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Explainable Machine Learning and 3D Visualization for Rotary Tube Bending: Expert Evaluation of a Web-Based Tool

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Abstract. When it comes to predicting quality-relevant outcomes of rotary draw bending procedures, like springback and geometric errors, machine learning algorithms have demonstrated primising results. However, the challenges associated with understanding these models' predictions still restrict their actual application in industrial contexts. A web-based 3D visualization designed to help with interactive exploration and explainability of machine learning predictions in rotary draw bending is evaluated through an expert-centered study. Based on an earlier Random Forest regression model, the visualization lets users change important process parameters and view the projected tube geometry and springback in real time. Sixteen experts participated in a structured online survey that combined open-ended comments, subjective agreement scores, and interactive parameter modification tasks. Results show that while multi-objective optimization remained difficult, participants with different degrees of machine learning knowledge and tube-bending experience were generally able to identify appropriate parameter settings in single-objective problems. Subjective assessment and qualitative feedback from the participants also highlight that the visualization could be used to assist in understanding model behavior and in early process design and training situations. Overall, our study suggests that experts in tube bending applications find benefit from the interactive 3D visualization of the predicted geometry and as an interface for exploring machine learning models' predictions.

1. Introduction

Rotary tube bending is used to manufacture bent tubular components for applications such as automotive structures, chassis and exhaust systems, fluid-transferring components, and architectural or load-bearing frameworks. These tubes should have precise geometries since shape variations can cause structural failures or assembly problems.

Tube components are often not produced by a single bending operation but by a sequence of multiple bends applied at different locations along the tube. After an initial bending process, the partially bent tube must be repositioned and clamped again to perform subsequent bends. In such multi-stage bending processes, the clamping dies used in later bending stages must be designed to match the geometry of the already bent tube, rather than a straight profile.

Designing a clamping die is challenging, since the exact geometry of the first bend is usually not known before the bending process is physically executed. In practice, this often leads to sequential workflows in which the first bend is manufactured, measured, and only then used as the basis for clamping die design. This trial-and-error-driven process can be time-consuming, costly, and difficult to integrate into efficient production planning, especially when new geometries or materials are introduced.

To improve this, expert knowledge is often used to estimate suitable process parameters and to anticipate the resulting tube geometry. Furthermore, FE simulations can be used to predict what the geometry will look like. While both approaches can reduce the need for repeated physical trials, they still rely on expert experience, and accurate prediction of the final geometry cannot always be guaranteed. Moreover, finite element simulations have high computational effort and setup time, which can limit their usage.

To resolve these issues, data-driven models have been investigated for predicting bending results. In particular, machine learning methods have been applied for finding and understanding the connections between the settings used in a process and the geometry results. However, although they can predict outcomes, these models have not yet been widely adopted in industry. One reason is that it is challenging to understand machine learning predictions for people who do not know much about data science. This makes it difficult for industrial engineers to trust or use the model results when planning processes or designing tools.

In industrial metal forming environments, process decisions are often based on accumulated experience, physical intuition, and visual inspection of the deformed parts. Machine learning models, however, typically provide predictions in numerical or statistical form, which may not directly correspond to the geometric reasoning employed by forming engineers. This mismatch between data-driven output and domain-specific mental models can limit the practical adoption of advanced predictive tools, even when their predictive accuracy might be high.

Using visualization makes a model's results easier to understand, and such an approach can be a way to inspect machine learning models. With interactive visualizations, users can see how changing process factors affects predicted geometries and learn how models behave in such cases. By linking numerical predictions to geometric representations that align with the mental models of domain experts, visualization can support explainability and help with decision-making in early process planning stages.

In this work, we look at how a fully web-based 3D model of the final geometry can help experts understand machine learning predictions in rotary draw bending. We add an interactive visualization to a previously created Random Forest regression model that predicts springback and geometry-related measures. This new tool lets users change process parameters and see the predicted tube shape instantly. The visualization is meant to be an exploratory and explainability-focused interface instead of an automatic optimization system. The primary objective of this study is to obtain experts' opinions on the suggested visualization. In particular, we find out how experts with varying amounts of tube-bending and machine learning experience use the system, how they can explore appropriate parameter settings, and how they feel about the method's usefulness and potential to be used in industry settings. For this we use a structured, online survey with interactive tasks, as well as several subjective ratings and open-ended questions.

The contributions of this work are threefold: (1) we present a fully web-based, interactive 3D visualization that links a previously developed Random Forest model to real-time geometric representations of rotary draw bending outcomes; (2) we conduct an expert-centered evaluation with 16 domain specialists, combining interactive optimization tasks, objective performance measures, and subjective explainability ratings; and (3) we provide empirical evidence that such a visualization enables experts with varying levels of tube-bending and machine learning experience to successfully explore parameter–geometry relationships, with up to 85.94% of agreement responses in the two highest rating categories.

Related work. For a long time, a widely used method for simulating and predicting the rotary draw bending (RDB) process was finite element analysis (FEA). Rajpal et al. [1] investigated springback in rotary draw bending using finite element analysis and analytical calculations. Sözen et al. [2] focused on numerical prediction of springback with experimental validation, while Zhao et al. [3] extended three-dimensional FE modeling to thin-walled rectangular tubes. These studies indicated that it was possible to predict changes in geometry before actual manufacturing began. They also showed how important process variables like friction conditions, pressure die gap, and mandrel location can affect the outcome.

