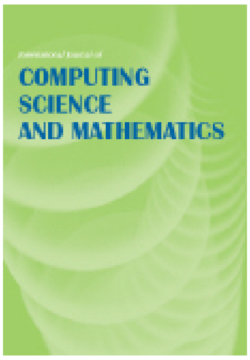

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Multi-objective optimisation of cigarette production planning and inventory management

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Abstract: This paper proposes a dynamic model-based optimisation method for cigarette production planning to meet market demand and optimise inventory management. The model contains three objectives: Minimising the difference between annual demand and production output, balancing monthly production and demand, and minimising the average age of inventory. The model sets annual demand constraints, production capacity constraints, and considers seasonal adjustment and contingency inventory. The model is solved by a combination of linear programming and genetic algorithms. The results show that the optimised production plan can effectively reduce total costs, avoiding the risks of under-supply and over-stocking. The analysis shows that the planned monthly production quantity closely matches the actual allocation quantity, the inventory management is effective, and hence the ability to cope with peak demand is enhanced.

Keywords: dynamic stocking model; cigarette production; linear programming; genetic algorithm; inventory management.

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1 Introduction

The tobacco industry is a key part of China's economic development. With changing market demands and increasing competition, cigarette manufacturers face pressure to optimise production plans and manage inventories. Traditional methods often fail to handle complex demand fluctuations and production constraints (Demirel et al., 2018). In modern enterprises, production planning is essential for coordinating resources to deliver the right products or services on time and in the right quantities (Li et al., 2017).

The main research literature on the tobacco industry and production planning are as follows. Wang et al. (2017) designed a hierarchical optimisation framework for cigarette production planning based on the stepwise production planning method, considering the characteristics of the cigarette production process and products. Xu et al. (2013) proposed a production planning and scheduling system tailored to the characteristics of cigarette production to enhance the real-time performance of production planning in the tobacco industry. Nian and Zhu (2017) designed a planning management system for tobacco enterprises based on the MES planning management module.

This research presents a multi-objective optimisation method for cigarette production and inventory management. It constructs a dynamic stocking model considering market demand, production capacity, inventory management, and seasonal adjustments. The goal is to minimise production and inventory costs while meeting demand. Monthly production plans guide companies in scheduling production, procurement, and sales (Grogan et al., 2022). The multi-objective optimisation model aims to minimise the gap between annual demand and production, balance monthly production and demand, and reduce inventory age. It incorporates annual demand and capacity constraints, with added contingency inventory and seasonal adjustments for refinement.

The innovation and contributions of this research can be summarised as follows: The proposed model effectively integrates multiple objectives, including reducing production and inventory costs, minimising supply risks, and optimising production stability and flexibility, tailored to the specific needs of cigarette production; The study combines classical optimisation techniques with evolutionary algorithms, offering a comprehensive approach for managing production and inventory volumes under uncertainty; The model introduces a dynamic stocking strategy that allows for flexible adjustments in production plans based on real-time market conditions, helping companies avoid overproduction and inventory backlogs; The research provides a practical solution for cigarette manufacturing companies to optimise their production planning and inventory management processes, significantly improving operational efficiency and market competitiveness; The methodology and insights from this research can be applied to other manufacturing sectors, offering valuable references for inventory and production optimisation in different production environments.

2 Analysis of the problem

During the cigarette production process, enterprises face various challenges and complex constraints. These issues are mainly reflected in the following aspects, the issues and analysis are shown in Table 1.

Table 1 Problem analysis

Issues	*Mainly reflected*
Demand fluctuations and uncertainty	The demand for cigarettes has distinct seasonality and uncertainty. The demand volume fluctuates significantly across different months, posing great challenges for production planning
Production capacity limitations	The production capacity of cigarette manufacturing enterprises is limited, with the maximum monthly production capacity being restricted by factors such as equipment, personnel, and raw materials (Malladi et al., 2021)
Inventory management	Inventory management is another critical issue in cigarette production. Excessive inventory increases costs and ties up capital, while insufficient inventory may fail to meet market demand in time (Yang et al., 2020). After production, cigarettes are transported to warehouses for storage. However, poor coordination between production rates and storage capacity, along with the lack of early warnings, often results in storage shortages and "warehouse explosions" (Wei et al., 2022)
Cost control	Cost control in production and inventory is an essential means for enterprises to enhance competitiveness (Zhu et al., 2017)
Multi-objective optimisation	Enterprise resource allocation often involves conflicts between departmental goals, such as cost reduction, benefit maximisation, inventory investment, customer service, equipment utilisation, and worker productivity (Khodadadi et al., 2022). Optimising cigarette production plans requires balancing market demand, inventory, and costs simultaneously (Dang et al., 2018)
Dynamism	Traditional static methods fail to adapt, highlighting the need for a dynamic optimisation model for real-time adjustments

