Integrating Statistical Methods in Engineering Technology Courses

Dr. Sanjeevi Chitikeshi, Old Dominion University

Dr. Sanjeevi Chitikeshi is an Assistant Professor in Electrical Engineering Technology program at Old Dominion University, Norfolk, VA. Prior to current position, he worked at Murray State University, Murray, KY and also as a control engineer in industry in California. He earned both his Masters and Ph.D in Electrical and Computer Engineering from Sothern Illinois University, Carbondale, IL, in 2004 and 2007 respectively. His research interests are in Mechatronics systems, Big Data Analysis, Smart instrumentation and Controls for Biomedical Applications and Structural Health monitoring. He worked on funded projects from NASA, Caterpillar and Federal High way. He published journals and conference papers in the areas of smart instrumentation and control and mechatronics systems.

Jake Hildebrant, Murray State University

Jake Hildebrant is an Assistant Professor in the Institute of Engineering at Murray State University and the program coordinator for the Electromechanical Engineering Technology program. He is also the program coordinator for the online Energy Management program at Madisonville Community College. He specializes in Motion Control, Robotics, Programmable Logical Controllers, Sustainability Management, Energy Systems, and Energy Management.

He received his Master's of Science Degree from Western Kentucky University in Engineering Technology Management and his Bachelor's of Science from Murray State University in Electromechanical Engineering Technology. Before teaching higher education, he worked over seven years for the federal government as an Instrument and Controls Technologist.

Dr. Otilia Popescu, Old Dominion University

Dr. Otilia Popescu received the Engineering Diploma and M.S. degree from the Polytechnic Institute of Bucharest, Romania, and the PhD degree from Rutgers University, all in Electrical and Computer Engineering. Her research interests are in the general areas of communication systems, control theory, and signal processing. She is currently an Assistant Professor in the Department of Engineering Technology, Old Dominion University in Norfolk, Virginia. In the past she has worked for the University of Texas at Dallas, University of Texas at San Antonio, Rutgers University, and Politehnica University of Bucharest. She is a senior member of the IEEE, serves as associate editor for IEEE Communication Letters, and has served in the technical program committee for the IEEE ICC, WCNC, RWW, VTC, GLOBECOM, and CAMAD conferences.

Dr. Orlando M. Ayala, Old Dominion University

Dr. Ayala received his BS in Mechanical Engineering with honors (Cum Laude) from Universidad de Oriente (Venezuela) in 1995, MS in Mechanical Engineering in 2001 and PhD in Mechanical Engineering in 2005, both from University of Delaware (USA). Dr. Ayala is currently serving as Assistant Professor of Mechanical Engineering Technology Department, Frank Batten College of Engineering and Technology, Old Dominion University, Norfolk, VA.

Prior to joining ODU in 2013, Dr. Ayala spent three years as a Postdoctoral Researcher at University of Delaware where he expanded his knowledge on simulation of multiphase flows while acquiring skills in high performance parallel computing and scientific computation. Before that, Dr. Ayala hold a faculty position at Universidad de Oriente at Mechanical Engineering Department where he taught and developed graduate and undergraduate courses for a number of subjects such as Fluid Mechanics, Heat Transfer, Thermodynamics, Multiphase Flows, Fluid Mechanics and Hydraulic Machinery, as well as Mechanical Engineering Laboratory courses.

In addition, Dr. Ayala has had the opportunity to work for a number of engineering consulting companies, which have given him an important perspective and exposure to industry. He has been directly involved in at least 20 different engineering projects related to a wide range of industries from petroleum and natural gas industry to brewing and newspaper industries. Dr. Ayala has provided service to professional organizations such as ASME. Since 2008 he has been a member of the Committee of Spanish Translation of ASME Codes and the ASME Subcommittee on Piping and Pipelines in Spanish. Under both memberships the following Codes have been translated: ASME B31.3, ASME B31.8S, ASME B31Q and ASME BPV Sections I.

While maintaining his industrial work active, his research activities have also been very active; Dr. Ayala has published about 90 journal and peer-reviewed conference papers. His work has been presented in several international forums in Austria, USA, Venezuela, Japan, France, Mexico, and Argentina. Dr. Ayala has an average citation per year of all his published work of 36.17.

