RESEARCH ARTICLE

Construction of a Practical Teaching System for Smart Logistics Course Integrating Operations Research and Intelligent Decision-Making

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Abstract

To address the current issue that the smart logistics course focuses heavily on hardware introduction while lacking practical training in operations research optimization and intelligent decision-making, this paper constructs a practical teaching system that integrates operations research and intelligent decision-making. Guided by industry demands such as the low-altitude economy, last-mile delivery, and automated warehousing, a three-tier progressive practical module "Basic, Comprehensive and Innovative" is designed. The system adopts project-based learning (PBL) and is organized in three stages: "Scenario Modeling, Code Implementation and Solution Decision-Making". A diversified process-based assessment and an open-source teaching case and code repository are established as supporting mechanisms. This system shifts the teaching focus from software operation to algorithmic decision-making capability development, effectively enhancing students' practical abilities in logistics modeling and optimization, and provides a referable curriculum reform solution for cultivating interdisciplinary talents in smart logistics.

Keywords: smart logistics, practical teaching system, intelligent decision-making, research-teaching integration.

1 Introduction

Against the backdrop of deep integration between the digital economy and the real economy, smart logistics has become a core pillar for the high-quality development of the modern logistics industry. The large-scale implementation of new business formats such as the low-altitude economy, intelligent last-mile delivery, and automated warehousing has reshaped logistics operation models. In these core scenarios, the upper limit of efficiency has shifted from hardware performance to underlying operations research optimization models and intelligent decision-making algorithms, placing critical demands on logistics talents' algorithmic thinking, scenario modeling, and decision-making optimization skills.

Currently, a significant structural disconnect exists between the Smart Logistics course offered in universities and industry needs. The prevalent issues

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are "emphasis on hardware over algorithms, and on theory over practice": teaching mostly focuses on introducing hardware facilities and information systems, while related cutting-edge content remains at the level of theoretical popularization. There is a lack of systematic cultivation of decision-making capabilities centered on operations research optimization. As a result, students struggle to complete full-process optimization practices, leading to a mismatch between talent supply and demand, which has become a core bottleneck for industry development and talent cultivation.

Existing research on curriculum reform mostly concentrates on content restructuring, university-enterprise cooperation, and teaching model innovation. Systematic research on a full-chain practical teaching system that deeply integrates operations research and intelligent decision-making remains scarce, and there is a lack of implementable practical paradigms. To this end, this paper constructs an integrated practical teaching system that takes operations research optimization as the underlying logic, intelligent decision-making as the core application, and programming practice as the implementation means. It aims to establish a closed-loop teaching logic of "scenario, model, algorithm and practice", cultivate students' core practical abilities, and provide a reference for the cultivation of interdisciplinary smart logistics talents and curriculum reform.

2 Literature Review

The rapid development of Industry 4.0 and the intelligent economy is driving a profound transformation of the logistics industry toward smart, digital, and intelligent directions, as noted by Temjanovski et al. [1] and Liu [2]. The deep integration of emerging technologies such as the Internet of Things, big data, artificial intelligence, and digital twins has fundamentally changed traditional logistics operation models and imposed entirely new requirements on logistics talent cultivation, according to Abdillah et al. [3] and Darmawan et al. [4]. Against this backdrop, how to construct a practical teaching system for the Smart Logistics course that integrates operations research optimization and intelligent decision-making has become a core issue urgently needing resolution in logistics education. However, current logistics education faces numerous challenges: teaching content lags behind industry practice, a disconnect between theory and practice, and students' insufficient ability to solve complex problems [5, 6]. The integrated teaching of operations research methods (e.g., Economic Order Quantity model, Vehicle Routing Problem, inventory optimization) and intelligent decision-making techniques (e.g., artificial intelligence, machine learning, big data analytics) has become a key breakthrough point for cultivating smart logistics talents [7, 8]. Based on a systematic review of relevant literature, this paper provides a comprehensive overview from the perspectives of the contemporary demand for smart logistics talent cultivation, innovative methods in teaching operations research and intelligent decision-making, pathways for constructing practical teaching systems, and evaluation of teaching effectiveness.

2.1 Contemporary Demand and Practical Challenges in Smart Logistics Talent Cultivation

The development of the smart economy has profoundly influenced the capability requirements for logistics talents. Liu [2] analyzed the teaching reform of logistics information technology in the context of "smart logistics," pointing out prominent issues such as outdated textbook content, insufficient practical opportunities, and a disconnect between theory and practice. Liu [9] further noted that in the era of smart logistics, demand for basic operational positions has significantly decreased, while demand for interdisciplinary talents has markedly increased, requiring logistics talents to undergo comprehensive upgrading across three dimensions: knowledge, ability, and quality. Temjanovski et al. [1] examined the new trends and challenges facing university logistics education in the 21st century from a macro perspective, emphasizing that artificial intelligence, logistics information systems, and supply chain management have become core components of logistics education in the context of Industry 4.0.

