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A Study of the Effects of Manufacturing Complexity on Product Quality in Mixed-Model Automotive Assembly

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A STUDY OF THE EFFECTS OF MANUFACTURING COMPLEXITY ON PRODUCT QUALITY IN MIXED-MODEL AUTOMOTIVE ASSEMBLY

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by
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ABSTRACT

The objective of this research is to test the hypothesis that manufacturing complexity can reliably predict product quality in mixed-model automotive assembly.

Originally, assembly lines were developed for cost efficient mass-production of standardized products. Today, in order to respond to diversified customer needs, companies have to allow for an individualization of their products, leading to the development of the Flexible Manufacturing Systems (FMS). Assembly line balancing problems (ALBP) consist of assigning the total workload for manufacturing a product to stations of an assembly line as typically applied in the automotive industry. Precedence relationships among tasks are required to conduct partly or fully automated Assembly Line Balancing. Efforts associated with manual precedence graph generation at a major automotive manufacturer have highlighted a potential relationship between manufacturing complexity (driven by product design, assembly process, and human factors) and product quality, a potential link that is usually ignored during Assembly Line Balancing and one that has received very little research focus so far. The methodology used in this research will potentially help develop a new set of constraints for an optimization model that can be used to minimize manufacturing complexity and maximize product quality, while satisfying the precedence constraints.

This research aims to validate the hypothesis that the contribution of design variables, process variables, and human-factors can be represented by a complexity metric that can be used to predict their contribution on product quality. The research will also identify how classes of defect prevention methods can be incorporated in the

predictive model to prevent defects in applications that exhibit high level of complexity. The manufacturing complexity model is applied to mechanical fastening processes which are accountable for the top 28% of defects found in automotive assembly, according to statistical analysis of historical data collected over the course of one year of vehicle production at a major automotive assembly plant. The predictive model is validated using mechanical fastening processes at an independent automotive assembly plant.

This complexity-based predictive model will be the first of its kind that will take into account design, process, and human factors to define complexity and validate it using a real-world automotive manufacturing process. The model will have the potential to be utilized by design and process engineers to evaluate the effect of manufacturing complexity on product quality before implementing the process in a real-world assembly environment.

DEDICATION

I dedicate this dissertation to the late Carol Strom Black and my advisor Dr. J T. Black who have been the prime source of inspiration and encouragement over the last sixteen years. They are the ones who motivated me to pursue my passion in Automotive Engineering and acquire a doctoral degree.

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CHAPTER ONE

1. RESEARCH OBJECTIVE AND MOTIVATION

The objective of this research is to test the hypothesis that manufacturing complexity can reliably predict product quality in mixed-model automotive assembly.

Originally, assembly lines were developed for cost efficient mass-production of standardized products. Today, in order to respond to diversified customer needs, companies have to allow for an individualization of their products, leading to the development of the Flexible Manufacturing Systems (FMS). Due to the high capital requirements when installing or redesigning an assembly line, its configuration planning is of great relevance for practitioners. Despite enormous academic effort in assembly line balancing (ALB) since the first mathematical formalization of ALB problem by Salveson in 1955 [1], there remains a considerable gap between requirements of real configuration problems and the status of research. Assembly line balancing problems (ALBP) consist of assigning the total workload for manufacturing a product to stations of an assembly line as typically applied in the automotive industry. Precedence relationships among tasks are required to conduct partly or fully automated Assembly Line Balancing. Efforts associated with manual precedence graph generation at a major automotive manufacturer have highlighted a potential relationship between manufacturing complexity (driven by product design, assembly process, and human factors) and product quality, a potential link that is usually ignored during Assembly Line Balancing and one that has received very little research focus so far. The methodology used in this research will potentially help develop a new set of constraints for an optimization model that can be used to minimize manufacturing complexity and maximize product quality, while satisfying the precedence constraints.

This research aims to validate the hypothesis that the contribution of design variables, process variables, and human-factors can be represented by a complexity metric that can be used to predict their contribution on product quality. The research will also identify how classes of defect prevention methods can be incorporated in the predictive model to prevent defects in applications that exhibit high level of complexity. The manufacturing complexity model is applied to mechanical fastening processes which are accountable for the top 28% of defects found in automotive assembly, according to statistical analysis of historical data collected over the course of one year of vehicle production at a major automotive assembly plant. The predictive model is validated using mechanical fastening processes at an independent automotive assembly plant.

This complexity-based predictive model will be the first of its kind that will take into account design, process, and human factors to define complexity and validate it using a real-world automotive manufacturing process. The model will have the potential to be utilized by design and process engineers to evaluate the effect of manufacturing complexity on product quality before implementing the process in a real-world assembly environment.

In order to fulfill the research objective, the following research questions need to be answered:

- **Research Question 1:** How is manufacturing complexity defined in the general context of assembly operations?

- **Research Question 2:** How is product quality defined for assembly of components in mixed-model automotive assembly? What is the effect of manufacturing complexity on product quality?
- **Research Question 3**: Several defect prevention methods are usually employed in practice. How can various classes of defect prevention methods be incorporated in the predictive model to lower complexity and minimize DPMO?

CHAPTER TWO

2. BACKGROUND

2.1. Basic Steps in Automotive Manufacturing

Since the days of the Ford Model T, automobiles have been the primary mode of transportation around the world. What makes the automotive industry very attractive for engineers is the fact that an automobile is a complex product that brings several different manufacturing processes together on one platform. Automotive manufacturing activities can be analyzed on two levels: the manufacturing system and the process levels. The manufacturing system view is further investigated from three different perspectives:

a. The structural aspect: Includes machinery and material handling equipment
b. The transformational aspect: Includes processes used to convert raw materials into finished or semi-finished products
c. The procedural aspect: Includes operating strategies, model-mix, sequencing etc.

The following sections provide a brief introduction to the transformational aspect of the manufacturing activities which includes a series of manufacturing processes that a car goes through before rolling off the final assembly line.

2.1.1. Stamping Process

The Press Shop receives a coil of sheet metal (typically steel or aluminum) from the supplier. This material usually goes through an inspection process to verify dimensional accuracy, metallurgical analysis, and heat treatment evaluation. Once approved, the coil may get stored or staged for blanking. The blanks are then transferred to large presses that use forming dies to convert the blanks into various vehicular panels. A typical body may consist of approximately 350 stamped pieces (e.g. trunk, under-body, A and B structural pillars, doors etc.) and the corresponding inner, middle and outer sections of these components. The stamping process requires mechanical and hydraulic presses with different capacities depending on the different panels that need to be formed. After stamping, the panels are stored and eventually get transported to the Body Shop, where they undergo the joining process.

Figure 2.1: Sheet metal stamping press

2.1.2. Joining Process

In the Body Shop, various stamped panels are joined to form the body / shell. The joining process includes tack welding to temporarily hold the pieces together. This process is followed by permanent spot welds. A combination of robotic and manual welders may weld approximately 5000 spots to join an average car body. Such robots are programmed to work with high accuracy and precision in tightly grouped cells. Programmable logic controllers (PLCs) are used to control and monitor these robots. The completed body also goes through a detailed dimensional verification process using laser illumination and charged coupled devices (CCD) camera system to monitor gaps between adjacent panels. This is an important quality characteristic that is closely monitored, especially in the premium car market. The completely welded car body (shell) is called the Body-in-White (BIW).

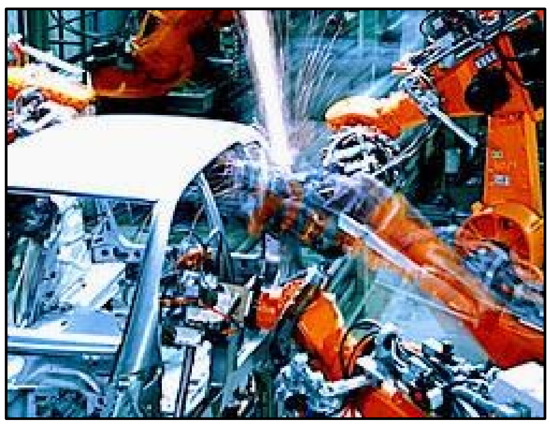


Figure 2.2: Spot welding of body panels using robots in the Body Shop

2.1.3. Painting Process

The completed BIW gets transferred to the Paint Shop. The vehicle goes through several immersion tanks to thoroughly clean the sheet metal panels and eliminate any foreign particles or adhesives left over from the welding process. Then a layer of iron phosphate or zinc phosphate gets applied followed by an electro coat layer. Robots apply under-body wax and sealants to critical areas of the vehicle to make the cabin water-tight and reduce the level of external road noise entering the cabin. The subsequent paint layers require curing through a combination of ovens. After the immersion process the body goes through paint booths that apply a primer, base coat, and a final clear coat. Several stages of inspection also take place in order to ensure that the painting process meets design specifications. After the painting process, the body enters the final assembly line.

Figure 2.3: Car body being painted by robots in a Paint Booth

2.1.4. Mixed-Model Final Assembly (MMFA)

A paced assembly line is a flow-oriented production system that employs some kind of material transportation system like a conveyor belt to transfer work-pieces successively to various stations at a given rate, such that the total duration over all operations at a station is limited to a cycle time.

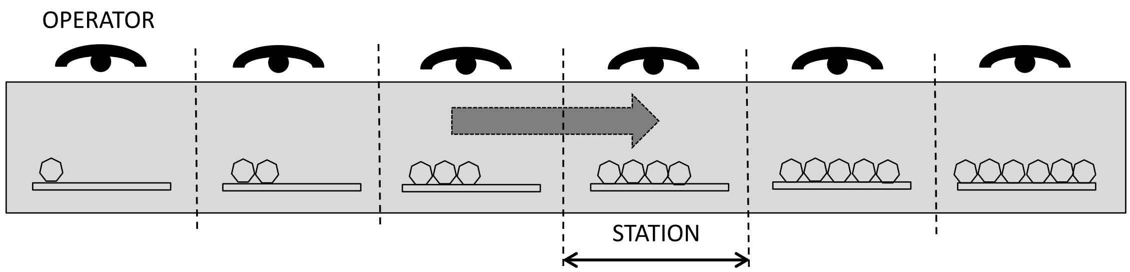


Figure 2.4: Conventional Assembly Line (Single Product)

Since the days of the famous Model-T produced by Ford, assembly lines have been widely used in many industries for the mass production of standardized products. The goal of mass production was to lower the unit cost by distributing the depreciation cost of specialized equipment and tooling over a large number of identical parts and by reducing the number of changeovers. In the early days of mass production, the lower selling price made products more accessible to common man, thereby creating a favorable environment for mass production of relatively identical products with very little variety. It was a seller's market in the early days of automotive manufacturing. The manufacturers assumed that whatever they built will get purchased promptly and hence they believed in the "push" system. Model changeover frequency was very low. The same model would run for days or sometimes weeks at a time. The two biggest downsides of this system were excess inventory and lack of flexibility.

The solution to this problem was developed by Toyota over the course of two decades and the comprehensive system was called the Toyota Production System (TPS). Toyota Production System is based on three basic principles [2]: Elimination of waste, Just-In-Time delivery, and Separation of worker from machine. These principles resulted in the ability to build customized products with a lot size of one on what is known today as the Mixed-Model Final Assembly (MMFA) line.

As a consequence of the increasing individualization of consumer products in many industries, a lot of effort has been directed to increase the flexibility and versatility of assembly lines, such that the benefits resulting from the high degree of specialization of labor and its associated learning effects can also be exploited in the assembly of low volume, highly diversifiable products. The use of advanced production technologies, such as machining centers with automated tool-swaps and welding robots with swappable component grippers and tooling, allows the manufacture of different variants of a common base product on the same line in subsequent production cycles without noticeable setup times or costs (lot size of one). These mixed-model assembly lines are widely employed in assembly-to-order production systems and enable mass customization. Important practical fields of application for mixed-model assembly lines can be found in the final assembly of cars which deals with an especially dramatic diversity summing up to 10^{32} different car models on the same assembly line [3]. A block diagram of the basic steps followed while manufacturing a car is shown in Figure 2.5. Final Assembly department is usually a maze of several sections of smaller assembly conveyors connected by transfer stations. A block diagram with several dock doors for raw material delivery is shown in Figure 2.6.

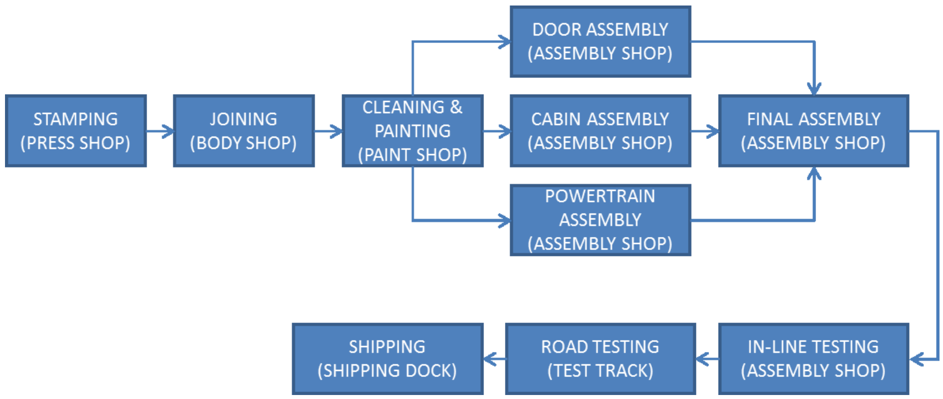


Figure 2.5: Block-diagram of automotive assembly steps

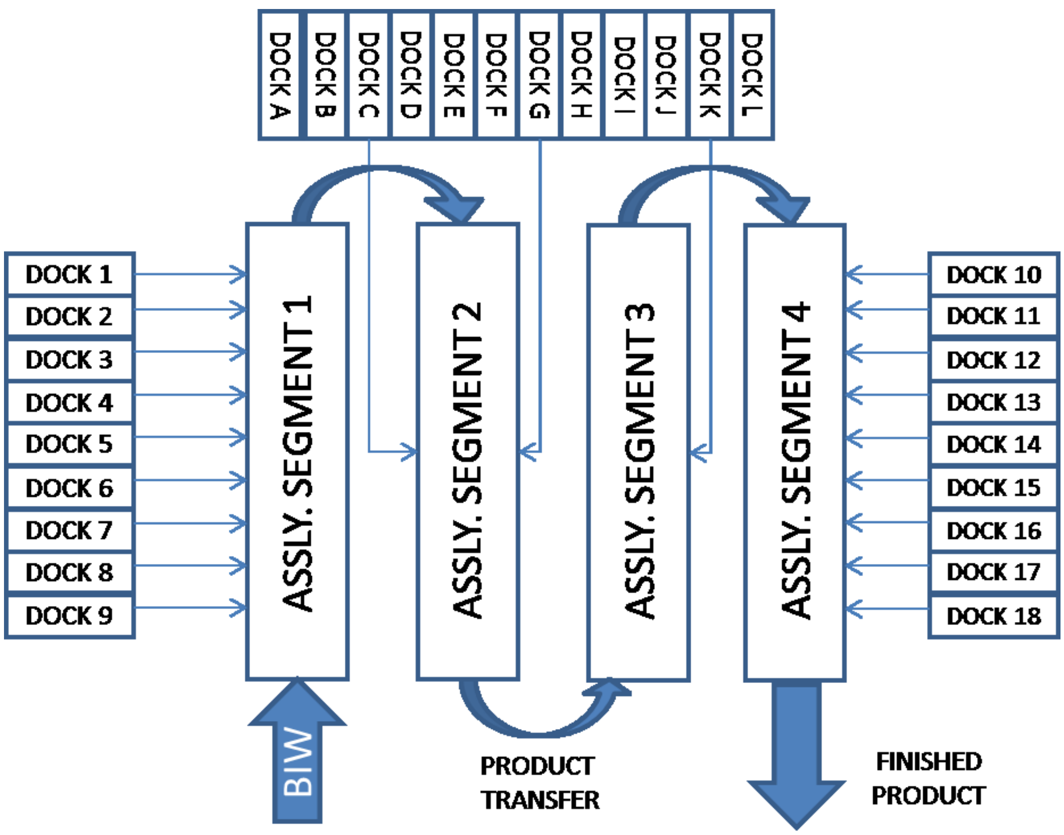


Figure 2.6: Block diagram showing product flow and parts supply

Each segment of an assembly line may have 20 to 25 stations, each of which may contain multiple *takts* (work-zones) where operators assemble components to the painted vehicle body. All conveyors are synchronized and move at a constant pace determined by the *takt-time*. Takt Time is defined as the ratio of total number of available seconds in a given work shift to the total number of products (vehicles) to be made, dictated by the demand of the end user.

$$\text{Takt Time} = \frac{\text{Total available time per shift (sec.)}}{\text{Total product demand per shift}} \qquad (1.1)$$

For example, a takt time at a major automotive assembly plant is 92.5 seconds. The takt time represents drop-off rate, which means every 92.5 seconds, one vehicle rolls off the end of the assembly line. This takt time is calculated as follows:

$$\text{Takt Time} = \frac{\text{9 hours x 3600 sec.}}{\text{350 vehicles per shift}} = 92.5\,\text{sec}. \qquad (1.2)$$

It is important to note that the denominator in this equation should be based on the rate at which the vehicles are sold to the final customer to maintain a Lean Supply Chain. Overproduction is a fundamental waste. The goal should be to produce the required 350 vehicles per shift with the least number of operators.

At each station, multiple assembly operators work in their respective zones of the vehicle as it travels on a constantly moving conveyor. The vehicle may be raised, lowered or tilted using programmable logic controllers to allow the operators to assemble components to the vehicle with the least ergonomic stress. Each associate has a set of tasks to be completed within the available takt time. This task assignment results in a non-polynomial (NP) hard problem called the Mixed-Model Assembly Line Balancing

Problem which will be addressed separately in the Key Enabling Systems section of this document. At the end of the assembly segment, there may be a quality check station that focuses on critical assembly characteristics associated with the tasks completed in that segment. At the end of the assembly segment, the vehicles get transferred across the logistics aisle to the next segment to continue the assembly process. This process continues along a serpentine sequence of conveyors until the entire assembly is complete. After the assembly is complete, the vehicle is driven using its own power to the testing area. All vehicles get driven into a booth that has a Dynamometer. The vehicle gets accelerated to its maximum rated speed and a series of tests are done on the Dynamometer. Finally the vehicle goes through a Road Test which includes driving it on a specially developed surface prior to certifying the vehicle for final delivery.

2.1.5. Real-World Example of MMFA

The following data shows a typical range of values for key parameters that will give readers feasible ranges of performance for a real-world Mixed-Model Automotive Assembly (MMFA) line:

a. Takt time: 60 to 125 seconds

b. Assembly takts (multiple per station): 355 to 450

c. Labor per vehicle (Joining, Paining, Assembly) = 25 to 30 hours

d. In-process dedicated quality-check takts = 8 to 10

e. Available labor hours per shift = 8 to 10 hours

f. Vehicle built per shift (9 hours) = 260 @ 60 s. and 540 @ 125 s.

g. Takt time utilization = 92% - 96%

h. Number of mixed base models assembled on a line = 2 to 3

i. Number of variants of each base model assembled = 20 to 25

j. Number of optional sub-assemblies per variant = 300

Note: Takt time utilization for a given takt is the ratio of the sum of task times assigned to the takt to the total available takt time. The range of the % utilization shown above is an average utilization percentage across a typical automotive assembly plant. This metric will be explained in greater detail in the Assembly Line Balancing section of this document.

Multiple base models may be assembled on the same assembly line. For example, a base model can be a small 5-seater Sports Utility Vehicle (SUV) and it can be assembled alongside another base model which can be a 7-seater large SUV. Each of these base models can have multiple variants such as Left-Hand Drive / Right-Hand Drive, choice of 2.5 liter gasoline engine / 3.0 liter larger gasoline engine or a turbo-charged diesel engine, or it can be a market specific variant that meets regulations of a certain country where the vehicle will be shipped, and many others. We have observed approximately 20 to 25 different variants per base model in a modern automotive assembly plant.

Option content refers to the possible option choices that customers have when they configure the vehicle. For example, a customer may be able to choose from up to 7 different roof-rails for a vehicle, depending on the selected variant.

The multiple base models, their variants, and the associated option content make Mixed-Model Final Assembly a challenging multi-disciplinary problem.

2.1.6. Key Enabling Systems

Mixed-Model Final Assembly is feasible because the following key enabling systems function seamlessly in the background:

Just-In-Time (JIT) Component Deliveries

The goal of Just-In-Time deliveries is to have the required components at the required time in the required quantities in order to prevent accumulation. One of the fundamental pillars of the Toyota Production System is Waste Elimination. Although inspection, transportation, and storage of inventory are required elements of a manufacturing process, only the actual processing is value added. JIT aims at eliminating one of the primary waste sources which is storage of raw material and finished goods. Mixed-Model Final Assembly reduces or practically eliminates finished goods accumulation because the vehicles are produced just-in-time, directly based on the customer orders and the same strategy is applied to the raw material receiving side.

Most automotive assembly plants that have implemented JIT deliveries have to place a tremendous focus on schedule and capacity. Some companies allow customers to place a completely customized vehicle order through a web-based configurator. These orders are then sequenced in the form of a production plan and broadcast to the respective vendors. On the other hand, some assembly plants operate on a sales forecast but divide their schedule into several layers. The top level master schedule is based on extensive market survey to estimate a relatively approximate demand for each model type. This high level planning is used to plan capacities in the plant and raw material suppliers. This estimate is given to the plants and vendors between 60 to 90 days in advance and firmed up usually 30 days before the planned production date. The firm numbers are used for the second level (weekly) and third level (daily) planning. A final leveled schedule is sent to the final assembly line which drives the demand using the kanban system. Kanban is a system of “pulling” components throughout the supply chain based on demand. Just-In-Time (JIT) deliveries prevent inventory accumulation and thereby reduce the working capital invested in inventory.

Instead of the long final assembly lines (Figure 2.6), the newer plants have a layout like the fingers of a hand (Figure 2.7). Just like airport layout planners would like to maximize the number of available gates, this floor layout allows the assembly plant to have a significant number of dock doors all along the various fingers for JIT deliveries of sub-assemblies and components directly at the point-of-use on the assembly line. This minimizes the need to move racks over long distances from the dock doors to the point-of-use, using forklifts.

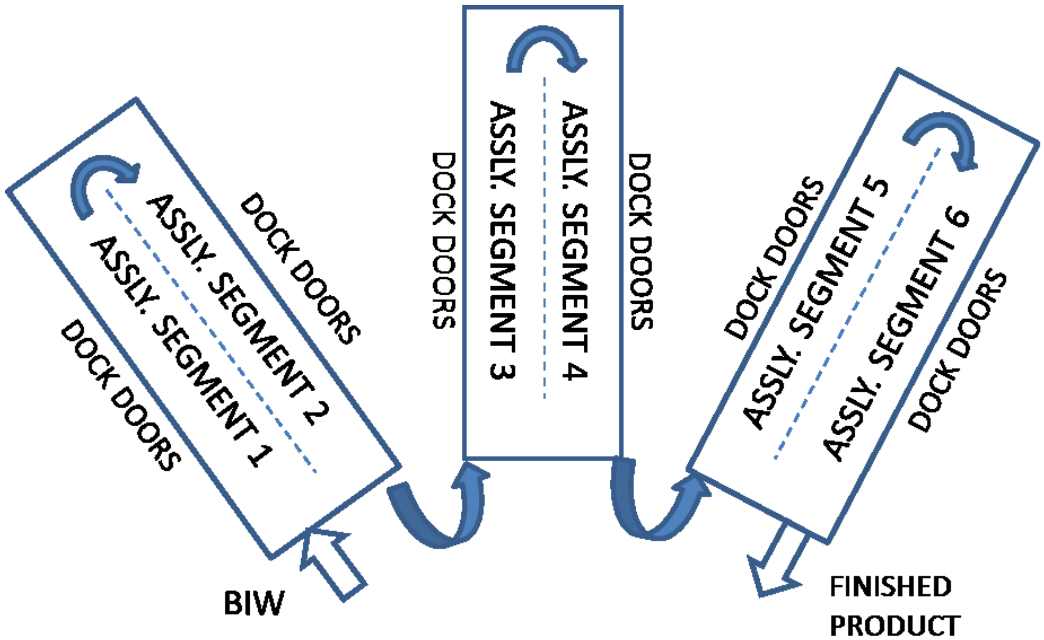


Figure 2.7: "Finger-Layout" with more dock doors for JIT part supply

Single Minute Exchange of Dies (SMED)

In order to support a Mixed-Model Final Assembly line, the Just-In-Time suppliers have to produce components in the same sequence as the final assembly line if they wish to operate in a lean manner. This would require the ability to produce parts in the same lot size (ideally one) as the Mixed-Model Final Assembly line. Another way to support the final assembly line would be to maintain high stock levels of each variety of supplied component and sequence it just before the components leave the supplier's dock. The latter alternative would be very expensive for the supplier due to very high inventory holding costs and potential quality issues associated with stored components. Most suppliers run a lean operation on the principles of Single Minute Exchange of Dies (SMED), developed by Shigeo Shingo [4]. Following are some key definitions:

a) **Changeover**: A changeover or setup is a set of tasks that must be undertaken to prepare the equipment to produce the next lot with a different part than the one already produced. It also includes the tuning time that is required to adjust the equipment to produce parts that meet the product specification.

b) **Changeover Time**: The total changeover time is defined as the time taken from the last good part of component A to the first good part of component B that follows component A in the production plan.

c) **Single Minute Exchange of Dies (SMED)**: SMED is a theory and set of techniques that make it possible to perform equipment setup and changeover operations in under 10 minutes.

This technique was first applied by Toyota to reduce the changeover time of conventional press dies, hence the acronym SMED has the word "Dies". Since then, the basic principles have been applied to quick changeover across various processes beyond conventional press dies but the original term SMED has continued to be applied. Also, the term single refers to single digit time unit (less than 10 minutes).

Fundamentally, SMED is based on waste elimination and careful separation of each and every changeover activity into two basic categories:

a) **Internal Setup:** Changeover activities that can be done only when the machine has stopped producing parts and is shut down (e.g. the physical removal of the tooling from the equipment).

b) **External Setup:** Changeover activities that can be done before the machine has stopped producing parts, in preparation for the changeover (e.g. having all the tooling available at the machine within the operator's reach, rather than looking for it once the machine stops producing parts).

The SMED activities can be divided into three major areas:

a) **Distinguish Internal and External Setup Activities:** This step includes a detailed recording of every step of the changeover and careful evaluation of each step to determine whether it is internal or external. An efficient way to carefully evaluate the steps is to record the entire operation using a video camera. Then the analyst and the experienced operator can review each step and note down the task, time required, tools required, and whether it was internal or external. The advantage of recording the entire changeover or setup is the ability to rewind and review the process as many times as required to understand the operation clearly.

b) **Convert Internal Activities to External:** Once the difficult part of the process of distinguishing between internal and external activities is complete, the most value added process of converting internal to external activities begins. A checklist which is very similar to a Bill of Material should be used to list every single tool, process setting, and part specification to be maintained in the process. This checklist will allow the operator to stage all the required components within arm's reach from the equipment to be changed over. An ideal technique to store these tools is by using a *Shadow Board* (Figure 2.8). It is a board that has a specific location for each tool and an outline of the tool is drawn for each tool. That ensures that every tool has a fixed place and every tool is in its place. If there is a "shadow / tool outline" that is visible, it signifies a missing tool which helps the operator locate it before the equipment is shut down for changeover.

Figure 2.8: Example of a Shadow Board

Another important part of converting the steps to external type is by staging the die sets or tool that has to be physically changed over inside the equipment. Any time lost in transportation after the machine has stopped producing parts would be categorized as internal setup and accounts for lost time. An ideal staging technique in relatively small machines is to have the tooling on a turn-table or turret so that it can simply be turned by say 180 degrees and can be locked in place for operation. This will convert all transportation time from internal to external. One final component of this process is to simplify the adjustment required after the new tooling / die-set is installed in the machine. Analysis of changeovers from a steel machining plant and a winder set operation for a motor manufacturing plant shows that approximately 40% - 50% of the total changeover time is attributed to adjustments that need to be made before the first good part that meets specifications is produced. This is a significant contributor to the internal setup which occurs after the machine has stopped producing parts.

Every second of adjustment time costs money and cannot be directly converted to external setup like the transportation of dies or shadow boards for tool availability. The only real way to reduce or eliminate this waste is by developing standardized locating devices such as dowel pins and mistake proofing devices which allow only one way to locate the parts. This eliminates the alternatives offered to the setup technician and makes it simple. Use of limit switches and proximity sensors can also be made wisely so that the technician gets a clear confirmation when the die-set or tooling has been located in its correct position. The input from such devices can be tied into the programmable logic circuit of the machine to prevent the machine from cycling unless the tooling has been secured in the correct position. Such use of mistake-proofing systems reduces the changeover time and it also reduces or potentially eliminates scrap that is generated every time a new batch is run.

c) **Standardize the Setup / Changeover operation:** When tooling or components related to a changeover are different, the operator has to make all those changes, usually with the machine completely shut down. This would be considered a waste of time as it is an internal set up and parts are not being produced. Those features that are directly interacting with the fixture in which the die set gets located, should be standardized. This also includes a set of standard shims that can be used to allow two or more different die sets to work with the same clamp height and shut height.

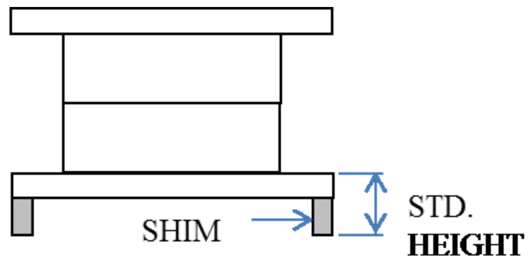


Figure 2.9: Standard Clamp height for all sets in the tooling family

Depending on the complexity of the changeover, it may be beneficial to divide the tasks across multiple technicians who can then execute the changeover in parallel. For this to work efficiently, a standard list of tasks need to be made and each task should have one owner. Primarily, the savings are driven by the fact that one operator does not need to walk around the machine back and forth in order to complete the setup. Once again, this is applicable only in the case of relatively complex setups and large equipment.

Use of standard settings using a mechanical or electronic controller would be beneficial. In the case of a resin trickle-oven used in motor manufacturing, when a changeover takes place from one frame size to another, the amount of trickle resin to be dispensed by each nozzle has to be altered in order to fill the armature winding per process specifications. If this was done manually each time and the armatures were weighed when they come out of the large oven, significant waste of time would occur. For example, at a motor manufacturing plant, a typical trickle oven with a capacity of about 100 armatures used to take about 90 minutes to changeover from the last good part of one batch to the first good part of the next batch. Multiple times the flow of resin would need to be adjusted and the armature would get sectioned using a band saw to observe the resin fill. To reduce the time required for this internal setup, a Lean Six Sigma Black Belt studied the operation by conducting a Design of Experiment (DOE) and suggested the use of flow control valves with specific settings that were controlled using programmable logic circuits. Several confirmation runs were conducted to study the expected variation from batch to batch and once the process was confirmed to be capable, the settings were recorded in the process control documents. After the changes were implemented, a complete changeover could take place within 8 minutes and the new batch would be loaded in the oven with only one empty collet between the two lots signifying a changeover. This also eliminated the scrap associated with trial & error based adjustments that were required prior to standardizing the resin quantities and the flow control system.

In summary, Single Minute Exchange of Dies is a very effective technique to reduce the actual down time of the machine during changeovers and setups. It includes a systematic analysis of every step of the changeover, conversion of internal activities to external activities, and finally standardization of the improved processes in order to sustain the improvement long term. An overview of SMED has been included in this section because several simple changeovers are part of the operator's routine work as part of the task. Such changeovers impact "Operator Choice Complexity" [5] which is based on the probability of choosing the correct tooling and components. We capture this input variable under human-factors in the generalized complexity model in Chapter 4.

2.2. Assembly Line Balancing

2.2.1. Introduction to Assembly Line Balancing (ALB)

The distribution of tasks among the work stations such that the precedence constraints and possibly other restrictions are fulfilled, is called Assembly Line Balancing

(ALB). The high practical relevance of mixed-model assembly is also reflected by the vast amount of academic research in this field. With only a few exceptions, the majority of the numerous mixed-model assembly related research papers treat either one of the following two planning problems:

1) The assembly line balancing problem constitutes a long-term to mid-term planning problem, which seeks to group the total number of assembly operations and assign them along with the required resources to the stations of the assembly line.
2) The short-term sequencing problem of mixed-model assembly lines assigns all jobs of the given production plan (model-mix) to the production cycles in the planning horizon.

The balancing and the sequencing problem are heavily interdependent. While the line balance decides on the assignment of tasks to stations and thus determines the work content per station and model, the production sequence of a given model mix is arranged on this basis with regard to minimum overloads. The amount of overload by itself is a measure of efficiency for the achieved line balance. That is why some authors have proposed a simultaneous consideration of both planning problems [6]. A simultaneous approach is, however, only viable under special conditions as both planning problems have completely different time frames, as explained above. Detailed forecasting of future model sales are often bound to inaccuracies, especially if the assembled products are in an early phase of their life cycle. It, thus, seems more meaningful to generally anticipate the sequencing decision at the higher balancing level within a hierarchical planning approach.

An assembly system performs a set of distinct minimum rational work elements for the assembly of products and it consists of a set of work locations linked together by a material handling mechanism and a detailed specification of how the assembly of the product flows from one station to another. Following are definitions of basic terms and the respective notation associated with Assembly Lines:

1) *Task* is a smallest indivisible work element n. Set $V = \{1, ..., n\}$.
2) *Station* is a location along the flow line where the tasks are processed and it consists of operators and/or equipment. Set $k = \{1, ..., m\}$.
3) Performing a task j takes a task time t_j and requires certain equipment and/or operators.
4) The total workload necessary for assembling a work-piece is measured by the sum of task times t_{sum}.
5) The tasks cannot be assigned to stations arbitrarily because of technological sequencing requirements, known as *precedence relations*. The processing of a task may not start until certain tasks, i.e. its immediate predecessors have been processed. The precedence relations are represented schematically by an acyclic digraph called a *precedence network/diagram* whose nodes correspond to tasks and if a task i is an immediate predecessor of task j (i.e., if the processing of task j cannot start until after the completion of task i), this relation is represented by a

directed arc (i,j) in the precedence network/diagram, joining node i to node j. The set of precedence relations is simply a partial ordering of the tasks.

6) The set S_k of tasks assigned to a station k constitutes its *station load* or *work content*.

7) The cumulative task time $t(S_k) = \sum_{j \in S_k} t_j$ is called *station time*.

8) A certain set of operations is performed repeatedly on a workpiece which enters the station. The time span between two entries is referred to as *cycle time.* In a paced line, the *cycle time* of all stations is equal to the same value c.

9) The series of stations and the material handling mechanism, usually a conveyor, is referred to as the *Assembly Line*.

The decision problem of optimally partitioning (balancing) the assembly work among the stations with respect to some objective is known as the assembly line balancing problem (ALBP) [7].The first mathematical formalization of ALB was done by Salveson [1]. When a fixed common cycle time c is given, a line balance is feasible only if the station time of neither station exceeds c. In case of $t\ (S_k) < c$, the station k has an idle time of c - $t\ (S_k)$ time units in each cycle. In order to ensure high productivity, any good balance should cause as few idle times as possible.

The basic ALBP can be distinguished into four types:

1) **Type 1:** For a given cycle time, minimizing the sum of station idle times is equal to minimizing the number of opened stations.

2) **Type 2:** Conversely, if the number of stations is given, the minimizing the cycle time guarantees minimum idle times.

3) **Type 3:** If both, number of stations and the cycle time, can be altered, the line efficiency E is used to determine the quality of a balance. The line efficiency corresponds to the productive fraction of the line's total operating time t_{sum} and is typically defined as $E = t_{sum}/(m.c)$. As the total idle time is equal to t_{sum} - $(m.c)$, a maximization of E also minimizes idle times.

4) **Type 4:** Finally, the problem of finding a feasible balance for a given number of stations and a given cycle time falls under this category.

Figure 2.10 shows a precedence graph with $n = 9$ tasks having task times between and 9 (time units).

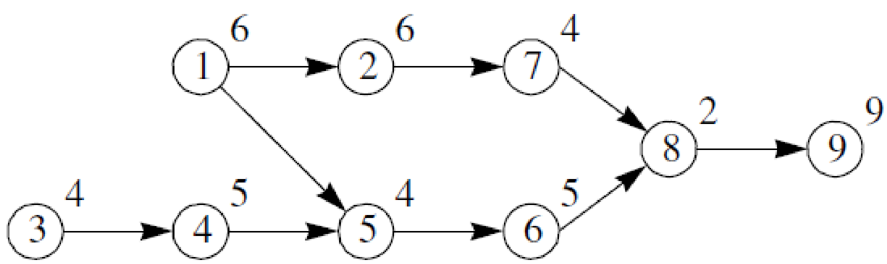


Figure 2.10: Precedence Graph

The precedence constraints in Task 5 for example express that its processing requires the tasks 1 and 4 (direct predecessors) and 3 (indirect predecessor) be completed. The other way round, task 5 must be completed before its (direct and indirect) successors 6, 8, 9, and 10 can be started. Any type of ALBP consists in finding a feasible line balance, i.e., an assignment of each task to a station such that the precedence constraints and further restrictions are fulfilled. For the example in Figure 2.10, a feasible line balance with cycle time $c = 11$ and $m = 5$ stations is given by the station loads $S_1 = \{1,3\}$,

$S_2 = \{2,4\}$, $S_3 = \{5,6\}$, $S_4 = \{7,8\}$, $S_5 = \{9\}$. While no idle time occurs in station load 2, station loads 1, 3, 4, and 5 show idle times of 1, 2, 5, and 2 respectively.

Assembly Line Balancing involves task assignments to various takts in order to maximize an objective such as Labor Utilization. Sequencing of tasks and Utilization are both input variables in the generalized complexity model that we will review in Chapter 4. Our research shows that these have an impact on process driven complexity and can be valuable input variables that can contribute in predicting product quality.

2.2.2. Manual Assembly Line Balancing

The study related to this research project was conducted at a major automotive assembly plant on a pilot line where the electrical harnesses, floor insulation, and curtain head airbags get assembled into the vehicle [8]. Typically, on a monthly basis, depending on the change in model mix, the assembly team reviews the work distribution and changes task assignment as needed, in order to maximize the labor utilization. The current manual process of reviewing the various operations and rearranging the tasks to improve the average utilization of the operators is labor intensive. To baseline the current line balancing process, we (the author and his research team) participated in two line balancing workshops. These workshops included the following steps:

- Generate a visual display of all takts in the assembly line,
- Analyze tasks that will exceed the cycle / takt time based on projected volume of vehicles,
- Re-balance each takt while ensuring that tooling / station / work zone constraints are not violated,

- Calculate the line utilization metrics,
- Conduct trial runs to verify feasibility, and
- Finalize the proposed line balance.

In each workshop, a cross-functional team was comprised of 5 experienced individuals from assembly, Industrial Engineering, training, and quality departments. Distribution of the average labor hours taken for this exercise is shown in Figure 2.11.

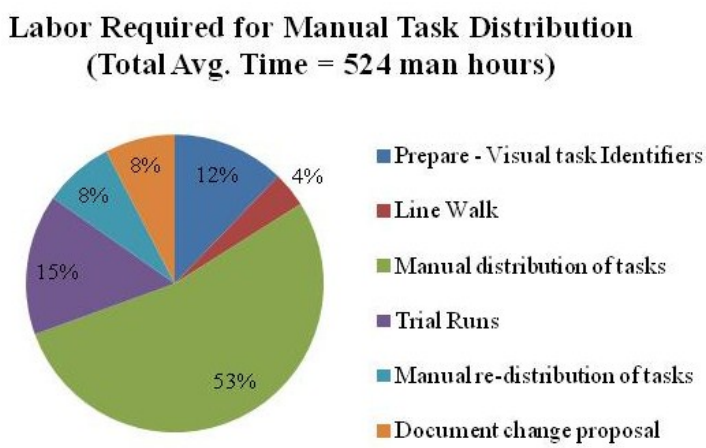


Figure 2.11: Distribution of Manual Line Balancing tasks (15 stations)

During the course of such a line balancing workshop that is typically done two times per year, for each assembly line, each participant focuses 100% on the work content evaluation and line balancing process. Tasks are manually arranged until the team reaches consensus on the organization and then line trials are conducted. Similarly, on a monthly basis, line gets re-balanced to account for the volume changes that have been forecast for the following month. This exercise is usually done on a smaller scale than the workshop described above, and includes 2 experienced associates who conduct the planning and analysis in one day followed by line trials for two shifts. Although it seems quite streamlined, this process relies heavily on the knowledge of the participants and during the workshops it was evident that several constraints that should have been taken into account were not easy to remember while making decisions manually, thereby requiring multiple iterations to correct the issues that were found.

2.2.3. Constraints definition

Besides balancing a new assembly line, a running one has to be re-balanced periodically or after changes in the production process or the production program have taken place. Balancing means assigning the tasks to the stations (workplaces) based on, among others, the precedence graph. In the automotive industry, typical information and planning system contains the description of tasks including their deterministic task times (derived by, for example a motion-time measurement MTM approach), the current assignment of tasks to takts and the execution sequences of tasks within each takt. However, almost no precedence relations are documented, not to mention an entire precedence graph. The huge manual input and the multitude of tasks (up to several hundreds or even thousands) prevent manufacturers from collecting and maintaining precedence relations [9].

This absence of documented information on precedence relations is the main obstacle in applying well explored theoretical assembly line balancing methods in practice. In practice, planning, balancing and controlling assembly lines are based on subdividing the production processes and, hence, the assembly lines into segments. Each segment is managed by a dedicated human planner, who becomes an expert for this part of the system. Though some software systems provide a component for automatic line balancing, the planners mostly balance their segments of the line by manually shifting tasks from one station to another, because precedence data is not available or existent data is not reliable. This is a very time-consuming and fault-prone job, which is solely driven by the experience and knowledge of planners. By appending the plans of succeeding line segments, the entire production plan is developed.

This author along with his research group performed a pilot manual precedence mapping exercise on an assembly trim (segment) comprised of 15 assembly stations at a major automotive assembly plant where the roof rails, electrical harnesses, sub-woofer, floor insulation, and curtain head airbags etc. get assembled into the vehicle [8]. The primary purpose of this exercise was to understand the various constraints that would need to be captured for the decision support system that would be the primary data source for the optimization algorithm / construction heuristic. It was during this manual constraints mapping exercise that the author observed that product quality could have an impact based on the way tasks are arranged and therefore motivated the author to pursue research related to manufacturing complexity, which includes several assembly line related variables as key inputs.

In order to understand the process instructions and the actual work content, the individuals who conducted this study underwent hands-on training on each assembly station involved on the pilot line. The key advantages of conducting this training were as follows:

1) Visualization of Process Instructions.
2) Understand precedence relationships.

3) Understand undocumented supporting tasks.
4) Gain basic understanding of additional complexity due to high option content.
5) Learn the effect of a work overload situation on operational metrics.
6) Awareness of the constraints that must be incorporated into the optimization model.
7) Experience the ergonomic impact of repetitive tasks.
8) Understand the human behavior to adapt the required task to make it less strenuous and more effective.
9) Gain input from assembly line associates based on their work experience.

After a thorough understanding of the tasks and the complexity, the precedence mapping was manually undertaken in the following manner:

1) Stage 1: Each takt was evaluated to determine precedence relationships between tasks within each takt.
2) Cross audit was conducted by multiple process experts to verify the precedence relationships
3) Stage 2: Scope of the mapping exercise was expanded to the entire assembly line and relationships were mapped across takts. In several cases, entire groups of tasks were found to be predecessors of another group of tasks in a downstream takt.
4) Data verification was done to ensure that cyclic relationships did not exist. A cycle refers to a relationship that points from task i to j and another points in the reverse direction, making j a predecessor for task i.

In addition to the basic task level precedence relationships, the following constraints were identified and recorded during Stage 1 precedence mapping:

1. **Product State constraint:** The "Product State" can be defined as the physical state in which the product gets presented at a certain assembly station (Figure 2.12).

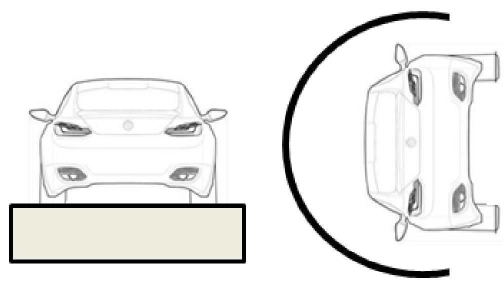


Figure 2.12: Product orientation for ergonomics [8]

2. **Assembly Zone constraint:** In the assembly of certain large products such as an automobile or a large machine, it would be critical to capture the location of the assembly operator with reference to the product while conducting the specific task. With reference to this study, the automobile would be divided into 9 assembly zones (Figure 2.13). This information needs to be captured as a constraint for each task so that the optimization algorithm takes the zone into account and prevents the assignment of multiple operators in the same assembly zone at the same time doing different tasks.

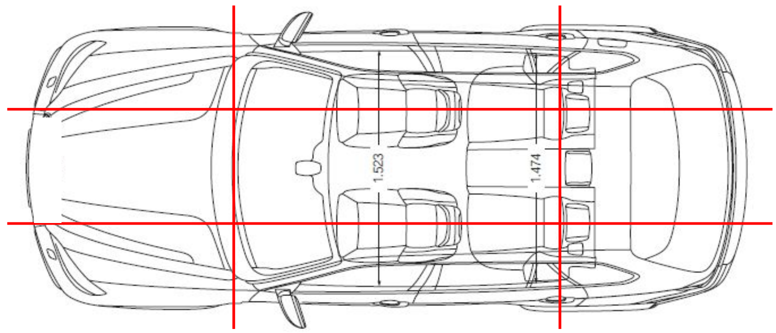


Figure 2.13: Top view of product showing 9 assembly zones [8]

3. **Ergonomic constraint:** Every assembly task is assigned an ergonomic rating. When tasks are not designed appropriately in systems that depend on human operators, the system is particularly vulnerable to problems associated with worker health, production, quality, and increased training costs. It is important to capture this information as a constraint for the task distribution algorithm to be able to set an objective to maintain the average ergonomic rating for a specific assembly station below a pre-determined target.
4. **Tooling constraint:** During the precedence & constraint mapping exercise, it is important to identify and record the specific tooling needed to execute a given task (e.g., overhead lift assist systems). Moving such capital equipment is expensive, so it should be kept at a certain station and included in the optimization algorithm as a constraint.

The basic precedence mapping exercise required us to identify enabling predecessors (tasks that need to be done before commencing the successor tasks). In principle, as long as each one of those preceding tasks was completed, the dependent task could be done, as shown in the battery installation example in Figure 2.14.

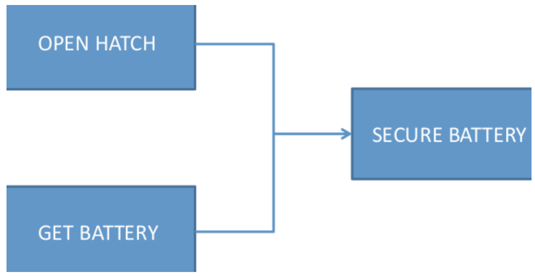


Figure 2.14: Successor is independent of Predecessor Task Sequence [8]

However, in reality there are tasks that need to happen immediately after a preceding task has taken place. For example, the windshield would needs to be assembled immediately after the adhesive is applied. This presents a challenge in terms of capturing the input data for the construction heuristic which is used for task distribution, as the intent is not to treat the preceding tasks as independent tasks. If treated independently, the task distribution process could potentially add several other tasks between the adhesive application and the windshield assembly operation in order to reduce idle time at each takt. From a process requirement standpoint, this would be unacceptable. A possible solution would be to group such tasks to ensure that they get executed in a sequence which would be pre-determined based on the design or process requirements (Figure 2.15). Such grouping is considered as an Adjacency Set. Another solution is to include time relations between tasks, such that minimum and maximum separation between tasks can be enforced.

