A Multi-variate Analysis of Fir Tree Mounting Plastic Hole Fasteners

by

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Abstract

The purpose of this paper is to report the results of a capstone project for the Milwaukee School of Engineering's (MSOE) Master of Science in Engineering (MSE) program. The contents of this paper discuss the overall purpose of the project and its justification in its field of research. In addition, the relevant published literature and final project results are investigated in detail. The general purpose of this project was to perform an analysis of various kinds of plastic hole mounts in multiple mounting situations that mimic common scenarios found in real-world applications. These plastic mounts or fasteners are associated with numerous applications in larger product assemblies such as automobiles. In the project investigation, the fastener's material, size, and moisture content were varied along with the size and geometry of the hole it was mounted in. These variables were tested in combination to measure the force required to mount the fastener (push-in force) and extract it (pull-out force) from the same hole. The collected data were then exported for statistical analysis within Minitab®. Applying a Multiway Analysis of Variance (ANOVA) general linear model approach, a residual analysis was conducted to determine if the data met the initial requirements for a Multiway ANOVA. A multitude of data outliers—the result in part of manufacturing defects—contributed to a dubious analytical result (i.e., extremely high push-in force values but negligible pull-out force values). All outliers were removed, and data were again tested for compliance with general linear model assumptions. Furthermore, Ryan-Joiner normality testing—with its powerful predictive ability in association with large data sets and long-tailed distributions—was employed and indicated normally distributed data. Regression models were then developed for push-in and pull-out forces, and a Box-Cox transformation was applied to each model, resulting in adjusted R-square values of 84% and 67% for the push-in and pull-out models, respectively. This result indicates that the models account for most—but not all—the behavior of the forces. Recommendations are also offered to improve the accuracy of the models, including the use of automated testing equipment, further standardization and conditioning of all tested parts, and the use of enhanced part identification methods, along with the need to investigate part geometric deformation with respect to part resin, as well as statistical noise associated with manufacturing inconsistencies. The primary goal of this research is to inform current and future manufacturing and design of similar products in this area. This knowledge will help mitigate unexpected failure of these products as they are used in the field and reduce waste via the manufacturing process.

Table of Contents

List of Figures

List of Tables

Nomenclature

Symbols

e – mathematical constant

M_c – Moisture Content

RH – Relative Humidity

λ – Box-Cox Transformation Value

Abbreviations

ANOVA – Multiway Analysis of Variance

CSV – Comma-Separated Values

EW – Electrical wholesaler

FEA – Finite Element Analysis

HT - HellermannTyton

MSE – Master of Science in Engineering

MSOE – Milwaukee School of Engineering

OEM – Original equipment manufacturer

UV – Ultra-violet

VP – Vice president

Introduction

Consumer products within the realm of manufacturing require extremely precise and niche standard adherences. These standards are typically for final products to meet safety, environmental, or even health standards [1, 2]. As a result, rigorous testing is required to ensure that all components of an assembled product are up to specifications and meet the certification requirements before going into final production. Furthermore, individual plastic components and parts can be essential pieces of much larger product assemblies, such as cars, boats, planes, and military equipment. Therefore, the associated testing can be even more important when compared to other supplementary pieces of assembly. However, the material properties of plastics can vary widely based on their use case, geometry, and level of degradation [3, 4, 5, 6]. As a result, specific use case material properties are relatively unknown or hidden behind proprietary barriers of businesses, making general application in the public difficult.

Additionally, due to this large variety, there are a multitude of different plastic grades used to fit the needs of individual applications. For example, components that will spend most of their lifetime outside should be made of an ultra-violet (UV) ray resistant polymer [7]. Extreme temperatures also require special resins, so that products last the lifetime of their larger assembled product [8, 9]. With this taken into consideration, recent research investigates how the base plastic will incorporate additives that may drastically alter the performance of the plastics [10].

A more common use case of plastic components is mounting brackets that are inserted into surfaces with pre-existing holes. These products are commonly used in the automotive, solar, original equipment manufacturers (OEM), electrical wholesale (EW) and aeronautical industry to aid in the routing of wires and other electrical components throughout the assembly. Figure 1 shows what a typical part for this mounting application can look like. Unfortunately, cable management within the scope of a much larger project is often an afterthought for project planners. For this reason, it is imperative that a wide range of options are readily available to fit the project's needs with minimal cost and customization. Within these products, there are a few common design types that define this area of application. The most popular type of mount is for standard round holes, but there are also mounts for oval-shaped holes and even products with different colors that are used for identification [1]. These mounts resemble a fir tree in appearance, and as such, they are referred to as "fir tree" mounts.

Figure 1: Picture of a Typical Plastic Hole Mount for an Oval Shaped Hole [1].

Historically, these kinds of products were constructed out of metal stampings that were then bent to the appropriate shape and length [1]. While metal materials exhibit excellent mechanical strength and resilience, they are susceptible to corrosion and other forms of degradation depending on the use case. More specifically, applications where metal parts are exposed to weather or extreme temperatures have a reduced product lifespan. Because of this possibility, their plastic counterparts are becoming an increasingly attractive option to eliminate the chance of corrosion or product failure with the added benefit of reduced production costs. When compared side by side, plastic parts are typically less expensive to produce, quicker to install, and lighter in weight [1, 11, 12]. This rapidly accelerating trend within the industry further highlights how important it is to quickly verify and test new parts for various compliances and material property standards.

