7

A MULTIVARIATE CONTROL CHART SCHEME FOR QUALITY MONITORING OF AUTOMOTIVE STAMPING PROCESS -AN EMPIRICAL STUDY OF A MALAYSIAN PLANT

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7.1. INTRODUCTION

Quality of automotive stamping process is often related to quality characteristics of automotive stamped panels. These are the panel's dimensional stability measured by deviations of panel's geometrical dimensions from the nominal design specification. Correspondingly panel geometry is deemed as one of the attributes to variation in stamping process other than material properties, stamping process variables and die engineering and construction (Hammett, Baron et al. 2000). More often that not, deviation in stamped automotive parts are claimed as the attribute of variations in assembly dimensions (Guzman, and Hammett 2003; Hammett, Baron, and Smith 2000; Kuzma-Smith 2000; Yang, and Trewn 2004). This is because good fits cannot be achieved when panels are of large variations. As such, continuous efforts should be made in improving the quality automotive stamping process by studying the dimensional stability of the stamped panels.

This study embarks on a statistical process control by specifically proposing a multivariate control chart scheme in monitoring the quality of stamping process of an automotive panel based on its geometrical dimensions. The need for a multivariate approach of control charting owes mostly to the multivariate nature of quality variable characterizing the manufacturing process as well as product dimension. Quality variables, namely, surface, trim, and hole eccentricity characterize the dimensional measurement of the panel. Even in a narrow sense, a single quality variable itself, for instance, surface is narrated by several different measure points. Monitoring large number of univariate control charts is almost impossible. Apart from the multiple nature of quality variables, these variables periodically demonstrate some form of correlation, either cross correlation or serial correlation, or even both (Hammett et al. 2000; Yang, and Trewn 2004). Managing separate univariate control charts, again, would not be able to take into account the correlation factor. A multivariate approach would, then, best serve the purpose of quality monitoring of automotive stamping process.

7.2. A REVIEW OF PREVIOUS WORK ON CONTROL CHART APPLICATION IN AUTOMOTIVE STAMPING PROCESS

Control chart is among the mostly applied statistical process control techniques. Control charts can actually allow companies to determine when something unexpected occurs in their manufacturing process. Without having this kind of information in hand, not only problems are discovered when it is already too late but it is more difficult to determine the cause. However, number of Malaysian studies unveiled many of the local automotive parts manufacturing companies find difficulties in applying statistical process control which include control charting methods to the optimal level (Jafri, Sha'ri, and ismail 2007; Noviyarsi, and Sha'ri 2004; Salimah 2001). This could explain why these automotive manufacturing companies failed to take advantage of SPC fullest benefits. Even many manufacturing companies abroad do not understand how, for example, control charting can provide the opportunity to identify unusual behavior before unacceptable products are produced (Wachs 2005).

The research activity in multivariate control charts has been reported to be at its highest level for the past decade which reflects increased measurement and computing ability (Woodall & Montgomery, 1999). Large and diversified research areas on the application of multivariate control charts in manufacturing areas are extensively discussed in many literatures (Tracy, Mason and Young (1992), Lowry and Montgomery (1995), Mason and Young (2002) and the references therein). In the international arena, studies on the application of control charts in the stamping of automotive panels have been evident for the last two decades, gradually progress from univariate to multivariate applications (Ceglarek 2000; Kuzma-Smith 2000; Hammett et al. 2000; Majeske 2000; Majeske, and Hammett 2003; Rolfe et al. 2003) although there is only a handful on multivariate techniques in the stamping of automotive parts (Wang 1995; Yang 1996; Yang, and Trewn 2004). Other studies on automotive part stamping demonstrate the use of principal component analysis and some extend to another multivariate application of experimental design. (Ceglarek 2000; Kuzma-Smith 2000)

While some literatures have opened their arms to control charts due to its many benefits, astonishingly, some studies argue against the need for control charting in the quality improvement of automotive stamped parts (Guzman and Hammett, 2001, Majeske and Hammett 2000). It was reported that there is evidence of weak relationship between components, in particular, the non-rigid components and their final assembly attributes. Another study concludes that the inevitable mean shifts in stamping process are regarded as insignificant process changes in stamping operation. They also claim it is difficult to change the mean target value of the automotive stamped component because manufacturers can rarely eliminate all stamping mean shifts that typically occur between die set-ups or after changes in material lots (Majeske, and Hammett 2000; Rolfe et al. 2003).

Despite such protracted remarks defying control charting as the appropriate quality improvement and monitoring tool in automotive stamping process, this study is very much motivated from the principle that "perfect parts make perfect assemblies". The correct use of control charts can actually help in convincing the manufacturers that control charts can be effective indicators of any process changes. The problem is many do not actually use these charts correctly as to identify process changes as quickly possible after the changes occur. This is the original objective of what control charts are invented for i.e. to better understand and ultimately improve the process (Hoerl 2000; Wachs 2005). Improved process is stabilized process. Only with stabilized process, manufacturer may seek to embark on other concomitant task for example tolerance adjustment, formability and dimensional validation (Guzman, and Hammett 2003).

7.3. METHODOLOGY

The main objective of this research is to propose a control charting scheme to check for the stability of the automotive stamping process based on the panel's geometrical dimension. Geometrical dimension is used as quality variables of stamping process of this study as process variable input settings have already been fixed.

