Industrial Engineering Across Disciplines:

Security, Data-Driven Decisions, and Operational Systems

Editor: Prof. Dr. Nilgün FIĞLALI

DUVAR

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Chapter 1

COMPREHENSIVE REVIEW OF SECURITY THREATS AND ATTACKS IN GLOBAL SUPPLY CHAINS

Tuğçen HATIPOĞLU [1]*, Alpaslan FIĞLALI [2]

1. INTRODUCTION

Today we now know that we live in a highly global and interconnected world, in which supply chains are more interconnected, connected and risky than at any other time ever. Today's supply networks consist of a variety of actors—suppliers, manufacturers, logistics companies, distributors, and government agencies—all of whom coordinate with different countries. A higher degree of risk that is threatening at the reliability and resilience level of these systems to such systems increases, as they grow and are more intercentric. supply chain security has come to the forefront of both public and business interests as a consequence of this. Disruptions can be from natural disasters, infrastructure failures, pandemics or breakdown of operations in natural systems or human work. At the same time, supply chains confront deliberate and malicious perils such as terrorism, cargo theft, smuggling, counterfeiting, and cyber attacks, as well as deliberate acts of fraud. The 9/11 attacks, Hurricane Katrina, global cargo theft incidents and recent software-based cyber hacking incidents demonstrate how rapidly supply chains can collapse and their effects can extend across borders. While the literature on supply chain risk is increasing, relatively few studies are dedicated to the criminal/malicious and security-related issues. But these threats are significant because they can lead to large financial losses, disrupt business, or jeopardize a country's national security and public health.

To mitigate these aspects, international programs like C-TPAT, AEO, ISO 28000, TAPA and StairSec have been created. These frameworks will facilitate collaboration between public and private actors, promote preventive security measures, and underpin the implementation of advanced monitoring and information-sharing tools.

More recent academic research investigates the following quantitative risk models, as well as machine-learning based methods of assessment, improved forms

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of cybersecurity, and blockchain-enabled tracking devices. In this regard, the current study presents a diverse collection of supply-chain-related threats—ranging from traditional physical disruptions to unlawful operations and emerging cyber risks. It also reviews important international security standards and discusses new challenges around climate change, digitalization, and organized crime. The objective is to gain a better understanding of the changing threats facing our supply chains and what can be done to be able to manage them effectively.

2. SUPPLY CHAIN THREATS

This section aims to prevent physical threats that the supply chain may face and to increase the reliability of the supply chain. In this context, physical obstacles or disruptions that may occur at any component along the supply chain can increase the cost of the supply chain, cause delays, or completely halt the chain's operation. These threats range from natural disasters to human-caused accidents and infrastructure problems. The main physical threats to the supply chain are listed below:.

2.1 Natural Disasters:

Natural disasters are among the greatest physical threats to the supply chain. Earthquakes, floods, storms, hurricanes, forest fires, and volcanic eruptions can seriously damage production facilities, storage areas, transportation routes, and logistics infrastructure, potentially disrupting transportation.

Successful risk management in the supply chain before, during, and after natural disasters also indicates successful crisis management. Successful planning before a natural disaster ensures preparedness, while operations such as relief, logistics, and search/rescue are equally important after the disaster.

In disaster supply chain management, which is as challenging as managing the complex supply chain, different solution methods are recommended depending on the type of disaster (Akbal, 2023). Earthquakes: Earthquakes may result in the destruction of factories and logistics centers and the disruption of transportation routes.

- As a result of the Hatay earthquake in February 2023, highways and airports were destroyed. Due to transportation disruptions and the large affected area, it was not possible to deliver aid and carry out simultaneous search and rescue activities, resulting in many difficulties during the process.
- Floods and hurricanes: Floods and hurricanes also have negative effects similar to earthquakes. The blockage of transportation routes (roads, railways, airports) can lead to a complete halt in supply chain processes. The 2005 Katrina Hurricane natural disaster is an important example of companies and

global supply chains operating in an unpredictable environment (Wagner and Bode, 2006).

- Fires: Fires in warehouses or production facilities also cause material loss and supply chain disruptions. In 2000, a fire at Ericsson's supplier resulted in a loss of $400 million for the company (Duran and Ünlü, 2024).

2.2 Transportation and Logstics Problems

Accidents that may occur during transportation and weaknesses in the logistics infrastructure prevent products from being delivered on time. This situation has a direct impact on the efficiency of the supply chain. For example, accidents involving transportation vehicles such as trucks, trains, ships, or planes cause products to be damaged or lost, creating disruptions in the supply chain. Another potential problem under this heading is traffic congestion. Especially in intercity travel, transportation times are extended due to traffic accidents or road works, which increases supply chain costs. Furthermore, with the increase in e-commerce volume, urban freight transport has also increased. This increase has led to a rise in incorrect deliveries and return rates, resulting in increased traffic congestion (Kazancı and Tanyaş, 2024). Similarly, breakdowns in transportation vehicles also cause delays in deliveries..

2.3 Physical Theft and Vandalism

Theft and vandalism are among the physical threats to the supply chain. Logistics centers, warehouses, and transport vehicles are particularly vulnerable to theft and vandalism (Burges, 2012). Cargo theft has become one of the most alarming risks affecting global supply chains, causing serious supply chain disruptions, injuries/fatalities, economic losses, and environmental damage (Liang et al., 2022). Examples of physical theft and vandalism are listed below:

- Theft in warehouses: Products, stocks, or raw materials are lost in warehouses due to theft, causing disruptions in the supply chain.
- Robberies in cargo vehicles: Similar to theft in warehouses, material losses in transport vehicles also disrupt the supply chain.
- Vandalism: Acts of vandalism also render products unusable and cause disruptions in the supply chain by damaging transport vehicles or infrastructure

2.4 Infections and Disease Outbreaks

Health crises that can affect the supply chain are also among the physical threats. Global health crises such as Covid-19 have led to the closure of production facilities, loss of labor, and logistical delays. This physical threat will be explained in detail in the next section.

2.5 War and Terrorism

Wars, internal conflicts, or terrorist attacks directly affect the supply chain. War and terrorist attacks, which are considered physical risks, cause destruction in the affected area and its surroundings, resulting in disruptions to the supply chains around the area. For example, following the September 11 attacks, Ford was forced to close its facilities for a period of time (Duran and Ünlü, 2024).

To cope with these risks, the characteristics that supply chains must possess are listed below (Tandler and Essig, 2013):

- The purpose is to secure a supply chain and its assets.
- The concept focuses on types of disruption that refer to any attack intended by human actions.
- It focuses more on protecting physical flow and less on protecting information flow.
- For the purpose of managing security, it is recommended to adopt preventive measures rather than reactive measures.

The following list of topics can be given as examples of such threats:

- Infrastructure damage: As a result of wars or terrorist attacks, logistics infrastructure, transportation routes, warehouses, or production facilities are adversely affected.
- Closure of trade routes: The closure of land, sea, and air routes in war zones causes major disruptions in material procurement and product distribution for all supply chains using the region.

2.6 Physical Infrastructure Weaknesses

Lack of proper transportation infrastructure is one of the most common barriers facing companies and organizations in developing countries to participating in global supply chains. Infrastructure of this kind is a major feature of many global indicators of domestic competitiveness. Public and private organizations use transportation and logistics systems to get supply lined to demand. Transportation infrastructure comprises all the systems that permit movement of people and resources, notably road networks, railways, waterways, airports, and canals. Logistics infrastructure is much broader and spans three areas: (i) loading, unloading, and storage equipment at terminals; (ii) information systems to direct physical and financial flows; and (iii) financial procedures that provide for these activities (Cedillo-Campos, 2022). If infrastructure is aging or not being kept current, we frequently see massive disruptions to supply chains. Power outages, water shortages and weak transportation networks are typical examples of physical infrastructure failures.

2.7 Climate Change and Long-Term Environmental Impacts

Climate change is among the most significant long-term physical threats facing global supply chains. More than half of the CEOs surveyed by Pankratz et al. (2024) say that climate-related risks are now among their top issues. However, adapting to climate change remains challenging for the majority of economic actors, especially for firms operating within complex supply chain networks. One challenge is uncertainty. Climate change also gives irregular, even noisy signals; it makes it challenging to predict weather-related disruptions in the short and medium term. Another issue is indirect exposure. Companies rely on numerous suppliers and customers, so it is sometimes difficult to pinpoint how climate risks that hurt one partner will flow through the remainder of a chain. Consequently, companies have difficulties evaluating when climate risks will make it necessary to terminate existing relationships or create new ones. Common climate-related threats include:

- Droughts and water shortages (impeding agriculture and manufacturing by reducing the availability of necessary raw materials).
- Temperature fluctuations, which may disrupt production processes and increase the chance of spoilage in temperature-sensitive goods such as food or pharmaceuticals (Rojas-Reyes, 2024). These environmental hazards can be very disruptive to operations and result in large economic loss. Getting ready for them is crucial. Organizations ought to conduct frequent risk monitoring, tighten up security measures and create backup plans to minimize the impact from climate-related shocks and enhance supply chain resilience.

3. LITERATURE REVIEW ON MALICIOUS ATTACKS IN SUPPLY CHAIN SECURİTY

Risk of supply chain risk management starts with identifying an initial risk; then estimate its likelihood and how much damage it is likely to cause. The main difference between risk and uncertainty is that risk can be measured. Global supply chains are large and complex, and uncertainty quickly wreaks havoc (Waters, 2011). As a consequence of this complexity, a number of studies have recently shifted their research focus in security to consider the entire supply chain and not only transportation. Each industry has its own special security approach. For example, Behzadi et al. (2018) on risk management in agriculture. Recent work has emphasized food security and bioterrorism is often seen in the context of food security. In the case of example, others like Edgerton (2021) and Jiang et al. (2021), explored risks in ports and maritime logistics. Nguyen et al. (2021) developed a detailed model to analyze risks on container shipping. Alora and Barua (2022) developed a risk index for small and medium manufacturers in India. It has been shown much of the research on supply chain disruptions however only some of the literature is concerned concerning specific forms of threats like terrorism, smuggling, counterfeiting and theft. Evidence on impact of crime-based regulations on the supply chain performance is scarce as well. Although the interest in Supply Chain Security rose after the attacks of 9/11, some companies still consider these threats improbable. But the harm from those types of attacks can be devastating. In this section, research on terrorism, piracy, theft, smuggling, counterfeiting, and cybercrime is discussed. The literature was gathered by searching the search history terms terrorism and supply chain with piracy, theft, smuggling, counterfeiting and cyber risks included as the relevant keywords. Some researches, including Jażdżewska-Gutta and Borkowski (2021) emphasize the need to identify the weakest link in the supply chain. They recommend utilizing existing data, experimentation, and survey data and emphasize interdisciplinary work in fields such as security, economics, criminology, and psychology. There is an alternate debate, in literature, regarding responsibility: Who should do responsibility for security? Companies typically do not invest enough in prevention when threat is low or high. The market could regulate itself as others (like Jonkeren and Rietveld, 2016) argue. Others, in the argument of Kanafani and Huang (2010), state that government should coordinate, regulate, or offer incentives to implement a more secure supply chain.

Different initiatives create supply chain security standards for different purposes. Gutierrez and Hintsa (2006) classified the following four types of voluntary security programme created by different organisations or institutions:

1) customs compliance programmes with added security layers, 2) government-originated standalone security programmes, 3) security standards programmes originating from international organisations, and 4) private-originated standalone security programmes. Examples of these programmes include TAPA (Transported Asset Protection Association), EU AEO (Authorised Economic Operator), C-TPAT (Customs-Trade Partnership Against Terrorism), StairSec (Swedish Customs Supply Chain Security Model) and ISO 28000.

C-TPAT (Customs-Trade Partnership Against Terrorism) is a voluntary joint government–private sector partnership launched by the U.S. Customs and Border Protection (CBP) in November 2001 in response to the 11 September terrorist attacks. It is defined as the implementation of policies, procedures and technology to protect supply chain assets (products, facilities, equipment, information and personnel) from theft, damage or terrorism, and to prevent the entry of unauthorised contraband, people or weapons of mass destruction into the supply chain. The programme's objective is to enhance supply chain security and prevent future attacks (Gupta et al., 2019). The C-TPAT programme provides greater control over security, leading to reduced transaction costs, effective audits, and faster shipment processing.

As a result, an increase in work safety and company performance overall is expected (Bakshi & Gans, 2007).

In their case study, Gupta et al. (2019) analysed the link between company size and participation in the C-TPAT programme using institutional and resource-based view theories. Ni et al. (2016) analysed data obtained from the C-TPAT Partners Cost-Benefit Survey using structural equation modelling and a quantitative evaluation method.

Tong et al. (2022) investigated whether adopting C-TPAT certification improves firms' operational performance. This study uses signal theory to determine its impact on the operational performance of publicly traded importing firms, analysing data from sample-control groups. Matching analysis and difference-in-differences methods emphasised that C-TPAT-certified importers perform better operationally than non-certified importers.

Lozano and Montoya-Torres (2024) present an up-to-date analysis of the relationship between various logistics security programmes (C-TPAT, AEO, BASC and ISO 28000) in the Latin American and Caribbean region. They conclude that implementing these programmes enables organisations to gain greater visibility in global supply chains, which are becoming increasingly fragile and complex due to the security risks they face.

Nikoofal et al. (2023) made a contribution to supply chain security literature by developing a game model involving the government, companies and a strategic adversary.

In their model, they defined compliance requirements, resources, audit rates and optimal capacity as levers for the government to use to encourage companies to cooperate in order to enhance security. Kusrini et al. (2021) assessed the security of a leather factory's supply chain in Indonesia in accordance with ISO 28001.

They classified security threats into five categories: asset security, personnel security, information security, goods and transport security, and closed cargo transport units. Using a priority system based on the risk score of the 22 security threat scenarios identified in the company's supply chain, they explained the necessary measures to reduce the threat to an acceptable level.

One of the regulations included in the supply chain security literature and widely used in international contracts is the Incoterms rules. These rules clearly define which party is responsible for which risks and costs during the execution of the contract. The Incoterms rules affect the rights and obligations of the parties to the sales contract, as well as the control and management of the logistics system and the transaction costs involved. Yang (2021) examined the potential effects of the 2020 Incoterms rules on logistics and supply chain management, analysing the factors to be considered when selecting Incoterms rules within the scope of a sales contract.

One global strategy designed to protect supply chains and facilitate international trade is the Authorised Economic Operator (AEO) strategy, created due to the ever-growing threat of terrorism and fraud associated with international trade. Established as part of the adoption of the 'Security and Trade Facilitation Standards', it is recognised by the World Customs Organisation (WCO) as one of the most important supply chain security initiatives. Amine and Boujelben (2024) use the 'AEO' example to demonstrate the benefits of cooperation between customs authorities and the private sector within a framework of mutual trust.

Chou et al. (2024) investigated the impact of AEO certification on export sales and corporate performance, using a sample of Taiwanese companies that obtained AEO certification between 2009 and 2018. Their results show that AEO-certified companies increased their export sales ratios and the scope of their export target regions.

One of the most challenging security issues in supply chains is cargo theft. It is estimated to cost companies $10 billion annually in the US and $30 billion worldwide. Over 90% of cargo theft incidents target the transportation component of the supply chain. Boone et al. (2016) discuss methods of combating transit cargo theft using a qualitative approach, as well as corporate responses to security issues.

Liang et al. (2022), on the other hand, aim to analyse the risk-influencing factors of cargo theft and predict the probability of different incidents occurring using a Bayesian network-based cargo theft risk analysis model developed with quantitative methods, using data from 9,316 incidents that occurred in the UK between 2009 and 2021.

Lorenc and Kuznar (2018) conducted risk analyses using artificial neural network-based algorithms, which take into account the probability of cargo theft at specific stages of the ordering process for different cargo types. As the article specifies estimated loss values, it can be used by insurance companies to determine cargo insurance rates.

In heavy industry, the value of cargo transported by rail is very high. Due to the high value of the cargo, the weak security and the volume of rail transport, theft is a frequent occurrence in this mode of transport. The most fundamental problem in ensuring the security of rail transport is predicting where the high-risk areas are. Lorenz et al. (2020) developed a model that uses artificial neural networks (ANN) and machine learning methods to predict the regions with the highest probability of railway cargo theft.

Ekwall et al. (2016) investigated the scale of cargo theft in the European pharmaceutical supply chain by sending a survey to all major pharmaceutical manufacturers and logistics providers in the sector.

Ekwall and Lantz (2022) examined the weekly and annual variation in the value of stolen goods, incident frequency and incident category. Incident frequencies and average values were analysed first using chi-square tests and analyses of variance (ANOVAs), which showed that the incident category exhibits both annual and weekly seasonality.

