International Journal of Engineering Education Vol. 38, No. 5(A), pp. 1377–1388, 2022
Printed in Great Britain

0949-149X/91 $3.00+0.00

Project-Based Learning in a Virtual Setting: A Case Study on Materials and Manufacturing Process and Applied Statistics*

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This paper details the case-study of incorporating project-based learning through a virtual materials characterization project. This project exposes students to characterization technology, manufacturing processes, data analysis and the application statistical tools. Moreover, by utilizing the project-based learning methodology, students develop skills in teamwork, oral and written communication, and problem solving that do not come from the back-of-the-book. In the present case study, material properties of a pair of failed multipurpose crafting shears labeled as 'stainless' are characterized. The student teams are challenged with identifying the manufacturing process that was used based on the data acquired from metal spectrometer testing, Rockwell C hardness testing, and scanning electron microscope (SEM) imaging of the failure surface of the sample. Based upon the analysis of this data, students are tasked with identifying the type of metal alloy for the crafting shears, the manufacturing process used, and possible root cause of failure. This case study provides a pedagogical framework to bridge concepts of materials science with manufacturing methodology and statistical analysis tools as well as creative thinking and problem-solving skills. By investigating and determining the root cause of failure the students have gained a better understanding of the relationship between manufacturing process, material properties, and product quality. The outcomes could be used directly in an existing course, since all the data have been provided or it could also be adapted for different contexts by replacing the existing data with a new data set.

Keywords: project-based learning; engineering education; distance learning; manufacturing process; materials science; applied statistics

1. Background

Understanding how student learning is accomplished is fundamental in developing course curricula to accomplish learning outcomes. As the Nobel Laureate in the field of cognitive science Herbert Simon said, "Learning results from what the student does and thinks and only from what the student does and thinks. The teacher can advance learning only by influencing what the student does to learn."

Research suggests that problem-based learning (PBL) is a successful and innovative method for engineering education [1, 2]. Learning outcomes can be achieved by exposing students to project work with key characteristics: theoretical principles of the problem analysis, knowledge and practice integration, collaborative group work, and real-world problems [1, 2]. To better prepare students to meet the demands of modern and future industry, engineering curriculum needs to include and focus more on skills that are difficult to assess in a classical examination or problem-solving format. One way to do this is by incorporating Project-based Learning (PjBL) challenges within the curriculum. These challenges are cross-disciplinary in nature. PjBL has similar pedagogical elements to PBL but compared with PBL, PjBL tends to entail multiple subjects, is longer in duration (weeks or months), follows general steps, results in the creation of a final product (report), and often utilizes real-world scenarios [3].

PBL was developed in 1965 by five Health Sciences faculty members led by John Evans, the founding Dean of McMaster University Medical School [2, 4]. It is a learning approach in which students solve problems in small groups under the supervision of a tutor [4]. The PBL process is driven by the students, facilitated by their tutor, and is based on an educational approach where the learning is driven by problems or can be thought of as "learning through application". In this approach, learners (students) are encouraged to pursue knowledge by asking questions. PBL has been regarded as a key strategy for creating independent thinkers and learners in the medical education community [3–6].

Following the implementation of PBL in the education of medicine, it has since been expanded

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* Accepted 28 June 2022.

to other fields and is considered a solution to some of the issues facing today's engineering education [5]. For example, faculty at Weber State University established a PBL center to achieve a double mission of being an active community member and providing opportunities for engineering students to gain needed skills in problem solving and project management [7–9]. It has been found that the PBL learning approaches greatly facilitated the training in competencies related to interpersonal skills and technical aptitude, experience of solving real-world problems from an engineering perspective, and collaborative learning [10–12]. Liu and coworkers successfully integrated the PBL mode in senior mechanical engineering design classes by introducing more than 20 projects from industry sponsors, university research centers, and a state agency [10, 12–14]. Working on those projects in teams effectively enhanced the students' capacity in solving problems of industrial relevance. It was found from Liu's practice that the implementation of PBL in course curricula struck the balance between achieving desired student learning outcomes and creating opportunities for enriching the student's educational experience [14–17].

One cross-disciplinary topic that is critical in mechanical engineering education is the quality of final products, which represents an intersection between product design, manufacturing process, and materials science. Engineering students need to understand how the quality and performance of a final product are affected and influenced by these factors. Understanding the mechanisms and modes of failure in an engineering product is crucial in evaluating its quality, design approach, and development process. For students to better understand these interactions, it is helpful to engage them in projects that incorporate each of these areas so that the collective effect can be better understood. Often it is difficult for beginning mechanical engineering students to bridge course contents and see how different course topics relate to design and fabrication of quality products. This paper presents a PjBL challenge that can be incorporated in a virtual setting to allow students to investigate and identify the material properties, manufacturing processes, and causes of product failure. Presented as a case study, this paper highlights the assessment of a failed product, analysis results, and student recommendations for future design improvements of the failed product. Using a common product as a case study is an effective way for students to gain experience in the application of materials science principles, manufacturing processes, and statistical analysis tools to assess the product quality and determine the cause of failure. By utilizing statistical analysis tools, Rockwell hardness testing, spectrometer testing, and scanning electron microscope (SEM) imaging, students are challenged to determine the role of materials, manufacturing process and design on the ultimate failure of a product or component.

