ANALYSIS OF TECHNOLOGICAL REGIMES OF OPEN-DIE FORGING WITH MODEL DEVELOPMENT FOR DIGITAL SYSTEMS OF METALLURGICAL PRODUCTION

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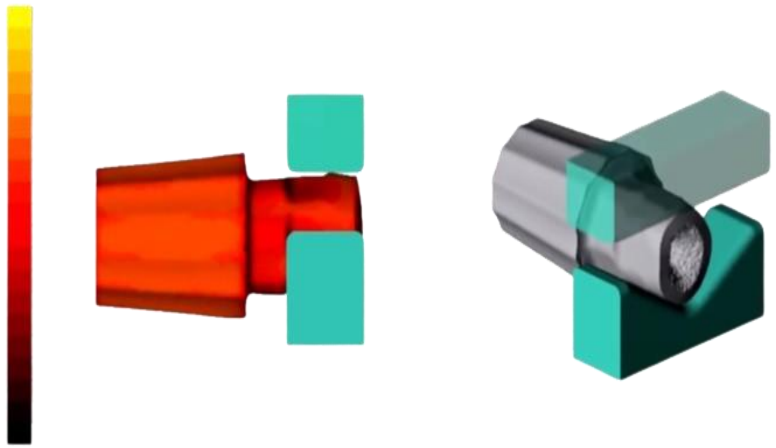


Literature Review

This research builds on four interconnected research streams in modern metallurgy due to 33 peer-reviewed sources covering metallurgical physics, FEM simulation, AI/ML approaches, and industrial implementation strategies:

Open-Die Forging Optimization	Studies on bite infeed, reduction, and die geometry effects on product quality and energy efficiency. Focus on rational pass scheduling and combined die configurations for flexible stress-strain control.
FEM Simulation & Modeling	LS-DYNA hot deformation analysis under isothermal conditions. Numerical prediction of stress-strain state, contact mechanics, and friction effects validated against industrial data.
AI and Surrogate Models	Neural networks achieving FEM-level accuracy with 36× computational acceleration. Deep learning methods optimizing forging schedules and microstructural control with minimal error.
Digital Twins & Real-Time Control	Generalized predictive control (GPC) stabilizing energy-force parameters. Automated decision-support systems with sensor integration for adaptive online process tuning.

Research Gap Addressed:

Combining FEM data generation with high-fidelity AI approximations to create fast, deployable surrogate models for embedding into digital twins and automated forging control systems.

Purpose

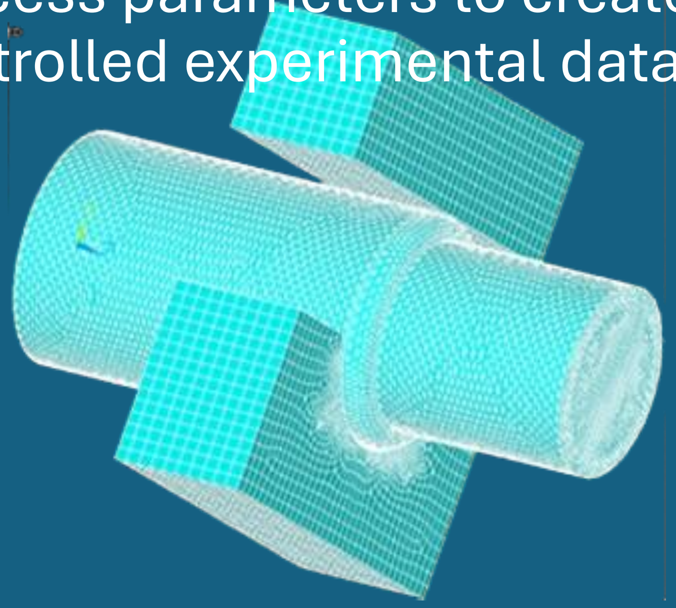
Analyze the technological regimes of open-die forging to develop mathematical models and AI-based surrogate models that can be integrated into digital systems for automated metallurgical production control. The research aims to establish relationships between key process parameters (bite infeed and per-pass reduction) and their effects on kinematic and energy-force characteristics of the forging process.

