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Enhancing metal-forming predictions with VR-infused digital twin models

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Abstract. This article presents a two-step method to enhance metal-forming predictions by integrating Virtual Reality (VR) into Digital Twin models, focusing on single-blow cold copper upsetting operations. The process begins with developing a real-time predictive surrogate model that considers actual process parameters, acting as a crucial link between conventional numerical simulations and immediate decision-making. Subsequently, the surrogate model is integrated into a realistic VR environment, aligned with the experimental forging setup. The study underscores the need and potential advantages of real-time digital twins in the forging field, emphasizing the bridging capability between numerical simulations and instant decision-making through predictive modeling and immersive virtual environments.

Introduction

In forging processes, numerical simulations are crucial for predicting outcomes without physical experimentation. They excel in estimating challenging-to-measure variables like deformation fields and temperature distributions. While effective for accurate predictions and exploring diverse scenarios, their time-consuming nature limits real-time application.

In recent times, thanks to technological advancements, the concept of digital twins has emerged. In the *JENII project* spearheaded by the Arts et Metiers Institute of Technology, immersive and interactive digital twins are developed to provide new training tools to students in specialized fields, such as the construction sector [1]. In this context, a digital twin of the VULCAIN laboratory's platform for forging is in progress. Immersion in a virtual environment allows students, among other things, to represent an industrial environment on real dimensions even if they do not have the machines, to see normally invisible things like the inside of a machine to understand its functioning or like a deformation field in a billet, to test several configurations in a trial-and-error approach at lower cost and in complete safety for men and machines. Moreover, this new educational tool will be accessible at any time, everywhere, for students, to prepare a practical work or to review their lessons for example.

There are several definitions of the digital twin, from the basic model (a physical and a digital environment with a data flow to update the digital environment) [2] to more expert models (also integrating a permanent connection between the two environments, prediction services by simulations or deductions via AI tools, human interactions or product life cycle concepts) [3]. We consider here that a digital twin includes five elementary building blocks: 1) a physical environment, 2) a digital environment, 3) a sensor data acquisition to update the digital environment, 4) advanced models to update the digital environment in real-time and predict future behavior, 5) a data flow from advanced models to control the physical system (Fig. 1).

