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Real-time forging process control: integrating billet-related surrogate and machine behavior models

David Uribe[1] · Camille Durand[1] · Cyrille Baudouin[1] · Régis Bigot[1]

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Abstract

This study introduces a predictive surrogate model for real-time control in cold upsetting processes, incorporating both material and machine behaviors. Traditional approaches often simplify machine behavior as rigid or with constant stiffness; however, the proposed method dynamically couples material and machine responses, accounting for efficiency changes across different upsetting operations. This is achieved through the integration of a data-driven billet-related surrogate model with a machine-related analytical blow efficiency prediction, accurately capturing elastic energy losses. For the construction of the surrogate model in this use case, a multilayer perceptron artificial neural network (MLP ANN) was employed, demonstrating high predictive accuracy with a dataset comprising 2000 entries generated using Latin Hypercube Sampling (LHS) and numerical simulations. The model provides precise predictions for key outputs like forging load and plastic energy. Experimental validation shows prediction errors below 5% for energy setpoints, reduced to under 1% with blow efficiency correction. The general methodology of surrogate model creation can be adapted for various metal-forming processes, providing a versatile framework for real-time simulation and control.

Keywords Surrogate model · Forging processes · Real-time control · Blow efficiency · Numerical simulation · Data-driven model · Machine behavior

Introduction

Forging processes play a crucial role in the manufacturing industry, enabling the production of high-strength and complex-shaped metal components. However, piloting the forging process presents challenges due to the inherent variabilities associated with the process (Douglas & Kuhlmann, 2000; Jia et al., 2023). These variabilities can arise from factors such as material properties, tool dynamics, and process parameters, leading to uncertainties in the final product's quality and energy consumption (Wang et al., 2023).

It is crucial to employ highly responsive approaches to address the challenges in real-time piloting forging processes and improving process control, especially considering the dynamics of the forging machine. One such approach is the Closed-Loop Control system, such as the Generalized Predictive Control (GPC) (Dindorf et al., 2021; Dindorf & Wos, 2020). GPC utilizes a mathematical model of the system and employs a predictive algorithm to determine the control actions. By predicting the system's behavior and optimizing control inputs, GPC offers the potential for precise control of parameters such as temperature, pressure, and deformation. However, GPC requires an accurate model of the system, including the interactions with the material, which can be challenging to obtain in practice. Another approach to pilot forging processes is through adaptive control techniques, such as fuzzy logic systems or expert systems (Garth Frazier, 1998; Osakada et al., 1990; Osakada & Yang, 1991). These methods aim to adjust the control strategy based on real-time feedback from the forging process.

✉ David Uribe
david_santiago.uribe_espitia@ensam.eu

Camille Durand
camille.durand@ensam.eu

Cyrille Baudouin
cyrille.baudouin@ensam.eu

Régis Bigot
regis.bigot@ensam.eu

[1] Arts et Métiers Institute of Technology, HESAM Université, Université de Lorraine, LCFC, Metz F- 57070, France

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However, their design is subjective and heavily relies on the expertise and experience of the control engineer.

Furthermore, achieving efficient control of forging processes necessitates considering not only the material and process parameters but also the dynamics of the forging machine (Vajpayee & Sadek, 1978). The dynamics of the machine encompass its mechanical response and vibrations, which can substantially impact the quality of the forged components, altering the energy distribution throughout the process. Consequently, comprehending and optimizing the blow's efficiency becomes of utmost importance. The blow's efficiency directly affects the energy allocation in the process and can influence both the energy consumption and the quality of the forged components. Hence, precise prediction and optimization of the blow's efficiency emerge as critical objectives for enhancing process efficiency and curtailing energy consumption (Mull et al., 2020). However, these dynamics have not yet been integrated into real-time applications. Typically, blow efficiency is assessed post-operation rather than predicted beforehand. This highlights the need to integrate real-time machine models with real-time product models. Furthermore, numerical simulations are often conducted under the assumption of rigid dies, which do not accurately account for the real behavior of the dies and the press during operation. This oversight can lead to suboptimal predictions and control strategies, emphasizing the importance of incorporating more realistic die behavior into the modeling framework. This approach aligns with the broader perspective outlined by (Zhang et al., 2019), which advocates for a comprehensive consideration of both infrastructure and material systems in process modeling.

Combining the inherent variabilities of forging processes with the energy losses resulting from the involved dynamics poses a dual and significant challenge. Effectively addressing these issues within the control system is essential to ensure the production of high-quality components. In this context, a range of predictive control models are available, from analytical approaches like the slab method (Zhang et al., 2012), which offers reactivity but lower accuracy, to numerical simulations (Yin et al., 2021), which provide higher accuracy but lack in reactivity. To bridge the gap between accuracy and reactivity, an intermediate model type widely employed in the literature is the simulation-based surrogate model (Liu et al., 2022; Song et al., 2022).

To address the limitations of these individual models, combining analytical models with surrogate models has emerged as a promising approach. Analytical models can provide a solid foundation for understanding the underlying mechanical behavior of the forging process, while surrogate models can be used to speed up predictions and account for the complex, nonlinear interactions that might be difficult to model analytically. By coupling these two approaches, we can achieve a model that balances the precision of FEM with the computational efficiency of surrogate models, leading to better real-time control of forging processes. The integration of machine learning models, such as artificial neural networks (ANNs), with analytical models has also proven successful in improving prediction accuracy in other domains, such as offshore gas field modeling (Etesami et al., 2021).

Despite the use of various algorithms in the literature, no methodology has yet focused on integrating variable selection into surrogate model development (Alizadeh et al., 2020). This step is crucial, as the selection of influential process parameters varies with the application case. Existing studies primarily concentrate on training algorithms (Hürkamp et al., 2020, 2020; Ryser & Bambach, 2021; Song et al., 2022), data preparation and database size (Liu et al., 2022; Slimani et al., 2023), or the use of model reduction techniques in their development (de Gooijer et al., 2021; Hamdaoui et al., 2014; Uribe et al., 2023).

In this context, this article presents a methodology for developing these product-related surrogate models and their integration with machine-related analytical models, with an application case in metal forming processes. This methodology spans crucial stages, including sensitivity analysis, database creation, and surrogate model algorithm selection and development. The developed surrogate model is coupled with a machine analytic model, or domain knowledge model, which considers the overall stiffness of the machine and tooling to predict the blow's efficiency (Brecher et al., 2009; Vajpayee et al., 1979), thereby extending beyond numerical simulation predictions, typically made in nominal tooling conditions. By integrating the blow's efficiency into the surrogate model, the accuracy of energy predictions is enhanced, improving overall process control. Both billet-related surrogate and machine-related analytical models enable the prediction of the energy setpoint, accounting for the elastic energy losses of the process.

Materials

Experimental setup

The mechanical screw press studied is a screw press LASCO® SPR400 of the VULCAIN platform in the LCFC laboratory at the Arts et Métiers in Metz (Durand et al., 2018). This press can provide a maximum forging energy of 28,9 kJ for a ram speed of 680 mm/s. A percentage of this maximum energy must be given as a setpoint. This setpoint is adjustable from 1 to 100%.

During the forging process, the ram displacement and the load along the forging axis are acquired respectively with three laser sensors and a strain gauge, all located on the lower die. For the lower and upper tools, dies with smooth flat surfaces were used, as it is typically used in open-die forging. In the tool holders, composite modular insulating plates were set up to ensure the tool's versatility and protect the sensors, allowing the tool to perform cold, warm, and hot-forging operations (see Fig. 1).

