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Data-Driven Modelling of a Pelleting Process and Prediction of Pellet Physical Properties

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Abstract

In the manufacture of pelleted catalyst products, controlling physical properties of the pellets and limiting their variability is of critical importance. To achieve tight control over these critical quality attributes (CQAs), it is necessary to understand their relationship with the properties of the powder feed and the pelleting process parameters (PPs). This work explores the latter, using standard multivariate methods to gain a better understanding of the sources of process variability and the impact of PPs on the density and strength of the resulting pellets. A Kilian STYL’ONE EVO Compaction Simulator machine was used to produce over 1000 pellets, whose properties were measured, with varied powder feed mechanism and powder feed rate. Process data recorded by the Compaction Simulator machine were analysed using Principal Component Analysis (PCA) to understand the key aspects of variability in the process. This was followed by Partial Least Squares (PLS) regression to predict pellet density and hardness from the Compaction Simulator data. Pellet density was predicted accurately, achieving an $R^2$ metric of 0.87 in 10-fold cross-validation, and 0.86 in an independent hold-out test. Pellet hardness proved more difficult to predict accurately, with an $R^2$ of 0.67 in 10-fold cross-validation, and 0.63 in an independent hold-out test. This may however simply be highlighting measurement quality issues in pellet hardness data. The PLS models provided direct insights into the relationships between pelleting PPs and pellet CQAs and highlighted the potential for such models in process monitoring and control applications. Furthermore, the overall modelling process boosted understanding of the key sources of process and product variability, which can guide future efforts to improve pelleting performance.

1. Introduction

Pelleting processes are used in the manufacture of a range of consumer and industrial products, including tableted pharmaceuticals, health products, consumer goods, food products and catalysts. In the manufacture of these pelleted products, it is important to produce pellets that are consistent in size, shape, composition, density, and strength to ensure that they are fit for purpose. Usually, several of the aforementioned variables will
be listed in the product specification along with appropriate bounds that need to be met. Poorly controlled pelleting processes can result in production of out-of-spec material, which is associated with negative economic and environmental impacts, and with potential safety implications in the case of pharmaceuticals for example. Conversely, operating pelleting processes with tight control over the critical quality attributes (CQAs) can allow manufacturers to operate closer to the specification limits and to improve the product and/or the process economics and sustainability.

To establish tight control over a manufacturing process, it is important to control all the variables in the manufacturing process that have the potential to impact the product CQAs. Before that can be achieved, it is necessary to understand the relationships between the manufacturing variables and the product CQAs and to identify those that are most influential, as well as those that can be manipulated to control the product CQAs (1). Henceforth, knowledge of the interactions between process variables and the response of the process is critical. Typically, models are deployed to help us gain understanding of process behaviour. In the literature, there are three main approaches that have been applied to modelling pelleting process behaviour, these are mechanistic, data-driven and hybrid modelling approaches.

Traditionally, mechanistic models such as the Drucker-Prager Cap model and Finite Element Models have been applied to better understand the behaviour of materials undergoing compaction and their resultant physical properties. Wu et al. (2) used Finite Element Methods (FEM) to gain understanding of the behaviour of pharmaceutical powders during compaction. The Drucker-Prager Cap (DPC) model was used as the yield surface of the medium, representing failure and yield behaviours. Experiments were carried out using a Compaction Simulator with an instrumented die to calibrate the DPC model and to investigate the relationship between relative density of the powder bed and the applied pressure during compaction. The DPC model generated realistic powder properties that were fed into finite element analysis (FEA), which was able to accurately model the relationship between relative powder bed density and the compaction force. FEA also allowed close examination of the evolution of stress distribution during relaxation, which revealed narrow bands of localised intensive shear stresses where potential failure mechanisms can initiate. Several other works have utilised purely mechanistic approaches to model pelleting behaviour (3–7).

The drawback to mechanistic approaches is that they take significant human resource to develop and they are not easily adapted to new processes or scenarios. In contrast, purely data-driven approaches are very fast to develop and deploy and are easily adapted to new contexts. Several works have focused on the application of data-driven models to pelleting processes (8–15). Haware et al. (9) applied multivariate analysis to
quantify the relationships between material properties of α-lactose monohydrate grades, process parameters and the tablet tensile strength. The materials were tableted on a compaction simulator and the collected data were analysed with principal component analysis (PCA) and partial least squares (PLS) regression. PCA provided insights into relationships between different powder and compression properties of the studied materials. PLS was successfully used to predict tablet tensile strength from the compression parameters, punch velocity and the lubricant fraction.

