PAPER • OPEN ACCESS

Bayesian Model-based State Estimation for Mass Production Metal Forming

To cite this article: Jos Havinga *et al* 2019 *IOP Conf. Ser.: Mater. Sci. Eng.* **651** 012095

View the article online for updates and enhancements.

Bayesian Model-based State Estimation for Mass Production Metal Forming

Jos Havinga[1], Pranab K Mandal[2] and Ton van den Boogaard[1]

[1] Faculty of Engineering Technology, University of Twente, P.O. Box 217, 7500AE Enschede, Netherlands
[2] Faculty of Electrical Engineering, Mathematics and Computer Science, University of Twente, P.O. Box 217, 7500AE Enschede, Netherlands

E-mail: jos.havinga@utwente.nl

Abstract. Modern metal forming factories produce large amounts of data, such as process forces and product geometries. These data contain indirect information about fluctuations in the manufacturing process, such as changes in temperature, material properties and lubrication conditions. In this work, Bayesian inference is used to obtain a probabilistic estimate of the process state based on force measurements in mass production metal forming. The procedure requires statistical assumptions about process state variations, which are often not known as it is usually not possible to directly measure the process state in-line. It is shown that unknown statistical model parameters can be estimated simultaneously with the process state. This leads to an improvement in the accuracy of the state estimate. The procedure is studied using pseudo-data from a mass production sheet bending process, using a finite element model with ten parameters. The material, friction and process parameters are estimated based on process force measurements.

1. Introduction

Many sources of variability affect the repeatability of industrial metal forming processes [1–5]. This may be caused by, for instance, variations in material properties, lubrication properties or tool wear. In this work, these properties are considered to be the process state. Modern factories are being increasingly equipped with real-time data acquisition systems [6, 7]. It is the question how these data streams may be used to estimate the process state. It is often difficult to measure the relevant state variables directly, but an estimate of these state variables may be obtained based on indirect measurements such as process forces.

A state estimation procedure requires accurate models that describe the relations between process state (e.g., material properties) and indirect measurements (e.g., process forces). In metal forming, these models are usually based on Finite Element (FE) simulations. Although increasingly detailed models are being developed in metal forming research, there is still model uncertainty, either originating from deliberate simplification or ignorance of the actual physics. Therefore, it is proposed to perform state estimation with probabilistic methods, in order to account for uncertainties in modelling. Statistics of process variations can then be used to guide the state estimation procedure.

In this work, we propose to use recursive Bayesian inference [8] to estimate the state (i.e. material, friction and tool properties) of a mass production sheet bending process. The state

estimation procedure is studied using pseudo-data obtained from a sheet bending model. Particle filtering (a numerical integration scheme for recursive Bayesian estimation) is used to track the process state. Bayesian methods are used in a wide range of application areas, but are relatively new to metal forming research. Statistical parameters are important components of the process state evolution models, but are very often not well known. Therefore, it is shown that these parameters can be estimated simultaneously with the process state.

The Bayesian state estimation procedure is explained in Section 2. The mass production sheet bending process and modelling thereof are discussed in Section 3, followed by the results in Section 4 and the conclusion and perspectives in Section 5.

2. Bayesian state estimation

The purpose of the state estimation procedure is to track process properties that change over time in metal forming mass production, such as material properties, lubrication properties or tool wear. An estimate of the process state can be used for process monitoring, predictive maintenance or real-time control. Bayesian inference is used to obtain a probabilistic estimate of the process state. In this section, the governing equations for Bayesian state estimation are given, and it is explained how these equations can be solved with particle filtering [8].

It is assumed that the change of state in metal forming mass production is discrete in time. Each product is a sampling point in time, and the state changes from product to product. Two different models are required for the Bayesian state estimation procedure: a process model and a measurement model. The process model describes how the state of the process is expected to change over time. The process is assumed to be a Markov process, meaning that the probability of the process state of the k-th product $\mathbf{x}_k$ is only dependent on the previous state $\mathbf{x}_{k-1}$:

$$\mathbf{x}_k = \mathbf{f}\left(\mathbf{x}_{k-1}, \mathbf{v}_{k-1}\right) \tag{1}$$

