount for the purpose of detection.

Sanjay Kher and others have reported the readings of their experiment in which they have detailed the presentation of turnaround-point long period fiber lattices for wavelength programmed detection of automobile fuel adulteration [7]. The authors have proved that high sensitivity of 0.96 nm% variation of kerosene mixed in petrol and up to 10% ruining is pointedly high as associated with other formerly published values in the literature. These field screens can effortlessly notice the occurrence of 1% adulteration of kerosene in petrol and thus offer chances for improvement of transferrable fuel adulteration sensors.

A low cost and miniature size sensor that uses fiber optics principle is designed by the researchers Shilpa Kulkarni and Sujata Patrikar in their work [8]. The sensor design proposed by the authors can detect the

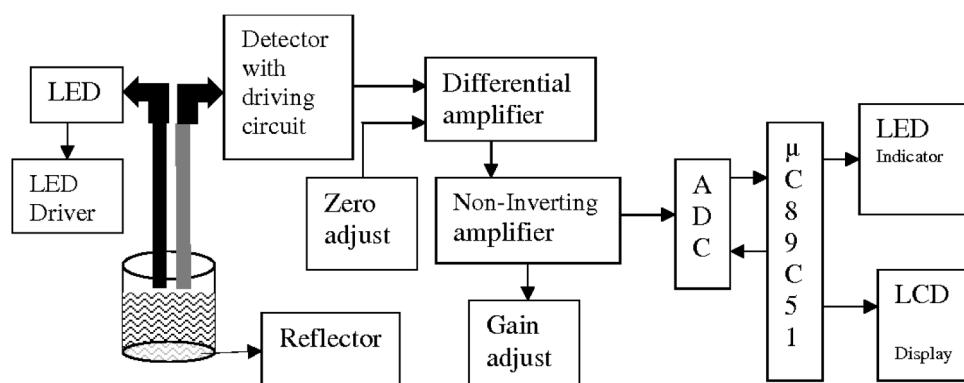


Fig. 2. Block diagram of adulteration detector instrument.

adulteration present in the fuel that is less than 5% and is also capable of identifying the variations of less than 1% in the adulteration.

Crude oil distillates along with the biofuels are the important energy sources that help to drive the manufacturing as well as the automobile industry. The distillates here include gasoline, diesel and kerosene. Due to the price disparity among these items, the marketers try to adulterate the product which helps them in their profit making. On the downside, this process reduces the engine performance and also causes harmful gasses to be emitted out of the vehicles. Gubihama Joel and Linus N. Okoro have made a review on the recent advances in the use of sensors and markers that is used for detection of fuel adulteration [9]. They have detailed about the fuel adulteration process, sensor details and the use of chemical markers in solvents.

S. Patil and A. D. Shaligram mentioned that contamination of diesel with kerosene is a common misconduct followed at most places since the added solvent is much cheaper than the diesel itself [10]. This results in pollution as well as reduced engine performance. The authors have presented a simple as well as extrinsic strength controlled fiber optic sensor for defining the mixing of diesel by kerosene. The block diagram of the discussed method is shown in Fig. 2 below:

The sensing principle described in this paper is built on the reflected light intensity variation that happens due to the variation in the adulterated diesel refractive index. A transmitting fiber along with the receiving fiber is used as a sensor in this work. The adulterated fuel is found in between the sensor probe and the reflector. This proposed prototype is concealed and also validated in lab for various degrees of adulteration of diesel with kerosene. A microcontroller is also added to the circuitry for the purpose of automation and sophistication. This way, a low cost and effective solution is proposed.

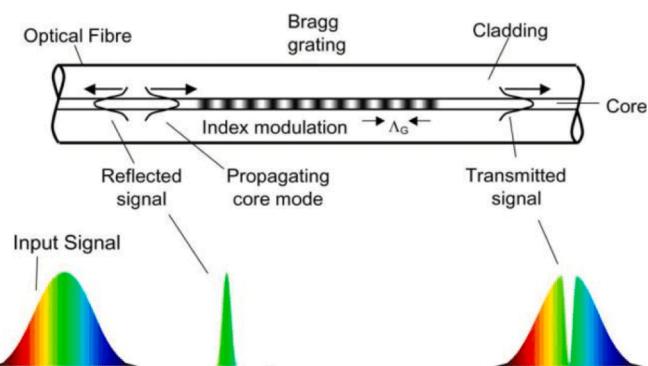
Muharrem Karaaslan et al. have recommended a novel shaped metamaterial sensor solicitation that can work in the X band [11]. A prototype holder is also designed and kept after the structure in this X band. The study is actually made to provide an alternate method towards the contamination sensing. This method brings in advantages like sensitivity, resolution and also the quality factor as well. Finally, the testing and experimentation of the plan has been carried out in three steps which include dielectric constant readings with the help of Agilent 85070E measurement kit, the study simulation and investigational validation study of the discussed structure with different kinds of sensor layers. The results from this experimentation displays that the method can effortlessly be altered for various electrochemical sensing devices, if the dielectric value is changing between 2 and 6. Along with this advantage, the other different side of this research study is the presentation of different type of adulteration solvents like olive oil adulteration with cotton oil as well as kerosene with ethanol and so on, provides mass application of the metamaterials.