Li et al. (10) used multivariate analysis to evaluate the fundamental and functional properties of natural plant product (NPP) powders and their suitability for direct compaction. NPP powders were prepared by three different methods and data were produced in a single-punch compaction simulator. Results from a one-way ANOVA, cluster analysis and PCA showed that the physical properties of the NPP powders were mainly determined by their particle structure, which derived from the preparation method. Stepwise regression analysis indicated that the compaction properties of the NPP powders could be improved by controlling physical properties, such as density, particle size, morphology and texture. Overall, the work provided guidance on the development of NPP powders for compaction.

Matji et al. (16) conducted a multivariate analysis on data from the production of ibuprofen tablets. In their study, regression methods were used to predict the CQAs of the tablets, such as disintegration time, dissolution, hardness, porosity and tensile strength, from the pressure applied in roller compaction (dry granulation) and tabletting. Tabletting compaction pressure was found to be positively correlated to disintegration time, tensile strength and hardness, and negatively correlated to the porosity and percentage of drug dissolved. Roller compaction pressure during dry granulation was observed to have those same correlations with the CQAs inverted.

More recent works have also focused on the development of hybrid models for pelleting processes, which combine mechanistic models with data-driven models to leverage benefits from both approaches (17, 18). For example, Benvenuti et al. (17) trained an artificial neural network (ANN) to model the relationship between macroscopic experimental results and microscopic parameters of discrete element method (DEM) simulations. The work showed that the ANNs could be used to generically identify DEM material parameters for any given non-cohesive granular material. Hybrid modelling approaches can offer great benefits where existing mechanistic models are available because they leverage the accuracy and interpretability of the mechanistic model, while offering increased flexibility.
In this work, a data-driven approach is used to model pelleting performance in order to gain a deeper understanding of the process behaviour and to understand the potential of such models for use in process monitoring and control. The work expands upon previous data-driven modelling of pelleting processes by exploring the impact of two different feeder mechanisms: a force feeder and a vibration feeder, operated at different speeds. Furthermore, the product studied is an inorganic catalyst material. Analysis of such materials in pelleting processes has not been widely reported in the literature. The pelleted catalyst product studied is manufactured by Johnson Matthey.

2. Equipment and methods

2.1 Equipment

A Kilian STYL’ONE EVO Compaction Simulator - The Compaction Simulator, shown in figure 1, is an instrumented single-punch pelleting machine that is designed to simulate production scale pelleting machines. The machine is fitted with an array of sensors, which record data throughout the pelleting process. The pelleting process can be broken down into four main events in sequence, these are 1) filling of the die, 2) pre-compaction of the powder to rearrange the particles, 3) main-compaction of the powder to form the pellet, and 4) ejection of the pellet from the die.

![Compaction Simulator](image)

Figure 1 Photos of the Compaction Simulator equipment. On the left is the paddle feeder mechanism showing the blades which can be flipped upside down to change the blade angle. In the top right is the vibration feeder, and the bottom right shows the upper punch and the feeder mechanism, which swivels out of the path of the upper punch after filling the die.
SOTAX ST50 – this machine is a semi-automatic tablet hardness tester, which was used to measure four properties of the tablets: weight, diameter, thickness (from which density is calculated) and hardness.

2.2 Experimental work

The Compaction Simulator was used to produce approximately 200 pellets for each of six experimental runs that used different powder feeder setups. Two different powder feeder systems were used a) a force feeder which pushes powder over the die to allow it to fill and b) a vibration feeder which vibrates so that powder falls into the die. The force feeder was used in both a left and right orientation, which changes the angle of the blade that pushes the powder over the die. Finally, the feeders were operated at different speeds. The six experiments were assigned the following labels for convenience in the discussion:

1. ‘Left40’ – force feeder in the left orientation at speed 40%.
2. ‘Left70’ – force feeder in the left orientation at speed 70%.
3. ‘Right70’ – force feeder in the right orientation at speed 70%.
4. ‘Vib20’ – vibration feeder at speed 20%.
5. ‘Vib38’ – vibration feeder at speed 38%.
6. ‘Vib70’ – vibration feeder at speed 70%.