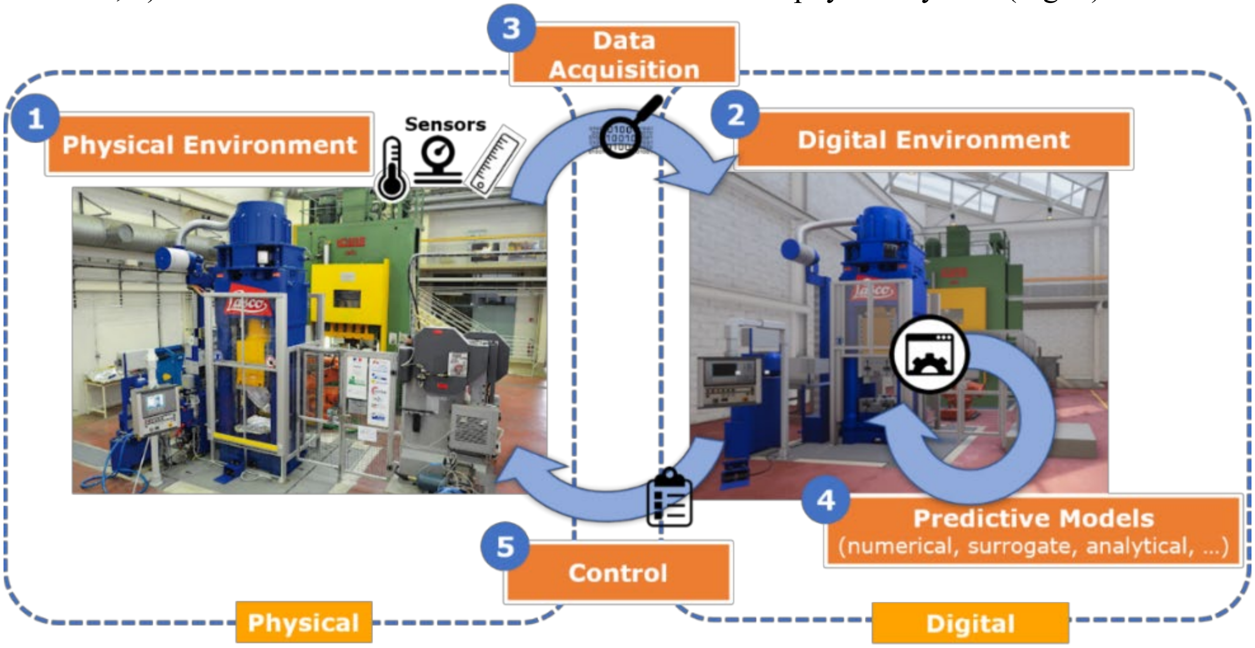

Fig. 1. Digital Twin Overview in a Cyber-Physical System.

In this paper, we are particularly interested in blocks 4) and 2) described previously for a single-blow cold copper upsetting operation. Digital twins aim to offer capabilities similar to numerical simulations (e.g., piloting, control, simulation, optimization), with real-time capability as a key differentiator [4]. To achieve real-time functionality, digital twins require highly predictive and responsive models of real-world processes [5], along with an accurate and realistic virtual representation.

To address these challenges, we propose a two-step approach. First, a surrogate model is developed. This model considers the actual process parameters and can make real-time predictions about the final operation's outcome [6]. Secondly, the surrogate is incorporated into a well-defined and realistic Virtual Reality (VR) environment, designed specifically from the experimental forging setup.

Experimental and Numerical Setup

The studied forging operation involves the cold one-blow upsetting of a cylindrical pure copper billet using a screw press.

The screw press employed in this experiment is a LASCO® SPR400, capable of delivering a maximum forging energy of 28.9 kJ at a ram speed of 680 mm/s (see Fig. 2a). Press control is achieved by setting the energy level between 1% and 100% of the maximum forging energy. The tools used in the press consist of flat surface dies located in both the press ram and the press table (see Fig. 2b).

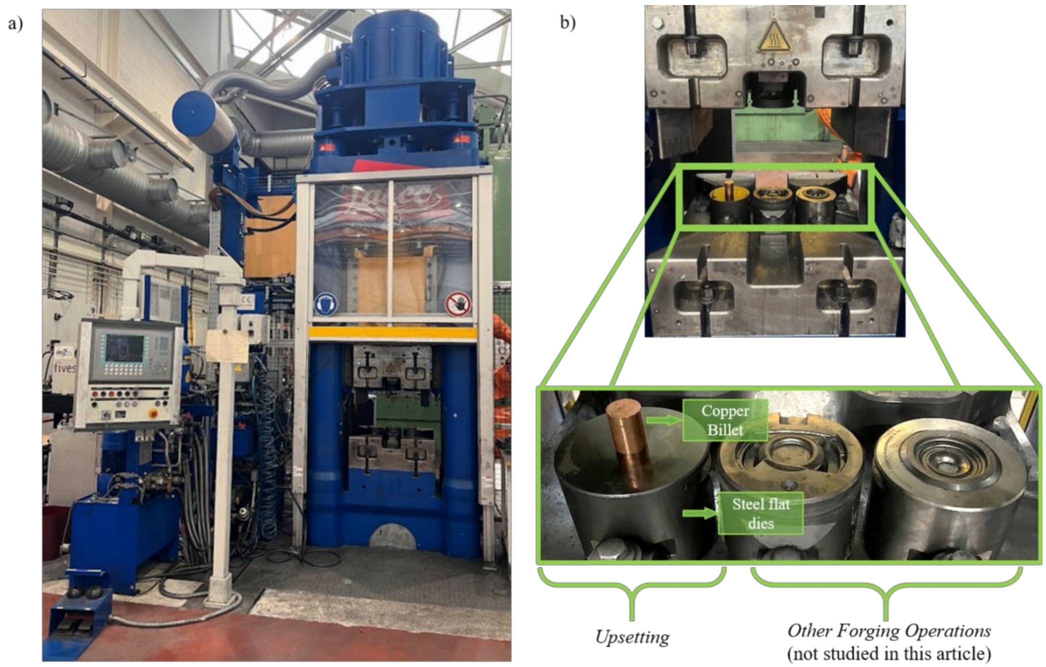

Fig. 2. Experimental setup. a) Screw Press b) Upsetting tooling and billet.

