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Autonomous Supply Strategy and Substitution Modeling for Critical Components in Complex Supply Chains

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Abstract

Amidst the current global landscape characterized by complex and volatile supply structures, the uncertainty in the supply of critical components has emerged as a significant constraint on enterprise development. This study focuses on constructing an innovative evaluation framework that integrates system dynamics (SD) modeling with stage-based substitution strategy simulation, with the objective of accurately identifying effective pathways for achieving autonomous supply of critical components. Through detailed analysis and simulation of three key stages—collaborative development, small-batch prototyping, and large-scale substitution—the study systematically investigates the substitution timeline and capacity transition patterns of critical components. Using 23 categories of heavy industrial equipment parts as case examples, relevant parameters were comprehensively collected for model construction. Simulation results reveal marked differences under various implementation pathways and strategy combinations. The proposed model demonstrates potential for integration with enterprise ERP systems, and is expected to provide robust quantitative early-warning support for the localization and substitution processes of essential materials.

Keywords

component substitution; autonomous supply strategy; system dynamics modeling; stage-based simulation; supply transition efficiency.

1. Introduction

Under the deep integration of economic globalization, the global supply chain has evolved into a vast and interdependent complex system [1]. As the fundamental support of many industries, the stability of critical component supply plays a decisive role in both the survival and development of enterprises and the broader direction of industrial evolution [2]. In recent years, the international situation has become increasingly volatile, with frequent geopolitical conflicts and the resurgence of trade protectionism [3]. Taking the China–U.S. trade friction as an example, as tensions have continued to escalate, many Chinese high-tech enterprises—such as Huawei and ZTE—have been arbitrarily placed on the U.S. entity list, facing severe obstacles in acquiring core components such as advanced chips [4]. According to relevant research statistics, in 2019 alone, over 200 incidents occurred in which the supply of core components to Chinese high-tech enterprises was disrupted due to trade friction, resulting in halted production operations and interrupted R&D processes [5]. In addition, global public health emergencies—such as the COVID-19 pandemic—have dealt heavy blows to the already fragile global supply chain. During the pandemic, countries implemented lockdowns, factories suspended operations, and logistics systems became paralyzed. Enterprises dependent on imported critical components quickly depleted their inventories, forcing production lines to shut down [6]. According to data released by Goldman Sachs, in 2021, due to the shortage of chips as a critical component, the global automobile industry reduced production by

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approximately 10 million vehicles, with direct economic losses reaching USD 210 billion [7,8]. This figure clearly illustrates the severe impact of unstable core component supply on industrial output. In the consumer electronics sector, data from IDC show that in the first half of 2020, due to the interruption of key component supplies, global smartphone shipments declined by 14% year-on-year, and tablet shipments dropped by 10.4%, leading to significant revenue losses across many electronics companies [9].

Recent studies further reveal that the vulnerability of the global supply chain continues to worsen [10,11]. According to the 2024 report by the International Supply Chain Institute, since 2022, supply disruptions of critical components have increased by 30% due to geopolitical conflicts and extreme weather conditions [12]. For example, in the semiconductor industry, export restrictions on manufacturing equipment by certain countries have left approximately 20% of global chip manufacturers facing difficulties in equipment upgrades and maintenance, hindering capacity expansion plans [13]. In the new energy vehicle industry, the supply of key raw materials such as lithium and cobalt has been heavily affected by geopolitical instability and policy adjustments in resource-rich countries, resulting in price volatility exceeding 50% during 2023–2024 and severely impacting production planning and cost control for automotive enterprises.

Enterprises' long-term over-reliance on imported critical components undoubtedly places their supply chain security at risk [14]. In high-end equipment manufacturing, once the supply of key components is disrupted, companies not only face penalties for failing to deliver orders on time, but also risk losing market share to competitors due to a weakened delivery capacity, along with potential long-term damage to their brand reputation [15]. For instance, certain aerospace companies have experienced delayed aircraft deliveries due to interrupted supplies of imported engine components, leading to declining customer trust and reduced global competitiveness [16]. Data show that Airbus's A400M military transport aircraft program, due to technical issues and delays related to gearboxes and other core components, had incurred EUR 1.2 billion in penalties by May 2023, and its first delivery was postponed by four years, significantly affecting its market share and follow-up orders [17,18]. In the construction machinery sector, Caterpillar experienced a 25% decline in the production of some excavator models in Q4 2022 due to supply shortages of key components such as hydraulic pumps, resulting in an 8-percentage-point market share gain by competitor Komatsu. In the face of such a severe and complex international supply environment, achieving localized and autonomous supply of critical components has become an imperative strategy for enterprises [19]. It is a necessary measure to safeguard supply chain security, improve resilience against external shocks, and enhance core market competitiveness [20]. More importantly, it represents a strategic path for enterprises to pursue sustainable development in a highly uncertain global environment [21].