The Compaction Simulator yields two datasets for analysis. The first dataset, $X_1$, is a 2D matrix containing both measured and derived variables ($M$) for the numerous pellets produced ($N$). This data table contains a summary of the pelleting process performance with the maximum force and displacement values in pre-compaction, main-compaction and ejection, as well as various derived parameters, for example, the compression energy. A full list of the variables in $X_1$ is provided in appendix A. The second dataset, $X_2$, is a 3D data matrix consisting of data collected for each measured process variable ($K$) regularly sampled over time ($J$) for numerous pellets produced ($N$). In contrast to $X_1$ which contains selected measured values and derived parameters, $X_2$ contains the raw data for the 8 variables listed in table 1, recorded by the compaction simulator at 0.01 ms intervals.

Table-1 Variables recorded by the Compaction Simulator in a time series format, $X_2$

<table>
<thead>
<tr>
<th>1</th>
<th>Lower punch displacement</th>
<th>5</th>
<th>Upper punch force</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>Upper punch displacement</td>
<td>6</td>
<td>Punches force difference</td>
</tr>
<tr>
<td>3</td>
<td>Distance between punches</td>
<td>7</td>
<td>Upper punch linear speed</td>
</tr>
<tr>
<td>4</td>
<td>Lower punch force</td>
<td>8</td>
<td>Lower punch linear speed</td>
</tr>
</tbody>
</table>
Pellets collected from the Compaction Simulator were manually transferred to the SOTAX ST50 machine to be measured. The pellets were retained in the order that they were ejected to ensure that the pellet measurements could be correctly aligned with the Compaction Simulator data. The measured properties of the produced pellets (e.g. density and hardness) are recorded in the 2D data matrix, $Y$. In this work, the dependent variables of interest were pellet density and hardness.

### 2.3 Principal component analysis

In this work, PCA was implemented on the summary data $X_1$ to understand the correlation between these variables and the similarities and differences between different shoe speed and feeder mechanism combinations. PCA involves decomposing the covariance matrix into a number of principal components (PCs), $P$, each of which is a weighted linear combination of the original variables. The scores of the PCA model, $T$, are the original data projected onto the new latent variable space. Plotting the scores against one another facilitates observation of the variance in the data in the latent variable space and allows patterns and clusters to be identified.

### 2.4 Partial least squares regression

PLS regression was used to model the relationship between the Compaction Simulator variables in $X_2$ and the measured pellet properties of interest: hardness and density. For model development, the data were split into a training set (80% of samples) and hold-out test set (20% of samples) for an independent test of model performance at the end of the process. Variable selection was carried out by the variable importance for projection (VIP) selection method (19). This involved fitting an initial model using all the variables and then selecting variables to keep based on their VIP score. Variables with a VIP score above 1 were selected. The optimal number of latent variables was determined based on minimisation of the mean absolute error (MAE) in 10-fold cross-validation. Python v3.7 was used for all modelling work.

### 3. Pellet density and hardness distributions

In order to compare the effect of the powder feeder mechanism and speed on pellet density and hardness, the distributions of pellet density and hardness were plotted for each experiment and pairwise t-tests were used to check for statistically significant differences in average pellet density and hardness. Figures 2a and 2b show the distributions of pellet density and hardness, respectively.
Figure 2 Boxplot and whisker diagrams showing the distributions of a) pellet density and b) pellet hardness, for each experiment. The orange line indicates the median, the edges of the box indicate the upper and lower quartiles and the whiskers mark the upper and lower quartiles extended by 1.5 times the interquartile range. The data shown is mean centred with unit variance.

Figure 2 shows that the feeder configuration greatly influenced the level of variability in pellet density and hardness. In particular, experiments ‘Left40’ and ‘Right70’ produced a large amount of variability, while the vibration feeder resulted in much less variability at all speeds tested. The pairwise t-tests revealed statistically significant shifts in average pellet density and pellet hardness between the six experiments. For example, with the vibration feeder and the force feeder in ‘left’ orientation, increasing the speed of the feeder resulted in statistically significant increases in pellet density. Importantly, the distributions indicate that the vibration feeder results in more consistent pellet density and hardness than the force feeder, although the force feeder may be used in the ‘left’ orientation at high speed to minimise variability.

