RELATING PROCESS MEASUREMENTS TO CUSTOMER DISSATISFIERS

by

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Submitted to the Sloan School of Management and the
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Abstract

Through the work of W. Edwards Deming, manufacturers have seen the benefits of improved quality and variation reduction on customer satisfaction. These manufacturers have sought to eliminate variation, expecting that all variation reduction would affect customer satisfaction similarly. Yet, there appears to be little understanding about how specific process variation leads to customer complaints. Thus, manufacturers have not been able to tune their quality improvement methodology

This internship focused on understanding what plant processes and critical dimensions, measured through existing plant systems, were most significant in predicting customer complaints. By targeting variation reduction efforts on these critical locations, overall customer satisfaction could be improved without the expense of reducing overall variation.

A technique is presented to correlate plant measurements with customer survey data. When combined with detailed measurements, this approach could be used to predict the probability of a customer complaint, given the critical dimensions. However, such data is not currently available in most plant measurement systems, so a second model shows how critical measurements can be obtained that can be used to focus variation reduction efforts. Although the current data available did not allow for such detailed analysis, the overall methodology is shown to be sound through correlation with existing data and surveys. Such a model could be used to accelerate critical design tradeoffs and the process of allocating tolerances.

The requirements for obtaining data useful for this technique are discussed, along with current inhibitors in the company studied and recommendations for implementation. These inhibitors include the push for high production numbers, lack of the information and organizational infrastructure required to distribute this data, and the primitive collection and storage processes for measurement data. Inhibitors to variation reduction in general within plants are discussed as well. These include mismatched process ownership, where responsibility is given without the required authority, and incomplete benchmarking, where industry-leading plants are studied, but the improvements required are not filtered throughout the company's plants.

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This thesis would not have been possible without the hard work, encouragement and dedication of a significant number of people. There is not enough space here to give them all their proper due; however, I will try to thank as many as possible in the limited space allotted.

First of all, I would like to thank the Leaders for Manufacturing (LFM) Program for its support. LFM has placed itself at the critical junction between management expertise and engineering know-how, and thus is able to thoroughly understand the requirements for world-class manufacturing.

I would also like to thank my thesis advisors, Professors Daniel Whitney and Roy Welsch. Their tireless support throughout the internship, and multiple thesis revisions was admirable. Their understanding of the manufacturing process was invaluable when I had difficulties.

I would also like to thank General Motors Corporation for the many resources they made available during and after the internship. I would especially like to thank the people at MEO&I: Jim R., Susan, Glen, Mark, Jim B., Anil, Naveen, Marty, Ron, and Raj. The variation reduction team at Lansing Car Assembly also was an invaluable resource. I would especially like to thank Joe for his tireless work, as well as keeping me safe during plant visits. The hours we spent e-mailing and talking about issues at GM and how to resolve them were critical in making this thesis a reality.

My family has been a great help throughout the program, from moral support during difficult times to storing my possessions during the many moves required by the program. I couldn't have survived the last two years without the constant encouragement of my family.

Last, but definitely not least, I would like to thank God, the creator of all wisdom and reasoning, without whom, nothing would be possible. The little confidence I have in approaching each day is due to the fact that God controls all things. Nothing escapes His plan.

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Section 1. Introduction

1.1. Problem Statement

Due to high incidences of wind noise problems company-wide, General Motors Corporation has initiated many projects to study the causes of wind noise and its effect on customer satisfaction. This thesis focuses on the relationship between measured variation in an automotive assembly plant and customer satisfaction reported through surveys. The research for this thesis was performed in a collaborative effort between Lansing Car Assembly (LCA) in Lansing, MI, and Manufacturing Engineering Operations and Integration (MEO&I) in Warren, MI.

1.2. Thesis Objectives

The objective of the research was to create a model for customer satisfaction using plant measurements and customer surveys, and use the model to warn the plant of impending failures.

Although the specific goal of the research was not met, research showed that customer satisfaction did correlate well with specific plant measurements. The limits of the analysis are identified and discussed, and better ways to measure and leverage existing plant measurements are promoted.

1.3. Thesis Overview

The thesis is organized as follows: Section 2 describes the recent history of quality efforts within General Motors and the automobile industry at large.

Section 3 describes the first project to correlate process measurements and customer feedback for individual cars, its history and the results. Section 4 describes a follow-on project, which sought to correlate daily measurement data available from in-plant databases with customer survey data.

Section 5 explains how analyzing and controlling build processes through customer feedback is superior to general variation reduction efforts, and how other organizations within General Motors can benefit from customer models.

Section 6 discusses inhibitors to General Motors' current variation reduction practice and how that affects the new methodology.

Section 7 reiterates the key findings and Section 8 shows areas for further research.

Section 2. Background

2.1. Car Body Quality

The quality of an automobile refers to the fitness to customer expectations, and a lack of defects. Customer-perceived quality is difficult to measure, and is usually assessed through surveys and service and warranty data.

Through the work of W. Edwards Deming, and Kaoru Ishikawa, manufacturing plant quality improvement efforts have moved from manual end-of-line inspections and audits towards an integrated system of automated measurement throughout the production process (Hu 1990). This has been enabled by the move from off-line inspection methods, where car bodies or parts are taken from the assembly line for measurement, to in-line methods where parts are measured on the assembly line.

2.1.1. General Motors Plant Quality Metrics

All cars within GM plants are measured at in-line inspection stations throughout the build process. The final measurement station measures a completed body-in-white (BIW). BIW is a term that refers to the completed, welded assembly of a car, before doors, hoods, or trunk lids are mounted. It typically consists of an underbody, two side panels, the roof and a trunk area. Nearly 100 critical points thought to affect customer satisfaction are measured at the final measurement station.

To provide a quick estimate of overall plant quality, GM plants report a number called the Continuous Improvement Indicator (CII). The CII is a daily indicator, created by taking all the measurements reported at the final BIW station for a given day, sorting them by variation, and then reporting the number closest to the 95th percentile. To match the variation and the designed tolerance for a given point, the variations are typically quoted as six-sigma – six times the standard deviation. Figure 1.2 shows a typical plant six-sigma chart. In this case, the CII is the fourth highest six-sigma, (5% * 79) locations, with a value of approximately 4.9mm. The average six sigma of this chart is 2.76mm.

2.2. 2mm Project

The 2mm Project was a partnership funded through Federal and private sources, officially organized in September, 1992. It was an automobile industry-wide attempt to understand, control and eliminate BIW variation systematically. GM, Chrysler, and an assortment of tooling and instrumentation suppliers signed on to the project. The University of Michigan and Wayne State University provided most of the academic and research support.

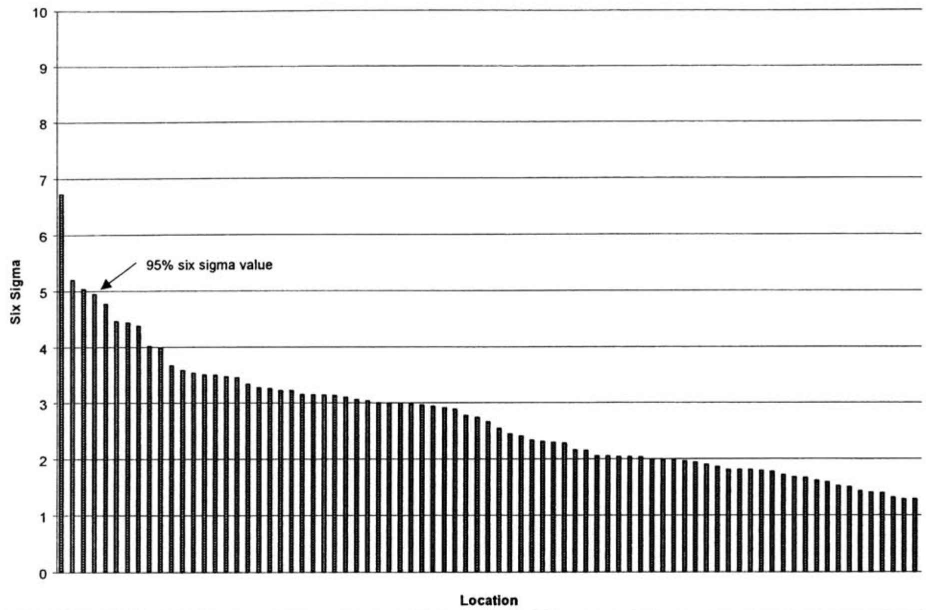


Figure 2.1 - Typical Six Sigma Chart

> The three stated goals of the 2mm Project were: (1) to achieve 2.0 mm variation for body-in-white (BIW) build, (2) to advance the understanding of the physical properties of sheet metal and the assembly of sheet metal parts, and (3) to enable the companies to perform the improvements on their own. (CONSAD 1997)

By the end of the Project in January, 1996, the initial GM and Chrysler pilot plants had successfully reduced their CII variation to 2mm, and the results of the 2mm Project were expected to be implemented company-wide by the year 2000.

2.2.1. 2mm as a stated goal

At the time of the Project, 2mm six sigma was considered world class – only a few of the Japanese assembly plants were able to control their variation to that extent. Although 2mm was the initial goal, the processes and learnings were to be used in further variation reduction efforts. In fact, some assembly plants within GM have broken the 2mm barrier and are continuing to reduce variation to world-class levels using 2mm Project principles.

2.3. GM's response to 2mm project

GM, as one of the leading sponsors for the Project, stood to gain the most from the findings. Of the first five pilot plants that saw themselves improved to 2mm six sigma, three were owned by GM. Since then, all GM plants have standardized to some of the 2mm Project reporting methods, such as quoting the CII. In-line Optical Coordinate Measuring Machines (OCMM) were dictated as the standard measurement tool for BIW, some sheet metal subassemblies that make up the BIW and even some doors. The extensive process measurements available through these systems, typically 100% sampling, provides much greater opportunity for advanced Statistical Process Control (SPC) techniques than plant measurement systems existing previously, which were only able to sample three parts per day.

2.3.1. Some cultural changes necessary

Instead of relying on "golden" parts – parts chosen to be the master due to their dimensional quality – the 2mm Project imposed a different standard on plant installation and variation reduction, one that relied on highly accurate measurement equipment. Using this equipment, production tooling could be installed and modified by following CAD models, instead of relying on parts that were deemed "exceptionally good." This also alleviated the storage requirements critical to keeping these parts in good condition for later use. (Hu, 1990, Pastorius, 1989)

The advent of 100% sampling, brought by OCMM adoption company-wide, allowed variation reduction teams to more quickly solve process problems. OCMM stations were installed at various upstream stages in the BIW assembly process, and their output was used to pinpoint equipment failures. (S.J. Hu, 1997)

Although in-line OCMM's opened great opportunities for understanding and adjusting processes, they also created much more data than previous off-line plant measurement systems, which typically measured three or four parts per day. The significant increase in data was overwhelming to the plant variation reduction teams. Due to the large number of individual measurement locations allowed by in-line measurement, false alarms were much more likely. Time correlation in the data streams, usually caused by tooling wear, led to erroneous results as typical SPC techniques were not capable of handling process drift. (Hu, 1990)

The result was that plant personnel were required to be trained in completely new techniques for variation reduction in order to handle the massive amounts of new data available through the adoption of the new 2mm process and equipment. From brief communications, it appeared that most of the variation reduction staff at the plants researched were at least familiar with the 2mm Project software and methodology, although the learnings may not have been as pervasive as hoped by the researchers.

2.3.2. Variation Reduction process still not standardized

The 2mm Project actually proposed a complete variation reduction methodology that could be used to understand and systematically eliminate variation through experimentation and statistical analysis.

The CII a plant reports (sometimes called plant six sigma) can encourage plants to tackle variation caused by dual-line mean differences first instead of reducing actual process variation. For example, a plant could have two separate subassembly lines that have low variation, but exhibit a large mean difference. The downstream measuring station would report that difference as overall six sigma. A single station exhibiting large variation might be considerably less of a concern to managers if the variation were less than the value of the mean shift. In fact, different plants have different ideas of how to treat this situation. According to some plants, moving the mean of a process with low variation is significantly easier, thus moving a low variation process with a mean difference would take higher priority than tuning a process exhibiting large variation. Other plants would rather tackle true process variation first before resolving mean shifts. Still other plants tackled variation in order of overall six sigma, whether the standard deviation was the effect of a single process or the effect of a constant mean difference between two lines.

Other parts of the variation reduction task still vary greatly from plant to plant. The physical locations and numbers of measurements may vary widely between upstream and downstream processes and from plant to plant. Matching measurements between upstream and downstream processes allows for easier troubleshooting of failed machines, by helping understand the most likely source of variation. (S.J. Hu, 1997, Ceglarek et. al., 1994)

Although not as critical to the problem-solving task, having common measurement locations and variation reduction methodologies allows for more synergy between plant personnel and manufacturing support organizations within GM. Having a common process reduces the ramp-up time required when support groups are asked to assist plant variation reduction efforts. Common process also allows variation reduction teams to share variation reduction stories with teams from other plants in a common language, thus allowing plants to benefit from lessons learned.

2.4. Is Variation Reduction the best Quality Improvement Strategy?

Although a move towards world-class variation performance was deemed necessary in order to compete with Japanese manufacturers, there was a concern within GM's Quality organization that variation reduction for its own sake was not really affecting customer satisfaction. What was needed, instead, was to focus the variation reduction efforts - most significantly, on measurements deemed most critical to customer satisfaction. The predicted result would be that some measurements would be seen as extremely critical, such as panel gaps and flushness, while some measurements that the customer was not sensitive to might vary by four or five millimeters without any perceived lack of quality.

A difference of opinion within GM organizations has yet to be settled about how best to approach variation reduction. All organizations feel that customer satisfaction is the final goal, yet some feel that the systematic reduction of variation is the key, while others say that customer feedback should be modeled to tune variation reduction.

2.4.1. Targeting Variation Reduction on Customers

GM's Manufacturing Engineering Operations and Integration (MEO&I) organization has begun to ask the question whether variation reduction for its own sake is the best way to improve customer satisfaction. A different, and perhaps better, approach might be to develop a procedure of variation reduction based on customer feedback – tight controls on what the customers are sensitive to and looser controls on things that the customer cannot perceive.

If GM is truly focused on customer enthusiasm, then it should be able to show a direct relationship between improvements made in the plant and overall customer satisfaction. Even plant metrics might be better if they were tied directly to customer satisfaction, instead of just variation.

2.4.2. Arguments that 2mm is now industry standard

Although using customer feedback to guide variation reduction seems logical, some critics have countered that 2mm is currently the industry standard, not the stretch goal it was during the 2mm Project years. As standard industry practice, the first goal should be to reduce variation to 2mm, and then, perhaps, target further efforts towards understanding customer quality concerns.

2.4.3. Less variation allows stronger correlation.

High six sigma values point to large variations in sheet metal components and assemblies. When these assemblies are welded together, the variation can propagate through multiple panels and joints based on component and joint design, causing an unpredictable shape. When variation is small, less variance stack-up occurs and the overall assembly can be better correlated with subassembly measurements. Trying to understand a specific customer problem where there is large and highly coupled variation would be much more difficult than trying to understand the same effects when variation was restricted to smaller areas.

Typical process failure modes are also much easier to recognize when variation is lower. Process mean shifts, for example, become more and more clear as the ratio between the mean shift and process standard deviation increases. (Hu, 1990)

So, in fact, variation reduction by itself can create an environment where customer satisfaction could be more easily correlated to process measurements. Where there is less process noise, customer complaints can more easily be matched with changing conditions.

2.5. Summary

GM has made vast quality improvements since the 1980's. Through membership in the 2mm Project, quality has become a central part of the automobile manufacturing process. Although GM has come a long way, there still is far to go. Different plant processes create difficulties in applying new learnings across the company.

