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Prediction of Defect Propensity for the Manual Assembly of Automotive Electrical Connectors

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Abstract

Assembly for automotive production represents a significant proportion of total manufacturing cost, manufacturing time, and overall product cost. Humans remain a cost effective solution to adapt to the requirements of increasing product complexity and variety present in today's flexible manufacturing systems. The human element present in the manufacturing system 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 defect, presented in the design, process, and human factors domain. A case study is offered that illustrates on a manual assembly process the effect that complexity variables have on assembly quality.

Keywords: Manual Assembly, Complexity Model, Quality

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} (BMW Group, 2013). The increased complexity and variety of modern assembly lines and vehicles has created corollary complexity in manufacturing which could introduce additional assembly defects but has also driven better understanding and control of assembly quality. The intent of this work is to further that understanding for a class of manually-assembled interfaces.

Assembly activities are very costly and time intensive, on average accounting for 40% of product cost and up to 50% of total manufacturing cost (Röhrdanz 1997; Bi et al. 2007). With such a large impact on the cost of a product it is clear how important reducing defects is to the success of an assembled product. This is especially true in automotive assembly where a single defect can result in the loss of thousands of dollars through delayed rework or recall.

In the automotive market, brand quality is a key factor in a customer's purchasing decision. During the purchasing decision, a customer will typically research the defect rates of vehicles, reported in databases such as J.D. Powers. Integrity of electrical connectors along with fit and finish of body panels and paint quality are some of their most emphasized defect categories. Such easily accessible defect data available to consumers has driven automotive manufacturers to continually increase their internal quality initiatives and adopt new practices in the mitigation of assembly defects. This is especially true in manual assembly where Su et al. (2010), Shibata (2002), and Vineyard (1999) found that up to 40% of total defects resulted from operator error and that these defects are not always obvious.

Research in defining strategies for characterizing assembly complexity has shown a relationship with final product quality. Some key assembly complexity models have previously been applied to such markets as home audio and office copier production.

1.1 Hinckley Model

Hinckley (2003), who based his data on semiconductor 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:

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

Where,

TAT = Total assembly time for the entire product

t_0 = Threshold assembly time

TOP = Total number of assembly operations

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:

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

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

Where, C and k are constants

1.2 Shibata Model

Shibata (2002) 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 a larger 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, 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 ($C_{f_{pi}}$) was defined as:

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

Where,

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

t_0 = Threshold assembly time

N_{ai} = Number of job elements in workstation i

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

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

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

Where, C and K are constants

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

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

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

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

Where,

K_D = Arbitrary coefficient for calibration with process based complexity

D_i = Ease of assembly of workstation i

a and b are constants

According to Mendenhall and Sincich (1995), 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):

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

1.3 Su, Liu, and Whitney Model

Su, Liu, and Whitney (2010) applied the Shibata model to copier assembly and found the Shibata model was not appropriate for larger electromechanical products. Su reported the R-squared value to be only 0.257 when using the Shibata model. Su et al. (2009) improved on the Shibata model for copiers partially by using Fuji Xerox Standard Time which was more suited to copier assembly than Sony Standard Time. Su's method also utilized Ben-Arieh's (1993) fuzzy expert system approach for analyzing difficulty of assembly combined with the analytic hierarchy process (AHP) and was able to achieve an R-squared value of 0.793 in the evaluation of three copier assembly products.

1.4 Antani Model

Antani (2014) built on the Hinckley, Shibata, and Su models by redefining manufacturing complexity as a measure of the impact of design, process, and human factor variability on assembly. It is the first

model to include human factors with design and process variables as one comprehensive measure of manufacturing complexity (Antani 2014). The generalized complexity model for defect rate (DPMO, defects per million opportunities) was empirically defined by:

$$DPMO = k_0 + [C_d C_p C_h] \cdot \begin{bmatrix} k_1 \\ k_2 \\ k_3 \end{bmatrix} \quad (11)$$

Where,

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

Antani further split the three sources of variability into subcomponents by categorizing the key input variables under each coefficient. The key input variables were derived through literature review in the areas of each source variability and observation in a manufacturing environment. The complexity factors were defined as:

$$C_d = \pm\alpha_1 D_{fd} \pm \alpha_2 D_{ad} \pm \alpha_3 D_{ac} \pm \alpha_4 D_{mc} \quad (12)$$