According to recent industry research, more than 60% of high-end manufacturing enterprises in 2024 still exhibit a dependency rate exceeding 40% on imported core components [22]. Taking the medical equipment industry as an example, in China's high-end MRI systems, over 80% of key components such as superconducting magnets and radiofrequency coils are imported [23]. This results in persistently high equipment costs, prolonged supply cycles, and slow maintenance responses, which have seriously constrained the development of the industry. In the industrial robotics sector, although the localization rates of critical components such as precision reducers and servo motors have improved, the average localization rate in 2024 remains only 35% [24]. Most enterprises still face challenges in matching the performance and reliability of international brands, thus limiting the applicability of domestically produced industrial robots in high-end manufacturing scenarios [25].

Although the issue of component substitution has attracted extensive attention from both academia and industry, a review of existing literature reveals significant limitations [26]. From

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the perspective of research dimensions, some studies focus solely on the technological R&D stage, aiming to overcome core technical bottlenecks to achieve localization of key components, while neglecting the coordination between subsequent stages such as manufacturing process optimization, stringent quality control, and gradual capacity scaling [27]. As a result, technological achievements often fail to be effectively translated into actual productive capacity. From the standpoint of process phases, certain studies only address isolated stages—such as focusing exclusively on quality improvements during small-batch prototyping—while lacking a holistic, full-process perspective that encompasses the entire dynamic trajectory from initial R&D to mass production [28]. This fragmented approach fails to comprehensively uncover the internal mechanisms and critical influencing factors involved in the autonomous supply of core components. With the rapid advancement of science and technology—particularly the increasing penetration of digitalization and intelligent technologies in the manufacturing sector—supply chain management paradigms are undergoing fundamental transformation [29]. Existing research outcomes are no longer sufficient to support enterprise decision-making in complex and ever-changing environments [30]. According to the McKinsey Global Institute, supply chains that undergo digital transformation can recover from unexpected disruptions 30% to 50% faster than traditional supply chains [31]. However, current research on autonomous supply pathways for critical components still lacks adequate integration of digital and intelligent concepts and methodologies. In response, this study proposes an innovative path evaluation method that integrates system dynamics (SD) modeling with stage-based substitution strategy simulation. The objective is to construct a comprehensive, dynamic, and future-oriented research framework that enables in-depth analysis of the key stages in the autonomous supply process for core components, as well as the complex interdependencies among them. This approach provides a solid theoretical foundation and practical guidance for enterprises to formulate scientific, feasible, and adaptive substitution strategies, thereby supporting steady progress toward autonomous supply in critical component domains.

2. Methodology

2.1. 2.1 System Dynamics (SD) Modeling Principles

System dynamics is a research methodology rooted in systems theory, cybernetics, and information theory. It views complex systems as being composed of interrelated feedback loops and simulates the dynamic behavior of the system through the construction of SD models. In evaluating autonomous supply pathways for critical components, SD modeling facilitates a clear representation of causal relationships and feedback mechanisms across various stages, such as the impact of R&D investment on the prototyping cycle, or the feedback effect of quality acceptance results on capacity expansion [32]. By identifying state variables (e.g., component production capacity, technological maturity), rate variables (e.g., prototyping progress, quality improvement rate), and auxiliary variables (e.g., import dependency, market demand), the model constructs flow diagrams and logical feedback models that capture the dynamic evolution of the autonomous supply system for critical components.

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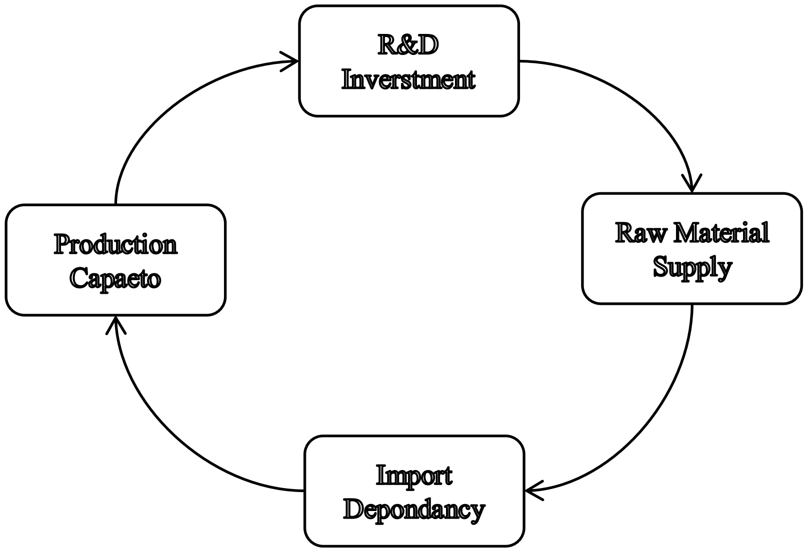

