This is the published version of a paper presented at the Conference NUMISHEET 2018.

Citation for the original published paper:

Sravan Tatipala et al 2018 *J. Phys.: Conf. Ser.* **1063** 012135

DOI

https://doi.org/10.1088/1742-6596/1063/1/012135

N.B. When citing this work, cite the original published paper.
Data-driven modelling in the era of Industry 4.0: A case study of friction modelling in sheet metal forming simulations

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Abstract. With growing demands on quality of produced parts, concepts like zero-defect manufacturing are gaining increasing importance. As one of the means to achieve this, industries strive to attain the ability to control product/process parameters through connected manufacturing technologies and model-based control systems that utilize process/machine data for predicting optimum system conditions without human intervention. Present work demonstrates an automated approach to process in-line measured data of tribology conditions and incorporate it within sheet metal forming (SMF) simulations to enhance the prediction accuracy while reducing overall modelling effort. The automated procedure is realized using a client-server model with an in-house developed application as the server and numerical computing platform/commercial CAD software as clients. Firstly, the server launches the computing platform for processing measured data from the production line. Based on this analysis, the client then executes CAD software for modifying the blank model thereby enabling assignment of localized friction conditions. Finally, the modified blank geometry and accompanied friction values is incorporated into SMF simulations. The presented procedure reduces time required for setting up SMF simulations as well as improves the prediction accuracy. In addition to outlining suggestions for future work, paper concludes by discussing the importance of the presented procedure and its significance in the context of Industry 4.0.

1. Introduction
Manufacturing practices are rapidly evolving with continual advancements in material sciences, production and information technology [1]. New generation products demand higher quality, better features, shorter development times, improved performance and customization at an affordable price. This trend appears to augment even further with the dawn of fourth-industrial revolution (Industry 4.0). Although, there are several definitions of the term Industry 4.0, at its heart, it aims to collect data in real-time for integrating and improving entire manufacturing process [2]. In the context of sheet metal forming (SMF) [3], this means to attain the ability to control product/process parameters through connected manufacturing technologies and model-based control systems that utilize process/machine data for predicting optimum system conditions without human intervention.

SMF is a complex nonlinear process with changing product/process conditions such as die deformations, tooling temperatures, material scatter, lubrication amounts and sheet mechanical properties [4]. Due to such variations, it is difficult to guarantee the quality of a manufactured part although a lot of new concepts endeavor on monitoring and controlling the production process [5]. One way to achieve control in manufacturing is through control systems. At an abstract level, a control system consists of a sensor that collects data (usually related to product properties), a prediction model that can predict appropriate future state of the production system based on its current state and a
controller that proposes required change to the production system (typically an input to the actuation mechanism) to get product properties closer to the desired specifications [2]. The data collected by sensors is used to assess whether current system settings are suitable to achieve desired product specifications. Using a prediction model, a controller determines the change required in production system. The effect of this change is again measured by sensor and the process is repeated. The efficiency of a control system depends on several factors such as the measuring capability of the sensor (sufficient bandwidth to capture variations [2], robustness to withstand high loads/disturbances [5]), production systems response to change (sensitivity, flexibility) and robustness of prediction mechanism (fidelity, timeframe, prediction model, knowledge management/re-use). Building a reliable prediction model, requires knowledge about how system behaves under various conditions. One way to derive knowledge about system behavior is via numerical SMF simulations. Since the reliability of simulation models is proved by real data [5], it is desirable to include data from production within simulation models.

However, building data-based simulation models suffers from several challenges amongst many such as, limited capabilities provided by modern SMF simulation softwares to incorporate production data, the time required to analyze data and translate it for use in simulations. This research presents an initial procedure to address these challenges in addition to discussing the significance of data-based simulations within an Industry 4.0 framework. Present contribution demonstrates an automated approach for analysis of data measured in production and its configuration for use in SMF simulations. Previous research [6,7] have shown influence of lubrication modelling on the prediction accuracy of simulation models and it is of interest at Volvo Cars to account for these in simulations. This research intends to lower the threshold for building data-based simulation models and the time consumed for the same through a preliminary case study. For this purpose, the case study has chosen to use pre-lube lubrication data on the blanks.