4. Principal Component Analysis of the Compaction Simulator summary data

PCA was used to assess the correlations between the variables in the Compaction Simulator summary dataset and their contributions to the overall process variability. The PCA model presented here was built on summary data from the experiments using the force feeder, namely ‘Left40’, ‘Left70’ and ‘Right70’. Figure 3 shows the variance explained by each PC in an 8 PC model. The first PC explains 49.3% of the variation in the data, while PCs 2 and 3 explain 14.1% and 7.2%, respectively. Collectively, the first three PCs capture 70.6% of the variance in the data, while PCs 4 and beyond explain less than 5% of the variance each. Due to the exploratory nature of this analysis, it is preferable to consider all the PCs that are likely to be informative; however, determination of the number of PCs to include in the model is not critically important. In this work, the first three PCs were analysed because PC 4 and beyond capture very little variance and likely feature a low signal to noise ratio.
Figure 3 Explained variance versus number of principal components in the PCA model, which is built on summary data from the three experiments using the force feeder mechanism: ‘Left40’, ‘Left70’ and ‘Right70’.

Figure 4 Plots showing the scores of the PCA model for a) PC 1 versus PC 2 and b) PC 1 versus PC 3. The percentage of variance explained by each PC is displayed in the brackets on each axis.

The scores of the PCA model for PCs 1 to 3 are displayed in figure 4 and the most important variables – those with loadings of the highest magnitude for each PC – are displayed in figure 5. PC 1 captures variation in the data that is present on a pellet-to-pellet basis within each of the three experimental runs and the scores overlap, i.e. there is no separation of the scores by experiment on PC 1. Figure 5a shows that the 49% of variation captured in PC 1 is attributed to the forces and energies involved in the pre-compaction, main-compaction and ejection events. The model also indicates that the forces and energies listed in figure 5a are all positively correlated with one another.

In contrast to PC 1, PC 2 captures variation that separates the different experiments. Figure 5b shows this is largely attributed to differences in die filling height, ejection force
and some derived parameters which are determined from die filling height, such as the compression and relaxation times. The large spread of the red markers in the vertical plane, corresponding to the ‘Right70’ experiment, indicates that this set up resulted in more variability in the die filling height compared to ‘Left40’ and ‘Left70’. The Compaction Simulator was calibrated to produce pellets of the same weight for each experiment; therefore, it is likely that the different feeder setups result in a different bulk density of the powder when it is initially filled into the die, explaining the differences in filling height.

Figure 4b shows the within group variability that is captured by PCs 1 and 3. All of the experiments overlap on PCs 1 and 3, while ‘Right70’ spreads across the largest area, indicating that this experiment has the largest variability on these PCs. Observing the distributions of the response variables, it is clear that ‘Right70’ produces pellets with the largest variation in pellet density and hardness. As shown in figure 5c, the main variables represented by PC 3 are the energies involved in the pellet ejection and the elastic energy calculated for the main-compaction event.
While the ejection plastic energy and compression energy correlated with the pre-compaction and main-compaction forces, the ejection energy and the ejection force appeared as key variables in PCs 2 and 3, indicating that there is variance in the ejection force that is uncorrelated to pre-compaction and main-compaction force. PC 2 shows that ejection force is positively correlated to die filling height. An additional factor that may be influencing the ejection force that is not monitored, so not captured by the dataset, is the amount of lubricant present in the material.

5. Modelling pellet CQAs

PLS regression models were developed to predict pellet density and pellet hardness, using the methodology outlined in section 2. Table 1 shows the performance metrics obtained from cross-validation and testing of the two models for pellet hardness and density.

Table 2 Performance metrics describing the quality of the model fit in cross-validation and testing

<table>
<thead>
<tr>
<th></th>
<th>No. of LVs</th>
<th>CV $R^2$</th>
<th>CV MAE</th>
<th>Test $R^2$</th>
<th>Test MAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Density PLS model</td>
<td>4</td>
<td>0.87</td>
<td>0.09</td>
<td>0.86</td>
<td>0.08</td>
</tr>
<tr>
<td>Hardness PLS model</td>
<td>3</td>
<td>0.67</td>
<td>0.44</td>
<td>0.63</td>
<td>0.53</td>
</tr>
</tbody>
</table>

