

CAREER EPISODE 1

INTRODUCTION

CE 1.1 During a transformative 9-month project on Tumbler Dryer Remaining Time Algorithm from [REDACTED], I worked with [REDACTED] University and [REDACTED] Global in [REDACTED]. Under the guidance of [REDACTED] [REDACTED] [REDACTED] department, I explored the connection between academic theory and industrial application. This experience provided me with an understanding of electronics engineering's real-world implications and enhanced my interdisciplinary skills.

BACKGROUND

CE 1.2 Arcelik is known as [REDACTED] leading producer of white goods. It's a multinational company with 30 R&D centers and 28 production facilities worldwide. This project was done with [REDACTED] which was responsible for creating 7% of Europe's total dryer machine output. At the heart of this partnership laid a crucial challenge; customer dissatisfaction with the tumble dryer's LCD, particularly its inaccurate display of remaining time as cycles reached completion. Our mission as guided by the mentors of the company was to improve this algorithm for accurate time estimation.

CE 1.3 As part of my final year project, I worked with a diverse team consisting of six fellow students in Electronics Engineering. The aim of this project was to tackle a real-world challenge. This involved initial proposal, regular progress reports, presentations, committee meetings and the display of the work at a final year project fair exhibition. In my senior year, the faculty of my University allocated several projects from various companies to student groups.

CE 1.4 I prepared a proposal and submitted it, which formed the basis for the faculty's assignment of these projects to student groups. I chose to work on the Tumble Dryer Remaining Time Algorithm Improvement project, based on my conviction that my team possessed the required expertise to achieve it within a single academic year. I worked with my team and had discussions with them to explore various facets of the project. Drawing on each individual's strengths as some team members were better in specific disciplines than in others, I divided tasks among them. This not only helped me identify the tasks which were needed in order to solve the challenge but also helped secure approval from the University faculty, resulting in the appointment of this project to my team.

CE 1.5 I created the Big Picture overview, to outline the process flow from data gathering to processing, resulting in the ultimate solution. This visual representation provided a detailed roadmap, guided my approach towards a solid resolution. I also developed the work breakdown structure which was a critical step to divide the overarching problem into manageable segments for team allocation. I engaged in literature reviews, selected, interfaced and tested the humidity sensors. I understood the existing algorithms and modules, data extraction and tests to validate the basic and updated algorithms using the new humidity sensor data. I made a timeline of tasks and their deadlines. The timeline helped me and my team be aware of the progress of the project. I developed a Gantt chart of the work breakdown structure.

