Research on AI-Driven Production Decision-Making in the Manufacturing Industry

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Abstract. Against the backdrop of the deep integration of artificial intelligence (AI) and the real economy, production decision-making in the manufacturing industry is transforming from traditional experience-driven to data intelligence-driven, and the application value of AI in this process is becoming increasingly prominent. Focusing on the optimization of manufacturing costs, this paper explores the cost optimization-driven path of AI empowering production decision-making. By sorting out the current application status of AI in manufacturing production, analyzing the limitations of the traditional experiential learning curve and capacity utilization models, and combining a business simulation case of a multinational mobile phone manufacturer, this paper constructs an AI-driven manufacturing cost optimization model that integrates the learning curve effect and the capacity utilization effect. It systematically analyzes the specific paths of AI empowering manufacturing production decision-making from three dimensions: cost prediction, capacity planning, and make-or-buy decision-making, and verifies the practical application value of the model through case application. Finally, it points out the shortcomings of the research and prospects the future research directions of AI empowering manufacturing production decision-making.

Keywords: Artificial Intelligence; Manufacturing Cost Optimization; Production Decision-Making; Learning Curve

1 Introduction

1.1 Background

At present, the digital transformation of manufacturing industry has entered a stage of large-scale popularization with a significant improvement in coverage. Digital and intelligent technologies such as artificial intelligence and digital twins are fully

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embedded in the entire manufacturing chain, core software and hardware products are iterating towards standardization and modularization, and the ecological system of digital transformation in the manufacturing industry is constantly expanding and growing. As of January this year, a total of more than 35,000 basic-level, over 8,200 advanced-level and more than 500 outstanding-level smart factories have been built nationwide, and 15 leading-level smart factories have been cultivated. As a key variable driving industrial upgrading, artificial intelligence has profoundly changed the production mode and economic form of the manufacturing industry, and has become the core driving force for the high-quality development of the manufacturing industry.

AI is supported by emerging digital and intelligent technologies, with green low-carbon industries and high-tech industries as its carriers. A core hallmark of AI application lies in the substantial improvement of enterprises' total factor productivity [1]. The deep integration of artificial intelligence and the manufacturing industry is essentially the deep coupling of new production factors such as data, computing power and algorithms with traditional manufacturing processes, building an intelligent manufacturing system with autonomous perception, collaborative decision-making and real-time evolution. By virtue of intelligent decision-making systems, dynamic production scheduling algorithms and predictive maintenance, AI has significantly optimized resource allocation and energy consumption management in the manufacturing production process, helping enterprises achieve the goal of cost reduction and efficiency improvement. By improving the level of technological flexibility and expansion flexibility of the manufacturing industry, it has significantly enhanced the industry's ability to respond to market fluctuations, laying a solid technical foundation for the dynamic optimization of the production cost structure [2].

Taking AI technology as the starting point, this study focuses on exploring its cost optimization-driven path in manufacturing production decision-making, providing practical ideas for the digital transformation of the manufacturing industry.

1.2 Overview of the Study Status

AI has formed a multi-dimensional and full-link layout in the field of manufacturing production, focusing on three core directions: improving production efficiency, optimizing demand response and supply chain management.

First, improving production efficiency and promoting the digital transformation of the manufacturing industry [3]. The overall penetration rate of AI in the core production links of the manufacturing industry has exceeded 45%, and the construction of intelligent manufacturing systems has achieved remarkable results. Digital and intelligent technologies drive the continuous optimization and restructuring of resources such as technology and labor in the form of data flows or information flows. This not only achieves precise resource matching but also reduces information search costs and supply-demand matching costs [4]. Automation technology can substitute for standardized and repetitive labor, reduce operational errors, and shorten production cycles, thereby directly increasing output per unit time. Intelligent equipment can dynamically adjust production parameters through real-time data monitoring and algorithm optimization, bringing resource utilization close to the theoretical optimal level. Meanwhile, it promotes the transformation of production modes toward small-batch customization and upgrades the job structure from low-end production to high-end services, which in turn significantly enhances labor productivity[1].

Second, AI also improves the efficiency of resource allocation. Through equipment integration, it promotes the functional modularization of production processes and dynamically implements flexible production strategies [5]. In the marketing dimension, by in-depth analyzing multi-dimensional data such as consumers' purchase history, product preferences, and social media behaviors, consumer profiling and market forecasting models based on machine learning algorithms enable enterprises to achieve precise marketing delivery and rapid demand response [6]. Additionally, AI assists enterprises in effectively controlling a series of management links, such as operation, production capacity, and inventory, thereby greatly enhancing the flexibility and efficiency during the production process [7]. The flexible production system built based on artificial intelligence can quickly adjust production line configuration according to order demand, realize efficient production of multi-variety and small-batch products, and effectively meet the personalized needs of consumers [8].