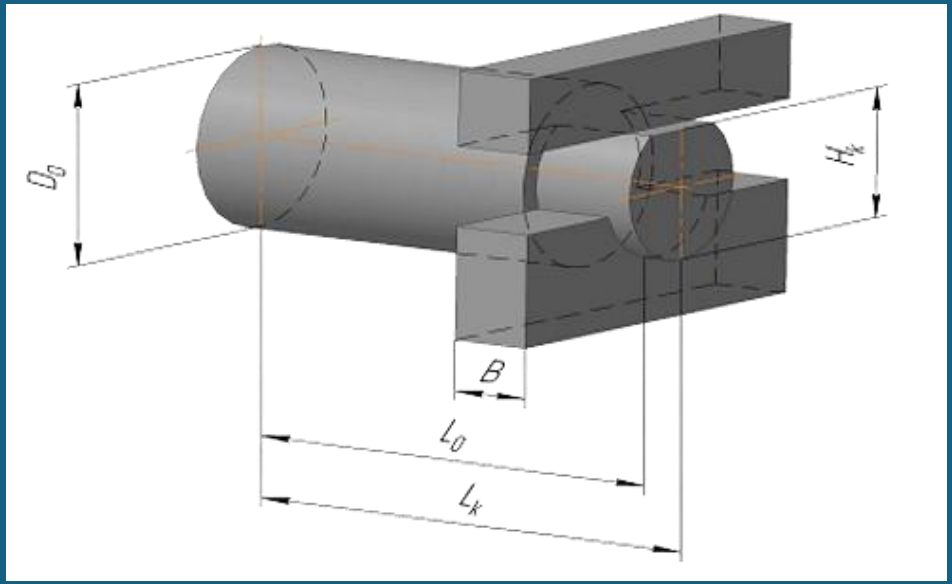
Artificial Intelligence & Data Analysis

Determine	Determine how relative bite infeed (B/D_0) influences elongation, forging force, and deformation work
Establish	Establish how per-pass reduction affects process characteristics
Develop	Develop high-fidelity analytical and AI models for real-time process optimization
Enable	Enable embedding of models into digital twins and automated control systems to improve efficiency and product quality in large-scale component production

Methodology: Resources

- **LS-DYNA** - Primary simulation software. Provides accurate physical simulation of the forging process, captures stress-strain state, and enables systematic variation of process parameters to create controlled experimental datasets.





- **Machine Learning Models** – Various approximation techniques evaluated, including linear models with interaction terms, power-law functions, exponential transformations, cubic polynomials, and high-accuracy quartic surrogates.
- **Statistical Approaches** – Coefficient estimation performed using ordinary least squares (OLS) regression and Levenberg-Marquardt optimization algorithms.
- **Full-Factorial 3×3 Experimental Design** – Systematic variation of bite widths (B = 180/240/300 mm) and reduction levels (Δh = 50/66/100 mm), ensuring thorough coverage of the parameter space with minimal computational expense while facilitating identification of optimal conditions.

Methodology: Design of computational experiments

Simulation Setup:

- Workpiece: 25Kh1M1F steel cylinder (D_0 = 550 mm, L_0 = 1300 mm)
- Dies: Combined tools (flat upper die, grooved lower die with 300 mm fillet radius)
- Method: LS-DYNA FEM simulation under isothermal conditions at 1100°C
- Die speed: 50 mm/s, rigid dies with Coulomb-type friction
- Mesh: Tetrahedral elements, 10 mm characteristic size

Rationale:

Analysis focused on the first reduction immediately after each feed, where die-workpiece contact area is maximal. This single pass governs the peak energy-force demand typical of industrial cogging routes and captures essential process physics without loss of relevance.

