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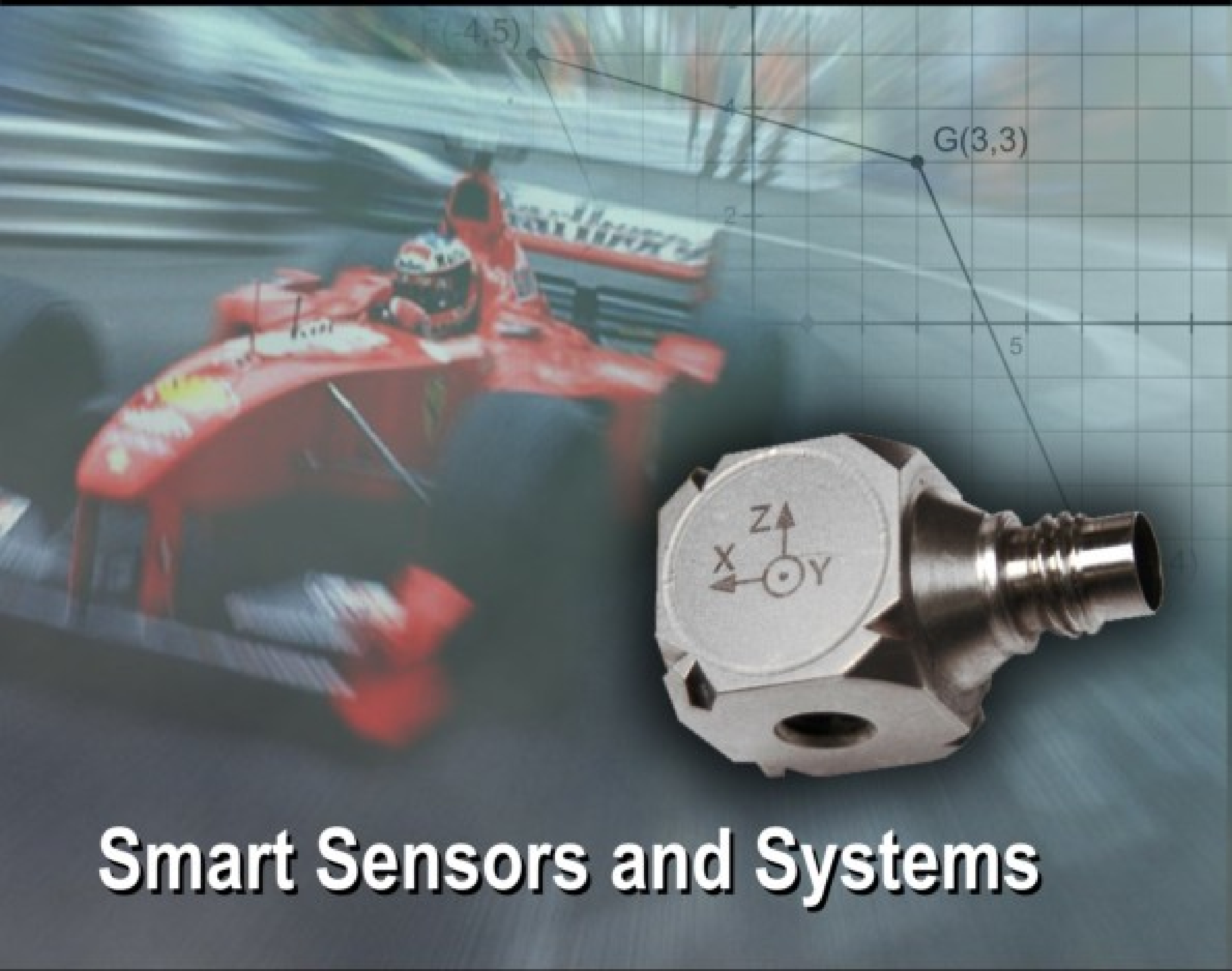

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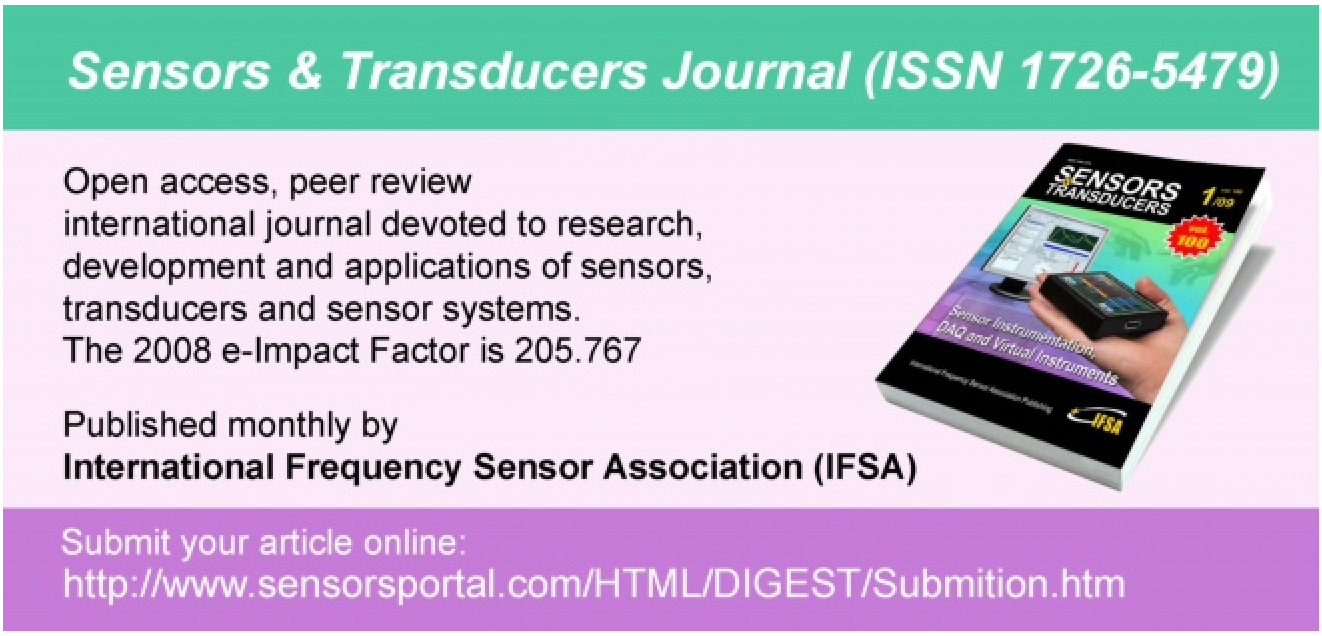