The purpose of this capstone project was to test a wide variety of these mounting solutions that vary by the diameter of the mounting hole, the shape of the mounting hole, and the type of plastic used for the mount. These parameters were paired with varying levels of moisture content within the component part that drastically alter performance in both push-in and pull-out scenarios [13, 14]. This testing was be used not only to verify industry material and safety standards, but mainly to identify common performance characteristics. For example, identifying plastic resins that minimize the push-in force while simultaneously maximizing pull-out force in all environments possesses great business value. A general linear model's predictive power would drastically cut the amount of testing time required to bring a part into full production. A further benefit would be the reduced amount of waste from materials used in the testing process. All parts used in this project were tested for push-in and pull-out strength and then analyzed via Minitab® software for normality. After data testing and cleansing, Minitab® will be applied to create a general linear model that will then be cross-referenced to the recorded data for accuracy.

Background

HellermannTyton (HT) is no stranger to the world of polymers and engineering. The company was founded in the mid-1930s in Hamburg, Germany in the wake of a brilliant cable management solution [1]. There was a large need to preserve existing and new electrical cables from fraying near the ends and other connection points, so Paul Hellermann developed and patented a three-pronged rubber binding system to contain areas prone to fraying [1]. He naturally expanded the business into the surrounding areas of market specialization in cable routing and management. As time progressed, the company thrived during World War II and expanded business overseas into Canada in 1955. As electronics took off in the 1960s and 1970s, so did HellermannTyton business with an increasing number of office and manufacturing facilities being opened worldwide. Today, HT operates in 39 countries and specializes specifically in custom made plastic injection molded parts for identification and cable management solutions [1].

Despite HT's global success over time, one constant in today's rapid business market is an expressed need to accelerate the development process of new products to meet customer demands and keep up with the fast pace of the industry. Most of a part's development time is spent on the testing of materials used for safety and environmental standards that are required by a customer and safety organizations [15]. A sizable number of specifications involve product performance in a wide variety of use cases, but more importantly, their resistance to degradation in those use cases over time. This is precisely why this project was selected. Developing a predictive performance model for even a single class of products at HT would greatly decrease the amount of testing and design time required. This would allow the company to remain competitive in the custom parts marketplace in terms of cost and product development time.

Unfortunately, studies on large scale and general application information in this field are few and far between. Because of the dynamic and complex nature of polymer material behavior, specific use case models need to be developed on a case-by-case basis [16, 17, 18, 19, 20, 21]. Additionally, finite element analysis (FEA) of these systems is not reliable on such a scale [15]. Engineers struggle to find an acceptable model that adequately represents the complex geometry of the cutting-edge parts HT sells. The development of an analytical model will serve as a strong starting point for HT's engineering department for future testing and design considerations without randomly guessing how the product will perform or relying on often inaccurate computer-based models.

Review of Literature

The field of research regarding polymer fasteners has been rapidly evolving and receiving increased levels of attention since the mid-1970s. The increasing interest stems directly from the utilization of polymers in manufacturing settings as alternatives to historically metal-based components. Additionally, polymers are an excellent addition to many biomedical components as a strengthening mechanism that also reduces the weight and cost of critical medical devices [18, 22, 23, 24]. As the dependence on these polymers has increased, the desire to understand more complex and specific applications has risen concurrently. The content of this research can primarily be defined by the approaches used concerning viscoelasticity [6, 25, 26, 27]. According to John J. Aklonis of the University of Southern California and William J. MacKnight of the University of Massachusetts: "Viscoelasticity is a subject of great complexity fraught with conceptual difficulties" [6].

Unfortunately, a common theme in these academic works is a failure to apply the advanced behaviors of viscoelasticity to more general use case scenarios. Researchers tend to focus on highly specific areas that may be useful for a narrow range of readers, but inevitably fail to meet a more general appeal. For example, there are studies that focus on viscoelasticity in medical situations, such as the modeling of artificial hinges in joints and muscular activation [18, 23, 24]. Logically, research has also been conducted on using polymers as additives to conventional construction materials to assist in long term strength and rigidity in both medical and commercial applications [17, 21, 22, 28]. This research is not directly linked to the experimentation outlined in this paper, but it does highlight the necessity for exploration and modeling in this field.

Thankfully, the state of research has not gone unnoticed. To bridge the gap in literature, there have been multiple attempts to compile books that explain these complex topics in layman's terms to make it more accessible to the public [3, 6, 29].

Much of the material is written in the context of manufacturing by experts in the industry [17, 30, 31]. As a result, most of the cutting-edge knowledge is locked behind proprietary barriers and other legal logistics, which results in the bulk of publicly available information coming from trial and error using these materials. However, even when the material is simply explained and tested via trial and error, the polymers are rarely tested in standalone application settings such as those outlined in this paper.

Furthermore, another issue that has been pointed out in the research is the lack of predictive data models. Once again, sources will generally confirm widely known mechanical properties, but neglect to recommend or create a model for predicting the behavior of the polymers when multiple degradation or fatigue factors are being applied [17, 19, 20, 21, 25]. Proprietary attempts of finite element analysis (FEA) at HT have proven unfruitful thus far. This method of computer modeling may find utility for larger products and models, but for the small geometry present in most products manufactured by HT, computer models produce widely inaccurate results.

Consequently, current future options for research are limited at this time. Researchers argue that truly accurate models must begin to focus on chemical and molecular interactions of individual plastics to be widely applicable and accurately modeled [19]. However, mathematical models presented as a basis for this line of research fail to unify and relate the complex equations needed to be widely applicable and accurate [19, 20]. With that in mind, much of the research conducted in this capstone project was investigated in the absence of specific literature related to the proposed use case. Instead, a critical analysis of the generalized findings in the field was used to inform potential behavior of the generalized linear model.