Dr. Vukica M. Jovanovic, Old Dominion University

Dr. Vukica Jovanovic is an Associate Professor of Engineering Technology in Mechanical Engineering Technology Program. She holds a Ph.D. from Purdue University in Mechanical Engineering Technology, focus on Digital Manufacturing. Her research is focused on mechatronics, digital manufacturing, digital thread, cyber physical systems, broadening participation, and engineering education. She is a Director of Mechatronics and Digital Manufacturing Lab at ODU and a lead of Area of Specialization Mechatronics Systems Design. She worked as a Visiting Researcher at Commonwealth Center for Advanced Manufacturing in Disputanta, VA on projects focusing on digital thread and cyber security of manufacturing systems. She has funded research in broadening participation efforts of underrepresented students in STEM funded by Office of Naval Research, focusing on mechatronic pathways. She is part of the ONR project related to the additive manufacturing training of active military. She is also part of the research team that leads the summer camp to nine graders that focus on broadening participation of underrepresented students into STEM (ODU BLAST).

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1. Abstract

Statistical methods and procedures are very important in engineering applications. In most of the engineering fields electronic devices are used as sensing and controlling components. Lack of proper calibration of these devices and of performance analysis using different statistical methods may lead to erroneous measurements and results. In medical or manufacturing areas such errors in the experimental results could be catastrophic. Applying different statistical tests and procedures enhance the quality of engineering work. Traditionally, most engineering curricula have at least one required course in applied statistics in engineering, but that is not generally the case in engineering technology programs. Most of the engineering technology BS graduates work as field engineers and collect the data from different physical processes and do data analysis to validate the systems performances. Exposure to statistical methods use and data analysis will provide technology graduates with valuable skills in the current high-tech job market.

This paper focuses on how statistical analysis and methods using hand calculations and software tools can be integrated in undergraduate engineering technology courses, enhancing the hands-on approach of real engineering projects with software assisted data analysis. Learning the skills of collecting experimental data from real processes and performing statistical analysis on it is the effective approach of solving engineering problems, and it provides higher learning outputs than simulation-based approach. Specifically, integration of statistical analysis was introduced in an industrial instrumentation class, in which the lab component included the use of various sensors and other measurement instruments. By the end of the class, students demonstrated newly acquired statistical skills by performing sensor calibration and they also applied simple linear regression analysis model on the experimental data.

2. Introduction

Statistical methods and tools are used in a wide variety of fields to analyze the data, make hypothesis testing, correlate the data sets and predict trends. Especially in engineering, statistical methods are used to ensure the engineering design quality and control different processes.

Traditionally, statistics is not rigorously employed in undergraduate Engineering Technology curriculum but any engineer needs these skills when working in any industry. Different effective approaches have been examined at different academic universities [1-4] and the most widely technique has been learned with the use of experiments and that is the main focus of this paper. Most of traditional engineering curricula require moderate to extensive courses in probability and statistics but that is not the case in engineering technology curricula. Most of the engineering students require to take some statistics courses from Mathematical departments but rarely used in engineering lab-based courses and also, they might forget the concepts when they work outside after the graduation. This missing link gave a path to develop extensive statistical courses in different engineering fields [5,6]. There is always room to improve statistical courses in undergraduate engineering curricula and there have been different NSF grant projects on this topic [7]. Active learning-based techniques are always very effective when employed in statistical courses for engineering students [8-9].

Statistics education is needed in diverse fields from agriculture to aerospace engineering. Over the years, it has grown from narrowly focused on professional staffs to a wide range of academic and technical institutions [10]. Not every field students need to take or need extensive mathematical knowledge, instead basic algebra and fundamentals of other areas are sufficient.

For example, medical or biology students don't need extensive mathematical background [11] but still they need knowledge in statistics to analyze the data from the experiments. Same can be said to some extent for engineering technology students, however, engineering technology students need some basic background in calculus. There are many introductory statistics books available for different fields including Engineering Technology and some of those cover basics to advanced statistical topics [12-15].

Statistical model can be univariate or multivariate. Univariate models need distribution of a single variable or measurement compare to multiple variables used in multivariate. Simple z-test can be used for univariate and Chi-squared tests and Fishers tests can be used for multi variable cases. The response or output of the process or system can be modeled using linear methods or non-linear methods depending on how output variable varies when there is a change in the input variables. Most of the engineering and other processes can be modeled using linear models such as linear regression [16-20]. In linear regression analysis, principles of least square sums is used to estimate the parameters, which are coefficients of input variables and there might be a constant offset. Simple linear regression gives a system single output variable and errors have to be independent and normally distributed. Multiple linear regression gives the linear models when the systems have more than one response or exploratory variable.