The upsetting operation is modeled using a finite element method (FEM) software (FORGE®). A 2D model was made, as the billet was supposed to be axisymmetric (see Fig. 3). A Hansel-Spittel constitutive equation was used to represent the billet's rheology:

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

where ε and $\dot{\varepsilon}$ are strain and strain rate respectively; T is the temperature; $A, m1, m2, m3, m4$ are material constants, with specific values of 411.19, -0.00121, 0.13, 0.01472, and 0.002 respectively. The tools consisted of flat rigid surfaces in both the upper and lower dies. A Coulomb-Tresca friction law was used with $\mu = 0.1$ and $\bar{m} = 0.2$ and low thermal exchanges were assumed (2000 W/m^2K).

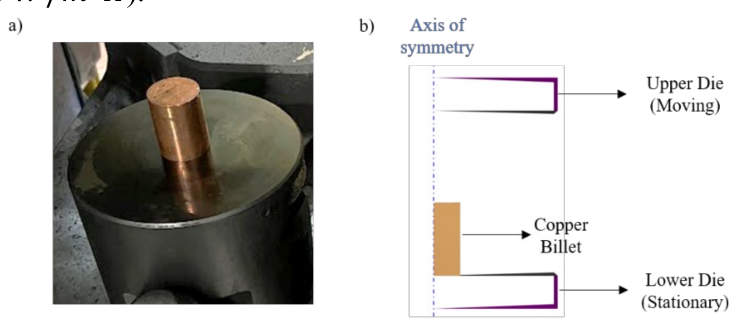

Fig. 3. Copper Upsetting: a) Experimental setup, b) Numerical setup.

Surrogate Model: Setting the Model's Architecture

Surrogate models, integral to this study, rely on constructing a training database, commonly from experimental trials or numerical simulations.

Numerical simulations, preferred for cost-effectiveness and flexibility, are advantageous over experiments. They enable exploring various process parameter combinations and excel in predicting multiple forging aspects, such as temperature gradients and stress distributions, crucial for comprehensive model training.

Reduced-order models, like surrogates, prioritize influential parameters for predicting desired outputs, omitting less impactful ones. Identifying these key input parameters is a pivotal step in surrogate model development.

In the final VR application for 'what-if' scenarios, defining primary outputs is crucial. These outputs, represented in VR through metaphoric visualizations, play a central role in exploring and understanding process variations.

In the current upsetting process, the aim is to predict the final shape of the copper billet and its deformation field after a single forging blow. A local sensitivity analysis around the billet's final height was performed, as detailed in [6]. The input variables selected for the desired predictions are the billet's initial height, initial diameter, and the setpoint for forging energy, collectively contributing to over 80% of the cumulative sensitivity. For a visual representation of the surrogate model's inputs and outputs, please refer to Fig. 4.

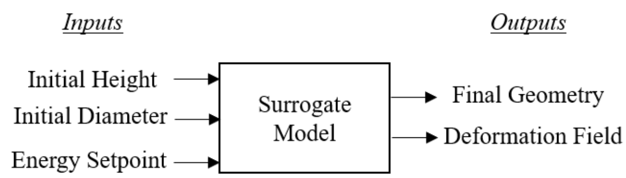

Fig. 4. Surrogate model's Inputs and Outputs.

For the model's training algorithm, the multilayer perceptron artificial neural network (MLP-ANN) was selected due to its effectiveness in applications within the field of metal forming [6-7]. However, these models are typically designed for regression or classification tasks where scalar inputs are used to forecast scalar outputs, while the outputs in this upsetting case are not exclusively scalar values (see Final Geometry and Deformation field in Fig. 4).

To address this data diversity challenge, model reduction techniques are employed. These techniques transform the non-scalar parameters into scalar variables. This reduction in complexity and dimensionality ensures the smooth integration of the geometry and field predictions with the neural network.