The operation studied is a cold single blow upsetting of a copper cylinder (Fig. 2).

For this operation, a cylindrical billet defined by its Initial Diameter (ID) and its Initial Height (IH) is forged along its axis of revolution until it reaches its Final Height (FH) (see Fig. 3).

Numerical setup

In addition to the experimental setup, a 2D axisymmetric Finite Element Method (FEM) simulation was performed to investigate the sensitivity of the forging process to various input parameters and to generate a database for the development of a surrogate model (see Fig. 4). The simulations were conducted using the commercial software package FORGE® by Transvalor. The FEM model employed tetrahedral meshing, with the number of finite elements ranging between 4000 and 8000, varying with the dimensions of the billets. The length of a mesh edge averaged 0.6 mm in the core of the billet and was refined to 0.3 mm in the external parts. Default FORGE® solver remeshing was activated during the simulation. The numerical setup was conducted with a rigid machine, and it is important to note that coupling with machine behavior is performed a posteriori. The average computation time is 15 min.

The numerical model was developed to represent the forging process, considering the capabilities of the screw press. This includes the forging tool, the workpiece, process parameters, and the appropriate boundary conditions (see Table 1). To capture the material behavior during forging, a reduced elastoviscoplastic Hansel-Spittel material model was employed in the simulation:

$$\sigma_s = A \cdot e^{m1 \cdot T} \cdot \varepsilon^{m2} \cdot \dot{\varepsilon}^{m3} \cdot e^{\frac{m4}{\varepsilon}} \quad (1)$$

Here, σ_s denotes the flow stress, ϵ and $\dot{\epsilon}$ represent strain and strain rate, respectively; and T stands for temperature.