Normalized (reduced) metrics. Normalized (reduced) metrics were defined as follows [units in square brackets]:
-reduced forging force (*f*):

$$f = B/F \quad [\mathrm{N/mm}],$$

where *F* is the forging force under the given cogging setting (N), and *B* is the bite (die) width (mm);
-reduced deformation work (*w*):

$$w = W/B \quad [\mathrm{J/mm}],$$

where *W* is the deformation work (J);

-relative elongation (δ):

$$\delta = 100 \times (\Delta L/L_0)\ [\%],$$

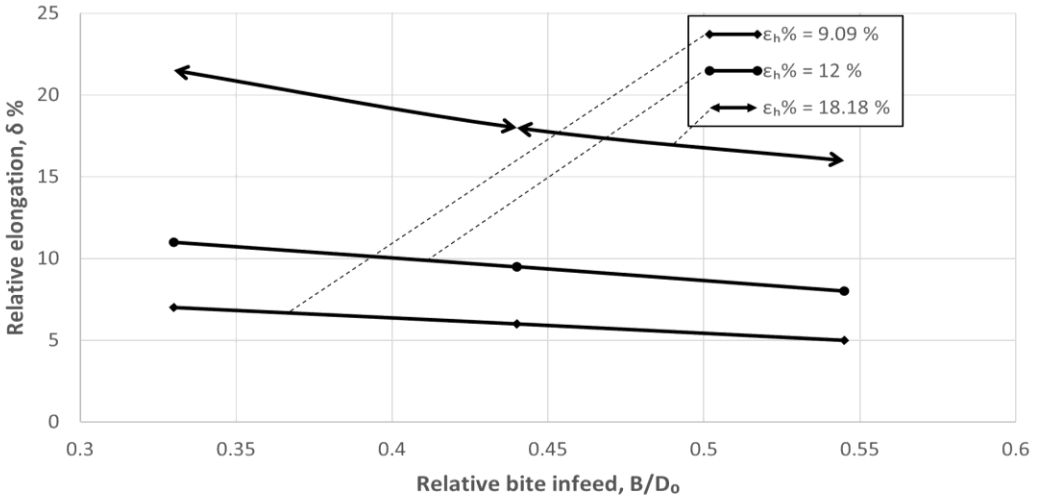
where ΔL = (Lf − L0) is the absolute elongation (mm), with L0 and Lf the initial and final billet lengths after the simulated reduction.