The performance metrics shown in Table 1 are for the models obtained after the variable selection procedure and tuning of the number of latent variables included in the model, as described in section 2.4. The models for both pellet hardness and density performed well in cross-validation and testing. Pellet hardness however proved to be the more difficult to model and predict accurately, as the performance metrics demonstrate. The pellet density PLS model explained approximately 86% of the variance in both 10-fold cross-validation and independent testing. The Mean Absolute Error (MAE) for the pellet density model was 0.17 and 0.18 in 10-fold cross-validation and independent testing, respectively. The cross-validation metrics indicate that the pellet density PLS model should have excellent predictive performance and the independent test on the held-out data supports this. The fit of the density PLS model to the training data and the testing data is shown in figure 6.
Figure 6 Plots showing the fit of the PLS model for pellet density. The plots show a) the measured versus fitted values for the training data, b) the residuals versus fitted values for the training data, c) the measured versus predicted values for the test data and d) the residuals versus predicted values for the test data.

Figure 6 shows that the density PLS model fits the data well in both training and testing, with the exception of a few outliers, which are likely to result from a mismatch between the X and Y data that occurred during the experimental process.

The pellet hardness PLS model explained approximately 67% and 63% of the variance in pellet hardness in 10-fold cross-validation and testing, respectively. The MAE for this model was 0.44 and 0.53 in cross-validation and testing, respectively. While this performance is not as good as the pellet density model, it indicates that the model has good predictive capability. Observation of the measured versus fitted values and the residuals in figure 7 reveals that the model is good at fitting and predicting the low-hardness pellets but is far less accurate for the high-hardness pellets. The residuals in figure 7b and 7d “fan-out” and become much larger from -1 and above on the x-axis (scaled pellet hardness). The increasing residuals with increasing pellet hardness could be related to missing factors that are not captured in the Compaction Simulator data. It could however equally be the result of changes in the sensitivity of the measurement.
device at different hardness levels. Unfortunately, it is difficult to gain a good understanding of the reliability of the hardness measurement due to the test being destructive. Given that the model offers accurate prediction of low hardness pellets, the model could still be valuable in a process monitoring or supervisory process control applications, where identification of low hardness pellets could allow operators to intervene early and adjust process parameters accordingly.

Figure 7 Plots showing the fit of the PLS model for pellet hardness. The plots show a) the measured versus fitted values for the training data, b) the residuals versus fitted values for the training data, c) the measured versus predicted values for the test data and d) the residuals versus predicted values for the test data.

4.1 Interpretation of the model coefficients

The key predictive variable identified in both the pellet hardness and pellet density PLS models was the lower punch force. This variable featured the largest magnitude standardised regression coefficient in both models and correlated positively with both density and hardness. For the pellet density PLS model, the variable selection process identified four variables as important: 1) the lower punch force, 2) the punches force difference, 3) the upper punch displacement and 4) the lower punch displacement. The lower punch force was the key predictor variable. The other three variables however
contributed positively to the cross-validation and testing performance metrics. The metrics dropped slightly when these features were left out. The variable selection process for the pellet hardness model revealed that the lower punch force was the only significant variable contributing to this model.

Figures 8a and 8b show the time series profiles for the lower punch force coloured by pellet density and hardness, respectively. The plots facilitate visualisation of the correlations between density and lower punch force and hardness and lower punch force. In both cases, it is clear that the lighter coloured lines (high density and hardness) correspond to high forces in pre-compaction, main-compaction and ejection, while the darker lines (low density and hardness) correspond to lower forces. In other words, figures 8a and 8b show that lower punch force correlates positively with density and hardness, respectively. The separation of the colours is clearer in figure 8a and the colour gradient appears to be linear, whereas in figure 8b the separation of the light and dark colours is less clear. In particular, the light colours corresponding to high hardness do not separate well from the red coloured average hardness pellets. This reflects the poorer predictive capability of the hardness PLS model, which produced larger errors for high hardness pellets.
Figure 8 The lower punch force profiles of the pellets from all six experiments coloured by a) pellet density and b) pellet hardness. The three peaks on each graph correspond to the pre-compaction, main-compaction, and ejection events.