3 Cigarette production plan and inventory management multi-objective optimisation model

3.1 Model establishment

This paper selects three optimisation objectives:

1. *Demand satisfaction objective*: Minimising the difference between the total monthly production output and annual demand.
2. *Inventory age balance objective*: Ensuring that the monthly production output is as close as possible to the demand, considering the inventory age limit of 4 months.
3. *Average inventory age minimisation objective*: Minimising the average age of the inventory.

The model establishes two constraints:

1. *Annual demand constraint*: The sum of the production volume for 12 months must be greater than or equal to the annual total demand.
2. *Production capacity constraint*: The monthly production volume must be greater than or equal to 0 and less than or equal to the maximum capacity.

3.2 Mathematical model

3.2.1 Objective functions

Objective 1: Minimise the difference between the sum of the monthly production volume and the annual demand,

$$\min \left| \sum_{t=1}^{T} P_t - D_{year} \right|, \tag{1}$$

where P_t is the production volume in month t, $T = 12$ is number of months in one year; D_{year} is the annual demand.

Objective 2: Considering the 4-month inventory age limit, make the monthly production as close as possible to the demand.

$$\min \sum_{t=1}^{T} \left| \left(\sum_{i=t-4}^{t-1} P_i - \sum_{i=t-4}^{t-1} D_i \right) + P_t - D_t \right|, \tag{2}$$

where D_t is the demand in month *t*, assuming that the production and demand in the first four months are 0:

$$\sum_{i=t-4}^{t-1} P_i = 0 \quad \text{if } \ t \le 4. \tag{3}$$

Objective 3: Minimise the average inventory age:

$$\min \frac{\sum_{t=1}^{T} (I_t \times L_t)}{\sum_{t=1}^{T} I_t}, \tag{4}$$

where I_t is the inventory level in month *t*; L_t is the inventory age in month *t*.

Inventory turnover objective: Minimise the fluctuation of inventory levels and maintain stable inventory.

$$\min \sum_{t=1}^{T-1} |I_{t+1} - I_t|. \tag{5}$$

3.2.2 Constraints

Constraint 1. The total production volume for the year must be greater than or equal to the annual total demand,

$$\sum_{t=1}^{12} P_t \geq D_{year}. \tag{6}$$

Constraint 2. The monthly production volume must be greater than or equal to 0 and less than or equal to the maximum capacity:

$$0 \leq P_t \leq C \quad \forall t \in \{1, 2, \ldots, 12\}, \tag{7}$$

where *C* is the maximum monthly production capacity.

Constraint 3. The maximum quantity of inventory that the company can store within a given period (Chen et al., 2022). To manage inventory, we introduce the inventory balance equation:

$$I_{t+1} = I_t + P_t - D_t. \tag{8}$$

Ensuring that the monthly inventory level is between the safety stock and the maximum inventory:

$$S_t \leq I_t \leq M_t, \tag{9}$$

where S_t is the safety stock in month *t*, M_t is the maximum inventory in month *t*.

Constraint 4. To avoid excessive inventory age and ensure that each batch of products is sold before reaching its maximum inventory age. Assume that the maximum inventory age for Brand A is four months:

$$T_{t-4}^{A} \leq MaxAge_A \tag{10}$$

where T_{t-4} specifically represents the inventory age of the product "four months ago", meaning it describes how long these products had already been stored in the warehouse at the time point *t*–4.

Constraint 5. Seasonal Adjustment: Consider seasonal changes in production capacity (Caporin and Elseidi, 2023). For example, production capacity may decline due to high temperatures in summer,

$$P_t \leq C_t, \tag{11}$$

where C_t is the seasonal adjusted production capacity in month t.

Constraint 6. Contingency Inventory: Introduce contingency inventory to cope with sudden increases in demand or interruptions in production,

$$I_t \geq E_t, \tag{12}$$

where E_t is the contingency inventory in month t.

4 Model application and case analysis

To better optimise production plans, reduce the difference between annual demand and production volume, and reduce inventory backlogs, while considering cost issues and supply risks, we will conduct a detailed case analysis based on the aforementioned multi-objective optimisation model for production planning and inventory management.