Illegal smuggling is considered a significant problem for supply chain security with negative economic and social impacts. Governments and companies often encounter networks of smugglers engaged in the illegal trade of goods at different levels with an anonymous structure. International smuggling employs new operational methods, multiple modes of transport, flexible transport routes and transport assets designed to conceal contraband goods, thereby evading border security and law enforcement controls (Basu, 2013). Therefore, resources should be managed by prioritising the identification of network members, the monitoring of identified members, and their subsequent arrest to remove their related illegal trade from the network. Najafi et al. (2023) proposed a mathematical model including a formulation and solution method to manage existing resources within the network and minimise illegal flows between threats and destinations.

Soon and Manning (2018) adapted the outputs from processes developed to reduce tobacco smuggling for use in food-related smuggling activities. Their work indicates that an effective strategy to address the illegal food trade requires the development of robust legal and institutional frameworks, alongside transparent communication and cooperation systems.

Another area of literature related to smuggling and supply chain security concerns wildlife. The illegal trade in endangered wildlife encompasses poaching, looting, fraud, distribution and the trafficking of rare plant and animal species. It is one of the world's largest criminal activities, with an estimated annual value of $19 billion. For instance, a kilogramme of ivory poached from an elephant can fetch $850, with around $31 million worth of ivory being smuggled from East African countries to consumer markets in Asia. The illegal supply chains that enable this trade are multi-layered, involving multiple stages from supply and transport to demand (Basu, 2014). Duensing et al. (2023) have developed a model that explains the vulnerabilities related to the wildlife trafficking supply chain and how it can be made more resilient.

Counterfeiting is defined as 'the unauthorised production of goods protected by special characteristics or intellectual property rights (trademarks, patents and copyrights)'. The disadvantages of counterfeiting for producers include high costs and financial losses, as well as various serious consequences such as delays, lost sales, product recalls, litigation, loss of revenue, and loss of image and customer trust (Partyca et al., 2024).

Supply chain security weakens when members act in their own interests; conversely, the ability of supply chains to combat counterfeiting effectively increases when all members contribute. Yi et al. (2022) investigated which supply chain members are best positioned to implement countermeasures, how these members can collaborate to combat counterfeiting, and the economic impact of anti-counterfeiting measures on the supply chain, individual companies, consumers, and social welfare. They applied and validated this research within a supply chain consisting of a manufacturer and a retailer, using a game theory approach.

The recent Covid-19 pandemic has also highlighted the importance of supply chain security, particularly with regard to counterfeiting. Thousands of counterfeit vaccines have been produced and delivered anonymously. Counterfeit vaccines are vaccines whose identity and source are unknown, intentionally misrepresented or mislabelled. Deficiencies in these vaccines include mislabelling, incorrect or insufficient ingredient quantities, unsuitable or missing packaging, and the consequences of unequal vaccine distribution. Munasinghe and Halgamuge (2023) developed smart contracts within a blockchain network to cover vaccine inventory, registration, regulatory compliance and traceability for supply chain traceability and counterfeit detection of the vaccines.

Falasca et al. (2022) developed a model to examine the relationship between supply chain counterfeiting risk management and healthcare supply chain performance. They investigated the difference between a healthcare organisation's philosophy regarding counterfeiting risks and the measures taken to eliminate or reduce the impact of counterfeiting.

Counterfeit products play a critical role not only in the healthcare industry, but also in manufacturing industries. Counterfeiting directly affects companies' sales and, consequently, their profits. Jayaprasanna et al. (2021) detect counterfeit products using a barcode reader that links the product's barcode to a blockchain-based management system. They obtain the product code from the customer and compare it with entries in the blockchain database. If the code matches, they notify the customer; otherwise, they ask the customer where they purchased the product in order to identify the counterfeit product manufacturer.

An effective cybersecurity management strategy is required for a supply chain network to monitor the most important components and resources in the supply chain system, as well as the cyber threats that could affect them. This strategy must also ensure preparedness for possible countermeasures. While digital technology increases information exchange, agility, and visibility in supply chains, it also increases the vulnerability of all members due to the shared information and security regulations throughout the supply chain. Research reports indicate that small organisations in the supply chain are often the target of cyberattacks and data breaches. Therefore, when larger companies contract these smaller organisations to produce specific products, they are exposed to certain cybersecurity threats (Latif et al., 2021). Syed et al. (2022) present research in the field of supply chain traceability and cybersecurity.

A software supply chain attack occurs when a cyber threat actor infiltrates a software network before the supplier sends it to its customers and inserts malicious code to compromise the supply chain software. The compromised software then compromises the customer's data or entire system. While these attacks initially impact software users, they can subsequently have far-reaching consequences for private sector software customers and government entities. The average cost of a supply chain data breach exceeds $3.86 million per company or organisation. Cyberattacks can take various forms, including malware attacks, phishing attacks, man-in-the-middle attacks, denial-of-service attacks, SQL code injection attacks, ransomware attacks and DNS attacks. Phishing attacks account for 80% of all cyberattacks and are the most common and costly type of software attack (Sullivan and Garza, 2021).

Effective supply chain risk management and security require the combination of risk mitigation strategies and effective decision-making practices. Hintsa et al. (2009) classified the practical supply chain security management measures proposed by various initiatives as falling into one of five categories: cargo management; facility management; information management; human resources management; and business management systems. Cargo management is defined as protecting cargo throughout all stages of production, transportation, and shipping. Facility management and human resources management, meanwhile, are associated with supply chain security programmes designed to either increase the security control capacity of customs authorities or reduce specific industry/geographical vulnerabilities. Practical measures falling under the category of information management are described as a crucial component of customs authorities' efforts to increase their control capacity. The 24-hour advance declaration rule and the 96-hour advance notification of vessel arrival, for example, are part of several mandatory measures consisting of managing the flow of information on cargo in such a way that risks can be identified before the physical flow reaches the border. Finally, business management systems include 'security creation' headings in internal and external organisational structures and company management systems, including supplier, partner and customer management processes.

The reviewed literature on supply chain security contains recommendations for security measures obtained using qualitative or quantitative methods. Qualitative methods include research such as Delphi analysis, focus groups, literature reviews and case studies, while quantitative methods include survey-based studies, simulation, mathematical modelling and other data mining techniques.

As high technology develops, security methods and technologies are rapidly being updated and changed. Important examples of these are: Automatic identification technologies, closed-circuit television (CCTV), global positioning systems (GPS) and X-rays. These methods can be used in various security activities, such as monitoring and tracking, field security, and goods control. Additionally, supply chain security standards can define the security environment and enhance security levels within companies and organisations (Zhang et al., 2011).

4. CONCLUSION

Supply chain security has become critical in safeguarding global trade, economic prosperity, and public safety. Modern supply chains risk a multitude of dangers from natural disasters, infrastructure failures, terrorism, smuggling, counterfeiting, and cyberattacks. And as supply chains become increasingly fragmented and digital, those risks compound and become more difficult to control. Security has gone from an operational issue to a strategic priority. The literature shows that even minor disruptions can cause massive financial, operational, and reputational damage. Transportation can be stopped by natural disasters. Theft and smuggling cause enormous economic losses. Counterfeit goods can pose a threat to consumer safety. Cyberattacks can reveal sensitive data or bring systems to a complete standstill. Because supply chains are interlinked, weakness in any one point can quickly spill over borders. Various key conclusions emerge:

It is vital risk management be proactive. Security needs to be a part of all the planning, technology, and logistics processes — and not bolted on after the fact following a crisis. The weakest link will be the overall security factor. All partners, small and large, must follow common standards and work together. Visibility is enhanced through advanced technologies. AI, blockchain, IoT, GPS tracking, and analytics help identify risks early and enhance real-time control. It takes regulation and cooperation. Various programs like C-TPAT, AEO, BASC, and ISO 28000 can help, but information sharing and cross-border cooperation are critical. Resilience also trumps efficiency. Systems that are highly optimized may be fragile. Stronger more stable supply chains with diversified and flexible sources can emerge. Supply chains will need to build integrated strategy in the future, where physical security, cybersecurity, data protection, and governance are used in conjunction. Climate change, geopolitical instability, cyber threats, and organized crime will become more significant. Supply chains will need to be stronger – and more flexible – to preserve global trade. Insights from logistics, criminology, information systems, and public policy should be integrated into future studies. Improving supply chain security is an urgent operational requirement but more importantly makes its way into the bedrock of safe and reliable global trade.

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Chapter 2

LINE FEEDING STRATEGIES IN A JUST-IN-TIME PRODUCTION ENVIRONMENT: CONCEPTS, METHODS, AND OPERATIONAL IMPLICATIONS

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1. Introduction

The large number of unique products, the complexity of variant structures, and the frequent evolution of consumer requirements in the current assembly and production systems require the reevaluation of the internal logistics mechanism. The shift from mass production to mass customization has enabled a new era: parts and types of product variants on assembly lines have grown markedly. As a result, the requirement for rapidity and accuracy in material flow has emerged as decisive competitive factors for firms. As a consequence of this shift, delivering the correct part to the assembly line in the appropriate quantity, at the appropriate time, and with the appropriate process form an important operational need. Underlying the requirement is the line feed strategy. Line Feed is an integrated decision-making process which decides upon the type, timings, and types of logistic means by which materials are delivered to the production line. It is a strategic function which affects production efficiency directly.

More product variety may translate into a need to consume in excess of hundreds of product elements at a given time on a factory line — hundreds of different parts to fill in the whole assembly line. As a result, the smooth working of an assembly line, not just the material supply but how parts are used, is directly affected by the supply process itself. Increasing the number of variants leads to the risk of incorrect parts, prolonged operator walking or searching times, limited use of lineside space, and ultimately, an elevated risk of logistical interruptions that result in production pauses. The feeding policy imposed on the assembly line of the Swedish automotive assembly industry had a direct influence on labor consumption, space requirements, and quality (Hanson, Brolin, 2013). Moreover, the fact is that, line feeding is not only a logistical issue but also an operational

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design problem, which is the essence of lean manufacturing and Just-in-Time (JIT) philosophy.

The basic principles of JIT, namely the pull system, zero stock approach, flow continuity and elimination of waste, require the precise and balanced management of the material supply process. In many examples, stock control, carrying the wrong inventory or excessive walking, searching time, and unscheduled line stops are the result of poor line supply design. In a JIT context, just a moment's delay in one component can bring whole production flow to a standstill and generate large losses in cost. Consequently, parts supply policy development is integrated into lean transformation projects for the large majority of business.

During the last twenty years, literature on classification, analysis, selection and optimization of line supply strategies have been highly discussed. Research on differences in the performance between various types of supply schemes is most noticeable in applications with a diversified product mix, such as automotive, electronics, white goods, or heavy machinery (Hatipoglu et al., 2017). Battini et al., 2009 - In their investigation of the effect line supply decisions could have on storage, receiving and transportation functions for mixed model assembly lines they stressed the interconnected nature of supply chain perspectives. In a similar vein, Caputo and Pelagagge (2011) developed a model which can be used by other decision makers who are trying to assess line supply strategies and in-depth analyzed the impact at different levels of continuous distribution on costs such as lineside stocking, kitting and Kanban-driven continuous supply.

Literature examines the line feeding issue from a variety of angles and techniques. In some studies (e.g., Limère et al., 2012; Sali & Sahin, 2016), mathematical models have been developed that specify the feeding mode the parts are to be assigned from one another. These systems have mixed integer programming models designed to optimize different factors in addition to transportation costs involved in kitting, such as labor and walking distance. Simulation-based studies (Faccio, 2014) have used parameters such as the volume of produced, mix product and length of the lineside area to evaluate feeding policy performance effects. Recently, data science and machine learning methods have been applied as well; Zangaro et al. (2021) constructed models that can predict which part belongs to which feeding policy dependent on feature of the part under classification algorithms.

This diversity is both a direct reflection of the effect that line feeding strategies have on production and indicative of the methodological depth of academic works in this field. While these strategies have far-reaching implications for logistics costs, they affect production line ergonomics, quality defects, operator efficiency, and line stability as well. Hence, selection of the right feeding policy of modern production systems is not only a technical logistics problem, but a system design problem in alignment with the JIT philosophy.

Line supply strategies are significant because that is part of the whole JIT framework. The low inventory levels demanded by JIT will require parts to be continuously moved at fixed intervals to be transferred to the edge of the line, (where they could be transferred in response to demand signals.) Kanban processes control the flow of goods via pull flow, while rotational conveying schemes like the milk runs maintain in sync the steady flow of the goods in the process as needed on time. When these 2 mechanisms perform in conjunction, line variability is minimized, allowing for more predictable flow. Kanban and milk runs are closely related topics and the integration of them has become a central element of line-supply in academic studies and industrial settings.

Due to such diverse and fast assembly lines, today line feeding is not just a complementary logistical activity, but also a design parameter to secure a production flow. Production's performance is shaped by things like the proportion of parts in line with the line's chain consumption pattern, the rhythm of train systems, the amount of room in linesides (few materials), the amount of walking-searching load of operator, and so on. Thus, in JIT-based organization, the choice of which section to delivery at what method to the line by what rate, at what preparatory level, and with the appropriate transportation arrangement is crucial for both operating costs and stable flow. An ever greater variety of forms, the shortened product lifecycles and a redefined human-machine interaction in internal logistics have made line feeding methodologies a central problem in contemporary production systems. The rest of this book chapter will analyse further the role of various line feeding policies in JIT terms, the operational effects, and the techniques suggested in the literature.

2. Line Feed Concept in the Context of JIT

In JIT production systems, the importance of the feeding process in the production of continuity of material flow, station synchronization and line rhythm was determined by the operational design. Thus, line feeding is one of the most important elements of practical operations of JIT's abstract concepts. JIT system design provides a functional setting which doesn't just require the minimum amount of inventory operated but also demands that demand-based flow, steady state conveying cycles and a fair division of labour between the stations be established. If under these conditions, the specific way material reaches the line edge along with the replenishment logic it uses can become a control variable that affect all of the system.

The pull logic of JIT is the deciding principle of material flow. In line with pull principle, one's material movement is not in the moment of consumption but dependent on a signal from a point in production flow, whether it be a physical card or digital notification, a message sent on sensor and or periodic conveying. The pull mechanism provides the primary purpose of avoiding the accumulation of undesired materials at line edges and the redundancy of the system to get rid of unwanted material. The feeding policy needed for this mechanism should fit with the signal generation and response processes. If this is not done, then the line feeding process can become a bottleneck for the JIT flow.

Timing accuracy is also an essential factor affecting the flow of material in JIT systems. On production lines, time to reach the line must be under controlled conditions as the stations need to use small variations in cycle times. Cycle time exceedances and line blockages can occur due to unplanned delays, disturbances in the flow of the rhythm, and changes in the conveying process. That is why you want a line supply strategy such as this, the lead times have to be stable and predictably predictable. To illustrate, manual conveying approaches that change for each line arrival are vulnerable to a JIT system, while tuggers that operate periodically are risky. Increased timing accuracy due to train or milk-run cycles.Timing accuracy is one of the main indicators for compatibility of a feed method with JIT.

A physical limitation of JIT is line-side space. With limited space, only a limited quantity and variety of material units can be placed on the line. Maintaining the lineside with such high volumes or parts with multiple versions for a longer period of time not only increases the walking distance, but also makes it harder for the operator to assemble. JIT does not tolerate overload, too, of material at the lineside as far as the materials are concerned, because excessive inventory leads visually to clutter, movement limitations and quality issues. Thereby the supply policy has the intention for the variety and amount of parts on the lineside to be controlled, and material presentation, as a process can be simplified by preparing materials using a process or method such as kitting or sorting, if required.

In the JIT context another important aspect of line supply is the stability of replenishment cycle. The replenishment cycle takes place in two phases. First, when a signal is generated, and later the transport responds to that signal. Kanban cards produce the replenishment signal, while milk-run cycles gather this signal to supply the necessary line materials. The most important point that is emphasized here is that rhythms in transportation help ensure a steady processing of signals, thereby minimising variations in inventory levels. If signal generation is constant, but transportation is irregular, the transport system becomes a bottleneck; if transportation is rhythmic, but signal generation is inconsistent, then unbalanced inventory levels occur at the edge of the line. JIT achieves operational stability through these two combined functional elements.

Control of inventory is another element, that is essential for JIT. In an environment based on JIT, the inventory not only adds to the financial burden but also disrupts internal flow balance of the system. At the core of this stock management mechanism is the supermarket. The supermarket space is recharged using a fixed replenishment logic determined by the consumption rate of parts, and the transportation system connects the space with the assembly line. Wrong sizing of the supermarket disrupts the JIT flow in two different ways: a lack of capacity causes transportation cycles to be carried out excessively frequently; the excess size makes JIT inventory insensitive. Supermarket design plays an important role in supply policy and should fit to JIT inventory philosophy.