where $\mathbf{v}$ is a stochastic variable. In metal forming, there is little knowledge about the evolution of process state during mass production. It is known that variations among different batches of material are larger than variations within a single batch of material [2]. Sheet thickness and uneven lubrication may be regarded as short-term variations and material properties may be regarded as long-term variations [3]. Recent studies have shown that product-to-product variations in metal forming can have a significant effect on final product properties [6, 7]. Furthermore, mean values and standard deviations of material properties have been quantified in several studies [4, 5]. As the amount of literature about variability in metal forming is limited, we propose a simple model for the evolution of process state, where each state variable is autocorrelated as:

$$\mathbf{x}_k^j = \left(1 - \rho^j\right)\mu^j + \rho^j \mathbf{x}_{k-1}^j + \mathbf{v}_{k-1}^j \tag{2}$$

$$\mathbf{v}_{k-1}^j \sim \mathcal{N}\left(0, (1-(\rho^j)^2)(\sigma^j)^2\right) \tag{3}$$

where $\mathcal{N}$ represents a normal distribution, with μ^j, σ^j and ρ^j being the mean value, standard deviation and correlation parameter of the j-th state variable respectively. All statistical parameters are gathered in the set $\boldsymbol{\theta}_s = \{\boldsymbol{\mu}, \boldsymbol{\sigma}, \boldsymbol{\rho}\}$. The value of ρ^j can be $0 \leq \rho^j \leq 1$, with a larger value indicating stronger autocorrelation, i.e. slower changes in process state. Little information can be found in literature in order to estimate values for $\boldsymbol{\theta}_s$. Hence, these parameters can be assumed to be unknown, and estimated simultaneously with the process state [9, 10].

The second model that is used in the state estimation procedure is the measurement model. As it is often difficult to measure the process state directly, we seek to exploit indirect measurements that carry information about the process state, such as force measurements [7]. The relation between process measurement and process state is given by the measurement model:

$$\mathbf{z}_k = \mathbf{h}\left(\mathbf{x}_k, \boldsymbol{\theta}, \mathbf{w}_k\right) \tag{4}$$

where $\mathbf{z}$ is a measurement, $\boldsymbol{\theta}$ is a set of constant parameters and $\mathbf{w}$ is a stochastic variable. The parameters $\boldsymbol{\theta}$ may be for example tool compliance or tool alignment parameters. Whether a parameter is assumed to be constant or to be part of the state is a matter of assumption, and may change from one application to the other. If the values of the parameters $\boldsymbol{\theta}$ are unknown, these can be estimated together with the process state [10].

The stochastic variable $\mathbf{w}$ accounts for measurement uncertainty. Usually, measurement uncertainty is mostly related to sensor accuracy. However, model uncertainty is typically larger than sensor inaccuracy in the case of metal forming. For example, process forces can be measured accurately, but the uncertainty in the models that relate forces with process state is much larger than the sensor inaccuracy itself. In metal forming, there is little knowledge about model uncertainty. In this work, a simple first guess of model uncertainty is obtained by sampling the process model $\mathbf{h}\left(\mathbf{x}, \boldsymbol{\theta}\right)$ using the prior statistics for $\mathbf{x}$ and $\boldsymbol{\theta}$, and then determining the covariance of the result space data. It is then assumed that the covariance of the measurement uncertainty $\mathbf{w}$ is equal to a fraction of the covariance of this result space data.

The state of the process can be tracked using the process evolution model (Eq. (1)) and the measurement model (Eq. (4)). An important question is whether the used measurement provides sufficient information to be able to track the state of the process. If the measurement is insensitive to the state of the process, it is not possible to obtain an accurate state estimate. Furthermore, the model must be sufficiently accurate and fast to be applicable for real-time state estimation. In recent decades, metal forming models have become increasingly detailed and refined, in order to improve predictive accuracy. Therefore, model solution times remain high, despite the continuous improvement in computer speed [11]. In order to benefit from the accuracy of these models without compromising too much on accuracy, an interpolation model can be constructed based on a large number of offline computations, using Proper Orthogonal Decomposition (POD, also known as Principal Component Analysis) for reduction of the result space [12]. In this work, an interpolation model of a sheet bending process is built using these techniques (Section 3.1). The model is used to study the state estimation procedure.