This research specifically demonstrates the application of multivariate statistical technique through its diagnostic features such as combining measurements from many different characteristics and simultaneously, analyzes the data. To achieve this, the research is devised as follow.

- Performing the multivariate analysis of the three quality dimensions of surface, trim and hole eccentricity. This is to study the process characteristics based on these quality variables.
- Estimating the parameters to be used in Phase I Multivariate Hotelling's T^2 control charting scheme. Parameter estimation would be based on the basic production process characterization obtained from the first objective.

- Proposing principal component chart and variation component chart as the diagnostic tools of the multivariate T^2 control charting

Statistical multivariate methods like factor analysis, principal component analysis and variance component analysis are some of the multivariate techniques to be applied here. Multivariate analysis of the production process is best done through the help of the appropriate software designed for these purpose. The statistical software used are SAS JMP 8 and SYSTAT 12.

7.3.1. MULTIVARIATE HOTELLING T^2 CONTROL CHART SCHEME

Hotelling's T^2 multivariate control charting scheme is a proposed for this quality study of automotive stamping process. Hotelling's T^2 control chart is the extension of Shewhart univariate control chart. There are two reasons opting for this scheme. Firstly, it is due the unknown population parameters of the automotive panel. Hotelling's T^2 control chart was originally developed for cases with unknown population parameters as proposed by Hotelling (1947) as cited by Cheng et al (2004) and as suggested by several others (Alt, and Smith 1988; Cheng, Away, and Hassan 2004; Lowry, and Montgomery 1995).

The second reason opting for Hotelling's T^2 control chart relates to the typical outcome of a stamping process itself. Automotive stamping process has been observed to produce large mean shifts (Hammett, Baron, and Smith 1999). A study by Hammett et al. (1999 reveals that stamping and die processes by nature are not stable enough and result in not insignificant mean shifts. Unlike the multivariate EWMA and CUSUM procedures which are more sensitive to small and moderate shifts in the mean vector, Hotelling's T^2 control chart is most suitable in the cases where mean shifts are not small (Cheng et al (2004) citing Montgomery (2005)). Thus, Hotelling's T^2 control chart suits to such condition of automotive stamping process.

There are two phases in establishing Hotelling's T^2 multivariate process control i.e. Phase I and Phase II. Phase I control charting is the preliminary control charting procedure whereas Phase II is the operational phase of process control (Yang, and Trewn 2004) (Mason, and Young 2001). Phase I control chart of this study is where process parameters are unknown. This is the case as multivariate control technique has never been applied before, thus, the parameters i.e. mean vector and covariance matrix has to be estimated. Therefore, the main focus of this study is on Phase I control charting and Phase II control charting will not be anyway discussed here in this study. For background readings on Phase II control charting, a list of reference is available in a review of literature by Willis et al. (2006) (Willis et al. 2006)

In general, control charting of Phase I is a stage of retrospective timing where data are collected with the purpose of setting a chart (Palm 2000), or simply, it is a chart 'start-up' stage. Two main objectives of Phase I control chart are to develop a reference sample from which the parameters are estimated and secondly is to devise the multivariate Hotelling T^2 control chart to check for the process stability.

7.3.1.1. Sampling Design

Sampling of automotive panels in this study is designed so that the data set collected in such a manner that variations within a subgroup reflects common variations only, while any significant variations between subgroups reflects special causes (Shefik 1998). The sampling method chosen is rational subgrouping. This method represents data collected over a short period of time under essentially identical condition of material, tool setting, environmental condition, etc. There are two basic reasons opting for a rational sub-grouping scheme. First, averages or mean values can detect process shifts more quickly than individual measurements. The second reason is averages from a stable process tend to follow a normal distribution, hence, it easy to estimate the control limits (Wachs 2005). Normality and independence are two fundamental assumptions in developing control charts (Bersimis et al. 2005). By employing rational subgrouping, the process can be assumed to follow normal distribution (Wachs 2005). The recommended number of subgroup is from 20 to 30 subgroups of size 4 and 5 (Montgomery 2005; Ryan 2000) and multiple production runs are suggested for better pooled estimate of a long term variation (Guzman, and Hammett 2003).

7.3.1.2. Data Preparation

This pre-processing task includes detection of problems in data by screening and cleaning the data. Possible problems in data likely to arise are the presence of multicollinearity and autocorrelation and outliers (Mason, and Young 2001). Diagram 7.1. illustrates the process of identifying problems in data.