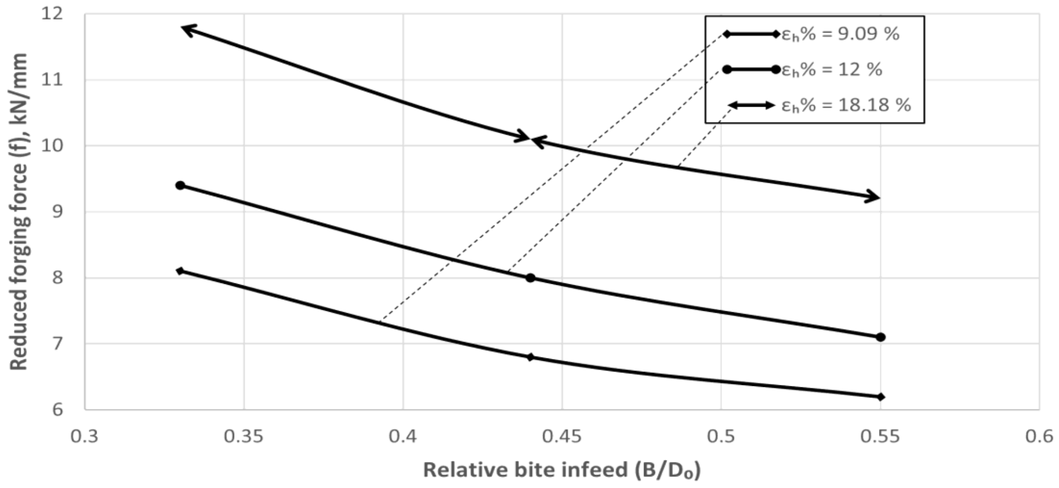
Results and Discussions

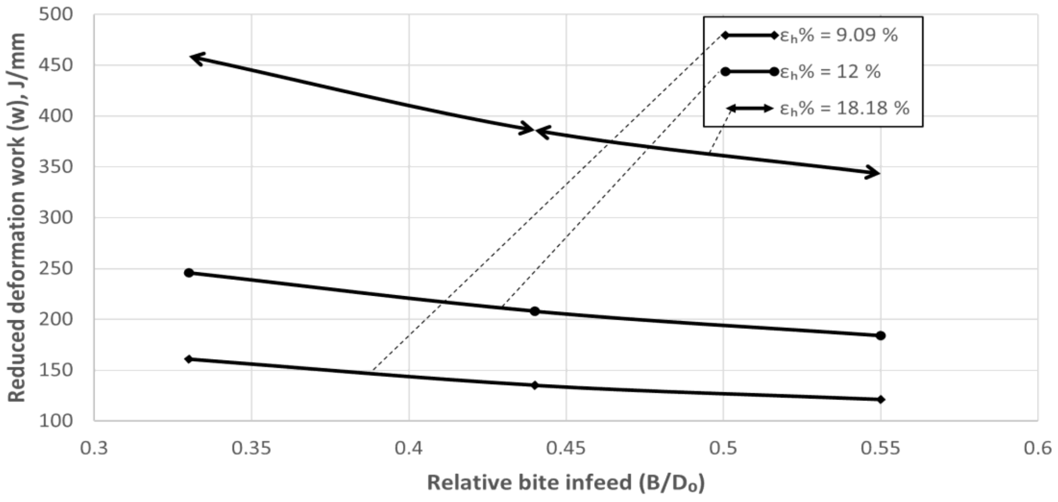
Table 1

Forging mode code (reduction*bite)

Forging mode code (reduction*bite)	ΔL, mm	δ, %	F, MH	f, kN/mm	W, kJ	w, J/mm
50*300	15.1	5.0	1.86	6.2	36.2	121
50*240	13.8	5.8	1.62	6.8	32.4	135
50*180	12.5	6.9	1.46	8.1	29	161
66*300	23.51	7.8	2.12	7.1	55.2	184
66*240	22.3	9.3	1.91	8.0	49.8	208
66*180	19.6	10.9	1.7	9.4	44.2	246
100*300	47.5	15.8	2.76	9.2	103	343
100*240	43.3	18.0	2.42	10.1	92.6	386
100*180	38.7	21.5	2.12	11.8	82.6	459







Results and Discussions: Mathematical Relationships

$\delta_{FEM} = (-1.92 \cdot \varepsilon_{h\%} + 8.766) \cdot (B/D_0) + 2.23 \cdot \varepsilon_{h\%} -$
$-10.84;\ (R^2 = 0.996);$

$f_{FEM} = a_f \cdot (B/D_0)^2 + b_f \cdot (B/D_0) + c_f;\ (R^2 \approx 1)$

where
$a_f = 0.5429 \cdot \varepsilon_{h\%}^2 - 14.343 \cdot \varepsilon_{h\%} + 114.98;$
$b_f = -0.4286 \cdot \varepsilon_{h\%}^2 + +10.931 \cdot \varepsilon_{h\%} - 98.35;$
$c_f = 0.0757 \cdot \varepsilon_{h\%}^2 - 1.4583 \cdot \varepsilon_{h\%} + 23.204;$