Fig. 1. Failed crafting shears used for a PjBL case-study.

2. Step 1: Project Description

In this project, a class of 30 students divided into teams of 5 students were presented with images of a pair of failed crafting shears as shown in Figs. 1 and 2. Their task is to investigate the shears based upon the given images and deduce the materials of the shears and their manufacturing process.

3. Step 2: Hypothesis and Assumptions

Based upon the labeling in Fig. 2, students may assume that the shears were made of a stainless steel. With this assumption and the assigned course resource materials, students may conclude that the stainless steel was selected due to its inherent mechanical properties such as hardness and corrosion resistance and hypothesize that the material is a 400 series martensitic stainless steel. This type of stainless steel offers excellent corrosion resistance due to the natural chromium oxide layer formed on its surface. That layer also has superior harden-

Fig. 2. Product labeling, where the word "stainless" is visible.

ability, a necessary property needed to maintain a sharp edge [17, 18]. The only product labeling is shown in Fig. 2 and clearly states "Stainless Pakistan". Based on that labeling, students may deduce that the product was made of a stainless steel and is capable of long-term use and performance.

Based on the material, students may hypothesize a manufacturing process that was employed to fabricate the shears. A high-quality tool made from a high-performance material such as stainless steel would require an appropriate manufacturing process in order to achieve the optimal microstructure of the material, which leads to the best material properties and desired performance of the finished product. Students may hypothesize that a forging operation was applied to produce discrete parts of the shears by shaping the stock material with compressive forces through various dies and tooling. This manufacturing process would allow workers to control the metal's grain structure and result in a finished product with good strength, toughness, as well as other properties required for high stress applications. Following the forging process, a machining process would be carefully selected to process the stainless steel to achieve the desired dimensional accuracy, which is followed by grinding and polishing to achieve sharp edges capable of shearing raw materials [17, 18].

Finally, students are tasked with hypothesizing the root cause of the failure of the product after evaluating the images provided and based upon their assumptions of materials and manufacturing processes. Moreover, since the material labeling contains the country of origin of this tool, the students are encouraged to investigate potential manufacturers in Pakistan and determine the one that made this tool. Students will then be asked to validate their hypothesis and assumptions through a series of experiments.

4. Step 3: Failure Imaging and Analysis

To examine the fractured surface of the shears, SEM was applied to produce high magnitude and high-resolution images, as shown in Figs. 3–7. Before the shears were observed under the SEM, a diamond, water-cooled cutting blade had been used to remove a section of material from the shears that was of a suitable size at the failure site. The sample was then sputtered for 30 seconds to clean the fractured surface without compromising the sample. The sample was then put under the SEM to record the fracture surface photographically.

Upon initial examination of the fractured surface of the shears, students will not see any evidence of failure from ductile fracture or fatigue. Students will instead see evidence of a martensitic structure as shown in red in Fig. 3. The martensitic structure could allow for brittle fracture of the material.

Another feature that the SEM images show is dendrites highlighted in Fig. 4. Dendrites are tree-like structures, formed by crystallization while the molten metal freezes. The presence of dendrite structures is evidence of rapid material cooling. Rapid material cooling would cause the generation of martensitic crystal structure that would exhibit less than expected mechanical properties (material failure under normal use) and be likely to fail in a brittle manner [18].

Fig. 5 was taken on the fracture surface. In this

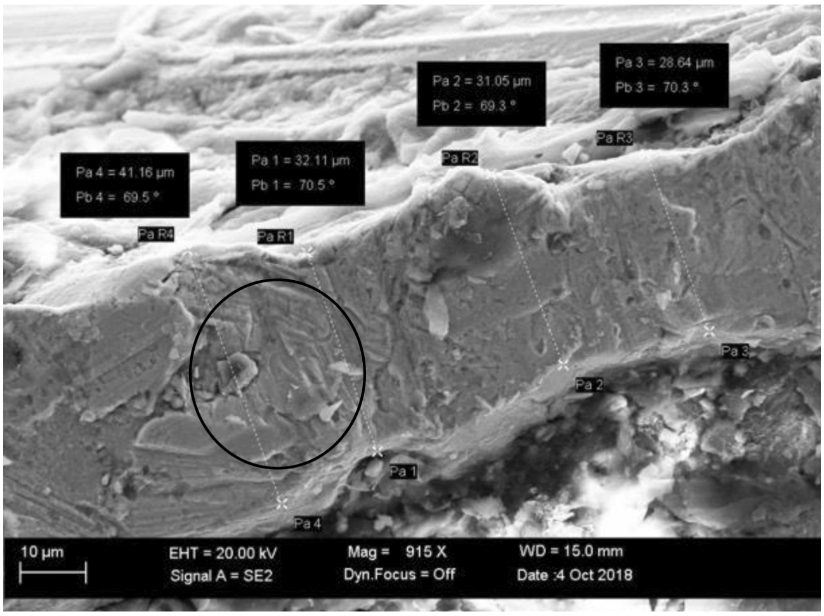


Fig. 3. SEM of a surface layer (martensitic structure).