Though various methods and technologies are discussed and proposed in the literature, a robust real time fuel adulteration technique is still required that can detect the presence of mixed solvents in a given fuel [12]. The existing diesel adulteration licences the start of strict agreement regulation. The proposed methods in this chapter addresses this problem and provides a robust fuel adulteration estimation technique in automobiles by using robust optical fiber sensors.

### 3. Fuel adulteration detection

Kerosene is commonly used adulterant that is utilized for mixing with diesel. This is because of the low cost of kerosene when compared with the diesel. While fuel adulteration is a criminal offense in most developed countries, they are still carried out in many places. This pushes a need for robust fuel adulteration detection system [13, 14]. In our work, along with this kerosene, five other different fuel-adulterant combinations in different sizes by volume were arranged and independently validated for the purpose of estimating density as well as kinematic viscosity.

The five mixes were controlled or tested on six light freight



**Fig. 3.** The proposed architecture of fuel adulteration detection using robust sensors.

automobile vehicles and the tail pipe drain gas release was taken for opacity value calculation. There was no significant density variation of adulteration observation at various levels. In fact, the density was very much within the prescribed value even after adding more adulterant substance. On the other side, considerable reduction in kinematic viscosity, a removal from recommended viscosity, was prominent at higher adulteration testing levels. The percent opacity rate which is considered in this work, reduced sharply even at minor level of adulteration. The likely quantity of kerosene existing as a contaminant in diesel distributed at filling stations in a particular city ranged between 40% and 55%. The interpretations advise that density validation carried out is not a good indicator of contamination in diesel. At the same time, the other two parameters namely the Kinematic viscosity as well as the opacity value are very useful diesel adulteration test classifiers.

### 4. Optical sensor method for determining adulteration

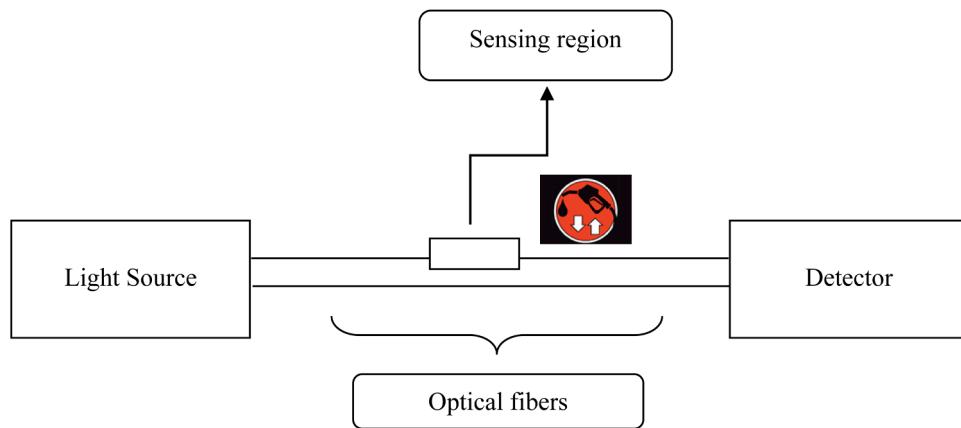
Optical fiber sensors which have grown over the past decade are used in this proposed work for determining the engine fuel adulteration. For the purpose of enhancing the sensitivity, the sensor structure is modified but at the same time it is made to be compact as well for easy movement and testing. We use the principle of refractive index for the purpose of identifying fuel adulteration. Refractive index is directly proportional to the medium concentration. We measure the solvent concentration through intensity examination and classify it using the machine learning algorithm for reporting.

For the purpose of detecting adulteration of different fuels like petrol, diesel etc., the intensity modulated sensor is proposed in this work and that uses the evanescent wave captivation principle. The research of fuel adulteration is performed multiple times for fuel of same concentrations in order to get consistent result. The suggested sensor in this work is less breakable as it does not necessitate much modifications and also gives us the fast response time within seconds. The proposed work representation is shown in Fig. 3 below.