Methods

This project started with the conditioning of the moisture content used in each of the parts that were to be tested throughout the course of the project. Conditioning in this scenario is the process of introducing a predetermined amount of moisture to each of the plastic parts to be tested. This is done by inserting the parts into a large humidity and temperature-controlled chamber, so moisture can gradually integrate with each of the parts. Typically, it takes around 18 hours for parts to be fully conditioned to the appropriate moisture level. For this experimentation, each batch of parts was conditioned for a total time of 24 hours at a temperature of 80 degrees Celsius. Because of limited size and time available to condition parts, the overall conditioning and testing process were done over the course of two weeks. Most importantly, each of the three levels of moisture content were done independently for all parts to minimize the time between conditioning and testing. This was done to reduce the possibility of the moisture content deviating from the conditioned level. Subsequently, all parts were conditioned to the lowest moisture content required, removed, and then tested. Next, a new batch of parts were conditioned to the mid-tier moisture content, removed, and then tested. This process was repeated for the highest moisture content level. There was a total of six different parts that were tested over the course of this project. For each humidity level, 90 of each part were conditioned so each of the three selected hole sizes could be tested with 30 samples. Therefore, a total of 270 pieces were required for each part in total for the duration of the experiment. Thus, the overall sample size for this experiment was 1,620. The selected moisture levels followed the range of normal operating conditions as specified by HT [15]. Figure 2 is a visual representation of the researched moisture content curve derived from other testing of the PA66 resin material. The tracked moisture content (M_c) is described by Equation (1):

$$M_c = -0.953617 + 1.02641 * e^{(0.02183*RH)}. \quad (1)$$

Normal operational range for products applies when M_c is between the values of 1 and 3. Therefore, the three testing levels selected for this project were when M_c was equal to one, two, and three. The values for M_c were then inserted into Equation (1) and used to find the relative humidity (RH) values required to condition the parts in a humidity chambered supplied by HT on site.

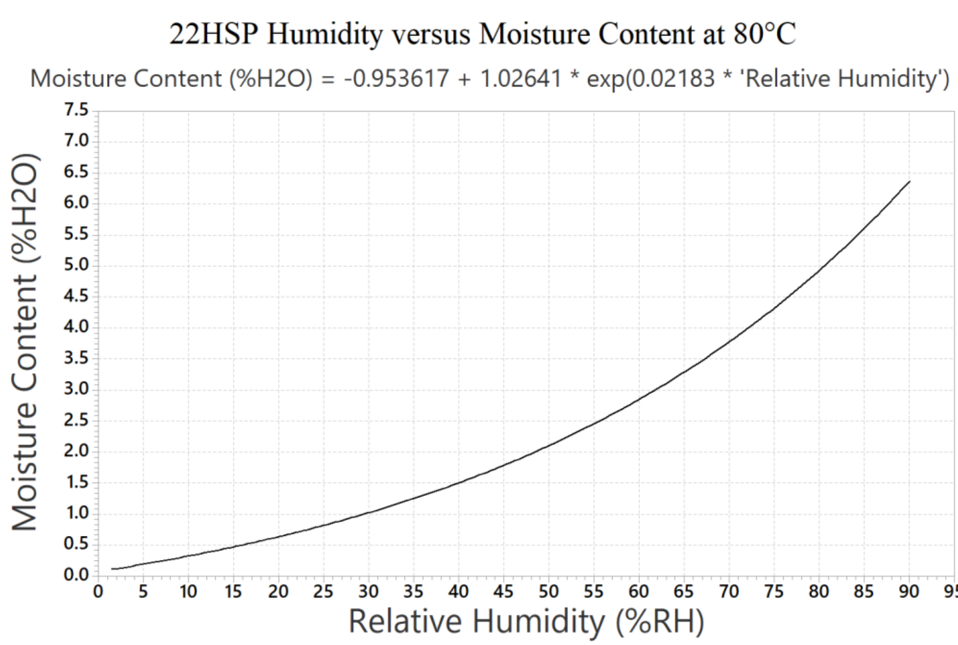

Figure 2: Typical Humidity versus Moisture Content Curve for PA66 Resin [15].

For analysis, all the preliminary testing information was exported out of the testing software and into a comma-separated values (CSV) file in Microsoft Excel ®. Testing information consisted of all variations of the variables used in this experiment. The main differences in testing order and grouping were the humidity level, or moisture content, of the parts that were tested. This was due to the conditioning time and space necessary to achieve the desired level of moisture within each part.

Once the data were exported from the testing software and grouped appropriately, they were then imported into Minitab® statistical software for preliminary analysis utilizing a Multiway Analysis of Variance (ANOVA) general linear modeling technique. Initial review of the data consisted of residual analysis to validate that the statistical model met the assumptions for the Multiway ANOVA. There are three primary assumptions when conducting a Multiway ANOVA test [32]. Firstly, the error terms for each factor level in the experiment must be normally distributed. A normally distributed set of data has an even distribution of data points both above and below the mean of the respective data. Secondly, the distributions of each level must not be biased by time order and be without major data anomalies or outliers. Finally, the residuals of the data must be independent from one another. For this project, the author exercised careful consideration in the sampling population to ensure no internal dependencies existed throughout the course of testing. Samples were selected at random from a large manufacturing run of the selected parts with no prejudice to the quality of individual parts.

Most notably, the normal probability plot was utilized to check the error terms for normality and to visually inspect the dataset for outliers. As seen in Figure 3, there were obvious outliers present that negatively impacted the data analysis and any final conclusions made from the data. Some examples of outliers have been circled in red in Figure 3.