The Bayesian estimation procedure is recursive, meaning that the estimate for a new product is determined based on the estimate from the previous product and based on the new measurement $\mathbf{z}_k$. The state estimate for the previous product is $p(\mathbf{x}_{k-1}|\mathbf{Z}_{k-1})$, with $\mathbf{Z}_{k-1} \triangleq \{\mathbf{z}_i\}_{i=1}^{k-1}$ being the set of measurements from all previous products. The probability of the current state $\mathbf{x}_k$ given all past measurements $\mathbf{Z}_{k-1}$ can be determined by integrating:

$$p(\mathbf{x}_k|\mathbf{Z}_{k-1}) = \int p(\mathbf{x}_k|\mathbf{x}_{k-1})\, p(\mathbf{x}_{k-1}|\mathbf{Z}_{k-1}) d\mathbf{x}_{k-1} \tag{5}$$

where $p(\mathbf{x}_k|\mathbf{x}_{k-1})$ is determined using the process evolution model, Eq. (1). This estimate of the state can be conditioned on the new measurement $\mathbf{z}_k$ using:

$$p(\mathbf{x}_k|\mathbf{Z}_k) \propto p(\mathbf{z}_k|\mathbf{x}_k)\, p(\mathbf{x}_k|\mathbf{Z}_{k-1}) \tag{6}$$

where $p(\mathbf{z}_k|\mathbf{x}_k)$ is determined using the measurement model, Eq. (4). The above equation is based on Bayes theorem. In order to estimate the process state during production, Eqs. (5) and (6) have to be solved after each new measurement. In this work, this is done with particle filtering, a numerical integration method for non-linear recursive Bayesian estimation, where the probabilities are approximated using Monte Carlo sampling:

$$p(\mathbf{x}_k|\mathbf{Z}_k) \approx \sum_{i=1}^{N} w_k^i \delta(\mathbf{x}_k - \mathbf{x}_k^i) \tag{7}$$

The Monte Carlo estimate has a set of N particles with corresponding states $\mathbf{x}_k^i$ and weights w_k^i. The strength of particle filtering is that the positions of the particles in the state space are concentrated in the region of higher probability.

Many types of particle filtering algorithms have been developed. In this work, a standard filter is used, the Sampling Importance Resampling (SIR) filter [13]. The algorithm is given in Algorithm 1. It consists of four steps. First, a set of particles is drawn in the importance sampling step, using the process evolution model. Then the weights are updated using the measurement model, and normalized such that $\sum_{i=1}^{N} w_k^i = 1$. Finally, a resampling step is used to redistribute the particles to the region of higher probability, eliminating the particles with negligible probability.

Algorithm 1 SIR filter

1: **procedure** Particle filter$\left(\{\mathbf{x}_{k-1}^i, w_{k-1}^i\}_{i=1}^{N}, \mathbf{z}_k\right)$
2:     **for** $i = 1 \dots N$ **do**
3:         Draw $\mathbf{x}_k^i \sim p\left(\mathbf{x}_k | \mathbf{x}_{k-1}^i\right)$ ▷ Importance sampling
4:         Update $w_k^i = p(\mathbf{x}_k | \mathbf{z}_k)$ ▷ Process measurement
5:     $t = \sum_{i=1}^{N} w_k^i$
6:     **for** $i = 1 \dots N$ **do**
7:         $w_k^i = w_k^i \,/\, t$ ▷ Normalize weights
8:     Resample$\left(\{\mathbf{x}_k^i, w_k^i\}_{i=1}^{N}\right)$ ▷ Resampling
9:     **return** $\{\mathbf{x}_k^i, w_k^i\}_{i=1}^{N}$

---

3. Modelling

In this work, a mass production sheet forming process is used to study the state estimation procedure. The demonstrator product is shown in Fig. 1a and the process tooling is shown in Fig. 1b. We focus on bending of the flaps in the bottom of the cup. The flaps are bent in two stages (Figs. 2a and 2b). After bending, a picture from one of the three flaps is taken to determine the final angle (Fig. 1c). During the first bending stage, the bending force is measured. A typical bending force curve is shown in Fig. 2c, with the lowest position of the punch at 0 ms. The force is used to estimate the state of the process.
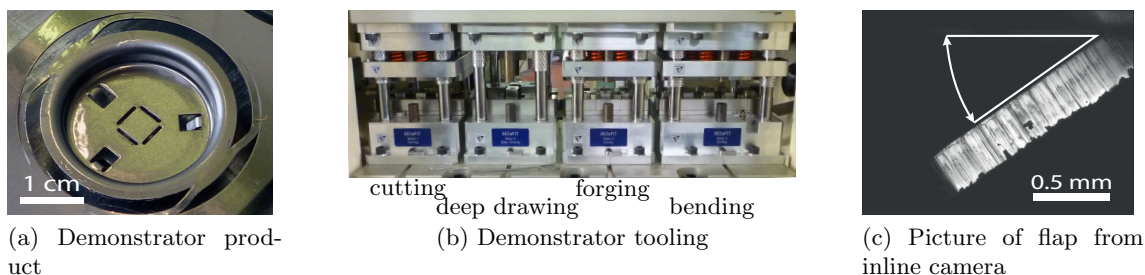