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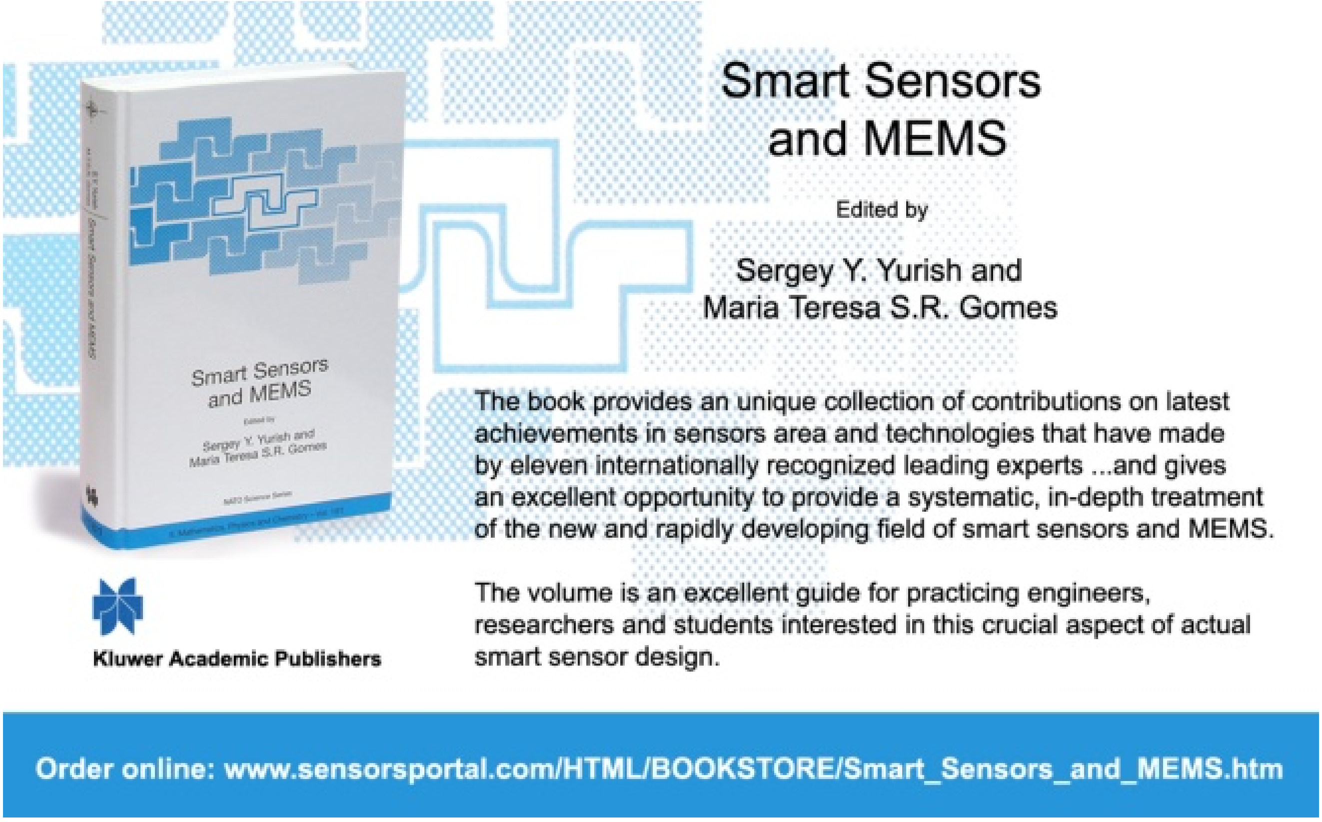

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A Neural Network Approach to Fluid Level Measurement in Dynamic Environments Using a Single Capacitive Sensor

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Abstract: A measurement system has been developed using a single tube capacitive sensor to accurately determine the fluid level in vehicular fuel tanks. A novel approach based on artificial neural networks based signal pre-processing and classification has been described in this article. A broad investigation on the Backpropagation neural network and some selected signal pre-processing filters, namely, Moving Mean, Moving Median, and Wavelet Filter has also been presented. An on field drive trial was conducted under normal driving conditions at various fuel volumes ranging from 5 L to 50 L to acquire training samples from the capacitive sensor. A second field trial was conducted to obtain test samples to verify the performance of the neural network. The neural network was trained and verified with 50 % of the training and test samples. The results obtained using the neural network approach having different filtration methods are compared with the results obtained using simple Moving Mean and Moving Median functions. It is demonstrated that the Backpropagation neural network with Moving Median filter produced the most accurate outcome compared with the other signal filtration methods. *Copyright © 2010 IFSA.*

Keywords: Accurate level measurement, Liquid slosh, Backpropagation Neural Network, Intelligent sensor

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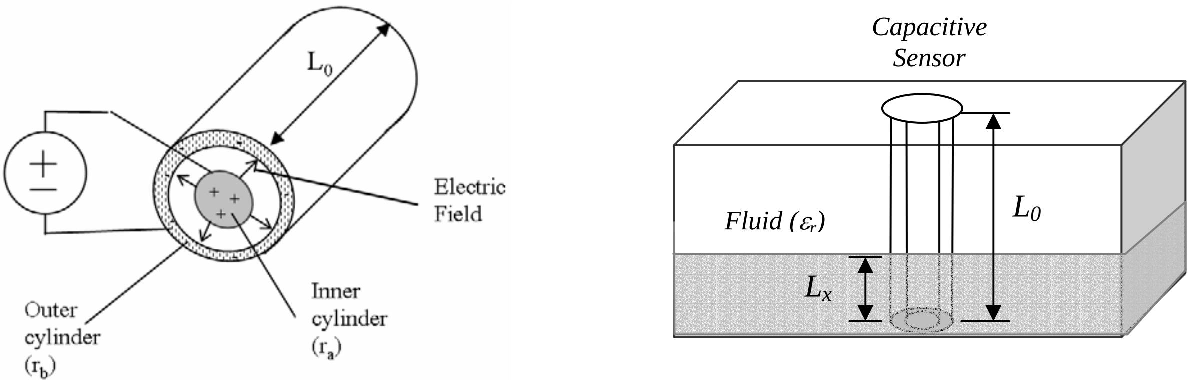
1. Introduction

Modern automotive vehicles are equipped with digital gauges as well as with additional functionalities that inform drivers about their vehicle's fuel consumption and the remaining distance that the vehicle can travel without refuelling. However, the high precision digital displays and these additional functions have to rely on the accuracy of the level sensor itself. The reliability and accuracy of the fluid level measurement system in a dynamic environment, which primarily depends on the level sensor, is increasingly becoming a concern for automotive industries as well as everyday vehicle users. The importance of level sensor reliability in hostile environments over long periods of time has lead to the introduction of various forms of motionless level sensors. The capacitive type level sensor is one such example that is increasingly being investigated as a substitute for mechanical level sensors in industrial and particularly automotive applications.

Tubular capacitive sensors determine the fluid level by measuring the dielectric constant (Fig.1), which essentially is the fluid itself, filled in between two cylindrical tubes of radii r_a and r_b. If L_0 is the length of the capacitive sensing tube, ε_0 is the permittivity of free space, and ε_r is the dielectric constant of the fluid being then the capacitance value can be calculated using (1):

$$C = \varepsilon_r \left(\frac{\pi \varepsilon_0 L_0}{\ln \frac{r_b}{r_a}} \right) \text{ F} \tag{1}$$



(a) (b)

Fig. 1. Tubular capacitive level sensor (a) showing the basic principle of capacitive level sensing; (b) a closed tank filled with fluid at level L_x.

