Pre-publication draft of paper accepted for publication in the Proceedings of the Ninth International Conference on Manufacturing Excellence (ICME 03)

Analysis of Stamping Production Data with view towards Quality Management

Bernard Rolfe[1], Yakov Frayman[1], Geoff Webb[2], Peter Hodgson[1]*

[1] *School of Engineering and Technology, Deakin University, Australia*
[2] *School of Computer Science and Software Engineering, Monash University, Australia*

Keywords

Signature analysis, feature extraction, quality control.

Abstract

A quality analysis trial was undertaken at Ford Geelong Stamping Plant on a press line that was fitted with standard press sensors to measure press and binder force over the stamping cycle for each panel. The quality of randomly sampled panels was measured by obtaining the panel thicknesses at five points, for 135 panels in total. These points were chosen such that they exhibited different forming modes. This paper analyses the input force data and the output quality data from the trial to determine any potential relationships. The analysis of the production data was performed using statistical correlation techniques to determine initial potential relationships between input and output variables. An Active Shape Model was used to extract features when identifying the major sources of variation within the input data. However, the initial analysis of the data elicited no direct relationship between the input variables measured and the panel thicknesses. This result is significant as the data collected is from a standard sensor configuration found in many press lines through-out the world. The reason for the lack of a direct relationship is believed to come from the lack of sensitivity in the force measurements which are not able to identify small changes in the process, whereas gross geometric variations have in previous studies shown an obvious relationship with changes in the force press profile. This means that existing force sensors require augmentation by additional sensors if a detailed automatic quality control system for the press lines based on input sensors alone.

1. Introduction

The stamping of sheet metal products is a process that exhibits a large amount of unexplained variation. Blümel et al. [1, 2] initially investigated variation of the sheet metal process with respect to the variation of material quality. They concluded that sheet metal forming has inherent problems with

[*] Elgar Rd Campus, Burwood, Deakin University, Vic. 3125 Australia. Email: brolfe@deakin.edu.au

process variation. More recently, Doolan et al. [3, 4] investigated the relationship between in-process variables, such as punch force, and quality outcomes, such as tearing and wrinkling. They developed a method to find an operating window for punch force as well as developing some empirical explanations for the causes of gross geometric variations in output. This study was based on non-production data.

This paper extends upon these studies by using the data from a quality analysis trial at the Ford Geelong Stamping Plant on a press line that was fitted with standard press sensors to measure the press force over the stamping cycle for each panel. The analysis of the production data was performed using statistical correlation techniques to determine initial potential relationships between input and output variables. Feature extraction was performed on the data set to extract out interesting information. The significance of this paper has been finding the lack of resolution in the current sensors for detailed quality control.

The structure of this paper is as follows. This paper first discusses the production set-up and the details of the production trial. This is followed by a review of the methods used to analyse the data. Finally, the results of the study are discussed.

2. Production Set-up

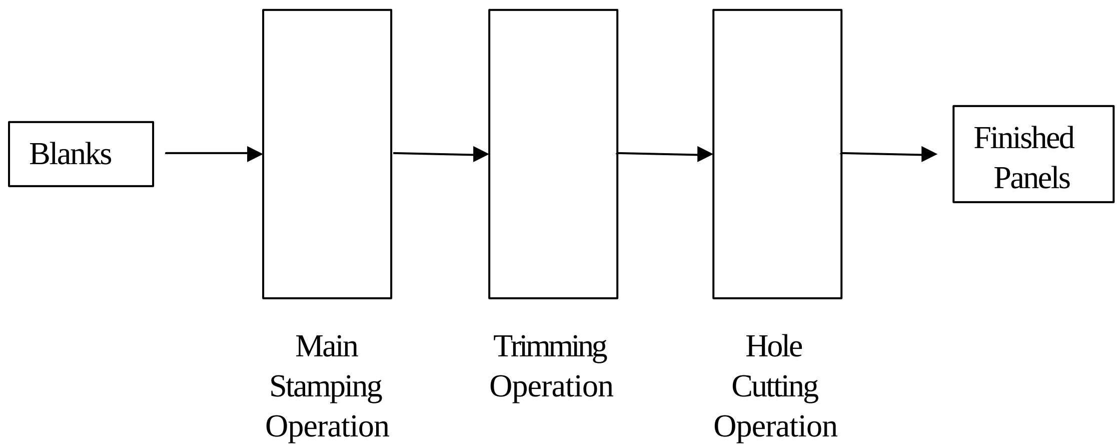

Figure 1 Example production set-up, real press line had six operations.

The press line consists of six operations (press stations), which included trimming and hole cutting. The first operation, however, did the most shape modification through deep drawing of the blank.

The binder force profiles were measured with a standard set of strain gauges which were attached to the binder connecting columns on the first press machine. The punch force profiles were measured by subtracting the binder force from the total force of the press measured on the outer press frame. Unfortunately, this means that the binder force profile is not a direct measurement of the binder/blank force, and the press force is even more indirectly measured as it is a fusion of the binder force and total force on the outer press frame.