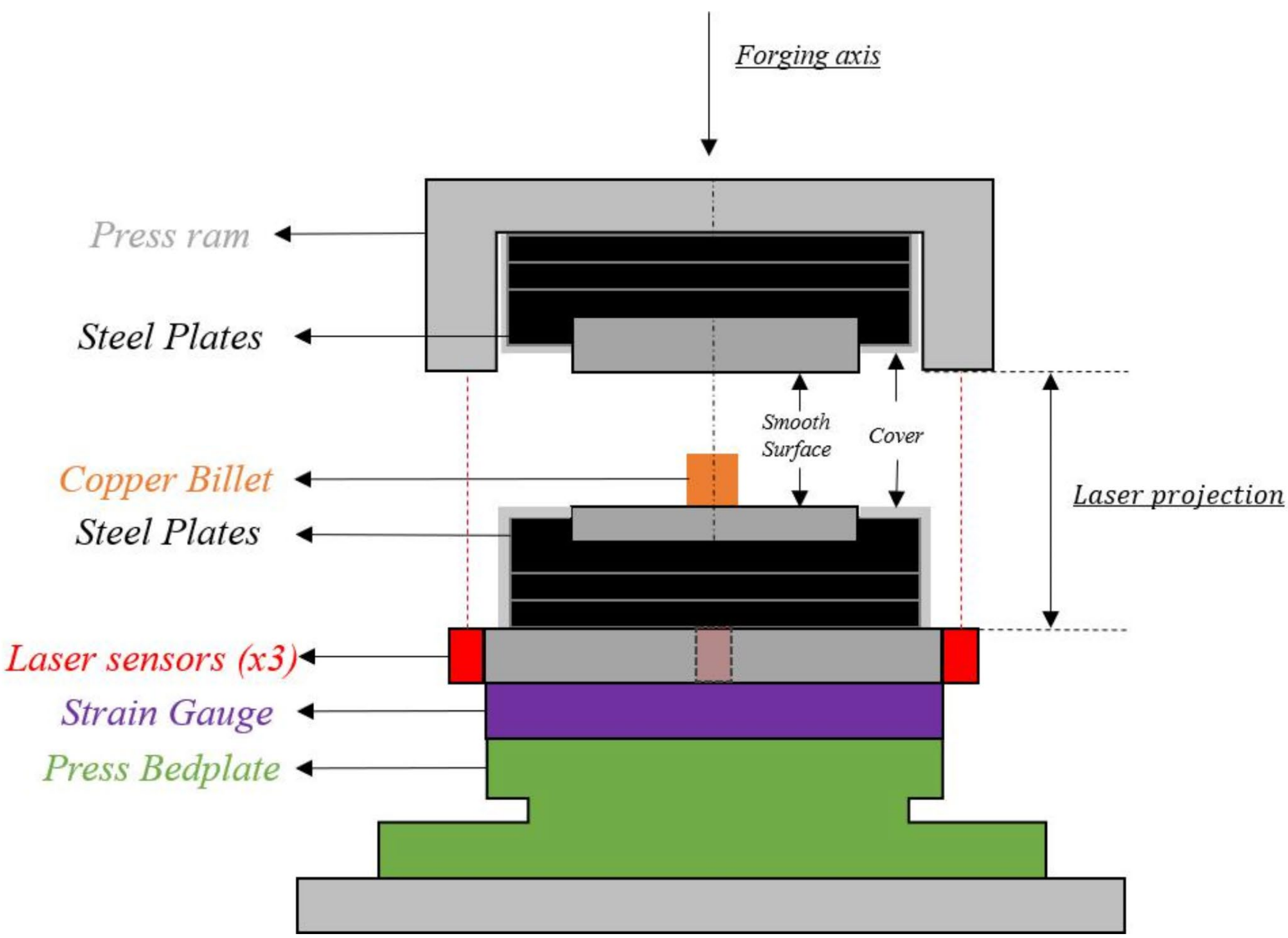

Fig. 1 Diagrammatic representation of the experimental forging setup

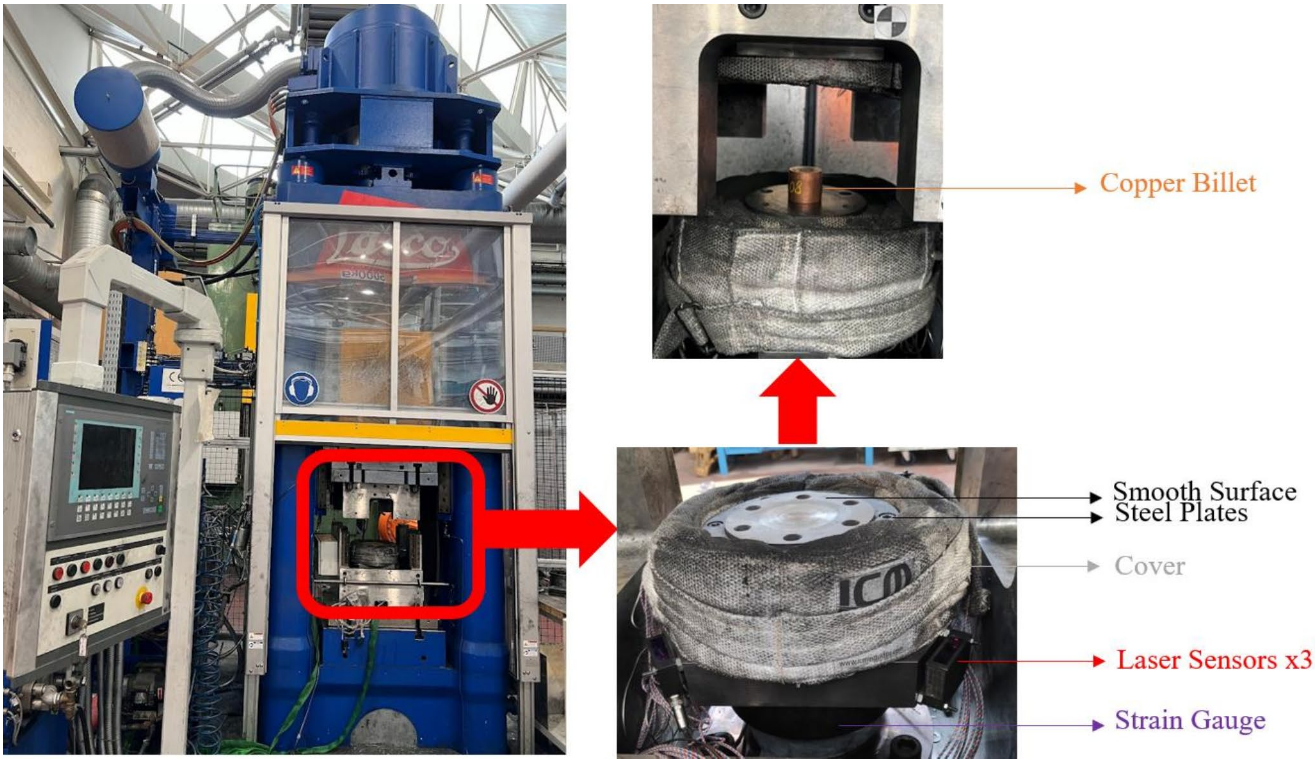

Fig. 2 The screw press and the tool holder for the cold copper upsetting

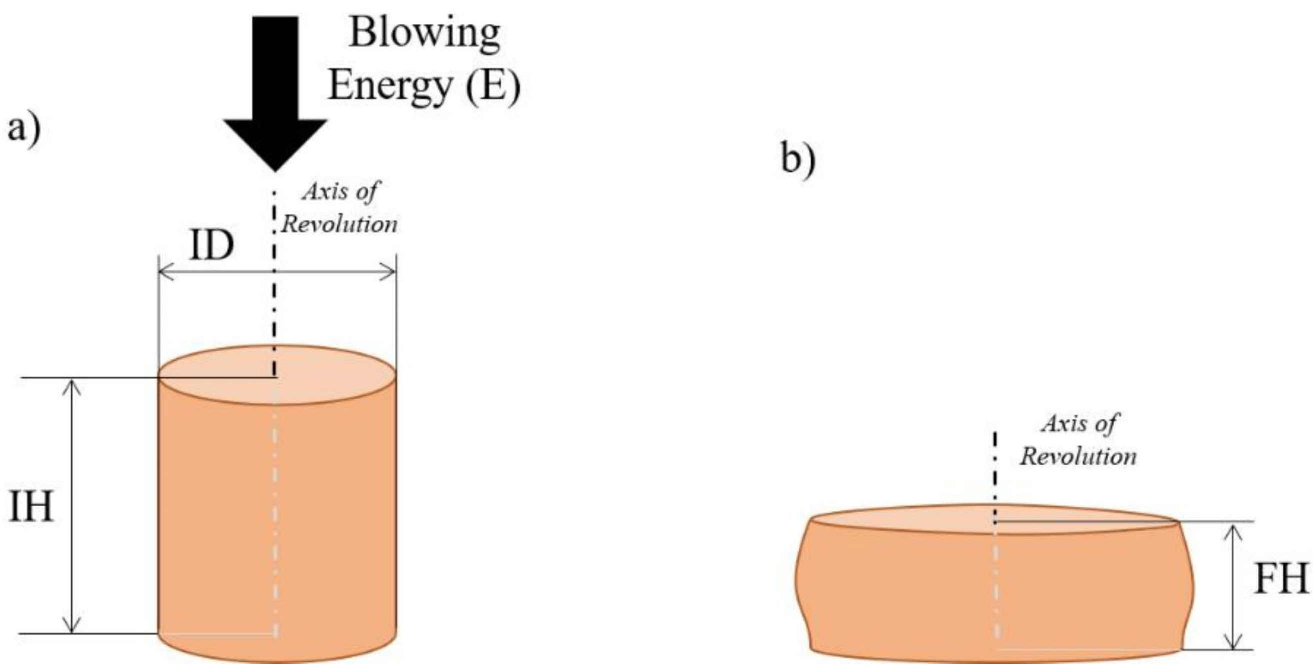

Fig. 3 Diagrammatic representation of copper billet upsetting process: **a**) Before Upsetting, **b**) After Upsetting

The material constants, namely A, m_1, m_2, m_3, m_4, are 411.19 MPa, -0.00121, 0.13, 0.01472, and 0.002 respectively. The numerical model underwent thorough calibration against experimental data to ensure its precision, adjusting parameters such as the friction conditions material rheology. Material physical properties are listed in Table 2.

Friction conditions follow a Coulomb-limited Tresca Model (D.-W. Zhang et al., 2021):