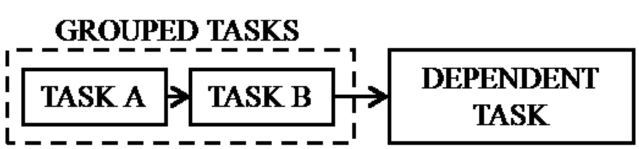


Figure 2.15: Task Grouping [8]

In summary, all these constraints were mapped for each takt during Stage 1 of precedence & constraint mapping. Once the precedence relationships and constraints for each takt were documented in Stage 1, the second stage included mapping the precedence relationships between tasks, across takts. It was important to review process sheets that had a detailed listing of every single task and the task time. The hands-on training was very beneficial to visualize the tasks and identify predecessors from stations that were not on adjacent stations.

The comprehensive precedence map which included Stage 1 and Stage 2 data was then created using Microsoft® Visio software to review the precedence relationships in a visual form. The visual representation was beneficial in highlighting circular references or "floating" processes that did not have any predecessors. In some cases, a large cluster of closely linked processes were found. This can occur when several small tasks such as individual wire connections are done at a specific station. As long as they are part of a sub-assembly (example, audio system), there was no additional advantage in trying to split each small task and set the precedence relationships to the upper level task which would in this case be the installation of the audio system. Instead it was found to be beneficial to link each of these tasks as an adjacency set and link the very first one to the preceding upper level task such as the audio system installation. This ensured that the small tasks did not get fragmented during the task distribution process.

Although generating a line balance based on precedence relationships and the above stated constraints could generate a potentially feasible sequence, an area not explored by researchers is the impact of task sequencing and takt utilization on product quality. A negative impact on product quality would certainly require the experts to reverse the changes and re-balance the tasks. Therefore, in order to understand the impact of Assembly Line Balancing on product quality, we include task sequence and takt utilization as input variables in the complexity model, along with other variables that will be explained in the following sections.

2.3. Complexity

2.3.1. Definition and previous work

Several scholars have attempted to define complexity at a manufacturing system level with limited success. This is primarily because there are a large number of contributors that prevent the functional objective from being achieved and depending on the application; authors have focused on limited number of variables and defined them as complexity drivers. A general definition of complexity is that a complex system is one which has a large number of elements, whose relationships are not simple [10]. Whereas static complexity describes the system structure at a defined point in time, dynamic complexity represents the change in system configuration in the course of time [11]. In order to understand how factors such as product variety, changing quality requirements or varying customer demand regarding packaging, or delivery service complicate manufacturing processes and in turn impact the performance of production systems, some research work has been conducted mainly in the investigation of the static manufacturing system complexity. Deshmukh et al. [12] derived an information-theoretic entropy measure of complexity for a given combination and ratio of part types to be produced in a manufacturing system. ElMaraghy et al. [13] proposed a code-based structural complexity index to capture the amount of information in the manufacturing systems as well as another complexity measure to represent the probability of a manufacturing systems success in delivering the desired production capacity. Suh [14] defined complexity in the context of manufacturing system design 'as the measure of uncertainty in achieving the functional requirements owing to a poor design or to the lack of understanding and knowledge about the system'. Suh introduced the Axiomatic Design (AD)-based complexity theory as a comprehensive approach to describe the mechanisms of a manufacturing system's static and dynamic complexity and illustrated the concept of functional periodicity in a scheduling problem of a machine cluster to control the system's time-dependent combinatorial complexity.

The variety of products offered in mixed-model assembly lines has increased dramatically over the past decade. For example, in a typical automobile assembly plant, the number of different vehicles being assembled can reach tens of thousands in terms of the possible build combinations of options. In fact, BMW claims that, "Every vehicle that rolls off the belt is unique" and the number of possible automobile variations in the BMW 7 Series alone could reach 10^{17} [5]. Such an astronomical number of build combinations undoubtedly presents enormous difficulties in the design and operation of the assembly systems. In the case of automotive assembly, it has been shown by both empirical and simulation results [15, 16] that increased vehicle product variety has a significant negative impact on the performance of the mixed-model assembly process, for example, on quality and productivity. Such impact can result from assembly system design as well as people performance under high variety. The effect from the latter persists since only limited automation can be implemented in the automobile final assembly [17, 18]. Thus, researchers have focused on this problem in two parts: how variety impacts people and system performance, and how to design assembly systems and organize production to allow high product variety without sacrificing quality and productivity. One of the possible approaches to assessing the impact of product variety on manufacturing system performance is to investigate how product variety complicates the mixed-model assembly process. However, only limited research has been done on defining manufacturing system complexity. For example, MacDuffie et al. [16] established an empirical relationship between complexity and manufacturing system performance. They defined product mix complexity by looking at product variety (product mix and its structure) in assembly plants. According to the differences in the levels of product variety, three types of product mix complexity were defined in terms of empirical scores: model mix complexity, part complexity, and option complexity. The result was based on the data from 70 assembly plants worldwide that participated in the International Motor Vehicle Program at MIT [16]. Besides empirical studies, attempts have also been made to analytically define complexity in manufacturing. For instance, complexity has once been associated with the amount of effort needed to make a part. The effort was quantified by a logarithmic function of the probability of achieving a certain geometric precision and surface quality in machining [19].The function is widely known as Shannon's information entropy [20]. Similarly, Fujimoto and Ahmed [21] defined a complexity index for assembling. The index takes the form of entropy to evaluate the *assemblability* of a product. The *assemblability* was defined as the uncertainty of gripping, positioning, and inserting parts in an assembly process. Also, complexity has been extended as a measure of uncertainty in achieving the specified functional requirements in an axiomatic design [22]. Recently, complexity has been defined in an analytical form for manufacturing systems as a measure of how product variety complicates the process. Fujimoto et al. [23] introduced a complexity measure based on product structure using information entropy in different assembly process planning stages. By reducing the complexity, they claimed that the impact of product variety on manufacturing systems could be reduced. However, the complexity measure does not incorporate the manufacturing system characteristics into the analysis.

2.3.2. Introduction to Axiomatic Design Principles [14]

Complexity theory based on Axiomatic Design (AD) was developed by Dr. Nam P. Suh. Therefore, it is important to provide a brief background on Axiomatic Design. AD theory is based on two fundamental axioms that eliminate the possibility of making mistakes when products – both hardware and software, are developed. The theory helps to overcome the shortcomings of the recursive product development process (design/build/test), which requires continuing modifications as issues are found through testing. There are several key concepts that are fundamental to AD. They are the existence of domains, mapping, axioms, decomposition by zigzagging between the domains, theorems and corollaries.

a. **The concept of domains:** The world of design is made up of four domains – the customer domain, the functional domain, the physical domain, and the process domain. The customer domain represents what '*we want to achieve'*, relative to the domain on the right, which represents the design solution, that is '*how we propose to satisfy the requirements specified in the left domain*'. In the functional domain, the customer needs are specified in terms of functional requirements (FRs) and constraints. FRs are a minimum set of independent requirements that completely characterize the functional needs of the product in the functional domain. In order to satisfy the FRs, we conceive design parameters (DPs) in the physical domain. DPs are the key physical variables in the physical domain that characterize the design that satisfies the specified FRs. Finally, we develop a process that is characterized by process variables (PVs) in the process domain, in order to produce the product specified in terms of DPs.

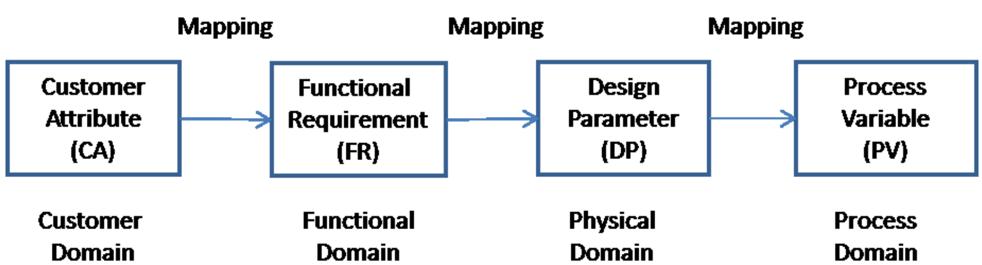


Figure 2.16: Four domains in the design world [14]

b. **Mapping from domain to domain:** Once the customer needs are identified and defined in the customer domain, these needs must be translated into the FRs in the functional domain. Dr. Nam P. Suh suggests that FRs must be defined without ever thinking about something that has already been designed or what the design solution should be [14]. After the FRs are chosen, they are mapped into the physical domain to conceive a design with specific DPs that can satisfy the FRs. For a given FR, there can be many possible DPs. The right DP should then be chosen while making sure that other FRs are not affected by the chosen DP and that the FR can be satisfied within its design range.

Axioms: Dr. Nam P. Suh defines axioms as truths that cannot be derived but for which there are no counter-examples or exceptions [14]. The basic postulate of AD theory is that there are fundamental axioms that define acceptable designs. The two axioms are: the Independence Axiom and the Information Axiom.

a. **Independence Axiom:** This axiom states that the FRs should be independent of each other. When there are several FRs, the design must be such that FR can be satisfied without affecting any of the other FRs. The relationship between FRs is decided by the choice of DPs. It should be noted that FRs are independent from each other by definition. Therefore, we have to choose a correct set of DPs to be able to satisfy the FRs and maintain their independence. After the FRs are established, the next step involves conceptualization of the design solutions. This is a mapping process from 'what' in the functional domain to 'how' in the physical domain. When there are many FRs, the design task may become difficult since the Independence Axiom may be violated. The mapping process between the design domains can be expressed mathematically in terms of two characteristic vectors as follows:

$$\{\mathrm{FR}\} = [A]\{\mathrm{DP}\} \tag{1.3}$$

where $[A]$ is called the Design Matrix that relates FRs to DPs and characterizes the product design. Equation (1.3) is a design equation for the design of a product. For a design that has three FRs and three DPs, the design matrix is of the following form:

$$[A] = \begin{pmatrix} A_{11} & A_{12} & A_{13} \\ A_{21} & A_{22} & A_{23} \\ A_{31} & A_{32} & A_{33} \end{pmatrix} \tag{1.4}$$

Equation (1.3) may be written in a differential form as:

$$\{\mathrm{dFR}\} = [A]\{\mathrm{dDP}\} \tag{1.5}$$

where the elements of the design matrix are given by:

$$A_{ij} = \frac{\partial \mathrm{FR}_i}{\partial \mathrm{DP}_j} \tag{1.6}$$

For a linear design, *A*s are constants; for a non-linear design, *A*s are functions of the DPs. There are two special cases of this design matrix:

1) The diagonal matrix, where all $A_{ij} = 0$ except those where $i = j$.

$$[A] = \begin{pmatrix} A_{11} & 0 & 0 \\ 0 & A_{22} & 0 \\ 0 & 0 & A_{33} \end{pmatrix} \tag{1.7}$$

2) The triangular matrix as shown below:

$$[A] = \begin{pmatrix} A_{11} & 0 & 0 \\ A_{21} & A_{22} & 0 \\ A_{31} & A_{32} & A_{33} \end{pmatrix} \tag{1.8}$$

For the design of processes involving mapping from the {DP} vector in the physical domain to the {PV} vector in the process domain, the design equation may be written as:

$$\{\mathrm{DP}\} = [B]\{\mathrm{PV}\} \tag{1.9}$$

where [B] is the design matrix that defines the characteristics of the process design and is similar in form to [A]. To satisfy the Independence Axiom, the design matrix must be either diagonal or triangular. When the matrix is diagonal, each of the FRs can be satisfied independently and such a design is called *uncoupled* design. When the matrix is triangular, the independence of FRs can be guaranteed if and only if the DPs are determined in a proper sequence. Such a design is called a *decoupled* design. Any other form of the design matrix is called a full matrix and results in a coupled design. Coupled designs are complex and cannot be decomposed readily because of the complicated relationships among the FRs. Therefore, when several FRs must be satisfied, designs must be developed in such a way that a diagonal or triangular design matrix can be created.

b. **The Information Axiom:** This axiom states that the design with the minimum information content is the best design. There may be many designs that satisfy the Independence Axiom and the Information Axiom can be useful in selecting the best among those designs.

The information content I_i for a given FR_i is defined in terms of the probability P_i of satisfying FR_i:

$$I_i = \log_2 \frac{1}{P_i} = -\log_2 P_i \tag{1.10}$$

The information content is expressed in bits of information. The logarithmic function is chosen so that the information content will be additive, which is useful when many FRs must be satisfied simultaneously.

In the general case of m FRs, the information content for the entire system I_{sys} is:

$$I_{sys} = -\log_2 P_{\{m\}} \tag{1.11}$$

where $P_{\{m\}}$ is the joint probability that all m FRs are satisfied.

When all FRs are statistically independent, as is the case for an uncoupled design,

$$P_{\{m\}} = \prod_{i=1}^{m} P_i \tag{1.12}$$

then I_{sys} may be expressed as:

$$I_{sys} = \sum_{i=1}^{m} I_i = -\sum_{i=1}^{m} \log_2 P_i \tag{1.13}$$

When all FRs are not statistically independent, as is the case for a decoupled design,

$$P\{m\} = \prod_{i=1}^{m} P_{i\{j\}} \text{ for } \{j\}=\{1,...,i\text{-}1\} \tag{1.14}$$

Where $P_{i|\{j\}}$ is the conditional probability of satisfying FR_i given that all other relevant (correlated) $\{FR_j\} j=1,\ldots,i-1$ are also satisfied. In this case, I_{sys} may be expressed as:

$$I_{sys} = -\sum_{i=1}^{m} \log_2 P_{i|\{j\}} \text{ for } \{j\}=\{1,...,i\text{-}1\} \tag{1.15}$$

The Information Axiom states that the design with the smallest *I* is the best design, since it requires the least amount of information to achieve the design goals. When all probabilities are equal to 1, the information content is zero and, conversely, the information content requires is infinite when one or more probabilities are equal to zero. That is, if the probability is small, we must supply more information to satisfy the FRs. Dr. Nam P. Suh's Information Axiom states that the FR must be satisfied within a specified range, which we define as the design range [14]. The probability of success is governed by the intersection of the design range defined by the designer to satisfy the FRs and the ability of the system to produce the part within the specified range. The probability of success can be computed by specifying the design range for the FR and by determining the system range that the proposed design can provide to satisfy the FR. To achieve a robust design, the system range should lie inside the design range, thus reducing the information content to zero.

2.3.3. Complexity Theory based on Axiomatic Design [14]

One of the major goals of engineering is to reduce complexity of engineered systems. Suh's complexity theory based on AD provides a theoretical framework for understanding and designing complicated systems. The theory gives guidelines for what is possible and desirable in these systems.

Complexity is defined as a measure of uncertainty in achieving the specified FRs. The complexity is measured in the functional domain rather than in the physical domain. Complexity can be a function of time or can be independent of time. Therefore, it is classified into two primary groups – Time-dependent complexity or time-independent complexity.

Time-independent complexity consists of two different types: real complexity and imaginary complexity. The information content defined by the Information Axiom is a measure of real complexity. It measures how well the design satisfied FR, i.e. the overlap between the design range and the system range. On the other hand, Imaginary complexity is not real complexity but appears complex due to the lack of knowledge about the design.

For a system range that changes as a function of time, there are two types of time-dependent complexity: time-dependent combinatorial and time-dependent periodic complexity. Combinatorial kind can lead to a chaotic situation if the number of combinations continues to grow as a function of time. On the other hand, time-dependent periodic complexity reduces the number of combinations to a finite set in a functional period and may reduce the complexity problem to a deterministic one.

The introduction of functional periodicity into a system that has time-dependent combinatorial complexity may substantially reduce the uncertainty of satisfying the FR. Whenever a system with time-dependent combinatorial complexity is converted to a system with time-dependent periodic complexity, uncertainty is reduced and the design is simplified.

An example of time-dependent complexity is airline scheduling. If there is a snowstorm at a hub airport that prevents airplanes from landing and taking off, other airports will be affected. While the storm continues, the problem will get worse as time passes. If the storm clears, the problem can be solved by reinitializing the system. It is worth noting that as the airline schedule is periodic each day, all of the uncertainties introduced during the course of a stormy day end after a 24-hour cycle. Such a time-dependent complexity falls under the periodic complexity category.

2.3.4. Reduction of Complexity in Manufacturing Systems [14]

To make a system robust and reliable by satisfying the FRs and constraints throughout the system's life cycle, the complexity of the system should be reduced starting from the design stage. Following are three primary ways of reducing complexity:

- Elimination of time-independent real complexity by making the design robust
- Elimination of time-independent imaginary complexity by writing the design equation.
- Transform time-dependent combinatorial complexity into a time-dependent periodic complexity by introducing a functional periodicity.

The first step in introducing a functional periodicity is to decouple a coupled system to make sure that the FRs can be satisfied independently and the system obeys the Independence Axiom. For example, in the case of cellular manufacturing system, processes are grouped according to the sequence and operations needed to make a product [24]. The cell is designed in a U-shape so that the workers can move from machine to machine, loading and unloading parts (Figure 2.17). The cell has one worker who can make a walking loop around the cell in 110 seconds. The machines in the cell have the capability to complete the desired processes untended, turning themselves off when the machining cycle is complete. The cell usually includes all the processing needed for a complete part or sub-assembly. If the machining time (MT) for a certain operation is greater than the necessary cycle time (CT), that process needs to be duplicated to ensure that MT < CT. By using multi-skilled operators, the need to balance the line is eliminated as these operators are capable of operating multiple operations and are motivated to provide support to every process in the cell that may need help. It is important to note that between such processes, several different types of decouplers may be placed. A decoupler may be designed to inspect the part before it gets picked up by the next process and feed the information back to the previous machining step if any corrective action is required. A decoupler may also help cool a heat-treated part before it gets picked up by the operator for the next process step. Thus, a manufacturing cell allows production of just enough parts to meet the production requirements without generating additional inventory. Based on the principles of axiomatic design and complexity reduction, functional periodicity is controlled in these cells by the removal of the product from the last machine of a manufacturing cell. This is in contrast to having a job shop type of a manufacturing system, where parts are pushed into the manufacturing system as soon as a machine becomes available. In such a system, the parts are moved to the next available machine. The number of combinations and permutations of processing the parts through a set of processes in a job shop increases with time, thus constituting a combinatorial complexity problem.

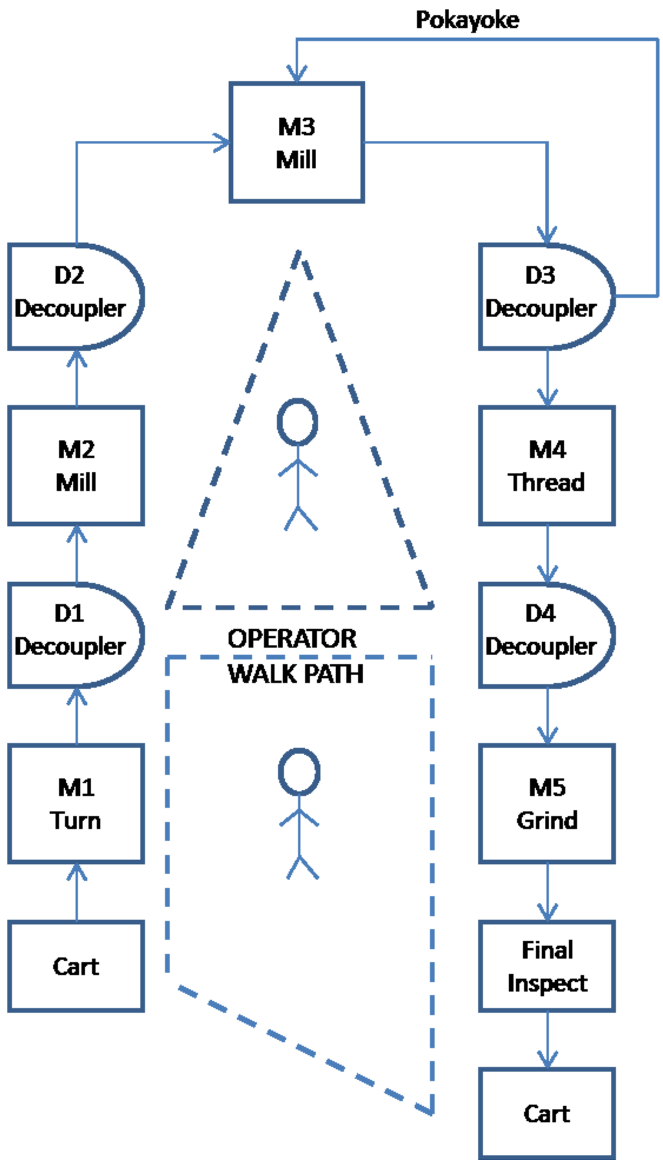


Figure 2.17: U-shaped cell with decouplers, [24]

2.3.5. Operator Choice Complexity

Variety has been shown to be a particularly important factor in error frequency. Gatchell [25] observed that operators with a choice of 10 parts made 46 percent more errors and needed 13 percent more decision time than operators who could choose from only 4 parts. In Zhu et al. [5] the variety induced manufacturing complexity in manual mixed-model assembly lines is considered where operators have to make choices for various assembly activities. The authors propose a complexity measure called ‘operator choice complexity’ to quantify human performance in making choices. Operator choice complexity is defined as the average uncertainty or randomness in a choice process, which can be described by a function *H* in the following form (2.1):

$$H(X) = H(p_1, p_2, ..., p_m) = -C\sum_{m=1}^{M} p_m \log p_m \tag{2.1}$$

Where, *C* is a constant depending on the base of the logarithm function chosen. If $\log_2$ is selected, *C*=1 and the unit of complexity is bit.

There is a close similarity and connection between the theoretical properties of the complexity measure and the experimental results found in human cognitive studies. The experiments were conducted to assess human performance when making choices. Coincidentally, information entropy was found to be one of the effective measures. The performance of human choice-making activities was investigated by measuring average reaction times (RTs), i.e., how quickly a person can make a choice in response to a stimulus. One of the earliest studies was done by Merkei in 1885, described by Woodworth [26]. In the experiment, digits 1–5 were assigned to the fingers of the right hand and the Roman numbers I–V were assigned to the fingers of the left hand. On any given set of trials, the subject knew which of the set of stimuli would be possible (e.g., if there were three possible stimuli, they might be 3, 5, and V). Merkel studied the relationship between the number of possible stimuli and the choice RT. His basic findings are presented in Figure 2.18, where the relationship between choice RT and the number of alternatives was not linear. This relationship in Figure 2.18 has been further studied by a number of researchers since Merkel's original observations.

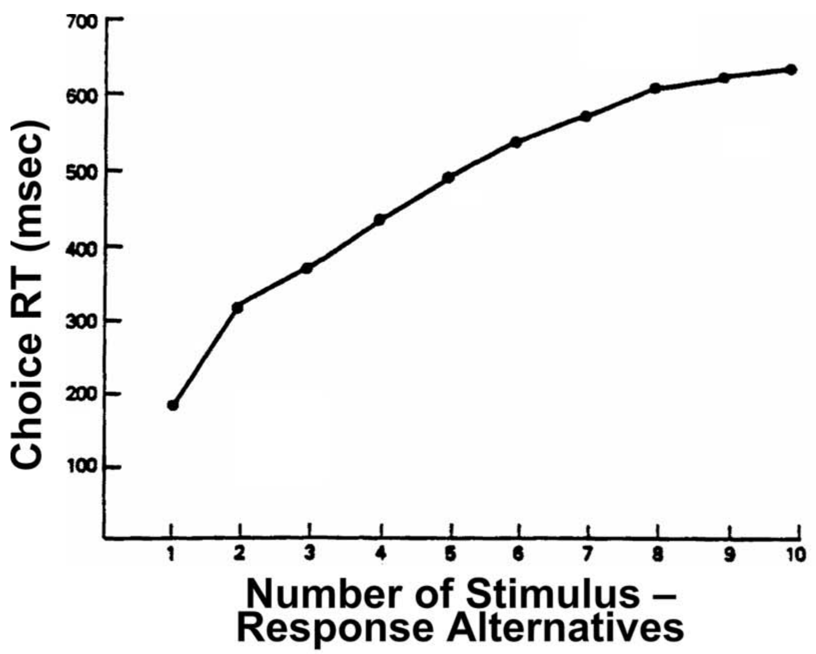


Figure 2.18: Mean choice RT vs. stimulus-response alternatives [26]

Among them, the most widely known one was Hick [27]. He discovered that the choice RT is linearly proportional to the logarithm of the number of stimulus alternatives if all the alternatives are equal (Figure 2.19), i.e.,

$$\text{Mean choice } RT = a + b[\log_2 n] \tag{2.2}$$

Where, n is the number of stimulus-response alternatives, and a and b are constants, which can be determined empirically by fitting a line to the measured data. This relation came to be known as Hick's law, which was regarded as one major milestone in the area of cognitive ergonomics.

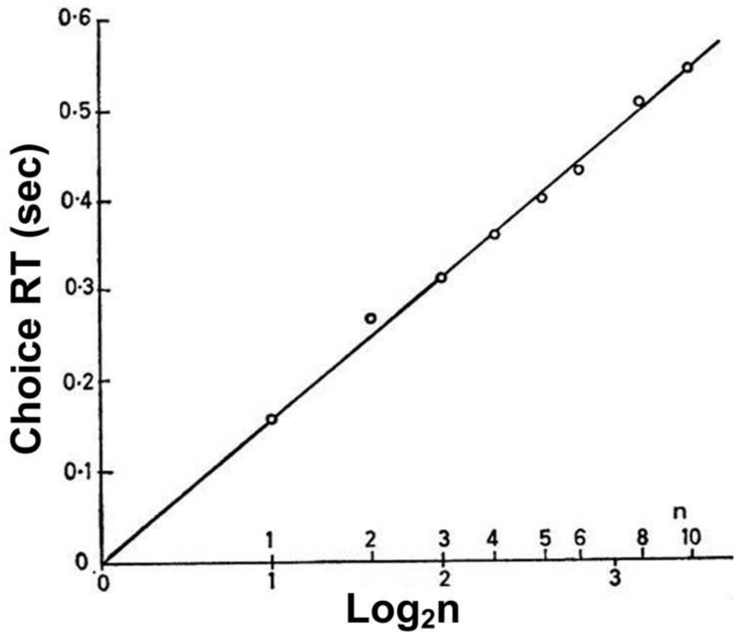


Figure 2.19: Mean choice RT as a function of log of the # of alternatives [27]

Coincidentally, the term ($\log_2$ n) is exactly the information entropy calculated in (2.1) if all the p_m's are equal, which follows from the experiment setting that the choice process is *iid* (independent and identically distributed) and all the alternatives likely occur equally. The above analogy was first discovered by Hyman [28], where he concluded that "the reaction time seems to behave, under certain conditions, in a manner analogous to the definition of information." Hyman also realized that, according to Shannon's definition of information entropy, he could change information content in the experiment by other means. Thus, in addition to varying the number of stimuli and letting each one of them occur in Hick's [27] experiment, he altered stimulus information content simply by:

- Changing the probability of occurrence of particular choices
- Introducing sequential dependencies between successive choices of alternatives (Figure 2.20).

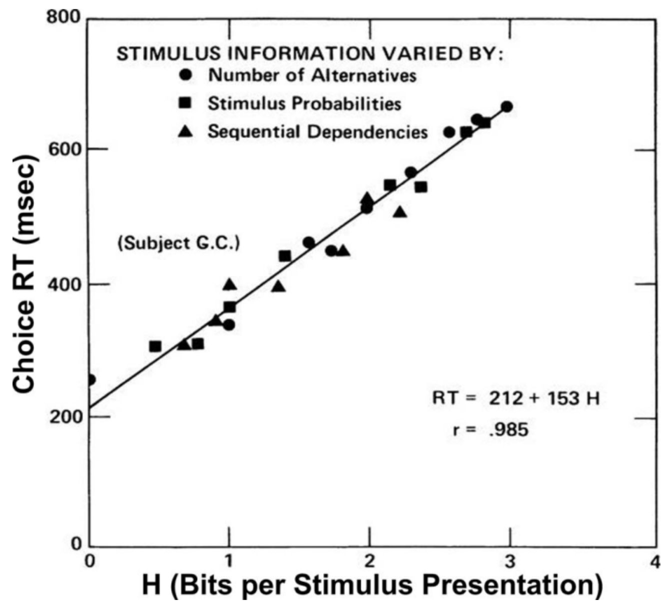


Figure 2.20: Choice RT vs. stimulus information H [27]

Thus, we can use H to replace the ($\log_2 n$) term; (2.2) becomes:

$$\text{Mean choice } RT = a + bH \tag{2.3}$$

Because of the significance of this generalization, Hick's law is also referred to as the Hick–Hyman law. The H term in the above equation is one of the variants of Shannon's information entropy [20] in the communication systems study. Thus, a fundamental assumption behind this analog is that the mental process of a human being is modeled as an information transmission process. Liu [29] suggested that at a level of mean RTs, a continuous-transmission fork-join network demonstrates the same logarithmic behavior as that of experimental results in the Hick-Hyman law. Hence, the legitimacy of applying this equation is limited to situations where individuals are asked to respond promptly to a stimulus, and the decision to be made is very simple, requiring little conscious thought. In mixed-model assembly process, we observe a very similar situation that the line associates are asked to handle variety in a very tight cycle time without time for deliberating over the decisions.

2.3.6. Cognitive Load Theory

Cognitive Load is closely linked to the Operator Choice Complexity described above. The objective of cognitive load theory (CLT) is to predict learning outcomes by taking into consideration the capabilities and limitations of the human cognitive architecture [30]. The theory can be applied to a broad range of learning environments because it links the design characteristics of learning materials to principles of human information processing. CLT is guided by the idea that the design of effective learning scenarios has to be based on our knowledge about how the human mind works. Starting from this premise, different processes of knowledge acquisition and understanding are described in terms of their demands on the human cognitive system, which is seen as an active, limited-capacity information processing system. Taking into account the demands on cognitive resources induced by the complexity of the information to be learned, the way in which the instruction is presented to the learner, and the learner's prior experience and knowledge, CLT aims to predict what makes learning successful and how learning can be effectively supported by teaching and instruction. A growing body of empirical research has become available in recent years that describes the relationships among human cognitive architecture, the design of educational materials, and successful learning. Moreover, the research conducted in past years has led to a more detailed description of the theoretical components of CLT, including processes of schema acquisition, capacity limitations, and different causes for load, namely, intrinsic load (generated by the difficulty of the materials), extraneous load (generated by the design of the instruction and materials), and germane load (the amount of invested mental effort).

In mixed-model automotive assembly lines, instruction about the option content to be assembled in a specific vehicle is relayed to the operator in multiple different ways:

- Bar-coded broadcast sheet placed on the vehicle body (Figure 2.21).
- Visual display screen triggered by the radio frequency (RF) device on the vehicle (Figure 2.22).
- Audio device coupled with the visual display to reduce the need for the operator to look at the screen to determine the option to be chosen.

Figure 2.21: Broadcast sheet on vehicle (BMW, Leipzig)

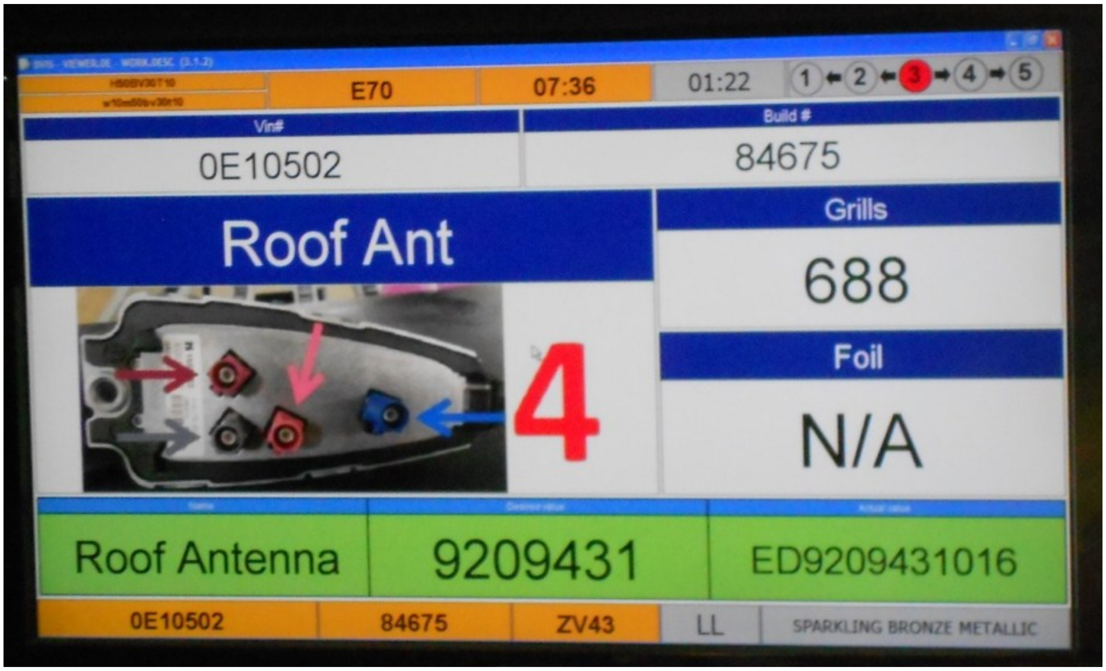


Figure 2.22: Visual display of options to be installed in a specific vehicle

In summary, several researchers have attempted to define complexity at a manufacturing system level. We now turn our attention to Automotive Assembly Quality before focusing on the correlation between Manufacturing Complexity and Quality.

2.4. Introduction to Automotive Assembly Quality

Buzzell et al [31] proclaimed that "Quality is King", affirming its dominant role in market share and Return on Investment (ROI). The principle measure of Conformance Quality for products, as described by Garvin [32] is product yield in terms of defects generated by the manufacturing process. In the Automotive industry, quality has become increasingly important as customers have several alternatives to choose from the marketplace. Market research firms such as J. D. Power routinely measure number of defects per 100 vehicles and publish the results. This survey is constructed to reflect only those defects that an assembly plant can affect, i.e. omitting defects related to the powertrain, while emphasizing defects related to the fit and finish of body panels, paint quality, and the integrity of electrical connections. On the other hand, Consumer Reports publishes reliability ratings for vehicles so that customers can evaluate the long term reliability of sub-systems inside the vehicle. Such readily available information has made vehicle manufacturers step up their internal quality measures and tie those metrics to ensure that the customer is delighted when he/she receives the delivery of a brand new car and more importantly to ensure that the customer stays loyal by enjoying the performance of the vehicle along with robust reliability. Several concepts and methods have evolved with the goal of improving conformance quality. Following is a brief review of the conventional quality control methodologies that are being used for the last several years and their respective limitations:

2.4.1. Statistical Process Control (SPC)

In virtually all manufacturing processes, the dimensions and quality of individual parts needs to be known and controlled to meet design specifications. If such dimensions are not controlled, costly delays and failures may result. Inspection strategy can fall into one of the three following categories:

a. 100% inspection: Each and every part can be measured, manually or by some automated method
b. Sampling: Some portion of the output can be measured by taking a sample lot of parts at a certain frequency
c. No inspection: Under the assumption that everything that is manufactured meets required specifications, none of the parts get inspected

Usually, manufacturers choose one of the first two categories depending on the risk associated with a defective part. Sampling strategy involves looking at a certain percentage of the entire population of parts using statistical techniques. This is known as Statistical Process Control (SPC). The basic SPC techniques are the histogram and control charts. The x-axis would represent various ranges of a dimension (e.g. a shaft length) and the y-axis would represent the frequency at which these measurements were found. The natural process limits of the measured distribution can be compared with the engineering specifications to determine if the process is centered at the nominal value or requires an adjustment. The location of the tails of the histogram with reference to the design specification limits for a given dimension would show whether the parts being produced are within specification or a small population does not meet the requirements. Control charts for variables are used to monitor the output of a process by sampling, by measuring selected quality characteristics, by plotting the sample data on the chart, and then by making decisions about the performance of the process. Three common types of charts that are used in typical manufacturing processes are:

1) X-bar chart: This chart tracks the aim / target (accuracy) of the process
2) R chart: The range chart tracks the precision or variability of the process
3) σ chart: The σ chart is used in place of R chart if the sample size is large

It is important to know that sampling errors can occur. Two kinds of decision errors are always possible:

1) Type I error: If the process is running well but the sample data indicates that an adjustment is required

2) Type II error: Contrary to the Type I error, in this type the sample data fails to indicate that something is wrong with the process, when indeed an adjustment is required

Many manufacturing companies determine the size of the errors they are willing to accept according to the financial loss associated with making the error plus the cost of inspection.

This conventional quality control method has two major shortcomings:

1. This method is reactive by nature. When the point of detection is downstream from the defect source, the delay in responding to a process variation can result in a significant number of defects.
2. SPC focuses on the manufacturing process and does not take product design into consideration. Although manufacturing process control plays a big role, several defects are caused due to a product design issue and this method does not take focus on the design.

2.4.2. Taguchi's Robust Design

In contrast with the reactive SPC technique, Taguchi's Robust Design considers defect issues relative to the product design as well as the manufacturing process. Quality Engineer – Genechi Taguchi must be credited with much of today's interest in the use of factorial and fractional factorial designs on the part of the automotive and assembly industries [33]. Within these industrial environments, experiments are run to identify the settings of both product design parameters and process variables that will simultaneously provide a manufactured item whose response is robust to process variability while meeting the customer's product expectations and possible environmental challenges. The adaptation of statistical experimental design to these objectives has its origins in Taguchi's early work in the communications industries in Japan in the 1950s. The strategy is called "parameter design" or "robust design". The word "design" takes different connotations: product design, process design, and statistical design.

A product's response *y* is considered to be a function of "controllable" factors *x* and the "noise" factors *z*. The objective is to choose settings of *x* that will make the product's response *y* insensitive to variability associated with both *x* and *z* and still meet target specifications with least variability.

2.4.3. Six Sigma and Process Capability

Six Sigma methodology seeks to reduce or eliminate defects caused by variation by assuring that design requirements have been established correctly in the design phase and that the manufacturing process capability meets these requirements. An important measure used in the Six Sigma methodology is the Process Capability index (C_p). For bilateral tolerances, this index is defined as:

$$C_p = \frac{|USL - LSL|}{6\sigma} = \frac{\text{Tolerance width}}{\text{Process capability}} \tag{2.4}$$

Where,

USL = Upper Specification Limit

LSL = Lower Specification Limit

σ = Standard Deviation of the production process

The process capability index can be used to predict how frequently the outcome of a process will exceed specification limits. This is a useful tool but focuses only on the design tolerances and ability of the process to manufacture parts consistently within those specifications. One of the drawbacks of analysis using these tools is that most quality engineers focus on the primary distribution followed by the data. For example, the data for a process could be normally distributed. In most cases, the tails of the distribution are not part of the consideration except for the defect rate estimation in Parts per Million (PPM). Understanding the nature of rare events and the limitations of statistical methods is particularly important when the goal is to achieve near-zero defect levels.

2.4.4. Self and Source Inspection

Shigeo Shingo has introduced several quality concepts that overcome some of the limitations of other methods. Self-inspection and source inspection have the goal of detecting and eliminating defects at their production source [34]. Self-inspection has the objective of detecting defects as close to the point of origination as possible or to reduce delays in feedback. By gauging tools, materials and activities upstream of the process, it is possible to eliminate any defects before they are created, using source inspection. However, like SPC, these methods are manufacturing focused and do not address design issues.

2.4.5. Pokayoke and 100 % Inspection

Shigeo Shingo makes an important distinction between human error and product defects. While errors are inevitable, defects are not. He has stated [34]:

“We should recognize that people are, after all, only human and as such, they will, on rare occasions, inadvertently forget things. It is more effective to incorporate a checklist, i.e. a pokayoke device into the operation so that if a worker forgets something, the device will signal that fact, thereby preventing defects from occurring. This, I think, is the quickest road leading to attainment of zero defects.”

Similarly, Rasmussen [35] concluded that the frequency of error derived from defect reports is dependent on the opportunity for people to detect and correct the errors immediately. No amount of vigilance or training will assure that unintentional errors will be recognized. Use of pokayoke is required to catch every single error and result in a defect free output. Using pokayoke devices, defect probabilities will be less than error probabilities. Consequently, defects are more likely to be related to the level of quality control than to the frequency of errors. Therefore, centering attention on error prevention and intervention is more productive than prediction of error rates for manufacturing problems.

In some cases, pokayoke has been incorporated in the design process, thereby preventing incorrect assembly [36]. However, pokayoke devices are generally used on the assembly line to prevent assembly defects rather than an available technique that can be incorporated into the product design.

2.5. Correlating Complexity and Quality

Efforts associated with manual precedence graph generation at a major automotive manufacturer have highlighted a potential relationship between manufacturing complexity (driven by product design, assembly process, and human factors) and product quality, a potential link that is usually ignored during Assembly Line Balancing and one that has received very little research focus so far.

Two models that have been developed based on assembly of home audio products and copier assembly have been summarized below:

2.5.1. Hinckley Model

Based on defect data of semiconductor products, Hinckley found that defect per unit (DPU) was positively correlated with total assembly time and negatively correlated with number of assembly operations [37]. He defined the assembly complexity factor (*Cf*) as follows:

$$C_f = TAT - t_0 \times TOP \tag{2.5}$$

where,

TAT=Total assembly time for the entire product

TOP=Total number of assembly operations

t_0 = Threshold assembly time

In order to calibrate the correlations between these parameters, he incorporated the threshold assembly time (t_0) which was defined as the time required to perform the simplest assembly operation. With this complexity index, Hinckley found that when plotting on a log-log scale, the complexity and the corresponding defect rate showed a positive linear correlation with each other, as in the following two equivalent equations:

$$\begin{gathered} \log DPU = k \times \log C_f - \log C \\ DPU = \frac{\left(C_f\right)^k}{C} \end{gathered} \tag{2.6}$$

where, C and k are constants.

2.5.2. Shibata Model

Shibata [38] remarked that the Hinckley model did not take the assembly design factors into consideration and could not evaluate the defect rate for a specific workstation. Therefore, Shibata proposed a prediction model for a workstation based on two assembly complexity factors: the process-based complexity factor and the design-based complexity factor. Assembly time was determined by Sony standard time, a commonly used time estimation tool for electronic products. Shibata used home audio products, a combination of CD player and a MiniDisc recorder/player as assembly cases. These had approximately 300 job elements and the total time was approximately 10 minutes.

The process-based complexity factor of workstation i is defined as:

$$Cf_{Pi} = \sum_{j=1}^{N_{ai}} SST_{ij} - t_0.N_{ai} \tag{2.7}$$

where,

N_{ai}=number of job elements in workstation i;

SST_{ij} = time spent on job element j in workstation i;

t_0 = threshold assembly time

Shibata used Sony standard time (SST), a commonly used time estimation tool, which is based on field studies and statistics. Home audio equipment served as a good vehicle for Shibata's analysis because its assembly process contained almost every type of basic assembly operation that is present in consumer electronic products.

Similar to the Hinckley Model, Shibata derived the following correlation between the process-based assembly complexity factor and DPU:

$$\log \mathrm{DPU}_i = K.\log Cf_{Pi} - \log C \tag{2.8}$$

$$\mathrm{DPU}_i = \frac{(Cf_{Pi})^K}{C} \tag{2.9}$$

where C and K are constants.

In addition to the process-based complexity, Shibata defined the design-based assembly complexity factor as:

$$Cf_{Di} = \frac{K_D}{D_i} \tag{2.10}$$

where, K_D is an arbitrary coefficient for calibration with process-based complexity; D_i is called the ease of assembly of workstation i, evaluates based on the method of design for assembly/disassembly cost-effectiveness (DAC) developed in Sony Corporation.

Shibata found that the correlation between the design-based complexity and DPU can be expressed as follows:

$$\begin{aligned} \mathrm{DPU}_i &= a.(Cf_{Di})^b \\ \log(\mathrm{DPU}_i) &= b.\log(Cf_{Di}) + \log a \end{aligned} \tag{2.11}$$

where, a and b are constants.

In response to the above model, Mendenhall and Sincich suggested that more independent variables can improve the accuracy and stability of the regression function. Shibata derived a bivariate prediction model by combining (2.8) and (2.11):

$$\log \mathrm{DPU}_i = k_1.(\log Cf_{Pi}) + k_2.\log(Cf_{Di}) + C \tag{2.12}$$

Su et al. [37] used the Shibata model to predict quality defects in a copier assembly operation and found the value of R-square in the regression model to be 0.257

versus a value of 0.7 reported by Shibata for the home audio products. This proved that the Shibata model was not appropriate for electromechanical products like copiers. One of the primary reasons was the fact that Sony standard time had a threshold assembly time of 2 seconds vs. 0.6 seconds in the case of the copier assembly.

Following is a brief description of additional work that has been done by researchers to correlate certain elements of a manufacturing system with quality:

2.5.3. Relationship between Ergonomics and Quality

Knowledge from research or practical evidence, of the relationship between ergonomics and quality is limited [39]. The literature contains a large number of studies showing clear relationships between poor lighting, noise, unfavorable climatic conditions and the effects on people's work in terms of increased error frequency. It has been observed that systematic quality work, as in quality circles for example, is also a method that can solve working environment problems [40]. Eklund [41] conducted a comprehensive study in a Swedish car assembly plant. The most physically demanding tasks, the tasks with the most difficult parts to assemble, and the most psychologically demanding tasks, were identified by interviews with experienced assembly workers. Designs involving difficult assembly accounted for the largest proportion of quality deficiencies, and psychologically demanding tasks showed the smallest proportion. The results showed that the quality deficiencies were three times as common for the work tasks with ergonomic problems, compared with other tasks. A quantifiable relationship using standardized ergonomics metrics and product quality has not been published.

2.5.4. Associate Training

Associate training plays an important role in the complexity model. Hancock et al [42] did not correlate training with resulting quality but demonstrated that the cycle time per task decreases as experience, measured by the number of repeated cycles (*x*), increases. They described this phenomenon as the "Learning Curve" which has the form:

$$Y_x = \frac{K}{x^{\alpha_L}} \tag{2.13}$$

where,
Y_x=cycle time per task for the x^{th}cycle
K=the time for the first cycle, and
α_L = a constant determined by the learning rate (usually 0.80)

2.5.5. Human Error

Although some authors have touched the topic of human error and variation, this distinction has not been accurately described in the literature. This is probably due to the fact that it is virtually impossible to accurately assess rare events using sampling methods. There are many types of error that can occur in an operation. While each of these are individually rare occurrences, collectively they can have a significant impact on conformance quality. Harris [43] concluded that 80 percent of the defects in complex systems could be attributed to human error. In an examination of 23,000 assembly defects, Rook [44] found that 82 percent of the defects were caused by human errors. Voegtlen [45] reported that 60 percent of product failures could be traced to workmanship defects. A recent study of automotive headlamps also showed that more than 70 percent of 6,600 observed defects were caused by assembly or handling errors. These studies point to human error as a significant contributor to the total defects.

2.5.6. Component & Assembly Quality

The National Research Council [46] study presented a combinatorial model of defects. This method of combining the probability of many independent events is the basis for all modern reliability evaluations and essential element of a sound defect model. Two useful defect categories are: part defects and assembly defects.

A part may contain material defects, or may not meet functional requirements due to variation or errors in processing or material handling. Variation can be due to process, gage response, tool wear, operator error, and multiple such factors. Hinckley [47] defined the probability of a part defect in the simplest terms consistent with the NRC model as:

$$\begin{aligned} &P\{i^{th} \text{ part is defective}\}=d_i \\ &0 \le d_i \le 1 \end{aligned} \tag{2.14}$$

Errors such as omitting a part, installing a wrong part, or placing the part in an incorrect orientation will result in defects. Several studies have shown that there is a correlation between an increased probability of an error and difficulty / time required to execute a task [48, 49].

Given that assembly operation involves the addition of a part, the part could contain a defect, the assembly operation could cause a defect, or both the part and assembly operation could result in defects. Thus, there are three separate ways of introducing one or two defects into a product when assembling a part. By contrast, there is only one way of having a defect free assembly – the part must be defect free and the assembly operation must not result in a defect. As a result, calculating the probability that an operation does not introduce a defect is much easier than calculating the probability that it will cause a defect. Thus yield would basically be a combination of the two probabilities: the probability that the part is defect free and that the assembly operation did not result in a defect.

2.5.7. Task (Assembly) Time and Quality

In late 1990, Brannan [50] at Motorola published the data shown in Figure 2.23, which demonstrated that the number of defects per million parts decreased dramatically for increases in the manual assembly efficiency, an arbitrary measure used in the Boothroyd Dewhurst® [51] Design for Assembly (DFA) method.