If the geometry of the sensing tube remains constant, the capacitance of the sensing tube can be seen in (2) as being proportional to the dielectric constant [1]:

$$C \propto \varepsilon_r \tag{2}$$

Since capacitance is dependant on the dielectric constant ε_r, any variation in the dielectric constant of the fluid will lead to errors in the level sensing measurements. These variations can be caused by contamination or different fluids with different dielectric constants being mixed together, e.g. fuel and water mixed together in an automotive fuel tank will lead to inaccurate results. Temperature variation is another factor that reduces the sensor accuracy by shifting the value of the dielectric constant. In summary, the output of the capacitive sensor will be subject to inaccuracy, due to the influence of contamination and temperature factors. As capacitive sensors typically exhibit non-linear response characteristics, an exact mathematical model describing the relationship of the sensor response to the effects of environmental factors becomes more difficult to develop. Reference capacitive sensors [2-6] have been used in the past that calibrate the dielectric constant parameter to improve the capacitive sensor accuracy, however, the cost associated with such a configuration that requires additional sensors prohibits its wider use, particularly in automotive applications.

Apart from the accuracy of the level sensor itself, the fluid level measurement system operating in dynamic environments (i.e. automotive fuel tank) is influenced by the sloshing effects caused by acceleration. In automotive fuel tanks, the vehicle acceleration induces slosh waves having natural frequencies whose wave pattern is dependent on the magnitude of the acceleration, geometry of the tank and the amount of fluid contained in the tank. Theoretical studies and numerical analysis have been carried out in the past to describe various sloshing phenomenon [7-11].

To compensate for the effects of sloshing in fluid level measurement systems, various mechanical dampening methods consisting of baffles, electrical dampening techniques, and statistical averaging methods have been used in the past. However, all these approaches lead to higher production cost. The accuracy of these measurement systems under sloshing conditions is also not satisfactory. The electrical dampening techniques and the statistical averaging methods primarily perform averaging on the raw sensor signals over some period of time. Averaging over a variable time frame has also been used in the past [12-14] to improve the level sensor accuracy under sloshing conditions by determining the running state of the vehicle using the vehicle speed data from the speed sensor. The fluid measurement system described by Kobayashi et al [13] employs a vehicle speed sensor to determine the running state of the vehicle. When the vehicle is operating at low speed (i.e. static condition), the averaging period is reduced to small values, and when the vehicle is operating at a higher speed, the averaging period is prolonged up to 90 seconds. Despite the dependence of the measurement system on the speed sensor, after analyzing the raw sensor data from a resistive type fuel level sensor in a moving vehicle, it has been observed that the averaging method still produces significant error after averaging the raw sensor signal over a longer period of time. Fig. 2 shows the raw volume signal obtained from a vehicle in motion, and two averaged signals calculated after averaging the raw signal over twenty seconds, which is the typical averaging time used in automotive instrument cluster; and the second signal is averaged over ninety seconds, which is a reasonably long period of time.

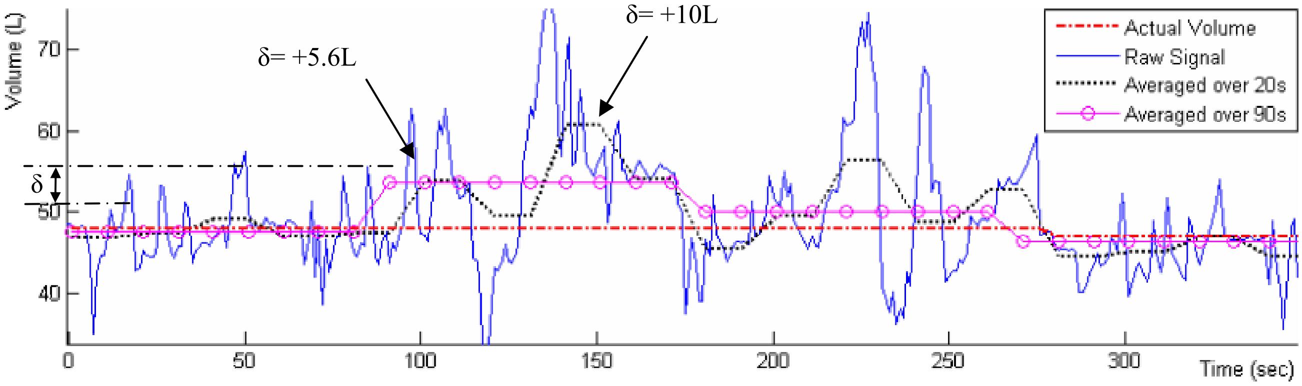


Fig. 2. Fuel level signal observed by the level sensor and the calculated average signal in a sample drive trial.

Shiratsuchi et al. [15] described a capacitive type fuel level sensing system that uses three capacitors to determine the fuel surface plane angle, and a fourth capacitor is used as reference capacitor to compensate for the variations in the dielectric constant. The high cost associated with having long multiple capacitors makes this approach infeasible. Furthermore Shiratsuchi et al. [15] have assumed the fuel surface as always a plane, whereas, even under normal driving conditions, the surface of the fuel actually portrays slosh waves that fluctuate at varying rate. The method described by Shiratsuchi et al. determines the fluid level when the slope angle is at zero or when the fuel level is at horizon, which relates to the static state condition and does not accurately determine fluid level under dynamic conditions.

To improve the accuracy of the fluid level measurement system in a dynamic environment and at a very low cost, a novel approach based on Artificial Neural Networks (ANN) is described in this paper. Neural networks can recognize patterns; and with sufficient number of hidden neurons having sigmoidal functions, they can be trained to produce any continuous multivariate function with any desired precision [16]. The complex behaviour of the sensors in harsh environments and the phenomena of sloshing can therefore be analyzed using artificial neural networks and any compensation to the sensor accuracy can also be made with it.

In this paper, a neural network approach has been described that accurately determines the fluid level under dynamic conditions. The approach described in here is also applicable to non-capacitive sensors such as ultrasonic and hall-effect sensors. For simplicity, the effects of temperature and contamination are eliminated by calibrating the capacitive level sensor to the ambient temperature and the surrounding fuel. The influence of contamination and temperature will however be investigated in the future. The primary focus as described here is on eliminating the effects of sloshing on fluid level measurement accuracy using the Backpropagation (BP) neural network. Some selected statistical slosh compensation methods, namely, Moving Mean and Moving Median are compared with the results obtained with the novel system.

2. The Measurement System

Artificial neural networks have been used extensively for signal classification in a wide variety of applications in the fields of Engineering, Medicine, Business, and Security. Supervised feed-forward neural networks are more flexible and can yield much better results when compared with the data clustering methods such as K-means [17]. Herein an approach is described using the Feed-forward Backpropagation (BP) neural network to accurately determine the fluid level in automotive fuel tanks in the presence of sloshing. An overview diagram of the measurement system is shown in Fig. 3.