For small data sets statistical interferences can be done using hand calculations but sometimes they may be very tedious. With available modern high-speed computing machines usually already available statistical software tools [21-27] are employed in data analytics and data mining. Since the data sets can be very large, special tools related to bid data analytics are generally employed. In academic setting, in traditional engineering or engineering technology fields software tools like Excel, MATLAB, R, Min-Tab, SAS and other software tools are generally used.

In this paper, a simple linear regression analysis on univariate process (pressure sensor measurements in a hydraulic system) and basic statistical parameters such as mean, median and standard deviation were integrated in a junior level engineering technology course laboratory experiment. Instead of focusing more on mathematics, MATLAB was used to model the measured pressure data to do simple linear regression analysis. The results were also compared with hand calculations.

3. Analog Pressure Sensor Measurements and Statistical Methods

3.1. Using Analog Pressure Sensor in a Hydraulic Trainer

The statistical methods can be used on a set of data points. To introduce these methods to engineering technology students, an upper level course called Industrial Instrumentation was chosen. The course has an integrated laboratory component. Most of the lab experiments include interfacing external devices in hydraulic or pneumatic applications and making measurements.

For the focus of this work, an analog pressure sensor interfacing to a hydraulic trainer was chosen, from which data collection and experimental analysis were performed. The main goals of the experiment were to teach students instrumentation concepts and applying statistical methods on measured pressure sensor data. The instruments include hydraulic trainer, DC power supply, Digital Multi-meter, hydraulic hoses and oscilloscope. Once data was collected, the following statistical methods were applied:

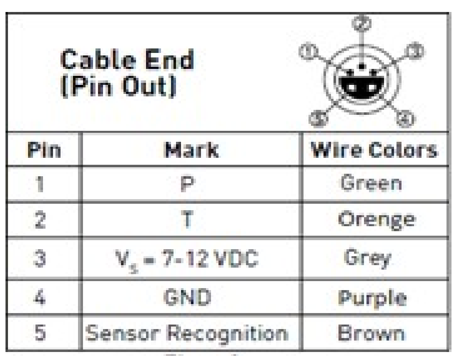
- Mean Value
- Median Values
- Standard Deviation
- Relative Error
- Full Scale Error
- Linear fit using hand calculation
- Linear fit using MATLAB software.

They include basic concepts to moderately complicated regression analysis.

In most of the engineering and technology departments, the basic introduction to statistics class from Mathematics department is part of the curricula, and that was the case for this work. It is also true that very seldom these students use the knowledge from statistics course in any other course. Sometimes they forget all the concepts and may encounter a situation of inability to do the work in industry after they graduate. To fill this gap, it is very important to reinforce the use the statistical skills from other courses in students, but not just as some problem-solving equations, instead use them in a laboratory experiment where they collect the data and apply the learned skills on the measured data. Based on this idea, this work started as an exploratory project in an upper level industrial instrumentation course, which perfectly satisfies the lab component and integration of statistical methods.

4. Experiment Setup

The main data collected in the experiment was hydraulic pressure data using an analog pressure transducer or sensor. The pressure transducer measures the process variable, in this case it is hydraulic pressure in PSI and outputs the DC voltage. The measurement data is DC output voltage for different pressure values. The first step was to find the wiring information and specifications using the transducer data sheet. Following Figure 1 and Table 1 show the transducer information.



Cable End (Pin Out)

Pin	Mark	Wire Colors
1	P	Green
2	T	Orenge
3	V_s = 7-12 VDC	Grey
4	GND	Purple
5	Sensor Recognition	Brown

Figure 1. Pressure Transducer Information

Table1. Specifications of Pressure Sensor

Pressure Sensor Input Range	0-2175 Psi
Pressure Sensor Output Range	0-3V (DC)

Knowing pressure transducer information is very important for the following purposes:

_ Power supply voltage needs to be used to excite the transducer;
_ Wire that has to be used to collect the data;
_ Low and Max pressure range the sensor can measure;
_ Output DC voltage range for calibration and regression.