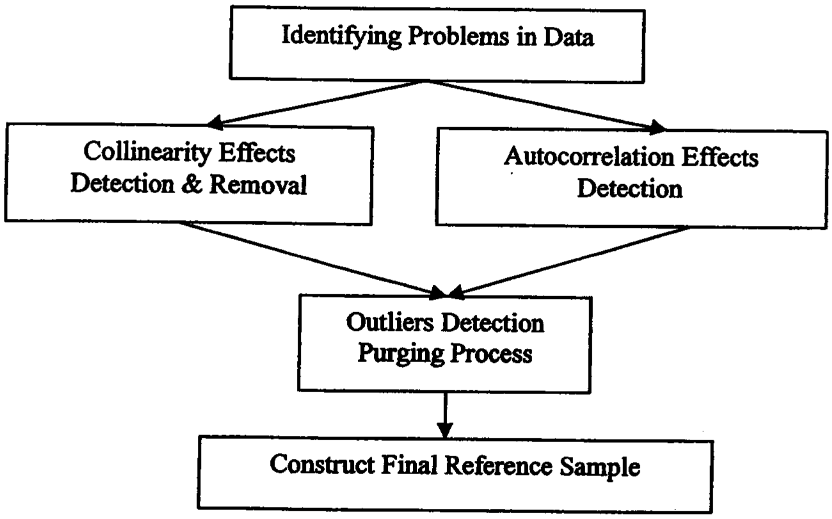


Diagram 7.1 Guidelines for Identifying Problems in Data set. (adapted from (Mason, and Young 2001))

In a multivariate analysis, collinearities pose a problem as it can have effect on the performance of T^2 statistics. Collinearities can result in singular or near singular covariance matrix, where as, T^2

statistics formula is based on a covariance matrix which is non-singular (Mason, and Young 2001). Principal component analysis (PCA) is a useful multivariate statistical technique in identifying collinearities. To identify the presence of collinearities, eigenstructure of correlation matrix is used to estimate condition index (Mason, and Young 2001). Condition index of size greater than 30 implies a problem of severe collinearities and some variables must be removed.

Checking for presence of autocorrelation is part of validating the identical and independent distribution assumption of control charting. Some presence of autocorrelation is a more realistic situation in automotive stamped panel data as process variables in many manufacturing background are often characterized as autocorrelated (Kalgonda, and Kulkarni 2004; Reynolds, and Lu 1997; Woodall, and Montgomery 1999). This is, particularly the case in stamped automotive panel data (Yang, and Trewn 2004).

As the goal of Phase I is to identify multivariate outliers, the estimated control limits must be sufficiently accurate for the Phase II process monitoring. Outlier detection problem of data preparation stage is essentially the same as statistical purging of outlier or unusual observations in Phase I (Mason, and Young 2001) and it is part developing a reference sample (Yang, and Trewn 2004). The process of outlier detection is discussed separately in the ensuing subsection.

7.3.1.3. Dimensional Reduction of Panel Geometry

Due to the multivariate nature of dimensional measurement of automotive panel, large number of measure points must be reduced for parsimonious analysis (Gnanadesikan, 1977). Dimensional reduction is also needed to meet certain mathematical 'requisite' of multivariate methods. The general rule of thumb in applying multivariate methods is multivariate methods do not work if number of observations, n, is less than number of variables, p. This is because if $p < n$, neither the inverse covariance matrix $\sum^{-1}$ nor its estimate S^{-1} can be computed (Mason, and Young 2001). So, sample size n must exceeds number of variables, p, or in this case the quality variables. Dimensional measure points of the automotive panel must be further reduced to meet '$n > p$' criteria.

Principal Component Analysis (PCA) and Factor Analysis (FA) can be used for reducing dimension (Yang, and Trewn 2004). These two multivariate statistical methods are profoundly powerful in extracting smaller number of factors which account for most variation in the large amount of multivariate data. PCA also serve a technique to identify variables belonging to the same factor based on variability. This technique is factor analysis. In this case, factor analysis aim to describe the set of quality variables in terms of a smaller number of factors. In a quality study of stamping process where mean deviation and variation is of major interest, PCA and Factor Analysis methods can be regard as most appropriate.

7.3.1.4. Outlier Detection

The T^2 statistic approach is applied to detect the multivariate outliers as T^2 statistic will be used repeatedly in this study (Mason, and Young 2001). Other classic multivariate outlier detecting technique are Mahalanobis distance (Rousseeuw, and Zomeren 1990). T^2 statistics of subgrouped data computed can be defined as the statistical distance between the observation vector and the sample mean vector, and it is compared to the upper control limit UCL of the T^2 control chart (Chou, Mason, and Young 1999). With k subgroups of multivariate observations for each of the p variables where each subgroup has n measurement data, the subgroup average, covariance matrices, grand mean vector and pooled covariance matrix are computed. The T_M^2 for each subgroup is also computed using the formula given as

$$T_M^2 = n(\bar{\mathbf{x}} - \bar{\bar{\mathbf{x}}})' \mathbf{S}^{-1} (\bar{\mathbf{x}} - \bar{\bar{\mathbf{x}}}) \qquad .....[1]$$

This T_M^2 for each subgroup is compared with the upper control limit of the following formula

$$UCL = \frac{knp - kp - np + p}{kn - k - p + 1} F_{\alpha, p, kn-k-p+1} \qquad .....[2]$$

T^2 control chart has only an upper control limit. If the computed T_M^2 exceeds UCL, then the corresponding subgroup is deleted for it is considered as an outlier and this subgroup should not be used to estimate the parameters of the control chart. Type I error $\alpha = 0.001$ (Mason, and Young 2001) is applied for the process of purging outliers.