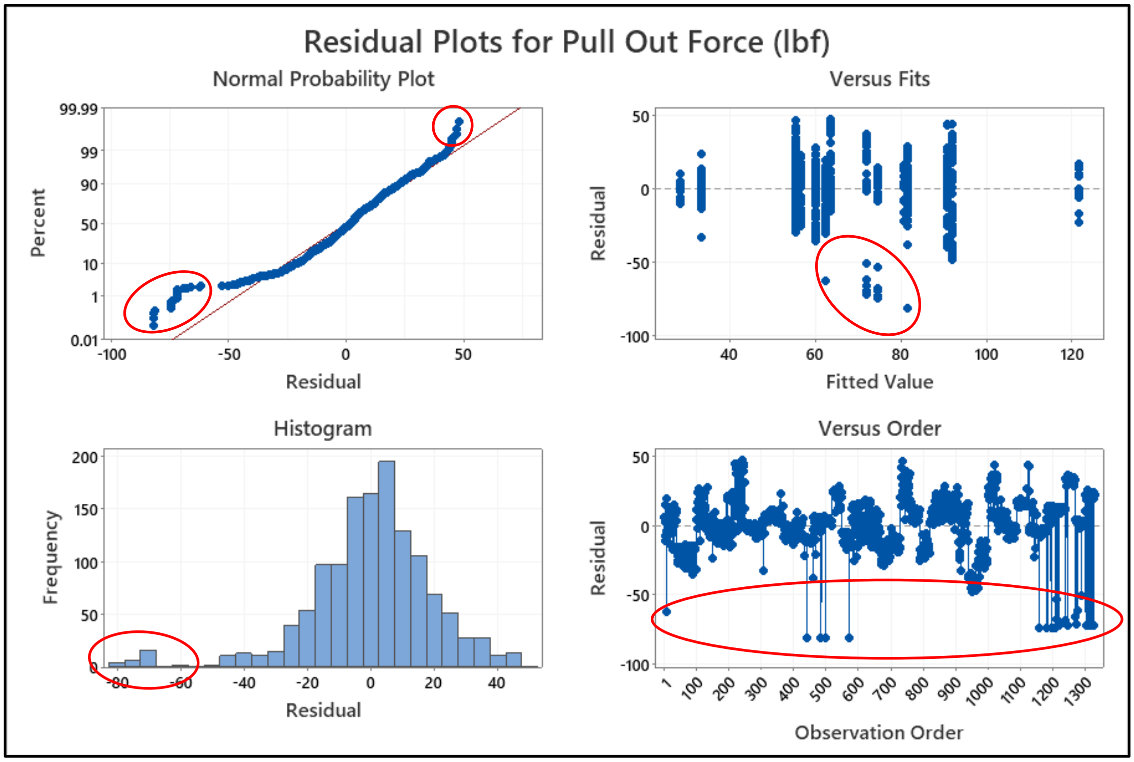

Figure 3: Residual Plot for Pull-Out Force Before the Removal of Outliers.

Thankfully, any potential outliers were noted in the testing software during data collection, which made them easy to identify in the source information. After investigation, it was learned that unsuccessful tests, and thus outliers, were caused by parts deflecting from the mounting hole when being pushed down. This occurrence was most frequent when the variables of moisture content and hole diameter were at their maximum and minimum, respectively. This event was further exacerbated when the variables were tested in tandem. A consequence of the deflections on the data was an extremely high value for push-in force required to apply the part, followed by no force required to extract the part. As a result, even if the deflection and ineffective test was not noted directly at the time of testing, the data itself could be used to easily identify any testing failures and outliers.

However, not all outliers in the data are because of this occurrence. The author suspects that defects in the manufacturing process in combination with a slight deviation in the angle the parts were applied to the whole may account for other outliers present in the data.

In the plastic manufacturing industry, parts are mostly produced in mass via large metal molds commonly referred to as tools. Hundreds of parts can be produced simultaneously from these tools. However, parts that do not receive enough or receive too much plastic during the injection molding process may experience significant alterations in the product's strength because of the thermal degradation to the plastic resin [15]. Furthermore, no testing apparatus is perfect in replicating a task repeatedly during experimentation. As it relates to this project, the author had to manually insert and remove parts before and after a test was conducted. Even though a robotic arm and mounting plate were used to administer the test, the resting angle of the part as it was inserted into the mounting hole may have deviated slightly due to the author's application.

Additionally, an entire part that was tested was removed from the final data model. This was done because the geometry of the part tested was not consistent with the others in the testing group. The shape of the branches on the fir tree were hollow in the center instead of solid when compared to the rest of tested parts. Figure 4 shows an example of the geometry inconsistency. Preliminary testing included this part solely as an extra variable to explore, but ultimately it negatively impacted the residual analysis so much, any potential for a linear model was negated. Therefore, it was removed from the information.

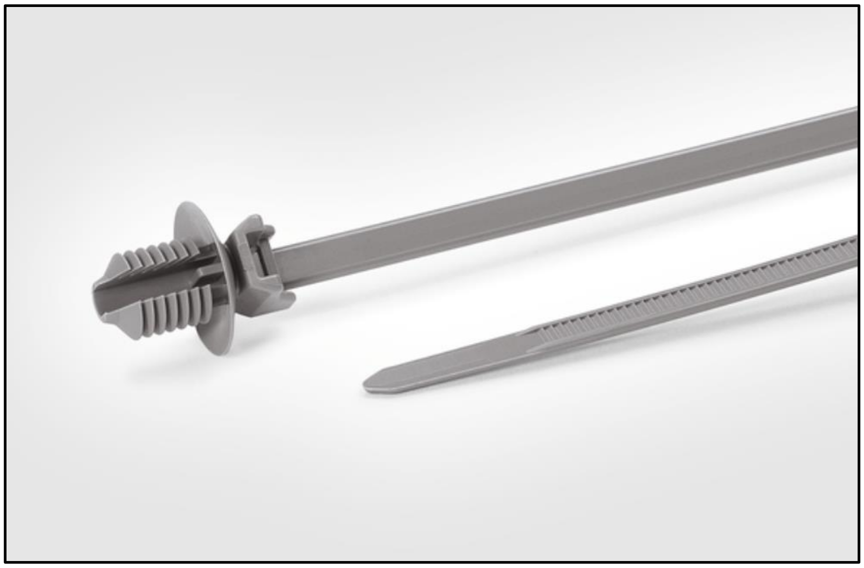

Figure 4: Fir Tree Mount with Non-Standard Geometry [1].