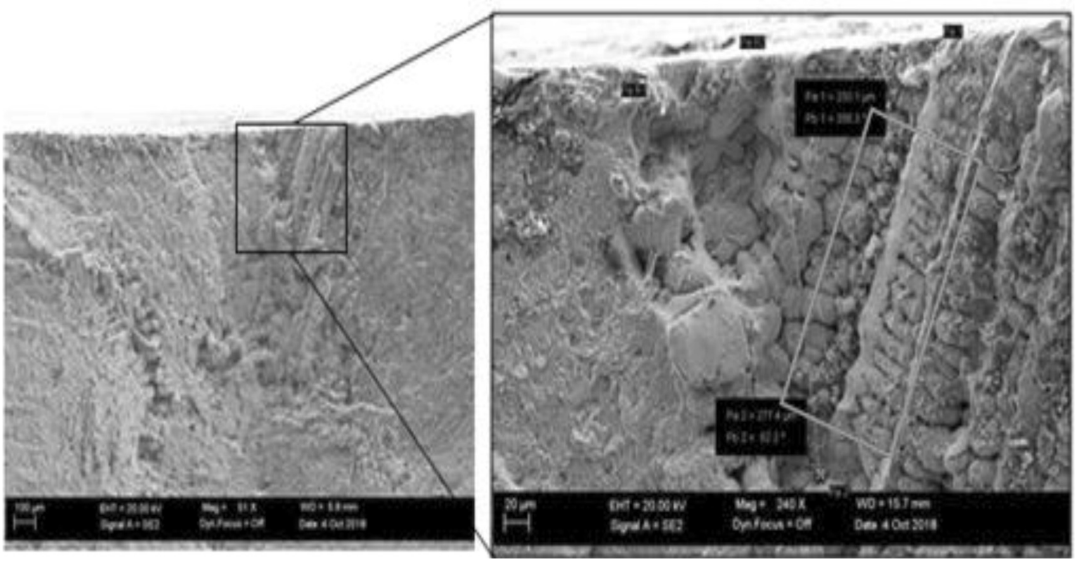


Fig. 4. Dendrites on fracture surface (rectangular region).

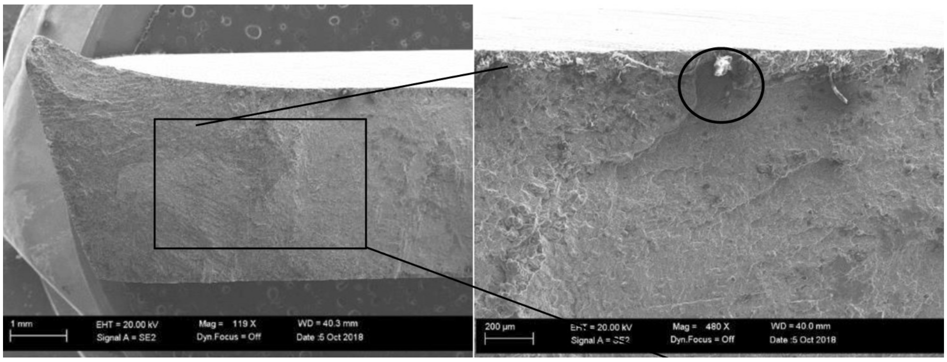


Fig. 5. Fracture initiation site with cleavage planes (circled).

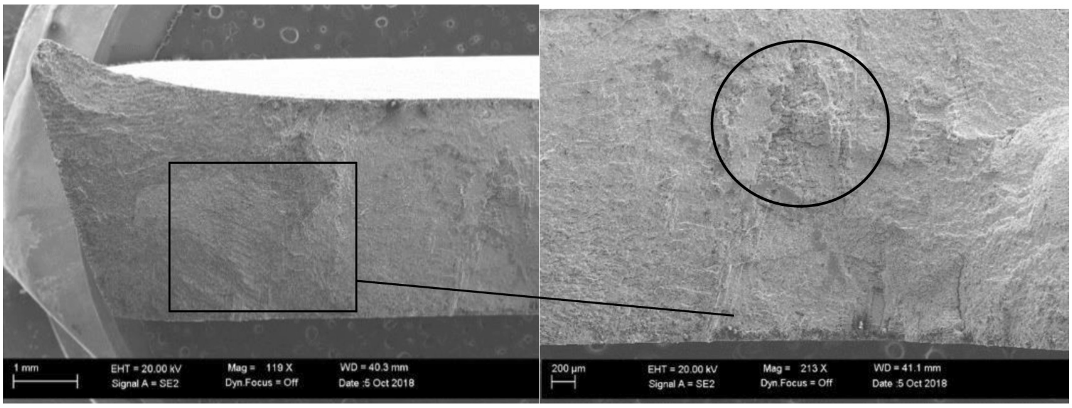


Fig. 6. SEM image of the bottom edge of fracture surface showing porosity (circled).

imaging, the potential fracture initiation site can be seen as a large cleavage plane and the porosity within the material can be visually confirmed via the presence of many voids that are indicated as dark shaded areas. Fig. 6 represents the opposite side of the fracture surface and shows evidence of another potential crack initiation site originating from the surface as well as extensive porosity. Fig. 7 also shows evidence of additional dendritic structures, along with cleavage planes.

