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RESEARCH ARTICLE **Open Access**

The Mathematical Model for Optimizing Accounts Receivable Financing in Production Planning: A Solution to Enhance Liquidity and Mitigate Financial Risks

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Abstract
Managing liquidity and inventory simultaneously remains a critical challenge in production planning, particularly for firms dealing with delayed receivables and financial constraints. This study proposes a novel mathematical model that integrates accounts receivable financing (ARF) into multi-period production planning. The model explicitly incorporates financial parameters such as cash inflows, advance payments, receivable discount rates, and bank credit limits, alongside operational factors like procurement and holding costs. The objective function is designed to maximize liquidity at the end of the planning horizon while ensuring demand satisfaction and inventory balance. A key innovation lies in the model's unified treatment of financial and operational constraints—an aspect often overlooked in existing literature. The model is solved using advanced optimization methods, including nonlinear programming and a genetic algorithm, to handle complexity and ensure convergence to near-optimal solutions. Sensitivity analysis demonstrates the model's robustness under demand fluctuations and financial volatility. Results indicate that the proposed approach can significantly reduce financial risks, improve cash flow stability, and support strategic decision-making. This framework offers valuable insights for managers seeking to align operational efficiency with financial resilience. Future research directions are also outlined to expand the model's applicability in dynamic production environments.
Keywords: Media, digital media, media policy, soft systems methodology, cognitive mapping.

Introduction

Liquidity management plays a critical role in production planning, particularly in environments where delayed receivables lead to operational disruptions. Accounts Receivable Financing (ARF) has emerged as a viable tool to address such challenges by converting receivables into immediate cash. This financial mechanism allows companies to accelerate cash inflows, mitigate payment default risks, and improve flexibility in procurement and production scheduling.

Despite its potential, effectively integrating ARF into production planning remains complex. Firms must balance the financial benefits of ARF—such as enhanced liquidity and risk reduction—against associated costs like discount rates and administrative expenses. Additionally, operational factors including inventory management, order scheduling, and

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fluctuating demand introduce further constraints, necessitating a unified optimization framework.

Existing literature has addressed ARF from various angles, including credit risk mitigation, supply chain coordination, and blockchain-based transparency. However, most studies treat financial and operational decisions separately, lacking an integrated perspective that reflects the realities of dynamic production environments. This gap limits the practical applicability of prior models.

To address this limitation, the present study develops a novel mathematical model that incorporates ARF directly into multi-period production planning. The proposed model simultaneously considers key financial variables—such as advance payments, bank credit limits, and receivable discounting—and operational elements like procurement costs and inventory levels. The objective is to maximize end-period liquidity while satisfying financial and operational constraints. The model is solved using a genetic algorithm, enabling effective optimization in nonlinear and constrained settings. The results offer practical insights for managers aiming to enhance liquidity and minimize financial risks in uncertain markets.

While previous studies have explored accounts receivable financing from diverse perspectives—such as game-theoretic coordination, risk-sharing mechanisms, and technological platforms—they rarely provide an integrated model that combines ARF with detailed production planning decisions. Most existing models separate financial flows from operational constraints, making them less applicable in dynamic and uncertain environments.

This study contributes to the literature by proposing a unified mathematical framework that embeds ARF directly into multi-period production planning. Unlike prior works, the model explicitly incorporates liquidity constraints, credit limitations, advance payment structures, and receivable discounting, alongside inventory and procurement decisions. The application of a genetic algorithm to solve the nonlinear optimization problem further enhances its novelty and practicality. The model not only bridges a major gap in the literature but also offers a robust tool for managers facing financial uncertainty in operational planning.

Literature Review

Recent studies on accounts receivable financing (ARF) have explored its impact on financial coordination, credit risk reduction, and production planning efficiency. (Yan et al., 2024) and (Zhang et al., 2023) used evolutionary game theory to analyze the strategic interactions among supply chain members, emphasizing the role of coordination and central bank digital currencies in enhancing financing efficiency. Similarly, (Xia, 2022; Zhao and Lu, 2023) examined ARF under uncertainty, proposing guarantee mechanisms and pledge financing models to mitigate liquidity risks.