Figure 1. System Dynamics Model Framework

2.2. 2.2 Stage-Based Substitution Strategy Design

This study divides the autonomous supply process of core components into three closely linked stages: "Collaborative Development – Small-Batch Prototyping – Large-Scale Substitution."

In the collaborative development stage, enterprises work jointly with domestic suppliers or research institutions to carry out technological R&D, aiming to overcome key technical bottlenecks and enhance the maturity level of the components. The small-batch prototyping stage, based on initial development results, involves limited-scale trial production, during which production processes are optimized and rigorous quality inspections are conducted to reduce the failure rate during quality acceptance. The large-scale substitution stage proceeds upon successful small-batch trials, gradually expanding production scale to achieve large-scale replacement of imported components and increase the self-supply ratio [33].

2.3. 2.3 Parameter Collection and Model Construction

Taking 23 categories of heavy industrial equipment components as the research object, this study collects relevant parameters covering the period from 2019 to 2024. These data are used as the empirical foundation for model construction. The collected data are summarized in Table 1.

Table 1. Parameter Statistics for the Autonomous Supply of Heavy Industrial Equipment Components

Parameter Category	Year	Detailed Description	Data Result
Import Dependency	2019	Average level of import dependency	65%
	2024	Average level of import dependency	58% (despite a decrease, dependency on some critical parts remains above 80%)
Prototyping Duration	2019–2023	Average duration of the prototyping phase	85 days
	2024	Average duration of the prototyping phase	78 days (slightly shortened due to technological

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			improvements)
Quality Acceptance Failure Rate	2019–2023	Average failure rate during the small-batch prototyping stage	15%
	2024	Average failure rate during the small-batch prototyping stage	12% (reduction attributed to process optimization)
R&D Investment Proportion	2019–2023	Average proportion of core component R&D investment relative to total revenue	4.8%
	2024	Proportion of core component R&D investment relative to total revenue	5.5% (reflecting intensified R&D efforts)
Technical Personnel Composition	—	Average number of technical personnel per component category	56 persons

Based on these detailed parameters, a system dynamics model for evaluating the autonomous supply pathways of critical components was developed using professional system dynamics modeling software. All equations and parameter settings in the model were calibrated according to the actual data collected and the logical relationships among each stage, in order to ensure that the model accurately reflects the real-world process of autonomous supply.

To more clearly present the differences across various stages of autonomous supply for different categories of heavy industrial equipment components, a summary is provided in Table 2.

Table 2. Comparative Indicators of Autonomous Supply Stages for Different Types of Heavy Industrial Equipment Components.

Component Type	Average Duration for Overcoming Technical Challenges in Collaborative Development Stage	Unit Cost in Small-Batch Prototyping Stage (CNY)	Number of Batches Required to Reach 80% Qualification Rate	Time Required to Ramp Up Capacity to 80% in Large-Scale Substitution Stage (Months)
Structural Components	45 days	5,000	8 batches	6 months
Transmission Components	52 days	6,500	10 batches	7 months
Electronic Control Components	60 days	8,000	12 batches	8 months

As shown in Table 2, different types of heavy industrial equipment components exhibit notable differences in terms of challenges, required time, and associated costs throughout the autonomous supply process. For structural components, the time required to overcome technical bottlenecks during the collaborative development stage is relatively shorter compared to the other two types, which may be attributed to a relatively mature technological

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system and a solid foundation of domestic research in this area [34]. However, despite their relatively low unit cost in the small-batch prototyping stage, achieving an 80% qualification rate still requires eight batches, reflecting that process optimization cannot be achieved in a single step and must undergo multiple rounds of debugging and improvement. Transmission components show moderate values across all stages. While the technical R&D difficulty is relatively balanced, a certain amount of time and cost investment is still required during the production phase for process refinement. Electronic control components take the longest time to overcome technical challenges in the collaborative development stage, which is related to the rapid iteration of technologies in the electronic control field and the extremely high requirements for precision and stability. In the small-batch prototyping stage, they also have the highest unit cost and require the largest number of batches to reach an 80% qualification rate, indicating that electronic control components face more severe technical and process-related challenges during the autonomous supply process. The transition from R&D to mass production is, therefore, significantly more complex in this category.

