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Artificial Intelligence in the Biomimetic Design of Rotary Tillage Blades

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ABSTRACT

Biomimetic rotary-tillage blades whose cutting edges are abstracted from the claws and cuticles of soil-dwelling organisms that can substantially lower torque, draft and specific energy. Their design space is high-dimensional and their evaluation, by discrete-element (DEM) and finite-element (FEA) simulation or soil-bin testing, is costly. Artificial intelligence (AI) offers a systematic route through this bottleneck. This paper presents a technical account of how machine learning (ML) and AI-based optimization are integrated into biomimetic rotary-blade design. The formalization of the design problem as the search for a geometry vector that minimizes energy and wear subject to structural constraints, and describe an AI-driven pipeline in which biological features are extracted and parameterized, DEM/FEA data train a fast surrogate model, and evolutionary, swarm or Bayesian optimizers search the surrogate for optimal blades. We review surrogate model families (ANN, support-vector, tree-ensemble, Gaussian-process and extreme-learning machines), their coupling with DEM and FEA, surrogate-accelerated and multi-objective optimization, topology and generative design, digital twins for wear-aware operation, and explainable-AI methods that restore physical insight. An illustrative workflow shows a surrogate achieving $R^2 \approx 0.98$ gainst DEM and a genetic algorithm converging to a claw-derived blade with 13-17% lower torque. This closes the principal challenges with data scarcity, generalization and field validation and future directions including physics-informed learning, generative bio-inspired design and self-optimizing blades.

1. INTRODUCTION

Mechanized soil preparation underpins crop productivity but consumes a disproportionate share of on-farm energy and rapidly wears the steel implements it relies on. For rotary tillers the problem is acute that is power-take-off-driven blades continuously cut and pulverize soil, so the torque at the soil-blade interface dominates specific energy and fuel use [22,23], while abrasive and adhesive wear blunt the edge and, in doing so, drive draft and torque still higher [24]. Energy and wear are therefore a single coupled problem. In conventional fixes, harder steels or heavier sections merely trade toughness for hardness or add mass and cost. Biological soil-engaging organs solve exactly this problem, achieving low cutting resistance, wear tolerance and anti-adhesion through graded, hierarchical and multifunctional design rather than brute hardness [1,2,5]. Three decades of bionic research have transferred such principles of edge curvature, surface non-smoothness and functional grading into working implements [5,6,13]. Progress, however, remains fragmented: geometry is usually optimized on conventional steel, materials are developed without reference to bio-inspired form, and performance, wear and sustainability are evaluated separately. This perspective addresses that fragmentation by organizing the field around a single systems-level

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framework (Figure 1) and synthesizing the evidence for an integrated, co-designed approach.

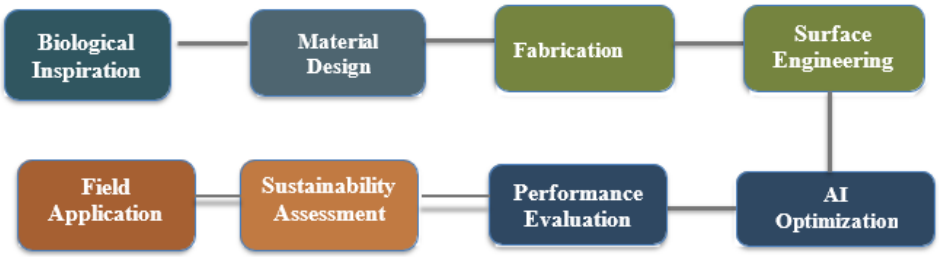


FIGURE 1. The systems-level framework for biomimetic, sustainable rotary-tillage tools

