

Voltage-Temperature Calibration of PT-100 RTD using the Callendar-Van Dusen Equation and Noise Reduction using Random Forest Regression

EE1030 : Matrix Theory

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1 OBJECTIVE

This experiment uses the Callendar-Van Dusen equation and the least squares method to model the relationship between temperature and voltage for a PT-100 RTD (Resistance Temperature Detector). The objective is to derive a polynomial calibration model that relates voltage output from the RTD to temperature, utilizing additional methods for improved fitting accuracy.

2 PROCEDURE

- 1) **Circuit Construction:** A circuit 1 was built on a breadboard to connect the PT-100 RTD sensor with the Arduino. The setup included necessary components such as resistors and a Wheatstone bridge for accurate voltage measurement.
- 2) **Temperature Measurement:** To validate the readings from the PT-100 RTD, an alcohol thermometer 3 was used to measure the ambient temperature. Since reading can be difficult with an alcohol temperature 3, a digital temperature 4 is a very good alternative for a reliable reference for comparison with the voltage output from the RTD sensor.
- 3) **Data Collection:** The output voltages from the PT-100 RTD sensor were recorded at known temperature points using the Arduino, while simultaneously measuring the temperature with the alcohol thermometer. The temperature data was logged for further analysis. **Data Note:** To achieve a closer and more accurate plot, analog readings from the PT-100 RTD sensor were used instead of voltage readings. This approach allowed for greater precision in calibration. The relationship between voltage and analog readings is defined by $V = k \times \text{Analog Readings}$, where k is a constant specific to the setup, which in the case of an arduino is $\frac{5}{1023}$.

3 TRAINING DATA

The training data collected by the PT-100 RTD sensor, as measured by an Arduino, are presented in Table I. This data will be used to fit the Callendar-Van Dusen model to describe the voltage-temperature relationship.

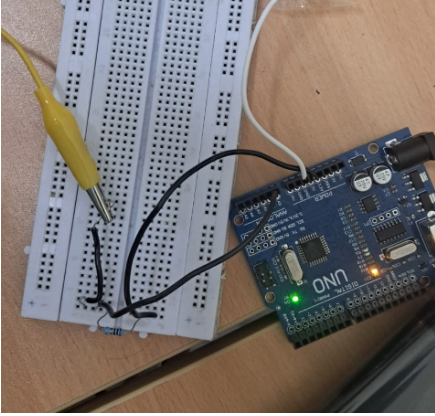


Fig. 1: Circuit for the PT-100 RTD setup.

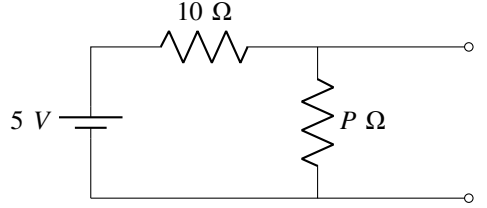


Fig. 2: Schematic Circuit Diagram to Measure the Output of PT-100.



Fig. 3: Temperature measuring setup using an alcohol thermometer.



Fig. 4: Temperature measuring setup using a digital thermometer.

4 RESULTS FROM LEAST SQUARES METHOD

The regression yielded the following model:

$$V(T) = V(0) \left(1 + AT + BT^2 \right) \quad (1)$$

with coefficients:

- $V(0) \approx 4.578899430486582$
- $A \approx 0.0002800324245079253$
- $B \approx -5.81408492749038e-07$

5 RANDOM FOREST REGRESSOR

To improve the fit of the polynomial model, a Random Forest Regressor was employed. This ensemble learning method constructs multiple decision trees during training and outputs the mean prediction of individual trees.

TABLE I: Training data for PT-100 calibration.

Temperature (°C)	Analog Input (A0)
73.0	953
46.8	948
40.8	947
54.5	949
59.4	950
56.5	950
50.4	949
36.0	946
61.8	951
91.2	956
96.1	957
89.4	956
33.8	945
86.3	955
28.4	944
83.9	955
67.2	952
64.5	951
44.9	947

TABLE II: Denoised training data for PT-100 calibration.

Denoised Temperature (°C)	Analog Input (A0)
70.72531286	953
45.85104667	948
42.50149357	947
52.20067667	949
57.41318143	950
57.41318143	950
52.20067667	949
36.08730167	946
62.59749571	951
89.68815429	956
93.74424429	957
89.68815429	956
33.07323	945
85.60526857	955
30.98883	944
85.60526857	955
65.92970619	952
62.59749571	951
42.50149357	947

- 1) **Training:** The training data was used to fit the Random Forest model, which captures complex relationships between the input features (temperature) and the target variable (voltage).
- 2) **Prediction:** The Random Forest model provides a flexible approach, accommodating non-linear relationships without requiring explicit polynomial terms. The predicted voltage values II from the Random Forest model were then compared against the measured voltages, demonstrating improved accuracy in fitting.