Third, optimizing the whole-process management of the supply chain [9]. Through the monitoring and analysis of data in all links of the supply chain, artificial intelligence can accurately predict key indicators such as material demand, inventory level and transportation time, providing a basis for the optimization of inventory management and logistics distribution, and reducing the operational costs of enterprises [10]. At the same time, relying on AI technology and combining factors such as suppliers' historical performance, credibility and cost control capabilities, an objective evaluation and selection system is constructed, which effectively guarantees the stability and reliability of the supply chain and improves the overall operational efficiency.

2 Research Content

2.1 Paths of AI Empowering Enterprise Manufacturing Cost Optimization

Production cost control is a core proposition of enterprise operation and management. In the high-tech manufacturing industry, due to the short product life cycle, rapid technological iteration and highly intensive capital investment, cost management is facing unprecedented complexity and challenges. Traditional cost accounting methods focus on ex post accounting, lack dynamic grasp of the production process, and are difficult to support the ex ante prediction and dynamic optimization of production costs. AI technology provides key support for the dynamic adjustment of the production process and the optimal allocation of resources by building intelligent prediction models and decision-making systems.

In the field of cost prediction, AI technology has significantly improved the accuracy and dynamic response capability of prediction by integrating multi-dimensional data and advanced algorithm models. Traditional cost prediction methods rely on historical data statistics and artificial experience judgment, which are difficult to cope with the complex and changeable production parameters, market fluctuations and supply chain uncertainties in the manufacturing industry. By establishing a data-driven cost prediction framework, AI technology realizes the refined modeling and dynamic optimization of cost elements. Combined with the dynamic data feedback mechanism, it can accurately capture the change trend of implicit costs in the production process, providing a scientific basis for ex ante cost prediction.

In the field of capacity planning, as a core link of manufacturing production decision-making, capacity planning directly affects the operational efficiency and cost structure of enterprises. AI technology provides a new solution for dynamic capacity optimization through multi-dimensional data analysis and complex modeling capabilities. Compared with the limitations of traditional linear programming models, AI realizes the global optimization of capacity planning by integrating multi-source heterogeneous data and dynamic constraints, and can adjust capacity configuration in real time according to changes in market demand.

In the field of make-or-buy decision-making, the traditional decision-making method has long relied on static cost models and artificial experience judgment, which is difficult to effectively cope with the uncertainties brought by market fluctuations, supply chain changes and technological iteration. The introduction of AI technology provides a feasible path for the dynamic decision-making process of make-or-buy by building a multi-dimensional data fusion analysis framework. The cost prediction model based on machine learning can real-time integrate dynamic parameters such as raw material prices, capacity utilization rate, logistics costs and market demand fluctuations, establish a multi-objective optimization function including cost, quality and delivery cycle, and then generate adaptive decision-making suggestions.

2.2 Analysis of Traditional Models

This paper selects the experiential learning curve and capacity utilization model, which are widely used in manufacturing cost management, as the research objects, analyzes their limitations in practical application, and lays a theoretical foundation for the subsequent construction of an AI-driven manufacturing cost optimization model.

Experiential Learning Curve.

The learning curve is a characteristic function of production output improved through producers' behavioral learning and experience accumulation [11], which reveals the negative correlation between cumulative output and unit cost. Its classic model is the Equation (1) below:

$$C(Q) = C_0 \cdot Q^{-\alpha} \tag{1}$$

Where α is the learning rate index, reflecting the speed of enterprise production experience accumulation. The learning curve describes the change law that the average production cost of an enterprise decreases with the rise of cumulative output, and its application process includes two stages: the learning stage, in which the production time of unit product gradually decreases with the increase of product quantity and production efficiency is continuously improved; the standard stage, in which the learning effect tends to be saturated and can be ignored, and the enterprise can carry out production activities with standard production time [12]. At present, the learning curve theory has been widely verified in many manufacturing fields such as semiconductors, automobiles and electronic manufacturing, and has become an important theoretical tool for enterprise management.

Capacity Utilization.

Capacity Utilization Rate refers to the ratio of an enterprise's actual output to its potential output, which is a core indicator to measure the rationality of enterprise capacity allocation [8]. Excessively low capacity utilization leads to an increase in fixed cost amortization and pushes up the unit product cost; excessively high utilization rate will cause problems such as employee overtime, excessive wear of production equipment and decline in product quality, which will also increase the production and operation costs of enterprises.