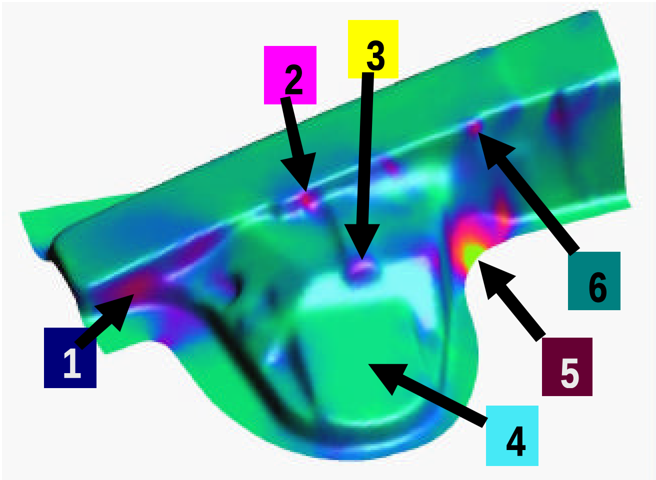

Figure 2 Upper front suspension housing panel with arrow noting the points where thickness was measured for each panel. The sixth measurement point was not used because of the difficulty in getting an accurate reading on the tight radius.

The part chosen for this study was an upper front suspension housing panel (as seen in Figure 2), which has been used for the latest sedan model. This panel was chosen because its production run length was acceptable to both Ford and the production trial, geometry data was available, and it was complementary to other aims of the STAMP project.

3. Plant Trial Set-up

A production trial was undertaken. The panels being analysed (excluding particular etched samples) were to be used in assembly; and therefore only non-destructive methods of strain estimation of the panels could be performed. An ultrasonic thickness sensor was used in order to not affect the panels in production. Other information was also recorded, such as ambient and die surface temperatures, and times and reasons for line stoppages.

Batches of five panels were randomly selected with time intervals of between 10 and 15 minutes. A batch size of five was chosen to provide statistically significant results when comparing means between batches. Random selection of time intervals was used in order to gain a better reflection of the variation throughout the shift, and to confound any systematic measurement error. Each panel within the batch had five thickness measurements taken. In addition, every fourth batch selected had four normal blanks replaced by four etched gridded blanks. The etched gridded panels were withdrawn at the end of the line for off-line measurement. A fifth normal (non-etched) blank was incorporated into the batch and its thicknesses were measured to complete the batch of five panels. The normal blank was included to determine if there was a major difference between the stamping of etched and non-etched panels.

Each panel was measured in five locations (as seen in Figure 2), the sixth location shown in the Figure was not measured because it was difficult to get an accurate reading on the tight radius edge section. Each of these points of interest was chosen from analysing the stamping behaviour of the blank using an *Autoform* simulation of the process. The points on the panel were chosen where there was a large amount of effective strain, a distinct forming mode, and the geometry of the point of the part was suitable for the ultrasonic thickness sensor. These five locations therefore provide the most quality information about the part because these were the points where the part was most likely to fail. Also, a minimum of points of interest were chosen because there were time constraints with the on-line manual measurement of parts during production.

The variables recorded during the production trial can be split into two categories, input and output variables (see Table 1). The only input variable considered in this paper is the force profile data.

Variables available for each measured panel	
Input Variables	**Output Variables ("Quality" Indicators)**
Force profile data Temperature readings of the die Anecdotal recordings of stoppages	Thickness measurements in five locations Strain measurements

Table 1 Input and output variables from the production trial.

4. Data Analysis Methods

The data analysis performed in this work consisted of three major operations:

1. Cleaning the data;
2. Extracting the features;
3. Analysing the data using correlation and other techniques.

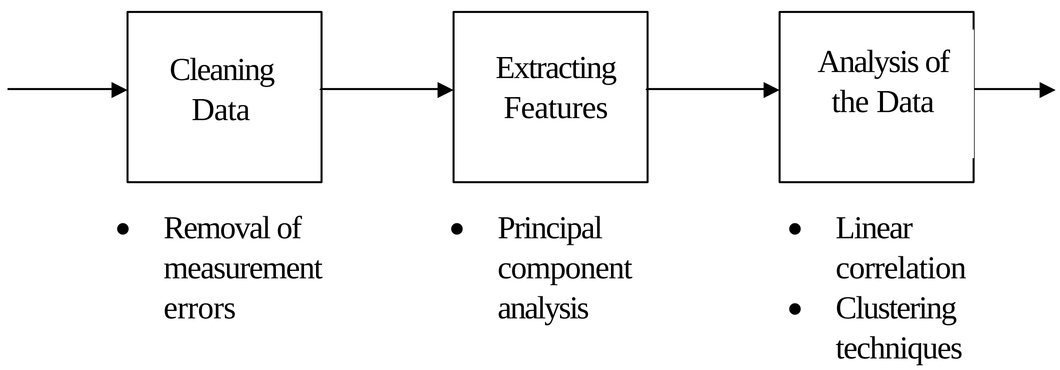

Figure 3 The flow of the data analysis

First, the data was cleaned to remove any measurement errors. Several thickness measurements were removed from the data for two panels because it was believed that the measurements were recorded incorrectly. The second operation was to extract the features from the data. Feature extraction tries to remove data of low importance, such as data that has low variance or noise. After these two stages, the data can be analysed by looking for correlations between the input and output data, and other associative relationships.