Once all outliers were identified, they were manually removed from the testing data. The data were rectified by simply removing the outlier row from the source data within Minitab® until no more noted outliers were present.

Once the data were cleansed, it was then retested within Minitab® for the general linear model assumptions and the normality plot was visually compared to the uncleansed data. Figure 5 shows the results after the removal of the outliers from the initial testing data.

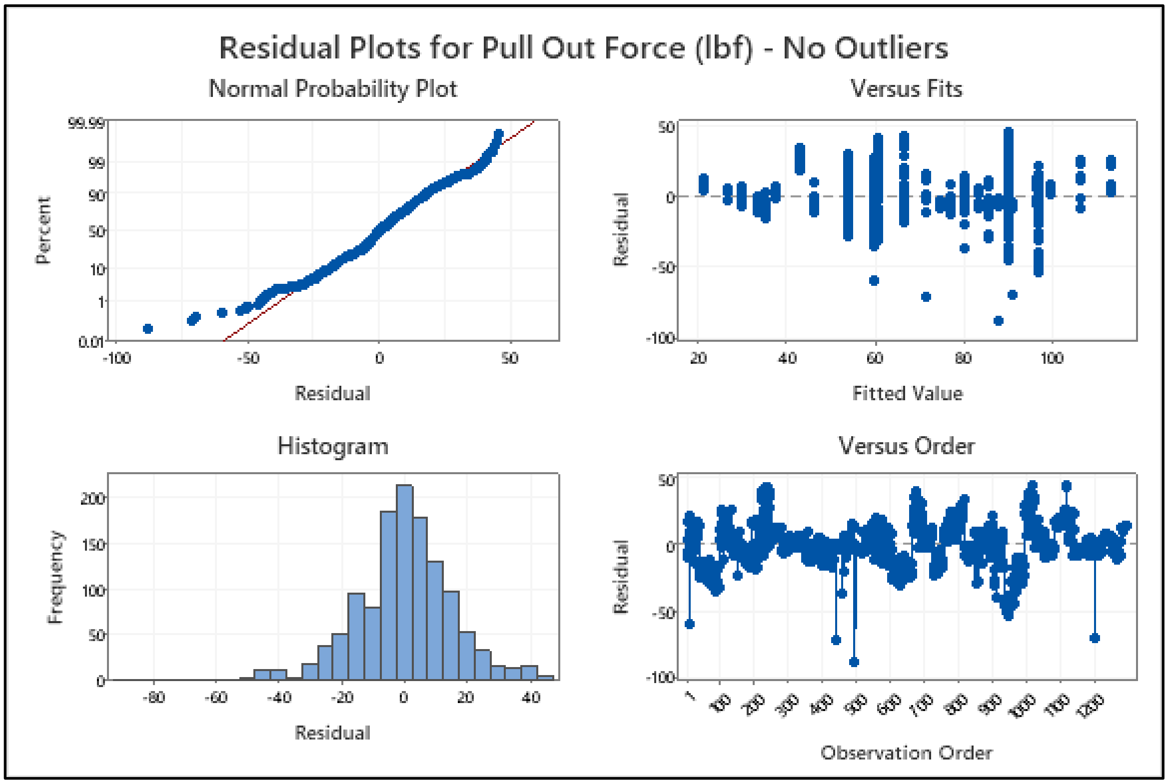

Figure 5: Residual Plot for Pull-Out Force After the Removal of Outliers.

In addition to visual inspection, empirical methods were also used to test the data. The Anderson-Darling (AD) test was originally considered for normality testing but yielded hyper sensitive results when dealing with the large data sets seen in this project. Any residual deviation towards the tails of the data sets were over exaggerated causing empirical testing to suggest the data was non-normally distributed. With conflicting visual and empirical testing, the Ryan-Joiner (RJ) test was used instead of the AD test to good effect. The RJ test was used in this experiment because of its more powerful predictive ability when dealing with large sample sizes and long-tailed distributions of data [33]. Thus, the RJ test had a greater ability to accurately detect outliers in manufacturing-based data when compared to other normality tests. Specifically, the RJ test is more successful at monitoring data that produces large outliers from time to time in addition to data sets that follow a non-normal distribution curve such as those seen in time-to-failure strength tests [34]. The RJ test is not appropriate to monitor data sets that may have an exponential or gradual shift in the distribution curve. In Figures 6 and 7 residual plots and RJ tests for the pull-out and push-in forces can be seen, respectively. Note that the RJ coefficient in both plots is near the value of 1, indicating the data are likely normally distributed [34, 35, 36].

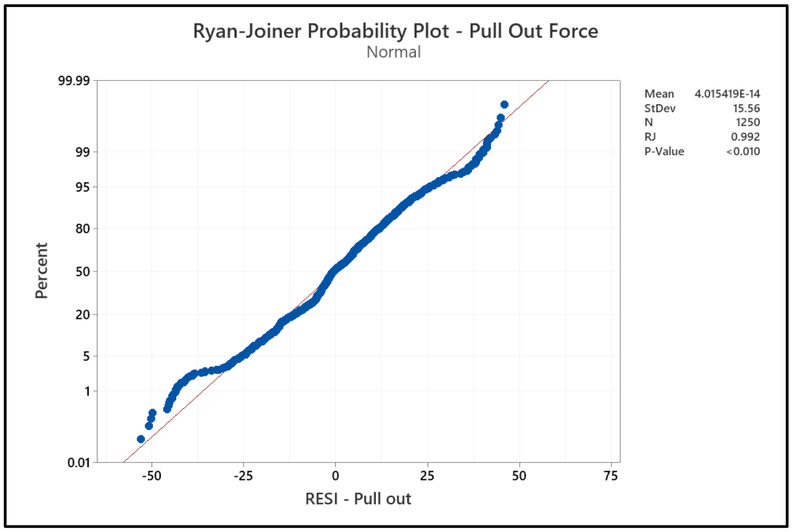

Figure 6: Ryan-Joiner Residual Plot for Pull-Out Force.

