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UNCERTAINTY ANALYSIS OF VOLTAGE MEASUREMENT USING ATMEGA328P MICROCONTROLLER: AN ANOVA TEST APPROACH

James Julian[1,] Ade Fikri Fauzi[2], Annastya Bagas Dewantara[2], Faiz Daffa Ulhaq[2], and Fitri Wahyuni[1]

[1] Mechanical Engineering, Universitas Pembangunan Nasional Veteran Jakarta
[2] Electrical Engineering, Universitas Pembangunan Nasional Veteran Jakarta

e-mail: zames@upnvj.ac.id

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Abstract: The voltage sensors are widely used in various applications. In certain applications, such as medical devices, autonomous vehicles, or the military, the sensor's accuracy and level of precision play an important role, making it necessary to evaluate the sensor's performance. In this research, testing of direct current (DC) voltage sensors was carried out using analysis of variance (ANOVA) and Tukey honestly significant difference (HSD) to test sensor performance in various voltage ranges. This research used an experimental-based quantitative approach, using the ATmega328P. Data collection begins by calibrating the analog-to-digital converter (ADC) readings against voltage values with linear regression, the Chauvenet criterion to eliminate outlier data caused by noise from the environment, One-way ANOVA is used to determine differences in variations between voltage distances, and a Q-Q plot is used to determine the normality of the sensor error distribution. This research obtained from Tukey-HSD that 9 comparisons accepting the null hypothesis (H_0). And 27 pairs accepting the alternate hypothesis (H_1). The data was found to be normally distributed through the calculation of residual ANOVA, and visualization of data with the Q-Q plot, and the use of the sensor was effective in the range of 3V to 24.5V.

1. INTRODUCTION

The development of electronic devices in the world industry continues to enter a new phase to achieve perfection. Electronic devices are applied in the industry mainly in measuring and automation. Changes in the measurement process are seen when previously measurements used an analog system, now most of the tools are working digitally (Davis & Clowers, 2023). In recent years, with the development of the industrial era 5.0, sensors have been integrated with Machine Learning and even Artificial Intelligence. Sensor measurement data is taken and then processed with an embedded program for analysis or making a decision. The application of sensors in the industry requires a high level of accuracy, and the need increases as sensors are combined with Machine Learning. The higher the measurement accuracy, the higher the price of the sensor (Abubakar et al., 2017). That makes electronic device developers continue to compete in designing a sound measurement system with high accuracy and precision.

Many studies have discussed the workings and accuracy of various types of sensors. In summary, sensor performance is determined by comparing analog signal readings more stable the analog value readings, the better the sensor's measurement results (Pahuja, 2022). Using the sensor must go through calibration first to set the measurement parameters. Use accompanied by calibration is carried out using Polynomial Regression with the Arduino Mega based ZMPT101B sensor (Abubakar et al., 2017). The results indicate that sensor measurements after calibration have increased accuracy, with error values calculated at 0.9% to 2.4%. The study shows the importance of the calibration process as the resulting measurement error changes with higher accuracy.

The accuracy of measuring voltage is essential because electronic devices support most human activities. Identification of the voltage is required to provide a response ranging from extra-high voltage devices to different low voltage devices. Roman, in his research (Hrbac et al., 2020), built measurement devices to measure high-voltage electricity, where its use can be implemented in transformers, high-voltage equipment, and electricity distribution networks. Contrary to this, Agustina (Lascano et al., 2017), in the scope of neurology, uses evoked potential devices utilizing extra-low voltage measurements to diagnose patients.

The role of voltage measurement is essential, so further discussion must be carried out regarding the calibration process and analysis of measurement results from measuring devices or sensors. Follow-up research was carried out using statistics to determine the measurement accuracy level from variations in data on sensors by applying the Analysis of Variance (ANOVA) test (Chen et al., 2022). The purpose of using the ANOVA test is to test differences in sensor measurement variations, with normally distributed data or not. The data obtained represents that the results have significant differences, so further tests, such as Tukey or Scheffe, must be carried out. This paper focuses on developing a calibration to reduce measurement errors. The ANOVA test was introduced to the data obtained to evaluate the normality results of the data plots. DC 0-25 volts used is low-cost if compared to others. The authors are interested in researching the accuracy and precision of sensor readings.