One fundamental question is how variation reduction relates to customer satisfaction. Some argue that all variation reduction improves customer satisfaction, while others say that variation should be reduced on areas the customer is most concerned with first. Although the processes are different, either methodology can result in the same benefits – since cars with less variation raise fewer complaints.

Section 3. Project to relate process measurements to end-of-line and customer complaints

Customer perception of quality has become an increasing concern within General Motors. The influence of such surveys as J. D. Powers' Initial Quality Survey on market share and sales has become increasingly clear. (Keebler, 1992) Company-wide problems, such as wind noise (which accounts for more than 75% of noise heard on the road), water leaks, and shakes and rattles have led managers to place high emphasis on solving these problems. (Wu, 1991) Numerous task forces with GM have been assigned to study these problems in-depth. One such project was within Manufacturing Engineering Operations and Implementation (MEO&I). Since MEO&I saw its strengths in understanding manufacturing process and variability and had a particular desire to make a connection between process variation and customer satisfaction, it felt uniquely qualified to participate in this project.

Since wind noise, water leaks and closing effort are primary contributors to J. D. Powers results, understanding their relation to process measurements could improve results company-wide. Those three were chosen since they are presumably all related to the interface between the door sheet metal and the BIW. Thus, a solution to one problem might solve all three simultaneously. The addition of closing effort reduction, which, theoretically, would be opposed to reducing wind noise and water leaks, allowed us to search for a solution that could be implemented without second-guessing the results.

Although wind noise affects all doors, limited plant resources forced us to focus our efforts specifically on driver side front door complaints and measurements. We felt that customer feedback from the driver side door would more accurately signal wind noise problems, while data from other windows may depend on whether the car was driven with many passengers. Cars must always have drivers, therefore wind noise in that particular door should be easy to perceive.

Within MEO&I, there was a concern that wind noise might be caused mainly by two unmeasured areas: the fitting process and the weatherstrip installation in final assembly. The fitting process generally occurs after the door has been painted and all the door hardware is installed. Plant personnel use special tools and brute force to move the door, optimizing flushness and closing effort. Internal studies have shown that the fitting process adds variation to the door without demonstrating a statistically significant improvement in wind noise performance. Since all of the BIW measurements occur before the fitting process, the effect of the fitting process in relation to customer quality is largely unknown.

The process of weatherstrip installation can also lead to wind noise concerns. An engineer for the weatherstrip supplier commented that when he visited the plant, he observed workers using different processes for the installation. Some workers installed the door seal from the back of the door around to the front, others installed the seal from front to back, or from the top of the door working towards the ends. Different installation methods could cause a significant amount of variation and possibly mask build-related wind noise performance. Poor installation could cause excess wind noise that could not be correlated with in-plant measurement systems, and thus would cloud any attempts at analysis.

3.1. Current Door Manufacturing Process

The door subassembly is manufactured outside the assembly plant by GM's Metal Fabrication Division (MFD). MFD plants supply most of the sheet metal components to the assembly plants as well as some subassemblies. An overall view of the stamped part supply is shown in Figure 3.1. The door subassembly manufacturing process is shown in Figure 3.2.

The door subassembly consists of a door outer, a door inner, a side-impact beam, and some interior hardware. The interior stampings are welded to the door inner, and then a bead of sealing and sound-deadening material is applied to the door inner before the outer is attached. The inner and outer are attached by bending the sheet metal of the outer around the sheet metal of the inner in a process called hemming. A typical door is shown in Figure 3.3.

Dimensional quality control of the door subassembly is maintained by a check fixture, which measures critical door dimensions. The check fixture is a frame that holds the door and has multiple holes where a probe can be inserted to check the distance to the door surface. The check fixture is described in greater detail in Section 3.3.1.2. One door per shift is measured in the check fixture for a few critical locations, and five doors are taken once per day and measured extensively using more locations on the same check fixture to give a snapshot of the current process. The doors are placed on a pallet and sent to the assembly plant.

3.2. Current Assembly Process

An automobile manufacturing plant is typically divided into three functional areas. The first is the body shop, where the sheet metal is welded and formed into a Body-In-White (BIW) and the doors, trunk lid and hood are installed. The doors, trunk (deck) lid and hood are informally called swing metal. The doors arrive as subassemblies, with some hardware installed. Before installation, an upper and lower hinge are located on the door. Figure 3.3 shows a door immediately before the hinge location process. The hinges are loosely attached as shown above, then located and tightened automatically in a fixture. A complete BIW with installed swing metal is then transferred to the second area – the paint shop. After the body has been painted, it is ready for the third step, final assembly, where all the small components are attached and the powertrain is installed. Figure 3.4 shows the door installation process, with the associated measurements. The measurements will be discussed in Section 3.3

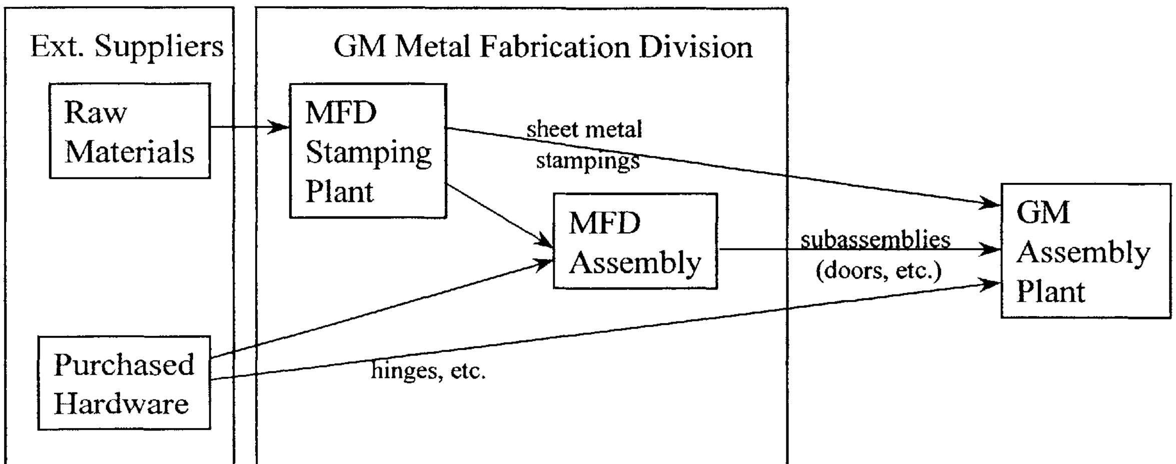


Figure 3.1: Typical Door and Stamped Part Supply

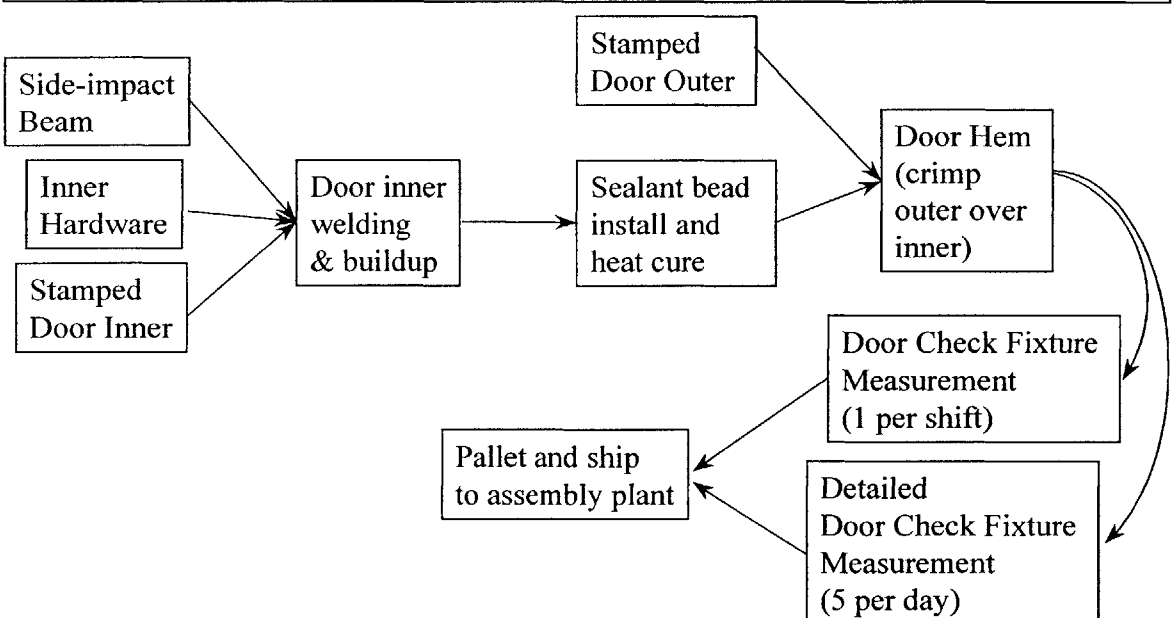


Figure 3.2: Door Manufacturing Process

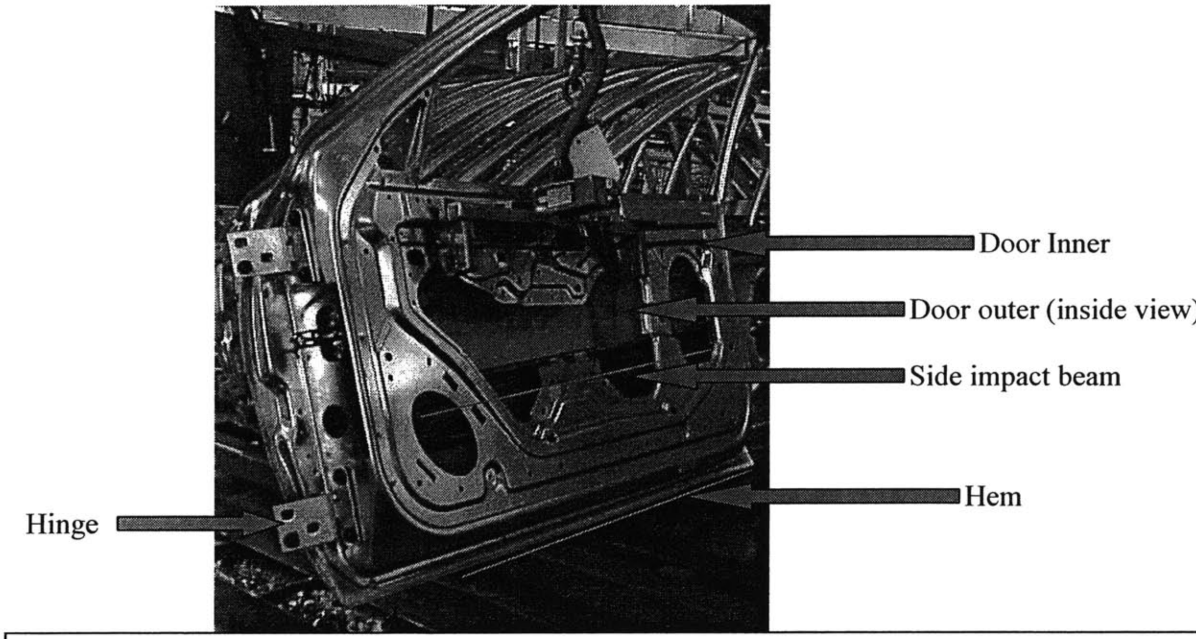


Figure 3.3: Diagram of Typical Door

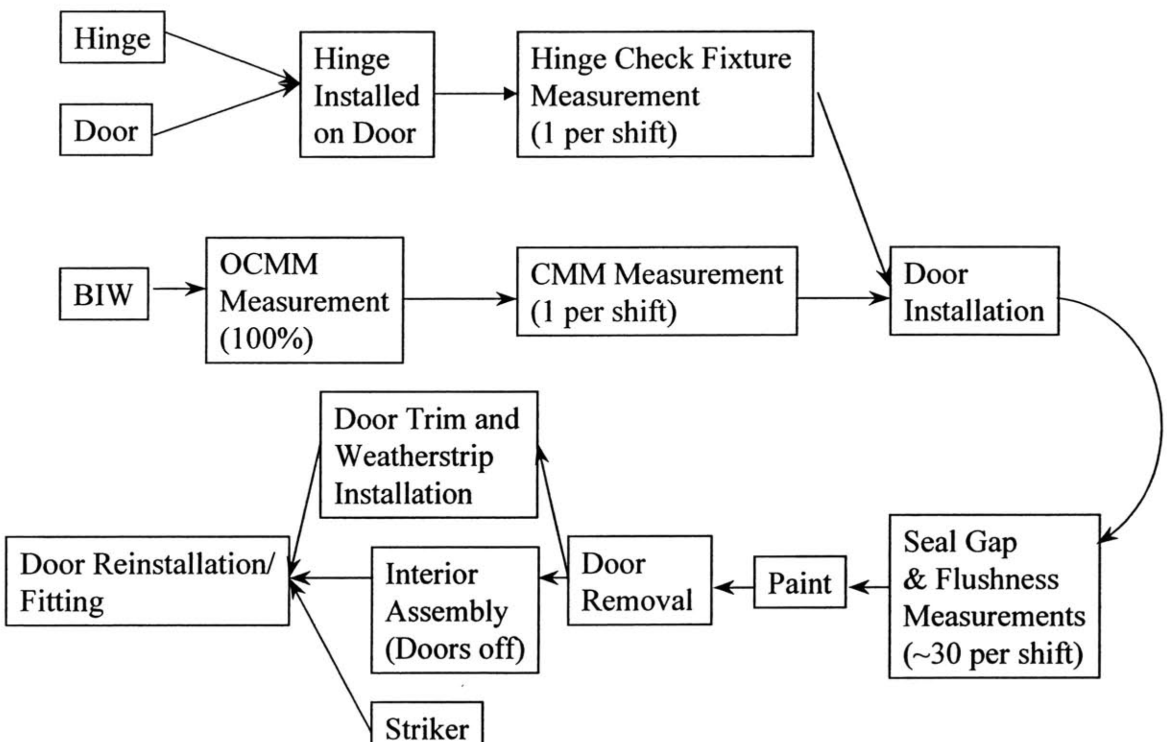


Figure 3.4: Door Assembly Process

3.3. Measurement types

3.3.1. Body Shop Measurements

3.3.1.1. Full Body Measurements

Each body made in an automotive plant is measured by an OCMM. Perceptron is a manufacturer of the standard Optical Coordinate Measuring Machine (OCMM) equipment used in GM plants. A typical Perceptron "TriCam" is shown in Figure 3.5.

A Perceptron measurement station is typically a set of LASER/cameras mounted to a stiff frame. The LASER shines a beam of structured light onto the body, while cameras use triangulation to measure the distance from the known camera location to specific locations on the car. Those locations can be bolt holes, slots, or surfaces. These measurements are performed on each body and stored in a variation reduction database. For the experiment measurements around the driver side front doorframe were used. Figure 3.6 shows the measurement locations used for the Perceptron analysis.

Measurement points are specified as an x,y,z (car coordinate) location, and an i,j,k (vector) location. The camera is mounted in such a way that the LASER beam shines along the i,j,k vector to the x,y,z point. Thus when the sheet metal moves, the camera can distinguish its movement along a specific vector. Cameras are typically mounted along the coordinate axes (i, j, or k) to isolate movement along that axis. Figure 3.7 shows a diagram of the camera coordinate system.