Bio mimicry can be applied at the morphological, structural, functional, material, surface and behavioral levels, and the most effective tools combine several at once. Burrowing and cutting organisms supply the richest geometric library (Table 1): the curved, graded claw of the mole rat minimizes cutting resistance [9]; the serrated forelimb of the mole cricket concentrates stress at discrete teeth to lower peak force [13]; the non-smooth cuticle of the dung beetle reduces soil adhesion and drag [7,16]; and the lotus leaf and shark skin provide self-cleaning and drag-reducing surface textures [17,18,19]. Translating the mole-rat claw into a multi-tooth rotary edge (Figure 2) is the most developed of these transfers, and repeatedly reduces torque, draft and specific energy relative to standard L-type blades in both discrete-element simulation and experiment [12,13]. Conventional tuning relies on factorial or response-surface experiments that scale poorly with dimensionality and treat each evaluation with a DEM run or soil-bin test as costly [19,28]. Machine learning changes this economy with the help of fast surrogate models learn the mapping from geometry to performance, and AI optimizers search that mapping efficiently, enabling many more designs to be explored than direct simulation permits [12,13,25]. Recent studies confirm that ML predicts tillage forces with high fidelity (R2 up to 0.99) and that surrogate-plus-genetic-algorithm schemes optimize rotary-blade torque and power effectively [11,12,13]. This paper gives a technical, methods-focused account of AI in bio mimetic rotary-blade design. It formalizes the design problem, sets out an AI-driven pipeline, and reviews performance-prediction models, AI-based optimization, AI–DEM/FEA coupling, topology and generative design, digital twins and explainable AI, before illustrating the workflow and identifying open challenges.

2. BIOMIMETIC ROTARY BLADES: DESIGN BACKGROUND

The dominant prototype is the fore-claw of burrowing rodents such as the mole rat, whose curved, tapering ventral edge cuts soil at low resistance [**?**]. Serrated insect mandibles and mole-cricket limbs, and the non-smooth cuticles of the dung beetle, provide complementary edge and surface motifs [**?**, **?**]. The transferable feature, typically the ventral cutting curve, is captured by three-dimensional scanning and digitization, then fitted with a smooth analytical function (for example, a cubic-plus-Gaussian curve, $R^2 > 0.99$) that becomes the mathematical carrier of the biomimetic geometry [**?**]. AI-based image and point-cloud methods increasingly automate this extraction and separate functional features from incidental ones.

Geometry Parameterization

For optimization, the blade is reduced to a compact design vector, Eq. (1), whose elements are the curvature radius r_c, tooth depth h_t, tooth number n, rake angle α, speed ratio λ, and working depth d. This parameterization defines the search space over which AI operates.

$$\mathbf{x} = [r_c,\ h_t,\ n,\ \alpha,\ \lambda,\ d] \tag{1}$$

Blade performance is quantified by mean and peak torque, horizontal draft, specific tilling energy, soil-disturbance and tilth indices, and, for durability, peak stress, factor of safety, and a wear index are considered important parameters. These metrics are the targets that the surrogate models predict and the optimizers minimize or constrain.

3. THE AI-DRIVEN BIO MIMETIC DESIGN FRAMEWORK

The overall framework (Figure 2) links biological inspiration to a validated blade through six computational stages: feature extraction, geometry parameterization, DEM/FEA data generation, surrogate modelling, AI-based optimization and validation, closed by iterative refinement and, within the loop, by active sampling that returns the optimizer's most promising or most uncertain designs to the simulator for evaluation.