Optical fibres are long thin elements of glass organised in bundles and used to communicate with light signals from one end to another. A single optical fiber contains three layers namely the core layer, buffer coating and cladding. Here core refers to the tiny glass center of the fiber through which the light voyages. Cladding is the outer optical item surrounding the core. It replicates the light back in to the core. The buffer coating on the other hand is the plastic coating that protects the fiber from moisture and from any kinds of external damages. The refractive index is defined by the factor of speed and the wavelength of the radiation which are condensed with reference to their vacuum values. This is represented as:

$$V = c/n$$

Where c refers to the light speed in a vacuum and the value of n in a



**Fig. 4.** Schematic representation of adulterated fuel in the sensing region.

vacuum is 1. The light frequency does not change as light moves from one type of medium to another. However, because the speed of the light in the new medium changes, the wavelength also changes accordingly. This is represented as:

$$\lambda u = c/n$$

When light is reflected, the reflection angle equals the incident angle. The path is also bent when light travels from one medium to another and this bending is refraction. Refraction is described with the help of Snell's law. This is given as:

$$\begin{aligned} n_1 \sin \theta_1 &= n_2 \sin \theta_2 \\ \sin \theta_r &= (n_1/n_2) \sin \theta_i \end{aligned}$$

Here  $n_1$  and  $n_2$  corresponds to the refractive indices of both the mediums. Also,  $\theta_1$  corresponds to incident angle while  $\theta_2$  is the refracted angle. We use two optical fibers in our setup in which one fiber acts as the illuminating fiber while the other fiber works as a receiving fiber. The absorption coefficient is given by:

$$u = NT$$

where  $N$  refers to the number of ray reflections for each unit length while  $T$  is the Fresnel transmission coefficient of light. If  $n_1 / n_2 \sin \theta_r$  is greater than 1, there are no possible values for  $\theta_r$  that satisfy:

- $\sin(x)$  cannot be greater than 1
- Therefore, no light is refracted

All of it is reflected and this principle is called as total internal reflection in theory. The largest likely angle of incidence in a refracted ray is called the critical angle. Within a certain cone of acceptance, all rays entering one end of the fiber exit the other and in reality, there are losses but are tiny in nature. We can deliver light to a sample from a light source via an optical fiber. We can then deliver light from the sample back to the spectrophotometer through an optical fiber. We use this principle in our work to identify the fuel adulteration and is shown in Fig. 4 below:

The percentage of concentration is given by:

$$\text{Percentage of concentration} = (\text{Adulteration}/\text{Total solution}) * 100$$

The sensor used in this work will transfer the light from one mode to another. This brings in the principle of interaction between two waves namely the evanescent waves and the surrounding environment. The reflected back light is then calculated and captured. The voltage readings are then sampled for noise removal, feature selection and classification. Finally the presence of additional solvent is detected with the help of classification algorithm.

#### 4.1. Principal component analysis in fuel adulteration detection

Principal Component Analysis (PCA) is an arithmetical procedure and the main purpose of the PCA is to represent low-dimensional variable in the multivariate database [15]. This transformation from high to low dimension is made in a way that the first component of the PCA has the largest likely variance and the following components in turn has the highest change possible with a restriction that it is orthogonal to the previous members. The final resultant vectors are an uncorrelated orthogonal basis set. Principal component PCA vectors are subtle to the relative ascending of the original variables.

In our work, we use PCA to excerpt the maximum data from the dataset and then build the models using the multivariate method for the machine learning algorithm to further carry out the statistical data examination and provide the final output.

A matrix is calculated that summarizes how all the variables present in our dataset will relate to each other. This is further broken down in to two components namely the magnitude and the direction. PCA algorithm then identifies which directions are important among them and project the original data in to smaller space by removing those directions that are not most important. By this way, the dimensionality is reduced and also made sure that the original important variables are still retained in the new model. The algorithm works as follows:

##### PCA Working Principle:

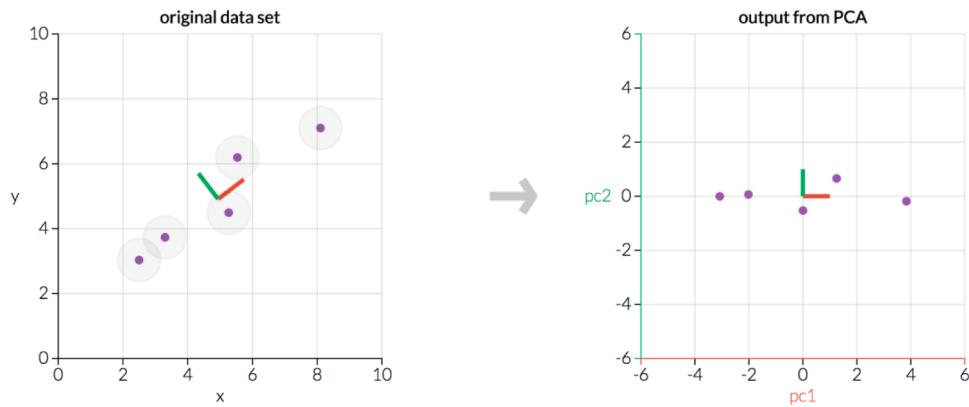
- Step 1: Get the fuel data samples both with and without adulteration independently.
- Step 2: Calculate the mean values of them and then subtract the mean value from each sample. This gives a new data set whose mean value is zero.
- Step 3: Determine the covariance matrix from this new data set. If the original dataset is 2 dimensional, then the resultant covariance matrix will also be  $2 \times 2$ . It is calculated as follows:

$$\sum = \frac{1}{n-1} ((X - x)^T (X - x))$$

Here  $x$  corresponds to the mean value for each feature of  $X$ . The original matrix is multiplied by the transpose matrix and the resultant is taken forward.

Step 4: Eigen vectors and Eigen values of the new covariance matrix are then calculated. Eigen vector is basically a non-zero vector that varies by a scalar factor when a transformation is applied. The scaling factor corresponds to the Eigen value.

Step 5: A feature vector is then formed by choosing the required components. The reduced dimensionality is actually achieved in this



**Fig. 5.** The original dataset for dimensionality reduction and the PCA output.

step. The Eigen vector with the highest scaling value or the Eigen value is the principle constituent of the original input data set.

Overall, the first component and the further PCA components are calculated as follows:

First component:

$$w_{(1)} = \arg \max \left\{ \frac{w^T X^T X w}{w^T w} \right\}$$

Further components:

$$w_{(k)} = \arg \max_{\|w\|=1} \{ \|X_k w\|^2 \} = \arg \max \left\{ \frac{w^T X_k^T X_k w}{w^T w} \right\}$$

Where

$W$  corresponds to the weight vector that maps each row vector  $x$  to a new set of principal components and the full decomposition of this mean  $X$  can be represented as:

$$T = XW$$

Here  $T$  = Transformed data

$W$  =  $p$ -by- $p$  weight matrix whose columns represent the Eigen vectors and the transpose of it is the sphering transformation.

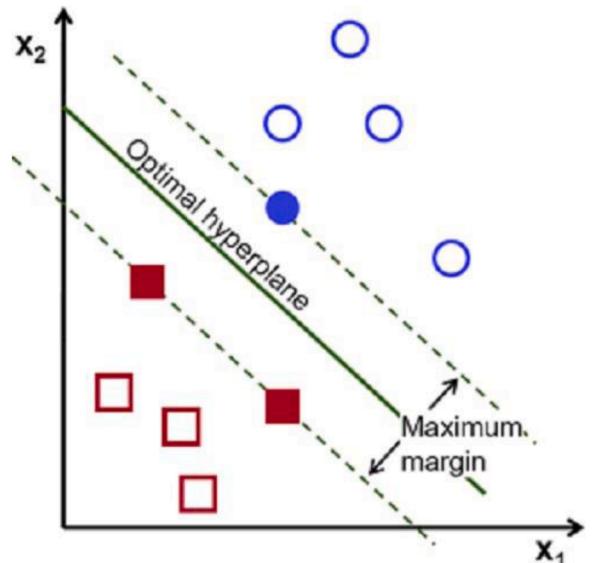
PCA is the simplest method when it comes to true eigenvector-based multivariate analyses and so we have used it in this work. It does not add computational complexity but rather helps the classification algorithm with reduced dataset. The original dataset and the output from PCA is shown in Fig. 5 below:

Once the reduced data set is obtained with the help of Principal component analysis algorithm, we make sure of the following for further SVM classification:

- Normalize the data: Center and scale the input fuel data. The transformation,  $C$ , that centers and scales the input data should be stored for further processing.
- PCA: This algorithm learns a variance exploiting linear transformation and converts to transforms onto a lower dimensional space. This newly transformed data is given as input to SVM algorithm.
- SVM training: SVM takes the PCA output and does the training first to identify the support vectors. When a new test input is provided, it makes use of the generated support vectors to classify the test data.

#### 4.2. Support vector machines for classification

A support vector machine (SVM) is a managed machine learning algorithm that uses classification methods for two-group classification datasets. They are considered to be the extension of the perceptron and has the ability to both minimizing the classification error as well



**Fig. 6.** A linearly separable case with the help of support vector machines.

maximize the geometric margin [16, 17]. Here we use SVM as the classifier for our fuel adulteration problem.