Operational integration of ARF has also gained attention. (Zhu et al., 2022; Cheng et al., 2023) developed joint financial-operational models to align cash flow and production schedules, demonstrating improved coordination and reduced costs. (Li et al., 2024; Cano et al., 2022) analyzed ARF in the context of SMEs and real-world case studies, confirming its positive impact on liquidity and investment capacity.

Emerging technologies have introduced new perspectives. (Yang, 2024; Wang 2023, 2024; Ma et al., 2023) emphasized the role of blockchain and smart contracts in increasing transparency, reducing administrative costs, and streamlining receivables financing. These studies highlight the potential of digital infrastructure in modernizing financial operations.

In addition, policy-oriented models by (Zhao and Lu, 2021; Feng, 2023) illustrated how government incentives and regulatory frameworks influence ARF adoption and coordination. (Zeng and Geng, 2022) addressed sustainability by integrating green finance into ARF strategies for environmentally conscious production.

Although these works offer valuable insights, most focus on specific financial mechanisms or strategic interactions, often excluding the operational side of production planning. This study distinguishes itself by proposing a comprehensive mathematical model that integrates ARF directly into multi-period production operations, explicitly addressing both financial and inventory-related constraints under real-world uncertainties.

Modeling

The proposed mathematical model for accounts receivable financing (ARF) is developed as an advanced tool for managing production planning in dynamic and complex environments. This model integrates financial and operational aspects of production to support strategic decision-making related to purchasing, selling, inventory management, and financing. The primary objective is to maximize available liquidity at the end of the planning horizon, ensuring financial stability by accurately managing resources and minimizing associated costs.

Parameters and Decision Variables

The model encompasses a set of parameters and decision variables that reflect the interactions among various production planning components, including suppliers, buyers, and financial institutions. Key parameters include purchasing, holding, and fixed costs, the percentage of cash and advance payments received from buyers, bank interest rates, and forecasted demand for products. Decision variables include the quantities of products purchased and sold during each period, end-of-period inventory levels, available liquidity, and the amount of financing received from banks. Additionally, binary variables are introduced to determine whether products are purchased during different periods.

Parameters:

MaxCred: Maximum credit limit provided by the bank in period t

DiscRate: Discount rate for receivables in period t, determined by the bank.

CashPerc: Percentage of cash received from buyer l for product k in period t

AdvPerc Percentage of advance payment received from buyer l for product k in period t−, with guaranteed delivery in period t.

w Initial liquidity at the start of the financial period.

MinOrder: Minimum acceptable order quantity for buyer l in period t

γ: Percentage of receivables from buyer l for product k in period t that can be converted into liquidity in period $t+h$

SellingPrice: Selling price per unit of product k to buyer l in period t

HoldingCost: Holding cost per unit of product k in period t

ProcureCost: Procurement cost per unit of product k.
FixedCost: Fixed costs incurred at the end of period t.
InitCash: Initial liquidity at the start of the financial period.
AdvPerc: Percentage of advance payment received from buyer l for product k in period t−h, with guaranteed delivery in period t.

Decision Variables:
X: Quantity of product k purchased in period t
S: Quantity of product k sold to buyer l in period t
I: Inventory level of product k at the end of period t
w: Liquidity available at the end of period t
R: Total receivables at the end of period t
Fin: Financing received from the bank through receivables factoring in period t
CashIn: Cash inflows during period t, excluding bank financing.
δ(X_i): Binary variable indicating whether product iii is purchased in period t (1 if yes, 0 if no).
If_{kt}: Warehousing cost at the end of period t
INC_t:Transportation and distribution cost at the end of period t
TRC_t : Amount of receivables from buyer I for product k in period t-h, with liquidity available in period t
$AR_{kIt,t+h}$: Amount of cash received from buyer I for product k in period t
Amount of advance payment received from buyer I for product k in period t, with a guarantee of delivery in period t+h

Objective Function:
Maximize w
Objective: Maximize liquidity available at the end of the planning horizon T. This ensures financial stability and optimal use of resources throughout the planning period.