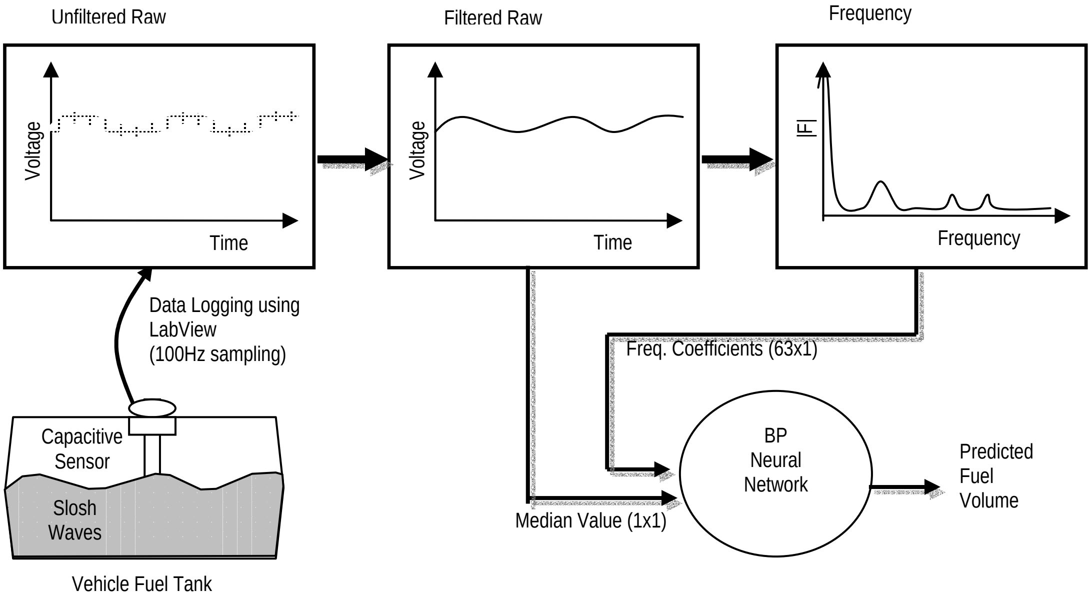


Fig. 3. Block diagram showing overview of the fluid level measurement system.

Four BP neural networks with the same network configurations were trained and verified with three filtration methods, Moving Mean, Moving Median, and Wavelet Transform; and one network was investigated with unfiltered signals. The capacitive sensor produced the fluid level signal as a continuous voltage signal, which was sampled at 100 Hz. The sampled level signal was gathered over twenty seconds, which is the typical hold-on time used in automotive vehicles for averaging the fuel level signal. This collective signal over twenty seconds was then filtered through the three investigated filtration methods. After filtration, feature extraction was performed on the filtered signals using the MATLAB built-in Fast Fourier Transform (*fft*) function and the obtained frequency coefficients were then fed through the BP neural networks.

2.1. BP Network Architecture

All four neural networks shared the common network configuration that consisted of a single hidden layer with sixty-four neurons as input, which is the same as the number of input coefficients. The transfer functions of the hidden and the output layers are *tansig* and *purelin*, respectively. The structure of each BP neural network is shown in Fig. 4.

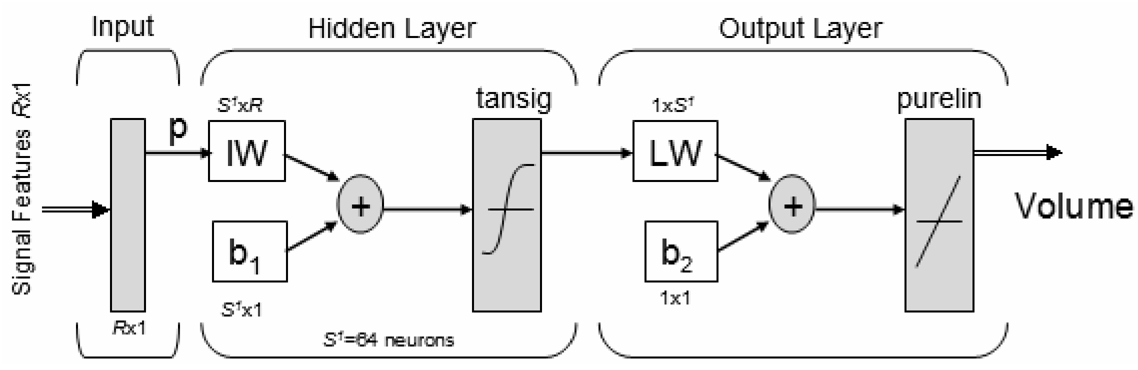


Fig. 4. Architecture of the BP neural network.

Input *p* is passed through input layer weights *IW*, and the sum of the product *IWp* and the bias b_1 is fed into the *tansig* transfer function. In the output layer, the output from the *tansig* function is multiplied by the output layer weights *LW*. Finally an output volume is produced by the *purelin* function by using *LW* and bias b_2. A general equation to determine the tank volume in a particular tank based on the slosh data *p* is given as:

$$Volume(p) = purelin\lfloor LW(\mathrm{tansig}(IW\ p + b_1)) + b_2 \rfloor \tag{3}$$

The hidden layer weights (IW), output layer weights (LW) and the biases (b_1 and b_2) are obtained using the MATLAB Neural Network Toolbox after the network has been trained.

2.2. Signal Filtration

In the signal filtration process, the raw signal is filtered to remove the signal noise by smoothening it with the three investigated methods: Moving Mean, Moving Median and Wavelet Transform. A raw signal over twenty seconds is passed through the investigated filters. The moving mean and moving median filters slide across the raw signal and calculate the mean/median values in the neighbouring sampled points. If x is the sampled raw signal of N length, and w is size of the moving window, then the filtered output y using mean and median can be obtained using (4) and (5), respectively. The width of the moving window w is set to 10, which implies that the sliding window function takes 10 sampled values (0.1 second values) of the raw signal and produces a mean or median value at the output.

$$\begin{aligned} y[i] &= mean(x[i-1], x[i-2], ..., x[i-w]), \quad for \;\; w \le i \le N \\ y[i] &= mean(x[1], x[2], ..., x[i]), \quad for \;\; 1 \le i < w \end{aligned} \tag{4}$$

$$\begin{aligned} y[i] &= median(x[i-1], x[i-2], ..., x[i-w]), \quad for \;\; w \le i \le N \\ y[i] &= median(x[1], x[2], ..., x[i]), \quad for \;\; 1 \le i < w \end{aligned} \tag{5}$$

The value of N for the twenty second signal at 100 Hz is calculated as (6):

$$N = 100 \;\text{ samples/s} \times 20s = 2000 \,\text{samples} \tag{6}$$

Fig. 5 illustrates the moving mean and moving median filters when applied to the raw signal data. As the moving window slides across the twenty second long raw signal, mean/median functions are applied to the raw signal values within the window range and a smooth signal is produced. The filtered versions of the raw signal do not contain high frequency noise.