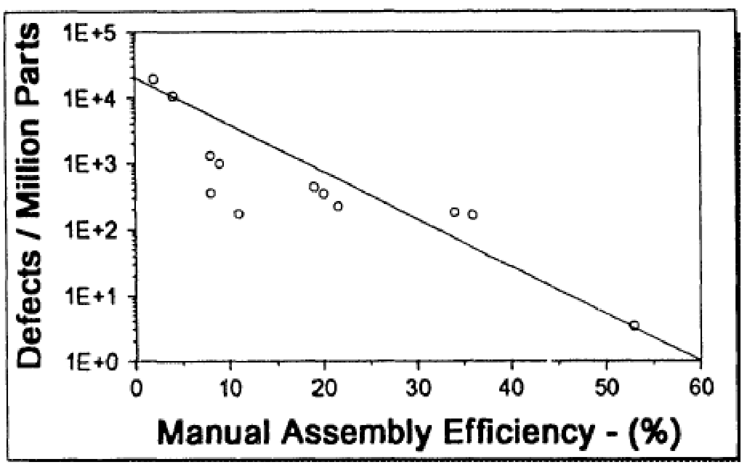


Figure 2.23: Observed DPMO vs. the Manual Assembly Efficiency [50]

In general, as the assembly efficiency increases the number of assembly operations and the average time required to perform each operation decreases. Assuming a constant probability of human error per unit time, the defect rate should increase as the assembly time per operation or complexity increases. Thus, the relationship between defects and assembly efficiency observed by Motorola is intuitively sound, but was not explained at the time. The data provided by Motorola suggested that there may be a quantifiable link between a criterion describing assembly complexity and product defects.

Such a theory could be used to evaluate the product quality of product concepts even before tolerance studies are initiated.

The Boothroyd and Dewhurst evaluation centers on establishing the cost of handling and inserting component parts [52]. Regardless of the assembly system, parts of the assembly are evaluated in terms of, ease of handling, ease of insertion and a decision as to the necessity of the part in question. From this, time and cost is generated for the assembly of that part. Each part is entered into the worksheet. The first stage analysis is an attempt at part reduction. Each part is examined with respect to the following questions:

1) During operation of the product, does the part move relative to all other parts already assembled? Only gross motion should be considered; small motions that can be accommodated by elastic hinges, for example, are not sufficient for a positive answer.
2) Must the part be of a different material in order to be isolated from all other parts already assembled? Only fundamental reasons concerned with material properties are acceptable.
3) Must the part be separate from all those already assembled because otherwise necessary assembly or disassembly of other separate parts would be impossible?

The Design for Assembly (DFA) methodologies have been used by Barkan et al. [53] to predict assembly complexity using assembly time as a standard. They have shown that the predicted times are superior to the simplistic measures such as number of components to be assembled and number of assembly operations. In general, for every factor that increases the difficulty of the action or the complexity of the assembly interface, there is an increase in the predicted time for execution. This approach is an evolution of Time and Motion studies that substantiate the general trend of increased execution time for increases in the difficulty and complexity of the assembly task. The DFA methods are better than the Predetermined Motion Time Systems (PMTS) for assessing assembly complexity because they are more directly related to product characteristics than production planning. Additionally, the DFA analysis can be done using drawings, without having to physically disassemble products or define each assembly motion. The databases and rules of use encourage a more consistent interpretation than can be achieved in a conventional tear-down analysis suggested by Womack [54].

2.6. Summary of Background Work

In this chapter we provided a brief overview of the automotive manufacturing processes and mixed-model final assembly along with an introduction to key-enabling systems for MMFA. We also reviewed the Assembly Line Balancing Problem, constraints definition and a method of manually gathering that information to solve the problem. This manual exercise highlighted a potential link between manufacturing complexity and product quality. We then provided a literature review on Complexity, Axiomatic Design principles, Operator Choice Complexity, and Cognitive Load Theory. This section was followed by a brief overview of the common methods to control quality in manufacturing plants. Finally, the last section in the chapter focused on previous work related to correlating Complexity and Quality. Researchers, Hinckley and Shibata focused on developing a global model for assembly complexity and product quality based on analysis of semiconductors and home audio appliances.

In the following chapters, gaps in the currently published research work will be highlighted, followed by definition & development of a general complexity model and finally it will be applied to a controlled fastening process in a real-world mixed-model automotive assembly plant.

CHAPTER THREE

3. GAPS IN CURRENT WORK AND RESEARCH PLAN

3.1. Research Objective

The objective of this research is to test the hypothesis that manufacturing complexity can reliably predict product quality in mixed-model automotive assembly.

3.2. Research Gaps

Several scholars have attempted to define complexity at a manufacturing system level with limited success. This is primarily because there are a large number of contributors that prevent the functional objective from being achieved and depending on the application; authors have focused on limited number of variables and defined them as complexity drivers. In order to reliably predict quality based on manufacturing complexity, we need to take into account an array of input variables that have the ability to statistically account for the variation in the resultant variable (product quality). Focusing on a few individual variables and prove that they have some impact on product quality would not be adequate in achieving the objective of this research.

Seminal work in this area has been done by Hinckley [47], Shibata [38], and Su et. al. [37].

The research gaps in the work done by these researchers are summarized as follows:

1) **Hinckley's Model [47]:** The mathematical model is as follows:

$$Cf = TAT - t_0 \times TOP \tag{2.15}$$

where,
Cf = Assembly Complexity factor
TAT = Total assembly time for entire product
t_0 = Threshold assembly time
TOP = Total number of assembly operations

$$\log \text{DPU} = k.\log Cf - \log C$$
$$\text{DPU} = \frac{(Cf)^K}{C} \tag{2.16}$$

where,
DPU = Defects per unit
C & K = Constants

Though this model enables us to grasp schematically the relative level of quality control among globally distributed manufacturing sites, a major shortcoming of the model is that it only reveals the product quality at an overall plant level. The model does not take the assembly design factors into consideration and could not evaluate the defect rate for a specific station. It does not assess process level complexity and its impact on quality. In order to reduce complexity, designers would need to know which part design produced increased levels of assembly complexity resulting in assembly defects. Also, Hinckley's model takes into account average assembly time and the threshold assembly time but does not take into account variation in assembly times, an important input for the complexity model that we found based on our study. We discuss this in chapters 4 and 5.

In order to validate the model in the automotive assembly environment for total DPU, we used a simple example as shown below:

Table 3.1: Application of Hinckley Model to Vehicle Assembly

Ref.	*TOP* (#)	Takt Time (s)	*TAT* (hr)	*TAT* (s)	t_0 (s)	C_{fpi} (#)	log (C_{fpi})	Actual DPU	log (DPU)
Model A	13,920	100	26.2	94,320	4	38,640	4.59	1.2	0.079
Model B	11,620	120	24.1	86,760	4	40,280	4.61	0.7	-0.155

Although the total assembly time is higher in the case of Model A, and the threshold time is 4 seconds, the complexity factor C_{fpi} is inversely proportional to the total assembly time and DPU (Figure 3.1). This contradicts the finding that Hinckley had when they applied it to semiconductor manufacturing which was perhaps a lot more repetitive in tasks as compared to automobile assembly tasks.

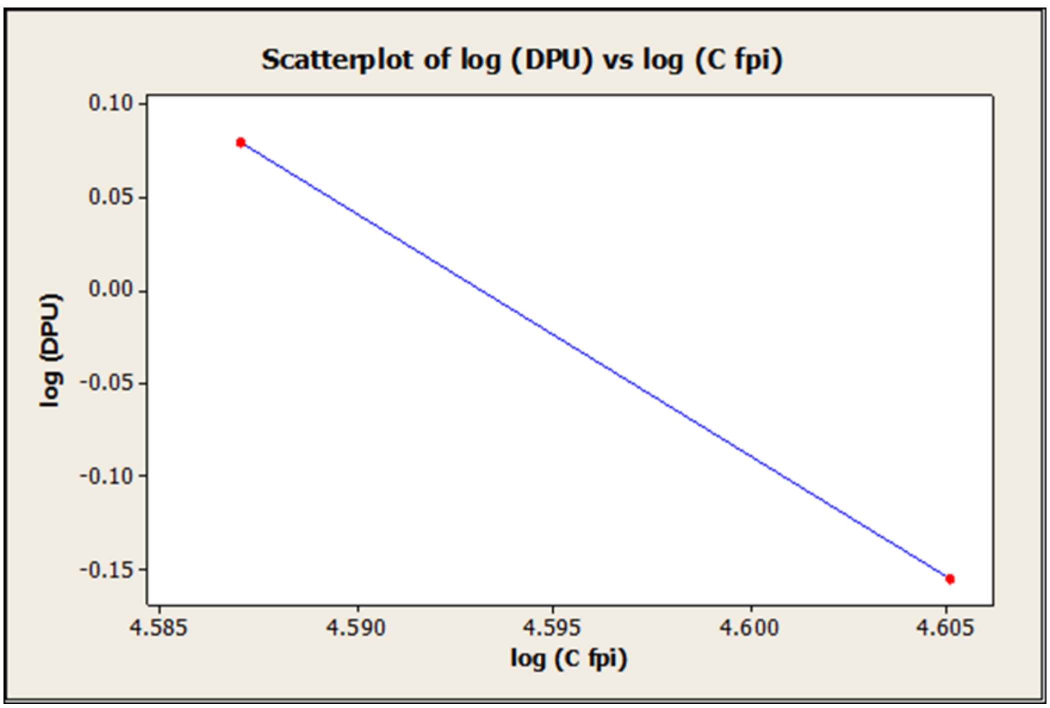


Figure 3.1: Hinckley Model validation

2) **Shibata's Model [38]:** In contrast to a model based on global manufacturing plants that provides a high level overview of a correlation between complexity

and product quality, Shibata considered process and design contribution in the research. Following is the mathematical formulation of the Shibata Model:

$$Cf_{Pi} = \sum_{j=1}^{N_{ai}} SST_{ij} - t_0.N_{ai} \tag{2.17}$$

where,
Cf_{pi} = Process based complexity factor
N_{ai} = # of job elements in workstation i
SST_{ij} = $Sony$ Time on job element j in workstation i
t_0 = Threshold assembly time

$$Cf_{Di} = \frac{K_D}{D_i} \tag{2.18}$$

where,
Cf_{Di} = Design based complexity factor
K_D = Coeff. for calibration with Cf_{pi}
D_i = Ease of assembly cost-effectiveness (*Sony*)

$$\log \mathrm{DPU}_i = k_1.\log Cf_{pi} + k_2.\log Cf_{Di} + C \tag{2.19}$$

where,
DPU_i = Defects per unit
C, k_1, k_2 = Constants

Shibata characterized complexity for electronic products and divided complexity into design driven complexity and process driven complexity. Shibata limited his work to electronic products/processes and used Sony Standard Time (SST) as the assembly time estimation database. To validate the Shibata Model, we applied the method and the mathematical model to mechanical fastening process used in automotive assembly. We applied it to 18 different fastening processes and found the regression analysis reveal a negligible R^2 (adj.) value (Figure 3.2).

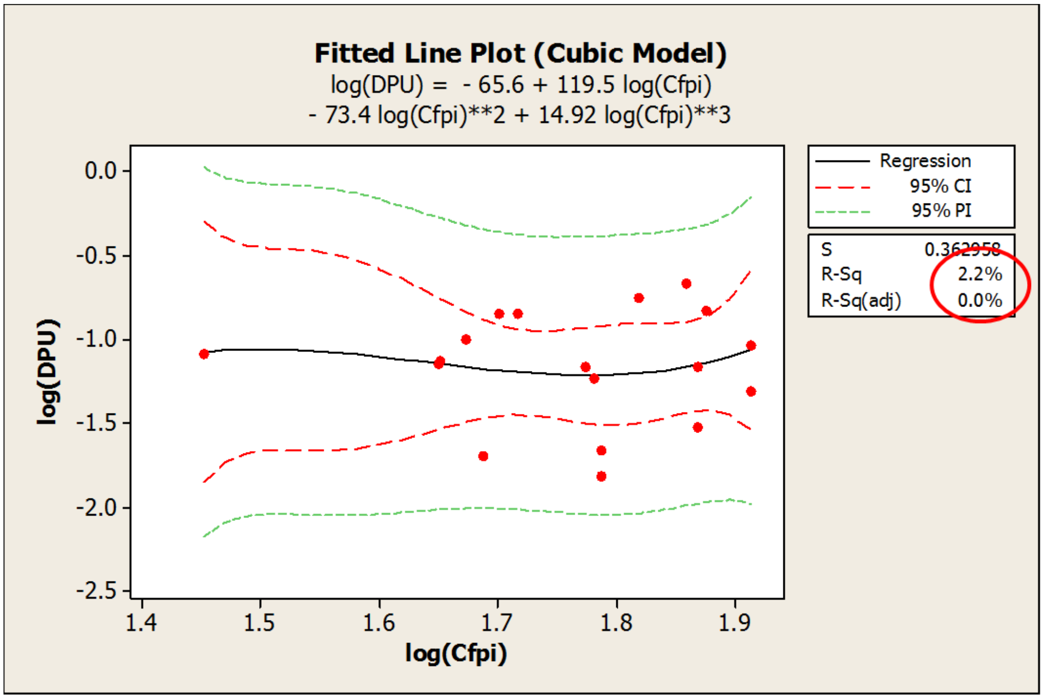


Figure 3.2: Shibata Model validation with fastening processes

Su and Whitney used the Shibata model and applied it to an electromechanical product – a copier. An alternative approach to complexity evaluation is required due to the following reasons:

a. While most of the processes in Shibata's study included simple inserting and soldering of small electronic components and electric wires on a printed circuit board, a multifunctional copier introduced a new level of challenges. A copier is 10 to 100 times larger in terms of size [37], weight or parts quantity compared to a Minidisk player or mini-stereo used by Shibata for his study. Differences in type or size of the products result in significant differences in parts, materials, and mating methods of components.

b. The Shibata model used a factor D_i (ease of assembly of workstation i), evaluated based on the method of design for assembly / disassembly cost-effectiveness (DAC) developed specifically by Sony Corporation. This was not applicable to a generalized model or specifically to the case of the copier studied by Su et al. because the criteria used in this method to evaluate ease of assembly were developed specifically based on electronic products and not on mechanical or electromechanical products like copiers.

c. Shibata used Sony standard time (SST), a commonly used time estimation tool designed specifically for electronic component assembly, based on field studies and statistics. This time database is also not based on standard MTM analysis and hence prevents the model from being generalized. For instance, in SST, the threshold assembly time t_0 is 2 seconds. However, in the case of copier assembly, the shortest adjustment action can be completed in 0.6 seconds according to standard time studies conducted at Fuji Xerox by Su et. al.

3) **Su and Whitney Model [37]:** The research conducted by Su and Whitney focused on understanding operator induced assembly defects for a copier based on assembly complexity factors. They attempted to overcome some of the shortcomings of the Shibata and Hinckley models (listed above). The researchers

used Fuji Xerox standard time instead of Sony standard time (SST) to evaluate the process-based assembly complexity factor in order to make it more suitable for copier production. Secondly, as the DAC based approach used by Shibata was developed by Sony Corporation based on small electronic products, it was found to be inapplicable in the case of the copier. Su & Whitney used Ben-Arieh's [55] fuzzy expert system approach for analyzing difficulty of assembly operations instead of using the DAC based design-complexity evaluation method used by Shibata. The researchers selected 11 parameters as the criteria for evaluating the design-based assembly complexity (part shape, force required, length of components, etc.). In order to obtain an integrated index, the weights of 11 criteria were allocated using the analytic hierarchy process (AHP) [56]. This approach is not suitable for a generalized complexity model for the following reasons:

a. AHP has the advantage of permitting a hierarchical structure of the criteria, which provides users with a method to prioritize them based on assigned weights. One of the known issues with AHP is that a different structure may lead to a different ranking. Several authors [57, 58] have observed that criteria with a large number of sub-criteria tend to receive more weight than when they are less details.
b. Second reason is that this model also uses a specific time standard – Fuji standard time. It would be beneficial to develop a model based on standard Methods-Time Measurement (MTM) analysis in order to make its applicability across several product types.

c. Based on the proposed model, for example, if a fixture is implemented to resolve an issue that is repetitive in nature, it could potentially add a few steps to the task. Additional steps would increase the process-complexity factor, which would result in a higher predicted failure rate. On the contrary, in reality, such fixtures reduce variation by improving repeatability of part location along with the stability of the component during the assembly process and generally reduce the defect rate. This shows that calculating process-complexity simply based on the number of tasks and task time is not adequate. Time variation should also be considered in complexity calculation.

3.2.1. Summary

In summary, in order to analyze the impact of manufacturing complexity on product quality in mixed-model assembly systems, a comprehensive approach needs to be taken to characterize and measure manufacturing complexity. To do so, one has to take into consideration product design characteristics, process characteristics, and finally human factors such as task ergonomics, operator training, and experience. Detailed analysis of assembly defects at a major automotive assembly plant has revealed that fastening of critical components using threaded fasteners is the number one driver of assembly defects and the top 28% of all in-process assembly defects can be attributed to a single type of controlled fastening process. Therefore, in order to study Manufacturing Complexity and its effect on Product Quality, first we define complexity, then develop a generalized model, use the controlled fastening process as a pilot process to validate the model, and finally we show four case studies from real-world mixed-model automotive assembly.

3.3. Research Questions (RQ)

In order to validate the hypothesis that manufacturing complexity can reliably predict product quality in mixed-model automotive assembly, the following research questions need to be answered:

3.3.1. Research Question 1

How is manufacturing complexity defined in the general context of assembly operations (Figure 3.3)?

Task 1-A:

- **Approach:** Conduct literature review specifically focused on *complexity* across various domains and identify the sources of complexity applicable to assembly operations in mixed-model assembly system. Conduct a Process Failure Modes and Effects Analysis (PFMEA) to determine various sources of defects for a generalized assembly process.
- **Outputs:** Ontology of manufacturing complexity related to the general assembly process and the corresponding ways to measure each source.

Task 1-B:

- **Approach:** Apply the Hinckley, Shibata, and Su & Whitney Models to the controlled fastening process to verify the validity of existing models and learn from the gaps observed.

- **Outputs:** Data driven understanding of the gaps in currently published research and a need to determine a new approach to defining and modeling manufacturing complexity, to ensure applicability across a wider array of general assembly operations.

Task 1-C:

- **Approach:** Develop a generalized model for assembly complexity based on the key inputs identified in Task 1-A. Apply the model to controlled fastening processes in real-world automotive assembly plant and determine whether the generalized model captures key variables observed in the fastening process.
- **Output:** Applicability of comprehensive generalized manufacturing complexity modeling approach based on literature review and hands-on understanding of the assembly variables to the mixed-model assembly domain.

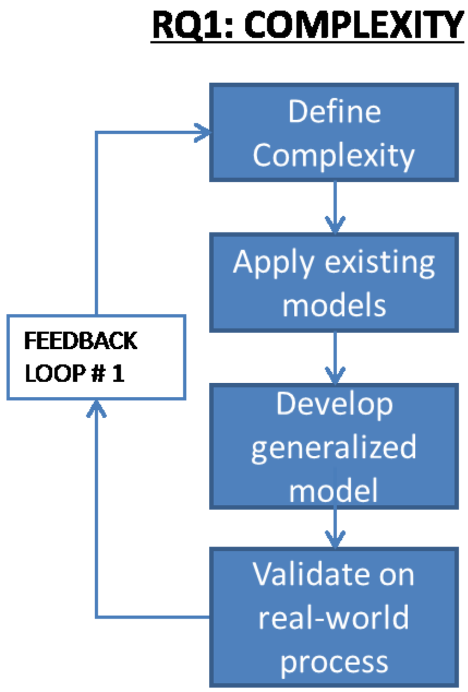


Figure 3.3: Flow of research tasks (RQ 1)

3.3.2. Research Question 2

How is product quality defined for assembly of components in mixed-model automotive assembly? What is the effect of manufacturing complexity on product quality (Figure 3.4)?

Task 2-A:

- **Approach:** Define important aspects of quality affected by complexity. Identify metrics to measure the effect on quality.
- **Output:** Process Failure Mode and Effects Analysis (PFMEA) for controlled fastening process. Comparison with generalized PFMEA & complexity model to

identify any additional inputs related to the fastening process that were not captured by the generalized model.

Task 2-B:

- **Approach:** Collect and organize the defects data for the last 12 months for four mixed-model assembly lines. Using the historical quality data, identify the processes that had the greatest impact and lowest impact on quality for the four assembly lines, and collect input data to compute complexity metric.
- **Output:** Controlled fastening processes and takts with the best and worst quality will be highlighted for detailed analysis of each complexity driving input.

Task 2-C:

- **Approach:** Using this information, conduct regression analysis with each source of manufacturing complexity as input and product quality as output to determine the effect of manufacturing complexity on product quality for 12 months of historical data from one automotive assembly plant.
- **Output:** A comprehensive model based on regression analysis that shows the relationship between manufacturing complexity and product quality for a controlled fastening process used in automotive assembly. Propose rules, constraints, and guidelines for product design, process selection and ergonomics that would reduce or eliminate the quality defects for the takts that were analyzed.
- **Assessment:** Apply the model to predict the quality of 20 processes in an independent automotive assembly plant. Compare the predicted values with actual results that were documented from historical data. Within limitations of technical

feasibility and plant approval, some of the proposed changes may be tried out on the assembly line for a limited period to evaluate the improvement in quality or identify the shortfalls of the predictive model.

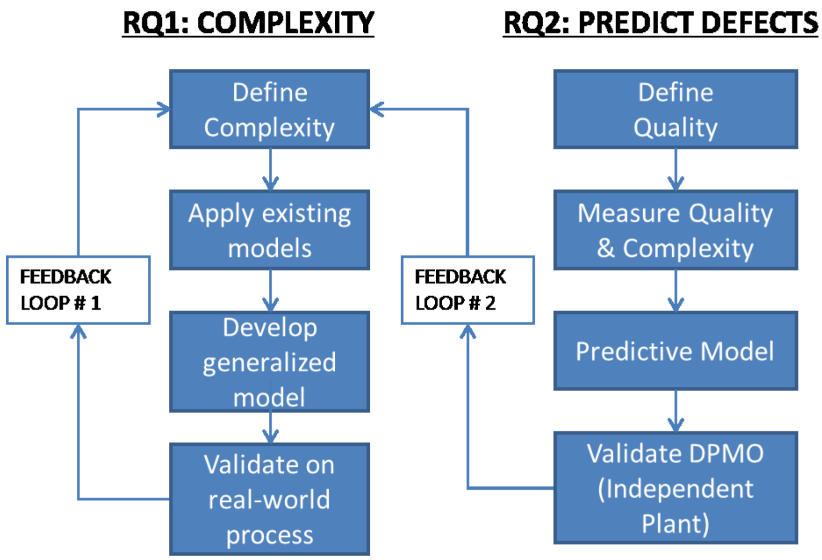


Figure 3.4: Flow of research tasks (RQ 1 and 2)

3.3.3. Research Question 3

Several quality defect prevention methods are usually employed in practice. How can these classes of defect prevention methods be incorporated to lower complexity and minimize DPMO (Figure 3.5)?

Task 3-A:

- **Approach:** Based on literature review, classify error-proofing systems generally used in large automotive assembly plants.
- **Output:** A comprehensive understanding of the classes of mistake-proofing devices actually used in the automotive industry.

Task 3-B:

- **Approach:** Incorporate mistake-proofing devices in the complexity model to enable prediction of Defects Per Million Opportunities (DPMO) based on the application of those devices.
- **Output:** An enhanced model of manufacturing complexity and product quality that includes quality defect prevention classes as inputs (e.g. active / passive information systems). A data driven understanding of the defect prevention methods and their impact on product quality.

Task 3-C:

- **Approach:** Use the revised model to predict the effect of using these classes of mistake-proofing or assembly aid devices on specific processes, historically known to exhibit a higher defect rate. Practically implement these defect prevention methods and monitor the actual change in defect rate and compare it with that predicted by the model to assess the ability of the model to predict product quality as a function of manufacturing complexity.
- **Output:** A case-study based data driven assessment of the validity of the predictive model and an assessment of the ability of classes of mistake-proofing devices to lower complexity and DPMO.

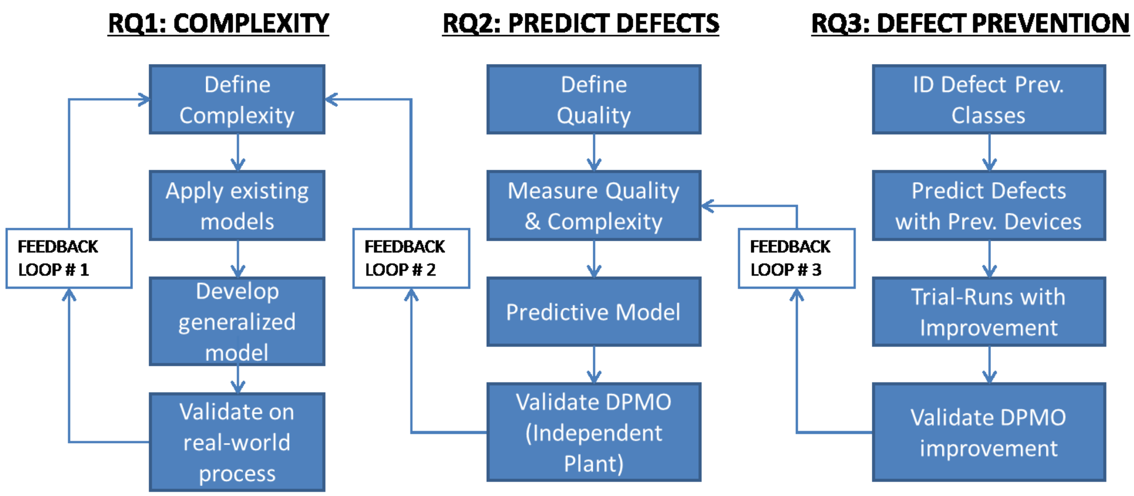


Figure 3.5: Flow of research tasks (RQ 1, 2, and 3)

3.4. Summary of Research Questions and Tasks:

Table 3.2: Summary of Research Questions & Tasks

	RQ1: How is Complexity defined in general context of assembly operations?	**RQ2: How is Product Quality defined? What is the effect of Complexity on Quality?**	**RQ3: How can classes of defect prevention methods lower complexity and DPMO?**
Task A	Literature review and PFMEA to define Complexity and its drivers	PFMEA for fastening, compare with generalized model & determine gaps	Identify defect prevention classes
Task B	Validate existing models and identify gaps	Collect input data and compute complexity metric for highest and lowest DPMO processes	Incorporate mistake-proofing devices in the complexity model to predict impact on DPMO
Task C	Develop generalized complexity model; verify applicability to an assembly process	Develop predictive model Input = Complexity Output = DPMO; Validate in independent assembly plant	Conduct experimental runs. Assess validity of the model and ability of these methods to lower complexity and DPMO

CHAPTER 4

4. GENERALIZED COMPLEXITY MODEL FOR MANUFACTURING

4.1. Complexity Measurement

Based on extensive literature review and the gaps in currently published work, a comprehensive generalized complexity model has been proposed in this research. The sources of complexity are determined based on the following:

a) Literature review
    i. Design factors [50-52, 59, 60]
    ii. Process factors [5, 24, 37, 38, 47, 60-64]
    iii. Human-factors [25, 37, 39, 43, 44, 60, 65-68]

b) Lessons learned from the our involvement in constraints mapping related to assembly line balancing at a major US assembly plant [8, 69]

c) Technical input from fastening process experts at the automotive assembly plant where this study was carried out [62]

d) Heuristic input from operators who work in mixed-model automotive assembly

All sources of complexity are then tested for statistical significance to quantify the ability of each input parameter (and its interaction) to account for the variation in the resultant variable (details in Chapter 5).

Figure 4.1 shows an overview of the Product Realization Process. The scope of this research work is limited to Product Design and Manufacturing elements of this entire process.

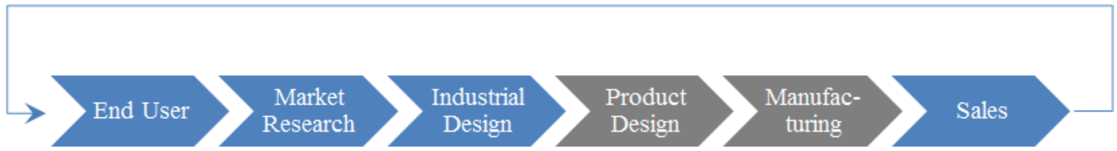


Figure 4.1: Product Realization Process

Based on the literature review on Design for Manufacturing (DFM), process factors, human-factors engineering (references noted in section 4.1), and complexity [5, 14-16, 38, 47], we take a holistic view in defining complexity. We re-define manufacturing complexity as a measure of variability introduced by design factors, process factors, and human factors that can impact functional requirements. In our research, the functional requirements have been limited to product quality.

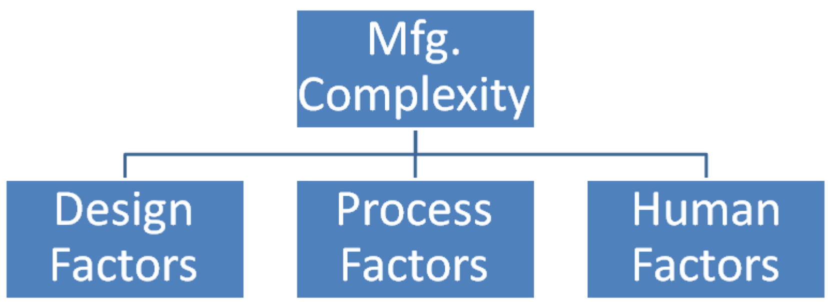


Figure 4.2: Key drivers of Manufacturing Complexity

4.1.1. Design Factors

Product Design is an important input variable that can impact manufacturing complexity in a product. Using Design for Manufacturing (DFM) principles [51, 70], we determine the input variables that can introduce manufacturing complexity. Design for Manufacturing / Manufacturability (DFM) is a philosophy and a mind-set in which manufacturing input is used at the earliest stages of design in order to design parts and products that can be produced more easily and more economically. Tooling costs, processing costs, assembly time, ergonomics, resulting product quality, and worker safety are examples of some of the objectives that are considered during the DFM driven design process [70].

The DFM process includes the following steps:

a. Determine the product characteristics
    i. Functional requirements and expected life
b. Conduct Product Function Analysis
    i. Design quality into the product (mistake-proofing)
    ii. Reduce the number of parts
c. Design for manufacturability and usability
    i. Determine materials and methods based on life expectancy
    ii. Define locating surfaces and eliminate need for special fixtures
d. Define assembly process using Design for Assembly methodology

Design for Assembly (DFA) found its beginnings in the late 1970s. Manufacturers realized that their designs were not suitable for automated assembly, and even very difficult for manual assembly. This became an important point as volumes and variety began increasing. Following is an example that lists a series of steps that show the manufacturing process and the impact of DFA:

1) Purchase raw-material
2) Incoming inspection

3) Place material in an inventory holding location

4) Present parts to the operator or automated equipment for assembly

5) An operator picks up the part, orients it, guides it into place into a fixture

6) An operator picks up a fastener, orients it, and assembles it to the part

7) An operator picks up a tool, orients the tool, and drives the fastener

8) Final part is inspected for cross-threaded fastener, alignment etc.

Integrating assembly features into the design of the components can help eliminate fastening components or minimize the number required. This approach would eliminate steps 6 and 7. Perhaps, step 8 could also be eliminated or greatly simplified. This is the basic principle of Design for Assembly (DFA). A design that is easier to assemble, is cheaper to assemble and should encounter fewer defects. Simplifying the design is therefore the core principle of DFA.

While using the Boothroyd and Dewhurst process [51], the following questions have to be asked:

1) Does the part move relative to all the other parts in the assembly? Only large motions need to be considered valid. Small movements, deflections etc. can be ignored.

2) Must this part be made of a different material from other parts in the assembly? Must this part be isolated from other parts in the assembly? Only fundamental reasons concerned with material properties are acceptable.

3) Must this part be separate from other parts of the assembly in order to make assembly, disassembly or maintenance possible?

If the answer to any of these is No, then the part in question is a good candidate for elimination or combination. In our research, we consider number of components being assembled as a design complexity driver.

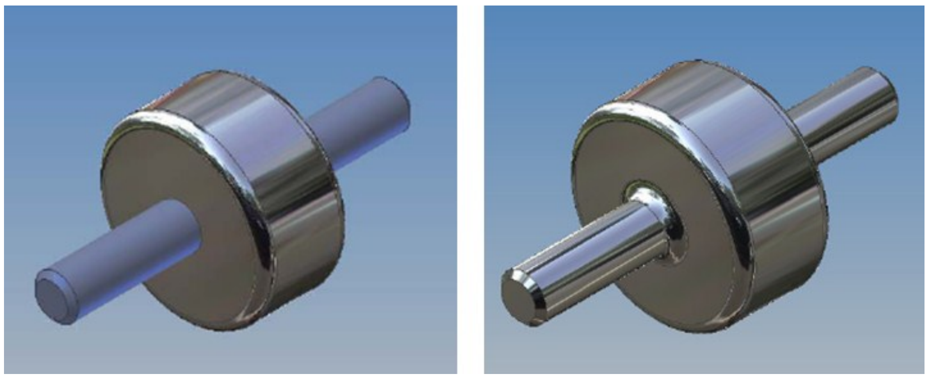


Figure 4.3: Design for assembly (Press fit vs. Integral shaft)

In Figure 4.3, there is a wheel pressed onto a shaft and an alternative design that has an integral shaft. There may be cost considerations in such a design decision but it shows how an assembly step can be completely eliminated. It is well known that threaded fasteners are penalizing in terms of assembly. They require more time than most other types of parts in assembly. Generally, designers recommend using snap fits for molded plastic parts and bend-over tabs in sheet metal parts instead of threaded fasteners wherever the functional requirements permit it. Wherever threaded fasteners must be used, it is recommended to integrate as many other joint accessories to be integrated in the interest of time (e.g. bolt, nut, washer, lock washer etc.). In several cases, designers use self-locking features in the fastener to eliminate the lock washer.

Based on literature review (section 4.1), technical input from process experts in mixed-model automotive assembly, findings from research project at an automotive assembly plant [8, 69], and heuristic input from experienced operators, we categorize the design driven complexity factors into four major categories of input variables. These can be used to define a design-driven complexity factor (C_d). Each category will be explained below and specific examples will be given to help the readers understand the context of the application and give them the ability to adapt this general model to their respective end-product / assembly being studied.

1) **Feature Design (D_{fd}):** The process of design changes the state of information that exists about a designed object. Features are characteristics that define the geometry, function, and aesthetics of a component [70]. A complete design also includes the relationships among these features in terms of physical connection, arrangement, and configuration to make up a whole part. In the generalized complexity model, this input category includes geometric and functional features. Aesthetic features can be added if they have any interaction with other features or an impact on functional requirements of the part and final assembly in which the part is used. All the features of a component that are available should be collected in the first iteration of the all-inclusive model. Using statistical analysis and test for significance, if the impact of a specific feature (variable) on the resultant functional requirement is negligible, then it can be eliminated from further analysis. The input can be qualitative or quantitative. We will cover a brief explanation on methods to convert qualitative information to quantitative for mathematical analysis, in the following section. Following is an example of a feature design that could impact functional requirements such as number of hours of continuous work

possible using a powertool. The handle may have a textured soft-grip material to aid ergonomics or it may have a solid handle without the soft-grip (Figure 4.4).

Figure 4.4: DeWalt Tools without (L) & with (R) black soft-grip handle

2) **Assembly Design ($\boldsymbol{D_{ad}}$):** The assembly process generally consists of two distinct operations: handling followed by insertion. Both these processes can be done either manually or automatically. In order to make the assembly process easier (which translates to reduced cost), Boothroyd [51] suggests three key guidelines – reduce the part count, reduce the manual handling time, and facilitate automatic handling of components. Assembly design impacts all three of these goals and therefore impacts manufacturing complexity. Part count can be reduced directly by achieving functional requirements with innovative designs and thereby eliminating components or by integrating multiple components into a larger single part by design. Manual handling time can be reduced by avoiding nesting of components (springs) because tangled components are difficult to grasp and manipulate with one hand. To facilitate ease of handling, parts should be designed with symmetry in mind. Parts that

do not require end-to-end orientation prior to insertion are easier to handle. Similarly, parts that have rotational symmetry take less time to orient than ones that have a flat feature (D-shape) because the latter would require alignment with another mating surface. Such end-to-end symmetry and rotational symmetry can also facilitate handling in an automated handling (bowl style component feeder). In our generalized complexity model, the input variables under this category can be a quantitative or qualitative that have been converted to a quantitative variable for mathematical modeling. For example, joint design variables such as clamp load or percentage visibility of a fastener would fall under the Assembly Design category.

3) **Component Accessibility (D_{ac}):** This input variable helps us capture the complexity introduced due to lack of direct access to the assembly area or components being assembled. We have included this variable in the study based on heuristic input from several experienced operators. Qualitative (subjective) measure of accessibility should be converted into a quantitative one based on the clear understanding of the components and the primary reason for lack of accessibility. In the case of the fastening case study, if multiple layers of components are between the feature to be accessed by the associate's hand-tool or an assembly device, then the number of layers of components can represent a quantifiable measure for component accessibility (Figure 4.5).

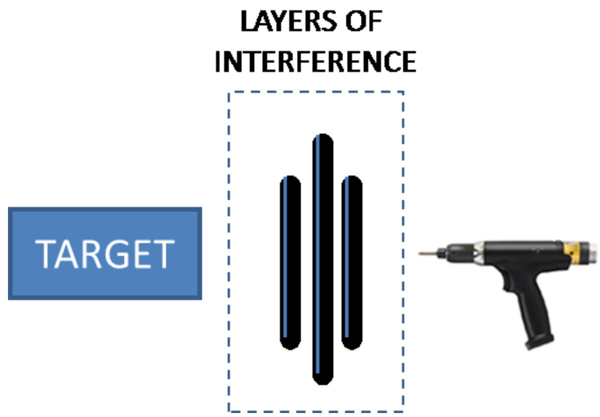


Figure 4.5: Layers of interference between tool and component

4) **Material characteristics (D_{mc}):** When selecting a material, the primary concern of engineers is to ensure that the material properties are consistent with the operating conditions of the component. The various requirements of each component including life expectations and operating environment are first estimated or determined. These may include mechanical characteristics (strength, resistance to fracture, rigidity, or the ability to withstand vibrations), physical characteristics (weight, electrical conductivity, or appearance), and service requirements (ability operate under extreme temperature or resist corrosion). The selection of the appropriate engineering material is often based on the tabulated or recorded results of standardized tests [24]. A certain property that may be required due to the function of the part can introduce complexity in the assembly process due to other inherent properties. In automobiles, light weight material is used wherever possible without compromising on strength to achieve higher fuel efficiency. In the case of fastening processes, aluminum brackets used to assemble larger parts to the

vehicle, introduce complexity because aluminum bends easily due to its ductility. The dynamic change in joint gap during the fastening process can introduce defects. Therefore, on one hand, while a certain material property is required, it can introduce complexity in assembly that can impact an output of interest (product quality). In the generalized complexity model, we include quantitative material properties as input variables.

4.1.2. Mathematical formulation

In summary, four key input variables have been highlighted as contributors to Design Complexity. If there are additional variables within each of these categories or a new category is required for a unique process that does not fit this general model, additional variables can be defined using the same principle. Design Complexity Factor C_d can be mathematically expressed as follows:

$$C_d = \pm\alpha_1 D_{fd} \pm \alpha_2 D_{ad} \pm \alpha_3 D_{ac} \pm \alpha_4 D_{mc} \tag{2.20}$$

where,
C_d = Design complexity factor
$\alpha_{1..n}$ = Empirical constants
D_{fd} = Feature design variable
D_{ad} = Assembly design variable
D_{ac} = Component accesibility variable
D_{mc} = Material characteristics variable

Figure 4.6 shows a block diagram of the four key input variables that contribute to design complexity.

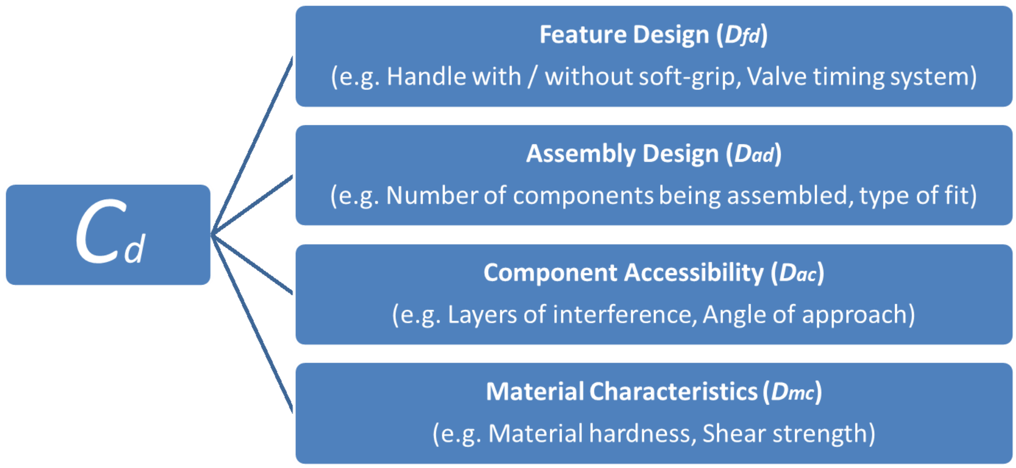


Figure 4.6: Input variables for design driven complexity

4.1.3. Process Factors

The goal of a process engineer is to design, develop, and implement a process that can manufacture components that meet design specifications consistently in a cost-effective manner. All manufacturing process display some level of variability, referred to as inherent capability. The variability may have assignable causes such as operator errors, defective materials, or progressive wear in the tools during machining. That variability to which no cause can be assigned and which cannot be eliminated is inherent in the process. Sources of inherent variability include variation in material properties, vibration or chatter caused by tool wear, and operator variability. Therefore, process factors play a very important role in the manufacturing complexity model. In this research, we define five major categories of input variables that can be used to define a process-driven complexity factor (C_p). Each category will be explained below and specific examples will be given to help the readers understand the context of the application and give them the ability to adapt this general model to their respective end-product / assembly being studied:

1) **Tooling / Fixture design (P_{tf}):** The process engineer designs tooling and fixtures to hold the workpiece securely and present the workpiece to the machining tool or to the operator to enable processing in an efficient manner while meeting dimensional specification and cycle (takt) time. The design of the fixture can introduce dimensional variation if there is vibration, chatter or movement in the workpiece in a way that is not part of the planned process. This category of input variables is used to capture specific features of the tooling or fixture design used to assemble a set of components together. Tooling / fixture design is important especially in mass production as the repeatability of locating and securing the components to be assembled is critical. The tooling and fixture have to be designed in such a way that they can tolerate the allowable component variation and the resulting tolerance stack-up when multiple components are assembled together. This variable is usually quantitative in nature. Examples in the context of assembly include tool extension length, tool tip play, and process parameters.

2) **Assembly Sequence (P_{as}):** This variable is binary and reflects whether a sequence in which components should be assembled is prescribed by the assembly planning team or not. Set the value of the variable equal to 1 if a sequence has been defined and set it equal to 0, if it has been left up to the operator to decide the sequence of assembly. In general, an assembly

sequence is defined in cases where there may be a locating reference associated with the first component or fastener that will be used by the subsequent components in the assembly process. For example, there are three bolt locations on the torsional cross-member of a Sports Utility Vehicle. One out of three holes is the locating hole and is round in shape. The other two holes are larger than the round hole and are usually oblong in shape to allow for tolerance stack up of multiple components in the assembly. Hole on the right is the locating hole (round) and the one on the left is the non-locating hole (oblong in shape). As a first step, a fastener would have to be assembled in the locating hole. This will help align the component with the base part. Once aligned, fasteners can be assembled in the remaining non-locating holes. Such requirements introduce manufacturing complexity in the assembly operation because the process requires the operator to follow a specific sequence of operations, without which the functional requirement of the assembly would not be achieved. Therefore, we include it in the generalized process model as a binary input variable.

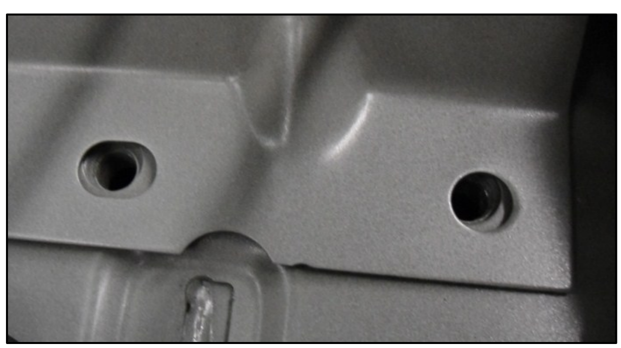


Figure 4.7: Assembly sequence driven by locating hole

3) **Number of tasks in the takt (P_{nt}):** This variable captures the number of individual tasks that have been assigned to the takt in which the assembly of interest is being carried out. Both the Hinckley Model and Shibata Model have shown a negative correlation between total number of assembly operations and manufacturing complexity, when applied to semiconductor manufacturing. A task is defined as the simplest element of work that can be done during assembly of components. Some examples of simple tasks are as follows:

    a. Pick component from rack
    b. Install component on primary sub-assembly
    c. Install plug (Note: If there are several such plugs to be assembled in a component, the installation of each plug would be considered as a task)

4) **Assembly Takt utilization (P_{tu}):** Labor utilization is a metric that manufacturing plants use to monitor and maximize utilization of the available labor in each takt. The mathematical formulation of labor utilization or assembly takt utilization is as follows:

$$\text{Labor Utilization (\%)} = \frac{\sum_{j \in s_k} t_j}{m \times c} \tag{2.21}$$

where,

j = Task that belongs to a set of tasks S_k

t_j =Time required per task j

m = Number of stations $k(=1,...,m)$

c = Takt time

Although the objective of the production management team would be to maximize labor utilization, manufacturing plants usually strive to achieve between 92% - 96% average value. Especially in manufacturing systems that are mixed-model in nature like most automotive final assembly lines, there is a vast variety of option content (variety of different components to choose from). Utilization value is a result of an assembly line balancing activity as explained earlier in the background section. As the takt utilization % increases, the process becomes less forgiving because there is little to no time left for the operator to deviate from the tightly controlled routine. Any deviation would introduce delay and there is no room to recover the lost time as the assembly line operates continuously and the next product has to be assembled in the given takt time. Therefore, we include takt utilization % as a process input variable in the generalized complexity model.

5) **Assembly Time Variation (P_{vt}):** Variability reflects lack of repeatability in completing a given task. If the same task is to be done over and over again, an operator gains experience over time and slowly improves the speed at which the same task gets done. In a mixed-model automotive assembly line, an operator deals with a variety of tasks, one after another. The time study analysis that helps determine how long a task takes is based on an average value. However, often the variation in time is not taken into consideration. In the generalized complexity model, this variable captures the time variation in the assembly process. The variance is calculated based on a statistically

significant data set of actual time taken to perform the assembly or manufacturing activity. In Shibata and Hinckley Models, work stations with the largest number of operations or the largest time duration per task were captured but this important input was not. From the current research, time variation has been observed to be a statistically significant contributor and therefore it is included in this proposed general complexity model.

4.1.4. Mathematical formulation

In summary, five key input variables have been highlighted as contributors to process driven Complexity. Although, every effort has been made to capture the sources of complexity in the general model, if there are additional variables within each of these categories or a new variable is required for a unique process that does not fit this general model, additional variables can be defined using the same principle. Process Complexity Factor C_p can be mathematically expressed as follows:

$$C_p = \pm\beta_1 P_{tf} \pm \beta_2 P_{as} \pm \beta_3 P_{nt} \pm \beta_4 P_{tu} \pm \beta_5 P_{vt} \qquad (2.22)$$

where,
C_p = Process complexity factor
$\beta_{1..n}$ = Empirical constants
P_{tf} = Tooling / Fixture design variable
P_{as} = Assembly sequence variable
P_{nt} = Number of tasks in takt variable
P_{tu} = Assembly takt utilization variable
P_{vt} = Assembly time variation variable

Figure 4.8 shows a block diagram of the six key input variables that contribute to process driven complexity.