Based upon these images, students can make following inferences:

- The material failed in a brittle manner based upon the presence of large cleavage planes.

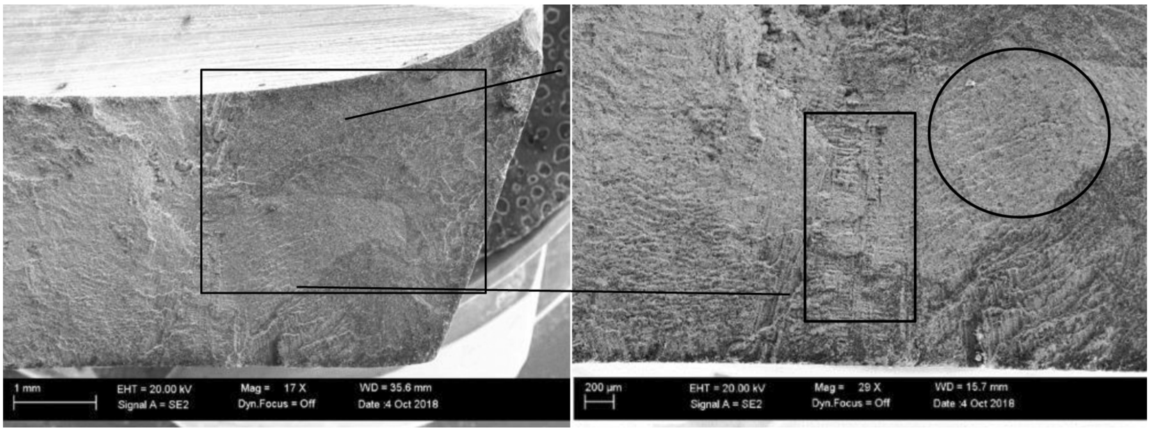


Fig. 7. SEM of the edge of fracture surface showing cleavage planes (circled) and dendritic structures (rectangular region).

- The material exhibited a martensitic microstructure.
- Dendritic structures provided evidence of rapid material cooling.
- Porosity existed in the material.

5. Step 4: Material Characterization and Analysis

Students are introduced to characterization techniques through a virtual demonstration and provided the characterization data and images upon completion. Techniques utilized are Rockwell C hardness testing, metal spectrometer testing, and SEM imaging. Through this activity, students are introduced to technologies used to characterize materials as well as limitations in those technologies.

5.1 Rockwell C Results and Analysis

Rockwell C hardness testing was performed at first following a procedure described by Reeves et al. [19]. In measuring the hardness (represented by HRC values) of this material, the Rockwell-C hardness machine was first calibrated using a standard sample with a known hardness of 62.2 HRC. Next, two test samples were taken from the blades of the crafting shears, which are labeled as A1 and A2 (Fig. 8). These samples were then mounted to a testing fixture to hold the specimens in place and polished to remove the surface finish. Fig. 8 shows the location of the test samples and Fig. 9 shows the fixtures that hold the specimens with indentions generated from the hardness tests labeled.

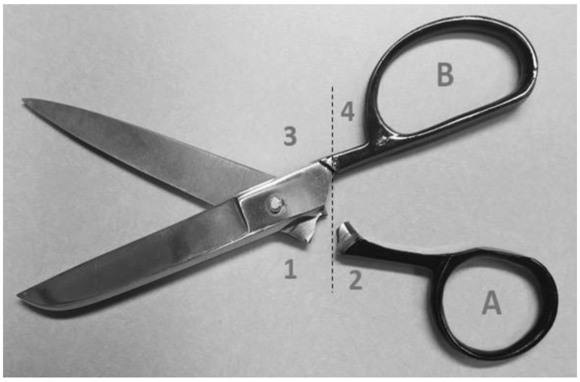


Fig. 8. Different parts of the crafting shears are labeled for use in hardness testing (A1 and A2).

The results from the Rockwell C hardness test are displayed in Table 1.

There are several potential learning outcomes

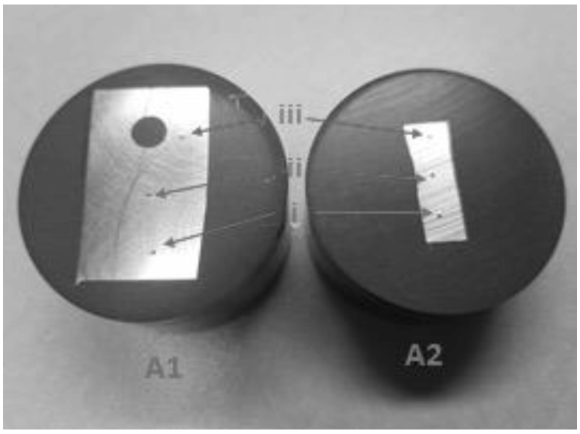


Fig. 9. Specimens after the Rockwell C hardness test labeled as A1 and A2 and i to iii indicate the locations at which the hardness test was performed.