$w_{FEM} = \mathrm{a_w} \cdot (\mathrm{B/D_0})^2 + \mathrm{b_w} \cdot (\mathrm{B/D_0}) + \mathrm{c_w};\ (R^2 \approx 1),$

where
$a_w = 8.8039 \cdot \varepsilon_{h\%}^2 - 156.75 \cdot \varepsilon_{h\%} + 1202.4; b_w = -8.2708 \cdot$
$\varepsilon_{h\%}^2 + +114.53 \cdot \varepsilon_{h\%} - 981.51;$
$c_w = 2.3417 \cdot \varepsilon_{h\%}^2 - 3.6815 \cdot \varepsilon_{h\%} + 150.98.$

$\delta_1 = -16.667 \cdot (B/D_0) + 1.408 \cdot \varepsilon_{h\%} + 0.298;\ (R^2 = 0.982);$

$\delta_2 = 9.938 \cdot (B/D_0) + 2.302 \cdot \varepsilon_{h\%} - 2.0329.938 \cdot (B/D_0) \cdot \varepsilon_{h\%} -$
$-11.408; (R^2 = 0.994);$

$\delta_3 = 9.938(\mathrm{B/D_0}) + 1.446\varepsilon_{h\%} - 2.032(\mathrm{B/D_0})\varepsilon_{h\%} + 0.031(\mathrm{B/D_0})^2 -$
$-5.94;\ (R^2 = 0.999);$

$f_1 = -10.3 \cdot (B/D_0) + 0.365 \cdot \varepsilon_{h\%} + 8.28;\ (R^2 = 0.999);$

$f_2 = 1.28 \cdot (B/D_0)^{-0.522} \cdot (\varepsilon_{h\%})^{0.562};\ (R^2 \approx 1);$

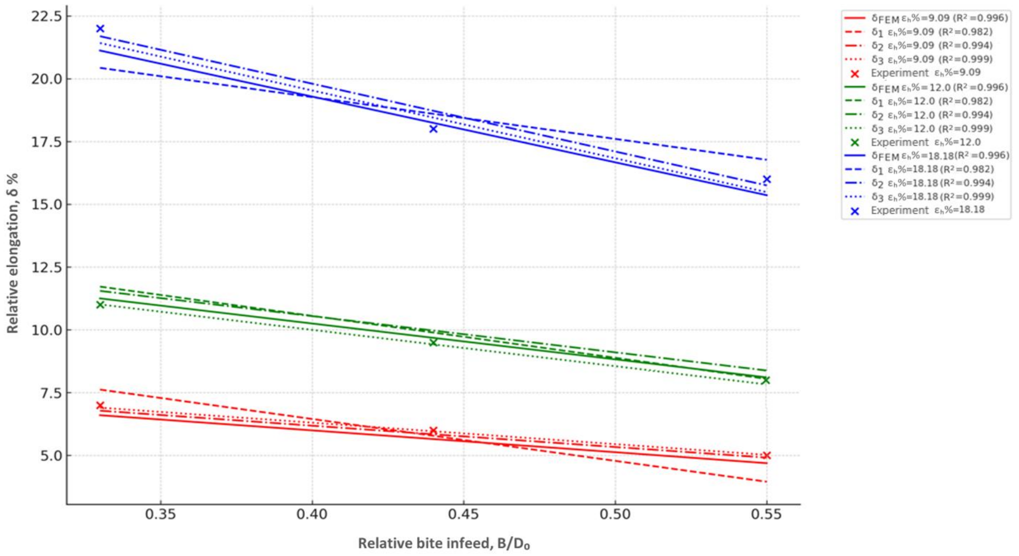
$f_3 = 30.23 \cdot (B/D_0) + 0.612 \cdot \varepsilon_{h\%} - 0.330 \cdot (B/D_0) \cdot \varepsilon_{h\%} + 27.55 \cdot (B/D_0)^2 +$
$-0.0036 \cdot \varepsilon_{h\%}^2 + 10.84;\ (R^2 \approx 1);$