Malka and Austin [5] employed Necessary Condition Analysis (NCA) to study the impact of learning modes (offline vs. online) on the successful employment of logistics graduates. The study found that mastery of logistics expertise and related technologies in offline learning modes is a significant necessary condition for graduates' success in the supply chain field. This finding offers important implications for constructing a practical teaching system for smart logistics: practice-oriented content such as operations research and intelligent decision-making is more suitable for offline or blended learning modes. Darmawan et al. [4], through a systematic literature review, pointed out that 65% of logistics education programs have not yet optimally integrated Industry 4.0 technology learning, while the logistics industry needs talents with composite capabilities in both traditional operations management and digital technologies. Simanjuntak et al. [10], through a qualitative analysis of 50 trainees, found that logistics education significantly enhanced trainees' understanding and application of logistics principles, improving operational efficiency in areas such as transportation cost control, service quality, and work processes.

2.2 Innovative Teaching Methods for Operations Research and Intelligent Decision-Making

Pacheco-Velázquez and Aguilar-Avalo [11] provided a detailed introduction to the development and application of the "GOAL Project" online platform and the LOST logistics simulator. This platform integrates videos, quizzes, exercises, notes, and business games, breaking the fragmented teaching model of traditional logistics courses. The study found that 98% of students were satisfied with the platform's support, and 92% hoped that all logistics courses would include similar supporting materials. Pacheco-Velázquez [12] systematically evaluated the application effectiveness of the "GOAL Project" online platform and the LOST simulation simulator in logistics education, finding that students rated key success factors such as perceived usefulness, satisfaction, and enjoyment highly, and that these factors were significantly positively correlated with intrinsic motivation, extrinsic motivation, learning engagement, learning reflection, and autonomous learning ability. Rzeczycki et al. [13], through simulation games covering supply chain management, production optimization, market strategy, and negotiation, found that serious games can effectively integrate theoretical knowledge with practice, cultivating students' problem-analysis skills, decision-making ability under uncertainty, and teamwork skills. Ammouriova et al. [8] introduced the application of heuristic algorithm-based simulation serious games in teaching logistics and transportation optimization, focusing on three classic optimization problems: the Vehicle Routing Problem (VRP), the Arc Routing Problem (ARP), and the Team Orienteering Problem (TOP). By having students solve practical problems using the Clarke-Wright savings heuristic algorithm, the SHARP algorithm, and biased randomization techniques, the study cultivated students' analytical skills, algorithmic understanding, and programming abilities. This research provides specific teaching tools for integrating operations research content into smart logistics courses. Sha'ari and Lahad [14] developed a simulation mobile learning application called "MyWarehouse Apps" to enhance warehouse management teaching in logistics education. The study found that students using this application achieved an average score of 83.7, significantly higher than the control group using Excel (74.7), with significant differences ($p < 0.05$) in four dimensions: usefulness, ease of learning, efficiency of use, and satisfaction.

Salinas-Navarro et al. [15] explored methods for reshaping the learning experience in supply chain management and logistics education under disruptive uncertain situations (e.g., the COVID-19 pandemic). Using a food supply chain disruption case at a private university in Bolivia, they proposed a teaching framework based on experiential learning and constructive alignment. The study found that integrating real-world disruption scenarios into learning activities significantly improved student engagement, motivation, and learning relevance, with a median final score of 88 and a 100% pass rate. Salinas-Navarro et al. [16] further demonstrated, through three cases in Bolivia, Mexico, and Peru, how real-world supply chain management operations can be transformed into unique educational opportunities. The study found that meaningfully connecting students' learning with local communities, enterprises, or specific contexts effectively promotes the achievement of expected learning outcomes in authentic situations. Mexico's "Sustainable Logistics Social Laboratory" project has produced approximately 100 student theses. Schinckus et al. [17], using the Vietnam Logistics E-Training Center (LETC) as a case study, explored the implementation of authentic context teaching methods in logistics education. Based on Aristotle's distinction between "episteme" (theoretical knowledge) and "techne" (practical knowledge), they proposed a conceptual framework using "epitaktike" (prescriptive knowledge) as a bridge between the two. The study found that by providing a real working environment (including physical facilities such as warehouses, forklifts, and containers), trainees could experience and apply knowledge in authentic contexts, with all indicators—course content, materials and equipment, organization, etc.—scoring above 4.5 out of 5.

Śląski and Grzelak [7] explored the application of lateral thinking in the education of logistics students.

Using the Economic Order Quantity (EOQ) model as an example, they adopted the "Six Thinking Hats" method and business process reengineering principles to guide students from traditional problem-solving approaches toward creative thinking. Sun [18], taking the course "Logistics Distribution Center Planning and Management" as an example, discussed the optimization of teaching routes for logistics management courses in the context of developing "golden courses." The study proposed a teaching route that includes optimization of teaching objectives, design of teaching models, and teaching evaluation feedback, employing methods such as case teaching, flipped classrooms, problem-based learning, and progressive learning.