Table 1. HRC values measured from the two specimens

Location	HRC Value
A1- i	50.1
A1- ii	57.9
A1- iii	62.5
A2 – i	54.4
A2 – ii	52.9
A2 – iii	56.8
Average	55.77

Table 2. One sample T-test results of the Rockwell hardness data

μ, Mean	Standard deviation	95% CI for μ (min)	95% CI for μ (max)
55.7	4.32	51.24	60.30

from the analysis of the Rockwell C hardness data. Students are tasked with utilizing statistical tools to understand what conclusions can be drawn from analyzing this data set.

Students will complete a statistical analysis and one sample T-test on the data set. The T-test results are listed in Table 2 (CI means confidence interval).

Based upon these results, students will understand that hardness testing only provides limited information. Students may conclude that these values do not allow for a conclusive material characterization as such results would be expected in a number of different alloys [17, 18]. Limitations of hardness testing can be better understood by calculating the number of samples that should be taken for statistical basis, n. This analysis does demonstrate to students that more testing is required to fully characterize materials than hardness testing alone. In general, hardness testing is helpful as an inexpensive and quick test but the results are insufficient for accurate material characterization.

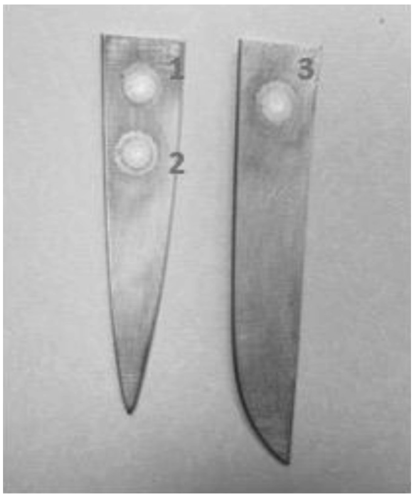


Fig. 10. Samples were taken from three different locations on the blades for spectrometer testing

5.2 Spectrometer Analysis Results

A Spectromaxx LMM04 spectrometer was used to determine the mass percentages of all chemical elements within the crafting shears. The spectrometer was calibrated using a standardized steel specimen with a pre-known composition. To prepare the shears for testing, a large portion of the blades were cut and polished to remove the surface finish. Three samples were taken at the locations indicated in Fig. 10.

The spectrometer results from 3 different tests (Table 3) were used to characterize the material of the product. The average results of the 3 different tests are also listed in Table 3.

5.2.1 Spectrometer Analysis: Carbon Content

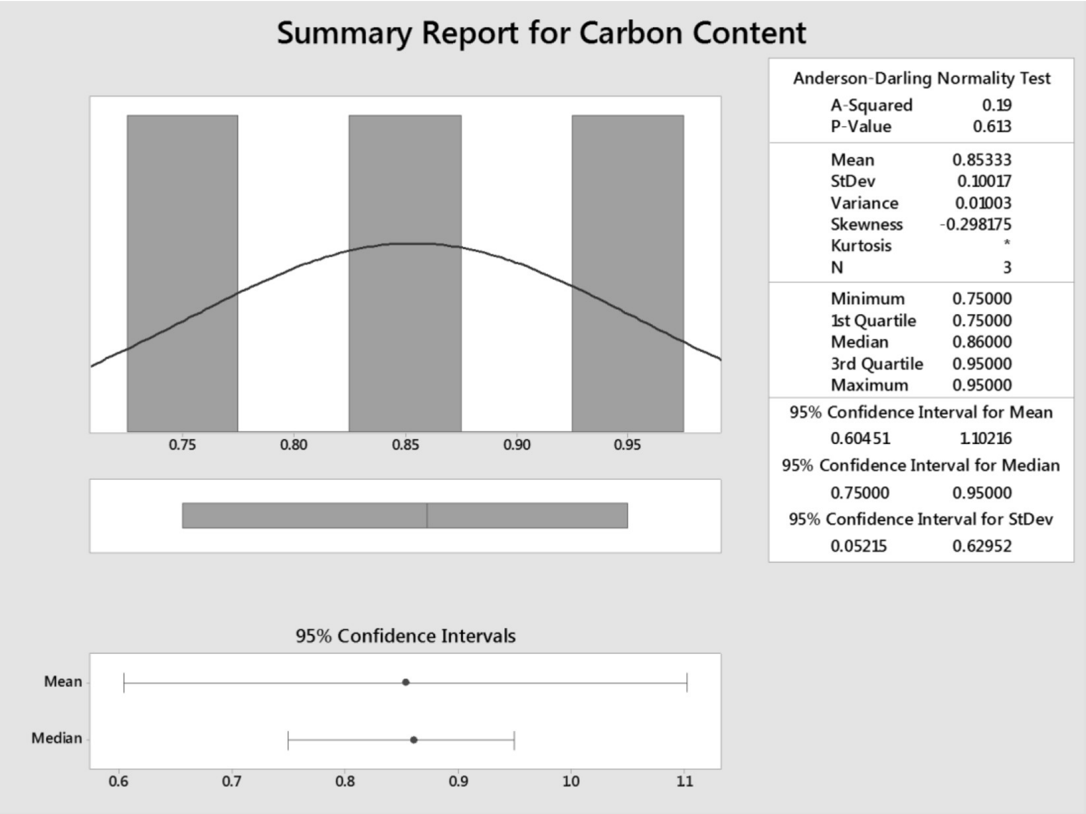
Carbon is the most important element in commercial steel alloys. Increasing carbon content increases hardness and strength and improves hardenability of steels. However, as carbon content increases, the steel will become more brittle and more difficult to weld because of the carbon's tendency to form martensite. Thus, to predict the properties of the material, its carbon content needs to be determined first.