(a) Demonstrator product

(b) Demonstrator tooling

(c) Picture of flap from inline camera

Figure 1: Demonstrator process [7]

3.1. Measurement model

A FE model of the process is built using MSC.Marc. The bending process is modelled in 2D, with elastic tooling (5370 elements). The sheet is modelled with 3600 quadrilateral linear plane strain elements. A Von Mises yield locus is used, with a tabulated hardening curve $\sigma_0\left(\varepsilon\right)$. Strain rate dependency is modelled using the Cowper-Symonds equation [14]:

(a) First bending stage

(b) Second bending stage

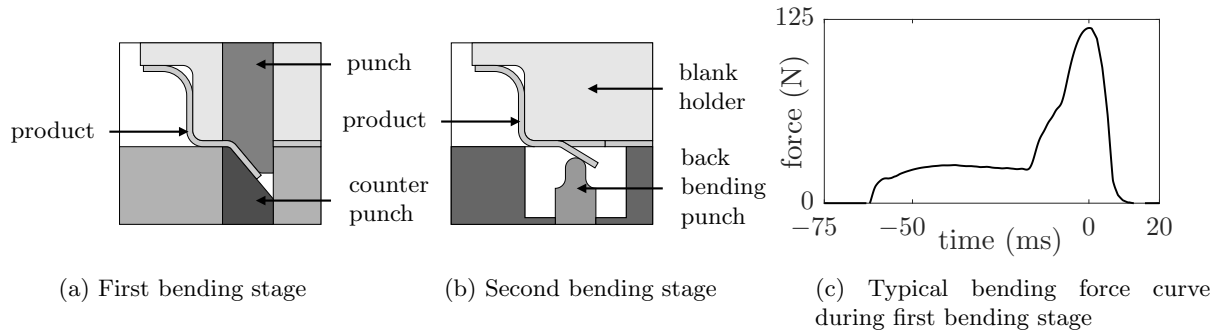(c) Typical bending force curve during first bending stage

Figure 2: Bending stages

$$\sigma\left(\varepsilon, \dot{\varepsilon}\right) = \left(1 + \left(\frac{\dot{\varepsilon}}{\dot{\varepsilon}_0}\right)^q\right) \sigma_0\left(\varepsilon\right) \tag{8}$$

The parameters of the model are listed in Table 1. These parameters are related to material, friction and tooling. The evaluation time of one simulation is approximately 10 minutes. A total of 6953 simulations have been performed, in order to construct a fast metamodel of the process. Proper Orthogonal Decomposition (POD) is used to determine the dominant modes of the force curve. The weight factors for these modes have been interpolated with Radial Basis Function (RBF) interpolation [12]. Following this procedure, a fast and accurate representation of the FE model is built. The POD-RBF model has an evaluation time of approximately 10 ms.

Table 1: Model parameters

		unit	min	max	$\mu_{\min}$	$\mu_{\max}$	$\sigma_{\min}$	$\sigma_{\max}$	$\rho_{\min}$	$\rho_{\max}$
							$\boldsymbol{\theta_s}$			
x	yield stress	MPa	275	336	294	318	3	6	0.7	0.95
	strain rate param. $\log\left(\dot{\epsilon}_0\right)$	$\log\left(\mathrm{s}^{-1}\right)$	1.5	2.5	1.8	2.2	0.02	0.05	0.7	0.95
	strain rate param. q	-	0.4	1.0	0.6	0.8	0.02	0.05	0.7	0.95
	sheet thickness	µm	295	305	298	302	0.5	1	0.5	0.9
	friction coefficient tool-tool	-	0.1	0.5	0.25	0.35	0.02	0.04	0.8	0.99
	friction coefficient tool-flap	-	0.01	0.3	0.1	0.2	0.02	0.03	0.8	0.99
	punch end distance	µm	310	410	340	380	5	10	0.7	0.99
θ	horizontal alignment	µm	-5	20						
	vertical alignment	µm	-20	0						
	press stiffness	$\mathrm{kN\,mm^{-1}}$	5	40						

