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Integrating stochastic effects and uncertainties into inverse analysis of hot bulk forging processes through automated API-driven finite element simulations and machine learning

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Abstract. At present, finite element simulation and inverse analysis are widely used for the design and analysis of metal forming processes, allowing the identification of possible defects at the pre-production stage and realizing the “First Part - Good Part” strategy. However, the forging process is generally considered in FEM simulations as a deterministic process without taking into account variations in material properties and process parameters, which leads to reduced forgings quality and process reliability. Considering uncertainties and stochastic effects is one of the major challenges in FEM simulations. Inverse analysis can be used to identify, characterize and integrate the uncertainties and stochastic effects into forging process analysis. Several works have attempted to include stochastic effects into sheet metal forming simulation as well as simulation of hot forging of turbine blades. However, issues of automating and utilizing inverse analysis in this field remain open and require further development. This paper develops an approach for analyzing uncertainties and stochastic effects based on automated API-driven finite element simulations. A control code that automatically varies the dimensions, position and orientation of the workpiece as well as process parameters, starts the simulation and performs automatic evaluation of the simulation results has been developed. Based on the obtained dataset, a parameter sensitivity analysis was performed and the relative importance of each parameter on the formation of defects such as folding or underfilling was determined. The developed approach is further verified through experimental trials on an industrial screw press equipped with a data acquisition system.

Introduction

Progress in computational technologies and developing metal forming simulation methods over the last decades have fundamentally changed the hot bulk forging process design approach. Simulation based on the finite element model (FEM) has become an essential attribute of the development of new forging processes, allowing to identify possible defects at the pre-production stage and realizing the “First Part - Good Part” strategy. Almost every important aspect of hot bulk forging processes can be included in the FEM-simulation [1]: workpiece and die geometry and material properties, elastic deflection, friction, heat transfer and thermal effects, microstructure evolution, damage, wear and much more. Enabling inverse analysis significantly extends the capabilities of FEM simulation [2]. The use of inverse analysis can significantly simplify the identification of material and process parameters and improve the accuracy of FEM simulations [3]. Inverse analysis allows optimizing a die design [4] and a workpiece geometry [5]. However, the forging process is generally considered in FEM simulations as a deterministic process without considering the variations in material properties and process parameters, which leads to reduced forgings quality and process reliability. In addition to modeling error analysis, uncertainties and stochastic effects modeling should be considered, which is one of a major challenges in FEM simulations [6]**.** The most important questions arising during the analysis of uncertainties and stochastic effects are: which input parameters are varied? What is their variation range? How does it affect output parameters? Data-driven models [7] could be efficiently used to identify and characterize parameter uncertainties based on real experimental data or synthetic data from FE simulations. Most data-driven models are based on the neural network [8] or utilize artificial intelligence techniques, particularly machine learning [9]. Considering the uncertainties is closely related to the process robustness and parameter sensitivity analysis. Snape et al. [10] carried out a response surface analysis in order to investigate the effect of process parameters on the maximum generalized strain, maximum load, forging work and final die fill during the closed-die forging process. Engel et al. [11] analyzed an extrusion process and showed that reducing the die strength dispersion effectively decreases the die failure probability. Koch et al. [12] developed a mathematical model of the cold forging process with a deterministic and a statistical component, which allowed to improve tool life by avoiding tensile stresses and strains in the die. Behrens et al. [13] analyzed the influence of the die material and workpiece and tool temperatures on the dimensional accuracy of the forged part. Lu and Ou [14] performed a reliability analysis to quantify stochastic characteristics of the dimensional and shape errors in the hot forging of 3D aerofoil components. A stochastic two-step optimization approach was used to minimize systematic errors of forged aerofoil shape.

Unfortunately, there are no commercial solutions for incorporating uncertainties and stochastic effects in bulk forging simulation in contrast to sheet metal forming simulation. Müllerschön et al. [15] performed reliability-based design optimization of a sheet metal forming process using the Monte Carlo method with commercial software LS-OPT and LS-DYNA. Brix et al. [16] carried out stochastic sheet metal forming simulation to predict the springback variation for large outer car-body panels using AutoForm R8 with Sigma module.