The next step is to insert the pressure transducer in the hydraulic circuit as shown in the Figure 2

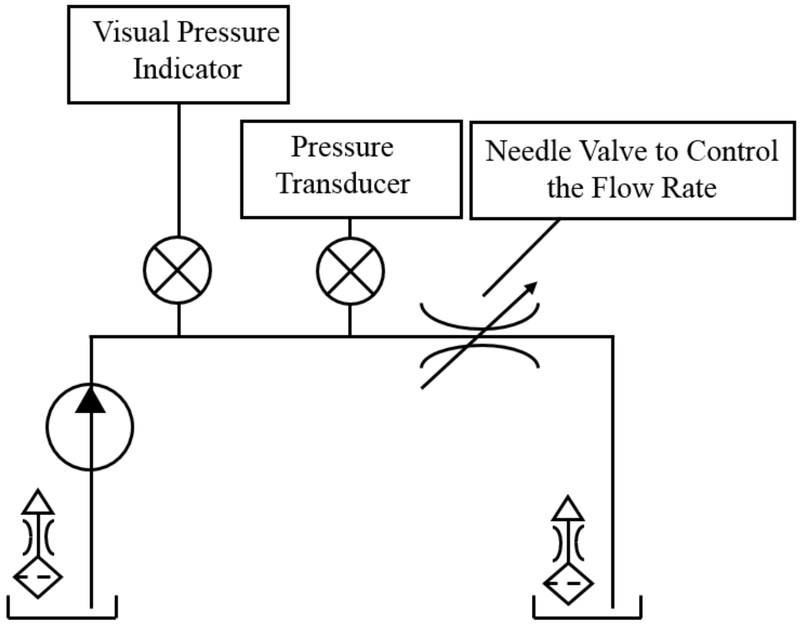


Figure 2. Pressure Transducer in Hydraulic Circuit.

Pressure gauge, hydraulic pump, relief valve are part of hydraulic trainer. The pressure values were changed using relief valve and measured by using on-board pressure gauge and pressure transducer. Most of the relief valve vents and on/off switches are located underneath the hydraulic trainer and they need to be set properly before using the trainer. These vents and switches are shown in following Figure 3. The main limitation of the trainer was the minimum pressure has to be maintained at 200 Psi. The maximum pressure the trainer can handle was 700 psi. The pressure data was hence collected in that range.

Figure 3. Hydraulic Trainer Valves - Parker

To build the above hydraulic circuit, the following safety procedural steps were followed to operate the hydraulic trainer:

1. Opened the relief valve vent by putting it horizontally straight.
2. Opened the relief valve by pulling it down and turning it clockwise at the same time.
3. Turned on the Trainer by pushing the pump start switch.
4. After that, closed the relief valve vent by pulling it down slowly until it is vertically straight.
5. After closing the relief vent, the relief valve was closed by pulling it down and turning it counter clockwise. (The pressure needle will be increasing as you close it.)
6. Set the pressure needle -gage- to 200 PSI.
7. Opened back the relief valve and turn off the Trainer.
8. Before using the transducer, the continuity of its wires were checked.
9. Now that everything was set, the hydraulic-transducer circuit was hooked as shown in the Figure 2.

5. Data Collection Procedure

After the hydraulic circuit was hooked up, the following steps were carried out to collect the DC output voltage from pressure sensor for pressure values from 200 Psi to 700 Psi in increments of 50 Psi.

1. The power supply (10V) to pressure transducer was applied them trainer was turned on.
2. The relief valve vent was then closed to apply pressure.
3. The relief valve was adjusted to read pressure from 200 to 700 in steps of 50 PSI.
4. At each Psi value, 5 readings were taken to calculate mean, median and standard deviation.
5. Measured output DC voltages were taken from the DMM at every PSI reading.
6. The trainer and the power were then turned off and everything was disconnected after finishing collecting the data.

Applying Basic Statistical methods on Measured Data: The pressure transducer measures the process variable, in this work it was the hydraulic pressure in PSI and outputs the DC voltage. The measurement data was DC output voltage for different pressure values.

6. Basic S`tatistical Parameters

To validate and get basic information from any data set, the fundamental three statistical parameters (mean, median and standard deviation) are used in any field.