6. Conclusions

The workflow for this study began with exploratory data analysis to observe and compare the distributions of pellet density and hardness and to understand the variance and correlation in the Compaction Simulator data. The distribution plots clearly showed that feeder configuration impacted both the average pellet density and hardness and the level of variability in those properties. Pairwise t-tests revealed that the shifts in mean density and hardness were significant in many cases. To minimise overall variability, the vibration feeder mechanism should be favoured over the force feeder mechanism, however, the force feeder mechanism can be optimised for consistency by running in the 'left' orientation at higher speeds.

PCA showed that the most important component of variance in the dataset was attributed to the forces and energies involved in the pre-compaction, main-compaction and ejection events. The main differences between the force feeder experiments that were highlighted were due to the die filling height and associated parameters, and some observable differences in overall variability. The high level of variability in pellet density
and hardness for experiments ‘Right70’ and ‘Left40’ was also reflected in the energies and forces recorded in the Compaction Simulator summary data through the principal component scores.

The PLS models that were developed for pellet density and pellet hardness performed well in cross validation and testing. The key predictor variable in the models for pellet density and hardness was the lower punch force, which correlated positively with both. The density PLS model explained around 86% of the variance in the response, while the hardness PLS model explained around 65%. Both models offer predictive capability, however, the hardness model underperforms at predicting the medium to high hardness pellets. Unfortunately, it is difficult to gain a good understanding of the reliability of the hardness measurement due to the test being destructive. The questions raised in this study highlight the need to further validate the pellet hardness measurement in future work. For now, the learning from this work indicates that the pellet density can be used more reliably as an indicator of product quality than pellet hardness. Pellet density should therefore be the preferred basis for process monitoring and control applications.

If a similar model for pellet density can be developed using the data available from production scale pelleting machines, then there would be the potential for such a model to be used for process monitoring and control. This could provide real-time process monitoring that greatly improves upon existing techniques for monitoring pelleting performance, which are based on random sampling and testing of the pellets. The information could be used by plant operators at a supervisory level or in an automated control system to help inform and guide decision making to keep the process on track and producing on-spec material.

References


**The Authors**

Joe Emerson is a Process Control Engineer in the Process Measurement and Control team. He joined JM in 2020 and his background is in chemical engineering, process control and multivariate data analytics.

Vincenzino Vivacqua is a Senior Scientist who has been working at Johnson Matthey since 2017, where his research focuses on the optimisation of processes involving granular material powder flow, powder compaction and modelling of particulate processes.

Hugh Stitt is a Senior Research Fellow in Johnson Matthey’s Technology Centre with over 30 years of experience in industrial research and development in reaction engineering as well as catalyst and specialist material manufacturing technology with specialisation in fluid processing and mixing, powder technology and advanced modelling. He has over 100 refereed publication and is a Visiting Professor at the University of Birmingham. He is a Chartered Engineer, FIChemE and a Fellow of the Royal Academy of Engineering.

**Appendix A**

**Table A 1 Variables in the Compaction Simulator summary dataset (X1)**

<table>
<thead>
<tr>
<th>No.</th>
<th>Stage</th>
<th>Variable name</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>Filling</td>
<td>Die filling height (mm)</td>
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<tr>
<td>2</td>
<td>Pre-compression</td>
<td>Upper punch compression force (MPa)</td>
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<tr>
<td>3</td>
<td></td>
<td>Lower punch compression force (MPa)</td>
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<tr>
<td>4</td>
<td></td>
<td>Upper punch compression displacement (mm)</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td>Lower punch compression displacement (mm)</td>
</tr>
<tr>
<td>6</td>
<td></td>
<td>Compression thickness (mm)</td>
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<tr>
<td>7</td>
<td></td>
<td>Corrected compression thickness (mm)</td>
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<td>8</td>
<td></td>
<td>In-die recovery thickness (mm)</td>
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<td>9</td>
<td></td>
<td>Compression radial pressure (MPa)</td>
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<tr>
<td>10</td>
<td></td>
<td>Residual die wall pressure (MPa)</td>
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<tr>
<td>11</td>
<td></td>
<td>Theoretical compression time (ms)</td>
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<tr>
<td>12</td>
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<td>Real compression time (ms)</td>
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<tr>
<td></td>
<td>Description</td>
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<td>13</td>
<td>Real dwell-time (ms)</td>
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<td>Theoretical dwell-time (ms)</td>
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<td>Rearrangement dwell-time (ms)</td>
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<td>Take-off maximum force (N)</td>
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<td>Ejection Energy (J)</td>
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