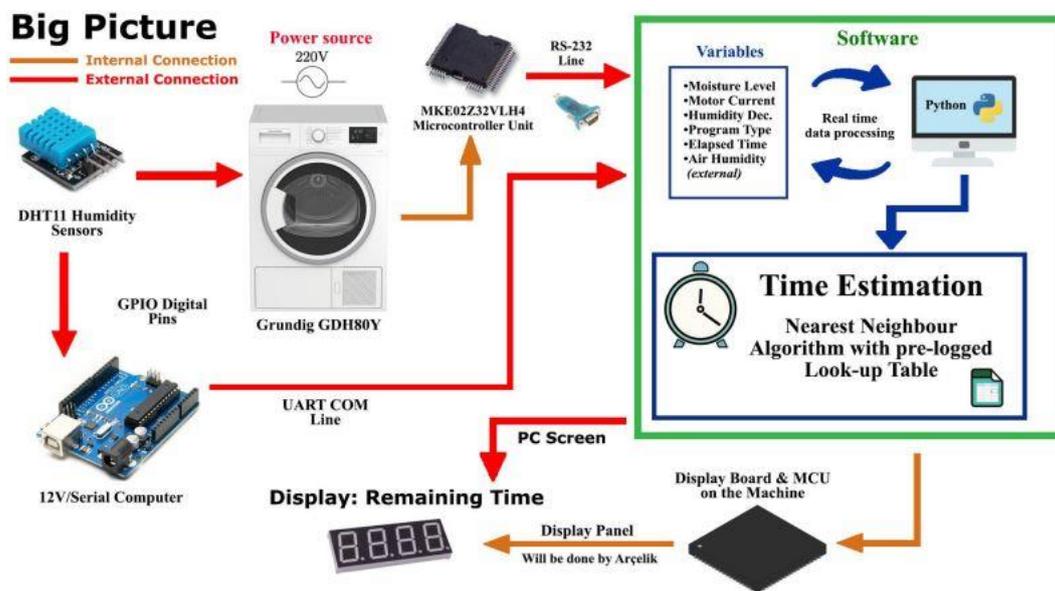


Figure 1: Big picture

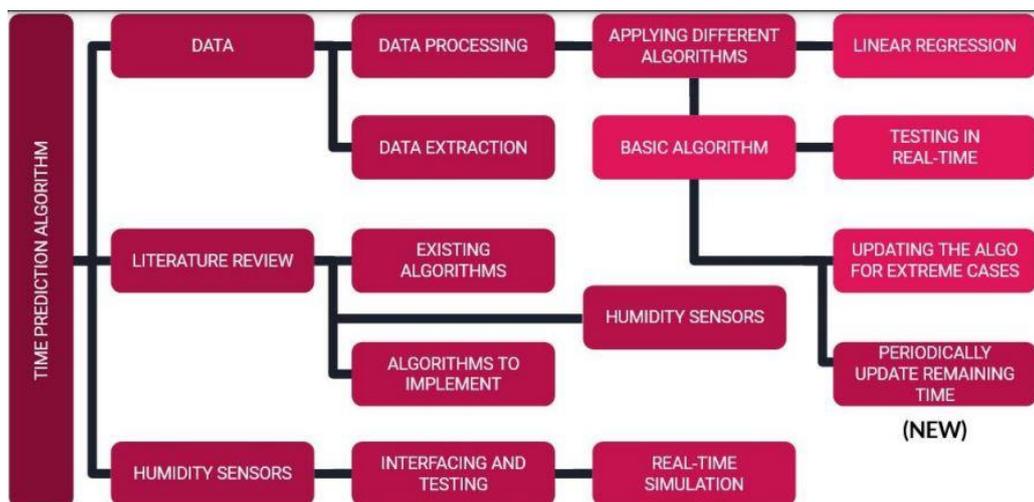


Figure 2: Work break down structure

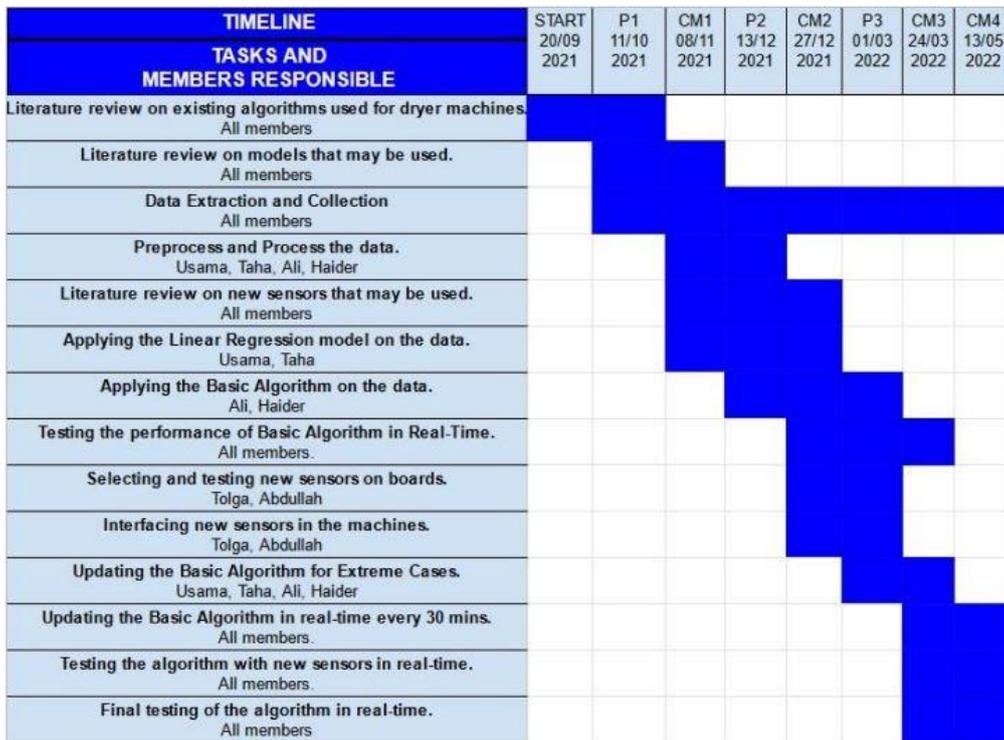


Figure 3: Gantt Chart of the work break down structure

PROJECT REPORTING HIERARCHY

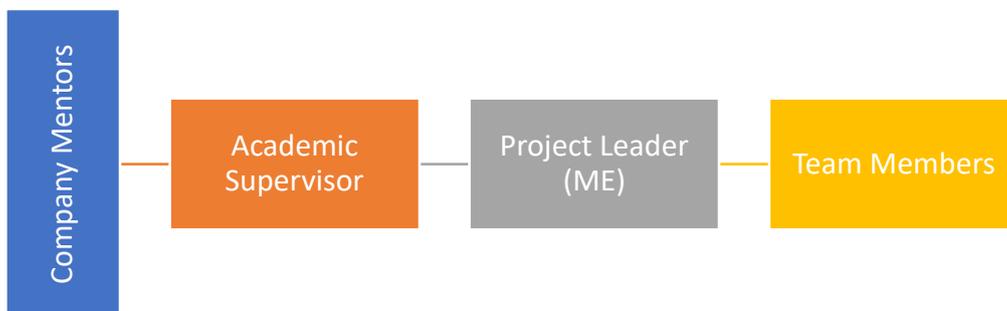


Figure 4: Hierarchy

PERSONAL ENGINEERING ACTIVITIES

CE 1.6 After getting this project, I plotted a graph that summarized the problem and my vision of the final solution to this problem. I started with the identification process for both functional and non-functional requirements, laying the foundation of my project structure and objectives. I defined the functional requirements and the accuracy threshold, targeting a min of 90%. To achieve this, I formulated the accuracy metric as a keystone measure for my project's success.

$$Accuracy = \left(1 - \frac{1}{M} \sum_{i=1}^M \frac{|Prediction_i - remaining_i|}{remaining_1} \right) \times 100$$

Where M: Total number of predictions;

In detailing the functional requirements, I methodically highlighted the input and output expectations. I defined the stringent parameters for inputs, set criteria for a total weight ranging between 1kg and 6kg, clothes to water ratio <2:1 and the acceptance of various clothing types. On the output side, I defined the time prediction methodology. This included initiating the first prediction after 5 minutes from the start of the program and strategizing subsequent updates based on the specific test run criteria.