2. LITERATURE REVIEW

2.1. Linear Regression

The calibration process in the regression analysis involves using an optimization model to match the linearity between the observed data of the independent variable, which is the value read by the sensor, and the dependent variable, which is the voltage from the measuring instrument (Maria et al., 2022). A linear line is drawn based on the measurement results of the digital multimeter and then intersects with the reading of the analog value on the sensor. Raw sensor measurements that fall outside the process distribution are more difficult to identify, as unobserved results during model training result in higher deviations (Tancev & Toro, 2022).

$$\hat{y} = \hat{a} + \hat{b}x \tag{1}$$

$$\hat{a} = \frac{\begin{vmatrix} \sum y & \sum x \\ \sum xy & \sum x^2 \end{vmatrix}}{\begin{vmatrix} n & \sum x \\ \sum x & \sum x^2 \end{vmatrix}} \tag{2}$$

$$\hat{b} = \frac{\begin{vmatrix} n & \sum y \\ \sum x & \sum xy \end{vmatrix}}{\begin{vmatrix} n & \sum x \\ \sum x & \sum x^2 \end{vmatrix}} \tag{3}$$

with y = dependent variable; $\hat{a}$ = intercept of the line; $\hat{b}$ = slope of the line; x = values of the independent data set; n = total number of values

$$\hat{y} = \left[\frac{\begin{vmatrix}\sum y & \sum x\\ \sum xy & \sum x^2\end{vmatrix}}{\begin{vmatrix}n & \sum x\\ \sum x & \sum x^2\end{vmatrix}}\right] + \left[\frac{\begin{vmatrix}n & \sum y\\ \sum x & \sum xy\end{vmatrix}}{\begin{vmatrix}n & \sum x\\ \sum x & \sum x^2\end{vmatrix}}\right] x \quad (4)$$

After formulation, a constant variable is obtained from the equation for the increase in the linear line. Then the equation is embedded into the Arduino ATmega328p program as the basis for processing the voltage sensor. The low error rate of measurement is obtained after the calibration process. However, it is necessary to conduct further analysis of the data to determine whether the measurements form normal variations or have significant differences in the data distribution. Before the ANOVA test is applied in analyzing data from sensor readings, the decision to remove outliers is made to reduce noise in the data. The difference between the actual and measured values in percentage form is a relative measurement error. It is used to evaluate the accuracy of a measurement or calculation. When the measurement deviation is too far, the data cannot be classified into relative error. Chauvenet's criterion is introduced to identify data that has a probability.

2.2. Outlier Data Classification

Data that can be categorized as abnormal is data with too large a deviation from other data. Chauvenet is used to control this error (Christensen, 2015), where data deviate too far from others. That can be due to noise from rapid, repeated measurement processes. Noise data falls under the category of random errors. Outlier noise data is categorized as invalid, as the values produced do not fall within the measurement distribution (Wang et al., 2018).

$$D_{max} \geq z_{score} \quad (5)$$

$$Q(P_z) \geq \frac{|x_{sus} - \bar{x}_{mean}|}{S_x} \quad (6)$$

with D_{max} = maximum allowable deviation; z_{score} = Z-score calculation; Q = quantile distribution; P_z = probability represented by one tail of the distribution; x_{sus} = value of suspected outlier; $\bar{x}_{mean}$ = sample mean; S_x = sample standard deviation.

Data is classified as an outlier when $D_{max} \geq z_{score}$ is rejected or inappropriate. Where it turns out that $z_{score} > D_{max}$ so that the data is classified as an outlier. If the conditions fulfill the equation $D_{max} \geq z_{score}$ accepted, the data still enters the distribution. Searching for outliers one by one will undoubtedly take quite a long time. D_{max} dan z_{score} calculations use programming to remove applied stress data outliers so that distribution results are obtained that are ready to be used in the ANOVA test.

2.3. Standard Deviation and Uncertainty Level

Adjustment of the distribution by removing data that is not needed is followed by looking for the standard deviation. All standard deviations of the nine measurement variations are calculated. After getting the standard deviation and mean, the analysis continues to find the sensor's uncertainty level. This level of uncertainty can be used as an indicator of measurement reliability (Aroulanandam et al., 2022). The 95% confidence level is determined by referring to several studies. The 95% confidence model with a statistical significance of 5% is often used for data representation (Van Der Veen, 2018).

$$\sigma^2 = \frac{\sum(x_i - \mu)^2}{n} \quad (7)$$

$$\sigma_{\bar{x}} = \frac{\sigma}{\sqrt{n}} \tag{8}$$

with σ = standard deviation; x_i = the i-th observed value; μ = mean value; $\sigma_{\bar{x}}$ = standard error.