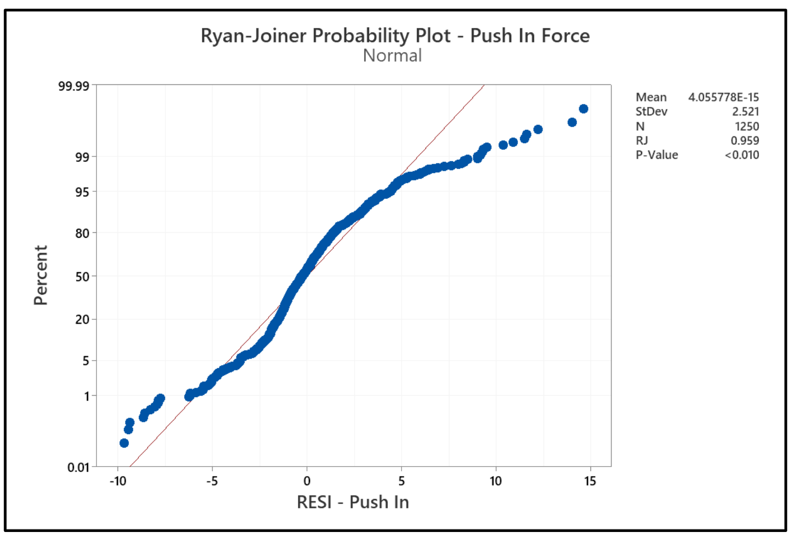

Figure 7: Ryan-Joiner Residual Plot for Push-In Force.

Once satisfied with the initial data cleansing and testing for normality, the author created models for push-in and pull-out forces separately while including all variables that were tested. The models were created by utilizing the general linear model platform within Minitab®. To explore the data further, various combinations of variables were included and excluded from the models to reduce the amount of variance to the linear trend. This was identified by analyzing the Minitab® analysis of variance output for each model and its factors as seen in Table 1 and noting its “lack of fit” p and R-squared adjusted values indicated in Table 2. Firstly, the p-values for each of the models were used to determine if the model itself was statistically significant. If the p-value was less than an alpha value of 0.05, the entire model, and or the individual factor, was statistically significant to the study. Furthermore, the adjusted R-squared value was considered for each model. The adjusted R-squared value reflects how much of the variation in the data is accounted for in the model. In other words, it indicates enough factors have been considered to describe how much, and how well, the system that is being studied is modeled. Conversely, for the lack of fit tests, a p-value above the alpha value of 0.05 indicated the model follows a linear fit.

At first, all the variables were included in the general linear model and analysis of various testing. Next, the adjusted R-squared value was noted to track how well the combination of variables described the system. Furthermore, each variable's respective p-values were noted for how much significance, or effect, it had on the model’s behavior. Any variables that had a p-value greater than 0.05 were then removed from the model one by one and in combination and retested. The model was then rerun to find the new adjusted R-squared value. This process was repeated for all combinations of variables with the goal of maximizing the adjusted R-squared value.

Additionally, a Box-Cox transformation was applied to the data to account for some of the curvature present in the data and the residuals were not found to be non-normally distributed. This curvature can be seen visually in Figures 6 and 7 towards the "tails" of the data set. The gradual sloping towards the ends of the data sets can be fit to a linear model using this transformation technique with the data set being assigned a corresponding transformation value of λ. A λ value of 1 is the standard for a perfectly linear set of data, while assigned values of λ that are less than 1 indicate that the data set is concave or downward facing. Conversely, values greater than 1 indicate a convex or upward facing set of data [36, 37].

Results

The goal of this project was to form conclusions based on all the tested variables to provide the most comprehensive and widely applicable data to HT's engineering and product development departments. Initial analysis of the data after testing, both tabular and visual, indicated that there were a significant number of outliers present in the data that were affecting overall model performance. As a result, the outliers were manually removed from the data and push-in and pull-out models were retested for accuracy. Nearly all variables saw an increase in their individual p-values post outlier removal. Additionally, both models saw improvements to their adjusted R-squared values that indicated more comprehensive and explanatory models for this system. In a pursuit to maximize each model's adjusted R-squared value, variables were omitted from the data model and retested following a similar process. Variables were excluded and included for testing based on their individual p-values during analysis. Fortunately, no tested combination of variables yielded a higher adjusted R-squared value than all variables tested simultaneously.

To further maximize the adjusted R-squared value, a Box-Cox transformation was applied to each data model to account for some nonlinearity seen towards the tails of each data set. The λ values for push-in and pull-out models were .377196 and .367873, respectively, with full detail available in Tables 1 and 2.

Table 1: Box-Cox Transformation Details for Push-In Model.

Factor coding	(-1, 0, +1)
Rows unused	30
Box-Cox transformation	
Rounded λ	0.377196
Estimated λ	0.377196
95% CI for λ	(0.324696, 0.429696)

Table 2: Box-Cox Transformation Details for Pull-Out Model.

Factor coding	(-1, 0, +1)
Rows unused	30
Box-Cox transformation	
Rounded λ	0.367873
Estimated λ	0.367873
95% CI for λ	(0.243373, 0.493373)

Expanding on the details in Tables 1 and 2, two model runs were conducted for the analysis of this project. One run was conducted on the push-in force required to apply the part to the selected mounting hole. The second run was created on the pull-out force required to extract that same part from the chosen mounting configuration. The difference in force required is rather substantial for nearly all the configurations used across testing. Typically, the required push-in and pull-out force required for a single test averaged around 8.4 newtons and 68.8 newtons, respectively. Tables 4 through 6 show the model summaries and analysis of variance for both push-in and pull-out models after the Box-Cox transformation was performed. Specifically, Tables 3 and 4 highlight the push-in force and Tables 5 and 6 indicate the pull-out force. Preliminary model summaries and analysis of variance for both the push-in and pull-out forces are available in Appendix A. These preliminary models do not include a Box-Cox transformation on the foundational dataset.