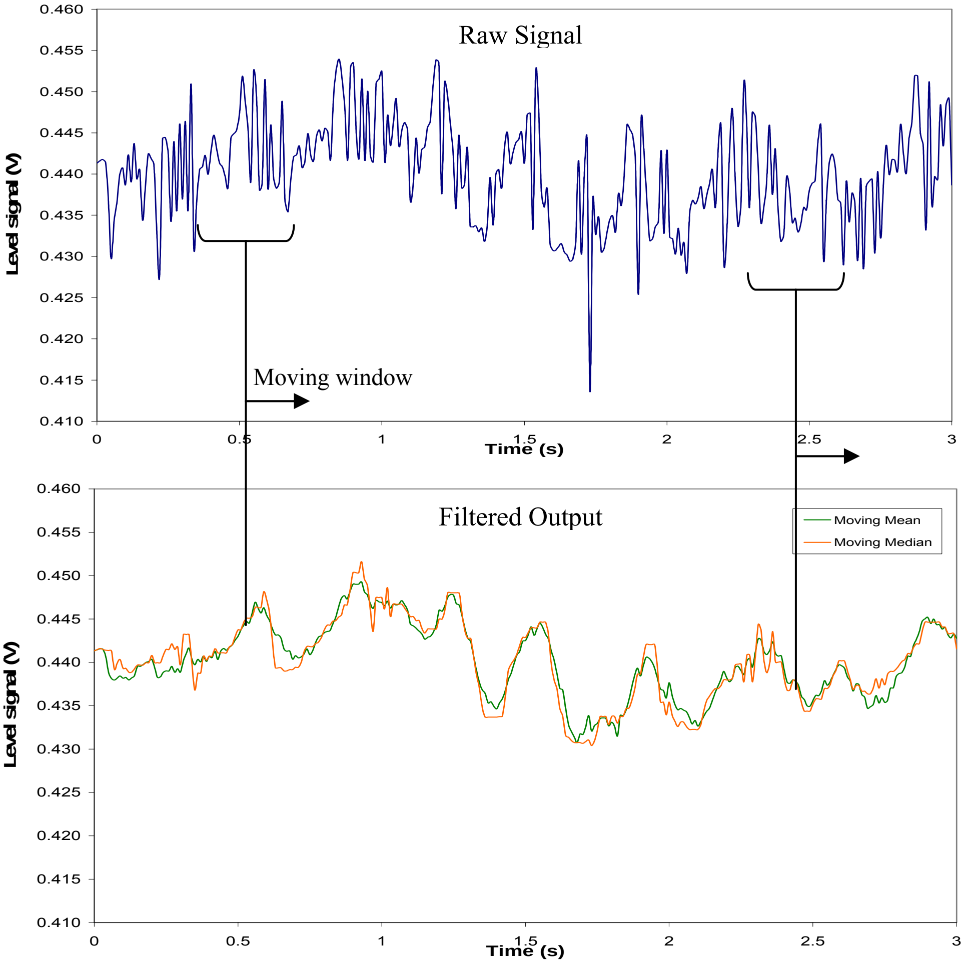


Fig. 5. Illustration of the moving mean and moving median filters.

Another filter investigated is the Wavelet Transform (WT) filter that analyses signals at different frequency bands by de-composing them into coarse information and detailed information sets. The coarse information set contains the low-frequencies, whereas, the detailed information set contains the high-frequencies of the input signal. Only low frequency components, which reflect a smoothened version of the raw signal, are used and the high frequency components of the raw signal, which usually contain noise, are eliminated.

Fig. **6** shows the high frequency signal (b) and the low-pass filtered signal (c) when the raw sensor signal (a) was processed with the Discrete Wavelet Transform (DWT) function. The Wavelet Transformation was processed through the MATLAB Wavelet Toolbox using the *dwt* function, which used *db1* wavelet.

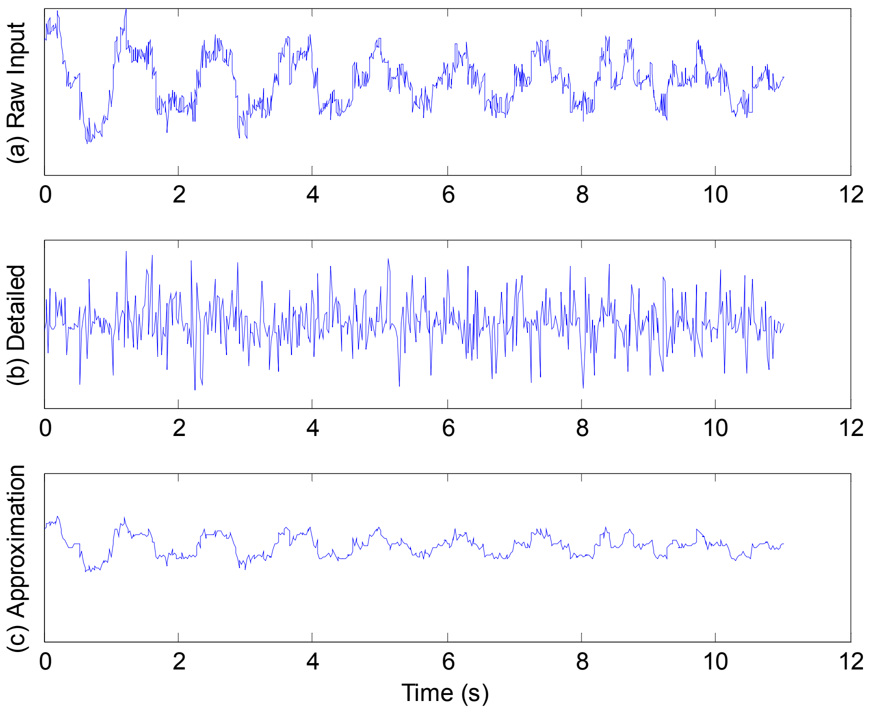


Fig. 6. Wavelet Filter applied on the Raw Signal.

All filtered signals using the investigated filtration methods were transformed into the frequency domain and the frequency coefficients are obtained, which were then fed into the neural network.

3. Experiment Setup

A fuel tank was fitted with a capacitive sensor near the center of the tank. The tank can be approximated as a rounded edge rectangle with dimensions 34 × 34 × 81 cm. The fuel tank was filled with fuel levels ranging from 5 – 50 L in the experiment, which corresponds to 6 % - 70 % of the tank capacity. Due to the limited length of the capacitive sensor tube used in the experiment, fuel levels below 5 L could not be determined. The fuel tank was mounted in latitudinal direction, where the longest length of the tank was in parallel to the direction of the vehicle. Table 1 lists all the fuel levels investigated in the experiment.

Table 1. List of tank volume levels investigated in the experiment.

Investigated Tank Levels
5L, 6L, 7L, 8L, 9L,
15L, 20L, 25L, 30L,
35L, 36L, 37L, 38L, 39L, 40L,
45L, 46L, 47L, 48L, 49L, 50L

The level signal obtained from the capacitive sensor was acquired using LabVIEW and a Data Acquisition Card, which was connected to the capacitive sensor in the vehicle. The capacitive sensor signal indicating the fuel level was sampled and recorded at 100 Hz. The capacitive sensor was calibrated to the ambient temperature and the fuel, therefore the effects of temperature variations and contamination can be ignored in the capacitive sensor output. Each experiment was conducted by driving a vehicle containing the instrumented fuel tank for 3 km in a suburban residential area, where occasional stops were made at some road intersections. Fig. 7 shows the typical speed and acceleration curves observed during the experiment.

