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A SIMPLE STRATEGY OF LINEAR REGRESSION ON 8-BIT MICROCONTROLLER ADC TO IMPROVE SENSOR VALUE READING ACCURACY

STRATEGI SEDERHANA REGRESI LINIER PADA ADC MIKROKONTROLLER 8-BIT UNTUK MENINGKATKAN AKURASI PEMBACAAN NILAI SENSOR

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Abstract

This study proposes a linear regression-based intelligent calibration approach to improve the accuracy of water turbidity sensor readings in an Arduino microcontroller-based embedded system. The primary objective of this research is to develop a mathematical model capable of converting analog values from the Analog-to-Digital Converter (ADC) into a numerical representation that reflects the actual water turbidity level in Nephelometric Turbidity Units (NTU). The calibration process was performed using a standard Hanna Turbidity Meter with water samples ranging from 0.56 NTU to 500 NTU. Measurement results demonstrated a strong linear relationship between the ADC value (495–686) and NTU, with an average system accuracy level above 90%. Comparison of sensor measurements with the standard instrument showed an error margin below 5%, confirming the reliability of the linear regression model in compensating for optical sensor nonlinearities.

Keywords : Linear Regression, ADC, Embedded System, Microcontroller, Turbidity Sensor.

Abstrak

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Penelitian ini mengusulkan pendekatan kalibrasi cerdas berbasis regresi linier untuk meningkatkan akurasi pembacaan sensor kekeruhan air pada sistem tertanam (*embedded system*) berbasis mikrokontroler Arduino. Tujuan utama penelitian ini adalah mengembangkan model matematis yang mampu mengonversi nilai analog dari *Analog to Digital Converter* (ADC) menjadi representasi numerik yang merefleksikan kondisi nyata tingkat kekeruhan air dalam satuan Nephelometric Turbidity Unit (NTU). Proses kalibrasi dilakukan menggunakan alat standar Hanna Turbidity Meter dengan variasi sampel air mulai dari 0,56 NTU hingga 500 NTU. Hasil pengukuran menunjukkan hubungan linier yang kuat antara nilai ADC (495–686) dan NTU, dengan rata-rata tingkat akurasi sistem mencapai diatas 90%. Perbandingan antara hasil pengukuran sensor dan instrumen standar menunjukkan *error margin* di bawah 5%, yang menegaskan keandalan model regresi linier dalam kompensasi non-linearitas sensor optik.

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Kata Kunci : Regresi Linier, ADC, Embedded System, Mikrokontroller, Sensor Turbidity.

1. INTRODUCTION

The development of regression-based data processing technology has significantly contributed to improving the accuracy of measurement and prediction systems in various engineering fields, including embedded and sensory systems. Linear regression, a classic statistical approach, is capable of efficiently identifying relationships between independent and dependent variables, even in data containing noise or high variability (Su et al., 2024). In the context of real-time calibration systems such as Synthetic Aperture Radar (SAR), iterative linear regression is used to correct data discrepancies due to sensory drift or environmental influences. This method results in a reduction in Root Mean Square Error (RMSE) of up to 0.156 dB compared to conventional methods. Similar approaches are also beginning to be applied to electronic instrumentation systems, where linear model-based calibration has been shown to significantly improve measurement accuracy without the need for additional physical calibrators.

Beyond remote sensing, linear regression models are also a crucial element in the development of machine learning-based predictive systems. For example, Narayanan et al. (2024) demonstrated that linear regression achieved a prediction accuracy of 94.88% in detecting digital data patterns, with competitive performance compared to modern logistic regression algorithms. In another predictive application, Treeratanaporn et al. (2021) used linear regression to model the relationship between macroeconomic variables and national electricity revenue. The results showed that variables such as population, energy prices, and GDP had a dominant influence on the prediction results. Implementing this method in embedded systems can add value to smart metering devices by integrating statistical models directly into microcontrollers for real-time data analysis.

Recent research extends linear regression into tensor space to handle multidimensional data, particularly in hyperspectral image classification. Zhang et al. (2024) introduced the Dual Linear Regression in Tensor Space (TSDLR) method, which combines linear regression with tensor decomposition to preserve spatial and spectral information without the need for vectorization. This approach improves the model's robustness against overfitting and optimizes the classification of high-dimensional data. Similar principles can be adapted in embedded systems to simultaneously process multisensor signals, enhancing spatio-temporal correlations often overlooked by conventional linear regression algorithms. Thus, transforming linear regression into tensor space opens new opportunities in signal processing and high-precision sensor calibration.

