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Statistical modeling of defect propensity in manual assembly as applied to automotive electrical connectors

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Abstract

Assembly represents a significant fraction of overall manufacturing time and total manufacturing cost in the automotive industry. With increasing product complexity and variety, humans remain a cost effective solution to meet the needs of flexible manufacturing systems. This element necessitates a better understanding of the human role in manufacturing complexity. Presented herein is a framework for enumerating assembly variables correlated with the potential for quality defects, presented in the design, process, and human factors domain. A case study is offered that illustrates a method to identify variables and their effect on assembly quality for a manual assembly process.

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1. Introduction

Automotive manufacturing industries comprise many diverse and critical processes that have continually become more complex due to decreasing product life cycles and increased demand for quality and product variety. Assembly, which is a significant portion of automotive manufacturing, is a crucial part of the automotive production process and greatly contributes to the cost and quality of the final product. Using the BMW 7 Series as an example, the projected number of variants of this single product line is 10^{17} [1]. The increased complexity and variety of modern assembly lines and vehicles has created new avenues for the introduction of assembly defects but has also left many opportunities for constant improvement and rapid progress.

Assembly activities are very costly and time intensive, on average accounting for 40% of product cost and up to 50% of total manufacturing cost [2, 3]. With such a large impact on the cost of a product it is easily seen how important reducing defects is to the success of an assembled product. This is especially true in automotive assembly where single defects can result in the loss of thousands of dollars through rework or the scrapping of entire vehicles and with frequently changing products, the potential for costly defects is rapidly increasing.

In the automotive market, manufacturer quality is a key factor in a customer's vehicle purchasing decision in part due to there being many alternatives for them to choose from. During the purchasing decision, a customer will typically research the defect rates of vehicles to aid in their decision. One source of defect data that is used is J.D. Powers, who measure the number of defects per 100 vehicles. Integrity of electrical connectors, fit and finish of body panels, and paint quality are some of their most emphasized defect categories. Having easily accessible defect data available to consumers has forced automotive manufacturers to increase their internal quality initiatives and adopt new practices in the mitigation of assembly defects. This is especially true in manual assembly where Vineyard [5], Shibata [6], and Su et al. [7] found that up to 40% of total defects resulted from operator error and that these defects are not always obvious.

Research into defining strategies for characterizing assembly complexity has shown a strong relationship with final product quality. The following is a brief review of these models and results.

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Nomenclature

a	Constant
b	Constant
C	Constant
C_d	Coefficient of design complexity
C_h	Coefficient of human factors complexity
C_p	Coefficient of process complexity
D_{ac}	Component design variable
D_{ad}	Assembly design variable
D_{fd}	Feature design variable
D_i	Ease of assembly of workstation i
D_{mc}	Material design variable
H_0	Null hypothesis
H_1	Alternative hypothesis
H_{cl}	Cognitive load variable (probability of choosing correct part)
H_{ef}	Ergonomics variable
H_{tr}	Training/Experience variable
H_{we}	Work environment variable
K	Constant
k_0	Empirical process constant
$k_{1,2,3}$	Empirical constants
K_D	Arbitrary coefficient for calibration with process based complexity
N_{ai}	Number of job elements in workstation i
P_{as}	Assembly sequence variable
P_{nt}	Number of tasks in takt variable
P_{tf}	Tooling/Fixture design variable
P_{tu}	Assembly takt utilization variable
P_{vt}	Assembly time variation variable
SST_{ij}	Time spent on job element j in workstation i
t_0	Threshold assembly time
TAT	Total assembly time for the entire product
TOP	Total number of assembly operations
$\alpha_{1\ldots n}$	Empirical constants
$\beta_{1\ldots n}$	Empirical constants
$\gamma_{1\ldots n}$	Empirical constants
μ_{s-}	Average of the low (-)
μ_{s+}	Average of the high (+)

2. Literature Review

2.1. The Hinckley Model

Hinckley [8], who based his data on semiconductors for home audio products, found that defect per unit (DPU) was positively correlated with total assembly time and negatively correlated with the number of assembly operations. He defined an assembly complexity factor as:

$$C_f = TAT - t_0 \times TOP \quad (1)$$

The threshold assembly time was included in order to calibrate the relationship between the total assembly time and the total number of assembly operations. The threshold assembly time was defined as the time required to perform the simplest assembly operations. Hinckley showed that the complexity factor and defect rate showed a positive linear correlation on a log-log scale or:

$$\log DPU = k \times \log C_f - \log C \quad (2)$$

$$DPU = \frac{(C_f)^k}{C} \quad (3)$$

2.2. Shibata Model

Shibata [6] studied the Hinckley model with the assembly of Sony's compact disc players and found that the Hinckley model did not consider assembly design factors nor could it evaluate a specific workstation in an overall assembly line. He proposed that a prediction model centered on process and design based complexity at the workstation level could improve on the earlier work. Shibata also used Sony standard time, which is a well-known estimation of the standard processing time for electronics, to determine assembly time. Similar to the Hinckley model, the process based complexity factor (Cf_{Pi}) was defined as:

$$Cf_{Pi} = \sum_{j=1}^{N_{ai}} SST_{ij} - t_0 \times N_{ai} \quad (4)$$

Shibata then described a similar correlation between the process based complexity factor and DPU (5) on a log-log scale:

$$\log DPU_i = K \times \log Cf_{Pi} - \log C \quad (5)$$

$$DPU_i = \frac{(Cf_{Pi})^K}{C} \quad (6)$$

Shibata defined a design based complexity factor (7) and then correlated it and DPU (8-9) on a log-log scale:

$$Cf_{Di} = \frac{K_D}{D_i} \quad (7)$$

$$\log DPU_i = b \times \log Cf_{Di} + \log a \quad (8)$$

$$DPU_i = a \times (Cf_{Pi})^b \quad (9)$$

According to Mendenhall and Sincich [9], adding independent variables to the regression function will help to improve the accuracy and stability. Using this, Shibata derived a bivariate prediction model by combining (5) and (8):

$$\log DPU_i = k_1 \times \log Cf_{Pi} + k_2 \times \log Cf_{Di} + C \quad (10)$$