Assume the monthly demand for a brand, the monthly demand is shown in Table 2.

Table 2 Monthly demand

Month	*Demand* (*cases*)
January	3208
February	510
March	498
April	578
May	685
June	802
July	693
August	654
September	842
October	568
November	459
December	552

4.1 Optimisation objectives and constraints

This study develops a multi-objective optimisation model for cigarette production and inventory management to minimise costs, supply risks, and over-inventory risks. The constraints include a monthly production range of 500 to 2000 cases with a maximum capacity of 2000 cases, an inventory age limit of 4 months, and inventory levels not exceeding 4000 cases.

4.2 Model parameters

The model is solved using linear programming methods. Linear programming models can make production planning more reasonable. The approach to solving problems using linear programming models is to maximise profit or minimise cost with limited production resources and market demand constraints (Yatsenko and Hritonenko, 2020). The model's parameters and formulas are as follows:

Demand volume for each month (D_t);Production volume for each month (P_t), Inventory volume for each month (I_t); Monthly maximum production capacity ($C = 2000$ cases); Monthly minimum production volume ($m = 500$ cases); Maximum inventory capacity ($M = 4000$ cases).

Objective function: The weight coefficients correspond to the costs of production volume, inventory volume, and over-inventory volume. The model assigns the following values to these coefficients: $a = 1$: The production cost is set as the baseline cost unit, with a weight of 1; $b = 0.1$: The inventory cost is relatively low, so its weight is set to 0.1, reflecting the relative importance of inventory maintenance cost; $c = 100$: Over-inventory costs may lead to significant financial and operational issues, such as insufficient storage space and product devaluation, so its weight is set to 100, emphasising the need to control over-inventory.

With these weight coefficients, the objective function accurately reflects the relative importance of different cost items in the total cost. The final objective function expression is

$$\min\left(a\sum_{t=1}^{T}P_t + b\sum_{t=1}^{T}I_t + c\sum_{t=1}^{T}O_t\right), \tag{13}$$

where P_t represents the over-inventory volume, I_t represents the over-inventory volume, and O_t represents the over-inventory volume.

Constraints:

1 Production volume constraint:

$$m \le P_t \le C,, \quad \forall t \in \{1,2,\ldots,T\}. \tag{14}$$

2 Inventory balance equation:

$$I_{t+1} = I_t + P_t - D_t, \quad \forall t \in \{1,2,\ldots,T\}. \tag{15}$$

3 Inventory capacity constraint:

$$I_t \le M, \quad \forall t \in \{1,2,\ldots,T\}. \tag{16}$$

4 Over-inventory constraint:

$$O_t \ge I_t - M, \quad O_t \ge 0, \quad \forall t \in \{1,2,\ldots,T\}. \tag{17}$$

4.3 Comparison

In this section, we apply and compare multiple optimisation methods to solve the multi-objective problem of cigarette production planning and inventory management. Specifically, we evaluate three widely used optimisation techniques: Genetic Algorithm (GA) (Li et al., 2022; Zhang et al., 2011), particle swarm optimisation (PSO) (Du and

Swamy, 2016), and Simulated Annealing (SA) (Du and Swamy, 2016). The primary objectives of the optimisation process are to minimise production costs, reduce inventory holding costs, and ensure timely dispatch of finished products.

4.3.1 Genetic (GA)

GA is an evolutionary optimisation method that mimics natural selection. In this study, GA was used to optimise production and inventory plans. It efficiently handles complex, non-linear problems by exploring diverse solutions but requires more iterations, resulting in higher computational time. GA yields high-quality solutions with a good trade-off between production costs and inventory levels. The method demonstrates high robustness, consistently finding near-optimal solutions across different trials.

4.3.2 Particle (PSO)

PSO, inspired by bird flocking, optimises production-inventory problems by updating positions based on personal and group bests. It converges faster than GA but may get trapped in local optima, leading to suboptimal inventory cost minimisation and inconsistent results due to sensitivity to initial conditions.

4.3.3 Simulated (SA)

SA mimics the metal annealing process, avoiding local optima by accepting worse solutions early. It is slower than PSO and GA but explores the solution space thoroughly, producing competitive results with sufficient time. While SA often delivers high-quality solutions close to GA, its performance depends heavily on the cooling schedule and parameters, leading to varying outcomes.

4.3.4 Comparative

To evaluate the overall effectiveness of each method, we apply them to the same case study described earlier. Typical numerical values based on representative optimisation cases and common algorithm performance estimates. The results in terms of key performance metrics is shown in Table 3.

