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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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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} [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
$\alpha_{1…n}$	Empirical constants
$\beta_{1…n}$	Empirical constants
$\gamma_{1…n}$	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:

$$C_f = TAT - t_0 \times TOP \tag{1}$$

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:

$$\log DPU = k \times \log C_f - \log C \tag{2}$$

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

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:

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

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

$$\log DPU_i = K \times \log Cf_{Pi} - \log C \tag{5}$$

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

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

$$Cf_{Di} = \frac{K_D}{D_i} \tag{7}$$

$$\log DPU_i = b \times \log Cf_{Di} + \log a \tag{8}$$

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

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):

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

2.3. Su, Liu, and Whitney Model

Su, Liu, and Whitney [7] 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 [10] 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 [11] fuzzy expert system approach for analyzing difficulty of assembly combined with the analytic hierarchy process (AHP) and was able to achieve a 0.793 in the evaluation of three copier assembly products.

2.4. Antani Model

Antani [4] built on the Hinckley, Shibata, and Su models by redefining manufacturing complexity as a measure of the impact of design, process, and human factors introduced variability. It is the first model to include human factors with design and process variables as one comprehensive measure of manufacturing complexity [4]. The generalized complexity model for DPMO (defects per million opportunities) was mathematically defined by:

$$DPMO = k_0 + \left[C_d C_p C_h\right] \cdot \begin{bmatrix} k_1 \\ k_2 \\ k_3 \end{bmatrix} \tag{11}$$

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

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

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

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

As stated above, each subcomponent variable was broken down into specific measureable input variables. Figure 1 outlines the input variables for the Assembly Design (D_{ad}) variable category of the design driven complexity factor(C_d) used by Antani.

Antani observed 46 mechanical fastening processes over a one year time span, and in turn developed a regression based 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 difference in actual vs predicted DPMO in each case to be statistically negligible and 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.

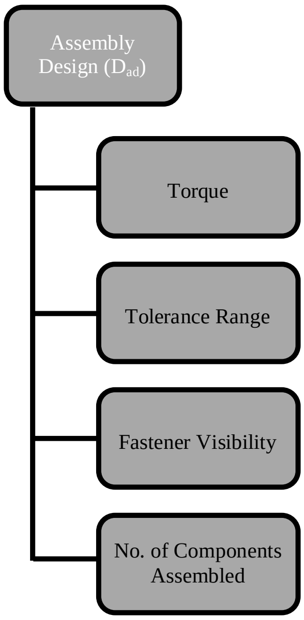

Figure 1. Adapted from Antani [4] Assembly Design Variables

3. Methodology

The methodology used in this research is based on the methods developed by Antani [4]. He validated the method against both fully-automated and semi-automated processes with favorable results as well as showing the potential for his model to be used in a much wider group of use cases. The research herein seeks to further validate the predictive model methodology against a fully manual assembly process.

3.1. Collected Data

The chosen process is the human assembly of automotive electrical connectors. Antani described electrical defects as second in line after mechanical fastening defects based on historical analysis of defects over one year of automotive production data. From this and knowledge of the readily available electrical connector defect data utilized by consumers during their vehicle purchasing decision, the human assembly of electrical connectors was chosen for this study. This study was conducted in an automotive assembly plant in South Carolina, USA.

During the research, 41 input variables were collected for 9 individual electrical connectors. The connectors were chosen based on their actual DPMO data to ensure that electrical connectors from high to low DPMO were represented and were evaluated on a single vehicle platform. Electrical connector defect and input variable information was gathered for 6 months' worth of vehicle production to limit the influence of production outliers on the results of the regression model.

3.2. Electrical Connector Complexity Input Variables

As in previous work, the relationship between complexity and defect rate was defined 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. The comprehensive tables of key input variables for each coefficient can be found in the Appendix. 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 pilot 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.