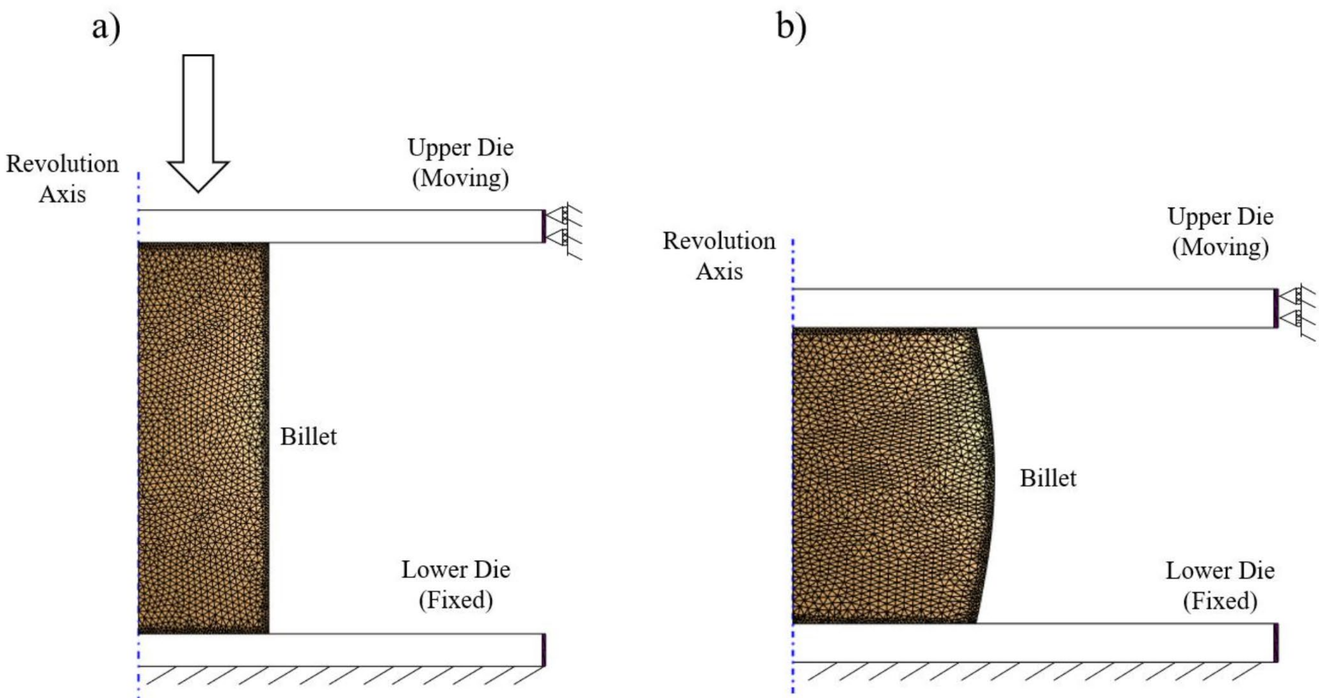

Fig. 4 Numerical setup: **a**) before upsetting. **b**) after upsetting

Table 1 Numerical model description

Parameter's type	Parameters	Value/ Range
Thermal	*Initial temperature of the Billet*	20 °C
	Initial temperature of the Tool	
	Room temperature	
Billet geometry	*Initial Diameter*	[15–35] mm
	Upsetting ratio (Height/Diameter)	[1.5–2.5]
Piloting parameters	*Energy Setpoint*	(0–11.56] kJ – (0–40] %
Boundary conditions	*Heat Transfer coefficient Billet-tool*	2000 W/m^2K
	Heat transfer coefficient Billet-room	10 W/m^2K
	Coulomb-Tresca friction model	$\bar{m}$= 0.2, μ = 0.1

Table 2 Physical properties of copper billet at 20 °C

Material	Young's Modulus (MPa)	Poisson's ratio	Density (kg/m3)	Thermal Conductivity (W/m-K)	Specific Heat (J/kg-K)
Pure Copper	110,000	0.3	8100	401	435

$$\tau = \min\left(\mu \cdot \sigma_n; \bar{m} \cdot \frac{\sigma_s}{\sqrt{3}}\right) \quad (2)$$

where σ_n is the contact pressure; μ and $\bar{m}$ the Coulomb and Tresca friction coefficients, respectively.

Methods

While several authors have developed FEM-based surrogate models for various manufacturing applications, to our knowledge, no methodology has yet incorporated a variable selection step or sensitivity analysis for creating these models, focusing instead on data processing, data reduction, and training algorithms. This study advances the field by introducing a methodology that incorporates sensitivity analysis for variable selection and integrates product-related surrogate models with machine-related analytical models. Additionally, the approach separates the simulation of the billet using a rigid machine and incorporates machine behavior, allowing for the dissociation of behaviors and the independent qualification of different components before facilitating their interaction.

Following the numerical simulation, the methodology encompasses the following stages (see Fig. 5):

1. *Sensitivity Analysis*, identifying the most influential process variables, guiding the selection of inputs for the surrogate model,

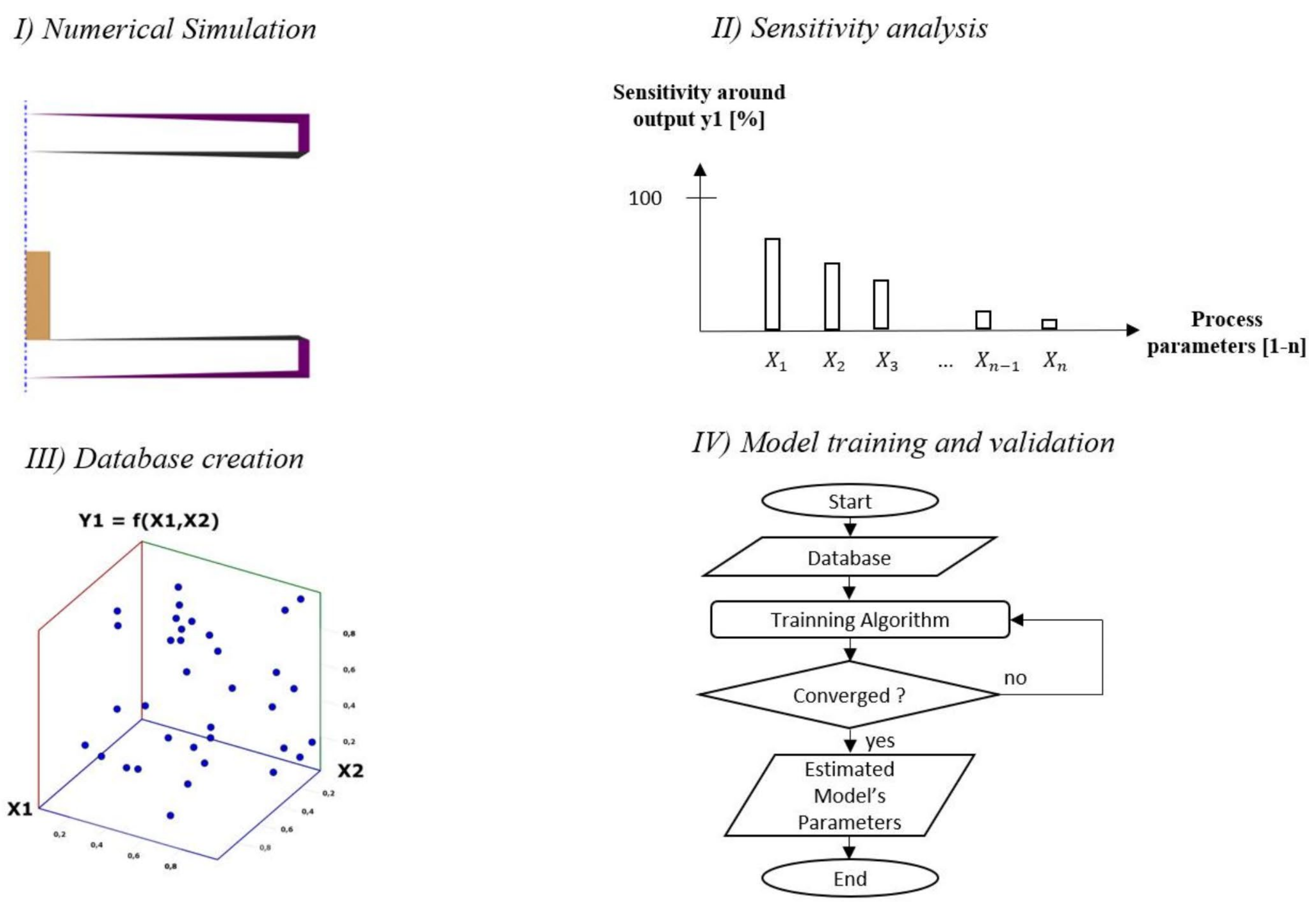

Fig. 5 Methodology for surrogate model creation in metal forming processes

2. *Database Construction*, using a customized Design of Experiments,
3. *Surrogate Model Training*, using an interpolation or regression algorithm.

In our specific case, an additional step is undertaken, involving the coupling of the surrogate model with an analytical counterpart to enhance prediction accuracy.

This multi-step methodology ensures the robustness and the applicability of the surrogate model, thus enabling accurate predictions and valuable insights in the area of metal-forming processes.

Sensitivity analysis

The evaluation of the local dimensionless SA for both physical and model-related factors around specific output variables (such as the billet's Final Height or Maximum Load) enables the identification of the most influential parameters in the process. This analysis helps in selecting the variables that will be integrated into the surrogate model (Liu et al., 2023).

For this, physical variables, such as billet's temperatures and billet dimensions, as well as model-related factors, such as workpiece rheology and coefficients of friction, must be exhaustively listed.