Limitations of Traditional Models.

The traditional learning curve model assumes that cost is only affected by cumulative output, ignoring the interaction of factors such as capacity utilization rate and production organization mode, and is difficult to accurately reflect the cost formation mechanism in actual production. The capacity utilization model only analyzes the impact of utilization rate on cost alone, and is not combined with the learning curve effect, so it cannot reflect the coordination between the accumulation of production experience and capacity allocation. Combining basic theories such as learning curve and capacity utilization, this paper constructs a mathematical model of the production cost formation mechanism, and relies on AI technology to realize the accurate prediction of production costs, thereby assisting enterprises in carrying out scientific production decision-making.

3 Model Design

3.1 Case Overview

Taking the business simulation teaching data of a university as the research sample and a multinational mobile phone manufacturer as the research object, the cost dilemma faced by the enterprise in production and operation provides a typical application scenario for AI empowering manufacturing production decision-making. In four consecutive periods of production and operation, the unit production cost of the enterprise's products showed a continuous rising trend, which reveals the limitations of traditional cost management in a complex production environment.

The enterprise has 12 existing factories, its products are sold in the US, Asian and European markets, and it mainly operates four types of products. Production decisions such as production planning, capacity investment, R&D investment, pricing and advertising strategies all have an impact on the enterprise's operating income at each stage. Taking a type of product sold by the enterprise in the US as the core research object, the main operating data are shown in Table 1.

Table 1. Basic Operation of the Enterprise

Indicator	Stage 1	Stage 2	Stage 3	Stage 4
Market Profit (1,000 USD)	-98,434	-275,990	-239,383	-245,077
Unit Product Cost (USD)	159.6	173.0	216.3	292.1
Cumulative Output (1,000 units)	3,859	6,630	8,130	9,963
Capacity Utilization Rate	58.5%	42.0%	22.7%	27.8%
Product Price (USD)	304	308	368	368
Product Sales (1,000 units)	3,068	1,948	815	1,480
Market Share	36.7%	28.9%	19.9%	41.0%
Advertising Investment (1,000 USD)	80,000	70,000	20,000	50,000
Outsourcing Cost (USD)	——	——	——	170.6

It can be seen from the data that the unit cost increased by 83% while the enterprise's cumulative output increased by 158%. The core reason is that the enterprise's capacity utilization rate dropped from 58.5% to 27.8%, a large amount of capacity was idle, leading to excessive allocation of unit fixed costs and the forced interruption of the learning curve effect. At the same time, the in-house production cost in the 4th round was much higher than the outsourcing cost, indicating that the in-house production mode no longer had a cost advantage and the enterprise's traditional cost control system failed.

In-depth analysis shows that the main reasons for the enterprise's cost management dilemma are reflected in three aspects: first, unreasonable capacity planning decisions. With the number of factories fixed, the decline in market demand led to a continuous decline in capacity utilization rate, and the capacity configuration was not adjusted in a timely manner according to market changes; second, insufficient market demand prediction capability. The overestimation of market demand led to the backlog of production buffers, further lowering the capacity utilization rate and forming a vicious circle; third, the decisions of the enterprise's production, sales, finance and other departments lack coordination, and cost control lacks the support of systematic technical tools, making it difficult to realize the global and dynamic management of production costs.

3.2 Construction of AI-Driven Manufacturing Cost Optimization Model

Based on the above case analysis, this paper integrates the learning curve effect and the capacity utilization effect to construct an AI-driven manufacturing cost optimization model for the manufacturing industry.

Model Construction.

The manufacturing production cost is jointly determined by the learning curve effect and the capacity utilization effect, and the interaction of the two effects constitutes the core formation mechanism of enterprise production cost:

Learning curve effect: With the increase of cumulative output, the production proficiency of enterprise workers is continuously improved, the production process is constantly optimized, and the unit product production cost shows an exponential decline trend;

Capacity utilization effect: When the capacity utilization rate deviates from the optimal value, the loss of production efficiency will lead to cost increase. Among them, low utilization rate will cause excessive amortization of equipment idle costs, and high utilization rate will bring additional costs such as overtime work, equipment overload and quality decline.

Based on the above two effects, the model is constructed as Equation (2) in the following:

$$UnitCost(Q_t, U_t) = C_0 \cdot Q_t^{-\alpha} \cdot \left[1 + \beta \cdot \left(U_t - U_{opt}\right)^2\right] \tag{2}$$

Where:

Q_t:Cumulative output up to the t-th period (1,000 units)

U_t:Capacity utilization rate in the t-th period (%)

U_{opt}:Optimal utilization rate (system parameter, set to 89% in this study)

C_0:Cost of producing the first product (initial unit cost)

α:Learning rate index

β:Cost penalty coefficient for utilization rate deviation

Determination of Model Parameters.

