

# Hardware Assignment

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## 1 Introduction

This report details the process of determining the voltage across a PT-100 RTD (Resistance Temperature Detector) as a function of temperature. The least squares method was used to estimate the parameters of the Callendar-Van Dusen equation.

## 2 Collecting Data

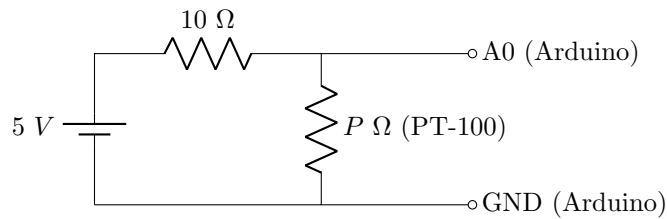
We were provided with the following components

- PT-100 Resistance Temperature Detector
- Arduino Uno and USB Cable
- $10\ \Omega$  resistor
- Breadboard
- Wires

We also made use of the following items from the EE Lab to control and monitor the temperature

- Electric kettle
- Digital Thermometer

The  $100\ \Omega$  resistor and the PT-100 were connected in series between the 5V output pin and the ground pin of the Arduino to create a voltage divider. The other pin of the PT-100 is connected to the A0 pin of the Arduino to measure the voltage across the PT-100.



The PT-100 was immersed in an electric kettle filled with water, and a digital thermometer was used to measure the temperature.

The kettle was turned on for some time, and then turned off. Once the reading of the digital thermometer became stable, a reading was taken, and the Temperature was increased again. A total of 30 readings were taken over a range of temperatures from  $26.8\ ^\circ\text{C}$  to  $97.8\ ^\circ\text{C}$ .

17 points were randomly chosen from the data set to form the training set. The remaining 13 points were put in the testing set.