2. Production system and measurement setup
The part considered in this research is a front door inner of a Volvo XC90 and is produced in a single-action transfer press. Firstly, a coil of sheet metal is converted into blanks at the blanking line in one manufacturing step involving trimming and piercing operations. Then the blanks are fed into a transfer press in groups of 200-300 blanks per pallet. The final geometry of the part is attained at the transfer press in five manufacturing steps involving drawing, trimming, flanging and restriking operations. The blank thickness is 0.7 mm and has a pre-lube (Fuchs Anticorit R P4107S) lubrication on it for corrosion prevention. An equipment to measure and monitor the amount of lubricant on the blank is installed in the blanking line at Volvo Cars which stores all measured data in a central directory. It stores data such as the coil number, coil feed rate, lubricant type, sensor tip as well as length position, lubricant amount and date/time stamp for each measured point. This data is available to visualize both on site at the blanking line and offline using a data viewer [8]. The visualization presents quick statistical analysis of the measured data such as standard deviation, minimum/maximum value of the lubricant amounts and contour plots of lubricant variation along the length/width of the coil. The expected lubricant amount throughout blank is 1 g/m². However, it is observed that the blank has a varying lubricant distribution along its length/width with values between 0.6 g/m² to 2.3 g/m². The variation could be due to several factors such as transportation of the coil, coiling/uncoiling, contact between the sheet surfaces when the coil is rolled. This variation is not accounted within SMF simulations at Volvo Cars today with a uniform lubricant amount assigned to the entire blank. The following section presents a detailed description of the proposed automated procedure.

3. Results

3.1. Automation strategy
To perform data analyses, configuration (that is to translate data into specific form) and geometry manipulation in an automated fashion, communication between involved modules is required. For this purpose, a strategy inspired from client-server model is adopted with 1 server and 2 clients where a
server (the controller) communicates with the clients (the service provider) for execution of a task. Present work uses an in-house developed application in VB.NET [9] as the controller, MATLAB [10], a numerical computing platform, as client 1 (for data processing) and CATIA V5 [11], a CAD software, as client 2 (for geometry manipulation and localized lubricant assignment). Figure 1 depicts a simplified workflow of the automated approach. In the first step, the controller launches the data processing module for data analysis. After the analysis is finished, arguments are passed back to the controller. In the next step, the controller launches CAD software for dividing the blank geometry into several sections. Finally, the result from this analysis is used as an input for SMF simulation which is performed in AutoFormR7 [12].

Figure 1. Workflow of the automated procedure.