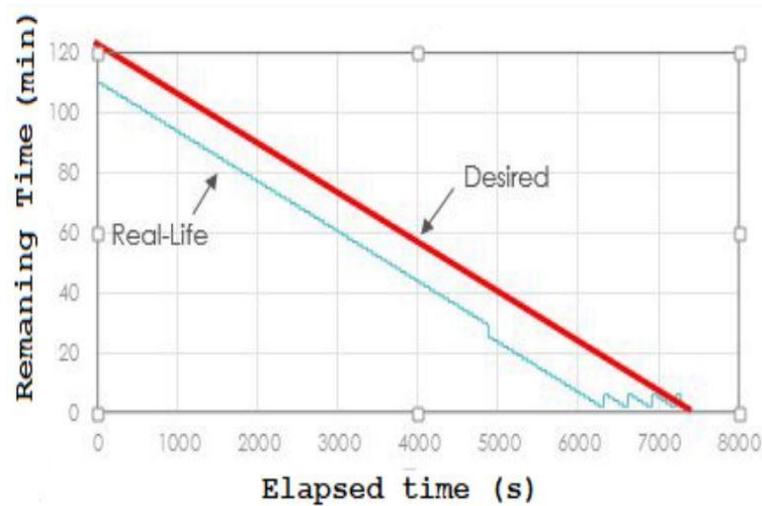


Figure 5: Desired vs Real-Life graph

CE 1.7 I evaluated the non-functional facets with the aim to improve feasibility and safety. I thoroughly evaluated the cost implications, where I included the hardware requirements provided by the company and assessed the potential need for supplementary sensors or equipment, accounting for associated costs. I defined parameters for size, weight and power dissipation of external sensors. By defining the realistic dimensions and weight considerations, I ensured smooth integration into tumbler dryer setup. I strategized to limit power consumption to under 100mW, for energy efficiency without compromising the core functionality of the appliance. I formulated precautions to prevent potential hazards, focusing on isolating sensors from high voltages for waterproof and electrically insulated interfaces and fortifying the chassis against short circuiting risks. For these non-functional aspects, I compiled a table which included constraints and detailed specifications associated with each non-functional requirement.

Non-Functional Requirements	Constraint	Details
Cost	Total cost of hardware used + sensors	3 machines, 3 data cables, 25kg clothes, external sensors
Size/Weight	Realistic sensor size and weight	-
Power Consumption	Power dissipation of external sensors < 100mW	-
Environmental Issues	N/A	-
Safety issues	Protection from short circuiting the chassis	Isolating external sensors from high voltages
Health issues	N/A	-

Table 1: Summary of non-functional requirements

CE 1.8 I divided my project into two segments, each addressing different aspects of the problem. The first segment was developing an algorithm using the existing sensors in the tumble dryer. To start this phase, I used the software, Unilog which was provided by the company. I established communication between the microcontroller and my PCs through RS 232 lines and delved into data visualization and recording. Within the dataset, I identified and selected three features; Conductivity values, BLDC current and Humidity Decision based on their relevance to the problem at hand. The conductivity value, reflecting the resistivity of moisture sensor inside the drum, exhibited a clear inverse relationship with moisture content during the drying process. I plotted a graph of conductivity versus time highlighting a distinct notch around the 7500s marks, indicating counter resets due to state changes in the drying process.