Thus, integrating uncertainties and stochastic effects in modeling bulk forging processes is an actual problem. However, the issues of automating and utilizing inverse analysis in this field remain open and require further development.

This paper develops an approach for analyzing uncertainties and stochastic effects based on automated API-driven finite element simulations. A control code that automatically varies the dimensions, position and orientation of the workpiece as well as process parameters, starts the simulation and performs automatic evaluation of the simulation results has been developed. Based on the obtained dataset, a parameter sensitivity analysis has been performed and the relative importance of each parameter on the formation of defects such as folding or underfilling using machine learning models was determined. The developed approach is further verified through experimental trials on an industrial screw press equipped with a data acquisition system.

Materials and Methods

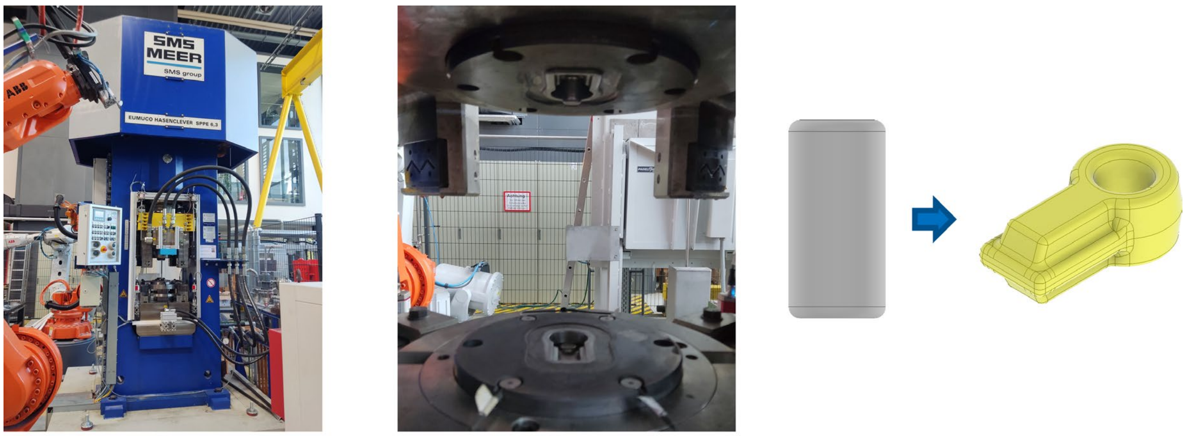
Materials. Workpieces were made from EN AW 6060 (AlMgSi, DIN 3.3206) D80x6000 mm bars provided by Gemmel Metalle GmbH. The chemical composition is presented in Table 1.

Table 1 – The chemical composition of used EN AW 6060

Element	Mg	Si	Fe	Cu	Mn	Ti	Zn	Al
Nom.	0.35-0.60	0.30-0.60	0.10-0.30	< 0.10	<0.10	<0.10	<0.15	Bal.
Fact.	0.436	0.596	0.186	0.004	0.012	0.015	0.003	

The forging dies were machined from hot work tool steel X37CrMoV5-1 (DIN 1.2343) and subsequently vacuum hardened and tempered to the final hardness of 45…48 HRC.

Forging. The forging was carried out on an SMS SPPE 6.3 screw press with a nominal force of 6.3 MN. The upper and lower dies were installed and aligned in the press using a die holder to ensure no misalignment or twisting occurred. The workpieces were cut on a band saw and then turned to final dimensions (D35 x h72 mm for the reference process). The dies were lubricated with a hexagonal boron nitride-based water solution before each forging. The workpieces were heated for 1.5 hours in a chamber furnace at 480 °C and then manually transferred to the dies using forging tongs. Forging was carried out in semi-automatic mode with 1 stroke. The SMS SPPE 6.3 screw press, the forging setup (b), the workpiece and the obtained forging geometries are shown in Fig. 1.



a) b) c)