2.4. Data Classification with ANOVA Test

The use of ANOVA assumes that the data is normally distributed and the groups being compared have the same variance. If this assumption is not met, the ANOVA results may be biased (Christensen, 2015). The type of equation used in the calculations is one-way ANOVA, with stress data used to compare variances between groups. Then, from the data, it can be seen that the distribution between groups, whether there is a significant difference or not. The data represented on the ANOVA distribution chart has an upper and lower bound, with continuous lines to represent the abundance of the distribution in the boxed region and little data in the striped portion. The equation used to calculate the ANOVA F-ratio is shown in equation (11).

$$SSG = \sum_{i=1}^{k} n_i(\overline{x_\iota} - x)^2 \tag{9}$$

$$SSE = \sum_{i=1}^{k} (n_i - 1){s_n}^2 \tag{10}$$

$$F = \frac{SSG/(k-1)}{SSE/(N-k)} \tag{11}$$

with SSG = sum of squares between groups; $\overline{x_\iota}$ = mean of group $i;k$ = number of groups; SSE = sum of square within groups; s_n= variance of each group; F = ratio.

2.5. Tukey's Honestly Significant Difference (HSD)

Tukey's method is then used as a companion to the ANOVA distribution plot. Tukey's HSD is applied to mathematically identify the plot against the results of the ANOVA distribution. This method is used to determine the hypothesis for nine variations of the data, classifying them as accepted or rejected. The equation for Tukey's HSD is shown in equation (12).

$$HSD = q\sqrt{\frac{SSE/(N-k)}{n_k}} \tag{12}$$

with MS_W = mean square for within group from the ANOVA; q = standardize range statistic; n_k = effective replicate n.

With H_0 is the average value of the data distribution is not significantly different, H_1 is the average value of the data distribution is significantly different. H_0 and H_1 describe conditions that can be seen from the data representation. To ensure the validity of the data, comparisons were made between the data each set. The results were considered valid when the p-value was greater than 0.05.

3. MATERIAL AND METHOD

Research equipment was prepared and designed as a measurement setup to support data collection with Arduino devices as shown in Figure 1. Voltage readings are taken using an adjustable power supply as the measurement source, with the supply terminals connected in parallel to the measuring instrument and the device under test. Sensor measurements are also displayed on the OLED display in real time, providing a clear and live view. Then software VS-Code used for digital data collection and statistical analysis.