The initial analysis functions were linear functions and visual inspection. The reasoning was to investigate using a standard linear analysis so that if such an analysis were able to reveal some form of promising information, then more complex methods could be utilised to extract more complex relationships.

4.1 Feature Extraction (Principal Component Analysis)

Principal Component Analysis (PCA) [6] (also known as Karhunen-Loève transformation in communication theory) is often used in pattern recognition to select features. PCA is a transformation of the data such that the number of "effective" features is reduced without removing much of the information content of the data. PCA maximises the variance of the "effective" features or components of the transformed data. Suppose the data consists of N samples with P dimensions, that is, a matrix of $N \times P$. By using PCA we can represent this data using only the Q significant components (where $Q \ll P$, often $Q = 2$ or 3 for ease of viewing).
PCA consists of the following steps:

1. Form the co-variance matrix, **S**

$$\boldsymbol{S} = \frac{1}{N}\sum_{i}^{N}\left(X_i - \overline{X}\right)^T\left(X_i - \overline{X}\right), \qquad (1)$$

   where X_i is the ith data sample ($1 \times P$)

2. Perform eigenvalue decomposition on **S**

$$\boldsymbol{S} = \mathbf{V}\ ?^{2}\ \mathbf{V}^{T}, \qquad (2)$$

   where **V** is a matrix of eigenvectors and **?** is a diagonal matrix of the eigenvalues of the matrix **S**.

3. Create the transformation matrix

$$\boldsymbol{M} = \left[\mathbf{f}_1 \quad \mathbf{f}_2 \quad \mathbf{f}_3\right], \qquad (3)$$

   where **M** is a matrix created from the first Q eigenvectors ($P \times Q$), and $\mathbf{f}_{\mathbf{i}}$ is the ith eigenvector ($P \times 1$).

4. Transform the data, data now has Q dimensions/features, where $Q \ll P$

$$Y_i = X_i\ \mathbf{M} \qquad (4)$$

Active Shape Models [5] are a specific example of PCA applied to image analysis, where the data vector X_i is the concatenated vector of all the Euclidean coordinates that describe the object. For this paper, the force values and ram angles for a single profile were concatenated together to make a single dimensional vector describing that force profile.

4.2 Linear Coefficient of Correlation

The linear dependence [7] between two variables can be measured via the linear coefficient of correlation, ?. The linear coefficient of correlation is a normalised value between −1 = ? = 1, where −1 implies a negative linear dependency between the two variables, 0 implies no correlation between the variables, and 1 implies a positive linear dependency between the two variables.

$$\mathrm{Cov}(Y_1, Y_2) = \frac{1}{N}\sum_{i=1}^{N}\left(Y_{1,i} - m_1\right)\left(Y_{2,i} - m_2\right), \tag{5}$$

$$\text{where } m_j = \mathrm{Mean}\left(Y_j\right)$$

The population linear coefficient of correlation, ?, is defined as,

$$r = \frac{\mathrm{Cov}(Y_1, Y_2)}{s_1 s_2}, \tag{6}$$

$$\text{where } s_j = \text{Stnd Dev}\left(Y_j\right)$$

5. Analysis of production data

5.1 Principal Components of the Force Profile

Principal component analysis was implemented using an Active Shape Model [5] on the 1440 panels' force profiles collected over the whole production run to extract out the profile regions with the most variance. The Active Shape Model was then applied to the 135 measured panels to extract out the principal component values. The average profile of Binder 1 and its principal components can be seen in Figure 4. The first principal component of the Binder 1 sensor shifts the curve up or down (depending on the sign of the principal component value) at the ram angles where the work is being performed. The second principal component adjusts the force spike at the ram angle of 120 degrees. The principal components for each sensor were different, reflecting the variation in the press.

5.2 Basic Clustering of the Thickness Measurements

The associated thickness measurements from the panels were split into five groups: low, medium, high, very high, and Missing (No measurement). The reason for separating thickness into groups was to look for any simple patterns/relationships between the force profile and increasing thickness. The histograms for the four groups can be seen in Figure 5. The thickness distribution across the five point measurements varies somewhat. Measurement "C" has a higher density in the higher thickness groups, whereas measurements "A" and "D" have higher density in the lower thickness groups. The thickness groups were chosen such that the distances to the centers of the groups were minimized to give four groups across each of the five point measurements.