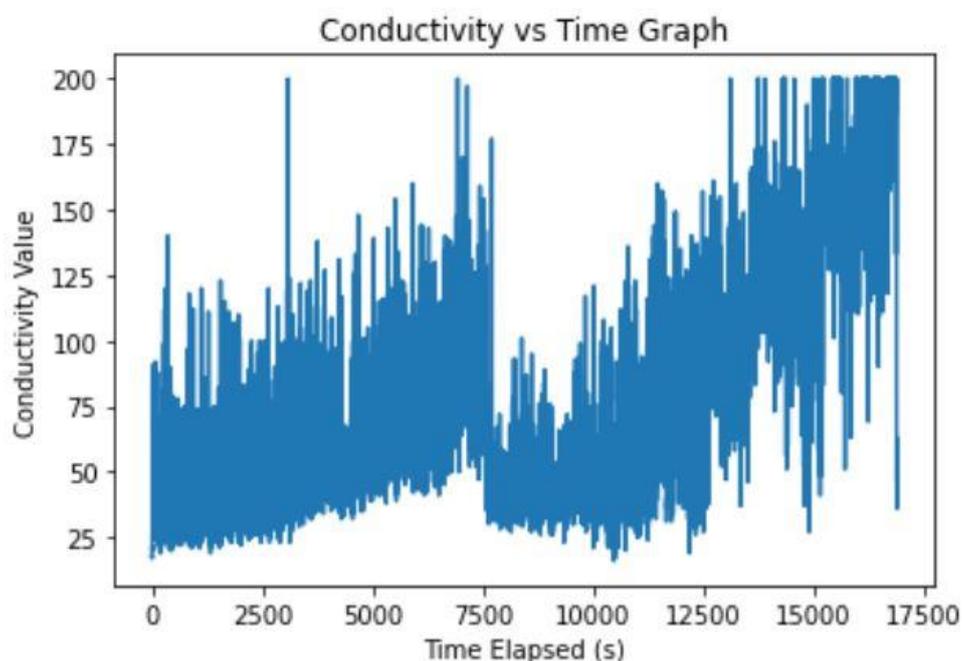


Figure 6: Conductivity value vs time elapsed

CE 1.9 The BLDC current, monitoring the brushless DC motor for drum rotation, acted as an indirect indicator of drum weight. As moisture levels reduced the total weight decreased causing fluctuations in BLDC current. I plotted a graph of BLDC current versus time and observed that the BLDC current value periodically and momentarily goes to 0 because the drum changes direction and stops. This data which included the Humidity decision marking drying process stages was collected. I used these datasets to develop and refine a predictive formula. My iterative approach was testing and constant adjustments to derive an accurate predictive model as per the objectives of the algorithm.

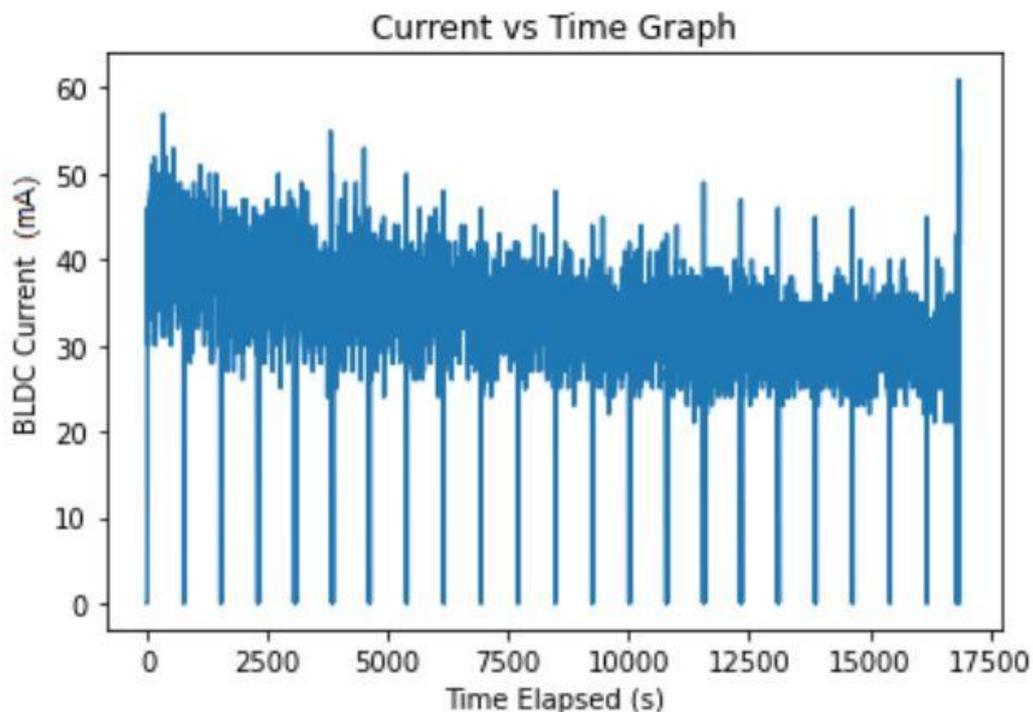


Figure 7: BLDC Current vs time elapsed

CE 1.10 I performed a series of tests to validate the accuracy of my predictions, conducted a comparison between my algorithm's estimations and the actual tumble dryer run times. For each test, I executed two predictions; one at the initial 5 minutes mark and the other when 30 minutes remained based on the first prediction. I detailed the results from five real-time tests in the table which reflected varying water and clothes weights and the predictive accuracy of my algorithm. Using the accuracy equation, I consistently achieved accuracy percentages exceeding 91% across all tests. This validation underscored the reliability and effectiveness of my algorithm in diverse test scenarios. I visualized and scrutinized the performance of my algorithm, focusing on test 2. I compared my algorithm predictions with the actual run times and those generated by the current algorithm.