SVM's can be used for solving both linear and nonlinear multivariate problems and a set of linear equations are derived to obtain the support vectors. The radial basis function is used as the kernel to get better performance. The SVM algorithm in the simplest form is represented as:

$$y(x) = \sum_{k=1}^N a_k K(x, x_k) + b$$

Here alpha corresponds to the LaGrange multipliers,  $K$  represents the kernel function and  $b$  is the bias value used in the SVM algorithm [18].

Support vectors that are obtained at the last step of this method are actually the data points that lie as close as possible to the decision plane or the surface. They are the ones which are most difficult to categorize. They have a direct behavior on the optimum location and in general the SVM's try to find an optimal solution. They maximize the margin and the decision function is stated by a set of training data provided. Hence, it becomes a quadratic problem to be solved with an efficient method. This is represented in Fig. 6 below:

Our fuel adulteration data can fall in to two categories depending upon the amount of adulteration. They can be easily classified with a linear separator or sometimes complex and require kernel tricks for classification. The algorithm is represented as follows:

**Table 1**

Covariance calculation for reducing the dimensionality through PCA algorithm.

Sample - H	Sample - M	$H_i - H$	$M_i - M$	$(H_i - H)(M_i - M)$
9	93	-4.85	-35.57	172.51
4	39	0.1428	18.42	2.630
10	66	-5.86	-8.57	50.22
0	32	4.14	25.42	105.23
1	42	3.14	15.42	48.41
2	50	2.14	7.42	15.87
3	80	1.14	-22.57	25.72

Input to SVM method: Set of I/O training pair samples – with adulteration is represented as -1 and pure fuel is given by +1. Normally, there can be lots of input features.

Output of the algorithm: Set of weight vectors, one for each feature and their linear combination will predict the value of the new test data 'y'.

SVM Method: Maximizing the margin in order to decrease the number of weight vectors. The support vectors produced are the critical elements of the data set. We use Lagrange multipliers for the optimization purpose. The optimization algorithm with the Lagrange multipliers are used to create the weights proceeds in such a way that only the support vectors will define the actual weights and thus the boundary as well.

The effectiveness of using the SVM method for fuel adulteration classification mainly depends upon the kernel selection, their parameters and the soft margin variables. Fine tuning of these parameters based on the sample set and application will give better results.

## 5. Implementation, results and discussions

Feature construction is the first step in testing the proposed method. Series of data are collected from the fuel samples and they tend to have higher dimensionality when captured over a wide spectral region. Large feature size will result in the "curse of dimensionality" and hence the size of the feature set has to be reduced to a reasonable or an accepting level. Principal component analysis is applied for this purpose in our work. **Table 1**

Once the feature construction is completed, we then proceed with

the feature selection for training and classifying the test sample. Effective feature selection from the subset aims to keep the feature set as small as possible but at the same time to cover the full spectrum of data without missing the important variables [19, 20, 21]. We have used Matlab for the purpose of implementing the principal component analysis and support vector machines algorithm. A sample data set and the PCA output is calculated as follows:

The optical fiber in the experimental setup works as a light wave conductor that works on the code of total internal reflection. The cladding material used in the optical fiber has inferior refractive index than the other core material. The total internal reflection happens at the core cladding boundaries. The evanescent wave discussed in this work is also associated at the same interface. While the fuel absorbs some portion of the evanescent wave, the power observed at the detector end would be much lesser with respect to the refractive index. The output light power is then recorded and is represented by:

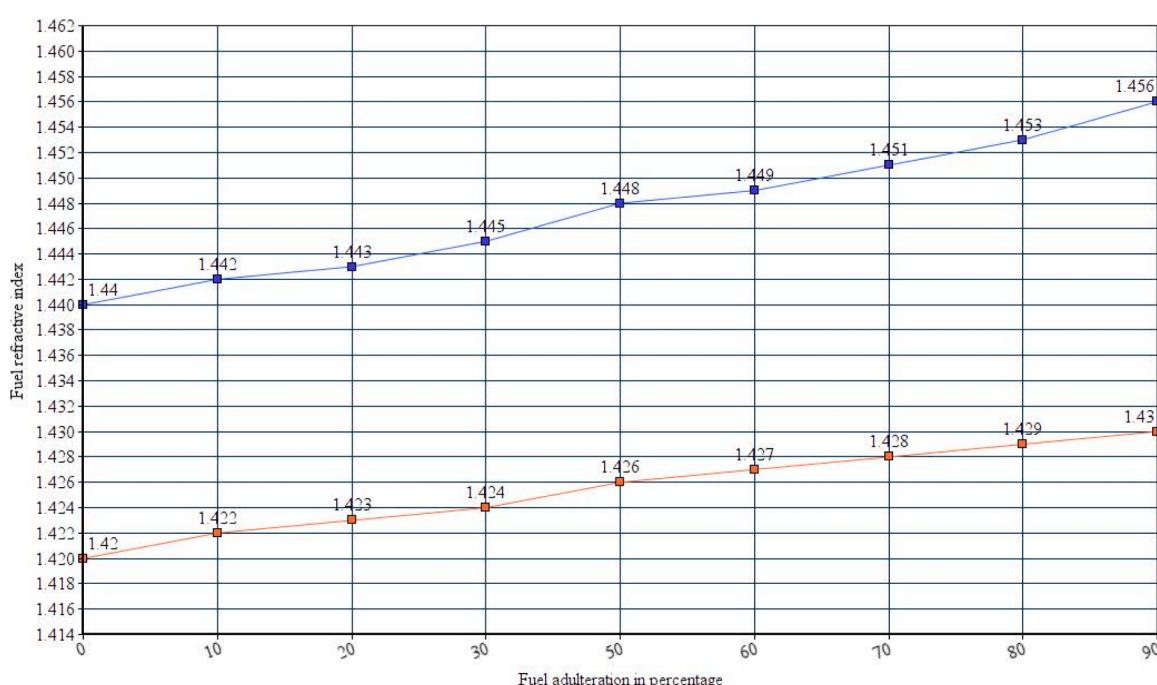
$$P_{\text{recorded}} = P_{\text{transmuted}} * \exp(-vL_{\text{etched}})$$