2.3 Pathways for Constructing a Practical Teaching System for Smart Logistics

Wang [19] proposed the concept of building a "whole-process practical teaching system," which includes the restructuring of the curriculum system (professional quality + core professional competencies + job-specific abilities + innovation and entrepreneurship capabilities), the construction of a university-enterprise collaborative education platform, and the establishment of an effectiveness evaluation system. Ye et al. [20] studied the design of an intelligent logistics training base system based on information technology integration and found that the industry-education integration model led to an 85% employment rate for graduates and an enterprise satisfaction score of 4.2 out of 5, significantly enhancing students' practical skills.

Yao and Fan [21] constructed a teaching system for cultivating vocational undergraduate talents in modern logistics management based on artificial intelligence, integrating an intelligent logistics unmanned warehouse system, a transportation monitoring system, a full traceability system, and a data analysis system. Abdillah and Wahyuilahi [3] found that virtual reality technology significantly improved student engagement and concept mastery in logistics simulations, while artificial intelligence technology enhanced the design of personalized learning paths. Pacheco-Velázquez et al. [22], through semi-structured interviews with six logistics experts, explored the characteristics of educational simulation platforms for addressing the complexity of Industry 4.0. They identified five key dimensions of educational logistics simulators: technical adaptability, educational objectives, industry-specific elements, user experience, and the development of reasoning skills. The study found that simulation tools play an important role in risk mitigation, operational planning, and decision support, with particularly significant value for small and medium-sized enterprises with limited resources. Ramírez-Montoya et al. [23] introduced the design and user experience pilot study of the "Virtual Logistics" simulation generator platform, which allows students to independently design and adjust logistics networks and create customizable simulation-based serious games. The research indicates that the platform can provide flexible and customized educational experiences.

2.4 Evaluation of Teaching Effectiveness

Fayezi [24], based on constructive alignment theory, developed a student-centered instructional design framework for logistics management courses. The study adopted the PDCA cycle, integrating four key factors: learning theory (Plan), learning models (Do), student diversity (Check), and teacher knowledge and skills (Act). The research proposed a course evaluation template encompassing stakeholders, potential uses, methods/sources, criteria, and required resources/skills/time frameworks, and elaborated on it through a teaching plan for an undergraduate logistics management course. Salinas-Navarro et al. [15], using a food supply chain case during the COVID-19 pandemic, validated the effectiveness of the experiential learning framework. The study found that by engaging in real-world problem-solving, students achieved a minimum acceptable level of 77% in ABET student outcomes (problem-solving ability, engineering design ability, experimental ability), 100% in creativity and innovation, and 69% in critical thinking. Student surveys showed that the relevance, interest, and motivation of the learning experience remained high after course completion.

2.5 Research Review and Conclusion

The era of smart logistics demands interdisciplinary competencies from talent cultivation, with operations research optimization and intelligent decision-making abilities becoming core literacies [1, 6]. Innovative teaching methods such as simulation, serious games, and experiential learning have shown significant effectiveness in cultivating students' operations research and intelligent decision-making abilities [8, 12, 13]. Industry-education integration, university-enterprise collaboration, and training base construction are effective pathways for building practical teaching systems [19, 20]. Curriculum design frameworks based on constructive alignment and experiential learning provide methodological guidance for teaching reform [15, 24].

However, existing research still has limitations: First, most studies are single-case or small-sample studies, and the generalizability of their conclusions needs further verification [17]. Second, research on teaching systems that deeply integrate operations research optimization and intelligent decision-making is relatively insufficient [3]. Third, there is a lack of comparative studies on the application effectiveness of blended online and offline teaching models in smart logistics practical education [5]. Future research should further explore deeply integrated teaching models of operations research algorithms and intelligent decision-making, the development of virtual-actual combined practical teaching platforms, and the design of personalized learning paths based on learning analytics.

3 Multi-level Design of the Practical Teaching System

Centered on "cultivating algorithmic thinking," this practical teaching system breaks through the traditional limitation of the Smart Logistics course, which emphasizes "hardware operation over decision logic." It restructures the practical components from "software usage training" to "optimization rule design." By applying "scenario desensitization + difficulty layering" to complex combinatorial optimization problems such as low-altitude delivery route planning and automated warehouse scheduling, these problems are transformed into teachable cases that are understandable, operable, and verifiable for undergraduate students. This establishes a three-level progressive practical teaching chain consisting of the Basic Level, Comprehensive Level and Innovative Level, enabling a capability leap from "data cognition" to "model construction" and then to "frontier exploration."