Once these parameters are established, it is crucial to quantify their sensitivity on the final state of the part. In our case, the influence on the Final Height of the billet is studied.

A SA can be conducted to compare the influence of different process variables. Various techniques can be employed, including screening, global, and local analysis. However, in metal forming cases, applying screening and global approaches might pose challenges due to limited knowledge of the range of variation for certain numerical variables, such as rheological law coefficients, and the associated uncertainty surrounding these values.

In this context, a local SA appears to be a suitable choice for conducting such a comparison. This approach involves perturbing the process variables around their nominal values, to allow a more focused examination of their impact.

In this regard, the following local adimensional SA is employed:

$$S_{o,i} = \frac{\Delta Y_{o,i}}{\Delta X_i}\frac{\widehat{X}}{\widehat{Y}_o} \tag{3}$$

The sensitivity analysis S of the model output o against the input i is represented by $S_{o,i}$. The specific parameter variation $\Delta X_i = X_i - \widehat{X}_i$. The output Y_o variation of the model given the X_i is represented by $\Delta Y_{o,i} = Y_{o,i} - \widehat{Y}_o$. The nominal input i and output o values are $\widehat{X}_i$ and $\widehat{Y}_o$, respectively.

A Pareto diagram could illustrate the results of the SA (Mizgier, 2017). In this phase, the inputs and outputs of the model are chosen, which are all scalar variables studied in this SA. Additionally, given our core goal of process control, the machine's piloting variable becomes a necessary prediction. In the case of our screw press application, the energy setpoint stands out as a vital and obligatory output variable.

Database creation

The numerical simulation described earlier is utilized to generate the database for constructing a surrogate model. During this phase, DoE techniques allow to systematically investigate the relationship between input variables and output responses. The full factorial design involves a comprehensive exploration of each variable's effects and interactions across the entire input space (Kroiß et al., 2013; Ryser et al., 2023), and the reduced factorial design, strategically selecting a subset of input variable combinations while capturing key factors and interactions, is commonly employed (Wiebenga et al., 2013, 2015). However, increasing variables lead to exponential simulations, posing computational complexity and time limitations. To address this, the reduced factorial design is employed, significantly reducing computational burden while maintaining crucial insights. Factors and their levels are chosen based on the surrogate model's type. The size and number of factors considered in the database creation phase are customized to ensure the effective capturing of underlying relationships, enabling accurate predictions and efficient analysis. At this initial stage, the determination of the number of points to be sampled is arbitrary. Nonetheless, certain authors have suggested starting with at least 10 points per active variable when employing a reduced factorial design (Schonlau, 1997). This recommendation aims to balance the acquisition of sufficient data for accurate modeling while considering computational time constraints. Additionally, if the surrogate model's performance is considered insufficient, additional points can be gradually added to enhance its accuracy and predictive capability.

Surrogate model training

Given that the model's inputs and outputs are scalar values, a fitting surrogate algorithm tailored to scalar prediction is implemented. The multilayer perceptron artificial neural networks (MLP-ANN) appear well-matched for various metal-forming process applications, especially when numerical simulations enable efficient database acquisition, as demonstrated by (Slimani et al., 2023). This substantiates our choice to employ this algorithm for scalar prediction in our particular case. Nevertheless, alternative regression or interpolation techniques could be explored, contingent on factors such as problem characteristics, data availability, and input/output parameter count (Hou & Behdinan, 2022).

The model is trained using the dataset generated from numerical simulations, which includes input variables and corresponding output responses. To enhance training efficiency, prevent gradient-related issues, and improve overall model stability and performance, the dataset is normalized (Shanker et al., 1996). Subsequently, it is partitioned into training and validation subsets.

There is no specific rule for the number of hidden layers and neurons in each layer of a Multi-Layer Perceptron Artificial Neural Network (MLP-ANN); these parameters are typically determined empirically. However, to fine-tune the network architecture, various hyperparameter optimization algorithms can be employed, such as Grid Search, Random Search, Hyperband, and Bayesian Optimization (Agrawal, 2021). These algorithms facilitate the systematic evaluation of different configurations, including varying numbers of hidden layers, neuron counts per layer, activation functions, and training optimizers. This approach aids in identifying the most effective network setup.

The learning process for the MLP-ANN utilizes the backpropagation algorithm. In this algorithm, the neurons' weights are updated in the gradient descent of the cumulative network error.

For regression tasks, the ReLU activation function is commonly recommended for hidden layers, while the linear activation function is suitable for the output layer (Goodfellow et al., 2016). To enhance generalization and prevent overfitting, dropout can be applied.

Application: development of a surrogate model for a cold upsetting process

Sensitivity analysis

Table 3 presents the list of physical and model-related factors employed in the SA. Each parameter was perturbed by 15% around its nominal value to assess its influence. The

Table 3 List of parameters and outputs for the sensitivity analysis

Parameter's Type	Parameters	Outputs
Thermal	Initial temperature of the Billet $(T_{0billet})$	Billet's Final Height (FH)
	Initial temperature of the Tool (T_{0tool})	Maximum forging load (F_{max})
	Room temperature (T_{room})	
Billet rheology	Hansel-Spittel's Law Parameters $(A1, m_1, m_1, m_3, m_4)$	
	Young Modulus, Poisson's ratio (E_m, ν)	
Billet geometry	Initial Height (IH)	
	Initial Diameter (ID)	
Piloting parameters	Energy Setpoint (E)	
Boundary conditions	Heat Transfer coefficient Billet-tool $\left(\varphi_{B-T}\right)$	
	Heat transfer coefficient Billet-room $\left(\varphi_{B-R}\right)$	
	Coulomb-Tresca friction model $(\mu, \bar{m})$	

results of the SA were presented using a Pareto Chart, highlighting in red the parameters chosen for inclusion in the surrogate model (see Fig. 6).

The SA supports the choice of the input and output variables of the surrogate model. It includes three input parameters: Initial Diameter, Initial Height, and Final Height. The output parameters of interest were the Plastic Energy and the Maximum Forging Load.

Database creation

For the DoE, a Latin Hypercube Sampling (LHS) approach was employed, consisting of 50 simulations. The variable bounds were defined according to the physical constraints and design specifications of the process.

The Initial Diameter was varied within the range of 15 to 35 mm. The Initial Height was defined based on a specific slenderness ratio (Initial Height/Initial Diameter), ranging from 1.5 to 2.5 times the Initial Diameter to mitigate the risk of buckling during the upsetting process. The Energy parameter was constrained to a range of 1 to 40% of the machine's capabilities, depending on the size of the billets.

By implementing the Hypercube Latin approach with these predefined bounds, the DoE enabled comprehensive exploration of the parameter space while considering the physical and design constraints of the process. The resulting simulations generated a diverse dataset encompassing various combinations of five input and output parameter values (Initial Height, Initial Diameter, Energy, Final Height, and Maximum Forging Load). In total, 2000 simulations were executed, resulting in a comprehensive database of 2000 input-output combinations.

Surrogate model training

The input and output data underwent a standardization process before training for consistent and normalized representation. The network was built using the Keras API within the TensorFlow framework in Python. GridSearchCV algorithm (Ma et al., 2023) has been chosen for the hyperparameter optimization process, various configurations were tested, including networks with 1, 2, and 3 hidden layers, as well as varying numbers of neurons in each hidden layer (48, 64, 128 and 254). Different activation functions were evaluated, including ReLU, Tanh, and Sigmoid. Additionally, both the ADAM and SGD optimizers were assessed.