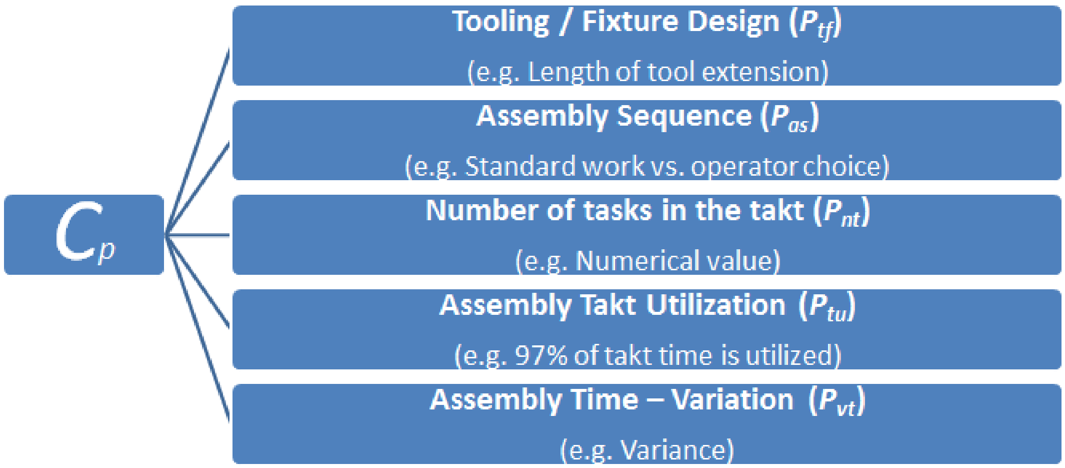


Figure 4.8: Block diagram showing input variables for process driven complexity

4.1.5. Human-Factors

In cases where humans interact with systems, human-factors involves the study of factors and development of tools that facilitate improved performance, safety, and user satisfaction. It is important to note that some inputs may have tradeoffs. Results from Eklund's work at a Swedish vehicle assembly plant shows that the quality deficiencies were three times as common for the work tasks with ergonomic problems, as compared with other tasks [41]. This work has motivated us to determine the factors that increase the ergonomic stress and thereby increase manufacturing complexity.

In this research, we define five major categories of input variables that can be used to define a human-factors driven complexity factor (C_h). Each category will be explained below and specific examples will be given wherever necessary to help the readers understand the context of the application and give them the ability to adapt this general model to their respective end-product / assembly being studied:

1) **Ergonomics (H_{er}):** Ergonomics examines the interaction between the worker and the work environment including such factors as machinery, the workstation, and climate [71]. If the match between worker and the work environment is poor, the worker's ability to perform the job will be severely compromised. Over a short period of time, this poor match may lead to fatigue and worker discomfort. If conditions persist, physical injury, and disability may result. Ergonomics as an input variable can be represented by a percentage value. The value reflects the percentage of the total task time when the stress level on a certain part of the body exceeds a threshold value. For example, if an object has to be gripped by an operator in a given task. If the stress on the lower arms and wrists is less than 125 N for up to 30% of the total task time, then it is considered acceptable. On the other hand, if the stress is between 190 and 285 N even for less than 5% of the total task time, actions need to be taken to reduce that stress. Stress is classified into multiple categories as shown in Figure 4.9.

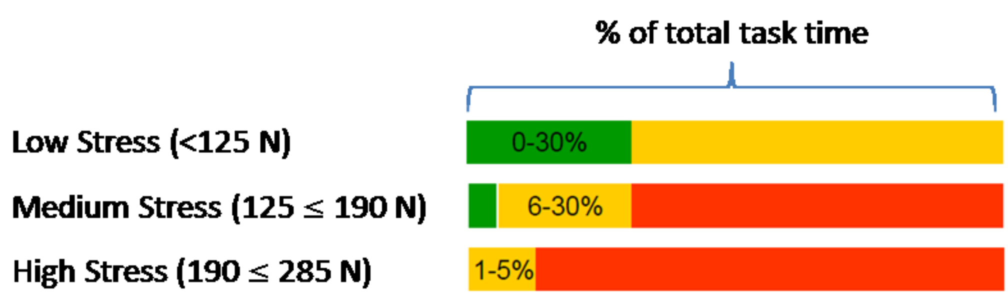


Figure 4.9: Stress on lower arms/wrists during gripping

Similarly, there are several different ergonomic input variables that need to be taken into consideration as individual input variables using the methodology used above. Given the scope of this research, we do not focus on the scoring methodology used in the ergonomic rating and rely on standards established at the Original Equipment Manufacturer (OEM) where this study was conducted. Potential users of this generalized model are advised to review the ergonomic standards related to their respective process and use them in the model. Following is a list of input variables tracked by the automotive assembly facility where the current research was conducted:

a. Work height
b. Stress on neck muscles
c. Work above shoulder height
d. Mobility of trunk
e. Mobility of arms
f. Stress on arms / shoulders
g. Stress on wrists
h. Stress on fingers
i. Mobility of knee joints
j. Standing, walking, sitting
k. Handling of tools

2) **Training / Experience (H_{tr}):** Argote et al. showed that large increases in productivity are typically realized as organizations gain experience in production [72]. These learning curves have been found in many organizations. However, the rates at which organizations learn are different and therefore the impact on

productivity or quality can differ from organization to organization. Motivated by this finding, in our research, we include training / experience in the generalized complexity model. For an assembly process, training can be provided to operators in various ways. A new operator can be given basic exposure to the process by showing an audio-visual presentation that includes step by step breakdown of the process to be followed by the operator. After an initial introduction, the operator is typically allowed to train on an off-line training station to implement the key points learned by observing the process in the presentation. This step is followed by on-the-job training under expert supervision. In our generalized complexity model, this input category can consist of a quantitative term that refers to the physical number of hours an operator has worked on the type of process being studied. It is important to note that the user of this generalized model should make a data driven determination whether training / experience gained on other "similar" processes can be taken into consideration due to the process characteristics or not. An appropriate measure of experience should be used, such as number of hours, number of quarters (usually 4 per shift), or number of shifts.

3) **Cognitive Load (H_{cl}):** The basic mechanisms by which humans perceive, think, and remember are generally grouped under the label of cognition. The human information-processing system is conveniently represented by the following three stages at which information gets transformed:

    a. Perception of information about the environment

    b. Central processing or transforming that information

c. Responding to that information

The first and the second stages stated above are highlighted as the processes involved in cognition and most typically represented in the study of applied cognitive psychology [73].

In a mixed-model assembly line, one of the variants from every feature is selected and assembled sequentially along the flow of the assembly line. For example, say a product has two features (F_i); each feature has several variants (e.g. V_{ij} is the j^{th} variant of F_i). As depicted in Figure 4.10, V_{12} is chosen for F_1 and V_{22} is chosen for F_2.

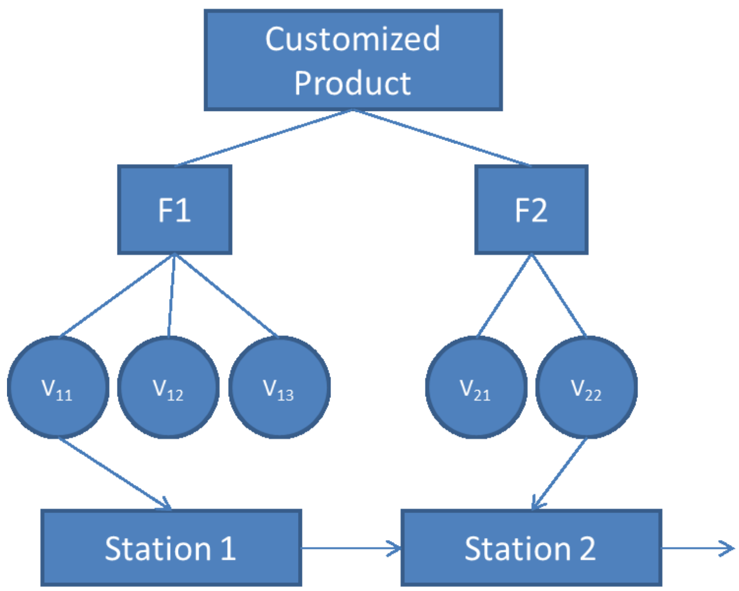


Figure 4.10: Product Family Architecture and Mixed Model Assembly

Operators at every station must make correct choices from a number of alternatives. The choices include choosing the right part, tool, fixture, and assembly procedure for the variant. To characterize the operator performance in making choices, the term operator choice complexity is defined as follows: Choice complexity is the average uncertainty or randomness in a choice process, which can be described by a function *H* in the following form:

$$H(X) = H(p_{1,}p_{2,\dots,}p_M) = -C\sum_{m=1}^{M} p_m \log p_m \tag{2.23}$$

Where *C* is a constant depending on the base of the logarithm function chosen. If $\log_2$ is selected, *C*=1 and the unit of complexity is bit. The properties of the function *H* are described in Ref. [20] and are suitable as a measure of choice complexity.

In this generalized model, we simplify operator choice complexity as a probability value. If the operator has to choose one object from a set of five variants, the probability of picking up the correct one out of the five variants would be 20%.

4) **Work environment (H_{we}):** Factors such as lighting, noise, motion, thermal conditions, and air quality contribute to the general category of Work Environment as a variable that can impact manufacturing complexity.
    a. Lighting: The amount of light energy that actually strikes the surface of the object being seen such as a component being assembled in a factory is described as illuminance and measured in units of *lux* or *foot candles*. How much illuminance an object receives depends on the distance of the object from the light source. As Figure 4.11 shows, the illuminance declines with the square of the distance from the source. This can be

quantitatively measured. In our research, gage repeatability and reproducibility showed that there was significant variation in the results. Therefore, we list this as an input variable for the generalized model but rely on the component visibility input variable that we capture as part of the process complexity factor.

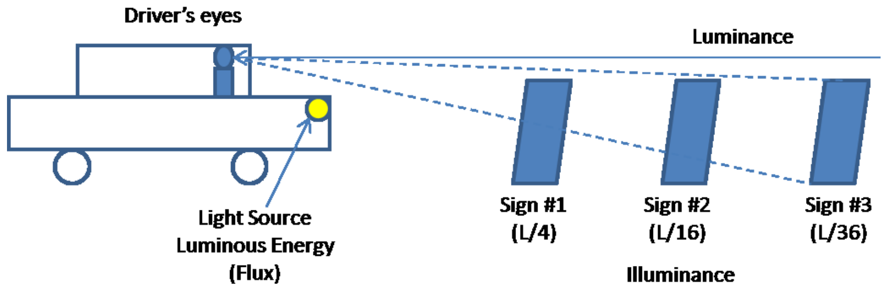


Figure 4.11: Illuminance declines as the square of the distance from the source

b. **Noise:** The stimulus for hearing is sound, a vibration (compression and rarefaction) of the air molecules. The acoustic stimulus can be represented as a sine wave, with amplitude and frequency. These are typically plotted on a spectrum and the position of each bar along the spectrum represents the actual frequency, expressed in Hertz (Hz). The height of each bar reflects the amplitude of the wave and is typically plotted as a square of the amplitude, or the power. The frequency of the stimulus more or less corresponds to its pitch, and the amplitude corresponds to its loudness. When describing the effects on heading, the amplitude is typically expressed as a ratio of sound pressure, *P*, measured in decibels (dB). As shown in equation (2.24), the measure *P2* is fixed at a value near the threshold of hearing (i.e., the faintest sound that can be heard under optimal conditions). This is a pure tone of 1000 Hz at 20 micro Newtons/square meter [68]. In this context, decibels represent the ratio of a given sound to the threshold of hearing.

$$\text{Sound intensity (dB)} = 20\log\left(\frac{P1}{P2}\right) \tag{2.24}$$

c. **Motion:** Stress effects of motion can result from either sustained motion or cyclic motion. Cyclic motion is also termed as vibration in the world of Human Factors. High frequency vibration may lead to performance decrements or repetitive motion disorders, and low-frequency vibration is usually a cause of motion sickness. The aversive long-term health consequences of the high-frequency vibration are well documented in the literature. Standard “dosage” allowances for exposure to different levels of vibration have also been established. Health consequences of full-body vibration have not been well documented [74]. However, such vibration has clear and noticeable effects on many aspects of human performance [66].

d. **Thermal stress:** Both excessive heat and excessive cold can produce performance degradation and health problems. A good context for understanding their effects can be appreciated by the representation of a comfort zone, which defines a region in the space of temperature and humidity and is one in which most work appears to be most productive [75]. The temperature range is 73 deg. F to 79 deg. F in the summer and

68 deg. F to 75 deg. F in the winter. The zone is skewed such that less humidity is allowed (60 percent) at the upper temperature limit of 79 deg. F than at the lower limit of 68 deg. F (85 percent humidity allowed).

e. **Air Quality:** Poor air quality is often a consequence of poor ventilation in closed working spaces like mines or ship tanks but also in environments polluted by smog or carbon monoxide. Any of these reductions in air quality can have relatively pronounced negative influences on perceptual, motor, and cognitive performance of an operator [76]. This variable has been highlighted in the generalized model for users that deal with environments that present conditions that may compromise air quality. Methods of quantifying this as a variable would need to be investigated and have not been considered within the scope of the current research.

4.1.6. Mathematical formulation

In summary, four key input variables have been highlighted as contributors to human-factors driven Complexity. Although, every effort has been made to capture the sources of complexity in the general model, if there are additional variables within each of these categories or a new variable is required for a unique process that does not fit this general model, additional variables can be defined using the same principle. Human Factors driven Complexity Factor C_h can be mathematically expressed as follows:

$$C_h = \pm\gamma_1 H_{ef} \pm \gamma_2 H_{tr} \pm \gamma_3 H_{cl} \pm \gamma_4 H_{we} \tag{2.25}$$

where,

C_h = Human-factors based complexity factor

$\gamma_{1..n}$ = Empirical constants

H_{ef} = Ergonomics variable

H_{tr} = Training / Experience variable

H_{cl} = Cognitive Load variable (Probability of choosing correct part)

H_{we} = Work Environment variable

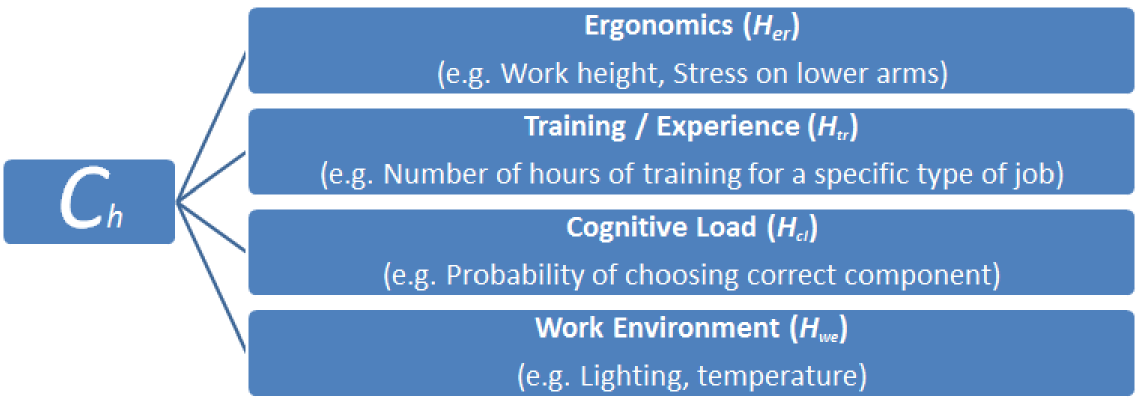


Figure 4.12: Input variables for human-factors driven complexity

4.2. Generalized Complexity Model

The generalized complexity model consists of three primary categories:

a. Design driven complexity

b. Process driven complexity

c. Human Factors driven complexity

This research aims to validate the hypothesis that manufacturing complexity (defined by product design, assembly process, and human factors) can be represented by a complexity metric that can be used to predict the contribution of these variables on product quality. The generalized model correlating Product Quality (Defects per Million

Opportunities - DPMO) and manufacturing complexity drivers can be mathematically described as follows:

$$\text{DPMO} = k_0 + \left[C_d C_p C_h \right] . \begin{bmatrix} k_1 \\ k_2 \\ k_3 \end{bmatrix} \tag{2.26}$$

where,
DPMO = Defects per million opportunities
k_0 = Empirical process constant
C_d = Coefficient of design complexity
C_p = Coefficient of process complexity
C_h = Coefficient of human factors complexity
$k_{1,2,3}$ = Empirical constants

In conclusion, this chapter addresses the first research question related to defining complexity in the general context of assembly processes. In the following chapter, we use this generalized model and apply it to a specific process that is widely used in the automotive industry. We will then share multiple case studies related to the application of this model to various processes in mixed-model automotive assembly and the results achieved in each case.

CHAPTER FIVE

5. APPLICATION OF MODEL TO CONTROLLED FASTENING PROCESS

To validate the generalized complexity model and correlate it with product quality, we analyzed various automotive assembly processes. Our analysis was based on quality data gathered from one year worth of production. This eliminates any outliers (caused by unique assignable causes) that may have contributed to a localized increase in defect rate. Specific annual quantity is not disclosed due to confidentiality reasons. As shown in Figure 5.1, mechanical fastening process is the largest contributor to the defect rate of vehicles based on our study at a major OEM. Based on the data, we chose mechanical fastening process as the pilot process to validate the generalized manufacturing complexity model and the hypothesis that complexity can be used to reliably predict the defect rate observed in a real-world assembly line.

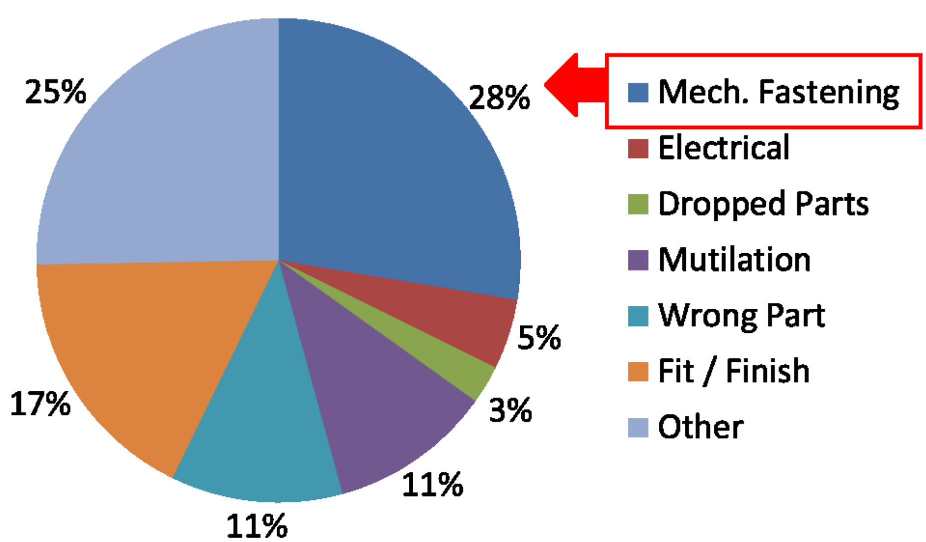


Figure 5.1: Breakdown of quality defects by root cause

5.1. Overview of mechanical fastening process

The automotive assembly processes rely on mechanical fastening and joining to a large extent to mount various components to the painted body. A major advantage of the mechanical joining process is the ability to remove and mount a new component when repair or replacement is required. Mechanical joining can also achieve an indirect way of joining dissimilar metals, hence avoiding the galvanic corrosion effects.

A fastener is used to apply a clamp load to two or more components and maintain it during the designed life expectancy of the assembly. The primary goal is to maintain adequate joint clamp load that meets the design specification. The means to achieve this goal is by tightening the fastener to a specific torque value.

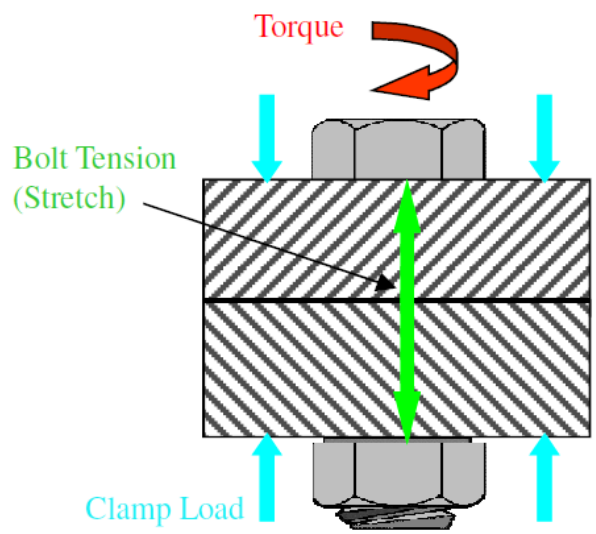


Figure 5.2: Cross sectional view of a mechanical joint

The tightening process is governed by a torque-tension relationship. The torque/tension relationship is shown in the Torque-Tension Curve [61].

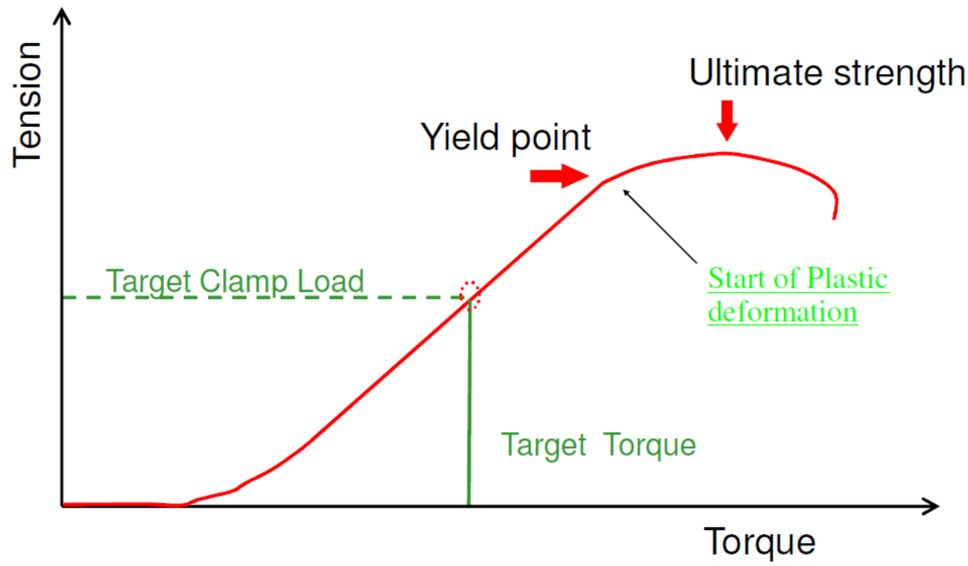


Figure 5.3: Torque - Tension curve [61]

As the fastener assembly begins, the initial *Rundown Zone* is where the fastener rotates and axially advances (Figure 5.4). The *Alignment or Snug Zone* is where the two or more base components have come together as the fastener completes the initial rundown phase. The *Elastic Zone* is where the materials begin to experience load and the fastener experiences tension. Finally, the *Yield Zone* is where the fastener and its head begin to experience permanent change in dimensions / shape and do not return to their original dimension. This is where the torque application process ends and the clamp load meets the design specifications.

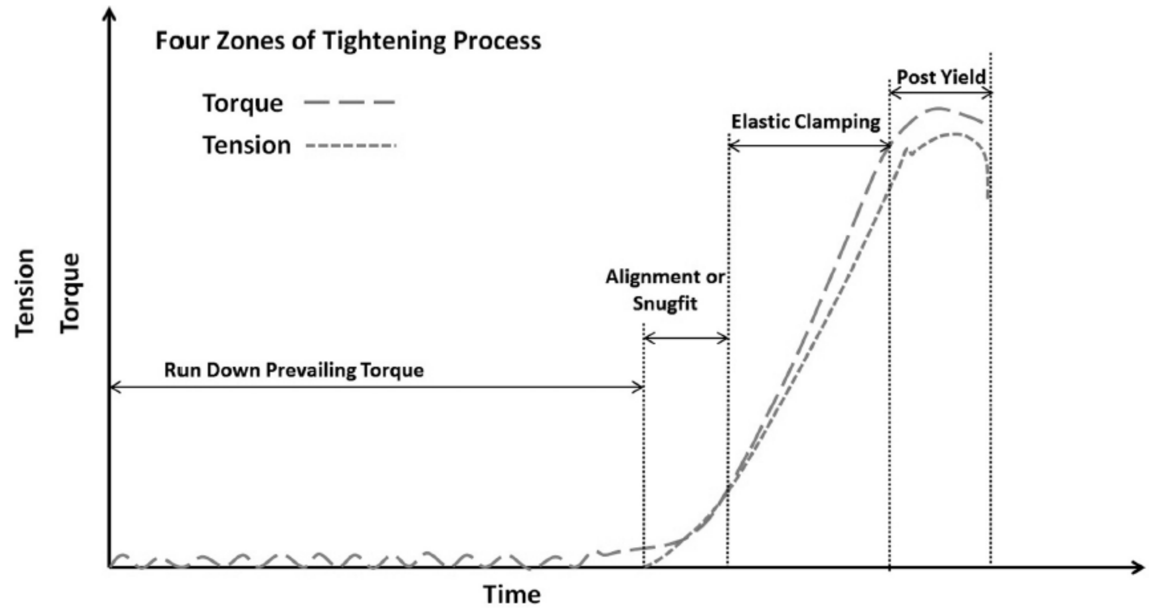


Figure 5.4: Tightening Zones

5.2. Thread Nomenclature

Common types of fasteners that are used in automotive applications are:

1. Bolt
2. Stud
3. Cap screw
4. Machine screw
5. Set screw
6. Nut

Basic fastening terminology is defined below [59]:

1. **Major Diameter:** Major diameter refers to the distance between crest to crest for an external thread and root to root for an internal thread.

2. **Minor Diameter:** This is the diameter of an imaginary cylinder that touches the roots of an external thread, or crests of an internal thread.
3. **Internal Thread:** A screw thread that is formed inside an internal diameter, such as the hole in a nut.
4. **External Thread:** A screw thread that is formed on an external cylinder, such as bolts, screws etc.
5. **Pitch:** The nominal distance between two adjacent thread roots or crests.
6. **Thread Crest:** The top part of the thread is called the Crest. For external threads, the crest is the region of the thread that is on its outer diameter. For internal threads, it is the region which forms the inner diameter.
7. **Thread Flank:** The flank is the straight side that joins the thread roots to the crest.
8. **Thread Runout:** The thread root is the bottom of the thread, on external threads the roots are usually rounded so that fatigue performance is improved.
9. **Thread Length:** The portion of the fastener with threads is referred to as Threaded Length.
10. **Thread Lead:** The thread lead is the axial movement of the screw once rotated one revolution.
11. **Thread Root:** The thread root is the bottom of the thread. On external threads the roots are usually round so that the fatigue performance is improved.
12. **Shank:** The portion of a bolt that is between the head and the threaded portion.

13. **Bearing Stress:** The surface pressure acting on a joint face directly as a result of the force applied by the fastener.

Basic screw thread nomenclature is shown in Figure 5.5.

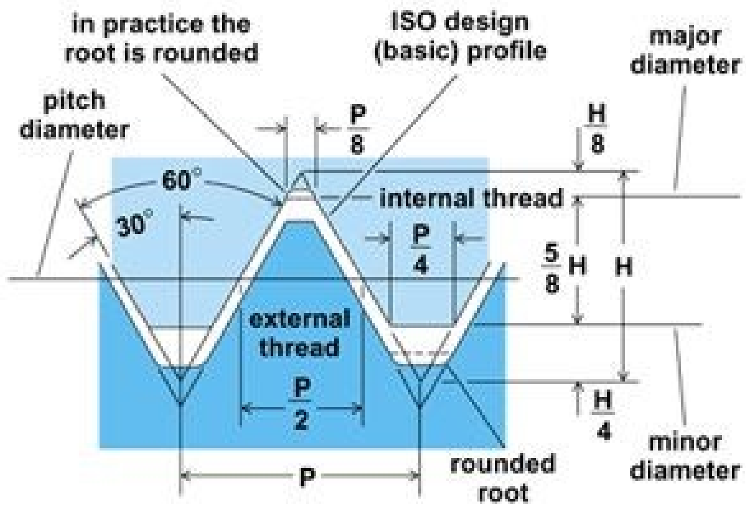


Figure 5.5: Thread Nomenclature [59]

ISO metric standards define the threads starting with the letter *M*, followed by the nominal diameter and the thread pitch, for example, an M8 x 1.5 is an ISO thread with diameter of 8 mm and a pitch of 1.5 mm.

An important parameter in the fastening process is the load-bearing surface area. This controls the fastener performance during the service life of the assembly. Typically, the average area can be defined based on an average diameter from the minor to the pitch diameters. It is numerically shown by the following relationship (2.27):

$$A_{avg} = \frac{\pi}{16}(d_p - d_r) \tag{2.27}$$

Minor diameters (d_r) and pitch diameter (d_p) for ISO threads are defined in the following equations. The nominal diameter is represented by d in the following equations:

$$d_p = d - 0.6495 \times p \tag{2.28}$$

$$d_r = d - 1.2268 \times p \tag{2.29}$$

$$d_p = d - \frac{0.6495}{N} \tag{2.30}$$

$$d_r = d - \frac{1.299}{N} \tag{2.31}$$

The required preload for non-permanent mechanical joints is given by:

$$F_{pre} = 0.75 \times A_{avg} \sigma_p \tag{2.32}$$

Here, σ_p is defined as the proof strength of the bolt and can be estimated as 85% of the bold material yield strength. For the permanent joints, the 75% factor can be simply changed to 90% to obtain the preload needed. And finally, the most important practical parameter for this process is the Torque value. This equation utilizes a constant K that is dependent on the bolt material and its size (range: 0.16 to 0.3):

$$T = K \times F_{pre} d \tag{2.33}$$

Where,

T = Torque

F_{pre}=Preload

d = nominal diameter

5.3. Controlled Mechanical Fastening

In the automotive industry, several safety critical and quality critical components are assembled using electric assembly tools with intelligent controllers and associated monitoring devices. These tools offer operator guidance in the form of clear result feedback via on-board LEDs or audio signals. The monitoring system for each tool is part of a larger network that associates the torque and angle information for each fastener with the Vehicle Identification Number (VIN). This association can prove to be useful internally to verify that all the defects on a given vehicle have been corrected before it gets an "all-clear" to ship out from the assembly plant. These records can also prove to be useful in the long term if a defect is found in the field by an end-user and the manufacturing plant needs to verify that a certain component (e.g. airbag) was fastened correctly per the engineering specifications for a certain Vehicle Identification Number.

5.3.1. Overview of equipment

The primary components in a controlled mechanical fastening system are as follows:

a. **Tool (e.g. nutrunner or screwdriver):** A nutrunner or a screwdriver is an electrical device that has a drive motor, internal bus connection for intelligent accessories such as a barcode reader, configurable LEDs and an optional integrated speaker for indicating via audio signals for operator feedback. It is also designed with an ergonomic sleeve to improve grip and comfort for the operator. Cordless drivers are also available and they have a battery as a power source and an on-board wireless device to communicate with the controller (Figure 5.6).

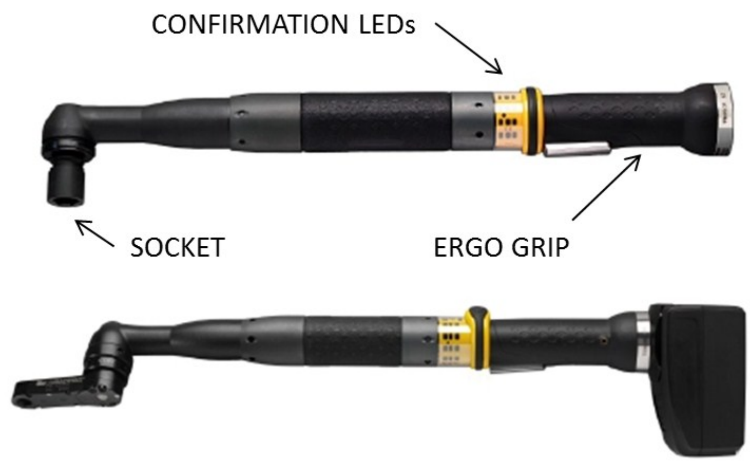


Figure 5.6: Atlas Copco Tools (Above: Corded, Below: Battery driven)

b. **Controller & Software:** With the help of onboard software, this device provides monitoring and control of tightening operations. The software enables a user to communicate easily with the tool controller using a user interface. The controller also collects data continuously throughout the tightening process.

Figure 5.7: Atlas Copco Controller unit

c. **Display unit:** The display unit shows multiple pieces of information to aid the operator, namely, torque value, angle through which the fastener turns beyond threshold torque, number of fasteners remaining to complete for a given vehicle, remaining task time, and most importantly a red or a green signal to provide a visual confirmation of incomplete or complete assembly to the operator.

d. **Electrical cords:** In the case of corded electrical units, the electrical cord is connected to the tool on one end and the controller on the other. The cordset conducts electricity as a source of power for the tool and it also has a network cable that allows the tool to communicate with the controller.

Figure 5.8: Electrical cord connects the tool with the controller

e. **Bits, Sockets, and Extensions:** Sockets / Drivers are based on the type of fastener being assembled (bolt, nut, hexagonal head, internal torx-drive, external torx-drive etc.). Primary goal of the extension is to adapt the drive type from the tool to the socket (3/8”, ½” etc.) and to allow the tool to access certain assembly areas depending on the component design. The extension also helps improve operator safety by avoiding the tool from being too close to the workpiece which may introduce a risk of pinching the operator's finger between the tool and the workpiece.

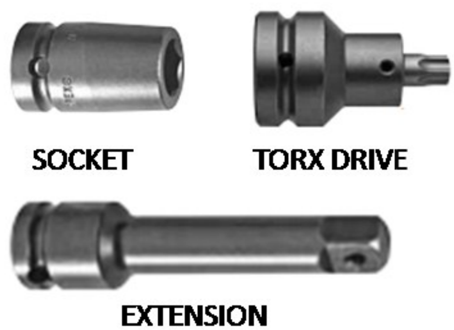


Figure 5.9: Apex Socket, Torx Drive Bit, and Extension

5.3.2. Types of fasteners

This section contains an overview of the types of fasteners and a brief overview of the manufacturing methods for each. Following are the primary types of fasteners and some of their variants:

i) **Bolts and Screws:** Even though individual bolts and screws may be interchangeable, a bolt is intended to be used with a nut. A screw, on the other hand, mates with preexisting threads, or in some configurations such as self-tapping screws, a screw can make its own threads in a component. Screws and bolts are both externally threaded fasteners that come in a variety of head/shoulder/shank/thread combinations, and are used to join separate elements, or to fasten something into place. Bolt heads are generally made using either forging or machining. Due to economies of scale and grain flow properties resulting from forging, it is the preferred method. Cold or hot forging may be used depending on the formability of the fastener material. Machining is used for very large diameters (> 1.5”) or small production runs [63]. The disadvantage of machining is that the process cuts the grain flow, thus resulting in planes of weakness at the critical sections such as the fillet area. This can result in reduced tension performance resulting from fracture planes. A generous radius should be provided under the head in order to minimize the notch effect, without losing too much load bearing area under the head.

ii) **Bolt forms:** Hexagon head bolts are available in two basic configurations: standard hex bolts, and heavy hex bolts. Heavy hex bolts have head dimensions that are approximately 1/8” wider than standard hex bolts throughout the range, thereby usefully increasing the bearing surface area. The material specification for both types is ASTM A307.

iii) **Nuts:** The most common shapes for nuts are square and hex. Square nuts are more liberal in their tolerances compared to hex nuts and therefore they are restricted to lighter-duty applications. Hex nuts come in many configurations, in standard and heavy versions, and in thinner sizes known as jam nuts. Jam nuts are used as locking nuts. During our research conducted at an automotive OEM, we have come across only hex nuts and therefore those are within the scope of our pilot application. For moderate temperatures and pressures, ASTM 194 Grade 2 nuts are recommended [63].

iv) **Common screws, machine screw head and thread configurations:** Hexagon head cap screws are the most commonly used screws. There are many standardized head configurations for machine screws. There are also many drive systems (Phillips head, slotted head, Torx, etc.). With the exception of the hex head screws, all machine screws have round heads when viewed from the top. Several types of head designs are available, such as, Binding Head, Cheese Head, Flat Countersunk Head, Hex Head, Hex Washer Head, Oval Countersunk Head, Pan Head, Round Head, Truss Head etc. In our research study, we have come across Cheese Head screws used for lighter duty curtain airbag assembly. For all these types, generally machine screws are available with UNC and UNF Class 2A threads, or UNRC and UNRF series threads.

v) **Self-tapping and thread cutting screws:** As the name suggests, these screws have the ability to tap the threads in the component that they get assembled in. Type AB point and type B point are the ones that are commonly used. Type B thread forming tapping screw is used for sheet metal, nonferrous castings, plywood and plastics. It is essentially a flat end Type AB screw, and the metric version is covered by DIN 7940 and ISO 1478.

vi) **Socket screws:** This type of screws was developed for applications with limited space. Their cylindrical head and internal wrenching features allow their use in locations where externally wrenched fasteners would be impractical. The two most pertinent classes, for socket head screws, are 10.9 and 12.9. The numerals used in Property Class designations refer to the nominal ultimate tensile strength and nominal percent yield strength. For example, a Property Class 10.9 fastener has 1000 MPa nominal strength, and a yield of 90% of ultimate. ASTM A574M provides additional information regarding metric, alloy steel socket head cap screws [63].

vii) **Retained nuts and speed nuts:** These are “clip on” internally threaded fasteners that offer several advantages for assembly operations. Since they are, essentially, floating nuts, they do not require drilling in the fixture being attached, and they do not require drilling or tapping. This system of floating alignment does not require special tools either. Retained nuts actually use a threaded square nut mounted on a retaining clip, while speed nuts provide a hole that accommodates a tapping nut.

5.3.3. Fastening Process Input Variables

Based on the generalized complexity model, we conducted detailed analysis of the controlled fastening process. In addition to a review of published literature [8, 59, 63, 69, 77], we consulted with fastening experts and technicians at the automotive assembly plant and gained hands-on assembly experience in order to identify and understand the input variables that can impact manufacturing complexity. Following section provides the description of each input variable.

5.3.4. Design factors driven Complexity (C_d)

As described in the generalized complexity model, Feature Design, Assembly Design, Component Accessibility, and Material Characteristics are the primary categories of input variables that impact design driven complexity. Figure 5.10 shows the input variables for design driven complexity related to the mechanical fastening process.

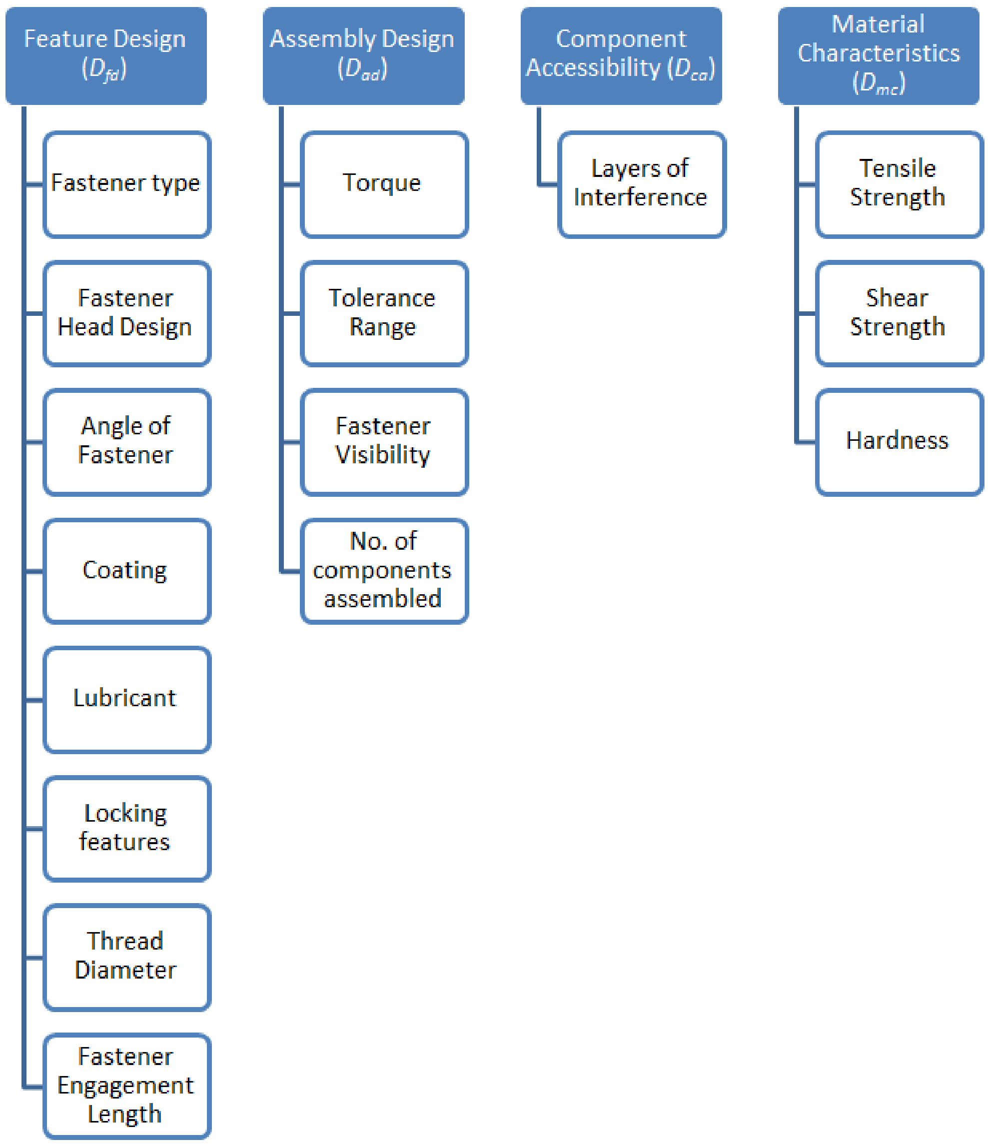


Figure 5.10: Input variables - Design based mfg. complexity in Fastening

Following is a brief description of each input variable:

a) **Fastener type:** In this study we categorize fasteners into two types – Nut and Bolt / Screw. In automotive fastening, there may be a stud that is welded to the body and the nut is the driven component. On the other hand, there may be a nut that is welded to the body or a component and the bolt / screw is driven into the welded nut.

b) **Fastener Head Design:** In our study, we encountered four different head designs – Hexagonal (1), Internal Torx (2), and External Torx (3). The numbers in the parenthesis are what we use to numerically identify the type of head design in the complexity model. The head design dictates the type of bit or socket to be used and also has a direct effect on the tool bit / socket slipping off during torque application, which would result in a defect, requiring a second attempt or rework. This was added to the study to understand whether the head design has an effect on the complexity because hex nuts, hex bolts, and external torx are driven by a socket that encapsulates the head completely during the torque application. On the other hand, in the case of a fastener that does not have a hexagonal head allows the driving bit to slip off, thereby leading to a defect.

c) **Angle of Fastener:** Angle of the fastener refers to the angle of the primary axis of the fastener as viewed from the direction of torque application, with reference to the vehicle floor.

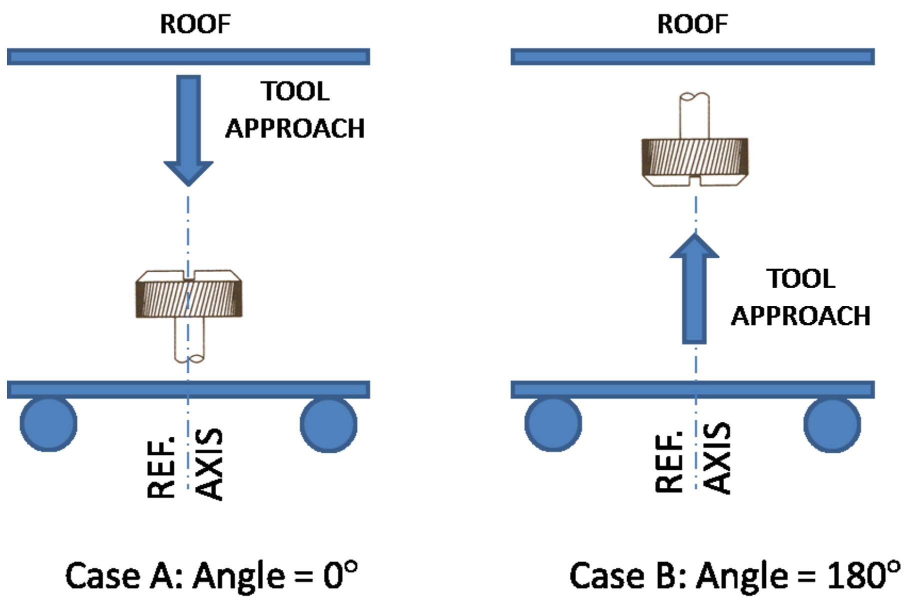


Figure 5.11: Angle of fastener with ref. to the vehicle floor

d) **Coating:** Fastener coatings usually protect against corrosion, can improve lubrication properties, and in some cases may be applied for appearance reasons to match with other parts being assembled. Electroplating and electro coating processes are used for coat application. Electrocoated fasteners offer good uniformity of coat application but are usually available in black. In contrast, electroplating offers good uniformity and multiple colors using various dyes and a top coat. From the corrosion standpoint, coated fasteners also reduce potential for galvanic corrosion in bimetallic assemblies. In Figure 5.12, five different B-7 Stud Bolts are shown after 2,000 hours of salt spray testing per ASTM B117, done by *MetCoat* the company that produces *FluoroKote*. Case A is coated with

FluoroKote, Case B with Zinc Plating, Case C with Cadmium plating, Case D was hot dip galvanized, and Case E was uncoated during this test.