3.2. State evolution model
The state evolution is modelled following Eqs. (2) and (3). The values for $\boldsymbol{\mu}$, $\boldsymbol{\sigma}$ and $\boldsymbol{\rho}$ are not known and will be estimated simultaneously with the process state. The bounds for these parameters are given in Table 1.

3.3. Simulation runs
A series of simulations using pseudo-data are used to study the performance of the state estimation procedure. Five different datasets have been built, by sampling a random value for the parameters $\boldsymbol{\theta}$ and the statistical parameters $\boldsymbol{\theta}_s$ (Table 1), and generating a random state

evolution $\{\mathbf{x}_i\}_{i=1}^{1000}$ using Eq. (2). The POD-RBF model is used to generate the 'real' datasets $\mathbf{Z}_{1000}$. Particle filtering with 500 particles is then used to infer the state $\mathbf{x}$, constant parameters $\boldsymbol{\theta}$ and statistical parameters $\boldsymbol{\theta}_s$ based on these force measurements. In order to understand the importance of the statistical assumptions, three different runs have been performed: one run where the statistical parameters $\boldsymbol{\theta}_s$ are known by the particle filter, one run where the statistical parameters $\boldsymbol{\theta}_s$ are unknown but are not being estimated, and one run where the statistical parameters $\boldsymbol{\theta}_s$ are unknown and are being estimated simultaneously. Five repetitions of each simulation are performed, as random sampling in the particle filter leads to slightly different results for multiple simulations with exactly the same dataset and particle filter configuration. Hence, a total of 3 runs $\times$ 5 datasets $\times$ 5 repetitions = 75 simulations have been performed. The algorithm is implemented and the simulation runs are performed in MATLAB.

4. Results

For each simulation run, the estimation accuracy increases with increasing number of processed products. Therefore, all results in this section are determined for the last 200 products of each run, allowing sufficient time for the algorithm to converge towards a stable estimate. Typical results for the state estimation procedure are shown in Fig. 3. These results are obtained in a simulation run where the statistical parameters are estimated simultaneously with the state. Most state variables can be estimated with good accuracy using the proposed procedure.
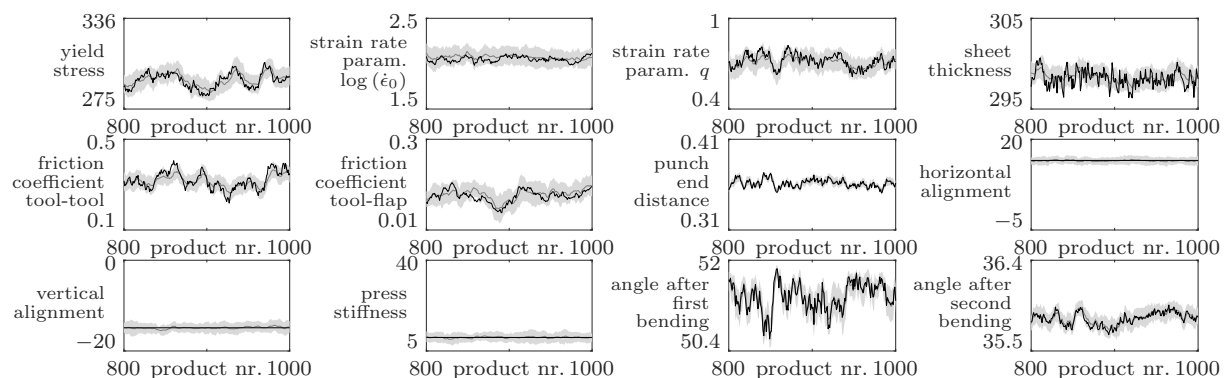

Figure 3: Estimates for simulation from run with 'estimated statistics'. Real values are shown in black, and estimates in grey, with a band of ± 3 times the standard deviation of the estimate.