To increase prediction reliability under realistic forming conditions, later studies expanded FE-based modeling by combining numerical simulations with experimental validation. Rajpal et al. [1] and Sözen et al. [2] demonstrated through numerical and experimental studies that springback strongly depends on tooling and boundary conditions. Amaral et al. [4] further validated FE predictions against experimental measurements under industrial forming conditions. Using a combination of experimental and numerical methods, local defects such as wrinkling, roundness, and collapse have been investigated in addition to global springback. These studies showed that, particularly for tight-radius or thin-walled tubes, defect formation is highly sensitive to tube alignment, mandrel support, bending radius, and initial defects [5, 6]. Together, this body of work highlights that accurate assessment of RDB outcomes requires consideration of multiple quality criteria along the bending region rather than relying on a single scalar indicator.

FE-based methods have a high computational cost and substantial setup time, regardless of their accuracy and physical interpretability. Simulation runtimes sometimes restrict their application to offline analysis rather than interactive exploration or preliminary process design, and creating detailed simulation models requires expert knowledge and careful parameter calibration. In multi-stage bending scenarios, the limitation of high computing costs and setup time becomes crucial, as subsequent clamping dies or tooling must be designed based on the geometry resulting from an initial bend. Therefore, there has been increasing interest in alternative methods that provide predictions faster without compromising acceptable accuracy.

The domains of formation and manufacturing research have investigated data-driven and machine learning (ML) methodologies. Recent reviews highlight the growing application of ML techniques in metal forming processes for prediction, optimization, and monitoring. Prates and Pereira [7] provide a focused review of machine learning applications specifically in metal forming, emphasizing the modeling of nonlinear relationships between process parameters and quality outcomes. In contrast, Plathottam et al. [8] present a broader overview of artificial intelligence adoption in manufacturing operations, with particular attention to predictive analytics and optimization strategies. Regression-based ML models, neural networks, and hybrid methodologies have demonstrated the capability to forecast material behavior, defect occurrence, and geometry-related metrics with smaller computational costs compared to finite element simulations.

In tube bending, ML-based methodologies have been suggested to forecast springback and help with compensating adjustments. Ma et al. showed that learning-based models can accurately forecast and make up for springback in tube bending operations, which means that fewer physical tests are needed [9]. More recent work has used sequence-based models, including long short-term memory (LSTM) architectures, to predict how the cross-sectional shape would change when the bending angle changes. These methods allow for spatially defined predictions of geometric changes across the entire bend, going beyond global measures and making it possible to look at the geometry in more depth [10].

In our previous work, we used Random Forest regression to predict springback and several geometry-related criteria in rotary draw bending using data from finite element simulations [11]. Our study revealed that machine learning models can provide precise and computationally efficient predictions for several quality metrics together. Even if these ML-based methods work well with numbers, most of the studies that are already out there just look at how accurate and valid the models are. They do not look at how these models are used, understood, or added to real engineering processes.

Recent recommendations for machine learning in manufacturing stress that successful use goes beyond just making accurate predictions. Samadiani et al. argue that successful ML implementation requires particular attention to workflow integration, human contact, and transparency to promote confidence as well as acceptance among engineers and experts [12]. Without mechanisms for engineers to understand, question, and connect model predictions to reasoning in their field, even very accurate models may not be used in industry. This problem is especially discouraged in forming processes, when expert knowledge and expertise are important for planning the process and designing the tools.

Consequently, research on explainable artificial intelligence (XAI) has become increasingly important in manufacturing settings. Goldman et al. [13] discuss explainability techniques in manufacturing processes with emphasis on model interpretation strategies. Tzionis et al. [14] provide a comprehensive review of explainable AI methods and their industrial applications. Visualization-based approaches have been recognized as particularly effective for connecting ML models with domain specialists, as they can present predictions in formats that correspond with traditional representations of physical processes. In manufacturing contexts, alternative visual encodings and interaction strategies have been tested to see how they influence users with seeing and understanding model outputs [15]. There has also been research on three-dimensional visualization and geometry-based representations to explain machine learning predictions about cost estimation, machining features, and defect analysis [16]. Visual analytics research highlights interactive exploration as a fundamental way to understand complicated industrial applications. Kucher et al. emphasize that explainability must be integrated into human-centered interfaces that enable users to investigate model behavior, validate ideas, and connect predictions to recognizable representations, rather than depending exclusively on abstract metrics [17].

Despite these advances, relatively few studies have investigated explainable ML interfaces in the specific context of rotary draw bending or evaluated them with domain experts. Most prior work either focuses on numerical prediction performance or on generic visualization concepts without domain-specific evaluation. Consequently, the question of how ML predictions for RDB can be effectively communicated to practitioners, and how visualization influences parameter exploration and decision-making, remains largely open. While existing explainable artificial intelligence (XAI) approaches in manufacturing frequently rely on feature importance rankings, sensitivity analyses, or post-hoc attribution methods such as SHAP values, these techniques typically present explanations in abstract, numerical, or statistical form [13, 14]. In metal forming processes such as rotary draw bending, decision-making is strongly grounded in spatial and geometric reasoning. Engineers evaluate outcomes based on physical tube deformation, cross-sectional distortion, ovalization, wrinkling behavior, and springback distribution along the bending arc rather than isolated parameter contributions [1, 2, 4, 5, 6]. Consequently, conventional feature-based XAI methods may not sufficiently support forming experts, as they do not directly map model predictions to geometry representations that reflect established domain-specific mental models. This limitation creates a gap between machine learning transparency and practical interpretability in forming applications.

This gap motivates the present work, which combines a previously developed ML prediction model for rotary draw bending with an interactive, web-based 3D visualization. By evaluating this visualization through an expert-centered study, the present work aims to contribute empirical insights into how explainable, geometry-based visualization can support understanding, exploration, and potential industrial adoption of machine learning models in tube bending applications.