Where,

$\alpha_{1...n}$ = Empirical constants
 D_{fd} = Feature design variable
 D_{ad} = Assembly design variable
 D_{ac} = Component design variable
 D_{mc} = Material design variable

$$C_p = \pm\beta_1 P_{tf} \pm \beta_2 P_{as} \pm \beta_3 P_{nt} \pm \beta_4 P_{tu} \pm \beta_5 P_{vt} \quad (13)$$

Where,

$\beta_{1...n}$ = 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

$$C_h = \pm\gamma_1 H_{ef} \pm \gamma_2 H_{tr} \pm \gamma_3 H_{cl} \pm \gamma_4 H_{we} \quad (14)$$

Where,

$\gamma_{1...n}$ = Empirical constants
 D_{fd} = Feature design variable
 D_{ad} = Assembly design variable
 D_{ac} = Component design variable
 D_{mc} = Material design variable

Figure 1 outlines the input variables for the Assembly Design (D_{ad}) variable category of the design driven complexity factor (C_d) defined by Antani.

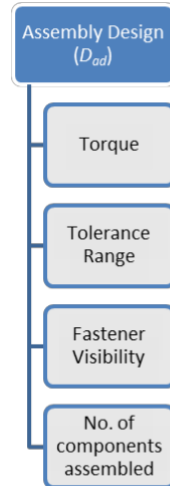


Figure 1: Antani (2014) assembly design variables

Antani observed 46 mechanical fastening processes over a one year time span, to eliminate production outliers, and developed a regression-based predictive model to predict defects in a fully automated and semi-automated automotive assembly process. He validated the model using three case studies, two highlighting quality improvements and one automated process where the human factors coefficient played no role, and found the actual vs predicted defect rate in each case to be highly correlated, with an R-squared value for the developed model of 0.919. Antani demonstrated the potential of the model as a design and optimization tool to evaluate the design, process, and human factors on product quality prior to entering real-world assembly, and as a process improvement tool.

2 Methodology

The methodology used in this research adapts the methods developed by Antani (2014) for use with electromechanical connections in a large complex system. Antani's model has previously been successfully validated against both fully-automated and semi-automated mechanical fastening processes. The research presented herein seeks to use a fully manual automotive electrical connector assembly process to further validate the predictive model methodology and introduces the concept of electrical signal continuity as a factor of quality.

2.1 Complexity Input Variable Ideation

Following the method described by Antani, the correlation between defect rate and complexity can be written as in equation (11). Due to variation in the design principles and manufacturing of mechanical fasteners and automotive electrical connectors, a new table of input variables was created. Due to the high variability and lack of substantial research into defining the relationship between complexity for fully manual assembly processes and defect rates, another goal of this initial study was to determine which key input variables had the most significant impact on the electrical connector regression model and reduce future data collection requirements as certain variables require a line stoppage to collect.

The sources of the complexity variables presented in this work were derived from literature, input from technical staff, production workers, and performing process connections on training simulators. The complete list of input predictor variables can be found below.

Class	Variable
Feature Design	Engagement length
	Connector width
	Connector height
	Number of conductors
	Lever direction
	Locking feature
	Sealing mechanism type
	Pigtail length (female)
	Pigtail length (male)
	Pin Style
	Surrounding color
	Male color
	Female color
	Assembly Design
Number of fixed ends	
Harness breakout direction (Bend angle)	
Verification operation	
Connector orientation	
Visible vs. Blind	
Connector in confined space	

Table 1: Product electrical connector input variables

Class	Variable
Tooling / Fixture Design	Assistance tooling?
	Are gloves required?
Assembly Sequence	Sequential requirement
	Part install immediately followed by connect?
	Where is defect caught?
	Where is defect corrected?
Takt information	Number of connections per takt
	Total tasks in takt
	Tasks at 100%
	Utilization of takt
	Utilization variation of takt (options) High
	Utilization variation of takt (options) Low
	Number of extra option tasks in takt
	BVIS notification of connection

Table 2: Process electrical connector input variable

Class	Variable
Ergonomics	Work height
	Sitting/standing

Cognitive Load	Finding connectors
	Verification mark/feedback
Work Environment	Stability of work base
	Presentation of vehicle
	Lighting

Table 3: Human factors electrical connector input variables

2.2 Data Collection

The chosen process of human assembly of automotive electrical connectors was found to be the second-most common source of automotive assembly defects by Antani (2014) based on his historical analysis of assembly defects over a one-year analysis of automotive production data. Also knowing that consumers use J.D. Power's easily accessible vehicle electrical connector defect data during their purchasing decision, the human assembly of automotive electrical connectors was chosen and carried out in an automotive assembly plant in South Carolina, USA.