Table 3: Analysis of Variance for Push-In Force Model.

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Material	2	0.112	0.0560	0.94	0.391
Hole Geometry	1	80.939	80.9390	1358.14	0.000
Hole Size (mm)	4	193.080	48.2699	809.96	0.000
RH (%RH)	2	17.044	8.5219	143.00	0.000
Error	1240	73.898	0.0596		
Lack-of-Fit	17	18.887	1.1110	24.70	0.000
Pure Error	1223	55.011	0.0450		
Total	1249	487.932			

Table 4: Model Summary for Push-In Force Model.

S	R-sq	R-sq(adj)	R-sq(pred)
0.244121	84.85%	84.74%	84.65%

Table 5: Analysis of Variance for Pull-Out Force Model.

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Material	2	7.614	3.8069	23.39	0.000
Hole Geometry	1	58.017	58.0167	356.45	0.000
Hole Size (mm)	4	356.821	89.2051	548.08	0.000
RH (%RH)	2	17.903	8.9516	55.00	0.000
Error	1240	201.823	0.1628		
Lack-of-Fit	17	22.696	1.3351	9.12	0.000
Pure Error	1223	179.127	0.1465		
Total	1249	616.225			

Table 6: Model Summary for Pull-Out Force Model.

S	R-sq	R-sq(adj)	R-sq(pred)
0.403436	67.25%	67.01%	66.84%

As seen in Tables 3 through 6, the results of product testing were reasonable for both push-in and pull-out forces. Most notably, moderately high values of the adjusted R-squared value indicated that they captured a significant portion of the system behavior with the variables tested in this model. However, as seen in Table 3, an adjusted R-squared value of around 67% leaves room for future improvement, meaning that other factors could be added to a future analysis. For the purposes of this project, an acceptable percentage would be around 80%. This value would indicate that about 20% of the model's behavior is not captured by the variables the author has chosen to test.

Upon consideration, the author suspects that adjusted R-squared values that did meet the given criteria would be the result of defects in manufacturing or inaccuracies through the testing process. It is difficult to adjust for manufacturing defects; however, a suggested future improvement for experimentation would be tracking the location of each part in the injection mold by labeling the mold cavities each part comes from. Thankfully, this tracking technology and process already exist and is utilized by HT on a day-to-day basis. Therefore, it will be a relatively simple enhancement to enact in the future. In addition, the mold number itself could be assigned to each batch of produced parts. Because of the sheer volume of parts that HT produces annually, the company requires multiples of the same tool to meet demand. No tool is an exact copy of another, which therefore introduces some level of uncertainty concerning how well each part is replicated across multiples of each tool. Ideally, testing would be done on batches of parts coming from only one tool, one section, and one production run of any part.

Finally, the regression equations were also inspected as part of the analysis done within this project. Overall, both models behaved intuitively when examining geometric variables. When considering the mounting hole's shape, slotted holes required less force to apply and extract a part, even though there was physically more of the part in contact with the surface. In addition, smaller holes required more force to insert and remove parts, due to increased overlap from the "limbs" of each fir tree mount. When examining the three humidity levels used in this experimentation, higher levels of humidity produced a softer feeling product that in turn was also easier to apply and remove.

Conversely, the three kinds of material resins used in this experimentation required a deeper investigation. The three resins tested consisted of a standard PA46 resin, a heat stabilized PA66HS resin, and a high impact modified, heat and UV stabilized PA66HIRHSUV resin. The PA66HS and PA66HIRHSUV were consistent across both models in their behavior. The PA66HS required more force to apply and extract from each hole when compared to the other two resins. In opposition, the PA66HIRHSUV required significantly less force in both categories when compared to the other two resins. However, the PA46 behaved somewhat differently between the two models. For the push-in force, it tended to perform between the range of its competitors, but the pull-out force required a notably larger amount of force when compared to the others. The author suspects that this increase in extraction force is due to some geometric deformation during the application process. Future exploration in this area of research should focus on this lower quality resin with special consideration taken to document if and how the plastic deforms at each stage of testing. The exact regression equations from this experimentation can be found in Appendix B.

Conclusions and Recommendations

The goal of this project and experimentation was to associate the testing variables with both the push-in and pull-out force required to successfully apply the product to a hole mount. The testing methods and combinations of specific variables introduced a notable amount of complexity to standard testing. Slight deviations in application angle of the parts and some testing failures were unexpected when originally conducting testing and resulted in a significant increase in the total time and parts required to collect data. As a result, this introduced outliers into the data and decreased sample size for select testing groups when removed for modeling. For future testing, it is recommended to consider the combination of mounting hole size and the relative humidity of each part. More specifically, when the mounting hole is at the minimum diameter of a part's specified application range and the relative humidity level is high, special care and attention should be devoted to the testing in this range. In addition, the implementation of automated testing apparatuses has already begun in this area, which will reduce the total amount of time to test parts in addition to ensuring they have minimal testing failures in critical variable ranges as outlined above. Moreover, increasing the sampling rate of the automated testing equipment to 4 millimeters per second from 1 millimeter per second will further reduce the total testing time while reducing sampling noise as reported by HT employees.