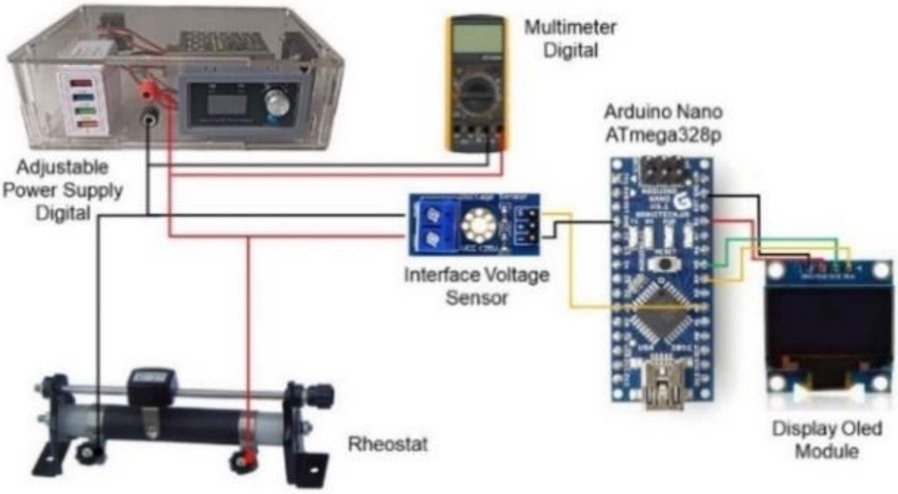


Figure 1. Setup Apparatus Voltage Measurement

The research method was carried out in several steps, as shown in Figure 2. The measurement value is taken with a multimeter as a readable instrument, with an assumed error of ±1-3%. The processing base uses an Arduino Nano ATmega328p 10-bit microcontroller. As stated in Moradi's paper (Moradi et al., 2019), it is confirmed that the sensor's value can shift during the measurement process as it reads the analog input value. A converging measurement value follows each increase in the analog signal value due to the influence of the formula, assuming the linearity between ADC reading and voltage measurement of the sensor. The use of a customized formula can increase the sensor's reliability. A one-way ANOVA was conducted to investigate the differences in variations among the different voltage values, with the assumption that the distribution of voltage values is normally distributed. If the ANOVA test rejected the null hypothesis, post-hoc analysis using Tukey-HSD was performed. The final analysis included computation of descriptive statistics such as the mean, standard deviation, standard error, and uncertainty.

3.1. Microcontroller

The microcontroller device processes the interfacing voltage sensor data and works with a voltage divider circuit. The circuit consists of two resistors: Resistor number one (R1) is 30K Ω, and resistor number two (R2) is 7.5K Ω. The interfacing voltage module can measure a voltage range of 0-25 volts. It is known that the measurement of the voltage value is carried out by connecting the measuring instrument in parallel with the voltage source. The voltage is divided into smaller quantities, then converted into analog signals (Junaldy et al., 2019). Then, the rheostat can be neglected because the voltage can still be measured without a load.

The processing speed of the Arduino ATmega328p is 16 MHz, equipped with a 10-bit ADC that can convert analog to digital with 10-bit resolution (Debnath et al., 2022). Measurements can be made using a 10-bit ATmega328p by converting the analog signal to be measured into a digital signal. The analog signal comes from various sources. After the analog signal is converted into a digital signal, it can be processed by the ATmega328p microcontroller using its program (Zhang et al., 2018). The ATmega328p divides the input voltage into 10-bit or 1023 decimal resolution, with 5 volts representing 1023 and 0 volts representing 0 decimal at V-reference 5V. The data collection technique was carried out by collecting nine sample variations ranging from 0-25 volts, with 1000 data points from each variation used to calculate the standard deviation and divide the level of uncertainty.

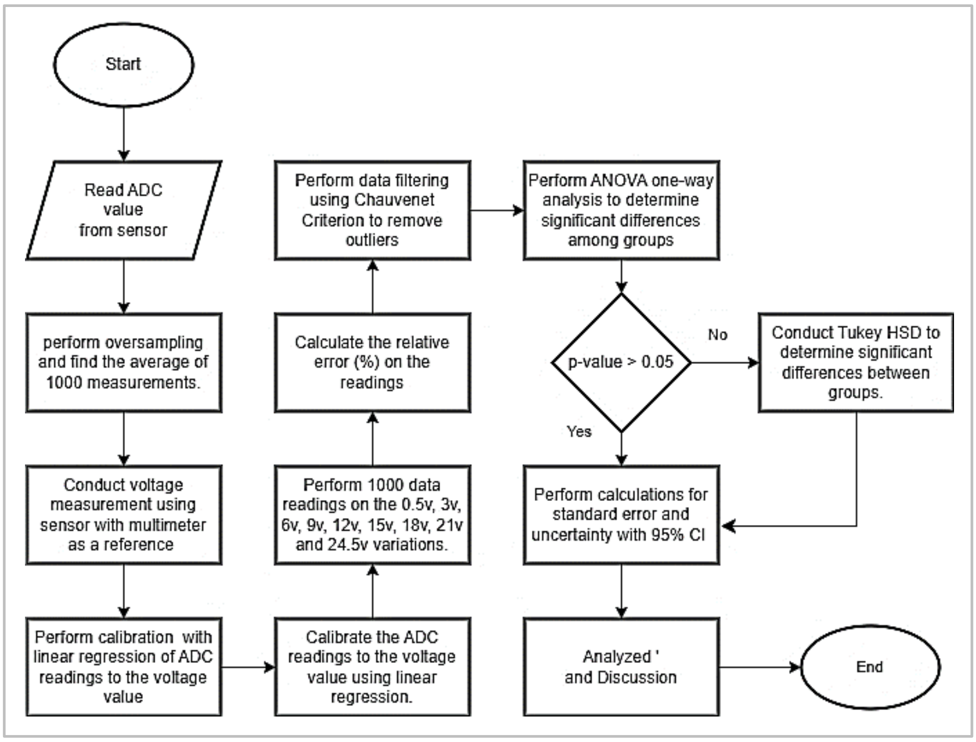


Figure 2. Research Process Flowchart

The research process on sensor measurement results is divided into two. The first stage is the pre-process, which includes sensor calibration with linear regression to find a digital value multiplier formula, then converted into a voltage quantity. The second stage is the analysis process, managing data that has been measured or retrieved by sensors to be processed into diagrams representing the data. The final result, as a process of analysis and discussion, describes the data management process and determines whether the quality of the sensor is feasible or not from the data produced.