In the field of marine technology and underwater positioning systems, elastic regression methods (ElasticNet) are applied to optimize the convergence speed and accuracy of electromagnetic data processing (Liu et al., 2022). The combination of electric and magnetic fields produces a stable and efficient three-dimensional mapping system. This study uses a regression model to estimate object positions based on the distribution of potential fields. This regression concept can be applied to embedded sensor systems for monitoring extreme environmental conditions such as the deep sea, underground mines, or heavy industrial spaces. This statistical approach demonstrates that linear regression and its derivatives are not only data analysis tools but also the foundation for autonomous sensing and navigation systems that require high accuracy.

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The application of regression methods is also widespread in the social and public security domains. Research by Nafi'iyah and Mauladi (2021) demonstrated that linear regression yielded the lowest Mean Absolute Error (MAE) of 34.26 compared to the Support Vector Regression algorithm (MAE 134.7) in predicting motor vehicle theft rates. Meanwhile, Zhang (2023) developed a linear regression model for high-accuracy food safety detection, demonstrating a strong correlation between the rapid detection method and the conventional method with no significant difference based on a t-test. This demonstrates that the linear regression model remains relevant in supporting smart technologies in industry, security, and healthcare. By integrating linear regression principles into embedded systems, this research seeks to develop a reliable, efficient, and adaptive automated calibration and measurement approach to environmental variations and dynamics in modern electronic systems.

2. RESEARCH METHOD

In designing this research, the researcher conducted two research steps: designing a system in the form of software and designing a system in the form of a project that can be applied and operated directly (hardware). The working system that the researcher used can be explained through a block diagram as shown in Figure 1. The input signal is in the form of a turbidity sensor that produces a 0-5 volt analog voltage at its output. This signal is used as input to the ADC of an 8-bit microcontroller, which in this study used an Arduino Mega 2560.

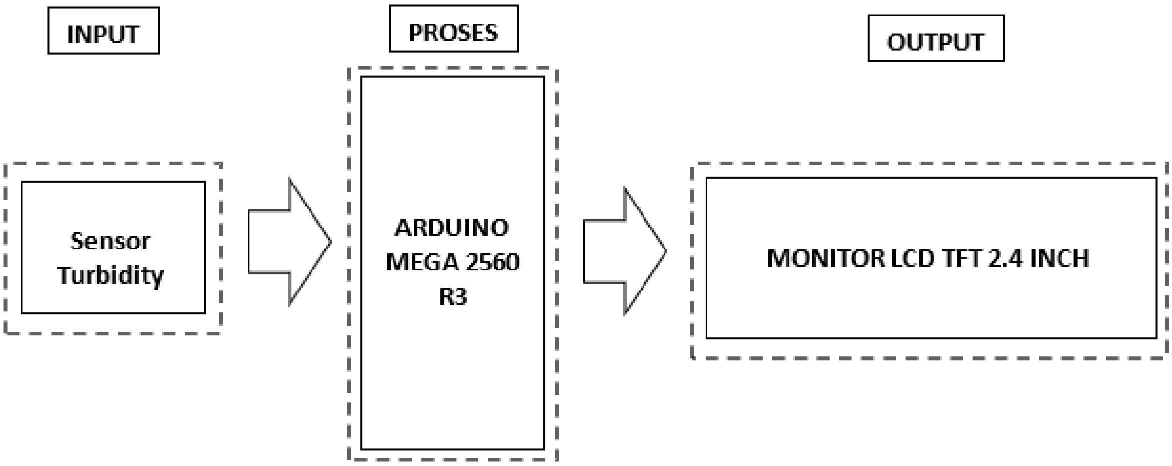

Figure 1. System Block Diagram.

In this hardware design stage, the researcher used the Arduino MEGA 2560 R3 microcontroller as the main controller. Analog Pin 8 is used as the input pin from the Turbidity sensor output as shown in Figure 2. The results of the Turbidity sensor reading carried out by the Arduino Mega 2560 microcontroller are displayed on the 2.4 Inch TFT Shield LCD layer in the form of ADC values, voltage values and NTU (Nephelometric Turbidity Unit). While the wiring of the 2.4 Inch TFT Shield LCD Pin on the Arduino Mega 2560 microcontroller is as shown in Figure 3 and Table 1.