2. Methodology

System overview. We evaluated a system in this study that combines a previously developed machine learning model with a web-based 3D visualization to support interactive exploration of rotary draw bending process parameters and their predicted effects on tube geometry (Fig. 1). The system allows users to adjust key process parameters in real time and immediately observe the resulting changes in the predicted tube shape, enabling an intuitive understanding of parameter–geometry relationships. The underlying prediction model is based on Random Forest regression and was introduced in earlier work [11]. It was trained using data from 162 finite element simulations of 90° rotary draw bending processes.

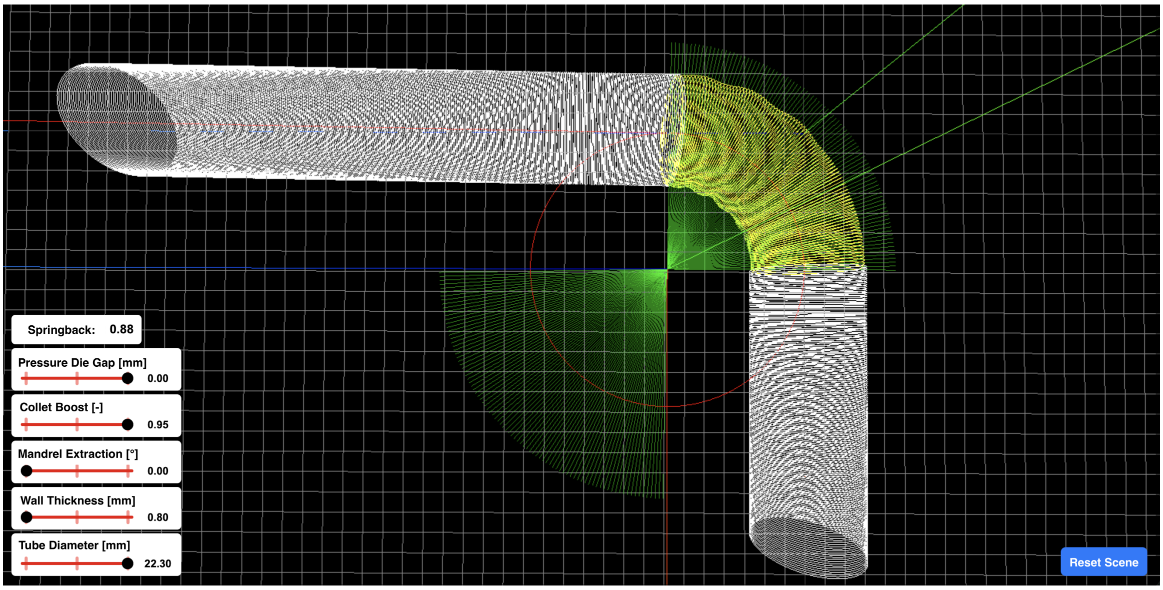

Fig. 1: The web-based 3D visualization of the predicted tube geometry used in our study: Users can adjust process parameters via sliders (bottom left) and inspect the resulting geometry and springback of the tube in real time.

For each simulated bending process, the model predicts the springback behavior of the bent tube as well as four geometry-related criteria: main axis, secondary axis, out-of-roundness, and collapse, which were evaluated along the bending region [11]. These quantities correspond to physically relevant deformation characteristics in rotary draw bending, particularly cross-sectional ovalization, geometric distortion, and collapse behavior observed along the bending arc [2, 5, 6]. The geometry predictions are provided for 91 cross-sections corresponding to bending angles from 0° to 90° in one-degree increments. In the present work, springback, main axis, and secondary axis predictions are used to construct a three-dimensional representation of the bent tube, enabling visual assessment of geometric deviations and deformation effects along the entire bend.

The model in its current state takes five process parameters as inputs: Pressure Die Gap, Collet Boost, Mandrel Extraction, Wall Thickness, and Tube Diameter. These parameters are briefly defined in Table 1 to clarify their physical meaning and units within the rotary draw bending setup. Each parameter could be selected discretely using slider controls in the visualization window, which, later in the evaluation, users were able to interact with. This feature made it possible for them to change the process settings themselves.

Table 1: Definition of input process parameters, along with their units, used in the Random Forest model for predicting the geometry after rotary draw bending.

Parameter	**Physical Meaning**	**Unit**
Pressure Die Gap	This refers to the positioning and distance of the pressure die relative to the tube	millimeters (mm)
Collet Boost	This parameter represents the speed of the collet relative to the tube speed	– (factor)
Mandrel Extraction	Degree at which the mandrel is retracted before the bending operation ends.	degrees (°)
Wall Thickness	Initial wall thickness of the tube before bending	millimeters (mm)
Tube Diameter	Outer diameter of the tube prior to deformation	millimeters (mm)

The visualization was made as a separate web-based application and deployed on GitHub Pages. To ensure that the evaluation is executed quickly and does not require a backend server, all the model predictions were exhaustively precomputed and saved in JavaScript (JS) arrays to be loaded on the client side. When users move one or more sliders, the predicted geometry and springback are retrieved and displayed in a few milliseconds, allowing for real-time feedback and exploration. Along with changing parameters, basic interaction tools like camera control and the ability to reset a scene were added to help people explore the 3D tube geometry.

The purpose of our system is not to perform automated optimization or decision-making but to support understanding and exploration of the relationships between process parameters and predicted bending outcomes. The visualization is intended as an explainability-oriented interface that allows users to interactively inspect model behavior and develop intuition about parameter effects, rather than as a replacement for expert knowledge or established process design methods.

Survey design and data collection. We used an online survey implemented with LimeSurvey to evaluate the experts. The purpose of the survey was to assess how effectively the proposed 3D visualization .supports understanding of the underlying machine learning model, to evaluate expert performance in interactive parameter adjustment tasks, to collect subjective assessments of usefulness and explainability, and to gather open-ended feedback for future improvements. The survey followed a fixed structure. After an initial consent and privacy notice, participants provided demographic and professional background information. They then completed three interactive tasks using the web-based visualization. Following the tasks, participants rated a set of statements related to explainability and industrial applicability using a five-point agreement scale ranging from "does not apply" to "completely true." Finally, open-ended questions were used to collect qualitative feedback and suggestions.