7.3.1.5. Construction of Reference Sample and Parameter Estimation

Unknown population parameters of Phase I is estimated from a reference sample that belong to an 'in-control' process (Mason, and Young 2001) that subsamples that are 'out-of-control' must be discarded. Deleting out-of-control subsamples is an iterative process as this continues until the process in brought into a state of statistically in-control where no more outliers are detected. Once this is achieved, the control chart is used to define what is meant by a state of statistical in-control. This step is similar to the approach using T^2 statistics to detect outliers.

Once a reference sample is obtained, parameters are and used to compute the baseline control limit. Using these parameters, Phase I charts are used for retrospectively testing whether a process was in control when the first subgroups were being drawn (Bersimis et al. 2005; Montgomery 2005; Ryan 2000). In general, Phase I chart is similar to a hypothesis that tests whether all of the data come from an in-control process (Champ, and Jones 2004).

7.4. IDENTIFYING CAUSES OF VARIATION

In this study, Hotelling's T^2 multivariate control chart is applied as the process control tool to check on stability of process. However, there are two basic problems in using T^2 based control chart. The first problem is values plotted in control chart are not original values because these are the T^2 statistics values. Secondly, whenever the statistics exceeds the control limits, it does not enlighten which variable that actually causes the out of control situation. A possible way to overcome the second problem is by plotting the values of every individual variable on separate charts alongside the T^2 based control chart to enable one monitoring the individual variables when ever T^2 is out of control. However, this approach may not be effective as there are cases where out of control are not due to excessive variations of an individual variable but caused by the change in the covariance or correlation structure. As such, by looking at one particular variable at a time does not help in detecting the root cause of the problem. Principal component chart and variation mode chart offer some solutions to this (Yang, and Trewn 2004). Principal component chart and variation mode chart can be used in conjuction to Hotelling's T^2 multivariate control chart as process diagnosis.

7.4.1. Principal Component Chart

Principal component charts are used in conjunction to Hotelling T^2 chart as the supplementary charts. Any assignable causes are identified from these principal component charts are studied together with the Hotelling T^2 control chart plotted earlier. Panel dimensional measurements may indicate variation but the source must be identified from the components adding to variations in the dimensional measurement. PCA has the ability to identify major component which contribute to most variations (Jackson, 1980; Montgomery, 2005) in real geometrical shape (Yang, and Trewn 2004). The important advantages of PCA are linear combination of its variables are not related to one another and only a few number of components that may capture most of the variability in the data set. As such, not all of the principal components are needed in analyzing variations. Yang and Trewn (2004) use the principal component chart on correlation. In this study however, the accompanying principal component chart to be introduced in based on covariance.

The number of principal component to be chosen is based on how much the cumulative percentage variation can be explained by these principal components. Principal component score are computed for each sub-sample in the reference sample. Based on these scores, the principal component chart is graphed. This will be explained in greater detail under the section on application of control chart.

7.4.2. Variation mode chart

Variation mode chart by Yang (1996) has been demonstrated as an effective tool for interpreting geometrical variation form of automotive panels (Yang, and Trewn 2004). Variation mode chart is a special PCA procedure developed for dimensional measurement data. With the purpose of identifying major components that account for most of the variation in the real geometrical shape, variation mode approach fit into a multivariate analysis for quality variables like surface, trim and hole variables of this study. The variation mode chart is devised such that the interval represented by $\mu \pm 3\sigma$ contains 99.73% of the observations in a normal distribution. This approach achieves the setting procedures of estimating control limits of the standard Shewart control chart. The general idea of geometrical variation mode is that the total dimensional variation of the data set of one measure point is equal to the summation of the total variances of the geometrical variation modes. 'Mode' in this scheme is simply a component in the PCA procedure. The variation mode chart consists of a centerline, variation extent limit 1 (VEL_1) and variation extent limit 2 (VEL_2) that resembles the respective mean, upper limit and control limit of the standard Shewart control chart. In this form of dimensional variation analysis, the centerline is $E(\mathbf{u}_j) = (0,\ldots,0)$. Variation extent limits 1 and 2 are

$$\mathrm{VEL}_1(\mathbf{u}_j) = (3a_{1j}\sqrt{\lambda_j}, \ldots, 3a_{pj}\sqrt{\lambda_j}) \qquad \ldots..[3]$$

$$\mathrm{VEL}_2(\mathbf{u}_j) = (-3a_{1j}\sqrt{\lambda_j}, \ldots, -3a_{pj}\sqrt{\lambda_j}) \qquad \ldots..[4]$$

a_{1j} is the eigenvector of mode j for variable 1, and λ_j is the eigenvalue of mode j. Using the computed VELs, variation mode chart is graphed for each component. While principal component chart indicate which component contribute as the source of variation signaled by the multivariate Hotelling's T^2 chart, variation mode chart serve to trace the point(s) that account for most variation in that component. An empirical study on the proposed Phase I multivariate control charting and its supplementary charts follow next.

7.5. EMPIRICAL STUDY OF A MALAYSIAN PLANT

This research project on statistical quality control and improvement focuses on the stamping process of a selected automotive panel, Reinforced Rear Floor Left Side Member (PW835685), a non rigid panel that forms the underbody substructure of automotive body-in-white of a national sedan model. This research is undertaken in a local automotive stamping plant specializes in the design, engineering and manufacturing of dies and moulds apart from producing automotive parts such as car roof, bonnet, fender, door and body panels. The panel is shown in Diagram 7.2. below.