Another crucial issue is the challenge with deciding supply strategies of a JIT system is demand fluctuation. With the variable product mix, the consumption rate and burden load on station level shifts, so that there is a demand for flexibility in the supply system. Preparation-based steps (eg, kitting, or sequencing) may decrease the cognitive load on the operators in an extensive environment, but such steps involve system installation and labour costs. In contrast, line-simpler feeding methods like stocking are counterproductive for JIT in high-variety situations, because they tend to increase search time. It is for this reason that the choice of the feeding strategy in a JIT environment must be sensitive to the variability in workload and mix ratios.

Last but not least, in fact a great deal of JIT systems is information flow-dependent. If this process is not provided based on continuous, accurate, and fast information flow from the source material to the source material, the line supply can not carry on with the JIT concept. The right return of Kanban cards, timing signal generation by digital monitoring devices, transmission signal at a right place and follow consumption in real time have been the basic information-flow processes of the supply policy. When there is a delay or mistake in flow, as there is in flow through a container, the integrity of the JIT system is impacted.

In this technical framework, the line feeding concept of JIT systems provides a systematic operation-design dilemma that handles material preparation, replenishing inventory, transport rhythm, space use, storage space, transportation of information, and information flow. Accordingly, next, the different line feeding policy of JIT will be systematically classified, and the operating principles and applications of each specific method with regard to the operating conditions are will be explained.

3. Classification of Line Feeding Policies

Line feeding strategies are a package of measures to determine how parts should be prepared for the production line and how they should go to the operator. Although there are different classifications in the literature, the configuration that is most appropriate for the processes of the contemporary assembly line is a configuration that separates the feeding method based on how the material is presented on the line. The section addresses line feeding strategies according to the following five basic line feeding methods that are used in production lines: lineside stocking, boxed supply, sequencing, fixed kitting, and mobile kitting. Advantages and disadvantages of these methods are different, both in terms of operational flow and in JIT principles.

3.1. Line Side Stocking

Line-side stocking is based on the principle of placing parts directly at the edge of the production line, where they will be used in assembly. In this method, after materials leave the supply unit, they are placed on designated shelves, boxes, or pallets along the line's designated stations without any preparation. The operator retrieves the required part directly from this stock area.

The most obvious advantage of this strategy is its simplicity. It requires no setup process, no additional labor, and reduces handling loads for high-volume parts. However, lineside space consumption is the most significant limiting factor of this method. Bringing parts into the line in full boxes, pallets, or large packages consumes significant space at the edge of the line. This increases operator walking and searching distances and creates unwanted inventory accumulation at the edge of the line, contradicting JIT principles.

Line stocking is preferred for low product variety, high consumption rates, and relatively large lineside space in production facilities. However, it is not practical in the case of assembly lines with increasing product variation because it increases process complexity and the probability of causing errors. Schmid and Limère (2019) observe that this approach seems to continue to work well, at least in volume-heavy settings, although this design does not achieve the flexibility required in mixed-model assembly lines.

3.2. Boxed Supply

Boxed procurement is the process of dividing parts and delivering them into standardized small boxes (e.g., KLTs, plastic containers, small packaging units), then delivering them to the production line. These boxes are usually prepared in the supermarket area to ensure several items reach the line in small batches. This technique mainly involves the utilization of lineside space and eliminates the space pressure incurred by bulk packaging units. It's simply easier for operators to find the stuff they need by dividing the boxes into more easily accessible elements, cutting time to find them down – which in some cases includes ergonomic design. Replenishment cycles are also relatively balanced here, as smaller boxes are replaced faster and pull signals provide more uniform flow. But it does have the expense of setup. Separating pallets or larger packages into smaller units is also laborious. However, boxed procurement is very well-suited for both Kanban and milk-run transportation systems, and has a good rhythm for JIT flow. This approach is well-suited for when parts have been created in great variety but is not quite complex enough to need kitting.

3.3. Sequencing

Sequencing is the method of placing parts in the consumption order and bringing them to the line that is exactly in accordance with the product flow at the line of the production. Particularly in assembly lines with high variants, it is important for each part of each product to reach the line in the right order. The sequencing system directly manages the variety of variants. This method arranges parts into a sequence, either in the supply chain or the staging spot relevant to the material. As the product sequence at the line changes, this material is presented to the operator in the same sequence. This is particularly common on automotive assembly lines; components carrying more than one variant often arrive at the line in order. Sequencing is advantageous in that it minimizes variant errors and eliminates operator search altogether. But the staging is tricky, and the information flow has to be maintained uninterrupted. One material prepared in the wrong order can destroy the production sequence of the entire line. Consequently, sequencing is a method that demands high accuracy but also incurs large setup costs when performing this task. Schmid & Limère (2019) point out that with the rise of mixed-model production sequencing has taken on the strategic importance it once did not.

3.4. Stationary Kitting

In a fixed kit operation, all the parts necessary for product assembly are prepared in a specific kit, which is then delivered to the appropriate station. A separate kit is prepared for each product and used in a fixed location next to the station. The main objective behind this approach is to simplify the assembly task by eliminating operator search and selection efforts. The key strength of the fixed kit approach is that it greatly diminishes part variety at the line edge. Since operators only work with parts within the relevant kit, the chance of errors is minimized, walking and searching time is eliminated, and the workflow is standardized. The fixed kit method is thus especially preferred in assembly environments where the number of variants is large. However, there is extra time and labor required for the kitting process. Not only does preparing separate kits for each product raise internal logistics overhead, it also increases sensitivity to kitting errors. In production lines with high variety and complexity, fixed kitting provides a solution compatible with JIT's objectives of error reduction and process standardization.

3.5. Traveling Kitting

The mobile kit application is a variation of the fixed kit logic; however, the kit isn't fixed in a station, so it accompanies the operator or conveyor system through the line during production. The kit tracks a product's life cycle, and the kit travels to whichever station the product arrives at in the same order. This makes it efficient for long and complicated assembly lines. In this manner, operators are faced with just the parts that they need in their stations as they go along with what they carry out there. In addition to the space-saving and error-reducing potential of fixed kit methods, movable kitting enables the kit to be transported in a continuous flow logic. The disadvantage of this approach is that the physical mechanism to transport the kit along the line must be sufficiently flexible. Incompetency of the transport system can lead to kit flow interruption. Nevertheless, such as in high product range lines, traveling kitting is regarded as a powerful approach to maintain flow stability required by JIT systems.

4. Operational Components of the Line Feeding Process

The line feeding, seen as one of the most conspicuous activities of the production system associated with external logistics, can be regarded as a comprehensive sequence of operations that determine the rhythm of the assembly line. Transporting parts from storage, managing intermediate storage areas, preparation, line transport, operator consumption, and return of empty packaging are the interconnected components of the JIT system. Any disruption of these process connections affects not only the flow of material but also assembly cycle time; it also influences line balancing, the carrying capacity of the conveying system, and the quality of the final product. Thus, a good understanding of how the operational structure of the line feeding process operates is essential for selecting the correct feeding policy.

4.1. Retrieval from Warehouse

The warehouse pick process forms the starting point for the entire flow of the line supply process. Retrieving parts from warehouse locations in the correct quantity and packaging type is critical not only for ensuring material availability but also for the timely and uninterrupted progress of the replenishment flow. Factors like the accuracy of the warehouse addressing system, material management according to FIFO or LIFO principles, the physical layout of the supply unit, and the capacity of the picking vehicles influence the speed of the process. One small delay in the warehouse affects the next conveyor cycle and introduces irregularities to the line supply. Because of the time sensitivity of the JIT system, the retrieval step should be designed to precisely obey the rhythm of the conveyor system. If the retrieval is done prematurely, excessive inventory can accumulate in the supermarket area, running counter to the JIT principle of minimizing inventory. Thus, retrieval is a decision-making task that needs to coincide with transport periods, replenishment signals, and preparation processes. Poorly designed, it can disrupt the balance of the entire system.

4.2. Supermarket Renewal

The supermarket is the interface between the warehouse and the line, where short-term inventory is held and replenishment signals are collected. Since JIT necessitates minimal stock levels, the supermarket has become an integral piece of buffering the transitions between transport cycles and material consumption. Supermarket design, unlike the physical layout, has direct implications for operational decisions such as which items will be retained in this area, how minimum and maximum levels will be determined, how the replenishment triggers will work, and how they will connect to the transportation system. Replenishing supermarkets too early can cause stock accumulation at the edge of the line, while replenishing too late can stimulate chain reactions that lead to line stoppages. JIT requires a delicate balance between these two extremes.

Supermarket design also influences the organization of the supply policy. In boxed supply systems, when small boxes are regularly replenished, the supermarket's load increases, whilst in preparation-based systems such as kitting or sequencing, the supermarket acts more as a staging facility. The manner in which the transport route starts at the supermarket and loops back implies that the return logistics are also determined by such structure. Thus, the supermarket is not merely an intermediate storage space but indeed the core control point affecting the entire behavior of a supply strategy.

4.3. Preparation Processes (Kitting, Sequencing and Repackaging)

Preparation is one of the most sensitive areas for affecting a supply strategy on the production line. This includes activities such as kitting, sequencing, or repackaging where parts are delivered to the assembly line for an operator who can use them. The primary objective of these methods is to eliminate complexity caused by more than one variant or part at the edge of the line; reduce operator search and walk-throughs; and assure that parts are prepared in line with the consumption flow.

The setup process always implies a logistical cost if implemented, but these costs must be adjusted considering the flexibility, accuracy, and time savings that it offers on the production line. As an example, in a fixed kitting approach, kit preparation for each product requires more manpower per kit, while optimizing the availability of the relevant kit at the line's edge to significantly alleviate the operator's workload. Sequencing is one of the most useful approaches for handling variant complexity, yet sequencing errors can interrupt production sequencing and incur much higher operational costs. Therefore, setup processes are critical processes determining the technical accuracy and timing precision of line feed strategies; even the slightest error in setup can have far greater consequences on the production line.

4.4. Transport System and Transport Rhythm

The conveying system is the step that takes materials from the supermarket or prep to the line edge and is the most critical component of the supply policy rhythm. In terms of JIT production, conveying is much more than just movement of a solid or a part—the rhythm of conveying has a strong impact on overall cycle time, stock replenishment timing, and inventory control. Hence, conveying system stability for long time-frame influences the stability for JIT manufacturing. There are different alternatives among the transportation methods as given below.

- ***Forklift-based handling:*** appropriate for high volume or heavy components, but introduces variance for JIT.
- ***Tugger train:*** A tractor-wagon system that feeds multiple stations rhythmically. It is compatible with the milk-run principle.
- ***AGV /AMR systems:*** Transport timing can be fixed using less human intervention.
- ***Milk-run cycles:*** A Fixed Period: Fixed Route Transport mode. It is the most reliable method of JIT transport.

Forklift-based handling is appropriate for large volumes of material, but poses potential risk to JIT because of significant time variance. The fixed-route and periodic structure of a train system ensures routine and standardization in transportation and serves as the foundation of the milk-run approach. Milk-run cycles have a scheduled sequence and duration that ensures each station is supplied on an ongoing, defined, and predictable basis. This cyclical configuration allows JIT to maintain inventory at a minimal level. AGV or AMR systems can operate in environments that are highly automated, which can simplify transportation operations, but the constraints in these systems (e.g., capacity, speed, and road access) should be properly managed. That is, if there is a little delay in conveying the system, it can cause a buildup in the kitting area or a missing part at the line edge. Accordingly, the conveying system and preparatory work should be compatible, the conveying period should coincide with the replenishment cues and the conveying capacity should be determined through the line complexity.

4.5. Behavior of Parts at the Point of Use (Assembly – Walking – Picking)

It is only at the point that the operator consumes the parts that we begin to see some of the consequences of the line feeding process. The operator's access time to the part, time to search and select, walking distance, and the ergonomics of the layout are directly associated with the chosen feeding strategy and are required to perform the assembly work. When the production line cycle times decrease, both physical and cognitive demand on the operator will also increase. As such, a fundamental objective for line-feeding strategies is to position the material in the right place at the optimal access point, decreasing the need for additional operator input. Line stocking makes the process simple and immediate, but will be detrimental to JIT's cycle-time accuracy by increasing the search time for several items that can be highly variable. On the contrary, kitting and sequencing algorithms reduce cognitive load as they deliver to the operator limited access to materials relevant to his/her own product. But in these techniques, if there is a setup issue, the operator will not have an opportunity to intervene in the system; interruptions in the system can result in a direct line stoppage. So, the real measure of supply strategy validity is point-of-use behavior.

4.6. Return of Empty Packaging and Containers

Empty container recovery is an often-overlooked, yet vital component of the line supply process that manages the flow of Kanban signals back. In a JIT system, feedback occurs at each replenishment movement when consumption is reported. This feedback could be delivered by the return of a physical Kanban card or by a digital signal. Delaying the return of empty containers postpones this signal, causing a chain reaction that interrupts the replenishment process. The return of empty containers has a significant effect on transportation system capacity. A milk-run train carrying a large number of empty containers may not have enough space for the full ones, thereby disrupting the transportation rhythm. Hence, return logistics should be prepared based on the transport period and the transportation vehicle's capacity. Otherwise, inventory levels will become unstable, replenishment cycles will be extended, and the JIT system's flow control will be weakened.

5. Factors Affecting Line Feeding Policy Selection

There is no single criterion that can describe the selection of a line feeding strategy, as many factors need to be analyzed at the same time, such as the physical constraints of the production line, the composition of the product mix, carrying capacity, labor profile, inventory policies, and cost structure. All these conditions affect the operational performance of each of the feeding policies. Thus, only after a well-rounded examination of the assembly system can the right strategy be selected. This section systematically examines the key factors that play a role in determining line feeding policies.

5.1. Supermarket Structure and Layout

In fact, the supermarket is the middleman of the logistics system between the warehouse and assembly line, not only a buffer for inventory but also, physically and operationally, a building block that informs the technical feasibility of the replenishment approach. Key characteristics such as the distance the supermarket is from the line, how transport vehicles can reach this zone, and whether the replenishment logic is pull-based or time-based determine the success of the replenishment policy. For example, in a preparation-based method (e.g., kitting and sequencing), the supermarket is nested within the preparation area, where the availability of the ingredient is only effective if the area has enough capacity. In methods such as stocking or boxed-supply, the supermarket acts as a classic intermediate warehouse, trying to balance the stock level.

Supermarket design is not only limited in space, but also in the way of flow. Improper placement of the supermarket creates pressure on the line itself, hindering flow on the line and stretching the tour times for the tugger trains, causing a disturbance in the milk run. So supermarket layout is a design decision which may need to involve mathematical modeling as appropriate to the replenishment frequency and transport route within the supply system to be compatible with the supply system.

5.2. Preparation Method (Manual / Automatic)

The preparation method determines both the labor load and the timing accuracy of the feeding policy. For processes like kitting, sequencing, or repacking, these can be performed manually or with advanced automated preparation stations. Manual preparation is more flexible, yet high variant complexity can lead to human error. Automated preparation systems, however, increase accuracy and are expensive, thus making them an economical option only for lines with high volumes and consistent product flow.

The choice of preparation method impacts not only the on-line operator but also the workload of the internal logistics workforce. Manual preparation can enhance the advantages offered by methods like kitting or sequencing; however, system backlogs can occur when the capacity of preparation stations is not compatible with milk-run periods. Thus, the preparation method is a direct determinant of the JIT performance of a feeding strategy.

5.3. Transportation System Capacity and Routing Constraints

The transportation system structure and capacity may be considered as one of the main technical constraints to decide whether a chosen feeding policy is feasible. In milk-run systems, direct factors such as the length of the transportation route, the number of stations, vehicle capacity, speed limits, and routing constraints all determine transportation time. Thus the transportation system, if not able to follow the feeding rhythm, cannot carry out time-critical policies like kitting or sequencing. Particularly the technical supply policy of tugger trains or AGV-based systems depends on characteristics such as the number of stations vehicles can supply in a trip, how to balance empty container collection with full container distribution, and the variable period lengths determining the technical limit of the supply policy. For this reason, a limited capacity tugger train may not provide enough volume to carry large kits, yet very efficient small totes can be provided. As a result, if the matching between carrying capacity and feeding method is not correct, the JIT flow becomes irregular and the line feeding system becomes a bottleneck.

5.4. Border of Line (BoL) Area Restrictions

The lineside space is frequently the most important physical constraint within the JIT system. Although stocking and similar methods let many boxes or pallets be kept at the edge of the line, assembly lines with more and more variety quickly become short of that space. One common reason preparation-based methods (kitting, sequencing, etc.) are widely used is that these methods require less BoL space and allow for only a minimum number of items to stay on the edge.