Constraints
The model is structured with a set of constraints that capture operational and financial limitations:

1. **Inventory Balance Constraint**: Ensures that the end-of-period inventory equals the initial inventory plus purchased quantities minus sold quantities.

$$I_t = I_{t-1} + Q_t - S_t$$

2. **Demand Fulfillment Constraint**: Ensures that sold quantities do not exceed the forecasted demand.

$$S_t \leq D_t$$

3. **Liquidity Constraint**: Ensures sufficient liquidity during each period to cover purchasing, holding, and fixed costs.

$$L_t \geq \text{Purchasing Cost} + \text{Holding Cost} + \text{Fixed Costs}$$

4. **Income and Expense Calculation**: Defines the total receivables based on cash and advance payments from sales, incorporating discount rates.

$$R_t = \sum (\text{Cash Payments} + \text{Advance Payments - Discounts})$$

5. **Bank Credit Constraint**: Limits financing to the maximum available credit from the bank.

$$F_t \leq \text{Max Credit}$$

6. **Liquidity for Financing Constraint**: Determines financing based on the difference between required liquidity and available liquidity during a given period.

$$F_t = \max(0, \text{Required Liquidity} - L_t)$$

7. **Liquidity Conversion**: Calculates end-of-period liquidity,

including cash flows and receivables converted into cash, minus fixed costs.

$$L_{t+1} = L_t + R_t - \text{Fixed Costs}$$

8. **Non-Negative Inventory**: Ensures that inventory levels remain non-negative.

$$I_t \geq 0$$

9. **Minimum Order Quantity Constraint**: Enforces a minimum order quantity for sales to buyers.

$$S_t \geq \text{Minimum Order}$$

10. **Binary Decision for Purchases**: A binary variable determines whether a product is purchased during a specific period.

$$B_t \in \{0, 1\}$$

11**. Warehousing Cost Calculation**

$$If_{kt} = I_t \times \text{HoldingCost}_k$$

(The warehousing cost is calculated as the inventory level multiplied by the holding cost per unit.)

12**. Transportation and Distribution Cost:**

$$INC_t = S_t \times \text{Transportation Cost F}$$

(Transportation and distribution costs depend on the quantity sold and the cost per unit.)

13**. Receivables Liquidity Conversion:**

$$TRC_t = \gamma \times R_{t-h}$$

(Receivables from buyer I for product k in period $t - h$ are converted to liquidity in period t using the conversion factor γ.)

14. **Cash Received from Advance Payments:**

$$AR_{kIt,t-h} = \text{AdvPerc} \times S_t$$

(Advance payments for guaranteed delivery are calculated as a percentage of sales in the relevant period.)

Objective Function

The objective function seeks to maximize liquidity at the end of the planning horizon:

$$\text{Maximize } L_T$$

Where L_T is the liquidity at the final period T.

The model incorporates a range of parameters, including purchasing costs, holding costs, fixed costs, cash flow rates, demand forecasts, and bank credit limits. Sensitivity analysis is performed to assess the impact of changes in key parameters, such as interest rates, demand fluctuations, and holding costs, on liquidity and financial stability. By addressing operational challenges like optimal order quantities and financial commitments, the model ensures liquidity preservation across all periods.

The proposed model provides solutions for real-world operational challenges, such as determining optimal order quantities and managing financial obligations to maintain liquidity throughout all periods. It reduces financial risks by accurately managing liquidity and limiting dependence on external financing. The model helps organizations utilize internal resources more effectively, reducing reliance on external financing and enhancing flexibility in responding to market changes.

Ultimately, the proposed model not only guarantees improved financial performance but also fosters better coordination among production planning components. By considering operational and financial requirements, it serves as a strategic tool for financial and managerial decision-making. The model is especially useful for industries that experience delays in accounts receivable, as it improves trust among production planning members, reduces costs, and enhances liquidity while ensuring operational stability. By offering practical solutions, this model plays a significant role in optimizing production planning management.