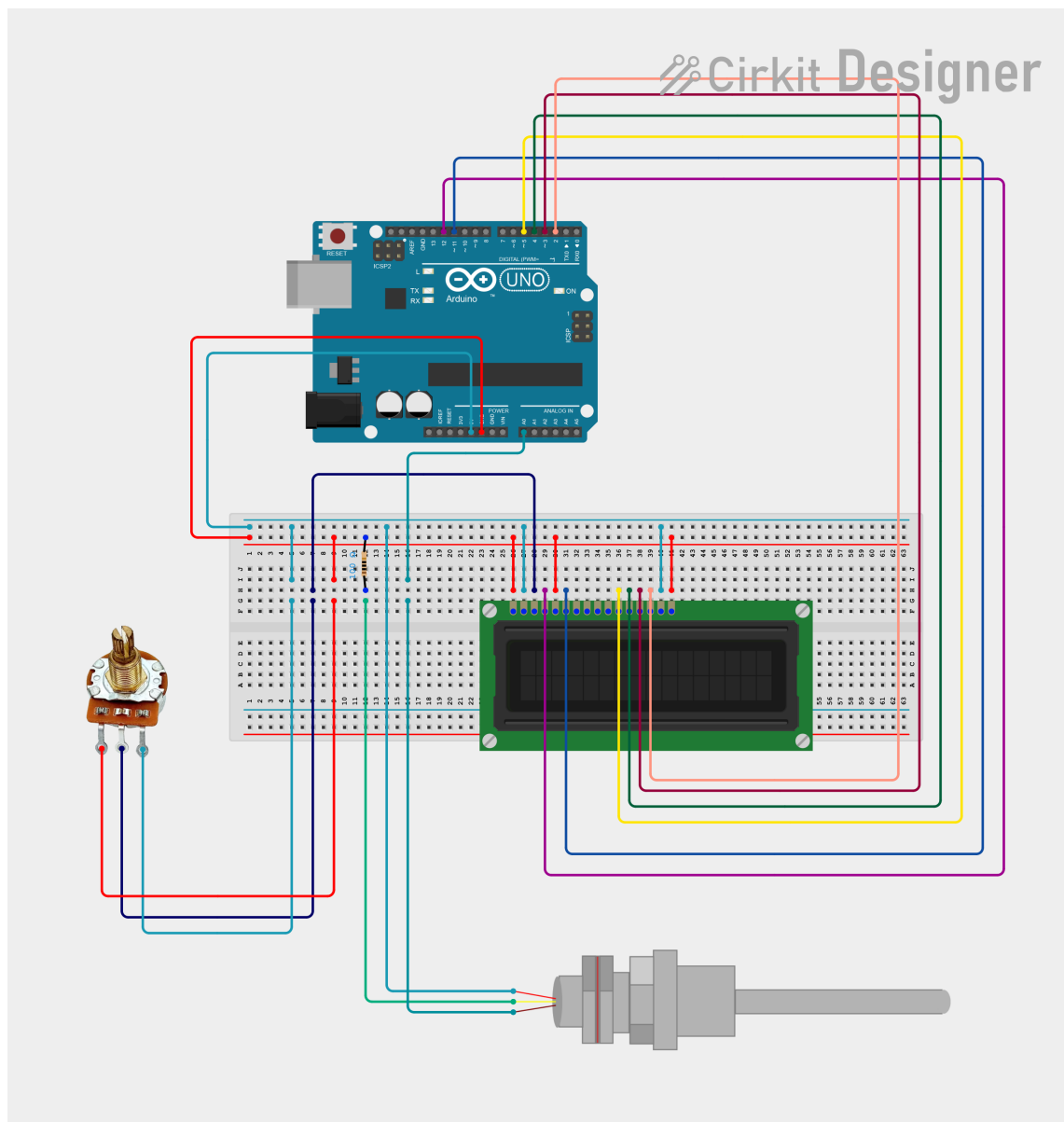


Figure 1: Circuit Diagram

### 3 Model

We use the Callendar-Van Dusen equation to model the voltage across the PT-100 as a quadratic function of temperature.

$$V(T) = n_0 + n_1T + n_2T^2 \quad (1)$$

$$c = \mathbf{n}^\top \mathbf{x} \quad (2)$$

$$(3)$$

where

$$c = V(T), \mathbf{n} = \begin{pmatrix} n_0 \\ n_1 \\ n_2 \end{pmatrix}, \mathbf{x} = \begin{pmatrix} 1 \\ T \\ T^2 \end{pmatrix} \quad (4)$$

We can write the equation in matrix form as

$$\mathbf{X}^\top \mathbf{n} = \mathbf{C} \quad (5)$$

where

$$\mathbf{X} = \begin{pmatrix} 1 & 1 & \dots & 1 \\ T_1 & T_2 & \dots & T_n \\ T_1^2 & T_2^2 & \dots & T_n^2 \end{pmatrix}, \mathbf{C} = \begin{pmatrix} V(T_1) \\ V(T_2) \\ \vdots \\ V(T_n) \end{pmatrix} \quad (6)$$

Using Least Square Method

$$\mathbf{n} = (\mathbf{X}\mathbf{X}^\top)^{-1}\mathbf{X}\mathbf{C} \quad (7)$$

For the  $PT - 100$  data, the approximate model is given by

$$V(T) = 2.23689 + 0.00130T + (-3.07 \times 10^{-5})T^2 \quad (8)$$

$$\mathbf{n} = \begin{pmatrix} 2.23689 \\ 0.00130 \\ -3.07 \times 10^{-5} \end{pmatrix} \quad (9)$$

Table 1: Temperature and Voltage Data

| Temperature | Voltage  |
|-------------|----------|
| 26.800000   | 2.270000 |
| 38.000000   | 2.228700 |
| 42.500000   | 2.250000 |
| 48.900000   | 2.240000 |
| 54.500000   | 2.210000 |
| 37.100000   | 2.228700 |
| 79.100000   | 2.150000 |
| 85.000000   | 2.130000 |
| 91.600000   | 2.100000 |
| 94.100000   | 2.080000 |
| 97.800000   | 2.070000 |
| 33.300000   | 2.230000 |
| 66.100000   | 2.200000 |
| 76.800000   | 2.170000 |
| 81.100000   | 2.140000 |
| 73.800000   | 2.150500 |
| 69.600000   | 2.170100 |