Figure 1 – SMS SPPE 6.3 screw press (a), forging setup (b), workpiece and forging (c) geometries

FEM Simulation. Simulations were carried out using the commercial FEM software QForm UK 11.1.0 (www.qform3d.com) in a general forming module. The workpiece was set as a-plastic body and the tools as rigid bodies. If workpiece or tool deflection may have a significant effect, it is recommended to consider elastic deformation. Remeshing was done automatically. Thermal processes were also considered. The initial temperature of the workpiece was 480 °C, with subsequent cooling in air for 2 s and cooling on dies for 1 s. The friction was experimentally investigated using ring compression tests and defined by a Levanov friction law with a friction factor linearly dependent on temperature between m = 0.54 at 300 °C and m = 0.70 at 500 °C.

The flow curves were experimentally investigated and approximated using the following equation with $R^2 = 0.94$. The workpiece flow stress is calculated as follows (Eq. 1):

$$\sigma_f = 667.6e^{-0.00649T}\varepsilon^{0.03}\dot{\varepsilon}^{0.11341}, \tag{1}$$

The workpiece's thermophysical parameters were set according to the EN AW6060 material from the QForm UK standard database. The environment was set as “Air” from the QForm UK standard database.

The die set material was set as H11 (1.2343) hot work tool steel from the QForm UK standard database. The environment was set as “air” from the QForm standard database.

The forging equipment was set as a screw press with a nominal load of 6.3 MN, maximum velocity of 700 mm/s and experimentally calibrated effective blow energy of 3.7 kJ; 5.5 kJ; 7.5 kJ for 50%; 75% and 100% of maximal crosshead velocity at impact, respectively.

The computational time required for every simulation was approximately 30 minutes due to the full 3D task. Using 2D simulations and considering symmetries it is possible to drastically accelerate the simulations.

The process parameters used in the reference simulation are listed in Table 2.

Table 2 – Process parameters used in the reference simulation

Parameter	Value
Workpiece temperature	480 °C
Cooling in air	2 s
Cooling on tool	1 s
Workpiece dimensions	D35x72 mm
Die temperature	20 °C
Blow energy	75%
Heat transfer model	Coupled
Emissivity	0.6
Environment temperature	20 °C
Heat transfer coefficient "Workpiece - Air"	30 W/(m^2*K)
Heat transfer coefficient "Workpiece - Die"	10^5 W/(m^2*K)

Integration of stochastic effects and uncertainties. For the integration of stochastic effects and uncertainties into FEM simulations, a control code in open source integrated development environment Spyder 6.0.0 has been written. The reference simulation should be provided and the parameters to be adjusted and their nominal values, as well as deviations, should be identified. The control code automatically varies the parameters, changes them correspondingly using API interface in the FEM software and starts the simulation. Parallelization with 8 simultaneous simulations to maximize the usage of computer resources and speed up computations is employed. When the simulation is complete, the control code collects the output data and closes the FEM software. If more simulations are required, they are simulated until the specified number of simulations is reached. It is also possible to perform simulations based on a specified parameter values table, e.g., using Latin hypercube sampling. The flow chart of the integration of stochastic effects and uncertainties is shown in Fig. 2.