The proposed mathematical model for accounts receivable financing is designed as an advanced tool for production planning management, aiming to optimize liquidity and reduce financial risks in complex and dynamic environments. This model considers all operational and financial aspects of the production planning, assisting in smarter decision-making regarding purchasing, selling, inventory management, and financing. The objective function is defined to maximize the available liquidity at the end of the planning period, ensuring the organization’s financial stability by accurately managing financial resources and minimizing costs associated with procurement and inventory holding.

The modeling process is summarized as follows

The model was formulated by translating real-world financial and operational processes into a set of mathematical equations. We began by defining decision variables representing key activities such as purchasing, selling, financing, and inventory holding. Parameters such as cash inflow ratios, procurement and holding costs, credit limits, and discount rates were included to reflect practical conditions. Constraints were then formulated to ensure inventory balance, demand satisfaction, liquidity sufficiency, and adherence to credit limits. The objective function—maximizing end-period liquidity—was constructed to capture the primary managerial goal. Binary variables were added to model purchasing decisions. Overall, the model took the form of a nonlinear, constrained optimization problem with both continuous and discrete variables.

The model includes a set of parameters and decision variables that reflect the interactions among various components of the production planning, including suppliers, buyers, and financial institutions. Key parameters include procurement costs, holding costs, fixed costs, the percentage of cash and advance payments received from buyers, bank interest rates, and forecasted product demand. Decision variables include the quantities of products purchased and sold in each period, end-of-period inventory levels, available liquidity, and the amount of financing received from banks. Additionally, binary variables are introduced to determine whether products are purchased during different periods.

The model is structured with a set of constraints that capture operational and financial limitations. Inventory balance constraints ensure that inventory levels in each period align with quantities purchased, sold, and carried forward from the previous period. Demand-related constraints ensure that sales volumes do not exceed the forecasted demand from buyers. Liquidity constraints guarantee that the available liquidity in each period is sufficient to cover procurement, holding, and fixed costs. Bank credit limitations restrict the available financing to prevent excessive reliance on external funding.

A key feature of this model is its consideration of all financial flows within the production planning, including revenues from sales, incoming cash flows, and funds obtained through bank financing. The model also analyzes the interactions between financial flows and physical operations, such as purchasing and selling products, and evaluates their impact on final liquidity levels. It enables organizations to use sensitivity analysis to assess the effects of changes in key parameters, such as interest rates, demand levels, and holding costs, and to make better decisions accordingly.

The model also aims to provide solutions to operational challenges within the production planning, such as determining optimal order quantities and managing financial commitments to maintain liquidity throughout all periods. Other advantages of the model include its ability to reduce financial risks through precise liquidity management and limiting external financing. The model helps organizations effectively utilize internal resources, reducing dependency on external funding and increasing flexibility in responding to market changes.

Benefits of the Model

1. **Financial Optimization**: Maximizes liquidity and minimizes costs associated with inventory holding and procurement.
2. **Risk Mitigation**: Reduces dependence on external financing by effectively managing cash flows.
3. **Operational Efficiency**: Aligns financial and operational priorities, ensuring stable production planning.
4. **Strategic Decision-Making**: Provides a robust framework for managers to evaluate and implement optimal production and financing strategies.

Solution Approach and Genetic Algorithm Parameters

The genetic algorithm (GA) used to solve the model was configured with parameters selected based on empirical tuning...Ultimately, the proposed model not only ensures improved financial performance but also facilitates better coordination among production planning components. By considering both operational and financial requirements, it serves as a strategic tool for financial and managerial decision-making. It is particularly applicable in industries that face delays in receivables collection. Using this model can increase trust among production planning members, reduce costs, and improve liquidity while ensuring the organization's operational stability. By offering practical solutions, this model plays a significant role in optimizing production planning management.

Table 1.