All participants completed the survey remotely using their own devices and web browsers. No time limits were imposed on any part of the survey. To reduce ordering and learning effects, the order of the first two tasks was randomized across participants, and the initial values of all process parameters were randomized for each task. The mixed optimization task was always presented last. During the survey, LimeSurvey automatically recorded the time spent on each section, the final parameter settings selected for each task, the agreement ratings, and all open-text responses. All data were collected anonymously, and participants were internally labeled using numerical identifiers (P1–P16) for analysis. Survey responses were exported in CSV format for subsequent quantitative and qualitative evaluation.

Data analysis. Sixteen experts evaluated our 3D demonstration using LimeSurvey. Collected data included their age, gender, education level, role, industry, experience field, company categorization, familiarity with machine learning, and which machine learning methods their organization uses. For each participant, we recorded task completion times, whether they achieved the springback and geometry quality indicators, how they rated the task's explainability and usefulness, and any open feedback they provided. Quantitative results are reported using descriptive statistics, including counts, means, standard deviations, and distributions. Where relevant, results are broken down by expert background, such as years of tube-bending experience, company type, and familiarity with machine learning. Qualitative feedback was analyzed using thematic coding, with recurring themes illustrated through anonymized participant quotations.

3. Participants

Participants were recruited through an existing collaboration between the Ubicomp and the Umformtechnik chairs at the University of Siegen. As part of this collaboration, simulation data related to rotary tube bending were provided by Umformtechnik, while data-driven modeling and visualization approaches were developed on the Ubicomp side. After the 3D visualization and the survey had been designed, Umformtechnik supported participant recruitment by inviting colleagues with tube-bending experience from the university as well as contacts from industrial partners specialized in tube bending. These industry contacts were approached through existing professional relationships. In addition, the survey was shared via the LinkedIn page of the Umformtechnik group; however, this did not result in additional completed responses.

Participation in the study was voluntary and uncompensated. All participants provided informed consent via a checkbox at the beginning of the survey, and responses were collected anonymously without storing any personally identifiable information. The recruitment and data collection phase took place over approximately three months (September–November).

Overall, sixteen experts from Germany with backgrounds in tube bending and forming processes from both industry and research participated in this study. The participants ranged in age from 20 to over 50 years. Most of them were between 30 and 39 years old (8 participants), while three were between 20 and 29 years, three between 40 and 49 years, and two were older than 50 years. In total, the group consisted of fifteen male participants and one female participant.

With respect to educational background, the majority of participants (12) held a university degree, two had completed vocational training, and two participants had a school-leaving qualification. The experts were employed across different company types, including bending machine manufacturers (8 participants), bending machine users (4 participants), and research or academic institutions (4 participants).

Most experts were working in development-related fields such as process, equipment, or software development (12 participants). In addition, two of them worked mainly in research, one reported involvement across multiple areas, and one worked in sales. In terms of industry categorization, mechanical and plant engineering had the most participants (9 people), followed by research-oriented institutions (6 people) and agricultural and construction machinery manufacturing (1 person).

In the scope of professional roles, most experts were engineers working in process or development positions (13 participants). Two participants held executive or management roles, and one participant worked as a technician. Experience in tube bending was different among the group, as shown in Fig. 2; six participants reported 0–2 years of experience, two reported 3–5 years, one reported 6–10 years, and seven participants had more than 10 years of experience. Only four participants indicated familiarity with machine learning methods, and the same number stated that machine learning techniques are currently used within their organization. The remaining participants reported no prior experience with machine learning and no use of such methods at the company level.

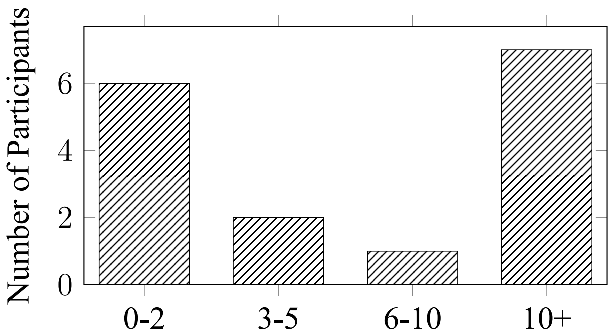

Fig. 2: Distribution of tube-bending experience among participants in years. The majority of participants (n=7) have more than ten years of industry experience, demonstrating this group's high level of knowledge. This graph reflects the recruitment approach of focusing on senior experts through professional networks.

4. Task Performance and Interaction Results

The expert evaluation included three interactive tasks derived from the developed 3D tube-bending visualization. Participants could change five discrete process parameters using sliders (Pressure Die Gap, Collet Boost, Mandrel Extraction, Wall Thickness, and Tube Diameter). After each adjustment, the predicted tube geometry was updated in 3D. Springback could be assessed both visually (deviation from a targeted 90° bend) and numerically, whereas wrinkles and deformations were mainly judged visually from the geometry.

The tasks were designed as follows: (1) Springback optimization: participants were asked to achieve the best springback value without considering geometry quality; (2) Geometry optimization: participants aimed to achieve the best possible geometry without considering springback; and (3) Mixed optimization: participants should try to achieve satisfactory geometry and springback simultaneously. The initial configuration for all five sliders was randomized for each participant. In addition, the order of Task 1 and Task 2 was randomized to reduce potential learning effects.

Interaction time was recorded for each task. Across all participants, Task 1 required on average 260.96 s (median 183.32 s, range 96.75–603.15 s). Task 2 required on average 150.21 s (median 109.51 s, range 47.44–539.91 s) and showed the largest variability, which is consistent with the fact that geometry quality had to be evaluated visually. Task 3 required on average 161.92 s (median 128.59 s, range 79.56–293.41 s).