However, BoL constraints have implications that extend beyond the operator's physical environment and the operating mode of the layout to the movement of the operator. Overcrowding the space increases walking distance to the assembly site and compromises assembly ergonomics but negatively affects the cycle times. So BoL constraints are also directly related to feeding strategies in the choosing strategy. Insufficient space can lead to line stoppages. While it can stop basic methods like stocking, it tends to introduce an unnecessary cost burden for methods that must be prepared with large areas.

5.5. Operator Walking Distances and Ergonomics

As assembly is human-based, ergonomics and operator walking distances play an important role in determining the feeding strategy outcome. Cycle time can thus be determined by the distance an operator must travel to access a part, the time it takes to search for a part, and the cognitive load they experience during assembly. Feeding strategies have different effects in this regard: in line stocking, the operator is presented with a large number of parts in a large area, which increases the search load. In boxed supply methods, search distance decreases, but some variety is still present. With techniques including kitting and sequencing, the operator is presented with only components of the relevant product, therefore eliminating the need for walking and searching altogether. Ergonomics is an important factor in comprehending the effect of the selected supply strategy on the production line.

5.6. Product Mix, Number of Variants and Model Diversity

And product mix and variant structure are two of the strongest drivers for decision on feeding strategy. In low-variety lines, stocking or boxed supply techniques are economically and operationally feasible. And the need to reduce search overhead, minimize risk of error, and control operator cognitive load make kitting or sequencing strategies critical in the high variation assembly lines where such operations are performed. Variant structure can affect not only the way the process and process of preparation is performed, it also has a greater accuracy requirement than the other methods. The use of sequencing has emerged as an essential tool for variant management, especially in automotive assembly lines where orders for products change frequently. On the contrary, fixed kitting provides a better and more effective option in low-volume, high-variety production lines.

5.7. Investment and Operating Costs

All feeding strategies require a certain amount of investment and operating costs. This implies that the preparation-based techniques like the kitting/sequencing methodology are more labor-intensive compared with line stocking, which is least preparation-costwise. But line stocking can increase costs gradually from higher lineside space consumption, operator walking costs and potential for errors. By contrast, although kitting at the time of implementation involves greater labour, over time the overall cost due to lower quality defects and assembly times may minimize it. Automated prep stations bring totally different costs vs. benefits, labor need is decreased, but due to the high investment cost, such systems have cost savings only in high-volume production lines. Investment costs thus represent a holistic aspect that must also be considered in feeding strategy life span and not at beginning.

6. Effects of Line Feeding Policies on JIT Performance

Strategies applied for line feeding have a decisive influence on the key performance indicators of the JIT production system. The presentation of parts at the edge of the line, operator workload, inventory levels, transportation cadence, error probability, and system flexibility all vary significantly depending on which feeding strategy is adopted. The low inventory, high flow stability, short cycle times, and minimal waste goals of JIT can only be supported by the right feeding strategy. In this section, we assess the influence of feeding policies on JIT performance across eight key performance dimensions.

6.1. Lineside Area Use

Lineside space utilization serves as an indicator of the extent to which the feeding strategy alters the physical layout of the line. Stocking takes huge amounts of space as materials are brought right to the edge of the line in boxes, pallets, or large packages. Not only that but this severely limits operator mobility and also produces traffic congestion along the line. Boxed supply can utilize space to a limited extent by minimizing packaging units, although the number of small boxes is a pressure on space and can increase in high-volume settings.

In contrast, preparation-based approaches such as kitting and sequencing reduce space usage dramatically, because only the material for those products is at the edge of the line. One example is the stationary kitting way where kits are presented one to several kits at each station from its minimalist material layout on the line. Kits in the mobile kitting method flow along with the product, thus freeing up BoL space rapidly to allow JIT flow in order. So the preparation methods increase the space utilization significantly with added variants.

6.2. Stock Level and Work in Process (WIP) Control

One of the principles of JIT is to avoid unnecessary inventory in the system. Consequently, the extent to which the supply strategy affects the stock levels is very important. Line stocking also maintains high inventories, as when large packaging units reach the line and material can get accumulated at the edge of the line until it is consumed. Boxed supply only tempers this impact, but inventory fluctuation is inevitable, even at high-utilization lines. Kitting and sequencing are the two optimal ways to reduce inventory levels, as there is nothing being kept at the edge of the line as all parts of the relevant product are contained in each kit. Using sequencing for stock, inventory goes near zero as materials can appear at the line in the exact order they will be consumed. From a WIP viewpoint, the two techniques further demonstrate excellent JIT results; since there is no buffer stock at the edge of the line, flow proceeds more "pull." To achieve high inventory sensitivity of production lines, preparation-based methods are indicated to be the most suitable alternatives.

6.3. Operator Walking Distance and Workload

Feeding strategy directly affects the physical load on the operator, which is responsible for the behavior throughout the cycle time. In the stocking method, operators will be confronted with many parts spanning an area, leading to search time and walking distance. For example, operator burden becomes even heavier when lineside space is relatively limited as the operator is required to move many times along the line to achieve assembly work under time pressure. Although the boxed supply method alleviates some of this burden, the walking distance and search times are significant as the varieties increase.

Kitting and sequencing — the complete elimination of the operator walking and searching — has all the required parts delivered immediately to the kit or sequenced set. This not only preserves consistent cycle times, but it helps reduce the cognitive load on the operator. There are clear advantages of kitting and sequencing in both ergonomics and workload management, especially on complex assembly lines. Moving kit applications, however, enable the operator to pull directly the part from the kit which moves with the product, thereby allowing increased ergonomic tasks.

6.4. Error Risk and Quality Impact

Quality throughout the whole process in JIT is one of the more important objectives. Quality is heavily influenced by supply strategy, as supply strategy decides whether operators will fail to choose the best part. In high-variety configurations, line stocking is such that an operator is at an increased probability of picking the wrong part and mistakes occur, but in the context of the same type of high-variety application where the operator is under time pressure, if they are searching a packed box with several parts, the probability of error is considerably larger. Reduced from boxed supply, the risk of error is mitigated slightly but this risk remains when variety is high.

Stationary kitting reduces the chances of error, with no risk of an operator having to pick out the part from a product-specific kit. Sequencing makes the possibility of errors more minimized as a part is prepared in the correct order, and as well as having been prepared on the same item, the part is prepared as well for the relevant variant on its own, then it arrives in accordance to the production line. But small mistakes in the preparation phase can lead to a decrease in final quality performance of the entire line so that the risk is offloading from assembly to preparation. In mobile kitting systems, the risk of error is similarly limited, but the kit flow cannot be disrupted, and the kitting contents must be made available. Taking this into account, production lines with such high-quality tolerance usually like kitting or sequencing.

6.5. Flexibility and Adaptation to Product Variability

The more variety in the product, the greater the variants required, and this further demands flexibility in feeding strategy. Simple methods such as stocking work well for low variety orders, but they result in ineffective setup times and poor lineside management when product mix becomes more diverse. Boxed procurement offers limited flexibility but is a more limited solution than prep-based methods on lines with very high variant counts.

Kitting and sequencing are methods for dealing with high variability. Even in the case of lots of variations in product variants, fixed kitting can help prepare the contents of the kit effectively and access the correct part immediately. Sequencing is nearly vital, particularly with complex production lines like automotive, due to the fact that you are managing variants as well as sequential production simultaneously. Whereas for long-line application or multi-stage assembly, movable kitting offers more flexibility, facilitating variant changeovers. As the flexibility requirement rises, the performance of preparation-based methods improves drastically.

6.6. Transport Rhythm and Flow Stability

Cadence at the conveying system is among the most important elements of a supply policy on the performance of JIT. As line stocking often requires irregular, demand-led transport movements, there may be variations in the cadence. Boxed supply generates more regular replenishment cycles but is associated with more frequent small unit replenishment, which increases the load on the conveying system. With kitting and sequencing, the cadence can become much more predictable. As kits can be moved at regular intervals, milk-run cycles are more stable, so as to keep a constant lap time of tugger trains or AGVs, further contributing to the stability of the conveying system. The cadence of mobile kit applications can be parallel to the product flow, thus producing the most consistent structure for JIT flow stability. For this reason, cadence is crucial for a stable JIT environment, and the supply strategy should support, not detract from, this cadence.

6.7. Workforce Requirements and Organizational Burden

Different labor requirements per supply strategy. Line stocking requires less pre-stocking, so logistics labor can be less demanding, but it increases the load on the operator. Boxed supply increases the pre-stocking load, though still less intense than kitting. Kitting and sequencing require more labor in the pre-stocking process—these kits must be developed by dedicated teams, ensuring that sequencing is accurate and the contents checked. Although pre-stocking costs are high, by keeping cycle times consistent it increases throughput and lightens the load on the assembly line. Kit handling demands further coordination for mobile kit applications, but the operator's workload is kept to a minimum. Hence, the labor balance is a trade-off between in-line activities and off-line work; which one is more important will depend on the construction of the production line.

6.8. Impact on Total Cost

The impact of a feeding strategy depends on factors which influence costs more than just setup or handling: for example, quality, cycle time, error risk, and levels of stock; these are all multidimensional performance indicators and all impact total cost. Although stocking may seem to be the best initial choice, its ongoing cost increases with respect to lineside space, quality errors, and operator losses. Boxed supply does add setup cost, but it also deals with the supply process in a better way. Hence, although kitting and sequencing is more capital intensive and labor costly at first glance, in the long run these methods can drastically decrease total expenditure because of the risk of mistakes, the effect on operator efficiency, stabilisation in conveying rhythm, and low inventory. As a result, cost analysis should be life-cycle and not just short-term oriented. Likewise, even if the initial cost of movable kit applications may be higher initially, it can provide substantial savings in cost on long lines due to the increased stability of flow and ergonomic convenience in operation.

7. Approaches Used in Literature

Line feeding problems are not only operational application issues but also one of the most intensively researched optimization areas in the production logistics literature. Increasing product diversity, increasing complexity of assembly processes, accuracy requirements in preparation processes, and carrying capacity constraints have necessitated the use of analytical methods in selecting feeding strategies. Consequently, many studies in this field have been carried out on assessing and tuning the feeding policies using different techniques such as mathematical programming, heuristics, discrete event simulation, and machine learning. This section systematically examines these approaches, exploring their theoretical foundations and application areas.

7.1. Mathematical Models

Mathematical modeling is the most commonly used approach to optimize line feeding strategy. Linear or integer programming models are used to determine which parts policies are applied such as stocking, kitting and sequencing, how lineside space use will be balanced, how carrying capacity will be allocated and how the preparation processes will be structured.

Limère, Van Landeghem and De Backer (2012) developed one of the first formal MILP models that was used in specifying stocking strategies. This research investigates the kitting and line-side area constraints under variant diversity and line-side area restrictions. This pioneering study aims to evaluate the effects of stocking overall on costs. The model compares the labor load during kitting with the line and mathematically optimizes the balance between the space usage cost of stocking. Sali and Sahin (2016) propose three policies (line A more comprehensive MIP formulation was developed which took into account the choice between the two (stocking, kitting and sequencing) within the same model and analyzed the influence of item-based policy choice on the total production line workloads.

Caputo and Pelagagge (2011, 2015, 2018) represent the most advanced uses of mathematical modeling in the literature. These studies adopt multi-dimensional models that analyse specifically effects of selection methods, lineside space constraints, carrying capacity limitations, preparation area load, and product variant structure on optimization. Baller et al. (2020) propose an advanced MIP method that integrates into the model the carrying system capacity and optimizes the line feeding strategy and milk run periods jointly. One of the common features in these studies is that feeding strategy is considered an optimization problem wholly. As the problem grows increasingly complex, the models evolve into multi-level, highly stable, and often NP-hard structures, using heuristics, decomposition algorithms, and metaheuristic approaches.

7.2. Classical Methods and Decision Support Frameworks

Mathematical models provide a pretty accurate view but are not often adequate in practice. Consequently, simpler but guiding decision support frameworks have been developed in the literature. Caputo and Pelagagge (2011) suggested a decision matrix which takes into account the physical properties of the components, consumption rates, lineside space utilization, and setup requirements. This matrix determines which part is kitting and which part is line. It provides businesses with a practical method to determine whether to feed with stocking or sequencing.

Karadayı Usta (2017) presented an ABC approach to classify production parts, with similar consumption profiles that were grouped using clustering algorithms. This study made a contribution to the literature with its simple yet actionable solution, especially for lines with more complex component types. The biggest advantage of decision support approaches such as this is that it enables businesses to determine efficient feeding strategies without involving heavy reliance on statistical or mathematical models that require tons of data. But these methods lack deterministic nature; the process results are a result of expert opinions, or the matrix for prioritization.

7.3. Simulation-Based Approaches

Discrete-event simulation is one of the most powerful methods for evaluating the real-world operational impact of line feeding strategies on a production line. Simulation can capture the real-time behavior of a feeding policy by modeling fluctuations in the conveyor system, operator walking distance, variability in setup times, and cycle time fluctuations.

Faccio (2014) developed a comprehensive simulation model to evaluate the effect of different feeding strategies on flow stability in a production line. This study particularly focuses on the differences between stocking and kitting in terms of transport cadence, operator workload, and line balance, and obtained findings that reflect real system behavior. Another advantage of simulation-based studies is the ability to incorporate stochastic elements such as setup errors, transport delays, and station disruptions into the model. While mathematical models are limited in managing such uncertainties, simulation fills this gap. Today, many businesses utilize simulation-based decision support systems before determining their feeding strategy, testing the expected effects of methods such as kitting or sequencing in digital twin environments.

7.4. Machine Learning-Based Methods

Since the last few years, the growing number of data-driven methods in the literature has greatly increased the solution space for line feeding problems. Zangaro, Limère, and Sali (2021) proposed a CART-based decision tree model that predicts which feeding method to choose on a per-part basis. For the inputs of the model, part size, number of variants, consumption rate, lineside space constraints, and carrying capacity were used. This study remains one of the first practical applications of machine learning in selecting line feeding strategies. The main benefit of machine learning methods is their capacity to automatically learn intricate, nonlinear relationships and leverage large amounts of data to provide higher accuracy over time. With digitalization of data collection efforts in industrial sites, such approaches are likely to become routine.

7.5. Hybrid Models and Integrated Approaches

Hybrid approaches work as mixed systems using a mathematical model and simulation technology. In these approaches, the mathematical model is used as the first filter for the policy selection; a set of specific policy candidates are moved to a simulation setting where they validate real-world system behavior. Hybrid solutions are more consistent in applications such as production lines, where carrying capacity is limited, preparation processes vary, or product mixes change often. Some studies have used metaheuristic algorithms to complement MIP models that develop more comprehensive models optimizing transport routes while also determining kitting frequency and kit sizes. These approaches are generally utilized in extremely intricate automotive and white goods assembly lines.

8. Conclusion, Evaluation and Future Research Areas

This section provides the role of line-feeding strategies in JIT production environments, a comparison of policies, and a general evaluation of the results exhibited by methods in the literature. As we mentioned earlier in this paper, line feeding is not only the organization of material transport between the warehouse and the line flow, but also a very broad system design problem concerning production logistics, transport timing, operational stability, labor force balance, and inventory management. The implementation decision is also a multi-dimensional trade-off between product mix, the density of variants, lineside space, ergonomic attributes, preparation methods, and carrying capacity. It is, thus, in line with JIT principles not to think that line feeding is merely a logistics operation, but rather an integral production management decision.

Due to its simple structure and low setup cost, lineside stocking keeps its applicability to certain scenarios but becomes limited on high variety lines because of space constraints, walking distances, and the risk of errors. Although the boxed supply method is well-suited for balancing space utilization, it can add logistical burden on lines with extreme variety. On the other hand, kitting and sequencing minimize the cognitive and physical costs of operators by minimizing lineside space, making them very suitable in advanced mixed-model assembly lines. Traveling Kitting is a new methodology for providing flow stability in long lines. These evaluations indicate that there is no optimal approach of choosing a feeding policy and other systems differ and work better at certain conditions for feeding at different types of systems.

If we look at literature methods, mathematical modeling provides a powerful framework for the analytical assessment of policy selection. Models based on MIP/MILP can optimize many constraint parameters like the front edge area, the load in preparation, and capacity to carry items in a single model and are helpful to understand the decisions that were made among stocking, kitting, and sequencing. Simulation methods, being suitable for the assessment of the operability of the system, with stochastic components, generate output closer to the reality, making it easier to determine the impact of practical risks such as variant variation, transport delay, or preparation error. Other machine learning approaches provide a data-oriented orientation, which allows modeling complex relationships and predicting policies based on large amounts of data that is taken (largely) from the organization's actual operating data. This variety reveals that the problem of line feeding has become an interdisciplinary problem.