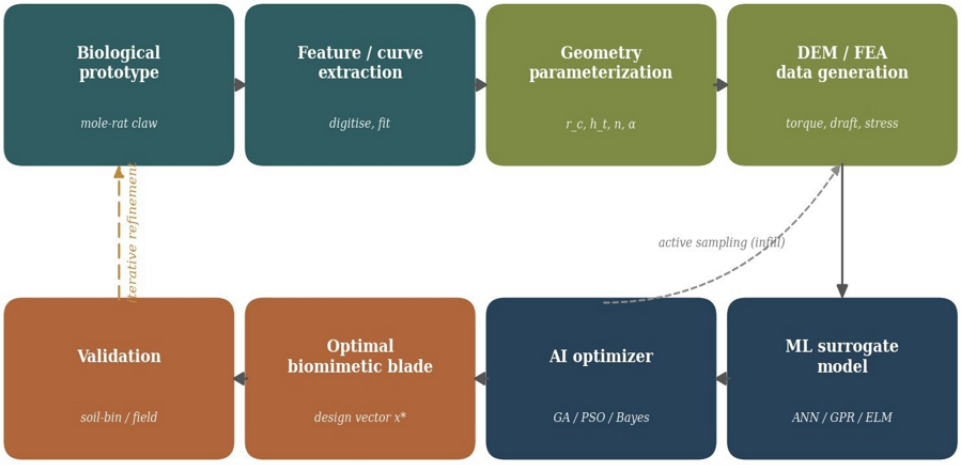


FIGURE 2. AI-driven pipeline for biomimetic rotary-blade design, with iterative refinement and active-sampling infill

Data sources

Training data come from calibrated DEM simulations of soil cutting, FEA of blade stress, and soil-bin and field measurements; each records a design vector and its measured performance [17,18,25].

Feature engineering and dimensionality reduction

Raw simulation outputs are distilled into informative features, and correlated or redundant variables are compressed by techniques such as principal-component analysis, improving surrogate accuracy and reducing data requirements.

Surrogate modelling

A surrogate learns the mapping from design vector to performance, Eq. (2), replacing each expensive simulation with a near-instant prediction and thereby making large design searches tractable [13,25].

$$\hat{y} = f(\mathbf{x}; \theta) \approx y_{\mathrm{DEM}}(\mathbf{x}) \tag{2}$$

Optimization

An AI optimizer queries the surrogate to locate optimal designs, occasionally verifying candidates with the full simulator; this surrogate-in-the-loop scheme is the computational heart of the framework.

Validation

The optimal blade is validated against independent DEM runs and, ultimately, soil-bin or field tests; discrepancies feed the refinement loop, progressively improving both surrogate and design.

TABLE 1. AI and machine-learning techniques and their roles in biomimetic rotary-blade design

Technique	Primary role	Typical use in blade design	Ref.
ANN / deep networks	Nonlinear regression	Predict torque, draft, energy	[11,12]
Gaussian-process regression	Surrogate + uncertainty	Bayesian optimization of geometry	[6]
Extreme-learning machine	Fast surrogate	Rotary-blade torque/power model	[13]
Tree ensembles (RF, boosting)	Robust regression	Draft prediction, feature ranking	[12]
Genetic algorithm / NSGA-II	Global / multi-objective search	Optimize curvature, teeth, angle	[4,13]
Particle swarm optimization	Global search	Continuous geometry tuning	[5]
Bayesian optimization	Sample-efficient search	Few-shot geometry optimization	[6]
CNN / image models	Field-based learning	Learn from DEM disturbance fields	[1]
Physics-informed NN	Constrained learning	Embed soil mechanics in surrogate	[7]
SHAP / explainable AI	Interpretation	Rank influential design variables	[8]

4. REGRESSION SURROGATES

The workhorse surrogates are feed-forward artificial neural networks, support-vector regression, tree ensembles and Gaussian-process regression. A single-hidden-layer network, Eq. (3), already captures much of the non-linear geometry–performance relationship, and comparative studies report ANN outperforming linear regression for tillage-force prediction, with R^2 approaching 0.99 [**?**, **?**].

$$\hat{y} = f\left(W_2\,\sigma\left(W_1\mathbf{x} + \mathbf{b}_1\right) + \mathbf{b}_2\right) \tag{3}$$

Training and Loss

Surrogate parameters are fitted by minimizing the mean-squared prediction error over the training set, Eq. (4), with regularization and cross-validation guarding against over-fitting on the typically modest simulation datasets.

$$\mathcal{L}_{\mathrm{MSE}} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{4}$$

Deep and Physics-Informed Learning

Where the DEM particle-velocity or stress field is available, convolutional networks can learn directly from these images, and physics-informed neural networks embed the governing soil-mechanics relations in the loss so that predictions remain physically consistent even with scarce data [**?**]. Recurrent architectures have been used to emulate the time history of soil-tool forces for near-real-time prediction [**?**].