	Water Weight (kg)	Clothes Weight (kg)	First prediction	Actual time	Second prediction	Actual time at second prediction	Accuracy (%)
Test 1	1	2	2:04:34	02:14:53	00:44:29	00:40:19	91.5
Test 2	0.7	1.5	01:35:02	01:34:00	00:33:20	00:29:02	96.3
Test 3	0.9	1.8	01:58:32	01:59:52	00:28:32	00:31:20	95.5
Test 4	1.1	2.2	02:11:49	02:12:45	00:31:50	00:30:54	98.1
Test 5	0.3	0.9	00:59:38	00:58:17	00:30:29	00:28:39	97.3

Table 2: Prediction test result summary

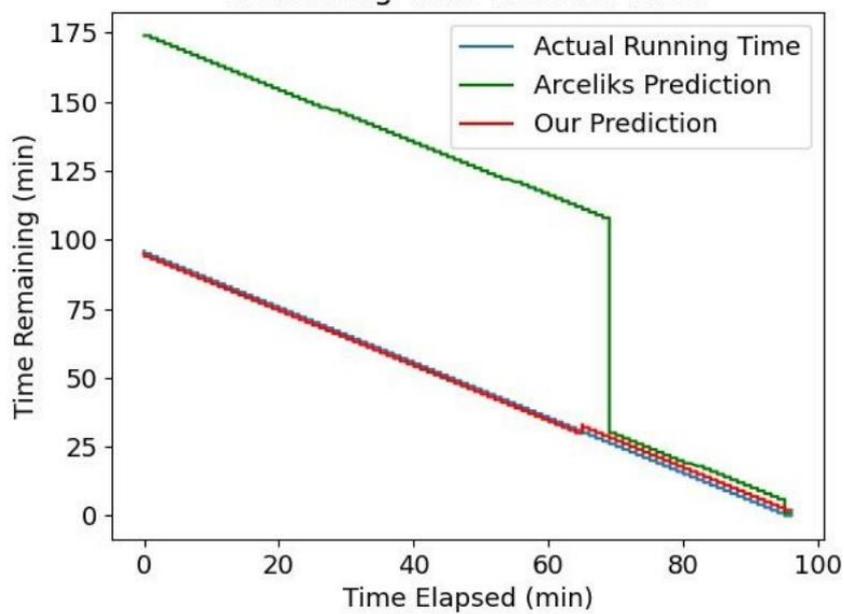


Figure 8: Test 2 visualization and comparison

CE 1.11 I integrated new sensors into the tumbler dryer's existing hardware which was a critical step aimed at improving the accuracy by using data from these humidity sensors. I researched to identify suitable sensors capable of measuring temperature differentials between the inlet and outlet of the dryer's air duct. After this, I shortlisted the DHT11 sensor, considering its accuracy, ability to withstand high temperatures, waterproof design, compatibility with power constraints, integrated ADC and serial data output for communication. Its operating voltage, current, temperature and humidity range and accuracy matched the requirements of the project.

CE 1.12 I positioned the DHT11 sensors at the air inlet and outlet of the dryer's drum to capture data. I interfaced sensors with an Arduino UNO microcontroller, programmed it to collect real time data at 1 Hz. For powering the sensor through Arduino's 5 V pin, I devised a data storage

solution due to the limited memory capacity of the microcontroller. To overcome this issue, I provided serial data transfer to my PCs using PuTTY software for efficient data storage and analysis. The humidity sensor data I obtained, confirmed the expected trends, a gradual decrease in output humidity levels during the drying process, while the input levels remained relatively stable. Notably, the linear decrease in output humidity levels indicated the use of the accurate end of cycle detection. Peaks observed in the data corresponded to brief moments when the drum and air pump momentarily paused, causing the temporary mixing of air at the inlet and outlet.