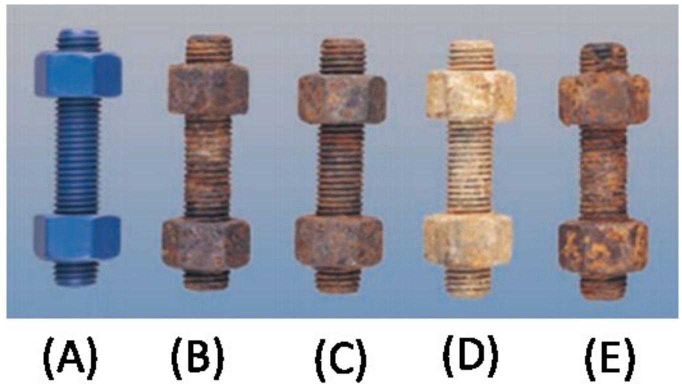


Figure 5.12: Effect of various coatings (Source: *Metcoat*)

In our study, the only coating we have come across is Black Oxide. Therefore, to convert this attribute information to the variable form, we use 0 for no coating and 1 if coating exists.

e) **Lubricant:** Thread galling is a common in applications where the joint is subjected to heavy load. During the tightening process, pressure builds up between the contacting thread surfaces and the protective coating can get broken down. Due to the absence of the oxide coating, the high points of the threads are exposed, which increases friction. This can lead to enough heat generation to fuse the nut and bolt together. Also, during tightening process, if the torque application is continued beyond the point of galling, the fastener head may get sheared off or the threads may get stripped. Galling can be minimized by thread lubrication. In several applications, a wax based coating is pre-applied to the fastener on the threads. This helps reduce friction but it can dissipate over time due to heat. In our study, we came across 25% processes that had a lubricant involved. Therefore, to convert this attribute information to the variable form, we use 0 for no lubricant and 1 if a lubricant exists.

f) **Locking Features:** Locking features are either designs in the fastener or are added in the form of an adhesive on the threaded region. Depending on the function of the joint and the assembly, locking features may or may not be required. If the assembly is going to be exposed to vibration in regular service, then locking features may be recommended to prevent the fastener from losing clamping load.

g) **Thread diameter:** Major diameter refers to the distance between crest to crest for an external thread and root to root for an internal thread. In our research, we measured this variable for each fastener with a micrometer. The unit of measurement was micrometer.

h) **Fastener Engagement Length:** As the name suggests, this refers to the actual length along which the screw and nut are engaged and can bear the load of the assembled joint. In our research, we measured this variable for each fastener with a pair of vernier calipers. The unit of measurement was micrometer.

i) **Torque:** Torque is the product of the magnitude of force and the perpendicular distance from the force to the axis of rotation (i.e. the pivot point). The SI unit of torque is Newton-meter (Nm). This value is specified for every joint and was recorded in our study as a numerical value in Newton-meter.

j) **Tolerance Range:** The tolerance range shows the total allowable range that the torque can vary across. This value is also specified by the joint designers and was recorded in our study as a numerical value in Newton-meter.

k) **Fastener Visibility:** If a fastener is not clearly visible to an operator, then it adds to the complexity of the operation and the operator would rely on experience to guide him/her due to the lack of visibility. This situation can occur either due to the way the joint is designed or due to poor illumination of the workspace. In this category under the design-driven complexity, we focus on the % visibility due to the way the joint is designed. The value is recorded in the form of percentage and can range from 0% in case of a completely obscured joint and 100% in the case of a completely visible fastener, as viewed by the operator during assembly. In our study, each joint was studied by 6 operators and an average value was recorded as the % visibility for a given joint. The operators were trained prior to the study to ensure that adequate repeatability and reproducibility existed statistically in their findings.

l) **Number of components assembled:** This variable captures the number of components assembled by a single fastener. As the number of components to be assembled by a single fastener increases, variability associated with the thickness of each component also increases.

m) **Layers of Interference:** We included this variable based on observation of the processes. This refers to the number of surfaces related to other components that the operator must pass the tool through in order to access the fastener to be assembled. It is a numerical value based on CAD data and manual observation done during the study. We have observed as many as 2 layers of interference in our study.

n) **Tensile Strength:** It is the maximum tension-applied load that the fastener can support prior to fracture. The tensile load that a fastener can withstand is determined as follows:

$$P = S_t \times A_s$$

where,

P =Tensile load (N) (2.34)

S_t = Tensile strength (MPa)

A_s = Tensile stress area of the fastener (mm^2)

Tensile strength can be found for a particular bolt by referring to Mechanical Properties table, typically provided by the fastener manufacturer. The guide may also provide tensile stress area directly in the form of charts. It is important to give significant consideration to the definition of tensile stress area, A_s. When a standard threaded fastener fails in pure tension, the threaded portion is usually the one that fractures as it has the smallest cross sectional area. Therefore, usually this area is calculated through an empirical formula involving the nominal diameter of the fastener and the thread pitch. Due to confidentiality reasons associated with the OEM where the study was conducted, we were unable to gain access to design documents that describe the material used to manufacture fasteners. Therefore, we do not consider Tensile Strength, Shear Strength, and Hardness in the complexity model at this point in time. We believe that these are important inputs and should be used in future work where the generalized model is applied to the fastening process or other processes; therefore we include a brief description here.

o) **Shear Strength:** It is defined as the maximum load that can be supported prior to fracture, when load is applied perpendicular to the axis of the fastener. Load occurring in one transverse plane is known as single shear. Double shear is a condition when load is applied in two planes and the fastener could get sheared into three pieces. When no shear strength is given, for common carbon steels with hardness up to 40 HRC, 60% of the ultimate tensile strength of the bolt is typically used as acceptable shear strength.

p) **Hardness:** Hardness is a measure of the material's ability to resist abrasion and indentation. For carbon steels, Brinell and Rockwell hardness testing can be used to estimate the tensile strength properties of the fastener.

5.3.5. Process factors driven Complexity (C_p)

As shown in the generalized complexity model, Tooling & Fixture Design, Assembly Sequence, Number of tasks in takt, Assembly Takt Utilization, and Assembly Time Variation are the primary categories of process factors driven complexity. Figure 5.13 shows the input variables for process driven complexity related to the mechanical fastening process.

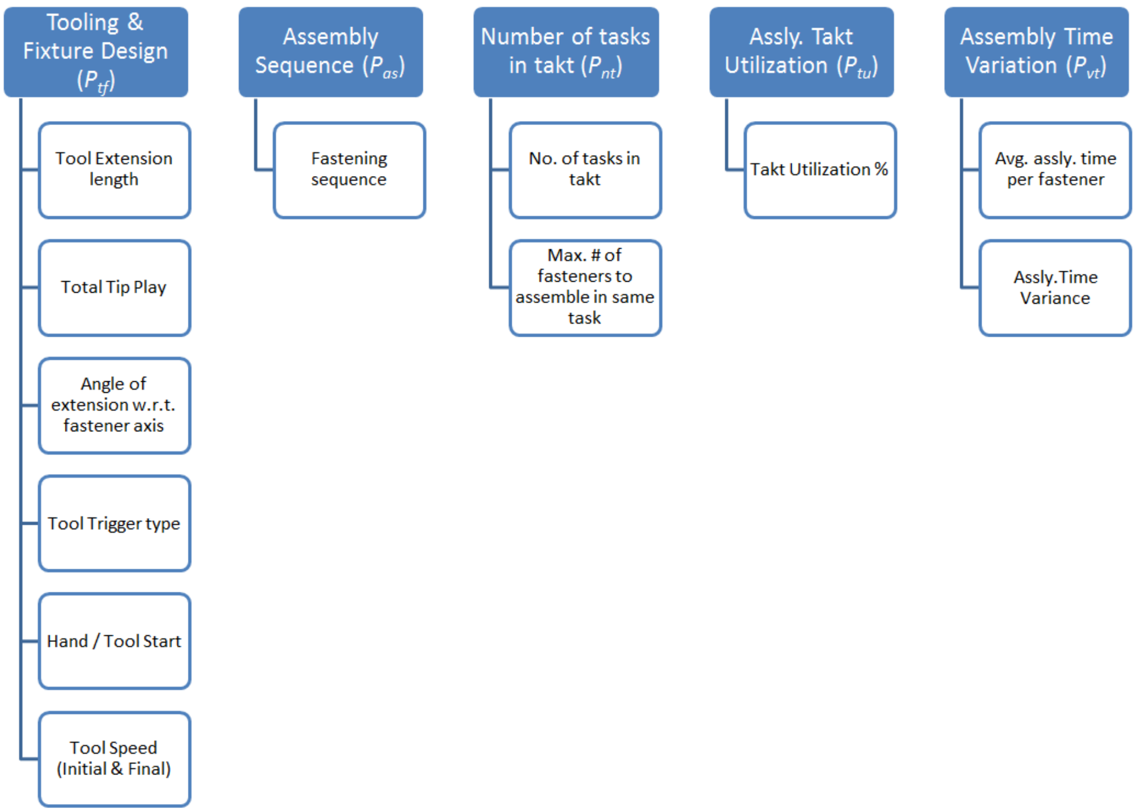


Figure 5.13: Input variables - Process based mfg. complexity in Fastening

Following is a brief description of each input variable:

a. **Tool Extension length:** Primary goal of an extension is to adapt the drive type from the tool to the socket (3/8", ½" etc.) and to allow the tool to access certain assembly areas depending on the component design. The extension also helps improve operator safety by avoiding the tool from being too close to the workpiece which may introduce a risk of pinching the operator's finger between the tool and the workpiece. The tool extension length is defined as the total distance from the end of the output shaft of the tool to the other end that touches the fastener. During our study, we have observed tool extensions that range from 0.5 inches to 24 inches in length. A longer extension can introduce a significant amount of wobble at the tip, therefore this information is recorded in the complexity model.

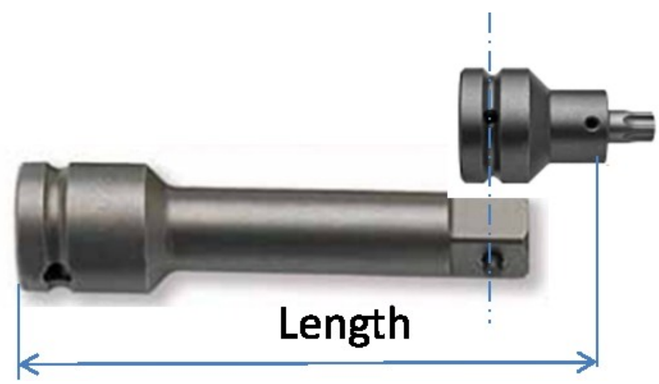


Figure 5.14: Extension and Socket

b. **Total Tip Play:** Every tool extension introduces multiple sources of play in the fastening system. There is some play due to the clearance between the output side of the tool and the driven side of the extension. Similarly, there is additional play due to the clearance between the output side of the extension and the driven side of the socket. At both these locations, there is a pin or a ball joint that secures the components. Longer the tool, the effective play increases at the tip, thereby introducing a potential wobble when the fastener is being driven.

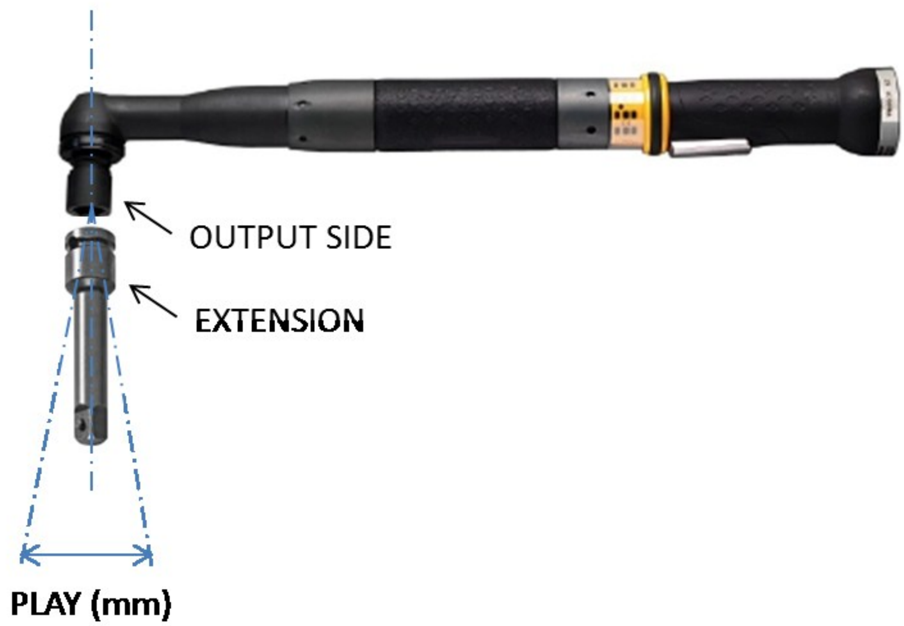


Figure 5.15: Tool extension - Total Tip Play

c. **Angle of extension w.r.t. fastener axis:** This variable refers to the effective angle of the extension with ref. to the axis of the fastener due to the play and angle at which the fastener is located with reference to the vehicle.

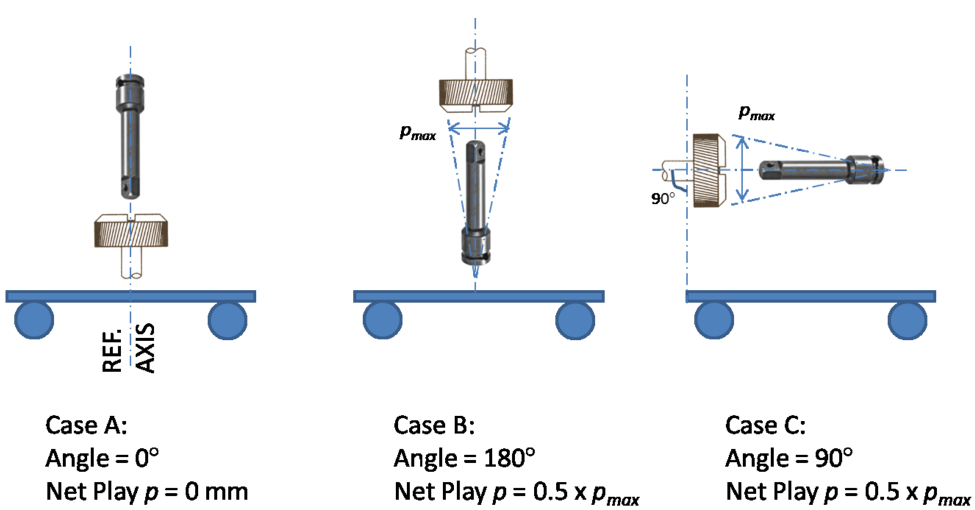


Figure 5.16: Effective angle of extension w.r.t. fastener axis

A schematic view of the angle of the extension with reference to the fastener axis is shown in Figure 5.17. This angle can be computed as follows:

$$\phi_e = \tan^{-1}\left(\frac{\left[p_{max}/2\right]}{l}\right) \tag{2.35}$$

where,

ϕ_e = Effective angle of extension w.r.t. fastener axis

p_{max} = Total tip play (both sides of axis)

l = Length of extension

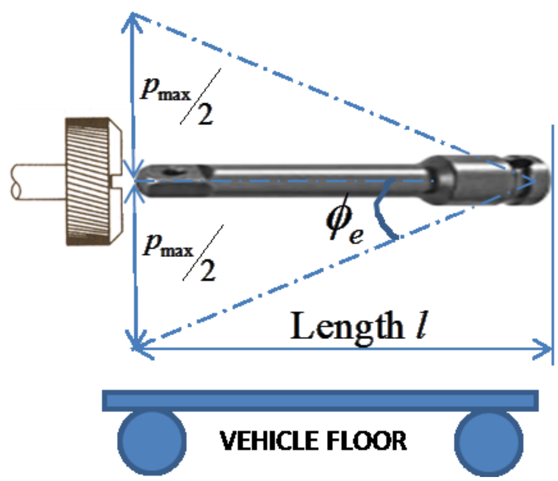


Figure 5.17: Schematic diagram showing effective extension angle

d. **Tool Trigger type:** This variable helps us capture the type of tool trigger mechanism. There are two types of mechanisms that we have observed: A trigger that needs pulled with one finger and another one that is larger paddle type trigger that allows the operator to pull it with four fingers. When the operator uses this several hundred times in a given shift, that can be a variable that impacts the number of trigger slip-offs. We capture this information numerically by using the digit 1 for one finger type activation and 2 for multiple finger paddle type activation.

Figure 5.18: Tool activation trigger: 1 finger vs. Multi-finger

e. **Hand / Tool Start:** This variable captures whether a fastener is hand-started or tool-started with a low torque tool before applying higher torque with a conventional tool, or not. Starting the fastener with a low torque (by hand or low speed, low torque tool) significantly reduces the probability of cross-threading the fastener when torque is applied with a conventional tool. We capture this as a binary input – 0 for no hand-start and 1 for hand-start.

Figure 5.19: Hand-starting a fastener to prevent cross-threading

f. **Tool Speeds (Initial and Final stages):** Typically in a controlled torque application, the tool is programmed to complete the torque application in two stages. The tool runs at a faster initial speed (e.g. 300 RPM) during the run-down stage (Figure 5.20) and once a designed threshold torque is achieved (e.g. 25 Nm), the speed is dropped (e.g. 100 RPM) until the fastener reaches the designed torque specification (e.g. 45 Nm). In our study both these speeds have been recorded for each joining process in Rotations per Minute (RPM).

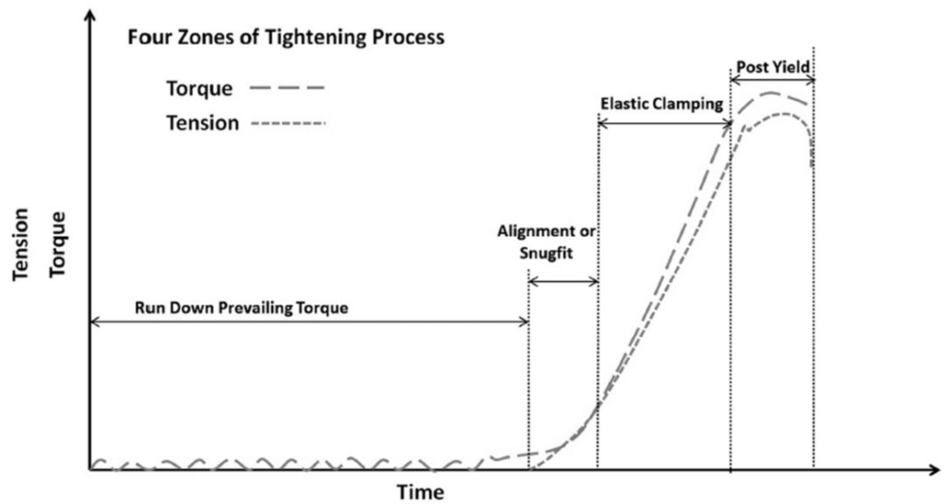


Figure 5.20: Torque-Tension evolution with time in a mechanical joint

g. **Fastening Sequence:** For certain component assemblies, a fastening sequence is required or recommended. This is usually because there is a locating hole in a component which needs to be aligned first using a fastener and then remaining fasteners can follow. In figure, a cross member of a Sports Utility Vehicle is shown. The hole on the far right (marked with the digit 1) is a round hole which locates the component with reference to the body and the remaining three holes (2a, 2b, and 2c) are oblong and these are designed to allow for variation associated with tolerances of multiple components. In our study, we capture this information as a binary variable as well. The digit 0 for no recommended sequence and the digit 1 for joints where a specific sequence has been recommended by process engineers.

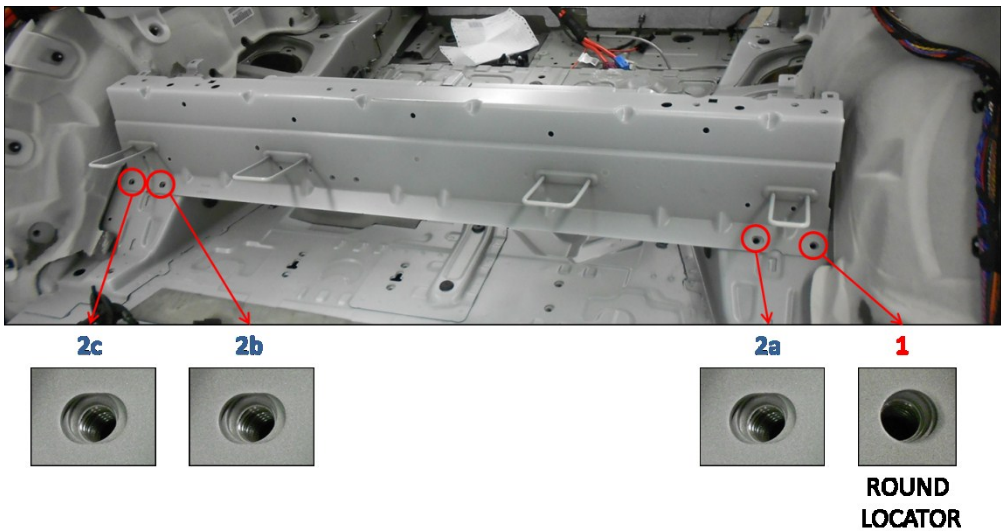


Figure 5.21: Example showing recommended sequence of fastening

h. **Number of tasks in takt:** As assembly line is a flow oriented production system where parts are assembled together to form an end product at work stations situated along the line. A station is a location on the assembly line where work is performed on the product. Each station may contain multiple takts defined by some criteria (e.g. 9 work zones on a station for car assembly). A task is the smallest, indivisible, and rational work element of the total work content. There can be multiple tasks assigned to an operator who works in a given takt. The process engineer's goal is to assign as many tasks as possible to a given takt (Figure 5.22), while ensuring that various constraints such as task precedence, tooling availability, available takt time etc. are satisfied. In this study we capture the total number of tasks that an operator is assigned, in addition to the controlled fastening operation in a given takt. This information was captured for each takt where the fastening operations that were studied, took place.

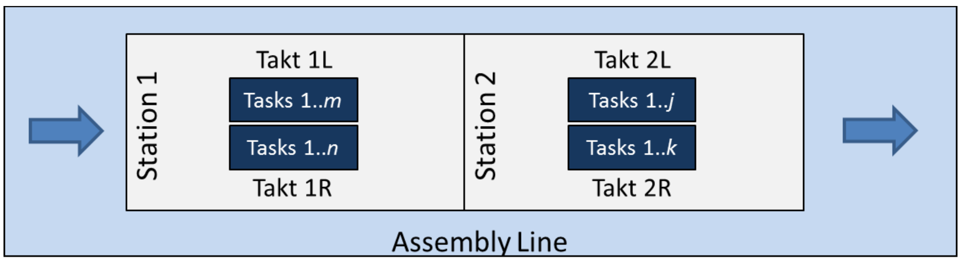


Figure 5.22: Assembly line showing stations, takts, and tasks

i. **Max. # of fasteners to assemble in same task:** This variable captures the total number of fasteners of the same type to be assembled by an operator to assemble a given component. During our study, we have observed components where up to 7 fasteners are assembled by an associate. This repetitive task impacts manufacturing complexity and product quality in an interestingly counter-intuitive way. The details will be discussed in the following sections along with regression analysis.

j. **Takt utilization %:** Takt utilization refers to a labor utilization metric that is generally followed by manufacturing plants to maximize the use of available takt time (cycle time) in each takt. Mathematically, labor utilization can be calculated as follows:

$$\text{Labor Utilization} = \frac{\sum_{j \in S_k} t_j}{m \times c}$$

where,

j = Task that belongs to a set of tasks S_k (2.36)

t_j = Time required per task j

m = Number of stations $k = (1, \ldots, m)$

c = Takt time or Cycle time

In our research, we have recorded takt utilization as a % value for each takt in which the fastening operations were carried out.

k. **Avg. time per fastener (non-defective):** This metric shows the average time actually taken by operators to complete assembly of one fastener per the required process specifications. The controlled fastening process captures the exact duration of the process by tracking the exact time when the trigger first gets pulled to the time when the torque and angle specifications reach their specified target values. The average values were computed from several thousand data points that represented processes carried out over several shifts by various operators, and utilized a large population of components, including fasteners. Data is captured in the form of a numerical value for each process in milliseconds.

l. **Assembly time variance:** This is an important variable that has not been used by researchers in modeling complexity, to the best of our knowledge. Although task time has been used by several researchers as a primary driver, we have observed that the variation in the time taken to complete the fastening process is a significant input variable in the complexity model. Similar to the method we used to capture average time per fastener, we used the same data set, although the only difference being the inclusion of all data points (defective and non-defective fastening cycles). Capturing those data points that reflect the struggle that the operator had in order to meet specification, is very important. Time variance is captured as the square of standard deviation calculated from the large population of data points for each process.

5.3.6. Human factors driven Complexity (C_h)

As shown in the generalized complexity model, Ergonomics, Training / Experience, Cognitive Load, and Work Environment are the primary categories of input variables that impact human-factors driven complexity. Figure 5.23 shows the input variables for human-factors driven complexity related to the mechanical fastening process.

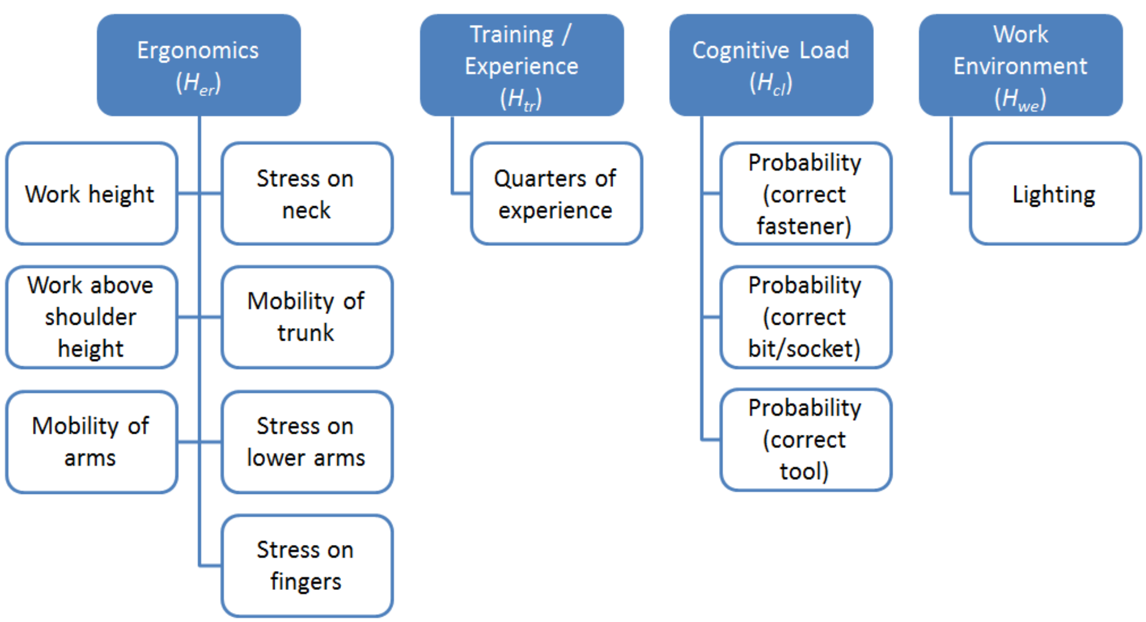


Figure 5.23: Input variables - Human-factors based mfg. complexity in Fastening

For this analysis, we used the ergonomic inputs that were recorded by the OEM for each fastening task based on standard OSHA regulations that apply to the automotive industry. Following is a brief description of each input variable and the acceptance criteria for each variable that the OEM follows. We have used this information to compare and contrast various fastening processes and have not considered challenging their validity to be within the scope of this research.

a. **Work height:** It is defined as the height at which the operator assembles the part with reference to the surface on which he/she is standing. This information is recorded in terms of linear height in centimeters. Ergonomically, work height between 85 cm and 120 cm is considered to be acceptable. Anything below or above would need improvement (Figure 5.24).

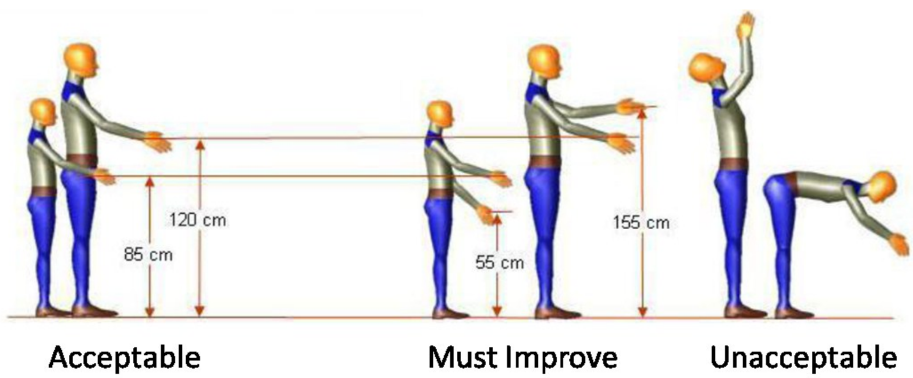


Figure 5.24: Work Height - Acceptance criteria

b. **Stress on neck:** Static stress and extensive deflection is recorded as a percentage of total time when the operator experiences it. Below 5% of total task time is considered acceptable. Between 5% to 30% is considered as an opportunity for improvement and above 30% of the total task time is considered unacceptable.

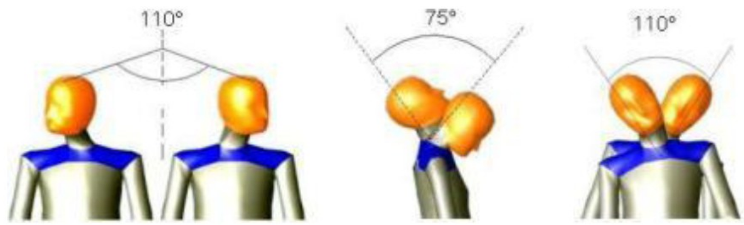


Figure 5.25: Stress on Neck Muscles - Acceptance criteria

c. **Work above shoulder height:** Working above shoulder height during fastening (e.g. working on sunroof or curtain airbag assembly from inside the passenger cabin in a car) can be difficult for the operator and can cause fatigue. It is important to note that the effort (load) also has to be considered along with the % of task time that the operator conducts work above shoulder height. For loads less than 10N, task time below 5% of total is considered acceptable. Between 5% to 30% is considered as an opportunity for improvement and above 30% of the total task time is considered unacceptable. Working in a lasting static posture is unacceptable above 5% of the time.

Figure 5.26: Work above shoulder height

d. **Mobility of trunk:** Fastening tasks that involve mobility of trunk are recorded using the following conditions:

1. Turning < 15° and/or bending 15° to < 30°: Acceptable upto 30% of total task time
2. Turning ≥ 15° and/or bending ≥ 30° to < 90°: Acceptable upto 5% of total task time
3. Bending ≥ 90° and or turning in difficult conditions: Considered unacceptable

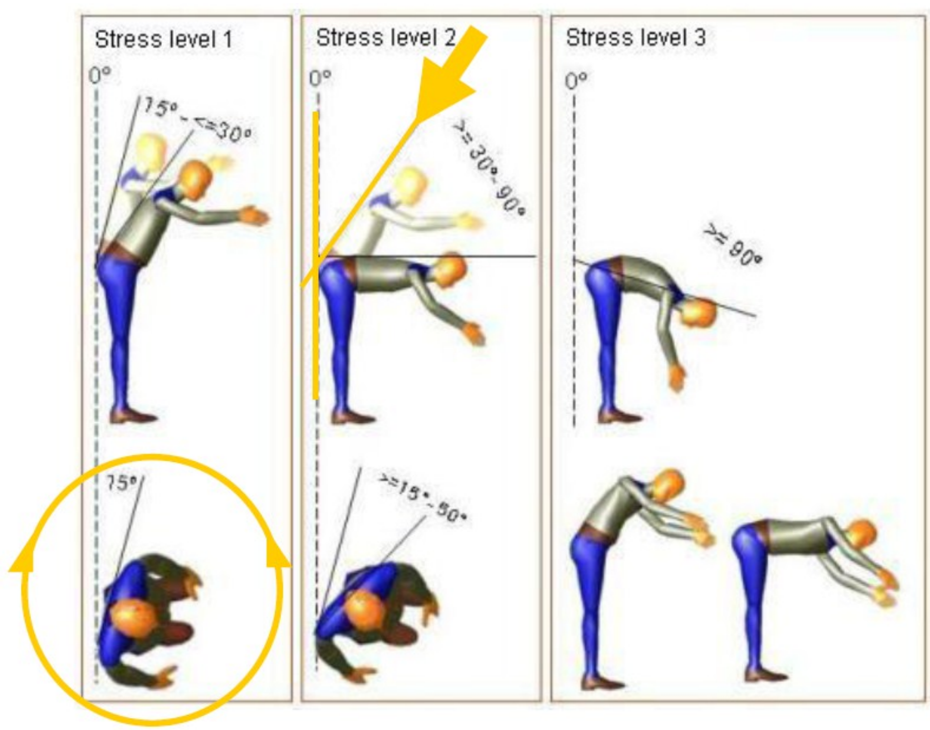


Figure 5.27: Mobility of trunk

e. **Mobility of arms:** This ergonomic variable helps us identify if the arm movement including shoulder joint exceeds 60 cm radius during the fastening operation. Less than 5% of the total task time is acceptable. If it is between 6% to 30%, it needs to be improved and greater than 30% is unacceptable.

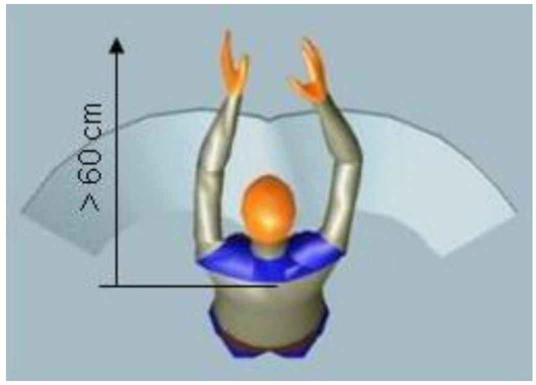


Figure 5.28: Mobility of the arms

f. **Stress on lower arms and wrists:** Gripping a component or tool while fastening can cause stress on the lower arms and wrists. If the stress on the lower arms/wrists is less than 125 N for up to 30% of the total task time, then it is considered acceptable. On the other hand, if the stress is between 190 and 285 N even for less than 5% of the total task time, actions need to be taken to reduce that stress. Stress is classified into multiple categories as shown in Figure 5.29.

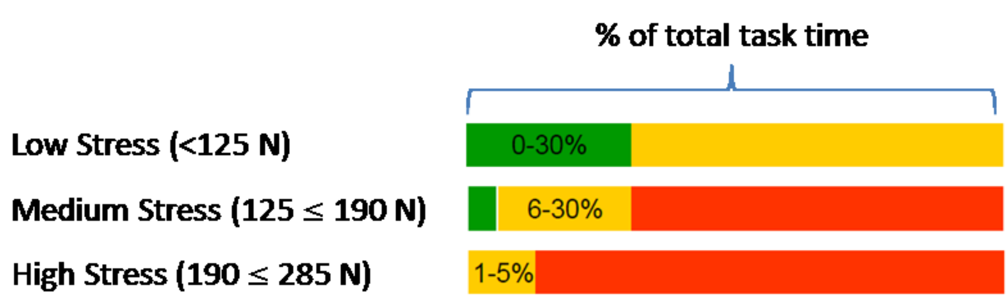


Figure 5.29: Stress on lower arms / wrists - Acceptance criteria

g. **Stress on fingers:** This ergonomic variable is important from the standpoint of dexterity related to hand-starting fasteners. If the force applied is less than 15N, the stress level is small and considered acceptable. Between 15 and 20 N, the stress level is considered medium and should be improved. Stress level above 20N is considered high and unacceptable.

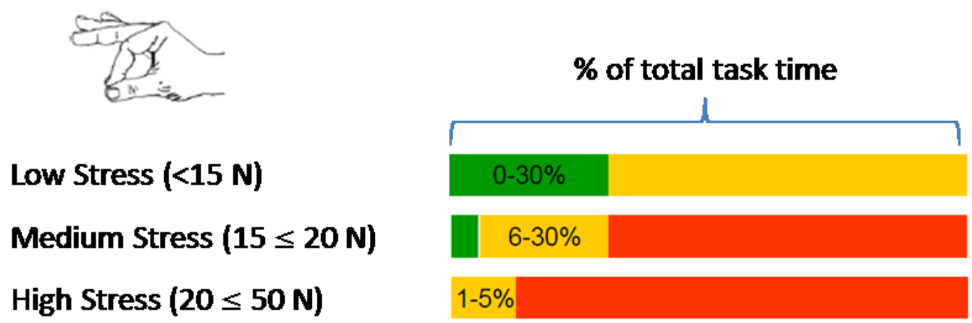


Figure 5.30: Stress on fingers during hand-starting of fasteners

h. **Quarters of experience:** For ergonomic reasons, a given shift is divided into four work-quarters. Operators do different tasks in each quarter in order to exercise a variety of muscles / body parts and reduce the impact of repetitive work. Every operator signs into a tracking system that associates the operators ID number with the takt where a specific task gets done. Access to this system allowed us to identify the number of quarters of applied experience that each operator has. In this study, we use the average quarters of work experience the operators have and use that as an input variable in the complexity model.

i. **Probability of selecting the correct fastener:** In several cases, an operator may be required to select a fastener from a variety of alternatives because the remaining fasteners are used at that takt for some other fastening operation. Mathematically, this probability can be expressed as follows:

$$p_f = \frac{1}{n_f} \tag{2.37}$$

where,

p_f = Probability of selecting the correct fastener

n_f = Number of available alternative fasteners are the same takt

j. **Work environment:** Under this category, we consider Noise, Lighting, Humidity, and Temperature. As noise, humidity, and temperature were quite similar in the manufacturing facility where the processes were studied, we do not consider them in the complexity model specifically for this pilot study. We consider lighting and as explained in Chapter 4, the term illumination characterizes the lighting quality of a given working environment. How much illuminance an object receives depends on the distance of the object from the light source. An alternative method is based on analysis of photographs to get a relatively subjective input from the operators and convert it to a numerical value on a relative scale. Pictures of the assembly process to be studied can be taken consistently with the same camera while maintaining the same average distance between the assembly and the operator's eyes. These photographs can be studied by various operators who are trained to work on similar assemblies and a score can be assigned on a pre-determined scale to compare the level of illumination for each assembly process being studied.

5.4. Application of proposed model to pilot process

In this section, we will focus on applying the proposed complexity model to the pilot process to calculate manufacturing complexity and correlate it with product quality. The data for this research project has been collected at a major automotive assembly plant that builds approximately 300,000 vehicles per year across three product families. Historical quality data for 12 months representing approximately 150,000 vehicles was analyzed (Figure 5.31).

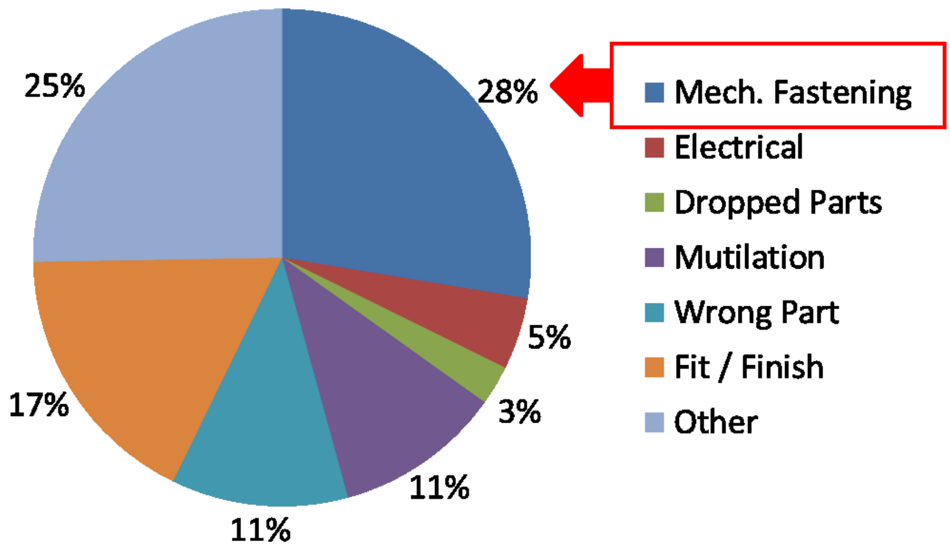


Figure 5.31: Analysis of defect data (Representing 1 year of production)

As observed, mechanical fastening is the top driver of defects on the assembly line. Although the mechanical fastening process has shown a first-time pass rate (FTP) of 98.6% on an average, the sheer number of total fasteners per vehicle makes the 1.4% defect rate very prominent to the assembly line. 46 processes representing a wide spectrum of joints were selected for the study out of a total 150 controlled mechanical fastening processes that are utilized in building a completely assembled vehicle. With this data, we develop a regression based predictive model to predict defects and validate the model in an independent automotive assembly plant.

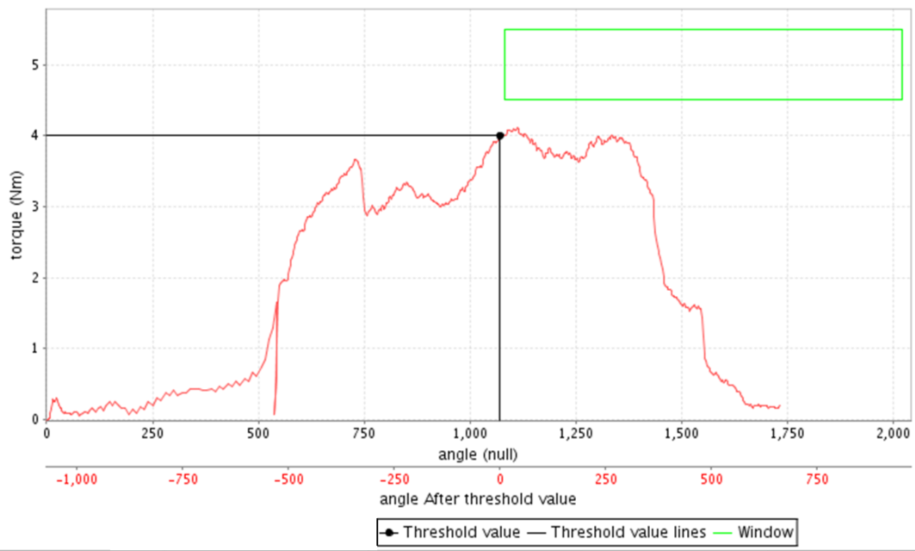
5.4.1. Quality Measurement

There are four key fastening process control strategies to the best of our knowledge. Table 5.1 shows the key characteristics and the potential variation that can be expected from each strategy.

Table 5.1: Fastening Process Control Strategies

STRATEGY	DESCRIPTION	VARIATION
Torque Control	Predetermined target torque. Torque-Angle window when coupled with angle monitoring.	+/- 30%
Angle Control	Monitors number of rotations after target torque is reached.	+/- 15%
Yield Control	Monitors amount of slope changes as torque progresses in terms of number of rotations. Sensitive to joined material behavior.	+/- 6%
Stretch Control	Monitors elongation within the fastener to estimate clamp load, using ultrasonic transducer.	< 1%

In the processes we studied, Torque and Angle Control strategies were being used. The closed loop control and monitoring process provides immediate feedback to the associate whether or not the fastener (joint) has met specified torque and angle requirements through LEDs that are mounted on the tool and also on another visual display that is connected to the tool and controller. The controller also records torque and angle values dynamically for each fastener and stores it for offline analysis. Figure 5.32 shows a plot with torque (N.m.) along the Y-axis and angle (deg.) along the X-axis. The red line shows the dynamic torque and angle values as the fastening operation progresses. The black dot at the intersection of 4 N.m. and a few degrees past 1,000 along the X-axis refers to a threshold torque. This is set up by the process engineer and the tool starts monitoring angle beyond that point until the final torque and angle specifications are reached. The secondary X-axis shown in red font reflects the angle value starting at 0 degrees, once the threshold value is reached.



Threshold value	Minimal torque	Maximal torque	Minimal angle	Maximal angle
4.0	4.5	5.5	10.0	950.0

Figure 5.32: An example of a defective fastening operation (torque-angle plot)

The green box shows the allowable tolerance window for torque and angle. In this case, the torque value crossed 4 N.m. but the fastener was unable to gain more torque and eventually dropped off as shown by the red line. This is typically associated with a large joint gap that the fastener is unable to close during the operation. Such a fastening process would be considered as defective. The tool would register it and that defect stays associated with the vehicle until it gets cleared manually by a re-worker on the assembly line. The vehicle cannot get shipped unless all defects are cleared from the system. The primary goal of process and quality engineers is to understand the root cause of such failures and systematically implement mistake-proofing systems to prevent them from recurring.

The quality defect rate can be computed as follows:

$$\text{DPMO} = \frac{\text{\# of defects}}{\text{\# of opportunities}} \times 10^6 \tag{2.38}$$

where,

DPMO = Defects per million opportunities

In this equation, the number of opportunities is defined as the total number of attempts (successful and unsuccessful) to assemble the fastener. For example, if on a given vehicle to be assembled, an associate has to assemble 9 fasteners. If the operator comes across one failure and has to make an extra attempt to complete the 9 assemblies, the total number of opportunities that the operator had = 9 + 1 = 10.

$$\text{DPMO} = \frac{1}{(9+1)} \times 10^6 = 100{,}000 \tag{2.39}$$

where,

DPMO = Defects per million opportunities

In a similar manner, 12-months of historical data was collected for all the processes that were studied.

5.4.2. Identification of significant input factors

A total of 36 input variables were recorded for 40 fastening process along with the respective Defects Per Million Opportunities (DPMO) for each process. Statistical analysis was conducted using *Minitab*. For regression analysis, the response variable in our study is DPMO and predictor variables are the 36 input variables that represent design, process and human factors driven complexity.

Analysis of variance (ANOVA) gives *p*-values for each input variable (Figure 5.33). *P*-value determines the appropriateness of rejecting the null hypothesis in a hypothesis test. The *p*-value is the probability of obtaining a test statistic that is at least as extreme as the calculated value if the null hypothesis is true. In our study, we use the standard alpha level of 0.05. If the *p*-value of a test statistic is less than the alpha, we reject the null hypothesis. The null hypothesis in this regression study is that the input variable does not have a significant effect on the response variable (DPMO), which means the coefficient for that variable will equal zero in the regression equation. If the *p*-value is less than 0.05, we can statistically conclude that the variable has a significant effect on the response variable and the coefficient is significantly different from zero.

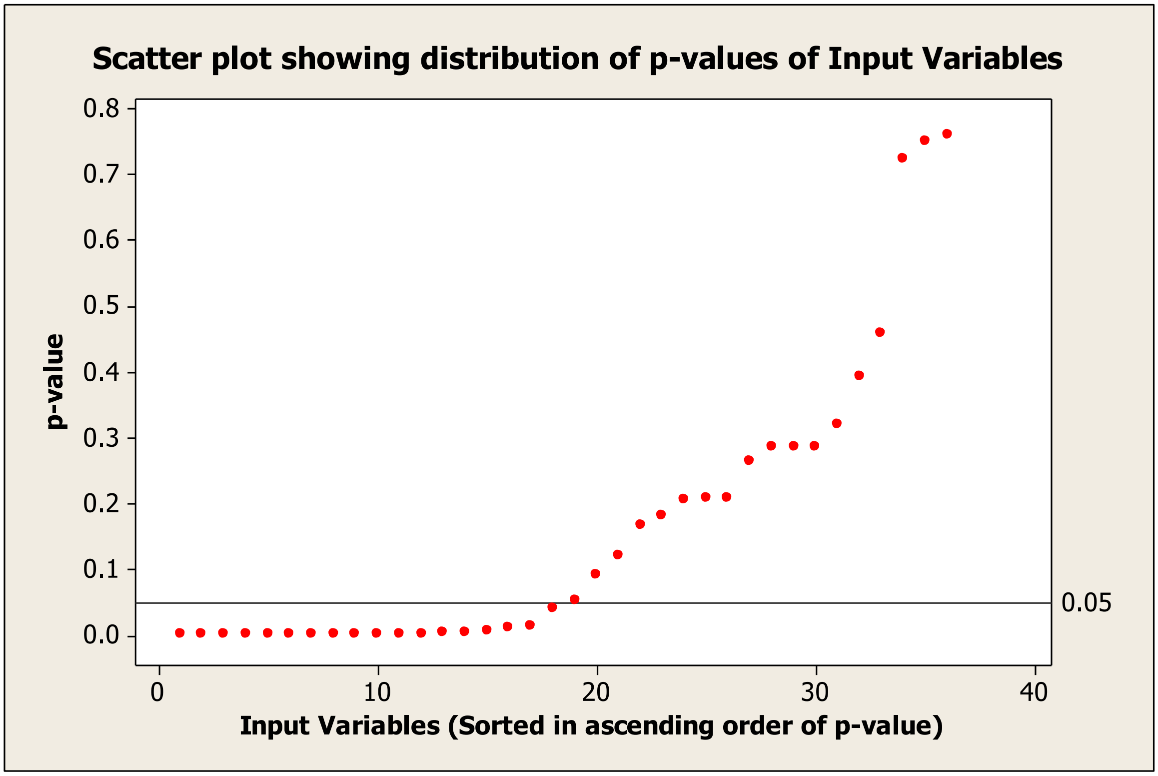


Figure 5.33: *P*-value distribution for 36 input variables (Alpha value 0.05)

Following table shows the reference number used in the plot, complexity factor of each input variable, names of input variables, and the corresponding p-value.