The normalized Root-Mean-Square Error (RMSE) between the estimated and the actual state values is determined for all runs. These results are shown for all state variables and constant parameters in Fig. 4. The run with known statistical parameters is the reference run. It gives an indication of the observability of the state $\mathbf{x}$ based on force measurements. The RMSE values are much lower than 1, indicating that a significant fraction of the variation of these state variables can be estimated using force measurements. The estimation accuracy depends on the state parameter, with the punch end distance being the easiest to estimate and the strain rate parameter $\log(\dot{\epsilon}_0)$ being the hardest to estimate. The estimate for the constant parameters $\boldsymbol{\theta}$ is almost perfect for all runs.

The 'unknown statistics' run has been performed with a wrong assumption of the statistical parameters $\boldsymbol{\theta}_s$. Fig. 4 shows that a wrong assumption may significantly reduce the estimation accuracy. This effect can be reduced by adding the statistical parameters $\boldsymbol{\theta}_s$ as unknowns to the estimation procedure (run 'estimated statistics'). The accuracy of the angle estimate is almost as good as for the runs with known statistics. The normalised RMSE for the statistical
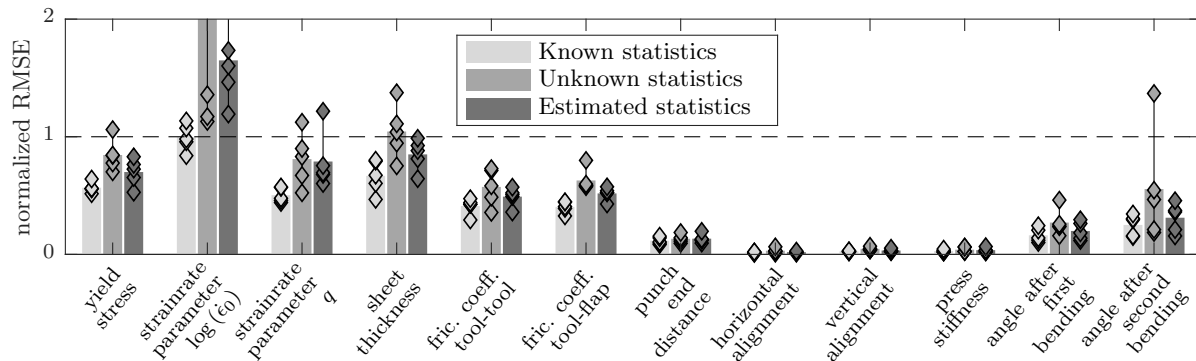
Figure 4: Average RMSE per state variable and parameter, averaged over all datasets. The RMSE values per dataset (averaged over five repetitions) are indicated with diamonds. The RMSE values are normalized by σ (Table 1) for the state variables, by $(\max - \min)/\sqrt{6}$ (the expected value of the RMSE for a random estimator with uniform probability) for the constant parameters, and by the standard deviation of the real angles for the angles. A RMSE larger than 1 indicates that the prediction error is larger than the variation in the data (for the state **x** and the angles) or that the estimator performs worse than a random estimator with uniform PDF (for the constant parameters $\boldsymbol{\theta}$).

parameter estimates is shown in Fig. 5. It can be seen that it is easier to estimate the mean values $\boldsymbol{\mu}$ than the standard deviations $\boldsymbol{\sigma}$ and correlation parameters $\boldsymbol{\rho}$.
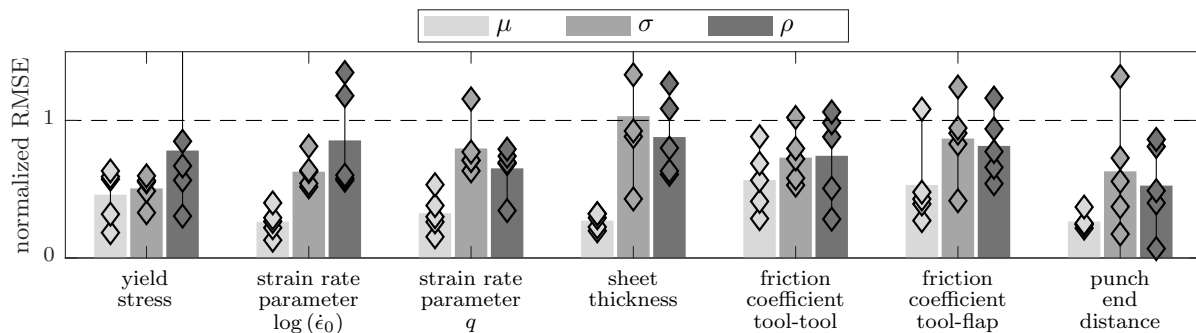