Managing Complexity: Model Reduction Techniques

Model Reduction Techniques serve as the essential bridge that allows to adapt the surrogate model to handle the non-scalar nature of the data effectively. Within the scope of this study, two distinct approaches are employed to reduce the complexity of the data: the Bézier curves for billet's geometry representation and the Proper Orthogonal Decomposition (POD) for deformation fields representation.

Simplifying Geometry Representation with Bézier Curves. The upsetting geometry is modeled in numerical simulation as 2D profiles, assuming an axisymmetric condition. This means that the overall geometry can be represented as a single cutting profile, specifically a scatter of 2D points (x, y) on the billet's external surface (see Fig. 5a).

However, this representation is not suitable for a surrogate model, as accurately representing a profile requires between 15 and 30 coordinates, resulting in 30 to 60 data points. To address this, a parametric representation of these profiles is necessary. In this regard, Bézier curves have been employed [5].

Bézier curves are a mathematical tool that enables the creation of a smooth profile connecting an initial and a final point via a set of strategically positioned Control Points (CPs). The adjustment of these CPs precisely defines the curve's shape. Consequently, the parametric representation of the geometries becomes a more concise set of 2D coordinates. The number of CPs required depends on the complexity of the shape being represented and the desired level of accuracy. For this case, with five CPs, the root-mean-squared error between the original FEM profiles and the Bézier-reconstructed bulging profiles is below 0.03mm and does not significantly decrease with the addition of more CPs. Consequently, five CPs were chosen for the parametric representation (see Fig. 5b).

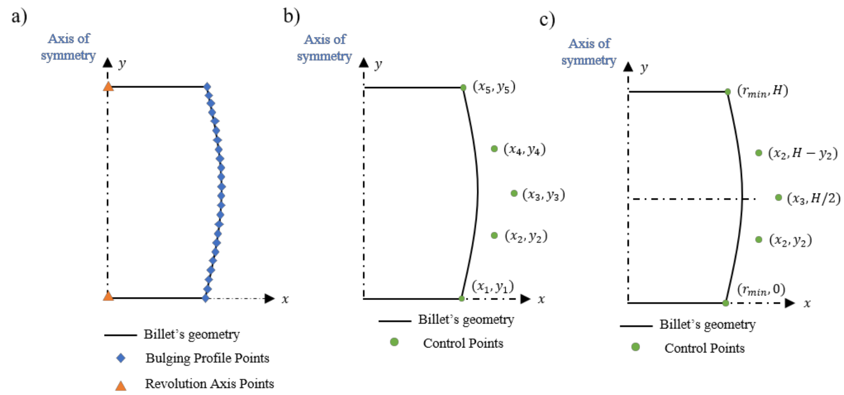

Fig. 5. Billet's Geometry representation: a) 2D Scatter, b) Initial Bézier's CPs, c) Reduced representation of the Bézier's CPs.

Additionally, considering the symmetry of the billet in its upper and lower portions, certain relationships were established: $x_1 = x_4, y_2 = H - y_4,$ and $y_3 = y_5/2$. As a result, a new set of point conventions was adopted, introducing r_{min} and H as new variables, as illustrated in Fig. 5b. This new convention allows for the representation of the entire billet geometry using only five parameters $r_{min}, H, x_2, y_2,$ and x_3 (see Fig. 5c).

Choosing the fourth-order Bézier curve strikes a balance between computational efficiency and accurately representing complex bulge patterns in upsetting geometry. This order provides flexibility in capturing curvature variations across different deformation states, friction conditions, and upsetting ratios.

Parametrizing deformation field data with Proper Orthogonal Decomposition (POD). The deformation fields of the billets are extracted from numerical simulations and are expressed as a 3D point cloud, encompassing two spatial dimensions (x, y) and a third dimension indicating deformation (ε), as illustrated in Fig. 6a. The point cloud's coordinates correspond to the nodes of the FEM simulation. To represent the deformation fields in the different upsetting cases under study, between 4000 and 15000 nodes are required, varying with the billet's size. This 3D point cloud poses challenges for integration into a surrogate model due to its size and variable node count because of re-meshing during simulations. Therefore, parametric reduction and representation are accomplished using POD techniques.