3.2. Data processing

The coil feed rate at the blanking line varies between 20 m/min and 40 m/min. The typical number of measured data points over an hours’ time for a coil feed rate of 25 m/min is equal to half a million. This, corresponds to approximately 200 measurement points on each trimmed blank. The data points measured across the blank is in a diagonal direction since the sensor moves back and forth along the width of the coil relative to the coil feed direction. Figure 2 (left) shows motion of sensor tip with respect to coil length. The data measured in production is exported as an excel file using the data viewer. The purpose of data analysis is to gain a deeper understanding of how data is varying over time, conduct statistical analysis and based on this understanding translate data into a specific format for use in SMF simulations. For this purpose, the controller, in the first stage, launches the data processing module and executes a script. The script contains a generic algorithm developed for handling lubrication data. Firstly, the algorithm loads the measurement data file from the directory and imports data. Present work considers measurement points of 200 blanks since it is assumed to satisfactorily represent the variation in lubrication profile for blanks corresponding to the same pallet. The data points are imported in a series format with each data type stored in a column vector having the number of rows equal to the number of data points. In the next step, the algorithm sorts the data such that all data points for a particular sensor tip position are aligned. It is observed that the variation of lubricant amount at a particular sensor tip position along the coil length is quite less when compared to the variation along the coil width. It is assumed that the mean of all lubricant values along the coil length corresponding to a particular sensor position satisfactorily represents the average lubricant amount at that position. Hence the next step of the algorithm calculates mean of all lubricant values corresponding to each sensor tip position. The plot depicted in figure 2 (middle) shows the same. It can be observed that the lubricant amount along the width varies in a pattern with higher lubricant amounts at the edges of the blank and lower lubricant amounts towards the center. It is not possible to use this lubricant profile directly within AutoForm. A workaround to mimic the trend of lubricant variation within SMF simulations could be divide the blank into several sections and assign average lubricant amounts to each section. However, the challenge is to decide the number and the position of each section along the blank width where the division should be made. One alternative is to create an algorithm which identifies point/s along the lubrication profile where the mean value changes abruptly and assign a section at that point. However, it is challenging to identify abrupt changes in the lubrication profile depicted in figure 2 (middle) which has several outliers (or points
away from the profile center). To get rid of these outliers the next step of the algorithm calculates a moving mean of lubrication profile plotted in figure 2 (middle) using the function `movmean` [10]. This function calculates a moving average along the lubrication profile, considering a user defined number of data points. In other words, it computes a centered moving average along the lubrication profile for a sliding window size of user-defined length [9]. Additional function arguments `Endpoints` and `shrink` are used to control the calculation of mean near the endpoints. This allows to reduce the window size near the end points when the number of data points is less than the window size. The window size is set to 80 data points, which means that 80 points along the lubrication profile will be considered at one time for calculating the moving average.

![Figure 2. Motion of sensor tip against coil length (left), Mean (middle) and moving mean (right) of all data points corresponding to each sensor tip position.](image)

If a small number of data points is considered within sliding window, it outputs a curve that better follows the previously plotted lubrication curve, hence also incorporating outliers. It is required to both follow the central tendency of the lubrication profile and eliminate the outliers. Since 80 data points within the sliding window satisfactorily achieves this and hence it is used. Figure 2 (right) shows a moving mean plot of lubrication profile depicted in figure 2 (middle) with 80 data points in sliding window. The next step is to identify the number/position of the sections to be created and this is achieved using function `findchangepts` [10]. This function allows to specify input arguments such as the maximum number of division points, input vector (lubrication profile in our case) and the statistical property based on which the division should occur. The statistical property could be variance, standard deviation, mean or a spectral characteristic, although the function works best for the statistic property `mean` [10]. Hence the statistical property chosen is `mean`. The function `findchangepts` runs an algorithm that identifies abrupt changes in the `mean` value along the lubrication profile while minimizing the total residual error [10]. This means that for a given signal with sample points \( x_1, x_2, x_3, \ldots, x_N \), and for a maximum number of \( K \) changes to be identified, the function minimizes \( J(K) \) in equation (1) [10]. Here \( k_0 \) and \( k_K \) are respectively the first and last sample of the signal, \( \chi \) is the section empirical estimate, \( \Delta \) is the deviation measurement and \( \beta \) is the proportionality constant corresponding to a fixed penalty added for each change point [10]. For an in-depth explanation of the algorithm, please refer [10].

\[
J(K) = \sum_{r=0}^{K-1} \sum_{r-k_r}^{k_{r+1}-1} \Delta \left( x_i; \chi \left( [x_{k_r}, \ldots, x_{k_{r+1}-1}] \right) \right) + \beta K
\]  

(1)

The maximum number of change points could be set to any number. In this case, a higher number of changepoints will lead to more sections as a lot of changepoints would be detected in the regions having steeper slope. More sections imply a computationally costlier SMF simulation. Hence 4 changepoints is decided to be a reasonable number. Figure 3 (left) shows the division of lubricant profile using function `findchangepts` with a maximum number of changepoints to detect equal to 4. The horizontal lines represent the calculated lubricant amounts corresponding to each section. In the next step, the algorithm passes the information about section division (i.e., position and the calculated lubricant amounts for each section) as an output to the controller.