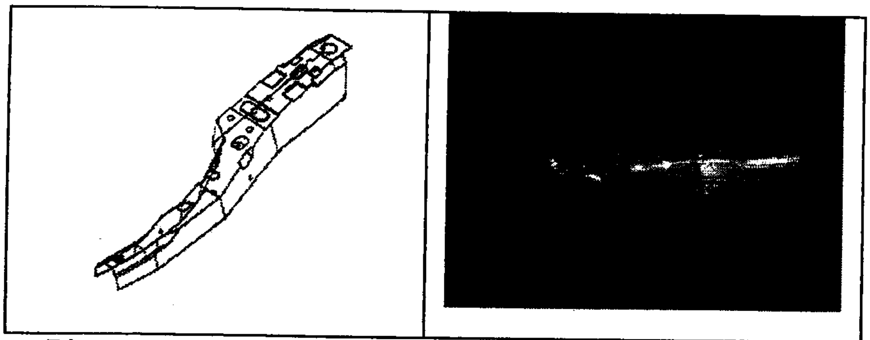


Diagram 7.2. Reinforced Rear Floor Left Side Member (PW835685)

As documented by the company, the quality definition of the stamped automotive panel (termed as the panel onwards) is the quality characteristic that describe the panel. The quality characteristics are the position of a flange surface dimensions, the length of trim edges and hole eccentricity (or sometimes termed as hole axial). These are the geometrical dimension of the panel categorized into three main dimensional variable namely surface, trim and hole location. The dimensional measurement are continuous variables measuring the deviation from the target mean value of zero measured in unit millimeter (mm). All the quality variables have the nominal value of zero and their specification limits are all within limits of ±0.5 mm. For didactic reasons, each of the quality attribute measurement of the panels is outlined and their respective notations are as below:

SPi = gap between panel's flange and jig's **surface**
TP_i = measurement lengthwise from the panel's flange end to the **trim** line on the jig
HX_i = the axial length from panel **hole** circumference and its reference line on the jig in *X*- direction
HY_i = the axial length from panel hole circumference and its reference line on the jig in *Y*- direction

i is the number of respective measure point on the panel. There are 35 surface measure points, 35 trim measure points and 12 locations of hole X- and Y-direction eccentricity. The stamping process involves multiple die operations in a series of presses in Line G. Four different operations take place in Line G, namely OP10, OP20, OP30 and OP40.

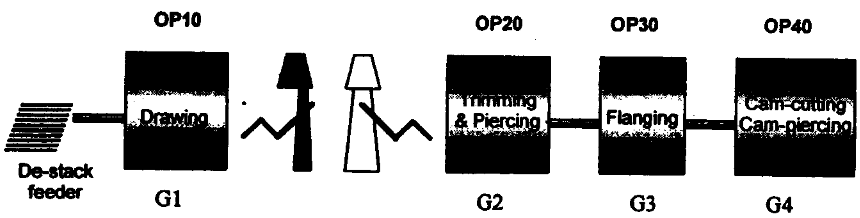


Diagram7.3. Stamping Operation of Part PW825685/688 on Line G

Drawing processes OP10 takes place at point G1, where most of the shaping and forming is done. Draw dies create the part shape by controlling sheet metal flow from a de-stack feeder into a cavity and over the forming punch. OP20, involves two operations of trimming and piercing. Two robotic equipments help loading and controlling the semi-finished parts from point G1 to feed into the die at point G2 where trimming and piercing operation take place. Piercing is the metal cutting operation that produced the special-shapes hole in the formed part. OP30 is called flanging operation. A flanging die wipes the metal between a punch and a lower die section to create flanges. During the final operation OP40, the formed part undergoes cam-cutting and cam-piercing process.

In this study of the stamping process where parameters are unknown the scheme proposed is T^2 control chart based on rational subgroups. The process parameters are estimated from some 28 initial subgroups of size 5 taken from four different production shifts totaling to 105 completed panels.

7.5.1. Variable Selection Analysis

In many other automotive stamping manufacturing plants, sophisticated measuring systems and automated data acquisition technologies supports dimensional measurement of automotive panels. In this manufacturing environment, the measuring work is automatically performed through Co-ordinated Measuring Machine (CMM). For this company, however, automotive panel dimensional measurement work is carried out manually. The measuring work is conducted manually using hard checking fixtures and measuring equipments. A caliper is used to measure punched hole X- and Y-direction and taper gauge is used to measure deviations in surface and trim.

Variable selection analysis serve to reduce the panel's dimensional measurement, hence can avoid overwhelming analysis of all numerous measurements. Some background information is used to select variables that should be included for the quality study of stamping process. This approach is expressed as the exclusion of quality features before experiment is used (Gnanadesikan 1977). In this case, the first background information is the Critical-to-quality (CTQs). With the help of the engineer and the quality team member, the CTQs are identified as the points which lie on the area where the panel is matched or termed as 'married' to other parts. The second background information leading to further reduction in number of measure points is based on exclusion of features by specific judgment (Gnanadesikan 1977). As suggested by the quality engineer, only 10 points from the CTQs are selected for surface and trim variables based on different formability modes on different locations of a panel.