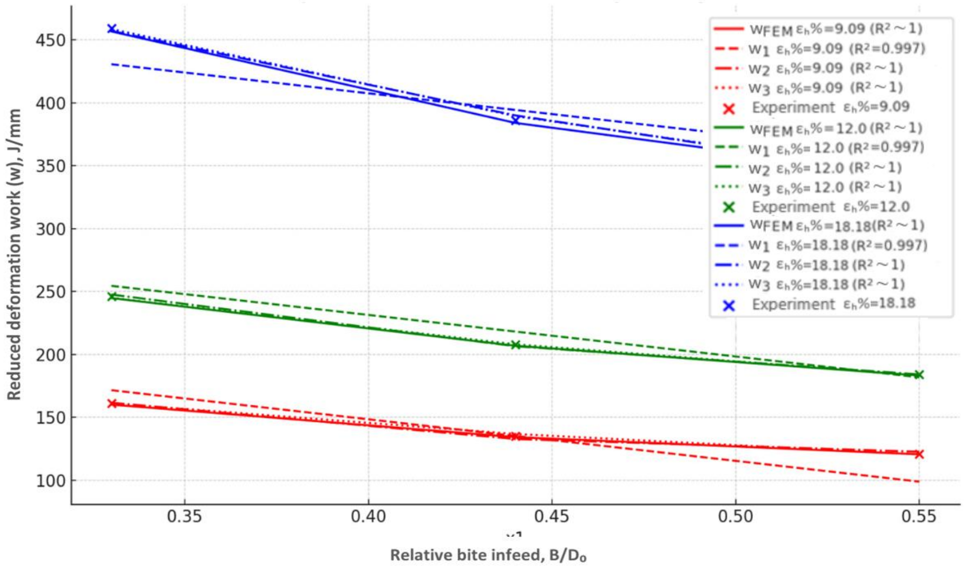
$w_1 = -330.30 \cdot (B/D_0) + 28.49 \cdot \varepsilon_{h\%} + 21.61;\ (R^2 = 0.997);$

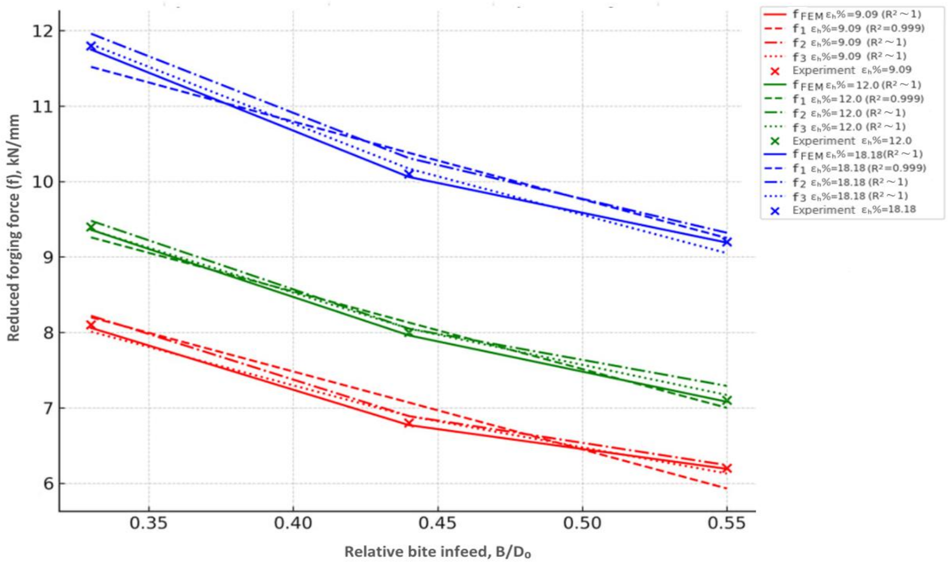
$w_2 = -508.11 \cdot (B/D_0) + 32.06 \cdot \varepsilon_{h\%} - 38.27 \cdot (B/D_0) \cdot \varepsilon_{h\%} +$
$+771.35 \cdot (B/D_0)^2 + 0.479 \cdot \varepsilon_{h\%}^2 + 29.11;\ (R^2 \approx 1);$