The results from GridSearchCV revealed that the optimal configuration consisted of a neural network with two hidden layers, each containing 128 neurons and utilizing the ReLU activation function. The dropout rate was set to 0.2, and the ADAM optimizer was used. This configuration yielded the

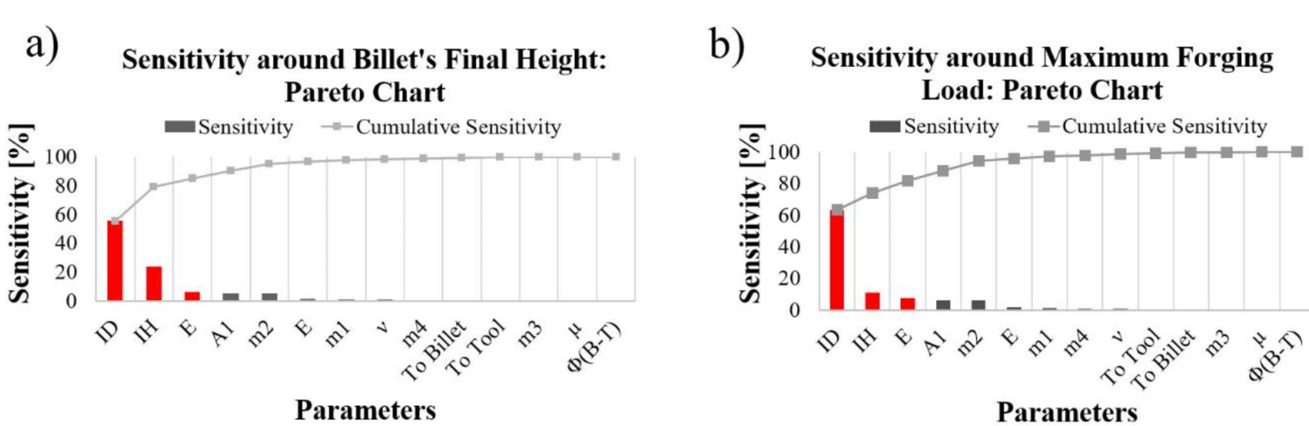

Fig. 6 Pareto chart for the sensitivity analysis around **a**) Billet's Final Height, **b**) Maximum Forging Load

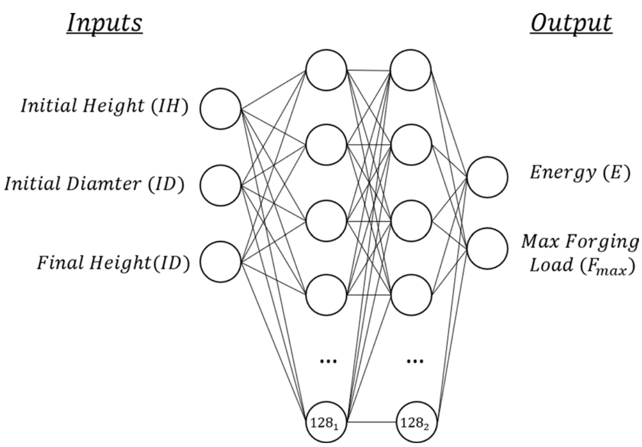

Fig. 7 Surrogate Model's (MLP-ANN) I/O architecture

best performance based on the mean squared error (MSE) metric (see Fig. 7).

The computation time of the trained model is below 50 *ms*. The training metrics are presented in Fig. 8a. The training results are compared to the FEM results in Fig. 8b.

Surrogate model results

To validate the accuracy of the surrogate model, an experimental campaign was conducted. Eight cylindrical billets with two different Initial Diameters, namely 32 mm and 18 mm, and different Initial Heights were selected for forging. This experimental campaign aimed to compare the actual results from the physical forging process with the predictions provided by the surrogate model. The energy setpoint for the experimental tests was carefully selected, ensuring a compression ratio below 50%. This energy setpoint selected, along with the maximum forging load measured were then compared to the energy setpoint and the maximum forging load predicted by the surrogate model. The prediction inputs were the initial conditions of the billet (Initial Height and Diameter), along with the measured experimental Final Height. Results are presented in Fig. 9.

Besides, comparing the surrogate model's maximum load prediction and the FE model prediction, the errors are below 2% corresponding to 4kN.

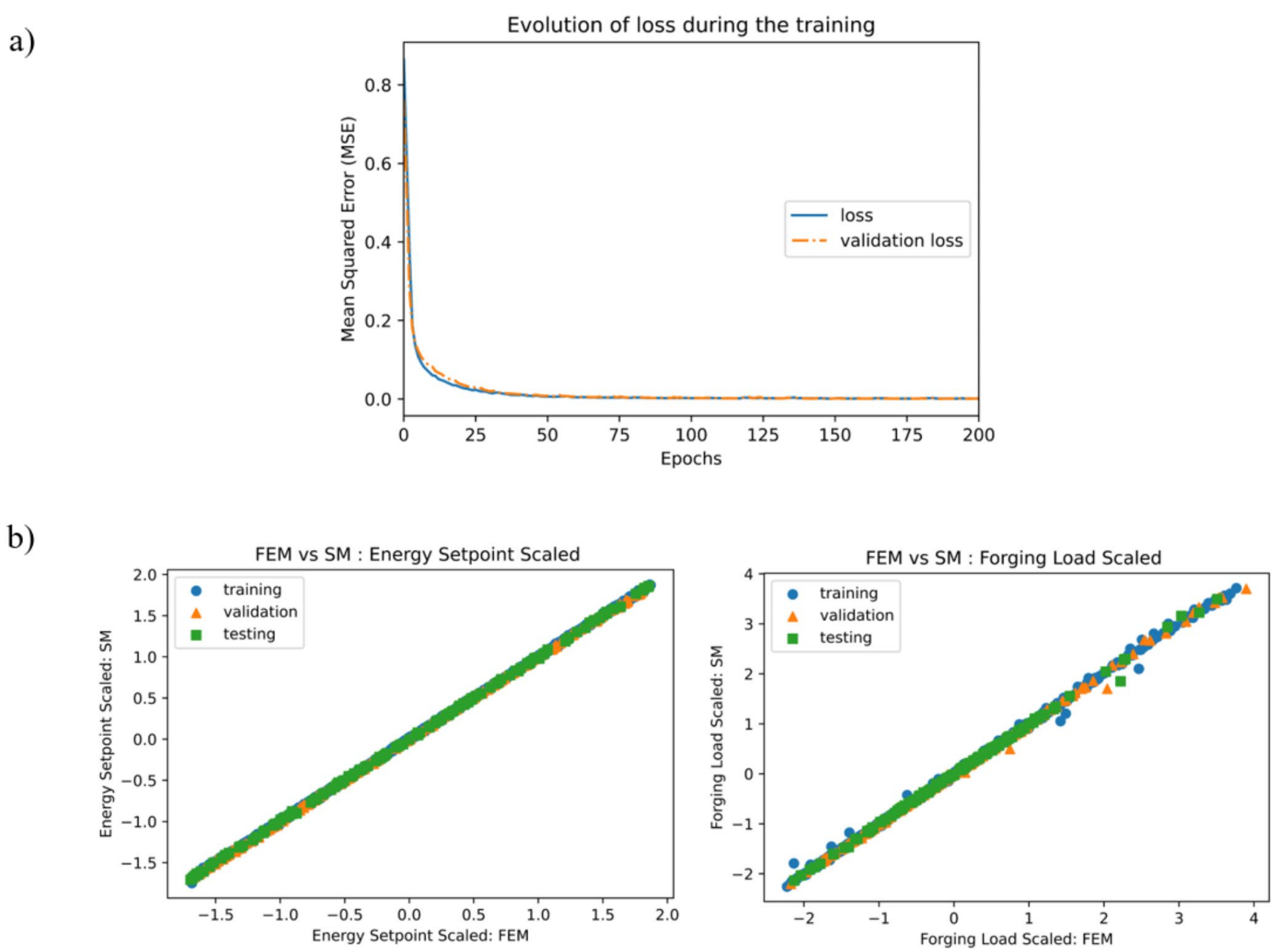

Fig. 8 Surrogate Model Training: **a**) Evolution of loss function, **b**) Surrogate Model vs. FEM