4. RESULTS AND DISCUSSION

Research on improving the accuracy and readings from voltage sensors has been widely carried out. However, in-depth discussions regarding error and normality analysis of these sensors have not yet been carried out. This research aims to evaluate performance based on error and normality analysis of low-cost voltage sensors. Linear regression is applied using equation (4) to determine the coefficient and constant. In the ATmega328p microcontroller's ADC, linear regression is used to find the best straight-line fit to the data points obtained by measuring the sensor's output voltage and comparing it to the ADC reading. The result obtained after calculation using linear regression shows more accurate measurements using oversampling and linear regression techniques, with lower error results, namely 0.32% higher than measurements without linear regression calibration and oversampling techniques. Accurate data collection from sensors is essential in order to obtain accurate results. It can be done by appropriately setting the measurement frequency, sample size, and the type of sensor. In this case, data sampling is performed by varying the voltage on the sensor with each data collection of 1000 samples. The voltage variations given are

3v, 6v, 9v, 12v, 15v, 18v, 21v, and 24.5v, with the following description of the data shown in Table 1.

Table 1. Data Summary

	0.5v	3v	6v	9v	12v	15v	18v	21v	24.5v
Sample size	1000	1000	1000	1000	1000	1000	1000	1000	1000
Mean	0.500	3.020	6.000	9.000	12.000	14.990	18.090	21.020	24.520
Std	0.023	0.016	0.017	0.016	0.018	0.0180	0.0180	0.020	0.0180
Minimum data	0.380	2.940	5.920	8.940	11.920	14.870	17.940	20.960	24.450
Q1	0.500	3.020	5.990	8.990	11.990	14.990	18.010	21.010	24.500
Q2	0.500	3.020	6.010	9.010	11.990	14.990	18.010	21.010	24.520
Q3	0.530	3.040	6.010	9.010	12.010	15.010	18.040	21.040	24.520
Maximum data	0.600	3.060	6.060	9.060	12.060	15.060	18.090	21.090	24.570

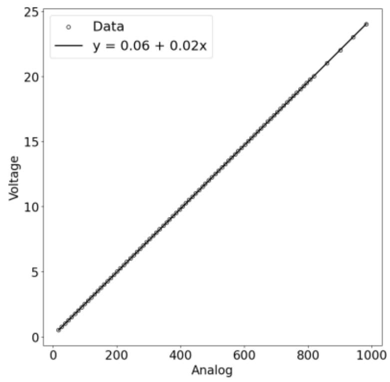
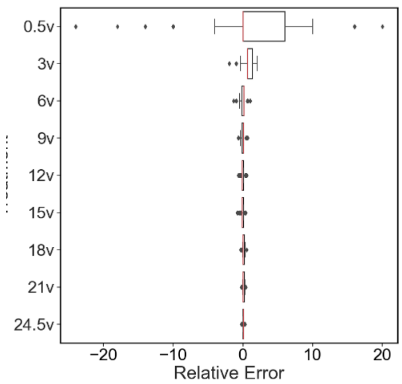
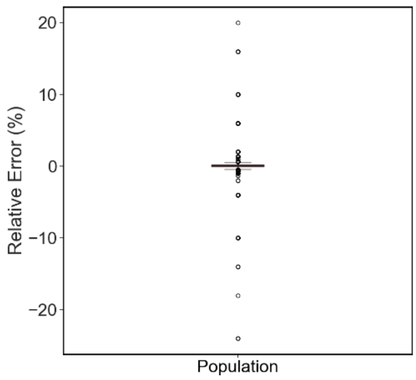


Figure 3. Linear Regression between ATmega328p Analog Readings to Voltage Reading



(a)



(b)

Figure 4. (a) Relative Error (%) Distribution for Each Sample, (b) Relative Error (%) Distribution for Population

In the boxplot graph in Figure 4(a), it is known that the voltage variation of 0.5v has the largest spread compared to other data, affecting the overall population distribution result as shown in Figure 4(b). The variation and deviation of this 0.5v voltage are caused by the floating pin effect of the ATmega328p, which reads electromagnetic signal noise inference inducing voltage and causing readings on the microcontroller. Each data is analysed for distribution and variation to determine the sensor's characteristics. A histogram of the data volume is also displayed to represent the volume of the distribution fraction. They are using equation (8) to find the standard deviation. The distribution of the data that has been standardized using the Gauss distribution and histogram is visualized in Figure 5.