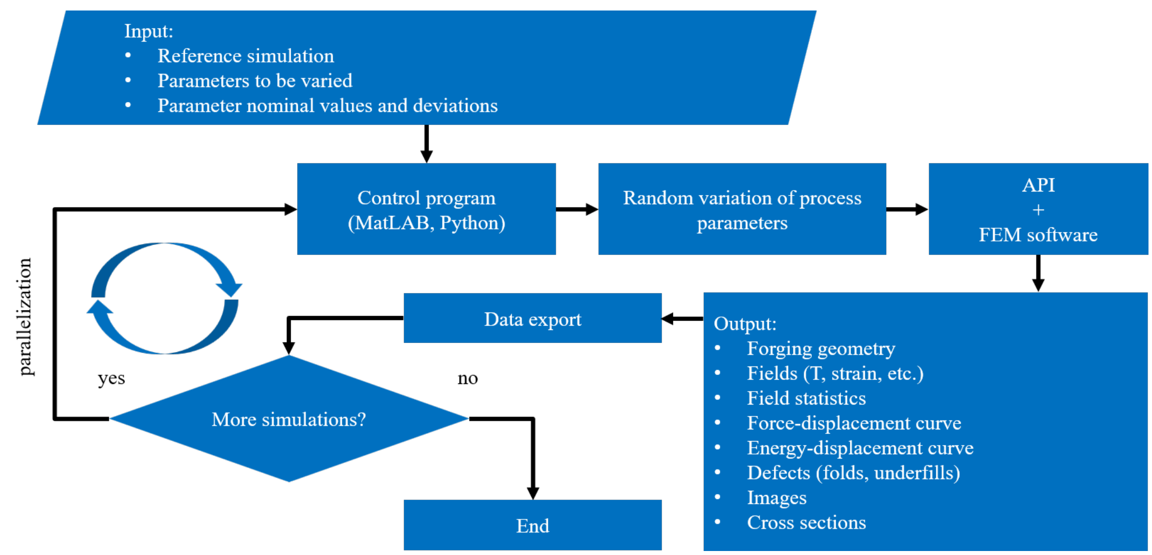


Figure 2 – Flow chart of the integration of stochastic effects and uncertainties in FEM simulations

The process parameters have been varied as follows (Eq. 2):

$$value_{var} = value_{nominal} + 0.01 \cdot variation \cdot randrange(-100d_{minus}, 100d_{plus}). \quad (2)$$

The varied parameters, as well as their mean values and variations, are listed in Table 3.

Table 3 – The varied parameters and their values

Parameter	Variable	Mean value	Variation	d_minus	d_plus
Initial workpiece temperature	wp_temp	480	20	1	0.5
A1 by flow stress equation	wp_flow_stress_A1	667.6	67	1	1
Workpiece diameter	wp_diameter	35	1	1	0
Workpiece length	wp_length	72	2	1	1
Workpiece displacement OX	wp_disp_x	0	5	1	1
Workpiece displacement OY	wp_disp_y	0	5	1	1
Workpiece rotation	wp_angle_z	0	5	1	1
Top die temperature	die_temp_1	20	130	0	1
Bottom die temperature	die_temp_2	20	130	0	1
Workpiece cooling in air time	cooling_in_air	2	2	0	1
Workpiece cooling in tool time	cooling_in_tool	1	1	0	1
Environment temperature	env_temp	20	10	1	1
Heat transfer coefficient	heat_transfer_coef	30	10	1	1
Emissivity	emisivity	0.6	0.1	1	1
Friction factor	m	0.6	0.4	0	1
Blow energy share	Energy	75	10	1	0

Different simulation results, such as values, arrays, graphs, images, cross sections, traced point values, simulation parameters, etc. may be used as output data. Data calculated by user-defined subroutines can also be used as exported values and fields. The workpiece and tool view can be customized to create the desired images: the object can be rotated, hidden or turned transparent, an arbitrary cross-section can be created, and the viewpoint and scale can be changed. The resulting output data is summarized in Table 4.

Table 4 – Output data

Parameter	Name	Type
Simulation time	op_sim_time	Value
Workpiece mesh nodes coordinates	wp_mesh_nodes	3D-Array
Force-displacement chart	force_disp_chart	Chart
Work-displacement chart	work_disp_chart	Chart
Field «Distance to contact»	wp_contact_dist_values	1D-Array
Field «Temperature»	wp_temp_values	1D-Array
Field «Plastic strain»	wp_strain_plast_values	1D-Array
Field «Flow stress»	wp_flow_stress_values	1D-Array
Field «Gartfield»	wp_gartfield_values	1D-Array
Plain surface	wp_plain_surface_screenshot	Picture
Field «Distance to contact»	wp_contact_dist_screenshot	Picture
Field «Temperature»	wp_temp_screenshot	Picture
Field «Plastic strain»	wp_strain_plast_screenshot	Picture
Field «Flow stress»	wp_flow_stress_screenshot	Picture
Field «Gartfield»	wp_gartfield_screenshot	Picture