3.1 Basic Level: Logistics Data Processing and Validation Experiments

3.1.1 Practical Content

This level focuses on "logistics data perception and preprocessing," using Python as the core programming tool. Experiments are designed around the full process of "data acquisition, cleaning, visualization and analysis." Specific contents include: (1) Using the Pandas library to read and clean logistics order data (handling missing values, outliers, duplicates) and to extract features (e.g., order time, geographic location, product weight, etc.); (2) Performing spatial data visualization with libraries such as Matplotlib, Seaborn, or Folium, generating order distribution heatmaps and time-series trend graphs;(3) Guiding students to interpret the data based on visualization results, identifying key characteristics such as delivery hotspot areas and peak order periods.

3.1.2 Teaching Objectives

Through the basic-level experiments, students develop "data sensitivity" and "fundamental engineering skills". First, they build an intuitive understanding of logistics data, recognizing that "data is the foundation of decision-making". Second, they master the core syntax of Python programming and commonly used libraries for data processing, moving away from reliance on "off-the-shelf logistics software". Third, they form a thinking habit of "identifying problems from data," providing scenario inputs for model construction at the subsequent comprehensive level.

3.1.3 Teaching Case Design: Analysis of Distribution Characteristics of Historical Express Orders in a Certain Region

Case Background: A historical express order dataset from a provincial capital city over a three-month period is provided (containing fields such as order ID, recipient latitude/longitude, order time, package weight, etc., with approximately 50,000 records). Students are required to analyze the spatial and temporal distribution characteristics of express orders in this region to provide data support for optimizing delivery station locations.

Data Preprocessing: Use Pandas to read the CSV-format data, removing orders with missing latitude/longitude or abnormal order times. Convert order times into dimensions of "hour, day, week," extracting features such as "weekday/weekend" and "morning/afternoon/evening periods." Apply grid-based processing to recipient coordinates (e.g., aggregating into 500m × 500m grids).

Heatmap Visualization: Use the Folium library combined with geolocation data to generate a spatial heatmap of orders, identifying the top-10 hotspots by order density. Use Seaborn to generate a temporal heatmap of order distribution (horizontal axis: hour, vertical axis: day of week), identifying peak periods (e.g., pre-warehouse order surges during "Double 11," weekday evening delivery peaks).

Analysis and Validation: Guide students to compare the heatmap with actual urban functional zones (e.g., CBD, university districts, residential areas) to validate the hypothesis that "hotspots are positively correlated with population density." Calculate order concentration indices for hotspot areas (e.g., CR5 index) and propose "preliminary site selection suggestions for delivery stations," laying the groundwork for the "location model" experiment at the comprehensive level.

3.2 Comprehensive Level: Implementation of Classical Operations Research Models in Logistics Scenarios

3.2.1 Practical Content

This level focuses on "scenario-based implementation of classical operations research models." Core logistics problems (Location, Routing, Inventory) are abstracted into mathematical models. Through a closed-loop training process of problem definition, model construction, algorithm implementation, and result comparison, students gain an understanding of "how optimization rules drive efficiency improvements in logistics systems." Specific contents include: Application of integer programming models in distribution center location; Implementation of heuristic algorithms for TSP/VRP problems; Visualization and business interpretation of model results.

3.2.2 Teaching Objectives

Through comprehensive-level experiments, students develop "modeling thinking" and "problem-transformation abilities". First, they learn methods for transforming "logistics business problems" into "mathematical optimization problems" (defining objective functions, decision variables, and constraints). Second, they understand the applicable scenarios and limitations of classical operations research models. Third, through comparison of "manual experience" versus "algorithmic decision-making," they build an intuitive understanding of the "value of algorithms."

3.2.3 Teaching Case Design

Case A: Logistics Distribution Center Location Based on Integer Programming

Case Background: Based on the "five order hotspot areas" identified in the basic-level experiment, it is assumed that three distribution centers need to be selected from ten candidate locations. Each candidate location has a construction cost and capacity limit, and each hotspot area has a fixed order demand. The objective is to make location decisions that minimize the "total construction cost + transportation cost." Model Construction: Define decision variables (0-1 variables: whether to build a distribution center at a candidate location; continuous variables: shipment quantity from distribution center i to hotspot area j). Objective function: min (construction cost + unit transportation cost × shipment quantity). Constraints: demand of each hotspot area must be met; shipment quantity from each distribution center cannot exceed its capacity; exactly three distribution centers can be selected.

Algorithm Implementation: Use Python's PuLP library (open-source linear programming solver) or the Gurobi educational interface to build the model. Input parameters such as candidate location coordinates, hotspot area demands, and transportation cost matrix, then call the solver to solve the integer programming problem. Result Comparison: Guide students to first manually select three locations based on "experience" (e.g., choosing geographic centers) and calculate the total cost. Then compare with the "optimal location solution" obtained by the algorithm, analyzing reasons for differences (e.g., the algorithm considers the trade-off between capacity constraints and transportation costs). Finally, use Matplotlib to draw a "location plan and transportation route map" for business-oriented interpretation.