Mean: It indicates the average of set of data points. To introduce this parameter usage and its importance to the students, in this experiment, the pressure sensor reading was measured 5 times at the same PSI value. In real time industrial applications, the data from any sensor is usually collected multiple times and an average value is then used. The main advantage is that the mean value compensates the any sporadic data points. Using single measurement data point in an application may lead to incorrect decision process if that data point happens to be a noise or an error. Sample data reading at pressure value of 300 PSI are shown in following Table 2.

Table 2: Pressure Transducer readings at 300 PSI

Pressure Value [PSI]	Transducer DC Output Voltage [V]
300	0.415
300	0.414
300	0.414
300	0.413
300	0.415

The mean value was calculated as Mean = Sum of Values/number of data points. Consequently, at 300 PSI the Mean DC voltage was calculated as 0.414V.

Median: It indicates the middle data point in a given data set. In any field it is very helpful parameter to see how data is spanned. The median value was calculated first arranging the data points in ascending order then choosing the middle point. The main learning outcome for the students was to teach them the main difference between mean value and median value. The following calculation shows again sample calculation at PSI value of 300 PSI using the data points in Table 2.

- Arrange the voltages in ascending order: 0.413, 0.414, 0.414,0.415,0.415
- The middle data point is median: 0.414V

Standard Deviation: It indicates how the values of measurements in the data set varies from its mean value. The variability is an important parameter to know as it shows how data points differ from one another. In general, in engineering experiments if the same data is measured for any fixed number of times, the data should not vary too much and this can be quantified using standard deviation. In this work, the pressure sensor output DC voltage was measured 5 times for the same input pressure value in the hydraulic system.

The sample standard deviation is calculated using

$$S = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(X_i - X \right)^2}$$

Where,

n is the sample size

X_i = ith measured data point

$\overline{X}$ = sample mean.

In this work, variable X was pressure sensor's output DC voltage for a defined input pressure value in Psi.

3.2 Sensor Calibration and Simple Linear Regression Analysis

For any transducer (or sensor) the data sheet provides the input range and output range specifications. In this experiment, the chosen pressure sensor had an input pressure range of 0 to 2175 Psi and output DC voltage range of 0 to 3V. The data collection process was to collect the DC voltage output values from sensor for the set hydraulic pressure values of 200 to 700 Psi in the increments of 50 Psi. Students were asked to find the linear line equation from the specs given in sensor's data sheet and also do the linear regression line fit equation using MATLAB software. The goal was to use the regression analysis on measured data.

Linear line fit model from sensor's specifications Let (x_1, x_2) are input pressure range: 0 to 2175 Psi (y_1,y_2) are output DC voltage range : 0 to 3V
Using linear algebra, students were asked to find the best fit line model equation that relates the input pressure values to output DC voltages. After finding the line fit equation, it was verified at some pressure value using actual pressure value that was measured using the pressure gauge on the hydraulic trainer.

$$(input):(x_1, x_2) = (0, 2175)$$

$$(output): (y_1, y_2) = (0, 3)$$

$$(x_1, y_1) = (0, 0)$$

$$(x_2, y_2) = (2175, 0)$$

$$m = \frac{y_2 - y_1}{x_2 - yx_1} = \frac{3 - 0}{2175 - 0} = 1.38 * 10^{-3}$$

$$c = y_1 - mx_1 = 0 - (1.38 * 10^{-3})(0) = 0$$

$$\text{the relation is: } y = (1.38 * 10^{-3})x + 0$$

$$ex: \text{input is 200 PSI}$$

$$y = (1.38 * 10^{-3})x + 0$$

$$y = (1.38 * 10^{-3}) * 200 = 0.276 V_{DC}$$

7. Simple Linear Regression Analysis on measured data

The linear line fit equation found in previous section using sensor's specifications may not be accurate because of environmental interferences and age of sensor and electrical noise etc. In the real world, the calibration equation is usually found using measured data. In this experiment, the DC output voltages were measured for input pressure values ranging from 200 to 700 Psi in the incremental step of 50 Psi. The actual pressure value in the hydraulic system was set by monitoring the pressure gauge reading on the trainer.