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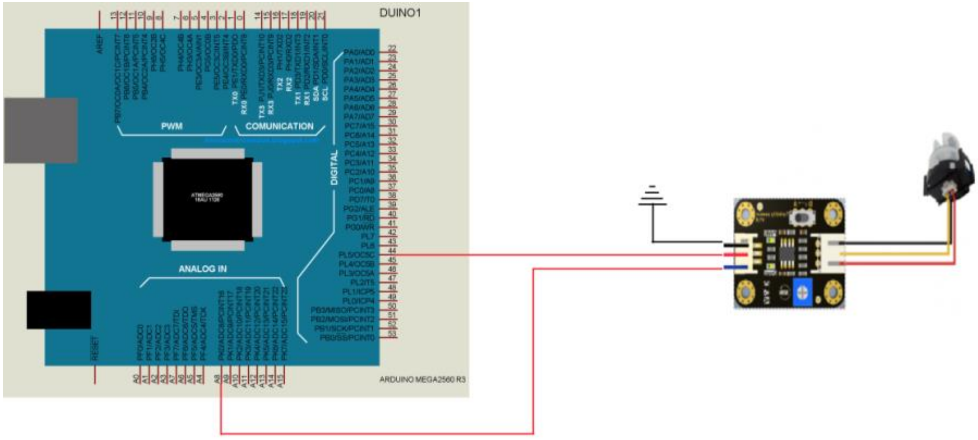

Figure 2. Turbidity Sensor Circuit.

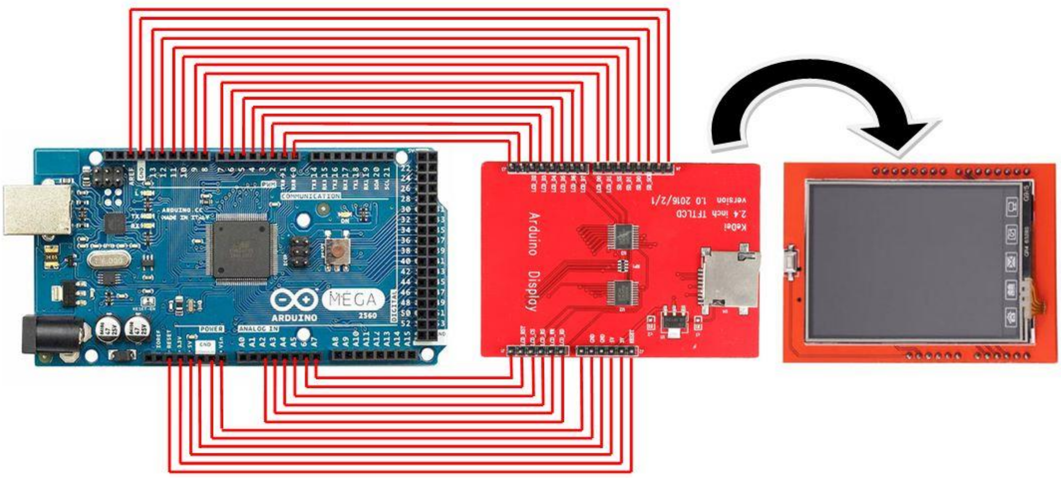

Figure 3. 2.4 inch TFT Shield LCD circuit on Arduino Mega2560

Table 1. 2.4 Inch TFT Shield LCD Pins.

No.	LCD TFT Pin	Arduino Mega 2560 Pin	No.	LCD TFT Pin	Arduino Mega 2560 Pin
1	2	LCD_D2	11	12	SD_D0
2	3	LCD_D3	12	13	SD_SCK
3	4	LCD_D4	13	3.3V	3.3V
4	5	LCD_D5	14	5V	5V
5	6	LCD_D6	15	GND	GND
6	7	LCD_D7	16	A2	LCD_RD
7	8	LCD_D0	17	A3	LCD-WR
8	9	LCD_D1	18	A4	LCD-RS
9	10	SD_SS	19	A5	LCD-CS
10	11	SD_D1	20	A6	LCD-RS

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This study uses the Nephelometer method to measure water turbidity on the Turbidity sensor, namely by emitting light from its source to the test liquid which is then scattered by particles in the test liquid. The scattered light is received by a photodiode sensor equipped with a convex lens to focus the received light. The received light is then converted into electrical quantities and processed by the Arduino through the ADC Pin. The ADC value of 0 is the lower benchmark for turbidity, namely 0 NTU, while the ADC value of 1023 is the upper benchmark value. After obtaining the values on several samples, they are then linearized to determine the formula in the program. This linearity is done to calibrate the sensor reading values to be more accurate when compared with sensor readings on measuring equipment in the laboratory. The following research formula is used:

ADC = analogRead .... (01)
V = ADC * (5.0/1023.0) .... (02)
NTU = (ADC – c) / mx → y = mx + c (linearity results) .... (03)

3. RESULTS AND DISCUSSION

The main thing that needs to be done to improve the reading results of the Turbidity Sensor ADC is to calibrate the water turbidity sensor so that it can read the water condition in real time and accurately. The calibration is done using a water turbidity measuring instrument. The Hanna turbidity meter is the measuring instrument used in this study. This tool is able to obtain standards in the NTU scale which will be used as a formula in this study. The first thing that needs to be prepared is a water sample with varying water turbidity, for example from 1 NTU, 50 NTU, 100 NTU to 500 NTU as shown in Figure 4. After calibrating using the Hanna turbidity meter, the ADC value measurement on the water sample is carried out 3 times. The ADC and NTU values are then used as calculation data in determining the linear regression value which will later be used in the Arduino program. The calculation of sample data for ADC and NTU values is done using Microsoft Excel to obtain linear values using formulas 1-3 above. In this study, the results of sample ADC and NTU values are shown in Table 2.