Case B: Algorithmic Implementation of Classical TSP/VRP Problems

Case Background: Assume a distribution center needs to deliver parcels to ten communities. Each community has a fixed location and order volume, and the maximum load capacity of a delivery vehicle is 500 kg. Requirements: (1) Solve the Traveling Salesman Problem (TSP): if one vehicle delivers to all communities, find the shortest route. (2) Solve the Capacitated Vehicle Routing Problem (CVRP): if multiple vehicles are needed, find a solution that minimizes the number of vehicles and the total route length. Manual Route Planning Experience: Have students first manually design TSP routes and CVRP solutions based on a map, recording route lengths and the number of vehicles to establish an "experience baseline." Algorithm Implementation: For the TSP, use a Genetic Algorithm (implemented with Python's DEAP library), defining "route encoding," "fitness function (route length)," and "crossover/mutation operators," then iteratively solve for the optimal route. For the CVRP, use the Clarke-Wright saving algorithm combined with PuLP, implementing a "cluster-first, route-second" approach.

Effect Comparison: Visually display the differences between "manual routing" and "algorithm-optimized routing," comparing route lengths (algorithms are expected to achieve reductions in total route length, as demonstrated in prior studies [8]). Guide students to analyze "how algorithms avoid local optima through global search" and discuss "the limitations of manual routing when the number of communities increases to 50."

3.3 Innovative Level: Intelligent Decision-Making and Exploration of Cutting-Edge Scenarios

3.3.1 Practical Content

This level focuses on "integrating cutting-edge algorithms with emerging logistics scenarios." It introduces industry hotspots such as the low-altitude economy, green logistics, and dynamic scheduling. Through "simplified models + simulation verification," students are exposed to advanced techniques like reinforcement learning and metaheuristic algorithms, fostering innovative thinking. Specific contents include: (1) Low-altitude logistics path planning under constraints; (2) Dynamic order allocation based on intelligent algorithms; (3) Simulation experiments and parameter tuning for cutting-edge scenarios.

3.3.2 Teaching Objectives

Through innovative-level experiments, students develop "innovative thinking" and "ability to apply cutting-edge technologies". First, they understand industry frontiers in smart logistics (e.g., low-altitude delivery). Second, they grasp the core ideas and applicable scenarios of reinforcement learning and metaheuristic algorithms. Third, they build "decision-making thinking in dynamic environments" to cope with uncertainty in logistics scenarios.

3.3.3 Teaching Case Design

Case 1: Low-Altitude Logistics Path Planning – Considering Drone Battery and Load Constraints.

Case Background: Assume a city pilot project for drone delivery. A drone has a maximum load capacity of 5 kg and a maximum range of 20 km (battery limitation). It must start from a distribution center to deliver parcels to eight communities (some communities require intermediate recharging at “virtual charging stations”). The task is to construct a path optimization model that considers both battery and load constraints, and find the shortest delivery route.

Simplified Model Construction: Abstract the problem as “constrained directed graph path planning.” Nodes include the distribution center, communities, and virtual charging stations. Edges have weights representing distance, and constraints include “load not exceeding capacity” and “battery level not below threshold.” The objective function is to minimize total flight distance.

Algorithm Implementation: Use Python’s NetworkX library to build the graph model. Combine it with a modified A* algorithm (incorporating heuristic functions for battery and load) to solve for the optimal path. Alternatively, simplify it as a mixed-integer programming model and solve using Gurobi.

Simulation Verification: Design comparative experiments with different order weight combinations (e.g., splitting orders that exceed the weight limit at some communities) and observe changes in the path. Discuss the impact of advancements in drone endurance technology on path planning, guiding students to think about the synergistic development of cutting-edge technologies and algorithms.

Case 2: A Preliminary Exploration of Intelligent Dispatching – Dynamic Order Allocation Based on a Metaheuristic Algorithm

Case Background: Assume an on-demand delivery platform has five riders and receives dynamic orders in real time (3–5 new orders every 5 minutes). Each order includes “pick-up point – delivery point – expected delivery time.” Rider status includes “location – current load – remaining battery power.” The task is to design a “dynamic order allocation strategy” that maximizes the “on-time delivery rate” and minimizes the “total travel distance of riders.”

Algorithm Selection and Simplification: Introduce a metaheuristic algorithm such as the Grey Wolf Optimizer (GWO) or a Genetic Algorithm. Encode “order–rider matching” as a solution vector, and define a fitness function (weighted on-time rate + travel distance). To reduce difficulty, simplify the dynamic problem into a sequence of static optimization problems re-optimized every 10 minutes.

Simulation Environment Construction: Use Python’s SimPy library to build a simple on-demand delivery simulation environment, simulating order generation, rider movement, order completion, etc. Preset order generation rates for two scenarios: “morning peak” and “off-peak.”

Parameter Tuning and Comparison: Have students adjust parameters of the Grey Wolf Optimizer (e.g., convergence factor, population size) and observe changes in algorithm performance. Compare the results of the metaheuristic algorithm with a First-Come-First-Served (FCFS) strategy (on-time rate improvement of 10%–20%). Discuss the potential application of reinforcement learning in fully dynamic environments to stimulate students' interest in further exploration.