Several issues can be discussed based on the spectrometer testing results. Firstly, students will be directed to perform a statistical analysis of the data from Table 3. Using the statistical software, Minitab, students can create a graphical summary report of the data as shown in Fig. 11.

Upon reviewing that figure, students can conclude that the variation present in the carbon content is high. The results of a one sample T-test give a 95% confidence interval, which is quite broad and overlaps two categories of alloy steels (medium and high carbon steel) with a potential mean of 0.60451% to 1.10216% as shown in the graphical summary. Carbon content representing bulk properties of the material is expected to have a much lower standard deviation.

Table 3. Spectrometer testing results

	% C	% Si	% Mn	% P	% S	% Cr	% Ni	% Mo	% Al
	0.86	0.98	0.317	0.026	0.021	7.82	0.2	0.035	0.0043
	0.95	1.02	0.32	0.022	0.027	7.49	0.188	0.035	0.0053
	0.75	1.18	0.283	0.025	0.021	8.63	0.182	0.037	0.0057
Average	0.8533	1.0600	0.3067	0.0243	0.0230	7.9800	0.1900	0.0357	0.0051
	% Cu	% Co	% Ti	% Nb	% V	% W	% Pb	% Mg	% B
	0.133	0.016	0.0011	0.012	0.016	0.045	<0.002	0.0029	0.0023
	0.136	0.01	0.0014	0.011	0.015	0.047	<0.002	0.0029	0.0026
	0.139	0.017	0.0011	0.016	0.016	0.026	<0.002	0.0035	0.0028
Average	0.1360	0.0143	0.0012	0.0130	0.0157	0.0393	<0.002	0.0031	0.0026



Anderson-Darling Normality Test	
A-Squared	0.19
P-Value	0.613
Mean	0.85333
StDev	0.10017
Variance	0.01003
Skewness	-0.298175
Kurtosis	*
N	3
Minimum	0.75000
1st Quartile	0.75000
Median	0.86000
3rd Quartile	0.95000
Maximum	0.95000
95% Confidence Interval for Mean	
0.60451	1.10216
95% Confidence Interval for Median	
0.75000	0.95000
95% Confidence Interval for StDev	
0.05215	0.62952

Fig. 11. A graphical summary of carbon content.

Students should be encouraged to understand the cause of the variation present in the carbon content. Upon reviewing the test procedure, students should make the following observations: (1) A small amount of the polished surface was removed prior to performing the spectrometer test. (2) The amount of material removed is inherently variable in the three different locations as shown in Fig. 5. This would contribute to the variations in the surface depth of each sample. (3) Due to the nature of how this test was performed, it is plausible that the data represent the surface properties of the shears and not the bulk material properties [17, 18]. Students can then be encouraged to investigate the manufacturing processes that might lead to the change in the surface properties. The case hardening process is a possible explanation for the inherent variation of surface concentration of carbon at different depths.

Utilizing a simple and cost-effective case hardening method such as pack carburization, carbon diffuses in accordance with Fick's Law into the microstructure of the material. As the depth of the material from the surface increases, the amount of carbon present is known to decrease. Surface carbon content can reach upwards of 1% at the surfaces but at depths on the order of 10^{-4} mm, the concentration quickly reduces to 0.75% and eventually levels out to the bulk properties of the material [20].

With an understanding of the case hardening process, students may conclude that the large variations present in the spectrometer results is in fact due to the inherent variations caused by the case hardening process and the testing location depth. Those results do not represent the mass percentages of the chemical elements in the bulk material. This hypothesis aligns well with the data gathered by Schneider and Chatterjee from their hardening tests which shows typical case depths of 1.5 mm [20].

