Numerical-Optimization-Based Implementation Strategies for the Mechanical Engineering AI Talent Granary Model in the Intelligent Digital Age

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Abstract: Amidst the digital intelligence age, the rapid evolution of intelligent technologies in mechanical engineering necessitates a critical demand for "AI-Mechanical" composite talent. To supersede the static and lagging nature of traditional cultivation models, this paper introduces an iterative optimization model as its core theoretical metaphor. This innovative approach informs the construction of the "AI Talent Granary Model for Mechanical Engineering" framework and its implementation strategy, which develops through three progressively advancing strategic phases: establishing a dynamic iterative model for talent development centered on the gradient descent method; constructing hybrid optimization strategies to effectively address elastic and rigid constraints in educational practice; and finally, utilizing a multi-objective optimization framework to achieve the "Dual-Helix" integration of technical capabilities and ideological-political literacy.. The series of strategies proposed in this study not only establishes the AI Talent Granary Model but also delivers a comprehensive, adaptive, and actionable solution. This approach systematically facilitates the intelligent upgrading of traditional engineering disciplines and the cultivation of outstanding engineers through a clear, visual implementation pathway.

Keywords: Numerical Optimization; AI Talent Granary Model; Implementation Strategy; Mechanical Engineering; Artificial Intelligence; Iterative Cultivation

1. Introduction

With the exponential advancement of technologies such as artificial intelligence (AI), the Internet of Things, and digital twins, the global manufacturing industry is undergoing a profound transformation driven by intelligent manufacturing. In the digital intelligence age, mechanical engineering has fundamentally shifted from traditional mechanical system design to complex system integration, incorporating intelligent sensing, autonomous decision-making, and precise execution [1]. This revolution has triggered an explosive surge in demand for versatile professionals within the industry—those who are proficient in both mechanical design and manufacturing while also adept at leveraging AI to solve complex engineering challenges.

However, the current talent cultivation system for mechanical engineering majors in Chinese universities still exhibits significant structural contradictions. On the one hand, the traditional curriculum focuses heavily on core mechanical knowledge; AI content remains scattered and isolated, failing to integrate organically with professional expertise. On the other hand, the existing training model is static and lagging, making it difficult to respond dynamically to evolving technological and industrial demands. Consequently, this results in a significant gap between talent supply and market demand [2].

To address this challenge, some scholars and practitioners have proposed solutions such as integrating AI courses and establishing dedicated laboratories. Nevertheless, these efforts remain largely confined to "layering knowledge modules" or "optimizing isolated components," failing to construct a talent supply system with intrinsic motivation and the capacity for continuous self-optimization at the systemic level [3,4]. Therefore, this study addresses a critical question: How can a mechanical engineering AI talent supply system be established that continuously iterates like an optimization algorithm, dynamically balances like an ecosystem, and operates with the security and reliability of a strategic reserve?

In response, the paper introduces an iterative optimization model as its core paradigm to construct the "AI Talent Granary Model" [5,6]. This approach follows a logical progression: from establishing the core iterative model to deepening constraint handling strategies and expanding value objectives, culminating in the exposition of the paradigm's essence as a "talent reservoir" and the planning of its implementation pathway.

2. A Constructing Framework for Optimizing and Iterating AI Talent in Mechanical Engineering

This research is fundamentally premised on viewing talent cultivation as a dynamic optimization problem. Iterative algorithms in numerical optimization progressively approximate the optimal solution through a series of directed, controllable steps within a multidimensional parameter space [7]. This iterative methodology exhibits a high degree of intrinsic isomorphism with the continuous learning and capability evolution required of AI professionals in mechanical engineering within the digital and intelligent age.

Modeling the complex talent development process as the gradient descent method in mathematical optimization is a novel approach. It provides a classical paradigm for efficiently finding optimal solutions in multidimensional parameter spaces. Its key iterative formula:

$$x_{k+1} = x_k - \alpha \cdot \nabla f(x_k) \quad (1)$$

Formula (1) contains the universal logic of "evaluation-orientation-advancement." Applying this logic to the field of talent development, a system of metaphors is constructed as follows.