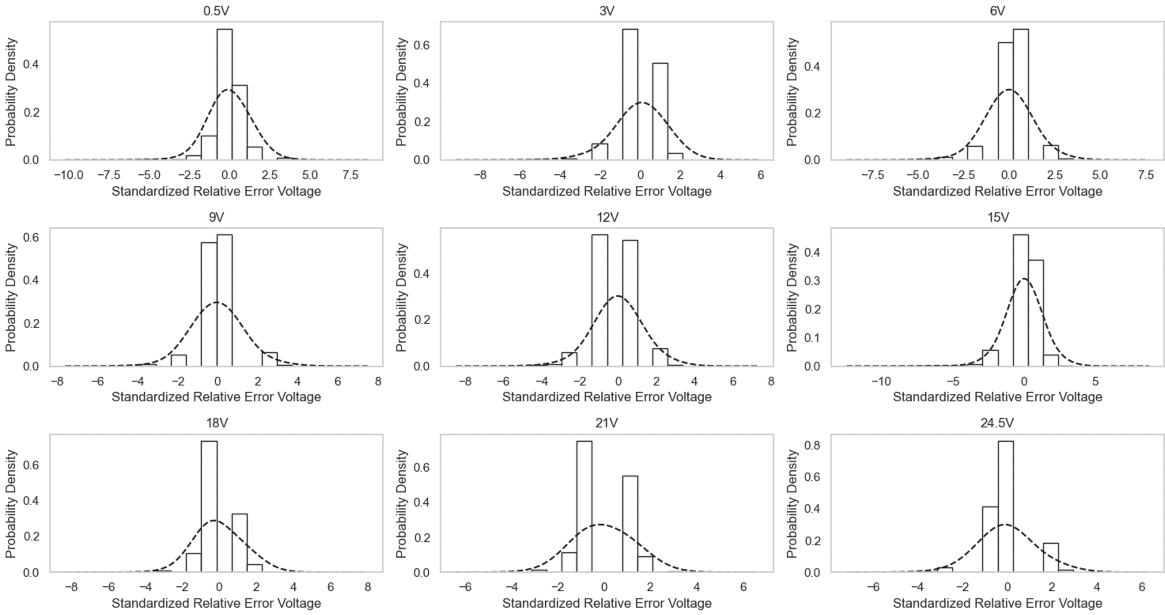


Figure 5. Standardized Relative Error (%) of each Sample

The Chauvenet Criterion is used to eliminate data probability of less than 0.5%, which is considered an outlier and must be removed. Calculate this probability. The mean and standard deviation of the data must first be determined. Then, the probability of each data is calculated using the normal distribution formula. Data with a probability less than 0.5% is considered an outlier and must be removed from the data, refer to equation (5), with the result shown in Table 2.

Table 2. Chauvenet Criterion Result

	Iteration - 1	Iteration - 2	Iteration - 3	Iteration - 4
Mean	0.32	0.09	0.13	0.08
Std. Dev.	1.67	0.56	0.34	0.21
Outlier	386	127	403	18

A one-way ANOVA, using equation (12), can be performed to determine if there is a significant difference between groups in the relative error of the treatment data for the dependent variable. If significant differences are found, it can be concluded that the independent variable influences the dependent variable. Conversely, if no significant differences are found, it can be concluded that the independent variable does not affect the dependent variable. In a one-way ANOVA, the grand mean represents the overall mean of all the data points in all the groups being compared. It is calculated by taking the average of all the data points in all the groups. The mean of each group, on the other hand, represents the average of all the data points in that specific group. The difference between the mean of each group and the grand mean can indicate how the groups differ from the overall population. If the means of the groups are similar to the grand mean, it suggests that the groups are similar to the overall population, whereas if the means of the groups are significantly different from the grand mean, it suggests that the groups are different from the overall population, the mean of each group is shown by boxplot graph with grand mean is shown by red line in Figure 6.