Under JIT evaluation, line feeding policy is an influential decision making variable that affect the stability factor of the production flow, inventory level, quality condition and price level. The above strategy is not only to improve operator efficiency, but also to increase periodicity of the conveying system, improve the layout of the linesides and allow for process standardization on the assembly line. In this sense, line feeding is not an outcome in the JIT system, but an input and a direct indicator of how sustainable the flow system becomes. This means the choice of policy should be more comprehensive and should follow long-term efficiency aims of the production system.

In conclusion, to address some of the future lines' research directions, trends in modern production in the transformation have shown new avenues for modern-day production to provide many new areas of focus for line feeding literature. In the first place, automation and robotic kitting technologies point toward the future that would eventually transition from manually prepared food preparation to self-service automation. This would help to improve both preparation accuracy as well as the dependency for manual labour which might aid in the scaling up of feeding systems. Second, machine learning-based policy recommendation systems have the potential to suggest dynamic policy to the business, through learning the characteristics of parts, the consumption rate, the variations rate, and the performance indicators for the lines. Third, such fully autonomous AGV/AMR-based conveying systems will facilitate real-time upgrading in milk run cycles along with instant optimisation in conveying-preparation synchrony. Moreover, digital twin applications will eventually mature into a framework that simulates line feeding strategies performance live; this framework then instantaneously investigates the effect of such policies. Digital models of this nature allow that testing of the different feeding policies across the production line can be performed without any risk and can enhance decision-making accuracy. Additionally, ergonomics-centred modalities -- such as sensor based monitoring of movements of operators and workload based data analysis -- will provide insights into the concrete physical and cognitive affect of feeding policies. Last but not least, with the upsurge of sustainability research about how line feeding policies affects carbon footprint, energy consumption, and packaging consumption, exploring such effects is becoming a new direction in the research.

Thus, in conjunction with JIT, the line supply system has made the role of line supply strategies in academia and industry have become more relevant and necessary. In the current manufacturing environment, where production channels of diverse products are required to be more flexible, in a world of increased product diversity, where systems of conveying are going into overdrive as well as toward automation, it is important to redesign the supply policy to meet today's supply demands, and future production models. This assessment made in this analysis shows that supply methods are not only operational actions, but also a point of the long-term competitive advantage of production systems, by providing a strategic view.

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Chapter 3

CURRENT OPTIMIZATION AND INDUSTRIAL ENGINEERING APPLICATIONS IN THE AVIATION INDUSTRY

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1. INTRODUCTION

The aviation industry — both large commercial jets and smaller aircraft — is under intense complexity, strict safety requirements, and financial squeeze. For this reason, optimization and industrial-engineering solutions have turned from add-ons into indispensable tactics. In the world of aircraft design, there are many manufacturers now working with better workflow design, line balancing and labour- and material-wise resources. Contemporary optimisation software and simulation techniques are enabling them to be effective in the management of complex assembly tasks and in the orchestration of complex interrelation of actions.

For the MRO world, it's about predictive maintenance, better spare-parts planning and more efficient scheduling of technicians to allow airplanes to be in flight without unnecessary costs. And airports have their own problems, from limited gates and overcrowded taxiways to tight turn-around times, and they've been using optimization more and more to orchestrate gate allocations, baggage operations and ground-support travel. These enhancements ease airport operations, and can cut down delays for airlines and passengers. There is also the advantage of airlines operating their flights using consolidated models, which tie the scheduling of flights, fleet assignments, matching of crews and air-traffic limitations.

When these decisions are made in a cooperative, rather than a stand-alone, manner, the airlines can provide a more reliable schedule, better utilize their planes and minimize a lot of the disruptions that normally have ripple effects over their networks. Each of these examples combined — from production to maintenance, airport logistics to flight scheduling — indicate that industrial engineering is less a peripheral detail than the heart and soul of keeping aviation systems running safely and efficiently. And as air travel continues to surge and environmental pressures become more prevalent, data-informed optimization will play an even greater role in

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helping the aviation industry continue to operate responsibly, reliably and, ultimately, sustainably.

2. OPTIMIZATION IN AIRCRAFT PRODUCTION

Aircraft manufacturing is complex in and of itself: it consists of a large number of subassemblies, a network of interdependent tasks, synchronized workflows, and stringent quality control. Aircraft production is in many cases performed on low-volume, labor-intensive and resource-constrained systems, often referred to as the final and sub-assembly lines of production, making such systems inherently different from mass-production lines, typical of automotive or consumer goods industries. The tools of industrial engineering (IE) — especially optimization methods — in such an environment could yield significant improvements enabling throughput improvements, work-in-process (WIP) reductions and resource utilization optimizations, all within safety and precedence constraints.

2.1 Line Balancing & Workflow Optimization:

Assembly line balancing and workflow optimization are some of the main contributions of IE in aircraft industry. The classical Assembly Line Balancing Problem (ALBP) is a well-studied problem in operations research; recent surveys suggest that on the actual lines and particularly with mixed or uncertain task times and resource limitations, operationally heterogeneous operators, sophisticated models beyond the simple deterministic one must be used (Sotskov, 2023)

In particular, studies have modified these models to be suitable for low-volume, large-job assembly lines in an aeronautical sector. For instance, in a mixed-model assembly environment—common in aircraft production—it has been studied whether it is feasible to develop time-indexed mixed-integer linear programming (MILP) formulations to flexibly delegate workers to work stations, and to schedule work accordingly in order to achieve a minimum cost in both manpower and inventory utilization within a determined airplane-sequence scenario (Biele and Mönch, 2018).

An integer-linear programming model was applied to the final-assembly line of an aircraft with the objective of balancing cycle times among workstations while minimizing total resource-investment costs by Bao et al. (2023). Another paper was specialized in subassembly (e.g., an aircraft flank), and to do so, a mathematical "fitness" function was built that synthesized prerequisites from task sequencing and resource constraints; a hybrid Genetic-Tabu heuristic was adopted to compute near-optimal task assignments under the constraints characteristic of aerospace subassembly (Yan et al., 2011).

More recently to literature, simulation-based work — which involves a blended discrete-event simulation coupled with optimization methods — has also been introduced, especially for engine assembly lines where multi-skilled operators and variable processing times are common.

hese mixed methodologies assist in uncovering bottlenecks, resource idle states, and workload differences that analytical models can overlook, especially when dealing with stochastic events.

Taken together, this framework demonstrates that line balancing and workflow optimization (when well-modeled in the context of precedence constraints, resource heterogeneity, and stochastic uncertainties) can lead to a considerable improvement in production efficiency, reduction of idle hours, and optimization of human and machinery resources in aircraft manufacturing scenarios.

2.2 Inventory and Supply Chain Optimization

In addition to balancing assembly processes, concepts from industrial engineering also pertain to the management of product inventory and the synchronization of the supply chain in aircraft factories. In assembly lines on a mixed model which means that different subassemblies or aircraft variants can be operated concurrently, procurement and production planning become closely interlocked. Optimizing the supply of costly aerospace parts (i.e., airframes, avionics, structural components) is extremely important: excessive inventory raises carrying and capital costs; stockouts or delays can stop entire production lines or incur costly rework.

In a study of the final assembly of airframes for a large aircraft OEM, a local order scheduling optimization model was created to assign orders to mixed-model lines. The model monetarized multiple objectives: procurement costs, order-spacing costs, workload deviation costs, and level-scheduling costs, providing an integrated view of production and procurement. Results showed cost savings compared to actual (non-optimized) planning (Buergin et al., 2018).

Although explicit research on just-in-time (JIT) or materials-requirements-planning (MRP) frameworks specific to aerospace supply chains is less common in public academic literature — perhaps the result of industrial data confidentiality — the mixed-model scheduling research reflects this finding, illustrating how IE-based optimization can align production demand with inventory inflows, reducing WIP and procurement costs while aligning parts availability with assembly requirements.

2.3 Resource Allocation and Layout Optimization

IE is also responsible for resource allocation and the optimization of production layout design. Assembly of aircraft typically involves labor-intensive specialized tooling, jigs, cranes, heavy equipment, and highly skilled labor. Optimizing the use of those resources — across workstations, shifts, and subassemblies — is key to reducing downtime and maximizing throughput. An optimization model that provided one approach for subassembly balancing when limited resources were given (that balanced both the precedence of work tasks and limited resources (e.g., tooling or handling equipment) using metaheuristic methods to assign work tasks in a manner that was sufficient to satisfy resource limits while achieving an acceptable throughput) (Yan et al., 2011).

Moreover, simulation (with integer programming) permits planners to consider "what-if" scenarios with engine assembly lines and other resource-constrained assembly environments: how to deploy multi-skilled operators, what is the trade-off between labor and machine resources, and how to respond to stochastic disturbances like equipment failures (Bao et al., 2023).

These techniques not only aid in designing optimized starting layouts but can also enable flexible reallocation when demand changes, more variants are introduced or resource availability fluctuates – thus improving the flexibility and resilience of the manufacturing system.

2.4 Industry Application: OEM Practices and Challenges

Peer-reviewed case studies are scarce (partly because much of the data and modeling work inside OEMs remains proprietary) but extensive research demonstrates that major aircraft manufacturers embed IE-based optimization into their processes. For example, in Boeing, the Applied Mathematics Group within Boeing Research & Technology is comprised of operations researchers who develop mathematical algorithms to inform process design, resource allocation, and cost reduction in aircraft manufacturing.

Similarly, academic literature that describes Airbus's final-assembly efforts (e.g., for the A320 family) shows how mixed-model scheduling and local order assignment models can result in cost savings when applied in production planning. However, it is not easy to translate academic optimization models to practical application in industry (Buergin et al., 2018).

The actual problems include uncertain task durations, operator heterogeneity, supply-chain variability, last-minute design changes, regulatory compliance demands, and the sheer scale and safety-critical nature of aircraft manufacturing. Hence, many OEMs may continue using their own proprietary and frequently heuristic, optimization routines — based on the principles of IE — instead of academic, "textbook" models. This reaffirms your earlier comment that publicly accessible, peer-reviewed case studies remain few.

3. MAINTENANCE, REPAIR & OVERHAUL (MRO) OPTIMIZATION

Maintenance, Repair, & Overhaul (MRO) domain is an essential part of the aviation industry that serves to maintain aircraft airworthiness, supports safety compliance, and has an important impact on cost-efficiency and operational readiness. Considering the high valuation of aircraft assets, together with the huge financial and reputational impact of unscheduled downtime, achieving proper MRO performance is of serious strategic significance. These various industrial engineering (IE) and operations research methods — such as those applied in scheduling, inventory control, maintenance planning, and workforce allocation — are increasingly used in modern MRO activities to facilitate reduced ground time, optimize resource utilization, and improve operational readiness. Here we give brief insights into three important optimization aspects of MRO operations and how research and applications have been advancing in each of them.

3.1. Preventive and Predictive Maintenance

One of the foundational concepts in modern MRO optimization is shifting from reactive maintenance toward preventive and predictive maintenance strategies. Traditional reactive maintenance often leads to unplanned downtime and inflated lifecycle costs. In contrast, preventive maintenance — scheduled regularly based on calendar time or usage thresholds — and predictive maintenance — driven by condition monitoring and data analysis — aim to perform maintenance only when needed, thereby improving reliability and minimizing unscheduled groundings (Jonge and Scarf, 2020).

More recently, along with the abundance of sensor data and associated analytics, predictive maintenance has come up a lot more. Condition-based monitoring and prognostics (e.g., Remaining Useful Life (RUL) estimates) can be incorporated into maintenance-planning frameworks: by predicting future failures, maintenance can be scheduled optimally, spare parts can be allocated in advance, and workload can be smoothed to avoid "maintenance bunching." For example, the use of a model integrated with PHM (Prognostics and Health Monitoring) data along with spare-parts availability was demonstrated to increase fleet availability while reducing life-cycle cost compared to non-optimized approaches (Rodrigues, 2013).

As one review of maintenance-optimization literature outlines, the objective functions in predictive and preventive maintenance frameworks often combine cost minimization (maintenance cost + repair cost + downtime cost) with availability maximization, and are solved via stochastic modeling, optimization, or machine-learning-based forecasting (Zhu et al.,2019).

Therefore, applying IE-based optimization for maintenance scheduling helps transform MRO from a reactive, risk- and cost-prone operation into a proactive, data-driven, reliability-centered process — essential for both safety and economic viability.

3.2. Spare Parts Inventory Management

Another domain that is crucial to optimize for MRO is spare-parts and logistics inventory management. Aircraft maintenance frequently requires a variety of high-cost, low-volume components. Maintaining spare-part inventories in MRO hubs or regional warehouses presents a trade-off: high inventory levels mean equipment readiness and rapid response (especially for AOG — Aircraft on Ground — events); excessive spare-part holding brings high holding costs, obsolescence risk, and capital lock-up.

To balance this trade-off, multi-echelon inventory optimization models, which consider central warehouses, regional depots, along with MRO facilities, are widely proposed. These models define optimal reorder points, reorder quantities, and safety stock levels to minimize combined inventory and shortage costs while achieving desired service levels (Ilgın and Tunalı, 2007).

For example, an example was applied recently in Türkiye to achieve a mixed-integer programming (MIP) model in optimizing spare-part inventory for narrow-body aircraft components. The model modeled 192 different parts and applied stochastic demand distributions, such as Poisson, to find the spare-part investments that were necessary to reach a target service level (e.g., 96 %). The MRO center was able to lower inventory costs while fulfilling service obligations (Ekin and Eroğlu, 2025).

Beyond classical inventory optimization, modern MRO operations also benefit from advances in logistics: in one recent study, a cyber-physical spare-parts intralogistics system (CPSPIS) was proposed, combining Internet-of-Things (IoT) technologies, real-time resource tracking, and unified system representation to synchronize parts availability, labor, and equipment. This approach supports rapid response for urgent maintenance (e.g., AOG) and efficient handling of scheduled overhauls (Chen et al., 2023).

So, optimization of spare parts inventory—especially when it is coupled with modern intralogistics and digital tracking systems—serves as a key factor to reduce ground time, ensure part availability, and lower holding costs.

3.3. Workforce Scheduling and Maintenance Resource Allocation

Aircraft maintenance is highly labor-intensive and often requires specialized skills, certified technicians, specialized tooling, and compliance with strict regulatory procedures. Hence, efficient workforce scheduling and resource allocation are crucial parts of MRO optimization to ensure that qualified personnel and equipment are assigned to the appropriate tasks at the appropriate time and location. A recent study utilizes IE and operations-research approaches like mixed-integer programming (MIP), constraint programming (CP), and hybrid heuristics/metaheuristics for scheduling maintenance tasks, technician assignments, hangar capacity planning, and multi-skill workforce allocation. An example of such an approach is in 2025, which suggested a resource-utilization and scheduling process for in-service aircraft maintenance based on multi-aircraft, multi-skill, and multi-shift scheduling with task precedence, technician-pool sharing, and capacity constraints. The proposed model showed reductions in aircraft turnaround time (ground time) by up to 30.68%, thus presenting great value in terms of resource efficiency along with improved aircraft availability (Chauhan et al., 2025).

There exists a fuzzy mixed-integer linear programming model for maintenance-workforce optimization in another study, which assigned maintenance work to technicians according to the focus of the task and the required experience level as well as the existing requirements based on the regulatory constraints and the configuration of shift patterns. When applied in a real MRO company in Türkiye, it helped prevent the overload of inexperienced technicians and improve the final throughput of maintenance (Hasancebi, 2023).

Also with hangar-based maintenance (especially for MRO-outsourcing type models), integrated planning models for hangar parking assignment, multi-skill technician assignment, and maintenance schedule development have been proposed, taking into consideration the geometric limitations, hangar capacity, and day-to-day operating conditions(Qin et al, 2020).

Some MRO optimization studies also incorporate workforce scheduling with spare-part logistics and maintenance planning, providing a holistic view of MRO operations rather than task scheduling or inventory management alone (Guraksin and Ozcan, 2023).

3.4. Benefits and Impact of MRO Optimization

IE-based optimization in MRO operations, if applied correctly, provides several concrete advantages to airlines, MRO providers, and aircraft operators:

- Lower ground time of the aircraft and quicker turnaround — scheduling and resource optimization can drastically reduce the duration of maintenance and allow for quicker return to service. As an example, the resource-scheduling model in the previous subsection achieved an improvement of 30.68% on turnaround time(Chauhan et al., 2025).
- Better fleet availability and reliability — predictive and condition-based maintenance planning help prevent unexpected failures, thereby reducing

unscheduled maintenance and improving dispatch reliability. papers.phmsociety.org

- Optimized inventory costs and spare-part availability — by balancing stock levels and service levels strategically, MRO centers avoid both shortages (which can cause delays) and excessive holding costs.
- Better workforce utilization and labor cost control — through optimized shift planning, skill-based task assignment, and better match between tasks and technician expertise, MRO operations can be more efficient and avoid over- or under-staffing.
- Enhanced responsiveness and flexibility — integrated optimization and logistics systems make it easier to respond to unexpected maintenance demand (AOG, unscheduled repairs) while balancing long-term maintenance cycles and resource constraints.
- These benefits, in aggregate, support safer operations, cost-efficiency, and improved asset utilization — all critical in a high-stakes environment such as aviation.