3.3. CAD geometry manipulation

In the next stage, the controller launches and executes CAD. This allows access to the objects, methods and properties in CAD. An algorithm is written to modify the blank outline in CAD. This
algorithm imports the blank outline, adds new lines to the blank outline at specified distances using the input from previous step (to divide blank into sections) and saves the geometry. Figure 3 (right) shows the automatically divided blank geometry. Finally, the sectioned blank is imported into AutoForm software and the calculated lubricant amounts are assigned to each section. This way pre-lube measurement data is incorporated into SMF simulations.

![Figure 3.](image)

**Figure 3.** Lubricant profile division in data processing module (left) and Automatic generation of blank sections in CAD with localized lubrication amounts (right).

### 3.4. Validation

Preliminary investigations to study the effect of lubrication profile on prediction of part quality were conducted in [6] using the same part as considered in this research. For a detailed explanation of the simulation setup refer [6]. The results predicted different part quality for two similar SMF simulation setups except that one had a uniform lubricant amount with no sections and the other had a varying lubricant amount with 5 sections. Figure 4 middle and right show the *formability* result for the two simulation models with no blank sections and five blank sections respectively. The result predicted with 5 blank sections is closer to the formability of the part in reality. The investigation also shows that prediction of *variation in major strain* for blank with 5 sections is larger than that with no section.

![Figure 4.](image)

**Figure 4.** Simulation setup with sectioned blank outline (left), Formability plot for model with no blank sections (middle) and 5 blank sections (right).

### 4. Discussion

Past decade has seen a rise in the usage of sensors to harvest production data with the aim to integrate and facilitate communication between various elements of production system. However, it has been a challenge to achieve this due to limited capability of analysing and interpreting data. Furthermore, due to inherent process variations and complexity, the ability to use this data to attain optimum production system settings has also suffered. Another challenge is the ability to include this data within SMF simulations to increase knowledge about how the system behaves under various conditions. Present contribution addresses these challenges through an initial case study. The work proposes an automated procedure to analyse, interpret and configure data measured from the production system. The present
work also demonstrates a procedure to model the pre-lube lubrication data within SMF simulations. It should be possible to extend and adapt this approach to other types of production data (for example, temperature variation of tool), however this is yet to be confirmed and could be a focus for future study. Adopting automated data processing procedures benefits by offering consistency, efficiency and reproducibility. Control nowadays is focussed on achieving desired product properties rather than controlling tool displacement. Model-based control systems hold potential to support in this context and rely upon robust prediction models [2]. The knowledge gained from data-based simulations, upon validation, can be used to build robust prediction models. Knowledge of cause and effect chains could also be used to describe the process characteristics in the form of mathematical models [5].

5. Conclusions
Present research has demonstrated an automated procedure to analyse, interpret production data and configure data for use within SMF simulations. The presented procedure reduces time required for setting up SMF simulations as well as improves the prediction accuracy.

6. Future work
Focus of future research will, in general, be concentrated upon automation and decision support systems to assist in making informed decisions in the early phases of product development. Future research will focus to extend the presented approach to include other data from production such as temperature variation of process tools. Present research considers pre-lube lubrication amounts while future research could add external lubrication and examine its effects. Measurement only on one side of the blank is considered in this work. In reality, lubrication is present on both sides of the blank. Next step could be to measure and model lubricant data on both sides of the blank. Future research could also focus efforts on building mathematical models representing production process characteristics.

Acknowledgments
The research leading to these results has received financial support from the Swedish Knowledge and Competence Development Foundation (Stiftelsen för kunskaps- och kompetensutveckling).

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