Model Evaluation

Surrogates are judged by the coefficient of determination and root-mean-square error on held-out data, Eq. (5); reporting both, together with the range of validity of the training set, is essential because a surrogate is only trustworthy within the design region it has seen.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2}, \qquad \mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{5}$$

TABLE 2. Surrogate model families for geometry–performance prediction

Model family	Inputs → outputs	Strengths	Limitations
ANN / MLP	$\mathbf{x} \rightarrow$ torque, draft, energy	Flexible, high accuracy	Needs data; opaque
Gaussian process	$\mathbf{x} \rightarrow$ mean + variance	Uncertainty, few samples	Scales poorly with data
Extreme-learning machine	$\mathbf{x} \rightarrow$ multi-output	Very fast training	Less robust extrapolation
Tree ensembles	$\mathbf{x} \rightarrow$ scalar metric	Robust, ranks features	Piecewise, non-smooth
CNN	DEM field → metric	Uses spatial information	Data- and compute-heavy
Physics-informed NN	$\mathbf{x} \rightarrow$ metric (+ physics)	Data-efficient, consistent	Harder to train

5. AI-DRIVEN OPTIMIZATION OF BLADE GEOMETRY

Evolutionary algorithms

Genetic algorithms encode candidate blades as chromosomes and evolve them through selection, crossover and mutation toward lower energy; they handle the multi-modal, non-convex blade design space well and have optimized rotary-blade torque and power in combination with ML surrogates [13].

Particle swarm optimization

Particle swarm optimization moves a population of candidate designs through the continuous parameter space under the velocity update of Eq. (9), balancing individual and collective best solutions; it is simple to implement and effective for continuous geometry tuning.

$$\mathbf{v} \leftarrow \omega\mathbf{v} + c_1 r_1(\mathbf{p} - \mathbf{x}) + c_2 r_2(\mathbf{g} - \mathbf{x}), \qquad \mathbf{x} \leftarrow \mathbf{x} + \mathbf{v} \tag{9}$$

Bayesian Optimization

When each evaluation remains expensive, Bayesian optimization builds a Gaussian-process surrogate, Eq. (6), and selects the next design by maximizing an acquisition function such as expected improvement, Eq. (7), reaching good designs in remarkably few simulations [6].

$$f(\mathbf{x}) \sim \mathcal{GP}\left(m(\mathbf{x}), k(\mathbf{x}, \mathbf{x}')\right) \tag{6}$$

$$\mathrm{EI}(\mathbf{x}) = (\mu(\mathbf{x}) - f_{\text{best}})\,\Phi\left(\frac{\mu(\mathbf{x}) - f_{\text{best}}}{\sigma(\mathbf{x})}\right) + \sigma(\mathbf{x})\phi\left(\frac{\mu(\mathbf{x}) - f_{\text{best}}}{\sigma(\mathbf{x})}\right) \tag{7}$$

Multi-Objective Optimization

The problem between energy and wear is genuinely multi-objective due to conflict, Eq. (8). Algorithms such as NSGA-II return a Pareto front of non-dominated blades, from which a knee-point design balancing torque and wear is selected [4].

$$\min_{\mathbf{x}} \quad \mathbf{F}(\mathbf{x}) = [E(\mathbf{x}),\, W(\mathbf{x})] \tag{8}$$

where $E(\mathbf{x})$ represents the specific tilling energy and $W(\mathbf{x})$ represents the wear index.

AI versus Conventional Optimization

Relative to response-surface or factorial methods, AI optimizers explore higher-dimensional spaces, capture stronger non-linearities, locate global rather than local optima and, once a surrogate is trained, iterate almost instantly; the trade-off is a larger data appetite and reduced transparency.

Surrogate-Accelerated Simulation

DEM predicts soil-cutting forces faithfully but is typically two orders of magnitude slower than real time, making direct optimization impractical [25]. Training a surrogate on a designed set of DEM runs and then optimizing on the surrogate, verifying only selected candidates by DEM, combines DEM accuracy with near-instant search (Figure 3).