7.5.2. Preparing data for Multivariate Analysis

Data collected are screened for any possible problems. Eigenstructures of Principal Component Analysis (PCA) on correlation matrix are used to compute condition index (Mason, and Young 2001) to check on collinearities. Results of these condition index show values much lower than 30 indicating no collinearities exist in the covariance matrix of the quality variables.

Autocorrelation functions of variables produced by SAS JMP8 indicate some presence of autocorrelation. The values, however, are fairly low and insignificant. Majority of quality measure points of the quality variables show autocorrelation functions of less than 0.4 at lag 1. So, the data set is said to be not affected by autocorrelation (Woodall 2000). Low level of autocorrelation of this sample data could possibly due to subsamples of panels which are sampled from different production runs (Reynolds & Lu, 1997).

Multivariate outlier detection is a vital stage in Phase I control chart. But before the purging process takes place, the term outliers must be defined. Ryan (2000) cites Rousseeuw and van Zomeren (1990) discuss the difficulty of defining the term outlier. Specification limits of ±0.5 mm are as documented by the company. But since the panel is a non-rigid panel, an 'acceptable limit' is of ±1.0 mm is defined for this study. Having defined this, outliers are those readings measured more than 1.0 mm or less than -1.0 mm. Those observations falls within this range of measurement (±0.5 mm) but are remotely located from the data swarm will not be considered as outliers. In locating outliers at this data cleaning stage, simple graphical technique of box plots of each individual point measurement are produced. Of the three quality dimensions, box plots of SP17, TP12 and TP28 are revealed as outliers due to their large deviations from the nominal value 0. These three point variables are, then, dropped and not included in Phase I control charting. The actual process of outlier deletion will take place in the later session. Diagram 7.4 depicts boxplot for surface data.

Diagram 7.4. Box plot for surface data depicts S17 as outlier.

It is noteworthy to examine the possible causes contributing to the existence of outliers. In this study, inaccurate sampling time, storage of the panel, and error in measurement reading and recording are the possible causes of outliers. Storage could be the contributing factor because panels sampled from different runs are stacked onto one another. This condition may put force on the lower panels and consequently contribute to inaccurate readings of surface measurement. But storage factor will not in any way effect trim and hole eccentricity measurement reading. Existence of outliers could also be due to error in measurement reading and recording. Here, data are recorded manually on check sheets and not by electronic recording. Error in dimensional measurement reading is likely to occur for this task is very work intensive and strenuous in nature. This is not the case in many other automotive stamping plants where measuring systems are supported by the measuring machine (CMM).

7.5.3. Reducing Geometrical Dimension

Variable selection based on judgments has reduced measure points to 10 for each trim and surface. At the data cleaning stage, SP17, TP12 and TP28 are dropped for they are detected as outliers. The 'mathematics' of multivariate methods require the number of variables, p to be more than number of observations, n. As sampling design employed is rational subgroup of size 5, the quality variables must be further reduced to only 4 measure points for surface and trim quality variables. Dimensional reduction is performed for the second time through factor analysis of PCA. SAS JMP8 is used for this purpose as this software allows the option of using principal components as initial factors. All PCA analyses were carried out through varimax rotation with Kaiser normalization.

The general rule is the number of eigenvalues greater than unity should suggest the number of factor components accountable for the variation in the data set (Manly 2005). These are factors contributing to most variation. Extract of the reports display two to four eigenvalues greater than unity as shown in Diagram 7.6.(surface and trim). But the selection of point variables would only be made based on two factor components because the objective of selection at this stage is only reducing number of points for control charting purposes.

Selected surface

Principal Components: on Correlations

Number	Eigenvalue	Percent	20 40 60 80	Cum Percent
1	2.0162	22.402		22.402
2	1.9067	21.186		43.588
3	1.2664	14.071		57.658
4	1.1254	12.504		70.163
5	0.7621	8.468		78.630
6	0.6216	6.906		85.537
7	0.5325	5.917		91.454
8	0.4447	4.941		96.394
9	0.3245	3.606		100.000

Selected Trim

Principal Components on Correlations

Number	Eigenvalue	Percent	20 40 60 80	Cum Percent
1	1.7750	22.188		22.188
2	1.4361	17.952		40.139
3	1.1203	14.004		54.143
4	0.9544	11.930		66.073
5	0.8598	10.747		76.820
6	0.7652	9.565		86.384
7	0.6458	8.073		94.458
8	0.4434	5.542		100.000

Diagram 7.6. Eigenvalues of PCA for quality variables

The other important result of PCA is factor analysis. Factor loadings of factor analysis determine the variable assigned to most variation as explained by the factor. Variables with high factor loadings (0.50 or more) indicate the variable is related to that factor component. Three different reports are produced for the three quality variables. Factor loadings of the three PCAs are used to finally select the surface and trim variables for control charting scheme. Only the four variables with high factor loadings are considered while those variables with low loadings are discarded from the selection list. The four measure points selected for control charting purposes are SP9, SP12, SP26, SP30 for surface feature and TP1, TP9, TP26 and TP32 for trim feature. Table 7.3. lists the measure points finally selected by factor analysis.