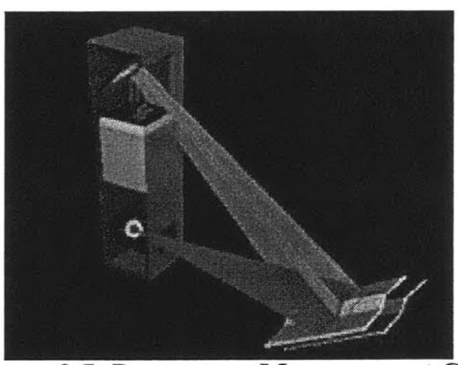


Figure 3.5: Perceptron Measurement Camera

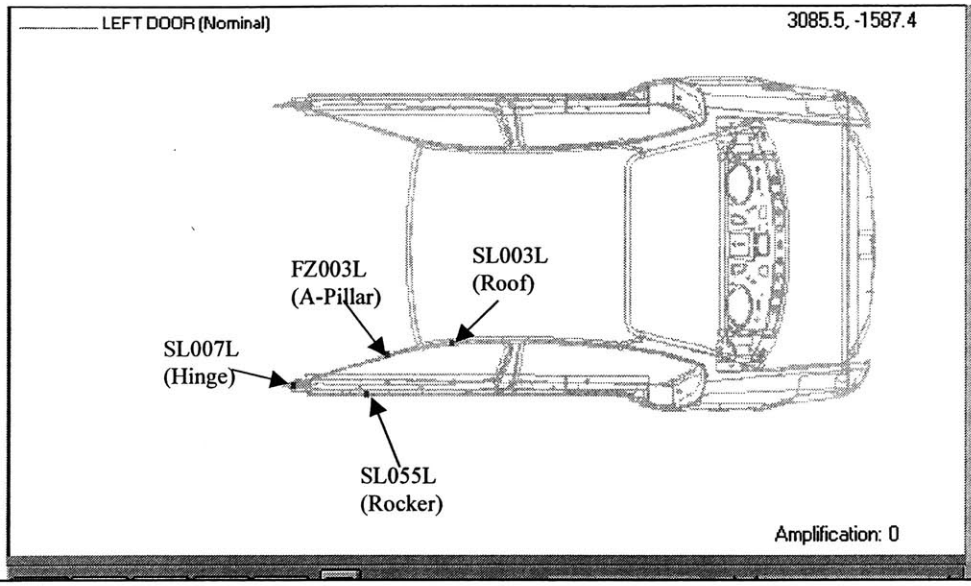


Figure 3.6: Perceptron Measurement Points

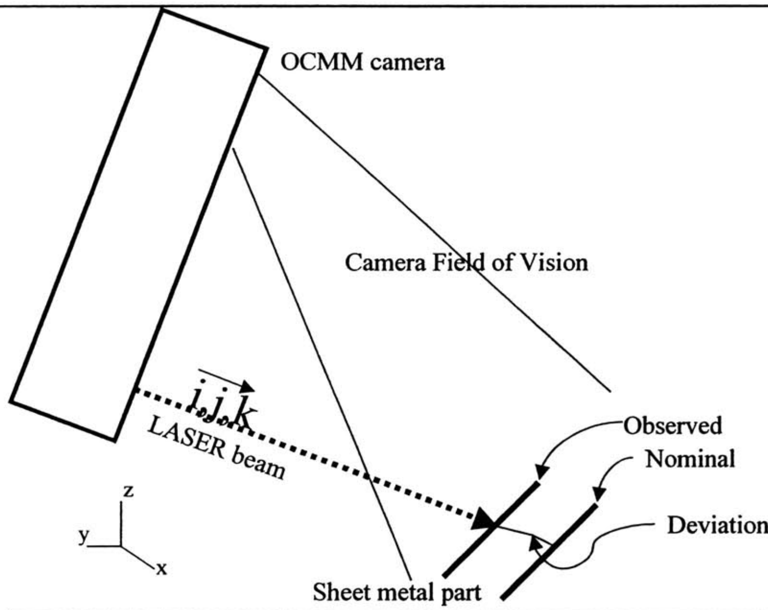


Figure 3.7: Perceptron Diagram

3.3.1.2. CMM

One body per shift is measured with a CMM. This is an extremely accurate measurement, typically +/- .015mm to .035mm, depending on the machine and environment. CMM measurements are used to supplement OCMM measurements and can be used to troubleshoot problems with the OCMM system. Typically, CMM and OCMM measurement locations are set up to be identical so that an accurate measure of OCMM variation can be obtained. Locations of CMM measurements are shown in Figure 3.8.

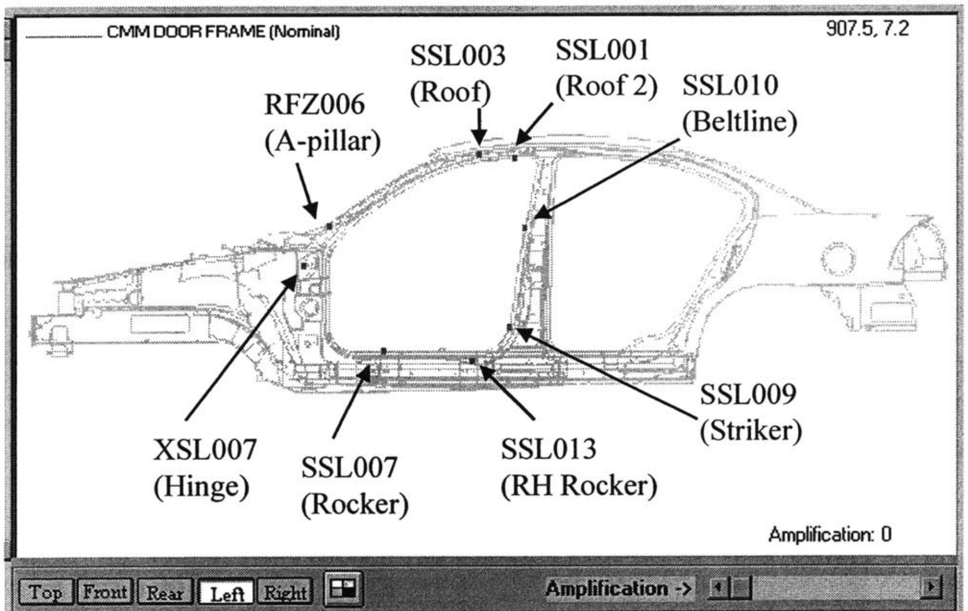


Figure 3.8: CMM Measurement Locations

3.3.1.3. Door Hard Check Fixture

One door per day is measured on a hard check fixture. This fixture is located in the process after the hinge placement – to perform process control for the hinge placement machine. The hard check fixture is a frame that holds the door just as it would be mounted on the car. Several points on the door are then measured using a data probe to see whether they are within the proper tolerance of the nominal door. Since the doors are measured so infrequently, we decided to put those doors on the CMM-measured body to gain more insight into consumer data. Check fixture measurement points are shown in Figure 3.9, and the check fixture is pictured in Figure 3.10.

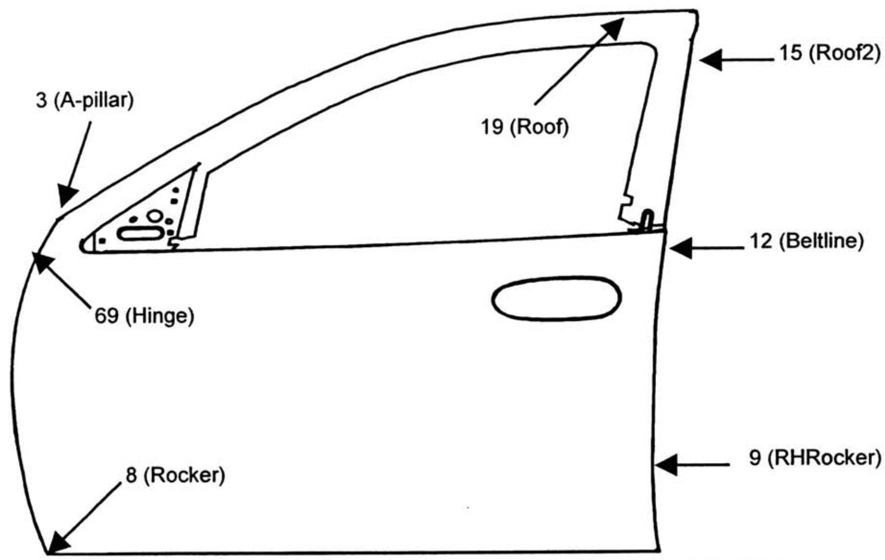


Figure 3.9: Check Fixture Measurement Locations

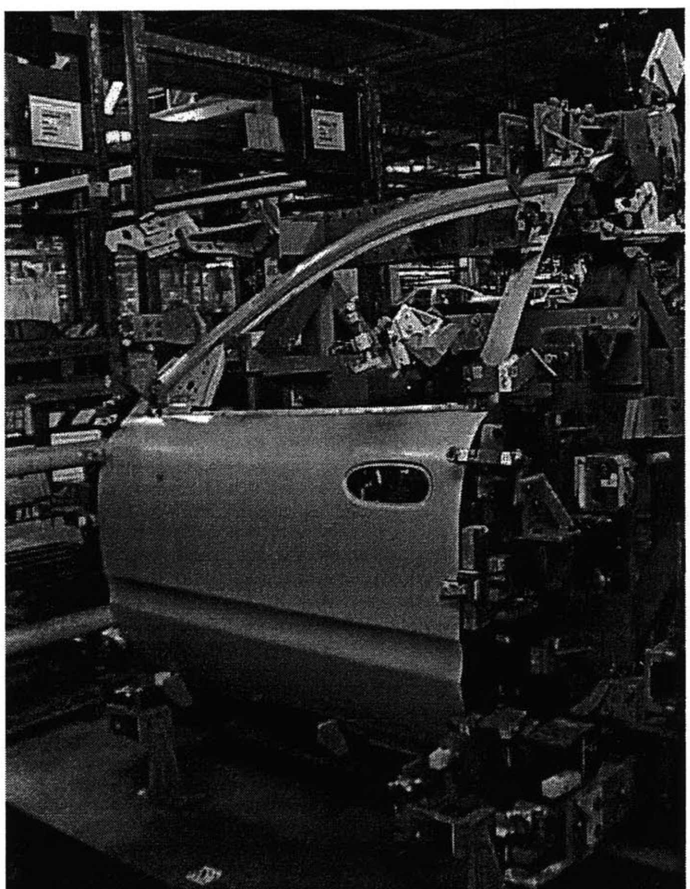


Figure 3.10: Hinge Placement Check Fixture

3.3.1.4. Seal Margin and Flushness

Seal Margin and Flushness are measures how well the door mates with the BIW. Errors will show up in flushness (level differences between the car door and frame), or seal margin (the location of the door inner with respect to the doorframe). These measurements are taken in the body shop after the door has been placed on the frame, and are not repeated after paint or fitting. See Figure 3.11 for locations of seal gap and flushness measurements, Figure 3.12 and Figure 3.13 for typical measuring methods.

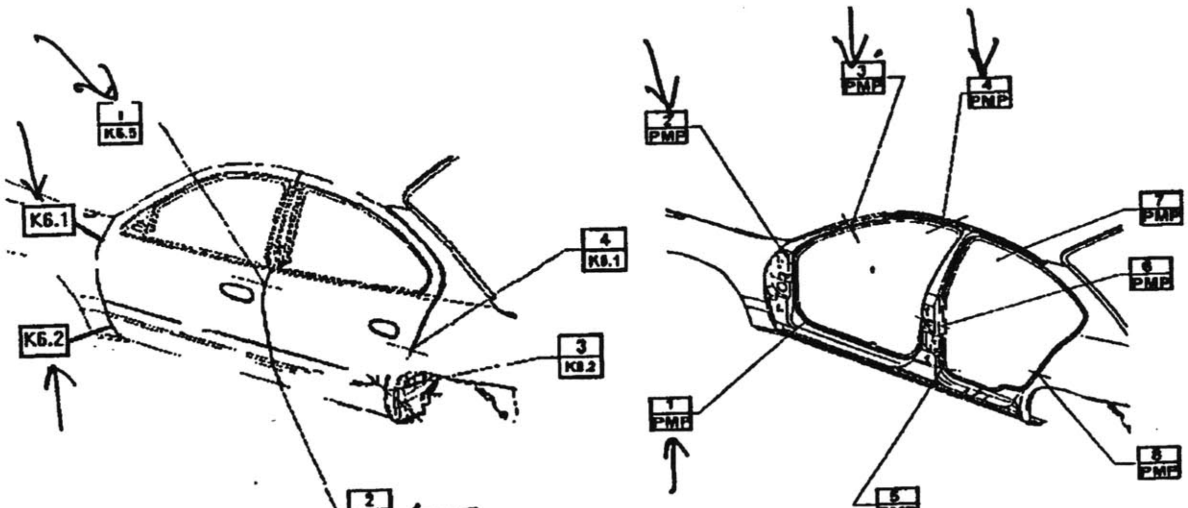


Figure 3.11: Seal Margin and Flushness Locations

Figure 3.12: Measuring Seal Margin at Hinge

Figure 3.13: Measuring Flushness

3.3.2. End of Line Measurements

For our project, special end of line measurements were taken on the cars under study. These measurements provided some data believed to be an accurate predictor of wind noise and door closing effort. This data would offset the possibility of limited customer feedback from the survey process and could also be used to establish the measurements as an intermediate proxy for customer satisfaction. The following measurements were obtained:

3.3.2.1. Door Closing Effort

This measurement is an extremely good indicator of closing effort a customer will experience. It involves using a slam cannon – a portable device that uses pressurized air to push a door shut with a known force. The door is considered shut when it is completely latched. Although the slam cannon is highly susceptible to operator differences, repeating the measurement process and using the same operator each time helps reduce the potential for error.

3.3.2.2. CFM Air Leakage

Air leakage measurements were made on the door as well as a potential proxy for water leak and wind noise complaints. Air leakage was measured by first sealing the main vent, called the pressure relief valve (PRV), between the passenger compartment and the trunk, then setting the AC in recirculate mode. This provided the minimal leakage from the passenger compartment. A plexiglass "window" was then sealed in place to replace the passenger side window. The plexiglass held a duct that was used to pressurize the car. A calibrated fan device forced air through the duct, and two gauges, a Cubic Feet per Minute (CFM) air volume gauge and a pressure gauge were used to report data. Strategic areas around the driver side door, including the mirror, window and door handle, were taped to eliminate leakage. These were the mirror face (where the mirror attaches to the car), the mirror glass (the side-view mirror itself), the door glass (the track along the outside of the car where the window glass slides), the beltline, and the door handle (completely sealing the door handle area). The car was then pressurized, using the forced-air system, to a pressure of ½ Atmosphere (roughly 7 PSI), and a baseline CFM was recorded, which corresponded to the normal volume of air leakage from the car. As each taped section was removed, the CFM leakage for that section was determined by how much additional air flow was required to return the pressure to ½ ATM. Figure 3.14 shows the locations covered by tape. No measurements could be obtained on seal leakage, because the front left fender would have to have been removed to tape around the door seals. This could have caused problems for the quality of these cars that were being sent directly to GM customers.