Where  $P_{\text{recorded}}$  corresponds to the recorded power,  $P_{\text{transmuted}}$  represents the transmitted modulated power and  $L_{\text{etched}}$  is the fiber etched length. The factor mentioned in this representation refers to the evanescent light wave energy engrossed due to the fuel passive cladding. The received power depends upon the surrounding test fuel refractive index. **Fig 7**

**Table 2**

Measured refractive index of adulterated fuel (petrol and diesel).

Fuel adulteration in percentage	Fuel refractive index (Petrol)	Fuel refractive index (Diesel)
0	1.420	1.440
10	1.422	1.442
20	1.423	1.443
30	1.424	1.445
40	1.425	1.446
50	1.426	1.448
60	1.427	1.449
70	1.428	1.451
80	1.429	1.453
90	1.430	1.456

**Fig. 7.** Measured refractive index of adulterated fuel.

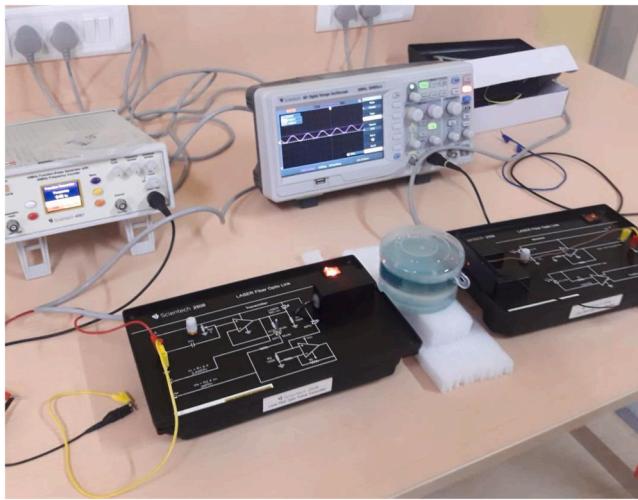


Fig. 8. Experimental setup for fuel adulteration detection.

Table 3

SVM training vectors.

a	Voltage readings (A)	Voltage readings (B)	Class
0		0	1
3		4	1
5		9	1
12		1	1
8		7	1
9		8	-1
6		12	-1
10		8	-1
8		5	-1
14		8	-1
b			
Voltage readings (A)	Voltage readings (B)	Predicted Class f(x)	
0	0	1	
3	4	1	
5	9	-1	
12	1	1	
9	8	-1	
8	5	-1	
14	8	-1	

below shows the observed refractive index for fuel adulteration and is also tabulated in table 2.

Adulterants are generally mixed by the business civic for their monetary gains and for other purposes. Detecting such added or mixed adulterant in fuels is a primary task in the interest of the end customer who is going to use the fuel. This will require quick test result. With this in mind, our experimental setup is made as simple as possible and shown in Fig. 8 below. The setup has the sensor, fiber optic source, the sample under test. Liquid chamber and finally the detector. We have recorded the output power using a power meter and tabulated it for further classification.

The computational techniques like PCA and support vector machines helps us to improve the fuel adulteration percentage detection. SVM is used in this work to achieve nonlinear classification and multivariate function estimation. The computational SVM calculations are simplified using least-squares version and hence it is not seen as an overhead for our experimentation thereby giving the results in quick time.