Table 5.2: Input variables and the corresponding p-value (ascending order)

Order	Factor	Input Variable	p-value
1	C_d	No. of components to be assembled	0.000
2	C_d	Thread diameter (OD)	0.000
3	C_h	Probability of choosing correct fastener	0.000
4	C_p	Max. # of fasteners in same task	0.000
5	C_d	Fastener head design	0.000
6	C_h	Stress on neck	0.000
7	C_d	Locking features	0.000
8	C_p	Assembly Time Variance	0.000
9	C_p	Tool speed (final stage)	0.000
10	C_d	Fastener engagement length	0.001
11	C_d	Fastener type	0.001
12	C_p	Takt utilization	0.002
13	C_d	Lubricant	0.002
14	C_h	Work above shoulder height	0.003
15	C_d	Fastener visibility	0.006
16	C_p	Tool speed (initial stage)	0.010
17	C_h	Stresses on fingers	0.012
18	C_p	Avg. assly. time per fastener	0.039
19	C_p	Hand / Tool start	0.052
20	C_h	Stresses on lower arms	0.091
21	C_p	Fastening sequence	0.120
22	C_p	Effective Tip Play	0.167
23	C_d	Coating	0.181
24	C_h	Mobility of arms	0.206
25	C_p	Tool trigger type	0.207
26	C_d	Layers of interference	0.208
27	C_d	Tolerance range	0.264
28	C_d	Angle of fastener	0.284
29	C_p	Angle of extension w.r.t. fastener	0.285
30	C_h	Work height	0.286
31	C_p	No. of tasks in takt	0.319
32	C_p	Total tip play	0.393
33	C_d	Torque	0.458
34	C_h	Mobility of trunk	0.722
35	C_h	Stresses on arms	0.750
36	C_p	Tool extension length	0.759

Following is a brief explanation and plots showing relationships of those individual input variables that have shown a R^2 (adj.) value of greater than 5% with Defects Per Million Opportunities (DPMO) as a resultant variable:

a) **Probability of choosing the correct fastener:** A fitted line plot (Figure 5.34) shows that as the probability of choosing the correct fastener increases, the potential for defects goes down, as intuitively expected. R^2 (adj.) value was 11.5%. In the data set, we encountered two processes with the least probability of correct choice (33.3%), where the associate had three fasteners with interchangeable thread size and design. An incorrect choice would result in a torque defect because the process specifications would fall outside specifications. Several more processes had a 50% probability as shown in the plot and most stations had only one choice of fastener which resulted in 100% probability.

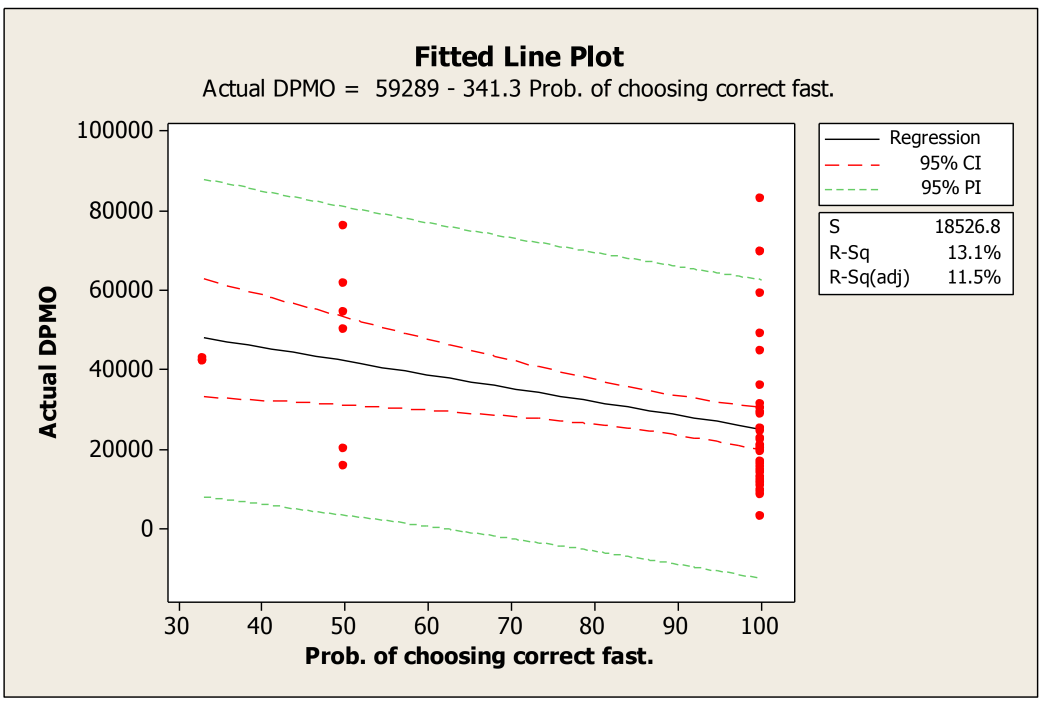


Figure 5.34: Probability of choosing the correct fastener vs. DPMO

b) **Assembly time variance:** Assembly time variance is an input variable that has not been highlighted before by Shibata [38] and Hinckley [47], who developed complexity models based on task time and number of operations. In our research, we calculated the standard deviation of time taken to assemble a fastener that meets specifications. In this calculation, we have excluded the data points for those fasteners that were linked to defects because clearly the processes that have more defects would have shown a correlation of the time variance vs. DPMO. From the analysis, we found that a quadratic fitted line plot shows a low R^2 (adj.) value but still significant compared to the < 1.6% R^2 (adj.) value that we observed with time and number of operations (Figure 5.35).

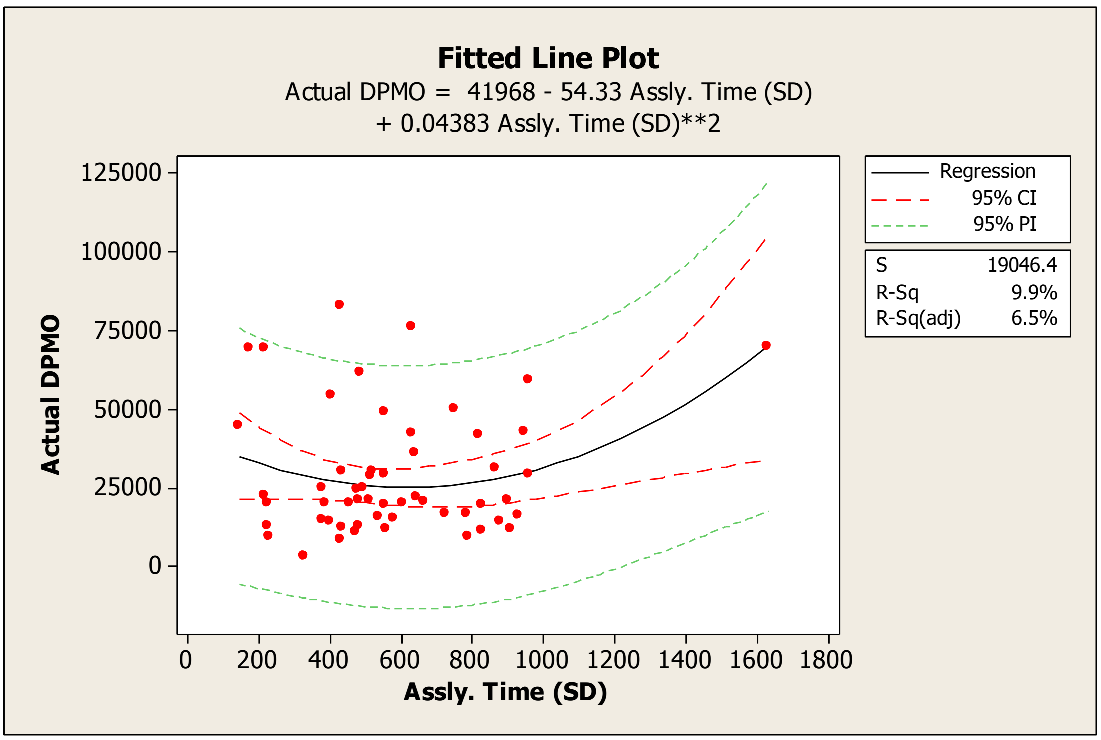


Figure 5.35: Assembly time Std. Deviation vs. DPMO (Quadratic)

c) **Fastener engagement length:** A linear fitted line plot (Figure 5.36) shows that as the engagement length increases, the potential for defects is higher. We came across a higher concentration of joints that had less than 10 mm total engagement length but there were several others with higher torque specifications that ranged between 15 to 40 mm. We found one process where several threaded components were stacked together and the total engagement length was 66 mm. The linear fitted line plot shows an R^2 (adj.) value of 15% and a quadratic fitted line plot shows a R^2 (adj.) value of 16.2% (Figure 5.37). As the benefit of using a quadratic model is very small in this case, we choose to use the linear relationship in the final regression model.

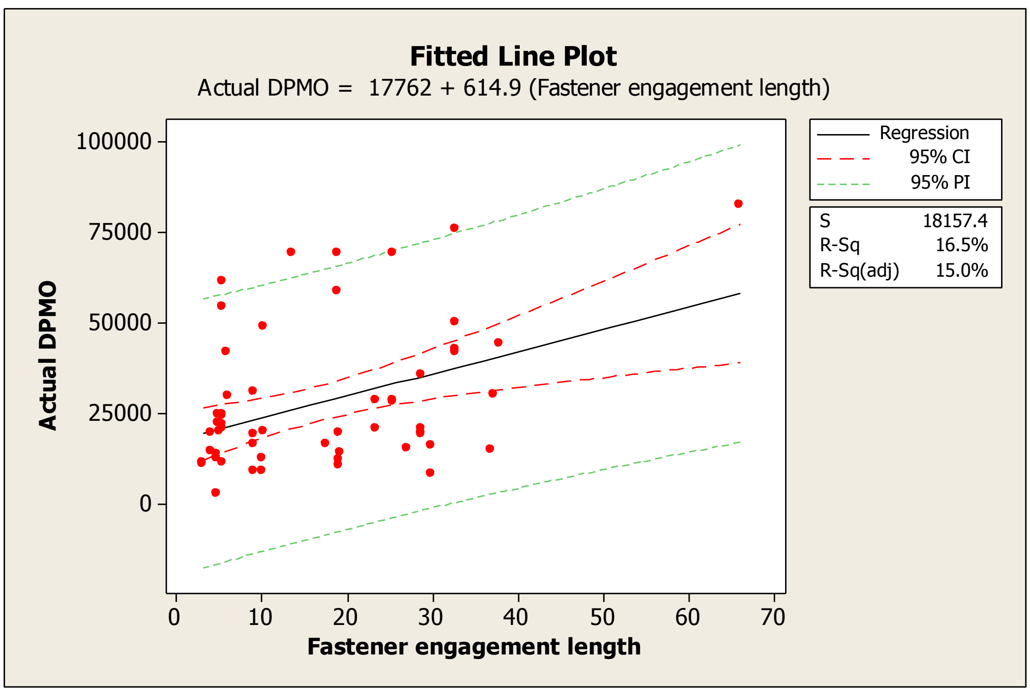


Figure 5.36: Fastener engagement length vs. DPMO (Linear)

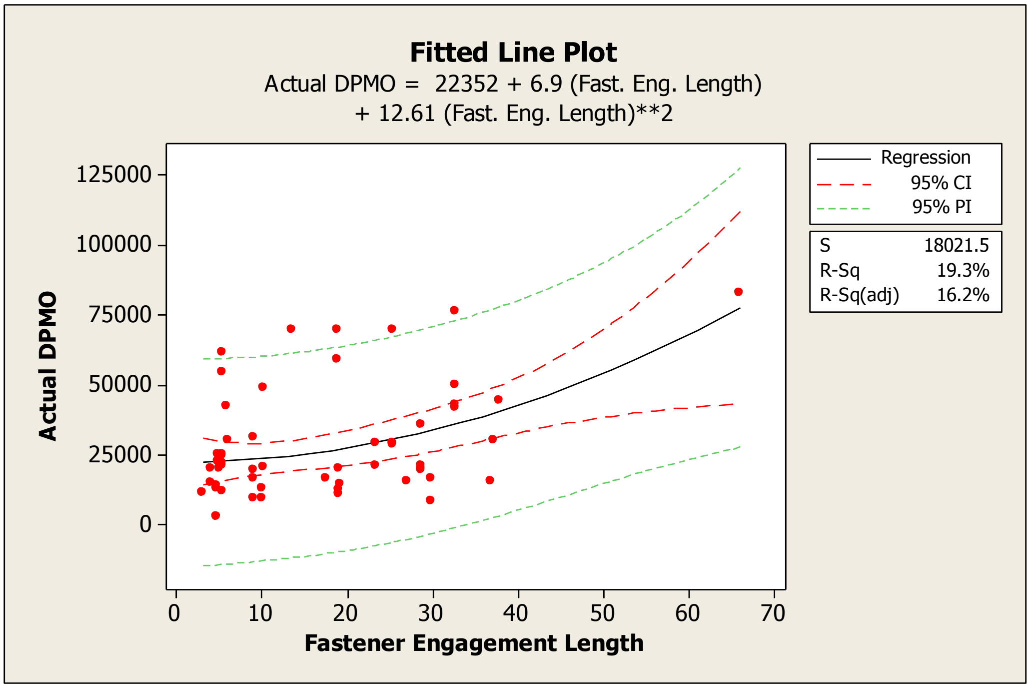


Figure 5.37: Fastener engagement length vs. DPMO (Quadratic)

d) **Takt Utilization:** As highlighted in the research motivation section, when our research group was working on an Assembly Line Balancing project at a mixed-model assembly plant, we observed the potential need to understand manufacturing complexity and product quality because the way tasks are arranged on an assembly line may bear an effect on product quality. Labor utilization is one of the primary objectives of Assembly Line Balancing. Fitted line plots of linear, quadratic, and cubic models show R^2 (adj.) values of 6.9%, 9.3%, 11.2% respectively (Figure 5.38). As utilization drops below 80%, the corresponding DPMO is higher. This may be due to interaction with other variables.

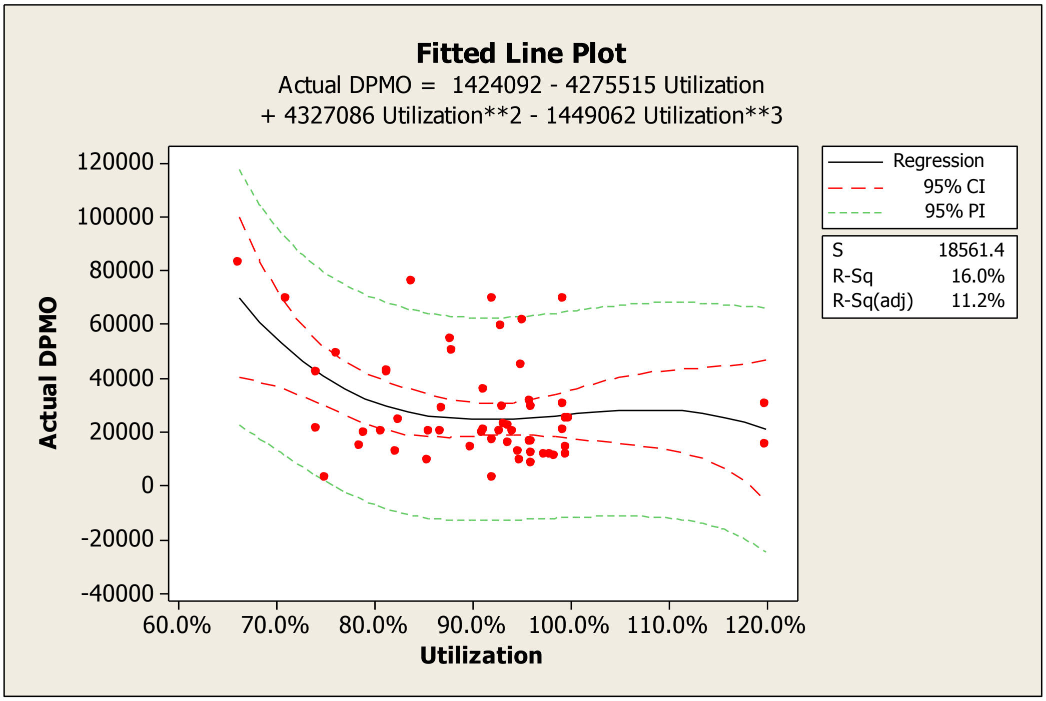


Figure 5.38: Takt utilization vs. DPMO (Cubic model)

e) **Work above shoulder height (% of task time):** Our study included a wide spectrum of mechanical fastening processes across the entire automotive assembly plant. We intentionally looked for processes that would give us a wide range of input variables such as work above shoulder height. In our data, we came across only 4 processes in which operators worked for 65% of their respective task times, above shoulder height. As shown in the fitted line plot for a linear model, the R^2 (adj.) value was found to be 10.0% (Figure 5.39). A quadratic model marginally increases it to 11.2%. However, there was a strong concentration of processes in which the work content above shoulder height was limited to 20% of the task time. Therefore, the decreasing trend of DPMO as the % of time increases may be limited to this data set alone and may not be valid across the entire range of processes. Also, there may be an interaction with another variable that explains why the DPMO drops with higher percentage of work above shoulder height.

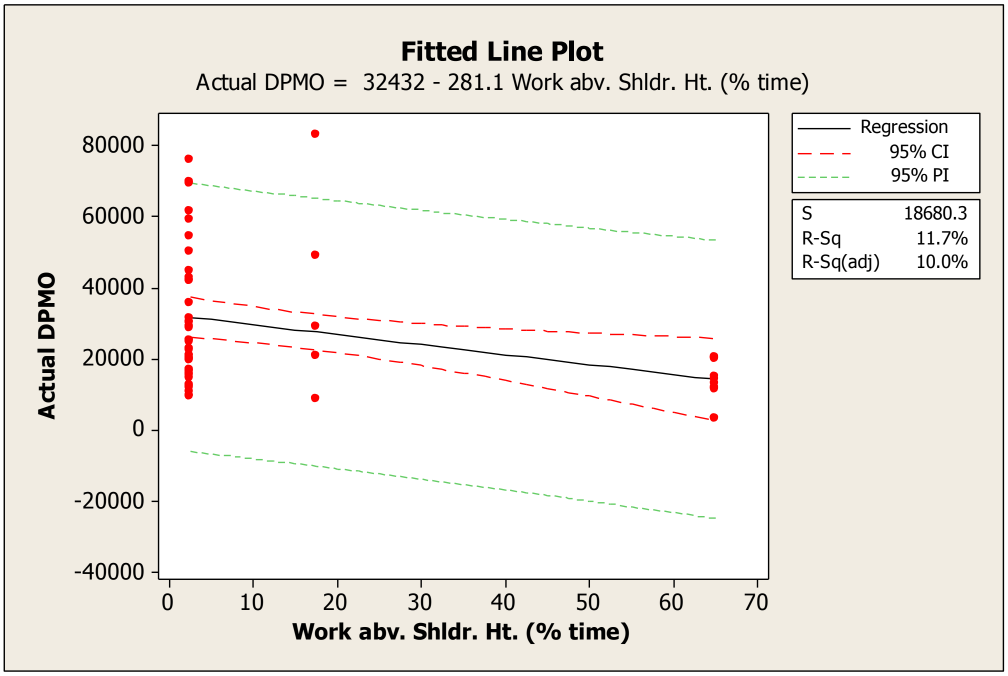


Figure 5.39: Work above shoulder height (% of task time) vs. DPMO (Linear)

f) **Tool speed (initial stage):** The torque application process is divided into two parts. The rotational speed of the tool is higher in the first part and once the threshold torque is reached, the speed drops to a lower value. This variable tracks the initial tool speed. As shown in the fitted line plot (Figure 5.40) using a quadratic model, the R^2 value is 8.3% and except for 4 processes on the low end below 225 RPM, the general tendency is for the DPMO to be lower as the speed increases.

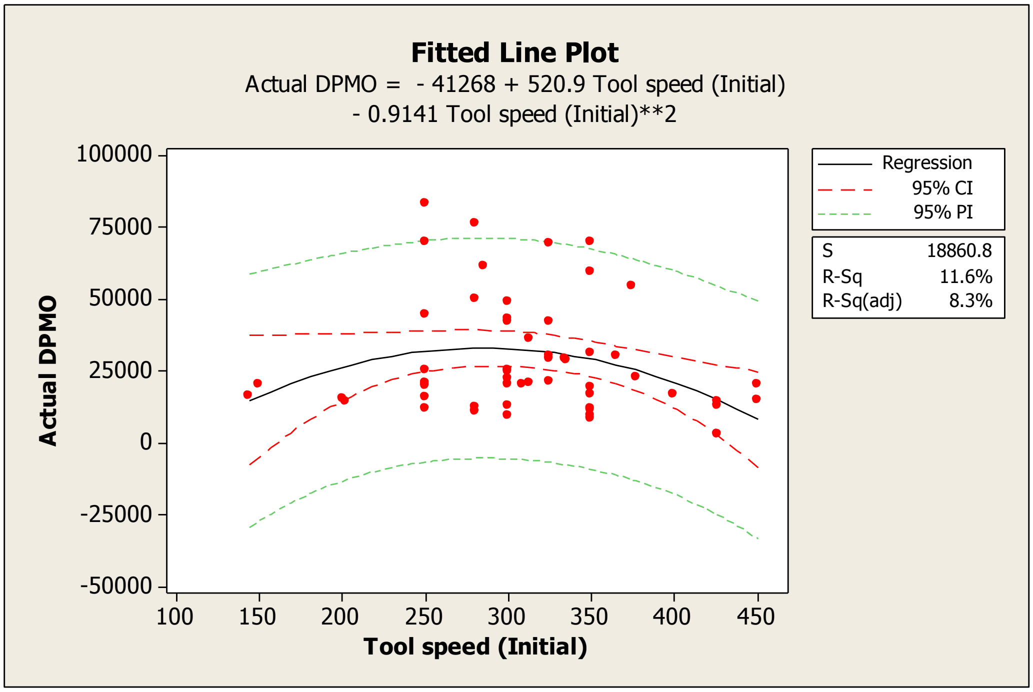


Figure 5.40: Tool Speed (Initial phase) vs. DPMO (Quadratic)

g) **Average assembly time per fastener:** Average assembly time is an input variable that was highlighted by Shibata [38] and Hinckley [47], who developed complexity models based on task time and number of operations. The general tendency is for defect rate to drop as the time taken to assemble a fastener is longer. This trend contradicts what was found in previous research associated with semi-conductor assembly and audio-players. In our study, average time per fastener was based on approximately 18,000 to 42,000 data points (fasteners) per process. The number of data points (fasteners) varied based on the quantity used per assembled vehicle. Using a quadratic model (Figure 5.41), the R^2 value was found to be 7.1%.

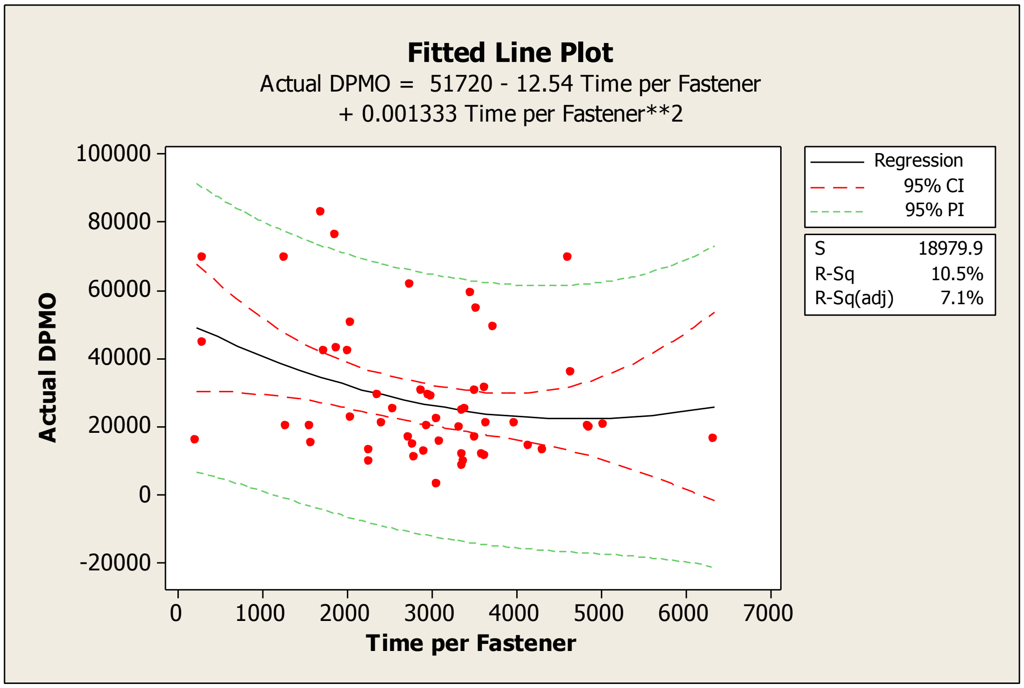


Figure 5.41: Average time per fastener assembly vs. DPMO (Quadratic)

h) **Work height:** In our study, most of the processes were conducted by operators between 100 cm to 140 cm. There were 4 processes that were conducted at 160 cm. with reference to the level at which the operators were standing. Although the quadratic fitted line plot shows the tendency for the DPMO to drop as work height increases beyond 140 cm, the available data may not be statistically sufficient to draw that conclusion. This should be noted as the framework of this model is applied to other processes in future. The R^2 (adj.) value was found to be 7.5% using a quadratic model (Figure 5.42).

Figure 5.42: Work height vs. DPMO (Quadratic)

i) **Tool extension length:** In our study, we were able to capture a very wide range of tool extension lengths (5mm to > 400 mm). The general tendency of the process is to have higher level of defects as the length increases because of the increased tip play (wobble) associated with the inherent vibration of the output spindle that is multiplied by the length of the extension. This causes slip-offs, a condition where the tool jumps off the fastener head and causes an intermittent drop in torque value or a complete shutdown of the process. The fitted line plot shows a R^2 (adj.) value of 5.3% using a quadratic model (Figure 5.43). The linear model and cubic model generate a R^2 (adj.) value of 2.3% and 6.8% respectively.

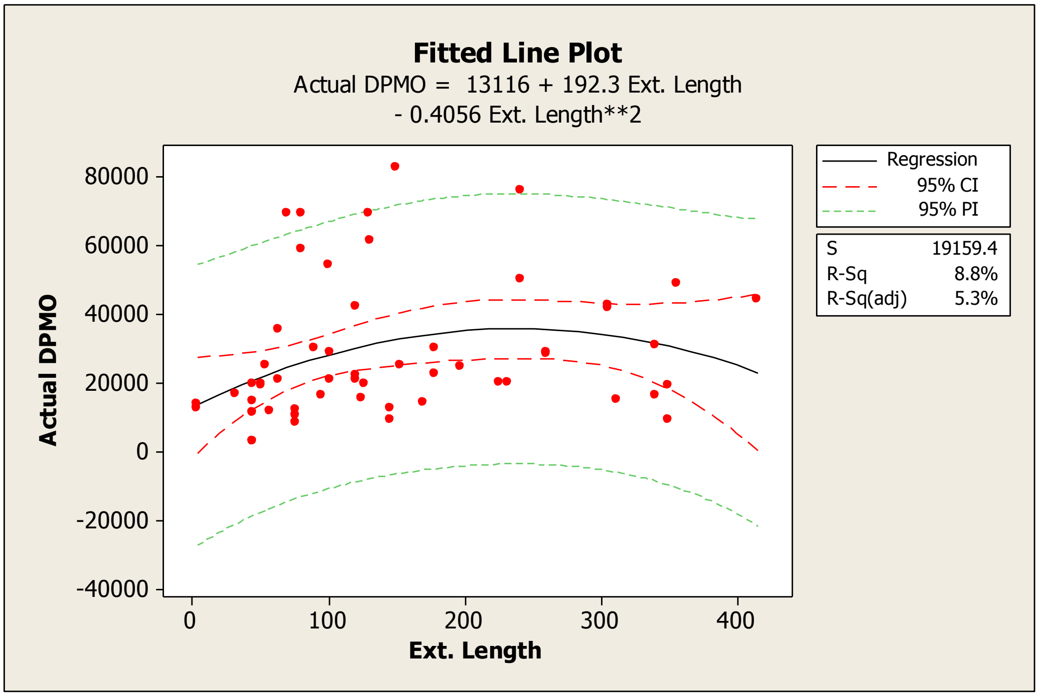


Figure 5.43: Tool extension length vs. DPMO (Quadratic)

In summary, these individual fitted line plots show some interesting correlation between these individual variables and product quality (DPMO). We gain a better understanding of the process using this information and develop a predictive model, details of which are shared in the next section.

5.4.3. Development of predictive model

Based on the statistical analysis, we know the factors that have a significant impact on product quality measured as DPMO. We conduct regression analysis to investigate the model the relationship between the response variable (DPMO) and the predictors (input variables). We perform Ordinary Least Squares (OLS) regression [78]. In OLS regression, the estimated equation is calculated by determining the equation that minimizes the sum of the squared distances between the sample's data points and the values predicted by the equation. OLS regression will provide precise, unbiased estimates only when the following assumptions are met:

1) The regression model is linear in the coefficients. Least squares can model curvature by transforming the variables (rather than the coefficients). Functional form of the equation needs to be specified in order to model the curvature. In our data, linear model was sufficient.
2) Residuals have a mean of zero. Inclusion of a constant in the model will force the mean to equal zero.
3) All predictors are uncorrelated with the residuals.
4) Residuals are not correlated with each other (serial correlation).
5) Residuals will have a constant variance.
6) No predictor variable is perfectly correlated with another predictor variable.
7) Residuals are normally distributed.

Because OLS regression will provide the best estimates only when these assumptions are met, it is important to test them. Common methods include examining residual plots and using lack of fit tests.

In regression analysis, R^2 (R-sq) is the coefficient of determination. It indicates how much variation in the response variable is explained by the model. The higher the R^2 value, the better the model fits the data set of predictor variables.

$$R^2 = 1 - \frac{\text{SS Error}}{\text{SS Total}} = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \tag{2.40}$$

where,
$y_i = i^{th}$ observed response value
$\overline{y}$ = mean response
$\hat{y}_i = i^{th}$ fitted response

Best Subsets regression is a method that is used to identify the subset models that produce the highest R^2 values from a full set of predictor variables [79]. It offers an efficient way to identify models that achieve the goals with as few predictors as possible. Minitab examines all possible subsets of the predictors, beginning with all models containing one predictor, and then all models containing two predictors, and so on. The two best models for each number of predictors are displayed. It also displays a Mallows' C_p value for each predictor set. Mallows C_p is a measure of goodness-of-prediction. The formula is as follows:

$$\text{Mallows' } C_p = \left(\frac{\text{SSE}_p}{\text{MSE}_m}\right) - (n - 2p) \tag{2.41}$$

where,
SSE_p = Sum of squares error for the model
MSE_m = Mean square error for the model with all predictors
n = number of observations
p = number of terms in the model, incl. constant

For analysis, we want to look for models where the Mallow's C_p is small and close to the number of predictor variables. A small C_p indicates that the model is relatively precise (has less variance) in estimating the true regression coefficients and predicting future responses. Models with poor predictive ability and bias have values of C_p larger than the number of predictors.

Three different cases of regression based predictive models are described below.

5.4.4. Regression Model – Iteration 1 (6 variables)

We conducted analysis of statistical-significance (*p*-value) and regression analysis with all the variables. Although the *p*-value for Work Height, Total Tip Play, Torque, Tool Extension Length, and Fastening Sequence was greater than the 0.05 threshold (Table 5.2), we observed an impact on the net R^2 (adj.) value, therefore we included them in the best-subsets analysis.

Table 5.3 shows a summary of top two subsets for each number of predictor variables. A total of 16 factors have the ability to account for 77% of the variation in DPMO. For ease of explanation, we have limited the best-subsets table to 77% (or 16 variables). Increasing the total number of variables to 24 increases the R^2 (adj.) value to 93% but we will cover this in iteration # 3. In this iteration, we select the subset with 6 variables that can account for 53.1% of the DPMO variation. Although the Mallows' Cp is significantly higher than the number of predictor variables, we select it as a baseline iteration that explains 50% of the DPMO variation (R^2-adj. value).

Table 5.3: Best-Subsets Analysis

# of Variables	R-Sq	R-Sq(adj)	Mallows' Cp	S	Work height	Stress on neck (% of time)	Work above shldr. ht. (% of time)	Fastener head design	Total tip play	Fastener type	Max. # of fasteners in takt	Locking	Sequence	Component Qty.	Thread OD	Tool speed (Final)	Prob. of correct choice	Assly. Time (Std. Dev.)	Fastener engagement length	Utilization
1	16.5	15.0	150.3	18,157															X	
1	13.1	11.5	158.7	18,527													X			
2	25.6	22.8	130.3	17,299													X		X	
2	24.1	21.2	134.0	17,478											X				X	
3	35.7	32.0	107.8	16,234											X		X		X	
3	30.4	26.3	120.8	16,902						X					X				X	
4	44.3	39.9	89.0	15,261					X						X		X		X	
4	41.2	36.6	96.4	15,675				X		X					X				X	
5	50.6	45.7	75.7	14,515				X		X					X		X		X	
5	46.6	41.2	85.5	15,095				X	X						X		X		X	
6	58.2	53.1	59.4	13,493				X	X	X					X		X		X	
6	56.0	50.7	64.5	13,832		X		X		X					X		X		X	
7	61.8	56.3	52.5	13,022		X		X	X	X					X		X		X	
7	61.0	55.3	54.5	13,164				X	X	X	X				X		X		X	
8	65.8	60.0	44.9	12,455		X		X	X	X	X				X		X		X	
8	64.2	58.1	48.8	12,751		X		X	X	X					X	X	X		X	
9	69.5	63.5	38.0	11,900		X		X	X	X	X		X		X		X		X	
9	68.6	62.5	40.1	12,061		X		X	X	X	X				X	X	X		X	
10	73.7	67.8	29.8	11,169		X		X	X	X	X		X		X	X	X		X	
10	71.5	65.1	35.2	11,632		X		X	X	X	X	X	X		X		X		X	
11	76.6	70.8	24.6	10,640		X	X	X	X	X	X		X		X	X	X		X	
11	74.8	68.6	29.0	11,043		X		X	X	X	X	X	X		X	X	X		X	
12	78.5	72.5	22.2	10,331	X	X	X	X	X	X	X		X		X	X	X		X	
12	77.5	71.2	24.6	10,566		X	X	X	X	X	X	X	X		X	X	X		X	
13	80.1	73.9	20.3	10,056	X	X	X	X	X	X	X		X	X	X	X	X		X	
13	79.5	73.1	21.7	10,204	X	X	X	X	X	X	X	X	X		X	X	X		X	
14	82.5	76.6	16.4	9,535	X	X	X	X	X	X	X	X	X	X	X	X	X		X	
14	81.6	75.3	18.6	9,784	X	X	X	X	X	X	X		X	X	X	X	X	X	X	
15	83.6	77.5	15.6	9,338	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	
15	82.8	76.3	17.8	9,584	X	X	X	X	X	X	X	X	X	X	X	X	X		X	X
16	83.9	77.3	17.0	9,380	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X

Using these predictor variables, we construct a regression model. Following are the equations for each complexity factor:

1) Design driven complexity factor (C_d):

$$C_d = -5499.4\left(D_{fd\_OD}\right) - 12197.8\left(D_{fd\_hed}\right) + 1352.72\left(D_{fd\_len}\right) + 27671.7\left(D_{fd\_typ}\right) \quad (2.42)$$

where,
D_{fd_OD} = Feature design - Thread Diameter (mm)
D_{fd_hed} = Feature design - Fastener head design (number)
D_{fd_len} = Feature design - Thread engagement length (mm)
D_{fd_typ} = Feature design - Fastener type (number)

2) Process driven complexity factor (C_p):

$$C_p = 467.8\left(P_{tf\_tip}\right) \quad (2.43)$$

where,
P_{tf_tip} = Tooling & fixture design - Total tip play (mm)

3) Human-factors driven complexity factor (C_h):

$$C_h = -362.46\left(H_{cl\_pro}\right) \quad (2.44)$$

where,
H_{cl_pro} = Cognitive load - Probability of correct choice (%)

4) Correlating Complexity to DPMO:

$$\text{DPMO} = 56600.2 + C_d + C_p + C_h \quad (2.45)$$

where,
DPMO = Defects per million opportunities
C_d = Design driven complexity factor
C_p = Process driven complexity factor
C_h = Human factors driven complexity factor

The following plots show the residual analysis based on the regression model with 6 input variables, applied to the 39 fastening processes. The normality plot shows that the *p*-value is significantly smaller than the threshold alpha value of 0.05 which shows that the residuals (Figure 5.44) are not normally distributed. Similarly, the histogram (Figure 5.45) shows a different view of the same data and shows the outlier with a large residual value of 36,000. Clearly, this shows that although we have a model that can account for 50% of the variability in the resultant DPMO, the model needs to be improved.

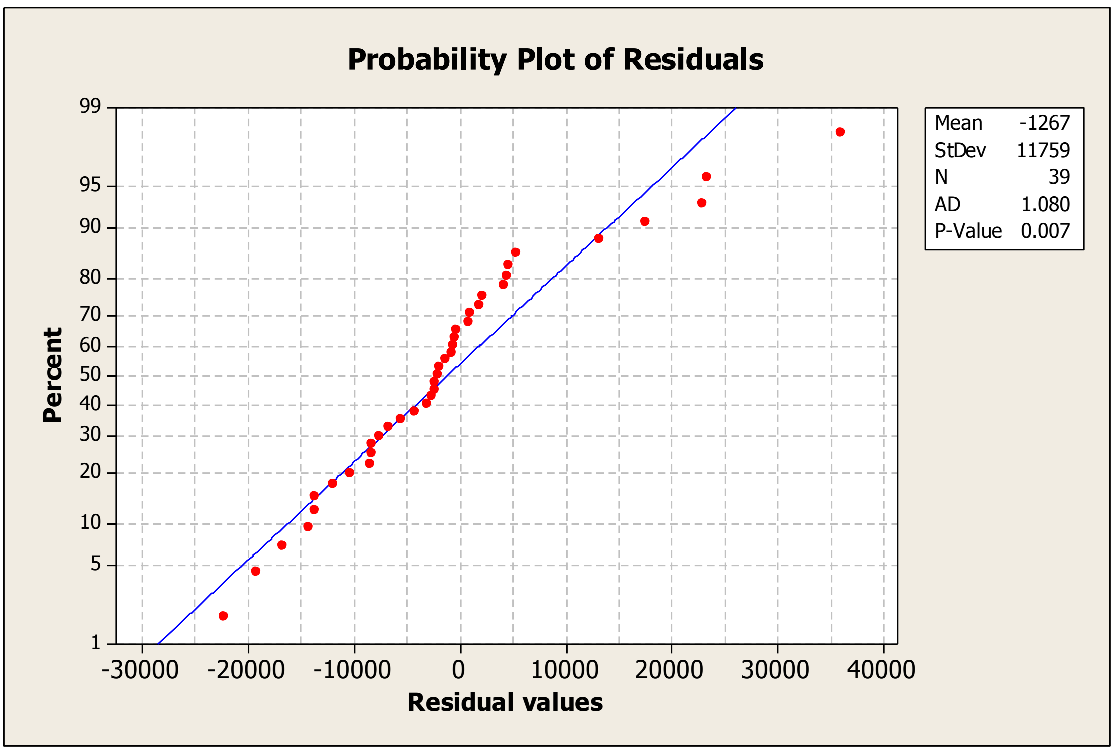


Figure 5.44: Normality plot of residual values (Iteration 1)

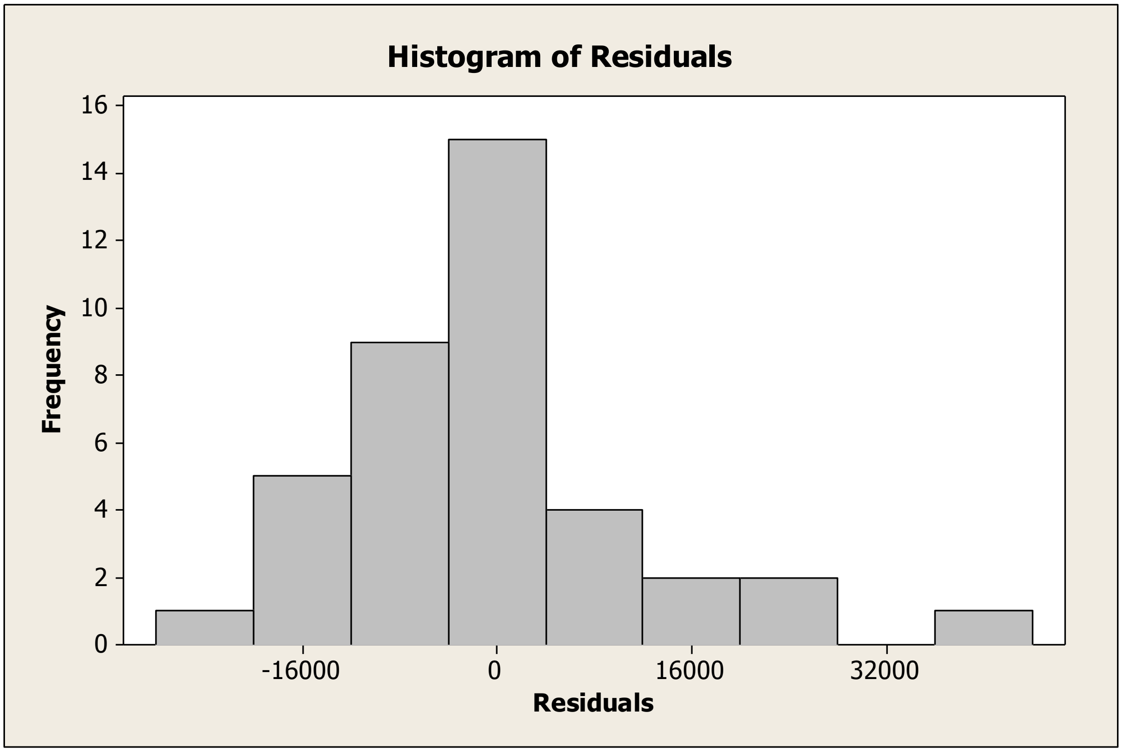


Figure 5.45: Histogram of Residuals (Iteration 1)

5.4.5. Regression Model – Iteration # 2 (16 variables)

Based on the best subsets analysis (Table 5.3), in this iteration we choose the subset with 16 variables. The estimated R2 (adj.) value is 77% and the corresponding Mallows Cp value is 17, which is very close to the total number of predictor variables in this model.

Using these predictor variables, we construct a regression model. Following are the equations for each complexity factor:

1) Design driven complexity factor (C_d):

$$\begin{aligned} C_d = {} & 6602.17\left(D_{ad\_qty}\right) - 7808.1\left(D_{fd\_OD}\right) - 14264.5\left(D_{fd\_hed}\right) \\ & -12259.4\left(D_{fd\_loc}\right) + 1223.2\left(D_{fd\_len}\right) + 34466.2\left(D_{fd\_typ}\right) \end{aligned} \tag{2.46}$$

where,
D_{ad_qty} = Assembly design - Assly. Component qty. (number)
D_{fd_OD} = Feature design - Thread Diameter (mm)
D_{fd_hed} = Feature design - Fastener head design (number)
D_{fd_loc} = Feature design - Locking (binary)
D_{fd_len} = Feature design - Thread engagement length (mm)
D_{fd_typ} = Feature design - Fastener type (number)

2) Process driven complexity factor (C_p):

$$\begin{aligned}C_p &= 648.8\left(P_{tf\_tip}\right)+21047\left(P_{as\_seq}\right)+12764.6\left(P_{tu\_utl}\right)\\ &-9.6\left(P_{vt\_sd}\right)-4335\left(P_{nt\_qty}\right)-92.14\left(D_{ad\_sp2}\right)\end{aligned} \tag{2.47}$$

where,
P_{tf_tip} = Tooling & fixture design - Total tip play (mm)
P_{as_seq} = Tooling & fixture design - Sequence (binary)
P_{tu_utl} = Assly. Takt utilization (%)
P_{vt_sd} = Assly. Time - Standard Deviation (ms)
P_{nt_qty} = Number of fasteners in takt (number)
P_{tf_sp2} = Tooling & fixture design - Tool speed final (RPM)

3) Human-factors driven complexity factor (C_h):

$$\begin{aligned}C_h &= 276.6\left(H_{er\_wkh}\right)+233.4\left(H_{er\_nec}\right)-349.4\left(H_{er\_sho}\right)\\ &-361.1\left(H_{cl\_pro}\right)\end{aligned} \tag{2.48}$$

where,
H_{er_wkh} = Ergonomics - Work height (cm)
H_{er_nec} = Ergonomics - Stress on neck (% of task time x 100)
H_{er_sho} = Ergonomics - Work above shoulder height (% of task time x 100)
H_{cl_pro} = Cognitive load - Probability of correct choice (%)

4) Correlating Complexity to DPMO:

$$\text{DPMO} = 33381.1 + C_d + C_p + C_h \tag{2.49}$$

where,

DPMO = Defects per million opportunities

C_d = Design driven complexity factor

C_p = Process driven complexity factor

C_h = Human factors driven complexity factor

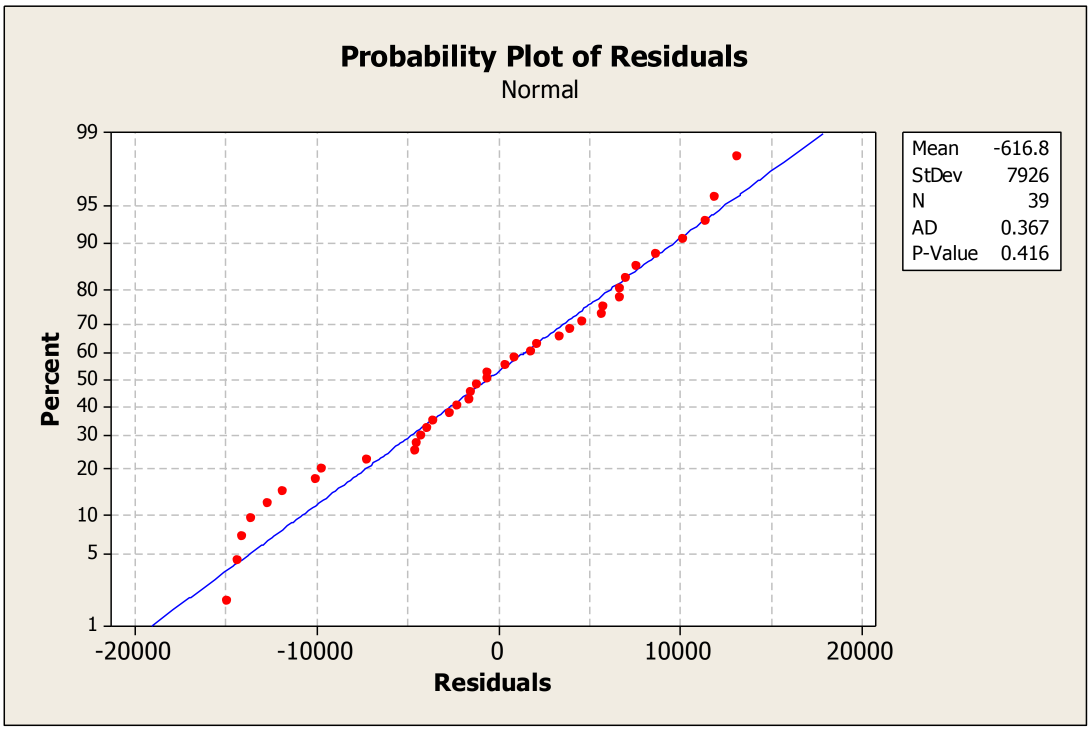


Figure 5.46: Normality plot of Residuals (Iteration 2)

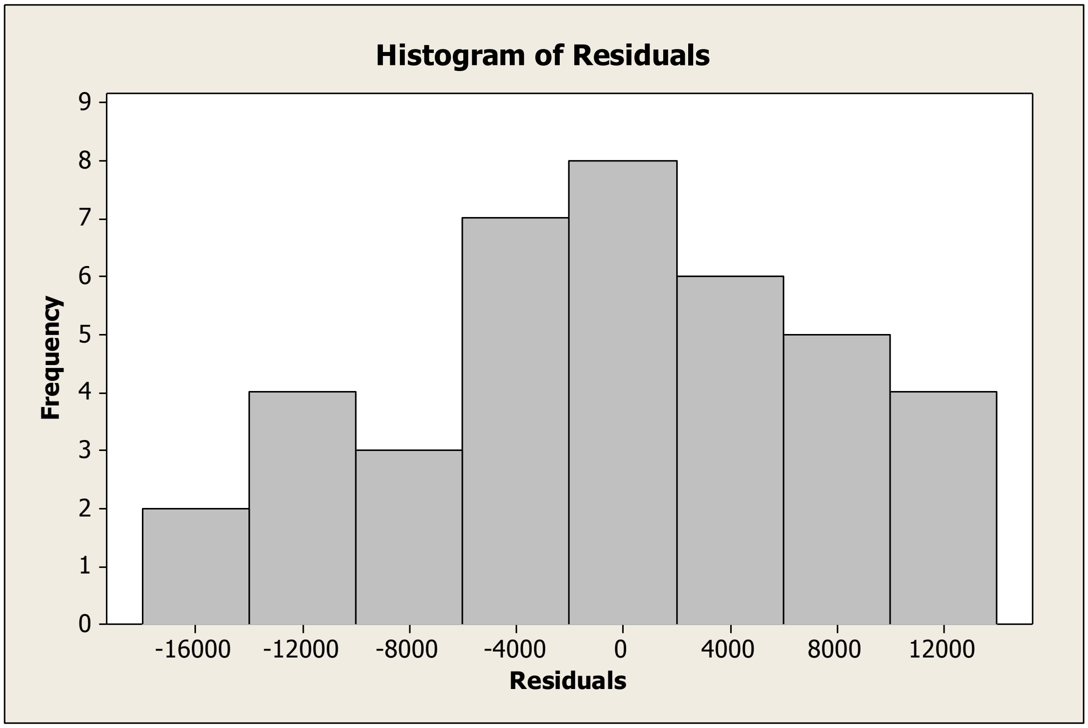


Figure 5.47: Histogram of Residuals (Iteration 2)

5.4.6. Regression Model - Iteration # 3 (24 variables)

Based on the analysis of statistical significance (p-value) and multiple regression analysis iterations, it was found that the following input variables consistently have a strong impact on the resultant variable (DPMO):

Table 5.4: List of statistically significant input variables (p-value < 0.05)

Order	Factor	Input Variable	p-value
1	C_d	No. of components to be assembled	0.000
2	C_d	Thread diameter (OD)	0.000
3	C_h	Probability of choosing correct fastener	0.000
4	C_p	Max. # of fasteners in same task	0.000
5	C_d	Fastener head design	0.000
6	C_h	Stress on neck	0.000
7	C_d	Locking features	0.000
8	C_p	Assembly Time Variance	0.000
9	C_p	Tool speed (final stage)	0.000
10	C_d	Fastener engagement length	0.001
11	C_d	Fastener type	0.001
12	C_p	Takt utilization	0.002
13	C_d	Lubricant	0.002
14	C_h	Work above shoulder height	0.003
15	C_d	Fastener invisibility	0.006
16	C_p	Tool speed (initial stage)	0.010
17	C_h	Stresses on fingers	0.012
18	C_p	Avg. assly. time per fastener	0.039
19	C_p	Hand / Tool start	0.052

Therefore, in the best subsets analysis, we keep these predictor variables in all models.