Figure 9: Positioning of DHT11 sensor at the inlet



Figure 10: Positioning of DHT11 sensor at the outlet

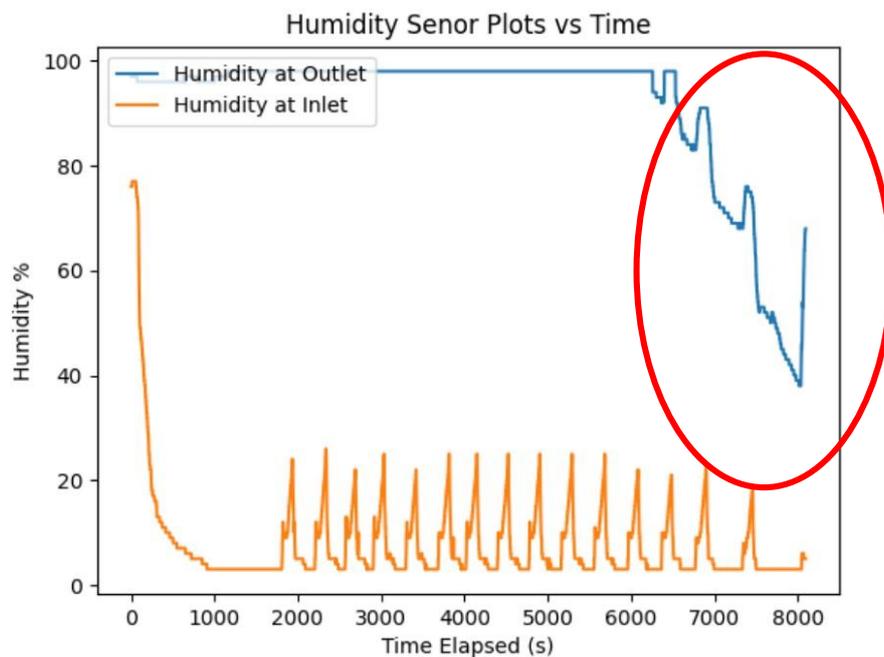


Figure 11: Humidity vs time elapsed

CE 1.13 I conducted a test following the installation of humidity sensors to collect data and refine my algorithm. One crucial addition to my feature set was the introduction of HUMIDITYCHANGE, designed to evaluate changes in humidity sensor output. I defined this feature to capture whether there was a significant alteration in humidity sensor output. When it equaled 0, it indicated no change in sensor output, while a value of 1 signified a notable shift in output. My algorithm underwent an update based on this feature. If it equaled 0, the existing algorithm continued to make predictions. However, when it was 1, a linear prediction model was applied.

$$HUMIDITYCHANGE = \begin{cases} 0, & \text{no change in humidity sensor output,} \\ 1, & \text{significant change in humidity sensor output} \end{cases}$$

$$Final\ time\ prediction = \frac{Elapsed\ time}{0.75} - Elapsed\ time$$

Where Elapsed Time is the time until *HUMIDITYCHANGE* goes from 0 to 1

This adaption was a result of my observation that during the last quarter of the cycle, when the output humidity changed, it did so almost linearly. Hence, I developed this specific linear precaution model to handle this observed pattern, improving the accuracy of my predictions during this phase.

CE 1.14 I performed real time testing and analysis, focusing on predictions made every 30 minutes following the integration of humidity sensors. This iterative process aimed to monitor and detect changes in output air humidity percentage, using this data to refine my algorithm’s predictive capabilities. I summarized the results of numerous real-time runs, detailing the water and clothes weights alongside the accuracy of my predictions, Notably, the accuracy percentages were lower compared to earlier tests without humidity sensors, indicating a decrease in predictive performance. To visually display these findings, I generated plots, showing the predictions made using the sensors against actual running times and Arcelik’s algorithm. These visualizations displayed the discrepancy in prediction accuracy between the two algorithms, highlighting the limitations introduced by 30-minute prediction intervals and the inclusion of HUMIDTYCHANGE as a feature.