Table 3 below shows the data from two different sets representing the ones with and without fuel adulteration. Here +1 corresponds to the data where there is no adulteration while -1 corresponds to adulterer samples. Table 3a corresponds to the SVM training set while 3b represents the testing ones.

At the end of the SVM training phase, we get the weight vectors and

Table 4

Medium of measurement and the voltage values.

Medium	Voltage in mV
Free space	67
Petrol with adulterant	
Only Petrol 200ml	54
Petrol 150 ml + 50 ml adulterant	50
Petrol 100 ml + 100 ml adulterant	47
Petrol 50 ml + 150 ml adulterant	47
Diesel with adulterant	6.8
Diesel 150 ml + 50 ml adulterant	52
Diesel 100 ml + 100 ml adulterant	52
Diesel 50 ml + 150 ml adulterant	47
Only Diesel 200ml	50
Kerosene with adulterant	
Kerosene 150 ml + 50 ml adulterant	58
Kerosene 100 ml + 100 ml adulterant	56
Kerosene 50 ml + 150 ml adulterant	55
Only Kerosene	54
Kerosene with petrol	
kerosene 50 ml + 50 ml petrol	16
kerosene 50 ml + 100 ml petrol	26
kerosene 100 ml + 100 ml petrol	11

other related parameters calculated. This is represented as follows:

$$W = A^T D u = (-0.2081, -0.2585)$$

$$\gamma = -e^T D u = -2.0817e \approx 0$$

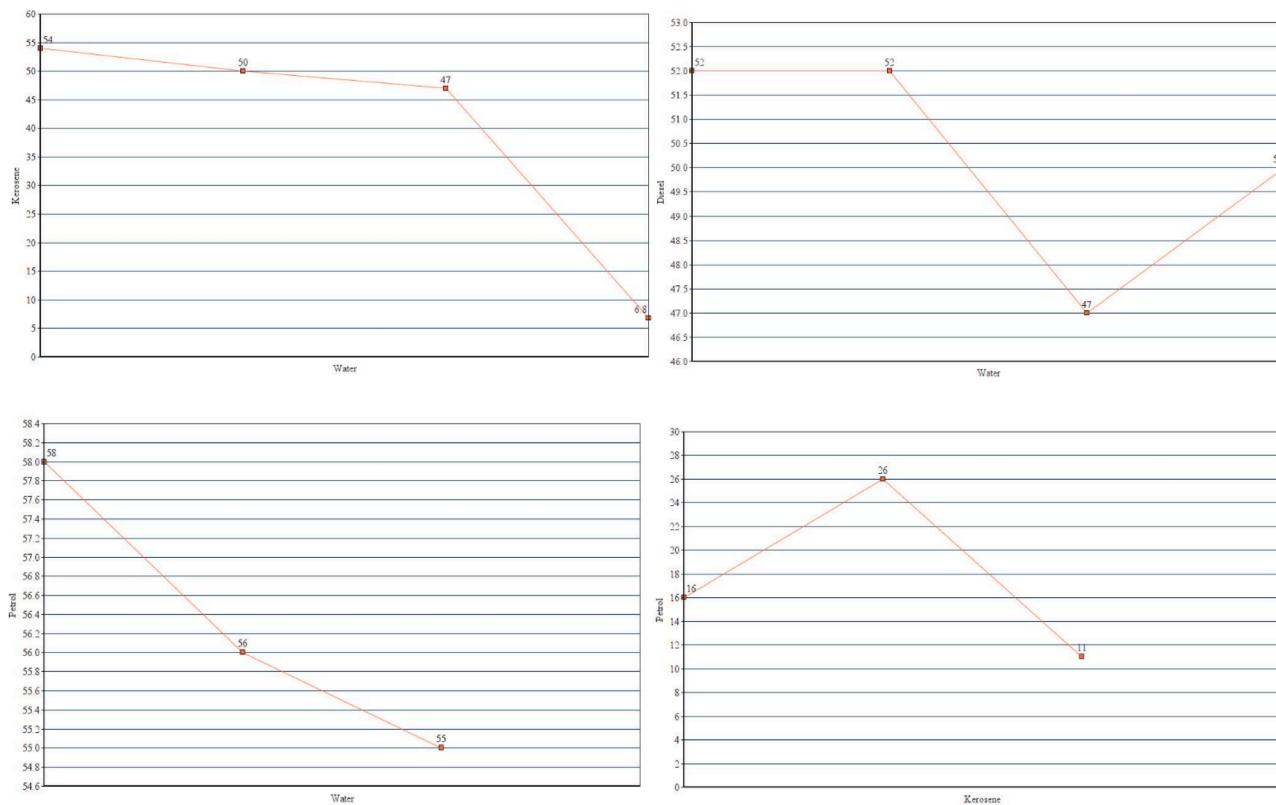
Here W and  $\gamma$  causes the maximum separation between the different bounding planes in the SVM hyperplane. These values will also help to classify a new data as follows. The final decision function is given by