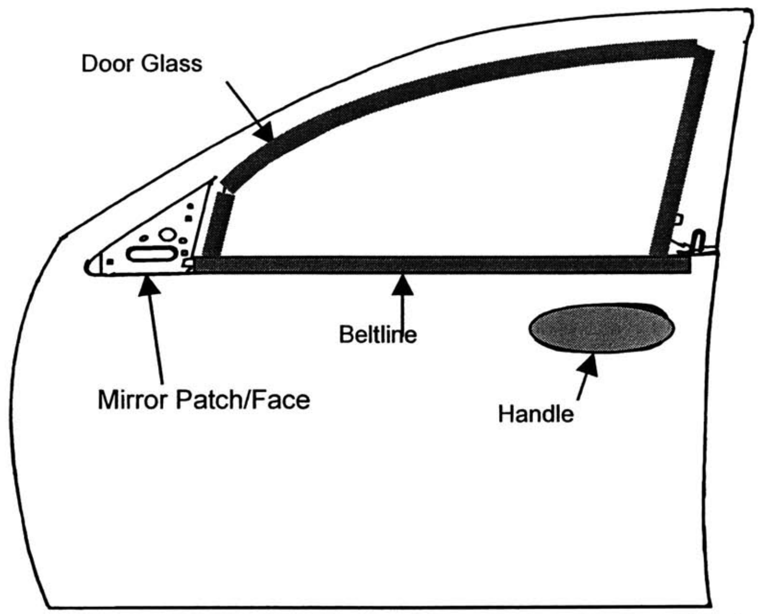


Figure 3.14: Tape locations for CFM Leakage

3.3.2.3. Seal Pressure Mapping

A Seal Pressure Mapping was obtained using a thin film gauge similar in principle to a strain gauge. This gauge was closed between the seal and the doorframe at predetermined locations. The pressure from the door seal caused the device to report differences in resistance along its grid. An attached computer computed an overall pressure and force, integrating the device's pressure measurements across its grid. Seal pressure was measured between the seal and doorframe near the hinge, A-pillar, roof, above the beltline (top striker), at the beltline and at the striker. See Figure 3.15 for the approximate locations of the measurements.

Seal Pressure Mapping was hypothesized to be a potential predictor for wind noise, water leaks and closing effort. High or uneven pressure across the seal could cause high closing effort, whereas low pressure would be a predictor of water leaks and wind noise, since air or water could force their way between the seal and doorframe.

3.3.3. Customer Survey Data

Each car was tracked based on its Vehicle Identification Number (VIN) to a dealer and then to the customer when the car was sold. Using the normal customer survey organization, special questions were given to the surveyors to more closely determine any wind noise characteristics. An internal 30-day GM survey, called Early Quality Feedback (EQF), was used to obtain customer feedback. EQF was created to be a proxy for J.D. Powers Initial Quality Survey results.

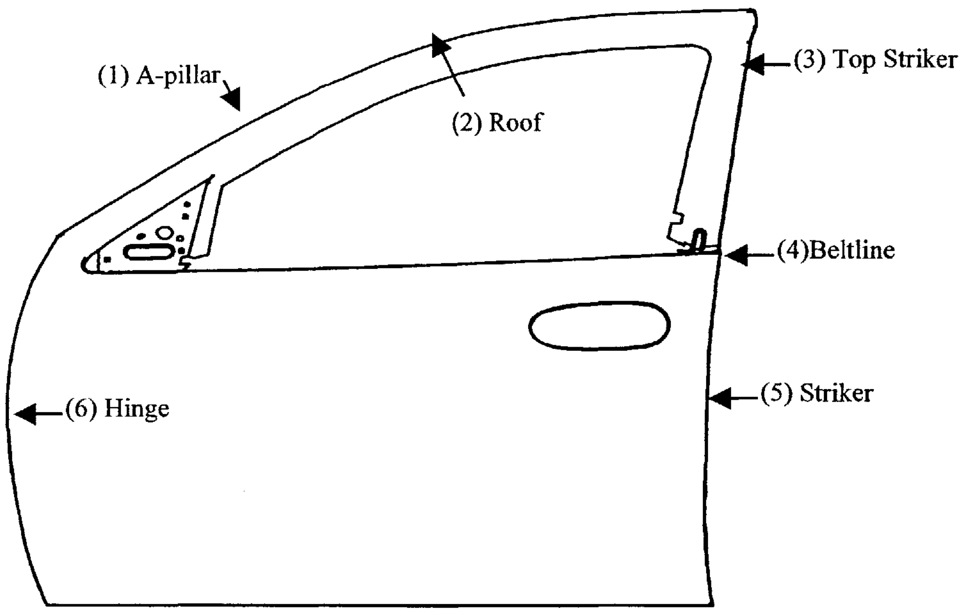


Figure 3.15: Seal Pressure Mapping Locations

3.4. Reasons for changing experiment

The project, as originally defined by MEO&I, was intended to collect as much data on a set of cars as possible, then use a more detailed survey to help determine what measurements correlate with customer problems. A model could then be created of customer perception that could be used to guide a focused effort in removing the causes of wind noise complaints, if the model showed problems in the body shop.

The experiment was modified due to a number of plant and personnel restrictions, and in further analysis could not have been used to provide such a substantial model due to the small number of customer complaints likely to be received.

3.4.1. Impending model changeover

When the measurement process was finally agreed to in principle, the model year was nearly over. Only a month remained in the current model year before a two-week shutdown and subsequent model changeover. The length of time between a car build and when the customer feedback was available meant that the first results would typically start trickling in two months after the measurements were started. Waiting for new model ramp-up to be complete would mean that measurements would not be available until late July and the earliest feedback would not be available until October.

3.4.2. Availability of manpower

Since the plants are typically staffed only with the people necessary for day-to-day operations, they are typically unable to handle special requests without outside support. Thus plant personnel voiced concerns about the required level of in-plant support. MEO&I, as well, did not have enough resources to fully support this operation, so the investigation was limited to approximately 100 cars.

3.4.3. Availability of measurements

Although extensive data was hoped to be collected on each car, it was discovered that the in-plant measurement systems were not optimized to collect large amounts of useful data. Earlier measurements could not be correlated with later measurements in the body shop. The summer intern working on the measurements spent most of his time making sure that the proper measurements were taken on the specific cars, and even then, not all measurements were collected for each car.

3.4.4. Concern about customer feedback

GM uses an outside contractor to collect customer feedback through phone surveys. This organization picks at random three to five cars, which are the correct age (30 days past sale), and attempts to contact customers about those cars. Since the data needed would be more detailed than the current survey and the specific cars would have to be tracked and tagged for survey, there was a concern that the survey organization would not accept the task. As a stopgap measure, measurements were taken at the end of line that would serve as potential proxies for customer satisfaction if the survey data were unattainable.

3.4.5. Concerns about measurement coordination

Each new set of measurements required coordination between the student intern and the personnel responsible for measurement. For example, tracking the left door required making sure the left door assembly arrived at the same time as the car that was separated for measurement. If the measurements had included tracking all four doors, the amount of coordination required would have proven too much for the limited resources. Instead, the effort was focused on front driver side door measurements. The data from the doors measured in the hard check fixture were obtained, and the doors were installed on the correct cars – those that were measured using the CMM.

3.4.6. Process suggested for measuring cars

The agreed-upon process for measuring the cars required an intern from MEO&I, and an engineer capable of taking the required end of line measurements in case the customer survey data was unavailable.

For all of the cars, automatic measurements would be collected from the OCMM database. Each flagged car would be measured for seal gap and flushness and labeled to be held after final assembly for end of line measurements.

The one car measured by CMM each day would be mated with the door measured in the check fixture to make the best use of the CMM accuracy.

At the end-of-line, a measurement engineer would take the closing effort, seal pressure mapping and air leakage measurements.

3.4.6.1. Car selection

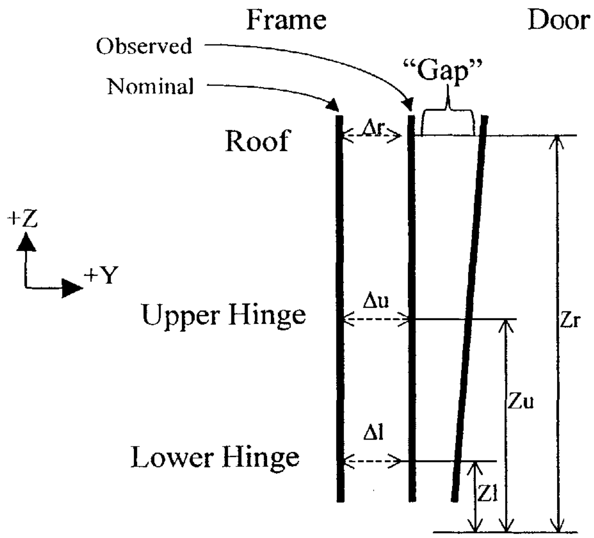
The best hypothesis offered by plant personnel was that wind noise could be caused by an excess gap between the door header and roof of the doorframe. A quick model was made based on using the hinge points for ascertaining the door location and using a measurement on the a-pillar to estimate the gap between the door and frame. By treating the upper hinge and lower hinge as a third- and first- class lever, respectively, an approximation of the door gap at the roof was obtained by comparing the predicted value for the door deviation (based on the hinge points) and the measured value for the roof measurement.

Cars with excessively large or small "gaps" were flagged each day for measurement.

Later, the time between end of line and receiving customer feedback (30 days after purchase) led the team to pick the best and worst examples solely from cars that were pre-ordered.

3.5. Problems encountered during data collection

The impending model changeover occupied the time of many of the plant personnel, leaving few resources for the data collection effort. As a result, the data collection effort was not as successful as originally hoped. Collecting the measurements required significant coordination between the variation reduction team, which operated the Perceptron, and measurement personnel who operated the CMM, check fixture and gap and flushness measurements in the body shop. Even with the reduction in scope, many cars slipped through the cracks and were missing certain sets of measurements. Collecting data at the end of line required collaboration with final assembly, and communication problems led to cars being shipped to dealers without the necessary end-of-line measurements.



$$Gap = \frac{Zr - Zl}{Zu - Zl}\Delta u + \frac{Zr - Zu}{Zu - Zl}\Delta l - \Delta r$$

Where:
Zr, Zu, and Zl are the vertical positions of the roof, upper hinge and lower hinge measurement points, respectively

And:
Δr, Δu, and Δl are the deviations from nominal measured at those points.

Figure 3.16: Predicting Gap from Frame Measurements

3.5.1. Inadequate sample size

With the lack of resources, the experiment had initially planned to measure 100 cars. By the end of the project, only 81 cars had been measured. Since wind noise has a Problems Per Hundred (PPH) rating of approximately 10 for the model measured, only 8 cars would be expected to have wind noise complaints. Since some cars were not pre-ordered, not all of the cars had been sold by the time the analysis was completed. At the time of this report, only 42 cars had survey results available. Survey information could not be obtained on some of the pre-ordered cars because they were designated to be fleet vehicles by the purchasers.

3.5.2. Not enough complaints from customers

There was only one wind noise complaint and only one closing effort complaint among the 42 survey results seen. The closing effort complaint was on a car that was near the average closing effort measured, and the wind noise complaint could not be differentiated in any way from other cars without such a complaint. Thus there was little hope of correlating these complaints with measurements taken in the plant.

3.6. Analysis

3.6.1. Inconclusive – due to lack of customer feedback

Since the goal of the analysis was to correlate process measurements to actual customer feedback, the result was unsatisfactory. With only one complaint, no process could be found to correlate. However, some of the end-of-line proxies were substituted as leading indicators of customer satisfaction, with some more encouraging results.

3.6.1.1. Binary nature of response variables and customer sensitivity

Even if more customer feedback had been obtained, one large concern about using customer feedback is that the customer either complains or does not. What is involved is that the customer has to perceive the problem, which means that the results will be based on the sensitivity of the customer to such issues. One such issue is the comparison to former cars, where people who owned more noisy cars previously would be less likely to complain about wind noise in the present car. Customers themselves may be more or less sensitive to wind noise. Wind noise is typically high frequency, and customers who aren't as sensitive to high-frequency sound would not be as likely to complain.

Also, customers may not be able to distinguish the sound's location. Thus a customer may attribute road noise to wind noise, or consider something that is in fact wind noise to be another type of noise. The typical approach in collecting data that has so much variability is to use the central limit theorem to show that the results will converge to an accurate measure of the wind noise as more and more measurements are collected.

According to a Project Manager working at Ford, customers of Ford and other manufacturers are brought in during quality research events, clinics where car owners of year-old cars are asked to participate in a survey. The engineers then take measurements of the various cars to see how Ford compares to other manufacturers, and how they can improve. One specific story mentioned was where a Ford customer complained about the closing effort on his car and a Honda customer who did not, even though the Ford's doors were all much easier to close than the Honda's. The difference was that the four Ford doors differed in closing effort, while the Honda doors were all equally hard to close. The customer complained about the variation in closing efforts, and not an absolute value. Even with binary response, the complaint may not be exactly what you've asked (i.e. is the door hard to close), but judged on customer perceptions (i.e. yes, it's harder to close than all the others).

3.6.2. Some end-of-line measurements correlate to process measurements

There was some weak correlation found between OCMM process measurements in the body shop and the seal pressure measurements at the end-of-line. No significant correlation was found between OCMM or door measurements and closing effort. Although air leakage measurements were not expected to correlate with process measurements, some correlation was found. However, since there was no proven link between air leakage at the door beltline and wind noise, any further analysis was considered superfluous for this investigation. It was originally hypothesized that closing effort and seal pressure would correlate strongly with door and doorframe measurements so the lack of correlation led to a search for factors that might decouple the body shop with the end-of-line. Appendix 1 contains a bivariate correlation analysis for process measurements vs. end-of-line.

3.6.3. Weak correlation between seal gap/flushness and door/frame

It was expected that door and doorframe measurements would contribute equally when calculating seal gaps and flushness, which are interactions between the two. In actuality, the correlation was found to be very weak and typically favored either the door or doorframe. The concern led to an investigation of the door installation process. Plant personnel explained that a problem with the hinge caused excess variation in the hinge placement on the doors, which was verified using check fixture data.

3.7. Conclusions from first experiment

3.7.1. Lack of correlation might be the result of fitting

In correlation studies, door and doorframe measurements correlated more strongly with pre-fitting measurements than measurements taken at the end-of-line. Extensive pre-fitting measurements of doors may then seem unwarranted, but equally troubling is the lack of a standardized process and the required measurements to control door fitting. The door fitting process is essentially open-loop – there is no plant process in place to measure and understand the results of the fitting process. The door fitters themselves were unaware of any wind noise studies on door location vs. wind noise. They locate doors to optimize flushness, at the expense of seal gap. Apparently, the results of wind noise studies had never filtered down to the people who are directly responsible for door placement. One of the door fitters requested to be informed of any results since he had never been told how to adjust the doors for wind noise. The fitters should be the primary beneficiaries of such studies since they are last to touch the doors before the car is shipped to the customer. One learning from this experiment was an understanding of the need to truly benchmark the fitting process and its effects on car quality.

3.7.2. Measured points do not line up

One large concern was that there was a significant distance between respective measurements on the body and door. There are many possibilities for the lack of coordination between these measurements. Check fixtures themselves are not easily alterable, while OCMM cameras and CMM programming can be altered with relative ease. Thus one possibility is that the OCMM measurements have changed as the frame assembly process has become better understood in the plant, while the check fixture was not updated. This is mainly due to the fact that check fixtures are manufactured by outside suppliers and must undergo a rigorous repeatability and reproduceability (R&R) study before they can be used in plant measurements. When attempting to predict seal gap and flushness from doorframe and hinge check fixture measurements, there was a lack of correlation. Quite possibly, this was due to the fact that a measurement on the door would be inches away from the corresponding measurement on the doorframe, which was again distant from the seal gap or flushness measurement points. Thus, door sheet metal inconsistencies could lead to inaccurate results, instead of the measurements benchmarking the assembly process.

3.7.3. Large variations in the doors compared to variation of the frame

The standard deviation of the door measured after hinge installation was much higher than the deviation of the doorframe. To further analyze the door process, measurement data were obtained from MFD. Figure 3.17 shows the six sigma charts comparing pre-installation door measurements with post-installation door measurements. The data show that the hinge installation process adds much of the variation seen at the hinge installation check fixture. In fact, the variation reduction team at the plant already understood that hinge placement was unacceptable, and was working to study the matter further.