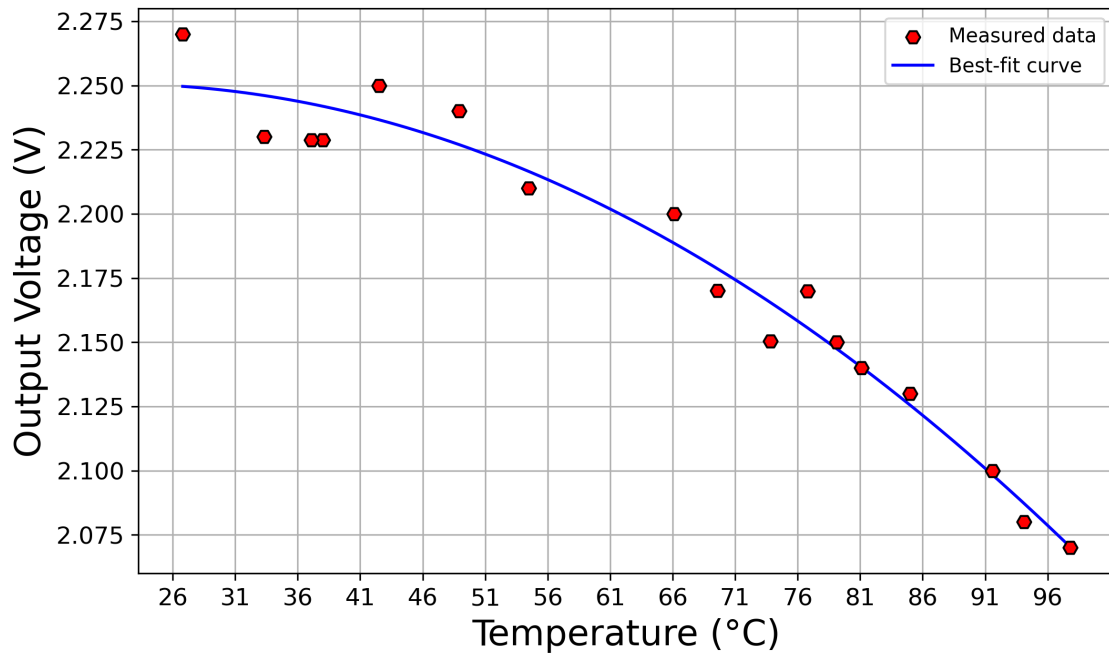


Figure 2: Training regression model

To obtain temperature as a function of voltage, we rearrange or numerically invert the above equation

$$T(V) = a_0 + a_1V + a_2V^2 \quad (10)$$

The coefficients can be again found by applying the least square method to given data

$$\begin{pmatrix} 1 & 1 & \dots & 1 \\ V_1 & V_2 & \dots & V_n \\ (V_1)^2 & (V_2)^2 & \dots & (V_n)^2 \end{pmatrix}^\top \begin{pmatrix} a_0 \\ a_1 \\ a_2 \end{pmatrix} = \begin{pmatrix} T_1 \\ T_2 \\ \vdots \\ T_n \end{pmatrix} \quad (11)$$

we get

$$\begin{pmatrix} a_0 \\ a_1 \\ a_2 \end{pmatrix} = \begin{pmatrix} -3460.32 \\ 3619.11 \\ -917.98 \end{pmatrix} \quad (12)$$

$$T(V) = -3460.32 + 3619.11V + -917.98V^2 \quad (13)$$

To obtain the temperature, we will use the above equation

## 4 Validation

The model can be validated by using test dataset

Table 2: Test Dataset

| Temperature | Voltage  |
|-------------|----------|
| 61.600000   | 2.200000 |
| 66.900000   | 2.180000 |
| 74.800000   | 2.170000 |
| 82.100000   | 2.150000 |
| 79.000000   | 2.160000 |
| 84.600000   | 2.130000 |
| 69.900000   | 2.175000 |
| 43.100000   | 2.240000 |
| 46.800000   | 2.228700 |
| 48.500000   | 2.214100 |
| 50.600000   | 2.209200 |
| 88.700000   | 2.087000 |
| 91.500000   | 2.077200 |