4. AIRPORT AND GROUND LOGISTICS OPTIMIZATION

Airports are complex logistical hubs, where the relationship between flights, infrastructure, ground support, and passenger traffic needs to be well-planned. This optimization of airport and ground operations can not only help minimize delays, facilitate the use of scarce resources (e.g., gates, ground-service vehicles, support equipment), but also greatly improve throughput and passenger satisfaction. This section summarizes two of the key subdomains related to optimization of ground logistics: the gate assignment problem; and the scheduling and allocation of ground vehicles and support equipment.

4.1. Gate Assignment Problem

The difficulty of assigning incoming and outgoing flights to available gates — known as the Airport Gate Assignment Problem (AGAP) — is a central problem in airport operations research. The challenge is to allocate a set of flights (with given arrival and departure times, aircraft types, and service requirements) to a set of gates (or, when gates are insufficient, to apron/remote stands), within constraints including but not limited to overlapping ground times, aircraft-to-gate compatibility, and facility limitations (Daş et al., 2020).

The goals of gate assignment models differ depending on stakeholder priorities: some have a passenger-focused objective — e.g., minimize total walking distance between the gates and baggage carousels or minimize connection times — while others have an airport/airline-focused objective — e.g., minimize the number of remote-stand assignments, taxi times, or optimize gate utilization (Cecen, 2020).

Since AGAP is often NP-hard, researchers have used a set of optimization methods, including MILP for precise models, metaheuristics (e.g., genetic algorithms, simulated annealing) for large instances, and hybrid "matheuristic" techniques, which use mathematical programming and heuristics (Karsu ve Solyalı, 2023).

Recently, a new MILP formulation was proposed to lexicographically minimize the number of aircraft assigned to aprons, and also minimize the total passenger walking distance, and in combination with a matheuristic, significantly outperformed several existing exact and heuristic approaches on benchmark instances. A different study applied multi-objective MILP — solved using simulated annealing — to balance passenger walking distance and aircraft taxi fuel consumption, and noted some notable changes (for example reducing walking distance by 22.8 %–46.9 % and fuel/taxi cost by 4.7 %–7.1 %, depending on objective weighting (Cecen, 2021).

More integrated approaches have been offered, beyond static gate assignment. One such study proposed a hybrid dynamic algorithm that handles gate assignments as well as taxiway/taxi-path allocation, recalibrating gates or taxi routes dynamically on the fly to avoid congestion and other delays and improves taxi times, ground delays, and gate utilization in real-time.

4.2. Ground Vehicle and Support Equipment Optimization

Apart from gate (or stand) allocation, modern airports are heavily using industrial-engineering and operations-research techniques to optimize scheduling and deployment of ground support vehicles (baggage tractors, push-back tugs, fuel trucks) and such. A huge number of work treats the ground-handling as a fleet-scheduling / vehicle-routing problem (VRP) with time-window and service-precedence constraints, and it can be solved through mixed-integer programming (MIP) or hybrid scheme. For example, one classic method suggested a mixed-integer linear programming approach to the scheduling of the dispatch of service-vehicles aimed at reducing both the delay in ground-handling and the service-provider fuel/travel costs (Kuhn and Loth, 2009).

More recent work applies a multi-objective integer programming approach to coordinate mixed-fleet vehicles (fuel and electric), thereby balancing both total travel distance and workload across vehicles, given heterogeneous equipment pools and dynamic airport demand (Fu et al., 2025).

Moreover, this concept of integrated optimization—in which stand/stand-assignment decisions are aligned with ground-vehicle scheduling—has produced identifiable gains: in case studies from busy airports, coordinated models have shown significant benefits over regular first-come-first-served dispatching: increased vehicle utilization efficiency (37.5%), ~20.4% reduction in total travel distance, and ~57.6% decrease in vehicle waiting times (Yao et al., 2024).

5. FLIGHT SCHEDULING AND NETWORK OPTIMIZATION

Coordinated flight scheduling and routing — including crew and aircraft assignment — is among the most complex and important optimization problems in the aviation sector. Given limited aircraft resources, crew, airport slots, and variable demand, airlines need to determine flight schedules and network plans that maximize utilization, minimize operational cost, satisfy regulatory constraints, and remain robust against disruptions. Below we discuss three of the main subfields: integrated optimization models, crew scheduling & pairing, and air-traffic flow / landing optimization.

5.1. Integrated Optimization Models

Historically, airline operational planning has considered subproblems, including flight scheduling, fleet assignment, aircraft routing, and crew scheduling, independently, leading to locally optimal and globally suboptimal solutions. Nevertheless, more recently, integrated optimization models are proposed to resolve multiple subproblems in parallel to capture their interactions with each other. For instance, a 2020 study introduces a model for multi-type aircraft scheduling and routing that dictates departure times in addition to scheduling trips using a fleet of heterogeneous aircraft. Another work shows that the integration of airline scheduling, fleet assignment, and aircraft routing with cruise-speed control to reflect fuel use and emissions demonstrates that integrated planning can in fact lead to a lower overall operating cost, even under realistic constraints that apply to maintenance and turnarounds. A recent work on flight-scheduling and fleet assignment used hub-and-spoke networks and explored these issues in a multi-objective approach (including cost reduction, utilization, and robustness). These integrated models can result in more efficient and robust flight networks than prior (traditional) sequential planning, in particular in scenarios of uncertainty and dynamic conditions of operation (Xu et al.,2024; Wei et al.,2020, Gürkan et al., 2016; Tacoglu et al., 2024)

5.2. Crew Scheduling & Pairing

An essential part of aviation operations is scheduling crew, which means ensuring that pilots, cabin crew, and staff are available for every flight as planned, within regulations (like rest times, qualifications), under budget and in the context of what they can do. Crew pairing (i.e., assigning sequences of flights to crew such that every flight is covered) is typically characterized as a set-partitioning/covering problem and solved by state-of-the-art combinatorial optimization methods such as column generation. With increase in size and complexity associated with airline networks (combination of crew bases, hub-and-spoke systems, thousands of flights), increasing efficiency is achieved by using better heuristics and hybrid approaches for scaling up the pairing optimization tasks. For example, in a new study a learning-based heuristic — namely using a variational graph auto-encoder — is applied to identify combinatorial dependencies in flight-connection graphs, thus speeding up the crew pairing adjustment on an extremely large scale (e.g., thousands) under legality and economic cost effectiveness. In addition to pairing, integrated scheduling frameworks also facilitate crew assignment with aircraft routing and fleet assignment which can help airlines to minimize dead-heading (crew repositioning), maximize utilization and deliver better crew and aircraft deployment. Because crew cost generally is the second-biggest expense for airlines after fuel, crew scheduling and pairing optimization — particularly where the airline is involved in an integrated system — is key to driving efficient operation and achieving a lower total cost for all (Xu et al.,2024; Aggarwal et al., 2020; Xu, 2024).

5.3. Air Traffic Flow & Landing Optimization

The current state of global air traffic, and the efficient management of airspace and runway usage are of utmost importance. Jet airlines and air traffic service companies need to optimize the takeoff, landing and en-route flow to minimize delays, congestion, fuel usage and ensure safety. Integrated Flight Scheduling and Network Optimization have a Place To Play in This Linked Function: By scheduling flights with reasonable 'latency', establishing correct flight routes and traffic control during flight, airlines can limit the impact of disruptions (weather delays, late arrivals). Additionally, recent developments are combining the use of operational research with predictive analytics to anticipate flight delays (e.g., machine learning to predict flight delays with high accuracy), thereby enabling planners to schedule and plan for disruption that may arise before they occur, with increased flexibility. By incorporating air-traffic flow constraints, runway capacity constraints and stochastic variability in flight-network optimization, state-of-the-art models provide more robust and efficient airline schedules – optimizing both on-time performance and fuel burn and emissions thereby ensuring efficiency at an airline and system levels (Arıkan et al., 2017; Zhong et al., 2025)

6. CONCLUSIONS

In aviation, where safety, costs, and complexities converge, optimization and industrial engineering techniques play a critical role. In aircraft manufacturing, more than simply balancing lines and distributing resources, new tools for optimizing the process with simulations streamline production. They enable manufacturers to orchestrate various stages of assembly — the assembly of aircraft, for example, the layout, distribution, management and final assembly or commissioning — much more accurately and reliably. In MRO operations, predictive maintenance methods, multi-level spare-parts planning, and smarter workforce scheduling minimize downtime, enhance overall reliability and reduce costs while controlling service and schedule-induced overages. That's the same logic at airports, with limited gates, packed ramps and busy terminals requiring meticulous thought. Optimization allows airports to get gates into the right places to avoid congestion, enhance the flows of luggage-handling, and the scheduling of ground-support vehicles as they go along, thereby keeping service times short and predictable. Airlines also greatly benefit from integrated planning models. If a company manages fleet assignment, crew pairings, route management and air traffic into one standard framework this yields much steadier schedules overall, better use of planes and fewer interruptions to operations. In all these areas–production, maintenance, airport logistics, schedule procedures–the examples prove that industrial engineering is not a means but the very essence of modern aviation. Growing global air travel demand combined with environmental pressure demands a kind of robust optimization from data that will not only meet environmental expectations but also become increasingly effective with modern analytics and big-data systems. Industrial engineering will be an important part of aviation safety, efficiency and sustainability.

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Chapter 4

MULTI-CRITERIA DECISION MAKING IN SUPPLY CHAIN MANAGEMENT: SUPPLIER SELECTION IN THE MACHINERY MANUFACTURING INDUSTRY

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1. INTRODUCTION

In today's increasingly competitive market, the sustainable success of businesses is indisputably directly linked to strategic supplier selection. Choosing the right supplier has become a critical function for businesses to achieve their strategies and objectives, ensure smooth process operation, and achieve competitive advantage through customer satisfaction. Choosing the right supplier is crucial for reducing costs, ensuring quality standards, ensuring on-time delivery, and increasing customer satisfaction (Kaya & Yet, 2019). Businesses that base short-term decisions on experience should prioritize leveraging technology, such as data collection and analysis, detailed research, and scientific methods, rather than intuitive methods, when making critical forward-looking decisions (Yalçıner, 2024).

In many industries, raw material and component costs constitute a large portion of the final product price (Coşkun et al., 2022). There are numerous factors to consider when selecting suppliers, and these factors interact. In this context, decision-makers need to use advanced multi-criteria decision-making (MCDM) methods to analyze these interactions.

MCDM methods are a subfield of operations research and management sciences and are the most widely used methods of decision theory and decision analysis. As the name suggests, they are a collection of analytical methods used to evaluate, rank, or classify alternatives based on multiple criteria. They can be classified as deterministic or stochastic based on the data type and as single or group decisions based on the number of decision makers (Yıldızatı, 2019).

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Supplier selection consists of four stages: defining the problem (target), determining the selection criteria, pre-eliminating suppliers that are not suitable for the purpose, and selecting among suitable suppliers (Coşkun et al., 2022).

In this section, the DEMATEL method, a multi-criteria decision-making (MCDM) technique, was used to analyze the cause-and-effect relationships among supplier selection criteria for a company operating in the machinery manufacturing sector. Then, criteria weights were determined, alternative suppliers were evaluated using the TOPSIS method, and the most suitable supplier was selected. A literature review examined supplier selection criteria discussed in various articles from past to present, and included preferred supplier selection criteria specific to the machinery sector. Six key criteria (unit cost, quality compliance, on-time delivery, technical support and service adequacy, communication and collaboration capabilities, and production flexibility) were analyzed based on expert opinions. The DEMATEL method allows decision makers to understand and prioritize the interactions between criteria, while the TOPSIS method ranks alternatives based on these criteria weights. The findings demonstrate that using scientific and systematic methods instead of intuitive approaches in the supplier selection process will improve decision quality and lead to more accurate decisions. This study aims to contribute to supplier selection decision-making processes in both academic and applied fields.

2. LITERATURE REVIEW

The supplier selection literature is a field that has been significantly enriched by multi-criteria decision-making techniques. Although methods such as the Analytic Hierarchy Process (AHP), TOPSIS, VIKOR, and ELECTRE are frequently preferred, these techniques generally ignore the interdependence among criteria. Whereas the DEMATEL method, when compared with other MCDM methods, yields a higher level of success in examining the complex relationships among factors in problems rather than classical methods such as AHP (Kabadayı and Dag, 2019). By considering cause–effect relationships, it offers a more dynamic analysis (Rodrigues et al., 2023).

Kabadayı and Dag (2019) divided the activities for improving dealer performance (KPIs) into causal and effect criteria using the DEMATEL method, and by combining it with the ELECTRE method, they identified the performance criteria that needed improvement. Polat et al. (2024) examined the factors affecting customer satisfaction and the changes in risk groups at different threshold values by using the DEMATEL, Fuzzy DEMATEL, and Grey DEMATEL methods. Buyukozkan and Cifci (2012) applied the DEMATEL method combined with fuzzy logic to the supplier selection process and demonstrated that this method produced stronger results compared to traditional methods. Similarly, Kumar et al. (2018) combined the DEMATEL and AHP methods in their study to develop a more robust decision model for supplier selection. Kaya and Yet (2019), on the other hand, conducted a more comprehensive evaluation by integrating the cause–effect relationships established using the DEMATEL method with Bayesian Networks.

Although the criteria used in supplier selection vary according to the sector and the company, the following criteria generally stand out: cost, quality, delivery performance, environmental sustainability, flexibility, and technological capability (Coşkun et al., 2022). Using the DEMATEL method, the relationships among these criteria can be determined, revealing which ones are more influential compared to the others.

The first scientific study on supplier selection was conducted by Dickson (1966), and this study also laid the foundations of the multi-criteria decision-making (MCDM) approach. In his study, he identified 23 selection criteria: quality, past performance, warranty terms, price, production facilities, operational controls, reliable delivery, communication capability, packaging ability, reputation and position in the industry, past data regarding employee–employer relations, willingness to collaborate, management and organization, customer service level, technical capability, repair service, location, volume of past work performed for us, contribution to training, financial statements, adherence to procedures, joint arrangements, and the impression it creates on us. According to the importance ranking based on the data collected by Dickson from 273 professional purchasing managers, the top three positions were, respectively, quality, delivery reliability, and past performance, while price did not make it into the top five criteria. This situation shows that criteria such as warranty and production facilities were ranked ahead of cost.

As a result of their study, Wind and Robinson (1968) suggested evaluating five criteria: bid price, product quality, delivery time, the supplier's reputation in the industry, and the supplier's communication and collaboration capability.

Cardozo and Cagley (1971) examined the criteria that industrial buyers considered in supplier selection, and the supplier selection criteria they identified based on buyers' preferences and risk perceptions were: price, delivery time and reliability, technical capability, and risk perception. In the study by Weber et al. (1991), the identified criteria were: quality, delivery time and reliability, price, production capacity, technical capability, management and organizational structure, geographic proximity, packaging and transportation capability, after-sales service and technical support, and attitude and willingness to collaborate.

Dada and Srikanth (1987) emphasized the criteria of quality, delivery time and reliability, price, production capacity, and technical capability in supplier selection.

Jacobson and Aaker (1987) emphasized the strategic role of product quality and identified the prominent criteria as product quality, price, delivery time, and the supplier's reputation in the industry.

Ronen and Trietsch (1988) suggested price, delivery time, quality, production capacity, and risk management criteria for large projects.

Chapman's (1989) article titled "Just – In – Time Supplier Inventory: An Empirical Implementation Model" examined the criteria to be considered in supplier selection within just-in-time production systems through an empirical model. The criteria he identified are as follows: delivery time and reliability, as the timely delivery of products is critical for JIT; production capacity, which must be sufficient to meet demand; and quality, which stands out as a criterion directly affecting the efficiency of the process, considering that products enter inventory immediately upon arrival.

Kannan and Jabbour (2014), in their study, identified four main criteria for green supplier selection for an electronics company in Brazil through an analysis using the Fuzzy TOPSIS method: top management's commitment to Green Supply Chain Management, product designs that provide material, component, or energy savings, compliance with legal environmental requirements and audit programs, and product designs that reduce the use of toxic or hazardous materials.

Kumar Kar, and Pani (2014) identified seven important criteria for supplier selection in the manufacturing sector in India. They defined these criteria using the Delphi method and subsequently analyzed them with Fuzzy AHP based on data obtained from 188 firms. According to their study, the seven criteria in order of importance were: product quality, delivery compliance, price, e-procurement capability, supplier reputation, technical capability, and communication and collaboration.