Due to the complex and highly variable nature of human assembly (Townsend & Urbanic 2015), a strong emphasis was placed on the formation and subsequent collection of the input variables. Through literature and process investigation, 41 input variables were collected for 9 electrical connectors. The electrical connectors used in this study were highlighted due to their historic defect rate so that a representative sample of both high and low rates were represented and evaluated using a single tool. Defect data and input variable information was gathered for six months' worth of vehicle production to limit the influence of production outliers on the results of the regression model.

3 Results

Minitab was employed to analyze the 41 input variables and defect rate which were recorded for 9 electrical connectors. The statistical model was generated by using the input variables as predictor variables and defect rate as the response variable.

3.1 Analysis of Predictor Variables

To better understand the relationship between the individual predictor variables and defect rate, fitted line plots were applied to determine their respective correlations or R-squared. The plots gave an indication whether a higher order fit would significantly benefit the final regression model fit. A lower order fit for each predictor variable was desired in order to eliminate the added complexity to the final regression model that higher order coefficients produce. The R-squared and R-squared (adj.) for each variable was calculated at a linear, quadratic, and cubic fit level. Figure 2 below represents the largest increase in fit from all variables analyzed. As seen in Figure 2(a), the linear fit has an R-squared of .847 and increases from the cubic fit in Figure 2(b) to .899 which also accumulating two additional terms and a higher order to the final model. The analysis of the input variables is a very important step that provides a better understanding of the relationships that are occurring within the predictive model. Additional Analysis of Variance (ANOVA) would provide the p-values for each predictor variable and assist in determining the appropriateness of the rejecting the null hypotheses in a hypothesis test. A p-value less than the standard alpha of 0.05 would statistically corroborate that the variable has a significant effect on the response variable. Continued analysis of the variables through an ANOVA analysis is planned to provide a supplementary understanding of the input predictor variables as well as statistically aid in the pre-model and final selection of key impact variables to include in the regression model.

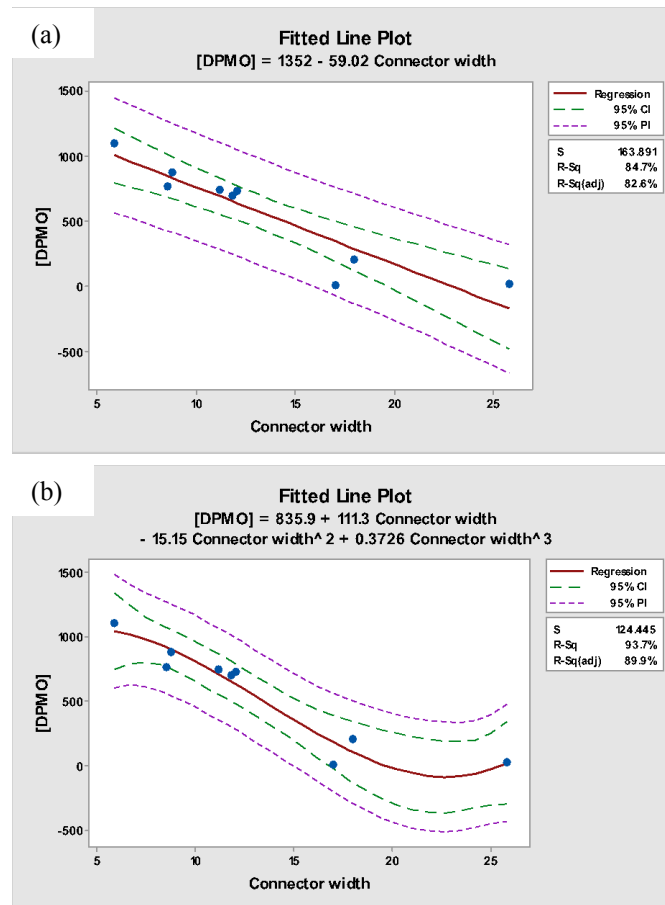


Figure 2: (a) Linear fit DPMO vs connector width, (b) Cubic fit DPMO vs connector width

3.2 Regression Model Building

As demonstrated by Antani, Ordinary Least Squares (OLS) regression was conducted to model the relationship between the response variable defect rate (DPMO) and the input predictor variables. OLS estimates the equation by determining the minimum sum of the squared distances between the sample's data points and the predicted values. Using the knowledge gained through the analysis of the input predictor variables, an initial model was built using OLS and can be found in Figure 3 below. The initial model achieved an R-squared of 0.576 when comparing predicted vs actual defect rate (DPMO) through the use of a linear fit line. A linear fit line was used to assess how well the predicted vs actual defect rates align since a 100 percent accurate predictive model should display an R-squared value of 1 as well as a fit line coefficient in the linear equation $y(\text{predicted DPMO}) = a \times x(\text{actual DPMO})$ of $a = 1$.