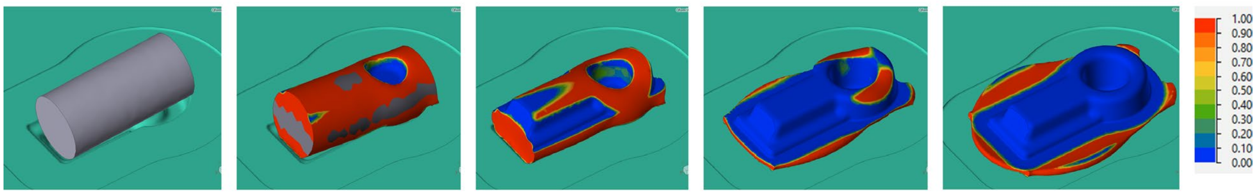
The designed methodology could be used almost for every cold or hot, bulk or sheet metal forming process with the appropriate setup of the variable parameters. However, the generation of a new dataset and machine learning analysis is a process-specific task.

Machine learning. A random forest [17] was employed to analyze stochastic effects and uncertainties due to its good performance on small datasets. A dataset based on 600 simulations was prepared based on the Latin Hypercube sampling. All (16) input parameters of the FEM simulation are initially considered as features. The effect of the individual features on the underfill defect formation probability was analysed using the explainable method SHapley Additive exPlanations (SHAP) [18]. For a detailed description of the implementation and methods used, please refer to [19].

Results and discussion

Analysis of the reference process. The reference hot bulk forging process was designed intentionally with low stability, so small deviations in the process parameters lead to defect formation. However, standard process parameters ensure defect-free forgings. Fig. 3 shows the metal flow and forging sequence. As can be seen, the wall of the ring section is filled last. Consequently, there is a possible underfilling defect due to a lack of metal volume.

Forging sequence (Field – Distance to contact, mm)

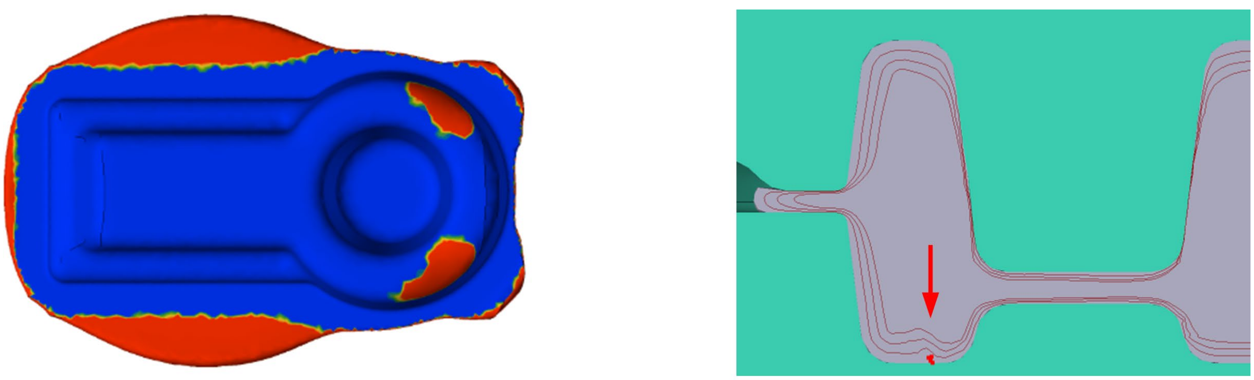


Distance between dies, mm

35.0 16.5 6.0 1.5 0.0

Figure 3 – Forging sequence (top die not shown)

In addition to underfill, fold formation due to unfavorable metal flow caused by process parameter variation is also possible. Defects possible in this hot bulk forging process are shown in Fig. 4.



Underfill Folding

Figure 4 – Possible defects

Further, the effect of uncertainties and stochastic effects on the sustainability of the studied hot bulk forging process and the defect formation probability should be evaluated.