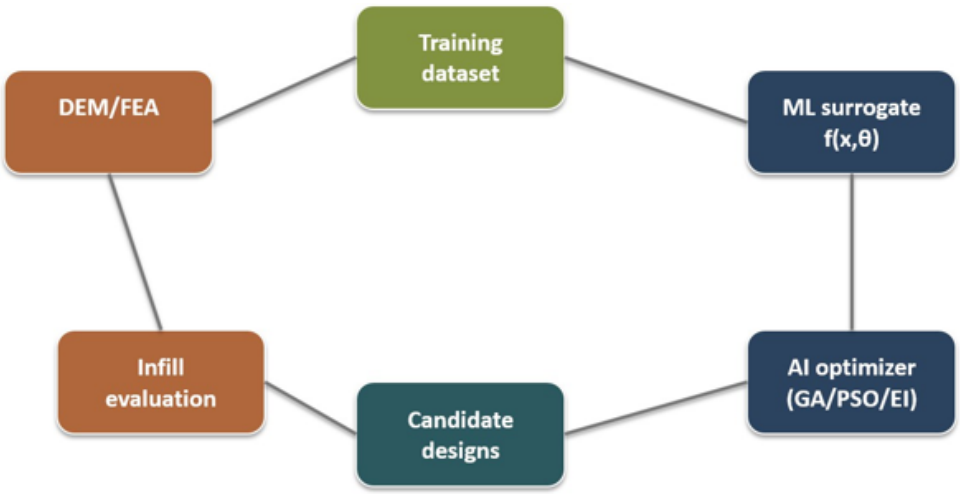


FIGURE 3. Surrogate-accelerated optimization loop

ML-assisted DEM calibration

Calibrating DEM contact parameters to match measured bulk density and shear is itself an inverse problem well suited to ML surrogates, which map parameter sets to bulk responses and let optimizers recover calibrated parameters efficiently [14].

Surrogate FEA for stress and wear

The same strategy accelerates structural evaluation: a surrogate trained on FEA results predicts peak stress and factor of safety across the design space, so that structural constraints can be enforced during geometry optimization without a full FEA at every step.

Reduced-order and hybrid models

Reduced-order models and hybrid physics uses ML schemes that retain the dominant mechanics while learning the residual, offering a favorable balance of speed, accuracy and physical consistency for coupled soil–blade problems [7,25].

6. TOPOLOGY AND GENERATIVE DESIGN

Topology optimization distributes material to meet stiffness and strength targets at minimum mass, and characteristically yields organic, graded, bone-like structures that align naturally with biomimetic and light-weighting goals [9]. Generative-design systems produce and evaluate many candidate geometries automatically under stated loads and constraints, exploring forms a human designer might not conceive and returning families of high-performing blades. Generative adversarial networks and related models, trained on libraries of biological and engineered edges, can synthesize novel claw-like or serrated geometries and, coupled with a surrogate evaluator, screen them rapidly an emerging route to AI-discovered biomimetic blades.

Digital Twins and Smart Adaptive Blades

A digital twin fuses sensor streams with physics- and data-based models to mirror a blade or implement in real time, supporting condition monitoring, wear tracking and what-if analysis across the service life [29]. Fast surrogates embedded in the twin estimate instantaneous draft, torque and accumulated wear from operating signals, enabling predictive maintenance and timely edge re-cladding rather than fixed-interval replacement. Coupling the twin to actuation via shape-memory

elements or adjustable geometry that points toward blades that adapt rake or engagement to real-time soil conditions, closing the loop between sensing, AI decision and mechanical response.

7. EXPLAINABLE AND TRUSTWORTHY AI

Attribution methods such as SHAP quantify how each design variable influences predicted performance, typically confirming curvature and tooth geometry as dominant and thereby restoring the physical insight that black-box model obscure [8]. Embedding soil-mechanics constraints, or preferring intrinsically interpretable model forms, yields surrogate whose behavior is both physically plausible and auditable which is important for engineering acceptance [7]. Gaussian-process and ensemble surrogates report predictive uncertainty, allowing the optimizer to avoid over-confident extrapolation and to target additional simulations where they most reduce risk.