Best subsets analysis produced the following output (Table 5.5):

Table 5.5: Results of Best Subsets analysis (preferred subset in red)

# of Variables	R-Sq	R-Sq(adj)	Mallows' Cp	S	Fastening sequence	Torque	Tool extension length	Total tip play	Tolerance range	Stress on lower arms	Work height	Stress on arms
1	84.8	76.1	59.6	9,623				X				
1	82.8	72.9	69.5	10,250					X			
2	89.3	82.7	39.7	8,185				X		X		
2	89.3	82.6	40.1	8,209				X	X			
3	92.2	87.1	27.6	7,083				X	X	X		
3	92.1	86.8	28.4	7,158	X			X	X			
4	93.1	88.2	25.4	6,777	X			X	X	X		
4	93.0	88.0	25.7	6,809	X	X		X		X		
5	94.0	89.3	23.2	6,443	X	X		X	X	X		
5	93.7	88.8	24.5	6,578	X	X		X	X		X	
6	94.2	89.4	24.0	6,414	X	X		X	X	X	X	
6	94.0	88.9	25.2	6,548	X	X		X	X	X		X
7	94.2	89.0	26.0	6,521	X	X	X	X	X	X	X	
7	94.2	89.0	26.0	6,521	X	X		X	X	X	X	X
8	94.2	88.6	28.0	6,635	X	X	X	X	X	X	X	X

As explained above, we choose the subset with 5 variables because it produced the highest R^2 (adj) value and the difference between the number of predictors (5) and the Mallows' C_p is the least. R^2 indicates how much variation in the response variable is explained by the model. If a relatively lower value is acceptable to get an estimated prediction with a higher level of uncertainty, less number of variables can be chosen. However, in the subset with 2 variables, the difference between the number of variables and Mallows' C_p is very high which means the model would not be very precise.

Using these predictor variables, we construct a regression model. Following are the equations for each complexity factor:

a) Design driven complexity factor (C_d):

$$\begin{aligned}
C_d &= 19498\left(D_{ad_qty}\right) - 17318.9\left(D_{fd_OD}\right) - 11940\left(D_{fd_hed}\right) \\
&-43885.3\left(D_{fd_loc}\right) + 974.5\left(D_{fd_len}\right) + 19441.6\left(D_{fd_typ}\right) \\
&+15693.8\left(D_{fd_luc}\right) + 421.6\left(D_{ad_vis}\right) + 1144.7\left(D_{ad_rng}\right) + 472.8\left(D_{ad_tor}\right)
\end{aligned} \tag{2.50}$$

where,

D_{ad_qty} = Assembly design - Assly. Component qty. (number)
D_{fd_OD} = Feature design - Thread Diameter (mm)
D_{fd_hed} = Feature design - Fastener head design (number)
D_{fd_loc} = Feature design - Locking (binary)
D_{fd_len} = Feature design - Thread engagement length (mm)
D_{fd_typ} = Feature design - Fastener type (number)
D_{fd_luc} = Feature design - Lubricant (binary)
D_{ad_vis} = Assembly design - Lack of fastener visibility (%)
D_{ad_rng} =Assembly design - Tolerance range (Nm)
D_{ad_tor} = Assembly design - Torque (Nm)
D_{ad_sp1} = Assembly design - Tool speed initial (RPM)
D_{ad_sp2} = Assembly design - Tool speed final (RPM)

b) Human-Factors driven complexity factor (C_h):

$$\begin{aligned}
C_h &= 254.6\left(H_{er_nec}\right) - 216.7\left(H_{er_sho}\right) + 324.4\left(H_{er_fin}\right) \\
&-241.1\left(H_{er_low}\right) - 666.7\left(H_{cl_pro}\right)
\end{aligned} \tag{2.51}$$

where,

H_{er_nec} = Ergonomics - Stress on neck (% of task time x 100)
H_{er_sho} = Ergonomics - Work above shoulder height (% of task time x 100)
H_{er_fin} = Ergonomics - Stress on fingers (% of task time x 100)
H_{er_low} = Ergonomics - Stress on lower arms (% of task time x 100)
H_{cl_pro} = Cognitive load - Probability of correct choice (%)

c) Process driven complexity factor (C_p):

$$C_p = 1.5\left(P_{tf\_len}\right) - 82.2\left(P_{tf\_sp1}\right) - 92.1\left(P_{tf\_sp2}\right) + 690.1\left(P_{tf\_tip}\right)$$
$$-8767.7\left(P_{tf\_han}\right) + 10441.3\left(P_{as\_seq}\right) - 5355.4\left(P_{nt\_qty}\right) \tag{2.52}$$
$$+47512\left(P_{tu\_utl}\right) + 6.2\left(P_{vt\_avg}\right) - 41.7\left(P_{vt\_sd}\right)$$

where,
P_{tf_len} = Tooling & fixture design - Extension length (mm)
P_{tf_sp1} = Tooling & fixture design - Tool speed initial (RPM)
P_{tf_sp2} = Tooling & fixture design - Tool speed final (RPM)
P_{tf_tip} = Tooling & fixture design - Total tip play (mm)
P_{tf_han} = Tooling & fixture design - Hand start (binary)
P_{as_seq} = Tooling & fixture design - Sequence (binary)
P_{nt_qty} = Number of fasteners in takt (number)
P_{tu_utl} = Assly. Takt utilization (%)
P_{vt_avg} = Assly. Time variation - Avg. time per fastener (ms)
P_{tf_len} = Assly. Time - Standard Deviation (ms)

d) Complete complexity model:

$$\text{DPMO} = 135822 + C_d + C_p + C_h \tag{2.53}$$

where,
DPMO = Defects per million opportunities
C_d = Design driven complexity factor
C_p = Process driven complexity factor
C_h = Human factors driven complexity factor

5.4.7. Residual Analysis

Results of regression analysis show that the R^2 value was 91.7% and R^2 (adj.) was 91.5%, using a linear model. The linear model accounts for 91.5% of the variation in the resultant variable (DPMO). Confidence and predictor intervals are shown by red and green dashed lines, respectively in Figure 5.48. Histogram of residuals shows a normally distributed data set and no outliers, in Figure 5.49. We conduct a normality test for residual values and it shows a p-value of 0.389 which shows that the data is normally distributed (Figure 5.50).

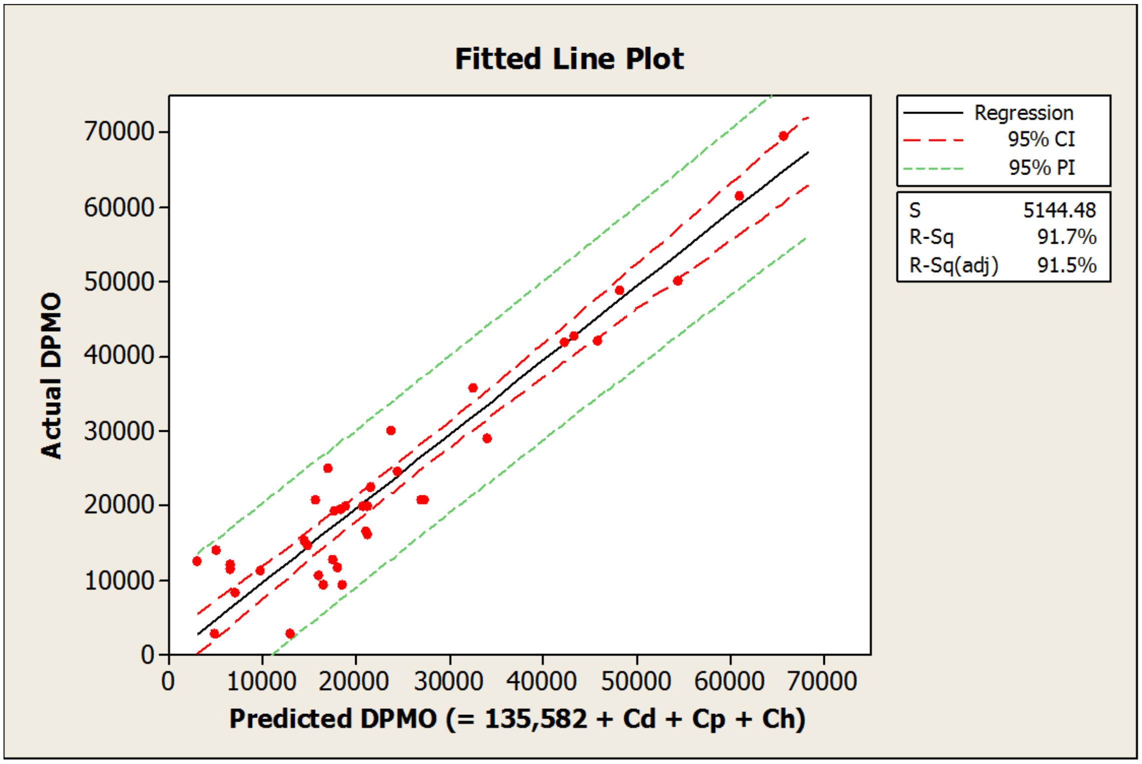


Figure 5.48: Fitted line plot based on 39 fastening processes (Linear)

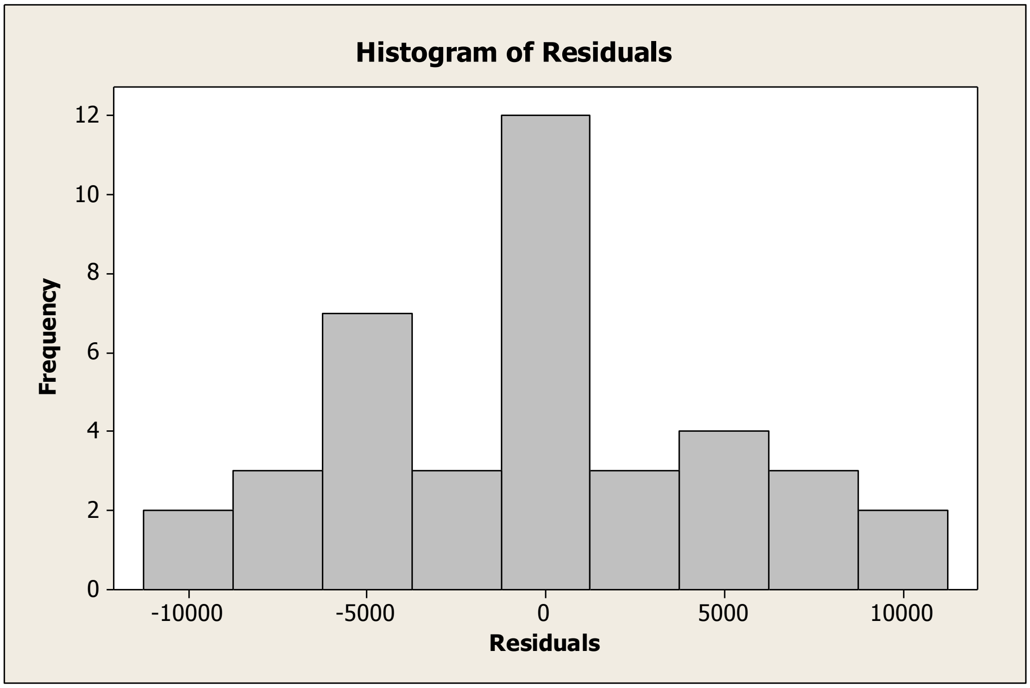


Figure 5.49: Histogram of residuals (Iteration 3)

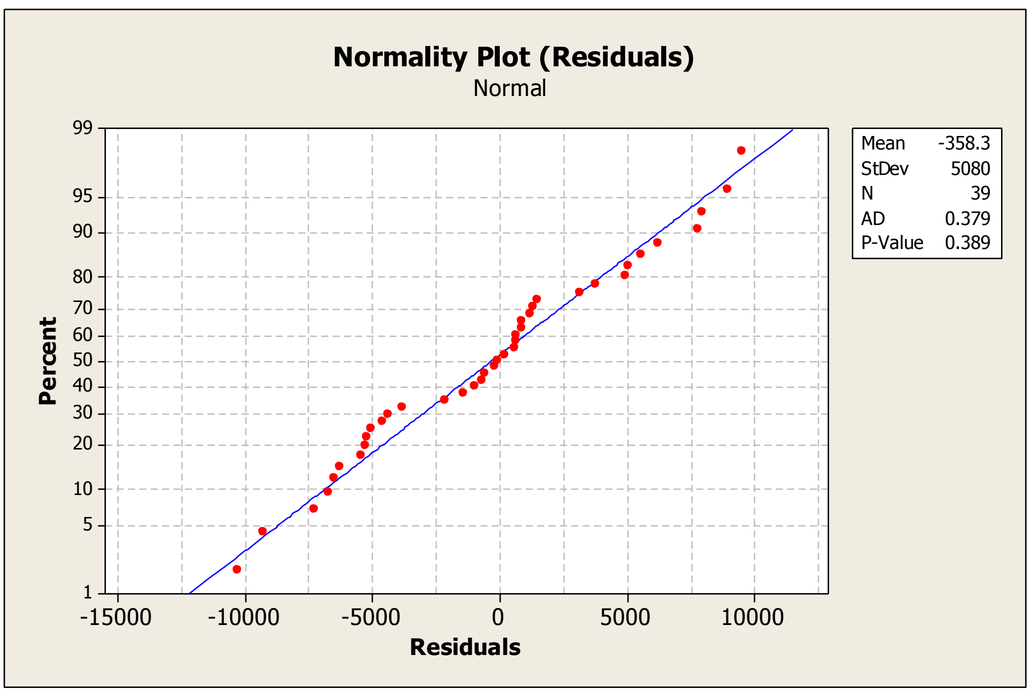


Figure 5.50: Normal probability plot of residual values (Iteration 3)

Plot of residual vs. predicted DPMO shows a random pattern, which suggests that the residuals have constant variance. The scatter plot of residuals (Figure 5.51) and the residuals vs. order plot do not show a pattern which means there is no time-related effect or non-random error in the data (Figure 5.52).

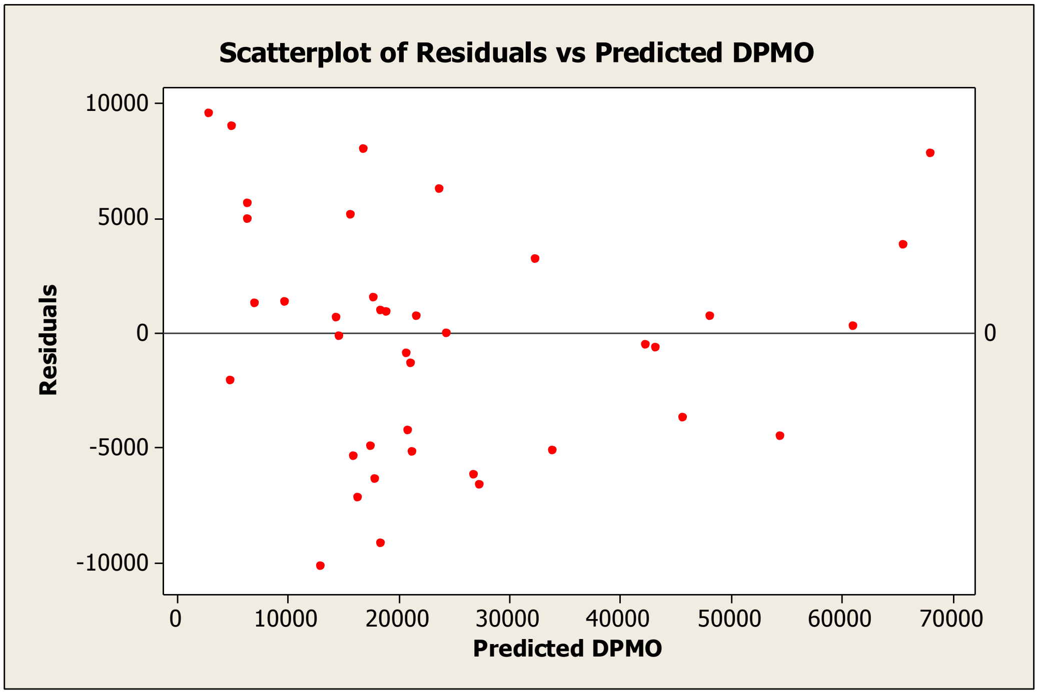


Figure 5.51: Scatter plot of residuals vs. Predicted DPMO (Iteration 3)

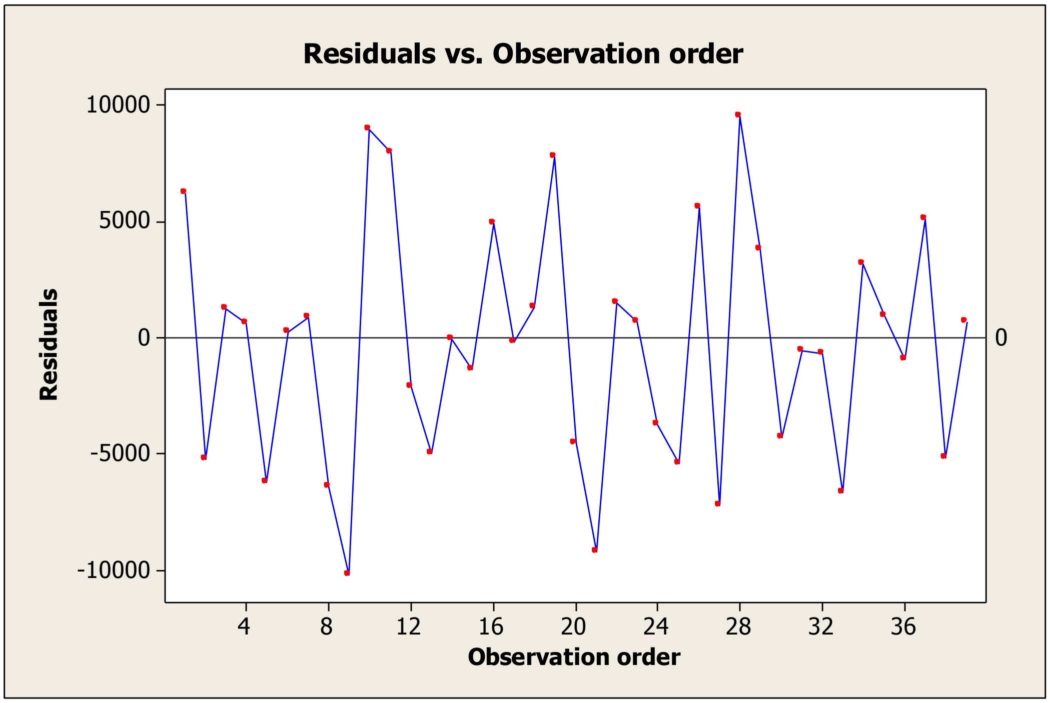


Figure 5.52: Residuals vs. Observation order (Iteration 3)

In summary, the predictive model based on regression analysis is statistically acceptable and can be used to predict defect rate. The next section covers the validation process of this predictive model.

5.4.8. Model validation using independent data set

In order to validate the model, we conducted analysis of similar mechanical fastening processes at an independent automotive assembly plant. Based on the experience gained in the source plant, we chose 18 processes that were representative of a larger population of processes across the automotive assembly plant.

We collected the input data for all the factors that were found statistically significant in the original analysis of 39 fastening processes at the source plant where the model was developed. The complexity model that we developed in each iteration was used to predict the DPMO and compare it versus the actual DPMO.

a) Validation using model from Iteration 1 with 6 variables:

A linear fitted line plot shows the predicted DPMO vs. actual DPMO with a R^2 value of 54% and R^2 (adj.) value of 51.2% (Figure 5.53). Although only 6 variables could account for this variation, the model clearly needs to be improved.

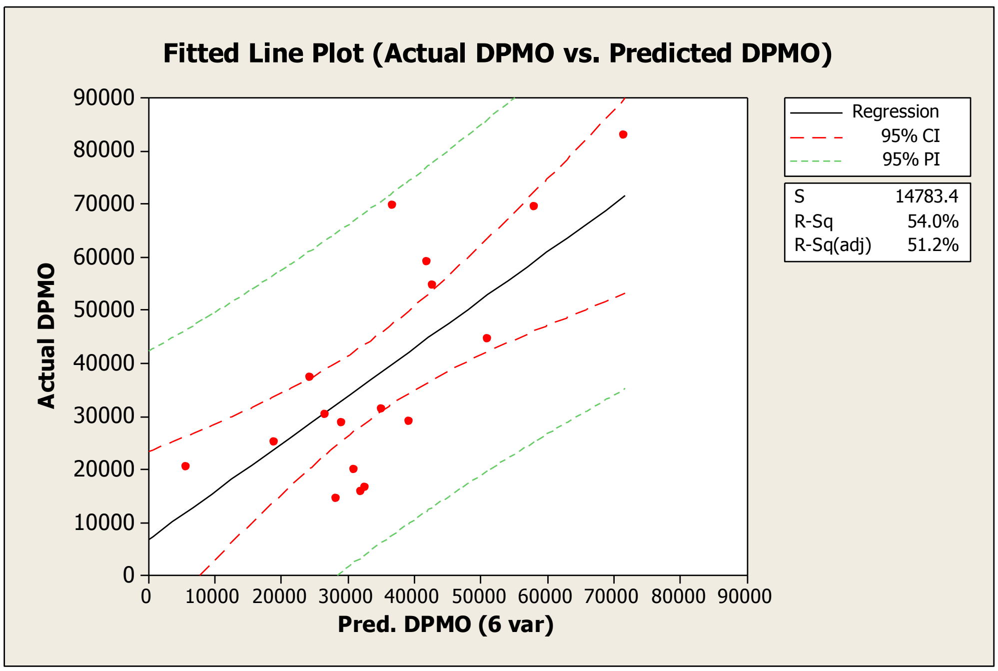


Figure 5.53: Validation on 18 processes at independent plant (Iteration 1)

b) Validation using model from Iteration 2 with 16 variables:

The linear fitted line plot shows the predicted DPMO vs. actual DPMO with a R^2 value of 85.1% and R^2 (adj.) value of 84.2%. There are no outliers outside the 95% prediction interval line shown in the plot (Figure 5.54). This model with 16 variables shows a significant improvement as compared to the model in iteration 1 with 6 variables.

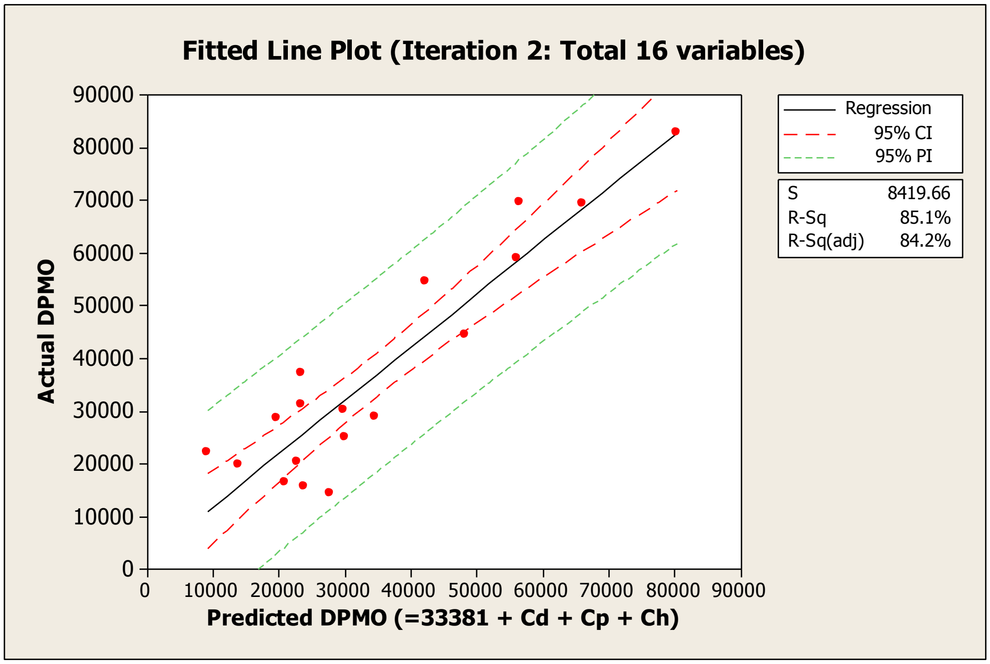


Figure 5.54: Validation on 18 processes at independent plant (Iteration 2)

c) Validation using model from Iteration 3 with 24 variables:

The fitted line plot shows the predicted DPMO vs. actual DPMO with a R^2 value of 93.7% and R^2 (adj.) value of 93.3%. There is one outlier outside the green 95% prediction interval line shown in the plot (Figure 5.55).

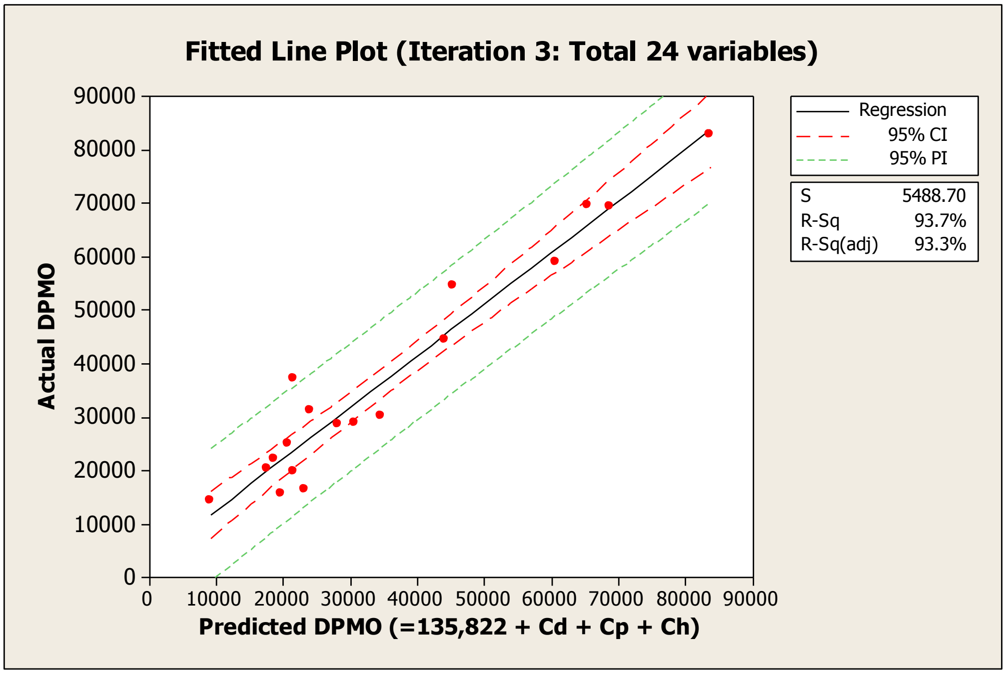


Figure 5.55: Validation on 18 processes at independent plant (Iteration 3)

The histogram shows one potential outlier in the data (Figure 5.56). The normal probability plot shows a linear pattern, consistent with a normal distribution, again with the same outlier highlighted above (Figure 5.57). The plot of residual versus fitted values shows a random pattern, which suggests that the residuals have constant variance (Figure 5.58). Also, the residual versus order plot shows the order in which the data was collected. It does not display a pattern which means there is no evidence of non-random error (Figure 5.59).

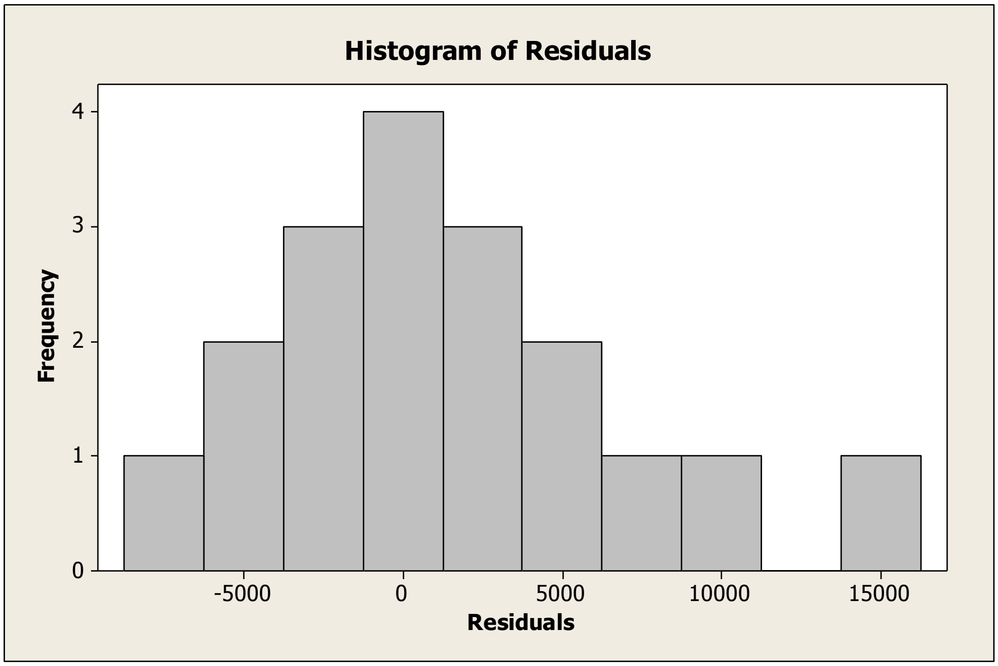


Figure 5.56: Histogram of residuals (Source: 18 fastening processes)

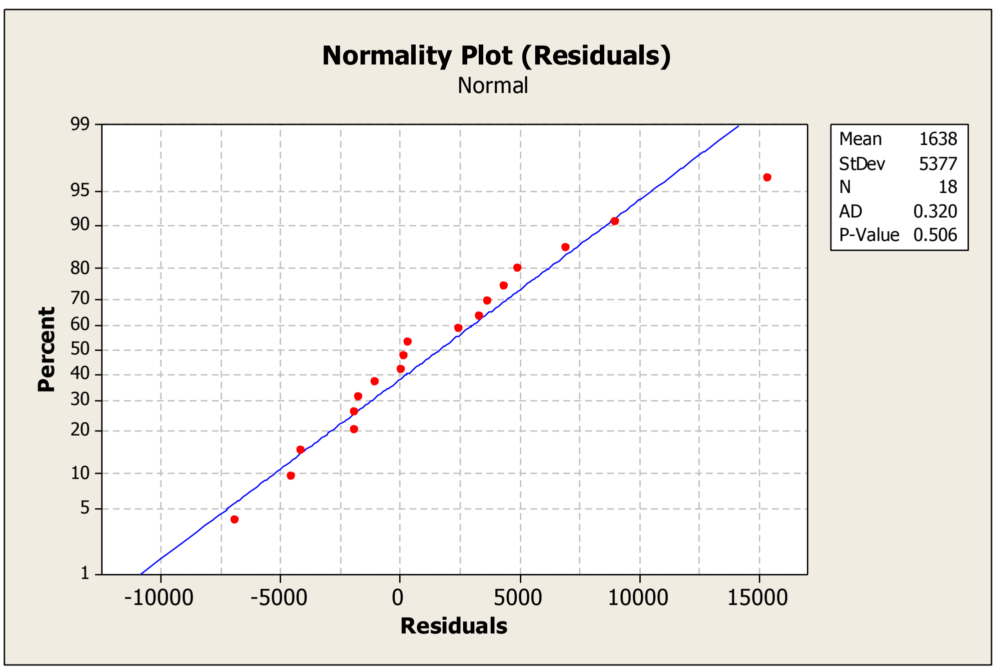


Figure 5.57: Normal probability plot of residual values (p-value = 0.506)

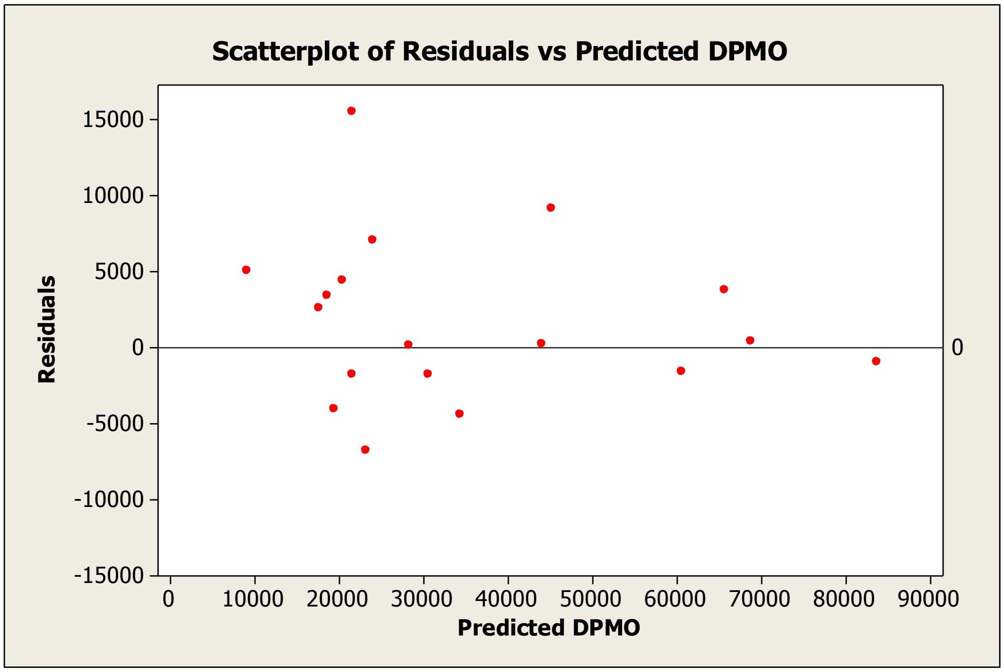


Figure 5.58: Scatter plot of residuals vs. predictor DPMO

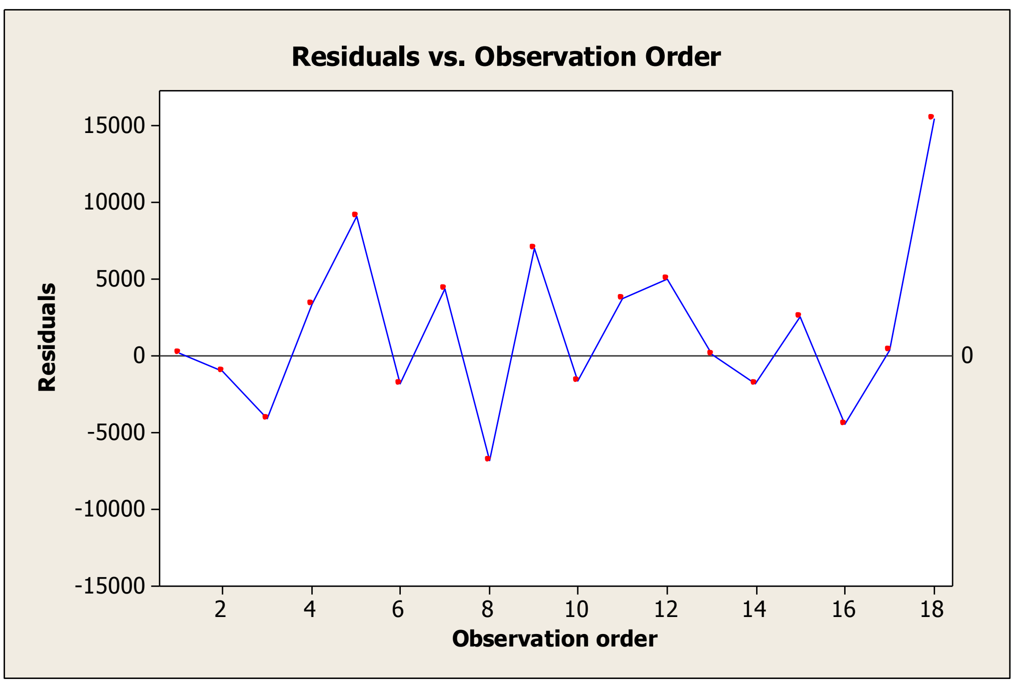


Figure 5.59: Residuals vs. Observation Order plot

In summary, the model with 16 variables generated a R^2 value of 84.2% (iteration 2) and the model with 24 variables generated a slightly higher R^2 value of 93.3% (iteration 3). Both models were validated successfully at an independent plant that used mechanical fastening processes for mixed-model automotive assembly.

5.5. Limitations in application of the Hinckley Model to the pilot process

Based on defect data of semiconductor products, Hinckley found that defect per unit (DPU) was positively correlated with total assembly time and negatively correlated with number of assembly operations [37]. He defined the assembly complexity factor (C_f) as follows:

$$
\begin{aligned}
&C_f = TAT - t_0 \times TOP \\
&\text{where,} \\
&TAT = \text{Total assembly time for the entire product} \\
&TOP = \text{Total number of assembly operations} \\
&t_0 = \text{Threshold assembly time}
\end{aligned}
\tag{2.54}
$$

In order to calibrate the correlations between these parameters, Hinckley incorporated the threshold assembly time (t_0) which was defined as the time required to perform the simplest assembly operation. With this complexity index, Hinckley found that when plotting on a log-log scale, the complexity and the corresponding defect rate showed a positive linear correlation with each other, as in the following two equivalent equations:

$$
\begin{aligned}
&\log DPU = k \times \log C_f - \log C \\
&DPU = \frac{\left(C_f\right)^k}{C}
\end{aligned}
\tag{2.55}
$$

where, C and k are constants.

One of the drawbacks of the Hinckley model is that the predicted quality is for an entire product. This would enable comparison of complexity and product quality across multiple entire products. A hypothetical application of the Hinckley Model to two different vehicles with different total assembly times has been shown in Table 5.6. Model A requires 26.2 hours for complete assembly and model B requires 24.1 hours for complete assembly. In Table 5.6, *TOP* refers to Total number of operations, *TAT* is the total assembly time in hours and in seconds, t_0 is the threshold time, and C_{fpi} is the complexity factor.

Table 5.6: Application of the Hinckley Model to automotive assembly

Ref.	*TOP* (#)	Takt Time (s)	*TAT* (hr)	*TAT* (s)	t_0 (s)	C_{fpi} (#)	log (C_{fpi})	Actual DPU	log (DPU)
Model A	13,920	100	26.2	94,320	4	38,640	4.59	1.2	0.079
Model B	11,620	120	24.1	86,760	4	40,280	4.61	0.7	-0.155

An example of the complexity calculation has been shown below for Model A:

$$\begin{aligned} C_{fpi} &= TAT - t_o \times TOP \\ C_{fpi} &= (93,600) - (4 \times 10,000) \\ C_{fpi} &= 53,600 \end{aligned} \tag{2.56}$$

According to Hinckley, there is a linear correlation between log(C_{fpi}) and log(DPU), where DPU stands for Defects per Unit. However, as shown in Table 5.6, actual DPU for Model B is 0.7 and that for Model A is 1.2. That is inversely proportional to the complexity factor that has been calculated for these two models. A modified version of this model can be applied at a process level, where the time is associated with a certain process instead of the entire product assembly and the defect rate is associated with the defects caused by a particular process. That is what Shibata has shown in his research. Validation using the Shibata model will be covered in the next section.

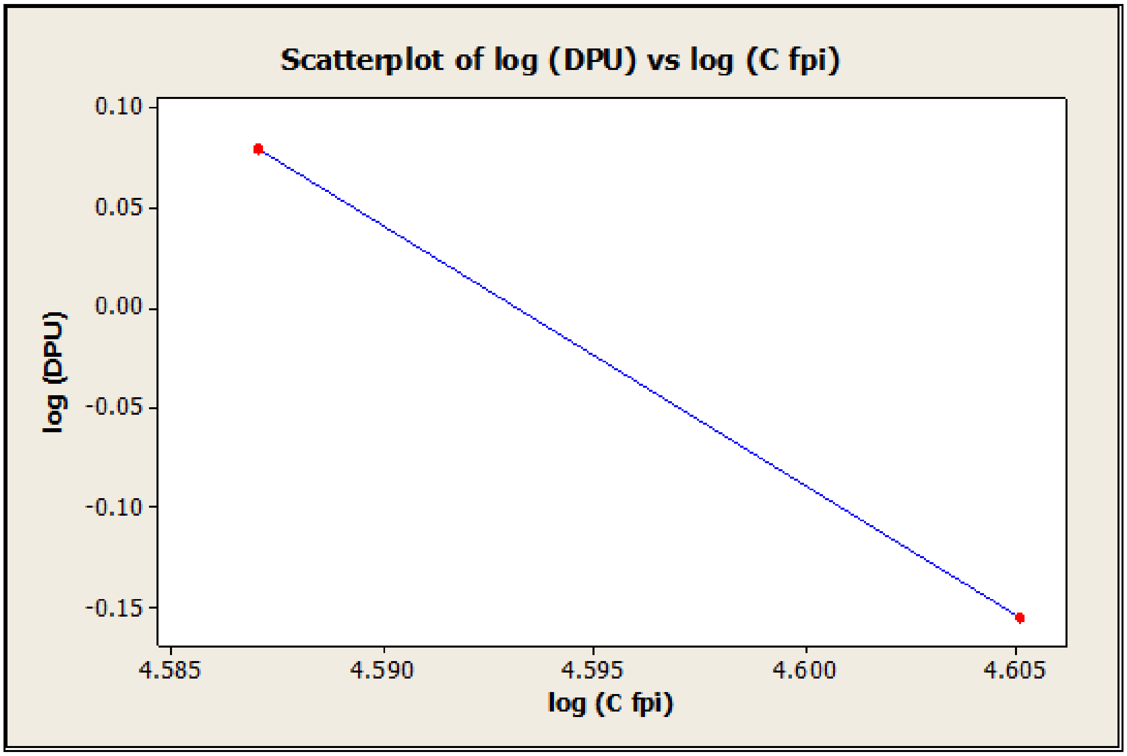


Figure 5.60: Hinckley model applied to vehicle assembly

5.6. Limitations in application of the Shibata Model to the pilot process

Shibata [38] remarked that the Hinckley model did not take the assembly design factors into consideration and could not evaluate the defect rate for a specific workstation. Therefore, Shibata proposed a prediction model for a workstation based on two assembly complexity factors: the process-based complexity factor and the design-based complexity factor. Assembly time was determined by Sony Standard Time (*SST*), a commonly used time estimation tool for electronic products. Shibata used home audio products, a combination of CD player and a MiniDisc recorder/player as assembly cases.

These had approximately 300 job elements and the total time was approximately 10 minutes.

The process-based complexity factor of workstation i is defined as:

$$Cf_{Pi} = \sum_{j=1}^{N_{ai}} SST_{ij} - t_0 . N_{ai} \tag{2.57}$$

where,

N_{ai}=number of job elements in workstation i;

SST_{ij} = time spent on job element j in workstation i;

t_0 = threshold assembly time

Home audio equipment served as a good vehicle for Shibata's analysis because its assembly process contained almost every type of basic assembly operation that is present in consumer electronic products.

Similar to the Hinckley Model, Shibata derived the following correlation between the process-based assembly complexity factor and DPU:

$$\log \mathrm{DPU}_i = K . \log Cf_{Pi} - \log C \tag{2.58}$$

$$\mathrm{DPU}_i = \frac{(Cf_{Pi})^K}{C} \tag{2.59}$$

where C and K are constants.

We apply the Shibata model to the mechanical fastening process to understand the applicability and gaps, if any. Data for 18 processes from the independent validation plant is used for this experiment.

Table 5.7: Application of Shibata model to mechanical fastening processes

									SHIBATA MODEL		
Ref.	No of tasks in takt (N_{ai})	Takt Utilization %	Opportunities per car	Actual DPMO	Actual DPU	Takt Time (s)	Sum of time spent in takt (s)	t_0 (s)	C_{fpi}	log (C_{fpi})	log (Actual DPU)
1	16	94.9%	4	44,380	0.18	120	113.9	3	65.9	1.82	-0.75
2	17	66.1%	1	82,799	0.08	120	79.3	3	28.3	1.45	-1.08
3	17	93.6%	1	15,459	0.02	120	112.3	3	61.3	1.79	-1.81
4	17	93.6%	1	22,007	0.02	120	112.3	3	61.3	1.79	-1.66
5	11	87.7%	4	54,350	0.22	120	105.2	3	72.2	1.86	-0.66
6	19	86.7%	5	19,831	0.10	120	104.1	3	47.1	1.67	-1.00
7	25	99.9%	3	24,947	0.07	120	119.8	3	44.8	1.65	-1.13
8	11	95.9%	3	16,465	0.05	120	115.0	3	82.0	1.91	-1.31
9	11	95.9%	3	31,045	0.09	120	115.0	3	82.0	1.91	-1.03
10	17	92.9%	1	58,953	0.06	120	111.4	3	60.4	1.78	-1.23
11	17	92.0%	1	69,390	0.07	120	110.4	3	59.4	1.77	-1.16
12	21	89.7%	5	14,175	0.07	120	107.7	3	44.7	1.65	-1.15
13	18	86.9%	5	28,430	0.14	120	104.3	3	50.3	1.70	-0.85
14	21	95.9%	5	28,834	0.14	120	115.1	3	52.1	1.72	-0.84
15	16	80.6%	1	20,190	0.02	120	96.7	3	48.7	1.69	-1.69
16	15	99.2%	1	30,009	0.03	120	119.0	3	74.0	1.87	-1.52
17	15	99.2%	1	69,314	0.07	120	119.0	3	74.0	1.87	-1.16
18	10	87.7%	4	37,002	0.15	120	105.3	3	75.3	1.88	-0.83

The complexity factor was calculated per the Shibata model. For example, C_{fpi} for process number 1 is calculated as follows:

$$\begin{aligned} C_{fpi} &= \sum_{j=1}^{N_{ai}} SST_{ij} - t_0.N_{ai} \\ C_{fpi} &= (113.9) - (3 \times 16) \\ C_{fpi} &= 65.9 \end{aligned} \tag{2.60}$$

As shown in Figure 5.61, the linear model is unable to explain the variation in the resulting variable (DPMO). Figure 5.62, shows a cubic relationship and that model has a negligible R^2 value as well. Similarly, a quadratic relationship also produced a negligible R^2 value. This shows that although the Shibata model was developed based on data from several factories where Sony products were built, the model seems to have limited application to small electronic products such as a MiniDisk Player [37, 38]. The electronics assembly processes are by no means considered low on the complexity scale but perhaps the repeatable tasks such as soldering components on printed circuit boards present a unique set of processes to which this model can be applied and quality can be reliably predicted.