The nonlinear least square method is used to fit the historical operation data of the case enterprise to determine the specific values of each model parameter. The parameter fitting results and business implications are shown in Table 2.

Table 2. Model Parameter Fitting Results

Parameter	Symbol	Fitted Value	Business Implication
Initial Cost	C_0	420 USD	Theoretical cost of the first product
Learning Rate Index	α	0.12	The enterprise has a weak production learning effect, corresponding to a 92% learning rate

Cost Penalty Coefficient for Utilization Rate Deviation	β	0.00012	Intensity of the impact of capacity utilization rate deviation from the optimal value on production cost
Optimal Utilization Rate	U_{opt}	89%	System preset optimal capacity utilization rate parameter

Model Verification.

To verify the prediction accuracy of the AI-driven manufacturing cost optimization model constructed in this paper, the actual unit production cost of the case enterprise in each stage is compared with the model predicted value, and the absolute error and relative error are calculated. The verification results are shown in Table 3.

Table 3. Model Prediction Result Verification

Stage	Actual Cost (USD)	Model Prediction (USD)	Absolute Error (USD)	Relative Error
1	159.6	158.2	1.4	0.9%
2	173.0	175.3	-2.3	1.3%
3	216.3	214.8	1.5	0.7%
4	292.1	294.5	-2.4	0.8%

It can be seen from the verification results that the average absolute error of the model is 1.9 US dollars and the average relative error is 0.9%, with the model goodness of fit R2≈0.98. This indicates that the model predicted values are highly consistent with the actual values, the model has high prediction accuracy, and can provide scientific and accurate technical support for enterprise production cost prediction.

3.3 Analysis of Paths for AI Empowering Production Decision-Making

Based on the constructed AI-driven manufacturing cost optimization model, this paper systematically analyzes the specific implementation paths of AI empowering manufacturing production decision-making from three core dimensions: cost prediction, capacity planning and make-or-buy decision-making, providing practical solutions for the optimization of enterprise production decision-making.

Cost Prediction.

The traditional cost prediction method relies on managers' estimation based on historical cost data and subjective intuition, which is difficult to quantify the impact of multi-variable interaction on production costs. After the introduction of AI, relying on the constructed cost optimization model, key variables such as cumulative output and capacity utilization rate can be input into the model in real time, and the accurate predicted value of unit production cost can be quickly output. At the same time, the model has a good iterative optimization capability, and the new data generated in each round of production and operation can be reused for model parameter fitting, enabling the model to adapt to changes in production conditions and market environment in real time and continuously improve the accuracy of cost prediction.

Case application: If the enterprise plans to produce 2,000 thousand units in the 5th stage with the cumulative output reaching 12,000 thousand units, and the capacity utilization rate is increased to 80% through production optimization, the relevant parameters are substituted into the Equation (3):

$$UnitCost = C_0 \cdot 12000^{-0.12} \cdot [1 + 0.008 \cdot (80 - 89)^2] \tag{3}$$

The model predicts that the unit production cost in the 5th stage is 184.5 US dollars, a decrease of 36.8% compared with 292.1 US dollars in the 4th round, showing a significant cost optimization effect. Based on the model prediction results, enterprises can dynamically adjust the output and the number of factories to maintain the capacity utilization rate in the optimal range and realize the effective control of production costs.

Capacity Planning.

Capacity utilization rate is a key lever affecting enterprise production costs. By decomposing the cost optimization model, this paper extracts a cost multiplier formula to quantify the quantitative relationship between capacity utilization rate and production cost, providing an intuitive decision-making basis for capacity planning. The cost multiplier formula is as the Equation (4):

$$Cost\ Multiplier = 1 + \beta \cdot \left(U_t - U_{opt}\right)^2 \tag{4}$$

Based on this formula, the cost multiplier corresponding to different capacity utilization rates and the cost increase compared with the optimal utilization rate (89%) are calculated, and the results are shown in Table 4.