$$f(x) = \text{sign}(W^T x - \gamma)$$

If all the points in the data set are not linearly separable, then we allow the training error to lie in between the bounding hyperplanes and beyond. From Table 3b, we can find that one of the sample (5, 9) is misclassified as sample with adulteration while the other sample predictions are correct. We can improve the prediction accuracy by further fine tuning the SVM learning parameters. Difficulty in the alignment of petroleum-derived fuels and their possible contaminants leads to a perplexing situation where compliance and application of standard norms are not easy. The fiber optic sensor based voltage readings proposed in this work along with the machine learning algorithm like support vector machines helps us to predict the fuel sample output in quick time with improved accuracy.

The box height is set to 5 cm, radius of the box is 4 cm and the adulterant capacity is limited to 200 ml for this testing. The distance maintained in the setup is 10.5 cm. An optical sensor has been established to evaluate the relative structure of two different liquids in the mixture. It is built on distinguishing the changes in the intensity of reflected light at the boundary of the glass-mixture carried about by variations in one liquid sample over that of the other sample in the given test mixture.

Sample mixtures for this training and experimentation is made by modifying the concentration of substances such as kerosene and diesel in a given petrol volume. A method for noticing as well as assessing the concentration of kerosene or of diesel or of a mixture of the both in a petrol sample has been detailed. There are different parameters that can be considered for fuel contamination detection. For petrol, these parameters corresponds to density, stability, distillation, octane number, hydrocarbon composition and multifunctional additive dosage. For diesel, these parameters include flash point, polycyclic aromatics, density, distillation, sulfur and cetane improver presence. The readings from the setup are presented in table 4. The table shows the medium and the calculated voltage values. The concentration of kerosene, diesel and petrol are shown in Fig. 9 below.



**Fig. 9.** Concentration of different fuel adulteration values (9a - Top Left: Petrol with adulterant, 9b - Top Right: diesel with adulterant, 9c - Bottom left: kerosene with adulterant and 9d - Bottom Right: Kerosene with petrol).

Our setup has used the fabricated sensor that has different concentration levels of kerosene values from 0% to 50% in clean petrol. We have repeated the same process of experimentation multiple times to make sure that the readings remain constant without varying much during adulteration process. The SVM classifier output predicts the sample has adulteration or not and the percentage of adulteration as well. The proposed method shows better performance than many other similar methods discussed in the literature. It will be useful in both automotive as well as in petroleum industries as the proposed method is easy to fabricate and robust in producing the desired results. They can be operated in inflammable environment and easy to use as well.

## 6. Conclusion and future directions

Fuel adulteration persuades economic losses to the end customer, as well result in higher emissions while decreasing the rated competence of the engines apart from the damage to the engine portions. Emissions from the tail pipe of the vehicles in the form of carbon monoxide (CO), hydrocarbons (HC), particulate matter (PM) and oxides of nitrogen (Nox) may lead to poisonous substances in the air thereby polluting the air as well. This paper aims to assess the viability of differentiating the pure fuel from the adulterated ones to overcome these effects. We have used robust optical fiber sensors that are capable of generating the data set with utmost accuracy as compared to other methods. The optical fiber used in the setup is robust and when the fuel is poured in to the sensor, the transmission loss is calculated which helps further in identifying the percentage of fuel adulteration with the help of change in output voltage. We have used samples from adulterant mixed with kerosene, petrol and diesel for testing purposes. Once the data samples are collected, we have used the principal component analysis for dimensionality reduction and feature selection purposes. They are less sensitive to noise, requires less capacity and memory and gives increased efficiency on the final output. We have also used support vector machine

algorithm for adulteration classification. They are found to give better results than artificial neural networks if used for the same purpose. Moreover with SVM, kernel tricks can be implemented if the data set is not linearly classifiable. Principal component analysis along with support vector machines is a novel attempt in fuel adulteration classification and it gives better results than many other threshold based classification systems. A packaged fuel sensor using multimode optical fiber that can detect contamination percentage of various other components and solvents will be the future direction for this work.

## Declaration of Competing Interest

We have also used support vector machine algorithm for adulteration classification. They are found to give better results than artificial neural networks if used for the same purpose. Moreover with SVM, kernel tricks can be implemented if the data set is not linearly classifiable. Principal component analysis along with support vector machines is a novel attempt in fuel adulteration classification and it gives better results than many other threshold based classification systems. A packaged fuel sensor using multimode optical fiber that can detect contamination percentage of various other components and solvents will be the future direction for this work.

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