$w_3 = 3.07 \cdot (B/D_0)^{-0.568} \cdot (\varepsilon_{h\%})^{1.509};\ (R^2 \approx 1).$

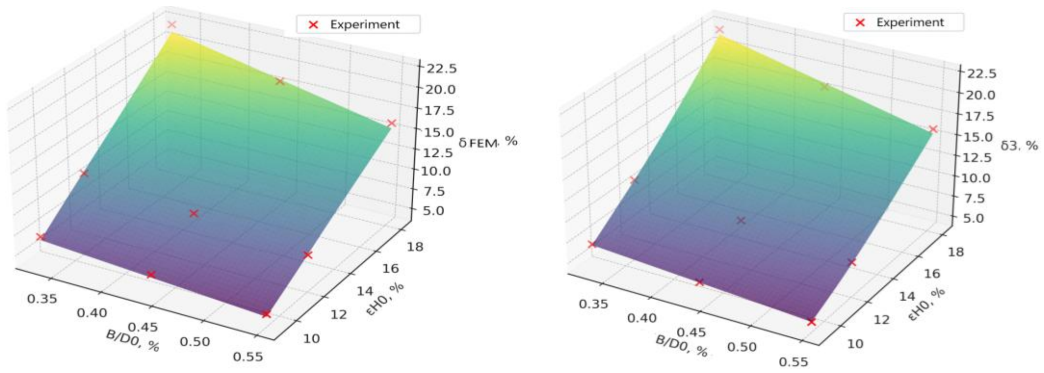
Results and Discussion: Graphs illustrating the dependence of δ, f_i, w on B/D_0 at different degrees of compression $\varepsilon_{h\%}$ were constructed using AI



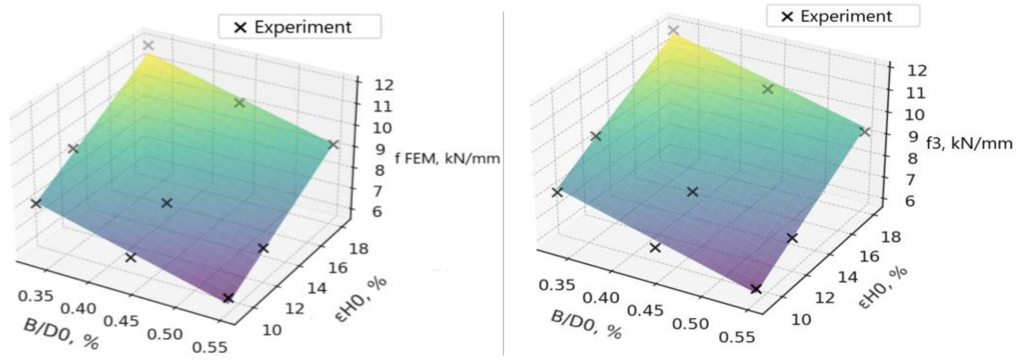




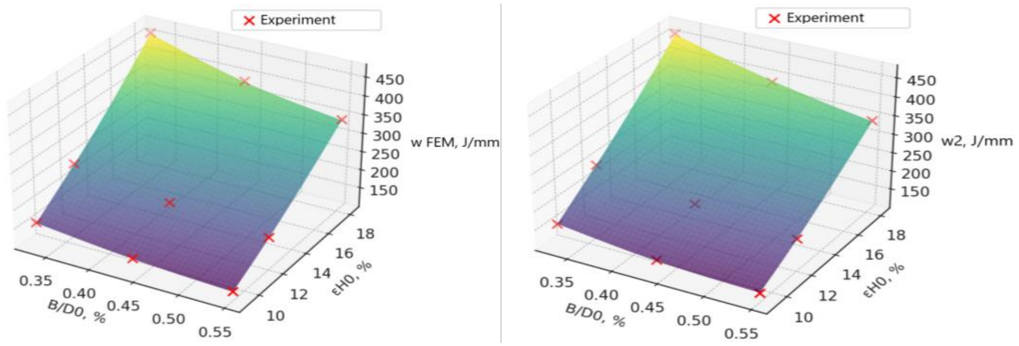
Results and Discussion: 3-D graphs of the dependences