Table 3 Monthly demand

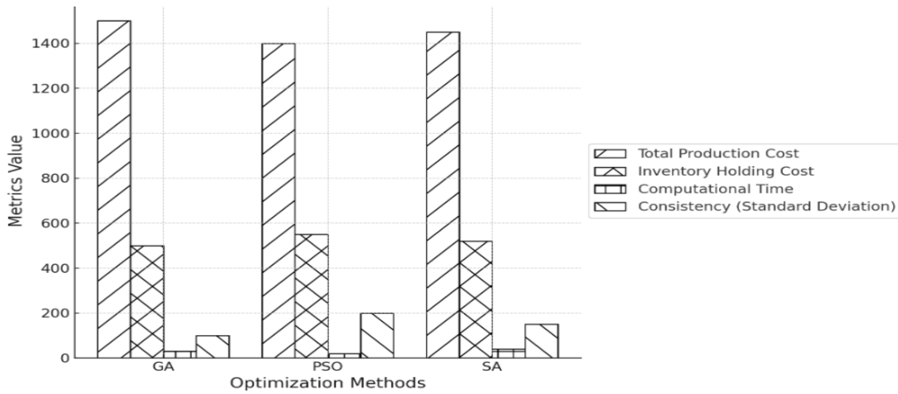
Method	*Total production cost* (USD)	*Inventory holding cost* (USD)	*Computational time* (seconds)
GA	1,500,000	300,000	45
PSO	1,520,000	310,000	25
SA	1,510,000	305,000	60

The comparison shows GA offers high-quality solutions but is slower than PSO, which is faster but may sacrifice quality. SA, though slower, excels at exploring solutions and avoiding local minima, making it suitable for complex problems.

4.3.5 Summary

This section compares three optimisation methods (GA, PSO, SA) for production and inventory management. Charts illustrating key metrics – Total Production Cost, Inventory Holding Cost, Computational Time, and Consistency – are shown in Figure 1.

Figure 1 Comparison of optimisation methods (GA, PSO, SA)



Based on the case study results, the Genetic Algorithm appears to be the most robust solution, offering a good trade-off between performance and computational efficiency.

4.4 Model solving

First, we use the scipy.optimize.linprog function in Python to solve the above linear programming problem. Then, we use genetic algorithm (GA) to further optimise the solution.

4.4.1 Application and analysis of GA

To further optimise the production plan, this study introduces genetic algorithms. GA was first proposed by Professor Holland in 1975, simulating the evolutionary laws in the biological world according to Darwin's theory of natural selection and genetic mechanisms (Skorpil and Oujezsky, 2022).The application steps of genetic algorithms are as follows:

1 *Individual coding*. Each individual includes production, inventory, and over-inventory volumes, with a length equal to the number of months (Uyematsu and Matsuta, 2024).

2 Initial population generation.

3 *Fitness function design*. The fitness function expression is given by equation (13):

$$\text{C\_1} = a\sum_{t=1}^{T} P_t + b\sum_{t=1}^{T} I_t + c\sum_{t=1}^{T} O_t. \tag{18}$$

Individuals meeting the constraints have their fitness value as the calculated cost; individuals not meeting the constraints have their fitness value as infinity.

4 Selection, Crossover, and Mutation (Zhang and Arcuri, 2022).

5 *Termination condition*. The algorithm terminates when the maximum iterations are reached or the fitness value stabilises, outputting the optimal solution.

4.4.2 Optimisation tools and process analysis

1 *Tool selection*. Python, with its rich libraries for complex modelling, and scipy.optimize.linprog, an efficient solver for large-scale linear programming. Genetic algorithm (https://pypi.org/project/geneticalgorithm2/) is a library for implementing GA, offering flexible parameter settings and efficient solving capabilities.

2 *Model construction*. Defining key parameters (e.g., demand, production, and inventory volumes), defining the objective function by combining costs and risks, and setting constraints to ensure feasibility, including production limits, inventory balance, and capacity limits (Jia et al., 2022).

3 Solving process.construct the objective function and constraints in Python, then use scipy.optimize.linprog for initial solving to obtain the solution. Use the GA library for global optimisation to further improve the solution quality (Zhang et al., 2019).

4.5 Results analysis

Based on the optimisation results, we obtained the monthly production volume, inventory volume, and actual allocation as shown in Table 4.