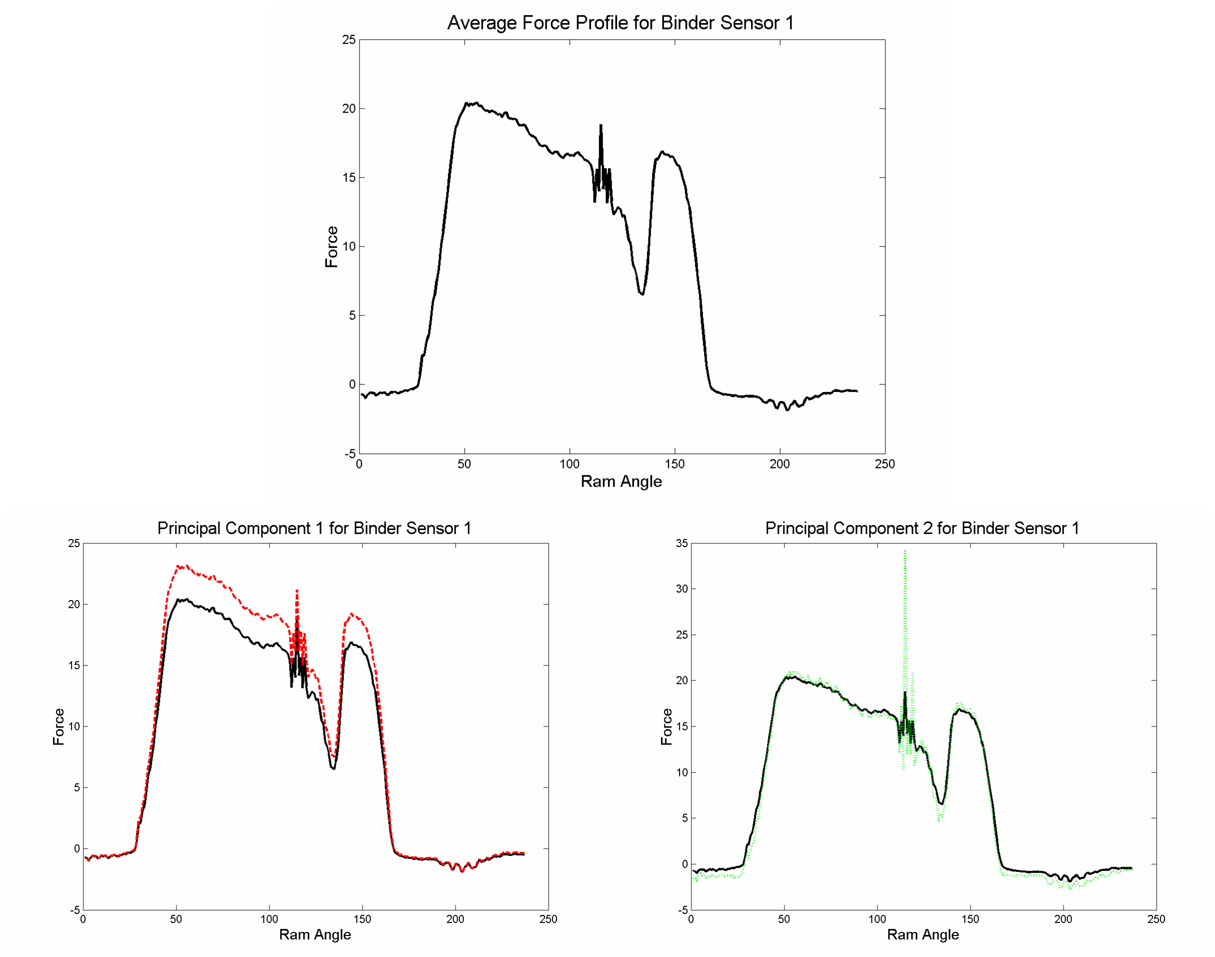

Figure 4 The average force profile and its first two principal components for Binder 1 which have been positively perturbated.

5.3 Correlation Between Thickness and Press Force

The correlation between the final thickness at the five points and the force profile was investigated by calculating the linear correlation between the principal components of the force profiles and the thicknesses measured at the five points on the panel. The correlation values are shown in Figure 6. The linear correlations between the force profile's principal components and the thickness measurements were generally very low, mostly below 0.2.

This implies that there is almost no correlation between the principal components and the thickness measurements. This can also be seen visually by looking at the average principal component values for the four thickness groups in Figure 7. A trend can be thought of as a situation, for a particular principal component, where the average principal component value for each of the thickness groups is in increasing or decreasing order.