5.2.2 Spectrometer Analysis: Manganese Content

Manganese is a key component of stainless-steel and medium and high carbon alloy formulations. In fact, in many stainless steels and medium and high carbon alloys, the manganese content is found to be 0.6% or even higher [21]. The manganese content detected by the spectrometer ranges from 0.283% to 0.320% (Table 3), which is well below what would be expected to be present in a stainless steel or medium or high carbon steel. The max 95% confidence interval for the mean shown in the one sample T-test results in Table 4 (0.3577%) also confirms the material is not a stainless steel nor medium or high carbon steel grade since it is well below an expected value of 0.6%. By eliminating the

Table 4. One sample T-test descriptive statistics of the Mn content

μ, Mean	Standard deviation	95% CI for μ (min)	95% CI for μ (max)
0.3067%	0.0206	0.2556%	0.3577%

Table 5. One sample T-test descriptive statistics of Si content

μ, Mean	Standard deviation	95% CI for μ (min)	95% CI for μ (max)
1.066%	0.1058	0.7971%	1.3229%

stainless steel grades as well as the medium and high carbon alloy grades, the low manganese content suggests that this material must have a low carbon content and further reinforces the theory that a case hardening process was applied to increase the surface concentration of carbon. However, further testing of the bulk material would be required to confirm this inference since the spectrometer results only reflect the surface properties [18, 20, 21].

5.2.3 Spectrometer Analysis: Silicon Content

The presence of other alloying elements at high percentages is also of interest when attempting to fully characterize this material. One interesting element detected by the spectrometer is silicon. Table 5 shows the statistical analysis results of the silicon content.

Students will be required to understand what inferences can be made from the present data. Silicon as an alloying element in steels increases strength, hardness, and corrosion resistance but to a lesser extent than manganese. Usually only small amounts of silicon ($\sim$ 0.20%) are present in steels but the quantities of silicon detected by the spectrometer are clearly higher than that level, which range from 0.98% to 1.18%. Since the silicon level in the material is high and exhibits a large variation as shown in the results from a one sample T-test (Table 5), it can be deduced that this element was not alloyed into the material. This will lead students to evaluate potential manufacturing processes that could increase the silicon content. In steel castings, up to 1.00% of silicon is commonly present. Therefore, it may be hypothesized that the silicon was introduced during a casting process.

There are many types of casting process but the traditional method is sand casting. Sand casting is the most prevalent of all the forms of casting, which uses silica sand (SiO_2) as the mold material. This sand is inexpensive, reusable, and believed to be the source of this higher-than-normal level of silicon detected by the spectrometer. With the knowledge that the spectrometer results represent the surface properties, it would be expected that the variation in silicon would be quite high as this process is inherently difficult to control. The presence of silicon is one of the most revealing elements in the spectrometer results. The presence of the dendritic structures in the failure image (Fig. 7) also supports the hypothesis that the process used was sand casting. Dendritic structures are commonly formed during casting processes [17].

Table 6. One sample T-test descriptive statistics of Cr content

μ, Mean	Standard deviation	95% CI for μ (min)	95% CI for μ (max)
7.980%	0.587	6.5228%	9.4372%

5.2.4 Spectrometer Analysis: Chromium Content

One critical element detected by the spectrometer is chromium. Table 6 shows the statistical analysis results of the chromium content.

Firstly, students will understand expected chromium levels in common stainless steels. The minimum content of chromium in a regular stainless steel should be 10.5% [17, 18]. The spectrometer results show that the chromium content only varies from 7.49% to 8.63% with a mean of 7.980%. With this knowledge, students can eliminate stainless steel as a possible material for this tool. This is noteworthy because this inference contradicts the label on the shears as shown in Fig. 2.

Students will then be directed to find a possible source of the chromium content. Other than stainless steels, there are no other steel alloys that would exhibit this high-level chromium content. For example, a common steel grade that contains chromium as an alloy may have only 1% or less chromium in content [17, 18, 21].

Students will then be asked to understand the processes that would result in a high surface concentration of chromium. From here, there are a number of options that students can choose to investigate.

At first, it is possible that the manufacturer employed chromizing by chemical vapor deposition or hard chrome. However, both methods were unlikely to be chosen by the manufacturer because they are costly. Therefore, it is reasonable to assume that the manufacturer chose a more cost-effective processing method consistent with other less expensive options such as sand casting, case hardening, and plain carbon steel chosen for making this product. It is logical to assure that the manufacturer's major goal in selecting materials and manufacturing processes for the shears was minimize the manufacturing cost. Chrome plating is a low-cost chromizing process which was likely chosen by the manufacturer. In addition, hard chrome plating is expected to have a high HRC value of up to 70 [17]. Chrome plating is performed by first plating the metal with copper, then nickel, and then chromium. This also explains the presence of copper and nickel in the spectrometer results. Although nickel is commonly added to steels to increase hardenability, copper is not a common alloying element. It is possible that nickel was added as an alloying element but usually the manganese content would be higher in order to achieve a higher quality steel [17].

One obvious concern is that this hypothesis (the shears were made of a plain carbon steel instead of a stainless steel) contradicts with the label on the scissors. Chrome plating a low carbon steel would not result in a stainless steel but would be a way for a manufacturer to mislead potential customers by making them think that they are purchasing a high-quality stainless-steel product. Product labeling is strictly controlled in many countries but not universally so. This aspect of the project allows students to explore product labeling requirements from an international perspective as well as challenge their initial assumptions made based upon the labeling.