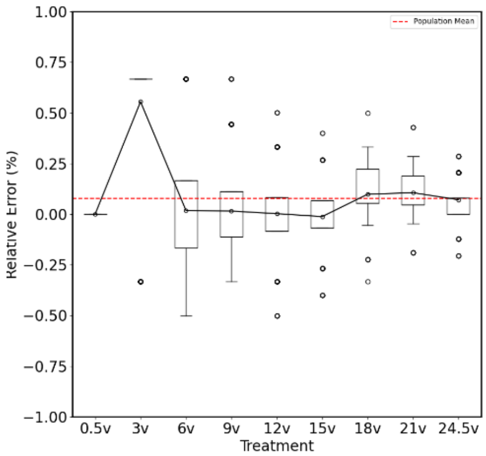


Figure 6. Relative Error (%) from Each Sample

The value of α = 0.05 is used in determining the p-value threshold of ANOVA. The calculation results shown in Table 3 show that the ANOVA test rejects H_0 and accepts H_1. That explains the difference between the treatment data groups on the dependent variable.

Table 3. ANOVA One-Way Result

	Sum of Squares	Degree of Freedom	F	PR(>F)
Treatment	977.53	8	152.04	0
Residual	6548.50	8148		

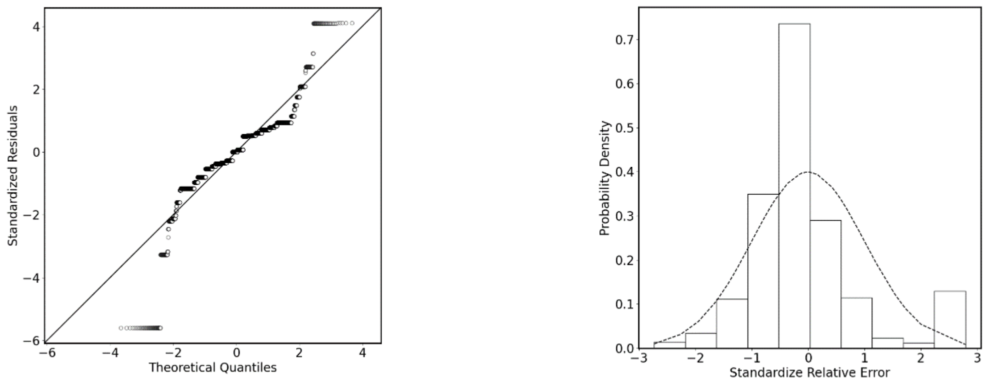
The Tukey HSD method compares each treatment by making 36 pairwise data comparisons using equation (13). Of these, nine paired comparisons reject H_1 and accept H_0, and 27 paired comparisons accept H_1 and reject H_0. Thus, the determination of using H_1 is more dominant as shown in Table 4.

Table 4. Tukey's HSD Result

Voltage (V)		Diff	Lower	Upper	q-value	p-value	H_0
0.5	3	0.55	0.52	0.58	81.74	0.00	Rejected
0.5	6	0.02	-0.01	0.04	3.00	0.46	Accepted
0.5	9	0.01	-0.01	0.04	2.48	0.68	Accepted
0.5	12	0.00	-0.02	0.03	0.38	0.90	Accepted
0.5	15	0.01	-0.01	0.04	1.98	0.90	Accepted
0.5	18	0.01	0.07	0.12	16.16	0.00	Rejected
0.5	21	0.11	0.08	0.13	17.43	0.00	Rejected
0.5	24.5	0.07	0.04	0.01	11.69	0.00	Rejected
3	6	0.54	0.51	0.56	91.33	0.00	Rejected
3	9	0.54	0.51	0.56	92.03	0.00	Rejected
3	12	0.55	0.53	0.58	94.30	0.00	Rejected
3	15	0.57	0.54	0.59	96.74	0.00	Rejected
3	18	0.46	0.43	0.48	77.96	0.00	Rejected
3	21	0.45	0.42	0.47	76.65	0.00	Rejected
3	24.5	0.48	0.46	0.51	82.61	0.00	Rejected
6	9	0.00	-0.02	0.02	0.63	0.90	Accepted
6	12	0.01	-0.01	0.04	3.16	0.38	Accepted
6	15	0.03	0.01	0.05	6.02	0.00	Rejected
6	18	0.08	0.06	0.10	15.86	0.00	Rejected
6	21	0.09	0.06	0.11	17.38	0.00	Rejected
6	24.5	0.05	0.03	0.07	10.47	0.00	Rejected
9	12	0.01	-0.01	0.03	2.54	0.66	Accepted