4 Project-Driven Teaching Organization and Implementation

Project-driven teaching serves as the core implementation vehicle of this practical teaching system. Its primary goal is to connect the knowledge points across the three-level practical chain (Basic – Comprehensive – Innovative), breaking down the barrier between "theoretical learning" and "engineering practice." By using complete projects based on real-world logistics scenarios as a driver, it simulates the full-process operation mode of enterprise smart logistics decision-making projects. This allows students to transition from "fragmented learning of knowledge points" to "integrated capability building across the entire chain" while "solving real problems," truly realizing the pedagogical shift from "software operation training" to "algorithmic decision-making design."

4.1 Project Topic Design Guided by Regional Characteristics

The project topics in this course strictly follow four principles: authenticity, adaptability, regional relevance, and innovativeness. They deeply align with the locational advantages and industrial development characteristics of the region. Priority is given to selecting real, desensitized business scenarios from local logistics enterprises. Complex industry problems are adapted in terms of difficulty and simplified into course projects that undergraduate students can realistically complete, ensuring that the topics are both aligned with industry frontiers and highly matched with the core knowledge points of the course. The core topic directions are divided into cross-border logistics and international supply chains, smart supply chains for specialty agricultural products, and intelligent decision-making for distinctive scenarios.

First, focusing on core cross-border logistics scenarios such as the cross-border railway corridor and the New International Land-Sea Trade Corridor, topics are set such as "Location selection for cross-border cold chain logistics hubs and multimodal transport route optimization" and "Intelligent inventory scheduling and order fulfillment optimization for cross-border e-commerce bonded warehouses," precisely targeting real business pain points in the cross-border logistics field. Second, focusing on specialty agricultural industries such as fresh cut flowers, specialty fruits and vegetables, and regionally advantageous cash crops, topics are set such as "Origin warehouse layout for fresh cut flowers and full-chain cold chain delivery route optimization" and "Last-mile node location and joint delivery optimization for upstream specialty agricultural products," deeply integrating teaching content with local industrial development. Third, considering complex environmental characteristics such as mountainous terrain and urban-rural delivery networks, topics are set such as "Low-altitude drone delivery route optimization for emergency supplies in mountainous areas" and "Rural logistics joint delivery network optimization," incorporating industry frontiers such as the low-altitude economy and green logistics, and forming a linkage with the innovative-level practical content.

The topics adopt a semi-open model: students can, under the guidance of instructors, independently engage with local logistics enterprises to obtain real needs and design project themes. While ensuring the feasibility and innovativeness of the projects, this approach cultivates students' abilities in demand discovery and business insight.

4.2 Team Role Design Simulating Real-World Enterprise Scenarios

In this course, project teams are formed in units of 3–4 students. The principle of heterogeneous grouping is adopted, with the instructor making fine-adjustments to ensure a reasonable mix of students with different programming backgrounds and disciplinary specializations (e.g., logistics management, logistics engineering, data science), thereby enabling complementary capabilities. The team division fully simulates the real R&D project structure of logistics technology enterprises, establishing three core roles with clear responsibilities and deliverables. At the same time, a role rotation mechanism is implemented to ensure that every student participates in the entire project process, avoiding "fragmented division of labor" and "unbalanced skill development."

The Demand Analyst interfaces with business scenarios and project requirements, translating logistics business language into standardized, modelable requirements. They clarify the core optimization objectives, business boundaries, and hard constraints of the project, and produce the Project Requirements Specification. They also take the lead in converting the final results into management decision recommendations. This role serves as the core bridge between the "business scenario" and the "mathematical model."

Based on the requirements specification, the Modeling Engineer abstracts real logistics business problems into formal operations research optimization models, clearly defining decision variables, objective functions, and various constraints in mathematical expressions. They select appropriate solution algorithms (operations research programming algorithms / heuristic algorithms / metaheuristic algorithms) and produce the Mathematical Model Design and Algorithm Selection Report. This role is the technical core of the project.

Using Python as the core tool, the Algorithm Developer implements the algorithm according to the model design document, calls relevant solvers to solve the model, conducts multiple rounds of parameter tuning and result validation, identifies logical flaws in the model and code, and delivers a reproducible complete code package, algorithm debugging logs, and a visualized report of the solution results. This role is key to transforming "mathematical formulas" into "executable solutions."

4.3 Phased Implementation Path with Full-Chain Closed Loop

The PBL project implementation cycle for this course is 8 weeks, conducted after the completion of the "Basic Level + Comprehensive Level" practical teaching, ensuring that students have already acquired fundamental programming and modeling skills. The project follows the core logic of "scenario restoration → model construction → code implementation → solution deployment" and is divided into three progressive implementation phases. Each phase has clear teaching activities, deliverables, and assessment checkpoints, which together form a complete teaching closed loop.