POD is a dimensionality reduction method that identifies dominant modes within the deformation field data. These modes, represented as a set of basis functions, capture the essential information while reducing the dimensionality. For the application of POD, an essential preliminary step is to discretize the deformation fields.

The discretization process involves performing linear interpolation to transform any deformation field into a 100x100 matrix, as depicted in Fig. 6 The choice of a 100x100 grid size was determined through gradient analysis of the deformation fields while varying the grid size, considering both the field quality and computer storage constraints.

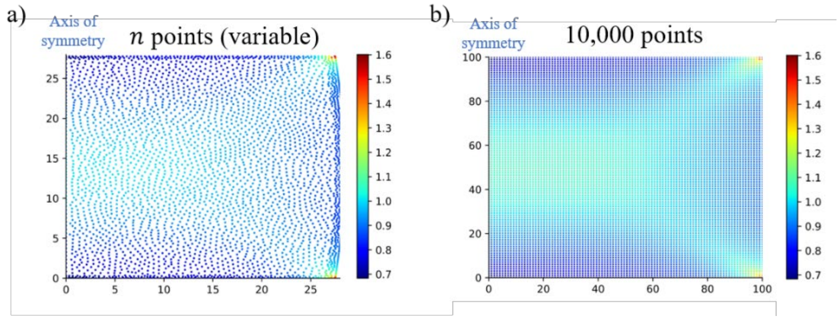

Fig. 6. Discretization Process of the Deformation Fields: a) Original Scatter, b) Discretized Field.

After defining the discretization process, a reduced Design of Experiments (DoE) is carried out using the Latin Hypercube Sampling (LHS) technique. In this approach, the three input parameters shown in Fig. 4 are varied within defined ranges:

- Initial Diameter= 15-50 [mm]
- Initial Height/Initial Diameter= 1.5-2
- Energy= 0-60 [%] of maximum energy
- Compression ratio (1-Final Height/Initial Height) = 0-50 [%]

Following the guideline of including a minimum of 10 combinations per active variable [8], 50 combinations were generated using Latin Hypercube Sampling (LHS). Each simulation produced around 660 data points, contributing to a total database size of 33,000 combinations. This database served for both applying the POD and training the surrogate model. The matrix for the POD was a 10,000x33,000 matrix, considering the number of discretized points and combinations. The deformation values span from $\varepsilon = 0$ to $\varepsilon = 1.5$.

The outcomes of the POD analysis revealed that the first basis function (mode) captured 75% of the energy in the dataset, while the inclusion of the second and third modes increased the energy capture to 79% and 82%, respectively. This implies that the first three basis functions (modes) collectively captured a substantial portion of the overall deformation variability in the dataset, enabling the reconstruction of a deformation field with only three basis functions associated with three single parameters:

$$DF_{100x100} \approx \overline{DF}_{100x100} + \sum_{i=1}^{n=3} b_i \cdot \emptyset_i = \overline{DF}_{100x100} + (b_1 \cdot \emptyset_1 + b_2 \cdot \emptyset_2 + b_3 \cdot \emptyset_3). \quad (2)$$

Here, $DF_{100x100}$ represents the discretized deformation field; $\overline{DF}_{100x100}$ is the mean deformation field obtained from the POD database; $\emptyset_i$ is the i_{th} basis function or mode obtained from the POD; and, b_i is the coefficient associated with the i_{th} mode.

Using three modes, the Mean Absolute Error and Mean Absolute Percentage Error were 0.012 and 0.16%, respectively, when comparing reconstructed and initial fields. No significant error reduction occurred beyond three modes, leading to their selection. This parametrized representation, using b_1, b_2, and b_3 as coefficients, enables field reconstruction with minimal error, streamlining the upsetting operation analysis. This parametrized representation, using $b_1, b_2,$ and b_3 as coefficients, enables field reconstruction with minimal error, streamlining the upsetting operation analysis.