9	15	0.03	0.00	0.05	5.40	0.00	Rejected
9	18	0.08	0.06	0.10	16.53	0.00	Rejected
9	21	0.09	0.07	0.11	18.06	0.00	Rejected
9	24.5	0.06	0.03	0.08	11.13	0.00	Rejected
12	15	0.01	-0.01	0.04	2.86	0.52	Accepted
12	18	0.10	0.07	0.12	19.10	0.00	Rejected
12	21	0.10	0.08	0.13	20.62	0.00	Rejected
12	24.5	0.07	0.05	0.09	13.69	0.00	Rejected
15	18	0.11	0.09	0.13	21.95	0.00	Rejected
15	21	0.12	0.10	0.14	23.48	0.00	Rejected
15	24.5	0.08	0.06	0.10	16.55	0.00	Rejected
18	21	0.01	-0.01	0.03	1.53	0.9	Accepted
18	24.5	0.03	0.00	0.05	5.41	0.00	Rejected
21	24.5	0.03	0.01	0.06	6.94	0.00	Rejected

Through filtering using Chauvenet, four iterations were obtained with a total of 843 data discarded. Analysis using Q-Q plot is performed to determine whether the data distribution is normally distributed or not by comparing the data distribution to the diagonal line. Through Q-Q plot and probability density chart, the normal distribution of residual ANOVA data is obtained as shown in Figure 7(a) and 7(b).



(a) (b)

Figure 7. (a) Q-Q plot from residual ANOVA;
(b) Probability density of residual ANOVA

The Q-Q plot is used to assess the normality of the deviation level of the data set by plotting the data being tested against the quantiles of the normal distribution. The data are represented as points, and the points will remain on the line formed by z_{score}. The outlier spread on the Q-Q plot is caused by the 0.5v variation that affects the Grand Mean value of the ANOVA residual and the standard deviation of the Chauvenet filtering process. This variation causes non-uniform outlier removal, resulting in outliers on the Q-Q plot. To estimate the likelihood of the sample distribution relative to the population distribution, and to describe the extent of uncertainty in measurement or statistical test data shown in Table 5.

Table 5. Final Result

	0.5V	3V	6V	9V	12V	15V	18V	21V	24.5v
Mean	0.50	3.01	6.00	9.00	12.00	15.00	18.01	21.02	24.52
Standard Deviation	0.00	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02
Standard Error	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Voltage	0.50 ±0.00	3.01 ±0.01	6.00 ±0.01	9.00 ±0.01	12.00 ±0.01	15.00 ±0.01	18.01 ±0.02	21.02 ±0.02	24.52 ±0.01

Based on the final results of the nine variations, the range of error variations at a value of 0.5 volts is 0. That is due to the excessive data loss caused by the filtering, resulting in the final results only considering data classification at the precise value of 0.50 volts.

5. CONCLUSION

The R2 value obtained from the linear regression analysis shows that the measurement results have a high enough correlation with a value greater than 0.99. This shows that the linear regression model can explain data variations well. The filtering process using the Chauvenet Criterion shows 9.3% or 843 data outliers caused by noise. The largest data variation occurred at a voltage of 0.5v, which was assumed by the floating pin effect of the ATmega328p, which can read electromagnetic signal noise on the microcontroller. Variation analysis was performed using the One-way ANOVA method and Tukey HSD, and the results showed that the data rejected H_0 and accepted H_1 with a total of 36 pairs of Tukey HSD data comparisons. Of these, 9 data pairs of comparisons rejected H_1 and accepted H_0, and the 27 data otherwise. Based on that, it can be concluded that measurements using a voltage sensor with an ATmega328p can be used from 3v to 24.5v. This research aims to provide contributions and knowledge regarding sensor quality evaluation methods through statistical and experimental approaches, which can be used as a reference and basis for further research. In the future, evaluate the performance of the voltage sensor. This research can be developed by taking pulse voltage data or alternating current data.

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