Phase 1: Scenario Restoration and Mathematical Description (Weeks 1–2)

The core goal of this phase is "to transform business language into mathematical formulas," completing the key conversion from business problems to optimization problems. In teaching implementation, the course instructor and industry mentors from partner enterprises jointly conduct scenario briefings, explaining real business scenarios such as cross-border cold chains and specialty agricultural product supply chains, and provide desensitized business data. The team, led by the Demand Analyst, then decomposes the business scenario, clarifies the core optimization objectives, and sorts out all business constraints, producing the Project Requirements Specification. Subsequently, led by the Modeling Engineer, the business problem is converted into a standardized operations research optimization model, with decision variables, objective functions, and constraints formally defined, resulting in the Mathematical Model Design Specification. At the end of this phase, a proposal defense is held, where university and enterprise mentors review the reasonableness of the requirements and the rigor of the model, correcting any directional deviations in a timely manner.

Phase 2: Code Implementation and Parameter Tuning (Weeks 3–6)

The core goal of this phase is "to transform mathematical formulas into executable code," completing the transition from theoretical models to engineering implementation. The teaching adopts a model of "small-group tutoring by instructors + independent student development." Targeted guidance is provided on technical difficulties such as solver usage and algorithm implementation. Simultaneously, a standardized course code library is opened, offering basic algorithm frameworks and templates to reduce the development difficulty for students without a computer science background. The team, led by the Algorithm Developer, reuses the Python programming skills acquired earlier to complete the entire development process: data preprocessing, model coding, solver invocation, and algorithm implementation. Through multiple rounds of parameter tuning and result validation, code bugs and model logic flaws are identified and fixed. Finally, a reproducible code package, algorithm debugging logs, and a visualized report of solution results are delivered. During implementation, a weekly progress report meeting is held, and the instructor follows up on project progress to ensure orderly advancement.

Phase 3: Solution Evaluation and Decision Report (Weeks 7–8)

The core goal of this phase is "to transform solution results into actionable management

Table 1. Assessment Dimensions and Weightings.

Assessment Dimension	Weight	Core Assessment Content
Performance in Layered Practical Exercises	30%	Quality of completion of Basic-level, Comprehensive-level, and Innovative-level experiments, including completeness of lab reports, correctness of code, and reasonableness of result analysis. Process scores are recorded progressively based on completion of each individual experiment.
Full-Process Performance in PBL Project	40%	Phased assessment: Phase 1 – Quality of requirements analysis and modeling (10%); Phase 2 – Code implementation and debugging ability (15%); Phase 3 -Project report and final defense performance (15%). Individual scores are adjusted based on team peer evaluation and personal contribution to prevent "free-riding."
Comprehensive Core Competency Assessment	30%	Assessment of three core abilities: rigor of model construction (alignment with requirements, completeness of constraints); code quality and readability (completeness of comments, structural clarity, reusability); problem-solving ability (reasonableness of logic for handling exceptional scenarios and constraints).

recommendations," achieving the leap from technical solutions to managerial decisions and breaking the teaching misconception of "emphasizing technology over business." The instructor first provides specialized guidance on writing the project report, helping students shift from a technical perspective to a managerial one. The team then compares traditional experience-based decisions with algorithm-optimized solutions from three dimensions: core optimization effectiveness, algorithm solving efficiency, and feasibility of business deployment, quantifying the application value of algorithmic decision-making. Finally, led by the Demand Analyst, the team completes the Smart Logistics Decision Optimization Solution Report, which, in addition to technical content, focuses on proposing actionable management decisions and operational optimization recommendations for the corresponding business scenario. At the end of this phase, a final defense is held, where each team presents their outcomes and is evaluated by university and enterprise mentors, completing the full-process closed loop of the project.

5 Evaluation System and Resource Construction

5.1 A Comprehensive, Multi-Dimensional, Process-Oriented Assessment System

This course breaks away from the traditional single assessment model of "one final exam" or "only looking at final results." It establishes a comprehensive, multi-dimensional assessment system that combines "process-oriented and summative evaluation" and places equal emphasis on "technical ability and business capability." The core assessment logic shifts from "whether the code runs" to "whether the model is rigorous, whether the logic is clear, and whether the solution is feasible," thereby comprehensively evaluating students' overall competencies. The total assessment score is 100 points, with an additional innovation bonus of up to 10 points. The specific assessment dimensions and weightings are shown in Table 1.

The innovation bonus points (maximum 10 points) focus on encouraging students' algorithmic innovation and in-depth exploration. Core scenarios eligible for bonus points include: conducting efficiency comparison and applicability analysis of multiple algorithms (e.g., comparing the solution efficiency and optimization performance of the Genetic Algorithm and Grey Wolf Optimizer on the same Vehicle Routing Problem (VRP)); improving fundamental algorithms and verifying their optimization effects; completing simulation and decision optimization for dynamic logistics scenarios; and aligning project outcomes with actual enterprise needs and obtaining actionable on-the-ground implementation feedback, among others.