4. Results

A total of 41 input variables were recorded for 9 electrical connectors along with DPMO data and are shown in the Appendix. Minitab was utilized to conduct statistical analysis of the predictor variables and to setup the regression model using DPMO as the response variable.

4.1. Analysis of Variables

Fitted line plots were utilized to analyze each input variable and show their respective relationship with DPMO. The plots were also used to determine whether higher order fits to the variable would significantly benefit the final regression model without adding unnecessary complexity.

Through the analysis of each variable, it was found that increasing the order had little to no effect on the increase of R-squared or R-squared (adj.) value significantly, the largest increase found being approximately 7%. Analysis of the input variables provides a better understanding of the relationships that are occurring within the predictive model.

4.2. Regression Models

As described by an Antani, Ordinary Least Squares (OLS) regression was conducted to model the relationship between DPMO (response variable) and the input variables. OLS estimates the equation by determining the minimum sum of the squared distances between the sample's data points and the predicted values.

After the initial analysis of input variables, an initial model found in Figure 2 was generated using OLS and Minitab.

The initial model achieved an R-squared of 0.576 when comparing the actual vs predicted DPMO values.

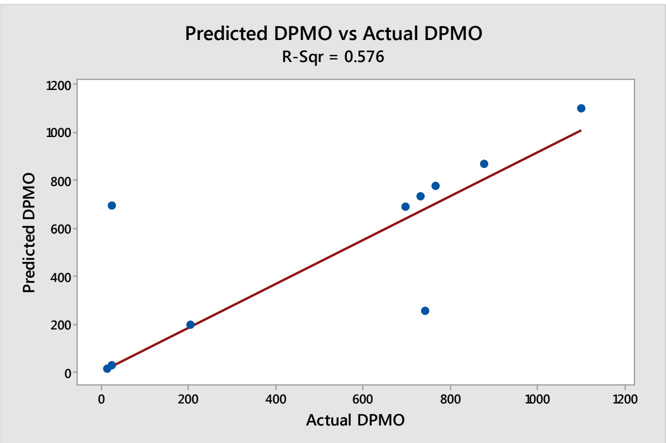

Figure 2. First iteration of electrical regression model

4.3. Best Subsets Analysis

A best subsets analysis was performed to help cut down on the number of variables used in the regression analysis. The best subsets analysis allows the computation of the projected predictability of the model, as well as easily compare the precision, bias, and variability between the various the models by re-computing the model with varied input variables to determine the combination of input variables that create the best fitting regression model. Through the best subsets analysis, the model was able to be reduced from 41 variables used in the first iteration to 6 variables during the first best subsets iteration while also increasing the R^2 to 0.923. The best subsets model with the highest R-squared value can be found in Figure 3 below.

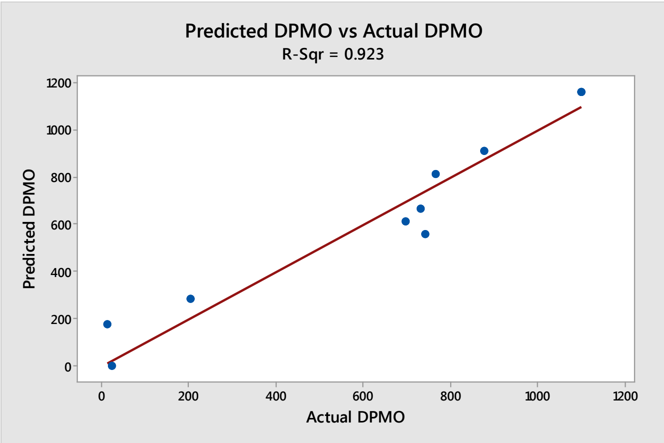

Figure 3. Best subsets regression model – 6 variables

Furthermore, by reducing the number of variables included in the model, it can be seen that the R-squared value has also been dramatically increased.