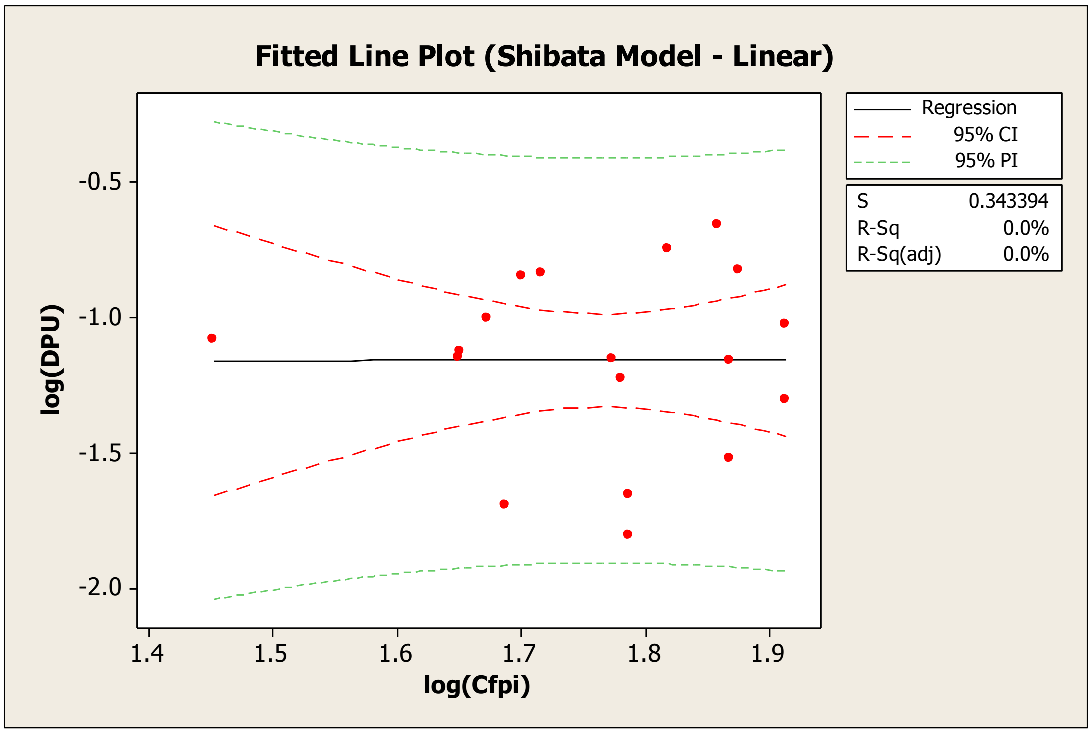


Figure 5.61: Fitted Line Plot – Shibata Model (linear)

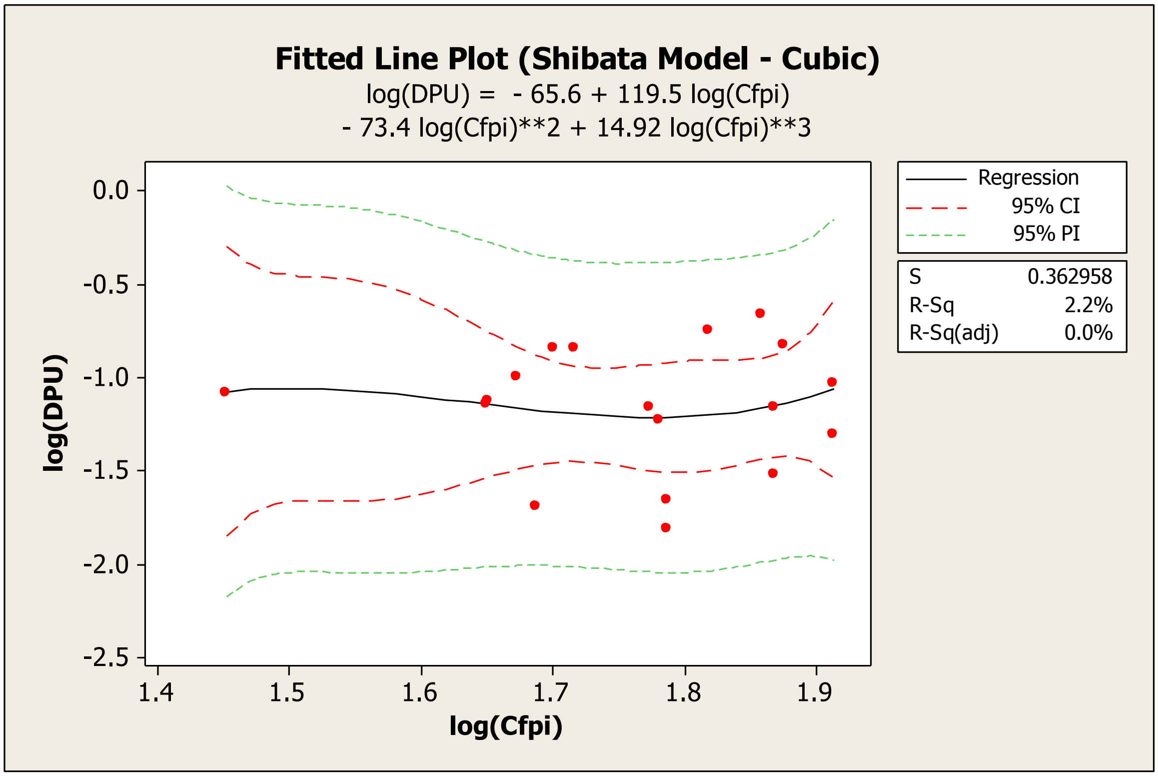


Figure 5.62: Fitted Line Plot - Shibata Model (Cubic)

In published literature [37], we also found a case-study in which Su, Liu, and Whitney applied the Shibata model to a Fuji photocopier and found R^2 values ranging from 0.153 to 0.169 (15.3% to 16.9%). It was found that the Sony Standard Time (SST) database was not suitable for analyzing the copier production. For instance, the threshold time t_0 is 2 seconds in SST while the shortest adjustment action can be completed in 0.6 seconds in the case of the copier assembly. They also concluded that, "the evaluation method of the assembly complexity factors should be redesigned to better match the characteristics of a copier."

In our study, we also came across an interesting situation that contradicts the findings from Shibata model. We added a fixture to a fastening operation. Using the new fixture increased the total time. The takt utilization in case 5 [Table 5.7], went up from 87.7% to 93.3%. This increased the C_{fpi} value from 72.2 to 79. This should have increased the defect rate. However, the fixture improved the repeatability of the process and thus reduced the assembly time variation. This finding prompted us to include Assembly Time Variation as one of the input variables in our complexity model.

5.7. Comparison with proposed Complexity Model

Based on literature review and the gap analysis based on application of existing models, we defined complexity from a broader view point and included design variables, process variables, and human-factors. Details of each input variable and the final model have been described in section 5.4.8. Comparison of the proposed complexity model (current research) with the complexity factors calculated using the Shibata Model is shown in Table 5.9.

Linear, quadratic, and cubic regression models were applied to the data and following R^2 values were obtained:

Table 5.8: Summary of R-Sq. values using various regression models

Regression Model	R^2	R^2 (adj)
Linear	91.9%	91.4%
Quadratic	92.0%	90.9%
Cubic	92.0%	90.3%

Based on this data, we choose the linear regression model. The fitted line plot is shown in Figure 5.63.

Table 5.9: Application of Shibata model and Antani Model (current research)

						SHIBATA MODEL			ANTANI MODEL		
No	No of tasks in takt (TOP)	Takt Utilization %	Opportunities per car	Actual DPMO	Actual DPU	C_{fpi}	log (C_{fpi})	log (Actual DPU)	Predicted DPMO	Predicted DPU	log(Pred. DPU)
1	16	94.9%	4	44,380	0.18	65.9	1.82	-0.75	44,172	0.18	-0.8
2	17	66.1%	1	82,799	0.08	28.3	1.45	-1.08	83,789	0.08	-1.1
3	17	93.6%	1	15,459	0.02	61.3	1.79	-1.81	19,525	0.02	-1.7
4	17	93.6%	1	22,007	0.02	61.3	1.79	-1.66	18,611	0.02	-1.7
5	11	87.7%	4	54,350	0.22	72.2	1.86	-0.66	45,276	0.18	-0.7
6	19	86.7%	5	19,831	0.10	47.1	1.67	-1.00	21,686	0.11	-1.0
7	25	99.9%	3	24,947	0.07	44.8	1.65	-1.13	20,561	0.06	-1.2
8	11	95.9%	3	16,465	0.05	82.0	1.91	-1.31	23,317	0.07	-1.2
9	11	95.9%	3	31,045	0.09	82.0	1.91	-1.03	24,045	0.07	-1.1
10	17	92.9%	1	58,953	0.06	60.4	1.78	-1.23	60,624	0.06	-1.2
11	17	92.0%	1	69,390	0.07	59.4	1.77	-1.16	65,678	0.07	-1.2
12	21	89.7%	5	14,175	0.07	44.7	1.65	-1.15	9,208	0.05	-1.3
13	18	86.9%	5	28,430	0.14	50.3	1.70	-0.85	28,326	0.14	-0.8
14	21	95.9%	5	28,834	0.14	52.1	1.72	-0.84	30,650	0.15	-0.8
15	16	80.6%	1	20,190	0.02	48.7	1.69	-1.69	17,654	0.02	-1.8
16	15	99.2%	1	30,009	0.03	74.0	1.87	-1.52	34,488	0.03	-1.5
17	15	99.2%	1	69,314	0.07	74.0	1.87	-1.16	68,916	0.07	-1.2
18	10	87.7%	4	37,002	0.15	75.3	1.88	-0.83	21,558	0.09	-1.1

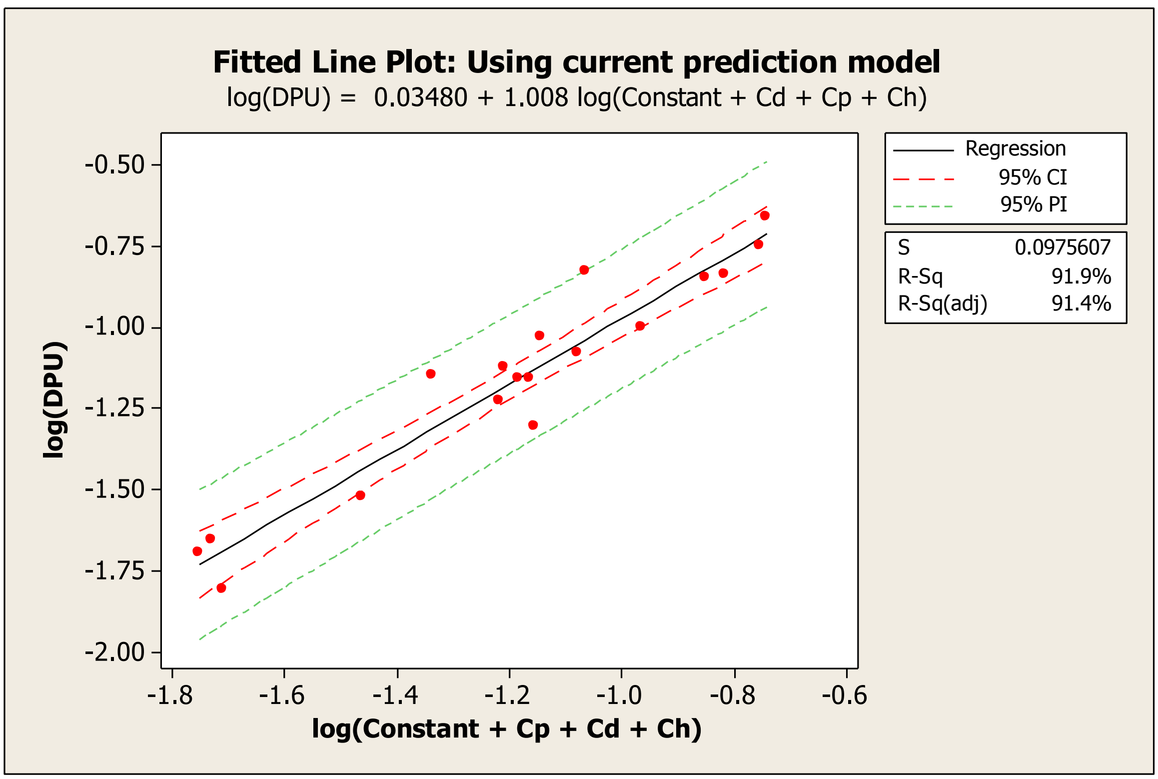


Figure 5.63: Fitted line plot showing application of Antani model

In summary, we tested the hypothesis that manufacturing complexity can predict product quality in mixed-model automotive assembly. The generalized model can be applied to other processes by identifying the relevant input variables under each of the categories listed under design complexity, process complexity, and human-factors driven complexity.

5.8. Error-proofing the process

An important element of process planning is the concept of designing the product and/or process to be error-free by using Poka-Yoke devices. Poka-Yoke is a Japanese word that means mistake-proofing and is a key element of the Toyota Production System.

An error-proofing system is economical if it can do the following:

a) Prevent defects that human beings (operators) would otherwise make due to lack of knowledge, understanding or inadvertence.
b) Provide a solution that would otherwise require significant re-training of many operators.
c) Bypass complex analysis for causes by finding a solution even though the cause of the defects remains a mystery [64].

5.8.1. Methods of error-proofing

Some of the usual forms of error-proofing systems / devices are summarized below:

a) **Fail-Safe Devices:** These devices consist of the one of the following or a combination of the following mechanisms / systems:
    a. **Interlocking sequences:** Mechanical or electrical logic that ensures that operation A is performed and subsequent operation B occurs only if

operation A has been completed. For example, operation B locates based on a hole machined in operation A.

b. **Alarms and cutoffs:** Mechanical or electrical devices that monitor a certain variable and produce an audible alarm when the monitored variable falls outside the specification limits or physically stops a process if programmed as a cutoff device or signal. The alarm would be considered passive as it still requires intervention to stop the process that can potentially cause a defect. A cutoff device or signal would be an active system that can stop the process without additional intervention.

c. **All-clear signal:** A signal of this nature monitors one or more variables and provides an audible, visual, or an electrical signal that allows the next step or process from taking place.

d. **Mistake-proof fixtures:** These are mechanical devices that may or may not be integrated with additional sensors (electronic, hydraulic, pneumatic) that monitor variables such as part features or quality from preceding operations and allow the next steps of the process to continue only if the monitored variables meet the specifications. Fixtures may also have features that prevent the release of a part unless the monitored variable meets the specifications in the process that was carried out in that specific process. Manual intervention would be required to release the part, thereby forcing the operator to recognize that an error has occurred.

e. **Limiting mechanisms:** These devices prevent a monitored variable from exceeding the predetermined specifications. For example, a slipping-torque wrench that prevents over-tightening.

b) **Magnification of senses:** Unlike the fail-safe devices listed above, these types of devices improve or extend the ability of a human operator to respond before an error occurs. For example, remote-control monitoring of a closed chamber to permit viewing despite distance, process temperature, or fumes. Another device in this category would be one that give multiple signals to improve likelihood of recognition and response. An example of such an audiovisual signal would be simultaneous ringing of bells and flashing of lights.

c) **Redundancy:** This consists of additional work performed purely as a quality safeguard. "Layered checks" fall under this category in the automotive assembly industry. Multiple checks are conducted as the vehicle progresses down the assembly line to catch the same problem if it exists.

d) **Audible countdown:** Countdowns are arranged by structuring sensing and information procedures to parallel the operating procedures so that the operational steps are checked against the sensing and informational needs [64]. For example, in a manual welding process that requires 18 spot welds, the tool would provide an audible countdown so that the operator knows clearly when all 18 spot welds are completed.

5.8.2. Error-Proofing Principles

In a classic study, Nakajo and Kume [80] discuss five principles of error-proofing developed from an analysis of about 1000 examples collected from assembly lines. The principles, objective, and an example of each are shown in Table 5.10.

Table 5.10: Error-proofing principles

Principle	Objective	Example
Elimination	Eliminate possibility of error	Redesign process / product
Replacement	Substitute current process with a reliable process	Robotics in welding
Facilitation	Simplify the work	Color coded parts
Detection	Detect error before further processing	Closed loop monitoring and part release
Mitigation	Minimize the effect of error	Utilize fuses for overloaded circuits

5.8.3. Error-Proofing methods in automotive assembly

Various error-proofing methods are used in automotive assembly based on the five principles highlighted above. The most common ones are explained below:

1) **Visual Display:** These are visual monitors that are synchronized with the database that consists of information about option content and the sequence of vehicles on the mixed-model assembly line. When the operator has to select a particular part from a part family of several options, these monitor help the operator see a number that refers to the part that needs to be assembled in the vehicle that is at the operator's station. The monitor can also include a picture Figure 5.64, color coded logo or any other visual identifier that would help the operator distinguish the part to be installed from the others on the storage rack.

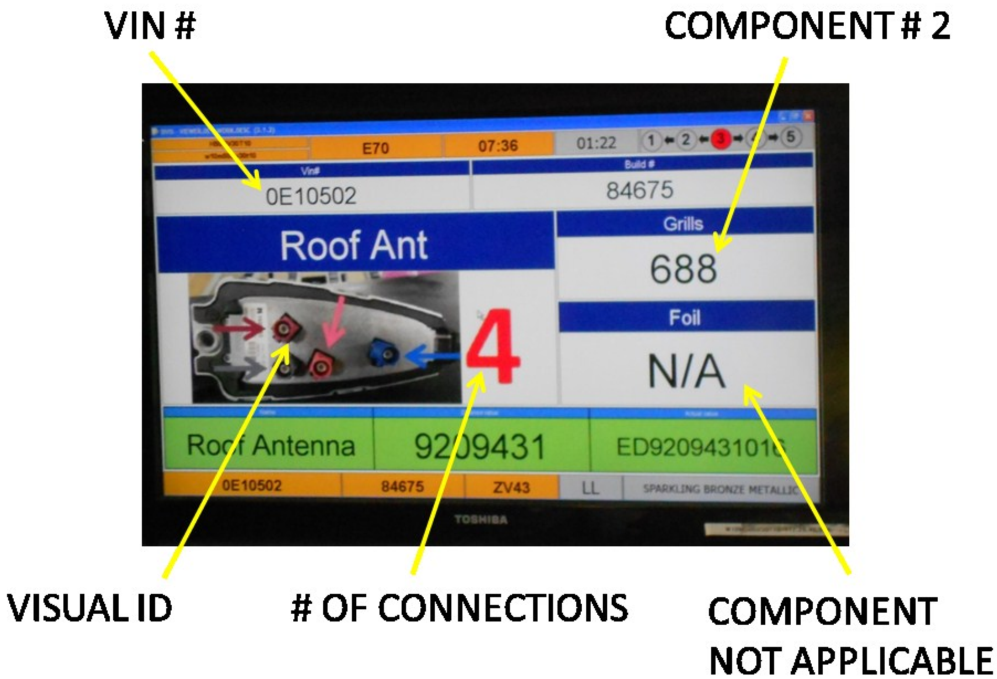


Figure 5.64: Visual display to aid component selection

2) **Audio Device:** An audio device plays a similar role as a visual display by announcing the component name or code of the part that needs to be installed in the vehicle that is at the operator's station. It is also linked to the vehicle sequencing and option content database. In some cases, quality engineers pair the audio device along with the visual display and provide an audio-visual alert to the operator if one of the two is not sufficient to prevent errors.

3) **Pick-to-Light system:** These systems are typically installed on part racks to aid selection of the correct part from a set of bins (part containers). The system is connected to the option content and sequencing database like the audio-visual systems. A light flashes on top of the bins from where the components need to be picked up. A sensor is installed on top of every bin to

sense the operators hand going into the bin. When a part gets picked up, the light stops flashing. When all the lights on the rack stop flashing the operator knows that all the components that needed to be picked up have been removed from the respective bins Figure 5.65. There are several different variants of this basic system.

Figure 5.65: Pick-to-light error-proofing system

4) **Error-proofing fixtures:** As described in the earlier section, fixtures are generally custom built to develop the error-proofing functionality depending on the type of error that needs to be prevented. In this research, we designed and implemented a fixture that reduces tool extension tip play (wobble), thereby reducing variability in the assembly process. A case-study highlighting its application will be described in the next chapter.

5) **Closed-Loop Monitoring:** Specifically in the case of controlled mechanical fastening processes, as described in section 5.3.1, various process parameters are tracked. Variables such as number of fasteners assembled, torque, angle, Vehicle Identification Number (VIN), and time stamp are captured by the monitoring system. When the torque and angle are within specifications, confirmation LEDs on the tool and the visual display screen turn green, in order to provide a clear confirmation to the operator about the status of the assembled fastener. If an error occurs, the operator can attempt the process one more time. If it fails again, the error code stays associated with the vehicle and is displayed at the end of every assembly line, all the way to the end of the final assembly process. Once the fastener is re-worked by the offline operator, the error needs to be cleared manually from the system to allow final shipment of the car from the assembly plant.

5.8.4. Incorporating error-proofing systems into predictive model

Process and Quality Engineers in automotive assembly plants focus on processes that are key drivers of the DPMO metric. Their primary goal is to implement error-proofing devices to eliminate or significantly reduce the potential for error in those processes. In our research, we studied various error-proofing devices and their impact on the predictive model. If the error-proofing device completely eliminates a type of error, then the input variables associated with that error would basically be reduced to zero. We conducted various experiments on real-world processes using the predictive model.

Highlights of these experiments have been covered in the form of case-studies in the following chapter.

In conclusion, this chapter addressed research questions two and three. We developed a generalized model to predict quality based on complexity and applied it to a specific controlled fastening process. We also determined classes of defect prevention devices used in automotive assembly and used the model to lower complexity and improve quality.

CHAPTER SIX

6. CASE STUDIES

6.1. Experimental Setup

In order to truly validate the complexity model, we conducted several experiments to reduce manufacturing complexity. Experiments were done by varying or eliminating the impact of complexity driving input variables offline on a new test and training station. This test and training station was developed specifically for this research project with all the standard equipment used on an assembly line for mechanical fastening.

Figure 6.1: Test Set-up for experimentation and Off-line Training Station

Two case-studies have been shown here to highlight the quality improvements that were made by taking specific steps to reduce complexity driven by design, process, and human-factors. The results shown here have been sustained for over 6 months since the time they were first implemented as a trial run on the final assembly line. A third case-study shows how the model applies to a fully-automated mechanical fastening process where the human-factors do not play a role.

6.2. Case Study 1: Seat Adapter Assembly Process

6.2.1. Overview of the Seat Adapter assembly process

Seat Adapter is a light weight, hard Styrofoam component that is assembled to the body inside the passenger cabin. The leather or cloth seat that passengers physically use gets mounted on top of the Seat Adapter. The tool extension has to be long because it is used to apply torque to multiple fasteners, including ones that are in the middle of the seat and are located in deep sockets inside the Styrofoam Seat Adapter (Figure 6.2).

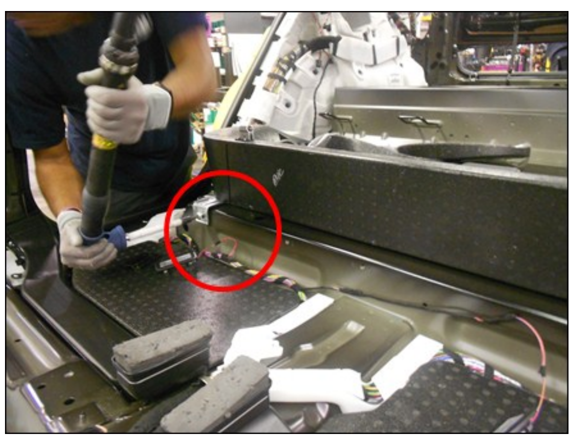


Figure 6.2: Seat Adapter assembly process

6.2.2. Problem Description

By nature of the mechanism inside the fastening tool, the output shaft of the tool vibrates. This vibration is propagated along the length of the extension and results in a significant amount of play (wobble) at the end of the extension that physically contacts the torx profile of the fastener. This tip play prevents the operator from aligning the tool into the head of the fastener promptly and more importantly, results in tool slip-off. This is a condition in which the tool momentarily loses alignment with the fastener and thereby drops torque instantaneously (Figure 6.3).

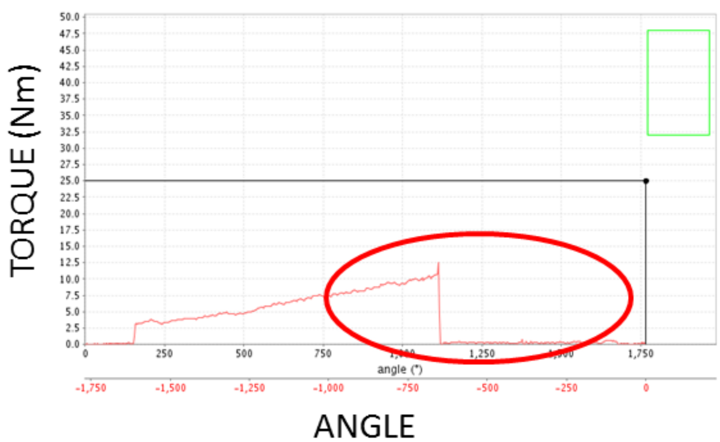


Figure 6.3: Defect caused due to tool slip-off

A diagram showing the total tip play (P_{max}) is representative of the fastening process for the Seat Adapter Figure 6.4.

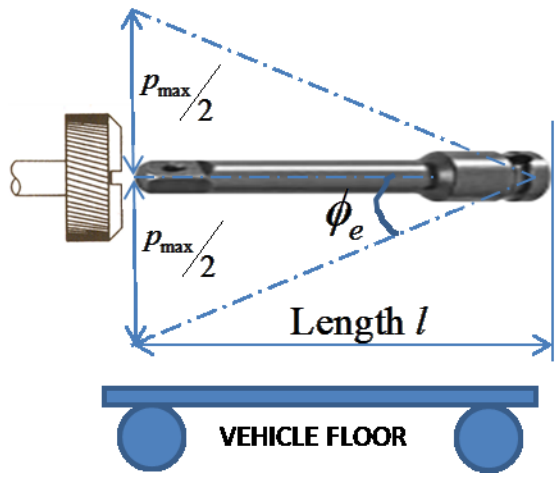


Figure 6.4: Seat Adapter - Tool Tip Play (P_{max})

6.2.3. Complexity and Quality measurement

Total Tip Play is an input variable under the Tooling and Fixture Design category which falls under the process driven complexity. In the complexity model, Total Tip Play is captured in millimeters (mm). The coefficient of Total Tip Play in the equation is 690.1.

Values of key parameters before improvement were as follows:

a. DPMO = 76,320

b. Length of extension and driving bit = 241.3 mm

c. Total Tip Play (P_{max})= 51 mm

d. Contribution of Total Tip Play to DPMO = 690.1(51) = 35,195

6.2.4. Implementation of revised process and results

In order to reduce Total Tip Play (wobble), we designed a supporting sleeve with a needle bearing. This sleeve had a threaded end that would directly fit the threaded end of the tool where the output shaft is located. The other end of the sleeve had a needle bearing that would support the extension. After three iterations, we developed a sleeve in the local machine shop that resulted in a Total Tip Play of 2 mm (a reduction of 49 mm). The operators on the assembly line noticed the difference right away during the trial runs. We validated the new sleeve offline on the training station and then implemented it on the assembly line for 2 working shifts (approximately 650 vehicles x 3 fasteners each).

Values of key parameters after improvement were as follows:

a. Length of extension and driving bit = 241.3 mm (un-changed)

b. Total Tip Play = 2 mm

c. Reduction in Total Tip Play = 51 – 2 = 49 mm

d. Predicted DPMO reduction = 690.1 (49) = 33,815

e. Predicted DPMO = 76,230 – 33,815 = 42,415

f. Actual DPMO = 39,280

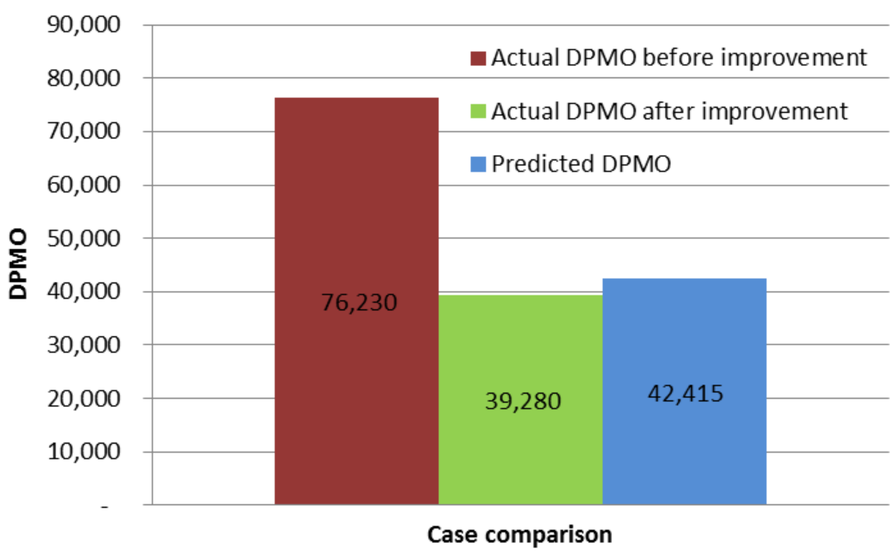


Figure 6.5: Before and After Process Improvement

6.2.5. Summary

This case-study represented a practical implementation of process driven complexity reduction. The resulting reduction of 48% in DPMO was predicted well by the complexity model. The improvement was monitored over a period of 6 months and was successfully sustained.

6.3. Case Study 2: Roof-Rail Assembly Process

6.3.1. Overview of Roof-Rail Assembly Process

Roof-Rails are assembled on top of the roof of a vehicle to hold luggage racks or other specially designed containers (Figure 6.6).

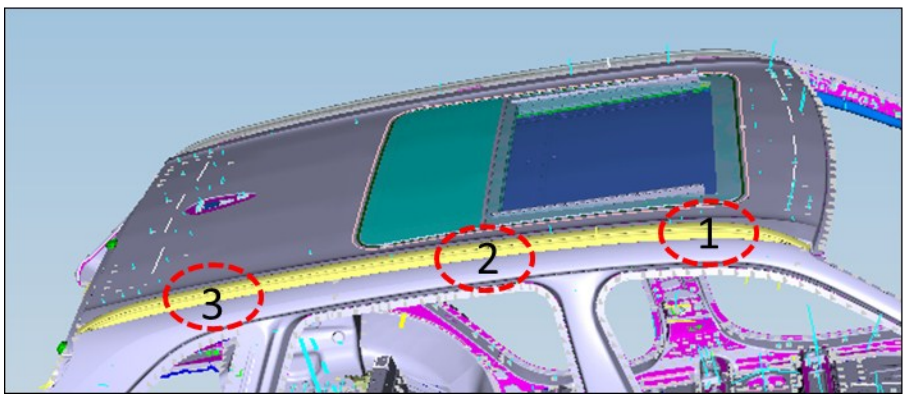


Figure 6.6: Roof-Rail assembly

In our study, each roof-rail was assembled using three fasteners. The roof-rail sub-assembly would arrive from the supplier to the final mixed-model vehicle assembly plant with integrated fasteners. The painted vehicle body has holes in which the roof-rail is placed. One hole near the A-pillar (hole # 1) of the car is the locating hole, therefore it is round in shape. There is another hole past the B-pillar (hole # 2) and the third one is between the C-pillar and the D-pillar (hole # 3). The roof-rail is placed from the top of the roof by an operator in those three holes. Another operator assembles a nut to each fastener from below the roof and secures the roof-rail to the body, using a mechanical fastening process.

6.3.2. Problem definition

In the case of the fastener that is closest to the back of the vehicle (# 3), the fastener visibility is negligible. This is due to the distance between the end of the fastener and point where the fastening nut has to be installed by the operator from under the roof. The inner body panel curves away from the roof line which causes the increased distance resulting in negligible visibility. An actual view of the access hole with a fastener is shown in Figure 6.7.

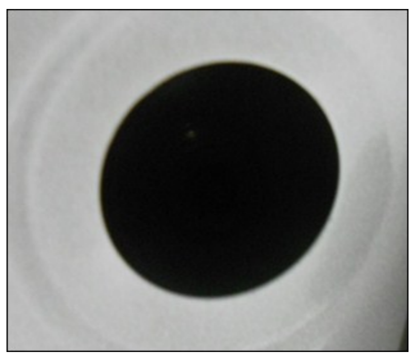


Figure 6.7: Actual view of blind hole

The operator uses a tool with a long extension that has a magnetic socket on which the nut is placed. As the bolt attached to the roof-rail is not visible at all, the operator uses the long extension to estimate the location of the bolt and drive the nut. This increases the potential for cross-threading because the nut may not be aligned with the threads on the bolt. The end result is a torque and angle value that is outside the specification, causing a defect.

6.3.3. Complexity and Quality measurement

Values of key parameters before improvement were as follows:

a. Actual DPMO = 26,210

b. % of fastener invisibility = 100 % (completely blind)

c. Coefficient of fastener visibility variable = 421.6

d. Contribution of lack of fastener visibility to DPMO = 421.6(100) = 42,160

6.3.4. Implementation of revised process and results

In this case the complexity was clearly driven by design factors. Due to limited access in that area of the vehicle, improving lighting would not improve the ability of the operator to improve fastener alignment. Therefore, we pursued this as a fastener design change. In collaboration with the design engineering team, we extended the unthreaded length of the fastener to provide a guidance path for the tool and nut (Figure 6.8).

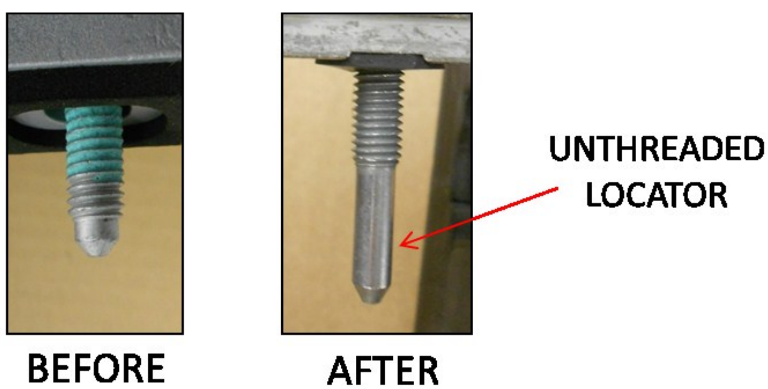


Figure 6.8: Fastener design - Before and After Improvement

We conducted trial runs with longer fasteners and found that the location ability and repeatability significantly increased. Therefore, based on feedback from the operators, we requested the design change.

Values of key parameters after improvement were as follows (Figure 6.9):

a. % of fastener invisibility = 50 % (reduced from 100%)

b. Coefficient of fastener visibility variable = 421.6 (unchanged)

c. Predicted DPMO reduction = 421.6(50) = 21,080

d. Predicted DPMO = 26,210 – 21,080 = 5,130

e. Actual DPMO reduction = 26,210 – 6,570 = 19,640

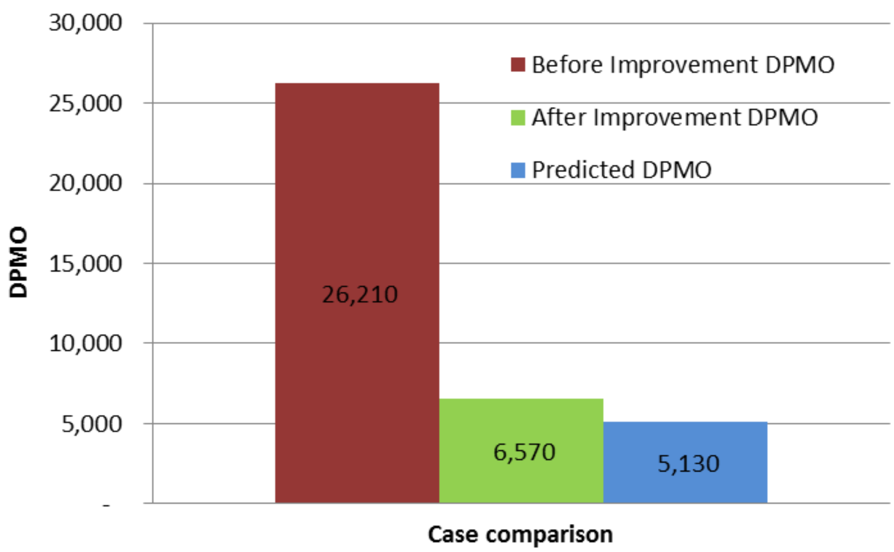


Figure 6.9: Before and After design improvement

6.3.5. Summary

This case-study represented a practical implementation of design driven complexity reduction. The resulting reduction of 74% in DPMO was predicted well by the complexity model. The improvement was monitored over a period of 11 months and was successfully sustained.

6.4. Case Study 3: Fully automated mechanical fastening process

The complexity model in our research is based on design, process, and human-factors. In a fully automated mechanical fastening process executed by a robot, there would not be any human intervention unless there is a maintenance issue. This case-study highlights how the current model applies to a fully automated process if we eliminate the ergonomic factors which clearly do not apply.

6.4.1. Overview of automated mechanical fastening process

In the automotive assembly world, process of assembling the powertrain and chassis to the body is called "marriage." The powertrain and axles are placed on a special conveying device which has locators to align it to the body. The body is gradually lowered on the powertrain and the conical locators help align the critical points to ensure alignment per the required specifications.

Figure 6.10: Fully automated mechanical fastening (powertrain & body)

Once aligned, automated tools assemble 10 critical fasteners on the new assembly to secure it before allowing it to move to the next station. For our analysis, we choose one sample process in which an automated tool assembles the fastener from the underside of the body.

6.4.2. Complexity and Quality measurement

We collected all the input variables that we use for the general model (design and process), with the only exception being ergonomic factors which do not apply to this process.

The only factor that does apply from the human-factors driven complexity is the probability of choosing a correct fastener. That value would be 100% as the automated tool does not have to choose from multiple different varieties of fasteners.

Based on this information, complexity driven by human-factors is calculated as:

C_h = 0 (Ergonomic variables) – 666.7(H_{cl_pro})

Where,

C_h is the complexity driven by human-factors

H_{cl_pro} = Probability of choosing the correct fastener

Coefficient related to H_{cl_pro} = -666.7

This results in the following predicted value:

$$\begin{aligned}&\text{Predicted DPMO} = \text{Constant} + C_d + C_p - 666.7\left(H_{cl\_pro}\right)\\&= 135{,}822 - 81245 + 20348 - 666.7\left(100\right)\\&= 8{,}255\end{aligned} \tag{2.61}$$

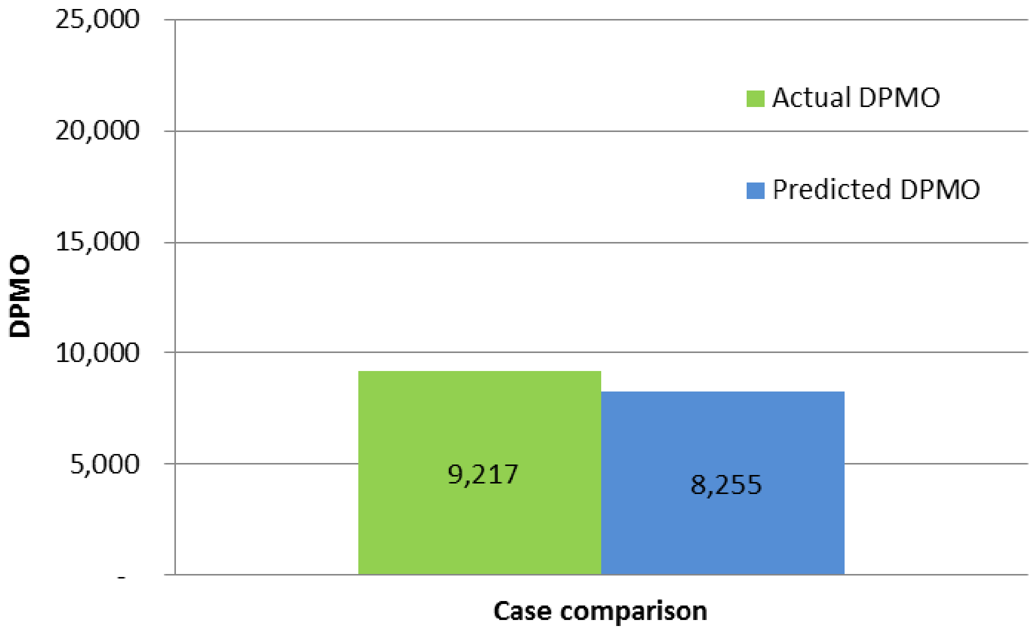


Figure 6.11: Actual vs. Predicted DPMO (Fully Automated Process)

6.4.3. Summary

This case-study represented a practical application of the complexity model to a process that was different than the other mechanical fastening processes that were studied. This process was fully automated; therefore the ergonomic factors did not apply to prediction of DPMO using the complexity model. The predicted DPMO value was 8,255 versus an actual historical average DPMO value of 9,217. The difference is statistically negligible and therefore it validates the robustness of the complexity model from the application standpoint.

CHAPTER SEVEN

7. CONCLUSIONS AND FUTURE WORK

7.1. Summary and Conclusions

In this research we successfully tested the hypothesis that manufacturing complexity can reliably predict product quality in mixed-model automotive assembly. We proposed a measure of manufacturing complexity that incorporates variables driven by design, process, and human-factors. In this research, we used controlled mechanical fastening as a pilot process to demonstrate that manufacturing complexity can reliably predict product quality in a real-world automotive assembly plant and validated the mathematical model in an independent assembly plant.

7.1.1. Intellectual Merit

To the best of our knowledge, based on extensive literature review, this is the first attempt at defining manufacturing complexity using variables driven by design, process, and human-factors as one comprehensive measure and correlating it to product quality in a real-world mixed-model assembly system.

The significance of this research includes:

a) Mathematical models that reveal the mechanisms that contribute to manufacturing complexity in mixed-model assembly systems
b) Assembly time variance as a new measure of complexity versus previous attempts of considering assembly time and number of assembly operations in a product as key indicators of product quality

c) Application to a real-world process in mixed-model assembly and a research framework to apply it to another process efficiently
d) Identified a new set of quality driven precedence constraints that will enable robust assembly line balancing
e) Framework for managing complexity during the design phase for new products as well as continuous improvement phase in the case of mature products

7.1.2. Broader Impact

The predictive model has the potential to be utilized by design and process engineers to evaluate the effect of product, process, and human factors on product quality before implementing the process in a real-world assembly environment. The methodology used in this research can potentially help develop a new set of constraints for an optimization model that can be used to minimize manufacturing complexity or maximize product quality, while satisfying the precedence constraints.

7.2. Future Research

Future research opportunities include the following:

a) Validation of the complexity model and predictive ability by applying this framework to electrical defects in mixed-model assembly. Electrical defects are second in line after mechanical fastening based on historical analysis of defects over one year of production at an assembly plant based in the United States.
b) Although we have shown successful application of this model to fully-automated mechanical fastening in case-study # 3 (Section 6.4), validating this model across

a statistically large sample of fully-automated processes could lead to interesting outcomes.

c) Test the hypothesis that Assembly Line Balancing with manufacturing complexity reduction as an objective function results in improved product quality

d) Application of axiomatic design principles to minimize complexity in mixed-model automotive assembly

7.3. Tools Developed as Part of Research Project

The following tools were developed / built as part of this research work:

a) Mechanical Tools:

   i. Training station with closed-loop Atlas Copco torque and angle monitoring system.

   ii. Fixture for the training station to test repeatability of a proposed process change before implementing it on the assembly line

   iii. Sleeve with needle bearing to reduce tip play of the tool extension as shown in case-study # 1 (section 6.2)

b) Software Tools:

   i. VBA based tool to efficiently pre-process defect data for individual processes from 12 months of historical data

   ii. VBA based tool to link defect time stamp with operator / station sign-in data to identify operator experience level

The mechanical tools that were developed as part of this research are currently being used by the sponsoring automotive assembly plant where this research was conducted.

The software tools will be converted to include a user-friendly user interface and transferred to the IT department at the sponsoring assembly plant for future use.

7.4. List of Publications

i. **Book Chapters:**

- *Antani, K.,* "Advances in Mixed-Model Assembly," in Lean Engineering, *Black, J T., Phillips, D.,* (Ed.), (ISBN: 978-1621373438) (2013)

ii. **Journal Publications:**

- *Antani, K., Mears, L., Funk, K., Kurz, M., Mayorga, M.,* 2013, "Manual Precedence Mapping and Application of a Novel Precedence Relationship Learning Technique to Real-World Automotive Assembly Line Balancing," (*J. Manuf. Sci. Eng.* – Submitted)

iii. **Peer Reviewed Conference Proceedings:**

- *Antani, K., Pearce, B., Mears, L., K., Kurz, M., Schulte, J.,* 2014, "Application of System Learning for Precedence Graph Generation for Assembly Line Balancing," Proceedings of the ASME 2014 Intl. Mfg. Science and Eng. Conference, Detroit, Michigan, 2014-3906 (accepted)
- *Antani, K., Mears, L., Funk, K., Kurz, M., Mayorga, M.,* 2013, "Manual Precedence Mapping and Application of a Novel Precedence Relationship Learning Technique to Real-World Automotive Assembly Line Balancing," Proceedings of the ASME 2013 Intl. Mfg. Science and Eng. Conference, Wisconsin, 2013-1235

- *Antani, K., Mears, L., Funk, K., Kurz, M., Mayorga, M.,* 2012, “Robust Work Planning and Development of a Decision Support System for Work Distribution on a Mixed-Model Automotive Assembly Line,” Proceedings of the ASME 2012 Intl. Mfg. Science and Eng. Conference, Indiana, 2012-7350
- *Antani, K., Black J T.,* 1999, “Machinability of Gray and Ductile Irons (An Orthogonal Approach of Experimentation),” SAE Technical Paper, 1999-01-3378
- *Antani, K., Black J T.*, 1999, “Cellular Manufacturing Insights in Lean Production Systems,” SAE Technical Paper, 1999-01-3380

iv. **Planned Journal Publications (2014-15):**

- *Antani, K., Mears, L., Kurfess, T., Kurz, M., Mayorga, M., Schulte, J.,* 2014, “Effect of manufacturing complexity on product quality in mixed-model automotive assembly,” (*J. Manuf. Sci. Eng.*- Submission target May, 2014)
- *Antani, K., Mears, L., Salandro, W., Schulte, J.,* 2014, “Complexity based predictive model for assembly of electrical components in powertrain assembly,” (*SAE Intl. J. of Matl. and Mfg.*- Submission target Dec, 2014)
- *Antani, K., Pearce, B., Mears, L., Kurz, M., Schulte, J.,* 2014, “Assembly line balancing to minimize manufacturing complexity and maximize product quality,” (*J. Manuf. Sci. Eng.* – Submission target Dec, 2014)

- *Antani, K., Mears, L., Brooks, J., Schulte, J.,* 2015, “Human-factors driven process improvements in high-option powertrain assembly,” (*SAE J. of Matl. and Mfg.* – Submission target Mar, 2015)
- *Antani, K., Mears, L., Schulte, J.,* 2014, “Application of axiomatic design principles to minimize complexity in mixed-model automotive assembly,” (*J. Manuf. Sci. Eng.* – Submission target Jul, 2015)

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