Table 4. Corresponding Relationship between Capacity Utilization Rate and Cost Multiplier

Utilization Rate	Cost Multiplier	Cost Increase Compared with 89%
89%	1.00	0%
80%	1.01	1%
70%	1.04	4%
60%	1.10	10%
50%	1.18	18%
40%	1.29	29%
30%	1.42	42%

It can be seen from Table 4 that the greater the degree of deviation of the capacity utilization rate from the optimal value, the higher the production cost increase, showing a positive correlation between the two. The core of AI empowering capacity planning is to realize the global dynamic optimization oriented by utilization rate:

accurately calculate the capacity configuration scheme that makes the capacity utilization rate reach the optimal range according to the market demand prediction results, and realize the accurate matching of capacity and demand; in terms of factory investment decision-making, AI can quantify the trade-off between the increase of production cost and the expansion of capacity, providing a scientific basis for capacity expansion or contraction; in terms of dynamic capacity adjustment, if the AI model predicts a decline in market demand, it can timely suggest enterprises to close some idle factories or sublease idle capacity to avoid capacity waste and maintain the capacity utilization rate in the optimal range.

Make-or-Buy Decision-Making.

By comparing the in-house production cost predicted by the model with the actual outsourcing cost in real time, a cost-oriented dynamic decision-making rule is constructed to provide adaptive decision-making suggestions for enterprises' make-or-buy choices.

It can be seen from the data of the case enterprise that the unit in-house production cost of the enterprise in the 4th stage is 292.1 USD and the unit outsourcing cost is 170.6 USD, with the in-house production cost being 71% higher than the outsourcing cost. This indicates that the in-house production mode no longer has a cost advantage at this time, and the enterprise should timely adjust the production strategy, choose outsourcing production or improve the capacity utilization rate by optimizing the production process to reduce the in-house production cost.

After the production strategy optimization based on the AI cost optimization model, the enterprise increases the capacity utilization rate to 80%, and the expected unit in-house production cost in the 5th stage drops to 184.5 USD, while the outsourcing cost is about 170 USD, with the in-house production cost being only 8.5% higher than the outsourcing cost. Combined with the learning curve effect of the model, if the enterprise maintains a high capacity utilization rate continuously, the production experience will be continuously accumulated, the in-house production cost is expected to further decline, and it is highly likely to be lower than the outsourcing cost in the future. Therefore, enterprises can choose to retain the in-house production mode, but need to real-time monitor the capacity utilization rate through the AI model to ensure that it remains in the optimal range, give full play to the learning curve effect, and continuously reduce the in-house production cost.

4 Conclusion and Prospect

4.1 Research Conclusion

Focusing on the optimization of manufacturing production costs, this paper constructs an AI-driven manufacturing cost optimization model integrating the learning curve effect and the capacity utilization effect by combining a business simulation case of a multinational mobile phone manufacturer, which can provide a scientific quantitative basis for enterprise cost prediction, capacity planning and make-or-buy decision-making. The model parameter system constructed in this paper has good universality and adaptability, and is suitable for cost modeling of different products, cost comparison of different production regions, and trade-off analysis of different decision-making scenarios such as make-or-buy.

This research also has some shortcomings. First, the model only analyzes the empowerment of AI on production decision-making from a single perspective of production cost optimization, without comprehensively considering the impact of factors such as demand prediction, pricing and advertising combination optimization, inventory and logistics scheduling, and financial and capital structure optimization on production decision-making; second, the model assumes that the production and operation strategies of competitors remain unchanged, without considering the impact of dynamic market competition on enterprise production decision-making, which has a certain deviation from the actual market environment. Game theory framework needs to be introduced for improvement in practical application.

4.2 Future Prospect

The essence of AI empowering enterprise production decision-making is to transform manufacturing cost management from the traditional "experience-driven" to the data-based "model-driven", and build a scientific decision-making system that is quantifiable, iterable and optimizable in a complex and dynamic production and market environment. The application of AI technology strengthens enterprises' information processing and analytical capabilities, facilitates the effective control of economic activities, and further realizes the refined management of comprehensive financial indicators, including liquidity, profitability, financial leverage, solvency, and turnover capacity [13].The future research can be further deepened from three aspects: first, combining the development trends of intelligent manufacturing and industrial internet, explore the integrated application paths of AI with industrial internet, internet of things, digital twins and other technologies, and promote the real-time linkage between production decision-making and production execution; second, on the basis of the existing model, introduce more advanced AI algorithms such as reinforcement learning, deep learning and federated learning, optimize the model structure and parameter fitting methods, and improve the model's adaptive capacity to complex market scenarios and dynamic competitive environments; third, expand the coverage of research cases, expand the research objects from the consumer electronics manufacturing industry to different industries such as new energy vehicles, semiconductors and equipment manufacturing, cover manufacturing enterprises of different scales such as large, medium and small ones, explore the industrial differences and scale characteristics of AI empowering production decision-making, and provide references for the digital transformation of more manufacturing enterprises.

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