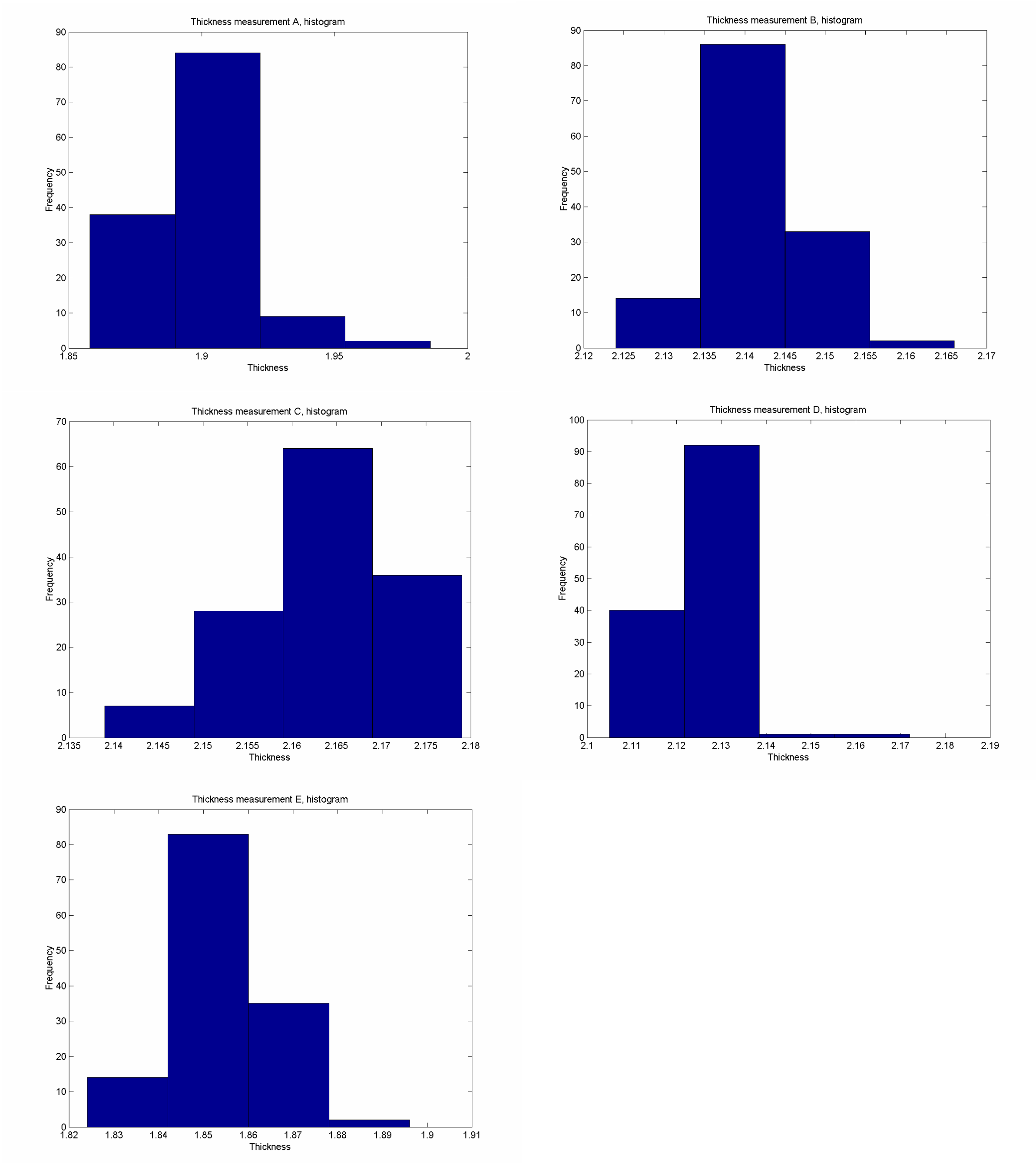

Figure 5 Histograms for the five measurement points over the 135 panels (excluding the points which had no measurement readings)