Participants' task completion times varied significantly, and there was no clear pattern related to either machine learning knowledge or tube-bending experience. One possible explanation is that some participants used the opportunity to investigate the visualization in more detail than was necessary to complete the task, which could have led to longer recorded interaction times. However, the majority of those with over ten years of experience were among the participants who could complete the task quicker than others. But not every experienced participant showed this tendency, and task duration's validity as a straightforward measure of skill is limited by overlaps with individual interaction styles. Figure 3 shows the time measures for each participant across 3 tasks.

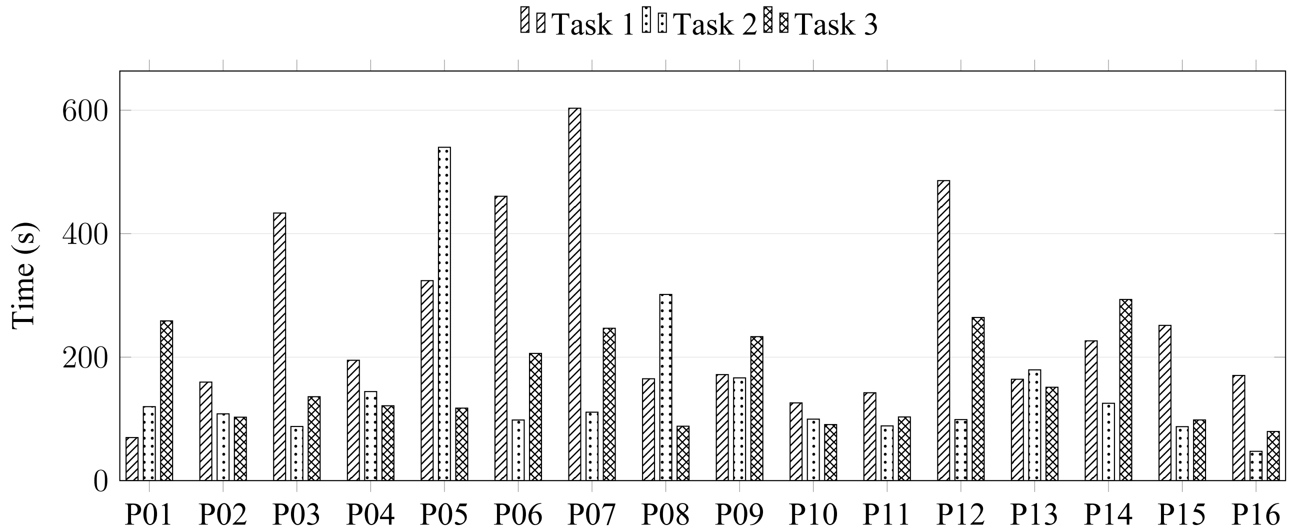

Fig. 3: Depiction of the per-user task completion times for the three optimization tasks. Each bar corresponds to the completion time of an individual participant (P01–P16) for Task 1 (springback-only), Task 2 (geometry-only), and Task 3 (mixed optimization). Participants are ordered from left to right according to their level of expertise: P01–P06 have 0–2 years of experience, P07–P08 have 3–5 years, P09 has 6–10 years, and P10–P16 have more than 10 years of experience.

To evaluate task performance, participant settings were compared against the known optimal configurations derived from the underlying prediction data. For the springback-only task, the most important parameters were Collet Boost (0.95), Mandrel Extraction (0.00), and Wall Thickness (0.80), while Pressure Die Gap and Tube Diameter had only a minor influence. Using these key settings as success criteria, 14 out of 16 participants achieved the optimal springback configuration. For the geometry-only task, the main driver was a low Collet Boost (0.85) or a high Wall Thickness (1.20). Under this criterion, 14 out of 16 participants achieved the optimal geometry configuration. For the mixed task, Mandrel Extraction needed to be set to 0.00 to minimize springback, while good geometry could be achieved with alternative parameter setups. In addition to configurations with high wall thickness (1.20) or low collet boost (0.85), an intermediate configuration combining a collet boost of 0.90 with a wall thickness of 1.00 also resulted in acceptable geometry. When success was defined as achieving Mandrel Extraction = 0.00 together with any of these geometry-favorable configurations, 10 out of 16 participants achieved a successful mixed configuration.

Task success was also evaluated across participant backgrounds. Considering participants' tube-bending experience, Task 1 (springback-only) showed high success rates among all experience levels, with full success in the 0–2 year group (6/6) and a high rate in the >10 year group (6/7). This result indicates that participants among all experience levels were able to identify the key parameter settings required for springback optimization. For Task 2 (geometry-only), the success rates were also high when success was defined as achieving either a high wall thickness (1.20) or a low collet boost (0.85). According to this standard, all of the participants with 0–2 years of experience (6 out of 6) and all of the participants with 3–5 years (2 out of 2) or 6–10 years (1 out of 1) had a satisfactory geometry configuration. Only 5 out of 7 participants in the +10 year group were successful in this task. For Task 3, 4 out of 6 participants in the 0–2 year group and 3 out of 7 participants in the >10 year group achieved a successful configuration. Participants in the 3–5 year (2/2) and 6–10 year (1/1) groups showed higher success rates.

Another finding from the task performance outcomes is that while some participants with over ten years of tube-bending experience completed the tasks more quickly, they were less likely than less experienced participants to achieve optimal parameter settings. This suggests that experienced users might depend more heavily on standard algorithms and past process experiences, which could limit the amount of parameter exploration that occurs while interacting with the visualization. It is important to note at this point that all the observations in this paper are to be taken as a preliminary result, due to the small sample size of our study. Table 2 shows the overall performance and average timing of participants in all three tasks based on their level of experience.