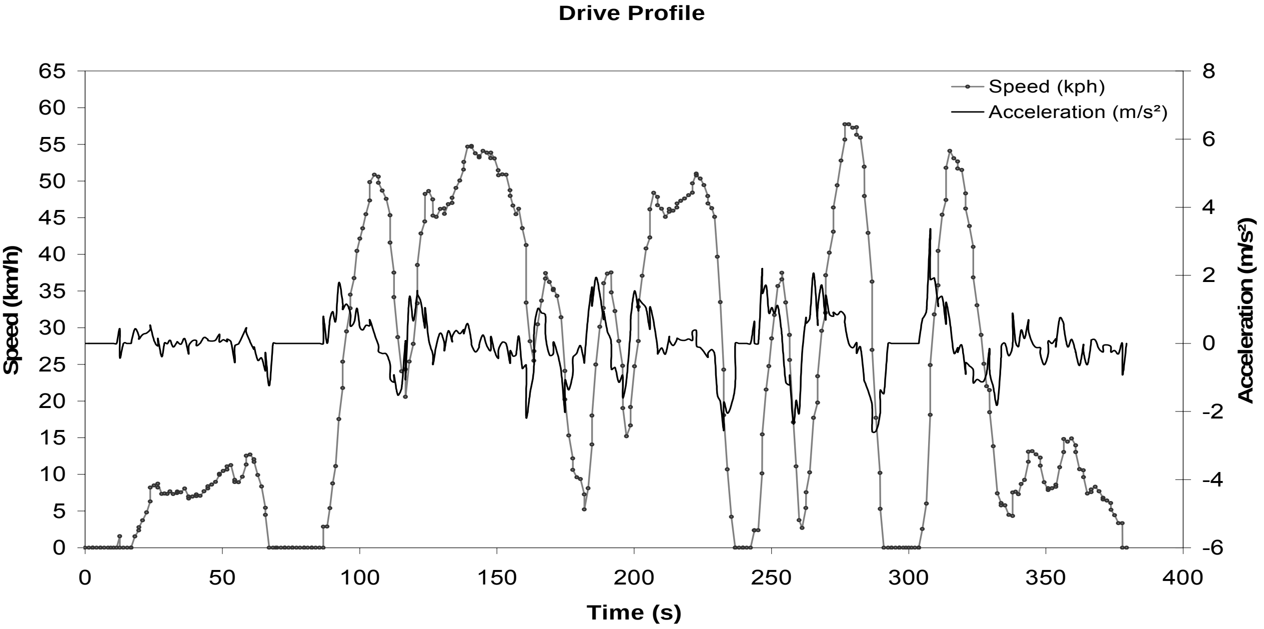


Fig. 7. Typical speed and acceleration plot observed during the experiments.

4. Validation Results

Each investigated filter was applied on a separate BP neural network, where the network configurations for all BP networks were the same. One half of the data from the first field trial was used to train the BP neural networks, and a half of the data from the second field trial samples was used for validation of the network performance. Network training and validation was carried out using the MATLAB Neural Network Toolbox.

Fig. **8** illustrates the neural network training and validation procedure.

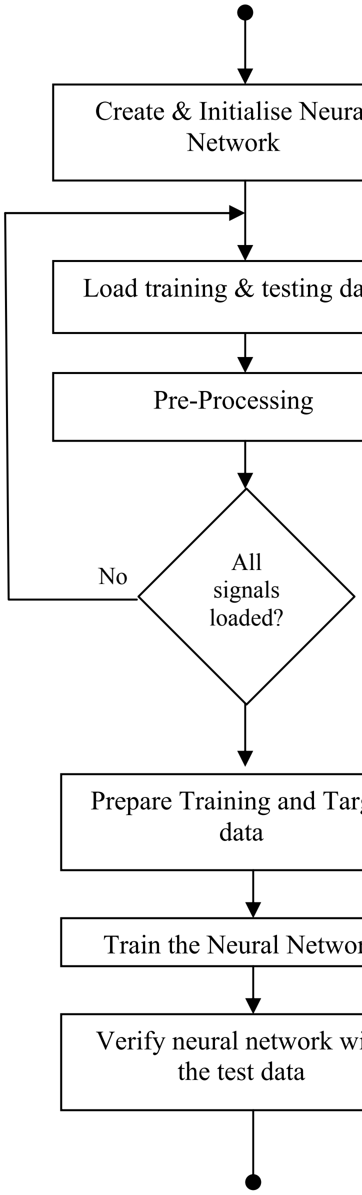


Fig. 8. Neural Network Training and Validation Flowchart.

Fig. **9** shows the frequency coefficients of the raw capacitive sensor signals generated with MATLAB software using the *fft* function. To increase the network training speed without incurring performance penalty, only the first sixty-three frequency coefficients that approximately correspond to the slosh frequency 0 – 6.5 Hz, were used for signal classification and validation. The frequency coefficients and the median value of the signals were all stored in an array vector of sixty-four elements, which were then used as inputs to the artificial neural network model.

After training the neural network, the network was validated using the test samples obtained from the second field trial. Table 2 lists the neural network weights obtained from the network on which the Moving Median filter was applied. The weights can be substituted into equation (3) to produce the output volume.

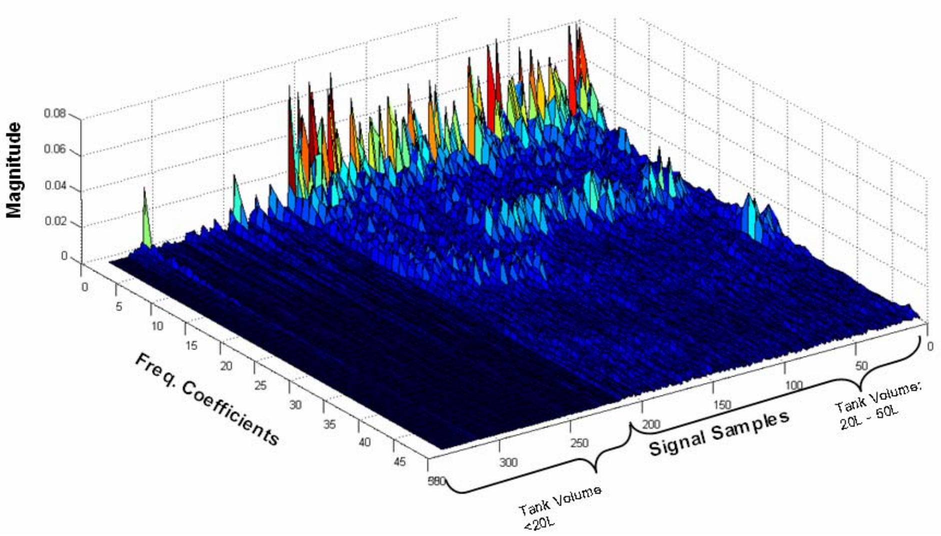


Fig. 9. Graph of the FFT coefficients obtained by using the training data.

Table 2. List of Input and output layers weights.

Input Weights (IW)						
Coefficients / Neurons	Coef$_1$	Coef$_2$	Coef$_3$	Coef$_4$	…	Coef$_{64}$
1	-3.67230	-2.69990	2.01490	-1.93900	..	0.08178
2	-0.31637	0.02187	-0.26951	0.77212	..	-0.55357
3	-0.63585	-0.24946	-0.71994	0.31545	..	-0.63257
…	…	…	…	…	..	…
64	-2.30790	-1.95100	-0.98339	0.04441	..	-5.16550
Output Layer Weights (LW)						
1	15.1550	-1.83800	2.62580	9.43560	..	-7.67050

Fig. 10 shows the output results obtained using different processing methods. The output volume was calculated as the overall average of each investigated tank volume. Field trial results for each investigated tank volume are placed adjacent to each other. The time length of each trial is indicated as 280 seconds. A closer look at the 49 litre trial is also shown in Fig. 10. The raw signal illustrated in Fig. 10 (A) was divided into twenty-second long signals, as shown in Fig. 10 (B), which were then filtered and processed through the neural network. The overall averaged volume Fig. 10 (C) was calculated by averaging the neural network outputs for each trial over 280 seconds.