2.1 Current Solution x_k with Respect to the Objective Function f

(x_k) represents after the (k^{th}) cultivation cycle (k) (such as an academic year), the current state of knowledge, skills, and competencies attained by the students. (f) represents the overall aim of talent cultivation: to develop outstanding AI professionals with multidisciplinary expertise capable of meeting the demands of the digital intelligence age.

2.2 Gradient $\nabla f(x_k)$

This core-driven orientation is derived from a gap analysis between the current competency level (x_k) and the desired target (f). This analysis precisely identifies the most urgent and critical reform directions by comparing capability gaps with industrial demands. For instance, corporate research and student competency assessments may reveal widespread deficiencies in "industrial vision inspection algorithm applications" or "digital twin modeling for intelligent manufacturing systems." This diagnosis ultimately constitutes the negative gradient direction ($-\nabla f(x_k)$), which represents the direction where capabilities improve most rapidly.

2.3 Learning Rate α and New Solution x_{k+1}

The learning rate (α) represents the efficiency and implementation intensity of curriculum and educational model renewal. An appropriate α ensures that the pace of reform responds swiftly to demands without causing systemic disruptions—such as in teaching staff or resources—due to overly aggressive measures. The new solution (x_{k+1}) then represents the expected state of talent achieved following this targeted reform iteration.

The essential value of this model, therefore, lies in its infusion of three core approaches—dynamic, precise, and systematic—into talent development. It transforms the cultivation process from a static plan into a data-driven, adaptive system capable of continuous self-optimization.

3. A Hybrid Constraint Optimization Strategy for AI-Composite Talents in Mechanical Engineering

The ideal iterative model must confront the complex constraints of reality. Constraints in educational practice can be systematically classified into two categories.

3.1 Rigid Constraints

It refers to non-negotiable requirements, such as the mandatory courses and practical component credits stipulated by engineering education accreditation standards, as well as the maximum total credit limit set by the university.

3.2 Elastic Constraints

It refers to constraints with variable

characteristics, such as the limited availability of teaching resources (laboratory equipment, computing resources), gaps in faculty expertise regarding AI knowledge, and time constraints imposed by fixed academic calendars.

To simultaneously address these two categories of constraints, this paper proposes a hybrid optimization strategy based on the iterative model in Equation (1). Its mathematical model is expressed as follows:

$$\min_{x} f(x) + \lambda \cdot P(g(x)) \quad \text{s.t.}\, h(x) \leq 0 \quad (2)$$

where: $f(x)$ is the core objective function, that is pursuing the integration of AI technology expertise with mechanical engineering professional capabilities.

$h(x) \leq 0$ represents the set of rigid constraints. For instance, $h_1(x) = 60 - \sum($ Required course credits $) \leq 0$ indicates a mandatory requirement that the total number of required course credits must not be less than 60 credits.

$P(g(x))$ is the penalty function, For processing elastic constraints, $g(x)$.

λ is the penalty weight, can be dynamically adjusted based on actual conditions.

$\lambda \cdot P(g(x))$ constitute a penalty item. Such as if $g(x)$ represents "the gap between the proportion of AI courses and the 30% target," then when the proportion falls short, the penalty term increases the total cost, thereby incentivizing optimization efforts toward allocating more resources to AI courses.

Solving this model is a sequential optimization process. In each iteration, determine whether the current solution xk satisfies all rigid constraints $h(x) \leq 0$. If the condition is not satisfied, the idea of the projection gradient method must be employed to "pull" the solution back into the feasible region. For example, the total credit requirement can be met by reducing non-core courses to fulfill the total credit requirement. Under the satisfaction of rigid constraints, exploration proceeds along the negative gradient direction of the composite objective function $f(x) + \lambda \cdot P(g(x))$.

3.3 Example of Application

Optimize the course system while maintaining the total credit (rigid constraint). If a significant increase in AI courses is required (to enhance $f(x)$), However, it faces the issue of insufficient teaching capacity (elastic constrains $g(x)$). The hybrid model balances both through the penalty term $\lambda \cdot P(g(x))$: Uncontrolled course proliferation risks declining teaching quality and increased regulatory penalties; consequently, policymakers must adopt balanced strategies. These include establishing moderate, incremental AI course targets alongside the simultaneous enhancement of teacher training, a duality that ensures reforms are both goal-oriented and practical.