Simple Linear Regression Analysis evaluates the relationship of one more independent variables (x_1, x_2,..., x_k) to single continuous output variable. In this experiment, the input variable or predictor (a single input) x1 is Pressure value in Psi and continuous output variable (Y) is DC voltage from sensor.

$$Y = \beta_0 + \beta_1 X + E$$

Where:

Y = Response variable

X = Predictor

β_0 = Intercetp of straight line model

β_1 = Slope of straight line model

E = error term

Alternatively,

$$Y_i = \beta_0 + \beta_1 X_i + E_i\,,\ i = 1, 2,3,..., n.$$

Model assumption is $E_i \sim iidN\left(0,\sigma^2\right)$

That is error terms are independent and normally distributed.

The next step is to find the coefficients of linear fit equations β_0 and β_1 using least square method. Consider the following fitted regression line

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_i \qquad (1)$$

Where, $\hat{Y}_i$ is estimate of the expected value of response variable (in this experiment, it was DC output voltage) at input variable (in this case, it was pressure value in Psi) *Xi* based on the fitted regression line (1) and $\hat{\beta}_0$ $\hat{\beta}_1$ and are estimates of the regression parameters β_0 and β_1.

The estimate of regression parameters (β_0 and β_1) that minimize the SSE (Sum of Squares of Errors) is called Least Square Estimator (LS) and the method is called Least Square (LS) estimation. It can be shown that the least square estimator of the regression parameters are calculated as

$$\hat{\beta}_1 = \frac{\sum_{i=1}^{n}(X_i-\bar{X})(Y_i-\overline{XY})}{\sum_{i=1}^{n}(X_i-\bar{X})^2};\ \text{or}\quad \hat{\beta}_1 = r\frac{s_Y}{s_X}\quad \text{and}\quad \hat{\beta}_0 = \bar{Y} - \hat{\beta}_1\bar{X}$$

where, $(\bar{Y}, \bar{X},)$ are sample mean of values of (*Y* and *X*) respectively. Students were reviewed all these concepts but due to tedious procedure of hand calculations, generally people use already available statistical software to do the math to estimate the regression parameters. In this work, MATLAB in-built function called polyfit() was used to estimate the regression parameters and polyeval() was used to estimate the error values. Polyfit(0 command requires input & output data points and the desired order of the model as input arguments. For this work, pressure values in Psi & DC voltages were given as input and output data sets and the order of the line equation was given as one because of the general idea got from sensor specs. Next section outlines the measured data sets and regression fit results using MATLAB.

8. Results

As explained in the previous sections, the main measurement data points are pressure sensor's output DC voltages at different hydraulic pressure input values in Psi. The desired pressure values were set by adjusting relief valve on the trainer and monitoring the Psi value on the pressure gauge on the trainer. Following Table 3 lists out expected DC voltage values at different pressure values. These expected DC voltages were calculated using linear line fit equation using sensor's specification as explained in the previous section

Table 3. Expected DC voltages using Sensor's calibration equation

Liquid Pressure	Expected Output Voltage
200	0.276
250	0.345
300	0.414
350	0.483
400	0.552

450	0.621
500	0.69
550	0.759
600	0.828
650	0.897
700	0.966

The other statistical parameters that were reviewed or integrated in this work were relative error and full-scale error. These two errors are also very important parameters in understanding the accuracy of a measurement instrument. Table 4 lists out relative error and full-scale error values using the expected DC voltages calculated from linear line sensor calibration equation.

Table 4. Relative and Full-Scale Error values using Sensor's calibration equation

Liquid Pressure	Expected Output Voltage	Measured Pressure Voltage	Relative Error %	Full Scale Error %
200	0.276	0.27	2.174	0.200
250	0.345	0.34	1.449	0.167
300	0.414	0.4	3.382	0.467
350	0.483	0.47	2.692	0.433
400	0.552	0.54	2.174	0.400
450	0.621	0.61	1.771	0.367
500	0.69	0.68	1.449	0.333
550	0.759	0.75	1.186	0.300
600	0.828	0.82	0.966	0.267
650	0.897	0.9	0.334	0.100
700	0.966	0.96	0.621	0.200