Table 3 shows the volume figures obtained using the statistical mean and median functions, and the neural network predicted results using different pre-processing filters. Average error values at a particular investigated tank volume are shown in Table 4. All values listed in Table 3 and Table 4 are in litres.

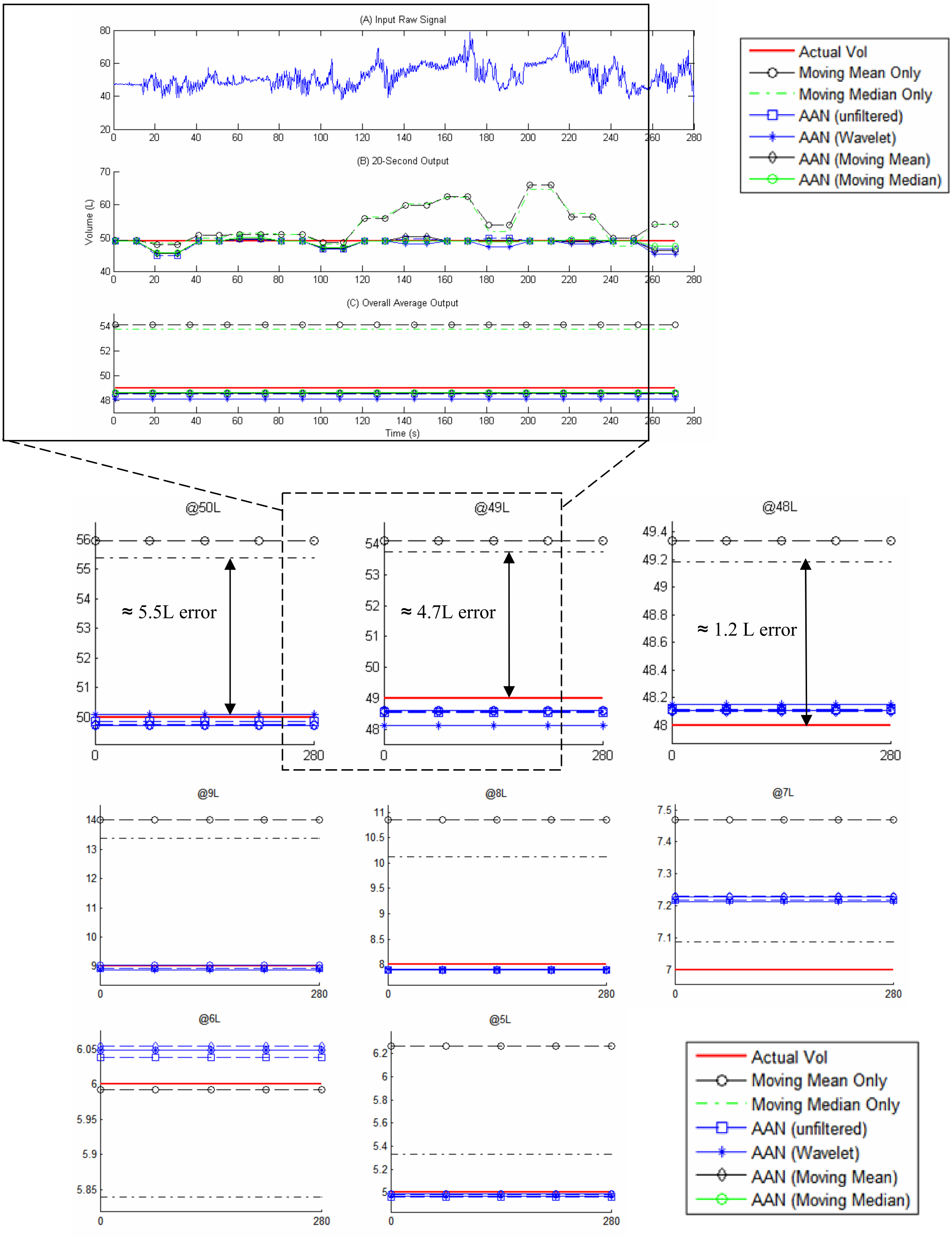


Fig. 10. Verification results obtained after training the neural networks.

Table 3. Validation results using statistical averaing methods and the neural network approach with different pre-processing filters.

Actual Tank Volume	**Statistical Averaging**		**Artificial Neural Networks**			
	Moving Mean*	Moving Median*	ANN (Unfiltered)	ANN (Moving Mean)	ANN (Moving Median)	ANN (Wavelet filter)
50	55.96	55.38	49.87	49.76	49.72	50.08
49	54.11	53.74	48.53	48.57	48.62	48.12
48	49.34	49.18	48.12	48.11	48.11	48.16
47	44.42	44.41	46.28	45.83	45.98	46.05
46	45.64	45.57	45.85	45.81	45.55	45.55
45	44.06	43.81	43.92	43.86	44.11	43.59
40	40.04	39.96	40.08	40.09	40.17	39.86
39	37.18	37.08	39.02	38.98	39.07	39.06
38	38.18	37.75	38.11	38.36	38.35	38.18
37	37.34	37.03	37.34	37.34	37.30	37.31
36	35.23	35.08	35.85	36.03	36.16	35.93
35	35.39	35.10	35.17	35.45	35.56	35.40
30	30.14	29.81	30.09	30.70	30.38	29.94
25	27.58	26.77	25.40	25.18	25.10	25.31
20	22.37	21.74	21.44	21.26	21.11	21.46
9	14.01	13.38	8.92	8.94	9.04	8.88
8	10.85	10.12	7.90	7.90	7.90	7.90
7	7.47	7.09	7.22	7.23	7.23	7.21
6	5.99	5.84	6.04	6.05	6.05	6.05
5	6.27	5.33	4.96	4.98	4.99	4.97

* Averaged filter values without using neural network.

Table 4. Validation error results for applied statistical and neural network methods.

Actual Tank Volume	**Statistical Methods**		**Artificial Neural Networks Methods**			
	Moving Mean*	Moving Median*	ANN (Unfiltered)	ANN (Moving Mean)	ANN (Moving Median)	ANN (Wavelet filter)
50	5.96	5.38	0.13	0.24	0.28	0.08
49	5.11	4.74	0.47	0.43	0.38	0.88
48	1.34	1.18	0.12	0.10	0.11	0.16
47	2.58	2.59	0.72	1.17	1.02	0.95
46	0.36	0.43	0.15	0.19	0.45	0.45
45	0.94	1.19	1.08	1.14	0.89	1.41
40	0.04	0.04	0.08	0.09	0.17	0.14
39	1.82	1.92	0.02	0.02	0.07	0.06
38	0.18	0.25	0.11	0.36	0.35	0.18
37	0.34	0.03	0.34	0.34	0.30	0.31
36	0.77	0.92	0.15	0.03	0.16	0.07
35	0.39	0.09	0.17	0.45	0.56	0.40
30	0.14	0.19	0.09	0.70	0.38	0.07
25	2.58	1.77	0.40	0.18	0.10	0.31
20	2.37	1.74	1.44	1.26	1.11	1.46
9	5.01	4.38	0.08	0.06	0.04	0.12
8	2.85	2.12	0.10	0.10	0.10	0.10
7	0.47	0.09	0.22	0.23	0.23	0.21
6	0.01	0.16	0.04	0.05	0.05	0.05
5	1.27	0.33	0.04	0.02	0.01	0.03
Absolute Average Error	1.73	1.48	0.30	0.36	0.34	0.37
Max. Error	5.96	5.38	1.44	1.26	1.11	1.46

* Averaged filter values without using neural network

The overall average error obtained using the statistical methods and the four investigated Artificial Neural Networks is shown in Fig. 11.