8. ILLUSTRATIVE WORKFLOW

To make the framework concrete, consider a mole-rat-claw blade optimized by a surrogate-plus-genetic-algorithm scheme. A designed set of DEM runs over the vector of Eq. (1) trains an ANN surrogate that reproduces DEM torque with $R^2 \approx 0.98$ and RMSE $\approx$ 3 N·m on held-out data (Figure 4a). A genetic algorithm then searches the surrogate, converging within about thirty generations to a design whose specific energy falls from roughly 255 to 214 kJ m^{-3} (Figure 4b). Treating torque and wear as competing objectives yields a Pareto front (Figure 5), from which a knee-point blade whose curvature radius $\approx$ 9.5 mm, with five teeth of $\approx$ 7 mm depth, is selected, giving a 13–17% torque reduction while respecting a factor-of-safety constraint (Table 3).

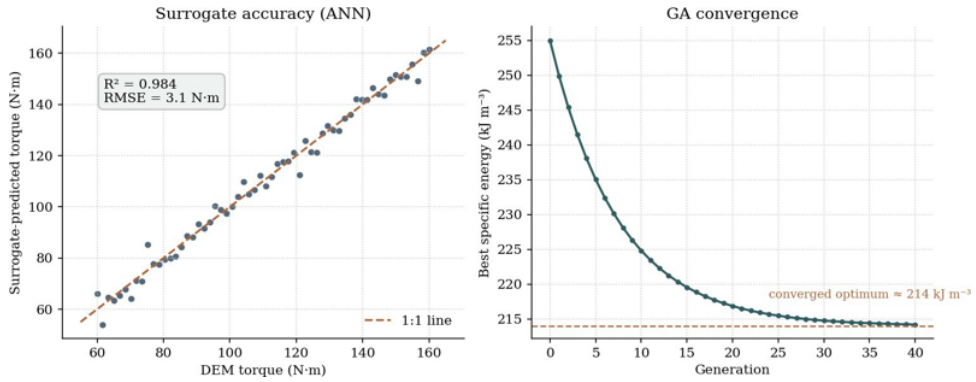


FIGURE 4. (a) Surrogate (ANN) predictions versus DEM torque; (b) genetic-algorithm convergence of specific energy.

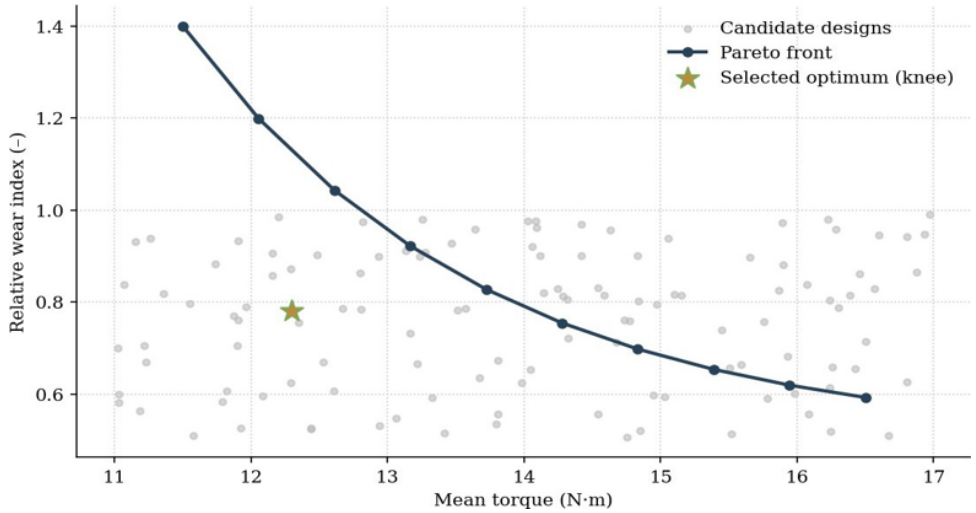


FIGURE 5. Pareto front for the torque- wear trade-off, with the selected knee-point optimum.