6. Student Recommendations for Failure Corrective Action/Product Improvement

Through this project, students are expected to know that statistical process control and basic statistics are powerful tools to understand the effects of a manufacturing process on the performance of final products. This understanding will allow future engineers to choose the most suitable manufacturing process and optimize the process parameters to fabricate products with desired properties. After completing above analysis, students will be required to summarize and describe the processes that were employed to manufacture the shears, their material, and the cause of failure and recommend changes to avoid such failure. This assignment will allow them to get a deeper perspective on the process-structure-property-performance relationship of the studied product.

From our results, the following conclusions can be made and potential future work can be shaped:

1. SEM imaging displays the martensitic grain structure and provides evidence of a brittle fracture mode and porosity.
    (a) The failure could be due to cracks originating from the surface resulting from porosity, which is known to be detrimental to the materials surface finish and ductility [17]. The porosity could be caused by entrained or dissolved gases and/or shrinkage of the solidified metal.
    (b) The failure could be due to discontinuities generated in the casting process such as hot tears, a common defect in castings. Hot tears occur when castings cannot shrink freely during the cooling process because of the constraints applied by the mold or core [17].
    (c) The brittle failure mode was confirmed by the SEM images at higher magnifications. Those images revealed more obvious signs of the brittle fracture such as more evidence of fracture developed along the cleavage planes.
2. The presence of voids and dendritic structures provide evidence that a casting process was employed in making the shears [17].
3. The large variation in the carbon content indicate that the spectrometer results only reflected the surface concentration but not the bulk properties of the material. This large variation is possibly caused by the application of a case hardening process.
4. Low levels of manganese content suggest that the material of the shears is a low carbon steel. This also supports the hypothesis that a case-hardening process was applied during the fabrication process.
5. The high levels of silicon content suggest the use of sand casting in manufacturing the shears.
6. Chromium content is too low for the material to be classified as a stainless steel and too high to represent a medium or high carbon alloy steel. The chromium must be introduced by surface treatment such as chromium plating. The application of chromium plating is further supported by the detected copper and nickel in the material.

In summary, students may deduce that the shears were made of a low carbon steel and the manufacturing process included a sand-casting process followed by case hardening and chrome plating.

Students are then required to review specifications for low carbon steels. The most common and cheapest option available is a plain carbon steel designated as AISI 1008 of ASTM A366. AISI 1008 steels only have a specification for maximum manganese content and typically will exhibit manganese levels similar to the material studied in the present project ranging from 0.30% to 0.50% [22]. Moreover, the AISI 1008 steels are cheaper than most other types of steel available on market [21]. This would align well with a manufacturing philosophy of targeting cost instead of quality. However, without further testing on the chemical composition of the bulk material, it is impossible to conclude with a high degree of confidence what the material actually is. Students may include this disclaimer in their conclusion and suggest what other types of testing is necessary to fully characterize the material.

Students can also make recommendations to improve the quality of the product. For example, sand casting mold chills may be introduced to increase the cooling rate in critical regions [18]. Students may also suggest redesigning the part geometry to decrease the stresses generated in the failure region and reduce the stress concentration.

Students may also propose different materials and processing methods for this product such as 400 series martensitic stainless steels and the application of a forging process [17]. This type of stainless steel is a common choice for cutlery due to its high hardness and corrosion resistance. Utilizing a forging process would align the grain structure of the material with the geometry of the part, which would result in optimal material properties in high stress regions. However, these changes will increase the manufacturing cost so students would need to carefully consider with a market analysis of the product. At the end of the semester, each student team will make an oral presentation about its findings to the entire class and document the project in a final report.

7. Conclusion

This paper presents a PjBL case study that can be done in either a face-to-face classroom or a virtual environment. The presented educational model could be used directly in an existing course, since all the data have been provided or it could also be adapted for different contexts by replacing the existing data with a new data set.

Given results obtained from the Rockwell C hardness testing, spectrometer testing, and failure site SEM imaging, students are required to perform statistical analysis on those results to determine the material of the product, its manufacturing process, and the root cause of its failure. This PjBL case study allows the students to understand the cross-disciplinary nature of product quality as an intersection of materials science, manufacturing engineering, and engineering design. This project and the employed PjBL methodology will expose the students to material characterization techniques, manufacturing processes, statistical analysis methods, and can help them develop professional skills such as teamwork, communication, problem solving, and project management. In summary, this case study provides a pedagogical framework to bridge the gap between materials science, manufacturing, statistical analysis, and professional skills. However, this paper does not include an analysis of student feedback to identify the students' perceptions of the presented learning activities. In the next phase, the authors will conduct qualitative research to evaluate the students' reactions employing semi-structured interviews, focus groups, as well as other assessment tools developed by Baker and Liu [23, 24]. The students will have to present their work before the class and submit a final report. The oral presentations and final reports will allow us to evaluate the course effectiveness and gauge student learning to promote student engagement and learning outcomes. A larger set of student feedback questionnaire data and student work samples will facilitate the assessment of the effectiveness of the presented educational model.

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