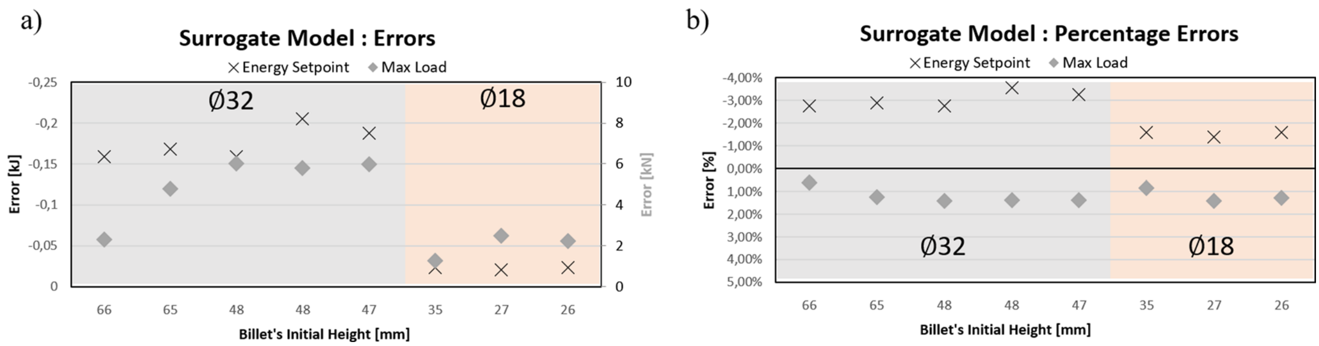

Fig. 9 Surrogate model prediction errors: **a**) Errors, **b**) Percentage Errors

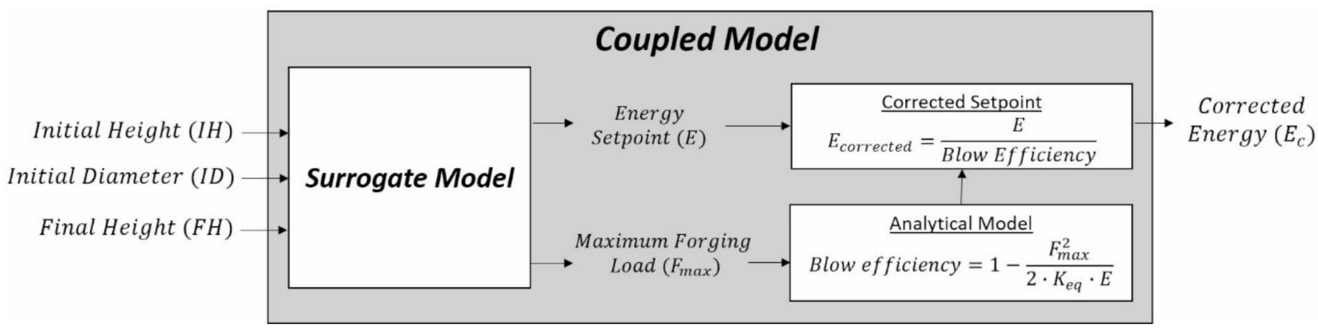

Fig. 10 Coupled model architecture

Coupling of surrogate and analytical models

The current model's prediction of the energy does not account for the elastic energy losses within the metal-forming process, as the simulation model does not consider the stiffness of the machine and tool. These losses can significantly affect overall energy consumption, process efficiency, and particularly, the accuracy of the energy setpoint prediction by the standalone surrogate model (Mull et al., 2020). Therefore, to further enhance the accuracy and comprehensiveness of the model, it is crucial to incorporate a blow efficiency prediction through an analytical model that considers the overall stiffness of the system. Furthermore, this late incorporation of machine stiffness will facilitate easier adaptation in cases involving modular tooling, eliminating the need to overhaul the entire surrogate model for modifications.

The first-order approximation model proposed by (Vajpayee et al., 1979; Vajpayee & Sadek, 1978) is used for the blow efficiency prediction:

$$Blow\ efficiency = 1 - \frac{F_{max}^2}{2 * K_{eq} * E} \tag{4}$$

Where F_{max} is the maximum forming load, K_{eq} is the equivalent stiffness of the system, and the energy setpoint is denoted by E. The surrogate model provides a prediction for the maximum forming load and the energy setpoint. The value of the overall stiffness was extracted from (Mull et al., 2021), for the same experimental setup. The corrected energy setpoint is finally calculated using the equation:

$$E_{corrected} = \frac{E}{Blow\ Efficiency} \tag{5}$$

where the blow efficiency is obtained from the analytical model and the energy setpoint is taken from the surrogate model. The coupled model architecture is illustrated in Fig. 10.

By combining the surrogate model's energy prediction with the calculated blow efficiency, the actual energy setpoint, accounting for elastic losses in the forging process, was determined. The results of the coupled model's prediction are compared to the same experimental campaign as before (see Figs. 11 and 12).

Discussion

The findings from the SA support the rational reduction of parameters for inclusion in the surrogate model, as demonstrated by effective performance achieved using just three inputs for the upsetting process.

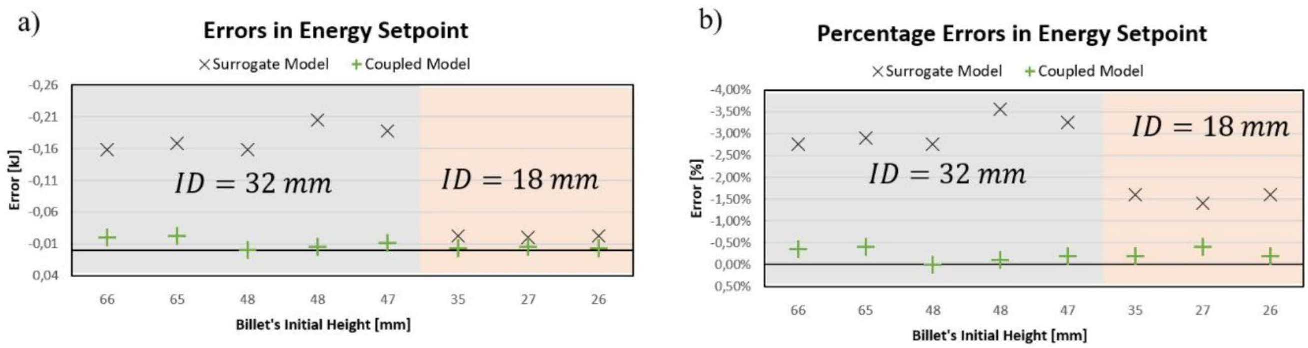

Fig. 11 Coupled model and Surrogate Model vs. Experimental Data: **a**) Errors, **b**) Percentage Errors