3.7.4. Suggestions for a follow-on project

Although some analysis could be made regarding plant process and measurement systems, the overall goal of relating in-plant measurements to customer feedback was not met. The small measurement set (81 cars) was too small to track down a complex problem such as wind noise, especially when customer survey results, which are typically very noisy, were used as the predicted value. Two approaches were suggested that would alleviate the difficulties with the first project. The first approach would be to track a similar number of cars, but then take real-world measurements for wind-noise, such as taking the cars to a wind tunnel. This would require more in-plant personnel to coordinate a larger experiment, but would quickly determine the relationship, if any, between the process measurements and wind noise. The second approach would be to use the current set of collected data from the OCMMs and any other measurements that can be associated with specific cars and correlate the measurements to customer feedback. This approach would require no plant resources, but would require more time to get results – approximately three months.

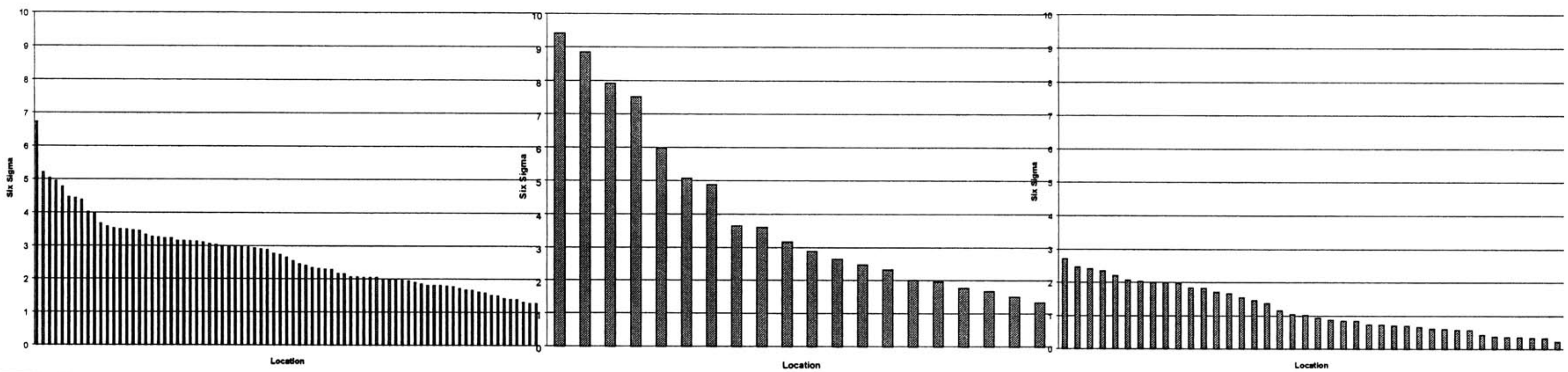


Figure 3.17: Doorframe, Post Hinge Install, and Door without Hinge Six Sigma Charts

Section 4. Second Project – Analyzing plant data to find customer sensitivity

Since GM considers itself a "data-rich" environment, the second approach, which leveraged existing data and theoretically used no extra resources, garnered more support from Quality and plant personnel. The ease of retrieving data compared to the complexity of coordinating a cross-departmental experiment to pin down wind noise contributors made the decision considerably easier. All that would be needed was EQF survey data, which is available for all truck and car models within GM, OCMM measurement data and a database to link an OCMM record to an EQF record, both of which are available in most plants.

The first approach, although it would have been able to scientifically measure wind noise, couldn't answer the key question of what caused customer complaints, although the two are presumably highly correlated.

4.1. Correlating in-line OCMM to EQF

Since OCMM data are collected for every car produced in a plant, one possible approach would be to use the central limit theorem (more samples reduces variation of the mean) to reduce the effect of individual preferences on survey data. Although this logic may seem somewhat flawed due to the differences in the reasons for customer complaints, the expectation is that a problem serious enough to warrant a customer complaint would probably have an underlying physical explanation. With the model year nearly complete, large amounts of in-plant data and EQF feedback were expected to be available. A database that linked the OCMM data, recorded by plant Job Sequence Number (JSN), to the Vehicle Identification Number (VIN) numbering system used for EQF results would allow a car-by-car correlation with customer feedback. Warranty data would provide a slightly more objective set of measurements for customer quality, but was not obtained by the time of this writing. Since the data was typically available within plant systems all across GM, it was surmised that the data would be easy to obtain. Figure 4.1 Shows the format of the three datasets, and how they can be used for analysis. As can be seen, the datasets may not match record-for-record, but there are other ways to summarize the data contained. For example, as shown above, cars could be referenced by build date instead of matching individual records.

The original reason for the research remained - determining what factors affected wind noise complaints at Lansing Car Assembly. Thus, the in-plant databases at LCA were used to provide the appropriate data. In retrospect, there would have been greater value in obtaining data from many plants, since the LCA dataset was incomplete. However, given the difficulty in obtaining the required data from LCA, retrieving data from other plants would have taken far too much time and effort.

A regression of actual OCMM measurements vs. EQF data (matched on a car-by-car basis) could produce a model of what dimensions customers are extremely sensitive to – in effect, what causes wind noise.

Used to find cars with both OCMM data and EQF data

Used to match feedback to daily OCMM averages

JSN	Date/Time	OCMM Data
012	5/5/1999	....
013	5/5/1999	....
......	....	....

OCMM Data - collected at most plants

JSN	VIN
012	1G43
013	1G44
......	....

PVI/VIN matching - stored at plants

VIN	Build Date	Feedback
1G43	5/5/1999	....
1G55	5/5/1999	....
......	....	....

EQF Data - available from Quality organization

Figure 4.1: Linking EQF to OCMM data

Car warranty data, which is obtained from GM service organizations and dealers, could provide a more scientific estimate of customer satisfaction and true problems. One advantage of having warranty data is that it reflects an actual cost to General Motors of certain problems. Major problems can significantly affect profit through warranty costs. Thus, plans to solve certain problems could be easily justified through warranty cost reduction.

4.2. Dataset problems

Although the EQF data and JSN/VIN matching spanned the entire 1999 model year - all cars built at the plant from July 1998 through July 1999 - the OCMM data were only available for cars built during the day shift from January 1999 through the end of the model year. Based on preliminary estimates, it was presumed that this would be enough data to show significant correlation, if any existed.

4.3. Problems with plant collection processes

Since there is no central data collection process within GM, collecting the required data was nearly impossible. For example, four separate organizations control the customer feedback, warranty, OCMM measurement data and VIN/JSN mapping. Warranty data were never obtained due to organizational difficulties. The customer feedback and warranty data are collected centrally, which means that all the customer feedback company-wide can be obtained from a single source. OCMM data and VIN/JSN mappings are maintained at the plants, thus investigating similarities in wind noise complaints across multiple models, or between plants producing the same models, would be a monumental undertaking.

4.3.1. Plants determine their own processes for data

Each plant maintains their own data collection and storage, primarily for their own variation reduction, process control and continuous improvement. The plant processes are fragmented company-wide, and finding sources of data at each plant requires almost intimate knowledge of their data collection and storage. Even with the organizational linkages between the Quality organization and Variation Reduction teams at the plants, the process of obtaining data was nearly impossible, assuming such data were available.

ISO-9000 certification requires that data be stored for six months, but makes no requirements on the quality of the data, or the availability. Subsequent investigation found that some plants have a disciplined data collection process – database storage and archival over multiple model years- while other plants provided no storage beyond the internal OCMM storage capabilities (approximately one month).

Since plants typically use measurement data for short-term variation reduction and plant performance indicators, there is no perceived need to keep the data for more than a few months. Some organizations within GM are favoring longer storage requirements for data, but there is currently no GM-wide standard length for data storage. Some plants store data permanently while others delete data after two or three months. Since OCMM stations have local data storage, the results from the latest month are available. However, new measurements will replace the older measurements on a first-come first-served basis. Many plants have no supplemental storage beyond the station's storage, or do not make use of the storage.

4.4. Analysis

The first attempt at analyzing this large dataset was to directly match cars to complaints using the PVI/JSN matching database. Each customer survey result would then be matched to the OCMM measurements taken, if available. The cars available for analysis had to contain both OCMM data and an EQF survey return. Only 196 of such cars were found, and of those cars, only one car had a wind noise complaint. Once again, the number of complaints prohibited detailed analysis, suggesting that more data must be obtained to make reasonable conclusions.

4.4.1. Low probability of so few cars having problems (1 out of 196)

Using a binomial distribution, with an average PPH of 10 (as reported by JD Powers), the probability of having only 1 complaint out of 196 cars is 2.3×10^{-8} whereas the probability of having 20 complaints is about .09. In fact, the probability of having less than 10 complaints in 196 cars is .01. Even using the 4 PPH average of the model year EQF data, the probability of having just one return is less than .003. The probability of having four or less is .101. This suggests that the cars available are significantly different than the normal car built at the plant and leads to a conclusion that cars missing from the dataset have a higher probability of wind noise. The first six months of production for the 1999 model year are conspicuously absent from the OCMM data. The fact that so few of the cars available have problems might suggest that the quality of the cars (predicted by the PPH of complaints in the EQF survey) is poorest at the beginning of the model year, and improves steadily during the model year. Another possibility would be the difference between cars built during the day shift compared to cars built during the night shift, since the OCMM data only contained day shift cars.

4.4.2. Comparing cars by daily measurements

Because the ability to analyze the dataset with only one customer complaint was limited and eliminated the possibility of using many measurements to eliminate noise, another approach was taken. All records for each available date were combined in both the OCMM data and the EQF surveys. The OCMM records were combined into a daily mean and standard deviation for each measurement location, and the EQF records were aggregated into a count of survey returns for each day, along with a sum of all complaints (e.g. wind noise, water leak, door closing effort) for that day. Thus the feedback that previously couldn't be used because they didn't match a specific car, and the OCMM data that couldn't be used because they referred to cars that weren't surveyed could still be used in the analysis.

4.4.2.1. Concern about a binary response

Because EQF surveys record either a positive or negative response to given questions, there is no ability to attribute scale. Although different customers have different sensitivities to the wind noise characteristics of the car, the massive datasets were expected to reduce the problems of differing customer sensitivity.

However, this becomes a problem for standard linear regression models. A standard linear regression model applied to binary data will output a model to predict probabilities. However, the standard analysis of variance (ANOVA) used to determine the accuracy of the model fails because the error terms are non-normal. Also, a model to explain a probability would, by necessity have a lower limit of 0 and an upper limit of 1. A better model for binary outcomes is a logistic model.

A logistic regression model replaces the linear model,

$$E\{Y\} = \beta_0 + \beta_1 X + \varepsilon$$

with a sigmoidal model.

$$E\{Y\} = \frac{\exp(\beta_0 + \beta_1 X)}{1 + \exp(\beta_0 + \beta_1 X)}$$

The sigmoidal model has asymptotes at 0 and 1 and is nearly linear between the probabilities of .2 and .8. This meets the criteria for analyzing probabilities better than a purely linear model. The Y variable predicts the probability of a positive response (1) for a given measurement values. The model can easily be extended for multiple independent variables. (Neter 96)

Since the response variable is the probability of a positive response, a cutoff probability must be established. Typically, the cutoff depends on the costs of a false positive (alpha risk) vs. the costs of a false negative (beta risk). In this case, the cost of a false positive would be a frame that was alarmed as a potential wind noise problem unnecessarily, and the risk of a false negative would be a customer-perceivable wind noise problem that was not predicted.

Figure 4.2 shows a comparison between linear and logistic regression. Since the regressions represent the probability of an occurrence, the linear model fails, since it is not bounded at zero and one, thus predicting a probability less than zero for the first observation and a probability greater than one for the last observation. The cutoff value shown above is at .5.

4.4.2.2. Reformatting data for logistic regression

Since the logistic model uses 0/1 values instead of the count of complaints/count of survey returns obtained from the aggregation, each survey return was separated. So, for a day where 20 surveys were collected and 2 had complaints, twenty records, each containing the same daily average and standard deviation, would be created, two of which would have a value of one for the response, and 18 would have a zero. This was used to get a rough indication of the validity of the technique and to utilize the available data.

4.4.2.3. Regression of in-line OCMM vs EQF

The first logistic regression model sought to link EQF wind noise complaints with daily in-line OCMM measurements. Using the datasets aggregated by day, the model found four of the terms to be

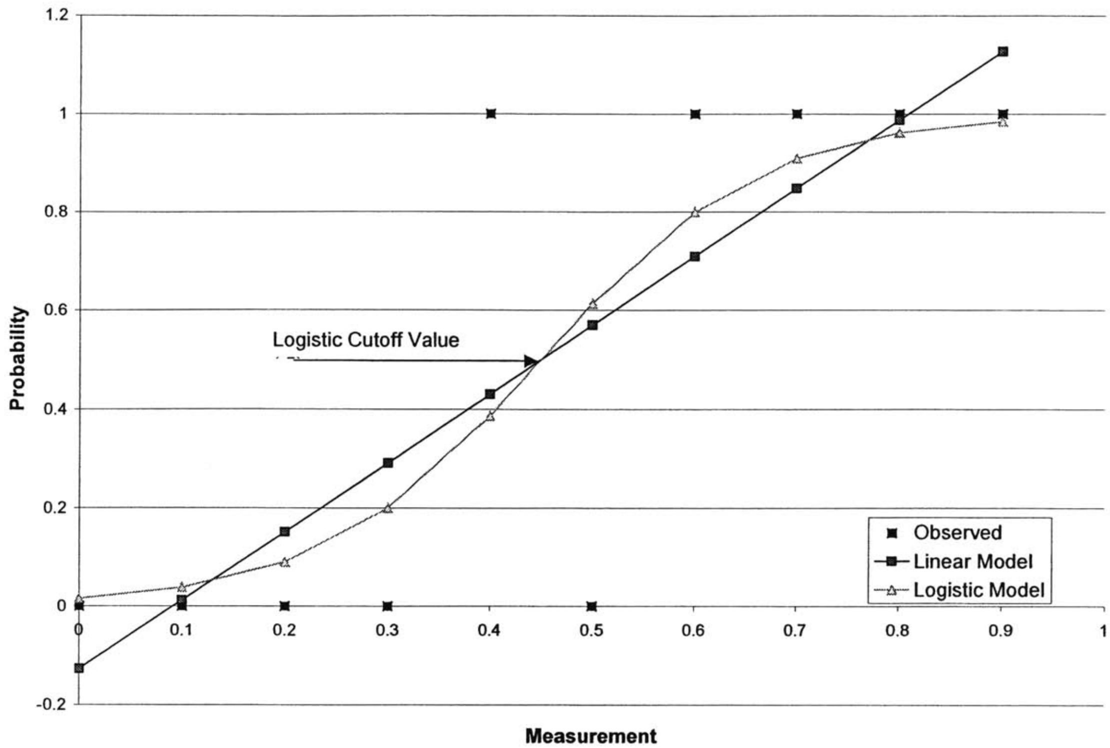


Figure 4.2: Linear vs. Logistic Regression

significant but was not able to easily separate the positive from negative responses. With a cutoff value of .5, the model was not able to predict any wind noise complaints. With a cutoff value of .1, the model correctly determines 33% of complaints, but would recommend corrective action on 13.6% of cars that had no complaints. The terms found to be significant were the mean (averaged by day) of two measurements near the doorframe, and the standard deviation of another two doorframe measurements. Although the terms were found to be extremely significant (P value > .05), the overall model accounted for very little of the overall difference in results (R-squared of .015). Thus the regression couldn't be considered significant. The regression results can be found in Appendix 3.

4.4.2.4. Adding door measurements

Daily measurements from the hinge placement check fixtures (for all four doors) were obtained from the Variation Reduction at LCA. The results were also aggregated by day like the body measurements. The measurements were not available for the same length of time as the OCMM measurements, thus they limited the analysis to the last four months of the model year. The door check fixture data added to the significance of the regression, but did not use the same measurements as predictors. One measurement on the right front door was flagged as an indicator for wind noise complaints. Again the regression provided insight into critical measurements, but was not significant by itself (R –squared of .028). The regression results can be found in Appendix 4.