Basic models of inventory and working capital management

Category	Parameter	Value	Unit
Problem Dimensions			
	Number of Periods (T)	6	Periods
	Number of Products (K)	3	Products
	Number of Buyers (I)	2	Buyers
	Prepayment Period (h)	1	Period
Financial Parameters			
	Maximum Credit (MaxCred)	10,000	Currency Units
	Discount Rate (DiscRate)	0.02	Percent

Category	Parameter	Value	Unit
	Initial Liquidity (InitCash)	5,000	Currency Units
Payment Conditions			
	Cash Payment Percentage (CashPerc)	0.7	Percent
	Advance Payment Percentage (AdvPerc)	0.3	Percent
Prices and Costs			
	Base Selling Price	100	Currency Units
	Price Increase per Product	10	Currency Units
	Random Price Fluctuation	N(0,5)	Currency Units
	Holding Cost (h_cost)	5	Currency Units/Period
	Procurement Cost for Product 1	50	Currency Units
	Procurement Cost for Product 2	60	Currency Units
	Procurement Cost for Product 3	70	Currency Units
	Fixed Cost (F)	1,000	Currency Units/Period
Demand Parameters			
	Base Demand	100	Units
	Sinusoidal Fluctuation	20×sin(t)	Units
	Random Demand Fluctuation	N(0,10)	Units
	Minimum Order (MinOrder)	10	Units
Genetic Algorithm Parameters			
	Population Size	100	Members
	Maximum Generations	200	Generations
	Crossover Rate	0.8	Percent
Penalty Coefficients			
	Negative Inventory Penalty	1e7	Currency Units
	Demand Violation Penalty	1e6	Currency Units
	Credit Violation Penalty	1e7	Currency Units
	Minimum Order Violation Penalty	1e5	Currency Units
	Inventory Change Penalty	1e4	Currency Units

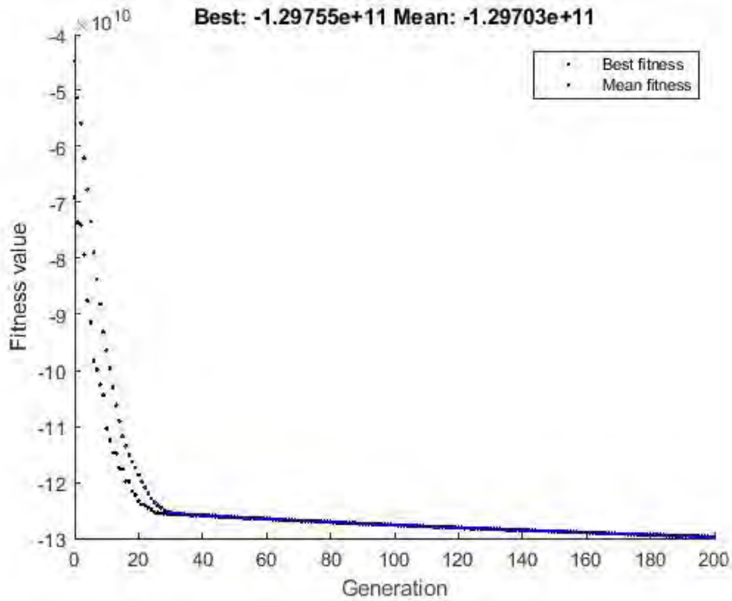
The initial hypothetical values in Table1 are considered for a medium-sized inventory and working capital management problem. In this model, a company with 3 products, 2 buyers, and a planning horizon of 6 periods is analyzed. The financial parameters include a credit limit of 10,000 units and an initial liquidity of 5,000 units, which seem reasonable given the problem's scale. Payment terms are set at 70% cash and 30% advance payment, reflecting a cautious financial policy.

Holding costs are relatively low (5 units), and procurement costs increase progressively (50, 60, and 70 units) for different products. Demand consists of a fixed component (100 units), a sinusoidal component to represent seasonal variations, and a normal random component to simulate unpredictable fluctuations.

The genetic algorithm parameters, with a population size of 100 and 200 generations, are configured to balance computational time and solution quality.

Figure1.

Genetic algorithm convergence diagram



The convergence chart of the genetic algorithm in Figure1 illustrates the improvement trend of the objective function over 200 generations. The chart displays the number of generations on the horizontal axis and the objective function value on the vertical axis, with two primary curves: one representing the best fitness value and the other the mean fitness of the population. The vertical axis scale ranges from -13×10^{10} to -4×10^{10}, indicating a minimization problem.