TABLE 3. Illustrative outcome of the AI-optimized biomimetic blade versus the standard blade

Metric	Standard blade	AI-optimized biomimetic	Change
Mean torque (N·m)	14.6	12.3	−15.8%
Specific energy (kJ m^{-3})	255	214	−16.1%
Mean draft (N)	182	158	−13.2%
Factor of safety	1.9	1.5	–
Surrogate accuracy (R^2)	–	0.98	–
Simulations vs. full search	–	$\approx 1/20$	−95%

9. COMPARATIVE ANALYSIS

Table 5 contrasts AI-based and conventional optimization across the dimensions that matter for blade design. The essential message is that AI does not replace DEM, FEA or soil-bin testing but it multiplies them. allowing far more of the biomimetic design space to be explored per unit of simulation effort while explicitly handling the energy-wear trade-off.

TABLE 4. AI-based versus conventional (RSM/DOE) optimization for biomimetic blades

Aspect	Conventional (RSM/DOE)	AI / ML-based	Advantage of AI
Design dimensionality	Low (3–4)	High (many)	Handles complex geometry
Response form	Polynomial	Nonlinear (ANN, GP)	Captures true response
Global optimum	Often local	GA / PSO / Bayesian	Better global search
Multi-objective	Limited	NSGA-II / Pareto	Explicit trade-offs
Cost after training	Re-run experiments	Instant surrogate query	Rapid iteration
Interpretability	High	Lower (needs XAI)	Mitigated by SHAP/PINN

10. CHALLENGES AND LIMITATIONS

Several obstacles temper these advantages. Data scarcity is foremost: high-fidelity DEM and field data are expensive, so surrogates risk over-fitting and poor extrapolation beyond their training region. Generalization across soil textures, moistures and seasons is unproven, and a surrogate calibrated for one soil may mislead in another. AI models can be opaque, hindering engineering trust unless explain ability is built in. Coupling AI with DEM/FEA still demands significant up-front simulation and expertise, and, critically, long-term field validation of AI-optimized biomimetic blades remains scarce—most evidence is computational. Recognizing these limits is essential to deploying AI responsibly rather than as a black box.

11. FUTURE DIRECTIONS

Promising avenues follow from these gaps. Physics-informed and hybrid models will reduce data needs and enforce mechanical consistency. Generative AI, coupled with fast surrogates, could autonomously propose and screen novel bio-inspired geometries, moving from optimization toward discovery. Transfer and federated learning could share models across soils and institutions without sharing raw data, improving generalization. Digital twins with embedded

surrogates will enable wear-aware, adaptive operation and, combined with shape-memory or actuated elements, self-optimizing blades that adjust to the soil in real time. Foundation models trained on large multi-source soil–tool datasets may eventually provide general-purpose predictors that are fine-tuned to specific implements. Pursued within the pipeline of Figure 2, these directions define a credible path to genuinely intelligent biomimetic tillage tools.

12. CONCLUSIONS

Artificial intelligence transforms biomimetic rotary-blade design from a slow, low-dimensional, trial-and-error activity into a fast, high-dimensional, data-driven search. Framed as the minimization of energy and wear over a biomimetic geometry vector subject to structural constraints, the problem is well matched to ML surrogates that emulate costly DEM

and FEA and to evolutionary, swarm, and Bayesian optimizers that search them. An illustrative workflow demonstrates a surrogate reproducing DEM torque at $R^2 \approx 0.98$ and a genetic algorithm converging to a claw-derived blade with 13–17% lower torque at roughly one-twentieth of the simulation cost of a direct search, while multi-objective optimization makes the energy–wear trade-off explicit. Realizing this potential at scale will require larger and better-shared datasets, physics-informed and explainable models, and, above all, rigorous field validation, but the trajectory is clear. AI is becoming an indispensable partner to biomimetics in the design of energy-efficient, durable soil-engaging tools.

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