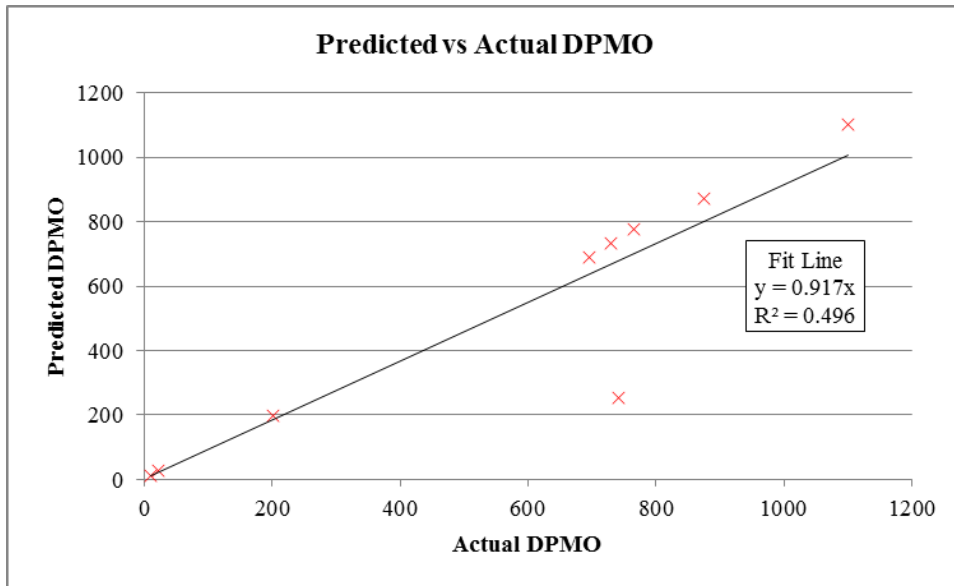


Figure 3: Regression model iteration 1

To improve the model, best subsets analysis was conducted to increase the R-squared value by cutting down on the number of variables used in the regression analysis. Best subsets analysis allows the projected predictability, precision, bias, and variability to be computed for each possible combination of variables possible in the model. This information will generate the best fitting regression model for the predictor and response variables provided.

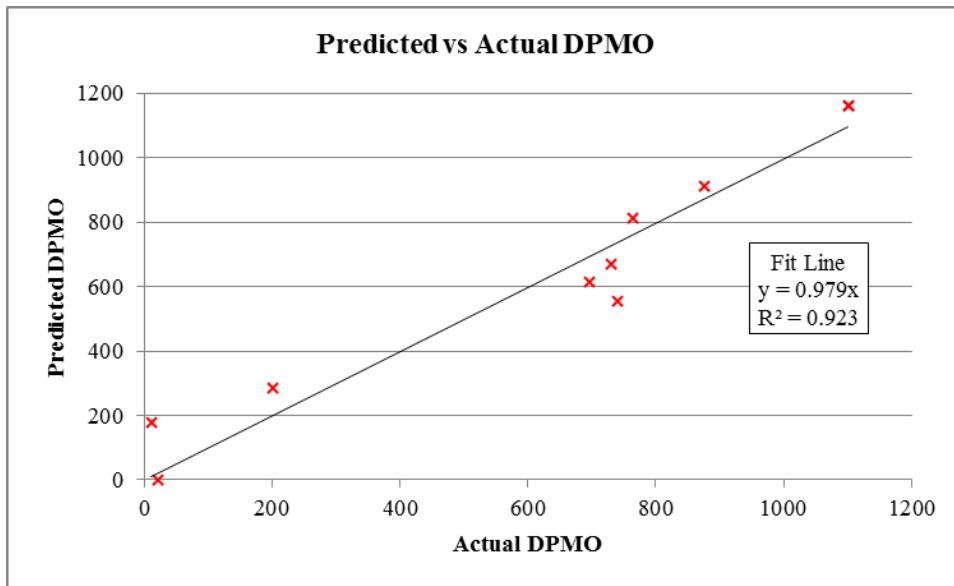


Figure 4: Regression model best subsets iteration

Through best subsets analysis, the model was able to be cut down from 41 input variables used in the first iteration to 6 input variables in the best fitting best subsets regression model. The reduction of

variables coincided with an increase in the R-squared value to 0.923 as seen in Figure 4. This was the model with the highest R-squared value found through the best subsets analysis.