Figure 4. Turbidity Calibration with Hanna Instrument

Table 2. Calibration of Turbidity Sensor or Water Turbidity Sensor

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No.	Turbidity ADC	Sensor Voltage	Hanna Instrument NTU
1	686	3.32	0.56
2	646	3.12	105
3	446	2.42	601

The linearity above is performed to calibrate the sensor that will be used in the program code to determine the actual water turbidity value. Figure 5. Shows a calculation graph using Microsoft Excel. Manual calculations are used to compare the results of processing in Microsoft Excel as follows:

$$\mathrm{y} = mx + c$$

$$\mathrm{m} = \frac{\Delta \mathrm{y}}{\Delta x}$$

$$m = \frac{y3 - y2 - y1}{x3 - x2 - x1}$$

$$m = \frac{446 - 646 - 686}{601 - 105 - 0.56}$$

$$m = \frac{446 - 646}{601 - 105}$$

$$m = \frac{-200}{496}$$

$$m = -0.4032x$$

$$y = mx + c$$

$$c = y - (-mx)$$

$$c = 446 - (-0.4032 \text{ x } 601)$$

$$c = 446 + 242.32$$

$$c = 688.32$$

$$\boldsymbol{y = -0.4032x + 688.32}$$

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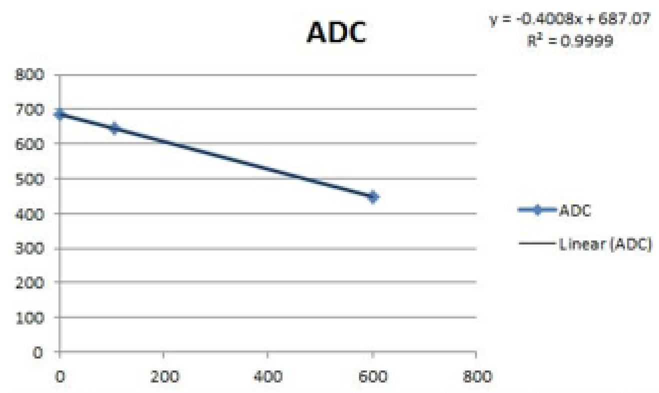

Figure 5. Graph of ADC calculation results with linearity.

After carrying out calibration and determining the formula to be entered into the program, it is necessary to carry out formula test results by measuring the condition and turbidity value of the water which will be compared with the lab results using the Hanna Instrument meter tool as shown in table 3.

Table 3. Water Turbidity Test Results

No.	Turbidity Sensor NTU	Turbidity Sensor ADC	Hanna Instrument NTU	Accuracy %
1	0.65	676	0.5	77
2	68	658	67	98.6
3	210	580	200	95.4
4	376	559	350	93.1
5	496	495	500	96

The ADC-based water turbidity sensor calibration process resulted in a significant increase in the accuracy of turbidity readings after applying the linear regression equation. Each measurement performed on a variety of water samples ranging from 0.5 to 500 NTU demonstrated consistent ADC data with the Hanna Instrument meter standard values. This indicates that the system has good internal compensation capabilities for variations in light intensity in the liquid medium. Differences between the sensor and standard measurements tended to be minimal. This indicates that the calibration algorithm implemented on the Arduino microcontroller effectively converts analog signals into digital values that accurately represent actual turbidity.

Meanwhile, inter-sample testing results showed accuracy variations ranging from 77% to 98.6%, with an average above 90%. This variation reflects the sensor's sensitivity to the physical conditions of the test medium, such as changes in temperature, suspended particles, and external light intensity. Despite this, the overall system performance remained highly stable, demonstrating the success of the linear calibration approach in producing a conversion model that can be generalized across a wide range of water conditions.

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4. CONCLUSION

Based on the research results, it can be concluded that the microcontroller-based water turbidity measurement system with a turbidity sensor that has been calibrated using the linear regression method shows excellent performance in accurately detecting water turbidity levels. The calibration process against the Hanna Instrument meter standard successfully produced a stable linear relationship between ADC and NTU values. The measurement accuracy level reached more than 90%. These results indicate that the applied conversion algorithm is capable of transforming analog data into a more precise digital representation, despite small variations due to environmental factors.

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