4. The Dual-Helix Integration from Technical Capabilities to "Cultivating Values" Expanding the Scope of Objectives

Remarkable engineers must be master craftsmen who wield cutting-edge technology while carrying a heart for their country and the world [8]. The immense power inherent in AI technology and its potential ethical risks make the cultivation of values among talent more crucial than ever before [9]. In doing so, we must expand our framework beyond the optimization of technical capabilities alone to pursue a dual-objective optimization that equally prioritizes both technology and ethics.

The "technology-ethics" dual-helix cultivation model constructed in this paper is mathematically expressed as:

$$\min_{\theta} \left[\alpha \cdot \frac{1}{N} \sum L_{tech}(x_i, y_i) + \beta \cdot \frac{1}{M} \sum L_{ethics}(z_j) \right] \quad (3)$$

where, L_{tech} is the technical loss function, is used to measure the technical performance gap among students when solving complex engineering problems, such as involves algorithm prediction accuracy, system response time, and performance metrics of design solutions.

L_{ethics} is the ethical loss function. This is an innovative design for quantifying the value considerations students weigh in technological decision-making. The evaluation criteria may include: algorithmic fairness, system explainability, solution sustainability, level of user privacy protection, and whether the design aligns with national strategic requirements.

α and β is the dynamic weighting coefficient, represent the relative importance of technical objectives and ethical objectives within the aim. For instance, When developing AI equipment for the medical field, the ethical weighting factor β should be significantly increased.

The model depicts a dual-helix structure that intertwines and co-evolves. Technological advancement (reducing L_{tech}) must be continuously balanced by reviewing its ethical consequences (reducing L_{ethics}). Crucially, the resulting ethical insight then actively steers innovation toward more responsible and human-centered development paths.

5. Paradigm Innovation and Visualization of Implementation Pathways for the "Talent Granary Model"

The "talent granary" proposed in this paper represents a quantum leap beyond the traditional "talent pool" paradigm.

(1) Paradigm Revolution: Although the term "talent pool" is widely used, its metaphor emphasizes the static storage and retrieval of established talent [10]. In contrast, the concept of a "talent granary" originates from agricultural ecosystems, highlighting the dynamic cultivation, continuous nurturing, and strategic reserve of talent. It focuses on future incremental supply and sustainability, with its core objective being the creation of an "educational fertile ground" where talent can continuously thrive.

(2) Strategic Implications: The term "talent granary" embodies four profound layers of meaning: a strategic security baseline (self-reliant and controllable talent supply), an ecosystem cultivation system (synergy among curricula, faculty, and industry), a value conversion chain (transformation from knowledge to engineering capabilities), and risk-resilient redundancy (capacity reserves to withstand technological disruption).

Ensuring this framework effectively guides practice, this paper visualizes it through three core figures:

5.1 "Talent Granary" Ecosystem Map

Figure 1 illustrates a dynamic, cyclical ecosystem centered on "AI+Mechanical Hybrid Talent," surrounded by three concentric layers: the "Data Intelligence Cloud" (technology empowerment), the "Educational Fertile Ground" (curriculum, faculty, and platforms), and the "Industrial Application Sphere" (demand-driven and value-replenishing). The bidirectional arrows indicate continuous energy exchange among knowledge, data, and feedback.

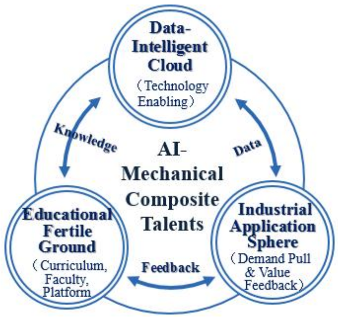

Figure 1. AI+Mechanical Hybrid Talent Ecosystem Map

5.2 Hybrid Optimization Strategy Logic Flowchart

Figure 2 demonstrates a closed-loop iterative process that progresses from "State Assessment" to "Demand Diagnosis Calculate Capability Gradient", "Handle Constraints", "Program Implementation" and finally to "New State Assessment".