The error equations used in MatLab are:

$$\%Relative\ Error\ = \frac{|calculated\ -\ measured|}{calculated} * 100$$

$$\%Full\ Scale\ Error\ = \frac{|calculated\ -\ measured|}{Full\ Scale} * 100$$

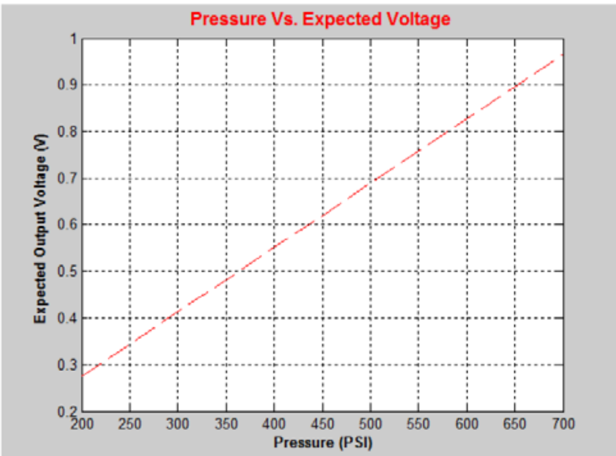
Following Table 5 lists out the Linear regression analysis results using in-built MATLAB function polyfit().

Table5. Linear Regression Analysis Results

Liquid Pressure	PolyFit (Measured Pressure PSI)	PolyFit (Relative Error %)	PolyFit (Full Scale Error %)
200	203.6852624	1.842631183	0.16943735
250	253.9935775	1.597430992	0.183612758
300	297.1149904	0.961669855	0.132644118
350	347.4233055	0.736198415	0.11846871
400	397.7316207	0.567094835	0.104293303

450	448.0399358	0.435569828	0.090117895
500	498.3482509	0.330349822	0.075942488
550	548.656566	0.244260727	0.06176708
600	598.9648811	0.172519814	0.047591673
650	656.4600984	0.99386129	0.297016018
700	699.5815113	0.059784094	0.019240858

The following two figures confirm that linear regression fit parameter estimators are very close to expected results according to the sensor's data sheet specs (i.e., hand calculated sensor calibration equation).



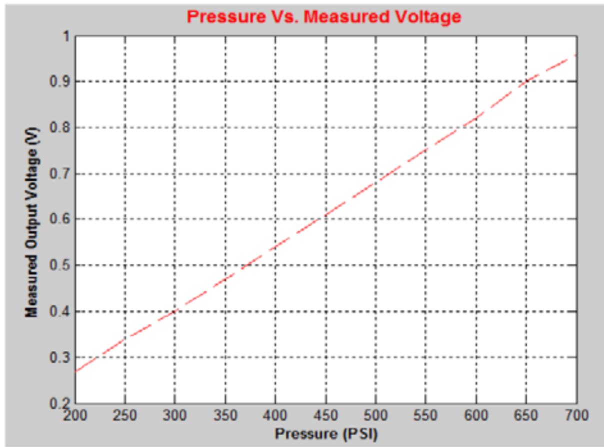


Figure 5. Expected Dc voltage values using Regression Fit and actual measured values

9. Conclusions and Future Work

The main objective of this work was to integrate statistical methods in undergraduate Engineering Technology courses. Students take lower level introduction to statistics course from mathematics department but seldom use those skills on other ET courses. To fill up that gap and reinforce the use of the statistical skills, an upper level course called Industrial Instrumentation was chosen which has integrated lab component. Statistical methods are used in every engineering filed, so reviewing and integrating these methods in other courses ensure that students will be ready to handle real world problems after they graduate and work in industry.

The following **tasks** were completed in this work:

1. Basic and Linear Regression analysis methods were integrated in a hydraulic laboratory experiment.
2. A pressure sensor calibration equation was developed using linear line fit equation using sensor data sheet.
3. Students were reviewed mean, median, stand deviation, relative and full scale error statistical parameters and were asked to apply those on measured data from pressure sensor.
4. Simple linear regression analysis was reviewed and again asked to apply on the measured data using MATLAB software.

This pilot exploratory laboratory project was tested for 3 years and student's feedback was very good and success rate was 100%. The success rate was measured based on the points given for successfully measuring each statistical parameter in the experiment. Each year in the fall semester, when the course was offered all the students got at least 90 points for this experiment and 90% was considered as very successful. This pilot experiment project had very positive effect on students learning in Engineering Technology programs. The skills they learned in this course was revisited in other upper level classes and in other Engineering courses and students were able to apply these methods in all those courses. The future work will be to add statistical methods in more courses and also introduce advanced concepts such as multiple linear regression, nonlinear analysis and time series analysis.

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