The six variables used in the best subsets model were:

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

4.4. Significant Factors in DPMO

Significant factors were determined by evaluating the effect of each input variable on the response variable, DPMO. The effect of each variable is the impact the factor has on the response when you change the level of the input variable. To determine whether or not the effect is statistically significant is tested by calculating the p-values while testing the hypothesis that:

$$H_0\colon \mu_{s+} - \mu_{s-} = 0 \tag{15}$$

$$H_1\colon \mu_{s+} - \mu_{s-} \neq 0 \tag{16}$$

Where H_0 is the null hypothesis or the assumption that there is no relationship between two measure phenomena and H_1 is the alternative hypothesis or the assumption that the samples were influenced by a non-random cause. The null hypothesis in this research was that the variables did not have an impact on the DPMO and the alternative hypothesis was that they did have an impact.

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.

From the plot in Figure 4, 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 (DPMO) while increasing the width.

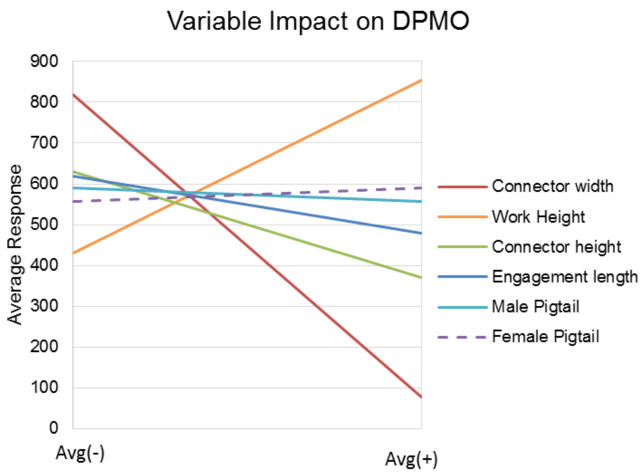

Figure 4. Impact effect of variables on DPMO

The six variables used in the best subsets model ordered from most significant impact on top to least significant impact on the bottom are:

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

4.5. Continuing Efforts

A completed ANOVA analysis of the input variables will lead to supplementary understanding of the relationship between each variable and DPMO as well as aid in the final selection of key impact variables. Further correlation analysis of the input variables is ongoing alongside ANOVA to better understand the relationship between the pairs of input variables themselves. Complete residual analysis is also ongoing to ensure that the regression models provide precise, unbiased estimates of the relationship between complexity and DPMO based on the requirements of the Ordinary Least Squares regression model.

4.6. Applications in Automotive Assembly

Using the results of the regression model and a better understanding of the significance of each variable's impact, a small pilot study was proposed to further conclude the validity of the generated model. Of the six variables used in the best subsets regression model above, the impactor that did not necessitate a very significant design change of the electrical connectors or fixturing was the variables relating to pigtail lengths. This limitation was put in place to prevent disruptions to scheduled production. It was proposed to complete a trial of a lengthened connector to compare actual vs predicted DPMO of the adjusted electrical connector. A connector with a high defect was chosen and the most likely connector was the front door map pocket ambient lightning connector that is located inside the left front door panel. The connector can be seen below in Figure 5(a).

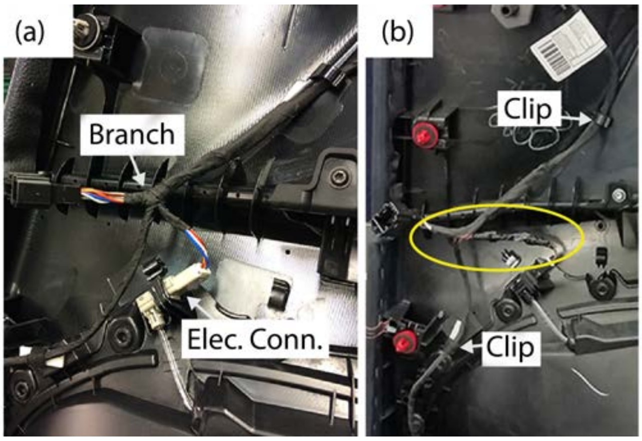

Figure 5. Impact effect of variables on DPMO

This particular connector was chosen due to its higher defect rate and ease of access to changes without disrupting production to run the trial.