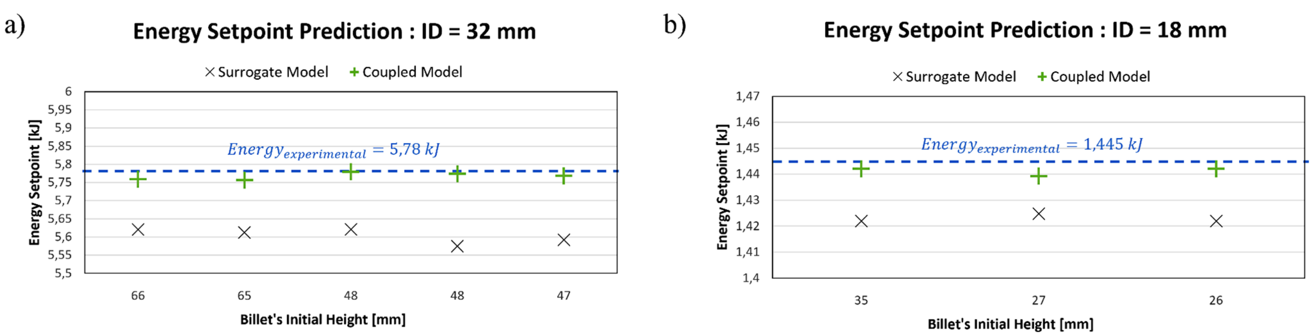

Fig. 12 Coupled model and surrogate model vs. Experimental Data: **a**) Energy Prediction in kJ for ID=32 mm. **b**) Energy Prediction in kJ for ID=18 mm

The use of LHS in the DoE demonstrated its effectiveness in generating a comprehensive and efficient training dataset for the surrogate model. The well-distributed sampling allowed for a thorough exploration of the parameter space, ensuring that the model could capture the relationships between the input variables and the output responses. Moreover, the reduced computational requirements made the approach computationally feasible and resource-saving.

The training of the surrogate model, employing an MLP ANN, yields precise outcomes. Nevertheless, similar accuracy might have been attained using alternative surrogate models, potentially with a simpler implementation. The selection of MLP ANN is substantiated by both the preferences of various authors and the substantial 2000-size database, which have been proven sufficient for the training phase. The number of neurons of the MLP ANN developed follows the recommendation made by (Rao & Prasad, 1995):

$$h = \frac{N^{\circ}\ Samples}{10 * (N^{\circ}\ Inputs + N^{\circ}\ Ouputs)} \tag{6}$$

where h is the minimum number of neurons recommended, resulting in a specific count of 40 neurons for our particular scenario.

In contrast to conventional numerical 2D simulations for these upsetting processes, the proposed model demonstrates exceptional responsiveness, achieving computation times roughly 900 times faster than rigid-machine numerical simulations. It completes calculations in less than 1 s while preserving high-quality results.

The surrogate's prediction for maximum load consistently yields accurate results, with errors remaining below 4% which corresponds to 8kN compared to experimental data, and errors below 2% or 4kN compared to FE results. Compared to traditional analytical methods such as the slab method, our model offers superior accuracy, notably overcoming the slab method's tendency to underestimate the maximum forging load and where a correction term is necessary for better results (Foster et al., 2009). Nevertheless, it's important to mention that the slab method allows for the inclusion of the friction coefficient as a parameter, a capability not employed in our case due to its absence in the DoE.

The integration of the blow efficiency prediction into the surrogate model further enhanced the precision of the results. By incorporating the maximum load prediction and accounting for the press and tools' equivalent stiffness for calculating the blow's efficiency, the coupled model achieved even greater accuracy, with errors reduced to below 1% or 0.05 kJ in the energy setpoint predictions. It's worth mentioning that our previous studies for the same forging process have shown errors below 0.2 kJ for the energy setpoint prediction (Uribe et al., 2023), indicating that the correction model in this case is effectively employed, leading to improved accuracy.

The proposed methodology allows for the integration of scalar variables as both inputs and outputs in the prediction model. However, it does not directly accommodate multidimensional variables, which are common in forging processes (e.g., temperature maps, deformation fields, stress fields). Integrating these multidimensional variables into surrogate model development would require an additional model reduction step, as suggested by various authors (Dang et al., 2017; de Gooijer et al., 2021; Hamdaoui et al., 2013).

Although the methodology provides a framework for surrogate model development in forging operations, several key considerations warrant attention. The performance of the surrogate model is closely tied to the quality and comprehensiveness of the training dataset. Despite the implementation of LHS, there remains a potential risk of not capturing critical parameter interactions, especially in complex, high-dimensional contexts. Furthermore, although the MLP-ANN demonstrates strong performance in various applications in literature, it may not be universally optimal; alternative models might provide simpler implementation or superior performance for specific applications. The integration of the surrogate model with the analytical blow efficiency model, while improving prediction accuracy, introduces additional complexity and necessitates precise knowledge of the system's equivalent stiffness, which may not always be available. Additionally, the methodology's focus on a cold one-blow upsetting process may limit its direct applicability to other metal-forming processes, particularly those involving more dynamic or multi-step operations. These considerations underscore the necessity for careful adaptation and interpretation of the methodology when applied to varied forging contexts.

Conclusions

This study presents a methodology for developing coupled models that enhance the real-time control of forging operations. This approach involves the creation of a surrogate model specifically focused on billet-related parameters, which is then integrated with a machine-related analytical model. By considering elastic energy losses during the forging process, the methodology significantly improves control predictions, leading to more accurate and efficient outcomes in forging applications.

Sensitivity analysis is crucial to the surrogate model's adaptability, enabling the selection of process parameters based on the desired output variable, which varies with the specific application. The surrogate model's database is generated using a Latin Hypercube Sampling (LHS) approach and is constructed using a multilayer perceptron artificial neural network. The methods for database creation and surrogate model training are grounded in various studies from the literature. Traditionally, blow efficiency calculations in forging operations were performed post hoc by integrating data from numerical or analytical models into a machine model. However, this methodology allows for efficient blow efficiency calculations to be made before the forging process begins by coupling a billet-related surrogate model with a machine-related analytical model.

The methodology has been validated through a single-blow upsetting process, demonstrating its real-time predictivity and accuracy. Specifically, the model's performance was evaluated, revealing errors below 5% for the energy setpoint prediction. Furthermore, the precision of the model was notably enhanced by incorporating elastic energy loss, a critical factor in the overall energy distribution, resulting in errors below 1% for the energy setpoint. Additionally, the model's flexibility allows for seamless adaptation to variations in equivalent stiffness (press and tool), enabling its application across diverse tool configurations without necessitating alterations to the surrogate model itself.

To further enhance its capabilities, future research should focus on incorporating additional energy losses such as friction or damping, as well as temperature fields in hot forging processes. Extending the model to predict microstructure evolution and deformation fields beyond the Final Height will offer a more holistic understanding of the forging process. Additionally, developing a model for multiple blow operations considering material work hardening during successive blows will improve the accuracy of predictions in complex forging scenarios.

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Declarations

Competing interests The authors have no competing interests to declare that are relevant to the content of this article.

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