The convergence process of the algorithm can be divided into three main phases:

Phase 1 (Generations 1 to 20):
A rapid and significant improvement in the objective function value is observed, reflecting the algorithm's capability to quickly identify promising regions in the search space. During this phase, the gap between the best solution and the population mean is large, indicating high diversity within the population.

Phase 2 (Generations 20 to 80):
The rate of improvement decreases, but a gradual downward trend continues. At this stage, the gap between the best solution and the population mean narrows, indicating a gradual convergence of the population towards better solutions.

Phase 3 (Generations 80 to 200):
The algorithm reaches an almost stable state, with only minor improvements in the objective function value. The final best value achieved -1.29755×10^{11}, and the mean fitness value is -1.29703×10^{11}.

The rapid convergence in the initial phase demonstrates that the genetic algorithm parameters (e.g., population size, mutation rate, and crossover rate) have been appropriately tuned. The close alignment between the best and mean values at the end of the execution reflects proper convergence but may also indicate a reduction in genetic diversity, raising the risk of the algorithm getting trapped in local optima.

While the convergence curve suggests that the algorithm has reached a stable solution, additional strategies could be employed to ensure solution quality. These include increasing the mutation rate in the final generations or rerunning the algorithm with different initial values. Another noteworthy aspect is the presence of minor fluctuations in the mean population curve, indicating that the mutation operator continues to introduce diversity within the population. This is a desirable feature, as it enables exploration of the solution space even during the final generations.

The numerical results presented in the table reflect the performance of the genetic algorithm during the final generations (183 to 200). These results include the generation number, individual ID, best fitness value, average fitness value, and the number of stalls (improvement stagnation).

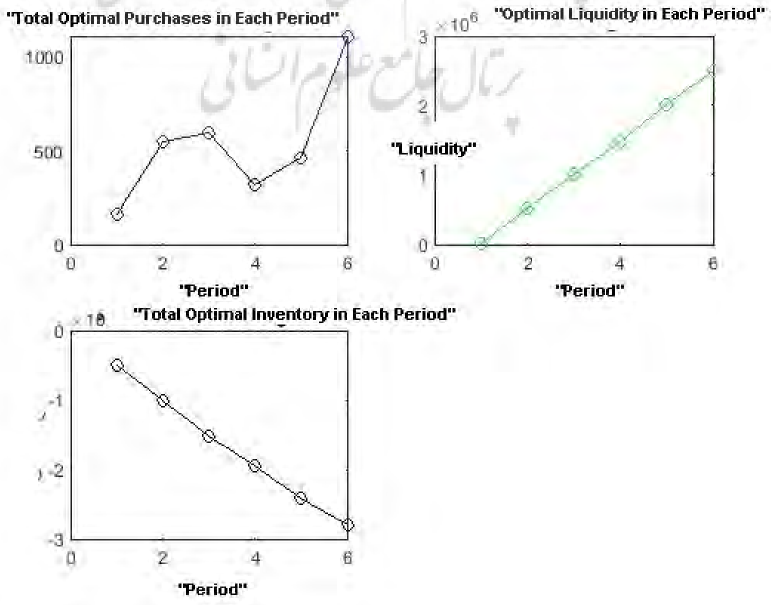
In Table 2 the final generations, the objective function value improves from -1.298×10^{11} to -1.295×10^{11}, indicating slight but continuous progress. The average fitness of the population is almost equal to the best value, demonstrating that the population has converged effectively. After 200 generations, the algorithm terminates due to reaching the maximum allowed number of generations.

Table 2.
The final optimization results

Value	Metric
-1.29755×10^{11}	Objective Function Value (Final Liquidity)
532.517	Average Purchases per Period
5210.855	Average Sales per Period
−16,999.553-16,999.553−16,999.553	Average Inventory Level
1,254,197.387	Average Liquidity

These results indicate that the algorithm has successfully achieved an acceptable solution.