3. METHODOLOGY

In this study, the DEMATEL method, one of the MCDM approaches, was used to determine the cause–effect relationships among criteria for a machinery manufacturing company, and based on these criteria, the supplier selection problem was analyzed using the TOPSIS method. While TOPSIS presents the best alternative to decision-makers using positive and negative ideal solution methods, the DEMATEL method is a systematic technique that allows determining the interactions among criteria and the direction of these interactions.

It reveals the relationships among criteria, is used to eliminate criteria, and, since the input data are based on expert opinions, it has high practical applicability.

3.1 DEMATEL Method

The DEMATEL (Decision Making Trial and Evaluation Laboratory) method, developed between 1972 and 1976 at the Geneva Research Center, enabled the identification of interactions among factors by revealing complex and intertwined cause–effect relationships within a system (Gabus and Fontela, 1972; Ozturk et al., 2021). Another purpose of the method is to guide decision-makers by visualizing the structure of causal relationships (Fontela and Gabus, 1976). Thus, DEMATEL distinguishes itself from other MCDM methods and stands out as an effective tool, especially in complex systems (Buyukozkan & Cifci, 2012; Şahin et al., 2022).

The DEMATEL method is particularly preferred in decision problems where dependent criteria exist. This method contributes to understanding system dynamics due to its effective structure that visualizes cause–effect relationships. The application steps for the method are as follows:

1. Definition of the problem
2. Determination of the criteria: The N decision elements (E_1, E_2, …, E_N) are evaluated on a five-level pairwise comparison scale, similar to the approach discussed by Ozaydın and Karakul (2024). It is important to correctly distinguish between influencing and influenced factors; therefore, this evaluation should be conducted by experts in the field.
3. Establishment of the Direct-Relation Matrix: The relationships among criteria are determined by the expert team using a pairwise comparison scale. According to this scale, experts are expected to assign a score ranging from 0 to 4. These scores indicate the extent and intensity with which any given criterion impacts another criterion. If there is more than one expert evaluator, the arithmetic or geometric mean of the scores is taken. Subsequently, the average direct-relation matrix, or the average direct matrix (X), is obtained by placing the average values into the matrix.

$$x = (0 \dots x_{1n} x_{21}\ 0 x_{2n} \vdots \ddots \vdots x_{n1} \dots 0) \tag{1}$$

Table 1: Rating Scale Table for DEMATEL Method

Value	Description of ratings
0	No Impact
1	Very Low Impact
2	Moderate Impact
3	High Impact
4	Very High Impact

4. Normalization of the Direct-Relation Matrix: After establishing the direct-relation matrix, the largest value among the sums of rows and columns is determined, as shown in Equation (1).

$$S = \max \left(max \sum_{j=1}^{n} x_{ij} , \sum_{j=1}^{n} x_{ij} \right) \tag{2}$$

Subsequently, each element of the matrix is divided by the value s, thereby forming the normalized direct-relation matrix (D).

$$D = \frac{x}{s} \tag{3}$$

5. The matrix D is subtracted from the identity matrix (I), the inverse of the resulting matrix is taken, and then it is multiplied by the matrix D again.

$$D + D^2 + D^3 + \cdots D^H \tag{4.1}$$

$$F = D + D^2 + D^3 + \cdots D^H \ = D(1 - D)^{-1} \tag{4.2}$$

As a result, the total-relation matrix (F) is obtained.

6. Determination of Relationships Among Criteria: By calculating the row sums (R) and column sums (C) of the total-relation matrix (F), the groups of influencing and influenced factors are identified. Using the obtained values, a causal relationship diagram is created to better visualize and analyze the importance and impact of the criteria.
7. Establishment of the Network Structure: To obtain the network structure, the threshold value of the matrix is first determined. Criteria exceeding the threshold value are considered influencing criteria, and their impact is represented by the direction of arrows in the network structure. The direction of the arrow goes from the influencing criterion to the influenced criterion. The threshold value can also be determined with the help of experts. In cases where expert determination is not

possible, the threshold value can be set by taking the average of the total-relation matrix (F).

8. To determine the criteria weights, the square root of the sum of the squares of R+Cand R-Cis calculated.

$$w_{ia} = \sqrt{(R+C)^2 + (R-C)^2} \tag{5}$$

Subsequently, each weight is divided by the sum of all weights.

$$w_i = \frac{w_{ia}}{\sum_{i=1}^{n} w_{ia}} \tag{6}$$

Thus, the criteria weights are determined.

3.2 TOPSIS Method

TOPSIS, which allows for the selection of the best alternative among options, is one of the MCDM methods and was developed by Hwang and Yoon (1981). Due to its ease of use and understanding, it has found applications in many different sectors (Şahin and Bozkurt, 2021). The method determines the distances of decision points from the positive and negative ideal solutions and ranks the alternatives based on these distances. The positive ideal solution, represented as "1," denotes the point to be achieved, whereas the negative ideal solution, represented as "0," indicates the point to be avoided. In this context, decision points can only take values between zero and one. Its steps are similar to those of other multi-criteria decision-making methods (Uludag and Dogan, 2016).

1. First, the decision matrix is constructed.

$$B = [b_{ij}] \text{ (i = 1, 2, …, n)} \tag{7}$$

2. Formation of the normalized decision matrix (R) using the normalized values (r_{ij})

$$r_{ij} = \frac{b_{ij}}{\sqrt{\sum_{i=l}^{m} b_{ij}^2}} \; (i = 1, 2, \dots, m; j = 1, 2, \dots, n) \tag{8}$$

$$R = [r_{ij}] \; (i = 1, 2, \dots, m; j = 1, 2, \dots, n) \tag{9}$$

3. Construction of the weighted normalized decision matrix (v). Here, w_j represents the weight of the j^{th}criterion, and v_{ij}denotes the weighted normalized value of the i^{th}alternative with respect to the j^{th}criterion.

$$v_{ij} = w_j r_{ij} \tag{10}$$

$$\sum_{j=1}^{n} w_j = 1 \tag{11}$$

$$v = [v_{ij}] \text{ (i = 1, 2, … , m ; j = 1, 2, … , n)} \tag{12}$$

4. Determination of the Positive Ideal Solution (A^+) and the Negative Ideal Solution (A^-)

$$A^+ = V_1^+, V_2^+, V_3^+, \ldots, V_j^+ \ (j = 1, 2, \ldots, n) \tag{13}$$

$$A^- = V_1^-, V_2^-, V_3^-, \ldots, V_j^- \ (j = 1, 2, \ldots, n) \tag{14}$$

5. Calculation of the deviations from the Positive (S_j^+) and Negative Ideal Solutions (S_j^-)

(i = 1, 2, … , m ve j = 1, 2, … , n)

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2} \tag{15}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2} \tag{16}$$

6. Ranking the alternatives based on their closeness coefficients and identifying the best alternative Calculation of the TOPSIS score:

$$c_i = \frac{S_i^-}{S_i^+ + s_i^-} \tag{17}$$

4. Parts Supplier Selection in the Machinery Manufacturing Industry with DEMATEL and TOPSIS Methods

4.1 Problem Definition

A company operating in the machinery manufacturing sector is seeking a new supplier for a critical machine part to be used on its production line. This part is of critical importance for ensuring production continuity. The company considers multiple criteria when evaluating potential suppliers and aims to understand the interactions among these criteria. In this context, the DEMATEL method has been integrated into the decision-making process.

4.2 Identification of Criteria

Supplier selection criteria may vary depending on the industry, production strategies, product types, and the structure of the supply chain. Eighteen articles related to supplier selection criteria in the machinery manufacturing sector have been reviewed. Arunkumar et al. (2011) identified the criteria used in supplier selection at a textile machinery manufacturing company located in South India using the AHP method. Sungur (2015) analyzed the criteria used in supplier selection in the automotive and machinery manufacturing sectors. Sivaraman and Gunasekaran (2015) made a significant contribution to the literature with their study on challenges encountered and improvement strategies in supplier selection in the machinery manufacturing sector using AHP. Tiwari and Kumar (2015) investigated how optimized decisions can be made in supplier selection in the machinery manufacturing sector by using genetic algorithms. Zeng and Tam (2016) emphasized the role and importance of environmental sustainability and green procurement in supplier selection. Ravichandran and Rajendran (2016) examined the effects of multi-criteria evaluation methods in supplier selection in the machinery manufacturing sector. Chin and Lee (2016) included environmental sustainability and performance factors in supplier selection using the AHP method. Goswami and Srivastava (2016) conducted research on the factors considered in supplier selection using MCDM methods. Choi and Lee (2016) addressed the role of emotional and relational factors in supplier selection. Tee and Hwang (2017) examined the factors to be considered in strategic supplier selection. El Mokadem (2017) classified supplier selection criteria according to Lean and Agile production strategies. Zhang and Liu (2017) emphasized the importance of the supplier selection process and performance evaluation. Agarwal and Narain (2017) investigated the effectiveness of MCDM methods, while Lee and Kim (2018) examined the impact of the Fuzzy AHP methodology on supplier selection. Mendez and Bernard (2018) analyzed the role of advanced manufacturing systems in supplier selection. Chung and Lee (2019) evaluated the importance of innovation management in supplier selection. Sharma and Gupta (2019) focused on supplier performance improvement processes. Wang and Li (2019) worked on supplier performance analysis and the interrelation of criteria.

Based on the selection criteria in the literature, the criteria were determined under six headings as follows (Table 2).

Table 2: Criteria of the Decision Problem

#	Criteria
C1	Unit Cost
C2	Quality Standard Compliance
C3	Actual On-Time Delivery Rate
C4	Technical Support and Service Capability
C5	Communication and Collaboration Capability
C6	Production Flexibility

4.3 Evaluations of the Experts'

The criteria were evaluated in terms of the extent to which they influence each other based on interviews conducted with purchasing, planning, logistics, quality conrtol, and project managers. Based on the scores provided (ranging from 0 to 4), the weighted average of the direct-relation matrix was obtained as follows (Table 3).

Table 3: Average Direct Relationship Matrix

Average Direct Relation Matrix (X)							
Criteria	C1	C2	C3	C4	C5	C6	Sum of the row
C1	0	2	3	1	2	1	**9**
C2	1	0	2	2	1	1	7
C3	1	1	0	2	2	1	7
C4	0	1	2	0	2	2	7
C5	1	1	1	1	0	2	6
C6	1	2	2	2	2	0	**9**
Sum of the column	4	7	**10**	8	9	7	

According to Equation (2), the maximum value of the row and column sums is found to be S = 10.

4.4 DEMATEL Analysis

1. Normalized Matrix: It is obtained by normalizing the direct-relation matrix using the maximum value of the row sums, as per Equation (3). The Normalized Relation Matrix is seen in Table 4.

Table 4: Normalized Relation Matrix

Normalized Relation Matrix (D)						
Criteria	C1	C2	C3	C4	C5	C6
C1	0	0.2	0.3	0.1	0.2	0.1
C2	0.1	0	0.2	0.2	0.1	0.1
C3	0.1	0.1	0	0.2	0.2	0.1
C4	0	0.1	0.2	0	0.2	0.2
C5	0.1	0.1	0.1	0.1	0	0.2
C6	0.1	0.2	0.2	0.2	0.2	0

2. Total Relationship Matrix (F): Using Equations (4.1) and (4.2), the total-relation matrix F is obtained, respectively.

Table 5: Total Relationship Matrix

F= Total Relation Matrix							
Criteria	C1	C2	C3	C4	C5	C6	Sum of the row R
C1	0.2475	0.5475	0.7610	0.5531	0.6670	0.4996	3.2758
C2	0.2816	0.3041	0.5884	0.5415	0.4978	0.4253	2.6386
C3	0.2804	0.3932	0.4119	0.5318	0.5699	0.4289	2.6162
C4	0.2041	0.3932	0.5722	0.3715	0.5699	0.5052	2.6162
C5	0.2677	0.3733	0.4703	0.4257	0.3639	0.4690	2.3698
C6	0.3315	0.5475	0.6847	0.6294	0.6670	0.4157	3.2758
Sum of the column C	1.6127	2.5590	3.4885	3.0531	3.3355	2.7437	

3. Calculations of (R+C) and (R-C):

$$R_i = \sum_j t_{ij}$$

$$C_i = \sum_j t_{ij}$$

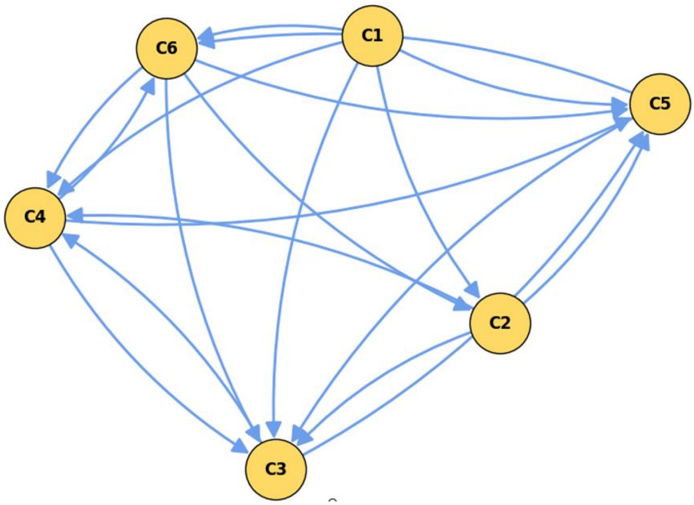
$$R_i + C_i = Interaction\ Level\ (Importance)$$

$$R_i - C_i = Causality\ Level\ (Positive: Cause, Negative: Effect)$$

Table 1: Determination of Criterion Weights and Priorities

Criterion	R (Influencing)	C (Influenced)	R+C	R-C	Criterion Weights (w)	Criterion Priorities
C1	3.2758	1.6127	4.8884	1.6631	0.1517	**7**
C2	2.6386	2.5590	5.1976	0.0796	0.1527	**6**
C3	2.6162	3.4885	6.1047	-0.8723	0.1811	**1**
C4	2.6162	3.0531	5.6693	-0.4368	0.1670	**4**
C5	2.3698	3.3355	5.7053	-0.9657	0.1700	**3**
C6	3.2758	2.7437	6.0195	0.5320	0.1775	**2**

4. Drawing of Directed Graph: As a result of the calculations in Table 6, the following graph was obtained



Graphic 1: DEMATEL Relationship Network: Arrow Direction from Influencing to Influenced

4.5 Findings and Discussions

Criterion 1 (Unit Cost)

R-C=1.663

A positive and high value indicates that it is a strong causal criterion, meaning that it influences many other criteria in the system while being less affected by them. The cost criterion acts as a trigger and a driver.

R+C=4.888 The interaction level is moderate, but its guiding role is strong. Criterion 1 is one of the key criteria that trigger the system dynamics.

Criterion 2 (Quality Standard Compliance)

R-C=0.080 Pozitive but very low value, near the threshold cause-effect

R+C=5.198 Its interaction is at reasonable level.

That is, it both influences and is influenced (acting as both cause and effect); its position in the system is balancing, making it a stabilizing criterion.

Criterion 3 (Actual On-Time Delivery Rate)

R-C=-0.872 Negative, indicating that it is an effect criterion. It is influenced by other criteria, showing that on-time delivery performance is affected by factors such as communication, quality, and flexibility.

R+C=6.105 It indicates that it has high importance in the system. Based on the combined assessment of both results, Criterion 3 appears to be the output of many factors in the system. For success, other criteria should be improved.

Criterion 4 (Technical Support and Service Capability)

R-C=-0.437 Negative, it is an effect criterion, shaped by the influence of other factors.

R+C=5.669 High importance indicates that it is a significant output of the system. It is a criterion that needs improvement, but it is an effect to be improved rather than a cause.

Criterion 5 (Communication and Collaboration Capability)

R-C=-0.996 It is a very strong effect criterion. It is clearly influenced by the rest of the system but has little impact on other factors.

R+C=5.705 High level of importance.

Criterion 6 (Production Flexibility)

R-C=0.532 Positive, meaning it is a cause criterion. It has a guiding role in the system.

R+C=6.019 It has the second-highest interaction strength. Production flexibility is a strategic decision in supplier selection and guides other decisions.

For comparison, it can be summarized in the table below:

Table 7: Analysis of the Roles and Importance Levels of the Criteria

Criterion	R – C	Role	R + C	Importance
Unit Cost	1.663	Stronge Cause	4.888	Moderate
Quality Standard Compliance	0.08	Balance	5.198	Moderate
Actual On-Time Delivery Rate	-0.872	Effect	6.105	High
Technical Support and Service Capability	-0.437	Effect	5.669	High
Communication and Collaboration Capability	-0.966	Strong Effect	5.705	High
Production Flexibility	0.532	Guiding Cause	6.019	High

These insights indicate which criteria the company should prioritize for improvement and how suppliers should be evaluated.