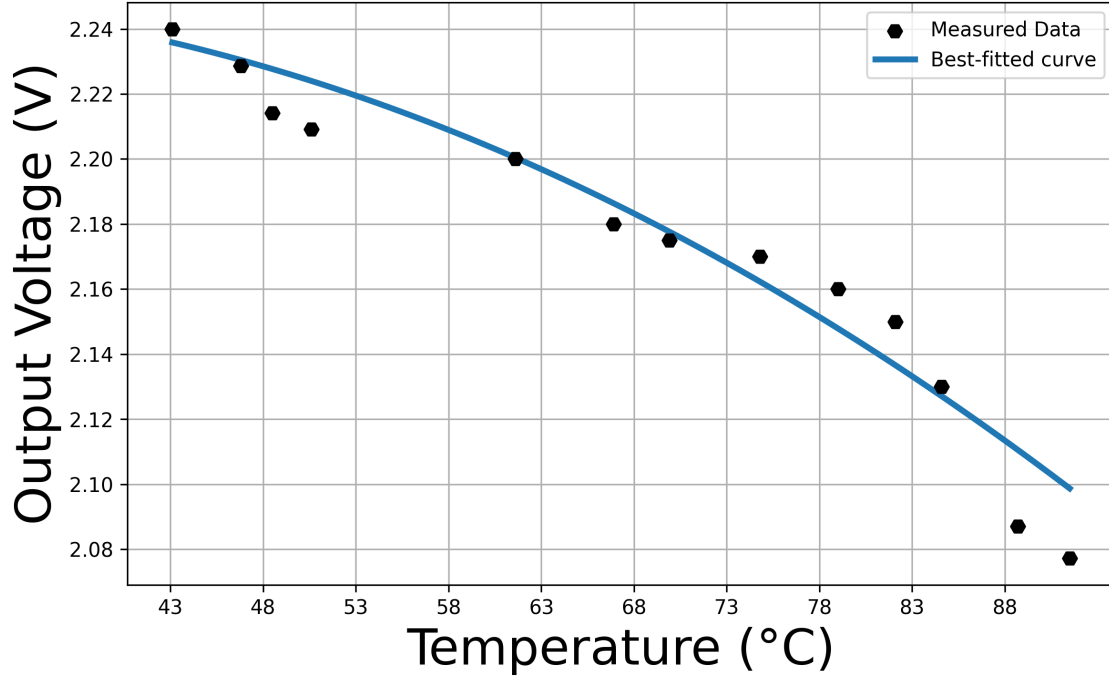


Figure 3: testing the trained model

## 5 Error & Conclusion

Calculating error by Mean Absolute Error (MAE)

$$MAE = \frac{\sum |T_{PT-100} - T_{A_i}|}{13} \quad (14)$$

where

$T_{PT-100}$  is Temperature from PT-100 Model

$T_A$  is Actual Temperature reading

we get

$$MAE = 3.58^{\circ}C \quad (15)$$

The model produces an error of  $3.58^{\circ}C$ , demonstrating reliable predictive accuracy for the system.

**Source of error may be:**

1. Measurement noise in voltage reading
2. Non-linearity in the PT-100 response
3. Approximation errors in the least square method
4. Temperature sensor calibration uncertainties

The PT-100 sensor, when integrated with machine learning calibration, provided consistent and interpretable results suitable for practical applications.