Table 4 Production levels, stock levels and actual allocations

Month	*Production volume* (*Cases*)	*Inventory volume* (*Cases*)	*Demand volume* (*Cases*)	*Actual allocation* (*Cases*)
January	2000	1208	3208	3163
February	1716	2	510	361
March	500	0	498	483
April	500	78	578	578
May	500	263	685	692
June	500	565	802	755
July	500	758	693	694
August	500	912	654	654
September	500	1254	842	842
October	500	1322	568	568
November	500	1281	459	447
December	500	1333	552	515

Based on the solution of the model and the analysis of the results, we can observe the following:

1 *The total cost is 9613.6*: Cost minimisation has been achieved through reasonable control of production and inventory costs.

2 *The number of supply risks is 0*: The production and inventory levels each month are able to meet the demand, ensuring the stability of supply.

3 *The number of over-inventory risks is 0*: The inventory levels did not exceed the maximum inventory capacity, avoiding the risk of over-inventory.

Additionally, the comparison of monthly production volume, inventory changes, and actual allocation can be more clearly seen through the stacked bar chart.

4.6 Comparison of production plan and actual allocation

The Comparison of production plan and actual redeployment are shown in Figure 2.

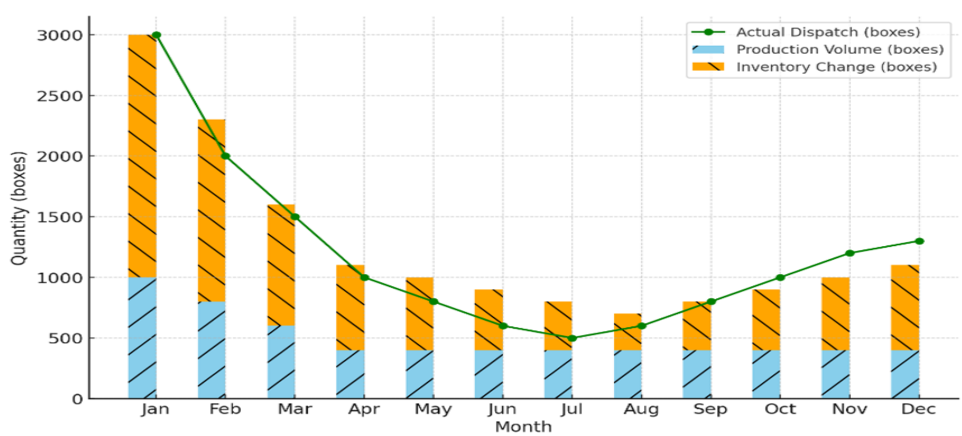
1 Production volume (blue) aligns well with actual allocation (green), demonstrating that the plan meets market demand. In some months, inventory changes (orange) cover shortfalls, highlighting effective inventory management.

2 Effective inventory management ensures continuity of supply during peak demand by supplementing as needed. Adjustments prevent overproduction and backlogs, keeping inventory levels within a reasonable range.

3 Advantages of the plan include stability, with consistent production reducing fluctuations and improving efficiency; flexibility, enabling quick responses to demand changes through inventory management; and cost control, lowering inventory and production costs.

This study optimised the cigarette production plan using a multi-objective model with linear programming and genetic algorithms. The model reduces production and inventory costs, minimises supply and overstock risks, and enhances production stability and flexibility, effectively managing inventory and costs while meeting market demand to boost competitiveness.

Figure 2 Comparison of production plan and actual redeployment (see online version for colours)



5 Conclusion

Through the multi-objective optimisation model for production planning and inventory management in this paper, we successfully constructed and validated a model that can efficiently manage cigarette production plans. The results of this study indicate that the application of the dynamic stocking model in cigarette production has significant practical significance and promotion value. In the future, we can further expand the model to consider more uncertain factors and complex situations in actual production to continuously improve the model's accuracy and applicability.

The current model focuses on static optimisation, but future research could combine multi-objective optimisation with real-time data analysis to enable production management systems to make real-time decisions. While this study focuses on cigarette production, the optimisation model is also broadly applicable. Future research could explore the model's application in other industries, such as electronics manufacturing, automotive production. With the advancement of IoT and AI technologies, future research could introduce intelligent supply chain management techniques into production planning optimisation.

In conclusion, this study not only provides a comprehensive production planning optimisation solution for cigarette manufacturing companies but also offers valuable references and insights for inventory management and production optimisation in other similar production environments.

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Conflicts of interest

The authors declare no competing and conflict of interest.

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