During the analysis for the trial it was found that when the door harness was plugged into the main harness, the connector cable going from the branch point to the electrical connector in question had a large amount of force able to be applied creating the possibility for the connector to be pulled out. In figure 5(b), the lengthened pigtail can be seen allowing more slack to be placed on the branch point of the harness as the clips now appropriately take the majority of the force when the electrical harness is being wired.

An extended trial is currently being conducted to determine the actual effect to the DPMO of the door harness during production as an evaluation of the best subsets model.

5. Conclusion

Increasing customer demand for greater product quality and variety is increasing the focus towards quality in the automotive industry as vehicles become more complex. 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 based on the Antani model 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.

6. Appendix

Table 1. Product Design Variables

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	Engagement force
	Number of fixed ends
	Harness breakout direction (Bend angle)
	Verification operation
	Connector orientation
	Visible vs. Blind
	Connector in confined space

Table 2. Process Design 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 3. Human Design Variables

Class	Variable
Ergonomics	Work height
	Sitting/standing
Cognitive Load	Finding connectors
	Verification mark/feedback
Work Environment	Stability of work base
	Presentation of vehicle
	Lighting

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References

[1] BMW Group, “How a Motor Vehicle is Born - Assembly,” *Automobile Production*, 2013. [Online]. Available: http://www.bmwgroup.com/e/0_0_www_bmwgroup_com/produktion/fahrzeugfertigung/automobilfertigung/erlebnis_produktion/prod_prozesse.shtml. [Accessed: 12-Nov-2015].

[2] F. Röhrdanz, “CAD method for industrial assembly, concurrent design of products, equipment and control systems,” *Comput. Des.*, vol. 29, no. 10, p. 737, Oct. 1997.

[3] Z. M. Bi, L. Wang, and S. Y. T. Lang, “Current status of reconfigurable assembly systems,” *Int. J. Manuf. Res.*, vol. 2, no. 3, pp. 303–328, 2007.

[4] K. Antani, “A Study of the Effects of Manufacturing Complexity on Product Quality in Mixed-model Automotive Assembly,” Ph.D. dissertation, Automotive Eng., Clemson Univ., Clemson, SC, 2014.

[5] M. Vineyard, “Failure rate distributions for flexible manufacturing systems: An empirical study,” *Eur. J. Oper. Res.*, vol. 116, no. 1, pp. 139–155, 1999.

[6] H. Shibata, “Global Assembly Quality Methodology: A New Method for Evaluating Assembly Complexities in Globally Distributed Manufacturing,” Ph.D. dissertation, Mech. Eng., Stanford Univ., California, 2002.

[7] Q. Su, L. Liu, and D. E. Whitney, “A systematic study of the prediction model for operator-induced assembly defects based on assembly complexity factors,” *IEEE Trans. Syst. Man, Cybern. Part ASystems Humans*, vol. 40, no. 1, pp. 107–120, 2010.

[8] C. M. Hinckley, “A global conformance quality model: A new strategic tool for minimizing defects caused by variation, error, and complexity,” Stanford University, 2003.

[9] W. Mendenhall and T. Sincich, "*Statistics for engineering and the sciences*," 4th ed. Upper Saddle River, N.J: Pearson Prentice-Hall, 1995.

[10] Q. Su, L. Liu, and S. Lai, “Measuring the assembly quality from the operator mistake view: a case study,” *Assem. Autom.*, vol. 29, no. 4, pp. 332–340, Sep. 2009.

[11] D. Ben-Arieh, “Analysis of assembly operations difficulty: a fuzzy expert system approach,” *J. Intell. Manuf.*, vol. 4, no. 6, pp. 411–419, Dec. 1993.