Table 2: Task success rates together with average completing time for the three optimization tasks, shown overall and categorized by tube-bending experience. While springback-only and geometry-only tasks show consistently high success across all experience levels, success rates decrease for the mixed optimization task, particularly for the 0–2 year and >10 year groups.

Task	**Overall**	**0–2 yrs**	**3–5 yrs**	**6–10 yrs**	**>10 yrs**
Springback Only	14/16 (260s)	6/6 (274s)	1/2 (384s)	1/1 (172s)	6/7 (224s)
Geometry Only	14/16 (150s)	6/6 (183s)	2/2 (206s)	1/1 (166s)	5/7 (104s)
Springback + Geometry	10/16 (162s)	4/6 (157s)	2/2 (167s)	1/1 (233s)	3/7 (154s)

If we classify task success by machine learning familiarity, we cannot see any significant differences for Task 1; here, all ML-familiar participants (4/4) and most non-ML-familiar participants (10/12) could set up the springback optimal configuration. For Task 2 (geometry-only), both groups were successful in parameter optimization; 3 out of 4 ML-familiar participants (75.0%) and 11 out of 12 non-ML-familiar participants (91.7%) could achieve a satisfying geometry configuration. For Task 3, we could see different success rates between the two groups: 2 out of 4 ML-familiar participants and 8 out of 12 non-ML-familiar participants achieved an acceptable configuration. In general, we can see from the results that machine learning familiarity did not play a notable role in springback or geometry-only tasks, and the mixed task was challenging regardless of ML background, which can be due to the increased complexity of simultaneously optimizing multiple quality criteria.

When we combine all results, the task performance results show that our 3D visualization program enables efficient communication with the core prediction model at different levels of machine learning and expertise in the field. Participants with limited tube-bending experience or no prior exposure to machine learning were generally able to identify suitable parameter settings in the single-objective tasks, while the mixed optimization task remained challenging for all groups. This suggests that the visualization may help users understand the model behavior and process parameter effects without requiring detailed knowledge of the underlying machine learning methods.

5. Subjective Evaluation

Personal impressions were collected using four statements rated on a five-point agreement scale (1 = “does not apply”, 5 = “completely true”). Overall, 85.94% of all responses fell into the two highest agreement categories, indicating that participants generally agreed that the 3D visualization was useful and showed potential for industrial application. The distribution of responses for all four statements is shown in Figure 4, while the corresponding descriptive statistics are summarized in Table 3. Statement 1 (“3D visualization helps to understand parameter effects”) achieved a mean rating of 4.13 (SD = 0.72), with 81.25% of participants selecting the two highest agreement levels. Statement 2 (“real-time feedback improves understanding”) was rated even higher (mean = 4.44, SD = 0.81; 93.75% agreement). Statement 3, which focuses on understanding the machine learning model predictions, showed the lowest mean and the highest variability (mean = 3.75, SD = 1.06; 75.00% agreement). Statement 4 (“industrial use case”) achieved a mean of 4.50 (SD = 0.63; 93.75% agreement). When all four items were combined (64 ratings), the overall mean agreement was 4.20 (SD = 0.86).

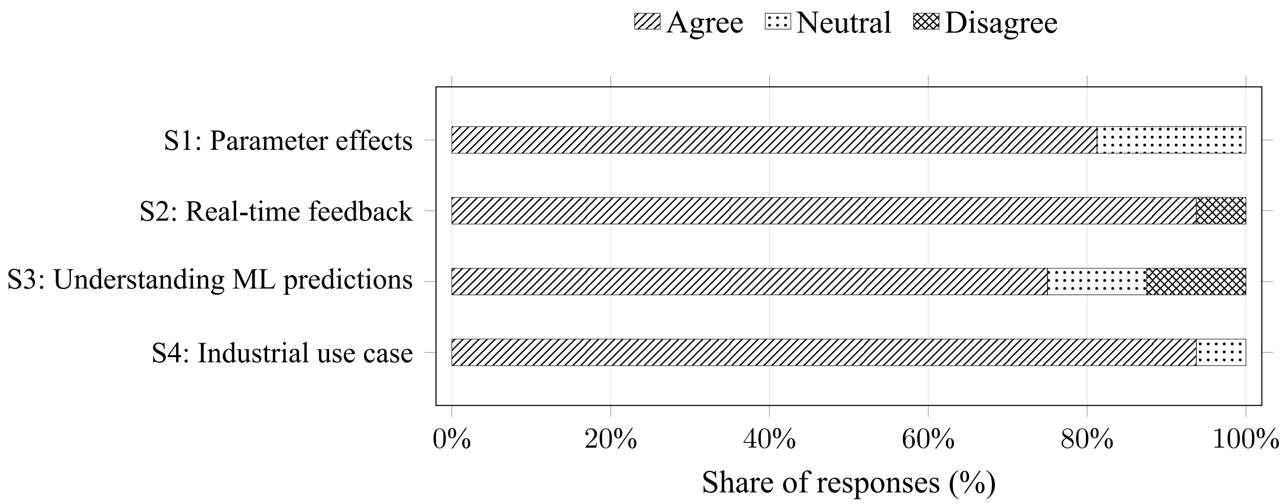

Fig. 4: Percentage distribution of expert agreement ratings for the four evaluation statements. Responses are grouped into disagree (ratings 1–2), neutral (rating 3), and agree (ratings 4–5). Full statements: S1—“3D visualization helps understand effects of process parameter changes”; S2—“Real-time feedback improves understanding of effects on predicted tube geometry”; S3—“3D + real-time feedback help understand machine learning model predictions”; S4—“Industrial use of data-driven model and visualization is conceivable”.