4.4.3. A second look at the daily data

The poor performance of the regressions led to a rethinking of what the available data could provide insight into. The fundamental fallacy seemed to be that the data could be leveraged to provide similar answers to the first approach (predicting complaints on a car-by-car basis). A new approach was to use the daily data to predict daily results. Instead of predicting a probability of bad cars given daily results, the data was reorganized to predict whether a day would be better than average (low PPH) or worse than average (high PPH). The results, seen in Appendix 5 and 6, were much more encouraging. Both the OCMM-only model and the model with door measurements have an R-Squared value greater than .35. These results lead to some confidence that logistic regression could be used as a powerful tool in correlating customer complaints to body shop measurements. The regression currently suggests that a few critical dimensions most significantly affect customer satisfaction. Although this does not give specific ranges where there will be less complaints, or allowable variation, even these simplistic results could be used to tune variation reduction efforts towards these areas. Further analysis with more detailed and complete datasets may indeed find critical regions for dimensions.

4.5. Conclusions

4.5.1. Significance of predictors

In all of the logistic models, the predictors are significant to at least a 95% confidence level. Although the models did not show themselves capable of predicting customer satisfaction on a car-by-car basis, there still is reason to suspect that the models tell a partial story. The model cannot be expected to tell the entire wind noise story because no measurements of the fitting process and other potential contributors to wind noise were available. However, variation reduction (if the standard deviation is significant), or a move towards nominal (if the average is significant), should make improvements in wind noise complaint levels.

4.5.2. Potential predictive capability

Even though customer feedback is typically difficult to predict, since different customers will have different sensitivities to problems, logistic regression can be used to provide the likelihood of a complaint. Because logistic regressions predict a probability of customer complaint, it can relate in-plant measurements to some measure of customer satisfaction. The currently limited models may still provide a better place to focus variation reduction efforts than merely chasing after the biggest six sigma.

4.5.3. Aggregation effects

The current models' use of measurement and feedback aggregation may also cause analysis problems. Cars with high wind noise would be expected to be outliers in several measurements; however, that level of detail is not captured by the dataset. The daily standard deviation measurements might account for the number of outliers in a given day, but the dataset was still missing much of the detail required for a significant study of the problem.

Section 5. Controlling manufacturing processes through customer feedback

Although continuous improvement is a necessity for building quality into automobiles, a mechanism to focus the continuous improvement areas could help significantly. What is required is a methodology of understanding high leverage areas for the customer – attributes of a car that greatly affect customer satisfaction. The lack of an effective feedback process can cause plants to take incorrect action, or prioritize goals incorrectly. One good example of the lack of feedback in the current manufacturing process is fitting. The fitters I interviewed made final adjustments on doors based mainly on common sense, because no engineers had told them the best place to locate the door. The company process dictated flushness as the key concern, but the fitter did not know how to balance flushness requirements with the potential effect on wind noise.

GM understands that variation reduction is good, but does not have a weighting mechanism to locate variation that can be perceived by the consumer. Instead, plants are told to seek out the biggest hitters, not in terms of customer satisfaction, but in terms of overall variation. A critical measurement may never show up on variation reduction's radar screen.

Work done at MEO&I centers around creating a process to bring customer feedback directly to the manufacturing and design floor. Currently, the plant and warranty groups are responsible for determining when a problem is severe enough. A problem has to be a big enough hitter for the plant to expend its resources to solve it. Feedback modeling techniques would help in providing a cursory analysis of problems before plant personnel investigate more thoroughly.

The process of placing customer feedback directly into a plant would be to use existing measurements combined with customer survey and warranty data to provide a response variable. Measurements that correlate significantly with customer feedback would be considered a key quality measurement. Continuous improvement efforts could then focus on reducing variation on the key measurements first. Measurements that don't correlate to customer feedback would not be considered as important, and larger variations found there could be left alone as long as they didn't affect product safety.

5.1. Measurement methodology

Until 100% sampling becomes common process for all automotive assemblies, a more disciplined methodology would be required to leverage higher-value cars – those with more measurement data. For example, surveying a car measured with both CMM and OCMM would be preferable to measuring one with only OCMM data. Doors that are measured in hard check fixtures should be mated with CMM cars.

Currently, no record is kept of which car is matched with the measured door. That information could be extremely valuable for customer feedback. Even without process changes, measurements should be meticulously kept to allow as much analysis as possible when customer data becomes available. This would require a significant investment in the in-plant data collection systems – to tie them together and store the outputs long-term, as well as a careful revisiting of the cross-departmental requirements for linking data with customer feedback.

Moving towards a more detailed measurement methodology – not necessarily making more measurements, but taking advantage of the measurements available, will greatly improve the chances of getting detailed customer response through data analysis.

Because the automobile assembly process is a set of steps, most of which are susceptible to variation from previous steps, and add their own variation, the data collection effort becomes essential in variation reduction. The door subsystem, for example, suffers from the sheet metal variation in each component, the variation of the door and BIW assembly, variation of hinge installation, variation in door installation, variation in door re-hang, variation in fitting, and variation of seal installation. The complete story of wind noise cannot be told until measurement systems instrument each component and process.

5.2. Build methodology

Once a model has been created of customer feedback, the model can be reversed to discover what measured variations may cause survey problems and warranty issues. Plant measurement systems can then alarm on mean shifts and variation only when customer complaints would rise. The current process of creating alarms based on control chart values may help tune the process, but there's no plant perception that a loss of control of a piece of equipment would necessarily lead to a customer complaint.

Current plant SPC techniques are not well suited towards multivariate data such as that recorded by in-line OCMM systems. Early research in 100% sampling data from OCMM showed time series relationships and correlation between station measurements. Typical univariate SPC, such as control charting, is not capable of dealing well with this data, and thus has been largely ignored by plant personnel. (Hu, 1990) For example, a typical control chart sets limits at +/- 3 sigma. The probability of a false alarm on such a control chart is .003; however, assuming that each measurement is independent of previous measurements and other locations measured simultaneously, the pooled probability of false alarm given 100 measurement points (such as an OCMM station) is .3. Thus, 3 out of 10 cars, on average, would trigger a false alarm.

Some univariate techniques can avoid this problem, but much of the research around dealing with 100% sampling OCMM, lies in using multivariate techniques to reduce the probability of false alarms.

5.3. Variation Reduction methodology

Using regression techniques, such as those described earlier, models of customer feedback could be used to focus variation reduction efforts.

One approach would be to create a probability model where each car would be rated by its predicted effect on customer satisfaction. The result could be analyzed using a control chart (to discover potential quality problems) or on a case-by-case basis, where high-probability cars are taken aside for further study.

Another, simpler approach would be to weight the six sigma value of each measurement by its perceived effect on customer satisfaction. By targeting high leverage areas first, variation reduction would focus on customer satisfaction as a priority.

5.4. Design methodology

The car design process is extremely complex and involves many groups within GM. Each group must decide what car characteristics are important as they negotiate sheet metal design, structural design, powertrain and many other components that must come together in harmony to have a successful car. Designers use their own insight and some process manuals that help focus the design effort on important characteristics.

By finding key customer measurements, the designers could focus on a design robust to that variation. Sheet metal joint types, for example could be optimized to reduce variation in a key area.

Costs could be optimized by spending more effort and time on the key areas, while using current technology on areas that aren't seen as important. With the proper feedback, computer models could test different designs' effectiveness in reducing customer complaints. The time required in tolerancing – the process of allocating allowable variation to various suppliers and assemblers – could be greatly reduced. The overall effect would be having a car perceived as being much higher quality, without additional design cost.

5.5. Requirements for utilizing customer feedback

The data requirements for utilizing customer feedback on the plant floor are no stricter than the requirements to analyze warranty data. Currently, the limits of GM data and process (shown by the difficulty in obtaining relevant data) severely limit the ability to understand customer feedback.

Small improvements in key areas could provide nearly free plant analysis from consumers.

5.5.1. 100% sampling

Currently, only the BIW assembly process is adequately instrumented through OCMM stations. Other processes, such as door, hood and trunk installation are only instrumented with check fixtures. Seal gap and flushness are also measured only on a small sample of cars each day. 100% sampling is the only effective strategy for truly understanding process mean and variation. Nearly 100 measurements are required to establish an accurate control chart, and with only one measurement per shift, check fixtures would take nearly a month. (Wu 1991) GM still relies heavily on check fixtures and CMM's with low sample rates to understand the process. Instead they should focus on collecting as much data as possible, understanding that the cost of the data may be much less than the cost of not collecting the data.

A disciplined data collection approach will be a great benefit for future process and manufacturing research. Having extensive process data available would be a boon for those investigating new process control techniques, or for finding cars that meet certain criteria for customer clinics, for example. Creating innovative ways to leverage data collection could create a large barrier to entry that might significantly prevent future competition. With large datasets available for analysis, new techniques could be discovered without requiring extensive in-plant efforts such as those currently performed.

5.5.2. Coordinated Data Collection

Data collection within GM must be coordinated three ways. First, measurement stations observing the same parts in different process steps should use the same locations. Second, internal and external supplier data should be tracked to specific cars and stored with car data. Third, plants within GM should strive towards a common measurement process so that learnings can be spread throughout the organization.

5.5.2.1. Matching measurements

Matching measurements between stations can provide greater insight into process variation. BIW measurement stations already take advantage of this fact, and methodologies for tracking down variation using data measured the same components have been shown to be valuable in process diagnosis. (S.J. Hu, 1997)

Coordinating subassembly measurements with the finished product data is also essential. Again, the BIW process is typically well measured. For example, a left and right body side are measured before being welded to the underbody, and the corresponding points are re-measured after assembly. Variations in the process can be located to a subset of the process by analyzing the locality of variation (S.J. Hu, 1997)

Components that are not welded to the BIW must also have coordinated measurements. Doors, for example, should be measured before and after installation to determine the capability of the installation process. Seal gap and flushness, if not measured at the exact locations of door and doorframe measurements, may be incapable of controlling the installation process due to sheet metal variation.

5.5.2.2. Tracking data across organizational boundaries

Measurements must also be coordinated between suppliers and GM to provide extensive knowledge about each car. For example, metallurgical information, stamping information, door measurement information and the like may become critical in fine-tuning the cars to increasingly discriminating customers. Currently, each part of the operation uses its own data collection to understand its process. This lack of inter-division cooperation means that the data can't be leveraged to understand how process fluctuations affect customer satisfaction, because there is no way to track customer complaints back to the source in a meaningful way. With 2mm six sigma, acceptable process variations could yield cars that deviate nearly 2mm on a critical customer measure. Being able to find a common thread would require much more in-depth knowledge about a specific car than is available today.

Measurements currently taken on components currently are of little permanent value, because the measurements are not tracked to a specific car. They can help control the supplier's process, but do not provide much insight into overall car quality.

A coordinated database could better leverage high-cost measurements such as wind tunnel testing. If GM had more data collected for each car, they could correlate real world measures back to process measurements as well.

5.5.2.3. Common measurement process

Although results would be found on a plant-by-plant basis, having identical process measurement types, locations and storage mechanisms could reduce analysis complexity. Having a common database format, for example, could allow automated analysis and plant report generation.

Techniques that worked in one plant would more easily transfer to another plant with similar processes. When manufacturing support groups are brought in to analyze complex situations, the required time to understand the plant process could be greatly reduced.

5.5.3. Extensive Data Modeling

Because there would be a vast amount of data, which would be cross-linked by car, model, dimensions, etc., the process of creating and proving meaningful models for customer satisfaction would require a large amount of work. Simple logistic regression techniques may not provide enough insight into customer complaints, and other techniques, such as Principal Component Analysis, which work well for multivariate data, may not be effective on the binary EQF responses.

As more and more in-plant data sources become available within GM, the data-mining and data modeling opportunities become almost too attractive to pass up. Analysts might be able to find similar issues between multiple models and allow plant teams to coordinate the solution process. They may find car designs that typically have better performance.

5.6. Analyzing current inhibitors

5.6.1. Legal issues question the wisdom of maintaining data long-term

Recent lawsuits against auto manufacturers have emphasized the need to corporations to shed old data. Cases show that detailed decision documentation that would normally aid in future product improvements are now becoming central in issues around litigation. In-plant data may have the same potential if it is stored indefinitely. Data sources might be used by lawyers to prove that GM "knowingly" produced a poor quality car and then sold it to the consumer. With recent penalties in the billions of dollars, a compelling argument might be made for GM to remain a historyless company. Hopefully, the legal implications of decisions and data will be resolved in the future, but there is reason for corporate-wide fear of the potential losses brought on by even the most innocuous documents.

5.6.1.1. Cost of living without history

Even with the fears of legal authorities, there still is a much more immediate concern of how to produce higher quality cars through measurements. Short-term quality problems are more widely understood, but there is relatively little data on longer-term issues. Such issues as the effect of tolerance allocation and design decisions on variation and customer satisfaction could prove essential to remaining competitive as more cost and design time are squeezed out of the vehicle development process. Modeling becomes more essential as well as design cycle times are reduced. More human insight and rules of thumb must be replaced by computer models that can produce detailed analysis and optimization of designs, reducing inter-organizational negotiations.

5.6.2. Lack of consistent and coordinated data collection

When the question was asked, "what causes customers to complain about wind noise?" the answer appeared easy to answer - analyze plant measurements on cars, looking for correlation with customer feedback. Many factors made the challenge more difficult than it should be. Different organizations within GM, including the plants, have different requirements for the data, and different levels of discipline in how they handle it. Some plants meticulously store and analyze data, while others do not store data at all beyond the reporting requirements. Even at a given plant, operators may have different approaches, the daytime operator might carefully store data while the nighttime operator would not retrieve data at all from the OCMM stations. Different sources of data required different processes as well. Some data was collected on paper, while other data was collected using handheld measurement devices.

Different plant measurements and different requirements for their storage and reporting makes collecting the data in a central, consistent repository quite difficult. Without the consistent measurements, detailed customer analysis is difficult.

Even the measurements themselves were suboptimized for the specific process they were being used to control. The measurements by the internal door supplier did not correspond to the same measurements on the hinge placement check fixture, which then did not correspond to the same measurements on the doorframe. Thus, it was difficult to analyze such derived measurements as seal gap, and flushness.

5.6.2.1. Developing a consistent measurement strategy across GM

To simplify data collection and analysis, measurements must be consistent across process, supplier, organizational and plant boundaries.

Within GM, this has become increasingly apparent. Already, some organizations are driving standard practices and measurement repositories through to the plants. Standard practices include how many measurements should be taken, where the measurements should be taken, and how often the measurements should be taken. Unfortunately, the common practice still relies on low sample rate devices such as check fixtures to take a significant role in plant process control. Yet, common measurement plans and methodologies are a quantum leap forward in moving GM towards rigorous quality control, and as plants incorporate company-wide practices, moving the whole company towards better sampling becomes easier.

5.6.3. Disjoint data sources

Different measurements on a given car have different measurement devices with different output. For example, check fixture measurements are taken with a digital probe and stored in a spreadsheet, while OCMM measurements are stored in a simple database at the measurement station that is read over a network.

Since each measurement controls a different part of the assembly process, plants have not seen the necessity for a central storage repository for the measurement data. Yet, having to collect data from different sources adds unnecessary delay when searching for correlation to customer feedback.

5.6.3.1. Developing a consistent database of plant measurements

Again, organizations within GM have already seen the need for disciplined and centralized data storage within plants. However, they may not have noticed the need to incorporate after-purchase data, such as warranty claims and survey results within these databases. Having such a database may raise security concerns, but these could be eliminated by sectioning the database to allow access only to areas that are necessary for each task.