Surface	SP9 SP12 SP26 SP30
Trim	TP1 TP TP26 TP32
Hole X-direction	HX4 HX5 HX6
Hole Y-direction	HY4 HY5 HY6

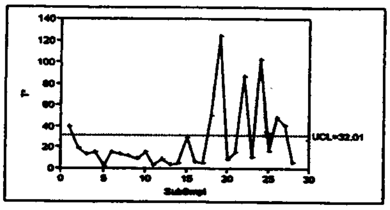
Table 7.3. The selected measure points for control charting scheme

7.5.4. Phase I Control Chart

The multivariate outlier analysis of the quality variables is made based on the subgroup analysis, thus, the presence of outliers is observed from 28 subgrouped observations, not from 105 individual observations. In the outlier deletion approach, T^2 statistics of all subgrouped observations in the data set is computed using equation [1]. For $\alpha = 0.001$, the upper control limit (UCL) is computed by equation [2]. From Pass 1 (term used by Mason & Young, 2001) observation subgrouped vectors whose T^2 values are less than or equal to the upper control limit (UCL) will remain in the data set, but if observation vector is found to have to value greater than the UCL, it will be discarded from the data set. The set of data then goes through a second pass with the new estimated mean vector and covariance matrix and the iterative process begins. Any outliers detected will be removed and the process is repeated until a homogeneous set of observations is obtained. Separate outlier analysis is performed for each quality feature.

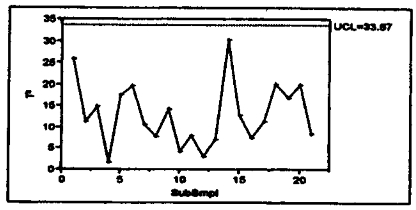
For descriptive purpose, only the purging process of 28 subgrouped surface data is briefly explained below. Pass 1 of purging process result in 7 subgroup outliers exceeding the upper control limit of 32.01. After discarding the seven outliers, the second pass does not produce any more outliers with UCL of 33.67. Diagram 7.7. below exhibits the Hotelling's T^2 control charts for outlier purging process with UCL calculated at $\alpha = 0.001$.

Pass 1



Subgroup Outliers – 1, 18, 19, 22, 24, 26, 27.

Pass 2



No subgrouped outlier detected

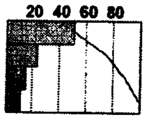
Diagram 7.7. Purging the outliers of surface data

Similar multivariate outlier analysis is performed on 28 subgrouped data of trim and hole. 8 outliers of trim data are detected at Pass 1 while all T^2 statistics of subgroup means are way below the UCL at Pass 2. Multivariate outlier analysis on hole data set only purge out two subgroups outlier on two separate passes and no more outliers detected at the third pass. Detecting for outliers is of paramount importance that failure to discard them will affect the parameter estimation of control chart for monitoring purposes at Phase II. The homogeneous set of data would be the reference sample for Phase II control charting. After discarding the outliers, the set of data variables are used for parameter estimation which is automatically computed by the software. These are the baseline parameters for computing the control limit of Phase II control chart for the actual process monitoring operation.

7.5.5. Principal component chart

Principal component analysis (PCA) on covariance matrix is applied in this study because the original variables i.e. all the dimensional measurements have the same meanings and are in the same unit (millimeter) (Yang, and Trewn 2004). PCA on covariance matrix is run on the 'cleaned' subgroup data. To illustrate this process, the final set of selected surface data (SP9, SP12, SP26 and SP30) with a total of 105 panels from four different production runs is utilized. The JMP8 outcome of PCA on covariance matrix for the data is shown as in Diagram 7.7. This printout displays the eigenvalues and eigenvectors of the sample covariance matrix. The percentage of eigenvalue for the principal component numbered 1 (PCA1) shows that 51.1% of variation is explained by the first principal component while 23.9% of the variation is explained by the second principal component (PCA2).

Principal Components on Covariances

Eigenvalue	Percent	20 40 60 80	Cum Percent	ChiSquare	DF	Prob>ChiSq
0.0536	51.129		51.129	63.298	9.000	<.0001*
0.0251	23.932		75.062	15.465	5.000	0.0085*
0.0155	14.754		89.816	2.869	2.000	0.2382
0.0107	10.184		100.000	0.000	0.000	

Eigenvectors

SP9	-0.06504	2.47240	2.28113	8.46870
SP12	0.38464	5.71946	0.21957	-3.99477
SP26	2.36990	-1.00720	6.43909	-1.73040
SP30	3.58939	0.09690	-4.23362	1.72403

Note: Eigenvectors were divided by square root of eigenvalues.

Diagram 7.8. PCA on covariance for surface

Based on the eigenvalues and eigenvectors of the PCA on covariances of subgrouped data, PCA charts are developed to find the causes of variation Component 1 or 2. Using these principal component values are the scores, two principal component charts are plotted at $\alpha = 0.0027$. These charts are shown in Diagram 7.9.