Table 3: Summary of expert agreement ratings for the four evaluation statements. Ratings were given on a five-point scale (1 = does not apply, 5 = completely true) and are reported as mean ± standard deviation and the percentage of ratings in the two highest agreement categories (4–5).

Statement	**Mean ± SD**	**Agreement (4–5)**
1 – 3D visualization helps understand effects of process parameter changes	4.13 ± 0.72	13/16 (81.25%)
2 – Real-time feedback improves understanding of effects on predicted tube geometry	4.44 ± 0.81	15/16 (93.75%)
3 – 3D + real-time feedback help understand machine learning model predictions	3.75 ± 1.06	12/16 (75.00%)
4 – Industrial use of data-driven model and visualization is conceivable	4.50 ± 0.63	15/16 (93.75%)
Pooled across all statements (64 ratings)	$\mathbf{4.20 \pm 0.86}$	**55/64 (85.94%)**

When we categorize responses by tube bending experience, participants with more than ten years of experience had a slightly higher average agreement (mean = 4.32; 89.3% agreement) than participants with ten years or less (mean = 4.11; 83.3% agreement).

6. Qualitative Feedback Analysis

We analyzed open-ended feedback from experts to identify common issues regarding the quality of the visualization, its desired functionality, and potential industrial usage. The participants suggested a few repeating design specifications and enhancement recommendations, highlighting both the strengths of the approach and directions for future development. The most frequently cited topic was visualization clarity and accuracy. Many participants reported that the current wire-frame or line-based representation made it impossible to accurately judge wrinkles, collapse, and other geometric anomalies. Along with using distinct colors, several experts recommended using closed-surface or area-based models rather than line representations. For example, one expert stated that *"the quality of the bend cannot be clearly determined with the current line frame"* (P12), and another suggested that *"different colors for deformed areas or the degree of deformation would improve visibility"* (P04).

Participants regularly pointed out the necessity for better visual representation. They suggested we add typical viewing angles (e.g., top or side views), and in addition to this, we should indicate the start and the end of the bend. They also suggested scaling or exaggerating deformations to make minor deviations more noticeable. These comments show that, although the existing visualization does a satisfactory job displaying the patterns, precise geometric evaluation is still difficult in the absence of additional visual aids. Model completeness and parameter coverage were the second criterion mentioned by participants. Some participants said that the visualization and setup parameters did not take into account some important factors, like the properties of the material, the initial position of the mandrel, the conditions of friction, the lubrication, or the configuration of the wiper die. Experts stressed that adding these characteristics will increase industrial relevance. To better reflect actual process tuning, one participant suggested adding continuous parameter adjustment rather than discrete steps (P05), while another pointed out that *"important influencing factors such as material properties and friction conditions are not yet taken into account"* (P12).

To have an assistance option for achieving an optimized tube was another common concern. A few participants suggested we implement targeted optimization tactics, in which the system could recommend appropriate parameter ranges for specific goals (such as low wrinkling for tiny bending radii). This idea suggests a desire to move from pure exploration to a partially assisted platform, which was made particularly by the participants with fewer years of experience.

In terms of industry applicability, most experts could easily see the proposed interactive visualization method being used in real-world scenarios. Process design, machine setup, tool design, operator training, and troubleshooting during production were among the suggested application areas. A number of participants highlighted how the visualization might help beginner operators or reduce the need for specialized expertise during setup and optimization. According to one expert, even without significant expert knowledge, the technology *"could allow operating personnel to resolve bending problems independently"* (P12). Others emphasized the importance of validating predictions against real-world behavior before deployment in industrial environments.

Lastly, interface design and usability were minor but important themes. Although most participants liked the idea, some said the visual style was out of date or not clean enough for industrial use. This implies that aesthetic interface design and modern user interface standards, along with technical robustness, may influence practical implementation.

Overall, the qualitative comments support the quantitative results by verifying that the visualization is seen as beneficial and promising in the industry if we support the mentioned specific needs to enhance usability, model realism, and visual clarity. These observations offer important direction for the future development of machine learning tools for rotary tube bending that are explainable and driven by visualization.

7. Discussion

The expert review results indicate that the suggested 3D visualization can help users understand machine learning predictions in rotary draw bending. This is especially true for tasks with only one goal, like springback or geometry optimization. People who had different amounts of experience with both tube bending and machine learning were able to complete these tasks successfully most of the time. This evidence suggests that the visualization gave users the ability to determine key parameter effects without needing to know a lot about the prediction model.

The mixed optimization task proved more demanding, as participants had to balance competing quality objectives. This reflects the inherent multi-objective nature of industrial tube bending, where springback and geometric stability interact. Although several participants identified alternative feasible parameter combinations, the reduced success rates indicate that visualization alone does not eliminate the complexity of multi-criteria process optimization.

Machine learning expertise had little effect on performance in single-goal tasks. Participants without prior machine learning experience were usually able to understand the visualized predictions and change the parameters to improve them. This supports the idea that geometry-centered visualization can reduce reliance on model understanding by presenting predictions in a form that aligns with established mental models of tube bending behavior. On the other hand, the mixed job did not show a clear benefit for participants who were familiar with ML. This shows that when you have to balance competing goals for a process, knowing how models work is not enough.