The reduction in input variables drastically reduced the data collection requirements for continued validation against additional manual electrical connector processes not currently included in the model. Additional connectors are needed for validation of the model to assess whether the model is capable of predicting more than the connectors used to build the model and has applicability to further automotive electrical connector assembly processes.

The six variables included in the best subsets model were:

- Engagement length
- Connector width
- Connector height
- Work height
- Female pigtail
- Male pigtail

3.3 Significant Factors in DPMO

Significant factors were determined by evaluating the effect of each input variable on the response variable defect rate (DPMO). The impact or effect of each variable is the measured response on the defect rate when the level of each input variable is individually changed. To determine whether or not the effect is statistically significant is tested by calculating the p-values while testing the hypothesis that:

$$H_0: \mu_{s+} - \mu_{s-} = 0 \quad (15)$$

$$H_1: \mu_{s+} - \mu_{s-} \neq 0 \quad (16)$$

The impact of the variable is simply the difference between the averages of the high and low with a larger difference indicating a more significant impact.

	Engage. length	Conn. width	Conn. height	Female Pigtail	Male Pigtail	Work Height
Conn. 1	-1	-1	-1	1	-1	1
Conn. 2	1	-1	-1	1	-1	1
Conn. 3	-1	-1	-1	1	-1	-1
Conn. 4	-1	-1	-1	-1	1	-1
Conn. 5	-1	-1	-1	-1	1	1
Conn. 6	1	-1	1	-1	1	-1
Conn. 7	-1	1	-1	1	-1	-1
Conn. 8	-1	1	-1	-1	1	-1
Conn. 9	1	1	1	-1	1	-1
Avg(+)	479	78	371	590	557	854
Avg(-)	618	818	629	557	590	430
Impact Effect	-139	-740	-259	33	-33	424

Table 4: Best subsets input variables impact factors

From the table above, the impact of each variable in the best subsets regression model can be plotted to better illustrate the response resulting from the change in a particular variable.

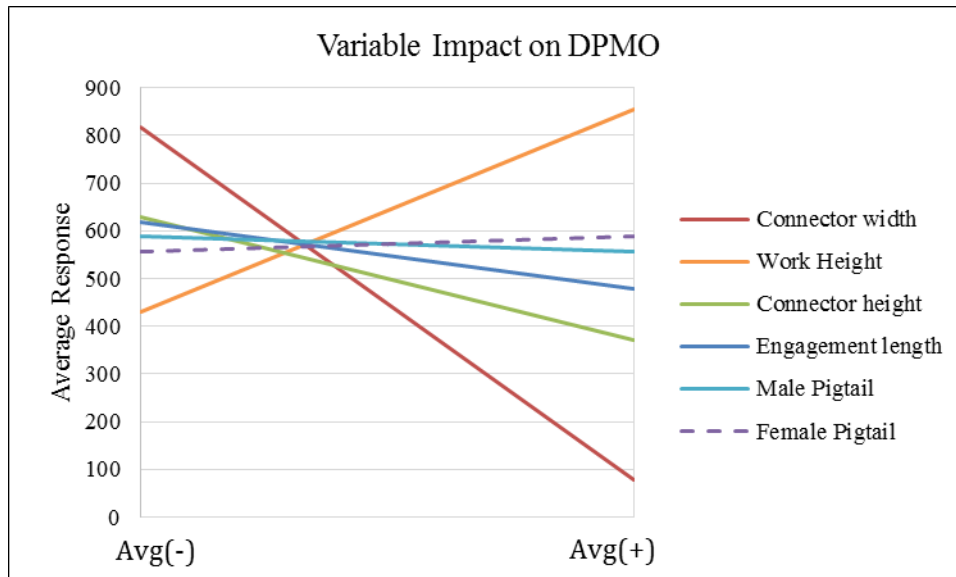


Figure 5: Impact effects of variables on defect rate

From Figure 5, it can be seen that the most significant impact for a variable in the best subsets model occurs from varying the connector width of the electrical connectors and that there appears to be a reduction in the response variable or defect rate (DPMO) while increasing the width. The impact variables from most significant to least significant:

- Connector width
- Work height
- Connector height
- Engagement length
- Male pigtail
- Female pigtail

3.4 Application in Automotive Assembly

A pilot study was proposed to test the results of the best subsets regression model and to further conclude the validity of the generated model. Of the six variables used in the final model, the highest impact variable that did not necessitate a very significant design or fixturing change to test were the variables relating to pigtail lengths. This limitation was imposed to not disrupt the current scheduled production. It was proposed to complete a trial of a lengthened connector to compare predicted vs actual defect rate of the adjusted electrical connector. A connector with a high defect, short lead time, and ease of change without disrupting scheduled production was desired and the most likely connector was the front door map pocket ambient lighting connector that is located inside the front left door panel. The connector can be seen in Figure 6 below.

During the analysis for the trial of the door wiring harness change, it was found that when the door harness was plugged into the main door harness, the connector cable going from the branch point to the electrical connector in question had the potential to have a large amount of force applied creating the possibility for the connector to be pulled out creating an electrical connector defect. In Figure 6(b), the lengthened pigtail highlighted allows for the majority of potential defect creating force to be placed on the clips holding the wiring harness rather than the electrical connector. An extended trial is currently

being conducted to determine the changes effect on the DPMO of the door harness connector during production as an evaluation of the final regression model.

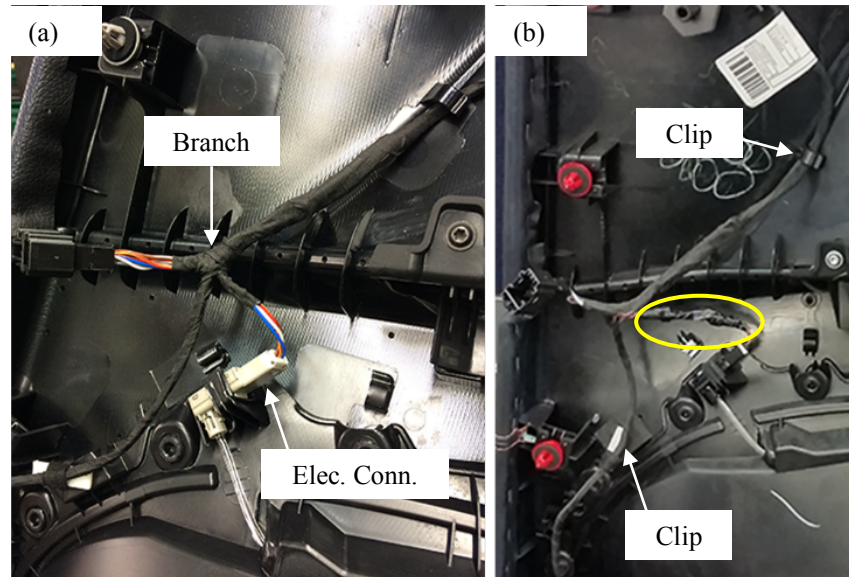


Figure 6: (a) Front door wiring harness prior to improvement; (b) Front door wiring harness post change, length change circled

4 Conclusion

Continuously changing and more complex products are increasing the focus towards quality in the automotive industry. This is especially true as vehicle assembly comprises such a large portion of the total cost and manufacturing time in the automotive industry making defect prediction and elimination more imperative.

The design, process, and human factors complexity model for the prediction of defect rates was applied to a fully manual automotive assembly process. Each of the 41 variables was analyzed to better understand its correlation with defect rate and recognize the relationships that are occurring within the model. A general regression model was created by applying all of the collected variables to an OLS regression model that resulted in an R-squared value of 0.576. The regression model was then simplified through best subsets regression modeling resulting in the use of only 6 variables in the final model, greatly reducing the data collection requirements of the model which were time consuming as well as greatly increasing the R-squared to 0.923. The significant impactors were then examined and ranked from most to least significant impact on DPMO to foster a more thorough understanding of the defect prediction model and its variables.

The model was validated by predicting and demonstrating an application on an automotive assembly production line by applying the prediction model to door wiring harnesses. A potential for defects was found and eliminated that matched the proposed significant impact variables for automotive electrical connectors and the change is being trialed for production release.

The methodology used in this research has previously been validated by Antani for fully-automated and semi-automated automotive assembly. With the current research, the model was validated against a fully-manual automotive assembly process of electrical connectors and shows aptitude as a robust and

comprehensive measure and correlation of manufacturing complexity and product quality for the automotive industry.

5 Acknowledgements

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