4.6 Ranking Alternative Suppliers Using the TOPSIS Method

1. Decision Matrix: The decision matrix is constructed according to Equation (7). Since C1 represents cost, it will be minimized, while the other criteria will be maximized.

Table 8: Decision Matrix

	Criteria					
Alternatives	C1	C2	C3	C4	C5	C6
A1	80	92	87	7	8	6
A2	100	85	90	5	7	9
A3	75	88	95	6	9	7

2. Normalized Decision Matrix: The decision matrix is normalized using Equations (8) and (9).

Table 9: Normalized Decision Matrix

	Criteria					
Alternatives	C1	C2	C3	C4	C5	C6
A1	0.5391	0.6010	0.5536	0.6674	0.5744	0.4657
A2	0.6738	0.5553	0.5727	0.4767	0.5026	0.6985
A3	0.5054	0.5749	0.6045	0.5721	0.6462	0.5433

3. The decision matrix is converted into a weighted normalized decision matrix using Equations (10), (11), and (12).

Table 10: Weighted Normalized Decision Matrix

	Criteria					
Alternatives	C1	C2	C3	C4	C5	C6
A1	0.0818	0.0918	0.1003	0.1115	0.0976	0.0827
A2	0.1022	0.0848	0.1037	0.0796	0.0854	0.1240
A3	0.0767	0.0878	0.1095	0.0955	0.1098	0.0964

4. Pozitive and Negative Ideal Solutions: For the positive ideal solution, the C1 criterion is minimized while the other criteria are maximized. For the negative ideal solution, C1 is also minimized and the others are maximized. Equations (13) and (14) are used for this purpose.

Table 11: Positive and Negative Ideal Solution Set

	Criteria					
Alternatives	C1	C2	C3	C4	C5	C6
A^+	0.0767	0.0918	0.1095	0.1115	0.1098	0.1240
A^-	0.1022	0.0848	0.1003	0.0796	0.0854	0.0827

Table 12: Distance From Positive and Negative Ideal Solution

Alternatives	Positive Distance Value S_i^+	Negative Distance Value S_i^-
A1	0.0444	0.0404
A2	0.0484	0.0415
A3	0.2368	0.0423

Table 13: TOPSIS Score and Rankings

Alternatives	S_i^+	S_i^-	C_i	Ranking
A1	0.0444	0.0404	0.4764	1
A2	0.0484	0.0415	0.4614	2
A3	0.2368	0.0423	0.0931	3

5. RESULTS

Within the scope of this study, the interactions among criteria used for part supplier selection in the machine manufacturing sector were analyzed using the DEMATEL method. The DEMATEL technique provided a numerical representation of cause-effect relationships and impact levels among decision criteria, offering decision-makers a strategic perspective.

Focus should be placed on the unit cost and production flexibility criteria, as improving these two criteria leads to overall system improvement. Result criteria, such as on-time delivery rate, technical support and service capability, and communication and collaboration ability, are influenced by other criteria, and their low performance stems from the weakness of the cause criteria. The quality criterion functions as a balancing factor within the system, establishing intermediate connections while also exhibiting outcome characteristics. In this context, DEMATEL proves to be a powerful analytical tool, allowing the differentiation between causes and effects.

The TOPSIS method, on the other hand, enabled the ranking of alternatives. In this study, the ideal solution approach indicated that Supplier A1 should be selected as the first priority, Supplier A2 as the second, and Supplier A3 as the last alternative.

One of the key contributions of this study is that it systematizes decision-makers' intuitive evaluations, enabling multi-criteria decision-making processes to be managed in a more transparent and objective manner. However, the reliance of the DEMATEL method on expert judgments implies that it is subject to subjectivity. Therefore, integrating approaches that reduce uncertainty is recommended for future research..

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Chapter 5

JOB SCHEDULING PROBLEMS IN INDUSTRIAL ENGINEERING

Ahmet CIHAN[1*]

1. INTRODUCTION

Job scheduling problems are encountered in a wide range of sectors, from the manufacturing sector to the software sector, from the logistics sector to the healthcare sector, from the communications sector to project management.

Mendez and Prata (2025) proposed a heuristic method to minimize setup times and make planning more efficient in a hybrid flow shop scheduling environment in the Brazilian electrical industry. They achieved a reduced delivery delay rate and improved the total weighted delay by 29.8% compared to manual planning. They also achieved significantly faster results compared to manual planning (Mendez & Prata, 2025).

Xu et al. (2025) addressed the three-machine flow shop scheduling problem by linearly modeling the fatigue effect of assembly line operators, established a mixed integer programming model of the problem, and designed an improved tabu search algorithm. They demonstrated the performance of their algorithm with the help of simulations (Xu et al., 2025).

Bahmani (2025) addressed the problem of a parallel flow shop with no waiting. He considered two separate objective functions in his study. He also required load balancing between the different shops. He proposed three different metaheuristic algorithms for the solution and compared the results with simulations. He stated that the particle swarm algorithm exhibited a high success rate in terms of its relevance to real-world applications (Bahmani, 2025).

In his study, Arık (2022) investigated the permutation-type flow scheduling problem using a genetic algorithm. He worked with Taillard benchmark datasets, which are quite common in the literature, and reported that his proposed genetic algorithm could solve problems with an average deviation of 2% to 10%. He also compared his proposed genetic algorithm with another study in the literature and showed that it achieved better results than the algorithm it compared to (Arık, 2022).

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Kaya and Fığlalı (2018) addressed the multi-objective flexible job shop scheduling problem in their study and gave the mathematical model of the problem, stating that the problem is in the NP-Hard class. The problem involves three different objectives to be minimized. They proposed a new algorithm that hybridizes local search with particle swarm optimization algorithms to obtain a Pareto solution (Kaya and Fığlalı, 2018).

In their study, Fığlalı et al. (2009) designed experiments using randomly generated problem samples of different sizes in order to optimize the parameters of the ant colony algorithm for the workshop scheduling problem and examined the parameter effects and interactions. They stated that using their proposed design would be a reliable method that would provide savings without compromising solution quality (Fığlalı et al., 2009).

In their study, Shahmaleki and Fığlalı (2021) addressed a scheduling problem that considered workload balance to improve the ergonomics of workers in the packaging department and proposed a heuristic method for its solution. They applied their proposed heuristic method to a real-world problem and achieved good results in a reasonable time (Shahmaleki and Fığlalı, 2021).

2. CLASSIFICATION OF SCHEDULING PROBLEMS

When classifying job scheduling problems, we can divide them into various categories according to the type of problem addressed, its goal, available resources, constraints, and the characteristics of jobs and machines..

Classification According to Number of Machines:

a) Single Machine Scheduling Problems

In this type of problem, there is a single resource (machine) and all jobs are scheduled on this machine. Problems involving a single machine on a production line or a single worker are considered in this class. While the goal is generally to minimize the total completion time (makespan) of jobs, criteria such as total delay time (tardiness), the total number of delayed jobs, or the total processing time are also considered in minimization problems.

b) Multiprocessor Scheduling Problems

In this type of problem, multiple resources (machines) are involved, and the tasks to be performed must be correctly allocated and sequenced across machines. In many cases, the characteristics of the tasks to be sequenced across machines are also essential in defining the problem. In production facilities, tasks performed simultaneously or sequentially across multiple machines are examples of problems in this class. The goal is to minimize the total completion time (makespan), total delay time (tardiness), and total number of delayed tasks, as well as factors such as balancing resource (machine) utilization.

Classification of Jobs Based on Sequencing Constraints:

a) Flow Shop Scheduling Problems

Problems in which all jobs are routed to machines in a specific order. In this type of problem, there is a fixed order between the stages for each job, and the jobs must adhere to this order. On a production line, each job must pass through the machines in a specific order. The goal is generally to minimize the total completion time for the jobs.

b) Job Shop Scheduling Problems

This type of problem involves processing all jobs in different orders across machines. This allows for flexibility across machines and the ability to change the order in which jobs are entered. The order of each job can vary for different machines, but each job must be produced through multiple stages. The goal is usually to minimize total processing time or idle time for machines.

c) Open Shop Scheduling

The order in which all jobs are performed is flexible, meaning that the stages of each job on each machine do not have to follow a specific sequence. It is possible for jobs to be produced on the same machine, so a flexible order is necessary. The goal is to use the machines efficiently.

Based on Job Timing and Dynamics:

a) Deterministic Scheduling Problems: The durations of all jobs and the parameters of the jobs and machines are clearly known and fixed in advance. There is no uncertainty in these types of problems. For example, parameters such as when incoming orders should be processed and when orders should be delivered, the processing time required for processing the job, as well as the number of machines, their speeds, and their costs per unit of time, are precisely determined in advance. The goal is to achieve the most appropriate scheduling with the given parameters. Criteria such as job completion time or minimizing job delays are often considered.

b) Stochastic Scheduling Problems

The durations of all jobs, the parameters of jobs and machines, are random in advance and are generally modeled based on probability distributions. For example, parameters such as when incoming orders will be processed, when orders should be delivered, the processing time required for job processing, and the cost of machines per unit of time can be expressed using probability distributions, but their value is not known with certainty in advance. For customer scheduling problems where the number of customers arriving is not precisely known in advance, or for situations such as disasters, a schedule can be generated using simulation models. The goal is to obtain a schedule that provides a certain level of confidence based on known probability distributions.

c) Dynamic Scheduling Problems

New information about jobs or resources may become available during scheduling or before the implementation of the established schedule is complete. Such problems require the planning process to update the existing schedule as new information is received. The need to update the existing schedule arises in cases such as sudden machine breakdowns on production lines, the addition of urgent new jobs, or changes to job priorities for customer satisfaction. In these situations, the schedule must be restructured in the most efficient way.

Based on Resource Constraints

a) Resource-Constrained Scheduling

Resources are limited, and each task requires specific resources to be completed. In such situations, the efficient use of resources is crucial. For example, in a production project, workers, machines, and materials are limited, so resources must be used as efficiently as possible. Utilizing available resources as effectively as possible and completing production on time is essential for customer satisfaction.

b) Time-Constrained Scheduling

Orders must be completed within a specific timeframe based on incoming requests. Time constraints can be determined by order deadlines. For example, in a cargo distribution business, a company must complete deliveries within a specific timeframe. The goal is to determine the distribution route to be used while adhering to these time constraints.

Optimization Objective

a) Minimizing Total Completion Time (Makespan Minimization)

The goal is to minimize the total time it takes to complete all tasks. This is often the goal in production and logistics distribution systems. For example, on a production line, minimizing the total completion time requires completing all tasks as quickly as possible.

b) Tardiness Minimization

This refers to minimizing delays so that work is completed within the specified timeframe. For example, a business that faces delays due to a malfunction may attempt to minimize the number of jobs delivered after the promised date to avoid inconveniencing its customers.

c) Flow Time Minimization

The goal is to minimize the time elapsed between the start of a job and its completion. This also means ensuring that machines are not idle. These types of problems are often encountered in the production and logistics sectors. For example, in factories, reducing the time products spend on the production line during production is considered a similar problem.

d) Load Balancing

The goal is to distribute resources or tasks as evenly as possible. This is typically done when one machine is underutilized while another is underutilized, or to ensure a balanced workforce among employees. For example, in a call center, each operator is expected to answer approximately the same number of calls.

Based on Real-World Applications

a) Production Scheduling

This problem involves scheduling production jobs in a specific order on resource-limited machines in a production environment. Scheduling jobs at various stages for vehicle production in an automotive factory is an example of production scheduling.

b) Project Scheduling

This is done to ensure that specific tasks are completed on time within limited resources in developed projects. In construction projects or software development projects, each task must be sequenced and completed with limited resources.

c) Logistics and Distribution Scheduling

This is a common problem in the logistics industry. It involves sequencing deliveries, transportation vehicles, loads, and delivery dates. A logistics company must distribute all deliveries as efficiently as possible.

3. ILLUSTRATION OF SCHEDULING PROBLEMS

When considering a scheduling problem, the triple $\alpha|\beta|\gamma$ is used as a notation to define the problem (Pinedo, 2016). This notation consists of three fields:

α field: Defines the machine environment. It provides information about the number of machines and how they are arranged.

β field: Defines job-related information, including job constraints and characteristics (interrupts, priorities, deadlines, etc.).

γ field: Defines the problem's evaluation criterion (optimization criterion - objective function).

α field	Machine Environment Description
1	Single machine problem
P_m	Identical parallel machines with the same speed
Q_m	Uniform parallel machines with different speeds

R_m	Unrelated parallel machines
F_m	Flow shop problem
J_m	Job shop problem
O_m	Open shop problem
FFc	Flexible flow shop problem
FJc	Flexible job shop problem

β field	Job Characteristics and Restrictions Description
$Prmp$	Jobs can be partially processed on machines
$Prec$	Job precedence constraints
r_j	Release dates / Ready times
d_j	Due dates
s_{jk}	Sequence dependent setup times
$Fmls$	Types of jobs are from different job families
$batch(b)$	Multiple jobs can be processed simultaneously
$brkdwn$	There are machine breakdowns
M_j	The machines that can process job j are specified
$Prmu$	Permutation flow shop (work order is the same on all machines)
$Block$	Jobs can block each other, usually due to stock space.
Nwt	Jobs cannot wait in intermediate stock areas
$Rcrc$	Jobs can be processed again on the same machines.

γ field	Objective Function Description
C_{max}	Makespan
$\sum w_j C_j$	Weighted total completion time
$w_j\left(1 - e^{(-rC_j)}\right)$	Reduced weighted total completion time
$\sum w_j T_j$	Weighted total tardiness
$\sum U_j$	Number of delayed jobs
L_{max}	Maksimum lateness
$\sum T_j$	Total tardiness

4. SOLUTION METHODS IN THE LITERATURE

While job scheduling problems are generally in the NP class, some specialized job scheduling problems are in the P class. One of the problems known to be in the P class and that can be solved is the two-machine permutation flow problem. This problem can be solved using the Johnson algorithm, developed by S.M. Johnson and named after its developer. The algorithm's steps are as follows (Johnson, 1954):

Johnson Algorithm:

The durations of all jobs are listed in columns.

The job with the shortest processing time in the list is found.

If the shortest processing time is on the first machine, the corresponding job is placed at the beginning of the schedule.

If the shortest processing time is on the second machine, the corresponding job is placed at the end of the schedule.

In the event of a tie, the job with the lowest index is considered first to ensure accuracy. In the event of a tie between two machines, the job is ranked according to the first machine.

The durations of the job are marked so that the same job is not reviewed again. These steps are repeated until no jobs remain in the list. This creates a job order from both extremes to the middle.

Although the Johnson algorithm works quite effectively on two-machine problems, two-machine permutation-type flow problems are not frequently encountered in real life. Therefore, a need arose for heuristic methods that can produce efficient solutions for more than two machines. A highly effective heuristic method, the NEH (Nawaz-Enscore-Ham) heuristic, was developed by Nawaz et al. (1983). The NEH heuristic is used to compare the performance of developed algorithms on problems in the literature. The steps of the NEH algorithm are given as follows (Nawaz et al., 1983):

NEH Algorithm:

The total processing times of all jobs on the machines are calculated.

The jobs are ranked in descending order according to their total value.

The two jobs with the largest totals are selected from the ranked jobs and removed from the list. The best order is determined by calculating two possible production times for these two jobs. In the following steps, the priority-recent relationship between these jobs will be maintained.

The job with the highest next-highest value is selected. This job is tested in all positions in the current order to create partial schedules. The job with the shortest processing time is selected from the partial schedules to determine its position relative to the existing jobs. The selected job is removed from the list. This step continues until no jobs remain on the list.

5. CONCLUSION

Effective work scheduling is the backbone of industrial productivity. In this regard, work scheduling problems are important optimization problems that find real-world applications and come in many different varieties. Using the $\alpha|\beta|\gamma$

notation, the complex constraints of modern production lines, from priority constraints to delivery dates, can be modeled.

It is known that the Johnson algorithm provides an elegant and exact solution for a two-machine flow shop and effectively determines the limit of polynomial solvability. However, when the problem is scaled to the typical m-machine environment of modern industry, it becomes NP-hard and renders exact methods unusable. This reality highlights the enduring value of the NEH heuristic method. The NEH algorithm prioritizes jobs based on total processing time, providing a robust mechanism for creating near-optimal schedules without the high computational costs associated with exhaustive search.

In conclusion, the examination of these classifications and algorithms bridges the gap between theoretical optimization and practical application. As production systems evolve toward more flexible and distributed models, the ability to correctly classify a problem and select the appropriate heuristic method (whether a deterministic method for simple cases or heuristic approaches like NEH for complex cases) remains a key determinant of operational efficiency.

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