Three-dimensional graphs of the dependences
$\delta(B/D_0, \varepsilon_{h\%})$ for FEM model (a) and
AI 2nd order polynomial model (b)



Three-dimensional graphs of the dependences
$f(B/D_0, \varepsilon_{h\%})$ for FEM model (a) and
AI 2nd order polynomial model (b)



Three-dimensional graphs of the dependences
$w(B/D_0, \varepsilon_{h\%})$ for FEM model (a) and
AI 2nd order polynomial model (b)

Results and Discussion

1. Monotonic Effect of Bite Infeed (B/D_0)

- Relative elongation (δ), reduced force (f), and reduced work (w) decrease monotonically with increasing relative bite infeed
- Narrower bites maximize elongation per pass
- Wider bites reduce peak force and work demand per unit bite width at fixed reduction
- Load reduction: ~15-25% over B/D_0 range of 0.33-0.55

2. Reduction Governs Absolute Load Level

- Per-pass reduction (ε_h%) primarily determines the absolute magnitude of all metrics
- Ranking: $w_{18 \cdot 18} > w_{12} > w_{9 \cdot 09}$ (same pattern for δ and f)
- Elongation more sensitive to reduction than bite infeed within tested range
- Highest reduction (18.18%) consistently produced largest δ, f, and w values

3. High-Fidelity Analytical Models Achieved

- FEM-based quartic relationships with $R^2 \geq 0.98$ (Equations 4-6)
- AI-based second-order polynomial models with $R^2 = 1.0$ (best results)
- Multiple approximation types tested: linear, power-law, exponential, cubic, quartic
- Least squares (OLS) and Levenberg-Marquardt optimization achieved excellent fit

4. Peak Load Focus Strategy Validated

- First reduction immediately after each feed governs peak energy-force demand
- Maximum die-workpiece contact area occurs at this critical pass
- Single-bite compression analysis captures essential process physics for optimization

Conclusions

Thank you for your attention

- Across all tested reductions, the key metrics (relative elongation (δ), reduced forging force (f), and deformation work (w)) decreased monotonically with increasing relative bite infeed (B/D_0). This trend indicates that narrower bites produce greater relative elongation per pass, whereas wider bites lower peak force and work demand per unit bite width for a fixed reduction.
- The magnitude of the per-pass reduction ($\varepsilon_{h\%}$) primarily governs the absolute level of elongation, reduced force, and reduced work. Relative elongation (δ) is more sensitive to the reduction magnitude than to the bite infeed within the tested range. The highest reduction tested (18.18%) consistently resulted in the largest values for elongation (δ), reduced force (f), and reduced work (w).
- The analysis focused on the first reduction immediately after each feed because this scenario corresponds to the maximum die-workpiece contact area, which governs the peak energy-force demand of the cogging process.
- Multiple approximation dependencies $\delta(B/D_0, \varepsilon_{h\%})$, $f(B/D_0, \varepsilon_{h\%})$, $w(B/D_0, \varepsilon_{h\%})$ were obtained using the finite element method (FEM) and artificial intelligence (AI). Both FEM- and AI-based models showed high reliability ($R^2 \geq 0.98$), indicating close agreement between calculated and simulated data. The quadratic polynomial provided the best results among AI-derived relations.
- These models are specifically intended for embedding into digital twins, decision-support systems, and model-predictive control (MPC) to support the subsequent automation of open-die forging optimization.