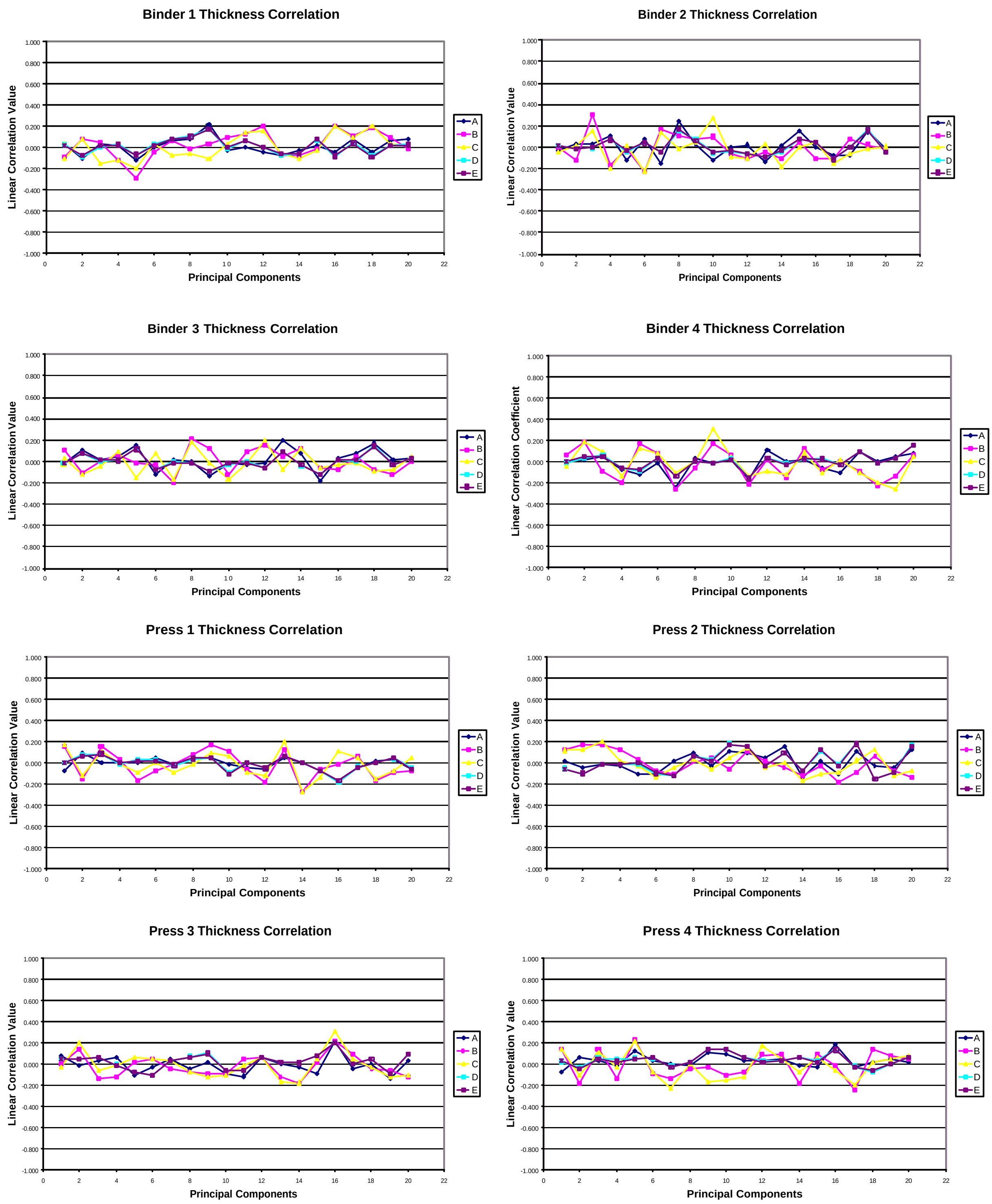

Figure 6 Linear correlation between the five thickness points for the 135 panels and the principal components of the force profiles for the four binder sensors and the four press sensors.

An example of a trend can be seen in principal component 5 (along the horizontal axis) for Binder 1, Thickness measurement A. The order of the average group values is as follows: the low thickness group (0.5), medium thickness group (0), high thickness group (-0.25), very high thickness group (-1.1). In this situation, significant trends should appear at the significant principal components (low values or the left hand end of the graphs). However, there does not appear to be many significant trends between the four groups. Moreover, the spread of the data, as seen in Figure 7, means that these average group trends are insignificant and perhaps spurious.

This means that either there is no correlation between the stamping and the final thickness (which is unlikely), or the sensors do not have the appropriate resolution to give us this detailed correlation. It is proposed that the sensors do not have the appropriate resolution or sensitivity. This is because the sensors are not measuring the binder or press force directly. The sensors are placed in the columns of the press which dampens the signal from the actual force being applied by the binder to the blank. Also, there may be other errors in the system such as material variation that affects the thickness variation but has low correlation with press variation.

If only gross differences in force are being transmitted through the binder sensors, then novelty detection may be possible to find major quality problems. Novelty detection is the process of finding outliers in the data. In this case, it would be a method that determines which panels had major quality problems, such as tearing or wrinkling, during a production run.

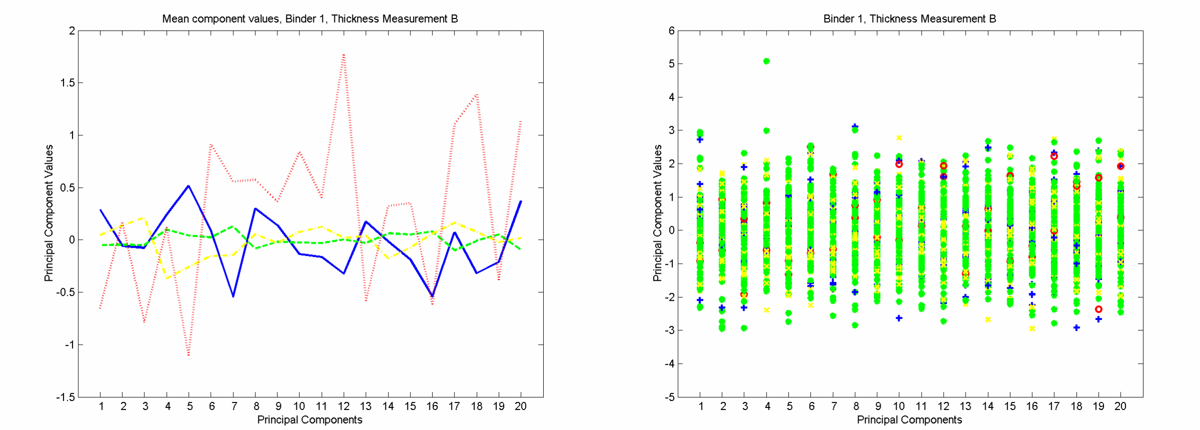

Figure 7 Mean principal components for thickness groups (low – solid blue line, medium – dashed green line; high – dot dashed yellow line; very high- dotted red line) for the five measured points (A,B,C,D,E). Figure on right shows the spread of the principal components of the thickness groups (low – blue plus, medium – green asterisk, high – yellow "x", very high – red circle) for the thickness measurement "B". All principal component values shown have been normalized to a zero mean, unit standard deviation for the ease of viewing.