Surrogate Model: Training, Validation, and Testing

The MLP-ANN featured a two-layer architecture with 20 neurons each, constructed using Keras API in TensorFlow with ADAM optimizer for backpropagation. A dropout of 0.2 was applied, and ReLU activation was used for hidden layers and linear activation for the output layer. Loss function: Mean Squared Error. The 33,000-combination database was split 80-20 for training and validation. Standardization addressed unit differences. Training metrics boasted an R2 of around 0.99 and a Mean Absolute Percentage Error below 1%. The model's computation time is under 500 milliseconds.

To evaluate the model's overall performance, an entirely independent subset, referred to as the testing subset, was examined. Within this subset, a comparison was made between the FEM geometries and deformation fields with those predicted by the Surrogate Model (refer to Table 1). The selected energies adhered to specific criteria, ensuring a compression ratio below 50% and deformation levels under 1.0. These criteria were crucial considerations, particularly for cold copper, aiming to prevent cracking and to remain within the domain defined by the rheology's law, used for the database.

Table 1. Billet Indexing: Testing Subset.

Billet	**Initial Diameter (ID)**	**Initial Height (IH)**	**Energy Setpoint: Experimental**	**Final Height (FH): Experimental**	**Compression ratio: (1-FH/IH)**
I	32 [mm]	44.30 [mm]	4.05 [kJ]	32.15 [mm]	27.42 [%]
II		56.85 [mm]	8.67 [kJ]	33.00 [mm]	41.95 [%]
III	24 [mm]	33.20 [mm]	2.31 [kJ]	25.80 [mm]	22.22 [%]
IV		37.75 [mm]	1.16 [kJ]	24.40 [mm]	35.36 [%]

The results indicate nearly overlapping geometries with a root-mean-squared error of 0.062 mm, a mean absolute error of 0.050 mm, and a mean absolute percentage error of 0.30% between every FEM bulging profile and every surrogate model's bulging profile prediction (see Fig. 7).

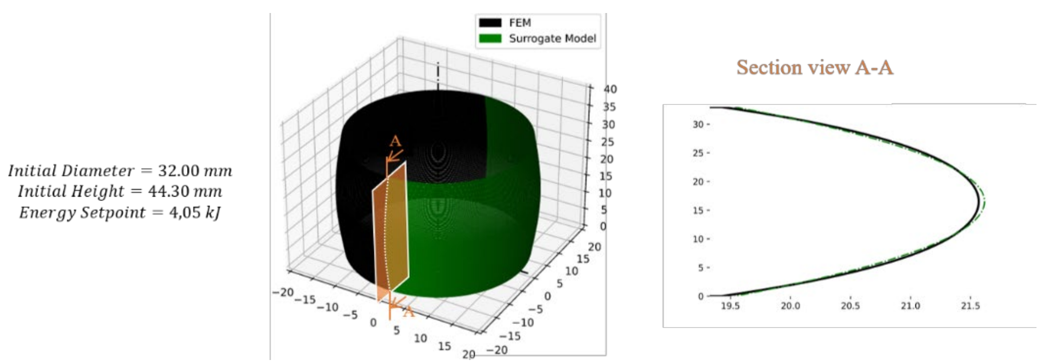

Fig. 7. FEM vs Surrogate Model Geometry Predictions for Billet "I" (see Table 1 for Billet Indexing).

The results of the deformation fields are presented in Fig. 8. Both the FEM and the Surrogate Model show similar forecasts, with a mean absolute error below 0.0040 and a mean absolute percentage error below 1.20% between them.

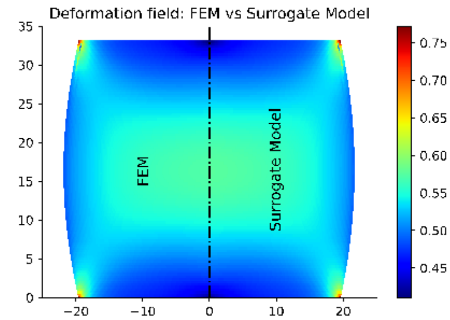

Fig. 8. FEM vs Surrogate Model Deformation Field Predictions for billet "II" (see Table 1 for billet Indexing).