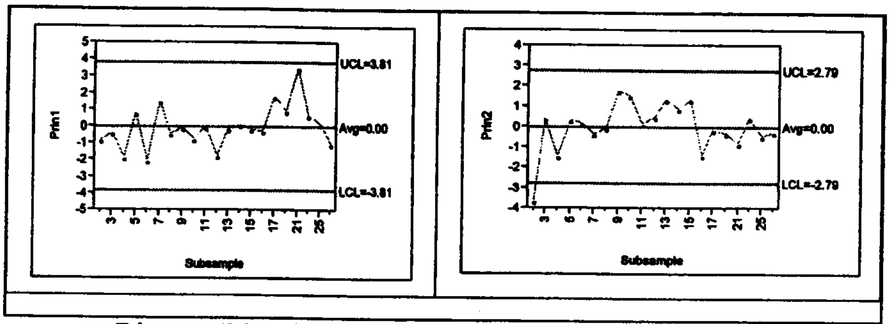


Diagram 7.9. Principal Component Chart of Prin1 and Prin2

For interpreting purposes, it is best to keep both Hotelling T^2 control chart and the principal component chart together. Each principal component is associated with a special type of correlated variation. Hence, any subsample that is out-of-control and has a very high principal component score on a component, this would be the extreme case for the cause of variation. The other case would be when an observation is found to be out-of-control in the Hotelling T^2 chart but is in control in each of the principal component chart, this simply indicate that the known principal component cannot be used to explain the variation for which further investigation may be needed.

7.5.6. Variation mode chart – Final Selected Surface

Eigenstructures of PCA output produced for principal component chart is used to plot variation mode chart. Principal components 1 and 2 each explain more than 70% of total variation of the final selected surface points. The eigenvalues of the first and second component are 0.0536 and 0.0251 respectively Eigenvectors of these surface points are utilized to estimate the VEL1 and VEL2 of both principal components 1 and 2 using equation [3] and [4].The center line of this dimensional variation is $E(\mathbf{u}_j) = (0,\ldots,0)$.

$$VEL_1(\text{mod}\,e\,1) = (0.0294, -0.0105,\ 0.1248,\ 0.5428, \ldots, 0.3948)$$

$$VEL_2(\text{mod}\,e\,1) = (-0.0294, 0.0105, -0.1248, -0.5428, \ldots, 0.3948)$$

The values of the two variation extent limits are exhibited in Table 7.3. Values of variation extend limits are used to plot two variation mode charts for the first principal component is illustrated as Table 7.3.

	Mode (PC) 1		Mode (PC) 2	
	VEL1	VEL2	VEL1	VEL2
SP3	-0.0454	0.0454	1.1751	-1.1751
SP12	0.2672	-0.2672	2.7184	-2.7184
SP26	1.6460	-1.6460	-0.4787	0.4787
SP30	0.0673	-0.0673	0.4606	-0.4606

Table 7.3. Variation extent limit (VEL) for Mode 1 and 2

With 51% of the total variation in the surface of the panel is explained by Mode 1, SP26 has the highest VEL values. This may indicates large variations of surface panel contributed by SP26 can be explained by the first component. Similarly, large variation exists in SP12 is identified from its large VEL of Mode 2, suggesting the cause of variation is from component 2. These variation mode charts, however, do not explain for variation of SP9 and SP30. The variation mode charts 1 and 2 are illustrated in Diagram 7.10.

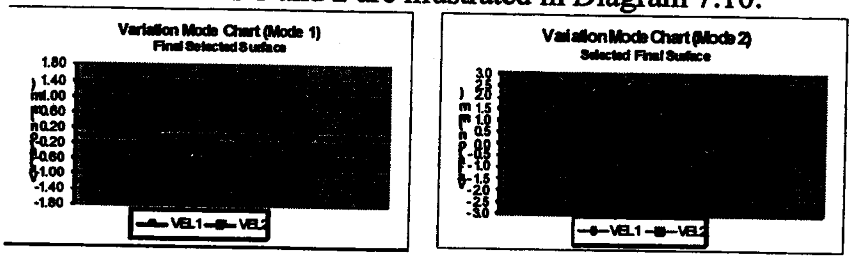


Diagram 7.10. Variation mode charts of PCA1 and PCA2 for final selected surface measure points

When new subgroups data is drawn, Phase II multivariate Hotelling T^2 control chart can be plotted based on the parameter estimated from Phase I. Supplementary principal component charts can be plotted to analyze any signal produced by the T^2 control chart. Principal component chart help to diagnose the source of variation from signaling out-of-control condition in the respective component chart. For instance, if Principal Component chart (PC1) signal out-of-control condition, Component 1 could be the attribute of variation in the process. Variation mode chart of a component can further rectify specific location on the panel from where variation has occurred.

8. CONCLUSION AND FURTHER DIRECTION

With the multivariate nature of manufacturing data, multivariate statistical techniques and quality monitoring of automotive stamping process is actually inseparable. In this study, Phase I Multivariate Hotelling's T^2 control chart is presented for quality monitoring of automotive stamping process based on panel's dimensional measurement. Phase I control chart is utterly important as it ensure the effectiveness of Phase II control chart where the actual process control operation goes on board. Principal component chart and variation mode chart are the other two multivariate techniques proposed as the analysis and diagnosis tools to process control and monitoring. Phase II of multivariate control chart of automotive stamping process is the most appropriate future direction to this research. Local automotive stamping plants must embark on sophisticated measuring systems and automated data acquisition technologies to support dimensional measurement of automotive panels. Only with the availability of good and sufficient data, research on effective automotive stamping process monitoring can be set in motion.

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