In this situation we are looking for gross changes from the average signature. It is an easier problem than finding variable correlations because it is a binary classification situation, and the variable changes should be significantly different from the norm. The clustering plots in Figure 5 indicated that measurement "A" was centred in the lower thicknesses, and therefore the panels with very high thickness measurements can be thought of as potential outliers or novelties. Figure 8 indicates that the principal component values of the panels' with very high thickness are on the outskirts of the spread graphs. Unfortunately, there are not enough samples within the data to properly address the significance of this preliminary result. This gives us hope that gross quality changes can be detected by analysing the force profile of the press. Further work is needed to actually prove this to be the case, including another production trial on a less stable panel.

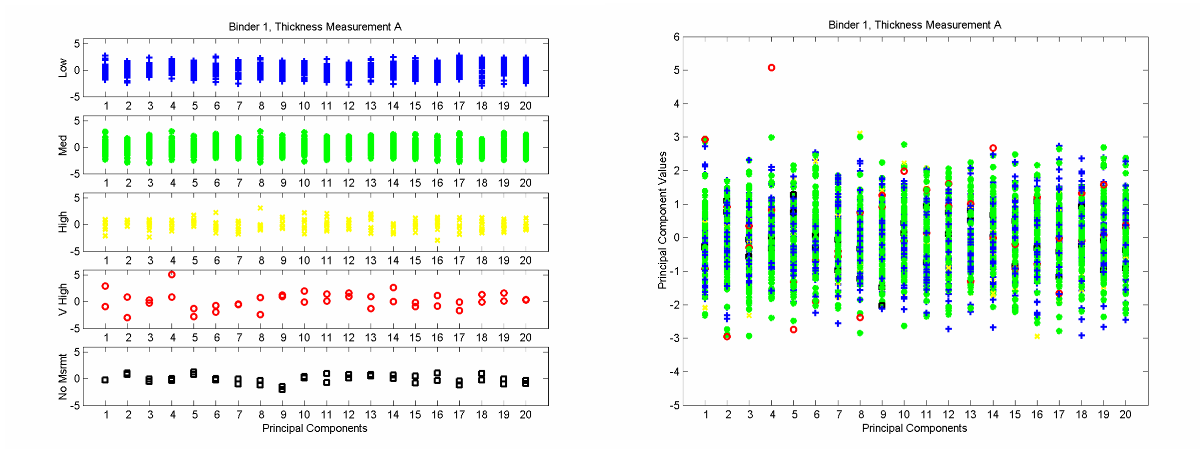

Figure 8 The spread of the principal components of the thickness groups (low – blue plus, medium – green asterisk, high – yellow "x", very high – red circle, No measurement – black square) for the thickness measurement "A". Novelty detection could be possible as the very high thickness measurements appear on the edges of the principal component spread. All principal component values shown have been normalized to a zero mean, unit standard deviation for the ease of viewing.

5.4 Other Interesting Analysis Results

One of the interesting results of our data analysis was the correlation between the production rate and the force level of the binders and the press. The production rate was calculated by using a smoothed average window sliding across the time of the production trial which counted the number of panels produced over a five minute period.

Binder sensors 1 and 2 have a very weak negative correlation with production rate; whereas Binder sensors 3 and 4 have strong positive correlations with production rate, particularly at early ram angles (around 75 degrees) (Figure 9). The reason for the binder applying more pressure on one side of the panel when the there is a high through-put of panels is unknown at present. Possibly it is the temperature build-up in the hydraulics system, though this still does not explain the skewness in the binder pressure in times of consistent production.

Press sensors 1 through to 4 have weak correlations, and the lack of significance in all these values means that it is not possible to make any real conclusions.