CE 1.15 Through analysis, it became evident that the initial algorithm, devised without the integration of humidity sensors, showed superior accuracy compared to the updated version. This decision to predict every 30 minutes introduced unwanted fluctuations, compromising the accuracy of my predictions. In addition, upon evaluation it was recognized that the inclusion of the HUMIDTYCHANGE feature might potentially constitute redundant information, considering the existing feature, HumidityDecision already in use.

	Water Weight (kg)	Clothes Weight (kg)	First prediction	Actual time	Accuracy (%)
Test 1	3	1.4	03:18:25	03:02:44	79.1
Test 2	4	1.8	04:08:12	04:00:37	81.1

Table 3: Prediction using humidity sensors test result summary

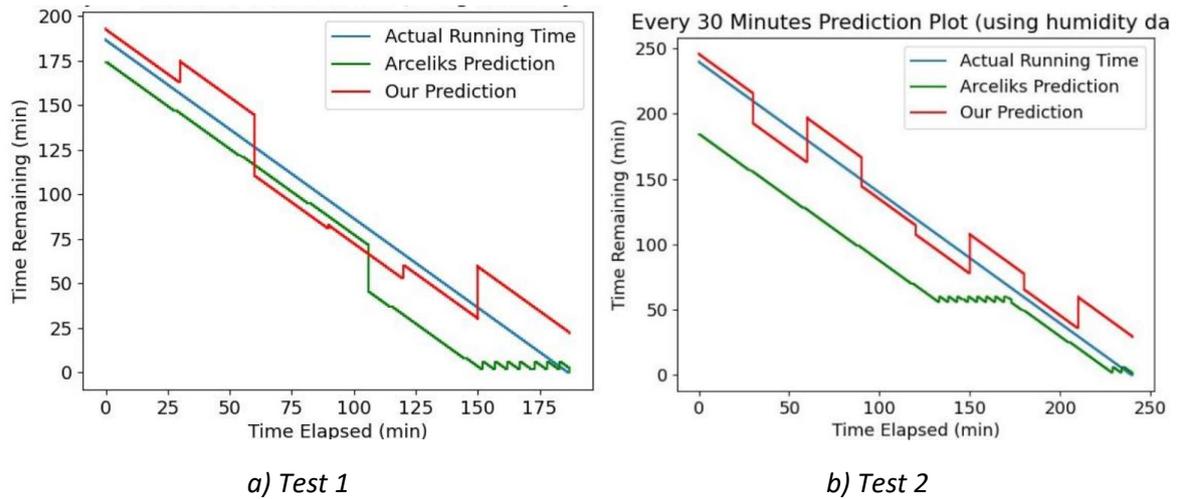


Figure 12: Visualization of tests corresponding to Table 3

CE 1.16 I estimated the cost which included the cost breakdown of the crucial components like dryer machines, humidity sensors, Arduino UNO boards, display boards, data logging cables and weighing scale. To conclude, I along with my team was able to produce an algorithm which was able to predict the remaining time with an accuracy of at least 90%, for different test cases. Extreme cases were catered for by taking more data by doing test runs for those conditions. The analysis phase, emphasized the importance of removing redundant sources of information. This move aimed to streamline my algorithm and prevent unnecessary complexities. I considered the environmental conditions impact on my experiments, recognized the significance of considering long term experiments and their potential implications on outcomes.

DHT11 humidity sensors	4	132.12TL x 4 = 524.48 TL
Clothes	25kg	38 TL x 25 = 950 TL
Arduino UNO	3	600 TL x 3 = 1800 TL
Extra display boards	3	800 TL x 3 = 2400 TL
Data logging cables	3	225 TL x 3 = 675 TL
Weighing scale	1	660 TL

Table 4: Project cost summary

SUMMARY

CE 1.17 I worked on an interdisciplinary project at [redacted] improving the tumbler dryer time prediction. I integrated DHT11 humidity sensors, refined algorithms

and conducted real time tests. My algorithm achieved over 90% accuracy, but further testing revealed challenges with 30-minute predictions and potential redundancies in sensor data. I understood the importance of testing, streamlining data sources and maintaining team communication throughout this project.