6 VALIDATION

To validate the models, additional temperature points were used. The measured voltage values were compared to those predicted by the models, as shown in Table III.

7 CONCLUSION

The derived models accurately capture the relationship between voltage and temperature for the PT-100 RTD, allowing the Arduino to estimate temperature from voltage measurements over the calibrated range. The Random Forest Regressor provided improved fits, demonstrating their utility alongside traditional least squares methods.

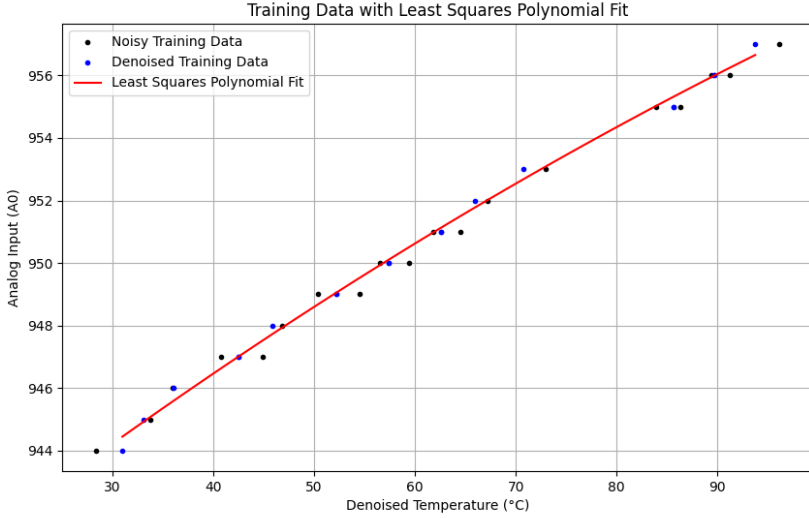


Fig. 5: Training data with least squares polynomial fit.

TABLE III: Measured validation data.

Temperature (°C)	Analog Input (A0)
69.1	952
80.7	954
48.6	948
63.6	951
38.4	946
50.6	949
95.5	957
58.1	950

TABLE IV: Denoised validation data.

Temperature (°C)	Analog Input (A0)
65.92970619	952
76.95450857	954
45.85104667	948
62.59749571	951
36.08730167	946
52.20067667	949
93.74424429	957
57.41318143	950

8 CODE

The calibration and regression processes were controlled using the C++ source file `codes/data.cpp`, which was uploaded to the Arduino using PlatformIO. The Random Forest regression was implemented using the `scikit-learn` library in Python, which provides an efficient way to fit ensemble learning models and improve prediction accuracy. The plotting and least square computation python file can be referred from `codes/lsqn.py`

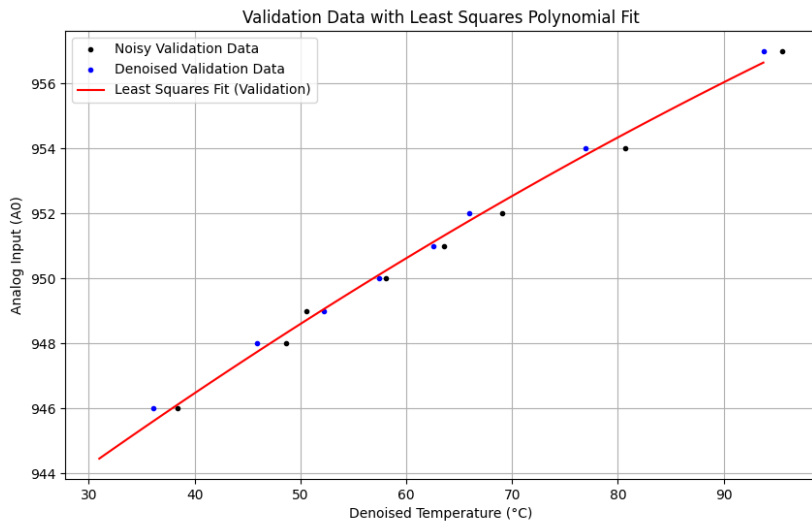


Fig. 6: Validation data with least squares polynomial fit.