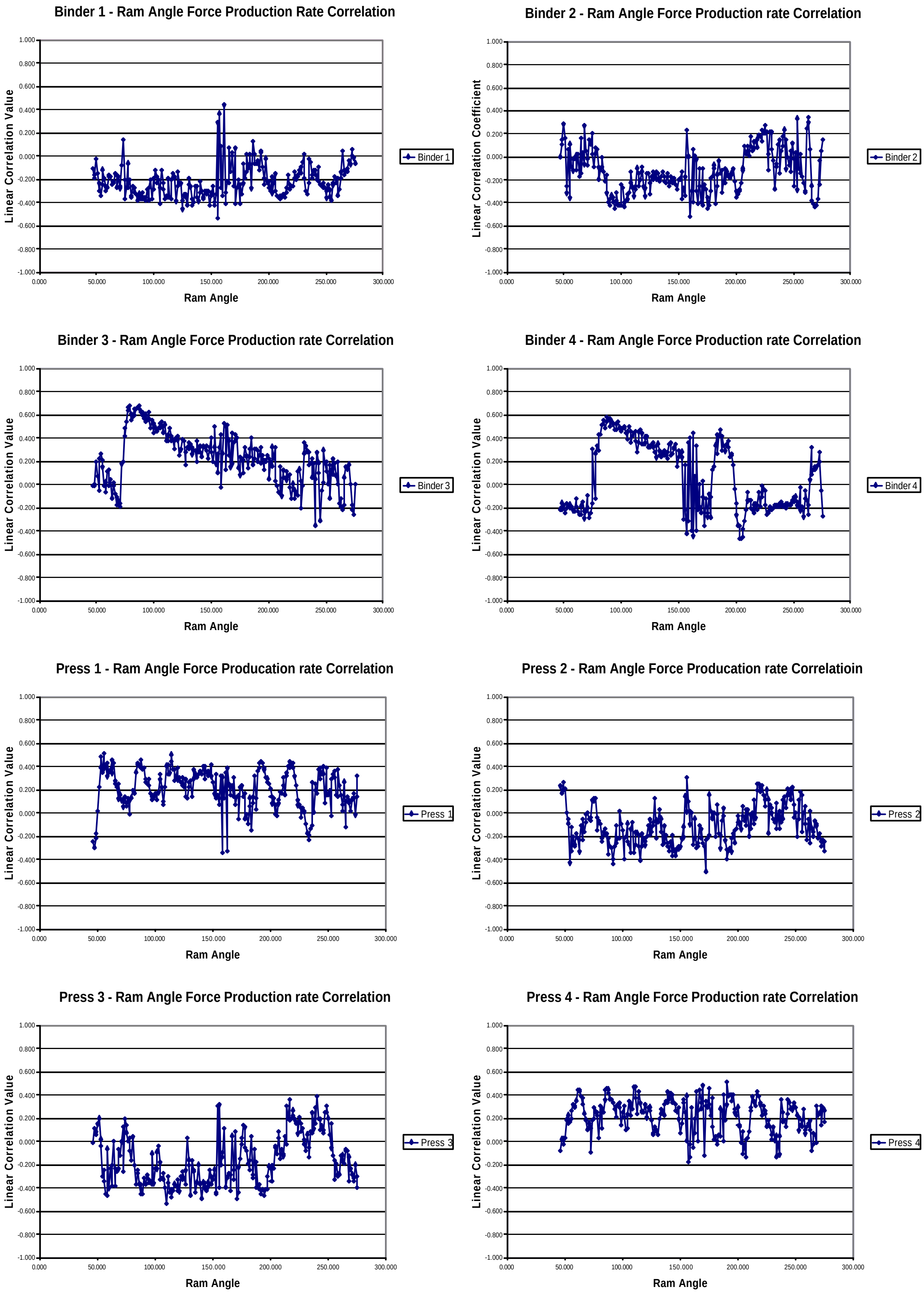

Figure 9 Correlation between force at particular ram angle and the production rate. The production rate is equal to the instantaneous speed of panel production averaged over a five minute period centred on the panel in question.

7. Conclusion

The initial analysis of the data from a stamping press line at Ford Geelong Stamping Plant elicited no significant relationship between the input variables measured (press and binder force) and the panel thicknesses. This result is significant as the data collected is from a standard sensor configuration found in many press lines through-out the world. The reason for the lack of a direct relationship is believed to come from the lack of sensitivity in the force measurements. The force sensors do not measure the binder or press forces directly, which means they are unable to pick up small changes in the process. However, classification of gross variations in thickness may be possible. Further study is necessary to ensure the significance of this finding. This means that additional sensors will need to be added to develop a sensitive automatic quality control system for the press lines based on input sensors alone.

8. Acknowledgements

We would like to acknowledge the support of Ford Australia for allowing us access to their facilities and data. Work done here was performed as part of the STAMP joint project between Ford, Deakin and ANU. We would like to also thank the STAMP staff and students for access to the production data, and thanks those who conducted the production trial (Matthew Dingle, Lincoln Crane, Victor Pantano, Fabian D`Souza, Alison Warrior, Greg Cheesewright, Jonathan Mullins, Leigh Robertson, Matthias Weiss, and Manjula Nanayakkara); particularly Greg Cheesewright, who collected the force profiles, Lincoln Crane, who developed the rig for measuring panel thickness, Fabian D'Souza for running Autoform simulations, and Matt Dingle for organising the trial.

8. References

[1] Blümel K.W., Hartmann G., Lübeck P., "Variations of automobile properties due to the manufacturing process", 14th Biennial Congress of IDDRG, 1986, pp. 179-187.

[2] Blümel K.W., Hartmann G, Lübeck P., "Variations of the Stamping Process", 15th Biennial Congress of IDDRG, 1988, pp. 9-16.

[3] Doolan M.C., Kalyanasundaram S., Hodgson P., Cardew-Hall M.J., "Identifying the variation in sheet metal stamping", Proceedings of the 7th International Conference on Sheet Metal SheMet'99, 1999, pp. 117-124.

[4] Doolan M.C., Kalyanasundaram S., Hodgson P., Cardew-Hall M.J., "Identifying the cause of variation in sheet metal stamping", International Conference on Manufacturing Excellence ICME 2000, 2000.

[5] Cootes T.F., Taylor C.J., Cooper D.H., Graham J., "Active Shape Models – Their training and application", *CVGIP: Computer Vision and Image Understanding*, Vol 61. Iss. 1, 1995, pp. 38-59.

[6] Ripley B.D., "Pattern Recognition and Neural Networks", Cambridge University Press, Cambridge, 1999, pp. 289.

[7] Mendenhall W., Scheaffer R.L., Wackerly D.D, "Mathematical Statistics with Applications", Duxbury Press, Boston, 1986, pp. 206.