When considering tube-bending experience, some highly experienced experts completed tasks more quickly, yet such expertise did not consistently translate into higher accuracy, particularly in the mixed optimization task. This observation raises a question regarding the relationship between data-driven model behavior and established shop-floor heuristics. In practical rotary draw bending, experienced engineers often rely on empirically developed rules of thumb, such as increasing wall thickness to improve geometry stability or adjusting collet boost to compensate for springback. However, the Random Forest model was trained on simulation data capturing nonlinear interactions between multiple parameters and cross-sectional deformation along the bending arc. The model reflects parameter–geometry relationships that may not align with simplified heuristic strategies. In the mixed optimization scenario, where both springback and geometric quality had to be considered simultaneously, optimal configurations required balancing competing deformation mechanisms. For example, reducing mandrel extraction minimized springback, while geometry quality could be preserved through alternative parameter combinations involving collet boost and wall thickness. Such trade-offs may not be intuitive when relying on single-parameter reasoning. The observed performance differences therefore suggest that the interactive visualization may expose non-intuitive multi-parameter interactions embedded in the simulation data, rather than merely confirming conventional process knowledge. At the same time, the results do not indicate that experienced expertise is inferior; rather, they highlight that multi-objective parameter optimization in forming processes involves complex nonlinear couplings that challenge both intuition and purely visual exploration. The findings also suggest that data-driven models may complement, rather than replace, expert knowledge by revealing parameter interactions that are difficult to isolate through traditional heuristic reasoning.

The qualitative comments further support visualization's function as an explanatory and exploratory tool rather than an automatic correction. The need for improved visual indicators—such as surface-based representations, color-coded deformation indications, and more accurate portrayals of wrinkles or ovalization—was underlined by participants over and again. Simultaneously, several experts indicated interest in using such a system for early process planning, training, or tool design, especially in situations where new geometries or inexperienced operators are involved. These responses suggest that the primary value of the system lies in supporting understanding, communication, and learning, rather than replacing expert judgment or established simulation workflows.

Beyond its exploratory function, the three-dimensional geometry representation provides a physically meaningful perspective on deformation behavior along the bending arc. In rotary draw bending, springback and cross-sectional distortion evolve continuously with bending angle, and geometric changes in one region may influence adjacent sections. A purely scalar or two-dimensional representation would isolate individual metrics, whereas the 3D visualization integrates angular deviation, ovalization, and global shape consistency into a unified spatial context. This form of representation more closely reflects industrial evaluation practice, where full-geometry inspection rather than isolated parameter curves determines component acceptability. Overall, the results indicate that interactive 3D visualization can serve as a useful bridge between rotary draw bending domain specialists and machine learning models. Without requiring an in-depth understanding of machine learning techniques, the system enables explanation and informed decision-making by allowing users to visually and interactively investigate parameter impacts. The findings, however, also highlight the ongoing importance of expert judgment in tube bending applications by demonstrating that visualization does not remove the basic complexity of multi-objective process optimization.

8. Limitations and Future Work

This study has several limitations that should be considered when interpreting the results. First, the number of participants was limited to sixteen experts; therefore, the findings should therefore be regarded as exploratory. Future studies with larger and more diverse participant groups could further validate the observed trends.

Second, the visualization was based on a discrete set of process parameter values. Although this simplified the evaluation, it does not reflect the continuous parameter adjustment common in industrial practice. Supporting continuous parameters may enable detailed exploration in future works.

Third, the underlying prediction model was trained exclusively on finite element simulation data. While simulation-based datasets are commonly used in forming research due to controlled boundary conditions and reproducibility, discrepancies between simulated and real-world behavior may occur. The training dataset comprised 162 finite element simulations covering discrete combinations of the five investigated process parameters. Although this number may appear limited from a purely statistical perspective, it represents a structured sampling of a physically constrained parameter space typical for rotary draw bending studies. The model inputs and outputs are low-dimensional, physically interpretable quantities derived from deterministic simulation results, and Random Forest regression is generally robust in such structured settings. Moreover, the objective of the present work is not to establish universal predictive generalization across arbitrary bending configurations, but to support interactive exploration and expert evaluation within the investigated parameter domain. Nevertheless, expanding the dataset with additional simulation cases and experimental measurements would further enhance robustness and industrial applicability.

Finally, the visualization focused on wireframe-based geometric representations. Participant feedback indicated that surface models and enhanced visual cues, such as color-coded deformation indicators, could improve interpretability. It is important to note that the underlying Random Forest model predicts global cross-sectional deformation measures, including main axis, secondary axis, out-of-roundness, and collapse indicators derived from finite element simulations. The model does not explicitly predict localized wrinkling phenomena such as wrinkle wavelength, amplitude, or local buckling patterns along the tube surface. Consequently, the visualization reflects global geometric trends rather than fine-scale surface instabilities. While collapse and ovalization metrics can indirectly indicate increased instability risk, detailed wrinkle formation would require either higher-resolution simulation outputs or dedicated instability descriptors as model targets. This limitation partly explains why participants reported difficulty assessing localized defects within the current wireframe representation. Future work may integrate local curvature- or instability-sensitive descriptors derived from higher-resolution simulation outputs into the model targets to enable more detailed visualization of wrinkle severity, and may further investigate integration of the system into industrial process planning workflows, including multi-stage bending and clamping die design scenarios.

9. Conclusions

This work evaluated a web-based 3D visualization for explaining machine learning predictions in rotary draw bending through an expert-centered study.

First, results from the interactive tasks show that experts were generally able to identify suitable parameter settings in single-objective problems, with 14 out of 16 participants successfully achieving optimal configurations for both springback-only and geometry-only tasks.

Second, subjective evaluation indicates high perceived usefulness and explainability of the visualization: 85.94% of all agreement ratings fell into the two highest categories, and 93.75% of participants agreed that real-time feedback improves understanding of predicted geometry.

Third, while the mixed optimization task remained challenging across all experience levels, qualitative feedback highlights the visualization's value for early process planning, training, and communication of model behavior, rather than as an automated optimization tool.

Overall, the findings suggest that interactive, geometry-based visualization is a promising approach for bridging the gap between machine learning models and domain experts in tube bending applications, supporting explainability and informed decision-making without requiring in-depth knowledge of machine learning methods.

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