Figure 5: Average RMSE per statistical parameter, averaged over all datasets. The RMSE values per dataset (averaged over five repetitions) are indicated with diamonds. The RMSE values are normalized by $(\max - \min)/\sqrt{6}$ (the expected value of the RMSE for a random estimator with uniform probability). A RMSE larger than 1 indicates that the estimator performs worse than a random estimator with uniform PDF.

5. Conclusion and perspectives
In this work, it is proposed to use Bayesian inference methods to track the variations of material, friction and process properties in mass production metal forming. A series of simulation runs using pseudo-data from a sheet bending model show that the procedure is promising, as several state variables can be tracked using process force measurements. Furthermore, it is shown that

unknown statistical parameters of the state evolution models can be estimated simultaneously with the process state itself.

The results from this work are a first step in the development of these methods. Many further steps have to be taken in order to reach a maturity level that enables industrial applicability of the method. We highlight some key components of the procedure that require further development. Firstly, the deviation between numerical model and reality must be characterized in order to develop sufficiently accurate models for state estimation with real process data. The development of hybrid models that combine physics-based models with real process data (i.e. grey-box models) is promising in this perspective [15]. Secondly, the uncertainty of metal forming models must be characterized to be used in probabilistic methods. Thirdly, better models for state evolution have to be developed, and data has to be gathered in order to obtain better statistics for these models. Lastly, customized particle filtering algorithms have to be developed that are accurate, fast and robust for these specific type of applications. These aforementioned developments are major steps yet to be taken. As the interest of the metal forming research community into smart manufacturing is continuing to grow, it is expected that probabilistic state estimation methods for metal forming mass production will continue to be developed in coming years.

References

[1] Col A 2003 *Proceedings of the Sixth International ESAFORM Conference on Material Forming* 183–186

[2] Hora P, Heingärtner J, Manopulo N and Tong L 2011 *AIP Conference Proceedings* **1383** 35–47

[3] Endelt B and Danckert J 2010 *International Journal of Material Forming* **3** 25–28

[4] Aspenberg D, Larsson R and Nilsson L 2012 *Journal of Materials Processing Technology* **212** 1288–1297

[5] Wiebenga J, Atzema E, An Y, Vegter H and van den Boogaard A 2014 *Journal of Materials Processing Technology* **214** 238–252

[6] Maier S, Liebig A, Kautz T and Volk W 2017 *Production Engineering* **11** 307–313

[7] Havinga J, van den Boogaard T, Dallinger F and Hora P 2018 *Journal of Manufacturing Processes* **31** 260–272

[8] Ristic B, Arulampalam S and Gordon N 2004 *Beyond the Kalman Filter* 1st ed (Artech House Publishers) ISBN 158053631X

[9] Storvik G 2002 *IEEE Transactions on Signal Processing* **50** 281–289

[10] Liu J and West M 2001 Combined parameter and state estimation in simulation-based filtering *Sequential Monte Carlo Methods in Practice* (Springer New York) pp 197–223

[11] Allwood J, Duncan S, Cao J, Groche P, Hirt G, Kinsey B, Kuboki T, Liewald M, Sterzing A and Tekkaya A 2016 *CIRP Annals* **65** 573–596

[12] Cornaggia A, Cocchetti G, Maier G and Buljak V 2018 *2018 IEEE EEEIC and 2018 IEEE I&CPS Europe* https://doi.org/10.1109/EEEIC.2018.8494215

[13] Gordon N, Salmond D and Smith A 1993 *IEE Proceedings F Radar and Signal Processing* **140** 107

[14] Cowper C R and Symonds P S 1957 Strain-hardening and strain-rate effects in the impact loading of cantilever beams Tech. Rep. 28 Division of applied mathematics, Brown University

[15] Chinesta F, Cueto E, Abisset-Chavanne E, Duval J L and Khaldi F E 2018 *Archives of Computational Methods in Engineering* https://doi.org/10.1007/s11831-018-9301-4