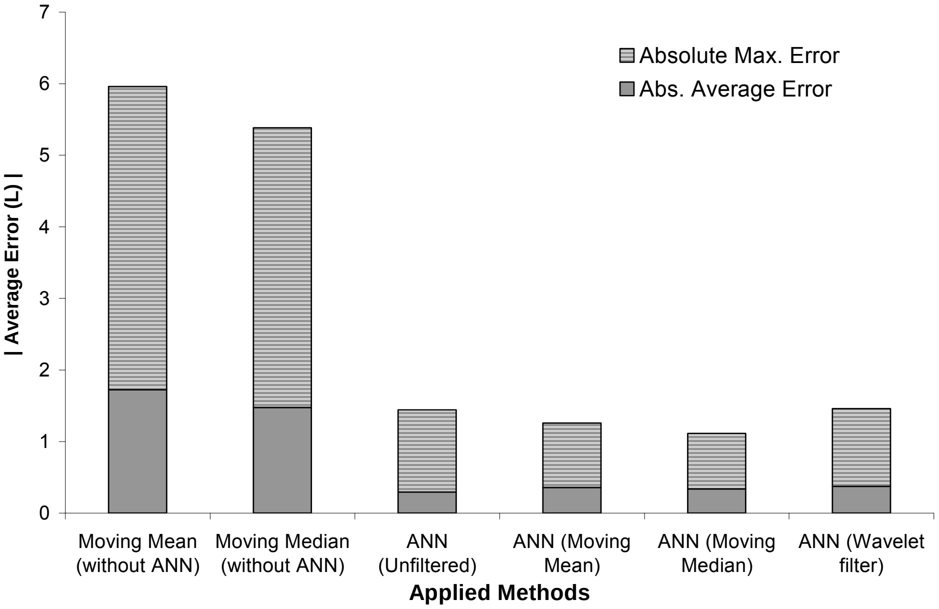


Fig. 11. Investigation summary results showing the maximum and average errors.

5. Summary

The neural network approach has been used to accurately determine the fuel level in an automotive fuel tank under real driving conditions. Four identical BP neural networks were developed and an investigation was carried out by applying three filtration methods and keeping one unfiltered raw signal to analyze the performance of the BP neural network approach in improving the accuracy of the level sensor in the presence of liquid slosh. The four neural networks with applied filters Moving Mean, Moving Mean, Wavelet, and Unfiltered had the same network configurations. The output response of each network with the same raw signals was also observed to be very similar. The BP network applied with the Moving Median filter produced a maximum averaged error of 1.1 litres, which is significantly better than the results obtained using the statistical and non-neural network Moving Mean, and Moving Median functions that produced a maximum averaged error of 6.0 litres and 5.4 litres, respectively.

6. Future Work

Neural networks will be used to address other influencing factors such as contamination and the tilt that causes liquid to shift to one side. With the rapid improvements in microprocessor technology, it will be possible to train the neural networks in real time, which will further increase the effectiveness of the measurement system in dynamic environments.

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Guide for Contributors

Aims and Scope

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Contributions are invited on all aspects of research, development and application of the science and technology of sensors, transducers and sensor instrumentations. Topics include, but are not restricted to:

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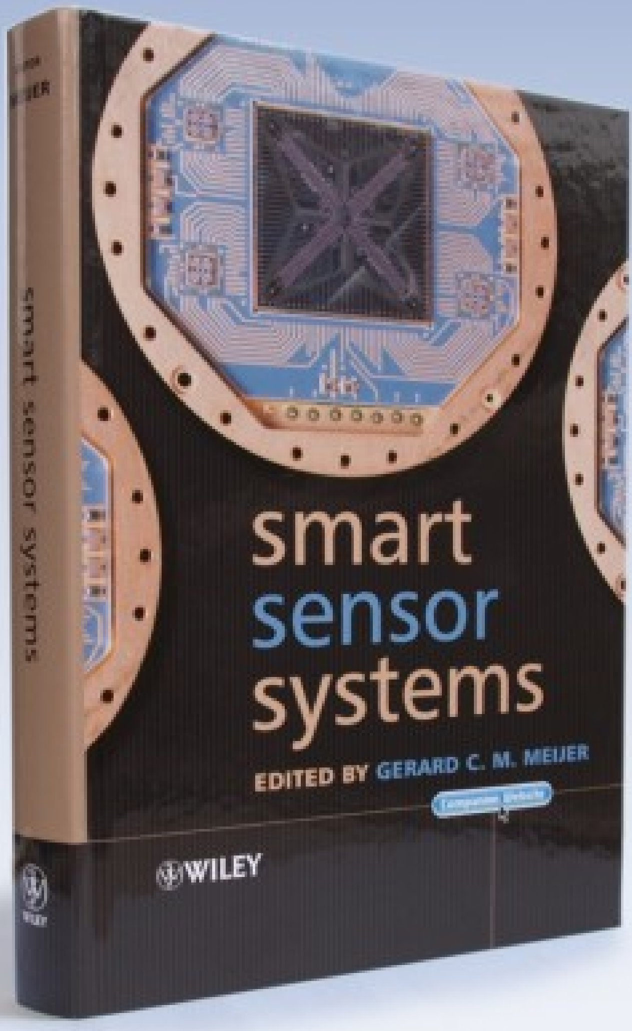
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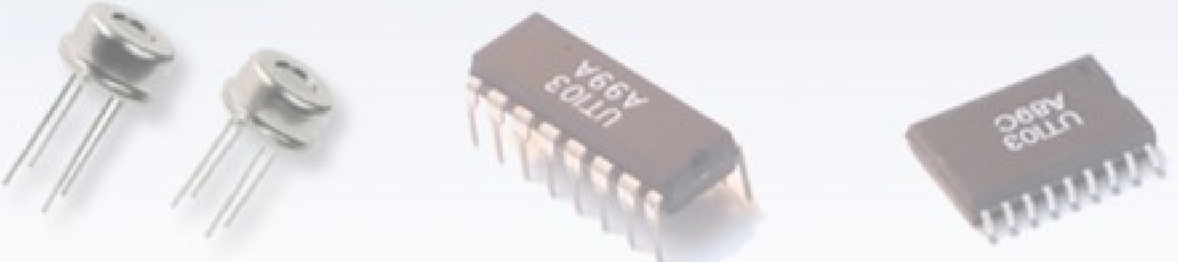
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