Figure 2.
Output Charts



The output charts in Figure2 consist of three graphs that illustrate the trends of key variables over six periods:

1. **First Chart (Total Optimal Purchases in Each Period):** A fluctuating trend is observed with a sharp increase in the final period. The purchase quantity starts at approximately 200 units in the first period, rises to around 500 units in the second and third periods, decreases slightly, and finally surges to over 1,000 units in the sixth period. This purchasing pattern indicates a stockpiling strategy towards the end of the planning horizon, potentially due to anticipated demand increases or price changes.
2. **Second Chart (Optimal Liquidity in Each Period):** A steadily increasing, almost linear trend is observed, starting from zero and reaching approximately 2.5×1062.5 \times 10^62.5×106 by the sixth period. This trend demonstrates that the liquidity management strategy has been successful, consistently improving liquidity throughout the periods.
3. **Third Chart (Total Optimal Inventory in Each Period):** A downward trend is evident, starting at around −0.5×106-0.5 \times 10^6−0.5×106 and declining to approximately −3×106-3 \times 10^6−3×106 by the sixth period. This suggests a consistent depletion of inventory levels, likely due to sales outpacing replenishment, which aligns with the strategy to optimize holding costs and manage cash flow effectively.

Managerial Implications

The proposed model offers valuable insights for decision-makers managing production planning under financial constraints. In real-world environments where delayed customer payments, limited credit access, and volatile demand conditions are common, this model enables managers to design more resilient and liquidity-focused strategies.

One of the key managerial advantages is the model's ability to simulate various financial and operational scenarios. Managers can evaluate how changes in parameters—such as customer payment patterns, interest rates, or inventory holding costs—affect cash availability and production efficiency across multiple periods. This helps in proactively adjusting purchasing schedules, financing plans, and sales policies, thereby reducing financial risk and avoiding liquidity shortages.

The integration of accounts receivable financing (ARF) directly into the production planning model is especially significant. It allows managers to assess the impact of offering credit to buyers and determine the optimal use of receivables discounting. Instead of relying on intuition or ad-hoc decisions, they can use a structured tool to align operational decisions (e.g., order quantities, procurement timing) with financial constraints (e.g., credit limits, cash flow availability).

Moreover, the use of genetic algorithms enables fast and robust optimization even in complex and nonlinear situations, making the model applicable to a wide range of manufacturing environments. Sensitivity analysis enhances this further by allowing managers to anticipate outcomes under uncertainty and to test the impact of extreme scenarios.

Overall, the model serves as a strategic decision support system, enabling production and financial managers to coordinate efforts, minimize risk, and improve both liquidity and operational efficiency.

Conclusion

This study introduces a novel mathematical model that integrates accounts receivable financing into production planning, addressing critical challenges in liquidity management and financial risk mitigation. By incorporating parameters such as cash inflows, advance payments, procurement costs, and bank credit limits, the model provides a robust framework for optimizing financial and operational performance.

The results demonstrate that the proposed model effectively enhances liquidity, reduces financial dependency, and supports decision-making under dynamic market conditions. Sensitivity analyses further validate its adaptability to variations in demand, interest rates, and operational costs, making it applicable across industries with diverse financial constraints.

Key findings underscore the strategic importance of ARF in modern production planning:

1. **Liquidity Optimization**: The model ensures stable cash flow across planning periods, reducing reliance on external financing and mitigating financial risks.
2. **Cost Reduction**: By integrating ARF with inventory management, the model minimizes holding and procurement costs, improving overall profitability.
3. **Scalability and Flexibility**: The framework adapts to fluctuating market conditions, offering managers actionable tools for both short-term and long-term planning.

Despite its strengths, the study acknowledges limitations, such as the exclusion of advanced market dynamics and the lack of real-time data integration. Future research could explore these areas, particularly the incorporation of blockchain technology and artificial intelligence to enhance model efficiency and transparency. Additionally, expanding the model to address sustainability goals and multi-tier supply chains could provide further value.

In conclusion, this research contributes to the growing body of knowledge on ARF by offering a comprehensive, practical, and scalable solution for production planning challenges. It equips managers with a strategic tool for aligning financial stability with operational efficiency, paving the way for sustainable growth and competitive advantage in today's dynamic industrial landscape.

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