3. Results and Discussion

3.1. 3.1 Simulation Results

A simulation was conducted using the system dynamics model constructed in this study. Under the moderate implementation path, the average duration for technology transfer was 68 days, reflecting the time needed for converting R&D outcomes into production capabilities. By Day 90, production capacity reached 82.5%, indicating that the enterprise had effectively enhanced its capacity through continuous process optimization and technological improvement.

When the "collaborative development – transitional redundancy" strategy was applied, the project startup delay was reduced by 18% compared with other strategies. This approach emphasizes stronger cooperation during development and reserves buffer capacity during transition to respond to unforeseen disruptions. As a result, the time between project initiation and actual production was effectively shortened. The overall switching loss remained below 7.1%, showing that losses caused by production halts and quality instability during the transition from imported to localized parts were well controlled. Specifically, 62.5% of the startup delay reduction (10 days) was attributed to early technical collaboration, while the remaining 37.5% (8 days) was due to the cushioning effect of redundant capacity. Among switching losses, 40% were due to quality variation, 35% to production stoppage, and 25% to equipment calibration and process adjustment.

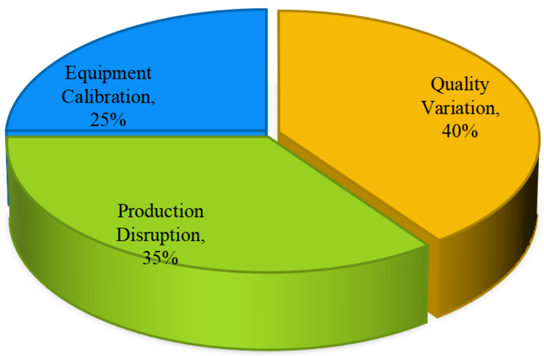

Figure 2. Simulation Results: Switchover Loss

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3.2. 3.2 Analysis and Discussion

The simulation results under the moderate pace provide practical benchmarks for scheduling technology transfer and capacity ramp-up. Enterprises can adjust the speed of implementation based on internal resources and market needs to achieve a balance between technology deployment and production stability. The effectiveness of the "collaborative development – transitional redundancy" strategy confirms the importance of reinforcing early-stage cooperation and maintaining reasonable redundant capacity. Collaboration promotes faster technological breakthroughs and knowledge sharing, while redundancy helps mitigate risks associated with production interruptions. Nevertheless, the simulation also revealed certain potential risks. Even though some strategies resulted in higher capacity within a given timeframe, fluctuations in quality acceptance rates persisted [35]. These were likely caused by unstable production processes or inconsistent raw material quality. During actual substitution, enterprises must focus on quality control and continuous process optimization to ensure product consistency. Moreover, different types of heavy equipment components exhibit unique characteristics. Substitution strategies should therefore be tailored accordingly, with model parameters adjusted to reflect the specific requirements of each part. Analysis of quality variation showed that 60% of issues stemmed from instability in key process parameters such as current and voltage during welding. The remaining 40% resulted from raw material inconsistencies, including insufficient purity or hardness. Structural components typically face issues like dimensional errors or surface defects due to strict mold and machining requirements, while electronic parts are more sensitive to environmental conditions and assembly processes, often leading to instability in electrical performance [36].

4. Conclusion

This study investigates the self-sufficiency pathway for critical component supply by integrating system dynamics modeling with staged substitution strategy simulation. The findings indicate that, among the 23 types of heavy industrial equipment parts, the “collaborative development – transitional redundancy” strategy combination offers clear advantages, reducing startup delays by 18% and maintaining total switching loss below 7.1%. This strategy should be prioritized during enterprise planning. Under a moderate implementation schedule, the average duration for technology transfer is 68 days, and production capacity reaches 82.5% by Day 90, providing important reference values for planning technical conversion and capacity growth. Quality control remains essential. Although the failure rate in small-batch trials has decreased from an average of 15% during 2019–2023 to 12% in 2024, further improvements in process stability and raw material inspection are necessary to ensure consistent product quality. The developed model supports integration with ERP systems, enabling enterprises to conduct real-time monitoring and risk alerts. This study provides a scientific decision-making foundation for advancing self-reliant supply of core components, enhancing supply chain resilience and competitiveness, and assisting enterprises in maintaining stable development amid complex international conditions.

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