5.6.4. Struggling with the organizational difficulties of a centralized process

Managing responsibilities, authority and incentives can be extremely difficult when centralized coordination is required. In a plant, variation reduction personnel are responsible for the quality of the assembly process. Unless a consensus-based system is used where individual plants are convinced that adopting the new systems is indeed beneficial, changes will probably be difficult to spread throughout the organization without significant backlash.

Although common processes and plant databases are a huge win for GM, they also create the opportunity for political opportunists to create niches for themselves. People who find themselves in control of central measurement process, or central storage can make themselves indispensable by enforcing their control over information and process. With every project to bring a more robust, easy to manage solution to GM, there are opportunists who only see desire to make themselves indispensable. There is already talk among plant personnel that the variation reduction methodologies aren't a very good fit for the specific plant environments and are being shoehorned in without regard to existing processes. The concern within the plants is that the common process puts people within the quality organization at powerful positions that may adversely affect GM's move towards higher quality.

5.6.5. Data availability to researchers and designers

GM's perception of being data rich and information poor may be somewhat true in the factories, however, GM is data-poor for researchers looking for long-term trends, such as modeling customer preference. While there are measures being taken within GM to correct the lack of long-term data, there are other issues to consider in terms of data availability and accessibility.

5.6.5.1. Understanding knowledge requirements can avoid GM's bureaucratic tendencies.

In GM, major cutbacks in the 80's, and the potential for more thinning leaves workers clinging to potential power sources. Knowledge is perhaps the best way to create that power at lower levels. Prusak suggests the creation of "knowledge markets" – places where employees can gather to exchange knowledge. Knowledge has a price, and companies should support an efficient market for that knowledge, such as a corporate web site where individuals can create web pages that show their knowledge "wares."

Controlling access to a central database of manufacturing and quality data might give rise to knowledge brokers. Brokers who decide which employees may access a database like this can create "knowledge monopolies" where the broker uses the knowledge to create political power. The problem for companies is that the knowledge will not be available when necessary, and the benefit gained from its use not realized. For GM, the result of having this data – creative solutions for improving perceived quality – could be thwarted by a knowledge monopoly. Freeing up this knowledge within the organization is one way of avoiding this monopoly. Having corporate understanding of knowledge and data source, and policies to establish fair use can keep opportunists from monopolizing information. (Prusak, 1998)

5.6.6. Linking data across processes and organizations

While each division must make measurements for their own SPC purposes, there is also a need to understand the entire build process and the impact of quality at each step. This requires a significant amount of cross-departmental coordination on measurement systems and storage. For example, measurements made on a door should be tracked along with that door to the car to which it is mated. Thus, there needs to be some way of tracking the door between the Metal Fabrication Division plant and the assembly plant. When more advanced measurements are done on cars, those cars become more valuable for further analysis. Thus, those cars should be the ones chosen for wind tunnel analysis, or for customer feedback. The current system places no higher value on cars with more measurements.

It also becomes important to repeat measurements through different steps in the assembly process. For example, the gap on an installed door before paint and fitting, may be altered by those processes. To get a better understanding on the effects, a gap measurement after paint, and after fitting might be used.

5.7. Summary

Directly using customer feedback to target the process of systematically reducing variation can reduce the costs of design, tolerancing and variation reduction. By changing the plant data collection process from one of short-term variation reduction, to long-term archival, GM gains the ability to analyze the manufacturing process in detail, for a miniscule cost of storage. However, these changes require a great deal of collaboration between different organizations, and could potentially give rise to knowledge brokers who could benefit from restricting this information. The legal implications of this long-term storage are still untested, and could become a thorn in GM's side.

Section 6. Analyzing current inhibitors to variation reduction

Problems with incorporating customer feedback directly into the plants are similar in many respects to problems GM faces with variation reduction in general. In fact, incorporating customer feedback into the plants could be considered "weighted" variation reduction – merely focusing variation reduction efforts on key customer concerns. Thus issues that inhibit variation reduction in general also limit efforts to incorporate customer feedback.

6.1. Capacity constraints

Many plants within GM, especially those building automobiles in high demand, find themselves capacity constrained, running three shifts (24 hours a day), with very little time for quality improvement tasks that might cause production shortfalls. Short daily shutdowns for required preventative maintenance allow some minor tweaks, but no major projects could be undertaken without causing plant disruptions. Quick model changeovers, and sometimes plant floorspace requirements, can impede the process of installing new measurement equipment on the plant floor.

6.2. Split streams

Another issue in general variation reduction within the body shop is the relative advantages and disadvantages of split manufacturing lines. Split lines are necessary when a set of operations has to be performed, that in total, take longer than the acceptable cycle time. This may happen at a tack station – where body panels are brought together, and must be welded enough to remain structurally solid for the next station. Since these split lines have different physical characteristics, the variation and nominal characteristics differ also. These values are reported in the plant six-sigma summary as high variation values, although the true physical variation may be significantly smaller.

6.3. Desire to retain profitability

GM's status as a profitable, capacity-constrained manufacturer, especially in those markets where customers are sensitive to high-quality products, could also cause large decline in profitability if the market begins to lose its momentum.

6.3.1. Buyers' market favors high quality, low cost cars

In a sellers' market – where demand is greater than supply, auto manufacturers can relax quality and cost requirements, merely passing them on to consumers. As long as the quality is high enough to avoid warranty work, each car sold brings additional money to GM. However, either new entrants or macroeconomic forces could create a buyer-friendly situation, allowing consumers to be much more price and quality conscious as the market becomes over-saturated with cars. Consumers can take their pick, rating the cars against each other, instead of being forced to take the next car off the lot as it becomes available. The result is that customers will favor higher quality, lower cost cars, and manufacturers who have not focused on quality and cost improvements will suddenly find themselves struggling to catch up.

6.3.2. Quality improvements lead to increased sales

It can't be proven whether GM's recent slip in market share is due to quality issues or whether it was due to GM's perceived lack of innovative styling (as designers would have us believe). Some articles and press releases might lead toward the conclusion that quality does indeed affect sales.

According to a 1992 article in Automotive News, A-cars (Pontiac 6000, Oldsmobile Cutlass Ciera, Buick Century) which were a 10-year-old design at the point had a sales surge as J.D. Powers results rated their quality higher than some of the Japanese imports.

An October, 1995 Press Release from GM claimed, "Combined sales of the all-new 1995 Lumina (231,304) and Monte Carlo (89,834) now total 321,138 units, shattering the previous generation Lumina model year sales record of 225,025 units in 1993. The new Lumina was also one of only two dozen car and truck models with fewer than 75 problems per 100 vehicles, according to the prestigious 1995 J. D. Power Initial Quality Studies.

6.3.3. Similar lessons seen in the 1980's

A similar situation occurred in the 1980's that pitted U.S. manufacturers against higher-quality Japanese imports. Although fuel prices boosted sales for the more economical Japanese cars, customers still saw them as higher quality at a similar price. GM's wake-up call required the ousting of two CEOs, Roger Smith and Robert Stempel, and even the new GM has struggled to maintain market share.

6.3.4. Using profitability to fund quality

GM's profitable position now should allow it to work on establishing its competitive advantage for the years to come. By focusing on automobile quality, GM could create the reputation of being the high quality manufacturer. Such a position would help reclaim market share and allow GM to command higher margins for the perceived quality.

6.3.5. Gap between upper-level dictates and plant reality

In some ways, the dictates from above still haven't filtered throughout the organization. In a May, 1995, press release, GM President and CEO, John F. Smith, Jr. was quoted as saying, "Across the industry there was a lot of pressure in 1995 to push product out to meet very high customer demand," Smith said. "We firmly believe that we cannot sacrifice quality. We owe it to our customers. As this survey illustrates, that commitment has paid off."

This may be true in some plants within GM, but some of the cultural artifacts suggest that production numbers are given higher credence. For example, one plant posted daily production numbers on their andon board, another announced production volumes over the loudspeaker during breaks.

6.4. Process ownership

Perhaps one of the most difficult managerial tasks within any company is matching power and responsibility. For example, plants are held accountable for the six sigma CII numbers. However, many suppliers are dictated company-wide, or are internal suppliers who have different motivations. In one example, a set of three sheet metal parts had tolerances of 2mm from the supplier, but when put together by the plant had to have an overall tolerance of 2mm. The plant was not able to push the suppliers to tighter specifications, but had to report the overall dimension as part of the six sigma, which, not surprisingly, averaged greater than 3.5mm.

Another example was dealing with a hinge supplier. A corporate-wide cost reduction led GM to use a low-cost single source supplier for bolt-on hinges. The hinges had a specification for the stiffness (the effort required to open/close the hinge), which the tooling was designed around. The supplier was unable to meet the specification, and was granted a variance. When the equipment was certified, the hinge placement machine could not place the stiff hinges consistently. The installation group refused to sign the machine as capable, and the car was produced with significant problems on all four doors.

Wind noise problems then led to a study of the plant from the GM's quality organization. As a member of the variation reduction team commented, "They send us a young engineer, who looks at the fire and says, 'fire'." The line workers knew what the problem was, the variation reduction team knew what the problem was, but no one was capable if taking ownership. No one within the plant had the authority to renegotiate terms with the supplier.

Assemblers who practice lean manufacturing typically overcome these problems by maintaining tight relationships with suppliers – not by aggressively seeking the lowest cost. Suppliers are judged more for their ability to deliver high-quality components on a just-in-time basis than the lowest cost.

Suppliers are also expected to improve their processes and share learnings. Since some process ownership is given to the lowest level – each worker is able to stop the line when problems arise – quality problems quickly become the responsibility of the whole plant. (Womack, 1990)

6.5. Incomplete application of benchmarking

6.5.1. Toyota / NUMMI

GM, through its joint venture with Toyota has been in perhaps the best position to learn from the Toyota Production System (TPS). However, GM managers at NUMMI were not brought back into positions where they could use their newfound process knowledge to benefit GM. (Keller, 1993)

6.5.2. 2mm Project

The 2mm methodology has demonstrated many ways of understanding variation in plants and finding and correcting the associated tooling problems. While GM has adopted some of the reporting mechanisms, there still are quality gaps between the plants who have followed the methodology more closely and those that have not.

The 2mm Project established a methodology that combined multivariate analysis techniques with the ability to incorporate in-plant expertise. It showed plants that 100% sampling provides much better process knowledge than low sampling rates. In-line OCMMs allow plants to quickly react to quality problems instead of relying on once-per-shift measurements. Wu's research shows that such infrequent measurements make SPC nearly impossible, and the result is that process changes are done in an ad-hoc manner, only when the problem is perceived downstream.(1991) However, GM has only required 100% inspection for the BIW assembly process and has let plants keep existing, low sampling rate devices for measuring components. Arguably, 100% measurements should be required on any major subassemblies, whose measurements would be expected to affect customer satisfaction. Doors, for example, are arguably 50% of the wind noise problem, and were exhibiting three times the variation of the doorframe, yet were still not being investigated as closely as the process variations that contributed to overall plant six sigma.

6.5.3. Company process

Standard application of company process allows plants to incorporate the benefits of advances that come through corporate research and development. Variation reduction processes are established company-wide to foster standard approaches to problem solving within plants.

By focusing on plant six sigma, GM hopes that plants will target the biggest problems – areas with the largest variation – first; however, different plants have reinterpreted the requirements to fit with their priorities instead of adopting corporate wisdom. One plant surveyed indeed attacked the largest variation first – whether that variation was due to process variation on a single line, or process differences between parallel lines. Another plant tried to line up parallel processes as long as the individual processes were somewhat well behaved. A third plant, which was running three shifts, was reluctant to shut multiple lines down and instead focused on eliminating single-line variation, even though line differences contributed to most of the plant's CII.

6.5.4. Plants within GM

Some plants within GM have successfully reduced variation and have implemented methodologies for analyzing the assembly process. These plants should be encouraged to share their knowledge to other plants who are struggling to control their process. This knowledge isn't being passed around, and plants are allowed to repeat mistakes and solve problems already found in other plants.

6.6. Overall mentality – if the car works, don't fix the process.

One of the biggest deterrents to building higher quality automobiles is the stigma that once a "good" car is built, employees should leave the process alone, and "don't fix what isn't broken." GM is no exception. There is great resistance to change in the plants, once a car has been shown to operate successfully. Competition with other manufacturers has slowly raised the bar on quality requirements – plants must respond to the need for higher quality, or discover themselves unable to compete.

The major indicator for process quality at an assembly plant is the CII. This number, only penalizes a plant for variation, and not for deviation from design nominal.

6.6.1. Issues in evaluating supplier/plant blame

One of GM's chief learnings from the Japanese seems to be the idea that nailing down variability is much more important than bringing the process to true nominal. GM, in some ways, has divorced itself from understanding true nominal by focusing on plant six sigma – which only accounts for overall variation. Dr. Chris Couch, an executive at Toyota explained that in the 1980's the Japanese typically focused on variation and not nominal. Honda made the process work first, and then created all the part drawings. Recently, though, nominal has become an essential part of variation reduction. "If you have two parts that have small variation, but are each 1mm off nominal, they might not fit. Then, which supplier do you tell to change?"

When nominal is not sacred, there is no way to evaluate supplier performance. Although six-sigma values are highly regarded, only the cars that do not fit together, or receive significant amounts of customer complaints or warranty returns generate corporate interest. At that point, vehicle engineers have to discover how the cars are not being made correctly. A supplier could be at blame, even if their six-sigma values are extremely tight – if they are delivering parts that are out of spec. Our analysis of one GM plant showed that they had effectively moved the nominal value on their own volition – because their six-sigma values were within the design tolerance. The nominal value had been move by approximately 1mm, thus nearly half the parts would have been out of the design tolerance limits. Because the cars built "correctly" there was no backlash for the change.

By changing the CII to a measurement including nominal differences, such as simply adding three times the deviation from true nominal to the CII (to scale it appropriately), plants could be held accountable for off-center processes using the in-place mechanisms.

6.6.2. Issues in evaluating design performance

Building cars that vary significantly from nominal reduces the ability to understand whether the design of the car is acceptable. Designers create a car to have specific measurements and tolerances. When the manufactured cars do not conform to the specifications, designers gain less insight into design improvements – because their designs end up being circumvented in the plant.

6.7. Summary

Some current issues, such as the stretching of company-wide capacity to produce more of the profitable cars, and chronic issues, such as the lack of ownership and the temptation to ship lower quality cars instead of overcoming problems, hinder GM's efforts to build the highest quality automobiles. Although benchmarking higher-quality competitors and leading plants within GM has created valuable insight, this insight needs to be applied judiciously. When the current lessons are implemented company-wide, follow-on benchmarking will provide greater insight into variation reduction efforts.

Section 7. Conclusions

Understanding the customer is a central part of every organization. Those companies that find better ways of incorporating customer feedback throughout the organization to maintain customer focus will have an advantage over those that a self-focused. The American auto manufacturers in the 80's were taught a hard lesson that customers can't be pushed forever into cars they don't want.

Thus, any methodology that can bring customer concerns and feedback closer to critical decisions, such as design, tolerancing, variation reduction and styling decisions will give manufacturers a key advantage.

The methodology proposed, although unproven scientifically, is a simple model used to correlate actual customer responses to plant measurements. The results obtained, although they don't tell the whole story, can guide variation reduction efforts to significant contributors to wind noise.

In order to leverage the methodology, higher quantities of measurements, and higher quality measurements are required. This can either be obtained by pushing 100% sampling through in-line OCMM installations, or by making better use of current plant measurements.

The process of obtaining data from different sources with General Motors and the quality of the data showed that GM has far to go in its quest to significantly improve quality. Organizational boundaries need to be challenged when researchers cannot obtain the data they need.