Analysis of stochastic effects and uncertainties using machine learning. Random and grid searches were combined for hyperparameter tuning to find the best estimator to ensure the highest predictability. The best estimator with a train accuracy of 0.83 and a test accuracy of 0.78 was found. The eight least important features were removed based on the feature importance, and half of the remaining features were retained. After retraining the model using the eight most essential features, the test accuracy of the best estimator remained at 0.78, which indicates that the model's primary knowledge and predictive capability rely on the eight most important features. Finally, the three most essential features significantly impacting the defect formation probability were identified: workpiece length, workpiece displacement OY, and workpiece diameter. Feature importance obtained through the machine learning analysis based on random forest is shown in Fig. 5.

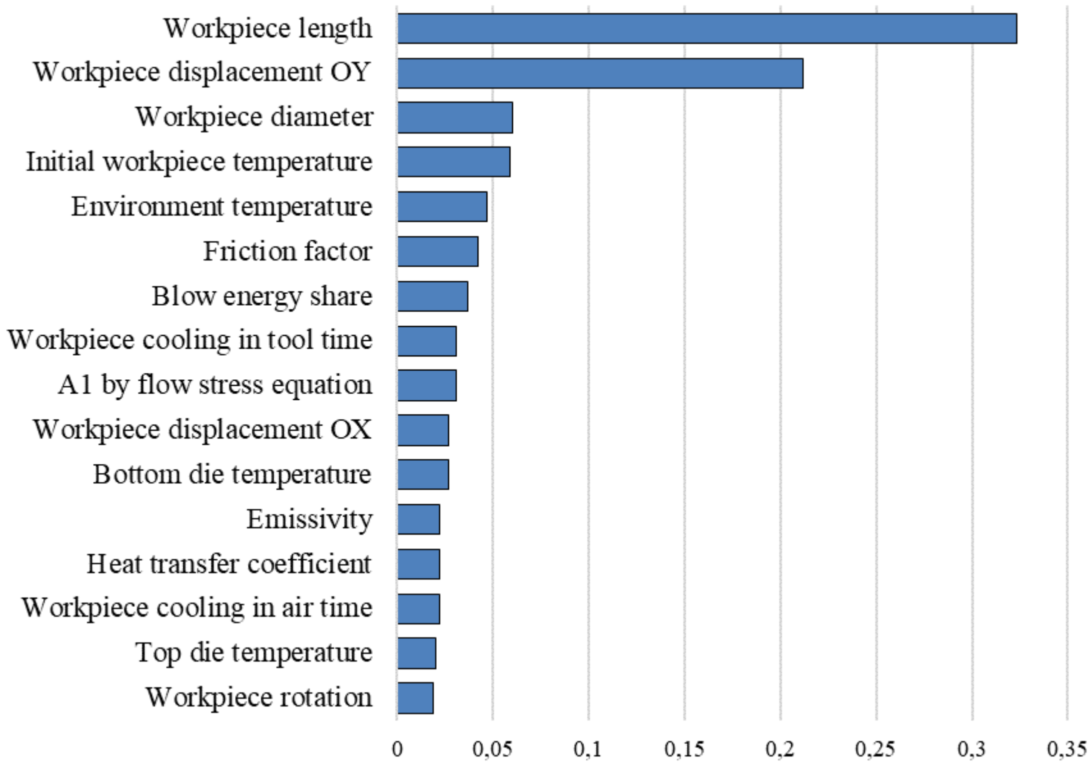


Figure 5 – Feature importance based on the machine learning analysis

Further analysis was conducted using SHapley Additive exPlanations (SHAP). The prediction $\boldsymbol{p(x)}$ for a single instance $\boldsymbol{x = (x_1, x_2, \dots, x_N)}$, which consists of $\boldsymbol{N}$ features $\boldsymbol{x_i}$, can be formally expressed using the SHAP method as the following mathematical equation (Eq. 3):