Virtual Reality Integration

Digital VR-environment creation. VR-environment is made according to a classic process [9]. First, all the machines are designed by CAD software. Secondly, the models are incorporated into Unity® and textures are applied from real environment photos for a realistic rendering. Then rigid body mobilities and other interactions between the components are managed by Unity built-in 3D physics (Nvidia PhysX) and by the XDE interactive physics engine developed by our partner CEA-LIST [10] (Fig. 11b).

Surrogate Model Integration. The dynamic incorporation of the surrogate model is presented in Fig. 9. The Keras neural network is converted to the ONNX format using tf2onnx, serving as the import format for Unity Sentis [11]. POD matrices are converted to .csv files and read at runtime for deformation field reconstruction. The model is deployed through the creation of the inference engine (GPU worker). The output tensor (1, 8) includes 5 geometric parameters and 3 coefficients of POD modes. A half-cylinder is constructed through a triangulated 3D geometric mesh and a corresponding UV-map is assigned (see Fig. 10b). Vertex positions are dynamically updated based on the geometric parameters (see Fig. 10c). Two-dimensional textures (100x100) are generated using POD for the deformation fields, enhancing visual representation with a color gradient. A standard material applies these textures to the constructed mesh using the corresponding UV map (see Fig. 10c).

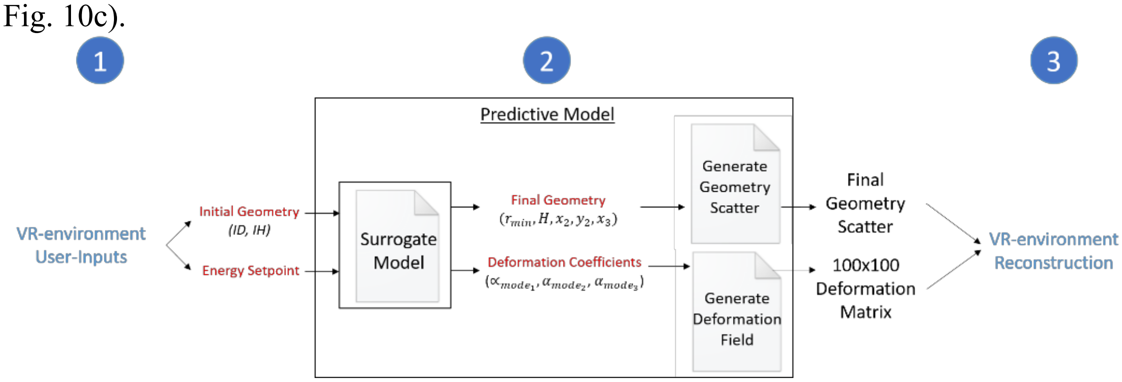

Fig. 9. Integration of the surrogate model in VR-environment: 1) Inputs defined in the VR-environment, 2) Real-time Predictive Model, 3) Visualization of the results back in the VR-environment.

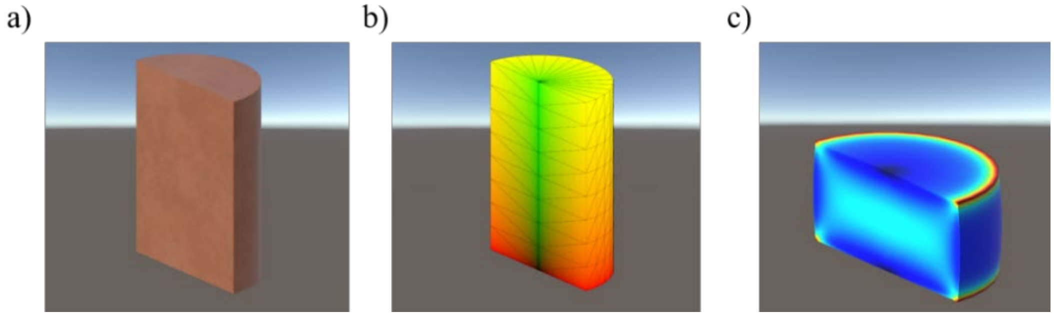

Fig. 10. Real-time billet generation: a) Initial Billet b) Triangulated 3D geometric mesh and Initial UV-map (U=red, V= green). c) Dynamic representation of the forged billet (geometry and deformation field).