Section 8. Further research

Even though the analysis suggested process improvements necessary for reducing variation, there is no data to suggest that those improvements would help any more than general variation reduction. Some follow-on research could include:

- Analyzing the relationship between Quality and Plant six sigma
- A case study in using this methodology to reduce wind noise complaints
- An organizational study of measurement and variation reduction ownership

All of these could provide significant insight into the validity of this methodology, potential manufacturing and organization improvements General Motors can make to streamline this type of analysis, and whether customer feedback could be incorporated into plants.

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Appendix 1: Correlation between process and end-of-line measurement

		PRSHINGE	PRSAPILL	PRSROOF	PRSTPSTK	PRSBELT	PRSSTRK	LKPATCH	LKBELT	LKHANDLE	CLOSEFF
PERROCK	Corr.	-.057	-.178	-.124	.096	-.276	-.132	-.122	-.181	.097	-.239
	Sig.	.689	.207	.382	.497	.048	.352	.388	.198	.495	.088
PERHINGE	Corr.	.069	.030	.048	.247	.204	.316	.092	.145	.024	-.172
	Sig.	.625	.832	.733	.077	.147	.023	.517	.306	.868	.222
PERAPILL	Corr.	-.065	.022	-.102	.151	.018	.085	.118	.145	.064	-.100
	Sig.	.649	.875	.473	.286	.899	.549	.404	.305	.654	.479
PERROOF	Corr.	-.038	-.015	-.004	-.097	-.063	.136	-.213	-.173	-.014	-.136
	Sig.	.787	.914	.975	.493	.655	.337	.130	.220	.922	.335
DRROCK	Corr.	-.122	-.039	-.195	-.186	.251	-.109	-.213	-.075	.144	-.029
	Sig.	.690	.900	.523	.542	.409	.723	.485	.808	.639	.924
DRHINGE	Corr.	.236	.206	.090	-.220	.314	.257	-.393	-.610	.521	-.340
	Sig.	.438	.499	.770	.471	.297	.396	.185	.027	.068	.255
DRAPILL	Corr.	.285	.428	.132	-.337	.294	.119	-.246	-.440	.494	-.395
	Sig.	.345	.145	.668	.260	.329	.700	.418	.132	.087	.182
DRROOF	Corr.	-.153	-.069	.098	.250	.028	.155	.276	-.028	.166	-.230
	Sig.	.618	.823	.751	.410	.929	.614	.362	.927	.588	.449
DRROOF2	Corr.	.274	.302	.310	.373	.271	.521	.022	-.176	.099	.071
	Sig.	.366	.315	.303	.209	.370	.068	.944	.565	.748	.818
DRBELT	Corr.	.340	.302	.324	.347	.214	.508	-.078	-.195	.178	.050
	Sig.	.256	.317	.280	.245	.484	.077	.801	.524	.561	.871
DRRHROCK	Corr.	-.289	-.139	-.163	-.300	-.115	-.372	.116	.336	-.222	.093
	Sig.	.338	.650	.594	.319	.709	.211	.705	.261	.466	.762
SEALROCK	Corr.	.115	.139	.088	-.065	.134	.203	.010	-.183	.060	-.022
	Sig.	.426	.335	.544	.656	.354	.157	.945	.204	.681	.879
SEALHING	Corr.	.190	.130	.087	-.033	-.099	-.139	-.053	-.211	-.032	-.161
	Sig.	.187	.367	.546	.819	.493	.335	.717	.142	.828	.264
SEALAPIL	Corr.	.090	.089	.031	.143	.119	.088	.053	.071	.166	-.212
	Sig.	.533	.538	.831	.322	.412	.543	.712	.622	.250	.139
SEALROOF	Corr.	-.020	.202	.004	.210	.066	.118	.055	.206	.144	-.145
	Sig.	.889	.159	.977	.143	.648	.414	.706	.151	.319	.316
FLSHSTRK	Corr.	.168	-.047	.172	-.181	-.095	-.051	.147	-.197	-.109	.219
	Sig.	.244	.744	.233	.208	.510	.723	.307	.171	.450	.126
FLSHROCK	Corr.	.038	.207	.377	-.022	-.154	.040	-.115	.105	-.086	.218
	Sig.	.857	.320	.064	.916	.462	.848	.585	.618	.681	.295
FLSHFNTP	Corr.	-.316	-.322	-.224	-.097	-.252	-.150	.105	.056	.014	.247
	Sig.	.124	.116	.281	.644	.225	.473	.617	.789	.946	.234
FLSHBELT	Corr.	-.055	.025	.016	-.020	-.081	.082	-.050	.074	.149	-.016
	Sig.	.702	.862	.912	.888	.578	.572	.728	.612	.303	.914

In this figure, 95% or greater significance correlations have been highlighted. Note the lack of correlation between process measurements and end-of-line measurements

Appendix 2: Correlation between body shop measurements

		SEALROCK	SEALHING	SEALAPIL	SEALROOF	FLSHSTRK	FLSHROCK	FLSHFNTP	FLSHBELT
PERROCK	Corr.	-.386	-.023	.160	.196	-.078	.554	.281	.287
	Sig.	.001	.848	.187	.104	.519	.000	.084	.016
PERHINGE	Corr.	.133	.021	.146	.163	.027	-.010	-.062	.180
	Sig.	.274	.866	.227	.177	.827	.951	.710	.136
PERAPILL	Corr.	-.127	-.021	-.022	.353	-.147	.296	.097	.126
	Sig.	.295	.866	.854	.003	.224	.067	.558	.297
PERROOF	Corr.	.034	.119	-.038	.132	-.096	.264	.163	.082
	Sig.	.780	.328	.756	.275	.427	.104	.321	.499
DRROCK	Corr.	.530	.028	.216	-.101	.048	-.192	.123	-.329
	Sig.	.013	.902	.347	.662	.836	.549	.704	.145
DRHINGE	Corr.	.271	.371	.168	.192	-.123	.094	.051	.091
	Sig.	.235	.097	.466	.403	.595	.772	.875	.696
DRAPILL	Corr.	.122	.332	.075	.229	-.219	.176	.162	.090
	Sig.	.597	.142	.746	.319	.340	.584	.616	.699
DRROOF	Corr.	-.479	-.155	.058	.248	-.185	.071	.029	.497
	Sig.	.028	.503	.802	.279	.423	.826	.930	.022
DRROOF2	Corr.	.223	.118	-.074	.241	-.106	-.042	-.673	.225
	Sig.	.332	.611	.750	.292	.646	.898	.017	.327
DRBELT	Corr.	.389	.149	-.093	.175	-.061	-.083	-.748	.150
	Sig.	.081	.521	.689	.449	.794	.798	.005	.517
DRRHROCK	Corr.	-.312	-.363	-.031	-.407	.254	.007	.516	-.155
	Sig.	.169	.106	.894	.067	.267	.983	.086	.502

Appendix 3: Logistic Regression of OCMM vs. EQF

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	1814	100.0
	Missing Cases	0	.0
	Total	1814	100.0
Unselected Cases		0	.0
Total		1814	100.0

a. If weight is in effect, see classification table for the total number of cases.

Block 1: Method = Forward Stepwise (Conditional)

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	26.811	1	.000
	Block	26.811	1	.000
	Model	26.811	1	.000
Step 2	Step	8.823	1	.003
	Block	35.634	2	.000
	Model	35.634	2	.000
Step 3	Step	5.944	1	.015
	Block	41.578	3	.000
	Model	41.578	3	.000
Step 4	Step	4.337	1	.037
	Block	45.915	4	.000
	Model	45.915	4	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	851.557	.015	.038
2	842.735	.019	.051
3	836.791	.023	.059
4	832.454	.025	.065

Classification Table[a]

Observed			Predicted WNTOTAL .00	Predicted WNTOTAL 1.00	Percentage Correct
Step 1	WNTOTAL	.00	1422	273	83.9
		1.00	78	41	34.5
	Overall Percentage				80.7
Step 2	WNTOTAL	.00	1483	212	87.5
		1.00	83	36	30.3
	Overall Percentage				83.7
Step 3	WNTOTAL	.00	1449	246	85.5
		1.00	80	39	32.8
	Overall Percentage				82.0
Step 4	WNTOTAL	.00	1464	231	86.4
		1.00	80	39	32.8
	Overall Percentage				82.9

a. The cut value is .100

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	AFZ03L_U	.896	.184	23.778	1	.000	2.451
	Constant	-2.778	.106	682.577	1	.000	.062
Step 2[b]	AQO08R_U	1.514	.519	8.501	1	.004	4.545
	AFZ03L_U	.886	.178	24.742	1	.000	2.424
	Constant	-3.434	.258	177.531	1	.000	.032
Step 3[c]	AQO08R_U	1.584	.521	9.256	1	.002	4.874
	AFZ03L_U	.769	.183	17.719	1	.000	2.159
	SQO04L_U	-5.859	2.448	5.730	1	.017	.003
	Constant	-1.891	.683	7.662	1	.006	.151
Step 4[d]	AQO08R_U	1.560	.519	9.026	1	.003	4.757
	AFZ03L_U	.615	.202	9.259	1	.002	1.849
	SQO04L_U	-5.517	2.400	5.285	1	.022	.004
	SRF04L_I	-4.877	2.379	4.204	1	.040	.008
	Constant	.562	1.366	.169	1	.681	1.755

a. Variable(s) entered on step 1: AFZ03L_U.

b. Variable(s) entered on step 2: AQO08R_U.

c. Variable(s) entered on step 3: SQO04L_U.

d. Variable(s) entered on step 4: SRF04L_I.

Appendix 4: Logistic Regression with door check fixture data

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	277	15.3
	Missing Cases	1537	84.7
	Total	1814	100.0
Unselected Cases		0	.0
Total		1814	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
.00	0
1.00	1

Block 1: Method = Forward Stepwise (Conditional)

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	7.753	1	.005
	Block	7.753	1	.005
	Model	7.753	1	.005
Step 2	Step	3.917	1	.048
	Block	11.670	2	.003
	Model	11.670	2	.003
Step 3	Step	5.102	1	.024
	Block	16.772	3	.001
	Model	16.772	3	.001

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	135.898	.028	.068
2	131.981	.041	.102
3	126.879	.059	.145

Classification Table[a]

Observed			Predicted WNTOTAL .00	Predicted WNTOTAL 1.00	Percentage Correct
Step 1	WNTOTAL	.00	209	48	81.3
		1.00	10	10	50.0
	Overall Percentage				79.1
Step 2	WNTOTAL	.00	203	54	79.0
		1.00	10	10	50.0
	Overall Percentage				76.9
Step 3	WNTOTAL	.00	177	80	68.9
		1.00	7	13	65.0
	Overall Percentage				68.6

a. The cut value is .100

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	SQO61R_I	-14.465	5.343	7.328	1	.007	.000
	Constant	3.181	2.067	2.369	1	.124	24.078
Step 2[b]	SQO61R_I	-21.412	6.805	9.900	1	.002	.000
	SRF36R_F	10.715	5.212	4.227	1	.040	45026.504
	Constant	3.453	2.022	2.915	1	.088	31.585
Step 3[c]	SQO61R_I	-25.591	7.573	11.418	1	.001	.000
	SRF36R_F	23.821	8.484	7.883	1	.005	2.2E+10
	ADR802K4	3.719	1.708	4.741	1	.029	41.231
	Constant	-16.838	9.301	3.277	1	.070	.000

a. Variable(s) entered on step 1: SQO61R_I.

b. Variable(s) entered on step 2: SRF36R_F.

c. Variable(s) entered on step 3: ADR802K4.

Appendix 5: Logistic Regression of OCMM vs. High Percentage of Wind Noise Complaints

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	124	100.0
	Missing Cases	0	.0
	Total	124	100.0
Unselected Cases		0	.0
Total		124	100.0

a. If weight is in effect, see classification table for the total number of cases.

Block 1: Method = Enter

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	108.725	.363	.493

Classification Table[a]

			Predicted		
			WNHIGH		Percentage Correct
	Observed		.00	1.00	
Step 1	WNHIGH	.00	66	11	85.7
		1.00	15	32	68.1
	Overall Percentage				79.0

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	ASL55R_U	9.013	1.978	20.760	1	.000	8211.847
	SQO06R_U	16.350	3.990	16.790	1	.000	1.3E+07
	ASL07L_I	-2.508	1.069	5.504	1	.019	.081
	ASL07L_U	12.531	2.671	22.004	1	.000	276746.6
	AQO06R_U	.271	.871	.097	1	.756	1.311
	SZZ06L_F	-33.491	9.679	11.972	1	.001	.000
	Constant	12.660	3.439	13.556	1	.000	314980.7

a. Variable(s) entered on step 1: ASL55R_U, SQO06R_U, ASL07L_I, ASL07L_U, AQO06R_U, SZZ06L_F.

Appendix 6: Logistic Regression: OCMM and Door data vs. High Percentage of Wind Noise Complaints

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	69	55.6
	Missing Cases	55	44.4
	Total	124	100.0
Unselected Cases		0	.0
Total		124	100.0

a. If weight is in effect, see classification table for the total number of cases.

Block 1: Method = Forward Stepwise (Conditional)

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	68.839	.112	.167
2	60.406	.214	.319
3	53.062	.294	.437
4	43.038	.389	.579
5	30.325	.492	.731

Classification Table[a]

			Predicted		
			WNHIGH		Percentage Correct
Observed			.00	1.00	
Step 1	WNHIGH	.00	52	0	100.0
		1.00	17	0	.0
	Overall Percentage				75.4
Step 2	WNHIGH	.00	48	4	92.3
		1.00	10	7	41.2
	Overall Percentage				79.7
Step 3	WNHIGH	.00	48	4	92.3
		1.00	8	9	52.9
	Overall Percentage				82.6
Step 4	WNHIGH	.00	49	3	94.2
		1.00	6	11	64.7
	Overall Percentage				87.0
Step 5	WNHIGH	.00	50	2	96.2
		1.00	4	13	76.5
	Overall Percentage				91.3

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	ASL07L_U	3.033	1.212	6.259	1	.012	20.750
	Constant	.045	.485	.008	1	.927	1.046
Step 2[b]	ASL07L_U	13.410	4.306	9.697	1	.002	666846.2
	AQO23L_F	5.042	1.923	6.870	1	.009	154.716
	Constant	6.290	2.444	6.623	1	.010	539.183
Step 3[c]	ASL07L_U	16.260	4.951	10.785	1	.001	1.2E+07
	AQO23L_F	5.816	2.156	7.278	1	.007	335.569
	ADR852K2	3.925	1.607	5.966	1	.015	50.670
	Constant	-14.959	8.928	2.807	1	.094	.000
Step 4[d]	ASL07L_U	21.845	6.303	12.011	1	.001	3.1E+09
	SQO23R_I	44.072	15.879	7.704	1	.006	1.4E+19
	AQO23L_F	6.178	2.548	5.878	1	.015	482.177
	ADR852K2	6.436	2.415	7.101	1	.008	623.692
	Constant	-42.129	16.573	6.462	1	.011	.000
Step 5[e]	ASL07L_U	43.513	13.804	9.936	1	.002	7.9E+18
	SQO23R_I	94.858	29.881	10.078	1	.002	1.57E+41
	AQO23L_F	11.580	4.422	6.857	1	.009	106905.6
	SQO61L_I	53.404	19.894	7.206	1	.007	1.6E+23
	ADR852K2	11.746	4.024	8.521	1	.004	126241.8
	Constant	-100.880	32.745	9.491	1	.002	.000

a. Variable(s) entered on step 1: ASL07L_U.

b. Variable(s) entered on step 2: AQO23L_F.

c. Variable(s) entered on step 3: ADR852K2.

d. Variable(s) entered on step 4: SQO23R_I.

e. Variable(s) entered on step 5: SQO61L_I.