A three-in-one validation model integrating "defense, documentation, and code" is adopted throughout the entire assessment process. All code must be submitted to the course's open-source code repository to ensure instructors can fully reproduce the solution results, eliminate plagiarism, and foster students' academic integrity and open-source spirit.

5.2 Development of a Hierarchical and Standardized Teaching Resource Repository

To alleviate programming anxiety among students from non-computer science (non-CS) backgrounds, and ensure the implementability and scalability of the teaching system, this course simultaneously develops two core teaching resource repositories: the standardized code repository and the scenario-based case repository, to realize the open-source sharing and continuous iteration of teaching resources.

5.2.1 Development of the Open-Source Standardized Code Repository

The code repository adopts a "dual-platform synchronization" model: the primary platform is deployed on GitHub for global open-source sharing, with a synchronized backup on the synchronized backup on the campus teaching platforms (Chaoxing or Rain Classroom) to resolve access restrictions under the campus network.

The repository is strictly structured in layers in accordance with the "Basic Level - Comprehensive Level - Innovation Level" practice system. All code is accompanied by detailed annotations and user manuals, forming standardized algorithm templates that are ready-to-use, modifiable, and extensible, which significantly lowers the learning threshold for students.

Basic Level code templates include standardized Python code for logistics data processing and spatial visualization, such as complete examples of order data cleaning with Pandas, order heatmap plotting with Folium, and time series feature extraction. Zero-based students can quickly reuse the code by modifying input data to complete basic experimental tasks. Comprehensive Level code frameworks include standardized implementation frameworks for classic operations research optimization models, such as a PuLP-based integer programming model for distribution center location selection, a basic Genetic Algorithm-based solution framework for the Traveling Salesman Problem (TSP)/VRP, and solution templates for inventory optimization models. Students only need to modify input parameters, constraint conditions, and objective functions to quickly adapt the frameworks to their own business scenarios, without writing code from scratch. Innovation Level algorithm examples include extended code templates for low-altitude logistics path planning, dynamic order dispatching, metaheuristic algorithms, and basic reinforcement learning implementation, providing foundational support for innovative exploration by high-achieving students who have mastered core content with ease.

The code repository adopts a maintenance mechanism of "instructor-led, student co-construction". Excellent student project code and innovative algorithm implementations are updated each semester to continuously enrich the repository content, while version control is implemented to ensure the reproducibility of all code.

5.2.2 Development of a Localized and Scenario-Based Case Repository

The case repository is deeply integrated with the course's practical training system and PBL project topics. All cases prioritize the use of anonymized real data and business scenarios from local enterprises, ensuring authenticity, practical applicability, and regional characteristics.

Basic verification cases focus on validation experiments for individual knowledge points, such as analyzing the distribution characteristics of express orders, solving for single distribution center locations, and implementing simple TSP problems. Each case is accompanied by a complete scenario description, data files, modeling guidance, and reference results, suitable for basic-level practical teaching.

Comprehensive application cases focus on multi-constraint optimization problems in core logistics processes, such as multi-hub location for cross-border cold chains, solving CVRP for urban last-mile delivery, and multi-product joint inventory optimization. These come with complete business backgrounds, real datasets, and modeling requirements, suitable for comprehensive-level practical teaching.

Innovative exploration cases focus on complex decision-making problems at the industry frontier, such as route optimization for drone low-altitude delivery, dynamic order dispatching for on-demand delivery, and multi-objective optimization for green logistics. They include scenario backgrounds, core constraints, and exploration directions, suitable for innovation-level practical teaching and PBL project topics.

The case repository adopts a school-enterprise co-construction model, establishing long-term collaborations with local logistics companies, cross-border logistics parks, and leading supply chain enterprises. It is regularly updated with the latest industry pain points and scenario cases, ensuring that teaching content evolves in step with industry development.

6 Conclusion

This paper addresses the core pain points prevalent in current Smart Logistics course instruction—namely, "overemphasis on hardware, underemphasis on algorithms; overemphasis on theory, underemphasis on practice." It closely aligns with the new "algorithmic thinking" requirements for logistics talents driven by industry developments such as low-altitude economy, intelligent last-mile delivery, and automated warehousing. A practical teaching system for the Smart Logistics course has been constructed, with operations research optimization as the underlying logic, intelligent decision-making as the core application, and programming practice as the implementation method.

In the future, this research will further explore optimization and upgrading of the teaching system. A digital twin virtual simulation experimental platform for smart logistics will be built, creating high-fidelity virtual logistics scenes that map 1:1 to the real physical world. These scenes will cover core scenarios including automated stereoscopic warehousing, urban last-mile joint delivery, low-altitude drone logistics, and cross-border multimodal transport, enabling real-time bidirectional interaction between "algorithmic models" and the "virtual physical environment."

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The author declares no conflicts of interest.

AI Use Statement

The author declares that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

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