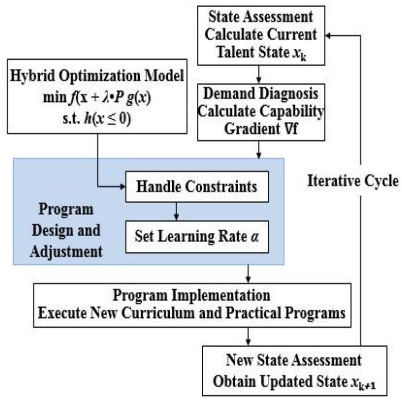

Figure 2. Hybrid Optimization Strategy Logic Flowcharts

5.3 Agricultural Parameters and Education Indicators Mapping Table

Table 1 maps "yield per hectare" to "patents/competition awards per student," "double cropping index" to "curriculum update frequency," and "hybrid breeding" to "interdisciplinary integration." This makes the metaphorical relationships immediately apparent, serving as a universal language for cross-disciplinary communication.

Table 1. The "Talent Granary" Metaphor: Mapping Agricultural-Educational Parameters

Agricultural Parameters	Mapping Logic	Education Indicators (Talent Reservoir)
yield per hectare (kg/ha)	Output efficiency per unit of land resources: Measures grain yield per unit of land area.	Number of high-level achievements per student: Measures output per student (or per faculty member), such as the number of patents granted per student or the number of awards won in high-level academic competitions.
Crop rotation index	Resource Reuse Rate and System Renewal	Course Update Frequency: The annual

Agricultural Parameters	Mapping Logic	Education Indicators (Talent Reservoir)
	Frequency: Measures the number of times crops are replanted on a piece of land within a year, reflecting land resource utilization efficiency and system renewal speed.	average update ratio of core course content and teaching cases, reflecting the teaching system's responsiveness to technological iteration.
Hybrid breeding	Interdisciplinary Genetic Recombination and Innovation: By combining desirable traits from different varieties, new superior varieties are developed.	AI-Mechanical Course Integration: The proportion and depth of interdisciplinary courses and cross-disciplinary projects in mechanical engineering and artificial intelligence within the curriculum system.
Organic Fertilizer/ Chemical Fertilizer Ratio	Balancing Foundational Cultivation and Targeted Intervention: Organic fertilizers represent long-term, foundational investments in soil improvement, while chemical fertilizers provide efficient, rapid-acting targeted nutrient supplementation.	Ratio of Theoretical Instruction to Practical Training Hours: The proportion of class hours allocated to foundational theory and principle instruction versus project-based learning, experiments, practical training, and other practical components within the training program.

6. Conclusion and Future Work

This study successfully constructed the comprehensive “AI Talent Reserve for Mechanical Engineering” framework using an iterative optimization model. The model’s primary contribution is its systematic approach to talent cultivation challenges, achieved by integrating dynamic iterative models, hybrid constraint strategies, and dual-helix objectives. This “talent granary” paradigm provides a new worldview and methodology for engineering education reform.

However, as a theoretical framework, its validity requires further validation and calibration through broader practical application. Future research should thus explore the following directions:

(1) Development of an Educational Digital Twin System: Constructing a virtual model of the talent reservoir to simulate the long-term effects of different cultivation strategies and conduct policy simulations.

(2) Reinforcement Learning Path Planning: Treating students' lifelong learning as a sequential decision-making problem to explore optimal personal growth pathways.

(3) Ethical Quantification Assessment Technology: Further research on how to leverage technologies such as explainable AI to conduct more precise automated assessments of the ethical implications of engineering solutions.

Acknowledgments

Supported by the Graduate Education Development Project(10-23-304-007), Graduate Student Teaching Achievement Award Cultivation Project(10-24-304-024), and Graduate Teaching and Research Programme (Mechanical Engineering) of University of Shanghai for Science and Technology(10-00-304-008).

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