Just as in reducing the amount of time while testing is underway, the author would also like to guarantee that the total time for conditioning, transfer, travel, and testing of each part is consistent across all moisture content variables. At the time of testing, space was extremely limited at HT due to market demand for other products and services that required the use of the conditioning chambers. As such, part conditioning times were inconsistent and extremely limited. By blocking out uniform set times ahead of testing, each moisture content variable will remain as close as possible to the predetermined value for each level.

Furthermore, future research is recommended on the PA46 resin within this area of manufacturing and application. Specific attention and effort should be given to the geometry of each part during the application process. As discussed earlier, it is suspected that significant geometric deformation played a role in some of the deviation seen in both push-in and pull-out forces.

The utilization of enhanced identification methods will also be essential to progressing this experimentation. Some examples of production identification parameters are mold and cavitation number, percentage of regrind resin used in production, and moisture content during creation. Likewise, the exact production location of each tested part should be imprinted on the side of the part to easily identify its production origin. A batch of randomly sampled parts could potentially come from multiple different production molds and mold quadrants that can perform differently during the manufacturing process. Deviations in the manufacturing process will significantly affect a part's mechanical performance, thus also affecting statistical analysis and modeling. As a result, efforts to track a part's physical properties from production to testing will be imperative to future enhancements.

The use of a Box-Cox transformation was essential to boosting the adjusted R-squared value of both data models presented in this paper and thus ensuring the model accommodated for as much of the response variables as possible. Additionally, the sample size used in this experiment is rather large, which led to hypersensitivity of the performance parameters. Therefore, the use of a Ryan-Joiner test instead of an Anderson-Darling was used to test for normality and ultimately concluded that the data was normally distributed despite a large sample size.

Additionally, the introduction of statistical noise should be further investigated with the research team and sponsoring company. Further discussion on this variance may explain any remaining adjusted R-squared percentage not obtained in the data models. Industry knowledge suggests that manufacturing inconsistencies may account for a large portion of any lost R-squared percentage. For instance, changes in the mixture of new and regrind resin along with the temperature of the screw and tool all can have a significant impact on the end performance of a given part. This noise should be tracked via tool, machine, and cavity identification methods already in place at HT.

Overall, adjusted R-squared values of 67% and 84% for push-in and pull-out models indicate this research may serve as a useful starting point for future statistical analysis and modeling in this area.

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Appendix A: Initial Model Summaries without Outlier Removal or Box-Cox Transformations

Table A-1: Initial Analysis of Variance for Push-In Force Without Outlier Removal or Box-Cox Transformation.

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Hole Size (mm)	4	37048	9262.04	186.45	0.000
Material	2	69	34.40	0.69	0.500
RH (%RH)	2	2867	1433.50	28.86	0.000
Hole Geometry	1	6073	6073.50	122.26	0.000
Error	1257	62443	49.68		
Lack-of-Fit	17	3323	195.45	4.10	0.000
Pure Error	1240	59121	47.68		
Total	1266	120863			

Table A-1: Initial Model Summary for Push-In Force Without Outlier Removal or Box-Cox Transformation.

S	R-sq	R-sq(adj)	R-sq(pred)
7.57509	51.34%	51.01%	50.56%

Table A-2: Initial Analysis of Variance for Pull-Out Force Without Outlier Removal or Box-Cox Transformation.

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Hole Size (mm)	4	277662	69415.4	174.10	0.000
Material	2	972	485.8	1.22	0.296
RH (%RH)	2	19347	9673.4	24.26	0.000
Hole Geometry	1	23599	23598.9	59.19	0.000
Error	1318	525498	398.7		
Lack-of-Fit	4	25503	6375.7	16.76	0.000
Pure Error	1314	499995	380.5		
Total	1327	1037985			

Table A-3: Initial Model Summary for Pull-Out Force Without Outlier Removal or Box-Cox Transformation.

S	R-sq	R-sq(adj)	R-sq(pred)
19.9677	49.37%	49.03%	48.67%

Appendix B: Full Regression Equations for Push-In and Pull-Out Models

Push-In Model Exact Regression Equation

Push In Force (lbf)^0.377196 = 2.26107 - 0.0087 Material_PA46
- 0.01128 Material_PA66HIRHS
+ 0.0200 Material_PA66HS + 0.5643 Hole Geometry_Round
- 0.5643 Hole Geometry_Slot + 0.5414 Hole Size (mm)_6.1
+ 0.4165 Hole Size (mm)_6.2 - 0.4481 Hole Size (mm)_6.5
- 0.7550 Hole Size (mm)_6.9 + 0.2453 Hole Size (mm)_7.0
+ 0.2140 RH (%RH)_29.4831 + 0.0147 RH (%RH)_48.4179
- 0.2287 RH (%RH)_61.7757 (B-1)

Pull-Out Model Exact Regression Equation

Pull Out Force (lbf)^0.367873 = 4.7068 + 0.0711 Material_PA46
- 0.1055 Material_PA66HIRHS
+ 0.0343 Material_PA66HS + 0.4778 Hole Geometry_Round
- 0.4778 Hole Geometry_Slot - 0.0068 Hole Size (mm)_6.1
+ 1.2195 Hole Size (mm)_6.2 - 0.0630 Hole Size (mm)_6.5
- 1.5581 Hole Size (mm)_6.9 + 0.4083 Hole Size (mm)_7.0
+ 0.2338 RH (%RH)_29.4831 - 0.1618 RH (%RH)_48.4179
- 0.0720 RH (%RH)_61.7757 (B-2)

Engineering

Capstone Report Approval Form

Master of Science in Engineering – MSE

Milwaukee School of Engineering

This capstone report, titled “A Multi-variate Analysis of Fir Tree Mounting Plastic Hole Fasteners,” submitted by the student Zachary Greenwood-Schaftary, has been approved by the following committee:

Faculty Advisor: ______________________________ Date: _______________

Dr. Douglas Grabenstetter, Ph.D.

Faculty Member: ______________________________ Date: _______________

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