Interactive Experience. The learner in the VR-environment can carry out its single-blow cold copper upsetting operation by adjusting the parameters as desired. In real time during the forging operation, he can visualize the internal workings of the machine and the deformation field (Fig. 11).

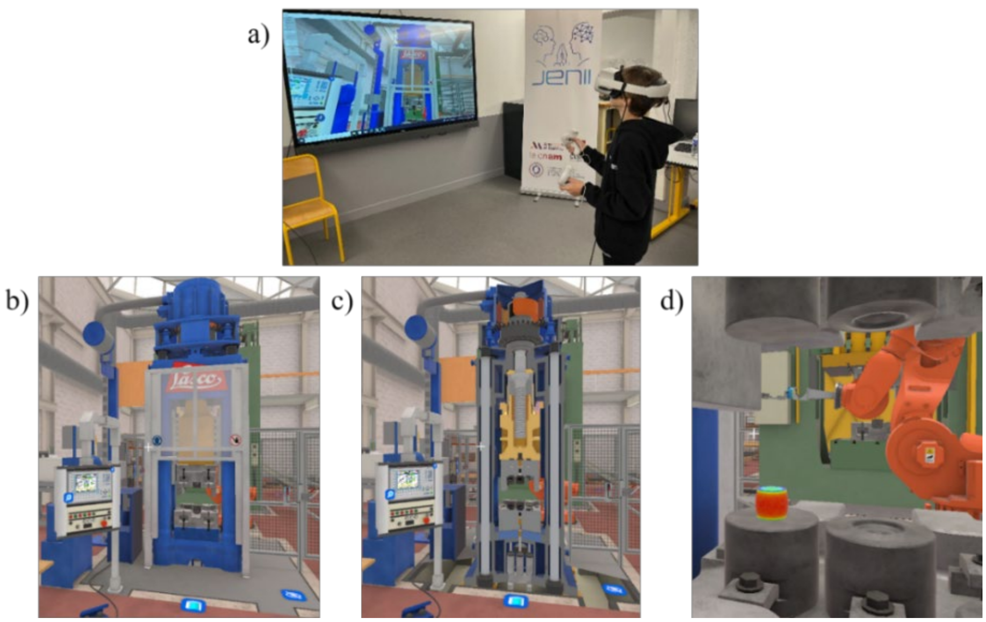

Fig. 11. Real-time Prediction of Upsetting Operations 'What-If' Scenarios within a VR-environment.

a) learner in VR-environment, b) screw press in VR-environment,
c) visualization of the internal working of the screw press, d) visualization of the deformation field of the billet.

Discussion

The surrogate model's assessment emphasizes geometry predictions, deformation field accuracy, and its potential extension for forecasting additional parameters in metal-forming processes.

Achieving precision comparable to Finite Element Method (FEM) simulations, the model excels in predicting geometry and deformation fields during cold copper upsetting, boasting a rapid computation time of 500 milliseconds for real-time decision-making. Its adaptability goes beyond, hinting at future applications like temperature and damage predictions.

The focus on predicting scalar outputs, facilitated by dimensionality reduction techniques, balances simplicity and interpretability. Emphasizing scalar predictions streamlines the modeling process and prioritizes interpretability. However, alternative approaches like Deep Neural Networks (DNN) could handle more complexity, depending on data nature, computational resources, and specific objectives.

Tailored criteria for energy selection, compression ratio, and deformation levels address unique considerations of working with cold copper. However, the methodology can be extended and applied to other materials, such as steels, and adapted for varying deformation levels.

Conclusions

This study introduces a two-step approach integrating Virtual Reality (VR) into Digital Twin models to enhance metal-forming predictions. Focusing on cold one-blow upsetting of a pure copper billet, the methodology combines surrogate models, model reduction techniques, and VR for real-time exploration of process parameters. It proves feasible, accurate, and cost-effective, with transformative potential in manufacturing efficiency and cost reduction. The research sets the foundation for refining the methodology, exploring new applications, and integrating advanced technologies for enhanced real-time decision-making in metal-forming processes.

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