$$p(x) = \phi_{base} + \sum_{i=1}^{N} \phi_i x_i', \quad (3)$$

where $\boldsymbol{\phi_i}$ denotes the SHAP value of the $\boldsymbol{i}$-th feature. SHAP values quantify the marginal contribution of each feature to the prediction. The baseline value $\boldsymbol{\phi_{base}}$ is a constant. $\boldsymbol{x_i'}$ is a binary indicator of whether feature $\boldsymbol{x_i}$ is included in the calculation. SHAP values quantify the marginal contribution of each feature to the prediction. The SHAP marginal contribution analysis shows the SHAP values assigned to each feature in the model. A positive SHAP value signifies a positive contribution to the prediction, whereas a negative value indicates a negative contribution. The absolute value of the SHAP value represents the strength of its influence. Contribution of major feature variations on the defect formation probability is shown in Fig. 7, where defect mitigating regions are highlighted in green and areas prone to defect formation are outlined in red.

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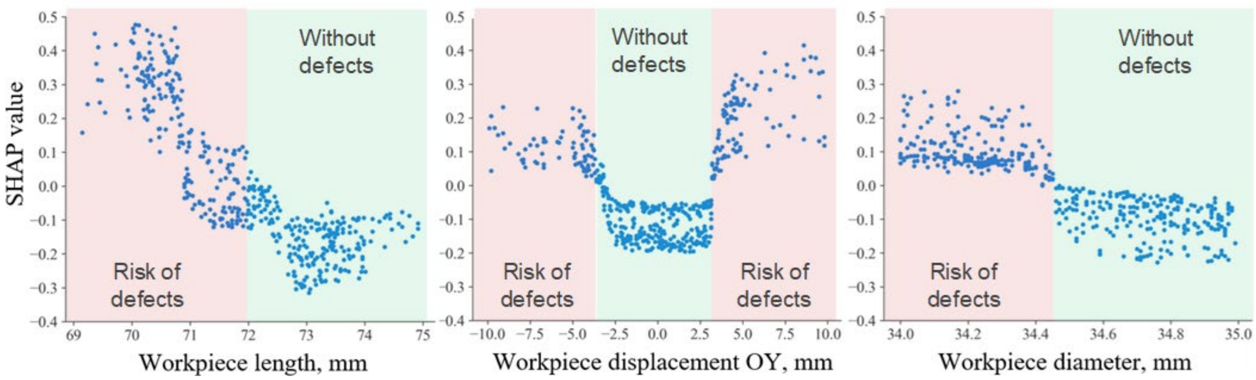

Figure 6 – Contribution of feature variations to the defect formation probability

From the learning results of the neural network, it can be observed that the workpiece length greater than 72 mm and the workpiece diameter greater than 34.5 mm tend to reduce the probability of defects. The y-axis displacement of less than approximately 4 mm is a safe region that does not increase the probability of defects. Therefore, it is possible to provoke the defect formation by changing the workpiece length to less than 72 mm, reducing the workpiece diameter to less than 35 mm, or displacing the workpiece in the OY direction by more than 5 mm.

Validation of the results using experimental data. The uncertainty and stochastic effects analysis, performed using machine learning, has been validated by experimental forging trials using process parameters that should lead to defect formation. The results of these trials are shown in Fig. 7.

Experimental forging				
Variation	Reference D35x72	Changed length D35x70	Changed diameter D34x72	Displacement OY +5 mm
Defect	Without defects	Underfill	Underfill	Folding

Figure 7 – Defect formation due to the hot bulk forging process parameter variations

It can be seen that changes in workpiece dimensions or process parameters result in defects as predicted. Thus, the efficiency of the proposed approach for uncertainty and stochastic effects analysis in hot bulk forging simulation is demonstrated.

Conclusions

This work developed the approach for inverse analysis of uncertainties and stochastic effects in hot bulk forging processes based on automated API-driven finite element simulations. The developed procedure has been used to generate a dataset that is further analyzed using machine learning. The analysis allowed us to identify the process parameters significantly impacting defect formation. Safe regions for these parameters, where defects are absent, were also identified. Experimental validation shows a good correspondence between predicted and experimental results, demonstrating the proposed methodology's efficiency and the potential of using machine learning for uncertainty and stochastic effects analysis in hot bulk forging simulation.

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